



Why predict climate hazards if we need to understand impacts? Putting humans back into the drought equation

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Received: 17 May 2019 / Accepted: 25 September 2020 / Published online: 09 October 2020
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Abstract

Virtually all climate monitoring and forecasting efforts concentrate on hazards rather than on impacts, while the latter are a priority for planning emergency activities and for the evaluation of mitigation strategies. Effective disaster risk management strategies need to consider the prevailing “human terrain” to predict who is at risk and how communities will be affected. There has been little effort to align the spatiotemporal granularity of socioeconomic assessments with the granularity of weather or climate monitoring. The lack of a high-resolution socioeconomic baseline leaves methodical approaches like machine learning virtually untapped for pattern recognition of extreme climate impacts on livelihood conditions. While the request for “better” socioeconomic data is not new, we highlight the need to collect and analyze environmental and socioeconomic data together and discuss novel strategies for coordinated data collection via mobile technologies from a drought risk management perspective. A better temporal, spatial, and contextual understanding of socioeconomic impacts of extreme climate conditions will help to establish complex causal pathways and quantitative proof about climate-attributable livelihood impacts. Such considerations are particularly important in the context of the latest big data-driven initiatives, such as the World Bank’s Famine Action Mechanism (FAM).

Keywords Drought · Impact assessment · Disaster resilience · Decision-support · Mobile technologies

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1 Introduction

Satellite-derived information has become an indispensable source of information for all phases of disaster risk management. The granularity and availability of satellite data to monitor climate hazards, such as floods and droughts, are increasing, resulting in image updates from intervals of 5 min, in the case of geostationary weather satellites with coarse spatial resolution, to revisit periods from less than one up to several days for very high spatial resolution optical imagery with up to 30-cm spatial resolution. However, climate hazards represent only one part of the disaster risk equation, which defines risk as the product of hazard, exposure, and vulnerability. Without up-to-date information about exposure, socioeconomic conditions, and the related vulnerability of communities at risk, we are facing several major limitations, ranging from weaknesses in the prediction of disaster loss and damage to the evaluation of disaster mitigation strategies.

The development of socioeconomic data collection strategies has failed to keep pace with both satellite and climate data processing and methodical advancements. These limitations are not primarily related to the technology or bandwidth needed to collect and analyze socioeconomic data. They are caused by weaknesses in existing human-centric household data collection and its lack of synchronization with existing climate and impact models. From a drought risk management perspective, for instance, analyzing climate along with complementary socioeconomic data could help generate more tailored early warnings and capture the impact of successive moderate drought events, whose impacts are comparable with individual extreme droughts (Delbiso et al. 2017). However, while climate data are harmonized globally and available at high temporal resolution, socioeconomic data are collected with limited collection standards among, or even within, the main data collection agencies, infrequently or exclusively in the context of emergencies.

The claim for “better” socioeconomic or behavioral data, meaning standardized, quality-controlled, harmonized assessments, is neither new nor specific to a particular hazard. However, only recently have low-cost mobile technology and social media analytics become available for the advanced collection and analysis of group or crowdsourced data (Resch et al. 2018; Kryvasheyeu et al. 2016). It is time to systematically connect information about extreme climate conditions to a human perspective via data from low-cost mobile technologies that cannot replace, but rather complement existing assessment strategies. We present a strategy to contextualize information about drought conditions via timely and frequently updated information collected from vulnerable communities in order to close vital information gaps in research, humanitarian aid, and policy making. The strategy aims to analyze climate, socioeconomic, livelihood, and health data as crucial components of a combined narrative.

