Early Warning and Early Action for Increased Resilience of Livelihoods in the IGAD Region

Report 1. Main Report, Findings, and Recommendations

A Feinstein International Center Working Paper

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The authors

Acronyms

ACAPS	Assessment Capacity Program
AFI	acute food insecurity
AI	artificial intelligence
AMN	acute malnutrition
API	application programming interfaces
BRCiS	Building Resilient Communities in Somalia
CAP	Consolidated Appeals Process
CERF	Central Emergency Response Fund
CEWARN	Regional Conflict Early Warning Project
CFI	chronic food insecurity
CSA	Current-Status Assessment
DL	desert locust
EA	early action
ECMWF	European Centre for Medium-Range Weather Forecasts
EFSNA	Emergency Food Security and Nutrition Assessment
EW	early warning
EW-EA	early warning/early action
EWS	early warning system
FAM	World Bank Famine Early Action Mechanism
FAO	UN Food and Agriculture Organization
FBF	forecast-based financing
FCS	Food Consumption Score
FEWS NET	Famine Early Warning System Network
FSNAU	Food Security and Nutrition Analysis Unit (Somalia)
FSNMS	Food Security and Nutrition Monitoring System
FSNWG	Regional Food Security and Nutrition Working Group
GHACOF	Greater Horn of Africa Climate Outlook Forum
HDDS	Household Dietary Diversity Score
HEA	Household Economy Analysis
HNO	Humanitarian Needs Overview
HRP	Humanitarian Response Plan
HSNP	Hunger Safety Net Program (Kenya)
ICPAC	IGAD Climate Prediction and Applications Centre
IDP	internally displaced person
IGAD	Inter Governmental Authority on Development
INT	Integrated Needs Tracking system
IO	international organization
IPC	Integrated Phase Classifications

IRI	International Research Institute for Climate and Society
JIAF	Joint Intersectoral Analysis Framework
KFFSG	Kenya Food Security Steering Group
KII	key informant interview
KRCS	Kenya Red Cross Society
MERIAM	Monitoring Early Risks Indicators to Anticipate Malnutrition
ML	machine learning
MUAC	Mid-upper arm circumference
NDMA	National Drought Management Authority (Kenya)
NDOC	National Disaster Operations Center (Kenya)
NDRMC	National Disaster Risk Management Commission (Ethiopia)
MHADM	Ministry of Humanitarian Affairs/Disaster Management (S. Sudan)
NGO	Non-Governmental Organization
OCHA	Office for the Coordination of Humanitarian Affairs
PA	predictive analytics
PIN	population in need
PSNP	Ethiopia Productive Safety Net Program
rCSI	Reduced Coping Strategies Index
RTM	real-time monitoring
SMART	standardized methods for assessment of relief and transition
TWG	Technical Working Group
UN	United Nations
WASH	water, sanitation and hygiene
WFP	World Food Programme
WFP VAM	WFP Vulnerability Analysis and Mapping Unit
WFP mVAM	WFP Mobile Vulnerability Analysis and Mapping Unit

A. Background to the Study

The East Africa region is amongst the most food insecure areas of the world. In 2021, an estimated 34 million people in the region covered by IGAD (not including Eritrea) are experiencing acute food insecurity, requiring food, nutrition, and livelihoods assistance (FSNWG 2021). In 2020, the combined threats of desert locusts, climate change, COVID-19, and conflict, hunger worsened significantly (FAO/WFP 2020) resulting in these figures. Looking forward, the number of crises affecting the East Africa region will likely continue to increase due to the effects of climate change and other drivers.

Multiple calls have been issued for better preparedness, early warning, and, above all, early action to prevent hunger and malnutrition, reduce the scale of food insecurity, improve resilience, and reduce the amount of money spent on responding to crises every year (FAO/WFP 2020). But nowhere have these challenges been greater than in East Africa. A recent review of early warning systems in East and Southern Africa by the World Bank found numerous difficulties with current systems, including that many have an "overly technical approach, externally imposed methods and institutional models, and short-term project horizons" (Braimoh et al. 2018). A recent study on food security information systems in East Africa (Maxwell and Hailey 2020a) noted that despite years of attention, the link from early warning to early action is not as effective as it could be. And although conflict is a common driver of humanitarian crisis, conflict early warning is weak to non-existent. Political interests play a role in influencing the outcomes of both current-status assessment and early warning.

New technologies involving remote sensing, satellite imagery, computational modeling, and artificial intelligence are all competing to improve early warning and humanitarian information systems (Hernandez and Roberts 2020). But it is not always clear whether these new technologies are being developed: (1) to complement or substitute for existing systems, (2) to address specific short-comings or because technology developers are in search of applications and new markets, or (3) to institutionalize agreed-upon approaches and thus ensure sustainability. While they have the potential to improve and support existing EW practices, these current initiatives run the risk of falling into the same problems identified by the World Bank study in current early warning systems (Braimoh et al. 2018).

1. Problem Statement

An earlier paper outlined the situation facing decision-makers (national and local governments, donors, humanitarian agencies, and at-risk communities) in East Africa in 2019:

> On top of long-standing conflict crises in at least five countries and political turmoil in several more, the long rains (*gu* rains in Somalia, etc.) in the first part of 2019 were delayed and, in many cases, well below average despite having been predicted to be about normal. However, by the time the effects of delayed rainfall were beginning to be felt, meteorological early warning systems (EWS) were forecasting a positive Indian Ocean dipole, indicating much heavier than average rainfall in the second half of 2019. Thus, while current information was suggesting that drought could impact livelihoods, early warning was forecasting flooding. At the same time (to anyone who was listening), early warning information identified an upsurge of desert locusts in the Arabian Peninsula that was likely to affect East Africa. All of these came to pass, as did the COVID-19 pandemic, which no humanitarian early warning or information system foresaw. None of this information was *wrong*. Some of it was delayed and, in some cases perhaps, people weren't paying adequate attention. But a significant part of the problem was that there was just *lots* of information,

> and to many humanitarian decision-makers, what to do with it or how to make sense of it all simply wasn't clear. For much of the ensuing year, a coherent analysis of all factors that could genuinely inform anticipatory—or even early—action was difficult to formulate. By mid-2020, the East African Food Security and Nutrition Working Group noted nearly 54 million people in immediate need of food assistance in the region (ICPAC 2020)—an increase of nearly 40 percent from 2019—and this assessment was missing information from several countries, meaning that the total would be higher (Lentz et al. 2020, p. 4).

In response to this kind of challenge, the demand for anticipatory action has increased (Lowcock 2019), but this example is indicative of the challenges of collecting and analyzing early warning data in such a way that informs rapid, early action to prevent or mitigate humanitarian crises. It is by no means the only example. As traditional EW-EA systems struggle to meet the challenge, new initiatives—the World Bank's Famine Action Mechanism (FAM), UN OCHA's anticipatory action approach, and the Red Cross/Red Crescent forecast-based financing (FBF) initiative—are also attempting to address this challenge, using advanced machine learning (ML) and predictive analytics (PA). But as noted above, part of the issue is the sheer volume of information and how well it informs some kind of coherent action. The issue of coherence of the system (or "eco-system") was the topic of the earlier paper (Lentz et al. 2020). This study reviews current EW-EA systems in East Africa, as well practices and emerging initiatives relying on predictive analytics and machine learning, to ensure early warning systems suit the needs of decisionmakers and enable early action for improved resilience in the IGAD region.

2. Objectives and Research Questions

At the request of the FAO Subregional Office for Eastern Africa, this study was commissioned to examine the links between early warning and early action in East Africa. The immediate objective relates to early warning and early action related to food security. Shocks of all kinds tend to affect food security in the region, so EW systems tracking multiple hazards were included, and impacts beyond food security were also considered in order to be complete. Largely—though not entirely—EW-EA systems in the region are driven by food security concerns. The broad objective of this study is to gain an in-depth understanding with regard to

- early warning and early action in the IGAD region;
- predictive modeling (both in the field and elsewhere);
- triggers and links to early action; and
- perceived gaps in the existing systems.

Key research questions included the following:

- What are the existing food security early warning systems in the IGAD region, and what are the main constraints they face?
- What predictive modelling and AI efforts are being developed that could improve early warning systems, and how would they trigger early action?
- What are the gaps in existing systems and needs of decision makers, and what practices from other countries or PA/ML initiatives could help address them?

For this study, we review documentation on existing systems and present analysis from interviews with information systems managers and decision-makers who rely on those systems. We also review new trends in predictive modeling and interview the people developing them. Finally, we make recommendations to the FAO Subregional Office for Eastern Africa, to IGAD, and through FAO and IGAD to IGAD member states.

B. Conceptual Overview on Early Warning-Early Action

1. Components of a Humanitarian Information System

Lentz et al. (2020) outlined "humanitarian diagnostics" as that which covers most of what is traditionally thought of as "early warning" systems, although the paper treats early warning per se as one of several components of such a (hypothetical) system. This section borrows heavily from that paper and aims to clarify parts of the (real-life) systems mapped out and analyzed below. This section reviews baseline analysis, early warning, current-status (emergency) assessment, projections, and real-time monitoring. Combined, these components make up the information systems in the IGAD region.

Baseline Analysis

Baseline assessment or analysis is a snapshot in time intended to capture "normal" or "usual" status. In monitoring and evaluation terms, baseline analysis occurs prior to any intervention. In diagnostic terms, baseline analysis is "normal" status information against which the extent of a shock or crisis is measured. Baseline data was (and remains) important as a point of comparison for both early warning and current-status assessment. In contexts with many years of trend data, the more accurate comparison is with those trends rather than with a particular point in time presumed to represent a "baseline."

Early Warning

Early warning (EW) has always tracked hazards and assessed the risk of those hazards causing damage to people and their livelihoods—i.e., *causal factors*. The assumption remains that not only can we track long- and short-term trends, seasonality, and relatively fixed drivers (like geography and infrastructure) as well as changing factors (such as climatic and environmental drivers), macro-economic and political factors, production estimates, markets and prices, population movements, and conflict …, we can also predict when and where hazards will manifest, which populations will be affected, and how likely crises are to occur. These predictions are typically "scenarios" that focus on most-likely outcomes, but with an emphasis on "*likely*," underscoring the probabilistic nature of EW.

Triggers (or "signals") are not the same thing as early warning, although they serve a similar purpose. Triggers are thresholds which, when breached, set in motion pre-arranged actions such as a payout for an insurance policy or a scaling up of cash transfers in a social protection program. Triggers have been suggested as one way to reduce the time for decision making or to take some of the politics out of decision making based on scenario analysis. For the most part (at least so far) triggers have worked best when linking a single threshold for a single hazard to a single response. However more recent efforts have considered using FEWS NET–projected transitions from IPC (Integrated Phase Classification) Phase 2 or below to Phase 3 or above as a trigger, which in effect, turns a scenario based on an in-depth analysis of multiple factors into a "trigger" for a multi-pronged response. But this is something of a departure from what "trigger" usually means.

Current-Status Assessments, Projections, and Real-Time Monitoring

Since 2003, the system has invested substantial money, time, and human resources into improving **current-status assessment**, particularly with the institutionalization of the IPC in the late 2000s, and the supporting surveys that go with IPC analysis. IPC regularly reports figures on the current status of populations, classifying them into *phases* or severity categories, either by livelihood zone or administrative zone, and providing a **population in need (PIN)** figure in each phase for each geographic unit. Anyone in IPC Phase 3 or higher is counted in the PIN for humanitarian food assistance. IPC has been instituted in some 35 countries—and a technically identical analytical protocol, Cadre Harmonisé, is used in 17 additional West African countries (IPC

2021). IPC analyses take place usually once or twice a year, covering entire countries at an ADMIN2 level. They are usually based on WFP FSNMS or EFSNA surveys, supplemented by SMART surveys, etc. IPC therefore compiles an impressive amount of data, but, as a result, it is time-consuming and is always a bit out of date by the time the data is collected, cleaned, and analyzed; the situation is classified and vetted; reports are written and cleared; etc. Even in the best case scenario, the information is likely to be at least two months old by the time a report is finally issued—in extreme cases, the information may be up to a year out of date (and frequently information is simply not available at all).

Projections

At least partially as a result of that, projections have become a much more important part of IPC analyses than they originally were. Projections take the current-status information as a kind of short-term baseline (not to be confused with baseline analysis) and draw on early warning information to craft the most likely scenario for the short- and medium-term future (2–3 months and 4–6 months), and then "project" the numbers of people likely to be in each IPC Phase by geographic zone (so the projections appear in the same form as the current-status assessment), numbers of people in different IPC phases, and an overall phase classification for geographic units of analysis.

While the current-status assessment is based on real numbers (i.e., empirical data), the projections are based on assumptions about what is likely to happen to the current numbers. Those assumptions ideally reflect a thorough analysis of early warning factors, the development of scenarios, and a judgment about which is the "most likely" scenario. A "most likely" scenario enables the projection of a number of people in each IPC phase by livelihood zone or administrative unit. But the projection is less transparent than the current-status assessment because it relies entirely on human judgment—there is no algorithm. According to a few published articles, FEWS NET and IPC both generate projections. FEWS NET projections have been shown to accurately predict future classifications about three-quarters of the time, but have particular difficulty dealing with uncertainty associated with complex weather patterns and conflict, as well as detecting crises in areas that experience them less often (Choularton and Krishnamurthy 2019; Krishnamurthy et al. 2020a). IPC projections have not been gauged for accuracy. Note that a reliable way to validate the accuracy of the projected PIN has not yet been identified.

Nevertheless, in the short term, the **projected PIN** is probably the single most important piece of actionable information that comes out of the entire system—because it refers to the future and at a range of time when governments, donors, agencies, and even local communities can still act. At a minimum, it says "humanitarian agencies are going to need to provide food assistance to this number of people in this place to deal with food insecurity 4–6 months from now." Sometimes, projections can be very effective at provoking early action. In early 2017, when FSNAU projected famine in Somalia (for the second time in six years), it helped to trigger additional resources and led to a more rapid response, and famine did not recur. (This is not to say that FSNAU information was solely responsible for preventing renewed famine: Somalia had a functioning government in 2017; a number of people in the humanitarian community were determined not to let famine happen again; donors weren't as concerned about counter-terrorism measures; etc. but the early warning played an important role).

Several points can be made about IPC projections: (1) the methodology for generating PIN is heavily based on human expert judgment; (2) currently, projections are based on the current status assessments, which are very expensive and time-consuming and are only mounted once or twice a year—a lot can change in between those times; and (3) while early warning indicators are monitored between IPC analyses, there is not yet any formalized monitoring of the assumptions on which projections are based.

Real-Time Monitoring

This is where the need for **real-time monitoring** (RTM) arises. If done well, RTM tracks changes in the context and notes whether current humanitarian conditions are improving or deteriorating. It thus serves as a form of "hotspot identification." In contrast to early warning, RTM happens in real time. It may be the only means of identifying rapidly worsening situations. RTM can also supplement information useful to early warning analysis (in fact in some situations it is indistinguishable from EW in practice). And RTM could be utilized to track the extent to which the assumptions in scenario development—and therefore projected PIN numbers—are borne out in reality, and therefore whether the projections are about right, too high, too low, etc. Unfortunately, RTM often doesn't do all of those things equally well.

Sometimes RTM systems operate where no EW system exists. That may mean that information is not generated in time for early action and at best can influence rapid response. But frequently, and importantly, many kinds of RTM information are simply collected, processed, and put out for general consumption, with no real analysis provided for what they mean, and often with confusing links back to the other parts of the formal system. Real-time monitoring is relatively new in humanitarian information systems and is still being developed in many contexts.

