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Seeing in the Dark
Real-Time Monitoring in Humanitarian Crises

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Daniel Maxwell, Erin Lentz, Kamau Wanjohi, Daniel Molla, Matthew Day, Peter Hailey, Christopher Newton, and Anna Colom

Tufts UNIVERSITY
FRIEDMAN SCHOOL OF NUTRITION SCIENCE AND POLICY
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Corresponding author: Daniel Maxwell
Corresponding author email: daniel.maxwell@tufts.edu

Author affiliations

Daniel Maxwell (Feinstein International Center, Tufts University),
Erin Lentz (LBJ School of Public Affairs, University of Texas),
Kamau Wanjohi (Integrated Food Security Phase Classification team, Food and Agriculture Organization-Yemen),
Daniel Molla (Food Security and Nutrition Analysis Unit for Somalia),
Matthew Day (REACH Initiative),
Peter Hailey (Center for Humanitarian Change),
Christopher Newton (Friedman School of Nutrition Science and Policy, Tufts University),
Anna Colom (Africa's Voices Foundation)

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Feinstein International Center, Friedman School of Nutrition Science and Policy
Tufts University
75 Kneeland Street, 8th Floor
Boston, MA 02111 USA
Tel: +1 617.627.3423
Twitter: @FeinsteinIntCen
fic.tufts.edu

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The Authors

Disclaimer

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Introduction

Humanitarian information systems typically provide analysis to predict crisis, assess needs, direct program resources, and assess short- to medium-term effects of programs. But much of this information is "chunky"—a single estimate of "needs," for example, can be expected to direct resources and programming for up to a full year (IASC 2020). A single early warning scenario might be expected to provide information about potential hazards and the exposure of population to the ill-effects of that hazard for three to four months. And almost by definition, early warning analyses are grounded in known and likely hazards, "population in need" (PIN) figures are based on the impacts of known shocks, and program resources are (or should be) allocated on the basis of known and projected PIN figures. There have long been questions about the timeliness of humanitarian information and especially about the extent to which information initiates appropriate and timely actions (Buchanan-Smith and Davies 1995; Bailey 2012; Lentz et al. 2020). And there have always been concerns that circumstances can change in shorter time periods than standard humanitarian analysis procedures can pick up, so interest in real-time monitoring (RTM) as a component of humanitarian information systems has increased for at least the past decade or so (FSNAU 2015).

But with the arrival of COVID-19 in 2020, an altogether different situation arose that dramatically increased the pressure for a different kind of monitoring. While the mainstay of humanitarian information systems has long been food security and nutrition information (especially the former), the COVID-19 pandemic has been first and foremost a public health crisis. Public health information systems exist, and indeed warnings of the possibility of something like COVID-19 have been around for some time. However, a variety of factors minimized the transmission of warnings in 2020 between public health information systems and humanitarian actors. First, food security and nutrition information systems had been focused on the usual drivers and outcomes; a pandemic was not in anyone's most-likely scenario. Second, the knock-on effects of the pandemic spread quickly to other sectors, particularly food security, livelihoods, and nutrition, but in ways that information systems weren't necessarily set up to track—with both supply- and demand-side impacts, some of which were novel and difficult to estimate. Third, and perhaps most critically, pandemic-control methods (particularly lock-downs and social distancing) prevented some of the standard information collection and analysis procedures—or at least made them much more difficult and costly.

System managers innovated quickly—physically-distanced information collection methods were developed or pre-existing initiatives expanded, remote analyses took place, and new factors were taken into consideration (FEWS NET 2020; IPC 2021). But methods that relied on close physical contact (such as anthropometric surveys) faced greater difficulties in adapting. The rapidly changing conditions made it clear that the time frames for standard humanitarian analysis could not keep up with the pace of change in the pandemic or its knock-on effects.

The impacts of the pandemic came on top of pre-existing confusion about some forms of humanitarian information and about what kinds of information were appropriate for what kinds of decisions and actions (Maxwell and Hailey 2020). Perhaps worst of all, the pandemic damaged the global economy significantly, leading to shrinking economic output in donor countries at a time when there were significant demands for domestic relief programs in those countries—all leading to shrinking budgets for humanitarian action at a time when needs were certainly expanding (WFP/FAO 2020; OCHA 2021). Already significantly challenged, information systems were being relied on to inform crucial decisions about resource allocation, leading to more demand than ever for precise, rapidly updated information on crises. The need for real-time information only increased as it became clear that, because of the global economic downtown resulting from the pandemic, the funding base was also going to shrink compared to rising needs.

Purpose of the Paper

There has probably never been a more urgent time to clarify the processes and outputs of information systems and ensure they provide a coherent picture to policy makers, donors, humanitarian actors, and local authorities. The paper reviews the objectives and purpose of RTM systems and recent advances in methods and analysis. It draws lessons learned from cases studies RTM systems—from 2020 and well before that. A previous paper (Lentz et al. 2020) addressed some of the questions facing humanitarian diagnostics generally. This paper addresses the specific question of real-time monitoring, drawing on recent experience, including several system adaptations proposed in response to the constraints of 2020. It briefly reviews some key learnings on real time-monitoring before the pandemic and the results of several initiatives undertaken quickly in 2020. RTM is not a stand-alone activity—the other purpose of the paper is to suggest how RTM information fits into the framework suggested by Lentz et al. that depicts the way different components of humanitarian diagnostics work (or should work).

The challenge is that while RTM systems can meet a range of objectives, not all RTMs are designed to do each objective equally well. This challenge is compounded by different stakeholders expecting RTM systems to accomplish them all at once, including the following:

- Collect, collate, and make available information in real time or near real time.
- Provide an analysis of the real-time impact of investment of resources in priority locations, populations, or activities.
- Feed into a common analysis framework that provides some analysis of real-time changes.
- Identify "hotspots" (i.e., geographic locations or populations experiencing rapidly deteriorating conditions) that had not been forecast or predicted to enable more in-depth assessment or rapid decision-making and action and to advocate for donor support.
- Link to periodic baseline updates such as Integrated Phase Classification or Cadre Harmonisé (IPC/CH) to fill in information gaps and update current status analysis in a language decision-makers understand and can act on.
- Provide real-time corrections to early warning and the assumptions on which projected numbers for populations in need (PIN) figures are based.

Role of RTM in Humanitarian Diagnostics

Lentz et al. (2020) laid out the basic components of a diagnostic humanitarian information system, which we review here to situate RTM among other components. RTM is not so much differentiated by objective of content as by frequency.

Early Warning

Early warning (EW) tracks hazards and assesses the risk of those hazards causing damage to people and their livelihoods—i.e., *causal factors*. Sometimes early warning produces a specific signal or trigger that sets in motion a specific response. More commonly, early warning produces a series of scenarios, with the "most likely" scenario serving as the basis for planning mitigation or response. A common example of the use of "most likely scenarios" in early warning is FEWS NET, and many national and localized EW systems also operate on this basis.

But good early warning forecasts also include possible scenarios that might not be "most likely," but still have a reasonable chance of occurring. A very severe outcome with only a small likelihood of occurring has to be taken seriously.

Current-Status Assessments

Current-status assessments report figures on the current condition of populations. A widely known example is the Integrated Food Security Phase Classification (IPC)—or Cadre Harmonisé (CH) in West Africa—that classifies populations into phases or severity categories and provides figure for the population in need (PIN). The food security data typically come from World Food Programme surveys, and nutrition data typically come from SMART surveys. IPC analyses typically take place only once or twice a year.

Definitions

For the purpose of this paper, terms are defined as follows:

A **prediction** is a definitive and specific statement about when and where an event will occur:

"Famine will occur in this location in June 2020."

A **forecast** is a probabilistic statement regarding the likelihood of future events:

"There is a 65% chance of famine in this location in the period June-August 2020."

A **scenario** is a possible future situation described in a hypothetical narrative in consideration of how key variables of interest may evolve over a given time period, often taken as a set of several possible situations of varying likelihood of occurring:

"The most likely scenario for this location in the period June-August, is famine."

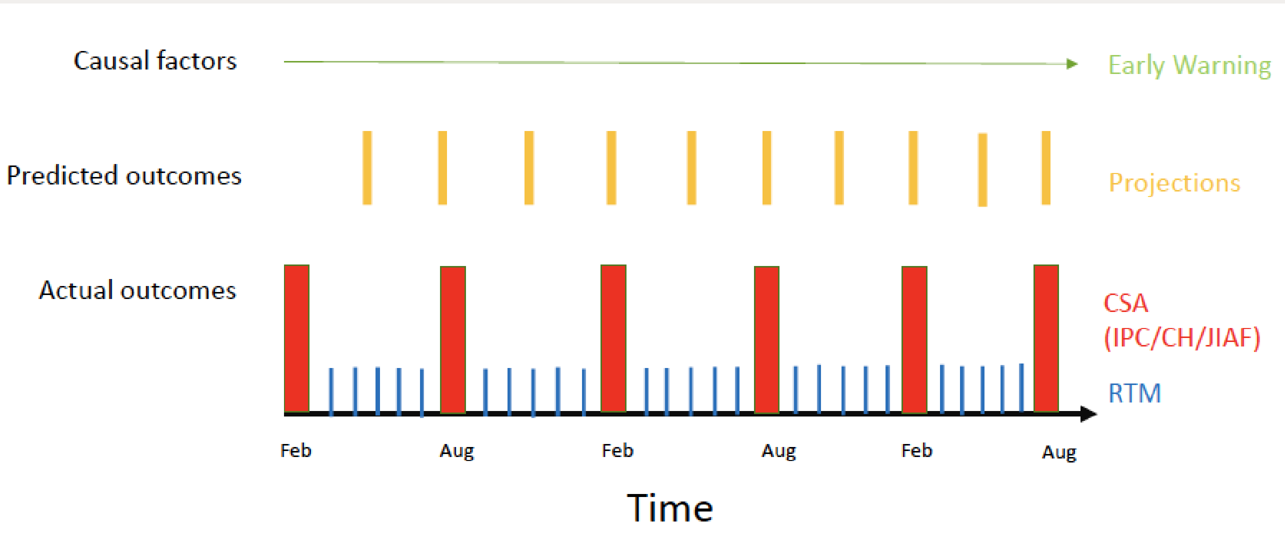
Projections

IPC also produces projections—a predicted figure for the population in need. Because the current status updates are infrequent, the projections have come to play an increasingly important role in humanitarian planning. The projected PIN is likely the single most important piece of actionable information that comes out of the entire system. But the PIN number is just an estimate, subject to errors. Given that a lot can change between IPC analyses, there are few efforts to monitor the assumptions on which PIN numbers are based.

Real-Time Monitoring

All of this gives rise to the need for more real-time monitoring. Figure 1 depicts these relationships. RTM can focus on overlapping types of information with other components of a diagnostic system, including causal factors (similar to EW) and outcomes (similar to current status assessment or CSA) as well as "hotspot" identification and the verification of the assumptions that drive projections.

Figure 1. Diagnostics: Relationships between EW, Projections, CSA, and Real-Time Monitoring



CSA	Current-Status Assessment
IPC	Integrated Food Security Phase Classification (standard for current-status assessment)
CH	Cadre Harmonisé (same protocol as IPC, used in West Africa)
JIAF	Joint Intersectoral Analysis Framework
RTM	Real-Time Monitoring

Source: Lentz et al. 2020

Objectives of RTM Systems

Observed RTM systems have a variety of objectives—and thus different operating procedures and outputs. Depending on the pace and scale of change in the context, RTM systems may have differing yet overlapping objectives with current status analysis or more conventional forms of early warning. Among the observed objectives of these systems, four are highlighted here:

Objective 1. Real-Time Outcome Monitoring

Real-time outcome monitoring allows for regular updates of outcomes (including specific indicators of food security, nutrition, mortality, WASH, and health). When done effectively, real-time outcome monitoring can provide decision-makers with sufficient information for "hotspot" identification, triggering either more in-depth assessment or rapid response. Other forms of outcome monitoring can track changes in knowledge, attitudes, and practices in response to novel shocks like COVID-19. Ideally, real-time information on current status operates as a feedback loop on how well programs are targeted and whether programs are meeting their objectives.