2 A single event can affect future generations

Despite the availability of various satellite-derived or modeled estimates that are capable of tracking critical thresholds related to hydrometeorological extreme events (e.g., rainfall, soil moisture, evapotranspiration, or vegetation greenness), their impacts tend to be observed as isolated events in space and time. Information about agricultural losses and food availability or consumption is usually part of the drought narrative, but questions related to coping capacities, migration, poverty, water supply, access to food and markets, or political conflict remain unanswered or are even decoupled from routine drought risk assessments. The severity of not

being able to “contextualize” extreme climate conditions becomes even more apparent when their impacts affect livelihoods far beyond one agricultural season. There is evidence about links between weather variables and childhood undernutrition (Phalkey et al. 2015), a causal association between climatological changes and various conflict outcomes (Hsiang and Burke 2014; Hsiang et al. 2013), as well as between drought conditions during birth, future education, and lifetime earnings (Fuentes Nieva and Seck 2010), but the absence of reliable long-term data at the household level makes it difficult to establish direct or indirect causal relationships. These limitations affect the comparability of data for scientific purposes across different global regions—farmers in Central America and West Africa, for instance, might face similar threats, but develop very different coping capacities—and the ability of drought early warning systems to issue more tailored alerts. To understand how drought or other climatic extreme events will affect socioeconomic outcomes and to use climate services for efficient climate action, environmental anomalies and information about changes in livelihoods need to be monitored together. However, without up-to-date and rapidly updated information about people’s vulnerabilities, risk perceptions, and coping capacities, the skill of climate information to predict impacts, often the basis for humanitarian activities, is severely hindered and impact mitigation strategies cannot be evaluated.

3 The most critical gaps

Drought impact assessment poses a unique set of challenges that ranges from the general definition of the term “drought” to clear thresholds for drought severity, extent, onset, and recovery (Wilhite et al. 2014). There has been a distinct gap in efforts to monitor global drought and related impacts. Many drought monitoring systems estimate drought hazard based on single or combined biophysical variables or indicators representing key elements of the hydrologic cycle. The handbook of drought indicators (Svoboda et al. 2016) lists more than 50 drought indices. Not a single one of these indices connects climate anomalies to socioeconomic vulnerabilities, coping capacities or impacts of previous droughts to estimate future drought risk and related impacts, even though measuring socioeconomic impacts provides the foundation for humanitarian decision-making.

A first attempt for a dynamic global agricultural drought risk assessment that includes information on exposure and vulnerability is described in Vogt et al. (2017) and is based on an indicator that evaluates the likelihood of drought impact for different socioeconomic sectors (Vogt et al. 2018); it has been implemented in an operational context in the Global Drought Observatory (GDO, <https://edo.jrc.ec.europa.eu/gdo>). In addition to the hazard, the indicator considers exposure and vulnerability, but the limitations of this indicator arise from the spatial and temporal resolution of available socioeconomic data and the lack of widely used data collection standards. These limitations are particularly critical, because comparable drought conditions over vast areas often result in idiosyncratic impacts at the household level, which can vary widely due to heterogeneous risk and vulnerability profiles.

Drought impacts are often exacerbated when government social safety nets and other programs are degraded by social conflict and/or societal dysfunction. In 2018, approximately 820 million people around the world were malnourished. Political conflict was a major driver of food crises in 21 countries, with 14 of them suffering from deep economic recessions (Food and Agriculture Organization of the United Nations 2019). However, in most cases, it is unclear if or to what degree drought or other extreme climate events contributed to conditions

resulting in political conflict or to what degree social conflict increased the vulnerability towards drought impacts, leaving humanitarian decision-makers with critical information gaps.