2. Clarifying the Role of Diagnostic Information

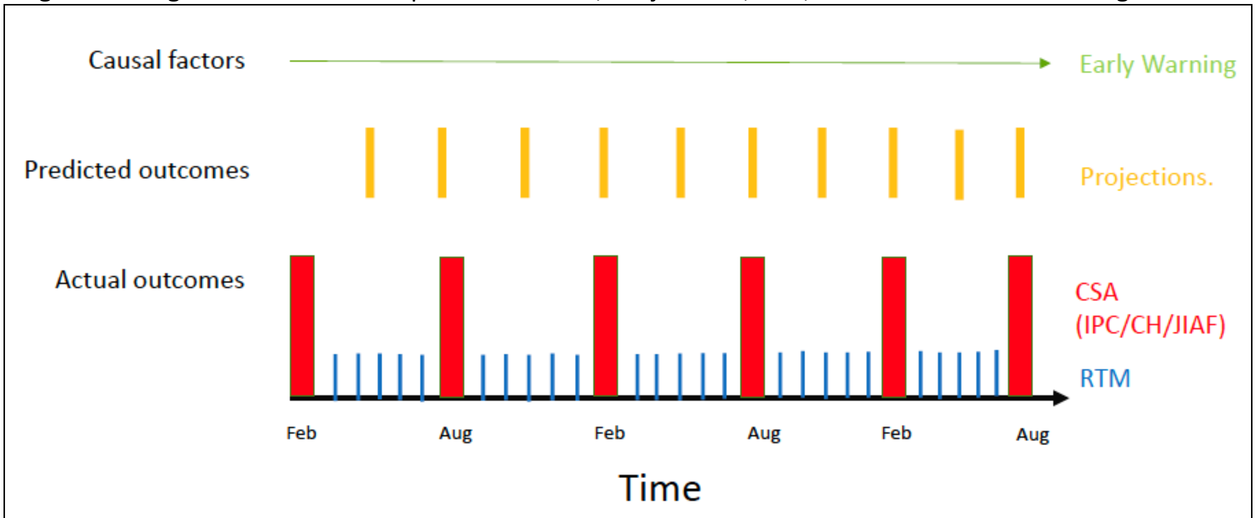
We propose that clarifying the role of diagnostic information could help to clarify the data confusion within the humanitarian sector, ultimately leading to more actionable outputs of the information system as a whole.

Figure 1 shows that different types of diagnostic information are collected at different times and inform different information activities. Table 1 describes the types of information and how frequently they are collected for each information activity on the right hand side of Figure 1. Real-time monitoring, for example, often occurs monthly and can include any combination of information types.

The reality is more complex than shown in Figure 1 and Table 1. Some humanitarian information systems do not treat these types of information as feeding into separate information activities. For example, "nowcasting," a type of predictive analytics (PA), can support out-of-sample predictions for locations lacking current outcome data. Nowcasting models can be built using causal factors, correlated factors, and actual outcomes—either from other locations or from historical data from that location—to predict current status. The ability to do out-of-sample predictions could cut information gathering costs.

However, unless and until there is a clear way of seeing how all the different bits work—or could work or *should* work—together, humanitarian diagnostics run the risk of producing a lot of noise and disjointed information without a clear idea of what it means or how it informs action.

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



Source: Lentz et al. 2020

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

Table 1. Activity, Information Type, and Frequency

Information activity	**Type of information**					**Frequency**
	Causal factors	Predicted outcomes	Actual outcomes	Hotspot identification	Assumption verification	
Early warning	X			X		Ongoing
Current-status assessment (IPC)			X	X (often late)		Every 6 or 12 months
Projections		X				Varying (4-6 months)
Real-time monitoring	X		X	X	X	Monthly
Baseline vulnerability assessment	X		X			Every 5 years/after a major change

Source: Lentz et al. 2020

3. Links to Early Action

Early action is defined as “actions taken to reduce the impact of specific disaster events” (FAO 2021). Anticipatory action is action taken even before a shock occurs to prevent, mitigate, or reduce the impact of the shock. The links between early warning and early or anticipatory action are not always clear or effective in practice. Various approaches include the use of triggers or scenarios as the link, but also the notion of “no regrets” programming (whether linked to *either* triggers or scenarios), the role of response analysis, and communications with affected communities (a seemingly obvious but frequently overlooked link to action).

Some early action decisions are based on a **trigger** system. These signal-driven systems may use current status assessment (CSA) information or EW information on hazards. A trigger does precisely what is implied—it triggers a pre-set action. The pre-set action may be a more in-depth assessment of the situation, or it may be an actual response.

A scenario is a more in-depth assessment of the situation, noting multiple causal factors and potentially multiple outcomes. Scenarios are more useful for an overall response than for a single action. But they also require further judgment with regard to the appropriate response. Knowing food security will get "worse" or become "bad" (or that a drought will worsen) does not answer the questions decision makers really want to understand (how many people? where? for how long? how severe? how much money is required?) and perhaps even what the appropriate response would be. This is what scenario building is about.

The "**no regrets**" approach to anticipatory action has grown in popularity—at least in principle—in recent years (Maxwell et al. 2013). In theory, this involves engaging in early action that will mitigate a crisis and will have beneficial impacts even if the crisis does not develop as anticipated. However, "no regrets" tends to assume that adequate resources are always available, and that investing in a particular kind of action in one place is not taking resources away from another place.

Constraints to early action (including "no-regrets" action) have long been assumed to relate simply to a lack of finances to enable a response. While finance is one critical component, having strong **contingency planning** in place, that lays out exactly what has to happen is critical in cases requiring more than one single response. In other words, if the *only* response is to set cash transfers in place, a detailed contingency plan may be less critical than if response options include cash transfers, asset protection programs, commercial livestock offtake initiatives, or other activities to be sequenced or undertaken at the same time. And it is critical to have the implementation capacity to rapidly put the plan into action.

Linking early warning to early action also requires **response analysis**, which is determining the most appropriate response or set of responses to a rapidly changing situation (Barrett et al. 2009). Ideally response analysis would be included in contingency planning, but in rapidly changing situations, the best response may change as well. Strong awareness of response options and when each is the most appropriate is a key consideration. For instance, providing cash transfers has proven to be an important intervention to mitigate food insecurity among urban populations during the COVID-19 pandemic, but in several cases—for reasons perhaps unrelated to the pandemic as such—food price inflation made cash transfers a less useful intervention than in-kind food or vouchers (Gentilini et al. 2020). It hasn't always been clear that all of these considerations were factored into contingency planning.

C. Brief Summary of Study Approach and Methods

This study relied on two main methods. The first was an extensive review of the literature on early warning-early action (EW-EA), consisting of peer-reviewed articles, agency reports and other "grey" literature, and methodological materials, with a focus on East Africa but drawing on the global literature. The second method was a series of interviews with key informants who either represented a regional overview or a country-specific perspective.[1]

A total of 84 interviews with 125 individuals were conducted between July and November 2020 (Table 2). Respondents included technical staff of EW systems in the region, government officials who rely on EW for

[1] A more complete description of study methods and approaches is found in Annex 2

decision-making, donors, and other end users including humanitarian agencies; as with individuals or organizations working to build predictive modeling or other algorithmic approaches, including, in some cases, artificial intelligence.

All interviews were conducted remotely, in accordance with the practices prescribed by the Integrative Safety Committee of Tufts University. Interviews with staff of existing systems and users were analyzed in two separate ways. First, *all* interviews were coded generally for the overall thematic analysis, using both deductive and emergent coding schemes. *Second, interviews related to specific countries were re-analyzed according to many of the characteristics found in Table 3 as well as for idiosyncratic, country-specific factors.* All interviewees' names and identifying information were considered confidential and anonymized in the analysis. Interviews are referred to in this report by number only. This study was approved by the institutional review boards of both Tufts University and the University of Texas.

Table 2. Interviews and Key Informants by Category

Country	Total Interviews		Respondents Working EW/Information Systems		Users					
					Government Users		Donor Agency Users		Humanitarian Agency Users	
	KIIs	People	KIIs	People	KIIs	People	KIIs	People	KIIs	People
Global	17	27	17	27						
Regional	21	27	18	20	1	3	2	3	0	0
Eritrea	2	2	1	1	1	1	0	0	0	0
Ethiopia	8	11	8	10	0	0	2	2	1	1
Sudan	7	12	6	8	1	1	2	4	1	2
S. Sudan	8	11	6	7	2	3	0	0	2	2
Uganda	2	3	1	1	1	1	0	0	0	0
Kenya	5	9	4	4	1	1	0	0	1	1
Somalia	12	21	5	10	2	2	3	6	1	1
Djibouti	2	2	2	2	2	2	0	0	3	3

Notes:
1. KII: Key informant interviews. "People" refers to number of individuals interviewed (some key informant interviews were with multiple individuals).
2. Many respondents represented multiple perspectives (especially those working in EW information systems and information users).
3. A total of 21 interviews (37 individuals) addressed, at least partially, the question of predictive modeling

The following section (Section 4) briefly summarizes existing EW-EA systems at the regional and national levels in the IGAD region. A separate document (Report 2) provides a full detailed mapping of these systems.

Section 5 is devoted to summarizing recent trends regarding the application of predictive analytics and machine learning to early warning and triggering early action. A separate document (Report3) provides a more detailed examination of these trends and issues. Section 6 provides a summary of issues emerging from the key informant interviews, the mapping of national and regional systems, and the review of predictive analytics/ machine learning, as they apply to the IGAD region. Section 7 provides recommendations to FAO and IGAD, growing out of the entire study. Annex 1 contains the results of polling during the global webinar presenting the report. Annex 2 is a more detailed description of the study methods. Annex 3 provides the key informant interview guide.

A separate document provides a brief executive summary of the study and its findings and recommendations.

D. Mapping EW-EA Systems in East Africa/IGAD Region

Regional systems and some of the cross-cutting themes emerging from the review of individual country systems are presented in Section 4. A complete description of country systems is in Report 2. Parts of that report are reproduced here.

1. Regional-Level Systems

While the nature of EW-EA systems is primarily national, there are a number of regional actors that support national level efforts. These are briefly reviewed here.[2] The main regional early warning overview is provided by the **Regional Food Security and Nutrition Working Group (FSNWG).** It is led by the IGAD Climate Prediction and Applications Centre (ICPAC) and FAO. In recent years it has provided regular updates at the regional level drawing on major UN Agency, IGAD and FEWS NET information, aiming to be a "one-stop shop" for information and early warning in the region. However, its main role is to collect and amalgamate information from agencies and countries, and present a regional overview, by country and by thematic area (food security, nutrition, displacement, markets, livestock and pastoralism, etc.). Though not linked directly to any early action mechanism, it works to raise attention about future food crises and advocate for early actions (FSNWG 2021).

The IGAD Centre for the Prediction and Analysis of Climate (ICPAC) is the regional climate prediction and seasonal early warning body. One of its main outputs is the medium-term, seasonal prediction—the "Greater Horn of Africa Climate Outlook Forum" (GHACOF): a probabilistic forecast of the likelihood of rainfall anomalies or failure. The GHACOF has recently changed its methodology in an attempt to improve forecasting (ICPAC 2021). Other, more global climate forecasts are provided by the **International Research Institute for** Climate **and Society** (IRI) at Columbia University, the **European Centre for Medium-Range Weather Forecasts** (ECMWF) and the **Red Cross/Red Crescent Climate Centre**.

The **FAO Regional Office for East Africa** is hosting an initiative to improve EW-EA in the region. The first step of this initiative is to conduct a review of EW-EA systems in the region (hence this report) as well as serving as the link to global early warning systems housed in FAO. The Regional Office has plans to roll out a real-time monitoring system, possibly similar to the Somalia Early Warning-Early Action dashboard.

At a more centralized level, FAO also operates the **Desert Locust Information System**, a permanent office in Rome dedicated to tracking desert locust activity. Given the recent upsurge of locusts in several IGAD

[2] This section and the following section on national systems draws on and supplements the previous report (Maxwell and Hailey 2020a).

countries, this office has once again emerged in the broader ecosystem of early warning systems in the region. Utilizing remote sensing information, data collected by country staff, and related weather data, the Desert Locust Watch team creates regularly published six-week forecasts of desert locust activity at global, regional, national, and subnational levels. This early warning system is also directly tied to early action as the office swiftly communicates any high-risk changes in locust activity to FAO senior leadership, which then prompts an emergency declaration, making fundraising for response relatively easy (004).

The **Integrated Food Security Phase Classification** (IPC) system, hosted globally by FAO, is an iniative of fifteen agencies, that now has three main analytical tools: one for assessing acute food insecurity (AFI), one for acute malnutrition (AMN) and one for chronic food insecurity (CFI). At least one of these IPC analyses is now conducted in all countries in the IGAD region with the exception of Eritrea. All the other countries conduct AFI analyses. The AFI was most recently introduced in Ethiopia (in 2019). Most of the same countries also conduct an AMN analysis (see Table 3), but nutrition analysis is more variable by country. IPC analysis is conducted by an in-country Technical Working Group (TWG), typically led by a government agency but with strong analytical capacity from UN agencies and FEWS NET. The process is usually funded as an FAO project (IPC 2021).

At its core, IPC is a data amalgamation tool, building multiple sources of information into an analysis and classification of food security and nutrition status, categorized by geographic area (usually either livelihood zones or administrative units). It relies on large-scale household surveys of food security and nutrition status, supplemented by SMART surveys' more in-depth coverage of malnutrition and mortality. IPC is not an early warning system *per* se. IPC's primary function is to classify current-status conditions according to severity, but IPC projections have come to be an important part of the early warning ecosystem in all the countries in the region where it is operating.

FEWS NET operates in all of the countries in the IGAD region except Eritrea with permanent staff and national offices in Kenya, Somalia, South Sudan, Sudan, Uganda, Ethiopia; and a regional office remotely monitoring other countries (including Djibouti). FEWS NET collaborates with national government partners, and is a part of IPC Technical Working Groups (and usually core analysis groups) while maintaining the independence of its analysis. FEWS NET uses scenario-building approach to early warning, measuring variation against baseline conditions in its short-term predictions, and uses IPC-compatible classification for its mapping of both current status and predicted outcomes. FEWS NET typically produces three forecasts per year (with updates in-between) and thus has more frequent updates than IPC, which produces usually one or two. However, unlike IPC, FEWS NET does not publish population figures by IPC category—rather it offers only ranges for the number of people in need (PIN) figure.

SMART. While most other systems are explicitly for food security analysis and classification or prediction of climate outcomes, the in-depth assessment of nutritional status is done by SMART (standardized methods for assessment of relief and transition) surveys. SMART is not specific to the IGAD region, and has strong ties to the Global Nutrition Cluster. SMART has a well-established set of norms and practices for assessing current nutritional status, but early warning systems for malnutrition, or predicting the prevalence of malnutrition, is a significant deficit. Several new pilot initiatives seek to forecast wasting prevalence based on sophisticated modeling (See Section 5).

Household Economy Analysis (HEA) is still in use by some agencies and notably in Ethiopia at the national level. HEA is included in IPC protocols, but is not used much in IPC analysis outside of Ethiopia. HEA "outcome analysis" is very applicable to early warning and to predicting populations in need, but this analysis is not broadly available. FEWS NET analysis is linked to HEA baselines in many cases, and relies on HEA analysis in some countries. Some have noted that HEA outcome analysis is very vulnerable to manipulation by policy makers seeking to alter the numbers (Maxwell and Hailey, 2020a).

