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Food Security Monitoring for Developing Countries in the Age of Big Data

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Regine Weber

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Referent: Prof. Dr. Joachim von Braun
Koreferent: Prof. Dr. Gerhard Schiefer

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ABSTRACT

Approximately 817 million people are currently estimated to be undernourished and 85 million people across 46 countries are estimated to be in need of food emergency assistance over the course of 2019. Conflict, migration and climate-related disasters are expected to further exacerbate already existing risks to food security. Important pillars that contribute to anticipating crises and informing a potential emergency response are early warning and monitoring systems. The emergence of big data as well as increasing Internet and mobile phone adoption rates across developing countries have enabled the inclusion of different, timelier, more frequent and spatially disaggregated data, as well as the at-risk population itself into monitoring systems. This dissertation is placed at the intersection of food security monitoring, early warning and big data.

The first part of this thesis focuses on exploring the information content of current early warning systems (EWSs) for food security risks. We evaluate the information content of the four largest international monitoring system for food security against a conceptual benchmark. We find that EWSs have partially moved towards the inclusion of more diverse indicators for risk monitoring. However, our results further show that timely information is missing, information is published irregularly and the geographical scope of monitoring systems is smaller than stated.

Subsequently, this thesis explores ways to improve monitoring systems for food security by using two strings of new data, i.e. Internet metadata and direct assessments from the at-risk population gathered via mobile phones. We test whether Internet metadata in the form of Google search queries (GSQ) can improve now-casts of crop prices in Ethiopia, Kenya, Mozambique, Malawi, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe. In an pseudo-out-of-sample, one-step-ahead forecasting environment, we find models containing the Google search-string *maize* to beat the benchmark model in 8 of the 9 countries. By including the GSQ data, we reduce the now-casting error of maize prices between 3% and 23% and achieve the largest improvements for Malawi, Kenya, Zambia and Tanzania with improvements larger than 14%.

Furthermore, using a citizen-science approach this thesis analyzes whether the at-risk population can validly assess the food security status of their community, by collecting near real-time food security assessments over an 8 month period from the local population in Kenya. We test the validity of the gathered information against standard food security indicators, i.e. the food consumption score (FCS) and reduced coping strategy index (rCSI), using Pooled Poisson, Negative Binomial and Poisson Fixed Effects models. We find robust results that the assessments from the at-risk population conform to the FCS and rCSI observed during the study period.

ZUSAMMENFASSUNG

Schätzungen zufolge sind derzeit rund 817 Millionen Menschen unterernährt und 85 Millionen Menschen in 46 verschiedenen Ländern werden im Laufe des Jahres 2019 auf Nahrungsmittelhilfe angewiesen sein. Voraussichtlich werden Konflikte, Migration und klimabedingte Katastrophen die bereits bestehenden Risiken für die Ernährungssicherheit in Zukunft weiter verschärfen. Frühwarn- und Überwachungssysteme für die Ernährungssicherheit sind in diesem Kontext wichtige Säulen, die zur Antizipation von Krisen beitragen und eine potenzielle Notfallintervention auslösen und gestalten. Das Aufkommen von Big Data sowie steigende Internet- und Handy-Nutzung in Entwicklungsländern haben die Einbeziehung verschiedener, häufiger und räumlich detaillierter Daten sowie die Integration der gefährdeten Bevölkerung selbst in Überwachungssysteme ermöglicht. Diese Dissertation befindet sich an der Schnittstelle von Frühwarnsystemen für die Ernährungssicherheit und Big Data.

Zunächst untersucht diese Dissertation den Informationsgehalt aktueller Frühwarnsysteme (EWSs) für Ernährungssicherheitsrisiken. Dabei wird der Informationsgehalt von vier großen, internationalen Überwachungssystemen für die Ernährungssicherheit anhand eines konzeptionellen Benchmarks für Frühwarnsystem analysiert. Wir stellen fest, dass EWSs eine breite Bandweite an Indikatoren abdecken und der anfängliche Fokus auf Verfügbarkeit ebenfalls um die Zugangskomponente zu Nahrung erweitert wurde. Unsere Ergebnisse zeigen jedoch weiterhin, dass zeitnahe Information fehlt, Information unregelmäßig veröffentlicht wird und die geografische Reichweite der Überwachungssysteme geringer ist als angegeben.

Anschließend untersucht diese Arbeit Möglichkeiten, Überwachungssysteme für die Ernährungssicherheit zu verbessern, indem sie das Potenzial zwei neuer Datenströme für Frühwarnsysteme untersucht, i.e. Internet-Metadaten und die direkten Einschätzungen der Risikopopulation selbst. Wir prüfen, ob Modelle, basierend auf Internet-Metadaten in Form von Google-Suchanfragen (GSQ) die *now-casts* von Maispreisen in Äthiopien, Kenia, Mosambik, Malawi, Ruanda, Tansania, Uganda, Sambia und Simbabwe verbessern können. In einer *Now-Casting, Pseudo-Out-of-Sample*-Umgebung, finden wir, dass Modelle, die den Google-Suchstring *maize* enthalten, das Benchmark-Modell in 8 der 9 Länder schlagen. Durch die Einbeziehung der GSQ-Daten reduzieren wir den Forecasting-Fehler von Maispreisen zwischen 3% und 23% und erzielen die größten Verbesserungen in Malawi, Kenia, Sambia und Tansania mit mehr als 14%.

Desweitern analysiert diese Dissertation anhand eines Citzen-Science Ansatzes, ob lokale Teilnehmer den Ernährungssicherheitsstatus der lokalen Bevölkerung einschätzen können. Anhand von Mobiltelefonen und in nahezu Echtzeit wurden dazu über einen Zeitraum von acht Monaten Bewertungen der Ernährungssicherheit von der lokalen Bevölkerung in Kenia gesammelt. In Pooled-Poisson-, Negative-

Binomial- und Poisson-Fixed-Effects-Modellen analysieren wir die Validität der gesammelten Informationen im Vergleich zu Indikatoren für die Ernährungssicherheit, i.e. Lebensmittelkonsum (FCS) und Bewältigungsstrategien (rCSI). Wir finden robuste Ergebnisse, dass die Einschätzungen der Risikopopulation mit den Werten des FCS und rCSI übereinstimmen, die während des Untersuchungszeitraums beobachtet wurden.

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ACHIEVEMENTS

I presented the different chapters of this dissertation at the following conferences and workshops: Chapter 2 of this thesis "Analyzing Monitoring and Early Warning Systems for Food Security Risks" was presented at the UN World Bosai Forum, in Sendai, Japan in November 2017; at the meeting of the UK Alliance for Disaster Risk Reduction in March 2018 in Bristol, England; at the annual conference of the American Association of Geographers in April 2018 in New Orleans, USA; and at the International Conference of Agricultural Economists in August 2018 in Vancouver, Canada.

Furthermore, Chapter 4 on "Citizen Science for Near Real-Time Food Security Monitoring in Kenya" has benefited greatly from fruitful discussions with the project partners, i.e. Welthungerhilfe and Kenya's National Drought Management Authority. Also members of Kenya's Food Security Steering Committee provided valuable feedback during a workshop in Nairobi, Kenya in January 2018. I presented a first version of this chapter at the community meeting of the "Forewarn" Group of the START Alliance Network in London, England in September 2018.

Chapter 3 of this dissertation "Can One Improve Now-Casts of Crop Prices in Africa? Google can." was published in February 2019 as ZEF Discussion Paper No. 271. Furthermore, the knowledge acquired throughout my PhD studies contributed to the following publication at the intersection of food security and health:

Bhopal, A., Blanchard, K., Weber, R. and V. Murray (2019). "Disasters and food security: The impact on health", International Journal of Disaster Risk Reduction, Vol. 33, pp.1-4, https://doi.org/10.1016/j.ijdrr.2018.05.008.

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ACRONYMS

ALPS Alert for Price Spikes

ASAL Arid and Semi-Arid Lands

AR Auto-Regressive

CATI Computer-Assisted Telephone Interviews

DRR Disaster-Risk Reduction

ETH Ethiopia

EWS Early Warning System

EWSs Early Warning Systems

FAO Food and Agricultural Organization of the United Nations

FEWS NET Famine Early Warning System Network

FE Fixed Effects

F2F Face-To-Face

FSNAU Food Security and Nutrition Analysis Unit

FCS Food Consumption Score

FCG Food Consumption Group

FPMA Food Price Monitoring and Analysis

GIEWS Global Information Early Warning System

GSQ Google Search Query

IASC Inter-Agency Standing Committee

ICT Information and Communication Technology

IPC Integrated Food Security Phase Classification

ISS Information Support System

IVR Interactive Voice Response

KEN Kenya

MSE Mean Squared Error

MOZ Mozambique

MWI Malawi

MSF Médicins Sans Frontièrs

mVAM Mobile Vulnerability Analysis and Mapping

NASA National Aeronautics and Space Administration

NB2 Negative Binomial

NDMA National Drought Management Authority (Kenya)

NDVI Normalized Difference Vegetation Index

NGO Non-Governmental Organization

Q1 Question 1 of the SMS Data

Q2 Question 2 of the SMS Data

rCSI Reduced Coping Strategy Index

RQ Research Question

RWA Rwanda

TZA Tanzania

SBIC Schwarz-Bayesian Information Criterion

SDGs Sustainable Development Goals

SMS Short Messaging Service

UGA Uganda

UN United Nations

URL Uniform Resource Locator

US United States

USAID United States Agency for International Development

WFP World Food Programme

WHH Welthungerhilfe

ZMB Zambia

ZWE Zimbabwe

1

INTRODUCTION & MOTIVATION

The state of food security has reached an alarming point: After years of decline, the number of undernourished people has started to increase again since 2014. While an improvement in the food security situation can be observed in many parts of the world, other countries experience persistently high levels of hunger and, in some cases, a deterioration in their food security situation (FAO et al., 2018). Currently, 817 million people are estimated to be undernourished and as of March 2019, 85 million people across 46 countries are estimated to be in need of emergency food assistance over the course of 2019, while three food insecurity hotspots, i.e. South Sudan, Yemen and North-East Nigeria, are at risk of famine. Compared to 2015, this represents an increase by 40 million people in need of emergency food assistance (FEWS NET, 2019; FAO et al., 2018).[1] After years of decline, this shift to increasing levels of undernourishment and food emergency assistance needs has been, to some extent, driven by droughts, economic slowdown and high food prices (FAO et al., 2018). Furthermore, conflict, forced migration, poverty and other climate related disasters are anticipated to contribute to a worsening food security situation in the future. In particular, climate change is expected to exacerbate already existing risks to food security, due to its association with an increasing number of extreme-weather events. This gives reason to assume that the demand for humanitarian emergency responses will increase further, after already growing in complexity and intensity in recent years (WFP, 2018b).

The aforementioned developments come in contradiction with four major international treaties agreed upon by the United Nations (UN) in 2015/16: the Sustainable Development Goals (SDGs) for human development; the Sendai Framework for disaster-risk reduction; the UN Decade of Action on Nutrition for food security; the Paris Agreement on climate change. All treaties are set to reach their goals between 2025 and 2030. All four agreements share important synergies with respect to food security and acknowledge the complex relationship between climate change, disaster risk reduction and food security outcomes (Bhopal et al., 2019). In the context of food security, particularly Goal 2 of the SDGs highlights the commitment of the UN, as it targets to "end hunger, achieve food security and improved nutrition and promote sustainable agriculture" by 2030 (United Nations General Assembly, 2015). Given the current developments in the food security landscape, it seems unlikely for the international community to achieve zero hunger by 2030 (von Grebmer et al., 2018).

1 These estimates exclude countries for which no data is available, i.e. Venezuela and North Korea.

An important pillar in the context of food security, humanitarian emergencies and disaster-risk reduction are early-warning and situation-monitoring systems. These systems provide decision support and contribute to: identifying risks to food security at an early stage of development; monitoring developing situations and the at-risk population; forecasting crises and to triggering, informing and shaping early interventions and the emergency response. The need for early warning systems and situation monitoring is driven by high demand of information in crises scenarios, given that decision making in the event of emergencies requires, timely, detailed and reliable information with the ultimate goal to trigger immediate action and to contribute to saving lives and livelihoods at risk (Buchanan-Smith & Davies, 1995; Davies & Gurr, 1998). Particularly the Sendai Framework, and by endorsement the SDGs, highlight the importance of multi-hazard early warning systems (EWSs) and the need to increase their availability, accessibility and scope (UNISDR, 2015).

In recent years, advances in technology, information and communication technology (ICT) and increasing Internet adoption rates, also in developing countries, introduced a new variable to the early warning landscape: big data. Big data is associated with potentially faster, more frequent and spatially disaggregated data, while simultaneously allowing for the cost-effective inclusion of the local at-risk population itself into monitoring activities. These developments have promising synergies with monitoring systems, whose major input variable is data. Across many developing countries, the availability of timely, reliable, high-frequency, high-quality and spatially disaggregated data is still insufficient (Carrière-Swallow & Labbé, 2013; Morrow et al., 2016; Kalkuhl et al., 2016). Hence, big data has the potential to bridge and improve currently used data and to facilitate new data streams.

This dissertation is placed at the intersection of food security monitoring, early warning, big data and new data sources. Given the above discussed aspects, it is of interest to disentangle the information provision of current EWSs for food security risks and to analyze the potential of new sources for food security monitoring with the ultimate goal to improve food insecurity predictions. The remainder of this introductory chapter provides a more detailed discussion of the background and synergies between big data and food security monitoring. Subsequently, we discuss the research questions studied in this thesis and outline the organization of the main chapters.

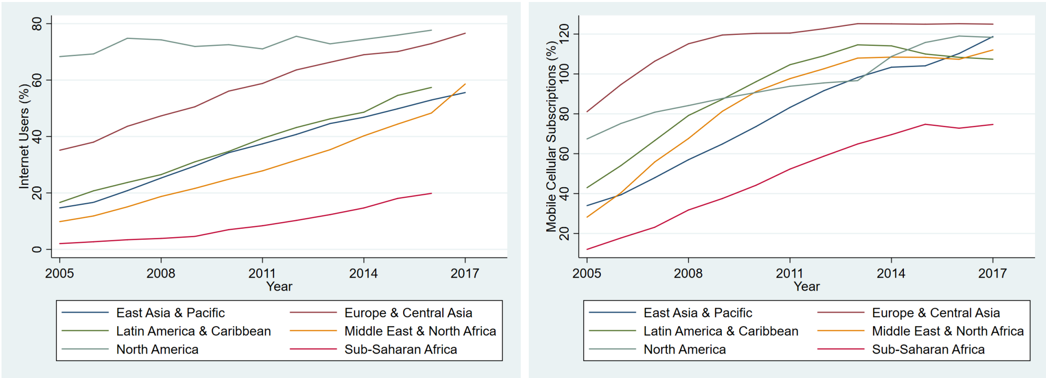
1.1 BIG DATA AND FOOD SECURITY MONITORING: BACKGROUND & SYNERGIES

The world creates 2.5 quintillion bytes of data every day. Approximately 90% percent of the world's data has been generated just within the last couple of years and data is being created at an ever accelerating pace today (Marr, 2018). The term *big data* has entered the debate around 2005, driven by advances in technology, ICTs and the Internet and the understanding that came with how much data is being produced in the process (Oracle, 2019). The original definition of big data was coined in 2001 and defined big data as "high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation" (Gartner, 2019). The so called "3Vs" of big data are derived from big data's main characteristics i.e. volume, velocity and variety. They refer to the vast amounts of data with which big data is associated; its time and frequency domain; and the diverse, unstructured and new types of data that have become available. Due to the many possibilities that arise with collecting and analyzing more comprehensive, timely and new data and due to its vast applicability, big data is associated with promising potential and has become the new normal since its origin in 2005 (Oracle, 2019).

Much of the data generating processes described above are driven by developed nations. A considerable digital divide, i.e. differences in usage of and access to ICTs and the Internet, is still present between and across countries. Still, developing countries are catching up as they are experiencing increasing numbers of Internet and (mobile) phone adoption rates (World Bank Group, 2016). Figure 1.1 illustrates both the digital divide and increasing trends in worldwide Internet use and mobile cellular subscriptions at the same time. Internet usage and mobile cellular subscriptions are the lowest in Sub-Saharan Africa. On average, in Sub-Saharan Africa 20% of the population uses Internet, which is less than half of the user rates observed in the Middle East and North-Africa, Latin America and East Asia (50%). Still, in North-America, Europe and Central Asia 80% of the population uses Internet. Regarding mobile cellular subscriptions, 75% of the population in Sub-Saharan Africa have a mobile cellular subscription. In all other regions more than 100% of the population are subscribed, indicating multiple subscriptions per person. Considering unique mobile phone subscribers, these figures are lower with 44% of the population in Sub-Saharan Africa, compared to the global average of 66% (GSMA, 2018). While Sub-Saharan Africa has the lowest Internet and mobile phone user rates, we still observe a drastic increase over the last decade and growth in user rates is expected to stay comparatively high. This indicates that an increasing amount of people in Sub-Saharan Africa is expected to get connected in the upcoming years (GSMA, 2018).

Due to increasing adoption rates of mobile cellular subscriptions and Internet user rates across Sub-Saharan Africa, more people located in more diverse regions are becoming reachable. Consequently, more online traffic and, as a by product, online metadata is being generated. This opens up cost-effective pathways to *inter*

Figure 1.1: Internet User Rates and Mobile Cellular Subscriptions, 2005-2017.



Note: Internet users refers to individuals that have used the Internet from any location and device in the last three months. Source: Own compilation based on data from The World Bank (2018).

alia directly connect to and communicate with the population, and to harness online signals, which have the potential to offer near real-time insights into processes within a society. These developments and inherent possibilities are contributing to new avenues in the realm of situation monitoring and early warning, as they directly relate to an important component of monitoring systems: data.

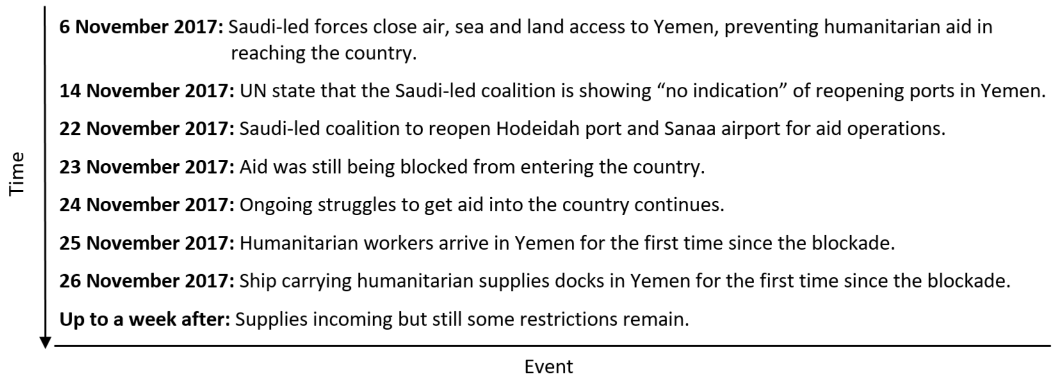
EWSs have high demands with respect to the time, frequency and spatial domain of data. These demands are driven by the time sensitive nature of decision making processes in crises scenarios. During humanitarian emergencies and when engaging in food insecurity anticipation and situation monitoring, timely and detailed information is required to inform and shape potential interventions and the emergency response, with the ultimate goal to save lives and livelihoods at risk (Buchanan-Smith & Davies, 1995; Davies & Gurr, 1998). Even after the identification of a potential deterioration in the food security situation, also the intervention itself needs to be funded, planned and deployed, which introduces further time delays (Barrett, 2010). The timely identification of risks to food security consequently plays an important part within this process.

However, food insecurity is oftentimes associated with drought, which is a slow-onset disaster. Information requirements may be perceived as less urgent compared to sudden-onset disasters, like tsunamis and earthquakes, where it is evident that fast information on the affected population is critical to safe lives and livelihoods. The food security situation is driven by a complex web of factors of underlying long term aspects and short term accelerators. While drought is one factor, also conflict, migration and other dynamic factors can contribute to a fast deterioration in the food security situation.[2] The following examples further underline the need of fast information requirements also in the case of food security monitoring. The most drastic illustration of information requirements in a food security context is starvation. A healthy adult dies within two months in a scenario of complete starvation (de Waal, 2018). While starvation as such is rarely documented, recent examples in the case of Yemen illustrate, how fully man-induced food crises can be

2 A detailed discussion of the drivers of food security can be found in Chapter 2 of this thesis.

triggered and unfold within a short time frame. Figure 1.2 shows the timeline of events, observed during the closure of the Hodeidah port in Yemen in November 2017. The intentional closure of the port caused sections of the Yemeni population to be cut off from crucial food aid. The chain of events from the closure of the port to its re-opening unfolded within just 20 days.

Figure 1.2: Chain of Events: Closure of Hodeidah Port, Yemen, Nov 2017.



Source: Own illustration, based on news reports retrieved from the Associated Press and Thomson Reuters Foundation News.

While these aspects underline the information characteristics required for situation monitoring and anticipation, particularly in developing nations, data-collection initiatives still face limitations: high frequency information is more difficult to obtain, and official statistics are published with a considerable time lag, at a lower frequency and quality (Carrière-Swallow & Labbé, 2013; Kalkuhl et al., 2016; Morrow et al., 2016). These considerations highlight the considerable synergies between big data and situation monitoring and early warning, due to similarities in information demand on one hand and information characteristics on the other. Hence, advances in technology hold promising potential to improve data characteristics in developing countries. Furthermore, increasing usage of ICTs and the Internet enable cost-effective possibilities for bottom-up data collection and for the extraction of signals from the at-risk population itself, ultimately, equipping the population with a direct communication channel to EWSs. Thus, this development enables citizen-science approaches, i.e. approaches in which the population take on an active role in monitoring systems, and contributes to the democratization of information and science. Big data does not only have the potential to bridge and improve data gaps, but it enables the generation of new and different data sources.

1.2 RESEARCH QUESTIONS

This dissertation investigates monitoring systems for food security risks from two different perspectives: information content and contribution. While information content is the focus of the first chapter of this thesis, the subsequent two chapters explore the contribution potential to monitoring systems.

The fist main chapter engages an analysis of the information content and gaps of current monitoring systems for food security risks. While many EWS for food security monitoring exist, there is little empirical and current knowledge on how the different systems compare to each other and what information is being provided. Thus, to understand the information content of current EWS and to identify potential pathways for improvement, we propose to address this research gap by answering the following research question in Chapter 2:

RQ1 What information is being provided by early warning systems and how do early warning systems for risk to food security compare to each other and to the conceptual benchmark?

The contribution of this thesis focuses on exploring ways to improve early warning systems by using two strings of new data, i.e. the Internet and direct assessments from the at-risk population gathered via mobile phones. The objective is to understand how digital signals and signals from the local population can be harnessed and integrated into food security monitoring systems and can ultimately contribute to forecasting the food security situation. The Internet as data source has gained in popularity over the last decade. So far, however, few examples have explored the Internet as a data source in a developing-country context and more specifically, the link between Internet data, early warning systems and food security. To understand how data derived from the Internet could contribute to food security monitoring, we extract a string of Internet metadata and ask the following research question in Chapter 3:

RQ2 Can an indicator based on Google Search Queries improve now-casts of crop prices in selected African countries?

Furthermore, the affected population itself has not been systematically integrated into monitoring systems. With increasing mobile phone adoption rates across developing countries, direct communication channels to the affected population become available. Limited research has explored the possibility of using a citizen-science approach to gather direct, near real-time food security assessments and, hence, to attempt to include the local population into monitoring efforts. Thus, we propose the following research question for Chapter 4:

RQ3 Can the at-risk population provide rapid and valid assessments of their communities' food security status?

1.3 ORGANIZATION OF THE THESIS

The remainder of this thesis is organized into four chapters to address the outlined research questions. In Chapter 2, we start with a detailed discussion of food security definitions and develop a theoretical framework of a people-centered early warning system for food security risks. Furthermore, we provide an overview over the four largest EWSs for food security risks and evaluate their performance against the theoretical benchmark to understand what information is being provided, at which frequency and spatial unit and to identify potential information gaps.

Subsequently, this dissertation explores two new sources of data, one harnessed from the Internet, the other one via mobile phones and their potential for food security monitoring and early warning in developing countries. More precisely, in Chapter 3 we analyze how Google search query data can contribute to nowcasting crop prices in nine African countries. In this context, we further discuss the characteristics and challenges of Internet data in a developing country context, where low Internet-adoption rates prevail. Chapter 4 explores how information from the population itself can be of use for situation monitoring and early warning. We outline how we implemented an SMS system, which we use to collect near real-time food security information from the at-risk population itself in four Kenyan counties. Chapter 5 summarizes the main findings of this thesis, its implications as well as suggestions for future research.

2

ASSESSING MONITORING AND EARLY WARNING SYSTEMS FOR FOOD SECURITY RISKS

2.1 INTRODUCTION

As of March 2019, approximately 85 million people across 46 countries are estimated to be in need of emergency assistance throughout 2019, while several countries, i.e. Yemen, South-Sudan and North-East Nigeria are at risk of famine (FEWS NET, 2019). Furthermore, since 2014 the number of undernourished people has started to increase after years of decline and is currently estimated to rank at 817 million people (FAO et al., 2018). In addition to these recent developments, the last decade witnessed a global food price crisis in 2007/08 (Kalkuhl et al., 2016) and a famine in Somalia in 2011 (Hillbruner & Moloney, 2012). Prolonged drought is one factor, which continues to contribute to increasing levels of undernourishment. Drought affects[1] by far the largest number of people and ranks as the third deadliest natural hazard across Africa (see Table 2.1). Still, food insecurity is driven by a complex set of underlying long term factors, like poverty, and short-term accelerators, such as conflict and forced migration.

Table 2.1: Natural Hazard Types, their Contribution to Affected People and Deaths in Africa, 2000-2017.

Hazard Type	Percentage of Affected People	Percentage of Deaths
Drought	77.5	18.4
Riverine Flood	13.5	8.5
Bacterial Disease	0.6	38.2
Viral Disease	0.4	22.2

Source: Center for Research on Epidemiology of Disasters, http : //emdat.be/emdat$_d$b/, accessed May, 2017.

In a crisis scenario, timely, detailed and reliable information plays an essential role in decision making. Immediate action is crucial to save lives and livelihoods at risk (Buchanan-Smith & Davies, 1995; Davies & Gurr, 1998). The need for better information on food security risks, however, has long been recognized by the global community: already the Sahel crisis in the 1970s triggered the develop-

1 Affected people refers to "people requiring immediate assistance during a period of emergency, i.e. requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance" (CRED, 2017).

ment of a variety of famine early warning systems, with the objective of better information provision (Wisner et al., 2004). Current developments come, hence, against the background of more than 40 years of investment in the development and improvement of early warning systems (EWSs) for food crises, including early action initiatives and humanitarian response mechanisms. Monitoring systems for food security risks have been associated with a range of limitations regarding *inter alia* their scope (Devereux, 2001), disconnection from the response capacity (Buchanan-Smith & Davies, 1995) and, partially, insufficient performance (Ververs, 2012). In developing countries also data itself, as the main input of EWSs, have constraints: High frequency information is difficult to obtain, official statistics are published with a considerable time lag, and lack the necessary spatial detail for precise monitoring and early warning (Carrière-Swallow & Labbé, 2013; Dubey & Gennari, 2015).

Due to these challenges, increasing adoption rates of information and communication technologies (ICTs) and the internet hold promising prospects particularly for developing countries and early warning initiatives, as they have paved the way for the integration of innovative data sources into food security monitoring (Morrow et al., 2016). Big data, *inter alia*, holds the potential of being available in near real-time and of providing bottom-up information, i.e. information from the at-risk population itself or people on the ground, which would be a step in the direction of a participatory approach and the democratization of information. So far, few analyzes have explored, how big data could contribute to systematically integrate citizen-science approaches within monitoring systems. This is due to the fact that a large share of the literature that analyzes EWSs was published around the year 2000, and hence before the mainstream adoption of ICTs and the Internet, see Buchanan-Smith & Davies (1995); Kelly (2003); Twigg (2003).

The objective of this analysis is threefold: we add to the literature by developing a conceptual framework of an efficient monitoring system for food security risk, by providing a comprehensive overview of early warning and monitoring systems for food security risk that analyzes a holistic set of system components, and by comparing the existing systems to each other and the conceptual benchmark. We base our analysis on four major international monitoring and early warning systems for food security risks: the Integrated Food Security Phase Classification (IPC), the Famine Early Warning System Network (FEWS NET), Vulnerability Analysis and Mapping (VAM), the Global Information and Early Warning System (GIEWS). These four systems were chosen due to their large geographical coverage and because they publish their own analyses and early warning information. All monitoring systems engage to varying degrees in information pooling, which enables the maximum dissemination of available information. Systems that are largely based on the collection and dissemination of existing reports are not considered in this study.

This chapter is structured as follows: In section 2, we engage in a literature review that enables us to identify long-standing problems associated with EWSs for food security risk. In section 3, we develop a conceptual framework for an efficient early warning system for food security risk, by combining the official United Nations framework for EWS for disaster risk reduction with drivers of food insecurity. In section 4, we provide an overview of monitoring and early warning systems, indicators and monitoring characteristics. In section 5, we compare the systems to each other with respect to their information content and monitoring characteristics. In section 6, we discuss our findings in relation to the previously developed conceptual framework of an efficient early warning system. We summarize our findings and give an outlook for future research in section.

2.2 LITERATURE REVIEW

The history of monitoring and early warning systems for food security risks, particularly for famines and droughts, is longstanding. Already in the 19th century, for example, a three-phased famine code was developed for India, which was used to classify the severity of the situation and provided instructions for relief workers (Brennan, 1984). The famines in the Sahel regions throughout the 1970s caused the international community to recognize the need for better information, food security monitoring and EWSs. This led to the development of a variety of famine EWSs (Wisner et al., 2004) and subsequently to the analysis of their assessment quality and limitations (Brown, 2008; Hillbruner & Moloney, 2012). The literature that analyzes monitoring systems for food security risks shows multiple long-standing problems. These are (1) a focus on the availability component of food security and a lack of information on accessibility of food, (2) a lack of spatial disaggregation, timeliness and comprehensive geographical coverage of indicators, (3) a lack of participation of the affected population itself, both as information source and recipient of early warning information and (4) a disconnection between early warning information and response capacity.