Objective 2. Real-Time Forecasting

Real-time forecasting includes tracking drivers or short-term early warning indicators (factors that may increase the magnitude or severity of the crisis) as well as mitigating factors (food assistance, nutrition and health programs, etc.). Under current circumstance, real-time forecasting may include elements of both outcome monitoring and tracking early warning indicators and well as noting unexpected changes in drivers (such as COVID-19). Real-time forecasting, as a standalone RTM objective, is less common. But when mixing predictive and current status indicators, careful analysis is required to disentangle them.

Objective 3. Real-Time Assumptions-Tracking

A third objective of the RTM system is tracking the assumptions on which forecasted outcomes or estimated PIN figures were based. Near-real-time data tracking can support the re-evaluation of the validity of assumptions used previously to generate forecasted outcomes and confirm whether the situation is developing in the manner forecasted.

Objective 4. Advocacy

Sometimes the ultimate objective of RTM is to highlight new needs or a rapidly changing situation in which there are no on-the-ground humanitarian programs, but in which the humanitarian situation (frequently driven by conflict) may be changing rapidly. The objective of advocacy may be for greater access or simply greater attention (and response).

Each objective can lead to rapid decision-making and action at local, national, or international levels.

Data Collection and Analysis in RTM Systems

RTM Data

Various data collection tools are used in RTM, many of which are standard in humanitarian information systems of all types. This section focuses on techniques that were particularly helpful in 2020. A more complete explanation of each is in Annex 9.

Remote Sensing

The availability of remotely sensed data has expanded rapidly. Remotely sensed data include data collected via satellite, primarily information on climate and weather, but all kinds of hazards are routinely monitored as leading indicators for humanitarian crises (Funk et al. 2019).

Social Media Monitoring and Crowdsourcing

Social media data on its own (Kryvasheyeu et al. 2016) or in combination with other forms of crowdsourced data (Jongman et al. 2015) can provide information on locations and types of disasters as well as responses.

Telephone Surveys

Telephone surveys have been used for some time, but COVID-19 dramatically increased their usage. Common phone surveys include computer-assisted telephone interviewing (CATI), interactive voice response (IVR) and short message service (SMS) surveys (Himelein et al. 2020a). While limiting contact between enumerators and respondents, using phone surveys brought its own challenges in 2020, including keeping call centers safe for enumerators and keeping productivity from dropping for enumerators working from home.

Community-Based Surveillance

Nutrition uses a wide variety of surveillance systems for RTM, including repeated anthropometric surveys, community health system monthly monitoring systems, and program data from nutrition and health clinics. A recent food-security RTM project drew enumerators from within the local communities prior to COVID-19, who, using additional safety protocols, were able to continue collecting monthly data (see Annex 5). Community-based enumerators are often part of a sentinel site approach (Headey and Barrett 2015).

RTM Analysis

Several forms of analysis are used with RTM, but many analysts tend to assume that "the data speaks for itself." A more detailed explanation of each is in Annex 9.

Dashboards

Dashboards compile and report outcomes and causal factors and present readily available, often dynamic data—but the use of the information to decision-makers is not always clear. Data checking and cleaning can also be slow, resulting in less that real-time updating. Only some RTM efforts are combined with expert analysis that synthesizes these and other factors to provide a holistic picture.

Nowcasting

Nowcasting relies on expert judgement and inference (in some cases, based on machine learning) to generate predictions of current status when it can't be measured directly, often using some combination of remotely sensed data, other secondary data, and primary data compared to historical trends. Other nowcasting efforts aim to predict outcomes for areas for which no data were collected. Forecasting is similar but forward looking and thus related to the objective of early warning.

Predictive Analytics and Machine Learning

Use of predictive analytics/machine learning. Predictive analytics or machine learning (PA/ML) can also be used to estimate current status (“nowcasting”) or prediction (“forecasting”). PA/ML can nowcast a (currently) uncollected outcome variable that is expensive and time consuming to collect, is unavailable in a certain location, or is infrequently collected and out of date by the time the data are processed. However, PA models of all sorts require historical data on which to “train” and “test” the model (McBride et al. under review). PA/ML models are only as good as the data they are trained on. Limited and infrequent outcome data and limited high-frequency data at district and sub-district levels hamper the development and validation of RTM models.

Key Issues and Questions Emerging

From the case studies in the annexes and the brief discussion above, a number of key issues and questions arise. These are mostly unresolved but are discussed here generically—they also need to be addressed in the specific context of existing and planned RTM systems.

What are the objectives of RTM and why are multiple objectives tricky?

Many existing RTM systems have a mix of objectives, and the end result is that they don't really fulfil any of their objectives very well. In many cases this is because RTM systems are trying to meet the needs of multiple stakeholders, each wanting something different from the system or even insisting on certain indicators being included. While not impossible to achieve different objectives (for example, hotspot identification and early warning of impending shocks), each objective likely requires its own subset of information and almost certainly requires its own analytical approach.

How does RTM information link to analysis?

An underlying assumption around improving RTM is that the "missing piece" is information. However, the lack of information may not be the primary constraint for at least two reasons. First, information without analysis or analysis based on an incomplete set of factors may be of limited value. Dashboards that present lots of indicators but are not paired with interpretative capacity (e.g., providing periodic written syntheses to accompany findings) can contribute to data confusion (Lentz et al. 2020). Second, donor allocations are often made far in advance of needs, with limited flexibility (barring unanticipated catastrophe) and limited appetite for revisions. The existing humanitarian system is not fully equipped to absorb genuine real-time data and analysis. Information may not be the constraint to action, and information systems may be more flexible than funding mechanisms or actual responses are. Without donor flexibility and strong analytical capacity, rapidly updated RTM information can contribute to data confusion rather than data clarity.

How does RTM/analysis link to action?

The issue of how well RTM informs the updating of preparedness, early action, and the rapid scale-up of humanitarian response remains an open question. This was an early complaint about the Somalia dashboard (Oxfam 2017), leading to some early changes in that system. This really depends on the linkages *external* to the RTM system itself, and ensuring that the RTM system is providing the kind of information needed, in the time frame needed, and to the constituencies that need it. In the case of 2020, this meant RTM systems had to be much more nimble—not only providing information in real time, but being prepared to adapt to changing demands for information on short notice as well. It may also mean that novel information or indicators may require additional explanation to decision-makers. And with increasing frequency, RTM also incorporates "triggers" that activate donor scale up and anticipatory financing.

How can assumption-tracking link to current status analysis and projections?

Humanitarians make assumptions about what will or will not happen, sometimes categorically and sometimes probabilistically. RTM enables assumptions to be frequently compared to reality and predictions to be adjusted. In 2020, it was clear that the drivers changed significantly almost overnight, and figures for projected populations in need were adjusted dramatically (OCHA 2020). However, for the most part, it is not clear that RTM systems informed these changes—indeed it isn't clear exactly what informed some of these changes in estimates. As noted above, this may inform whether the projected drivers of PIN numbers are correct, but it may also inform the way that humanitarian assistance is affecting the situation, including exclusion error. In this way, RTM should feed into subsequent current status analyses, such as IPC or Joint Intersectoral Analysis Framework (JIAF) and inform Humanitarian Needs Overviews.

What are the main constraints to RTM?

RTM is all about gathering, assembling, and analyzing information and making it available in as near to "real time" as possible. But the circumstances under which it is most needed (very dynamic, rapidly evolving crises—often conflict crises) are precisely those that make information gathering and analysis the most difficult. Governments or other parties to a conflict may deny permissions, security concerns may inhibit access, and managers may fear the consequences of making information public and refuse to share data or even self-censor—all of which undermine the objectives of RTM in the first place. RTM is not the only kind of information system that faces these challenges (Maxwell and Hailey 2020), but the very nature of the operating environment that requires real-time information and analysis is characterized by these challenges, giving rise to the emphasis on remote sensing, machine learning, and prediction. Even where the information exists, the level of trust among actors prevents data sharing and undermines real-time analysis.

What is the role of causal analysis in RTM?

Both of the linkage questions above (linking RTM information to analysis and linking information/analysis to action), the implication is clear that only rarely does "data speak for itself." Simply amalgamating data and making it available is frequently not adequate for either understanding what is happening or making predictions. A "mash-up" of information about both "drivers" and "outcome" indicators is frequently the output of an RTM system, which can be confusing if not analyzed separately. Not only is an analysis of the information required, the causal logic behind analyses should also be transparently presented. And crucially, for RTM to make sense in light of other sources of early warning information and especially large-scale but intermittent current status assessments such as the IPC or a Multi-Sector Needs Assessment (MSNA), a common analytical framework is critical.

Who are the users of RTM?

The information or the level of detail required for RTM systems and for synthetic reporting depends on the constituency or users. Donors often need comparative information that is consistent across countries and regions. National-level decision-makers need information disaggregated within countries about needs, while aid programmers and practitioners may need information on causal factors and outcomes. Presenting high-level graphics with details available as needed is one approach (e.g., FSNAU's dashboard—see Annex 1). Collaboration between information systems and users can help to fine-tune both the information and the presentation. RTM can also inform program managers and response analysis, depending on the content of the information.

Meeting the needs of diverse users often leads to one of the most frequent challenges for RTM:

geographic specificity. An RTM system may use the same unit of analysis as one audience—such as practitioners of IPC—while failing to provide information that is sufficiently granular for program staff to act on and that is sufficiently high-level for others to use for advocacy. RTM systems are often designed according to only one dimension of information needs (timeliness) while neglecting issues of geographic scale.

Where does RTM "fit" in an on-going humanitarian information system?

Up to the present, RTM has often been a "stand alone" activity or has been integrated into existing humanitarian information systems as an "add on." Existing information systems (such as IPC, for example) should consider how to incorporate RTM information. While the data categories may overlap, and the conceptual links may seem obvious, the actual operational links—and especially the ways in which RTM may update existing information system outputs—may be more complex.

Note that not all RTM outputs are depicted in "dashboard" format. The use of dashboards has become popular, and indeed many RTM systems use a dashboard format to display data. But not all RTM information can be displayed this way, and even when it can be, it frequently requires further analysis or interpretation to be practically useful.

How can "non-traditional" contextual information be incorporated into RTM systems?

Traditional approaches may use criteria such as distress migration, reports of hunger deaths, or the severity and magnitude of a recent shock. However, other methods are being put forward, such as local phrases to categorize the period concerning different extreme needs. An at-risk population doesn't always share the same view of the short-term future as formal information systems do, and incorporation of indigenous knowledge and practices can inform RTM and hotspot identification as much as commonly used indicators. How to synthesize (and report) these non-traditional streams of information—such as increased use of hunger courts in South Sudan (Newton et al. 2021) or reliance on social networks, alongside more "typical" data such as market prices or food consumption indicators, may require deep understanding of local context.

How can predictive analytics and machine learning be incorporated into RTM?

PA/ML present an new opportunity for RTM nowcasting. However, incorporating PA/ML into RTM requires not just paying attention to the models and their results. Careful attention must be paid to identifying how to incorporate PA/ML into existing RTM systems and how to link PA/ML findings to a decision-making framework for RTM. Forecast-based financing, which is forward looking, is one such approach. PA/ML models generate forecasts, which are tied to early action (i.e., release of funds if the model estimates a pre-defined threshold will be crossed). One possible approach to incorporating PA/ML into RTM is to use PA/ML to support event monitoring and assumption tracking. Rather than looking at "most likely" scenarios, PA/ML could simulate a series of possible scenarios that reflect changes in underlying EW assumptions. This would provide decision-makers with a greater understanding of the range of possible outcomes.

What RTM information is publicly accessible?

Dashboards often present a wide range of indicators but can never be comprehensive. Expert analysts often combine analysis of dashboard indicators with non-traditional findings or other information not included in the dashboard. Some information may only be collected to support analytical confidence and is not shared publicly (especially information on sensitive topics such as conflict). As a result, experts may come to different interpretations than someone who has access to the public facing dashboard information alone. Synthetic reporting can help aid in the interpretation of RTM indicators.

What are the limits of RTM?

By definition, real-time monitoring can only capture a limited amount of information. Collecting and processing too much information inevitably slows down the process, making it less than "real time." Different clients are likely to want different information streams, meaning that managers of RTM systems face real trade-offs in what data to gather (drivers? outcomes? both?), what analyses to prioritize (identifying hotspots? predicting short term trends? checking assumptions?) and even balancing RTM with other components of an overall information system.