Several global initiatives on anticipatory action have been piloted in the IGAD region—most notably in Somalia, given both is strong longitudinal data going back nearly 20 years, and its exposure to repeated shocks. The **World Bank** FAM initiative (Famine Early Action Mechanism) was piloted in Somalia, and could have application in other countries. FAM was initially focused on improved prediction and linking to early action through artificial intelligence-assisted early warning. In 2020, it decided to use a more standard form of information to trigger financing mechanisms and finance: transitions in FEWS NET projections. Somalia is the first of the "first mover" countries to take on the FAM initiative. South Sudan is also a "first mover" country, but the current context in South Sudan may not be as conducive to FAM's approach, which requires at least some degree of government leadership. **OCHA** has likewise invested heavily in improving predictive analytics through the Center for Humanitarian Data, with links to existing financing mechanisms such as the Central Emergency Response Fund (CERF). OCHA and the World Bank have been collaborating in work on Somalia.

2. Country-Level Early Warning and Early Action Systems

Table 3 provides a summary of the key features of EW and EA systems by each country. While most countries rely on government-led systems, some countries have a mix of government systems, UN systems, and NGO systems. Key informants report coordination of data collection, data sharing, harmonization of findings, and dissemination across multiple systems can be challenging (Grunewald et al. 2019).

Report 2 contains a brief summary and assessment of the EW-EA system of each country in the IGAD region, according to the same criteria. Report 2 describes existing information systems, governance of EW systems, data collection and analysis, and links to early action dissemination and responses. Each section concludes with a short assessment of strengths, gaps, and responses to COVID-19.

A few generalizations can be made regarding EW-EA systems in the region. Most countries have EW systems that monitor meteorological hazards, agricultural production and or vegetation. Information on prices, pests, conflict, health factors, and displacement is more uneven. Food security EW is well-established. EW for WASH, health, and nutrition are less common, although WASH could be a useful leading indicator for food insecurity (021). The link to early action is weak across the region, although it is variable. Countries with established, government-led social safety net programs (notably Kenya and Ethiopia) have stronger linkages. Some countries have relatively well-developed NGO systems—operating collaboratively with government in some cases (Kenya) and independently in other cases (Somalia, South Sudan).

Table 3. Characteristics of EW-EA Systems in IGAD Region

Component	DJI	ERI	ETH	KEN	SOM	SSD	SUD	UGA
Early Warning								
IPC: Type of analysis								
AFI	**		**	**	**	**	**	**
AMN				**	**	**		**
CFI	**							
FEWS NET	Remote		**	**	**	**	**	**
Govt-led system	**	**	**	**	New	**	**	**
UN-led system			VAM	VAM	FSNAU	FAO&VAM	VAM	
NGO-led system			Multiple	KRCS	BRCiS	REACH	?	
Seasonal assessment	**		**	**	**	**		
Sentinel sites				**				
Real-time monitoring					**	**		
Data: Hazards								
Climate	**	**	**	**	**	**	**	**
Prices/Mkts		Urban	**	**	**	**	**	**
Vegetation	**	**	**	**	**	**	**	**
Production		**	**	**	**	**	**	**
Pests/DL	?		**	?	?	?	**	**
Conflict						?	Ltd	
Displacement					**	**	Ltd	?
Data: Outcomes								
Food Security	**		**	**	**	**	**	**
Nutrition	**		**	**	**	**		?
Health	**		**	?	**	?	?	?
WASH			?		Price only	?	?	?
Early Action								
Responsible body	Min of Interior	Gov't Ministries	NDRMC	NDMA NDOC	Multiple	MHADM Agencies	FS TS Ministries	
Links								
Triggers				Some	**	INT		
Gov't agency	**	**	**	**	**	**	**	**
Clusters						**	**	?
Contingency planning	?		**	NDMA	??	?	?	?
Scalable safety net			PSNP	HSNP				
Other ("surge," crisis modifier, "no regrets")			**	**	**	?		?

Source: Key Informant Interviews

AFI Acute food insecurity
AMN Acute malnutrition
BRCiS Building Resilient Communities in Somalia (NGO consortium)
CFI Chronic food insecurity
DL Desert locust
FAO Food And Agriculture Organization
FSNAU Food Security and Nutrition Analysis Unit (Somalia)
FSTS Food Security Technical Secretariat (Sudan Ministry of Agriculture)
HSNP Hunger Safety Net Programme (Kenya)
KRCS Kenya Red Cross Society
MHADM Ministry of Humanitarian Affairs and Disaster Management (South Sudan)
NDOC National Disaster Operations Centre (Kenya)
NDRMC National Disaster Risk Management Commission (Ethiopia)
NDMA National Drought Management Authority (Kenya)
NGO Non-governmental organization
PSNP Productive Safety Net Programme (Ethiopia)
UN United Nations
VAM Vulnerability and Mapping (World Food Programme)

In general, the more support a national EW-EA system has from the national government, the stronger it is. Countries that have been in prolonged crisis (Sudan, South Sudan, Somalia) tend to have systems that are dominated by external agencies—typically but not always UN agencies. On the other hand, some countries that have multiple systems creating confusion regarding information availability and the linking of information to action. Several countries have nascent national EW-EA systems, and negligible investment or engagement from external agencies.

Externally-led processes (such as the World Bank's FAM initiative, or the UNOCHA anticipatory action initiative) have made extensive use of predictive analytics, as have the World Food Program and other actors. National systems have been less eager to adopt PA methods. PA could significantly worsen the confusion over information and the link of information to action unless there is a concerted effort to coordinate with national systems and work towards mutually identified objectives.

In recent years, much of the focus appears to be on supporting or improving EW systems. There has been less attention to EA products, although several countries are pursuing innovative early action interventions, such as linking EA to existing social protection programming (Fitzgibbon 2019, Kimetrica 2020).

The impact of COVID-19, and the way in which national systems dealt with the challenges of pivoting to the information and response requirements demanded by this novel threat, were highly idiosyncratic across the region. Some countries and some systems were able to pivot to the challenges of both monitoring COVID's impact and monitoring food security under the circumstances of lockdowns, distancing, etc. Some were very challenged, and there is little information about some of the ways in which country systems responded.

An analysis of issues arising from the assessment of country systems are found in Section 6.

E. Predictive Analytics and Machine Learning to Improve EW-EA Systems

1. Overview

Predictive analytics (PA) for EW systems hold great potential *for East Africa EW-EA information systems.* The introduction of much higher-speed computers and increasing availability of data has allowed predictive analytics (including machine learning, big data, and statistical modelling) to take off (Varian 2014; Hernandez and Roberts 2020). PA is "technology that learns from experience [historical data] to predict the future behavior of individuals in order to drive better decisions" (Siegel 2016, 15). Predictive analysts often use techniques of **machine learning** (ML) to generate predictions. ML is one type of **artificial intelligence (AI)** used in humanitarian contexts; other forms of AI, including robotics, artificial swarm intelligence and image classification tools, do not prioritize predictions.

This section summarizes key findings from the review of PA and ML. For a more in-depth review, see the accompanying "Report 3."

PA has recently received a great deal of interest in the practitioner, researcher and donor communities because it offers a way to synthesizing large amounts of data to generate diagnostic evidence. PA can be used at multiple stages in the humanitarian diagnostic and analysis system. It can be used to predict hazards (e.g., future drought) or predict outcomes (e.g., future food security status). These forecasts can feed into scenario building or directly trigger responses (e.g., forecast based financing). PA can also be used to estimate current status ("nowcasting") for locations where data are not available (e.g., WFP's Global Hunger Map). Other AI tools can also facilitate reaching conclusions about an assessment, for example by weighing analysts' responses in an online forum (e.g., artificial swarm intelligence). See Box 1 for more details on machine learning.

Some people propose that PA models are more objective than current EW tools because the outcomes are generated by the model (O'Neil 2016; Coyle and Weller 2020; 044). Others believe that PA models can bury assumptions. While all models are driven by data and assumptions, PA models often lack transparency about what assumptions have been made (sometimes implicitly) and how these assumptions influence the outcomes (O'Neil 2016; D'Ignazio and Klein 2020; Coyle and Weller 2020; 052). As a result, it may be harder to build trust in machine-learning outcomes compared to consensus based approaches (Coyle and Weller 2020; 019).

It is critical that modelers, decisionmakers and analysts understand and carefully define the goals, risks and assumptions embedded within a model. In some cases, these results may not be what policymakers need for decision-making. Policymakers may have (implicit) competing goals or tradeoffs and may prefer to strike a balance among various objectives rather than seek to optimize a single model outcome. The successful incorporation of predictive analytics into a humanitarian diagnostics system will require modelers, analysts and decisionmakers to make choices about what their objectives for the model are, and what they prioritize in their models. Some choices depend on the broader goals of the humanitarian diagnostic system. Others depend on data availability, capacity, and usability. Collaboration and transparency between end users and modelers are essential to ensuring models are solving the right problems.

To make transparent these decisions, tradeoffs, and factors transparent (Coyle and Weller 2020), we first define a few key terms before discussing usability and the role of PA within the broader EW system. We then frame this discussion on usability and the role of PA as a series of questions. For further information, see Lentz et al. (2021) "Predictive Analytics and Machine Learning Approaches to Support EW-EA." That report discusses several predictive analytics (PA)-related topics, and is organized by topics and question within each topic. The four topics include (1) detailed discussion on the usability and role of PA within the broader early warning system (2) overview of machine learning (3) a discussion of model outcomes and predictors used in EW PA and (4) a discussion of modeling choices. The report concludes with findings related to PA and EW systems.

All models start with an objective or goal, with an outcome, and require predictors to predict that outcome. The following are definitions used throughout the report.

- **Objectives** are the goals of the model. Models may help end users to triangulate findings, to fill in gaps where data are missing, or to identify and target populations in need. Such models are part of scenario planning. Others PA models provide a "signal" and can trigger a response, such as drought insurance or funding due to a change in IPC status. Models can vary by spatial scale, by predictive window, by generalizability, among others.
- **Outcomes of models** can include malnutrition status (e.g., MERIAM project), food security status (e.g., rCSI or FCS), estimated IPC phases, or estimates of the likelihood of a hazard (e.g., meteorological forecasts of flooding). Models could also predict estimates of PIN, although we are currently unaware of any models doing so.
- **Predictors (independent variables)** can be high frequency observations (e.g., meteorological data, price data), can be low frequency (e.g., changes in roofing material), or even single observations for a particular area (e.g., geographic attributes, such as proximity to a river). These data can also be at high spatial disaggregation (e.g., village level) or more aggregated (e.g., at nation level). Many models use a mixture of high and low frequency data; each predictor is generally scaled to the same spatial level as the outcome (e.g., if outcome is the IPC scale, the predictors may be aggregated to the IPC livelihood-zone). Because most models rely on historical data, any unmodeled changes may render findings obsolete.

- **Models:** Predictive Analytics (PA) prioritizes prediction of outcomes using historical data. Machine learning techniques are commonly used tools to generate such predictions. Because most models rely on historical data, any unmodeled changes (e.g., export bans, pandemics) may render findings obsolete. Further, models ought to be rigorously validated; yet, this is often a major challenge due to data limitations. Several modeling decisions influence what kind of information PA can provide to early warning analysts and decisionmakers; we highlight these decisions in accompanying Report 3 by Lentz et al. (2021).
- **Ethics:** Accountability, equity, transparency, and ethical use of data and modeling should inform decisions and model objectives. See **Section 6** for more details.

A summary of models, including outcome measures, data requirements, and modeling choices is presented in Table 4. Table 4 is organized by outcome: food security and nutrition measures, IPC-based measures, and hazards. While the food security and nutrition measures reviewed here focus on nowcasting, both early warning forecasting and nowcasting are pursued with IPC-based models. Several of the models remain in the "proof of concept" phase, reflecting challenges identifying adequate data for external validation. The third part of Table 4 shows there has been significant research on prediction of hazards. Generally, among the studies reviewed, the researchers commonly use secondary data to forecast the likelihood of hazards for scenario development. Some new work has examined the use of hazard-based predictions (e.g., droughts and floods) for trigger-based systems, such as forecast based financing or impact based financing (IFRC 2020). Prediction windows vary across models; there is not a best practice regarding "how early is early enough," although accuracy declines as the predictive window extends. In the accompanying Report 3, Lentz et al. (2021) include a more detailed table.

Table 4. Selected predictive analytics models that focus on food security and related hazards

Authors	Location	Spatial scale	Modeled outcome	Role in System		Timing		Data	
				Scenario	Trigger	Fore casting	Now casting	Secondary	Primary
FOOD SECURITY and NUTRITION MEASURES									
Knippenberg et al. (2019)	Malawi	Household level predictions within several villages	Resiliency; rCSI	x		x			x
Lentz et al. (2019)	Malawi	IPC zone, Admin 3 (traditional authority) and Admin 4 (village)	rCSI; HDDS; FCS	x			x	x	
Baez et al. (2019)	Malawi, Tanzania, Mozambique, Zambia, Zimbabwe	Admin 1 (province)	Children at risk of stunting		x		x	x	
FRAYM (2020)	Nigeria, Pakistan	1 km squared	Localized Food Insecurity Index (from IFPRI's Global Hunger Scale)	x			x	x	
IPC									
Coughlan de Perez et al. (2019)	Ethiopia, Kenya, Somalia	IPC zone	IPC classifications	x	x	x	x	x	
Choularton and Krishnamurthy (2019)	Ethiopia	Admin 3 (woreda)	IPC classifications and transitions	x			x	x	

Krishnamurthy et al. (2020b)	Theoretical	IPC zone	IPC transitions	x	x	x		x	
Andree et al. (2020)	21 countries	Admin 2	IPC transitions	x	x	x		x	
HAZARDS									
Dreschler and Soer (2016)	Ethiopia (Theoretical)	Admin 3 (woreda)	Drought	x		x		x	x
Funk et al. (2019)	FEWS Net countries	Subnational	Drought	x	x	x		x	
Gros et al. (2019)	Bangladesh	Admin 4 (community)	Poverty and wellbeing		x	x		x	x
McNally et al. (2019)	Africa	Gridded streamflow per capita	Water scarcity index	x			x	x	
Arsenault et al. (2020)	Africa and Middle East	IPC zone	Drought	x		x		x	x
Getirana et al. (2020)	Niger, Chad: Volta	River basins	Flood prediction	x		x		x	x
Kuzma et al. (2020)	Global		Localized conflict	x		x		x	
Matere et al. (2020)	Kenya	Admin 3 and Admin 4	Forage Condition Index	x		x		x	x
Shukla et al. (2020)	SADC countries	0.25 degree x 0.25 degree spatial resolution	Drought (Root zone soil moisture)	x		x		x	
van den Homberg et al. (2020)	Philippines	Admin 2 (Municipalities)	Typhoons		x	x		x	

2. Usability and Role of PA within Broader EW System

Sustained, in-country investment and engagement are requirements for PA models to deliver on their promises (069). For models to deliver on promises to fill EW gaps and needs, modelers, EW technical analysts, decisionmakers and donors should consider the following questions on coordination, capacity, and usability, among others.

In assessing the role of PA within the existing system and issues around the usability of PA and the capacity of existing systems, we pose seven questions, each addressed below.

How should modelers engage and coordinate with stakeholders for input and buy-in?

A number of key informants have little formal coordination with end users, reporting uncertainty about who to engage with, when and how (033; 042; 059). Others are trying to have conversations early in the development of models with end users, although modelers report that it can be hard to find the right EW systems personnel with whom to coordinate (059; 060; 070).