Most EWSs for food crises focus on production forecasts and the monitoring of droughts, hence, on the availability component of food security. Wisner et al. (2004) and Devereux (2001) criticize famine early warning systems for being supply side focused and, hence, for not covering the access and utilization criterion of food security. Also data availability and quality plays an essential role for the functioning of monitoring systems (Brown, 2008). The information and indicators that are being published, as well as the underlying data which are being collected, are associated with multiple problems regarding their spatial unit, frequency and comprehensiveness. Usually, indicators are at a national level, thus lacking spatial disaggregation and localized information. Buchanan-Smith & Davies (1995) argue that multi-level and localized indicators are necessary to detect risks to food security at the early stages of development, to issue a timely response, and to monitor how food insecurity processes develop within different parts of a society. High frequency information, however, is still missing in many developing countries, official statistics are published with a considerable time lag, and lack the necessary spatial detail for precise monitoring and early warning (Carrière-Swallow & Labbé, 2013; Dubey & Gennari, 2015). Further, official statistics are generally associated with a lack transparency and credibility (Cavallo, 2013) and data collection is at risk of breaking down in periods of emergency and crisis (Bauer et al., 2015). In addition to a lack of localized information, an up-to-date and comprehensive global picture of the food security situation is still unavailable, due to the incomplete geographical coverage of data on food security (FSIN, 2017).

Furthermore, the literature discusses the role of affected local communities in EWSs, regarding their representation as a bottom-up information source (Buchanan-Smith & Davies, 1995; Twigg, 2003; Kelly, 2003; Basher, 2006). Affected local communities are rarely included as an information source for risks, risk perception and coping strategies. EWSs are typically expert-led, top-down monitoring systems (Twigg, 2003). We hypothesize that this is, to some extent, a consequence of the aforementioned lack of data availability on the demand side and the challenges associated with data (collection) in developing countries. There are, however, strong arguments in favor of the inclusion of bottom-up information: Perceptions of risks differ across communities, individuals and experts. For example, the risk of not being in control over assets in evacuation scenarios may be regarded as higher than the immediate risk of a hazard (Twigg, 2003). Hence, individuals at-risk hold valuable information that could improve the functioning of EWSs. There is a lack of understanding of what affected communities actually need and expect of early warning systems (Buchanan-Smith & Davies, 1995; Twigg, 2003). This lack of inclusion further causes a lack of sense of ownership by users as well as a lack of feedback from communities on EWS (Basher, 2006). These shortcomings, i.e. the focus on the supply side, limitations in data quality and frequency and lack of participation of communities, have consequences for the outcomes of monitoring systems: Even though EWSs might issue alarms for an impending, naturally invoked threat or shortages in food availability, EWSs are not able to pinpoint which part of a population will be at risk of having limited access to food, due to their geographic location and their position within a society.

The typical recipients of early warning information are actors and decision makers. The creation of an effective EWS, however, requires timely, non-technical and understandable warnings that can also be communicated to communities at risk, most of which are not usually included in communication strategies (Twigg, 2003). Basher (2006) identifies communication as one of the typical points for failure of EWSs. Kelly (2003) further argues that effective early warning comprises more than mere warning; it ideally offers potential strategies to communities on how to cope with the situation itself, e.g. providing information on feeding centers and employment options.

Throughout the 90s, a line of thinking emerged that more precise and better information is crucial for the prevention and tackling of famines (Buchanan-Smith & Davies, 1995). Many resources have been invested in the development of EWSs, with the goal to making famines predictable. This progress in EWSs, however, has not been equally followed by improvements in humanitarian response (Devereux, 2001; Bailey, 2012). Buchanan-Smith & Davies (1995) extensively discuss the missing connection between early warning information and humanitarian response and conclude that the response side is in need of improvement. Also Basher (2006) identifies the response capacity as one typical point of failure of EWSs and Barrett (2010) discusses delays in the emergence response. This highlights the importance of systematically communicating early warning outcomes and having strong ties to the response capacity.

Different case studies already addressed one problematic component in the design of EWSs: their performance. Hillbruner & Moloney (2012) as well as Ververs (2012) analyze the actual capacity of various systems to issue warnings in the context of the Somalian famine of 2011 – with mixed results. Both studies construct an ex-post timeline of events and warnings. Hillbruner & Moloney (2012) find that during the 2011 famine in Somalia, both FEWS NET and the Food Security and Nutrition Analysis Unit for Somalia (FSNAU) issued timely and accurate warnings to decision makers. They identify a late emergency response as a key driver to a deteriorating situation. Also Ververs (2012) finds that FEWS NET and FSNAU issued timely warning during the 2011/12 food crisis in East Africa; three other analyzed EWSs, however, failed to do so, because their reporting frequency is not sufficiently high enough for forecasts to be on time (IPC), or no warnings were provided (GIEWS, Inter-Agency Standing Committee and WFP). Both studies focus, however, on a singular event and do not provide a comprehensive analysis of system components, indicators and outputs.

One factor that has not been discussed so far is the development and adoption of ICTs and the opportunities that this development holds to overcome the above discussed data limitations and to engage in the (near) real-time monitoring of the food security situation. The potential of big data and increasing adoption rates of mobile phones (including smartphones) for food security monitoring, particularly in developing countries, as means to reach hard-to-access areas and to gather bottom-up information, has entered the discussion over the last years (Bauer et al., 2015; Morrow et al., 2016; Meier, 2015). There is, however, a lack of literature that analyzes EWSs in light of technological innovations and that assesses the progress of EWSs in adopting innovative data sources for their monitoring purposes.

This review shows that the largest share of literature that systematically deals with early warning information has been published in the 90s and 2000s and, hence, does not provide an updated assessment of EWSs, also with respect to recent technical developments; while the more current studies focus only on one component in the design of EWSs, i.e. the performance. This review shows that there are multiple issues associated with the different elements of monitoring systems. Most analyses, however, focus on one aspect of EWSs or on the performance of EWSs, in consequence they conclude with hypotheses about the shortcomings in the design of EWSs. This indicates that a holistic approach and perspective is required to assess the complete early warning cycle, from data collection and analyses, to the communication of information to decision makers and communities, to the provision of coping strategies and the coordination of the response capacity.

The objective of this study is threefold: We add to the literature by (1) developing a conceptual framework of an efficient monitoring system for food security risks with the aim to analyze EWSs based on a holistic set of design components, by (2) systematically comparing different monitoring systems against it each other and to the conceptual benchmark and by (3) particularly focusing on the adoption of new technologies and innovative data sources for food security monitoring.

2.3 THEORETICAL CONCEPTIONS

We combine different theoretical frameworks to develop a model of an efficient EWS for food security risks. Below we discuss the concept of food security risk as a function of hazard and vulnerability. This allows us to disaggregate food security risk into its natural, economic and political drivers. Subsequently, we integrate these factors into a comprehensive theoretical framework of an efficient EWS.

2.3.1 *Food Security Risks*

Monitoring the food security situation requires definition of food security as baseline. The Food and Agricultural Organization of the United Nations (FAO) provides a normative definition of food security. "Food security exists when all people at all times have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life. This entails to secure the availability, access, utilization and stability of food. The nutritional dimension is integral to the concept of food security" (FAO, 2009). The opposite of food security is food insecurity, with famine and starvation being the most severe and extreme form of food insecurity. Famine is extensive spread of extreme hunger, which is associated with a stark loss of body weight and growing levels of morbidity and death rates (von Braun et al., 1998; IPC Global Partners, 2012)

The monitoring and forecasting of food security, however, requires quantitative definitions and thresholds for terms such as food security, food crisis or famine. To that end, IPC was introduced in 2006 to provide an internationally accepted, quantitative classification of the different phases of food insecurity (IPC Global Partners, 2012). IPC differentiates between five different stages, i.e. from minimal food insecurity, to stressed, crisis, emergency and famine. Within this classification, food crisis (phase 3) requires urgent action. It is defined as a situation in which food consumption and livelihood indicators show at least 20% of households in the area being affected by the crisis; acute malnutrition rates lie between 10% to 15%, or are higher than usual and increasing; 10% to 20% of people have a body mass index below 18.5; the crude death rate lies between 0.5 – 1 / 10,000 people per day, and the children under five death rate lies between 1-2 / 10,000 people per day (IPC Global Partners, 2012).[2]

Monitoring and early warning systems for food security risk are, at their core, a form of disaster risk assessment. Therefore we base our theoretical framework on the discipline of disaster risk reduction. A disaster is the actual materialization of a complex interplay between natural hazards and human action, which can materialize also in the absence of a natural hazard. It causes significant and exceptional damage to vulnerable people, their families, settlements and livelihoods, and disrupts human and economic development at the household and the national level. Disasters can be a set of reoccurring, reinforcing shocks (Wisner et al., 2004;

2 This refers to IPC's area classification; IPC further provides a household group classification (see IPC Global Partners, 2012, p. 32-33).

Smith & Petley, 2009). We use Wisner et al. (2004) definition of risk and apply it to food security:

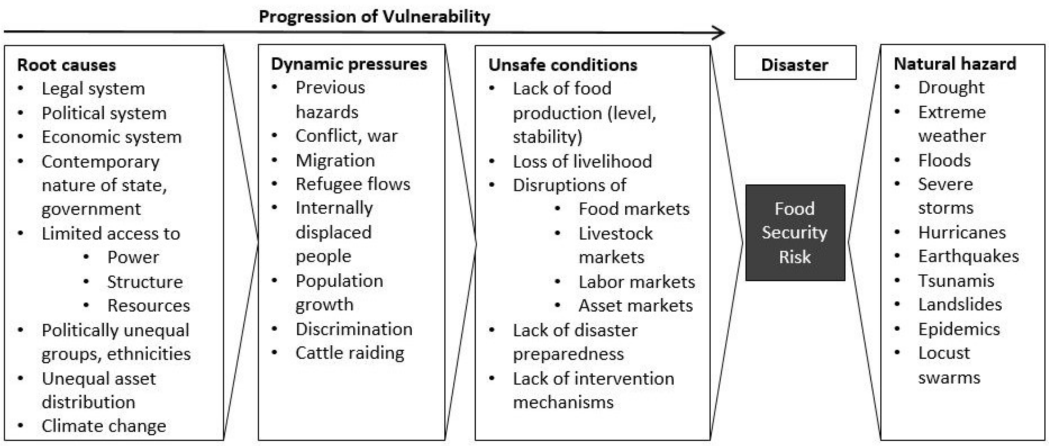
$$FoodSecurityRisk = f(Hazard, Vulnerabilty)$$

where the hazard can be a natural hazard and/or human-induced. Hazardous events can generally be organized in three sub-categories: hydro-meteorological hazards (e.g. floods, severe storms and hurricanes), droughts and extreme weather, geological hazards (e.g. earthquakes), and biological hazards (e.g. epidemics) (UNISDR, 2006; Smith & Petley, 2009). Compared to sudden impact, natural hazards, such as floods and earthquakes, drought is categorized as a slow-onset hazard, which may take weeks or months to materialize (Wisner et al., 2004; Smith & Petley, 2009).

Vulnerability describes the circumstances and characteristics of people, groups of people, societies and their livelihoods and assets that influence their likelihood to suffer harm and damage from the impact of single or multiple hazards. Vulnerability varies in magnitude across nations, within a society and individuals (Wisner et al., 2004; UNISDR, 2009; Birkmann et al., 2013). According to Birkmann et al. (2013), vulnerability is comprised of four elements: "(1) exposure to a hazard or stressor, (2) susceptibility (or fragility), (3) societal response capacities or lack of resilience, and (4) adaptive capacities". Exposure refers to the degree to which elements are located within the scope of a hazardous event, while susceptibility is the likelihood of exposed elements to suffer harm. The discipline of disaster risk reduction generally agrees that resilience, or the lack of it, is a component of vulnerability. Resilience is a measure of the desirable capacity of people, groups of people and societies to anticipate, absorb, cope with and recover from the impact of a hazardous event (von Braun & Thorat, 2014; Smith & Petley, 2009; Wisner et al., 2004). This capacity is dependent on exclusion, access to resources to deal with a hazardous event, before, during and after its materialization (von Braun & Thorat, 2014; Birkmann et al., 2013). The larger the degree of resilience, the less vulnerable are people and societies. Even though disaster is the materialization of hazardous and vulnerable conditions in a single momentum, disaster risk should not be regarded as static, as both vulnerability and hazard phenomena are dynamic and change over time. Societies face a continuous exposure to changing environmental conditions, and vulnerability can only be reduced if societies adapt accordingly by reducing their exposure and susceptibility, and also by improving their resilience (Wisner et al., 2004; Birkmann et al., 2013).

Risk knowledge is an essential element of EWSs (UNISDR, 2006). To identify factors contributing to food security risk knowledge, we combine the Pressure and Release (PAR) model by Wisner et al. (2004), with a framework that considers the determinants of famine and underlying drivers, as developed by von Braun et al. (1998) (see Figure 2.1). As discussed above, risk is a function of hazard and vulnerability and the PAR model disassembles risk accordingly. The right section of 2.1 is a list of natural hazards, such as drought, extreme weather and locust swarms. On the left side, vulnerability is depicted as a progression of events that can be separated into root causes, dynamic pressures and unsafe conditions. Hence, the PAR model enables us to show that vulnerability is driven by both system intrinsic factors and short term accelerators, which define the general situation of a society to cope with hazardous events. As shown in Figure 2.1, root causes *inter alia* refer to the contemporary nature of state, the political and economic system and the degree of inequality within a country. Dynamic pressures are, e.g. previous hazards, conflict and discrimination. Unsafe conditions are i.e. a lack of production, disruption of markets and lack of intervention mechanisms. These factors potentially drive the materialization of a disaster, which in the context of food security risk is a food crisis and, ultimately, famine. This framework contributes to the understanding that food security is driven by processes that are distant to the disaster event itself, depicted as root causes, and that a decrease in vulnerability would require root causes needing to be addressed.

Figure 2.1: Food Security Risk.



Source: Own development, based on Wisner et al. (2004) and von Braun et al. (1998).

Famine is unique in the fact that it can occur without a natural hazard event. Food crises are often associated with hazardous events, like droughts, epidemics or floods, but they are driven by a complex web of factors that goes beyond natural hazards. For example, limiting the access to food can be a strategic and intentional war weapon and could also be used as a measure of "ethnical cleansing". As mentioned in the introduction of this thesis, access to food could be limited if people are trapped within the frontiers of an ongoing civil war, or while fleeing a conflict (Wisner et al., 2004; de Waal, 2018). The literature shows that the majority of food crises in Africa have been driven by complex emergencies[3] , where multiple factors materialize in parallel, like war, rainfall deficiency and poverty (Wisner et al., 2004; Devereux, 2001; von Braun et al., 1998) and, only recently in 2007/08, through disruptions on international agricultural commodity markets (Kalkuhl et al., 2016). This demonstrates that there is an essential need for EWS to monitor a comprehensive set of risk factors.

3 "Complex emergencies are situations of disrupted livelihoods and threats to life produced by warfare, civil disturbance and large-scale movements of people, in which any emergency response has to be conducted in a difficult political and security environment" (WHO, 2002), p. 4.

2.3.2 *A Conceptual Framework for an Efficient Early Warning System for Food Security Risks*

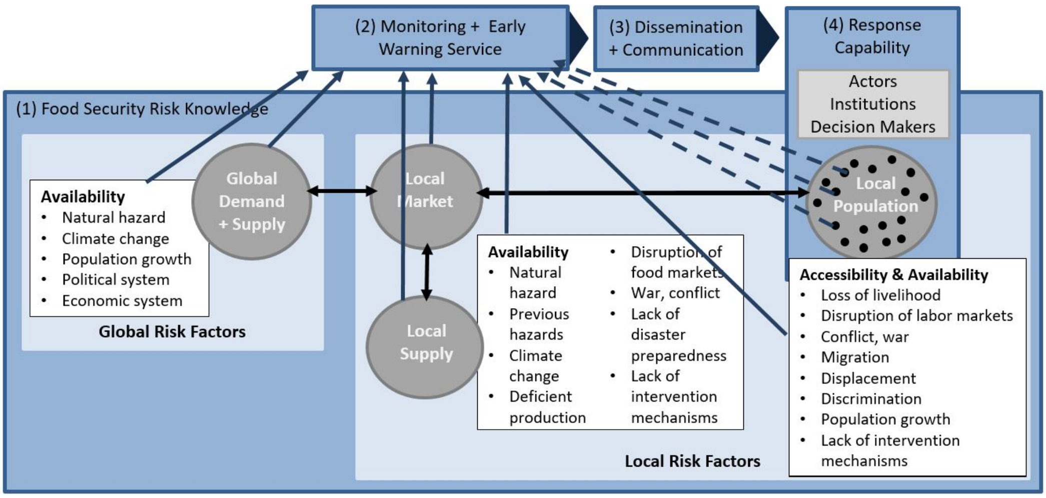
The purpose of EWSs for food security risks is to inform about emerging food scarcities and to prevent a potential food crisis. An efficient system manages to gather information across a variety of drivers that are linked to people's vulnerability and to natural hazards, to use this information in meaningful models, to translate this information into warnings and to communicate its analysis to individuals at risk and responsible institutions (Basher, 2006; Brown, 2008; Twigg, 2003). According to the UN, EWSs aim to: "empower individuals and communities threatened by hazards to act in sufficient time and in an appropriate manner so as to reduce the possibility of personal injury, loss of life, damage to property and the environment and loss of livelihood" (UNISDR, 2006). Figure 2.2 shows the adapted UN framework for early warning systems, which we modified to the case of food security risk. It stands on four pillars: (1) risk knowledge, (2) monitoring and warning, (3) dissemination and communication and (4) response capability (UNISDR, 2006; Basher, 2006).

The first pillar, risk knowledge, deals with the systematic conceptualization of drivers of food security risk, which can be separated into global and local risk factors. Local risk comprises socio-economic, political and institutional factors, such as the state of the agricultural production at a given area and time, governance capacity or existence and management of emergency stocks. In parallel, global risk factors have to be identified, due to the ever increasing integration of agricultural markets. Events on international markets can have strong (adverse) effects on the food security situation. For example, extreme price surges on international commodity markets during the 2007/08 food crisis had strong negative impacts in many developing countries (Kalkuhl et al., 2016).

Risk factors can be associated with the availability and accessibility pillars of food security. The factors discussed so far relate to the supply side and hence affect the availability of food. Also the demand side, i.e. the population itself, is associated with risk factors regarding the accessibility of food. Here, disruptions in labor markets and loss of livelihood can determine capacities of individuals to buy food. Also political aspects, like conflict, displacement and the position of individuals within a society, e.g. discrimination against gender and ethnicity, or the extreme case of starvation as measure of "ethnical cleansing" impact accessibility of food (Wisner et al., 2004). The second pillar, the monitoring system, collects and processes data on a comprehensive set of risk factors and their proxies, e.g. weather, market prices and livelihood coping strategy indices (see solid arrows in Figure 2.2. Usually, EWS engage in top-down monitoring of secondary data. The risk factors and there weighting should vary across regions, as, e.g., migratory pressures are of varying importance across countries. The monitoring entity needs to define transparent thresholds for different crisis scenarios, and use this to decide on how, when and with which frequency potential warnings and updated information should be issued and disseminated.

The first and second pillars are connected by an information flow (see arrows in Figure 2.2). As a complex web of factors drives food security risks, their monitoring requires information with specific characteristics. We argue that fast and spatially disaggregated information is an essential input into EWSs. Drought, which is one driver of food security risk, is typically a slow-onset disaster, which has become rather predictable, due to the wide availability of remotely sensed weather data and vegetation monitoring. The majority of food crises in Africa, however, have been caused by complex emergencies (von Braun et al., 1998). War, civil unrest and riots can involve and trigger a chain of events. The monitoring of volatile situations and rapidly changing environments requires timely, near real-time and geographically detailed information on the events, emerging pressures and the population at-risk. This is a prerequisite for the identification of food insecurity (also localized events of food insecurity) at an early stage of development.

Figure 2.2: Elements of an Early Warning System for Food Security Risks.



Note: Solid arrows: information flow; dashed arrows: bottom-up information flow.
Source: Own development, based on UNISDR (2006) and Basher (2006).

Our framework explicitly includes the local population as bottom-up information source (dashed arrows). With increasing ICT adoption rates being experienced in developing countries (World Bank Group, 2016), the possibilities of including the population at-risk as an information source is becoming more available. Bottom-up information, i.e. information provided directly from the population itself or representatives of the population, has been gaining importance in the realm of food security monitoring. Bottom-up information is of particular interest for food security monitoring due to a variety of reasons: (1) an effective EWS gathers information on a range of risk factors, this explicitly includes information on the vulnerability associated with the population at-risk. Information on accessibility of food and sensitive topics, like discrimination within societies, is usually not easily obtained on a continuous basis. (2) Official statistics lack transparency and food security is still a politically sensitive topic. (3) In emergency scenarios, official data collection initiatives tend to break down, leading to a lack of information about the situation at hand. This was, e.g., the case during the 2014 Ebola outbreak in West Africa, see Bauer et al. (2015). Including the population has the potential to overcome the limitations mentioned above, as well as it enables people to communicate directly about current developments and their environment. Bottom-up information is possibly available in a timely fashion, at a faster pace than traditional surveys and at a high spatial resolution. Furthermore, institutional decision making requires information to be convincing and reliable. We hypothesize that bottom-up information has the potential to put actors under pressure and, hence, to potentially trigger an earlier response and, hence, to impede the development of a full-scale food crisis.

The third pillar, dissemination and communication, distributes early warning information to actors, decision makers and the population at-risk. In people-centered EWSs, the at-risk population plays an essential role in receiving early warning information. Availability, accessibility and understandability of information are essential for fast decision making. Therefore, information dissemination strategies and access to the most up-to-date information are important aspects when assessing EWSs. The recipients of information, however, are diverse and have, presumably, different information needs, regarding the content and the timing of messages as well as the communication channels that are being used. For example, while humanitarian actors require detailed information on the cause, the location, the number of affected people and the severity of a crisis to coordinate their intervention efforts, the population at-risk needs to be informed when and how they will be affected and how to cope with the situation at hand. This also holds for the timing of information: Humanitarian actors and affected people need the information as soon as possible, and the information on affected people and coping strategies would need to be continuously adapted to a changing environment. This variety of recipients also requires different communication channels. While humanitarian actors and decision makers are literate and are likely to have access to the internet and other information channels, this is not necessarily the case for people at-risk. This shows that each recipient of early warning information has specific communication and information needs, which would, in an efficient early warning system, be incorporated into an effective and well-developed communication strategy.

The fourth pillar reflects the response capability, comprising the population at-risk, actors, institutions and decision makers. The provided information enables responders to manage the situation at hand, take action and to reduce risks for the affected people in the beginning of a crisis, throughout the event, and in its aftermath. People-centered EWSs explicitly consider the population at-risk as a part of the response capability. This enables individuals to undertake timely and appropriate responses, as well as to pursue coping strategies to minimize their exposure to risk, thus increasing their resilience. This could be facilitated by, as stated previously, explicitly by communicating up-to-date information about the event itself as well as potential coping strategies, for example, where to find support structures. This is particularly important due to the weak link between EWSs and the response capacity. As mentioned, there is a lack of knowledge on whether early warning information is able to trigger a response (Hillbruner & Moloney, 2012;

Ververs, 2012), and, if a response is triggered, how fast this response takes place after the original receipt of the warning.

2.4 EMPIRICAL STRATEGY AND DATA

Based on the theoretical framework for an efficient EWS for food security risks developed above, we evaluate the selected EWSs and their reports according to the four elements of a people-centered EWS. These are:

1. Risk Knowledge
    - Global and local food security risk factors that are being monitored
2. Monitoring Service
    - Classification of information
    - Spatial unit of analysis
    - Number of countries covered
    - Top-down, bottom-up information
    - Ex-post, real-time analysis or forecasting
    - Frequency of analyses
3. Dissemination and Communication
    - How and what kind of information is communicated
    - Who are the main recipients
4. Response Capacity
    - Direct link to the response capacity (humanitarian actors, decision makers, population at-risk).

Based on those aspects, we first provide an overview over the four EWSs and their features. We continue with a systematic comparison of EWSs according to risk knowledge, monitoring service, dissemination and communication as well as the link to the response capacity. Our theoretical framework shows the importance of information and its characteristics within early warning processes, as well as the importance of reliable information for decision making in emergency situations. Therefore, we subsequently analyze the reporting frequency, reliability and spatial coverage of reports. Based on the comparison in step 1, we select in a second step the report of each EWS that covers the most comprehensive set of risk factors to assess the availability of information for two time horizons, a long term period of eight months and a short term period of one month. The objective is to understand what information is *de facto* being provided and updated in a timely manner and to identify the countries, for which no information is available. We base our analysis on four major and international monitoring and early warning systems for food security risks: IPC, FEWS NET, VAM, and GIEWS. These four systems were chosen due to their large geographical coverage and because they publish their own data,

Table 2.2: Overview over analyzed EWS and Reports.

EWS	Report/Tool	Source
IPC	Acute Food Insecurity Situation Overview	http://www.ipcinfo.org/
FEWS NET	Integrated Food Security Analysis Price Bulletin Global Price Watch Food Assistance Outlook Brief Global Weather Hazards	http://www.fews.net/
VAM	Agro-Climatic Monitoring Market Watch Market Monitor Mobile VAM	http://vam.wfp.org/
GIEWS	Country Briefs Food Price Monitoring and Analysis Earth Observation Crop Prospects and Food Situation Food Outlook	http://www.fao.org/giews

Source: Own compilation.

analyses and early warning information. We focus our analysis on reports that are updated on a continuous basis with the aim to provide information on the current situation. Hence, baseline studies are excluded from the analysis. Table 2.2 provides an overview over the reports that are included in the analysis. The number of reports varies across EWSs, according to availability. The analysis covers a total of 15 reports.

2.5 MONITORING SYSTEMS FOR FOOD SECURITY RISKS

In the following, we provide an overview over the different monitoring systems according to the four elements of early warning.

2.5.1 *Integrated Phase Classification*

IPC provides an internationally accepted categorization of acute and chronic food insecurity. It was developed by the Food Security and Nutrition Analyst Unit (FSNAU), motivated by the lack of consistent and comparable food crises definitions. It was first employed during Somalia's food crisis in 2004. In 2011, IPC was used as a reference to declare a famine in Somalia, which was the first internationally accepted famine declaration in 20 years (FAO, 2017b). The first official IPC manual was published in 2006 by FSNAU and FAO and has since been revised in 2008 and 2012. It is managed by a global steering committee whose members comprise CARE international, FEWS NET, FAO, the Food Security Cluster, the Joint Research Centre of the European Commission, Oxfam, Save the Children and WFP (IPC, 2016). IPC pursues four main objectives: (1) to build technical consensus in food security analyses, (2) to classify the severity and causes of food insecurity, (3) to communicate for action and (4) to assure the quality of food insecurity analyses. IPC supplies a detailed classification, a range of standardized protocols for food security assessments, technical infrastructure for food security analysis to governments and training to food security analysts (IPC Global Partners, 2012).

IPC's core output is its "Acute Food Insecurity Situation Overview". IPC reports provide an estimate of the number of people according to their phase classification, key outcomes for worst affected areas (food consumption, livelihood change, nutrition and mortality rates), a summary of causes, contexts and key issues, a regionally disaggregated map that shows regions in the color of their phase classification and a display of analysis partners. This overview is then followed by a more detailed description of key findings and issues, methods and processes, a seasonal calendar and recommendations and a population table that shows in detail the classification of regions and people (IPC Global Partners, 2012). At the core of IPC are its food insecurity classifications, providing standardized and internationally accepted classifications for acute and chronic food insecurity. As this analysis focuses on emerging and acute crisis situations, we limit the discussion to the classification of acute food insecurity. As briefly outlined above, IPC defines five phases of food insecurity: (1) minimal, (2) stressed, (3) crisis, (4) emergency and (5) famine. The phase classification is defined in detail in IPC's Acute Food Insecurity Reference Table and draws upon quantitative thresholds for food consumption and livelihood change, nutritional status and mortality rates. IPC provides both a situation assessment as well as a forecast on future developments for early warning and decision making (IPC Global Partners, 2012). IPC simplifies quite complex information and analysis (myriad of indicators, methodologies, statistics, etc.) into actionable knowledge and identifies response objectives (FAO, 2017c).

IPC analyses are based on multi-sectoral expert knowledge. Participating experts, so-called Food Security Analysts, should hold expertise in areas surrounding e.g. food security, nutrition, markets and gender, and should be objective and non-biased (IPC Global Partners, 2012). IPC provides three levels of e-learning courses and tests for IPC analysts, trainers and experts, which are not mandatory for participants willing to engage in IPC assessments (IPC, 2016). Experts are required to base their assessments on data, to provide the underlying sources and to assign confidence levels to their analyses, which serves as a validation mechanism. Experts gather in technical working groups to assess the current food security situation. IPC provides protocols regarding the composition of working groups, thus, requiring the inclusion of representatives from government, international and local NGOs, the UN and technical agencies. Technical working groups should consist of 5 to 20 members and are, in general, chaired by a representative from the national government (IPC Global Partners, 2012). One of IPC's key mandates is the consensus building among experts and key stakeholders. Hence, IPC reports entail the harmonization of expert assessments and results are required to be presented and discussed with key decision makers before their publication. Technical working groups may operate at regional, sub-regional or at national levels (IPC Global Partners, 2012).

IPC's country coverage is at different stages of implementation. With regard to its implementation, IPC differentiates between (1) consolidation stage, i.e. advanced implementation and adoption, (2) introduction stage and (3) a selection of countries to which IPC could potentially be expanded in the future. As of November 2016, IPC is fully implemented in 21 countries[4] in Asia, East and Central Africa and Latin America.[5]. Furthermore, 13 countries[6] are in the introduction phase and an additional 15 countries are considered for expansion (IPC Partners, 2017; IPC, 2016).