Does RTM magnify some of the more general shortcomings of information systems?

In general, information systems are operated by UN agencies, donors, and governments. The role of national and local actors is not always clear. Likewise, humanitarian information systems rarely provide any degree of sex and age disaggregated data. Whether RTM addresses or exacerbates these more general concerns is an open question, and the answers depend on the exact nature of each system. There is no reason why these shortcomings cannot be addressed if that is an explicit objective.

What role does qualitative information play in RTM?

RTM does not need to be, and should not become, only an amalgamation of quantitative data and remote sensing. Methods should match information needs, not determine them. In reality, mixed methods approaches would likely address many of the recurring challenges faced by RTM.

Conclusions

The year 2020 shone a light on the challenges with current RTM and showed the value of RTM systems designed to meet a clearly defined set of objectives with consistent analysis. It also spurred or strengthened a number of innovative approaches to RTM and demonstrated that good real-time information gathering and analysis is possible, even in countries facing complex humanitarian crises, such as Yemen and South Sudan. RTM is adding value not only to the response to humanitarian crises but also to prevention and mitigation. The case studies included in the annexes show how an adaptive approach to RTM helped to make sense of, and improve the response to, the rapidly changing situation in 2020.

The annexes include the following case studies:

- Annex 1. Somalia: The FSNAU Early Warning-Early Action Dashboard
- Annex 2. South Sudan: The Integrated Needs Tracking
- Annex 3. Yemen: Tracking Assumptions in the IPC Food Security Projections
- Annex 4. Bottleneck Analysis: Using Real-Time Program Information for Needs Assessment
- Annex 5. Malawi: CRS' Rapid Feedback Monitoring System (2020–25)
- Annex 6. Somalia: Africa's Voices Foundation Crowdsourcing Community Perspectives
- Annex 7. REACH: Humanitarian Situation Monitoring in Insecure and Inaccessible Areas
- Annex 8. South Sudan: Qualitative Approaches to Monitoring and Forecasting Armed Conflict
- Annex 9. RTM Data Collection and Analysis

Several cases show how different RTM systems can support meeting the desired objectives, be it current status monitoring, hotspot identification, forecasting, or assumption tracking. Annex 1 reviews how Somalia's FSNAU combines a dashboard with analysis. Annex 2 describes how the Integrated Needs Tracking system in South Sudan can be used for hotspot identification. Annex 3 examines how assumptions were used to monitor the IPC food security classifications in Yemen. Note that each of these does incorporate a "dashboard" format to visualize the data. Annex 4 demonstrates the role of routinely collected program information in RTM, with an example of "bottleneck analysis" in nutrition and health programs. This data could potentially be included in a dashboard format, but to the best of the authors' knowledge, it has not been included in any so far.

Several cases highlight innovative approaches to collecting RTM information that have been successfully deployed. The Malawi Rapid Feedback Monitoring System (RFMS) case study (Annex 5) introduced safety protocols to allow its embedded local enumerators to transmit information on COVID-19 to respondents while collecting monthly data on shocks and food security. The Africa's Voices case (Annex 6) shows that collecting qualitative data, and pairing radio announcements and text messages can provide rich insights into how people are coping with COVID-19. Annex 7 (humanitarian situation monitoring) and Annex 8 (conflict monitoring) provide examples of qualitative and key informant data collection.

Finally, Annex 9 provides more information on RTM data and analysis.

Annex 1. Somalia: The FSNAU Early Warning-Early Action "Dashboard"

Background

The Somalia Food Security and Nutrition Analysis Unit (FSNAU) is the birthplace of the Integrated Food Security Phase Classification (IPC) analysis and is the longest standing, independent food security and nutrition information system in East Africa. Twice-yearly seasonal assessments are carried out using IPC methodology. The Somalia Humanitarian Country Team (HCT) is more rapidly updated. FSNAU responded and developed an interactive online database and dashboard approach. In February 2016, FSNAU rolled out the Early Warning-Early Action Dashboard. The dashboard compiles multiple indicators on risk factors related to food security and nutrition at the district level. Data are compared against reference thresholds, and maps and charts display the severity of the situation—both for individual indicators as well as across all indicators—and amalgamates the degree of seriousness into a national overview. The objective of the dashboard is to facilitate decision-making for early action based on monitoring a consistent set of indicators with established thresholds.

Methodology

Overview

The FSNAU dashboard[1] compiles and displays data on several sets of indicators on risk factors closely related to food security and nutrition. Unlike the IPC, which focuses heavily on outcome indicators, the intent with the dashboard is to focus on predictive indicators. The indicators included thus far are:

1. climate: vegetation cover (NDVI), rainfall, price of water, and flooding;
2. market: prices of maize, sorghum, rice, and goat; wage labor; terms of trade between goat and cereals; terms of trade between wage labor and cereals; and the cost of a minimum expenditure basket for poor households;
3. nutrition: new admissions of acutely malnourished children to treatment programs;
4. health: cholera cases and deaths, measles cases, and malaria;
5. population movement: arrivals and departures; and
6. insecurity: incidents and fatalities.

Data

Each indicator is tracked and compared to long-term-average values for that indicator, by time period or other normative thresholds established in consultation with subject matter specialists. Deviations from the threshold values in a "negative" direction, whether that is a decrease (in rainfall, for example) or an increase (in the price of water, for example) are categorized and mapped as an "alert" or "alarm." Data is collated and tracked on a monthly basis, and current indicators are compared to the long-term average for that indicator in that month or other normative thresholds.

The online database/dashboard displays color-coded data (green=normal, yellow=alert and red=alarm) for monthly values of each indicator at district level. It also displays the data in the form of a map. This format enables users to explore both the current

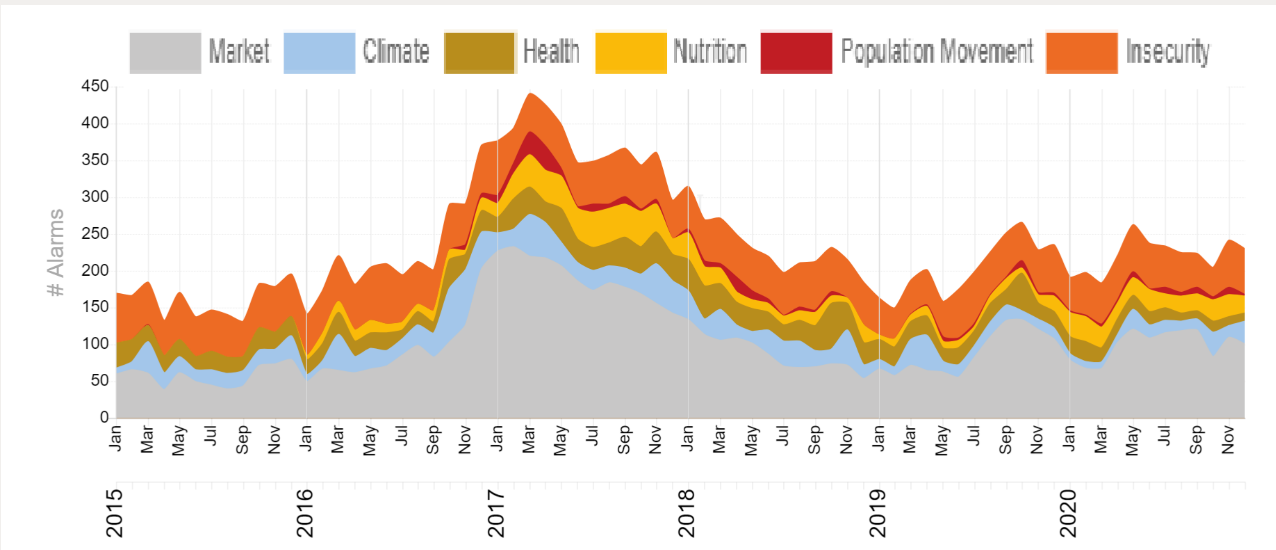
[1] The FSNAU dashboard can be found at https://dashboard.fsnau.org

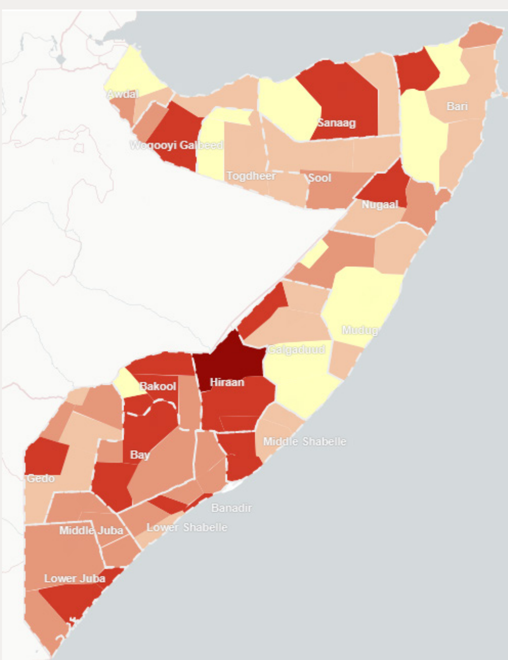
situation as well as trends over time and relationships between various indicators and associated consequences.

Analysis

While the FSNAU online EW-EA database and dashboard is intended and designed to support users' own analysis, it also includes a built-in analysis in the form of the monthly aggregate EW-EA map, which displays the number of indicators in "alarm" phase as shades of red. This amalgamation function simply counts up the number of alarms and maps them by district, with greater numbers of alarms depicted with deeper shades of red. In addition, placing the mouse cursor in any district on the EW-EA map dis-

Figure A1. Analytical Outputs of FSNAU Dashboard





ABOVE. Total district-level indicators in "alarm" phase by month aggregated at the national level for January 2015 to December 2020.

LEFT. Total indicators in "alarm" phase at district level for December 2020.

Source: FSNAU

plays the color-coded current values of all indicators for the district, enabling users to see which and how many indicators are in "alarm" phase.

While the FSNAU database and dashboard has not yet incorporated elements of forecasting (e.g., climate forecast and price forecast/projections), its choice of indicators, thresholds, and trends in these indicators over time have inherent early warning/predictive value. For example, consecutive months of new admissions to treatment centers or poor rainfall could be symptomatic of a situation that is likely to worsen in subsequent months. The chart in Figure A1 shows the total count of "alarms" by month from January 2015 to December 2020, including clearly depicting the crisis of 2016–17. The chart also shows periods of improvement and deterioration in recent years, although these are of a lesser magnitude/severity compared to 2016–17.

Links to Early Action

FSNAU is simply an information and analysis unit—it does not operate any programs or interventions. So the link to EA relies almost entirely on the extent to which other actors make use of the information. It was up and running in time to help predict the crisis of 2016–17, and indeed some donors attributed their earlier action in 2016–17 (compared to 2011) largely to the existence of the dashboard. The dashboard depicted the situation quite accurately. But in other cases, the link to early action is less clear (and even in 2017, the link was more correctly described as rapid response, not preventive action).

The intended link of the dashboard to action is a monthly analysis to be undertaken by the Inter-Cluster Coordination Group (ICCG) and IASC clusters with the support of FSNAU. The analysis discussion is anticipated to be a regular agenda item in ICCG meetings to be held, ideally, on a monthly basis. The envisaged analysis would use data in the FSNAU EW-EA database and dashboard and any other relevant secondary data to produce a synthesis report of two to three pages, along with recommendations to the HCT. The recommendations could include the following:

- Triggering a more in-depth assessment if available information is not sufficient to take action.
- Cluster-specific or multi-sector response intervention/action if available information is adequate.
- No further action if the dashboard information indicates a "false alarm."

As the deliberations and decisions of the HCT are formally recorded by minutes of meetings, this was expected to facilitate accountability for both the analysis presented to and the decisions taken by the HCT. However, thus far, the monthly analysis discussions have not yet taken place and FSNAU has only produced a prototype of the report for discussion with various stakeholders (ongoing).

Lessons Learned

The FSNAU EW-EA dashboard serves as a comprehensive one-stop shop where users can find information to help track the evolving humanitarian situation.