4 Current data collection efforts and interoperability

Existing historical records of drought impacts on livelihoods show large spatial and temporal gaps, in particular on a sub-national scale. The following programs offer data at the sub-national, household, or individual scale in some regions. However, interoperability is severely limited due to lack of ontologies and an active community of practice to establish best practices, different objectives, data collection methods, and collected variables: USAID Demographics and Health Surveys (DHS) Program, the UN World Food Programme (WFP) (mobile) Vulnerability Analysis and Mapping Units, UN Children's Fund's Multiple Indicator Cluster Surveys (MICS), the Standardized Monitoring and Assessment of Relief and Transitions (SMART) surveys in crisis zones, and the World Bank's Living Standards Measurement Study (LSMS, <http://surveys.worldbank.org/lsms>) or Rapid Emergency Response Surveys (RERS). Every 3 to 5 years, the WFP carries out baseline household surveys, complemented by Food Security Monitoring System (FSMS) surveys, which are rapid, less-detailed household surveys. FSMS surveys are undertaken once or twice a year to evaluate and identify deviations from that baseline. Since 2014, the use of mobile phones to carry out surveys was expanded to obtain data in areas where access is unsafe, but still necessary. The data need to be interpreted carefully due to possible bias in their collection, as the sampling is restricted to individuals who own a mobile phone and/or to accessible populations. However, the WFP's mobile assessments proved to be faster and cheaper (3–9 US\$/household) than conventional WFP assessments (20–40 US\$/household) (Robinson and Obrecht 2016) and far less expensive than the World Bank's surveys in sub-Saharan Africa (322.99 US\$ per household in 2014) (Kilic et al. 2017). These mobile assessments could be expanded to include information on vulnerability and exposure to climatic shocks without disrupting the continuity of historical socioeconomic assessments.

The International Disasters Database (EM-DAT) (<https://www.emdat.be/>) and the United Nations Office for Disaster Risk Reduction Desinventar (Sendai) Database (<https://www.desinventar.net/>) are two of the main data sources for analyzing natural disasters for many global policy-setting organizations and national governments. They list loss data for various disaster categories and dozens of sources, partly at sub-national scale. Both data sources, however, do not differentiate between direct and indirect socioeconomic impacts of extreme climate events. There are large differences in the damage estimates reported in the two databases (Panwar and Sen 2019), not least because a robust methodology to capture the human impact of drought is missing. This also leads to a strong bias when it comes to recording drought-related casualties. Unless there is a famine, where deaths are caused by outright starvation, the most vulnerable people die of a specific disease or condition (e.g., dehydration), aggravated by malnutrition and thereby (statistically) decoupled from the climatic root cause.

Economic losses, mainly consisting of agricultural impacts, are increasingly reported to global disaster databases. However, to our knowledge, regularly updated and maintained drought impact inventories that cover both direct and indirect impacts exist exclusively for high-income countries like the USA, Canada, and various European states.

5 New ways to engage with rural communities

Despite highly variable growth rates (GSM Association 2016), the advent of accessible mobile technologies in rural areas across the globe, coupled with the development of user-friendly platforms for data exchange, creates the opportunity for regular sampling of day-to-day conditions. There is evidence that the communication of agricultural information through mobile devices in sub-Saharan Africa and India increased yields by 4% (Fabregas et al. 2019). By redefining the modes through which we engage with rural communities, we can develop a continuously updated baseline for socioeconomic conditions that we established long ago for environmental conditions.

Generating these socioeconomic data, sampled regularly in space and time, presents a novel challenge because instruments like space-based sensors are easier to “encourage” than people. Since current frontiers of mobile data collection, such as citizen science (Callaghan et al. 2019), crowdsourcing (Hunt and Specht 2019), Short Message Service (SMS)-based surveys (Bell et al. 2016), or interactive voice response (IVR) calls (Morrow et al. 2016), fail to establish a baseline if they are event-driven or carried out irregularly, self-reporting can fill critical gaps. There are strategies to incentivize truthful self-reporting, but incentives vary across different cultural backgrounds, climate impact scenarios, and socioeconomic contexts. Sheriff and Osgood (2010), for instance, suggest linking incentives to an audit system. If a truthful smallholder farmer, or shepherd in the case of the Sheriff and Osgood study, is selected for an audit, this corresponds to “winning a lottery,” incentivizing other farmers to also report truthfully. Research on this strategy is exploring if providing monetary rewards for accuracy can improve accuracy or reduce biases in self reporting. “Gamification” strategies involve the use of games in “non-game contexts” with the goal of communicating information, information gathering, and encouraging actions in an ongoing set of interactions (Seaborn and Fels 2015; Johnson et al. 2016). In these strategies, the incentive may be earning points or badges in an app on a smartphone, as commonly implemented in fitness and health apps. While self-reporting in conflict zones is very limited, because mobile devices might be perceived as “spy tools,” there are several open-source offline solutions, such as ODK (Open Data Kit), that allow data collection in regions with insufficient network coverage.