Furthermore, IPC collaborates with Cadre Harmonisé, i.e. the regional early warning system of West Africa. Cadre Harmonisé covers 16 countries in the region and has started to integrate a selection of IPC elements, i.e. inclusion of indicators, adoption of the severity scale and mapping, in 2008 (IPC 2016). Therefore, accounting for its own coverage and its support to Cadre Harmonisé, IPC covers a total of 37 countries. With respect to the timing of reports, IPC reports are issued on an irregular basis, as IPC operates in a "demand oriented" manner. This means that working groups decide on the timing of analyses that can be both regular and on an ad hoc basis. In its manual, however, IPC considers its assessments to be the output of situation analyses, providing "real-time updates of current and projected food security and nutrition condition" (see IPC Global Partners, 2012, p. 80). The Cadre Harmonisé, however, meets regularly on a bi-annual basis (February/March and October/November) (IPC Global Partners, 2015).

IPC communicates its analyses in the form of country reports. As one of IPC's key mandates is communicating for action, IPC provides standardized templates for IPC Situation Overviews, which are used by working groups to integrate their findings (IPC Global Partners, 2012). Countries have the possibility to use IPC's Information Support System (ISS) to coordinate, integrate and illustrate their analyses. The final output of the ISS is a geographically disaggregated world map that provides both acute and chronic IPC analyses at regional levels. The sharing of analyses with the public, however, is not mandatory. Only a few analyses are publicly available through the ISS (IPC Global Partners, 2012). With respect to its link to a response capacity, IPC is supported by a range of international institutions and NGOs, like WFP, CARE international and the FAO. One of its goals is communication for action and the use of IPC results as support for decision making and emergency interventions. Care international, for example, states on the IPC website that it they are integrating the tool in their country level emergency planning (FAO, 2017b).

4 Asia: Afghanistan, Bangladesh, Nepal, Pakistan, Philippines, Tajikistan, Yemen; Latin America & Caribbean: Honduras; East and Central Africa: Burundi, Central African Republic, Democratic Republic of the Congo, Djibouti, Kenya, Somalia, South Sudan, Sudan, Tanzania, Uganda; Southern Africa: Lesotho, Malawi, Zimbabwe= 21.

5 IPC has multiple documents and maps indicating its coverage. Contrary to what is stated on IPC's website, 26 vs. 21, with Haiti, El Salvador, Rwanda and Swaziland still in the introduction stage and Botswana is considered a country for expansion (IPC 2016; IPC Global Partners 2014)

6 Cambodia, Guatemala, Haiti, El Salvador, Ethiopia, India, Kyrgyzstan, Lao People's Democratic Republic, Madagascar, Mozambique, Rwanda, Zambia, Swaziland (IPC Global Partners 2014).

Even though IPC has an indirect link to the response capacity, Cadre Harmonisé, its regional cooperation partner, is directly connected to the emergency food reserve of the Economic Community if West African States (IPC Global Partners, 2015).

2.5.2 *Famine Early Warning System Network*

FEWS NET by the US Agency of International Development (US AID) was launched in 1986 in the aftermath of the East African famine (Brown, 2008). It is among the oldest and most comprehensively analyzed and discussed early warning system for food insecurity (Brown, 2008; Ververs, 2012; Hillbruner & Moloney, 2012).

Remotely sensed data is FEWS NET's core input for acute food insecurity assessments. The data collection, processing and analysis are supported by a range of multi-disciplinary US institutes: the National Aeronautics and Space Administration, the National Oceanic and Atmospheric Administration (NASA), the US Geological Service and the US Department of Agriculture. Satellite imagery is used for agro-climatic monitoring, comprising *inter alia* the monitoring and/or forecasting of weather and weather events, rainfall estimates, drought monitoring, climatic events and prediction, such as el niño and la niña, land surface temperatures, geo-spatial water requirements, crop assessment and agricultural production estimates (FEWS NET, 2017b). The use of quantitative satellite imagery has a range of advantages: for example it can generate sound and early evidence of a potential drought that can be directly distributed to decision makers. Further, it is an independent information source that is not exposed to potential political interest, an issue regularly associated with food security data. However, as the food security situation depends on a complex web of interacting variables, strongly driven by economic and political factors, remotely sensed data cannot provide a full picture (Brown, 2008). Therefore, FEWS NET further engages in a scenario-building process that takes into account other variables, such as e.g. nutritional status, livelihood change and mortality rates (Hillbruner & Moloney, 2012).

Among its core outputs is FEWS NET's "Integrated Food Security Analysis" that comprises four reports, the Food Security Outlook, Food Security Outlook Update, Remote Monitoring Report and Key Message Update. These four reports contain, to a large degree, the same risk indicators and are published in a quarterly and bi-monthly frequency, so that *de facto* monthly information is provided. The Food Security Outlook contains both near and medium term (upcoming six months) food insecurity forecasts that are based on a comprehensive set of indicators and a complex, nine-step scenario-building process. They cover market information, production, supply, price developments, weather forecasts, livelihood and coping strategies indicators, an overview over humanitarian activities, conflict and civil unrest and a food security outlook according to livelihood zones. Forecasts are based at a sub-country level, which results in highly spatially disaggregated information (FEWS NET, 2017b). The Remote Monitoring Report provides information for countries that are remotely covered by FEWS NET. Usually, these reports are less comprehensive than the Food Security Outlook and provide mostly information on prices, the supply situation and food security classification, refugee flows and humanitarian assistance funding gaps (FEWS NET, 2017c). Since these four reports are similar in their content, we consider them as one report in the subsequent analysis. In addition to near- and mid-term forecasts, FEWS NET publishes monthly reports that inform on the global and local price developments: the "global price watch" and a national price and market bulletin; covering both the international and national price and supply situation (FEWS NET, 2017b). The Food Assistance Outlook Brief is a monthly report that gives an overview over countries in need of food assistance. It provides a six month forecast for the number of people per country that require food assistance and the situation according to the IPC severity classification. It also provides a comparison to the situation last year as well as to a five year average (FEWS NET 2017b). FEWS NET provides detailed information on the cause of a particular crisis and its severity. The information focuses on the number of people who are food insecure. Furthermore, FEWS NET publishes a Global Weather Hazards Summary, which contains weekly, regional forecasts of weather hazards for Africa, Central Asia, Central America and the Caribbean (FEWS NET 2017d).

In 2011, FEWS NET adopted the IPC classification for food insecurity and provides its outputs accordingly. FEWS NET extended the IPC terminology to indicate countries for which only remotely sensed information is available. Moreover, FEWS NET does not comply with IPC's standard of consensus making among experts within the process of analysis, to ensure their ability to provide timely assessments in times of emergency (FEWS NET, 2017b). As of October 2016, FEWS NET provides early warning for 36 countries. The majority of monitored countries are located in East, South and West Africa, five countries are in Central America and the Caribbean, and two countries are in Central Asia. The monitoring is directly supported through on-site country offices and is further extended to neighboring countries through remote sensing. FEWS NET's focus is on acute famine that is caused by drought or flooding as well as on staple commodities such as wheat, rice, maize and soybeans (FEWS NET, 2017b).

FEWS NET communicates findings through regular country or topic-related reports (Brown, 2008), e.g. the country related Food Security Outlook and reports on Global Weather Hazards. These reports are compiled in FEWS NET country offices (Brown & Brickley, 2012). FEWS NET publishes its near- and medium-term food security assessments through a static map on their website, which shows both near- and mid-term assessments for monitored countries according to IPC phase color coding. Due to the static nature of the map, detailed geo-information is lost. In addition to its map, FEWS NET provides a dashboard which lists the areas of highest concern and other areas of concern (FEWS NET, 2017b), and major findings from reports are published on Twitter and Facebook.

Through USAID, FEWS NET has a direct link to an emergency response capacity. USAID uses FEWS NET reports for decision making and emergency planning (Brown & Brickley, 2012). After famine EWSs came under scrutiny throughout the 1990s for their missing link to the response capacity (Buchanan-Smith & Davies, 1995), FEWS NET actively took on that critique and started to integrate both contingency and emergency planning, i.e. emergency preparedness based on scenario analysis and responding to an acute emergency (Brown & Brickley, 2012). FEWS NET further reports WFP funding shortages in its Food Assistance Outlook Briefs, and hence, directly appeals to decision makers (FEWS NET 2017c). FEWS NET's dependency on USAID and its Food for Peace Office has advantages and disadvantages. On the one hand there is a direct link to a response capacity whereas, on the other, this exclusivity creates a dependency on USAID's operational mode and its potential limitations (Brown, 2008). USAID's emergency response relies on the distribution of in-kind food aid, which is produced in the US and distributed to emergencies by US cargo facilitators - three factors that have received wide criticism. The Food for Peace Reform Act, as recently proposed, is an urgent and promising reform of USAID's emergency response, as it shifts the focus to cash transfers for people in need and to the purchasing of local produce for distribution (Glauber et al., 2017).

2.5.3 *Vulnerability Analysis and Mapping*

WFP's VAM engages in a range of initiatives with the aim to provide holistic and timely information on food insecurity, focusing on who and how many people are food insecure, their location and the underlying causes: "who, where, how many and why". The information is pooled in one information system that is WFPs' Vulnerability Analysis and Mapping (VAM) (WFP, 2015).

VAM provides global and country-level assessments and data and offers a range of tools for food security analyses that differ in both their country coverage and report frequency. It comprises information on prices, price trends, crowd seeded price information and sentiment analysis, agro-climatic monitoring and visualization, currencies, and several baseline and in-depth assessments and supply of models (WFP, 2017c). In May 2016, WFP VAM introduced a data visualization platform (WFP 2016) that, as of July 2017, provides a Seasonal and Economic Explorer. Hence, WFP is transitioning findings that have been published before in their "One Stop Shop" to the new visualization platform. The Agro-Climatic Seasonal Monitoring (complementing the seasonal monitor) comprises rainfall data and the Normalized Difference Vegetation Index (NDVI) and their respective averages and anomalies. Data is available in intervals of 10 days. A wide range of countries, from 50th north to 50th south, is covered and data and visualization mapping is available from country to sub-country levels. The rainfall data is provided by CHIRPS, the Climate Hazard Group of the University of California, and NDVI is from MODIS NASA. Data is available for download as well as for visualization (WFP, 2017b).

The Economic Explorer provides, e.g. market prices, exchange rates, GDP and inflation rates, alert for price spikes and forecasts (WFP, 2017b). Since 2008, VAM has been collecting monthly food price data that is spatially disaggregated (at the country, regional and sub-regional level) and covers 78 countries and 1535 markets. As the focus is on crops that are most relevant for food security, VAM provides information on both staple crops, like wheat, rice, maize, soybeans, as well as other relevant commodities, e.g. millet, beans, sweet potatoes. The information is published in the “Monthly Market Watch”. VAM uses the main staple commodity price data for its Alert for Price Spikes (ALPS) analysis that monitors abnormal price changes and, thus, is used to detect markets in crises. Based on the standard deviation from the normal seasonal price trend, markets are listed in four categories: normal, stress, alert and crisis. Markets that have been in crisis within the last six months are listed in a table (WFP, 2017b). ALPS further provides, if the quality of the data series allows, automated price forecasts. Market price information, trends and impacts are summarized in WFP VAM’s quarterly "Market Monitor".

Since 2013, WFP VAM engages in the remote collection of crowd seeded information, i.e. bottom-up information, on food security. In the face a potential breakdown of data collection during the Ebola crisis in 2013, WFP launched its Mobile Vulnerability Analysis Mapping (mVAM) initiative. mVam collects food security related data on market, nutrition and households through SMS questionnaires, live voice calls or interactive voice calls. Participants receive a small air time credit as incentive to participate. The initiative started in Liberia, Sierra Leone and Guinea (Bauer et al., 2015; WFP, 2015). As of July 2017, mVAM covers 30 countries, including countries like Chad, Mali, Cameroon, Zambia, Zimbabwe, as well as conflict zones, like Syria, Iraq and Somalia. The information is published in monthly mVAM country bulletins that contain information on Food Security Indicators, e.g. price of the food basket, food consumption score, reduced coping strategy index and information on nutrition diversity, like consumption of proteins, dairy and, if applicable, access to public distribution system. This information is disaggregated at the sub-country level and accounts for displaced households (mVAM, 2016). This initiative represents a first move in the direction of bottom-up data collection, i.e. direct inclusion of information from the population at-risk.

The starting point of WFP’s VAM "One Stop Shop" is the "Food Insecurity Hotspots". The Food Insecurity Hotspots, visualized as a world map, highlight countries of concern over time as well as indicating the cause of food insecurity, e.g. conflict and drought (WFP 2017b). Countries of concern are countries in Level 3 emergencies , as recognized by the Inter-Agency Standing Committee (IASC), and countries where a degradation of food security has taken place (J.-M. Bauer, personal communication, October 12, 2016). Food Insecurity Hotspots are irregularly updated (most likely in accordance with bi-annual IASC reports). As of July 2017, the information was last updated in May 2017. Apart from regular assessments, WFP engages in a range of irregular in-depth and baseline assessments. Jointly with FAO, WFP have developed a Shock Impact Simulation Model (SisMod) that provides a model for market, economic and climatic shocks and analyzes their ex-ante and ex-post impacts. It currently is available for Bangladesh, Guinea, Liberia, Nepal, Niger, Pakistan, Sierra Leone, Tajikistan and Yemen (WFP, 2018a). In addition, WFP VAM engages in in-depth analyses such as the Comprehensive Food Security and Vulnerability Analysis (CFSVA) baseline scenario that is used during a non-crisis setting, the Emergency Food Security Analysis (EFSA) that is run after a shock or disaster, the FAO / WFP Crop and Food Security Assessment Mission (CFSAM) and Food Security Monitoring Systems (FSMS).

VAM's new visualization platform illustrates information through spatially disaggregated maps at the sub-country level, and graphs. In its other portal, the "One Stop Shop", the majority of findings is published as reports. This indicates that VAM started to communicate information in a more interactive way. As VAM is embedded in WFP which is the world's largest humanitarian organization, also the information that it produces is directed towards experts and decision makers at WFP, as well as decision makers at international and national levels. Even though the mVAM initiative started to integrate the population at-risk as a bottom-up information source, early warning results and potential coping strategies are not systematically communicated back to affected people. The information that is provided through VAM is used for decision making and for the planning of WFP's operations, emergency and relief missions. One goal of VAM is to identify crises and "what should be done about it" (WFP, 2015). So VAM has a clear link to the response capacity. Nevertheless, it remains unclear how the information is used, as no standardized protocol is available that delineates which actions are to be taken in the case of a deterioration of the food security situation. A clear code of conduct is available for so called Level 3 emergencies, which are declared by the IASC and trigger a pre-defined intervention protocol (IASC, 2012). VAM's Food Security Hotspots highlight current Level 3 emergencies. This is the only instance for which a pre-defined intervention protocol that is acted upon can be observed. Still, VAM's Food Security Hotspots is a display of Level 3 emergencies, hence the information flow is reversed: from decision making to the integration of information into EWSs.

2.5.4 *Global Information Early Warning System*

FAO GIEWS was established in 1975 in the aftermath of the world food crisis of the early 1970s (Rashid, 2003). GIEWS is the oldest available early warning system for food crises. GIEWS's mission is to monitor the global and national supply and demand situation. More specifically, GIEWS provides regular information on agricultural production and crop prospects, country specific food production, international, national and sub-regional markets monitoring and vegetation and precipitation.

In its section "country analysis", GIEWS provides information on 112 countries in Africa, Asia, Latin America and the Caribbean and Europe and Oceania. GIEWS' main output is country briefs that are issued on a quarterly basis. These reports provide information on agricultural output and harvest prospects, weather incidents, vegetation health and precipitation, crop calendar, import requirements and consumer prices. To some extent and if available, these briefs also include IPC analyses (FAO, 2018a). Furthermore, GIEWS lists countries that require external assistance for food along with a brief overview explaining the main reasons, which is updated on a quarterly basis, as well as countries with unfavorable prospects for current crops.

After the food price crisis in 2007/08, GIEWS was extended to the monitoring and analysis of international, national and sub-national commodity markets. The tool on "Food Price Monitoring and Analysis" (FPMA) provides information on monthly retail and wholesale prices covering 91 countries, as of July 2017 (FAO, 2018b). GIEWS' FPMA Tool is a database containing monthly international and domestic prices at the sub-country level, monthly price series for *inter alia* cereals, vegetables, breads and meat. In addition to its data tool, the FPMA issues monthly national price warnings (high and moderate warnings) for staple commodities. Warnings are based on the compound growth rate of prices (Baquedano, 2015). It further provides regional roundups that give regional summaries of the market situation. In addition, the FPMA has information on international commodity and export prices, domestic price volatility, currency depreciation, oil prices and lists changes in food policies affecting international markets and trade (Baquedano, 2015). GIEWS further contains information on "Earth Observation for Crop Monitoring", providing various indicators on the state of vegetation and water availability. The seasonal global indicators, i.e. the Agricultural Stress Index (developed by FAO), progress of season and mean Vegetation Health Index, which are provided in near real-time (10 days); global indicators, i.e. NDVI anomaly, Vegetation Condition Index, Vegetation Health Index; these indicators are also available at the country level, at a resolution of 1 km (FAO, 2017a).

Furthermore, GIEWS issues a variety of regular reports that provide information on the global, regional and country specific agricultural production and supply situation. It is a quarterly report on "Crop Prospects and Food Situation" and provides information on countries in need of emergency assistance and an estimate of the number of people in need based on reports from IPC and Cadre Harmonisé. It further contains an overview of the global cereal supply and demand situation, a food situation overview for Low-Income Food-Deficit Countries, cereals production and imports. The "Food Outlook", a biannual publication, contains forecasts of the global supply and demand situation; information on food and feed market, a focus on international market developments, production, utilization and stocks, prices, trade and policy developments.

In addition to regular reports, GIEWS issues a variety of irregular reports that are published in the event of unusual developments. "GIEWS Updates" are published in case of abnormal developments of food supply, giving assessments of sudden changes. It is published to inform the international community that action needs to be taken. Also, "Special Alerts" are published to highlight a particularly alarming food security situation. As of December 2016, GIEWS had published 337 Special Alert reports, which provide information on the agricultural stress index (percentage of cropped areas suffering from water stress), the vegetation condition index, agricultural prices and the supply information and, if available, IPC reports (FAO, 2018a). GIEWS further publishes "Special Reports". These are irregular reports focusing on problematic developments to the food supply and agricultural situation, and are usually issued after a CFSAM in-depth assessment. It covers topics such as the overall economic setting, cereal production, supply and demand situation, household food security and vulnerability and recommendations. Market Profiles are irregular collections of a country's market baseline information based on emergency food security assessments. Five reports have been produced since 2005/06 (FAO, 2018c). The El Niño collection further provides a country's El Niño response plans as well as preparedness and situation reports (FAO, 2018b). The section on risk knowledge above shows that the majority of information by GIEWS is published as reports. The main recipients are decision makers both at a global and country level. No effort is evident that includes the population at-risk as recipient of warnings. GIEWS has no direct link to the response capacity. The aim of GIEWS is to provide reports, databases, methods, tools and capacity building (FAO, 2018c). Even though there might be no direct link to a response capacity, FAO GIEWS and WFP VAM operate both under the United Nations umbrella and cooperate on many levels, e.g. CFSAMs. Hence, there is reason to hypothesize that information provided GIEWS is incorporated into decision making at WFP (FAO, 2018c).

Excursion on Local Early Warning System: The example of NDMA, Kenya:

The Kenyan National Drought Management Authority (NDMA) established their early warning system in 2013. NDMA publishes monthly early warning reports with information on biophysical indicators, production and access indicators as well as utilization indicators at the county and sub-county level. The information is collected through a system of local food monitors and key informants.

Reports contain information on (1) climatic conditions, like rainfall, impacts on vegetation and water, water sources, household and livestock access to water. (2) Production indicators, like livestock body conditions, milk production and diseases, livestock migration and rain-fed cropping. (3) Agricultural markets, i.e. prices of livestock, cattle and goats, food prices i.e. maize, beans, milk. (4) Household food consumption and nutrition status is assessed based on milk consumption, the food consumption score and human diseases. Furthermore, (5) reports contain a food security prognosis, current interventions recommendations for policy actors and NGOs. The classification is currently not aligned to IPC. Risk is categorized into three phases, i.e. normal, alert and alarm and compares current values to long-term averages. NDMA provides their early warning classification according to livelihood zones and also provide a trend, i.e. stable, improving, and deteriorating (NDMA, 2019).

Early warning information is published in monthly. County-related reports are distributed to the respective county government and NGOs after its release and publicly available on NDMA's website. Reports include an alert status in Kiswahili. NDMA acknowledges that reports might me too technical to be understood by the general population. Hence, NDMA uses various channels across counties to disseminate easily understandable information to the population at-risk through its data collectors, community chiefs and other community touch points, like key informants and opinion leaders. Furthermore, results might be communicated through radio shows, or through community feedback sessions during public gatherings, i.e. immunization sessions, political rallies and trading centers, where information e.g. about an impending drought and what could be done about it, is shared. Another option is the positioning of early warning flags on strategic community points, to account for easily accessible information in regions with potentially low literary rates (O. A. Abdi, personal communication, June 23rd, 2017).

NDMA's mandate is crisis response and its early warning bulletins are distributed to all actors and organizations by the 5th of each month. Usually bulletins entail a section where the appropriate interventions are indicated per sector, which is essential to facilitate decision making and the taking of action. As a result, NDMA has a direct link to a response capacity. The information produced by NDMA is integrated into FEWS NET reports (see monthly Kenya assessment).

2.6 COMPARISON BETWEEN SYSTEMS AND TO THE CONCEPTUAL BENCHMARK

In this section, we compare the four analyzed EWSs, and the information they provide, to each other and to the theoretical benchmark. We start with a systematic comparison of the four EWSs, which is followed by reliability tests of frequency and spatial coverage

2.6.1 *Risk Knowledge and Monitoring Characteristics*

Figure 2.3 gives an overview of the four analyzed EWSs, i.e. IPC, FEWS NET, VAM and GIEWS, and shows which local and global risk factors are monitored along with their monitoring characteristics. From a risk knowledge perspective, the monitoring systems cover a range of global and local indicators, such as agricultural prices, weather, vegetation, livestock and livelihood indicators as well as migration flows and the political situation. Six out of fifteen analyzed reports provide information on a holistic set of risk factors, covering both availability and access indicators and the political situation, while the nine remaining reports have a more narrow scope, covering mostly prices and supply (six reports) as well as agro-climatic conditions (three reports). FEWS NET and IPC cover the largest set of global and local risk factors, providing information on a range of indicators that serve as proxy for both the availability and accessibility component of food security, followed by GIEWS and VAM. In particular FEWS NET publishes a large number of reports (five) that provide information on a variety of risk indicators. Five reports estimate the number of people at-risk, and three reports list the number of counties requiring emergency assistance. IPC and FEWS NET include mortality rates, and three reports contain information on internally displaced people and refugee flows.

With regards to monitoring characteristics, we find that the majority of reports are not classified according to IPC. Since the establishment of IPC in 2006, FEWS NET is, apart from IPC itself, the only EWS that adopted IPC compatible classifications and changed its output accordingly. GIEWS includes, to some extent, IPC analyses in their reports and hence provide the information accordingly. We show in the sections above that EWSs use a variety of classifications for their assessments and warnings, which to some extent is necessary due to the diverse set of information that is being analyzed. However, this leads to different food insecurity classifications across EWS that often remain unclear and that are at-risk of being chosen arbitrarily.

We find that ten of the analyzed reports and tools engage in ex-post reporting, while five engage in forecasting. Three out of these five reports are published by FEWS NET, which, according to this overview, provides the largest number of food security forecasts.

Figure 2.3: Overview over Early Warning Systems, Risk Monitoring and Monitoring Characteristics.

		Local Risk														Global Risk			Characteristics						
EWS	Report / Tool	Prices	Supply	Weather	Vegetation	Demand	Livestock Markets	Livelihood Indicators	Population at risk	Countries requi. ext. assist.	IDPs, Refugees	Mortality Rate	Civil Unrest, Conflict, War	Policies	Humanitarian Assistance	Prices	Supply	Policies	IPC Classification	Spatial Unit	Assessment	Frequency	No. Countries	Published as	Bottom Up Info
IPC	Acute Food Insecurity Situation Overview	x	x	x	x		x	x	x	x	x	x	x	x	X				x	SC	EX	IR	15	R	
FEWS NET	Integrated Food Security Analysis	x	x	x	x	x	x	x	x		x	x	x	x	X				x	SC	FC	M	30	R	
	Price Bulletin	x	x																	C	EX	M	23	R	
	Global Price Watch															x	x			G	EX	M	-	R	
	Food Assistance Outlook Brief	x	x	x	x	x		x	x	x	x	x	x	x					x	C, SC	FC	M	33	R	
	Global Weather Hazards			x																R	FC	W	-	R	
VAM	Agro-Climatic Monitoring			x	x															SC	EX	Dek	122	T	
	Market Watch	x														x				SC	FC	M	78	T	
	Market Monitor	x														x				G, C, SC	EX	Q	-	R	
	mVAM	x	x	x				x			x		x		x					SC	EX	M	22	R	x
GIEWS	Country Briefs	x	x	x	x		x		x		x									C	EX	Q	81	R	
	FPMA	x	x													x	x			G,R,C	EX	M		R	
	Earth Observation			x	x															SC	EX	Dek	-	T	
	Crop Prospects and Food Situation	x	x			x			x	x			x			x	x		x	G, R, C, SC	EX	Q	-	R	
	Food Outlook															x	x	x		R, C	FC	BA	-	R	

Note: This table gives on overview over regular assessments and does not account for irregular baseline studies. Spatial Unit: G: global, R: regional, C: county, SC: sub-country. Assessment: FC: forecast, EX: ex-post. Frequency: BA: bi-annual, Q: quarterly, M: monthly, Dek: Dekads, W: weekly, IR: irregular. Published as: R: Report, T: Tool. Source: Own compilation, based on content provided on the websites of the respective early warning system and own frequency analyses.

All EWSs still engage exclusively in the top-down monitoring of events. The only system that is moving into the direction of actively integrating bottom-up information is WFP's mVAM initiative.

Our analysis further shows that six of the reports exclusively provide information that is at the sub-country level and, thus, spatially disaggregated, two reports provide information on a national level and five reports mix global, regional, national and sub-national information. The number of countries that are covered and the frequency in which reports are published varies highly across EWS and reports. The country coverage is particularly high in the case of agro-climatic monitoring, which is provided by FEWS NET, VAM and GIEWS with near-global coverage. This is due to the wide availability of remotely sensed weather and vegetation data. When it comes to the monitoring of a more varied set of indicators, GIEWS still provides quarterly information for *de facto* 81 countries and on a variety of risk factors. The number of countries monitored, however, drops significantly for the remaining, more frequent reports. VAM still covers 78 countries through its monthly market watch, exclusively focusing on food prices. With regards to accessibility and livelihood indicators, the number of countries drops substantially to thirty or less. IPC, for example, publishes reports for 15 countries, while FEWS NET provides different reports with information for 30 countries. The the following sub-chapter will test for which countries timely information is de facto available and the areas, for which crucial information is missing and risks to food security are not being identified.

Regarding the frequency of reports, FEWS NET achieves the maximum velocity with its weekly weather forecasts. Also VAM and GIEWS engage in earth monitoring and have a comparatively high frequency in regards to satellite-data-based weather and vegetation monitoring, which is provided in 10 day intervals. However, the majority of assessments that do not deal exclusively with earth observation, but with availability and accessibility indicators have a monthly (6 reports), or a bi-monthly, quarterly or bi-annual frequency (7 reports). GIEWS' country reports, for example, are only available every quarter. Apart from the agro-climatic monitoring, the highest reporting frequency is, thus, still monthly. We find that none of the systems engages in near real-time analyses, i.e. the daily, sub-daily or live monitoring of indicators.

With respect to the third pillar, i.e. the communication and dissemination of results, we find that nearly all analyzed EWSs publish their assessments in the form of reports, whereas only three assessments are provided as tools, i.e. VAM's agro-climatic monitoring and market watch and GIEWS's earth observation tool. The recent introduction of visualization tools shows a transition towards the integration of results into more interactive systems and maps, like WFP's new visualization platform (WFP 2017a). We, hence, conclude that targeted recipients of early warning information are decision makers at the international, national and local level, governments and NGOs. This conclusion is driven by the fact that access to early warning reports requires an Internet connection and high literacy levels. Aspects that are usually not sufficiently found across the at-risk population. We find no documentation on efforts of EWSs to integrate the population at-risk as a target group for their early warning messages. Regarding pillar four, the direct connection of the EWS to a response capacity, we find mixed results. Only one report, IPC's Acute Food Insecurity Situation Overview, contains recommendations for action. The sections above show that FEWS NET and VAM are directly connected to and embedded in a humanitarian agency, i.e. USAID and WFP respectively, while IPC and GIEWS do not have any direct connection. Nevertheless, we observe that all EWSs strongly cooperate with each other, as information is shared, integrated into reports and cross-published. FEWS NET's information, for example, is integrated into GIEWS reports (FAO, 2017b), while many reports include IPC assessments. Furthermore, IPC was established *inter alia* by FAO, which suggests that they will be incorporated in the decision-making capacities in the future. So, even though theoretically, IPC and GIEWS do not have a direct link to a response capacity, we would expect them to gain exposure to decision making.

2.6.2 *Reliability Tests: Country Coverage and Reporting Frequency*

Based on the results in Figure 2.3, we are able to identify the report of each EWS that provides information on the most comprehensive set of risk factors. These are IPC's Acute Food Insecurity Situation Overview, FEWS NET's Integrated Food Security Analysis, VAM's mobile VAM and GIEWS's country reports. We use these reports to test the reliability of information provision. We analyze (1) how reliably information is published and (2) which spatial coverage is *de facto* provided by EWSs, based on two different time horizons, i.e. a long term period of eight months and a short term period of one month.

Table 2.3 shows the number of countries for which the respective reports were updated between January and August 2017, compared to the actual number of countries that the EWSs claim to cover. We find that FEWS NET has the most reliable update-ratio, providing updated information for more than 90% of their monitored countries, followed by VAM and GIEWS. IPC's update-ratio is, however, less than 50%, having provided updated information for 13 out of 37 countries between January and August 2018. The results show a strong variation in the reliability of information provision across EWSs.

Table 2.3: Number of Countries with Updated Information, Jan - Aug 2017.