- However, it is not clear to what extent the objective of triggering early action has been achieved. While there has been anecdotal evidence that the dashboard is being used, at least by some donors, delays in the envisaged analysis by the ICCG and subsequent presentation to the HCT may have reduced the scope of its wider use for decision-making.
- The dashboard provides a wide variety of indicators, including inherent early warning information embedded in the trends of indicators over time. It doesn't, however, provide explicit early warning scenarios or analysis.
- Data is sometimes not available in a timely fashion for some indicators. This reflects challenges for the agencies that collect and make the data available than a critique of the "dashboard" itself. This has improved over the past year, with monthly data regularly available by the middle of the following month.
- The analysis needs to be presented more simply and clearly. It is one thing to count up alarms, but it is another to understand what they actu-

ally mean. The envisaged monthly two to three page analysis through the ICCG and supported by FSNAU and other partners could help address this gap. (Scenario analysis may be found in other reports or bulletins from FSNAU or FEWS NET, which cooperate closely in Somalia.)

The dashboard is changing in response to these criticisms. A series of workshops was held in 2018 to improve the analysis of the dashboard, clarify the notion of triggers, and build an accountability framework for early action and an enforcement mechanism through the ICCG and HCT in Somalia. A task force met regularly during 2019 to build on the initial FSNAU dashboard model to include more analysis and a stronger link to early action, and particularly to understand the indicators at a district level (as opposed to giving a general snapshot at the national level). But at a minimum, the dashboard shows an up-to-date snapshot of the country and suggests where current status assessment resources—as well as rapid response—should be focused.

Annex 2. South Sudan: The Integrated Needs Tracking System

Background

The Integrated Needs Tracking (INT) system is a tool for identifying and flagging "hotspots," facilitating analysis discussions, and supporting resource prioritization decisions for severely vulnerable areas. The need for a real-time monitoring system became clear in early 2018, as humanitarian response lacked a transparent and regularly updated system that could identify potential "hotspot" counties to prioritize for further analysis or response. Led by REACH, four clusters (Food Security and Livelihoods; Water, Sanitation, and Hygiene; Health; and Nutrition) designed the INT to provide monthly updates through a multi-dimensional framework reflecting five conceptional indicators (for each of the four clusters plus mortality), leveraging existing data collection initiatives, and (integrated within existing response structures) emphasizing direct linkages to country-level prioritization mechanisms. The INT dashboard is accessible through an online portal that is updated monthly—allowing stakeholders to view aggregated risk categories or filter specific indicators and themes at the county (Admin2) level.

The INT emphasizes direct linkage to analysis groups, which act as a platform for ensuring that it does not supersede human contextual analysis and is linked directly to rapid response and resource prioritization. For example, INT has been used to identify and support flood-affected populations and provide trend analysis in between Integrated Phase Classifications (IPC) workshops in January and September 2020. As a result, the system supports monitoring between outcome analysis processes, such as the Humanitarian Needs Overview or the IPC.

Methodology

The INT strengthens the connections between data collection, analysis, and response, with an emphasis on expert judgment to flag hotspots for subsequent in-depth analysis or prioritization discussions. The INT is designed to be a real-time needs tracking system and does not provide forecasts of needs.

Data

The INT system relies on several data sources, each aligned with specific conceptual indicators,[2] from pre-existing data collection cycles—mostly from remote sensing, key informant interviews, and service reporting—collected at multiple levels and aggregated at the county level.

Data categories include rainfall patterns, pasture availability, level of livelihood engagement, market monitoring, physical access to resources, health and nutrition admissions, and acute shocks. Each data category may pull from one or multiple sources. Data examples include:

- rainfall and vegetation anomalies from Climate Hazards Group Infrared Precipitation—monthly support for WASH and food security;
- livelihood engagement, access to food, perceived impact of recent reports from REACH Area of Knowledge surveys—monthly support for food security;
- access to water from REACH Area of Knowledge—monthly support for WASH;

[2] See INT Indicator diagram: INT Documentation, https://ssd-int.reach-info.org/documentation.

- health admission data from WHO Early Warning and Response System (EWARS) data—monthly support for the health cluster; and
- changes in market prices from WFP VAM, and Joint Market Monitoring Initiative (JMMI)—monthly support for food security.

Additionally, for food security and malnutrition, the INT includes the IPC outcomes as a baseline intended for monitoring IPC projection periods. During periods when the IPC analysis is quite current, IPC outcomes supersede INT risk categories; for IPC projection periods, the INT is intended to support monitoring of IPC projections through tracking key assumption (i.e., market prices, rainfall patterns, access to services, insecurity).

Analysis

Analysis of the INT information is done by the Needs Analysis Working Group (NAWG), which then makes recommendations to the Inter-Cluster Coordination Group (ICCG). The ICCG is responsible for the scale up of humanitarian response in South Sudan. The analysis framework assesses the risk of reaching a threshold that will trigger a response. The triggers include populations in IPC Phase 5, a sudden increase in mortality, an influx of displaced people greater than 5,000 in number, a confirmed disease outbreak, or a prevalence of global acute malnutrition greater than 15 percent of children from 6 to 59 months old.

Risk Categories

INT risk categories reflect the likelihood of reaching the triggers outlined above. Each risk category is determined by the likelihood of surpassing trigger thresholds. Indicator thresholds are intended to align with other, established frameworks, such as the IPC reference table, SMART methodology, WFP or WHO guidance. Risk categories are outlined in Table A1. In the event data categories diverge from

Table A1. Risk Categories for the South Sudan INT

Category	Description
Confirmed trigger	One of the five NAWG triggers is confirmed. Each of the triggers represents a severe level of need that is currently present in the county.
Very high risk of reaching trigger threshold	Based on the convergence of available data, there is a very high risk of reaching the trigger threshold. No single conceptual indicator can trigger a very high-risk categorization—as data converges, the risk of a trigger increases.
High risk of reaching trigger threshold	One of the indicators suggests a very high level of risk, but other indicators suggest a high level or lower level of risk.
Moderate risk of reaching trigger threshold	One indicator suggests high risk, but other indicators diverge at average or low risk.
Minimal risk of reaching trigger threshold	None of the indicators directly indicate significant risk.
Insufficient data	There is insufficient data available to meet any of the requirements to reliably provide a category to the county.

key assumptions, the interpretation of overall risk category may change.

To ensure transparency, the INT has a publicly available online dashboard allowing the user to "unpack" the data, to see what indicator(s) drive risk categories. Unpacking alert levels allows the user to make their interpretation of the warning, ensures that all actors have the opportunity to verify the accuracy of the alert, and ensures there is no mis-prioritization based on the system.

Links to Early Action

While the focus of the INT is real-time monitoring, the INT can facilitate rapid response and resource prioritization resulting from large shocks. For example the INT facilitated a rapid response to significant flooding across large portions South Sudan in November 2019. Further, INT factsheets support IPC analysis in prioritizing resource allocations across South Sudan for a period following an analysis. A future need is for real-time monitoring of IPC projections using INT indicators with the assumptions from the "most likely scenario" from the IPC.

Lessons Learned

Multiple lessons were learned throughout the development and early roll out of the INT. The first is the importance of buy-in at multiple levels and stages of the process. Technical design (INT team), analysis process (NAWG), and coordination/decision body (ICCG) were engaged with varying success. Strong engagement with high-level coordination led to the fast-tracking of the INT from concept to development. However, a lack of early engagement with mid-level coordination contributed to lower than expected buy in, leading to uncertainty about the INT's purpose and need for continued explanation and follow up. Additionally, admissions data sharing varied across government officials. Health admission data was shared regularly without major barriers. However, nutrition admission data—overseen by different officials within the same ministry—was blocked from being shared, despite requests from nutrition clusters leads. This prevented a critical data category from being integrated.

Another lesson is the need to balance complex systems with realistic expectations for monitoring of drivers and outcomes. Prior to the INT, NAWG triggers included a combination of area and household outcomes, shocks, and vulnerabilities. The INT's "risk" based approach became increasing complex to capture and categorize across a wide range of indicators, complex pathways and severity outcomes—each with unique methodologies, data sources and indicator thresholds. As a result, communication barriers emerged when interpreting INT risk levels.

Annex 3. Yemen: Tracking Assumptions in the IPC Food Security Projections

Background

Integrated Phase Classification (IPC) analysis has been used in Yemen to assess food insecurity and the number of people in need of food assistance since 2011. IPC analyses provide "*current*" and "*projected*" analyses; the former is based on recent empirical data and the latter is based on assumptions built on the "most likely" scenario. The projection function of IPC was initially a secondary product of the analysis. However, the demand for anticipatory action and forecasting needs to guide allocation of humanitarian resources using "hard numbers" have both increased the reliance on IPC projections. Projections are based on all available evidence of both current status and the main drivers of food insecurity for the coming four to eight months and are based on a set of carefully considered assumptions about the likely trend of both aggravating and mitigating factors driving food insecurity in the projection period. Nonetheless, IPC projections often remain fixed over the period of analysis, even though the drivers—and the assumptions about projections that the drivers informed—are frequently observed to change within the projection period. Hence the IPC team in Yemen has proposed a system to monitor key drivers of food insecurity and, whenever certain thresholds are passed, trigger rapid action including a rapid re-assessment, an IPC update, or (in some instances) appropriate direct response. The objectives of the systems are the following:

- Collate multiple indicators reflecting the assumptions used in projection analysis.
- Monitor the assumptions on which projections are based to update likely scenarios.
- Produce frequent reports to support rapid decision-making.
- Improve coordination of data collection and analysis.

Methodology

Overview

The IPC food security conceptual framework remains the foundation of the proposed system. The system will follow the same concepts of the consensus of indicators, similar to the IPC convergence of evidence concept. Thresholds for triggering an IPC update will be defined as the system is developed. The system will cooperate with other information organizations (ACAPS, FEWS NET, IPC, iMMAP, and REACH, among others). Eventually the system will manage a continuous process of monitoring and updating the assumptions on which IPC projections are based.

Data

Five main drivers of food insecurity in Yemen were identified for the projection period in the most recent IPC analysis. Within each of these five categories of drivers, specific indicators will be monitored, as depicted in Table A2. A more comprehensive table will be produced in the development phase of this proposed system. These can be tracked at the governorate or district level. Crucially, none of the data categories in Table A2 require a new means of data collection—data for these categories are already collected by existing mechanisms. The main purpose of this system is to collate this information to track the assumptions on which projections are based.

Analysis

Since 2013, FAO (through funding from the European Union) has been managing food security information, including the IPC, and working closely with partners, including the government. The monitoring system has been embedded as part of this food security information systems project within FAO. Data collation will be done by FAO staff in collaboration with other partners to generate meaningful outputs for further analysis and interpretation. A matrix of the indicators in Table A2 will be created and raw data for each of the indicators will be fed into the matrix. The outputs will include trend analyses and qualitative information describing the trends (causal factors). The process of consensus of indicators will be done through consultations with other information organizations including those mentioned above.

Links to Early Action

The results of the analyses will be made available through quarterly food security reports disseminated

Table A2. Indicator Categories for Projections Tracking in Yemen

Assumption/Main driver	Indicators to be monitored (high-level)
Worsening economic crisis	*Macroeconomic* • Trends in foreign reserves and financial support to the central bank • Trends in fiscal and monetary policies • Trends in other foreign direct inflows (FDIs) *Microeconomic* • Trends in the value of the local currency (YER) against the USD, remittances • Trends in imports and exports, including associated costs • Trends in food commodity prices (minimum food basket) • Information on incoming sources, including public sector payments
Food availability (own production)	Agriculture (including fishing) production, cost of inputs (fuel, labor), area planted, impact of natural hazards on production (floods, cyclones, dry spells, desert locusts, fall armyworm), and livestock off-take
Conflict	Conflict dynamics and the impact on indicators that directly affect food security, e.g., blockade on fuel imports, siege, etc.
COVID-19 and effect on food systems	Impact on indicators that directly affect food security, e.g., wage labor incomes, remittances, agriculture production, etc.
Humanitarian assistance	Amount and timeliness of humanitarian funding compared to the population in need

to decision-makers. Shorter reports or updates are envisaged should the need arise, such as following an abnormal jump in staple food commodity prices or significant conflict leading to a large population under siege. The primary objective of the monitoring system is to inform significant deviation from the projection assumptions while at the same time providing information on the food security situation. Thresholds for triggering an IPC update will be defined as the system evolves.