When modelers do find the right individuals to speak with, most report it is valuable (033; 060; 061). Field-research and conversations with NGOs operating in an area, government officials, and impacted community members can help to understand how to turn data into interpretable indicators, for example through the identification of contextually appropriate cut-offs (069; 071).

How will predictive analytics complement other EW approaches?

Few modelers expect EW models to "stand alone," fully replacing current food security EW systems; rather, they are intended to be complementary (see also Hernandez and Roberts 2020). This is consistent with Hernandez and Roberts (2020) who found that most humanitarian predictive analytics projects aimed to complement existing systems rather than replace them. At least for the time being, many perceive human analysts remain better suited to identifying hard-to-predict drivers (e.g., locusts, COVID-19) (019; 042; 044) relative to more predictable, higher frequency hazards (e.g., drought). This perspective means modelers (implicitly) expect human analysts to read model results against what else is happening (042; 044; 052; 060) and to be able to triangulate findings from several different information-generating processes. Yet, EW systems are already in place, and "dropping" a PA model into an existing EW system is not straightforward (060), even if the goal is to provide complementary data for triangulation. Identifying how to support analysts to make sense of different streams of information has not received much attention thus far by the modeling community.

Will modeling occur in-house? If so, what are the data platform needs? What are the capacity needs?

Modeling as "the easy part" (060). Setting up the data gathering, processing, and platform, and updating and interpreting the model all takes institutional commitment and capacity building of both the analysts and decisionmakers. A host of difficult questions include: where in the government? With what funding? How does it differ / complement existing systems? How much analytical capacity is required and will there be a long term investment to build data skills and capacity? Will data be available for updating it? etc. NGOs, UN agencies, and other IOs using PA face similar questions.

Data platforms. Any EW system that pursues modeling "in-house" will need to invest in easily updateable data platforms and data systems (e.g., application programming interfaces (APIs) to WFP data sources, etc.). Data sharing, data management and data platforms gets less attention than they should (019; 027; 044; 052;

056; 060; 061). At least one respondent opined that too much attention is being spent on the predictive modeling and more should be spent on getting data systems and data sharing right (029).

Capacity. Several concerns regarding the capacity of food security analysts to interpret, use, and update PA models included helping analysts understand and communicate performance metrics to decisionmakers; and ensuring that modelers, technical analysts, and decisionmakers reach consensus on what is a statistically meaningful relationship; and reaching consensus on when the evidence is enough to support interventions (019; 060; 070; 071). One way to support analysts is to address issues of capacity and how models fit within the broader humanitarian diagnostics architecture early in modeling decisions.

How can accountability to and participation of affected and at risk populations be better incorporated into PA efforts?

This study has found few examples of incorporating affected populations in model development, in reporting, or in feedback on model outcomes (although see ACAPS South Sudan (ACAPS 2020) study for initiatives to incorporate affected populations). For model developers, the main end users are thought to be in four categories: governments, established EW providers (e.g., FEWS NET), donors and humanitarian actors. Rarely are at-risk communities mentioned as important end users of information (033; 056). Yet, foregrounding affected and at risk populations can improve models and support fairness and inclusivity (Paul et al. 2019; Hernandez and Roberts 2020). There are a variety of ways to better incorporate affected populations into the modeling process, including participatory data collection and model development; reporting findings back to communities for triangulation and validation; working with communities to incorporate learning from indigenous EW systems and identify locally adapted models and triggers (033, 039, 056; 072).

What are the costs of inaction and when is the model good-enough?

An important area for future research is to assess the valued added of models. One approach is to compare, on average, the costs of early action against the costs of later actions. EA will have more inaccuracies (i.e., intervening when it wasn't needed (that is, "false positives" predicted by the model) than waiting for a crisis to unfold. But imperfect models may still be good enough. In many cases early action may be cheaper even accounting for the false positives than intervening after crises (019). Cabot Venton (2020) finds that an earlier and more proactive intervention, based on good early warning (whether PA or more traditional means) could have saved donors up to 30% of the costs of subsequent humanitarian spending. This would have amounted to $1.6 billion in just three countries (Kenya, Somalia and Ethiopia) over the past 15 years.

Can PA help bridge the humanitarian-development divide and improve resilience?

Forecast based financing and impact based financing have the potential to bridge the development-humanitarian divide by producing predictions that lead to both early action in response to humanitarian crises and longer-term development-based funding. Collaboration among humanitarians, development practitioners, and modelers will be necessary to most effectively leverage PA as a possible bridge. For example, data platforms can be integrated across the humanitarian-development spectrum, although specific data requirements and different PA approaches may be better suited to meeting the objectives of development and humanitarian information systems.

What role can donors play?

Several KII discussed the important role(s) donors could play in supporting the use of PA in EW-EA systems (033, 056, 059, 060, 070). Donors could support the building of PA models, which may require more money up-front, even if the models might save money and or increase speed of data analysis later. Donors could also support the transformation of EW systems to be flexible enough to incorporate such models, for example by addressing data gaps (e.g., prices), encourage data sharing, supporting local-level engagement, and supporting data platforms.

F. Key Issues Emerging

1. Overview

Two dominant themes run throughout the interviews on existing EW-EA systems. First, there is plenty of information but frequently a sense of confusion about what the information means or what to do about it. Second, the sense is that this information has no strong link to early (or even responsive) action. These issues are closely related and can be broken down in much greater detail. This section reviews issues related to (1) data and data collection, (2) analysis, (3) the role of PA in analysis, (4) the linkage from information and analysis to early action, (5) other (non-information-related) constraints on early action, and (6) the COVID-19 pandemic. A separate sub-section addresses key issues related to predictive analytics and artificial intelligence and the extent to which these can help address some of the issues raised here.

2. Information and Data

"Too Much Information" and Confusing Outcomes

A previous study (Maxwell and Hailey 2020a) henceforth referred to as the "2020 study") on EW-EA systems in East Africa noted a significant degree of confusion—particularly about making sense of early warning information. The issue wasn't that information was missing or inadequate, but that it was too much, too contradictory, or simply didn't add up to a coherent picture—and to some degree, therefore, it actually hindered decision making rather than helping it. Numerous interviews in the current study reiterated this finding (001, 013, 019, 022, 025, 037, 038, 045, 046, 062, 065, 068). Repeated references were made to the fact that while there is no shortage of "early warning" information, the information or analysis available fails to distinguish between different kinds of information. For example, information about drivers or causal factors is frequently mixed with information about food security (and other) outcomes (001, 025), and information about current status is often mixed with projected future outcomes (001).

Numerous are bodies engaged in some kind of information collection and analysis. While each output produced may be a good representation of whatever element of the overall picture is being assessed, these "elements" are, for the most part, not brought together into a coherent, overall analysis of either the current situation or the likely scenarios for the near-term future (001, 025, 037). Even instruments that are intended to specifically monitor early warning indicators and link them to early action are frequently a "mash-up" of current status, predictive and outcome indicators (013, 022). Unfortunately, this leads to "information overload" (001, 019, 038) and in many cases "paralysis" (038) when it comes to informing early action.

Information is generally adequate for humanitarian response—it is clear where the crisis areas are, and generally what the needs are in terms of current status. However, the plethora of information is largely not facilitating early action in terms of prevention or mitigation. A contributing factor is that while current status and drivers may be assessed, few of the existing systems incorporate any analysis of the appropriate response or mitigation measure (025, 046). This underscores the need for improved contingency planning and early action—the topic of the next section.

Of course, exceptions to this general observation exist—but not necessarily from the East Africa region (046) There are good examples of predictive information being linked to early action that demonstrate some impact in mitigating a crisis (012, 044, 079), but most of these are relatively small scale, often NGO-led, initiatives and mostly focused on climatic hazards—particularly floods. In some countries, the abundance of information and the number of sources of information are actually perceived as counter-productive to good decision making on early action (043, 062)—an observation that was particularly voiced by donors (019, 022, 038, 063, 065). Even some government policy makers noted this concern (053, 067, 0680).

Lack of Data/Data Quality Issues

Numerous respondents noted that, while overall there may be too much information, very frequently certain kinds of information are lacking and may be precisely the kinds of information needed to trigger action (024, 026, 030, 062, 066, 073, 076, 079, 082)—findings echoed by other studies (Maxwell and Hailey 2020a and 2020b). These missing data may include drivers such as conflict (see below), outcomes such as mortality (032, 055) or nutrition (006, 008, 015, 025, 038, 047), or critical information that helps turn assessment data into future projected need—particularly accurate population estimates (024, 072, 074). Related to the dearth of population figures is the dearth of figures related to displacement and displaced populations (058).

Several additional categories of missing information were highlighted by the 2020 study. Almost all information systems examined lack data about people's social connectedness and social networks (Majid et al. 2016) and people's coping strategies, despite coping being recognized as an important category of both early warning and current status (an exception being WFP/VAM surveys that include a livelihoods coping module). The 2020 study also noted that much of the early warning information is not disaggregated by gender. The dearth of up-to-date information on population and estimates of mortality was highlighted by Maxwell and Hailey (2020a and 2020b). The dearth of information on conflict was mentioned by so many respondents that it is discussed separately.

In addition to the lack of data, many respondents raised concerns about the quality of the data available (015, 022, 026, 030, 041, 054, 082). However many respondents were quick to note that major improvements in data quality have been achieved, and it is important to differentiate between the quality of data and the quality or accuracy of forecasts—and not confuse the two. The issue of data quality is especially concerning where the analysis is highly politically fraught (Maxwell and Hailey 2020b). Many respondents reported that additional data collection is unrealistic, leading them to focus on building models with already existing data.

Data Sharing (and the Lack of Data Sharing)

The ability of systems to share data, and the unwillingness of managers or owners of data to share it, is a major constraint to good analysis (005, 009, 014, 029, 037, 045, 053, 055, 067, 068, 080) (Maxwell and Hailey 2020a). This is particularly the case with information that might be sensitive, such as conflict information (009), but in many cases, it has more to do with bureaucratic procedures, or worries about the quality of the data and fear of being criticized by other organizations if data is shared. This leads to duplication of data collection and contributes to the problems outlined above regarding too much information or even contradictory information.

Information about What?

Respondents expressed concerns that information about current status outcomes tended to dominate over predictive information (019, 025, 053, 079, 080). When predictive information is gathered, the major emphasis seemed to be on the projected population in need (PIN) figure, rather than on scenarios or projected hazards (003, 031, 045, 058). And when the emphasis is on drivers or causal factors, the available information is overwhelmingly about climatic drivers—particularly drought (010, 011, 058). Given that drought is one of the two major drivers of food insecurity in the region, this is understandable and necessary, but many respondents worried about the preponderance of attention to drought and lack of attention to conflict and other drivers (see below).

Among outcomes, food security information tended to be much more dominant than information on related outcomes that would have a strong effect on (or interaction with) food security—notably nutrition, health, and WASH (021, 025, 026, 081, 082).

Links between Local and National Information Systems

A number of smaller, more localized, or even community-based information systems operate in the IGAD region, but they are often linked to the programs or program coverage area of a single organization (usually an NGO or, in the case of Somalia, an NGO consortium). While producing useful information for the organization operating them—and probably producing the most instructive information for the affected communities—these systems are often not well integrated into national systems (023, 055, 062, 079). This is a loss of both information and experience—as well as a loss of a two-way link that feeds information back to local communities. The primary reasons for the lack of a linkage is that local or NGO systems desire more specialized and context-specific information categories, and national systems frequently complain about data quality.

3. Analysis

Information and Analysis of Conflict

Many respondents expressed a concern about inadequate or missing information or analysis of conflict (001, 002, 004, 010, 024, 029, 032, 044, 050, 051, 053, 054, 058, 063, 066, 067, 080, 082). In fact, key informants expressed more concern about this issue than any other single issue. Many of the concerns were similar: the relative dearth of information about conflict, the inability to include even the information that is available on conflict in the analysis and early warning because it is considered too "political" or at least too sensitive, very underdeveloped conflict early warning capacities in comparison with those related to drought or pests, and even limited ability to project the humanitarian consequences of conflict beyond simply saying that conflict is a "contributing factor" to food insecurity. The problematic nature of this observation was perhaps best expressed by one respondent, who said "Conflict is still there and still the major driver, but we're not focusing there right now" (054).

The regional conflict early warning mechanism (CEWARN) is still functioning and reports to the regional Food Security and Nutrition Working Group meetings. Its information is not shared widely, and its website is not a source for any up-to-date information about conflict in the region. Some individual agencies have good conflict analysis capacity in house because they need the information and analysis for their own operations (024, 032, 044) but do not (or cannot!) share the information outside the organization for reasons noted above. Other actors are forced to act on speculative information or without conflict information (063).

There is significant experimentation using predictive analytics to analyze conflict (Kuzma et al. 2020) or to incorporate it as an explanatory variable for predicting other outcomes (Andree et al. 2020, Tandon and Vishwanath 2020). These efforts have been supported by increased publicly available data—information both about conflict incidence and fatalities and about drivers. Some attempts have been made to use predictive modeling for both the incidence of conflict itself and the humanitarian impacts of conflict (029, 044, 049, 060, 061, 066, 071, 080), but much of this is being done completely outside the existing humanitarian and early warning systems, and so far, there has been limited incorporation of this work into the EW-EA systems in the IGAD region.

Closely related to conflict is the issue of internally displaced people (IDPs) and IDP numbers (058). Capacity for estimating displacement—and the effects of displacement on food insecurity and other humanitarian outcomes—is highly variable. Countries that have long experienced displacement as the result of conflict or natural hazards tend to have better systems than countries experiencing a recent upsurge in conflict and displacement (058, 063).

At the same time, however, much of the conflict analysis work happening within the realm of EW-EA or humanitarian response is more qualitative in nature, relying on deep contextual knowledge and a network of human key informants (014, 042, 032). Thus, there is a knowledge base on which to build better conflict analysis—both through existing systems and practices, and through greater employment of predictive modeling analysis. But a concerted effort is required to make this a practical reality (082).

Timeliness of EW Analysis

While early warning information has traditionally been based on seasonal patterns (given the preponderance of livelihood systems linked to seasonal calendars and climatic factors), for agencies to be able to base operations on timely information. However more recently, global information demands have pushed early warning—or at least the projected PIN numbers—towards deadlines that are often quite dissociated from local seasonal patterns. The most common complaint is the timing mismatch between seasonal information and the information demands of the global Humanitarian Needs Overview (HNO) and the associated Humanitarian Response Plan (HRP) (035, 037, 046, 058, 063, 068, 077). This disjunction is so pronounced that some donors reported having to make “wild guesses” (063) about resource requirements, based on analysis that is backwards looking, not forward looking or predictive (058).

Current Status or Predictive Analysis?

A closely related complaint is that currently there is too much focus on current status and not enough on predictive analysis (015, 020, 026, 045, 063), a finding echoed by the 2020 study. This relates to a common misperception about the current information categories, which is the difference between “projections,” an integral component of IPC analysis (002, 006, 008, 010), and “early warning.” The IPC has noted numerous times that it is not an early warning organization per se. However, the projections of populations in need has become probably the most sought after piece of information in the entire analytical process. Indeed, in many cases, the PIN number is mistaken for the only kind of early warning that is needed. But the PIN is the number of people expected to be in need of humanitarian food assistance, which while important is not what most respondents think of when they think of “early action” (see below).

Closely related to this is the observation that, while the projected PIN numbers are explicitly based on a number of assumptions about what is likely to happen during the projected period, only rarely are these assumptions formally monitored—and projections altered accordingly (002, 006, 025, 030, 074, 081). The most notable exception is outside the IGAD region, in nearby Yemen. While this monitoring was the original intention of early warning, with the exception of FEWS NET updates, this is mostly not formally done through much of the region. That doesn’t mean that individual analysts and agencies aren’t doing it as part of their daily work, but it rarely comes together in any formal (or public) analysis. Even the FSNAU dashboard, which monitors a number of indicators on a near-real-time basis, doesn’t routinely change anything about its formal projections. While FSNAU does update its projections based on updated information, it is an extraordinary process when it happens.