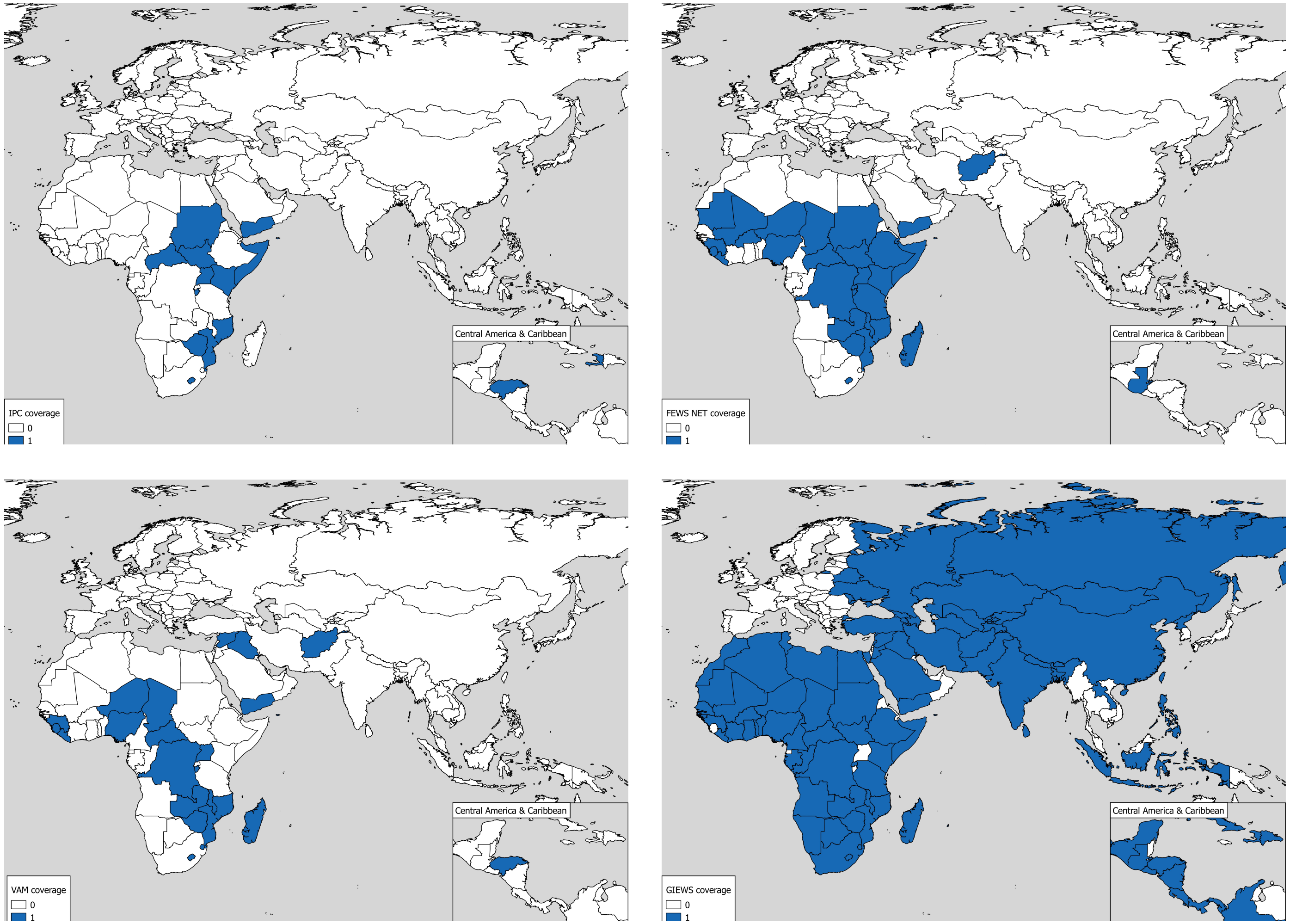
EWS	Report	No. of Countries
IPC	Acute Food Insecurity Situation	13/37
FEWS NET	Integrated Food Security Analysis	33/36
VAM	mVAM	22/30
GIEWS	Country Briefs	81/112

Source: Own compilation based on selected reports published by IPC, FEWS NET, VAM and GIEWS. Last assessed on September 1st, 2017.

Based on this analysis, Figure 2.4 shows the spatial coverage for which information *de facto* has been published within the eight month time period. Here, GIEWS covers the largest amount of countries, followed by FEWS NET, VAM and IPC. The only system that covers Iraq and Syria is WFP's mVAM, providing regular, monthly information on selected regions within the two countries since 2016. Afghanistan, however, is covered by three out of four systems.

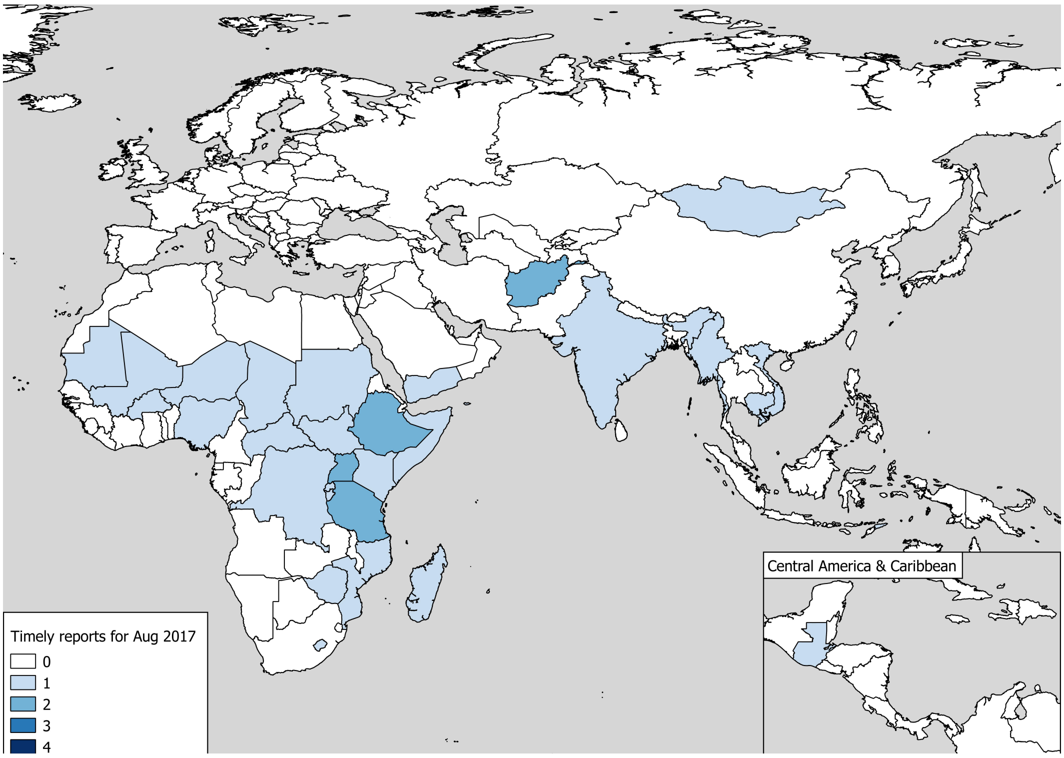
To understand which most up-to-date information is *de facto* available for decision making at the first day of a given month, we further analyze for which countries monitoring systems have provided information for August 2017, assessed on September 1st. Figure 2.5 shows the number of reports published in August 2017 and the spatial coverage of information. Information is available for 30 countries, while the maximum number of timely reports that can be found is two (Tanzania, Uganda, Ethiopia and Afghanistan), while one report is available for the remaining countries. We can identify that up-to-date information is missing for a variety of countries that are engaged in complex emergency, i.e. Syria, Iraq, Djibouti, and Eritrea. We further find that two reports are available for Afghanistan, which are reports published by mVAM covering single provinces within Afghanistan.

Figure 2.4: *De facto* Spatial Coverage of Selected Reports by (1) IPC, (2) FEWS NET, (3) VAM and (4) GIEWS.



Source: Own compilation based on selected reports published by the four EWS, Jan – Aug 2017, assessed on Sep, 1st 2017.

Figure 2.5: No. of Reports Published per Country in August 2017.



Source: Own compilation based on a count of reports published, assessed on Sep 1st, 2017.

2.7 DISCUSSION

The analyzed early warning systems addressed part of the long standing critique, i.e. (1) the focus on droughts and availability of food, (2) the lack of spatial disaggregation, timeliness and comprehensiveness of geographical coverage, (3) the missing integration of the affected population itself, both as an information source and recipient of early warning information and (4) the missing connection between early warning information and the response capacity.

We show that the focus on the availability of food, prices, weather and supply (Wisner et al., 2004; Devereux, 2001) has shifted towards covering also the accessibility pillar of food security and that EWSs have started to engage in a comprehensive, multi-indicator analysis of the food security situation.

With regard to the lack of spatial disaggregation, timeliness and geographical coverage of indicators, we find that EWSs have transitioned towards geographically more disaggregated information and hence dis-confirm the claim that EWSs engage in pure country-level analyses (Buchanan-Smith & Davies, 1995). We show that a large part of the analyses has shifted to the inclusion of spatially detailed, sub-country information. Regarding the spatial coverage of EWSs, we find that the country coverage varies substantially. Agro-climatic monitoring has a near global coverage, as satellite data is widely integrated into EWSs and three out of four systems provide weather and vegetation data. The coverage of accessibility indicators is less holistic, with a maximum coverage of 30 countries (in the case of FEWS NET). When looking at the reliability of information and the *de facto* spatial coverage of EWSs, we find that there is a deviation from the coverage and frequency of reports as claimed by EWSs. We further show that there are blank spots on the map, as there is no up-to-date information for countries like Syria, Iraq Djibouti and Eritrea. This finding underlines the vulnerability of data collection initiatives in complex emergencies and shows the need for systems that are able to provide information to humanitarian actors also in challenging environments.

We find that all EWSs engage in top-down monitoring; only WFP's mVAM initiative has started to directly obtain information from the population at-risk. Thus, our findings are in line with Kalkuhl et al. (2016), who also conclude that bottom-up information has not been systematically integrated into EWSs. We further find that some of the analyzed EWSs engage in forecasting, but the majority still engages in ex-post analysis. We also show that highest frequency is achieved by weather data that is published in ten day intervals, while the majority of reports are published at a monthly or less than monthly frequency. No near real-time monitoring has been implemented to date, contrary to what is claimed by some EWSs, such as WFP mVAM (VAM, 2019) or IPC (IPC Global Partners, 2012). Our analysis shows that there is a deviation from actual country coverage and frequency of reports, from what is claimed by EWSs. Our analysis of frequency and country coverage shows that all EWSs provide less information than stated and that there are reporting irregularities[7]. This finding undermines the reliability of EWSs.

Despite the fact that rising mobile phone and Internet adoption rates are paving the way for the integration of bottom-up information and potentially near real-time and real-time data sources, in practice, we observe that the analyzed EWSs are still one step behind. No EWS makes use of user-generated online content and WFP's mVAM initiative is the only example that demonstrated the integration of bottom-up information through an SMS- and voice-call-based system. Despite today's era of digitalization and advances in rapidly available big data, current EWSs fall short of their potential to use innovative data sources for bottom-up monitoring.

Furthermore, no progress was made to tackle the disconnection between early warning systems and the people at-risk, neither from a data collection perspective (expect for WFP mVAM), nor from a communication perspective. None of the analyzed EWSs integrated the population at-risk in an information loop, neither regarding the information itself nor regarding situation-specific communication of coping strategies. We find that the majority of early warning information is published online and in the form of reports. This result corroborates the findings of Twigg (2003), Basher (2006), Kelly (2003), who highlighted the importance of timely, non-technical and understandable information for the communities at-risk. In that regard, valuable lessons could be learned from local EWSs that attempt to communicate results back and that have experimented with different and more easily understandable ways of presenting the information to the population at-risk.

7 Reporting irregularities refers to information being provided at less regular intervals than what is stated by the respective EWS.

Even though the recent tendency to include interactive tools is a necessary change to increase the understandability and accessibility of information, this development still caters to the needs of affluent people with a good internet access and high literacy levels and ignores the needs communities at-risk. Hence, we find that EWS fall short of their potential to inform the at-risk population about an impending crisis and to include potential expectations from the at-risk population towards EWSs.

Given these two findings, e.g. the focus on reports and the lack of communication to the at-risk population, EWS should start to facilitate more intuitive ways of communicating their results, in order to harmonize the information content, and to develop strategies on how to diversify their communication strategies to different recipients. This underlines Twigg (2003) finding that EWSs need to be both experts in food security monitoring, as well as in communications.

We show that, in theory, EWSs have a direct or in-direct link to a response capacity. So our results show that Buchanan-Smith & Davies (1995) observation of a missing link between early warning information and humanitarian response, has improved. FEWS NET and VAM have a direct link to response agencies, i.e. USAID and WFP respectively. However, the existence of a link does not necessarily show that information is used and that it is acted upon. Much of the decision making processes are not transparent and even though there might be a direct connection to, for example, WFP and USAID, we find that none of the analyzed early warning systems or corresponding humanitarian agencies provide a clear-cut protocol or a contingency plan on the retrieving of early warning information. Bailey (2012) and Hillbruner & Moloney (2012) already discussed the issue of political unwillingness to respond to probabilistic warnings issued by EWSs in the context of the Somalia crisis of 2011. Thus, we identify a research gap with regards to the evaluation and testing of how early warning information contributes to decision making and its impact on triggering preparedness measures, emergency funds and emergency assistance, not only from an international organizations perspective, but also across national governments and NGOs.

2.8 CONCLUSION

The recent years witnessed a deterioration in the food security situation and approximately 817 million people are currently considered to be undernourished (FAO et al., 2018) and the humanitarian emergency response is increasing in size and complexity (WFP, 2018a). Over the last 40 years, EWSs have been developed to detect and provide information on emerging food crises. These systems, however, have been criticized for not providing a holistic picture of the food security situation by focusing on availability indicators, for lacking timeliness, geographical coverage and detail, for excluding the population at-risk and for being detached from response agents.

We find that EWSs partly addressed this critique and moved towards the diversification of risk monitoring from availability to accessibility indicators, towards the expansion of country coverage and the inclusion of geographically more detailed information. With regards to other assessment criteria, which we developed in a conceptual framework of an efficient EWS, we find that the majority of information is not harmonized, as a variety of thresholds is being used, and published at a monthly or less than monthly frequency. Also timely information is missing for a number of countries and the geographical coverage of EWSs is smaller than stated. Furthermore, bottom-up information is hardly integrated into EWSs and generally, the population at-risk is still disconnected, both as information source as well as recipient of early warning information. Hence, we conclude that monitoring systems fall short of their potential to inform the population at-risk about an impending food crisis.

Future research is needed to systemically identify strategies that effectively communicate early warning information to the population at-risk, the design of effective messages, adequate communication channels and how to integrate up-to-date coping strategies. In that context, we show that local EWSs hold valuable knowledge. Furthermore, we identify a knowledge gap regarding the communication of early warning messages. Future research needs to evaluate how early warning information is used, when it is received, by whom, and how it is put into action. It would be of interest to analyze the impact of early warning reports on decision makers and their effectiveness in triggering emergency funds and humanitarian response. This would also require an analysis of how early warning reports could be targeted at decision makers on the global and decentralized government level, accounting for political decision making cycles.

This study aims to provide an overview over monitoring systems for food security risk, the information that they provide and their monitoring characteristics. Our analysis does not account for the assessment of information and data quality, which has formerly been criticized (Kalkuhl et al., 2016) and mixed results were found when analyzing the performance of EWSs (Hillbruner & Moloney, 2012; Ververs, 2012). Further research is needed to systematically assess EWSs regarding the quality of information and the validity of warnings that are issued.

Food security monitoring is at an innovative stage of development given increasing ICT adoption rates and the potential these data sources hold for bottom-up monitoring and for EWSs. Contrary to Davies and Gurr's (1998) expectation that along with the adoption of ICTs, the lack of early warning information will be overcome, we find that EWSs have not yet fully tapped into the possibilities that emerge with this development, as the vast majority of analyzed EWSs have not adopted potential, innovate data sources or engage in (near) real-time analyses. In particular satellite imagery has been adopted by EWSs for weather, crop and yield monitoring. This is due to its wide available and the fact that satellite-based analyses have been found to perform as well as traditional survey-based measures, also in a small-holder farming environments (see Burke & Lobell (2017)). This study, however, shows that new data sources, like Internet metadata or ICT for a direct integration of the at-risk population, have not been systematically integrated into EWSs so far. This information could contribute to overcome the shortcomings, which are currently associated with data across developing countries and enable completely new data sources, which could give near real-time insights into processes within societies. We expect this to change in the upcoming years, given the amount of newly emerging initiatives that seek to integrate big data for crisis monitoring, like price monitoring through pictures of price tags (Premise, 2017) or food price monitoring using social media signals (UN Global Pulse, 2014). Future research is needed to understand how online content and the direct contact to the population through mobile phones can be used and integrated into EWSs, which would be particularly interesting and beneficial for hard-to-access areas and complex emergencies and has the potential to decrease the number of blank spots on the map, for which information is still unavailable.

3

CAN ONE IMPROVE NOW-CASTS OF CROP PRICES IN AFRICA? GOOGLE CAN.

3.1 INTRODUCTION

With the emergence of the Internet, new, online data sources have become available, as people produce digital traces when using the Internet. This online metadata, which is usually aggregated over a vast body of Internet users, contains a signal derived from a larger number of people than usually covered by surveys. In that regard, particularly search engine metadata, that is data representing the contemporaneous online-interest in a specific topic, or more specifically, what people currently search for as they navigate the Internet, has gained considerable interest. Tapping into this kind of information holds the potential to extract a near real-time online signal about the current interest of a society.

Across many African countries, Internet-adoption rates have started to increase significantly and more than doubled in many countries over the past decade. Average Internet-user rates currently range at around 24% of the population (International Telecommunication Unit, 2018). This development coincides with a persistent risk to food security, driven by *inter alia* recurrent droughts, extreme weather events and conflicts. Therefore, early warning systems and situation monitoring play a crucial role in decision making processes and facilitate preventive action and early interventions. As discussed in the previous chapters, early warning and situation monitoring require fast, disaggregated and reliable information to produce timely forecasts and potential warnings. In many African countries, however, high-frequency information is difficult to obtain and official statistics are published with a considerable time lag, at lower frequency and quality (Kalkuhl et al., 2016). Hence, decision makers face the challenge of having to make decisions in scenarios, where information is lacking (Carrière-Swallow & Labbé, 2013). Given these factors, particularly in the context of developing countries, extracting a near real-time online signal about the contemporaneous interest of a society could help identifying upcoming crises and has the potential to contribute to and improve current models and decision making processes. Therefore, there is considerable interest also in Africa, to explore the prospect of online, high-frequency information for now- and short-term forecasting models, i.e. models that predict the present or the very near future (Bańbura et al., 2013).

In the realm of search engine metadata, Google search query (GSQ) data is of particular interest, due to Google's dominance in the search engine market and its search engine meta data being published free of charge. GSQ data reflects the search volume of a specific keyword entered into the Google search engine at a certain location and point in time, hence, representing the contemporaneous online interest in a specific topic. GSQ data holds promising potential for the now-casting and inter-period forecasting of a variety of indicators, since Google releases its query data on a daily basis and, hence, earlier than standard reports and data. The use of GSQ data has found wide applications during the last decade: from epidemics (Ginsberg et al., 2009; Lazer et al., 2014), to political attitudes (Stephens-Davidowitz, 2013; Marthews & Tucker, 2014) and human behavior (Stephens-Davidowitz, 2017), as well as the field of economics, to now-cast and forecast private consumption (Vosen & Schmidt, 2011), inflation expectations (Guzmán, 2011), stock market volatility (Hamid & Heiden, 2015), developments on financial markets (Preis et al., 2013), exchange rates (Bulut, 2018), and unemployment rates (Askitas & Zimmermann, 2015; Suhoy, 2009). These studies, however, share one aspect: the use of GSQ data in the context of industrialized countries, where high Internet-adoption rates prevail. Two notable exemptions are Carrière-Swallow & Labbé (2013), who use GSQ data to now-cast automobile sales in Chile as well as Seabold & Coppola (2015), who now-cast consumer price indices and staple food prices in Costa Rica, El Salvador and Honduras.

To date, we are unaware of any attempt that explores the link between food price developments, as a proxy indicator for food security, and online-signals in the form of search query data in Africa, i.e. in an environment with relatively low Internet-adoption rates. The objective of this study is to address this research gap and to answer the research question whether GSQ data can be used to now-cast maize prices in a selection of African countries. This study does not aim to seek a substitute for price data, it rather seeks to investigate whether models including GSQ data can serve as a proxy for price developments. Our study focuses on nine African countries. These are Ethiopia, Kenya, Malawi, Mozambique, Rwanda, Tanzania and Uganda, Zambia and Zimbabwe.

3.2 studies using google search query data

Various disciplines have explored GSQ data to predict the present and near future. In the field of epidemics, Ginsberg et al. (2009) use a non-public data set of GSQ data to monitor flu trends in the US, while Lazer et al. (2014) develop an improved flu map based on public GSQ data. GSQ data has further been used to explore people's attitudes towards sensitive topics that are either not covered by surveys or that are usually prone to be over- or under-reported. Stephens-Davidowitz (2013) *inter alia* develops a GSQ measure for racial animosity in the US to analyze the percentage points Barack Obama lost in the 2008 presidential election. He finds that Obama lost 8 % due to racial animosity, a larger estimate compared to traditional survey estimates of racial bias. Marthews & Tucker (2014) use GSQ data to analyze the attitude towards internet privacy of the US's top 40 trading partners before and after the PRISM revelations, i.e. information leaks about the large-scale surveillance program of the US National Security Agency. Their findings show that post PRISM, search engine behavior changed in relation to sensitive queries, such as health queries and that this effect on search engine behavior is more pronounced in countries that are usually considered US allies.

In the field of economics, GSQ data has been used for the intra-period forecasting of economic indicators and consumer sentiment. Choi & Varian (2012) show that the inclusion of GSQ data in simple auto-regressive models of automobile sales, unemployment claims, travel-destination planning and consumer confidence, improves the model fit and that models with Google data outperform models without Google data by 5 to 20 %. The forecasting capacity of Google Trends with regards to unemployment rates has further been analyzed for Germany (Askitas & Zimmermann, 2009) and Isreal (Suhoy, 2009). Vosen & Schmidt (2011) show that the forecasting performance of private consumption in the US can be improved by including an index based on Google search queries. They find that the Google index outperforms standard survey based indicators, like the University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index, in both in- and out-of-sample forecasts. With regards to studies on financial markets, Guzmán (2011) analyzes the predictive power of various standard measures of inflation expectations in the US as well as the Google search volume for *inflation*, with focus on differences in data frequency. She finds the GSQ indicator to have the lowest out-of-sample forecasting error. Preis et al. (2013) analyze the relationship between Google search volume and financial markets in the US. They find that the Google search volume of selected keywords related to financial markets increases before stock markets fall. They further show that trading strategies including information on search query changes yield higher returns compared to random trading strategies. Hamid & Heiden (2015) use daily and weekly Google search volume data to forecast the volatility of the Dow Jones based *inter alia* on the concept of empirical similarity. The model performs better than traditional models in in-sample and out-of-sample forecasting, particularly when using weekly data.

The literature discussed so far uses GSQ indices in the context of countries with high internet-adoption rates. Carrière-Swallow & Labbé (2013) and Seabold & Coppola (2015) are, to our knowledge, the first studies to use GSQ indices in contexts associated with significantly lower internet adoption rates. Carrière-Swallow & Labbé (2013) develop a GSQ index of online interest in automobile purchases in Chile to now-cast automobile sales. They test the now-casting capacity by comparing a benchmark model to a GSQ-augmented model. They find that models including the GSQ index can outperform benchmark models in in- and out-of-sample forecasts. Seabold & Coppola (2015) use a GSQ index to forecast aggregate consumer prices and a selection of staple food prices (beans, maize, rice, wheat, and soy) in Costa Rica, El Salvador and Honduras. Similar to Carrière-Swallow & Labbé (2013), they use a out-of-sample estimation scheme to test the now-casting capacity of GSQ-models and non-GSQ benchmark models. They were partially successful in improving now-casts of food prices and indicate that the food price crisis of 2007/08 could be one driver, which complicates food price forecasts.

This overview shows that GSQ data has been successfully used in a variety of disciplines, while few analyses have linked Google Trends to a developing country context or food price monitoring and early warning. Therefore, our contribution to the literature is threefold: (1) we are the first study to use GSQ data in an African context, (2) to analyze a larger country panel, (3) to explicitly link GSQ data to food security and to add to the knowledge on how citizen science can help to improve early prediction of food insecurity and crises.

3.3 SAMPLE CONSIDERATIONS OF INTERNET DATA IN AFRICA

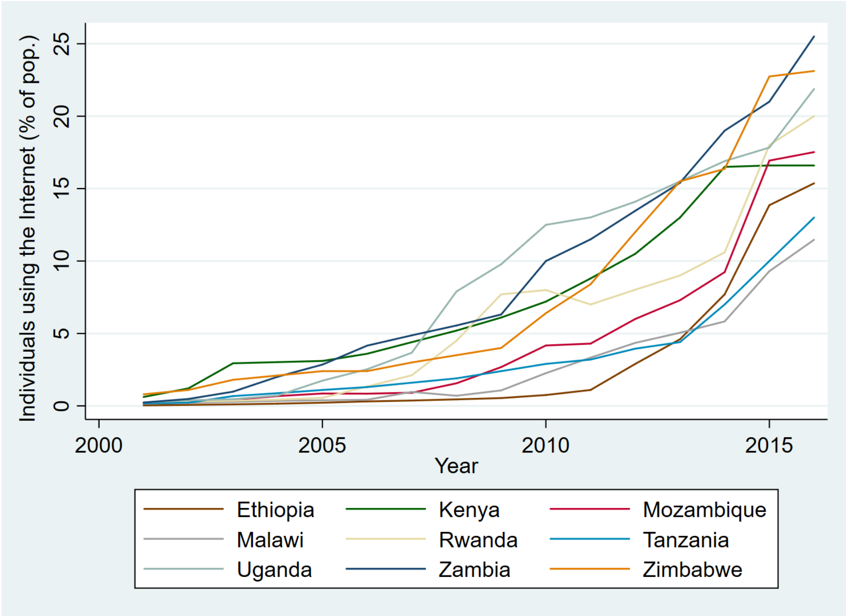
When analyzing data derived from the Internet in a developing country context, the underlying sample characteristics are, to a large extent, unknown. This is due to a general lack of comprehensive, disaggregated end-user and infrastructure statistics across Africa. This is even more evident in the case of Google data. No information on the sample characteristics is available, as Google generally does not publish information about its end-users and their search history due to privacy concerns. Nevertheless, the following is an attempt to approximate the sample characteristics of Internet data in the underlying nine countries, by investigating the spatial spread of certain infrastructure, on which Internet access, to some extent, depends and by extrapolating from market developments on other continents.

In the introduction of this dissertation, we discussed the digital divide between Africa and the rest of the world, showing that Internet user rates across Africa are comparatively low. Figure 3.1 shows the development of Internet user rates in the nine countries underlying this study. Internet user rates start to increase significantly between 2007 and 2010 and (more than) doubled in the nine countries between 2010 and 2016. As of 2016, Zambia ranks as the country with the highest Internet user rate (25%), followed by Zimbabwe and Uganda. In Rwanda, Mozambique, Kenya and Ethiopia between 15-20% of the population use the Internet, while Tanzania and Malawi rank at 10-15%.

Given Africa's extensive landmass, the provision of cable-dependent broadband Internet is not cost effective. This is why mobile data and smart-phone adoption play a significant role in accessing the Internet and much of the increase in Internet adoption rates has been driven by mobile Internet subscribers (GSMA, 2018). This is why we refrain from using the distribution of (optic fiber) cables as proxy location for Internet users. In that regard, electricity is a predominant feature necessary to access the Internet. People require a connection to an electricity grid, either to charge their mobile devices or to power their computer and modem. We hypothesize, that the availability of electricity correlates with population density. This correlation is visualized in Figure 3.2, where we plot the population density per km^2 in the nine African countries, as well as the available electricity grid[1]. The map underlines the previous hypothesis, indicating that electricity grids are more

1 Africa Electricity Grids Explorer (2017) states that the here shown electro-grids data is the most comprehensive and up-to-date public data set available for Africa. Nevertheless, the data is part of an ongoing mapping initiative and maybe, to some extent, outdated and should be used for illustration purposes only.

Figure 3.1: Internet User Rates in the 9 Study Countries.



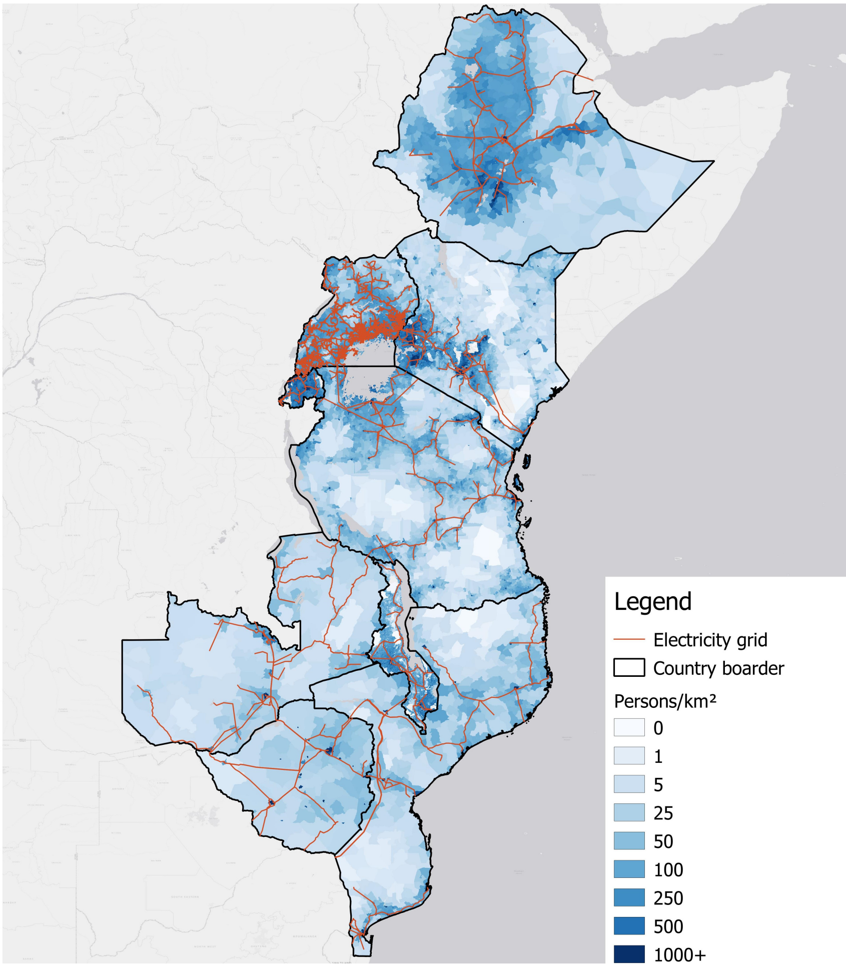
Note: Internet users refers to individuals that have used the Internet from any location and device in the last three months. Source: Own compilation based on data from The World Bank (2018).

prominent in urban areas and regions associated with higher population density. This indicates that data derived from the Internet is biased towards urban areas.