Our vision is to develop a true global socioeconomic baseline derived from current data collection approaches, complemented with high-frequency community-based assessments. Such a dataset would require a re-thinking of how to collaborate with rural communities, so that individuals remain engaged in reporting, even when there is little to report, because the conditions are “normal.” One promising incentive to keep data suppliers engaged over longer periods of time is a constant feedback loop with analysts and researchers. Establishing such a feedback loop through mobile devices would require a transparent “trade” between community-supplied data to develop, run, and calibrate decision-making models and the transmission of model outputs in the form of actionable information back to data suppliers.

6 Concrete steps to connect the dots

We recognize that fundamental changes to the overall strategy or parameters that are collected in the standard assessments of the world’s leading aid or emergency organizations might easily have a detrimental impact on longitudinal studies, which rely on updates of the same parameter, in the same region over long periods of time. There are also practical limits to

the number of questions that can be posed within any one survey instrument. Instead of replacing comprehensive demographic and health surveys, we suggest that the most promising approach would be to complement them with a strategy that relies on (1) mobile technologies for complementary high-frequency surveys, (2) advanced methods to recognize patterns and identify hotspots of likely socio-economic drought impacts, and (3) the consideration of climate data/services to better understand complex drought impact pathways and facilitate more tailored mobile assessments.

6.1 Step1: Mobile devices to complement traditional surveys

Recent studies have shown that it is not only possible to train community health workers for targeted, high-frequency food security assessments via a “train the trainers” approach (Enenkel et al. 2015), but that call detail records can be used to monitor climate-related migration movements at large scales (Lu et al. 2016). In addition to potential issues related to the long-term engagement of data suppliers and the need for more field tests of incentives for truthful reporting, the main question is which parameters the next generation of mobile surveys should focus on to establish a robust, interdisciplinary baseline while simultaneously complementing existing survey strategies. There is a need for research exploring if marginalized perspectives are excluded in crowdsourcing and self-reporting approaches, the recall bias and measurement error in self-reporting (Bell et al. 2019), and if incentives, memory triggers, or other mechanisms can be used to address these issues. Table 1 lists interdisciplinary variables that are already collected via standard socioeconomic assessments to fill critical spatiotemporal gaps and additional, interdisciplinary parameters that could complement these surveys via high-frequency community-based mobile assessments.

Network analysis, potentially combined with semi-structured interviews (McAllister et al. 2014), can help to tailor the choice of variables to regional or national, or local, climate, and socioeconomic conditions by identifying key stakeholders, decision-makers, communities at risk, data collection agencies, etc. However, more research is needed to quantify the added value of collecting certain variables, such as the perception of climate anomalies, with regard to concrete objectives, such as the understanding of climate impact pathways (e.g., agricultural investments in drought-resistant seeds).

6.2 Step2: Connecting top-down weather and climate data with bottom-up socioeconomic data via machine learning

Advanced statistical methods or machine learning and their application to global monitoring have made considerable progress in recent years. Different kinds of machine learning approaches are used to detect extreme weather in climate datasets (Liu et al. 2016), to explain the variation in poverty characteristics via high-resolution optical satellite imagery (Jean et al. 2016), or even to harmonize the humanitarian data collection process (Swamy et al. 2019). However, attempts to use machine learning to recognize and predict socioeconomic patterns related to climate patterns have so far been restricted by the lack of a standardized, socioeconomic baseline dataset to train the algorithms. At the same time, the household economy approach (HEA) (Seaman et al. 2014) and livelihoods framework are widely and successfully used by many humanitarian aid agencies. Yet, both machine learning and HEA analyses face critical limits in terms of input or training data. As a consequence, we do not know how localized socioeconomic vulnerabilities translate the impacts of drought into consequences on