Lessons Learned

Given that this system is in the proposal stage, lessons are yet to be learned from its actual operation. But the design of the system is itself an important lesson learned: namely that between major analytical outputs, like IPC assessments, not only does current status change, but the assumptions on which projections are based can change as well. In order to maintain preparedness and rapid response (if not necessarily anticipatory action in this case) these assumptions—and the projections that are based on the assumptions—need to be monitored on a more frequent basis.

Annex 4. Bottleneck Analysis: Using Real-Time Program Information for Needs Assessment

Background

In early 2020, as the scale of the COVID-19 pandemic became clear, the impacts on food and nutrition security quickly became concerning, although highly variable, depending on local situations.[3] Nutrition Information Systems (NIS) had to adjust not only to highly dynamic conditions but also to the fact that their main form of needs assessment—the Standardized Monitoring and Assessment of Relief and Transitions (SMART) survey that collects anthropometric, care, and health information—were halted due to the social distancing requirements imposed to help control the spread of the virus. SMART survey information is used to estimate the prevalence of global acute malnutrition (GAM), classify the severity, and calculate the anticipated child malnutrition case load for the coming period. In 2020, at the very moment that updated information was needed, the standard means of providing it stopped.

By mid-2020, GAM prevalence estimates were updated based on causal factors and analysis of past trends. However, this resulted in widely varying estimates, as analysts were left to rely on their best collective judgements to determine funding needs, which led to many questions about resource allocation. However, it is also possible to adjust the resulting prevalence estimates using existing program and surveillance information on undernutrition causal factors and expert judgement. During 2020, the absence of SMART surveys has shown that the analysis of causal factors is weak and the analytical framework and associated tools used for this analysis needs to be refreshed. A tool known as bottleneck analysis (BNA) can strengthen this causal analysis by measuring the effective coverage of health and nutrition services to make judgments about how these services contribute to reducing GAM incidence.

Methodology

Tanahasi (1978) defined effective health system coverage as being the supply, demand, and quality of health services and described a tool to analyze the effective coverage of health services known as bottleneck analysis. The objective of BNA is to measure health services to identify the bottlenecks to effective coverage of health services by using routinely collected information from programs. This information can be used to not only to monitor the response, but also as a contributing factor to consider in an analysis of the causes of undernutrition.

Data

The type of health/nutrition services data commonly available in emergencies is given in Table A3.

[3] This case study is excerpted from a longer briefing paper, "Estimation of Prevalence of Acute Malnutrition in Real Time and in the Absence of SMART Surveys: A Proposed Approach" (Hailey and Maxwell 2021).

Table A3. Dimensions of a Health/Nutrition Information System

Dimension	Determinant	Indicator
Supply of health/ nutrition services	Geographical access	Percentage of health sites offering SAM (severe acute malnutrition) management services without interruption for the previous time period.
	Commodity availability	Percentage of health facilities that did not run out of stocks of RUTF for two or more weeks in the previous time period.
	Human resources	Percentage of health and nutrition workers who have been trained on IMAM in the previous time period.
Demand for health/ nutrition services	Initial utilization	Percentage of children 6 to 59 months admitted to SAM management services as a proportion of estimated burden in the previous time period.
	Continuous utilization	Percentage of children 6 to 59 months who did not default from SAM services as a proportion of estimated burden in the previous time period.
Quality of health/ nutrition services	Effective coverage	Percentage of children 6 to 59 months cured from SAM services as a proportion of estimated burden in the previous time period.

Source: Adapted from https://www.ennonline.net/fex/60/bottleneckanalysissomalia

Analysis

BNA computes effective coverage of a health or nutrition service. If a service is not 100 percent available and accessible to the intended population, then a proportion of the population is not covered by the services. Of those to whom the service is available and accessible, some do not use the service and some default before completing the course of the full service. Thus a proportion of the target population does not benefit from the service. And, of those who use the service fully, some are not successfully discharged. The proportion of the target population that is successfully discharged is called the effective coverage. At each step of the BNA, an increasing proportion of the total target population does not receive the benefit of the service. In different contexts, different steps in the BNA are more of a "bottleneck" on the effective coverage than others. The BNA analysis can identify where in a health and nutrition service the bottlenecks are occurring.

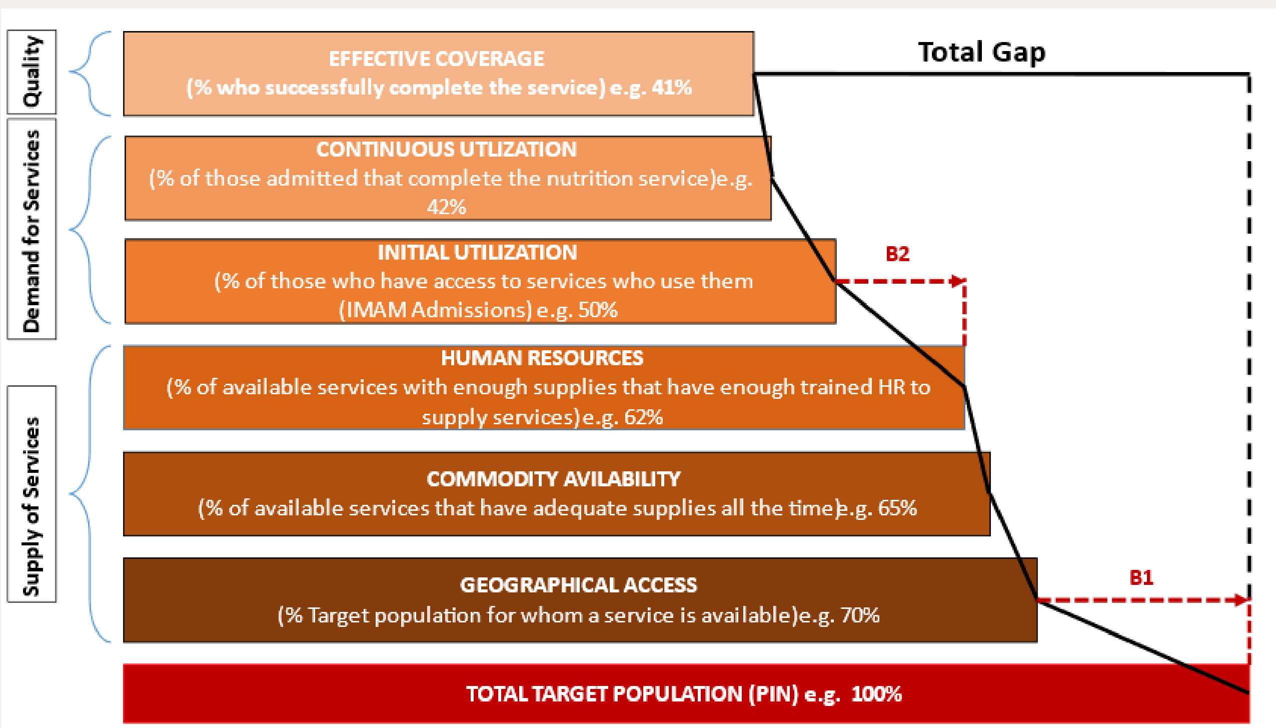
An illustrative example, Figure A2, shows that as a result of the combined ineffective coverage in supply, demand, and quality of Community Management of Acute Malnutrition (CMAM) services, only 41 percent of the total target population are effectively covered by the CMAM service. There are losses in effective coverage at every step. The biggest service supply gap is in the geographic access of services—the first "bottleneck" (B1). The example indicates that 30 percent of severely malnourished children do not have CMAM services available to them. Five percent of available services are not functional because there are regular or long supply chain breaks. Three percent of the services that are available and have regular supplies are non-functional because they do not have enough trained staff present to provide the services. As a result, only 62 percent of the total target population are supplied with functional CMAM services.

The biggest service demand bottleneck is in the initial utilization—the second bottleneck (B2)—of the functional services supplied. Of the 62 percent of the target population who can utilize functional CMAM services, only 50 percent are actually admitted. A further 8 percent default and do not complete the full service. A further 1 percent are discharged but are not cured. As a result, the effective coverage of the total target population is 41 percent.

While the BNA is useful for demonstrating where program improvements are needed, it also gives a measure of the likeliness that the existing program is having the intended effect on reducing undernutrition. If a program is having the intended effect because it has high effective coverage, it would tend to push the prevalence down, even if other causal factors remain the same.

But in the example shown, the program is reaching less than half of the intended case load, implying that the overall prevalence may well be going up (depending on the contribution of the other causal factors). As with all food security and undernutrition analysis, there is no algorithm for the analysis of causal factors—it is based on expert judgment, requiring knowledge of the context. The BNA tool provides a more systematic and quantifiable measure of the effective coverage of health and nutri-

Figure A2: Bottleneck Analysis Model for CMAM Nutrition Services



Source: Adapted from Henriksson 2017

tion services and their contribution to mitigating undernutrition.

Links to Early Action

BNA can be used in real-time assumptions tracking to monitor the validity of previous assumptions about how health and nutrition services will affect undernutrition prevalence and severity and how nutrition caseloads change over the projection period. Large changes in effective coverage—for instance as a result of the direct and indirect impact of COVID-19 on the supply, demand, and quality of health and nutrition services—could then be used to adapt the forecast outcomes for undernutrition and nutrition caseloads and, in turn, to justify funding.

Regular collection of BNA measures is also a powerful tool for advocacy, particularly for conflict- and pandemic-induced rapid and severe reductions in the effective coverage of health and nutrition services.

Lessons Learned

Regular use of the BNA allows a nutrition and health program to monitor changes in dimensions of effective coverage and to respond to them. BNA also contributes to the analysis and expert judgement on how changes in contributing factors are likely to be affecting the prevalence of undernutrition in information systems such as the IPC and in real-time monitoring mechanisms.

Annex 5. Malawi: Rapid Feedback Monitoring System (2020–25)

Background

In 2016, Catholic Relief Services (CRS) implemented the Measurement Indicators for Resilience Analysis (MIRA), piloting monthly collection of food security and shock indicators from households in southern Malawi. The second phase is on-going in three southern districts and the third was launched in 2018 in southern Madagascar. CRS, with multiple partners, recently built on and expanded the MIRA approach to create the Rapid Feedback Monitoring System (RFMS), launched in August 2020. CRS implements data collection in a consortium of stakeholders on the project, which include USAID, FCDO, World Bank, WFP, Concern Worldwide, the Malawian National Statistics Office, the Center for Social Research at the University of Malawi's Chancellor College, and Cornell University, among others. Project goals include (1) provide real-time feedback for better collaboration, learning, and adaptive management; (2) enhance sustainable local capacity to improve resilience and wellbeing; and (3) improve the evidence base around Malawi's resilience and wellbeing. Ultimately, the consortium aims for the RFMS system to be country-led and to support and inform Malawi's National Resilience Strategy.

Methodology

Recognizing that poverty and food insecurity are often dynamic rather than static indicators of wellbeing, the RFMS in southern Malawi collects high-frequency indicators on shocks, food security status, and other key indicators. Community-based enumerators reside in the communities where they collect data. The enumerators are tech-savvy and literate. CRS periodically trains new enumerators who must pass a competency test before they collect data. Enumerators are paid per survey and are given a smart phone or tablet on which to collect results and transmit them to CRS. A challenge with community-based enumerators is attrition due to other employment opportunities. In Madagascar, due to capacity constraints, local CRS field agents collect data from households.