Apart from the basic infrastructure that is required to go online, also socio-economic aspects drive access to Internet. A digital divide is not only prominent across countries, but also within countries, as access to Internet depends on education, literacy and income levels, as well as age (Pew Research Center, 2018b; World Bank Group, 2016). For example, GSMA (2018) states that affordability of mobile services will be the major challenge in the upcoming years, with respect to increasing mobile broadband use. Across many African countries also a gender gap is still prominent, with men having more access to the Internet than women (Pew Research Center, 2018b; World Bank Group, 2016). Furthermore, Weidmann et al. (2016) highlight that ethnicity plays a role in infrastructure provision, showing that different ethnic groups are discriminated with regards to Internet provision. These factors lead us to conclude that our sample is biased towards urban areas and is driven, to some extent, by younger end-users with a higher education level, who are more likely to be male. We acknowledge that the sample is non-representative of the society at large.

We further hypothesize that the sample characteristics of Internet data are not constant over time. This study covers an eleven year time span from 2006 to 2017, a period that has been marked by significant growth in Internet user rates in the nine countries. This in turn has consequences for the sample composition. Even though Google standardizes its search-query data to remove any trend stemming from increasing Internet use, we hypothesize that the sample composition did

Figure 3.2: Population Density and Electricity Grids.



Source: Own cartography based on population data by Center for International Earth Science Information Network Columbia University (2017) and electro-grids data by Africa Electricity Grids Explorer (2017).

change over the study period. As Internet provision, mobile data and devices have become significantly cheaper over time (GSMA, 2018), the Internet has become more accessible to a wider range of people and, consequently, more inclusive. We assume that this has been particularly the case after the year 2010, the point from which Internet user rates started to increase significantly (see Figure 3.1).

After narrowing the sample characteristics further down to the average composition of the present sample, the question arises who is interested in information acquisition about food commodities. We hypothesize that these could be farmers, growing and selling their crops, traders, interested in buying and selling commodities, as well as financial institutions, insurers, governmental institutions, NGOs, international organizations, researchers and the interested public interested in monitoring the market. As some of these actors, *inter alia*, represent the supply and demand side of the market and as prices are a function of supply and demand, $P = f(S, D)$, we assume that GSQ data could have the potential to capture a contemporaneous price signal.

After having hypothesized about the sample characteristics of Internet data in a developing country context, we now continue to outline, why Google's search engine data can be considered a valid sample of the population with Internet access. Even though there is a lack of credible and accessible data on Google's share in the African search-engine market, we hypothesize that Google has a dominant role in Africa given the following aspects: Its search engine market share exceeds 90% in most European countries (The Economist, 2017); Google's global market share is 59% and its dominance is even larger in the mobile and tablet devices market, owning 90.8% (Bulut, 2018). Android-based smartphones and tablets, i.e. devices with an operating system developed by and based on Google, are dominant across Africa. GSMA (2018) reports that Samsung devices are still the leading player in the African device market. These devices are Android-based, which means that Google Chrome is the pre-installed browser and, hence, Google is the default search engine. Due to these aspects, we assume that Google's search engine data, to some extent, captures a representative sample of the population that uses the Internet. Hence, we do not assume that the presence of other search engines introduces further bias in our sample.

3.4 DATA

As data availability and quality is a major limitation across African countries, we use a data driven approach to select the countries for our analysis. We include all countries, in which maize plays an important role as staple crop in the country's food basket and a sufficient amount of data is available. This refers to monthly agricultural price data and GSQ data with a sufficient search volume. We include Ethiopia, Kenya, Malawi, Mozambique, Rwanda, Tanzania and Uganda, Zambia and Zimbabwe in our analysis. Due to data constraints regarding food prices, the time period for the analysis ranges from 01.2006 to 07.2017. GSQ data are generally available since 2004.

We use monthly staple food price data as provided by FAO GIEWS. The data availability of food prices varies across countries. We retrieve maize prices in nominal US Dollar/tonne at the respective capital markets (in the case of Tanzania, we download maize prices for Dara salaam). Due to many missing variables in the maize price series of Malawi and Zimbabwe, we retrieve maize prices for the two countries from the ZEF price data base. We use simple linear interpolation in case of missing observations.

We download monthly GSQ data from Google Trends, https://trends.google.com, as this matches the frequency of the maize price data.[2] Google Trends provides an index of search activity for a specified search word at a given location and point in time. The index is a measure of the relative popularity of one search term as a fraction over the total body of search volume, hence Google does not publish its

2 Generally, GSQ data is available at higher frequency but for short time series. This higher-frequency data could also be explored for forecasting

absolute search volume. GSQ data is further being transformed by two steps prior to publication: the index is normalized, meaning that it is divided by total search queries in a given location at a specific point in time. This normalization removes any trend from the data that could stem from growth in Internet users or changes in Google's popularity as search engine (Carrière-Swallow & Labbé, 2013). It is also standardized, as it is scaled from 1 to 100 and averaged to the nearest integer.

There are a variety of challenges and particularities associated with GSQ data, which have strong implications for the analysis and data sampling: Firstly, GSQ data is a relative index. When comparing two series to each other, one particularly popular series might push the more unpopular series towards zero. To overcome this issue, we download each series separately for each country, by restricting the geographical unit. When downloading the series separately, we lose the ability to compare the normalized series to each other, which leaves us with an analysis of growth rates across series.

Secondly, Google changes its data provision. At two points within the sampling period, Google implemented changes to the data, noting that on 01/01/2011 "an improvement to our geographical assignment was applied" and on 01/01/2016 "an improvement to our data collection system was applied" (Google, 2018). Google does not provide any further information on the adjustment procedure, hence, these changes in the data cannot be explicitly taken into account in the analysis.

Thirdly, Google Trends has an unreported privacy threshold. This means that the search index is only reported in case the search volume exceeds a specific threshold, which is based on absolute search volume and unknown to the public. If the threshold is not passed, the search volume is automatically reported as zero (Stephens-Davidowitz & Varian, 2014). The observance of zero values is problematic, as we do not observe a signal, where, theoretically, there should be one. The fact that search volume is only reported after passing an unknown threshold is particularly problematic in developing countries, where the search volume is generally lower, given that there are lower internet-adoption rates and, hence, less signal-producing users. When downloading the data for African countries, we observe a large occurrence of zero values. It is unknown whether Google has different privacy thresholds for different countries. This threshold is further the reason, why we choose country-level data for the analysis. Currently, Google Trends provides data at the sub-regional level for all analyzed countries, with Kenya being the only exemption. The sub-regional search volume, however, is still very low. Hence, we observe a very large amount of zero search volume or no search volume is reported at all. We follow Stephens-Davidowitz & Varian (2014) and download the data for a coarser geographic unit, i.e. at the country level.

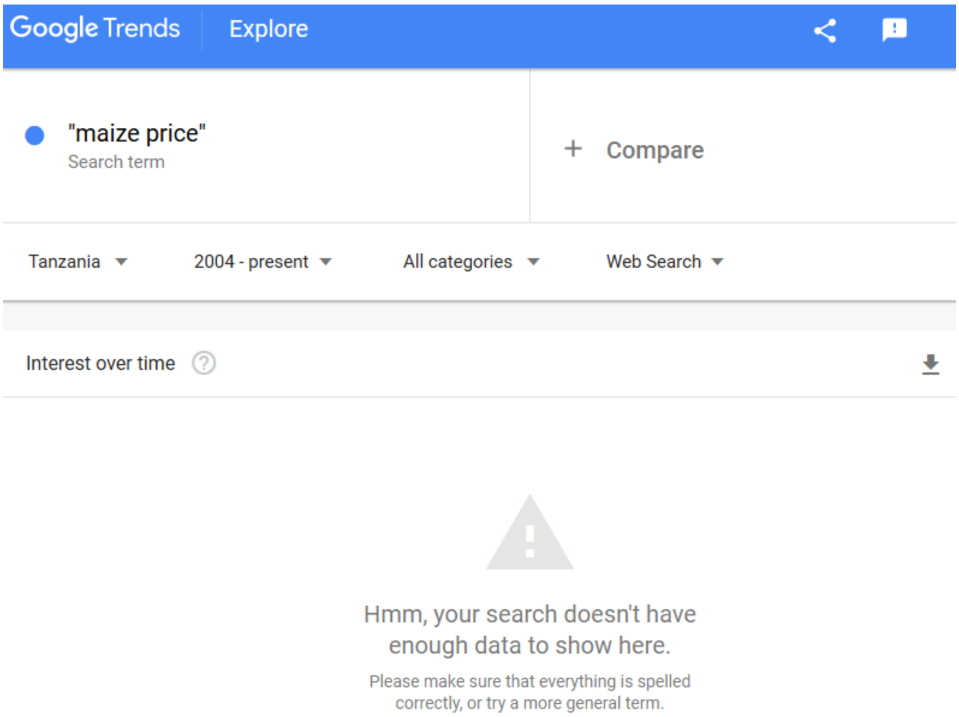
Fourthly, GSQ data is unstable over time. This means that downloading the same sample on different days yields a different time series of search volume. The data, however, remains stable within the same 24 hour period. This is due to Google drawing the single, requested sample from its absolute body of search volume, while Google seems to cache its data daily, this is why the same sample request remains the same over 24 hours (see Stephens-Davidowitz (2013), Seabold & Coppola (2015) and Carrière-Swallow & Labbé (2013). To deal with this instability of data over time, previous studies chose to draw samples of the same search query over a longer period of time in an attempt to approximate the “true” Google search volume. Carrière-Swallow & Labbé (2013), for example, downloaded GSQ data on 50 occasions, while Seabold & Coppola (2015) drew samples on 10 days within one month.

To choose potential search terms or predictors, Stephens-Davidowitz & Varian (2014), Scott & Varian (2013) and Lazer et al. (2014) highlight the importance of using variable selection techniques instead of simple judgment. This is to achieve a better model fit and to avoid so called "fat-regression" problems, i.e. models where the number of possible predictors exceeds the number of observations. These studies, however, use Google Trends in a non-developing country context and rely to a large extent on Google Correlate. Google Correlate is an online tool, where one can upload a given time series and will be provided a ranking of search-term series depending on the degree of correlation between the two series (Google, 2018). At the time of this study, Google Correlate is unavailable for the study countries. Hence, we proceed with simple judgment regarding the selection of Google search terms and choose the most parsimonious keyword, i.e. *maize*. This keyword was chosen *ex-ante* (1) due to the belief that it contains relevant information that will allow us to use it as a proxy for price developments and (2) due to Google's privacy threshold, which does not only have consequences for the choice of geographical unit, but also influences the choice of search terms. Any potential and more precise combination of words, like *“maize price”*, frequently pushes the search volume below its reporting threshold and, hence, defaults to not being reported. This scenario can be seen in Figure 3.3, which shows that the search volume for the term *“maize price”* in Tanzania does not exceed the privacy threshold and is, consequently, not reported.

Furthermore, this study deals with nine different countries, where different languages are being spoken. To choose the language of search terms for each country, we compare the search volume of the English keyword, to the search volume in the respective national language, for example Kiswahili in Kenya and Luganda in Uganda, with the aim to understand how Internet users interact with Google. The direct comparison of search terms needs to be performed within the Google Trends tool, as this is the only way to ensure the comparability of search volume across keywords at a given point in time and spatial unit. An exemplary illustration of this comparison of search terms in English (*maize*) and the official language (*kasooli*) for the case of Uganda can be found in Appendix B. We find that for all countries the volume of English keywords exceeds the volume of keywords in other official languages and, hence, proceed by using the English search term. By doing so, we follow other studies, like Almanzar & Torero (2017), who compare the Google News Feed in English to the local language and also opt for English search terms.

After delineating the search term and language choice, we now address the above discussed instability of GSQ data. To approximate the “true” GSQ value, we follow Seabold & Coppola (2015) and Carrière-Swallow & Labbé (2013) and draw samples of each data series of each country on 30 different days. We calculate the

Figure 3.3: Privacy Threshold and Search Term Choice in Tanzania.



Source: Screenshot taken from https://trends.google.com on Nov, 16th 2018.

"true" GSQ value as the mean of 30 samples, which we will continue to use in the analysis. Figure 3.4 illustrates the maximum and minimum GSQ value observed for the search word *maize* within the 30 samples, as well as the calculated mean GSQ value. For illustration purposes we show the data for Ethiopia, Kenya, Uganda and Tanzania.[3] We can see that the variation in the sample reduces significantly post 2011, which coincides with Google's "improvement of geographical assignment". We further see that we draw many samples with zero search volume. The incidents of zero search volume, however, could be reduced significantly by averaging over the samples and we observe few observations where the search volume is zero at mean, which is still the case particularly in earlier periods of the series. This reduction in zero observations leads us to assume that we are able to approximate the "true" signal by the repeated sampling of GSQ data.

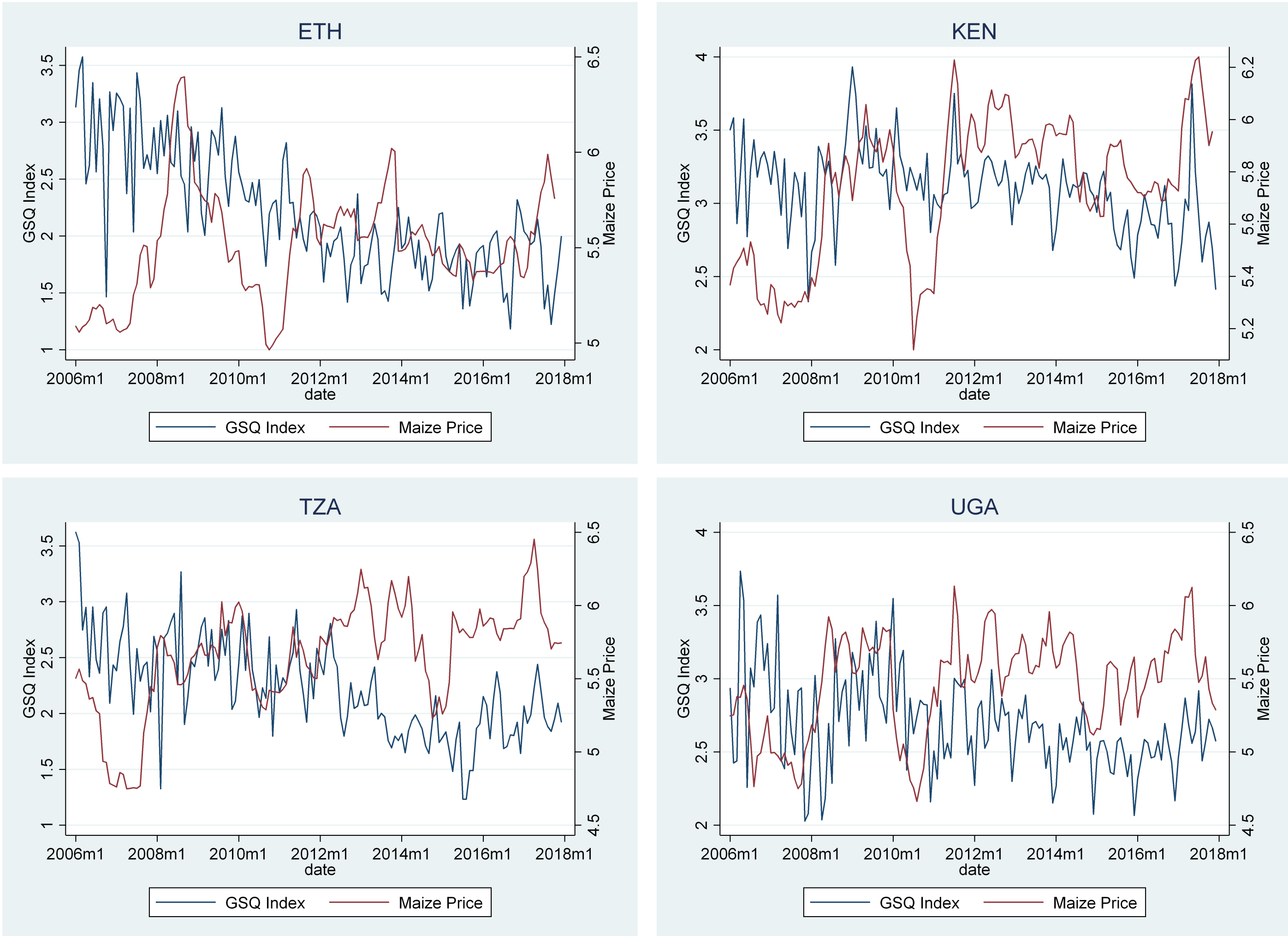
In Figure 3.5, we plot the development of the mean GSQ value of the keyword *maize* as well as maize prices in the same countries. We observe that the GSQ data is generally more volatile than the maize price series. In all countries, an increase in maize price around the food price crises of 2007/08 and 2011/12 is visible. We further note that spikes in GSQ data coincide with spikes in maize price data, which is particularly visible the case in Kenya around 2010, 2012 and 2018.

3 Figures for the remaining five countries can be found in Appendix B.

Figure 3.4: Sampling Noise of GSQ Data for the Search Term *maize* in Ethiopia, Kenya, Tanzania and Uganda.

Source: Own compilation based on data extracted from https://trends.google.com, sampled over a period of 30 days in December 2017.

Figure 3.5: GSQ Data for the Search Term *maize* and Maize Prices in Ethiopia, Kenya, Tanzania and Uganda.



Source: Own compilation based on data extracted from https://trends.google.com and FAO GIEWS.

3.5 METHODS

To test whether GSQ data can contribute to the now-casting of maize prices in selected African countries, we pursue a two-tiered estimation strategy. We start with the in-sample estimation of a benchmark and a competing, GSQ-augmented model for each country. We subsequently continue with the evaluation of the two competing models in a pseudo out-of-sample forecasting environment to test the now-casting performance of the two specifications based on their out-of-sample forecasting errors.

Before the estimation, we inspect the respective data series with regards to their time series properties. After replacing missing values in the price series by simple linear interpolation and logarithmizing both price and GSQ data, we assess the order of integration of each series using Philips-Perron unit root tests (Philips-Perron test statistics are reported in Appendix B, Table B.1). In the case of Kenya and Zimbabwe, the respective series are non-stationary and we proceed with first differences, given as $\Delta Y_t = Y_t - Y_{t-1}$, where ΔY_t is the change of Y between periods t and $t-1$.

3.5.1 *In-Sample Estimation*

To analyze whether GSQ data improves the now-casting accuracy of maize prices, we follow Choi & Varian (2012) and Carrière-Swallow & Labbé (2013) and formulate a benchmark model and two competing, GSQ-augmented models. The objective of this study is to forecast the present. Assessing the in-sample fit of models is not sufficient to draw conclusions about a model's forecasting ability, due to issues of over-fitting and data mining, as well as the potentially large differences in model fit of in-sample prediction and out-of-sample forecast (Stock & Watson, 2015). This is why we use this in-sample estimation solely (1) to understand the relationship between maize prices and GSQ data and (2) to show that the benchmark model is an appropriate specification, given that a causal interpretation is irrelevant for forecasting, as the focus is on a predictor's ability to improve a model's forecasting capacity and not on causality (Stock & Watson, 2015).

As benchmark, we fit simple, linear auto-regressive (AR) models to the maize price series y in each country i. We determine the optimal number of lags of the dependent variable y_i based on the Schwarz-Bayesian information criterion (SBIC) (test statistics are reported in Table B.2). As both series exhibit a degree of seasonality, we control for the presence of deterministic seasonality by including monthly dummy variables. As benchmark, we estimate

$$y_{i,t} = \alpha_{a_i} + \sum_{k=1}^{p} \beta_{a_{i,k}} y_{i,t-k} + \sum_{j=1}^{s-1} \gamma_{a_{i,j}} D_{j,t} + \epsilon_{a_{i,t}} \tag{3.1}$$

where $y_{i,t}$ is the maize prices in country i and time t, $t-k$ is the optimal number of lags of the dependent variable of country i based on the SBIC, $D_{j,t}$ is the seasonal dummy variable with $s = 12$ and $\epsilon_{a_{i,t}}$ the white noise error term.

We augment this model by adding the contemporaneous GSQ value. We estimate the following GSQ-augmented model, GSQ(1), for each country i

$$y_{i,t} = \alpha_{b_i} + \sum_{k=1}^{p} \beta_{b_{i,k}} y_{i,t-k} + \sum_{j=1}^{s-1} \gamma_{b_{i,j}} D_{j,t} + \delta_{b_i} GSQ_{i,t} + \epsilon_{b_{i,t}} \tag{3.2}$$

where $y_{i,t}$ is the maize prices in country i and time t, $GSQ_{i,t}$ is the Google keyword *maize* in country i and time t; $t-k$ is the optimal number of lags of the dependent variable of country i based on the SBIC and $\epsilon_{b_{i,t}}$ the white noise error term.

Moreover, we hypothesize that the value of GSQ_t depends on the state of maize prices. To further dis-entangle the relationship between maize price developments and GSQ data, we estimate a second GSQ-augmented model, GSQ(2), in which we interact GSQ_t with a dummy variable for maize price change:

$$y_{i,t} = \alpha_{c_i} + \sum_{k=1}^{p} \beta_{c_{i,k}} y_{i,t-k} + \sum_{j=1}^{s-1} \gamma_{c_{i,j}} D_{j,t} + \delta_{c_i} GSQ_{i,t} + \zeta_i GSQ_{i,t} \, x \, Z_{\Delta Y_i} + \epsilon_{c_{i,t}} \tag{3.3}$$

where $y_{i,t}$ is the maize prices in country i and time t, $GSQ_{i,t}$ is the the Google keyword *maize* in country i and time t; $t-k$ is the optimal number of lags of the dependent variable of country i based on the SBIC, $GSQ_{i,t} \, x \, Z_{\Delta Y_i}$, is the interaction term based on the current GSQ value and the dummy variable Z, with $Z = 1$ if $\Delta Y_i > 0$ and $Z = 0$ if $\Delta Y_i < 0$ and $\epsilon_{c_{i,t}}$ the white noise error term.

3.5.2 *Out-Of-Sample Now-Casting*

After assessing the in-sample properties, we continue with the evaluation of the out-of-sample forecasting performance of the competing models. The objective is to understand whether contemporaneous GSQ data contains information that improves the now-casting accuracy of regular, auto-regressive maize price models. The forecasting accuracy of different models is tested in a pseudo out-of-sample context by restricting the number of observations and re-estimating the model for the remaining time periods.

We follow Carrière-Swallow & Labbé (2013) and Seabold & Coppola (2015) and estimate a linear, static, one-step-ahead model that is based on a recursive window scheme. We choose a static model and a recursive estimation scheme, as we anticipate this to be the scenario decision makers would engage in. The recursive window implies that the actual observation is added for each estimation period.

It hence is similar to a scenario in which decision makers would add variables to their model once they become available.

We restrict the full sample to training and pseudo-out-of-sample sections, to test the forecasting accuracy against observed values. Under the recursive scheme, we begin by estimating the models over the first S periods of time. These estimates are then used to formulate the first out-of-sample now-cast for period $S+1$. We then re-estimate the model for each time period by extending the estimation window forward until the end date $t \in (S+1, ..., T+1)$, where $T+1$ is the last period in the full sample. We choose the window size S to be 36, corresponding to a time frame from January 2006 to December 2008. Hence, the forecast starts at 12.2008, which leaves us with 108 forecasted values to assess the forecasting accuracy of the competing models.

We subsequently evaluate the out-of-sample forecasting performance of the two specifications by calculating the Mean Squared Forecast Error (MSE). Following Stock & Watson (2015), the one-step-ahead forecast error of each model i and is given by

$$\hat{e}_{i,t+1} = y_{i,t+1} - \hat{y}_{i,t+1|T} \tag{3.4}$$

where $y_{i,t+1}$ the observed value in country i and $\hat{y}_{i,t+1|T}$ the forecast of model i, estimated using observed data through time T. The MSE of country i and follows as

$$MSE_i = \frac{1}{N_T} \sum_{t=1}^{N_T} (\hat{y}_{i,t} - y_{i,t})^2 \tag{3.5}$$

where N_T is the total number of observed time periods in the out-of-sample window. The model associated with the smaller MSE beats the competing model.

3.6 RESULTS

3.6.1 *Results: In-Sample Estimation.*

The results of the in-sample estimation are reported in Tables 3.1, 3.2 and 3.3, where we show the results of the benchmark estimation (Eq. 3.1) and the two GSQ specifications (Eq. 3.2 and Eq. 3.3). Based on the SBIC, we estimate a parsimonious AR(1) for seven out of nine countries, while we estimate AR(2) specifications in the case of Ethiopia and Zimbabwe. When considering the R^2, the parsimonious AR specifications prove to be a good fit in the majority of countries (0.99). This is, as expected, due to the highly auto-regressive nature of price series. We achieve the lowest fit for Kenya and Zimbabwe.

When considering the first GSQ-augmented model, GSQ(1), in Table 3.2, we find the contemporaneous GSQ-value, GSQ_t, to be significant in four of the analyzed countries. These are Rwanda, Uganda, Zambia and Zimbabwe. We can reject the null that the coefficient of GSQ_t is equal to zero at the 5% significance level in the case of Zambia and at the 10% level for Rwanda, Uganda and Zimbabwe. The estimated coefficients are negative for Rwanda, Uganda and Zambia, indicating that an increase in maize prices in associated with a decrease in search volume of the term *maize*. When further disaggregating the effect of GSQ_t in a second GSQ-augmented model, GSQ(2), Table 3.3, we find the interaction term, interacting GSQ_t and with a dummy for positive price change, to be positive and significant at the 1% level in the 9 countries. These results indicate a positive relationship between maize prices and search volume, when allowing for a different slope in case of a positive price change from period $t-1$ to t. However, in the case of Rwanda, Uganda and Zambia, for which we found a negative effect of GSQ_t in GSQ(1), the positive and negative coefficients are close to offsetting each other. This implies that a reduction in GSQ_t is associated with decreasing prices, but an increase in GSQ_t is not associated with higher maize prices.[4]

4 We also investigated the possibility of a non-linear relationship between GSQ data and maize prices. Results did not indicate a non-linear relationship between the two variables.

Table 3.1: In-Sample Estimation, Benchmark Model.

Variables	ETH	KEN	MOZ	MWI	RWA	TZA	UGA	ZMB	ZWE
Maize Price (y_{t-1})	1.176***	0.155*	0.896***	0.910***	0.911***	0.937***	0.900***	0.940***	-0.350***
	(0.0913)	(0.0919)	(0.0490)	(0.0299)	(0.0368)	(0.0313)	(0.0372)	(0.0341)	(0.121)
Maize Price (y_{t-2})	-0.241***								-0.304**
	(0.0885)								(0.144)
Seasonal Dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	140	141	143	143	143	143	143	143	134
R^2	0.9998	0.1574	0.9997	0.9905	0.9997	0.9995	0.9993	0.9999	0.2122

Note: Kenya and Zimbabwe are estimated using first differences of maize prices. Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Seasonal dummy variables omitted for brevity. Source: Own estimation.

Table 3.2: In-Sample Estimation, GSQ-Augmented Model (1).

Variables	ETH	KEN	MOZ	MWI	RWA	TZA	UGA	ZMB	ZWE
Maize Price (y_{t-1})	1.176***	0.153*	0.904***	0.912***	0.901***	0.919***	0.900***	0.948***	-0.376***
	(0.0915)	(0.0913)	(0.0559)	(0.0292)	(0.0405)	(0.0348)	(0.0371)	(0.0333)	(0.115)
Maize Price (y_{t-2})	-0.240***								-0.289**
	(0.0892)								(0.133)
GSQ_t	0.00168	0.0241	-0.00501	0.0111	-0.0366*	-0.0447	-0.0736*	-0.0280**	0.161*
	(0.0126)	(0.0276)	(0.0100)	(0.0160)	(0.0214)	(0.0363)	(0.0406)	(0.0113)	(0.0891)
Seasonal Dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	140	141	134	142	134	143	143	143	134
R^2	0.9998	0.1615	0.9997	0.9909	0.9998	0.9995	0.9994	0.9999	0.2649

Note: Kenya and Zimbabwe estimated using first differences. Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Seasonal dummy variables omitted for brevity. Source: Own estimation.

Table 3.3: In-Sample Estimation, GSQ-Augmented Model (2).

Variables	ETH	KEN	MOZ	MWI	RWA	TZA	UGA	ZMB	ZWE
Maize Price (y_{t-1})	1.086***	0.0654	0.931***	0.937***	0.959***	0.946***	0.941***	0.938***	-0.359***
	(0.0628)	(0.0509)	(0.0526)	(0.0232)	(0.0283)	(0.0255)	(0.0267)	(0.0247)	(0.0766)
Maize Price (y_{t-2})	-0.108*								-0.259***
	(0.0602)								(0.0976)
GSQ_t	-0.0375***	-0.00543	-0.0329***	-0.0110	-0.0691***	-0.0468	-0.0850***	-0.0434***	0.0640
	(0.0112)	(0.0166)	(0.0106)	(0.0135)	(0.0179)	(0.0289)	(0.0317)	(0.00986)	(0.0722)
GSQ_t x $Z_{\Delta Y}$	0.0527***	0.0418***	0.0805***	0.0729***	0.0691***	0.0807***	0.0798***	0.0417***	0.138***
	(0.00553)	(0.00341)	(0.0125)	(0.00889)	(0.00713)	(0.00773)	(0.00744)	(0.00389)	(0.0233)
Seasonal Dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	140	141	134	142	134	143	143	143	134
R^2	0.9499	0.6003	0.8352	0.8842	0.9211	0.9424	0.9105	0.9482	0.5348

Note: Kenya and Zimbabwe estimated using first differences. Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Seasonal dummy variables omitted for brevity. Source: Own estimation.