4. The Role of PA in Early Warning Analysis

Detailed findings that underpin these emerging issues can be found in the accompanying Report 3 (Lentz et al. 2021).

Modelers and End Users Face a Series of Choices

Applications of PA to food security and food-security related problems are developing quickly. As of yet, there are no established "best practices." What can be done with PA models depends on several factors, including model objectives, data availability, capacity, and ethics, among others. For EW system users, it will be critical to engage modelers, decisionmakers, analysts, and donors interested in using PA in collaborative discussions not only about what is possible and feasible but also to identify assumptions within models that may otherwise remain implicit.

"Looking for Keys under the Street Light" Syndrome

The easy availability of certain data can overly focus attention on these data at the risk of missing other important factors, causing a "**streetlight effect"** (i.e., models are built using only the data that can be easily seen and accessed). A model that starts with (causal) factors and builds out a predictive model may require additional targeted data collection to address shortfalls in coverage of specific causal factors. Price data, for example, is limited and primarily collected from large markets, which may not be accurate proxies for prices in rural areas.

Novel and Rare Events Are Currently Challenging for PA Models to Predict

PA initiatives may be most helpful in identifying and monitoring the "usual" drivers of food insecurity. Human analysts will likely remain essential in monitoring and addressing less easily identifiable drivers and their impacts. Further, PA can be used for **nowcasting and forecasting.** Nowcasting models predict results for areas without data, but places without data may systematically differ from places with data. For example, if conflict limits data collection from some areas but not others, models built using information from conflict-free areas will generate predictions that are inaccurate for conflict locations. If intending to nowcast outcomes for data-sparse areas, analysts and decisionmakers must have an understanding of *why* some areas are data sparse and whether the model results are truly transportable from data-rich to data-sparse locations. At the same time, forecasting accuracy decreases as the forecast window increases. Decision makers will face tradeoffs regarding accuracy and duration of early warning. On average, some early action interventions that require longer early warning windows may be cost effective even if sometimes the model predicts false positives.

Scenario-Driven Models Are Often Complementary to Existing Systems

Even if a model is intended to inform scenarios and capture multi-hazard multiple-actions contexts, no model is entirely comprehensive and, for that reason, scenario-based models are thought to be complements to EW systems rather than replacements. How to interpret PA results and incorporate them into established scenario building has not yet received adequate attention.

Trigger-Based Models Are Increasingly Common

Currently, trigger-based models are used mostly for single-hazard/single-response actions, such as forecast-based financing. Research on PA generating reliable and valid triggers for multiple hazards is needed; work on impact based forecasting seeks to combine risk assessments with weather forecasts (IFRC 2020).

Ethics, Bias, Privacy, and Equity Concerns

All data collection and information systems run the risk of failing to capture relevant indicators and accurately interpret them. This is, perhaps, an even greater concern when using PA techniques (O'Neil 2016). It can be difficult for non-modelers to understand the modeling and data choices (Coyle and Weller 2020). At the same time, modelers may not have adequate understanding of implicit biases or gaps in data, or of historical and contemporary contexts that could shape the choice of analyses and interpretation (D'Ignazio and Klein 2020). Below are several ethical concerns. Some are applicable generally to EW systems and some are of particular concern when using PA models.

The first of these is **inaccuracies, biases, and inequalities** in historical data can replicate and amplify inequalities, including racism and sexism, urban bias, and class privilege. A second major concern is about **data privacy.** As new data sources become more common, privacy concerns also increase. As models become more "automated" in decision-making, a growing concern is that analysts and others place **excessive trust** in predictive analytics. PA may have **limited external validation**, meaning the usefulness and applicability of some models may not be adequately evaluated. Most modelling approaches have only limited **local engagement** and **accountability to affected populations;** and most **lack gender disaggregated data** and are blind to **social inequalities.**

5. Linkage from Information and Analysis to Early Action

More accurate predictions may not be the binding constraint to improved EW and EA.

Information that Has No Clear Links to Early Action

A common sentiment expressed by respondents across many different categories was that, while there may some quibbles with the information or analysis coming from early warning systems, inadequate information is not really the problem—the problem is simply that the links between information and action are inadequate, and so action is frequently late, misdirected, or non-existent (002, 007, 009, 010, 012, 014, 015, 025, 030, 036, 037, 038, 043, 045, 050, 055, 057, 058, 063, 065, 077, 078, 081).

There are a variety of reasons for this. Developing data platforms and EW analyst capacity to update and use these platforms may be more useful than PA for improving confidence in EW and produces actionable information (029, 052, 056, 060). A common refrain was that more tinkering with the information system isn't going to fix the early action issue. Other issues are more important. These are outlined below.

The Link that Initiates Early Action

Information is intended to initiate action by a variety of means. They can largely be boiled down to two approaches, which can be summarized as "triggers" and "scenarios"—summarized in the 2020 paper as "signals" and "scenarios" and also discussed in Section 5. Scenarios are the more long-standing mechanism and provide a fleshed out, overall picture of what the short-term future will likely look like. Indeed this is the kind of analysis that many observers think is often missing (001, 019, 046, 063, 079, 080, 081, 082). The issue with scenarios is that, while they without doubt provide a more fleshed out analysis, they do not necessarily link directly to any action. Human judgment and decision making is a necessary step. And as past failures to act on early warning repeatedly testify, sometimes human decision makers do not act on early warning scenarios. This is almost without exception because, unlike the "hard data" of current-status assessments, "scenarios"—and indeed all early warning information—are probabilistic (010, 044).

For this reason, many decision-makers have preferred to take a "wait and see" approach and act when the "hard data" of current-status assessments confirm a crisis (see below for a variety of reasons for this). The most devastating example of this in the IGAD region in recent history was the Somalia famine of 2011. There were clear early warnings (Hillbruner and Moloney 2012) but a response at a scale able to address the problem wasn't really mounted until after the famine was declared by the UN (Maxwell and Majid 2016).

That experience led to experimentation with the other main form of linking, which is "triggers." Triggers are intended to put in motion an action—whether preventive or responsive—immediately when a certain threshold in one or more carefully selected indicators is surpassed. The idea is to anticipate what *might* happen and pinpoint a means of identifying the process and take action without having to wait for a human (political) process to make a judgment and act (Maunder 2013). Triggers have been used quite successfully in some circumstances (010, 019, 020, 044, 046, 078) but experience seems to indicate that triggers (by themselves) work best when limited to a single driver and a single outcome—so, for example, drought (or significantly diminished rainfall) as the trigger and crop failure as the outcome (019, 024) or storm prediction as the trigger and flood damage as the outcome (012, 044, 078).

Several questions arose about the use of triggers: Should they be based on outcome or on drivers? Should they involve some level of human decision making or be completely divorced from (the politics of) human decision making (010)? But somewhere in the debate over scenarios and triggers, a "data speaks for itself" approach emerged, in which information systems began producing a lot more data and making it available but mostly without much interpretation.

Significant pressure for more certainty from donors as well as for greater speed in the allocation of resources to prevent a crisis (019, 058, 063) have led to a search for triggers than can capture the complexity of a multi-causal crisis with multiple outcomes. And these triggers would need to operate far enough in advance to enable the kinds of actions that would prevent or at least mitigate the crisis and thus prevent or dramatically reduce human suffering as a result (and, of course, reduce the cost of response!). Achieving this would more or less describe the "holy grail" of early warning/early action.

This was the task that the World Bank Famine Action Mechanism (FAM) set for itself, using machine learning and artificial intelligence. In FAM's case there was no single indicator, but rather a complex predictive model to identify the "signal" to act. Several IGAD region countries were pilot (or "first-mover") countries (024, 027, 074, 080). FAM had an additional objective, which was to mobilize non-traditional forms of finance, including private insurance and disaster bonds—hence heightening the requirement for a "hard" signal, rather than a probabilistic forecast. FAM developed a predictive model, but it also found that reinserting some amount of human judgment into the process was necessary—and increased the confidence of donors. Eventually the modeling approach itself was replaced by the use of FEWS NET forecasts as the trigger—in other words merging the two approaches into one. FAM deliberately worked with governments on contingency planning and longer-term solutions, and the OCHA-led UN "anticipatory action" plan began to take on the question from a more humanitarian angle, working with UN agencies as the responders, but relying on the same mechanism to trigger action. Both programs eventually relied on more conventional sources of funding (FAM on the World Bank's Global Crisis Response Platform and OCHA on the Central Emergency Response Fund (027, 080).

As these programs were starting to bear fruit, the COVID-19 pandemic struck. It is not fair to suggest that the possibility of a global pandemic had not been foreseen by anyone. However, for the most part, there was no forecast and certainly no scenario planning in the world of food security EW-EA or humanitarian information/action systems more generally that included anything like a global pandemic. This led to the need for much more real time monitoring of both drivers and outcomes, as the rapidly spreading pandemic upended planning of all kinds, rapidly shifted priorities, and demanded very different approaches (020, 025, 081).

Several other factors also limit the extent to which early warning informs early action:

Limited Regional Integration

Several respondents noted the limited extent to which early warning information is shared across borders or regionally (001, 014, 024, 036, 043, 045, 054, 057, 073, 082). With the exception of the IGAD Centre for Prediction and Analysis of Climate (ICPAC) for climatic information, and the regional Food Security and Nutrition Working Group (FSNWG), there are few mechanisms for information sharing. Several respondents suggested a regional coordination approach similar to approach taken in West Africa , which takes a much greater regional ownership of the Cadre Harmonisé process (similar to IPC) and greater regional investment in response (010, 014, 018). Sometimes there is hostility, rather than cooperation, across national boundaries. Perhaps the most serious is the hostility between Sudan and Ethiopia over water in the Blue Nile, which resulted in very limited warning for serious flooding that hit Khartoum in mid-2020 (055, 058).

Inadequate Links to Affected Communities

While localized EW-EA systems have strong links to at-risk communities because they are built into their operation (023, 036, 078), at a higher level the "customers" of early warning are usually perceived as national governments, donors, and agencies—both humanitarian and developmental (001, 082), a point also emphasized in the 2020 paper. Some government EW managers mentioned at-risk communities as their primary constituency (045, 053), notably in Somalia—using local radio and local civic and religious leaders to get messages about impending hazards to at-risk communities.

PIN Figures as "Early Warning," Humanitarian Response as "Early Action"

Too often, the focus is on the population-in-need figures found in IPC projections as the only required "early warning" and budgets for humanitarian aid—especially food assistance—as the main "early action" (010, 031, 050, 051, 053, 058). While, in some cases, prepositioning food aid is an important component of early action (032), in other cases looking only at PIN numbers and food assistance responses amounts to the dumbing down of the whole notion of EW-EA.

Limits to Contingency Planning

While good information, financing, and a rapid decision-making mechanism are three critical components of EW-EA, contingency planning and response analysis are often overlooked until it is too late (029, 036, 037, 050, 053, 065). Operational readiness and capacity are also critical parts of contingency planning, but again, they are often overlooked (025, 046, 053, 079, 082).

Limits on Evidence and Learning

Several respondents pointed out the failure to learn from experience (057, 058), noting that some mistakes had been repeated over time and that some high profile initiatives had not learned from past experience (019, 045). This is compounded by the relatively limited evidence for the impact or cost effectiveness of early action (013, 019) and the fact that much of the analysis is based on modeling rather than empirical evidence. On the other hand, it is hard to demonstrate empirically that a crisis was mitigated by a particular action because of the lack of a counter-factual (029).

“Show Me the Dead Bodies” Syndrome

The preference by some actors for hard evidence, rather than probabilistic forecasts, was noted above. In its most egregious form, this comes across as a “wait and see” attitude about excess mortality. In situations where Humanitarian Response Plans are already underfunded, arguing for preventive or mitigative action can be difficult (012, 036). As on respondent noted, “It is easier to ask relatives for contributions to funeral costs than to ask for money for someone in a hospital” (013). The notion of investing to prevent mortality is not always widely shared among stakeholders.

Scalability or Surge and Links to “No Regrets” and Crisis Modifiers, Forecast-Based Financing

There are a number of strategies by which to put early action into motion, but most require prior planning. The most commonly discussed strategy in the notion of scalable social safety nets, with Kenya and Ethiopia having the best working programs in the region (023, 029, 046, 046, 058). A similar tactic, used in the region with health systems, is the “surge approach” (019, 025). Crisis modifiers, or putting money in a longer-term budget for flexible response in the event of shock was mentioned by some respondents (022, 023, 057, 063). “No regrets” programming—investments in crisis prevention that would have useful benefits even if the crisis did not materialize as forecast—is also a widely used approach (012, 13, 019, 082), frequently relying on cash transfers as the modality (019, 063). A no-regrets perspective presumes there is low or no opportunity costs to responding. Whether that is accurate depends on the interventions, funding streams and availability, and specific context.

6. Other Constraints on Early Action

(Lack of?) Capacity Building

A major constraint on early action, particularly from government and local organization respondents, is the lack of capacity building efforts. This is true both on the information and early warning side and on the early action and contingency planning side (035, 053, 054, 057, 062, 064, 067, 068, 078). On the other hand, many of the international actor (including donor) respondents mentioned that capacity building was an important component of the work they are doing in this area (001, 005, 011, 012, 026, 027, 036, 082). This would imply that there are some fundamental differences in views about what constitutes “capacity building” between governmental actors in the region and their external partners, as well as what the content of that effort should include. The 2020 paper noted that some long-standing EW-EA systems in the region had recently lost capacity, either through retirement of senior staff or through staff leaving government-led systems to join international agencies.

The Politics of Information and Analysis

A recently completed study (Maxwell and Hailey 2020b) considered the way in which political interests sometimes undermine good information collection and analysis. While the study included case studies outside the IGAD region, four of the eight countries were included (Kenya, Ethiopia, South Sudan, and Somalia). The concern about information and analysis—as well as response or action—being politicized was raised in numerous interviews in this study as well (015, 018, 030, 032, 050, 062, 065, 073, 076).

Maxwell and Hailey (2020b) noted, “political influences are the most flagrant where the data collection and the technical capacity of analysis teams are the weakest. Therefore, it makes sense to focus on *strengthening capacity”* (p. 34). But that study also carefully considered the question of the leadership of information and response systems (i.e., including EW-EA but also wider information questions and wider areas of response). In that regard, the study noted:

> The *role of national governments* in humanitarian information systems varies and, in some cases, should be reviewed. The normative view is that governments *should* lead these processes. Indeed, the initial purpose of the [Integrated Food Security Phase Classification] was both to provide a consensus analysis and *to build the capacity of government to lead that analysis*. But … this becomes a much more complicated issue where governments are parties to conflicts that at least partially cause the emergency.

In a region where conflict is a significant driver of crisis, and in which governments are parties to those conflicts, this raises serious questions about the trade-off between national sovereignty and protecting the lives and rights of citizens.

Even when crises are the result of climatic hazards or other drivers, some respondents noted the reluctance of governments to declare an emergency—even when good information is available (i.e., again, not a question of technical constraints) (017, 054). This point was raised in the 2020 study as well. This issue raises questions that go far beyond the realm of technical capacity but that urgently require high-level attention.