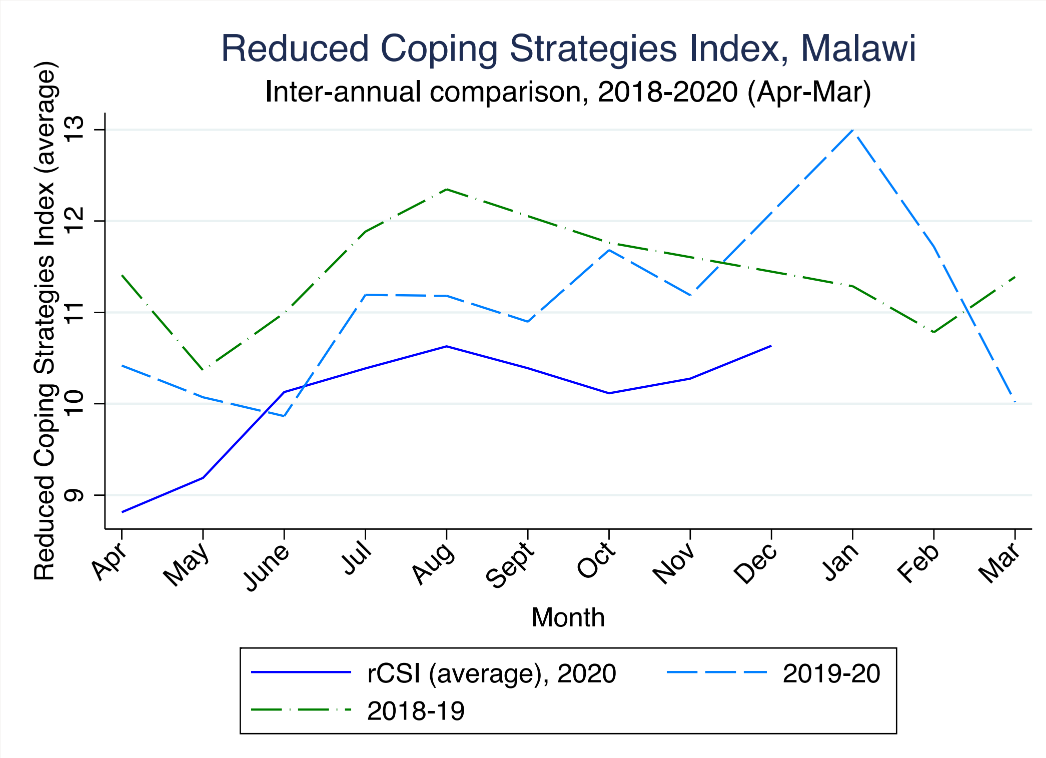
Data

To decrease the survey burden, sampled households respond monthly to a subset of indicators and quarterly or semi-annually to other indicators (a sequenced structure that is new to the RFMS, as MIRA only had the monthly short module and an annual survey). Monthly indicators currently include food security measures, shocks experienced, receipt of support (e.g., food assistance), and a COVID-19 module. Quarterly and semi-annual indicators include asset measures, livelihood indicators, and WASH-related indicators. Currently, data collection is from 7 districts and includes 4,200 households. Time series data from 2017 onward exists for 2,200 households in 3 districts. Additional data sources (e.g., prices and remotely sensed data) are planned for the RFMS system.

Analysis

Currently, RFMS data are used to create descriptive reports by trends and by categories (e.g., by household head status). For example, Figure A3, using

Figure A3. Reduced Coping Strategies Index, Malawi



Source: CRS Rapid Feedback Monitoring System

MIRA data, shows that the rCSI scores in 2020 appear relatively "normal." Additional modelling work, using both the longer MIRA panel and the RFMS data (Table A4), shows that an exceptionally good harvest in early 2020 has appeared to mitigate the adverse economic impacts of COVID-19 (Upton and Yoshimura 2021).

Other work includes using available data and PA/ML to (1) estimate food security status one month ahead as a form of RTM and (2) estimate food security status six months ahead as a form of EW. Other analysis (Knippenberg et al. 2019) used machine learning to identify which subset of indicators were most predictive of key outcomes, including food security status. Modeling could improve the lean season forecast. Currently in Malawi, the forecast for January, in the lean season, occurs in March (and is revised in October), and is based almost entirely on climate information. A more frequently updated and better timed forecast could improve accuracy of estimates and inform adaptive programming.

Links to Early Action

CRS produces snapshot reports that it shares with the food security cluster and local communities, with plans in place to extend tailored reports to local traditional authority leaders and other interested stakeholders. A goal is for communities to engage with data to identify uses, including having information to help them advocate for locally led action. These data can also be used to identify unanticipated needs or needs at a different magnitude than initially expected. Such findings inform advocacy, re-orienting, and adapting existing and future programming (e.g., to decide to change targeting).

Table A4. Select Indicator Categories for RFMS in Malawi

Assumption or main driver or outcomes	Indicators to be monitored (high-level)
Shocks	Collected monthly; details on shocks asked only if a specific shock is reported.
COVID-19	Information on economic (e.g., changes in prices) and health (e.g., illness in the household and access to testing) impacts, as well as information about symptoms of COVID-19 and ways to minimize infection and transmission risks.
Livelihoods, income	Wages, livelihoods (e.g., livestock holdings, crops produced), asset stocks (including the World Bank SWIFT poverty estimation module), asset sales, and social protection (e.g., receipt of food assistance).
WASH	Access to clean water, sanitation, and health services, etc.
Food security	rCSI, HHS (in MIRA); in RFMS, also dietary diversity (FCS, HDDS)

Source: CRS Rapid Feedback Monitoring System

Lessons Learned

The RFMS project is expanding. Currently, data are collected in both Malawi and Madagascar, with more locations within each of these countries being added. CRS is currently developing a dashboard to support evaluation, adaptive management, targeting, and local action.

Annex 6. Somalia: Africa's Voices Foundation Crowdsourcing Community Perspectives

Background

Somalia recorded its first case of COVID-19 on March 16, 2020. A year after, in March 2021, the country recorded a cumulative of over 7,700 cases and 260 deaths according to the Johns Hopkins Coronavirus Resource Centre.[4]

Africa's Voices (AVF) conducted an initial diagnostic SMS survey in April 2020[5] by reaching out to its interactive radio *Imaqal* (Listen to Me) audiences. The objective was to inform the work of AVF as well as other international and local organizations in Somalia in deploying risk communication strategies and activities to provide Somalis with accurate information and prevention strategies. Messages were sent out to 53,000 recipients and responses collected on April 3 through April 6, 2020. A total of 7,747 listeners responded (approximately 15 percent) with over 18,222 text messages received. The question asked: "Dear Imaqal Listener, your voice is important for the response to COVID-19. What are your thoughts on COVID-19?" ("*Dhageystaha sharafta leh ee Imaqal, Codkaaga wuxuu muhiim u yahay la tacaalidda xanuunka COVID-19. Waa maxay fikradahaaga ku aadan xanuunka Koroona fayraska?*"). During the last week of August 2020, the survey asked the same question to find out how people's opinions had changed regarding critical COVID-19 issues in Somalia and therefore align the priorities and strategies of AVF and other organizations providing support and risk communication.

In both phases (April 2020 and September 2020), AVF organized webinars with relevant stakeholders and implementers in Somalia, especially those working on Risk Communication and Community Engagement (RCCE) such as FCDO (formerly DFID), IOM, World Bank, and USAID. The first seminar was held just ten days after data collection, on April 16, 2020 and the second was done on September 16, 2020.

Methodology

AVF interactive radio uses a mixed-methods approach. Participants are invited to answer a question posed during a radio promo, radio show, or an SMS ad. When participants responded (receiving and sending texts is free for participants), they were informed that their views were analyzed to guide actions by government or other relevant stakeholders and they had the option to withdraw by replying "STOP."

The research team—fluent in Somali—went through the text messages received to develop a coding frame following a process of qualitative thematic analysis. The coding frame that resulted was then applied to every text (each message was coded with the relevant theme). This labelling process resulted

4 Johns Hopkins Coronavirus Resource Centre, "Somalia," https://coronavirus.jhu.edu/region/somalia.

5 Africa's Voices, "IMAQAL (Listen to me!)," https://www.africasvoices.org/case-studies/promoting-greater-gender-equality-and-social-inclusion-through-media-in-somalia-somalia-stability-fund/.

into a dataset which, after a validation process, was analyzed using statistical methods to assess the relative prevalence of the various ideas emerging from the conversation collectively and across demographic groups.

When someone participated, a brief series of demographic questions was triggered, also by SMS. This allowed AVF to check for significant differences across demographic groups on the extent to which different views and opinions are held.

Following the analysis, AVF then followed a mixed-methods insight-generation process where a thick description of the themes in the dataset was provided alongside the prevalence of these themes across groups to provide nuanced meaning into the findings and people's views. AVF also provided anonymized quotations directly from citizen voices to illustrate the depth in the themes in people's own language and terms.

Respondent Demographics

Of those who sent a text message, 5,494 and 3,924 were included in the analysis for phase 1 and phase 2 respectively. The demographics of participants were similar in the two phases. It was a predominantly young audience with the majority (approximately 60 percent) aged 18 to 35 years. In addition, gender distribution of participants was consistent in both phases, with approximately 61 percent of respondents being men. Approximately 40 percent of participants in both phases identified as recently displaced.

Analysis

The analysis from the first phase resulted in the following insights from the 5,494 participants whose views were analyzed.

1. Respondents fell into two broad camps: those invoking community action aligned to expert/government advice with a "call for right practice" (34 percent) and those invoking religious hope, practice or guidance as the right way forward (39 percent).
2. The religious frame was more salient among relatively older groups; younger age groups (notably young women) are more likely to advocate for people to follow the right health practices.
3. A message denying the existence of coronavirus was twice as likely to come from a man than a woman. Men were significantly less likely to speak about "collective hope" than women.
4. Over one in ten respondents (12.2 percent) expressed thoughts on COVID-19 that involved rumor, stigma, or misinformation. Recently displaced people were significantly more likely to express such misinformation than those who were not. Respondents from Puntland were significantly more likely to speak about factual aspects of COVID-19 (and less likely to speak about religion) compared to those from Banadir.

Links to Early Action

AVF engaged in multiple conversations with stakeholders following the dissemination of these findings in April 2020. A clear lesson was the need for a religious lens with any community engagement and for bringing in trusted religious leaders to help communicate risks. Various organizations asked for the results of the research and informally mentioned that the rapid diagnostics had informed their approach. Similarly these insights informed the work of AVF, which adapted its weekly *Imaqal* radio shows to tackle topics related to COVID-19 and address the barriers to COVID-19 prevention uptake that the diagnostics insights revealed.

In addition to the webinars and newsletters, AVF created visual output to disseminate COVID-19 communication needs and the value of the method to the RCCE community.[6]

Lessons Learned

The analysis of text messages received to the same question during the second phase found a change in

6 Elena Georgalla and Sharath Srinivasan, "Religion, Rumor, and Right Practice: Somali Views in the Early Days of COVID-19," Africa's Voices Foundation, https://interactive.africasvoices.org/somalia-covid19-diagnostic/index.html.

the levels of misinformation among participants (by then, *Imaqal* had also held radio programming providing accurate information on COVID-19). Responses changed from reliance on fate and religion to more concrete knowledge on the virus and emphasis on its existence. This change was particularly seen among displaced persons, who in the first phase were more likely to report misinformation. There was however a persistent minority that denied the existence of the virus, which showed the need for ongoing information efforts. The second phase also revealed the concerns of people about the impact of the pandemic containment measures on their jobs and businesses, education, healthcare access, and social interaction. This allowed AVF and partners to adapt the programming. For example, after this second phase, AVF facilitated radio dialogues on the priorities and support needs of Somalis affected by the pandemic containment measures.

This exercise reinforced AVF's evidence on the value of interactive radio and SMS communication to reach diverse and hard-to-reach communities with immediacy and at scale. COVID-19 proved the importance of this immediacy and scale especially in a context like Somalia where conducting research is risky, complex, and costly.

Annex 7. REACH: Humanitarian Situation Monitoring in Insecure and Inaccessible Areas

Background

In dynamic and evolving crises, humanitarian actors require access to a consistent flow of up-to-date information that can highlight populations and areas in the most need—especially in places that are the hardest to access. REACH conducts Humanitarian Situation Monitoring (HSM) in a number of such contexts, where logistical difficulties, high levels of insecurity, or the need to cover large geographic areas presents significant challenges to directly collecting household data. It is therefore not unusual for REACH HSM data to be the only information source available to decision-makers in such places, as operational actors are unable to access these areas directly.

REACH rolled out its first HSM program in Syria in 2014, which was adapted in South Sudan the following year. In 2019, REACH teams operating in the Central Sahel region conducted an HSM pilot project covering the tri-border region between Burkina Faso, Mali, and Niger, which was then adapted and scaled up to become a recurring monthly data collection exercise in 2020. The Sahel tri-border HSM is a key source of information for an area that has experienced chronic insecurity, conflict, communal violence, and very limited direct humanitarian access. As of 2021, REACH conducts HSM in 11 crises.