3.6.2 *Results: Out-Of-Sample Estimation*

We continue with the evaluation of the now-casting performance of the competing models. In Table 3.4, we report the MSE of the one-step-ahead out-of-sample now-cast of the benchmark and the two GSQ-augmented models. We observe that the MSE of the benchmark specification is relatively low, indicating that past price observations are a good basis to forecast maize prices and that the estimated AR models perform well also in out-of-sample forecasts.

When comparing the MSE of the benchmark with the first GSQ-augmented model, we achieve a reduction in MSE in 7 out of 9 countries. We obtain the largest improvement of MSE in the case of Zambia and Tanzania, with an improvement in forecasting fit by 14.95% and 14.23% respectively. This is followed by Uganda, Rwanda, Kenya and Mozambique, where improvements range between 3% and 8%. Also the forecast for Malawi could be improved, if marginally, by 0.82%. In the case of Ethiopia and Zimbabwe, the GSQ-specification yields larger errors and, hence, a reduction in forecasting fit. Particularly in the case of Zimbabwe, we observe a large increase in MSE. In summary, the first GSQ specification, GSQ(1), beats the benchmark model at mean in 7 out of 9 countries and including contemporary GSQ data improves the fit of maize price now-casts.

When comparing the forecasting errors of the second GSQ-augmented model to the benchmark model, we find an improved forecast fit in 4 out of 9 countries. These are Malawi, Kenya, Tanzania and Ethiopia, with a reduction in MSE by 23.41%, 17%, 5.29% and 3.62% respectively. For Malawi, Kenya and Ethiopia, the second GSQ specification also provides the smaller MSE when compared to the first GSQ specification, which is not the case for Tanzania, where the first GSQ specification yields better now-casts. Overall, the first GSQ-augmented model achieves an improved now-cast in more countries, when compared to the second GSQ specification. This might be due to the fact that interaction terms tend to be variations of already included information in the forecasting model and hence lead to imprecision in an out-of-sample, forecasting setting (Lindh, 2011). Still, in the case of Ethiopia, Kenya and Malawi, GSQ(2) provides the better forecast fit. When considering both GSQ specifications, we achieve an improvement in forecasting fit in 8 of 9 countries. Hence, by including contemporaneous search engine metadata, we improve the now-casting capacity of simple AR models that are based on past price realizations. The only exemption is Zimbabwe, where the benchmark model beats both GSQ-augmented models.

Figure 3.6 shows the results of the one-step-ahead out-of-sample forecast for Ethiopia, Tanzania and Uganda, for which we find the GSQ-augmented models to beat the benchmark model at mean (see Figure B.6 for the remaining figures). We can see that forecasted values of the benchmark and GSQ-augmented model follow the actual maize price movements, illustrating the low MSE of the competing models. Following Choi & Varian (2012), we display the forecast error over time and show in which instances the GSQ-augmented model beats the benchmark model (grey shading). The aim is to understand whether there are certain time periods in which the GSQ-specification provides the better forecast fit. In Zambia

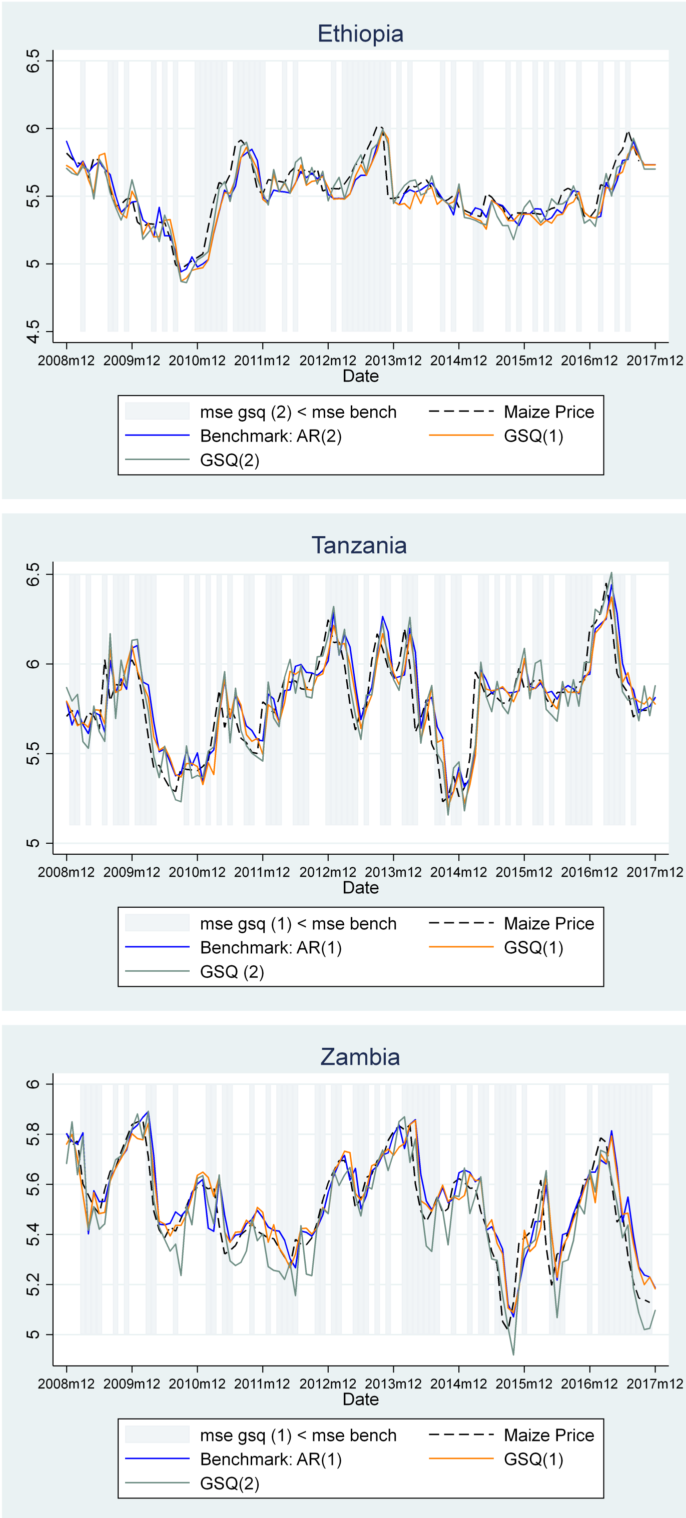
Table 3.4: MSE of One-Step-Ahead Forecast, Out-of-Sample Estimation.

				Change (%)	
	Benchmark	GSQ (1)	GSQ (2)	BM vs GSQ (1)	BM vs GSQ (2)
ETH	0.0118009	0.0133103	0.0113734	12.79	-3.62
KEN	0.0118079	0.0112409	0.0098007	-4.80	-17.00
MOZ	0.0159205	0.0154354	0.0160858	-3.05	1.04
MWI	0.0343752	0.0340937	0.0263279	-0.82	-23.41
RWA	0.0122697	0.0114407	0.0148660	-6.76	21.16
TZA	0.0226334	0.0194128	0.0214364	-14.23	-5.29
UGA	0.0323994	0.0299403	0.0413469	-7.59	27.62
ZMB	0.0097904	0.0083270	0.0103709	-14.95	5.93
ZWE	0.0662437	0.1194399	0.1362193	80.30	105.63

Note: BM=Benchmark. Source: Own estimation.

the GSQ(1) provides the better now-cast of the increase and decline of maize prices in late 2013 and it provides a better forecast fit for the year 2017. In the case of Tanzania, we observe a cluster of smaller now-casting errors during the maize price increase and decrease around 2009, 2012 and 2016/2017. In Ethiopia, GSQ(2) seems to identify price increases and peaks better in the period from 2010 to 2012 as well as in 2013. While the second GSQ model seems to be a good specification in the case of Ethiopia, it overshoots price spikes and fails to identify price developments in the forecasts for Tanzania and Zambia, which can also be observed in the remaining countries, where the first GSQ model provides better forecasts. This corroborates the point that the interaction term introduces inaccuracies in the majority of now-casts. From visual inspection, the GSQ-augmented models seem to, *inter alia*, outperform the benchmark models around peaks and turning points. It would be of interest to explore this relationship further in the future, in particular in light of the special interest of the development community to predict those peaks and turning points.

Figure 3.6: Benchmark vs. GSQ-Augmented Out-Of-Sample Forecasts for Ethiopia, Tanzania and Zambia.



Note: In-sample training period (01.2006 - 12.2018) not displayed. Source: Own estimation.

3.6.3 *Discussion*

In the in-sample scenario, we find the inclusion of the GSQ keyword *maize* into simple AR models for maize prices to be significant in four of nine countries in the analyzed panel. These countries are Rwanda, Uganda, Zambia and Zimbabwe. Unexpectedly, we find this relationship to be negative, i.e. an increase in maize prices is associated with a decrease in search volume. When we further dis-entangle the relationship between maize price developments and GSQ values by inter-acting GSQ_t with a dummy indicating a positive change in maize prices, hence, allowing for a different slope in the event of a positive price change, we find a significant and positive relationship between maize prices and GSQ values in all countries. Thus, in the majority of countries, an increase in maize prices is associated with an increase in search volume of the term *maize*.

When tested in an pseudo-out-of-sample, one-step-ahead forecasting environment, our results indicate that the GSQ-augmented models beat the benchmark model in 8 out of 9 analyzed countries. By including contemporaneous search engine data into now-casting models, we achieve a substantial improvement in forecasting fit that ranges between 3% and 23%. We achieve the largest reduction of now-casting error for Malawi, Ethiopia, Kenya, Zambia and Tanzania. Our results indicate that online signals in form of search engine meta data contain information that helps to identify maize price developments, also in environments with low Internet-adoption rates. Hence, it would be of interest to further analyze this relationship and how online signals could be systematically harnessed and integrated in forecasting and early warning models.

Zimbabwe is the only country for which the benchmark model beats both GSQ specifications. This is an unexpected finding, given that Zimbabwe has one of the highest Internet-user rates in the country panel, and, presumably, a relatively strong online signal. Also Seabold & Coppola (2015), who were partially able to improve now-casts of food prices in Costa Rica, El Salvador and Honduras by including GSQ data, hypothesize about potential reasons for difficulties in forecasting. They hypothesize that the complication in now-casting of food prices is likely due to the occurrence of the global food price crisis in the years 2007/08. Also in our case, the food price crisis coincides with our in-sample training period, which runs from 2006 to 2008. In the case if Zimbabwe, the nature of the underlying maize price series could drive this difficulty in forecasting, since it exhibits a strong degree of price volatility prior to 2010 and hence during our in-sample training period, followed by little to no variation in the years 2010-14 (see Figure B.5). During the sample period, Zimbabwe experienced multiple periods of hyperinflation, which might contribute to difficulties in taking up price signals with GSQ series.

Lastly, and not limited to the case of Zimbabwe, doubt about the quality of the maize price data may well be justified. In this case, GSQ data might reflect the current food security situation, while the price data does not (e.g. in the case of political influence on price series). It is unclear, to what extent price data might be affected by quality issues. Furthermore, it should be taken into consideration that the quality of price data might have changed throughout the analyzed time period

(2006-2018). For example, Ethiopia introduced its agricultural commodity exchange in April 2008. This contributed to making markets more efficient and transparent and, hence, is associated with an improvement in the quality of price data (Rashid et al., 2010). Generally, it should be considered that the model can only perform as good as the underlying maize price series.

As part of this empirical exercise, our study identifies various challenges that arise when working with GSQ data in a environment with low Internet-adoption rates: Google's opaque data sampling characteristics, data instability, the relative nature of the index, and Google's manipulations of data sampling techniques without providing details, is particularly problematic. Furthermore, the unknown privacy threshold complicates analyses in environments with low Internet-adoption rates, as the signal is frequently too low to pass the reporting threshold and consequently pushes researchers to adopt coarser geographical units, data frequencies and broader search terms. Hence, valuable signal is lost. This experience might help to inform other researchers and practitioners, interested in similar research questions and contexts.

Nevertheless, the exploratory nature of our study and our study being, to our knowledge, the first attempt at using GSQ data in an African context, gives reason to further investigate the potential of GSQ data as signal for (food) price developments across Africa and other environments with low Internet-user rates. With its search engine data, Google provides a stable, cost-effective source of online signal that proofed itself to be of interest for future research. Furthermore, the continuous increase in Internet-user rates across Africa will contribute to a more robust online signal in the upcoming years, which would mitigate some of the challenges that currently arise when working with GSQ data.

3.7 CONCLUSION

This study focuses on exploring the link between search engine data and food prices and analyzes the potential of search engine meta data for food price monitoring in an African context. More precisely, this analysis evaluates whether GSQ data can improve now-casting models of maize prices in nine African countries, namely Ethiopia, Kenya, Mozambique, Malawi, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe.

Our study finds the inclusion of the GSQ keyword *maize* into simple AR models for maize prices in an in-sample scenario to be significant in four of the analyzed panel of nine countries. These are Rwanda, Uganda, Zambia and Zimbabwe. Furthermore, a specification in which we include GSQ data as interaction term with a price change dummy, shows a significant and positive relationship, i.e. an increase in maize prices is associated with an increase of the search term *maize*, in all nine countries.

In an pseudo-out-of-sample, one-step-ahead forecasting environment, we find the GSQ-augmented models to beat the benchmark AR model in 8 of the 9 countries included in this study. Zimbabwe is the only country, for which forecasts could not be improved. By including the GSQ data, we reduce the now-casting error of maize prices between 3% and 23% and achieve the largest improvement of maize price now-casts for Malawi, Kenya, Zambia and Tanzania with improvements larger than 14%. Our results indicate that including contemporaneous search engine data can improve the now-casting capacity of maize price models, which are solely based on past price observations.

The exploratory nature of our study gives reason to further investigate the potential of GSQ data as signal for prices developments. Future research should explore ways for the systematic harnessing and integration of online signals for forecasting and early warning models; the options of using higher frequency data, as GSQ data is potentially available at weekly frequency; more sophisticated variable selection techniques and models, like mixed frequency times series models; as well as the construction of a search-query index that includes English and non-English search words and multiple crops.

4

CITIZEN SCIENCE FOR NEAR REAL-TIME FOOD SECURITY MONITORING IN KENYA

4.1 INTRODUCTION

Chapter 2 of this dissertation shows that the at-risk population has not been sufficiently integrated into monitoring efforts so far. Advances in information and communication technology, in particular increasing mobile- and smartphone ownership across developing countries (GSMA, 2018), have paved the way for the inclusion of the population itself into monitoring processes. In that context, participatory citizen-science approaches, i.e. approaches drawing *inter alia* on observations from the local population itself, have gained considerable interest, as they are associated with many advantages.[1] For instance, the food security status of a community can be accessed via a local's daily routine, when purchasing food from the market, when harvesting or when fetching prices for livestock and crops, allowing for instantaneous data collection. Tapping into this information stream could provide valuable near real-time and spatially disaggregated signals for situation monitoring, ultimately equipping the population at-risk with a direct communication channel to monitoring systems. Timely and disaggregated information can contribute to indicating crises at an early stage of development, to triggering early intervention before crises become emergencies and *vice versa* to identifying decreasing risk levels. Hence, particularly humanitarian agencies, NGOs and government institutions have an interest in this kind of information. Across many developing countries, local, high-frequency information is still missing (Kalkuhl et al., 2016; Mock et al., 2016, 2013) and traditional surveys take multiple months to complete, hence, inhibiting the continuous monitoring of an evolving situation (Enenkel et al., 2015). A participatory citizen-science approach has the potential to yield local, high frequency information for situation monitoring, to provide rich, complementary information for early warning and to contribute to bridging current data gaps.

Furthermore, having a direct communication channel to the at-risk population could contribute to insulating data collection initiatives against crises and potential break downs, as information flows without the need of a third party and movement of people. Particularly those countries, where high security risks prevail and access by third parties is limited, could benefit from a direct channel (Bauer et al.,

1 For an elaborate discussion on the terminology of citizen science, see Eitzel et al. (2017).

2015). Additionally, providing a communication channel to the population at-risk contributes to the democratization of science, as affected individuals are provided both a platform and voice that allows for their perspective to be heard.

The objective of this chapter is to understand whether a participatory citizen-science approach, which draws on local knowledge holders, can be used as a complementary, valid data source for continuous food security monitoring. To answer this objective, we implemented an 8 month pilot study in four Kenyan counties (Kajiado, Makueni, Kitui and Tana River), in which we collected information on the local food security situation from selected local knowledge holders based on a pre-defined questionnaire. As a communication channel, we implemented a SMS system with which we sent push-SMS every two weeks and through which participants could directly communicate with us, free of charge. This chapter focuses on analyzing the validity of the gathered SMS data, by evaluating it against existing and established data and indicators. In our assessment of the SMS data, we focus on answering the following research question:

> Research Question: Is the data provided by local participants a valid data source for food security monitoring?

The remainder of this chapter is organized as follows: Firstly, we provide an overview over the literature that explores the use of mobile phones for data collection in developing countries. Subsequently, we describe the study area, which is followed by a detailed description of the study set-up. Thereafter, we describe the methodology and provide results. Lastly, we discuss the results, provide a section with lessons learned and summarize our main findings.

4.2 Literature review

The following initiatives have started to explore the option of integrating the local population via phones into data collection initiatives in developing countries.[2] In general, there are four ways through which mobile phones can be used to collect information: via SMS (short message service), interactive voice response (IVR), unstructured supplementary service data (USSD) and computer-assisted telephone interviewing (CATI) and telephone interviews.

Ballivian et al. (2015) and Croke et al. (2014) outline the general usability of mobile phones to conduct representative household surveys and gather high-frequency panel data in developing countries. While Ballivian et al. (2015) employ IVR, SMS and CATI to gather household data in Honduras and Peru, Croke et al. (2014) collect household surveys in Tanzania and South Sudan via CATI. Both studies focus on gathering a broad range of data, with the objective to evaluate feasibility, non-response, attrition and cost-effectiveness. For example, Ballivian et al. (2015) indicate costs of 8 US$ per SMS interview, compared to 40 US$ per interview in a classical face-to-face (F2F) interview setting. Both studies find that mobile phones can be a cost-effective, complementary survey mode compared to F2F surveys.

2 This overview does not include studies that use mobile phones to disseminate information e.g. market information or weather forecasts.

WFP's mobile Vulnerability and Mapping (WFP mVAM) unit is one of the leading initiatives that uses mobile phones to collect information on internally displaced people living in refugee camps, people living in conflict zones and in chronically vulnerable and hard-to-access regions. Information is usually gathered via SMS and IVR and comprises, e.g. food consumption scores, dietary diversity scores and market prices. In that regard, Bauer et al. (2015) discuss mVAM's data in the context of the Ebola crisis in West Africa in 2013. The data collected shows, beneath other things, that the food security status during the Ebola crisis was negatively affected by low wages and, hence, indicating a lack of access to food. Furthermore, Morrow et al. (2016) give an overview over different mVAM pilots and assesses the usability of high-frequency information for decision making. The study concludes that high frequency data has been used in different cases for decision making and has the potential to further inform operational decisions, while better training is required to make full use of the data. From a limitations perspective, mVAM report the lack of functioning mobile networks (given that cellphone towers are particularly at risk in conflict zones) and, to some extent, the under-reporting of actual food consumption by respondents.

In cooperation with mVAM, Lamanna et al. (2019) use CATI and traditional F2F surveys to collect nutrition data (Minimum Dietary Diversity for Women, Minimum Acceptable Diets for Infants and Young Children) in two Kenyan counties (Baringo and Kitui), with the objective to evaluate the accuracy and bias of data gathered using CATI versus F2F. To do so, the sample is split into different data gathering modes, which samples and re-samples the different modes over a period of nine days. The findings show *inter alia* that nutrition scores of children are significantly higher when collected via CATI, compared to F2F surveys, while the different data collection modes have no significant effect in nutrition scores observed for women.

Also Dillon (2012) investigates the possibility of collecting a panel data set in rural Tanzania based on interviews via mobile phones, to analyze cotton farmers' expectations regarding e.g. agricultural production. For this purpose, mobile phones were provided for participants. While the a panel data set could be completed successfully and at comparatively low costs (6.98 US$ per interview), the author highlights among the limitations the charging of phones, network access and replacement of materials

Enenkel et al. (2015) explore the potential of using smartphones to collect food security information in a sub-prefecture of the Central African Republic. In cooperation with Médicins Sans Frontièrs (MSF), they developed an app with which MSF associated community health workers collect food security information from the local population, after receiving a one day training. The survey covers *inter alia* the household food consumption, existence of edema and coping mechanisms. The data was evaluated against rainfall, precipitation and soil moisture indices. They find that food insecurity (on average, households consumed 0.9 meals per day, while children below five where still not showings signs of under-nutrition) was related to violent conflict and not driven by climate shocks.

Furthermore, multiple initiatives have started to crowdsource information in on-demand platforms, for example, in the case of sudden-onset disasters. A prominent example in that regard is the Ushaidi network, which provides a platform to gather geo-coded citizen reports on selected topics, via e-mail, SMS and Twitter. The information is subsequently mapped. Ushaidi was developed in the aftermath of the Kenyan electoral violence in 2007/08 and subsequent media ban, to collect citizen reports on events and to bridge the government induced lack of information (Okolloh, 2009). Also Meier (2015) describes how he used Ushaidi to develop a crisis map after the 2010 earthquake in Haiti to compile a near real-time map of the hardest hit areas, which enabled first respondents and humanitarian actors to coordinate their emergency efforts.

Contrary to the majority of studies discussed above, the objective of our study is twofold: (1) to engage representatives of the at-risk population in a direct classification of their communities' food security situation and (2) to continuously monitor the food security situation over a longer time period and information being provided by the same individuals, i.e. to collect a panel data set. The approach that is closest to our study is that of WFP's mVAM initiative, which uses mobile phone surveys in the context of humanitarian action and which similarly aims to continuously monitor the situation on the ground. While mVAM focuses on collecting food consumption scores and coping strategy indices, this study aims to collect *inter alia* a direct classification of their communities' food security situation from the at-risk population. Generally, few panel studies using mobile phones have been gathered in humanitarian contexts (Mock et al., 2016). Also mVAM's success rate to compile panel surveys varies across countries: While mVAM was able to follow the same individuals over time in a setting with live voice interviews in a refugee camp in the Democratic Republic of Congo, mVAM experienced high attrition rates (50-70%) in its panel surveys using SMS in Ebola affected countries (Mock et al., 2016; Morrow et al., 2016). This underlines the need to further understand the possibilities for continuous situation monitoring.

4.3 PILOT STUDY: AREA AND DESIGN

4.3.1 *Study Area*

Kenya is a country in East Africa, bordering Tanzania, Uganda, South Sudan, Ethiopia and Somalia. It has been selected as pilot country for this study due to its advanced technical infrastructure and high mobile phone adoption rates, while exhibiting a continuous risk to food insecurity at the same time. In 2016, 81% of the Kenyan population had a mobile cellular subscription (WB 2018), while between 5% and 20% of Kenya's population, that is 2.5 to 4.9 million people, is currently estimated to be acutely food insecure (FEWS NET, 2018). In recent years, Kenya has been exposed to a combination of slow-onset and sudden-onset disasters. In 2016 and 2017, Kenya, as all countries located in the Horn of Africa, experienced a prolonged and severe drought. This drought triggered large scale food insecurity and left many people across Kenya in need of (food) assistance (FEWS NET, 2017a). In the first quarter of 2018, the situation, however, changed swiftly, after the long rains set it in and brought above average rainfall, causing severe flooding across many parts of Kenya, with the South-East of the country being most affected (UN OCHA, 2018a,b).

The pilot study was rolled out in four Kenyan counties (see Figure 4.1). These are, from west to east, Kajiado, Makueni, Kitui and Tana River. The four counties are located between Nairobi and Mombasa and stretch from the Kenyan boarder with Tanzania to the east, where Tana River is located around 170 km southern of the border with Somalia. They belong to the group of arid and semi-arid lands (ASAL). Counties classified as ASAL face a high risk to recurrent droughts and have been prone to conflict, political neglect and under-investment (Government of the Republik of Kenya, 2012). Consequently, they are particularly vulnerable and exposed to food security risk. The food security situation of the four counties can be illustrated using nutritional indicators: Kitui has the second highest share of stunted children in Kenya (46%). For Tana River (28%) and Makueni (25%), child stunting rates are closer to the national average (26%), while Kajiado has comparatively lower stunting rate, but it still ranges at 18% (Kenya National Bureau of Statistics, 2014).

The four counties are characterized by different livelihood zones. Kajiado is part of the southern pastoral zone, characterized by the Masai tribe and, hence, a large pastoralist community. Makueni and Kitui belong to the zone of south-eastern marginal mixed farming and Tana River is categorized as South-Eastern pastoral zone and the Tana Riverine Zone (FEWS NET, 2010). In total, the four counties have a population of approximately 2,835,448 people (own calculation).

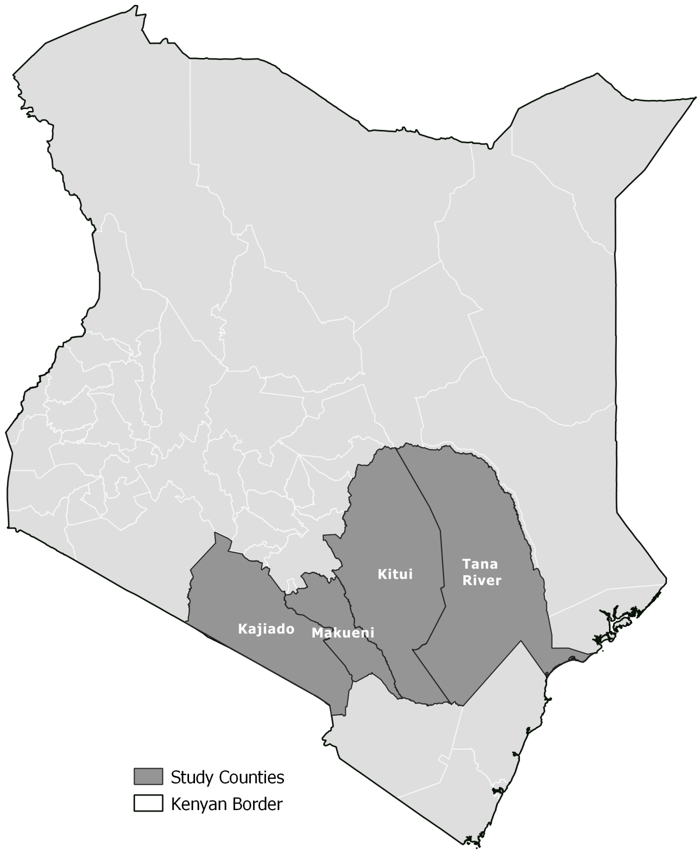
The pilot study was rolled out in cooperation with Welthungerhilfe (WHH), a large German NGO and Kenya's National Drought Management Authority (NDMA). Both have an interest in near real-time food security monitoring, as they tackle food security emergencies on the ground. Both partners advised on the technical design of this study, the different implementation steps and contributed to the selection of participants, as well as the training workshops.

4.3.2 *A SMS System for Direct, Near Real-Time Information*

When trying to reach the local population, a simple, accessible and cost-effective system is required that taps into the existing technological infrastructure, i.e. a system that caters to the devices the local population currently uses. A system that is (1) able to reach people where they are without any further investments into devices, (2) allows for rapid, near real-time assessments and (3) is potentially easy to scale-up. After initial discussions with our two cooperation partners on the ground, regarding the development of a system that would require an internet or mobile data connection, we decided that the most accessible system would still be a SMS-based system, as access to the Internet (26% (The World Bank, 2018)) and smartphone-adoption rates (30%, (Pew Research Center, 2018a)) across Kenya are still significantly lower than mobile phone adoption rates (80%).[3]

3 The author, however, would like to note that she had a full 3G/4G data coverage during her stay in the field, even in the remotest areas of Kenya, which is a significantly better network coverage compared to many parts of Germany.

Figure 4.1: Pilot Region within Kenya.

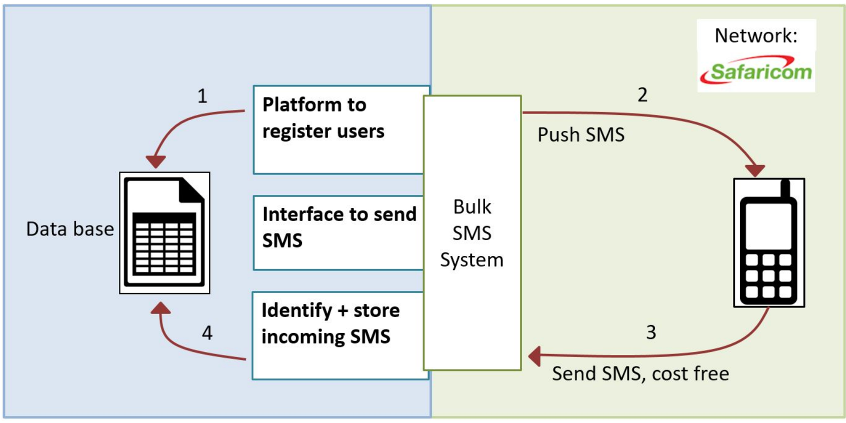


Source: Own cartography, shape-files downloaded from www.arcgis.com.

Accordingly, we implemented a SMS-System, which enables us to automatically push SMS to registered participants, manually or at pre-defined intervals as well as at marginally low costs, i.e. 0.8 US$ per SMS. Participants, on the other hand, send their answer-SMS to a specified short code, free of charge. Figure 4.2 illustrates the technical setup of the SMS-system and its connection to a data gathering algorithm. The system operates on Safaricom, Kenya's largest mobile network provider with the widest network coverage and, hence, ensures the reach-ability of participants (Safaricom, 2017). A specifically designed algorithm then automatically filters answers according to phone numbers, displays them on the web-interface and stores them in a data base. The SMS-system allows us to collect assessments in near real-time, i.e the system introduces a processing delay of less than 1 minute between observation and data output.[4]

4 Terminology usually encountered in a big-data environment and referring to the velocity of data is real time and near-real time. In telecommunication and computer processing, near-real time data refers to the delay in data introduced by automated processing or network transmission. While real-time, in its most strictest sense, refers to data being observed live, near-real time refers to a minimal delay in data processing, which needs to be defined depending on each application. NASA, for example, define for their near-real time products a processing delay from 3 hours or less from observation (NASA, 2019).