The relationship between international information systems and government-led systems clearly needs to fit the context—a view also noted by Buchanan-Smith and her team (FAO 2019). This concern is mirrored in a way by a concern on the part of governmental actors about external control of information (045, 057, 076, 078). This is particularly an issue with information systems for Somalia, but to a degree in several other countries as well.

Flexibility and Accountability

Two additional factors that limit early action include ear-marked funding, which allows little flexibility in the way allocated funding can be spent, and the lack of accountability mechanisms. With regard to the question of funding, information systems analysts, early action specialists, and donors alike noted that in at-risk contexts, flexibility is critical to early action (012, 015, 023, 025, 036, 057, 084). Yet, a major constraint to flexibility is donor earmarking of funds (024, 037, 044, 050). This is the issue that "crisis modifiers" are supposed to address. Other mechanisms—such as funding held by donors and not in program budgets—also are attempts to address this issue (022, 065). Clearly these mechanisms do not fully address the issue of flexible funding within a rapidly changing situation, either by the extent to which crisis modifiers are incorporated into programs or the amount of money set aside in crisis modifiers.

The second factor is a lack of accountability mechanisms—in response to either bad analysis or inaction (032, 050, 057, 058)—also highlighted in the 2020 paper. Accountability for bad analysis is difficult. In some cases, it can be clearly demonstrated that analysts ignored certain factors or were influenced into making politically contingent, rather than evidence-driven, forecasts (032). However, forecasting is by definition probabilistic and is going to be "incorrect" sometimes—in the sense that the "outcome" (whatever it is, food insecurity in this case) turns out to be different from the forecast.

Accountability for action—i.e., failing to act on information in a timely manner—is a different matter. Accountability still tends to be toward donors, such as accounting for *how* money was spent (not *when*—especially with any regard to when information became available). While there are many codes of conduct or other voluntary compliance mechanisms that stress the importance of early or rapid action, few mechanisms exist that require hard accountability (031, 032, 057). Putting them into donor contracts doesn't necessarily solve the problem, since it is a problem that affects donors as much as everyone else (036, 058).

7. Challenges Arising from the COVID-19 Pandemic

The COVID-19 pandemic of 2020 touched every country in the region and changed the way early warning systems have operated in 2020.

Unanticipated Shocks and How Systems Adapted

Most EW-EA systems were not prepared for the rapid onset of the crisis. Simply said by one key informant, COVID-19 “caught everyone off guard” so they “had to make do” (047), forcing drastic changes in everything from how information was collected to what information was collected to how it was analyzed. It was also clear across the board how volatile and uncertain the impacts of the pandemic would be on different populations across the region, impacting different factors in yet-to-be-determined ways (such as employment, labor demand, exports, imports, livestock markets, input prices, movement, prices, other macroeconomic factors, etc.). Clearly the initial or anticipated impacts of the crisis as a whole were quite puzzling to most, before systems adapted more strategically.

Challenges in Urban Analyses

Inextricably tied to the pandemic was a shift away from focusing predominantly on rural populations to focusing more on urban contexts, where the pandemic (and secondary impacts of lockdowns) hit hardest. Many raised concerns about the challenges of predicting, monitoring, or analyzing the impacts of the crisis on urban populations (003, 008, 011, 047, 051, 054, 055, 058, 076), predominantly because it wasn’t really done before. In many cases, data was being collected for the first time in larger towns and cities (002, 003, 047, 051, 055). By definition, it was impossible for the existing early warning systems in the region to have predicted, or pre-positioned a response for, the fallout of the crisis. The sense is, then, that early warning systems widened in scope and shifted the lens toward urban contexts, managing what was, in effect, a real-time monitoring system of the crisis on “new” populations.

Remote Data Collection and Analysis

Almost all respondents had shifted to remote operations, although the shift was often haphazard. While many systems in the region focus on household surveys or other in-person data collection, COVID-19 forced most into almost entirely remote data collection methods (002, 003, 005, 008, 011, 015, 016, 047, 051, 054, 058, 081). Phone surveys replaced household surveys to become the primary method. Data collectors and analysts relied most heavily on Geo-Poll and mVAM. SMART surveys and other nutrition information was replaced by MUAC data collected at home by mothers. Analysts relied more heavily on fewer key informants to both gather new information to replace surveys and to make sense of the data they were reviewing (008, 016). Relatedly, this also meant a heavier reliance on qualitative information from these key informants, over quantitative information from surveys (016, 054). Where in-person data collection was a possibility, like in South Sudan, it was delayed, and therefore data collection did not occur during critical seasonal time periods (051).

In remote information collection, some nuance is missing: body language of respondents and other nonverbal cues (008), verification of information via observation or cross-referencing multiple sources (005, 008, 011, 016), and a reduction in the amount of information. One key informant estimated that coverage of information collection was down by 80 percent compared to pre-COVID times (016). This raised some serious concerns about the quality of the information, the assumptions underlying any analysis, and ultimately the faith which could be placed in these quickly adapting systems in the context of COVID. Because the pandemic has had varied impacts, existing information systems may be operating on untested assumptions, or in the case of urban contexts, have no baselines or sufficient background information about the affected populations, with no way to verify the information or assumptions (005, 008, 016, 081). One key informant simply said, "We've had to do a lot of our own interpreting" (003).

A significant issue among many was the extent to which this reduced access introduced bias into the data. While mobile phone access is ever-growing, some key informants pointed out that those who do not own cell phones are likely be among the most vulnerable to various crises (003, 008, 016). On the other hand, others said that it wasn't so much a concern in cases where phones are more ubiquitous, and even the poorest households would have them (047, 051).

While most changes in the context of COVID were framed as challenges or new gaps in the early warning systems, some reflected on positive changes they expect (or hope) are here to stay. First, the reliance on remote tools seems to have naturally and drastically accelerated the use of online platforms and tools, which are "likely to change the way we do early warning moving forward" (015, 058). Others noted an increase in the frequency and quality of communication within early warning systems as a result of working remotely and largely separately now (047). Still another, reacting to the clear reduction in the amount of information collected, hoped this would be a positive trend into the future—focusing more on the quality of data collected than on the quantity (002).

Real-Time Monitoring

A more common improvement in the early warning systems brought on by the pandemic is the rate of information gathering, analysis, and sharing—what has effectively been a robust real-time monitoring program throughout the crisis. Many said that as a result of the rapidly changing situation in COVID and its knock-on effects, they were looking at more information more often—shifting from monthly to weekly, for example (003, 011). IPC published a guide to data collection in the COVID context that operates on a four-week timeline (006). In specific areas—price monitoring, macroeconomic factors, for example—the system has actually improved in terms of data scope from field monitors (047).

Challenging Assumptions

More broadly, the COVID-19 pandemic may be challenging assumptions about crises in the region as a whole. One informant noted that the whole system of humanitarian response in East Africa has been focused on the food security impacts of climate shocks, and for the majority of the humanitarian system, the appeals process and response planning is predicated on a seasonal, rural-based system. The pandemic and its impacts, this informant said, have been a good way to challenge some of those assumptions (025). While this view was not shared by all respondents, it does reflect several points of consideration discussed in this report, namely how EW systems are often overly focused on singular climatic hazards and food security at the expense of other key drivers like conflict (or a public health crisis).

8. What Is Working Well?

Finally, it is worth noting that despite many challenges, several things are working well and should be capitalized on. More will be said about this is the recommendations section, but countries in the IGAD Region have gained a lot of experience with publicly led safety nets, most prominently the Productive Safety Net System in Ethiopia and the Hunger Safety Net Program in Kenya. This study was not an attempt to assess either program, but the general agreement is that scalable safety nets are the most effective means of linking an early warning system to a ready-made response mechanism, and one that can be tuned to intervene early, especially in contexts where cash transfers are an appropriate early action mechanism (010, 013, 058, 065, 080, 081). The use of trigger mechanisms has proven valuable, particularly where a single hazard can be monitored and tied to a specific action (020, 029, 044). The region has a wide range of experience with no-regrets programming and crisis modifiers (019, 029, 036, 057), and at least some success stories with forecast-based financing (012, 044, 079). Each of these is a form of early action set in motion by some kind of EW signal or scenario. All of these can be scaled up.

G. Recommendations to FAO and IGAD

1. Introduction

The findings were presented in a common order, beginning with information collection, analysis, use of predictive analysis, the links of action to early warning, other constraints on early action (not directly related to early warning), challenges resulting from the pandemic, and some lesson on things that seem to be working well. Our primary recommendation puts the order differently.

The major constraints emerging from the analysis above are the confusion that sometimes exists around the information available, and the lack of strong links from information to action. The primary recommendation, therefore, is to start with the actions that can be taken to mitigate known or expected shocks, and derive the information needs and the means of addressing those needs—including the use of predictive analytics—from those considerations.

There remains, of course, the question of "how" to put some of these recommendations into action. That issue will be the subject of a regional consultation with key stakeholders, once the substantive recommendations can be agreed. This section presents a number of recommendations, with an initial prioritization. Prioritization will also be an activity of the regional consultation.

2. Plan from Known and Likely Hazards and Actions

Plan from Interventions back to Information Needs

Typically, information systems are designed based on what other information systems are doing. To enable early or anticipatory action, it would make more sense to start with an analysis of hazards and potential shocks, and identify all actions to mitigate those shocks first. Then build this into contingency planning, and information systems. This would entail addressing several questions long before an information system is designed (or redesigned in most cases):

- What are known or expected hazards?
- What *could* be done to mitigate known or expected hazards?
- What capacity would be needed to implement the action? Does that capacity exist?
- What information would be needed?
- How would it trigger action?
- How far in advance would it be needed?

Answers to these questions then become the basis on which to (re)design an information system, as well as the contingency planning needed to adequately plan for and respond to the information it would generate. But too often EW systems are designed without any of these questions having been addressed.

Improve Contingency Planning

Improving information systems goes hand in hand with improving contingency planning. Not only is there a need to revisit the information systems on which early action depends, but also to revisit the process of planning what to do if and when hazards threaten to turn into actual shocks. Too often—even when funding may have been set aside through crisis modifiers or other mechanisms—neither agencies nor local governments have action plans ready. That is, the link from early warning to early action runs directly through contingency planning.

Identify Early Actions for Conflict

The hazard that is largely still lacking direct and effective early action mechanisms is conflict. Yet, conflict is either the single biggest, or second biggest, threat in the region. Examples of early action to prevent conflict are emerging out of the experience of the Conflict Early Warning and Response Network (CEWARN) but these are rarely scaled up. In some cases, humanitarian agencies rely on conflict analysis to, at a minimum, be prepared to respond rapidly to displacement or acute food insecurity but not necessarily to mitigate conflict itself. This remains a major challenge—one on which IGAD should be positioned to lead.

Assess Capacity to Mitigate or Respond

Contingency planning alone is inadequate without the capacity to rapidly implement the plan. Finance is clearly one major obstacle to implementation, but it isn't the only obstacle. It is one thing to *talk* about scalable safety nets or crisis modifiers, etc., but to have programs in place and ready to move is another. Building scalable social safety nets was beyond the remit of this study, but all of these clearly need to be considered hand in hand with improving information systems—and neither of these (improving contingency planning or response capacity) is going to be improved by predictive analytics!

Assess the Timeliness Requirements for Information

For each of the projected early actions (or for that matter, even just timely humanitarian response), calculate how far in advance information would be needed to enable such actions, and what degree of certainty would be required to enable action—bearing in mind that no prediction or forecast is ever 100% correct.

Coordinate the Multiple Demands on Timeliness

Early warning for early or anticipatory action must, by definition, be timed according to the likelihood of the hazard or potential shock. In much of the IGAD region, one of the major expected shocks is the "hungry season"—that period, usually during the rainy season, just prior to the harvest. At that time, food is likely to be relatively less abundant and prices are likely to be higher—restricting access to food whether from own-production or market purchase. But other hazards may have other timelines. For instance, in some cases, conflict may be worse during dry seasons when movement is less restricted, etc. The point is that to enable early action, the timeliness of information should be driven by the timing of the likelihood of shocks.

However, in situations of protracted crisis, the international system has developed an annual funding cycle—previously known as Consolidated Appeals Processes (CAPs) and now known as the Humanitarian Response Plan (HRP) and the Humanitarian Program Cycle (HPC) and their affiliated needs-estimation process, the Humanitarian Needs Overview (HNO). HNOs are typically conducted late in the calendar year such that they feed into the following year's HRP on a timely basis, and funding can be allocated globally by donors according to (an admittedly very imperfect) impartial process.

The problem is that these two demands for information rarely align perfectly. HNOs need a projected population in need (PIN) number; early action requires a scenario or trigger. Yet, these two different kinds of information frequently substitute for each other. As a result, the projection of a *current-status* assessment like the IPC (or more recently the JIAF) is frequently confused with *early warning* information. These need to be teased apart, and information needs to be targeted to its intended purpose.

Share Information across Borders

Crises cross borders in the IGAD region. Drought is rarely restricted to a single country; heavy rains in one country can lead to flooding in a neighboring country; and of course, by definition, refugees cross borders. But information is only sporadically shared between countries. IGAD needs to lead here.

Involve At-Risk Communities!

Just as at-risk communities must be involved in both the collection and dissemination of EW information, they are central to any early action planning. This is too frequently forgotten.

Learn from Existing Success

As noted in Section 6, numerous examples are available in the IGAD region to draw on to improve both early warning and early action. the Productive Safety Net System (PSNP) in Ethiopia and the Hunger Safety Net Program in Kenya (HSNP) are both examples of solutions in the IGAD region to the issue of predictable food insecurity that can be scaled up to meet irregular demands. There are also examples of “no regrets” programs and the use of crisis modifiers and forecast-based financing. All of these should be studied and their lessons applied more widely. A promising PA approach to improve the link between EW and early or anticipatory action is the use of PA for forecast-based financing. Forecast-based financing offers new mechanisms to trigger early action. To date, most forecast-based financing responses are linked to single hazards (e.g., flooding or drought). Forecasts from such models should not be directly applied to multi-hazard crises. To best use PA to improve EA, the timeframes required for different EA responses should inform the prediction window of the PA models. That is, if a goal for the EW model is to provide enough EW to deploy contextually relevant responses, that goal could inform the choice of predictive windows.

3. Information and Analysis

Focus Information Needs on Contingency Planning

Embrace an “ecosystem of information,” but build coordinated analysis within It. There are distinct advantages to having more than one source of information but the information should be prioritized according to what is needed for actually make early action work. Triangulating across different sources of information can correct for an error or misinterpretation (or politicization) from a single source. But conflicting or confused analysis is deleterious to coordinated action. Mechanisms must be strengthened to build a coordinated analysis from diverse sources. The IPC was initially premised on the notion of a “technical consensus” among all information actors. In many cases, IPC—or some of its derivatives such as the Data and Information Sub-Committee of the Kenya Food Security Steering Group (KFSSG)—continue function in this manner. In other cases, these mechanisms either have become heavily dependent on a very limited and restrictive set of information sources or have become politicized. And much of the information emerging from institutions active in the field of early warning are now separate from IPC.

Such an ecosystem by definition addresses the need for different kinds of information and analysis, including early warning about hazards and risk, but also current status assessment, projections of future status, and, increasingly, real-time monitoring to cross check whether those projections are proving correct. This will require a clear differentiation between types of information to meet the needs of different stakeholders, including “hard” evidence that is sometime required for response and the probabilistic evidence needed for anticipatory action. This is not an either-or question—rather both kinds of information and analysis are needed, but for different purposes.