the livelihoods, long-term agricultural decision-making, and risk-taking of vulnerable communities. Testing the data collection strategy described in step 1 to complement traditional assessments via mobile technologies could pave the way for a new generation of algorithms to recognize patterns and predict hot spots. Just like convolutional neural networks can be trained to identify features in satellite imagery to explain variations in livelihood changes, it is possible to train neural networks to detect socioeconomic patterns in climate hazard data, if standardized training data about changes in livelihood conditions are available at sufficient spatial and temporal resolution.

However, even if machine learning can help to strengthen the development of interdisciplinary climate impact narratives, it is by no means a silver bullet from an operational perspective. Humanitarian users will have to make decisions about the integration of new information into existing workflows with potentially far-reaching consequences and answer questions, such as

- What are the trade-offs between high-performance model outputs that might be more difficult to communicate and more simple statistical model results?
- How can complex technical information be translated into actionable knowledge on the ground?
- Is there a sustainable, cost-efficient way to rely on external, commercial, or academic machine learning model developers, or are internal resources required?
- What are the requirements for an operational workflow regarding human resources?
- What are the benchmarks for the added value of machine learning outputs (i.e., when is it worth the investment)?
- To what degree does qualitative expert assessment play a role?
- To what degree can machine learning algorithms be de-biased by the selection biases inherent to self-reported data?

6.3 Step3: Climate forecasts as a trigger

Climate services are currently used for a multitude of applications, ranging from the prediction of extreme rainfall events and crop yields (Burke and Lobell 2017) to related financial instruments. Regarding the latter, climate forecasts are used to trigger payouts for early action against potential hydrometeorological disasters before their impacts are detectable through forecast-based financing (FBF) (Coughlan de Perez et al. 2014). Once a standardized socioeconomic baseline dataset is available (step 1) and its spatiotemporal links with drought are established (step 2), similar climate-based mechanisms can be established to trigger more targeted livelihood surveys. In a region where migration is one of the main coping mechanisms for drought, a targeted survey focusing on the early detection of migration movements would help mobilize the timely allocation of resources by humanitarian decision-makers or even the mitigation of drought impacts. Regular surveys, aiming to understand farmers' agricultural drought risk perception and related disaster management and agricultural coping mechanisms, could support the more efficient use of limited resources and the sustainable development of financial instruments (Osgood et al. 2018).

Figure 1 integrates these steps into the larger picture of high-frequency data collection, the joint analysis of climate and livelihood conditions to detect patterns or to predict hot spots, and the identification of climate-attributable impacts to strengthen impact forecasts. The illustration