Figure 4.2: Technical Setup and Sequence of the SMS System.



Source: Own development.

4.3.3 *SMS Questionnaire*

When gathering data via SMS, it is crucial to keep questionnaires short, simple and understandable, to provide easy answering options and to focus on the most relevant indicators (WFP, 2017a). These aspects have contributed to shaping the questionnaire of our pilot study, in which we focus on four questions that assess the local food security situation. We draw on previously established and tested standard questions to assess the food security status, to analyze whether the affected population itself has the capacity to provide valid assessments of their food security situation.

Figure 4.3 shows the SMS-questionnaire. The first two questions assess the current local food security situation at the community level, relating to food availability and accessibility. Question 1 (Q1) focuses on the food availability aspect and groups the food availability on the market into 3 categories. Question 2 (Q2) asks participants to assess the current local food security situation. Q2 mirrors the official 5 phase IPC scale, ranging from "no food insecurity", "stressed", "crisis" and "emergency" to "famine". The IPC scale comprises a variety of aspects, such as the state of agricultural markets, food consumption scores, the prevalence of coping and livelihood strategies. Questions 3 and 4 are of relative nature, asking for an assessment of the past and future situation with a recall / expectation period of two weeks respectively (e.g. “How to you expect the situation to change in the next two weeks?”). All variables are of categorical nature. In addition to these four questions, participants could leave a comment, describing the situation on the ground, i.e. to describe in their own words what they are currently observing in relation to the food security situation of their community. This could be, for example, in relation to weather events, quality of harvest, occurrence of pests, market access, infrastructure incidents, elections and political tensions.

Figure 4.3: SMS Questionnaire.

- **How is the food availability on the local market?**

  a = readily available
  b = somewhat available or at high prices
  c = not available or at very high prices

- **How is the current local food security situation?**

  1 = None / minimal food insecurity
  2 = Stressed
  3 = Crisis
  4 = Emergency
  5 = Humanitarian catastrophe / famine

- **How has the local food security situation changed in the last two weeks?**

  f = Improved
  g = Same
  h = Worse

- **How do you expect the local food security to change in the next two weeks?**

  x = Improved
  y = Same
  z = Worse

- **Any comment on the situation?**

Source: Own development.

In county-specific, half-day workshops participants were sensitized to terms, such as food security, food availability and livelihood coping strategies.[5] In particular, they were trained on how to categorize their current food security situation according to IPC's five phase classification used in Q2. A detailed list describing "which signals to watch" for Q2, as well as how to differentiate between different classifications of the food security situation can be found in the user's manual in Appendix C, Figure C.7, which was distributed to participants.

The participants were subsequently trained on how to send their coded answer. The numbers and digits associated with each answer represent their respective code. So the final answer-SMS comprises just one number and three digits. Figure 4.4 provides an illustration of SMS received by the participants, as well as an example answer-SMS. In Figure 4.4, we see the four answer codes, as well as an exemplary free comment, describing the situation in Tana River.

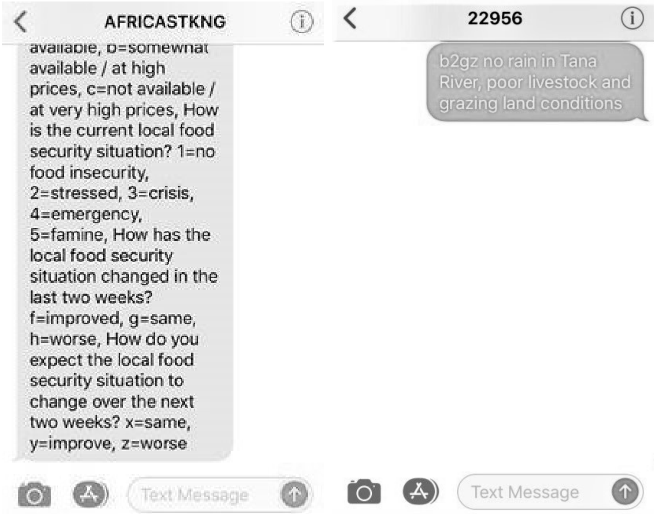
4.4 DATA

4.4.1 *Food Security Data collected via SMS*

We collected data every two weeks in the eight months between January and August 2018, hence, yielding a panel data set of N=404, after accounting for non-response and attrition. Initially the pilot study was scheduled to start in August 2017. Due to general elections and its subsequent annulment and repetition, the start of the pilot

5 During the workshop, each participant signed a consent form, agreeing on the compilation and storage of his/her personal information and on being contacted via SMS.

Figure 4.4: Push SMS and Example Answer Code.

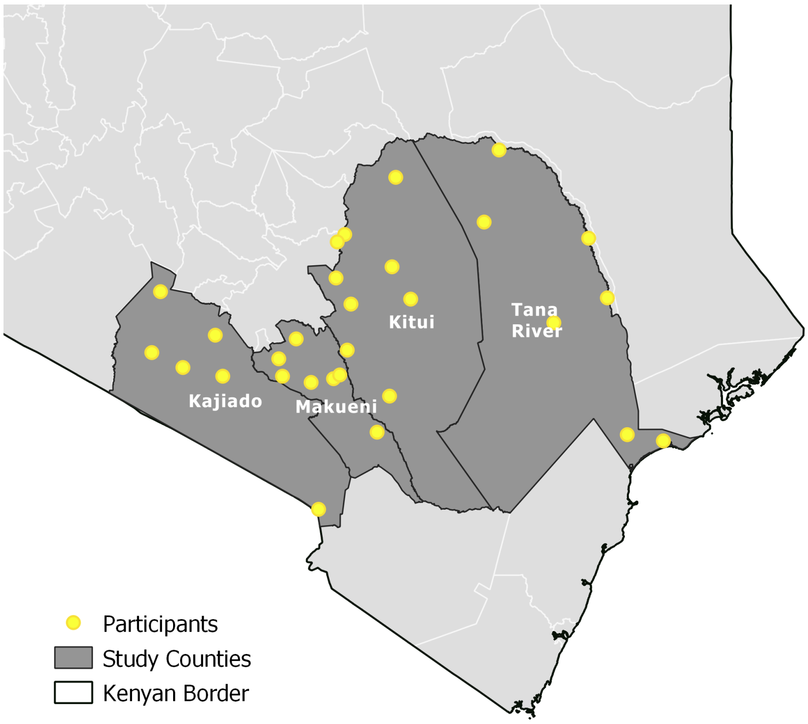


Source: Own depiction.

had to be postponed to early 2018. After years of repeated and prolonged drought (2016 - late 2017), we observed torrential rains during our pilot study. This leaves us with a lack of coverage of a slow-onset disaster. The abundant rains caused severe flooding in our pilot region around April 2018, with Tana River being most affected (UN OCHA, 2018b). Hence, are pilot study, unexpectedly, covers a sudden onset disaster instead.

Food security information was provided by 29 participants. Six participants are located in Kajiado, seven participants in Makueni and Tana River and nine participants in Kitui. We manually collected geo-information of each participant's location, which we use to map the data. Figure 4.5 illustrates the spatial spread of participants within the pilot counties, showing that participants are fairly spread across the pilot region. The participants are associated with NDMA and usually collect NDMA's monthly household data in the first 10 days of each month. In Table 4.1, we summarize the characteristics of participants with local knowledge. The group composition is rather diverse in Makueni, Kitui and Tana River, with around 40% of females, while 84% of participants in Kajiado are male. The average age of participants ranged between 38 and 42.5 years across counties, overall we observe a relatively large age range with a minimum of 22 years and a maximum of 57 years. In Kajiado and Tana River, 50% and 43% of the group had previously received a training on food security assessments. This share is considerably lower in Kitui (22%) and Makueni (0%). Hence, we observe a rather mixed picture, when it comes to previous exposure to food security training.

Figure 4.5: Spatial Spread of Participants within the Pilot Counties.



Source: Own cartography, shape-files downloaded from www.arcgis.com.

Table 4.1: Participant Characteristics.

	Kajiado	Makueni	Kitui	Tana River
Gender of participant (female, %)	16.7	42.9	44.4	42.9
Age (mean)	38.7	39.2	42.5	37.6
Food security training (yes, %)	50	0	22	43
N	6	7	9	7

Source: Own calculation.

4.4.2 *Secondary Data*

To evaluate the SMS data, we pursue a data driven approach and include all available secondary data that match frequency domain and spatial detail.[6] The ultimate goal is to use this data to predict the actual food security situation in different locations. As benchmark, i.e. a representation of the food security situation on the ground, we use monthly household surveys as provided by NDMA, which *inter alia* provide information on food consumption and (livelihood) coping strategies. The household data has an equal degree of spatial disaggregation, as the data is collected around the same sentinel sites as the SMS data, but at a lower, monthly frequency. After cleaning the data, we proceed with N=6635

6 An overview over secondary data sources can be found in Appendix C, Table C.6

for the 8 month study period. Table 4.2 describes the household characteristics, dis-aggregated by counties. We observe that the majority of households is headed by a male, while the main source of household income is casual labour. On average, households comprise 3 male members, 3 female members and between 1 and 4.5 children below 5.

We further use monthly maize price and livestock price data as provided by NDMA, at the county level. Consequently, we assume that county level prices serve as proxy for price developments at the district level. Lastly, we include the total cumulative precipitation as provided by NASA, which we download for each geo-location as observed in the SMS data.[7]

Table 4.2: Household Characteristics.

	Kajiado	Makueni	Kitui	Tana River
Gender of hh head (male, %)	95.6	83.9	69.2	82.6
Main income source (%)				
a) Employment	7.0	11.8	14.2	7.5
b) Sale of livestock	17.9	2.1	0.5	25.8
c) Sale of crops	0.1	5.2	21.8	17.6
d) Casual labour	75.0	71.3	55.5	48.2
e) Trade	1.1	9.6	8.0	1.0
Household composition (Ø, %)				
Males	3.3	2.8	2.9	3.6
Females	3.6	3.2	3.3	3.5
No. of children < 5	4.5	1.4	4.6	1.4
N	210	210	285	210

Source: Own calculation.

4.5 METHODOLOGY

As a first step, we construct a pseudo panel data set using the NDMA household data. While the SMS data is a panel data set that follows the opinion of the same individuals over time, the NDMA household data collects information on different individuals located within the same district over time. Usually, NDMA visits households repeatedly, yet, probably to minimize the hassle for the respondents, household are exchanged after few visits. We follow the standard procedure (see Baltagi (2005)) and pool the different cross sections by replacing individual observations by cohort means at the district level.

To answer our research questions, we pursue the following strategy: Firstly, we use the NDMA pseudo panel data to derive the main dependent variables against which we validate the SMS data. These are the food consumption score (FCS), food consumption group (FCG) and reduced coping strategy index (rCSI). To analyze, whether the SMS data performs as expected, we assess the categorical

7 The area-averaged of daily accumulated precipitation was produced with the Giovanni online data system, developed and maintained by the NASA Goddard Earth Sciences Data and Information Services Center.

concordance of the data, engage in a visual comparison and estimate a simple model, in which we explain the variation in FCS and rCSI based on the SMS data. Subsequently, to understand, whether the answers provided by the local population can improve current food security models, we estimate as first step a model that includes standard food security drivers available to us, i.e. food prices and weather data, to explain FCS and rCSI. Subsequently, we augment this model with the SMS data and compare the model fit using standard criteria.

We use the NDMA household data to calculate the main dependent variables, FCS, FCG and rCSI, as developed by WFP.[8] Generally, the FCS reflects the household's food frequency and dietary diversity based on relative nutritional weights and consumption frequencies over the last 7 days (IPC Global Partners, 2012). The rCSI captures the frequency of coping strategies used by households, e.g. reduction of portion size and/or numbers of meals, and assigns universal severity weights to each coping mechanism.[9] Given that the data structures requires an analysis at the district level we calculate the mean FCS, FCG and rCSI observed in district i at time t, following WFP (2009):

$$FCS_{it} = \sum_{m=1}^{F} x_{m_{it}} * w_{FCS_i} \tag{4.1}$$

where x_i is food group i, with $x_i \in [1, 7]$, as 7 is the maximum number of frequencies per week, w_{FCS_i} is the standard, nutritional weight of food group i, $F = 9$ is the maximum number of food groups. The FCS can further be categorized into three food consumption groups, classifying the food consumption status into three categories:

$$FCG_{it} = \begin{cases} \text{poor, if } FCS_{it} \in [0, 21.4] \\ \text{borderline, if } FCS_{it} \in [21.5, 35] \\ \text{acceptable, if } FCS_{it} > 35 \end{cases} \tag{4.2}$$

where FCG_{it} is the FCG of district i at time t. Similarly, the rCSI is calculated observed in district i and time t as

$$rCSI_{it} = \sum_{n=1}^{G} z_{n_{it}} * w_{rCSI_i} \tag{4.3}$$

where $z_{n_{it}}$ is the respective coping strategy, $w_{rCSI_{it}}$ the severity weight associated with coping strategy i, $G = 5$ as the maximum number of coping strategies included. We round the FCS and rCSI to the nearest integer.

8 The household data does not allow for the calculation of different measures, e.g. household hunger scales or dietary diversity scores.

9 A detailed list of index components and weighting can be found in Appendix C, Tables C.3 and C.4.

Furthermore, we manipulate the remaining secondary data as follows: We use simple linear interpolation in case of missing values in the maize and goat price data and proceed with logs. Given the excessive precipitation observed in some instances during the pilot study, we expect precipitation to have both a positive and negative association with the FCS and rCSI: positive, if observed sufficiently and negative, if observed excessively (e.g. flooding). To account for this relationship, we calculate the mean cumulative precipitation observed in district i and time t over the past three years (2015-2017) and construct a dummy variable that takes on the value 1 if the precipitation observed in district i and time t is larger than the three year average, and 0 if equal or lower than the three year average.

Given that the secondary data sources are of monthly nature, while the SMS data has a fortnightly frequency, we restrain from calculating mean observations but proceed with the data we collected on the first day of each month, as also the household data is collected within the first days of each month. When participants sent multiple SMS a day with differing answers, we use the SMS with the latest time stamp, as participants were instructed during the training that they can overwrite their answer if necessary, by sending another SMS. Furthermore, this assessment focuses on evaluating Q1 and Q2 of the SMS data.

4.5.1 *Categorical Concordance*

Given the categorical nature of the outcome variables collected through SMS, we follow Vaitla et al. (2017) and start with an inspection of data by analyzing the categorical concordance of SMS data against a set of proxy indices. The aim is to classify, whether the categories of the information gathered match the food security classification of other indicators. To do so, we compare Q1 "How is the food availability on the local market" to the development of FCGs over time.

The FCG category is the closest available proxy to Q1, and we expect a higher FCG to be associated with food being available on the local market (i.e. categories 1 of Q1). We group the categories that indicate a risk to food security (i.e. categories 1 "poor" and 2 "borderline" of the FCS and categories 2 and 3 of Q1 respectively) together. We define two concordance measures:

$$\mathrm{Concordance}(1) = \begin{cases} \text{agree, if } \mathrm{FCG}_{it} = \mathrm{Q1}_{it} \\ \text{discord, if } \mathrm{FCG}_{it} \neq \mathrm{Q1}_{it} \end{cases} \tag{4.4}$$

where FCG_{it} is the food consumption group in district i and time t, $\mathrm{Q1}_{it}$ are the answers to Question 1 in district i and time t. This, however, is a measure of deviation of categories of Q1 from the FCS.

To understand, whether participants over- or underestimate their answer to Q1 relative to the mean FCG observed in their location, we define a second concordance measure as follows

$$\text{Concordance}(2) = \begin{cases} \text{agree, if } FCG_{it} = Q1_{it} \\ \text{overestimate, if } FCG_{it} > Q1_{it} \\ \text{underestimate, if } FCG_{i} < Q1_{it} \end{cases} \tag{4.5}$$

where FCG_{it} is the food consumption group in district i and time t, $Q1_{it}$ are the answers to Q1 in district i and time t. Participants overestimate the lack of food on the local market, if the FCG is larger than Q1. Similarly, participants underestimate the lack of food if the FCG is smaller than Q1. Following Mude et al. (2009), we evaluate this classification based on notions of type I and type II errors (see (Cameron & Trivedi, 2005)) and apply them to the context of food security and early warning. A type I error occurs, if food security is at risk and the risk is not being identified (underestimation of risk to food security), while a type II error occurs, if a risk to food security is being identified that does not exist (overestimation of the risk to food security). In the context of EWSs, particularly type I errors are problematic, given that the aim of monitoring systems is the timely identification of risks. We expect this analysis of categorical concordance to provide a first, preliminary assessment of Q1. Nevertheless, it is to consider that FCG and Q1 are not substitutes, hence, a perfect degree of accordance cannot be expected.

With respect to Q2 ("How is the current local food security situation"), we engage in a different form of analysis. Q2 and its categories mirror the IPC food security classification. To understand, whether food security assessments of the SMS data match the official IPC classifications, as published during the pilot study, we map the two assessments and compare the different food security classifications. In January and August 2018, IPC published food security classifications for Kenya. We map and compare the SMS data collected in January and August to the respective map from IPC. Given that IPC publishes two reports per year in Kenya, a visual comparison of these two points in time is the only available measure to evaluate Q2 against its closest proxy indicator.

4.5.2 *Pooled, Negative Binomial and Fixed Effect Models*

To further analyze, whether the SMS data performs as expected, we estimate a simple model in which we seek to explain the variation in FCS and rCSI with the SMS data. Furthermore, to analyze, whether the SMS data can improve current models, we estimate a second model, in which we explain the variation in FCS and rCSI based on standard drivers of the food security situation, i.e. crop and livestock prices, precipitation. Subsequently, we augment this model with the SMS data.

The nature of the calculated FCS and rCSI, which we use as independent variables in our models, has implications for the model selection. Both FCS and rCSI are derived from different sets of count data, e.g. the number of days during which the household consumes food, and are, hence, non-negative integers with $FCS \in [0, 78]$ and $rCSI \in [0, 112]$, and zero being a natural outcome. Consequently, ordinary estimation techniques based on probability density functions of the normal distribution are inappropriate. A standard way to model count data is to use the Poisson distribution, which provides a functional form that yields non-negative conditional expectations (Verbeek, 2012).

Even though the Poisson distribution is suitable to model count data, it is usually associated with limitations if the count variable is overdispersed. In the case of overdispersion, the variance exceeds the mean and, hence, violates one assumption of the Poisson distribution, which is equi-dispersion or variance mean equality. Overdispersion is associated with inflated standard errors and significance levels (Hilbe, 2014). Overdispersion is common across many count variables and both FCS and rCSI exhibit overdispersion (see Table C.5). Two alternatives are available to handle overdispersion in the data. One option is to use a negative binomial model, which is less restrictive than the Poisson model, as it does not assume equidispersion of mean and variance, but allows the variance to increase with the conditional mean. Consequently, negative binomial (NB2) models usually provide a better model fit, if data is overdispersed (Hilbe, 2014). Alternatively, in the case of panel data, both Hilbe (2014) and Cameron & Trivedi (2015) recommend to use panel-robust standard errors clustered on the individual level to correct inflated standard errors, as Poisson models still yield consistent coefficient estimates, also in the case of overdispersion.

Following these considerations, we pursue a three tiered estimation strategy. As a first step, we estimate pooled Poisson regression models, assuming that observations are independent and any potential panel effects are not large enough to bias results. As robustness check for overdispersion, we subsequently estimate a pooled NB2 model. Lastly, we control for a potential violation of the independence assumption and estimate a Poisson fixed effects (FE) model, controlling for unobserved, time-invariant fixed effects. The decision to estimate both pooled and FE models is driven by the fact that much of the variation in FCS and rCSI stems from variation across observations (see descriptive statistics). Hence, controlling for district FE could reduce meaningful variation of an already limited number of observations.

To explore any potential relationship between the two main dependent variables and the SMS data, we estimate models for all possible combinations, regressing both the FCS and rCSI on Q1 and Q2. In the following we start with specifying a pooled Poisson regression model with cluster robust standard errors, to account for overdispersion and potential correlation across observations and time (Hilbe, 2014; Cameron & Trivedi, 2015). For notational simplicity, we first derive a general model. Following Cameron & Trivedi (2013) and Hausman et al. (1984), a pooled Poisson regression model assumes a dependent variable y_{it} given x_i to be Poisson distributed with probability density function, defined as

$$f(y_{it}|x_{it}) = \Pr[y_{it} = y|x_{it}] = \frac{\exp(-\mu_{it})(\mu_{it})^{y_{it}}}{y_{it}!}, y = 0, 1, 2, 3... \tag{4.6}$$

where μ_{it} is the mean parameter and $y_{it}!$ is a factorial function. The mean parameter μ_{it} is a function of explanatory variables given by

$$E[y_{it}|x_{it}] = \mu_{it} = \exp(x'_{it}\beta) \tag{4.7}$$

where x_{it} is a set of explanatory variables and β are the coefficients to be estimated. This specification of the functional form yields the required, non-negative conditional expectations (Verbeek, 2012). Furthermore, the mean is equal to the variance, i.e. the equidispersion assumption is given by

$$E[y_{it}|x_{it}] = Var[y_{it}|x_{it}] = \mu_{it} \tag{4.8}$$

Let the FCS_{it} and $rCSI_{it}$ be the dependent variable, as represented by y_{it} above, where FCS_{it}, is the food consumption score in district i at time t and $rCSI_{it}$, is the coping strategies index in district i and time t, where $i = 1, ..., N$ is the number of districts and $t = 1, ..., T$ the time index. For each dependent variable, we estimate two models, for Q1 and Q2 respectively.

For FSC_{it}, parameter μ_{it} depends on a set of explanatory variables, given by two models:

$$\mu_{FCS_{it}} = \exp(x'_{it}\beta) = \exp\left(\beta_0 + \sum_{j=1}^{3} \beta_{1j} Q1_{j_{it}}\right) \tag{4.9}$$

$$\mu_{FCS_{it}} = \exp(x'_{it}\beta) = \exp\left(\beta_0 + \sum_{k=1}^{4} \beta_{1k} Q2_{k_{it}}\right) \tag{4.10}$$

where FCS_{it}, is the FCS observed in district i at time t, $Q1_{it}$ is a dummy variable representing the answers to $Q1_{it}$ in district i at time t, and $Q2_{it}$ is a dummy variable representing the answers to Q2 in district i at time t.[10]

We similarly estimate these two specifications with $rCSi_{it}$ as dependent variable, such that

$$\mu_{rCSI_{it}} = \exp(x'_{it}\beta) = \exp\left(\beta_0 + \sum_{j=1}^{3} \beta_{1j} Q1_{j_{it}}\right) \tag{4.11}$$

$$\mu_{rCSI_{it}} = \exp(x'_{it}\beta) = \exp\left(\beta_0 + \sum_{k=1}^{4} \beta_{1k} Q2_{k_{it}}\right) \tag{4.12}$$

10 As further discussed below, Q2 is based on 5 categories. Category 5 "famine" has not been used during the pilot study, hence, Q2 enter the models with 4 categories.

where $Q1_{it}$ is a dummy variable representing the answers to Q1 in district i at time t. $Q2_{it}$ is a dummy variable representing the answers to Q2 in district i at time t, respectively.

Given the degree of overdispersion inherent to the two dependent variables, we further estimate a NB2 model, as robustness check. The NB2 model is an extension of the Poisson model and loosens the equidispersion assumption. It is based on a Poisson-gamma-mixture distribution which models overdispersion by allowing the variance to increase with the conditional mean (Hilbe, 2011). Following Cameron & Trivedi (2005), the NB2[11] regression model is defined by a density mass function, given by

$$f(y_{it}|x_{it}) = \frac{\Gamma\left(\alpha^{-1}+y\right)}{\Gamma\left(\alpha^{-1}\right)\Gamma\left(y+1\right)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\frac{1}{\alpha}}\left(\frac{\mu}{\mu+\alpha^{-1}}\right)^{y} \tag{4.13}$$

where μ is the mean parameter, Γ is a gamma function and α is the dispersion parameter. As before, the mean parameter μ is given by

$$\mu_{it} = \exp(x'_{it}\beta) \tag{4.14}$$

Contrary to the Poisson regression model, mean and variance are given by

$$E[y_{it}|x_{it}] = \mu \tag{4.15}$$

$$V[y_{it}|x_{it}] = \mu + \alpha\mu^2 \tag{4.16}$$

where the variance now depends on parameter α that is jointly estimated with the model parameters. Equivalent to the Pooled Poisson model, we estimate two NB2 regression models for each dependent variable, where mean parameter $\mu_{FCS_{it}}$ and $\mu_{rCSI_{it}}$, depend on the explanatory variables Q1 and Q2 respectively.

Due to the panel structure of the data, there is reason to assume that observations are not independent. To control for this fact, we further estimate a Poisson FE model, controlling for individual specific, unobserved factors that do not vary over time. Given the relatively small number of individual units (N=29) in the panel, we estimate unconditional fixed-effects, i.e. by using a categorical predictor variable.

Folllwing Hilbe (2014), in a FE Poission model, the mean parameter μ_{it} depends on a set of covariates and the individual fixed effect. Let δ be the district specific, individual effect, such that the mean parameter takes the following form

$$\mu_{it} = \exp(x'_{it}\beta + \delta_i) \tag{4.17}$$

11 A detailed derivation of the NB2 model can be found in Hilbe (2011) and Cameron & Trivedi (2005).

where μ_{it} is the mean parameter, x_{it} the explanatory variables as above, β the coefficients to be estimated and δ_i the time-invariant district FE. Similar to the two models above, we estimate the unconditional FE Poisson specification for the FCS and rCSI, depending on Q1 and Q2 respectively. In summary, we hence estimate three different models for dependent variable and Q1 and Q2.[12]

In a similar fashion, we use a Pooled Poisson, pooled NB2 and FE Poisson model to estimate a full model, based on drivers of the food security situation to explain the FCS and rCSI. Subsequently, we augment this model with Q1 and Q2 of the SMS data and compare the fit of the different models.

In the full model, let the mean parameters, $\mu_{FCS_{it}}$ and $\mu_{rCSI_{it}}$, depend on the following set of explanatory variables. The Pooled Poisson model is given by

$$\mu_{FCS_{it}} = exp(x'_{it}\beta) = exp\left(\beta_0 + \beta_1 MP_{it} + \beta_2 GP_{it} + \beta_3 PCPT_{it}\right) \tag{4.18}$$

where MP_{it} is the log maize price in district i at time t, GP_{it} is the log goat price in district i and time t and $PCPT_{it}$ is a dummy variable for above average precipitation. Equally, $\mu_{rCSI_{it}}$ is given by

$$\mu_{rCSI_{it}} = exp(x'_{it}\beta) = exp\left(\beta_0 + \beta_1 MP_{it} + \beta_2 GP_{it} + \beta_3 PCPT_{it}\right) \tag{4.19}$$

where MP_{it} is the maize price in district i at time t, GP_{it} is the goat price in district i and time t, $PCPT_{it}$ is a dummy variable for above average precipitation observed in district i and time t.

We subsequently augment these models by Q1 and Q2 of the SMS data, such that

$$\mu_{FCS_{it}} = exp(x'_{it}\beta) = exp\left(\beta_0 + \beta_1 MP_{it} + \beta_2 GP_{it} + \beta_3 PCPT_{it} + \sum_{j=1}^{3} \beta_{4j} Q1_{j_{it}}\right) \tag{4.20}$$

$$\mu_{FCS_{it}} = exp(x'_{it}\beta) = exp\left(\beta_0 + \beta_1 MP_{it} + \beta_2 GP_{it} + \beta_3 PCPT_{it} + \sum_{k=1}^{4} \beta_{4k} Q2_{k_{it}}\right) \tag{4.21}$$

where MP_{it} is the maize price in district i at time t, GP_{it} is the goat price in district i and time t, $PCPT_{it}$ is a dummy variable for above average precipitation

12 We restrain from estimating a FE NB2 specification, as the Poisson FE has been found to perform better in a panel setting and the FE NB2 specification is not associated with efficiency gains, see Cameron & Trivedi (2013) and Cameron & Trivedi (2015)

observed in district i and time t and $Q1_{it}$ and$Q2_{it}$ are the answers to Q1 and Q2 in district i and time t, respectively.

And similarly for $rCSi_{it}$,

$$\mu_{rCSI_{it}} = exp(x'_{it}\beta) = exp\left(\beta_0 + \beta_1 MP_{it} + \beta_2 GP_{it} + \beta_3 PCPT_{it} + \sum_{j=1}^{3} \beta_{4j} Q1_{j_{it}}\right) \tag{4.22}$$

$$\mu_{rCSI_{it}} = exp(x'_{it}\beta) = exp\left(\beta_0 + \beta_1 MP_{it} + \beta_2 GP_{it} + \beta_3 PCPT_{it} + \sum_{k=1}^{4} \beta_{4k} Q2_{k_{it}}\right) \tag{4.23}$$

where MP_{it} is the maize price in district i at time t, GP_{it} is the goat price in district i and time t, $PCPT_{it}$ is a dummy variable for above average precipitation observed in district i and time t and $Q1_{it}$ and$Q2_{it}$ are the answers to Q1 and Q2 in district i and time t, respectively. As above, we estimate these three models also as NB2 and Poisson FE specification, as outlined in Eq. 4.13 - 4.16 and Eq. 4.17 respectively.

4.6 RESULTS

4.6.1 *Descriptive Statistics*

We start the results section by discussing the descriptive statistics of all variables, as shown in Table 4.3.[13] The mean of Q1 is 1.71, i.e. close to category 2 "food somewhat available or at higher prices" and the mean of Q2 is 2.02, indicating a "stressed" food security situation. Both variables are of categorical nature and it is to note that we have not observed category 5 "famine" of Q2 during the pilot period. This is why the analysis is based on the remaining four categories. The mean FCS ranges at 39 and the mean rCSI is 10. The mean of the precipitation dummy indicates that the sample is more or less split into above average and normal precipitation. Mean values of logged maize and goat prices are 3.69 and 8.16 respectively. Particularly the goat price data shows relatively little variation with a standard deviation of 0.12.