Strategically Embrace PA/ML

Many actors are interested in or are using PA. As more models are "rolled out" the risk is that models will come to different conclusions, adding to data confusion. The reasons for models reaching different predictions could be due to different model objectives, data sources, techniques, or underlying assumptions. Transparency of modeling approaches should be prioritized to ensure that decisions makers can understand what might drive different outcomes and, therefore, how to use model results as another source for triangulation. But modeling should be subject to the same constraints as conventional information gathering: in what way does it enable early or rapid action?

Building a coordinated ecosystem of information and analysis is a major undertaking. Getting back to the notion of a "technical consensus" among information analysts—whether at the national or a more localized level—is a critical step towards improved action. But consensus-based processes need a way of dealing with dissenting or "minority" views as well (Maxwell and Hailey 2020a).

Clarify Approaches

Information systems need to distinguish clearly between what is a trigger or signal and what is a scenario. They also need to distinguish between the way these two different information outputs are used in decision-making, resource allocation, and response. Some forms of information require a clear signal in order to be acted on, but for the most part, human decision-makers really want an overall picture of what is happening and what is likely to happen, with some indication of the likelihood of those events. Both triggers and scenarios are tools towards the same end, and indeed "most likely" scenarios can be and are used as triggers (for example the FAM initiative). The purpose of both is to inform and enable timely action.

Improve Conflict Analysis

Although mentioned as a general concern in the previous recommendation, if conflict is a major driver of crisis, and conflict mitigation actions are identified, there is a strong case for strengthening the analysis and early warning for conflict. This needs to include conflict at all levels, ranging from localized through international armed conflict. The IGAD region is among the most conflict affected, and conflict is a major driver of food insecurity as well as other negative outcomes. Yet the lack of good conflict analysis and early warning were among the most frequently repeated issues of key informants. The challenge includes both early warning about the likelihood of conflict itself and early warning about the humanitarian consequences of conflict—be they food insecurity, displacement, or a host of other potential outcomes.

Improve Data and Information Availability

Certain kinds of information are routinely available to decision makers across the region, but many kinds of information are not available, or even blocked. This needs to be addressed as a matter of urgency. Some of the information that is frequently *not* available is in the form of outcomes (sometimes nutritional status; frequently mortality, health, and WASH status) that are necessary for tracking current status and the impact of programs. Some is in the form of drivers (particularly conflict and, in some cases, market information), and some of it is in the form of information needed to interpret drivers and project the impact on outcomes (particularly information on population and population movement). There may be more specific categories of information missing in any given context or country—these tend to be the prevalent kinds of missing or difficult-to-obtain information across the region. Adopting region-wide standards on the kinds of information that systems need to regularly collect and analyze would be a step towards addressing these constraints, but in many cases the constraints are political, not technical.

Broaden the Information Base

Growing out of the previous recommendation, a related need is to broaden the base of information collected and analyzed. In terms of outcomes, food security information has tended to dominate, but other outcomes are at least as harmful to human well-being and indeed are closely related to food security, and may be important drivers of food insecurity. This includes especially good and representative information on nutrition, health, WASH, conflict, and mortality outcomes. Nutrition is sometimes included, but sometimes missing. Health, WASH, and mortality are *frequently* missing. In terms of drivers, climatic factors and production have tended to dominate; other drivers are often more difficult to track or are simply mentioned as “contributing factors” and then ignored.

Improve Information Sharing

In many cases, information may exist, but it is collected and controlled by a single actor within the information “ecosystem,” which can cripple a consensus analysis and lead to inadequate or even harmful actions. Information about humanitarian crises or the drivers that can lead to crises *must* be treated by all as a “public good”—meaning paid for by public funds (whether from a government or an international donor) and meant to identify, anticipate, and prevent public harms. As such, it should be made available to all actors and to the public. There are many constraints to achieving data transparency—some of them technical, some political, and some ethical or even legal. In every given situation, these constraints need to be addressed by the ecosystem of stakeholders.

Build In Goal-Oriented Predictive Analytics

It should be clear from Section 5 that predictive analytics, machine learning, and even artificial intelligence will play an increasing role in EW-EA systems—both in the IGAD region and globally. It is equally clear that much is still to be learned about exactly how PA can bolster existing systems. It is not clear that existing systems will ever be entirely replaced. But at the moment, there are only limited links between efforts to improve and experiment with PA and the actual needs or gaps in existing systems on the ground. Actively building these links would involve a serious effort on the part of both existing systems and predictive modelers to identify the gaps that modeling can help to fill and designing modeling systems in such a way that they actually do so. PA models can be very “data thirsty”; existing systems may need to collect different kinds of information to address the data needs.

Make Better Use of Predictive Analytics

EW has two different, but related, prediction challenges: (1) predicting common, high-frequency hazards’ (e.g., drought, price fluctuations) impacts on food security and (2) identifying (or, ideally predicting) acute, unexpected, rare, and hard-to-predict things (e.g., pandemics, conflict, locusts). Currently, PA appears best suited to supporting EW related to common hazards. To assess and monitor rare events, real-time monitoring systems should be bolstered, and EW analysts will remain essential to identifying rare events and evaluating how they may interact with other drivers of food insecurity.

Build Real-Time Monitoring into Information Systems

The primary goal of EW-EA systems is to identify hazards in advance, anticipate their impacts, and introduce actions to mitigate those impacts. However, the events of 2020 have made it clear that EW systems cannot adequately identify and anticipate all hazards. Nor are all early warning predictions necessarily accurate. This calls for greater investment in real-time monitoring—to track both novel and unexpected hazards, as well as to track the extent to which predicted hazards are having the predicted impacts—temporally, spatially, and socially. The IGAD region has a variety of good experiences with real-time monitoring systems from which more generalized learnings can be gleaned. And real time monitoring is one potentially powerful application of PA. The trick to real-time monitoring, however, is to design systems to be light and flexible and to link data collections systems to interpretive analysis.

More collaboration between researchers and EW end users is needed on defining what the relevant problem is and identifying what data should and can be brought to bear on the problem. This also speaks to a need for frank assessments on what the data gaps and priorities are and whether additional data, if any, can be collected (with what funding, processed by whom, and accessible by whom).

Prioritize Capacity Building

Across the region, stakeholders noted that one major challenge is capacity, and the need to prioritize capacity building. But the specific capacity gaps vary by country or even sub-national region. The need for capacity building is linked to the issue of the leadership of systems, whether government, UN, or civil society.

Involve At-Risk Communities

A major gap in many existing systems is that much of the linkage between information, analysis, and action is conducted by governmental or external systems, many of which have ironically few linkages to the communities they ostensibly exist to protect against hazards and risk.

Build in Vulnerability and Disaggregate Data in the Analysis

Humanitarian information systems have long been criticized for overlooking gender, age, and other vulnerable groups or social categories—on the assumption that shocks and hazards affect everyone. The experience of 2020 should finally put a stop to this misperception. The year 2020 highlights the need to analyze and forecast the impact of shocks *as they potentially affect different social groups.*

4. Cross-Cutting Recommendations

Clarify the Role of Government

As noted elsewhere (Maxwell and Hailey 2020a and 2020b) the role of government in information and analysis needs to be clarified. On the one hand, there is little argument that governments *should* lead these systems; on the other hand, there are numerous examples in which government-led systems have politicized information and analysis, and even covered up humanitarian crises. And in some cases, there is an on-going disagreement over how information systems that have operated independently can be brought into a government-led system without the loss of the independence of analysis. There is no one-size-fits-all solution to the debate between sovereign control and the independence of a humanitarian information and analysis system. But the lack of dialogue on this issue is seriously impeding efforts to prevent and respond to humanitarian crises across the IGAD region.

Face Ethical Issues Head On

Gathering and analyzing information of any kind when it may live in perpetuity on a server somewhere presents ethical dilemmas. The use of predictive analytics only heightens these concerns. They have to be addressed in context—which may vary considerably, making general recommendations difficult. But that is not a reason to shy away from facing the issues.

Learn from Mistakes

Across the region, there is much to be learned from the trial and error of both implementing early action plans and designing early warning systems. This report has been a compendium of these lessons. The lessons need to be taken on board and learned from to avoid reinventing the wheel.

Depoliticize Information, Analysis, and Action

Information is power, and power can subvert or manipulate or squelch information. And without information, early action to prevent or mitigate shocks is impossible. Governments, donors, humanitarian actors, and local leaders across the region must come to grips with the politicization of information and analysis if any progress is to be made in terms of preventing or mitigating shocks. See Maxwell and Hailey (2020b) and associated case study reports for more information on this topic.

Build In Accountability

Few systems prioritize accountability. Yet, the goals of EA are to minimize harm to and support the resilience of affected populations. To do so, EW-EA must better incorporate accountability to affected populations during development, validation, and reporting back to affected populations in EW-EA systems in general and in PA models specifically. This is especially true for marginalized populations. For example, building communication strategies into early warning systems to alert the affected population of a likely impending crisis (e.g., via radio or SMS) could provide them—and not only governments and other humanitarian actors—advanced warning. At the same time, PA models should prioritize early warning prediction windows and timelines—that may be less accurate but better aligned with the needs of affected populations and requirements for early action—rather than prioritizing shorter prediction windows with more accuracy.

Learn from COVID

While 2020 represented many setbacks, it also brought many improvements that were perhaps long overdue, including greater capacity to analyze and forecast urban food insecurity; improvements in (or at least highlighting the need for investment in) real time monitoring for novel, unexpected or unforeseen shocks; highlighting of the broad range of causal factors and a focus on the need for a broader range of considerations in analysis and response; and the greater use of remote data collection and analysis procedures. While none of this should *replace* existing systems or methods, they collectively add to the range of options for EW-EA systems in the region.

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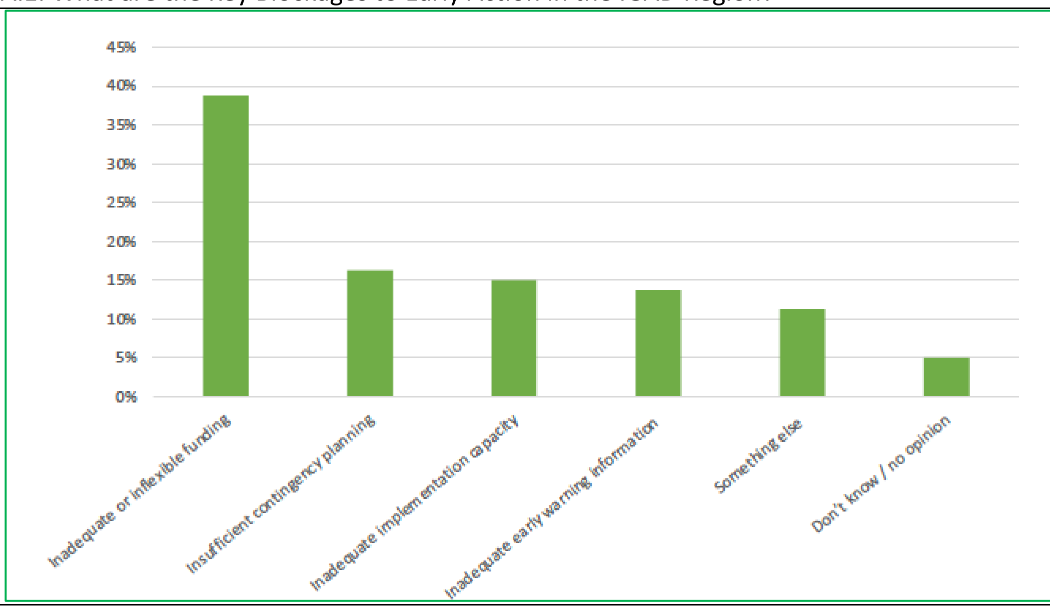
Annex 1. Results of Webinar Polling

On April 28, 2021, a webinar presenting the results of this study was held. As part of that webinar, the global audience of over 150 people was polled on several questions. This annex presents the results of the polling. This is not presented as representing anything other than "the sense of the group" during the webinar, and the sample is certainly not scientific. But the invited audience for the webinar was from the constituencies that are directly concerned with the results of the study, and their views largely reflect the findings of the study, which of course was not quantitative in nature. Of the global audience attending the webinar, 41% self-identified as early warning analysts; 29% self-identified as program staff responsible for early action; 12% as donors; 10% as government policymakers; 5% as predictive modelers, and 4% as something else.

The first substantive question posed to this diverse group was about the key blockages to early action in the IGAD Region. The results are in Figure A.1. The level and degree of flexibility of funding was by far the most frequently mentioned constraint, followed by difficulties with contingency planning and implementation capacity, followed by insufficient early warning information and a handful of additional concerns. In a similar question, other challenges to early action included confusion (too much or contradictory information), political interference and poor communication with affected communities.

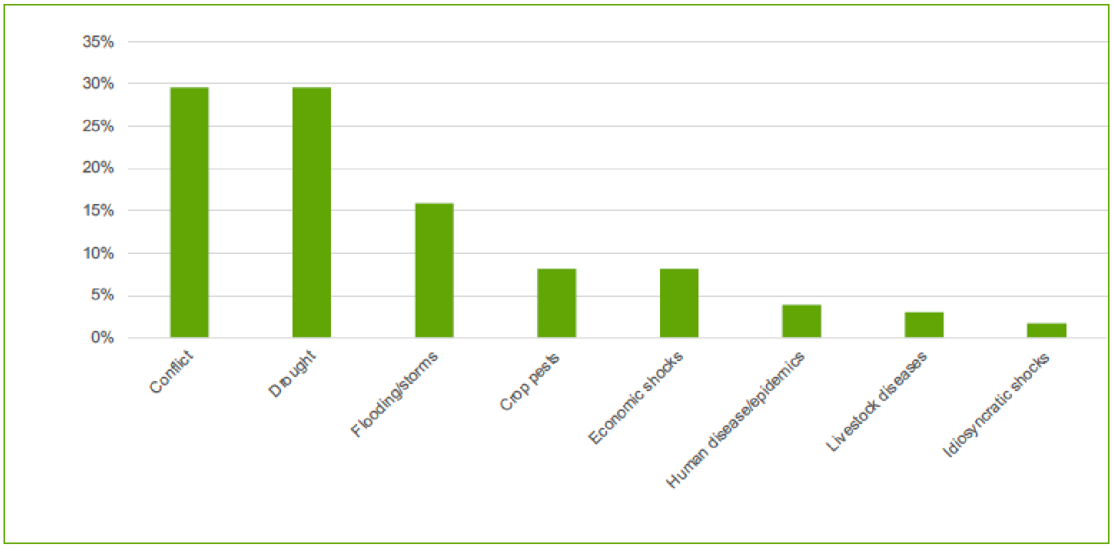
Figure A.1. What are the Key Blockages to Early Action in the IGAD Region?



Source: Authors

This result echoes one of the major findings of the study: that inadequate early warning information is usually *not* the major constraint to early or anticipatory action, but early warning and humanitarian information systems do sometimes put out information that is confusing or even contradictory. There are many challenges to early action—information and early warning is only one of them.

Figure A.2. What are the Most Challenging Hazards to Food Security in the IGAD Region?