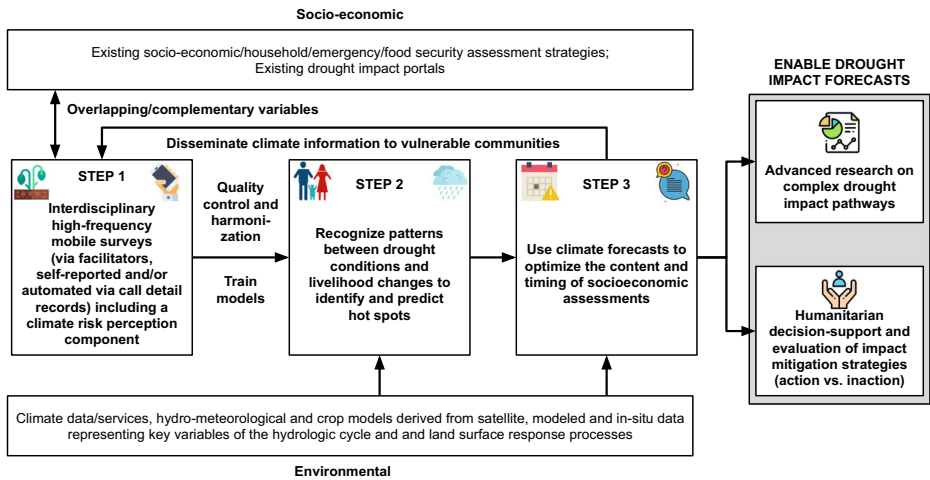


Fig. 1 Idealized strategic framework to link complementary high-frequency socioeconomic surveys (step 1) to climate data (step 2), more targeted assessments (step 3) for improved drought impact forecasts (icon credit: www.flaticon.com)

does not imply an automatic translation of new data into actionable knowledge, but it highlights the need for new links between data collection and decision- or policy-making strategies. Since drought impacts and their root causes cannot be regarded as isolated environmental or socioeconomic issues, data collection serves multiple analytical purposes, resulting in the cross-fertilization with other disciplines and extreme events (e.g., floods or wildfires).

7 Conclusions

The synchronized collection and assessment of data representing the dynamic nature of environmental and socioeconomic conditions would result in advantages for research, operational humanitarian activities, and climate adaptation strategies. A joint analysis of synchronized data allows for developing new ways of understanding the relationships between drought hazard, water and agricultural management, food access and security, health issues, education, migration patterns, poverty, individual risk perception, and risk taking (Table 1) at different spatial and temporal scales. From a data collection perspective, both objective and subjective approaches to resilience measurement can be combined to improve our understanding of drivers of resilience (Clare et al. 2017). A contextualized drought-impact monitoring approach would foster the generation of new knowledge regarding the benefits of early action compared with the costs of inaction (World Meteorological Organization and Global Water Partnership 2017) via direct feedback loops between data suppliers, humanitarian agencies, and (non-) governmental organizations. In addition, the impact of agricultural conditions that are not necessarily related to climate shocks, but to other factors such as pests or social conflict, could easily be monitored and used to issue early warnings and raise emergency funds before any kind of impact on crops or socioeconomic conditions is visible.

Climate change and accelerating extreme hydroclimatic events will continue to disproportionately affect vulnerable populations and low-income countries (Centre for Research on the

Table 1 List of climate-related parameters to complement existing socioeconomic assessments

Data category	Question linking drought risk to socioeconomic or livelihood conditions/drought impact	High-frequency community-based assessment possible	Current source of info	Data type	Scale	Units
Climate/Agriculture	Has the agricultural season started yet?	Yes	Individual projects	Qualitative	Locality	Yes/no List
Climate/Agriculture	Did it rain an average amount during the last 30 days? If not, was the rainfall higher/lower than normal.	Yes		Qualitative	Locality	List
Climate/Agriculture	Did you experience average temperatures during the last 30 days? If not, were temperatures higher/lower than normal.	Yes		Qualitative	Locality	List
Climate/Agriculture	Current crop health conditions are far below/below/average/above average	Yes		Qualitative	Locality	List
Climate/Agriculture	Yield this season was far below/below/average/above average	Yes		Qualitative	Locality	List
Climate/Agriculture	Start of Season analysis (consecutive rainfall events of X mm)	No	In-situ, remote sensing, modeled, assimilate (e.g., FEWS NET, GEOGLAM, Copernicus Land Monitoring/Emergency Management Service, JRC, FAO, WFP, Insurance	Quantitative	> 1 km	Date/10-day periods
Climate/Agriculture	Crop condition analysis	No		Quantitative	30 m (ET); 1 km (soil moisture); 4 km (rainfall)	Sensor-specific
Climate/Agriculture	Crop yield analysis	No	Remote sensing, modeled, insurance	Quantitative	> 30 m (most vegetation indices 250–500 m)	Sensor-specific
Climate/Agriculture	30-year standardized Rainfall/Soil Moisture/Evapotranspiration/-Vegetation health Anomaly over 10 days, 1 month, 3 months, year anomaly/standard deviation	No	In situ, remote sensing, assimilated	Quantitative	> 4 km	Percent
			(Sub-)seasonal rainfall/temperature forecast	No	Modeled	Quantitative