Methodology

Overview. The HSM framework is multi-sectoral in nature and informs emergency prioritization on a recurring basis across the humanitarian program cycle. HSM data collection methods are designed around the use of secondary data and recurrent primary data collection through focus group discussions and key informant interviews. These fill information gaps and provide an understanding of the level of humanitarian needs and conditions in difficult-to-access areas. The central approach that enables HSM data collection in insecure or inaccessible areas is the "area of knowledge" or AoK methodology, where field teams interview populations recently displaced from crisis-affected areas to gather information on the deterioration of security conditions, movement intentions, and prevailing humanitarian needs of populations remaining in these areas.

The AoK approach provides regular, reliable indicative tracking of humanitarian needs over time, to support prioritization and identification of "hotspot" areas experiencing a deterioration of humanitarian needs. To ensure this data is directly informing humanitarian response planning, data is shared through formal coordination structures, active clusters, and other key actors like the IPC/CH. In many cases, feedback from partners is subsequently used to both triangulate gathered data and inform research design and geographical targeting.

Data

The HSM uses three data collection tools. The first is a structured questionnaire on displacement dynamics, multisectoral humanitarian needs, and access to affected populations. The second is focus group discussions (FGD) on displacement and humanitarian needs. The third is focus group discussions for conducting participatory mapping of displacement.

Additionally, where key informants agree to be interviewed at a later date or refer contacts as potential informants, a short contact form is administered with the structured questionnaire to record these details.

Analysis

Qualitative FGD data is analyzed using a saturation grid, organized by thematic topics and sub-topics from the discussions, to identify key trends and areas of disagreement both within and between geographic zones. Quantitative data is aggregated and analyzed using Tableau software. Data is weighted by the total number of localities in the administrative enclave. This ensures that in the provinces (or departments or circles) where more localities have been assessed relative to the total number of localities, this does not disproportionately influence outcomes at the regional or country level.

Links to Action

In the event of a significant shock, HSM's network of key informants can also be used to gather critical data rapidly during an evolving crisis. The links to action can be through decision-making forums, such as assessment working groups or inter-cluster coordination groups, directly to implementing agencies or cluster coordinators, or through donors and high-level stakeholders for advocacy purposes. One very recent example of multiple links to actions is the current mass displacement and elevated risk of famine in Dikwa Local Government Area (LGA) in northeast Nigeria.

In early March 2021, a series of attacks were carried out by non-state armed groups (NSAGs) on Dikwa town, Nigeria, which triggered humanitarian actors' evacuation in an area heavily dependent on life-saving assistance for food, water, and healthcare. A rapid HSM assessment was conducted by REACH to provide donors, programmatic decision-makers and analysis groups with in-depth information on the evolving humanitarian needs in and outside of Dikwa town, including the population movement routes reportedly being used. Given the sudden onset of the shock, HSM did not independently "trigger" the rapid assessment. Instead, HSM's structure and networks were leveraged for a rapid remote assessment of a highly insecure area in a timely and effective manner.

Lesson Learned

Given that HSM targets the most insecure and inaccessible areas within a humanitarian crisis, the AoK methodology, albeit both innovative and practical, does have some notable limitations. The primary limitation is that the data can only provide an indicative picture of humanitarian needs and conditions, as it is collected through key informants and focus groups rather than household surveys using probability-based sampling techniques. Moreover, since it is often impossible to select localities at random, the results of the analysis cannot be presented as being representative of the prevailing situation.

Additionally, this methodology requires stringent data cleaning protocols with regular monitoring of incoming data and a series of both automated and manual data cleaning checks to meet data quality standards. This is due to the remote, phone-based methods for interviewing key informants used in some contexts, as well as the higher need to cross-check and triangulate information that is being provided by respondents who have recently been displaced from an area, rather than reporting directly from the area of interest itself.

As HSM situation analysis is indicative in nature, one longer term aim with this program is to consolidate best practices cultivated across REACH country teams and develop a framework for systematically triangulating and validating HSM data. This triangulation system will support efforts to build a wider analysis framework that bolsters HSM data with remote sensing analysis, cash and markets data, and other sources, with the ultimate aim of enabling a more robust inter-sectoral analysis of needs in hard-to-reach areas.

Annex 8. South Sudan: Qualitative Approaches to Monitoring and Forecasting Armed Conflict

Background

Armed conflict is a primary driver of need in humanitarian crises today, especially extreme food insecurity, through its direct and indirect impact on civilian lives and livelihoods. Humanitarian response is also often inhibited by armed conflict directly through attacks on program staff, assets, and activities and indirectly through disrupted supply chains, commodity losses in transit and storage, and the forced evacuation of humanitarian staff. Mitigating the risks that armed conflict presents to programming often raises costs—such as through increased use of aircraft or helicopters for the movement of cargo and personnel—and limits the coverage and duration of activities. Not only must humanitarians find ways to program effectively within armed conflicts, but they must also ensure that their actions are conflict sensitive. This includes doing as little harm as possible while also maximizing positive impacts and also contributing to peace as feasible regardless of the type of program.

To achieve all of this, humanitarians require real-time monitoring and analysis of armed conflict. Current status analysis informs ongoing programming and near-term operational planning, while forecasting is needed for mid- to long-term planning. The delivery of in-kind food assistance presents one of the greatest needs for real-time monitoring and analysis, as it is supported by extensive logistical operations that often include long ground, water, and air supply chains and the prepositioning of commodities in high-risk areas. When alternative options, like giving cash, are not available, such as due to non-functioning markets, humanitarians have no choice but to assess and mitigate the risks of using in-kind food aid within armed conflicts. In South Sudan, qualitative methods have been used to meet the need for real-time monitoring and analysis of armed conflict to support operational planning.

Methodology

Data

Quantitative data for armed conflict is often incomplete or inaccessible.[7] The Armed Conflict Location and Event Data (ACLED) project is the best public source available, although it has gaps in coverage and accuracy. In some cases in South Sudan, entire military offensives may go largely unreported due to inadequate open-source coverage of events for ACLED to collate. Other quantitative tracking—such as by various units within the United Nations Mission in South Sudan (UNMISS) peacekeeping operation or by the International NGO Safety Organization (INSO)—are often only available to a select audience, and the raw data are considered highly

[7] The full overview of key concepts and terms described briefly in this section can be found in "Adjusting Terminology for Organized Violence in South Sudan," jointly produced by the Conflict Sensitivity Resource Facility (CSRF) and the World Food Programme in South Sudan in 2020. Available online at https://www.csrf-southsudan.org/repository/adjusting-terminology-for-organised-violence-in-south-sudan/.

sensitive. Additionally, the quantification of armed conflict in general is often insufficient to infer likely humanitarian consequences, establish an understanding of current conflict dynamics, and forecast future conflict dynamics and their impact on needs.

Analysis

Qualitative conflict monitoring works to build and refine over time a model of armed conflict in a given context. This differs from quantitative tracking in that it is more concerned with how and why organized violence is used rather than with only how many events occur and how many fatalities are caused. This approach allows events and patterns of events to be analyzed in terms of their broader significance for conflict dynamics in current-status analysis and forecasting. It is a constant exercise in basic "if-then-because" analysis of key aspects of current and potential situations of violence of concern to humanitarian operations.

Qualitative conflict monitoring first considers all organized violence, rather than only violence that occurs within an armed conflict as defined by International Humanitarian Law (IHL). This broadens coverage beyond national-level armed conflict, such as a state of civil war between a recognized national government and a formally identified armed opposition group. Other layers of conflict include sub-national violence and localized violence, with all three layers frequently overlapping and interacting.

Determining the most applicable layer at a given point in time and place involves analysis of the purpose, severity, targeting, and tools of organized violence. The purpose of organized violence considers the objectives of the armed actors involved, often disaggregated into macro, meso, and micro objectives. In any situation of violence, there are frequently diverse, sometimes contradictory, objectives motivating different segments within the armed actors. The severity of organized violence considers the dimensions of scope—including social, geographic, and temporal—as well as the capacity of armed actors—such as the difference between a small, local militia and a professionalized militia of thousands—and the impact of organized violence on civilians. These use a series of metrics and categories to guide analysis.

The targeting and tools of organized violence are often mistaken for tautological causal explanation. In South Sudan, this often takes the form: "There are raids because these people are raiders." In reality, analyzing which groups are being targeted with what forms of violence can help make inferences about wider conflict dynamics. For example, there is a large difference between scattered, small-scale, and mobile raiding and the establishment of a staging area by a large number of combatants for a series of major raids in the same area over a period of weeks or months.

Even with sufficient descriptive analysis, drawing out operationally relevant conclusions can remain difficult if conducted in a contextual vacuum. After considering different aspects of organized violence, historical reference periods can help guide understanding of how similar situations have occurred and evolved in the past within the same context and across other contexts. This part of the analysis can make use of historical knowledge of the context, such as previous periods of organized violence in South Sudan, as well as comparative cases from other contexts. Broader theoretical advancements, such as the academic literature on the micro-dynamics of civil war[8] or the Political Marketplace Framework (PMF),[9] can also be used to support conclusions about how different aspects of organized violence are likely to structure organized violence now and in the future.

Links to Early Action

Qualitative monitoring and analysis of conflict has many possible applications. It can support program

8 This can range from insights into the efficacy of co-ethnic counterinsurgent forces (see J. Lyall, "Are Coethnics More Effective Counterinsurgents? Evidence from the Second Chechen War," *American Political Science Review* 104 (2010): 1–20) to the conditions under which paramilitary groups may be most likely to form (see Julie Mazzei, *Death Squads or Self-Defense Forces? How Paramilitary Groups Emerge and Challenge Democracy in Latin America*, University of North Carolina Press, 2009).

9 An in-depth description of the PMF, as well case studies of its application to the Greater Horn of Africa, can be found in A. de Waal, *The Real Politics of the Horn of Africa: Money, War and the Business of Power* (Polity, 2015).

implementation, including through informing safety and security assessments, activity site selection, key stakeholder engagement, and access negotiation. Other operational planning may use it to inform risk analysis for commodity prepositioning and supply chains. Program design can also benefit by tailoring program objectives and activities to changes in conflict dynamics over the life of a program. Advocacy efforts can also benefit from having a nuanced understanding of conflict dynamics to assist in communicating the drivers of current and projected needs and the funding requests to address them. In general, conflict sensitivity mainstreaming across all humanitarian programming is contingent on the availability of robust conflict analysis, which qualitative approaches can help provide in contexts where other information is inaccessible, unavailable, or otherwise insufficient for the task.

For now, qualitative conflict monitoring and analysis is typically done internally within operational agencies, given its political sensitivity. Its links to humanitarian action in real time and in the short term have the potential to be strong, depending on internal organizational structures and processes for dissemination and uptake. It can be most effective when operational decision-maker buy-in is already high, including through standing briefings. The potential for early action is often more limited unless the analysis is used for advocacy and is effective in persuading other operational agencies and donors that forecasts are sufficiently reliable. Rather than forecasting through quantitative data and tools like statistical inference or algorithms, forecasting based primarily on qualitative approaches is inherently an exercise in storytelling based on causal reasoning.

Lessons Learned

Qualitative approaches are often suspected of being too subjective to meet operational needs and to persuade key stakeholders. Countering this challenge requires, in part, rigorous transparency and standardization of the process and products. In South Sudan, substantial progress in the improvement and standardization of the approach was made throughout 2020. This included an inter-agency process, facilitated by the Conflict Sensitivity Resource Facility in South Sudan (CSRF), to refine and gain acceptance of an initial overall framework for analyzing organized violence, including key terminology and concepts. Templates for standard analytical products, including a six-month outlook, also went through several iterations to become more succinct and digestible for wider audiences. Probabilistic terms and the explicit delineation of assumptions, evidence, and analytical conclusions were also standardized.

Key areas for future improvement include how this analysis is disseminated within an organization, even when considered highly sensitive. To achieve the greatest utilization with the highest impact on humanitarian programming, the analysis must be delivered and explained within all relevant organizational units. Most importantly, logistics and emergency staff must be better supported, including within capital and field offices. Another gap is sustainability, as these approaches are often utilized by long-term staff that have organically built up causal models of organized violence in a specific context over time, often years. Exploring ways to rapidly teach this approach to new staff must be undertaken.