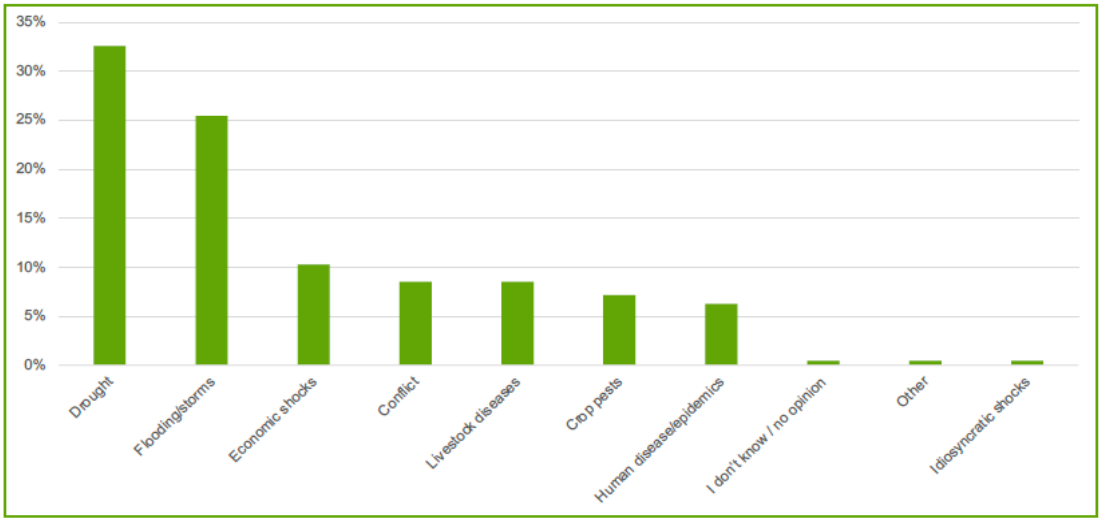


Source: Authors

Participants were then asked what they believed were the most challenging hazards leading to food insecurity in the Greater Horn of Africa. These results are in Figure A.2 (note that participants could select up to 3, so the results sum to considerably more than 100%). Conflict and drought were by far the most prevalent—which is certainly not news to anyone familiar with that region—with flooding the third most common answer. Crops pests was the fourth most common—perhaps in part because 2020 saw a major upsurge of desert locusts. Economic shocks was the fifth most common answer. Perhaps surprisingly, given the COVID-19 pandemic that was still raging at the time of the webinar, human disease and epidemics was only the sixth most common answer, followed by livestock diseases and idiosyncratic shocks.

Later in the webinar, participants were polled on which hazards they believed early or anticipatory action could best address. These answers are depicted in Figure A.3. Drought was similarly the most common answer. Many fewer people reported that conflict—while similar in the extent of its threat to food security—could be addressed effectively through early action. Flooding/storms and economic shocks were widely believed to be better managed through early action than conflict. Oddly, even though control measures for both fall army worm and desert locusts exist, crop pests were thought to be less susceptible to early action measures than conflict, and human epidemics even less. These findings suggest a need for wider dissemination about successful early warning and action relating to crops pests and epidemics.

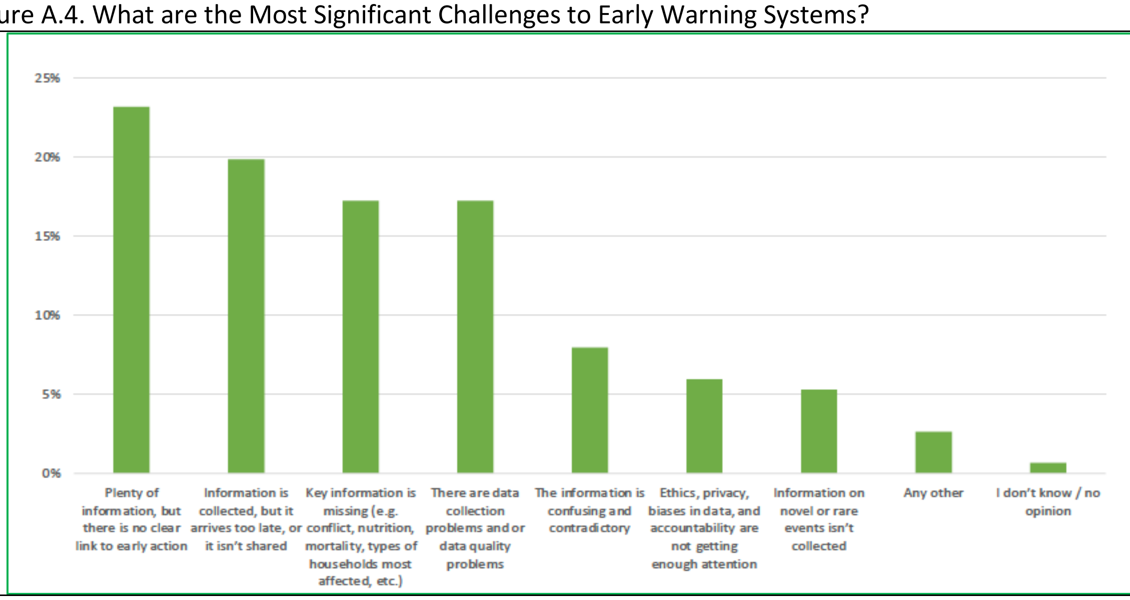
Figure A.3. Which Hazards Can Early Action Best Address?



Source: Authors

Finally, to return to the early warning theme, participants were polled more specifically about the most significant challenges to EW systems. The results are in Figure A.4. Again participants could select up to three challenges, so the results do not sum to 100%. The top challenges were about the lack of a clear link to early action, and the timeliness of the information and the ability (or willingness) to share information. The lack of key components of information (mortality, displacement, etc.) and data quality concerns were effectively tied for the third most salient concern. Others included the issue of confusing or contradictory information, ethics and privacy concerns, and the lack of means to track, collect and analyze information on novel or rare drivers of crisis. Again, these results are strongly aligned with the findings of the study.

Figure A.4. What are the Most Significant Challenges to Early Warning Systems?



Source: Authors

Annex 2. Study Approach and Methods

This study relied on two main methods. The first was an extensive review of the literature on early warning-early action (EW-EA), with a focus on East Africa but drawing on the global literature. The second method was a series of interviews with key informants who either represented a regional overview or a country-specific perspective.

Review of Existing Documentation and Literature

The review consisted of peer-reviewed articles, agency reports and other "grey" literature, and methodological materials. The literature review included descriptions and assessments of existing EW-EA systems as well as models aiming to predict future security and to nowcast food security contemporaneous with the time period of the model, and predictive analytics (PA) approaches aiming to estimate outcomes related to food security (e.g., drought). The review of existing EW-EA systems was significantly bolstered by documentation received from key informants—much of which is not searchable through usual means. Research sources included Google Scholar, Google, Tufts University library system, University of Texas library system, and key repositories such as ReliefWeb and the World Bank.

Search terms for existing EW-EA systems included combinations of the following:

- early warning, early action, humanitarian diagnostics information, humanitarian information
- needs assessments, humanitarian assessments, real-time monitoring
- East Africa, IGAD, Djibouti, Ethiopia, Somalia, Eritrea, Sudan, South Sudan, Kenya, Uganda
- food security, agriculture, nutrition, conflict analysis, conflict early warning, livelihoods

The search terms for the predictive analytics component included

- (food insecurity OR nutrition) AND (artificial intelligence OR machine learning OR predict* OR early warning systems)

Non-exhaustive search to identify approaches to estimating components of food security included

- (machine learning OR predictive analytics) AND (crop production OR income OR drought OR conflict OR water security).

Note that the field of predictive analytic techniques to model food security and related outcomes is moving quickly. The review presented here draws on materials available as of October 2020.

Key Informant Interviews

Table 2 depicts the interviews conducted. A total of 84 interviews with 125 individuals were conducted between July and November 2020. Respondents included technical staff of EW systems in the region, government officials who rely on EW for decision-making, donors, and other end users including humanitarian agencies. Of the 84 interviews, 18 were specifically with individuals or organizations working to build predictive modeling or other algorithmic approaches, including, in some cases, artificial intelligence. Many of the categories in Table 2 overlap (in other words, an interview may show up in more than one category).

Respondents were selected purposively, based on respondents' positions in existing EW-EA systems, expert knowledge, or authorship of key documents or research papers. A "snowballing" sampling strategy was adopted to identify further key respondents, requesting key informant interviewees to suggest additional respondents and, critically, further documents for review.

Given the prevailing global pandemic in 2020, all interviews were conducted entirely remotely, in accordance with the practices prescribed by the Integrative Safety Committee of Tufts University. Interviews were recorded and transcribed. Interview transcripts were analyzed manually. Interviews with respondents who work in existing information systems and interviews with predictive modelers were analyzed separately.

Interviews with staff of existing systems and users were analyzed in two separate ways. First, all interviews were coded generally for the overall thematic analysis, using both deductive and emergent coding schemes. Results of that coding were recorded on separate analysis notes and formed the basis for the discussion of key issues emerging in Section 6. Second, interviews related to specific countries were re-analyzed according to many of the characteristics found in Table 3 as well as for idiosyncratic, country-specific factors. The comparative country descriptions are found in The Report 2 on Regional and National EW-EA Systems.

Interviews with predictive modelers were coded deductively and emergently. Issues identified specific to the application of PA are found in Section 5; key issues related to the incorporation of PA into existing EW-EA systems are in Section 6. Detailed findings on PA are available in Report 3. Codes were derived from questions listed in the key informant interview guides provided in Annex 2.

Even with FAO's assistance, obtaining interviews in some countries proved difficult. Only two key informants were willing to be interviewed in each of the three countries of Uganda, Eritrea, and Djibouti, and no key informant from government in Ethiopia was willing to be interviewed (although several former government officials were interviewed).

All interviewees' names and identifying information were considered confidential and anonymized in the analysis. Interviews are referred to in this report by number only. This study was approved by the institutional review boards of both Tufts University and the University of Texas.

Annex 3. Key Informant Interview Guide

Three Groups of Key Informants

1. Information systems professional and managerial staff
2. Decision-makers who use the information/analysis generated by info systems
3. Predictive modelers developing new approaches, different from existing information systems

Questions for First Group: Professional analysts in existing early warning/information system, government officials and policy makers from the IGAD region

<Voluntary consent process here>

Thank you for agreeing to speak with us today. The objectives of this interview are severalfold.

- First, we want to get a basic sense of how the information/EW systems in <country or organization> works, and what its inputs, processes and outputs are?
- Second, we would like to get your views of barriers, gaps, or opportunities in the way that EWS/Humanitarian Information Systems do or do not inform early action or rapid response.
- Third, we'd like to request any documentation on information systems in your <country/ agency> that would explain how your early warning systems operate and how, specifically, they are linked to early action or emergency preparedness planning
- Fourth, we like to ask you about other key informants we should interview in <country>

Group 1 Questions

1. Can you briefly map out the existing early warning/ food security information system in <country>?
2. What data is collected, what data is analyzed, what data informs?
3. What outputs are issues and how often
    a. Periodic?
    b. Continuously updated?
4. Differences in data collected:
    a. Current-status assessment
    b. Early Warning (EW)?
    c. Real-Time Monitoring (RTM)?
5. How do different data streams inform each other: current status inform EW? RTM update current status, etc.
6. Does <system> make use of qualitative data; subjective data; community data?
7. Does <system> use scenario planning? If not, what EW products produced?
8. Does <system> rely on surveillance (sentinel sites) or on population coverage?
9. Can you explain the different levels of information and analysis:
    a. Community-based/ local/ participatory
    b. Geographic/area based
        - Administrative divisions
        - Livelihood zones
    c. National or sub-national
    d. Satellite imagery
10. Outcomes: what is being forecast?
    a. General humanitarian situation
    b. Food insecurity? Malnutrition? Health/WASH outcomes? Mortality

11. Who is the “audience” or “recipients” of analysis (who gets the information)?
12. How does information lead to early action (EA)?
13. What are constraints with EA?
14. What other gaps or constraints does the system face?
15. What is required to address those gaps/constraints?
16. Some possible gaps/issues to explore
    a. “Signal” vs. “scenario”
    b. Difference current-status data vs. EW data
    c. Qualitative and quantitative data
    d. Random vs. purposive sampling
17. Finally, what changes to the system have already been made to deal with the unanticipated impacts of the COVID-19 pandemic?
18. What changes are still needed to deal with situations like the one faced in 2020 with usual seasonal impacts, conflict, locusts and the pandemic?
19. Request any descriptive or explanatory documentation
20. Ask about other key informants in country

Questions for the Second Group: Donor officials charged with resource allocation decisions

<Voluntary consent process here>

Thank you for agreeing to speak with us today. The objectives of this interview are severalfold.

- First, we want to get a basic sense of the information/EW systems in <country or organization> that you rely on to make decisions about resource allocation and program responses
- Second, we would like to get your views of barriers, gaps, or opportunities in the way that EWS/Humanitarian Information Systems do or do not inform early action or rapid response.
- Third, we’d like to request any documentation on EW-EA systems in your <country/ agency> that would explain how your early warning systems operate and how, specifically, they are linked to early action or emergency preparedness planning
- Fourth, we like to ask you about other key informants we should interview in <country>

1. What are the main sources of information you rely on for decision-making with regard to food security and nutrition programming?
2. What are the main constraints to getting access to that information?
3. Do you consider that information accurate and valid?
4. If not, what are the main gaps
5. Is it adequate for decision making?
6. If not, what are the main gaps?
7. If you find the information from standard sources inadequate, what do you do to try to fill the gaps?
    a. Who do you talk to?
    b. What alternative sources of information?
8. Do you have in-house analytic/information gathering capacity you can call on?
9. Does someone help you interpret the information you receive? If so, are they from your institution or an outside one?
10. What recommendations do you have for improving the information and analysis system?
11. Request any descriptive or explanatory documentation for how early action functions in country
12. Ask about other key informants in country

Questions for Third Group: Developers of analytical modeling and artificial intelligence approaches to forecast or predict the onset and course of crises

<Voluntary consent process here>

Thank you for agreeing to speak with us today. The objectives of this interview are twofold.

- First, we would like to better understand your work in the areas of analytical modeling and artificial intelligence approaches to forecast or predict the onset and course of crises.
- Second, we would like to discuss with you what you perceive to be barriers, gaps, or opportunities in connecting your own (and others') early warning research to end users.

This interview will be open-ended, to reflect the different interests in and approaches to forecasting and predicting crises. Responses to questions will be kept anonymous.

I. Clarifying Questions

Interviews will occur after published material by the developers has been reviewed during the desk review. The desk review aims to identify the following:

1. Geographic scope (e.g., are predictions at country-level? IPC zone? District?)
2. Objective (e.g., early warning for food security; early warning to trigger insurance payouts)?
3. How outcome is measured (e.g., type of food security measure)?
4. Inputs into the model and data sources for inputs (e.g., secondary, primary)?
5. Predictive window?
6. Measures of Accuracy (e.g., reporting R-squared; Type 1 and 2 errors; machine learning indicators such as precision)?
7. Sample: purposive or random? What is the geographic level of specificity?
8. How and whether the findings have been validated?
9. Limitations of the approach?
10. Type of dissemination (peer reviewed articles; interactive dashboard; in development)?

The specific clarifying questions will be drawn from the above set to answer anything that could not be answered during the desk review.

II. Perceptions about Modeling and End Users

1. If any, what kind of outreach or discussions did you have with end users during the development of this model?
2. If any, what kind of feedback or discussions have you had with end users after developing this model?
3. What are the gaps you perceive in linking early warning to early action?
4. What are the opportunities?
5. What are the limitations?
6. If anything, what would be required for your model to be deployable on a wide scale?
7. What sort of skills would end users need to update the model?
8. What sort of skills would end users need to interpret the model?
9. Can your model be adjusted to be more or less sensitive to Type 1 (false positive) and Type 2 (false negative) errors?
10. What is your perspective on models such as yours being used to trigger early action (e.g., insurance payments)?

11. Is your model intended to be stand-alone or integrated within a broader early warning system? What needs to be included in that broader system?
12. How have covid-19 and desert locusts influenced your thinking and approach to modeling for early warning?