Table 1 (continued)

Data category	Question linking drought risk to socio-economic or livelihood conditions/drought impact	High-frequency community-based assessment possible	Current source of info	Data type	Scale	Units
> 10 km	Terciles, flexible (percentile chosen by user)				(multi-model ensembles), e.g. IRI Columbia	
Food Security	During the last 12 months (30 days for mobile assessments), was there a time when, because of lack of money or other resources: (1) You were worried you would not have enough food to eat?; (2) You were unable to eat healthy and nutritious food?; (3) You ate only a few kinds of foods?; (4) You had to skip a meal?; (5) You ate less than you thought you should?; (6) Your household ran out of food?; (7) You were hungry but did not eat?; (8) You went without eating for a whole day?	Yes	mVAM (Reduced Coping Strategy Index), Gallup, FAO Food Insecurity Experience Scale (FIES)	Qualitative	Locality	Selection 1–8
Food Security	If sometimes or often not enough to eat, which is a reason why: Not enough money for food; Too hard to get to the store; Kinds of food we want not available; Good quality food not available; Did not produce enough in the past year	Yes	Gallup	Qualitative	Locality	List
Food Security		Yes		Quantitative	State	Prevalence rates

Table 1 (continued)

Data category	Question linking drought risk to socio-economic or livelihood conditions/drought impact	High-frequency community-based assessment possible	Current source of info	Data type	Scale	Units
	Malnutrition of kids between 6 and 59 months via Mid-Upper Arm Circumference (MUAC)		US AID DHS, MICS, SMART (assessments in complex emergencies)			
Food Security	Integrated Food Security Phase Classification (IPC)	No	FEWS NET, WFP	Qualitative	Regional	IPC levels
Water/hygiene	Access to water/sanitation facilities over the last 30 days has been problematic	Yes	mVAM	Qualitative	Locality	Likert scale
Health	Outbreak of diseases—dysentery, cholera, influenza, measles, HIV, other	Yes	WHO	Qualitative	Locality	List
Economics	Price of main staple crop on the local market is abnormally high	Yes	mVAM	Qualitative	Locality	Likert scale
Economics	Price of local food basket in representative Regional market	Yes	FAO FPMA	Quantitative	Regional	Percent anomaly
Education	School Attendance interrupted - Yes/No	Yes	DHS/MICS	Qualitative	Locality	Yes/No
Migration	People joined/left the household (migration)	Yes (general trends, no clear distinction between migrant/-refugee)	DHS	Qualitative	Locality	Yes/No
Migration	International migration/refugee databases	NA	OECD, IDMC, Landscan, IOM, UNHCR	Quantitative	State/national	Totals
War, social conflict	Conflict Present? Yes/No	Yes	ACLED, International Crisis Group	Qualitative	Sub-national	Report, Yes/No (ACLED)
War, social conflict	If recorded conflict in ACLED: event type (civilians affected?)	Yes	ACLED, International Crisis Group	Qualitative	Sub-national	Event type (ACLED)
Humanitarian needs/data	Crisis level/trend estimation	Yes (after analysis of NGOs)	ACAPS, different (inter)national NGOs	Qualitative	Sub-national	Text

Table 1 (continued)