Annex 9. RTM Data Collection and Analysis

Data

Remote Sensing

The availability of remotely sensed data has expanded rapidly. It includes data collected via satellite (information on climate and weather, pollution, night lights, roofing materials, and various greenness indices) or captured from smartphones, cell towers, etc. Climatological data and climate hazards are routinely monitored by early warning systems analysts as leading indicators for humanitarian crises (e.g., FEWS NET, ICPAC, ICRC; see also Funk et al. 2019) and as potential triggers for forecast based financing and impact-based financing (Coughlan de Perez et al. 2019; Gros et al. 2019; Future of Forecasts n.d.). RTM analytical frameworks can combine remote sensing with other indicators. The UN World Food Programme's Hunger Map, which combines remotely sensed data with other sources (e.g., telephone surveys), is one example. Whether specific types of remotely sensed data are useful for RTM depends on the specific monitoring needs and context.

Social media monitoring and crowdsourcing for RTM is rapidly emerging. Social media data on its own (Kryvasheyeu et al. 2016) or in combination with other forms of remotely sensed data (Jongman et al. 2015) can provide information on locations and types of disasters as well as responses. Further, social media can also track real-time crises as they unfold, such as population movements (Palotti et al. 2020). Dedicated online data entry sites can be used to provide real-time information on violence (Elamein et al. 2017). Research and field-testing of drones for humanitarian information gathering and aid are rapidly evolving. For example, UNICEF (n.d.) is testing drones for aerial imaging, vaccine distribution, and other uses.

The potential of remote sensing to inform RTM is huge. The research community is still learning which indicators are dynamic enough and granular enough to identify affected populations or those at risk and which indicators are most helpful for which outcomes. McBride et al. (under review) note that some remotely sensed data, such as night lights and call detail records, lack adequate variation to differentiate among poor households (e.g., poorest and less poor) or are relatively static (see also Blumenstock 2016). In contrast, analysis of satellite imagery can be very useful in identifying the scope and scale of conflict. For example, recent analysis of imagery in Tigray, Ethiopia, identified buildings destroyed by fire due to conflict by comparing imagery from December 2020 to January 2021, after conflict started.

Telephone Surveys

While telephone-based surveys have gained traction at least since the 2014 Ebola outbreak, COVID-19 dramatically increased their usage. Several types do not require access to smartphones, which are still uncommon in low-income countries (although see Quinn et al. 2011 for using smartphone cameras to identify crop diseases in Uganda). Common phone surveys include computer-assisted telephone interviewing (CATI), interactive voice response (IVR), and short message service (SMS) surveys (Himelein et al. 2020a). The sorts of questions being asked, the time and costs required to field the surveys, and literacy requirements for respondents, among other details should inform which approach will be most suitable (Himelein et al. 2020a; UN Department of Economic and Social Affairs 2020). In some cases, phone surveys also provided an opportunity to pass on information to respondents (e.g., about safety protocols). Ideally, findings from phone surveys undertaken by researchers are fed to governments and nongovernmental agencies (see Chaskel and Holloway 2020).

While limiting contact between enumerators and respondents, phone surveys bring their own challenges. One challenge that is unique to COVID-19 is keeping enumerators working in call centers safe and avoiding transmission of COVID-19 among enumerators. Productivity and quality dropped when enumerators switched to working from home. Reasons include competing demands on time (e.g., due to lack of childcare) and decreased motivation outside of the call center environment. Other challenges related to phone surveys are not unique to COVID-19. Not all households (and individuals) are equally likely to own a phone or answer a phone. A carefully crafted sampling frame can improve the representativeness of phone-based surveys (Himelein et al. 2020a; Himelein et al. (2020b). A further challenge is that individuals may be less willing to spend time completing a phone-based survey than an in-person survey, adding to issues of sample representativeness. Survey modes (e.g., SMS and CATI) can be combined as a way to increase response (Himelein et al. 2020a). Cellphone data records, when available, can provide useful, household-level data (McBride et al. under review). However, Barriga Cabanillas et al. (2021) found that call detail records may fail to capture variations among poorer cellphone owners.

Community-Based Enumerators and Nutrition Surveillance Systems

The nutrition field has used a wide variety of surveillance systems in an attempt to monitor nutrition outcomes in near real time. These include repeated anthropometric surveys, community based surveillance sites, community health system monthly monitoring systems, admissions data from nutrition services, and data from health clinics. These approaches have had a variety of methodological and practical challenges with direct implications for quality, validity, and interpretability of collected data. Nutritionists are still struggling to achieve consensus on the best ways to collect anthropometric data through surveillance. One recent food-security-focused RTM project, the Rapid Feedback Monitoring System (RFMS) in Malawi (see Annex 5), had drawn enumerators from within the local communities prior to COVID-19. After lockdown eased and additional safety protocols were implemented, the community-based enumerators have continued to collect monthly data from other community members. Further, enumerators disseminated information on the prevention of COVID-19 and its symptoms to respondents. If the monitoring project is not clearly explained to respondents, collecting data regularly on outcomes but not providing responses may create false hopes.

Community-based enumerators can provide detailed, on-the-ground perspectives but costs can limit the number of sites where they are located. Therefore, community-based enumerators are often part of a sentinel site approach, where sites are purposively sampled because of their specific characteristics, although sentinel site monitoring can occur without community-based enumerators. Headey and Barrett (2015) have argued that a longer-term, high frequency sentinel site approach to data collection would allow the better understanding and tracking of resilience because high frequency data can better capture dynamics that cannot be collected with infrequent nationally representative surveys (e.g., the Demographic and Health Survey).

RTM Analysis

Dashboards

Dashboards compile and report outcomes and causal factors. Several new dashboard initiatives have emerged after COVID-19 as a means of presenting data in one location. Often implicit in dashboard development is the decision to build them to present readily available, dynamic, secondary data; these data may not be the data most needed for decision-makers. A resulting challenge for end users is how to make sense of and interpret data that may be distantly related to the outcomes they wish to track. In contrast, one recent dashboard (World Bank 2020) presents new, primary information. Data checking and cleaning can also be slow, resulting in recent interest in experimental statistics (i.e., those not yet vetted by statistical agencies).

While dashboards generally present descriptive statistics and many display trends, only some RTM efforts (e.g., FSNAU's dashboard, see Annex 1) are combined with expert analysis that synthesizes these with other factors to provide a holistic picture. When a dashboard does not include rapid analysis, an implicit assumption seems to be that analysts and decision-makers can effectively ingest dashboard information to reach conclusions. How to support analysts to synthesize dashboard information and complement it with information not tracked in the dashboard is less clear.

Nowcasting

Nowcasting aims to generate predictions of current status, often using some combination of remotely sensed data, other secondary data, and primary data. Historical data and contemporary data are often both included in nowcasting models. Some nowcasts aim to predict current outcomes of hard-to-measure indicators (e.g., poverty). Other nowcasting efforts aim to predict outcomes for areas for which no data were collected.

Forecasting

Forecasting, by virtue of being forward looking, is often less directly informative for RTM, although forecasts can help analysts assess whether the current status is expected to deteriorate or improve in the future. Forecasting can take several forms, including scenario development as a form of analysis and PA/ML models. Compared to RTM analysis, forecasting tends to be in greater depth and less frequent.

Predictive Analytics/Machine Learning

Predictive analytics/machine learning (PA/ML) can generate both nowcasted and forecasted estimates. Siegel (2016: 15) defines predictive analytics as a "technology that learns from experience [historical data] to predict the future behavior of individuals in order to drive better decisions." Machine learning is one tool used by predictive analysts. PA can be used to forecast hazards (e.g., future drought) or outcomes (e.g., future food security status). PA can also be used to estimate current status ("nowcasting") either for locations where data are not available or for outcomes lacking current data (e.g., nowcasting food security status based on current data on prices or drought). As Siegel indicates, PA models require historical data on which to "train" and "test" the model. Without high-quality historical data on which to train the data, accurate predictions are unlikely (McBride et al. under review). Assessing the prediction accuracy, costs of interventions, costs of delaying interventions, and also the types of errors in prediction (e.g., risks of false positives versus false negatives) can assist in determining the costs and benefits of acting on forecasted outcomes (see Zhou et al. under review and Maxwell et al. 2021).

As several researchers have pointed out, implicit and explicit assumptions shape a model's outcomes (see Coyle and Weller 2020; Maxwell et al. 2021; McBride et al. under review; Zhou et al. under review). Making visible these choices and understanding their implications requires collaboration between modelers, policymakers, and analysts. For example, policymakers may prefer simple models developed using dynamic (and policy-relevant) variables or may prefer highly accurate models with many variables (Maxwell et al. 2021). Or, policymakers may wish for models to be used to target households or may wish for a geographic mapping of predicted outcomes at a higher spatial level (McBride et al. under review). PA for real-time monitoring face similar choices and similar tradeoffs.

PA/ML is being used to nowcast a (currently) uncollected variable. Some outcomes, such as poverty measures, are collected infrequently, are expensive, and time consuming, and frequently out of date by the time the data are processed. Researchers at the World Bank (Lakner et al. 2020) have estimated changes to poverty using nowcasting at both a global scale and within some countries (e.g., Malawi). First, Lakner et al. use machine-learning simulations for 166 countries to nowcast and forecast 2030 global poverty. Their models include data on GDP, household surveys, Gini coefficients, and COVID-19 projections. Results can be reported globally, regionally or for specific countries. Their results change as new information becomes available. They find, for example, that estimates of poverty in India jumped between April and June, due to macroeconomic changes. Their country-level analysis does not provide insight into the specific individuals at risk, but does show which factors are contributing to changes in their estimates.

PA/ML is being used to nowcast to other locations. An important recent RTM effort by the UN World Food Programme (WFP) combines PA with an easy-to-navigate dashboard. To generate estimates for Hunger Map Live, WFP applies machine learning to estimate food security status in locations without data or with limited data. In over 30 countries (as of January 2021), they collect high frequency, real-time data on food security and other measures via computer-assisted telephone interviews. In locations without such data, they use machine-learning models to predict current food security. These models are trained on data from 63 countries and over 14 years, and they include a wide range of variables (e.g., nightlights, prices, vegetation). Resulting predicted levels of food insecurity are updated near daily, as new food security information from phone surveys becomes available and as predictive models are revised (re-trained) to incorporate new data.

Much of the RTM nowcasting is at nation-state scale in part due to the limited availability of intra-country indicators (e.g., prices are collected for only a handful of markets). One response is to apply machine learning tools to downscale estimations to more disaggregated levels (Fraym n.d.). The limited localized data against which to test the accuracy of their predictions remains a challenge. PA can be paired with primary data collection (e.g., via telephones or using sentinel sites) to nowcast to other locations. To generate localized estimates of poverty in Malawi, a research consortium combines high frequency wellbeing data collected by telephone with machine learning to estimate poverty at a district and subdistrict level (Upton and Yoshimura 2021).

PA/ML challenges. Applying PA and ML tools to RTM is challenging. First, a goal of RTM is to provide insights relatively quickly (in "real time"). Yet, as with other components of the humanitarian information system, the sharing, cleaning, and analysis of data can be cumbersome and slow (see Maxwell et al. 2021). Second, the lack of high-frequency historical outcome data at district and sub-district levels has limited the development of RTM models. Without more spatially disaggregated data to benchmark against, it is difficult to replicate these approaches at more localized levels and many models remain as "proofs of concept" (e.g., Lentz et al. 2019). A third challenge is that models can only predict based on the types and quality of data they are trained on. Models generated using training data without conflict, for example, will not provide accurate outcomes when applied to locations with conflict (Maxwell et al. 2021; Zhou et al. under review).

Future directions. One important direction for the development of RTM systems could be using machine learning techniques to identify which subset of indicator variables from a larger set are most predictive of food security (or other humanitarian outcomes). This could help streamline future RTM data collection by identifying which subset of variables to collect (Knippenberg et al. 2019). Best practices on combining nowcasted PA findings with more established RTM analyses have not yet emerged. An important area for future research is to understand how to combine nowcasts with expert consensus building and with other sources information to generate coherent real-time assessments of people in need.

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