Data category	Question linking drought risk to socio-economic or livelihood conditions/drought impact	High-frequency community-based assessment possible	Current source of info	Data type	Scale	Units
Humanitarian needs/data	General humanitarian data on emergencies, migration/displacement/refugees, food insecurity, poverty, damages, etc.	assessment results) NA	HDX	Qualitative/quantitative	Sub-national	Various data formats and units
Source of information:						
ACAPS: Assessment Capacities Project						
ACLED: Armed Conflict Location and Event Data						
Copernicus: Earth Observation Programme of the European Commission/European Space Agency						
eVAM: Emergency Vulnerability Analysis and Mapping						
FAO FIES (Food Insecurity Experience Scale)						
FEWS NET: Famine Early Warning Systems Network						
FPMA: FAO GIEWS Food Price Monitoring and Analysis of main markets						
GALLUP Analytics						
GEOGLAM: Group on Earth Observations - Global Agricultural Monitoring						
HDX: Humanitarian Data Exchange						
IDMC: International Displacement Monitoring Center						
International Crisis Group						
IOM: International Office for Migration						
IPC: Integrated Food Security Phase Classification (IPC)						
IRI Columbia: International Research Institute for Climate and Society (seasonal climate forecasts)						

Table 1 (continued)

Data category	Question linking drought risk to socio-economic or livelihood conditions/drought impact	High-frequency community-based assessment possible	Current source of info	Data type	Scale	Units
JRC: Joint Research Center of the European Commission						
Landscan: annual population density, incorporating camps, displaced persons, and migration					https://ec.europa.eu/jrc/en/research-topic/global-food-security	
UNICEF MICS: Multiple Indicator Cluster Survey					http://web.ornl.gov/sci/landscan/	
mVAM: Mobile Vulnerability Analysis & Mapping					https://www.unicef.org/statistics/index_24302.html	
					https://www.wfp.org/content/2016-mobile-vulnerability-analysis-mapping-mvam	
OECD: Organisation for Economic Co-Operation and Development					http://stats.oecd.org/	
RS data: Satellite remote sensing data from geostationary and polar orbiting sensors working in the optical, infrared and microwave domain					various	
SMART: Standardized Monitoring and Assessment of Relief and Transitions					http://smartmethodology.org/about-smart/	
UNHCR: Office of the United Nations High Commissioner for Refugees					http://www.unhcr.org/	
US AID DHS: Demographic and Health Survey					https://dhsprogram.com/data/	
WHO: World Health Organization Disease Outbreak News					http://www.who.int/csr/don/en/	
World Bank Living Standards Measurement Study (LSMS)					http://surveys.worldbank.org/	

Epidemiology of Disasters (CRED) 2015). As highlighted in the 2018 State of Food Security and Nutrition report of the UN Food and Agriculture Organization (2018), food insecurity is increasing because we are failing to adequately manage climate variability and change. Policy-makers will require more complete quantitative data that measure climate change impacts, as well as the efficiency of mitigation policies via comparable metrics. The proposed framework can be embedded in existing strategies, such as the Global Partnership for Sustainable Development Data (<http://www.data4sdgs.org/50by2030>) and big data-driven initiatives such as the World Bank's Famine Action Mechanism (FAM; <http://www.worldbank.org/en/programs/famine-early-action-mechanism>). It can serve as the strategic, interdisciplinary baseline to fill this critical gap, help to justify investments in emergency preparedness, and open new communication channels to disaster-prone communities via mobile devices—also in places that are currently not connected. By 2025, more than half the population of Sub-Saharan Africa will be subscribed to a mobile service (GSM Association 2019).

If or how the suggested framework ultimately finds its way into the operational toolboxes of decision-makers in humanitarian and development aid will largely depend on the willingness of stakeholders to investigate which drivers and mechanics are needed to adapt the generic approach to concrete use cases and applications. Research organizations will have to fill critical gaps and work as closely as possible with agencies on the ground. Particularly in the face of compound risks, such as extreme climate and COVID-19, which might push another 130 million people into acute malnutrition (<https://www.wfp.org/news/covid-19-will-double-number-people-facing-food-crises-unless-swift-action-taken>), an in-depth understanding of climate impact pathways will be more important than ever.

Compliance with ethical standards

Competing interest The authors declare that they have no competing interest.

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Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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