The development of situation assessments gathered every two weeks with Q1 and Q2 in the four counties over time is shown in Figures 4.6 and 4.7. In Figure 4.6, we observe a rather stressed situation across all counties from January to April/May, with food being reported to be somewhat available or at high prices. Particularly in Kitui and Makueni, the situation improves over time and an increase to food

13 We only show figures for the SMS data in this section. Figures for the remaining variables can be found in Appendix C.

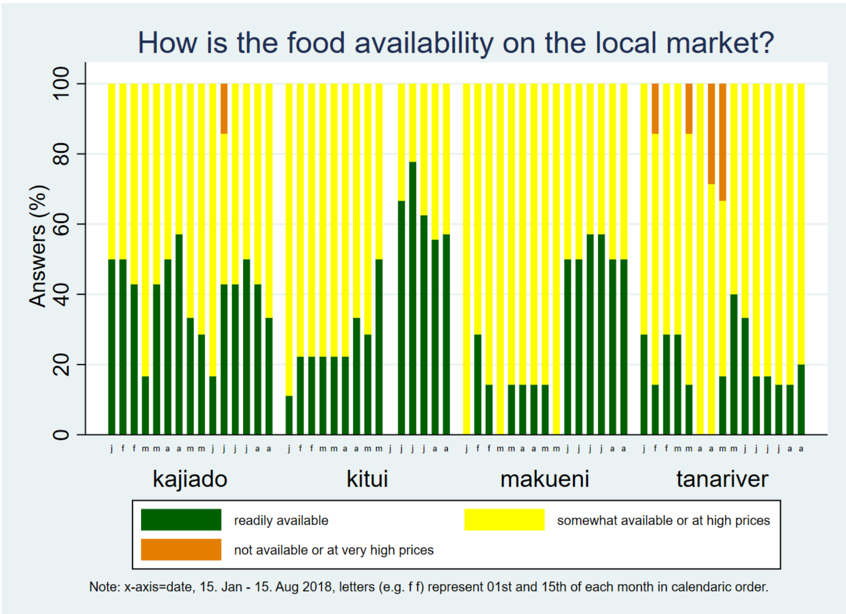
Table 4.3: Descriptive Statistics.

	Mean	SD	Min	Max
Q1 SMS	1.71	0.49	1	3
Q2 SMS	2.02	0.63	1	4
FCS	39.37	14.71	5	87
rCSI	10.7	12.4	0	64
Precipitation	0.44	0.50	0	1
Maize Price	3.69	0.24	3.37	4.09
Goat Price	8.16	0.12	7.94	8.43

Note: Maize and goat prices in logs. Source: Own Compilation.

being readily available can be observed for the majority of participants within the two counties. Food availability is the worst in Tana River. In particular during the first half of the assessment, we observe that food is not available or available at very high prices in some districts. The situation is the worst during in mid-April and early May, which coincides with the severe flooding experienced in Tana River during that time period (UN OCHA, 2018b). Even though the food availability improved over the study period, the majority of participants in Tana River reported in late August that food is somewhat available or at high prices.

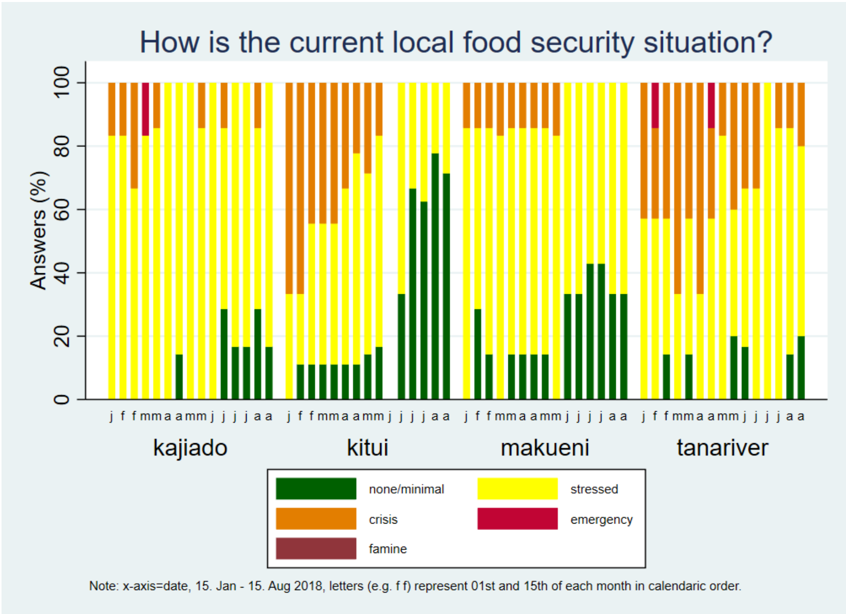
Figure 4.6: Answers to Questions 1, Jan - Aug 2018.



Source: Own compilation.

Figure 4.7 shows the answers to Q2, "How is the current local food security situation". Similar to the results from Q1, the situation in all counties was particularly tense in the first half of the pilot period. Most prominently, we see many "crisis" classifications in Kitui and Tana River between January and April, indicating a relatively tense food security situation. While the situation improves in Kajiado, Kitui and Makueni, we observe a deterioration of the food security situation in Tana River around March and April. At the end of August, we observe almost no risk to food security in Kitui, while a mixed picture prevails for Kajiado, Makueni and Tana River. Over the whole pilot period, we observe three emergency declarations, category 4 of Q2, one in Kajiado in March and two in Tana River in early February and late mid-May.

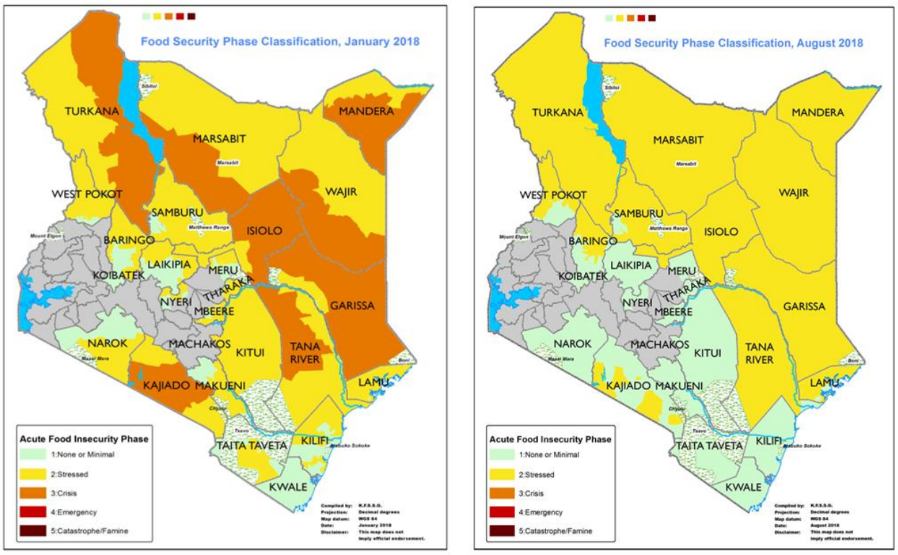
Figure 4.7: Answers to Question 2, Jan - Aug 2018.



Source: Own compilation.

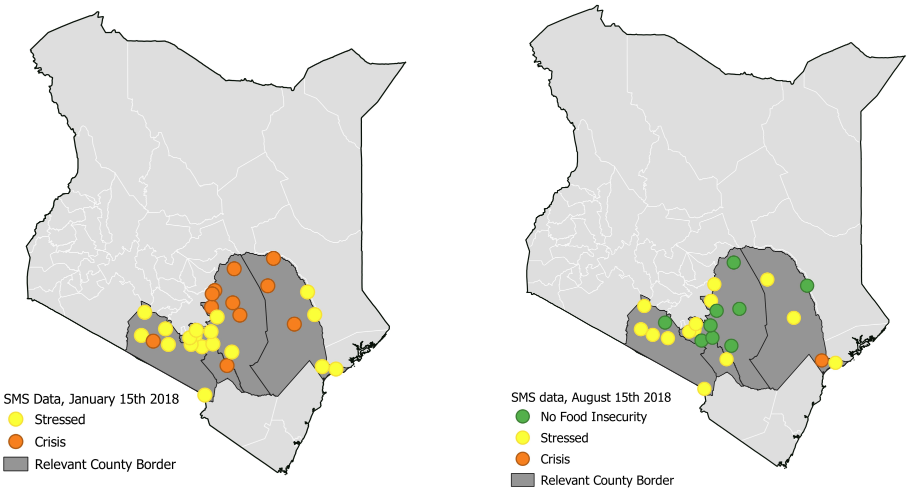
Furthermore, Q2 and its categories mirror the IPC food security classification. To understand, whether food security assessments of the SMS data match the official IPC classifications, as published during the pilot study, we map the two assessments and compare the different food security classifications. In January and August 2018, IPC published food security classifications for Kenya. We map and compare the SMS data collected in January and August to the respective map from IPC. Given that IPC publishes two reports per year in Kenya, a visual comparison of these two points in time is the only available measure to evaluate Q2 against its closest proxy indicator. Both variables are categorical, with 5 scales, ranging from scale 1 "no risk to food security" to scale 5 "famine". Figure 4.8 illustrates the IPC classification for Kenya in January and August 2018. For January 2018, the situation in Kajiado was classified as mixed between stressed and crisis, with the crisis classification prevailing mostly in central Kajiado. In Makueni we observe a mix between no risk to food security and a stressed situation. In Kitui, the situation was classified as stressed, while Tana River was classified as "stressed" and "crisis", with the classification "stressed" mostly prevailing in the riverine area and in Southern Tana River. In August (right map), the situation had improved: Kajiado was classified as minimal risk to food security, apart from multiple hotspots where a stressed situation prevailed. We observe no risk to food security in Makueni and Kitui. Tana River is fully classified as "stressed".

Figure 4.8: IPC Classification of Kenya, Jan & Aug 2018.



Source: Government of Kenya / Food Security Steering Group (2018), p.8.

Figure 4.9: SMS Data, Answers to Question 2, Jan & Aug 2018.



Source: Own compilation.

Figure 4.9 shows the situation assessments obtained in January and August 2018. When considering the SMS data collected for January 2018, we observe a similarly tense food security situation in the SMS data, as none of the participants categorized their food security as "no risk to food security". We see that participants in Kajiado rated the food security situation as "stressed", while we observe one "crisis" classification, around the same area, where also the IPC map indicates a crisis. While the IPC map classifies Makueni and Kitui mostly as stressed, we observe "crisis" classifications, particularly in northern Kitui. In the case of Tana River, the SMS data fully matches the IPC classification. With respect to the August assessment, Kajiado was mostly rated as "stressed" with one "no risk" classification. In Makueni and Kitui, who were fully classified as "no risk to food security" we observe a mix of "no risk" and "stressed" classifications, which particularly cluster in the northern regions of both counties. For Tana River, we see a more mixed picture, with classifications from "no risk to food security" to "crisis". This visual comparison indicates the SMS data seems to capture general trends also observed in the IPC map. In some cases, we observe identical situation assessments (see Tana River in January 2018), while we observe deviations, both under- or overestimating the food security classification at the same time.

4.6.2 *Categorical Concordance: Results*

In Figure 4.10, we show the categorical concordance of measure (1) and (2) in the upper and lower part respectively. The results are displayed over time (left) and by county (right). When considering concordance (1) over time, we find that between 40% and, in some instances, more than 60% of the categories of Q1 match the classification of FCGs. Interestingly, the share of answers that agrees increases over time. When considering concordance (1) by county, we find that Kajiado achieves the highest percentage of concordance, followed by Tana River, Makueni and Kitui.

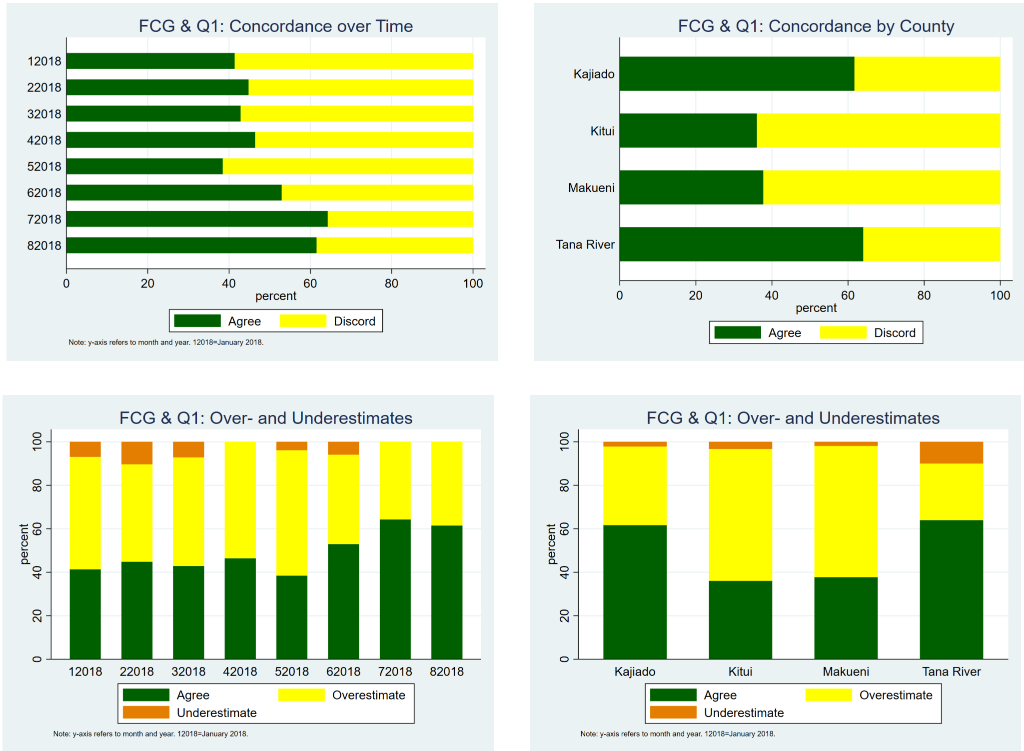
When considering over- and underestimations of the situation, we are able to dis-entangle this relationship further: Over time, we find the share of agreement to increase from about 40% to 60%. We further see, that the larger share of discord is driven by over-estimations, while observing underestimations at the same time. If shown by county, we see that particularly in Tana River around 10% of answers tend to underestimate the lack of food availability on the market. We further observe the largest share of agreements in Kajiado and Tana River. In Kitui and Makueni, we observe that the majority of answers overestimate the lack of food availability, when compared to the mean FCGs observed at the district level.

When put in the context of type I and type II errors, we find that the majority of discord to be type II errors, hence, identifying a risk to food security where there is none, while a rather small share of answers fail to identify a risk to food security. In the context of EWS and timely detection of potential crises, a type I error of failing to identify a risk to food security is more severe than identifying a risk to food security risk that is not there. Still, these results should be considered in the context that Q1 and the FCG are proxy indicators and not perfect substitutes. This analysis has been a comparison of levels, which is interesting in the context of information validation.

4.6.3 *Results: Regression Models*

In the following, we report the results of the empirical analysis, starting with the simple model. Table 4.4 shows the estimation results of the FCS for the three different models (i.e Eq. 4.9, 4.16 and 4.17). Given that Q1 and Q2 are categorical

Figure 4.10: Results: Categorical Concordance (1) and (2).



Source: Own compilation.

variables, the respective baseline category has been omitted from the regression and results should be interpreted in relation to the baseline.

For the pooled models $((1) - (2))$, we find a negative relationship between FCS and category 2 of Q1 (Q1_2) and we can reject at null the 10% level that Q1_2 is equal to zero. More precisely, a one unit increase in FCS is associated with a decrease of Q1_2 in the difference in the log of expected counts by 0.2 units. When controlling for district FE, we fail to reject the null that Q1 is significantly different from zero.

Models $(4) - (6)$ report the regression results for the FCS and Q2 across the three specifications. We find the inclusion to be significant and negative across all models. In more detail, when considering, e.g., the FE specification of model (6), we can reject that null that Q2_4 and Q2_3 are equal to zero at the 1% significance level, and for Q2_2 at the 5% significant level. Furthermore, we see the largest, negative coefficient for Q2_4, which is decreasing in magnitude across categories. In summary, we find that both Q1 and Q2 have a negative relationship with the FCS, i.e. an increase in FCS is associated with a decrease of Q1 and Q2, or put differently, an increase in availability of food in the local market and an improvement in the food security classification. This finding confirms the expected relationship.

The estimation results for the rCSI are reported in Table 4.5. When considering Q1 (models $(1) - (3)$), we find a positive association between rCSI and Q1. In the fixed effects specification, we find both categories, Q1_2 and Q1_3 to be positive and significant at 1% and 5% level respectively. Hence and increase in rCSI is

Table 4.4: Results: FCS, Q1 and Q2.

Variables	(1) Pooled Poisson	(2) Pooled NB2	(3) Poisson FE	(4) Pooled Poisson	(5) Pooled NB2	(6) Poisson FE
Q1_2	-0.200*	-0.200*	-0.0569			
	(0.119)	(0.119)	(0.0435)			
Q1_3	-0.468	-0.468	0.173			
	(0.485)	(0.485)	(0.210)			
Q2_2				-0.260*	-0.260*	-0.0855**
				(0.137)	(0.137)	(0.0430)
Q2_3				-0.291*	-0.291*	-0.129***
				(0.160)	(0.160)	(0.0427)
Q2_4				-0.412**	-0.412**	-0.208***
				(0.174)	(0.174)	(0.0430)
Constant	3.812***	3.812***	3.948***	3.894***	3.894***	4.005***
	(0.110)	(0.110)	(0.0119)	(0.142)	(0.142)	(0.0364)
N	211	211	211	210	210	210
District FE	No	No	Yes	No	No	Yes
LL	-1128	-987.2	-677.5	-1121	-982.4	-673
AIC	10.72	9.386	6.441	10.72	9.394	6.438

Note: Panel-robust standard errors, clustered on the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. District FE omitted for brevity. Q1_2 and Q1_3 refer to the categories of Q1, while Q2_2 – Q2_4 refer to the categories of Q2. Source: Own estimation.

associated with an increase in Q1. Similarly for Q2 (models (4) – (6)), we find a positive and significant relationship between Q2 and the rCSI. While the pooled models show a positive and significant relationship between Q2_2 and Q2_3, the FE model finds a positive and significant relationship between Q2_3 and Q2_4. More precisely, a one unit increase of the rCSI in model (6) is associated with an increase in the difference in the log of expected counts by 0.92 units in the case of Q2_3 and 0.63 units in the case of Q2_4. Hence, a one unit increase in rCSI is associated with an increase in Q1 and Q2, i.e. a reduced availability of food on the local market and a deterioration in the food security classification, respectively. This confirms that relationship of Q2 with the rCSI is as expected. The results of this first analysis confirm the expected relationship between the two main dependent variables, FCS and rCSI, and the SMS data.

Generally, we can observe that magnitude and significance of coefficients are similar across the three different models, i.e pooled Poisson, pooled NB2 and Poisson FE. The standard errors are significantly lower in the FE specification, which also exhibits the lowest AIC and Log-Likelihood, hence, controlling for FE provides the best model fit.

In Tables 4.6 and 4.7, we show the estimation results of the full models of FCS and rCSI respectively. Models (1) – (3) do not include SMS data, models (4) – (6) include Q1 and models (8) – (10) include Q2. Starting with the results of the FCS model (Table 4.6), we find that a one unit increase in the FCS is associated with a decrease in maize prices. Coefficients are similar across all models specifications.

Table 4.5: Results: rCSI, Q1 and Q2.

Variables	(1) Pooled Poisson	(2) Pooled NB2	(3) Poisson FE	(4) Pooled Poisson	(5) Pooled NB2	(6) Poisson FE
Q1_2	0.477	0.477	0.657***			
	(0.326)	(0.326)	(0.197)			
Q1_3	1.455***	1.455***	0.386**			
	(0.421)	(0.421)	(0.160)			
Q2_2				0.581*	0.581*	0.524
				(0.341)	(0.341)	(0.322)
Q2_3				1.304***	1.304***	0.925**
				(0.435)	(0.435)	(0.390)
Q2_4				0.593	0.593	0.632*
				(0.620)	(0.620)	(0.368)
Constant	2.001***	2.001***	2.067***	1.658***	1.658***	1.839***
	(0.360)	(0.360)	(0.0857)	(0.459)	(0.459)	(0.293)
N	211	211	211	210	210	210
District FE	No	No	Yes	No	No	Yes
LL	-1465	-717.6	-562.8	-1355	-704.4	-559.2
AIC	13.91	6.830	5.354	12.94	6.746	5.354

Note: Panel-robust standard errors, clustered on the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. District FE omitted for brevity. Q1_2 and Q1_3 refer to the categories of Q1, while Q2_2 – Q2_4 refer to the categories of Q2. Source: Own estimation.

More precisely, in the case of a one unit change in the FCS, the difference in the logs of expected counts is expected to decrease, e.g. by 0.73 units in the case of model (1). Furthermore, we find goat prices to be negatively associated with the FCS, e.g. in the case of a one unit change in FCS, the difference in the logs of expected counts is expected to decrease by 0.59 units. In specification (3), we find a one unit increase in FCS to be associated with an increase in goat prices. We do not find the precipitation dummy variable, measuring the deviation from three year average precipitation to be statistically significant.

Considering Q1, we find similar results in the full model compared to the simple model, as discussed above. In the two pooled models, category 2 of Q1 (Q1_2), is statistically significant at the 10% level and a one unit increase in FCS is associated with a decrease of Q1_2 in the difference in the log of expected counts by 0.17 units. This effect vanishes when controlling for district FE. In the full model, we do not find Q2 to be statistically significant.

Table 4.7 shows the results for the rCSI models. For the pooled models, we find the maize price to be positively associated with the rCSI. More precisely, given a one unit increase in the rCSI, the difference in the log of expected counts is expected to increase by 1.67 units in the case of model (2), the pooled NB2 specification. This finding is in line with our initial expectation. This relationship is not statistically significant, when controlling for district FE. When controlling for district FE, we, however, find goat prices to be statistically significant at the 5% and 1% level and to be negatively associated with the rCSI. For example, given a one unit increase in rCSI, the difference in the log of expected counts of goat prices decreases by 1.95 units in model (6).

Furthermore, we find the precipitation dummy to be positively associated with the rCSI in the majority of the models. For example in model (5), given a one unit increase in rCSI, the difference in the logs of expected counts is expected to be 0.17 units higher compared to the baseline category with no abnormal precipitation. This finding confirms the initial expectation, that above average (excessive) precipitation can have a negative impact on the food security status, here measured by the rCSI.

Considering Q1 of the SMS data, we find a positive association between rCSI and multiple categories of Q1. For example, in model (5) we find both categories of Q1 to be statistically significant. When controlling for FE (model (6)) this still holds for Q1_1. So, with respect to model (5) and compared to the baseline, a one unit increase in rCSI is associated with an increase in the difference in the logs of expected counts by 0.59 units in Q1_1 and by 1.09 units in the case of category Q1_2. Moreover, with respect to Q2, we find particularly classification 3 "crisis" (Q2_3) to be statistically significant and positive. More precisely in model (9), the difference in the logs of expected counts is expected to be 1.3 units higher for the "crisis" category, compared to the baseline "no food insecurity".

In summary, for the rCSI, we still find different categories of Q1 and Q2 to be statistically significant. Furthermore, when considering the model fit, we find the inclusion of Q1 and Q2 to improve the model fit, as we observe a reduction in AIC. For example, in the case of the FE specification, i.e. models (3), (6) and (10), we find the AIC to be 5.4, 4.9 and 5.1 respectively. Hence, the models including Q1 and Q2 provide the better model fit.

Given that coefficients are similar in magnitude across model specifications, we are confident that we have obtained robust estimation results and have controlled for relatively large degree of overdispersion observed in the two dependent variables. From a model specification perspective, we find the AIC to be smaller for the NB2 model, compared to the pooled Poisson, which could further be reduced when controlling for unconditional FE. A comparison between AIC values across models, shows that particularly in the case of the rCSI, we find the inclusion of SMS data to reduce the value of the AIC, and, hence, to improve the model fit.

Table 4.6: Results: FCS, Full Model.

	No SMS Data			Q1			Q2		
Variables	(1) Pooled Poisson	(2) Pooled NB2	(3) Poisson FE	(4) Pooled Poisson	(5) Pooled NB2	(6) Poisson FE	(8) Pooled Poisson	(9) Pooled NB2	(10) Poisson FE
ln Maize Price	-0.736***	-0.736***	-0.312**	-0.699***	-0.704***	-0.289*	-0.663***	-0.674***	-0.303*
	(0.251)	(0.246)	(0.141)	(0.222)	(0.216)	(0.152)	(0.228)	(0.232)	(0.155)
ln Goat Price	-0.580	-0.559	0.269*	-0.590*	-0.557*	0.282	-0.722*	-0.637*	0.229
	(0.367)	(0.370)	(0.157)	(0.309)	(0.318)	(0.198)	(0.413)	(0.379)	(0.153)
Precipitation	-0.0432	-0.0423	-0.00809	-0.0299	-0.0352	-0.00624	-0.0247	-0.0321	-0.00557
	(0.0298)	(0.0329)	(0.0148)	(0.0306)	(0.0323)	(0.0163)	(0.0329)	(0.0335)	(0.0136)
Q1_2				-0.172*	-0.174*	-0.0281			
				(0.0974)	(0.0900)	(0.0361)			
Q1_3				-0.193	-0.238	0.200			
				(0.377)	(0.389)	(0.251)			
Q2_2							-0.154	-0.131	-0.0342
							(0.122)	(0.115)	(0.0436)
Q2_3							-0.211	-0.181	-0.0337
							(0.160)	(0.148)	(0.0472)
Q2_4							-0.204	-0.159	-0.0763
							(0.219)	(0.213)	(0.0539)
Observations	211	211	211	211	211	211	210	210	210
District FE	No	No	Yes	No	No	Yes	No	No	Yes
LL	-1043	-985	-669.4	-1017	-984.4	-667.6	-1020	-979.8	-666.2
AIC	9.925	9.375	6.374	9.694	9.387	6.375	9.782	9.398	6.402

Note: Panel-robust standard errors, clustered on the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. District FE and constant omitted for brevity. LL: Log-Likelihood. Q1_2 and Q1_3 refer to the categories of Q1, while Q2_2 – Q2_4 refer to the categories of Q2. Source: Own estimation.

Table 4.7: Results: rCSI, Full Model.

	No SMS Data			Q1			Q2		
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)
	Pooled	Pooled	Poisson	Pooled	Pooled	Poisson	Pooled	Pooled	Poisson
Variables	Poisson	NB2	FE	Poisson	NB2	FE	Poisson	NB2	FE
ln Maize Price	1.606***	1.666**	0.245	1.515**	1.740***	-0.0703	1.401**	1.804**	-0.513
	(0.612)	(0.655)	(0.491)	(0.639)	(0.666)	(0.488)	(0.642)	(0.709)	(0.420)
ln Goat Price	0.834	0.409	-1.740**	0.684	0.389	-1.950***	0.964	1.509	-1.541***
	(0.913)	(1.003)	(0.806)	(0.862)	(0.864)	(0.559)	(0.769)	(0.919)	(0.562)
Precipitation	0.215**	0.295***	0.173***	0.171	0.213**	0.0927*	0.134*	0.134	0.136
	(0.0950)	(0.0880)	(0.0652)	(0.104)	(0.106)	(0.0474)	(0.0790)	(0.0880)	(0.0921)
Q1_2				0.414	0.599**	0.667***			
				(0.277)	(0.251)	(0.148)			
Q1_3				0.985***	1.087***	0.420			
				(0.347)	(0.360)	(0.297)			
Q2_2							0.292	0.350	0.416
							(0.370)	(0.386)	(0.285)
Q2_3							1.011**	1.305***	0.775**
							(0.492)	(0.413)	(0.346)
Q2_4							0.0774	0.0987	0.221
							(0.599)	(0.559)	(0.341)
N	211	211	211	211	211	211	210	210	210
District FE	No	No	Yes	No	No	Yes	No	No	Yes
LL	-1365	-708.4	-570.1	-1317	-701.6	-515.6	-1218	-686.2	-533.7
AIC	12.98	6.752	5.433	12.54	6.707	4.935	11.67	6.602	5.140

Note: Panel-robust standard errors, clustered on the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. District FE and constant omitted for brevity. LL: Log-Likelihood. Q1_2 and Q1_3 refer to the categories of Q1, while Q2_2 – Q2_4 refer to the categories of Q2. Source: Own estimation.

4.7 DISCUSSION

We tested the food security assessments gathered from representatives of the local population in a series of specifications. The first step of our analysis comprised an analysis of categorical concordance of Q1 against FCGs. We find the level of concordance between the FCGs and Q1 to range between 40% and 60%. While we find the majority of discord to stem from over-estimations of participants, we also find a share of underestimations, particularly in Tana River. This preliminary analysis of levels showed that the answers provided by the local participants to Q1 can capture general trends also observed in the FCGs. The advantage of this kind of analysis is that it can contribute to understanding answering patterns of participants, i.e. identify participants that tend under- or overestimate the situation, and to model these explicitly in the future. Also Mock et al. (2016) find that people underestimate their FCS in voice recording settings, compared to the FCS observed in F2F surveys. They also suggest to explicitly account for the differences in answering patterns observed across interview modes.

In the simple models, our findings show that answers provided by the local population to Q1 and Q2 perform as expected: an increase in the FCS is associated with a decrease in Q1 and Q2, and an increase in the rCSI is associated with an increase in Q1 and Q2. This leads us to a to confirm that the data provided by the local population performs as theoretically expected. Hence, the participants provided valid information on the food security situation of their community.

We are able to dis-entangle this relationship further, when estimating the full model based on crop and livestock prices, as well as weather data. Considering the rCSI, we still find a similar relationship between the rCSI and answers to Q1 and Q2. Furthermore, with respect to the rCSI the inclusion of SMS data seems to improve the model fit, compared to the specification containing no SMS data. Also the remaining explanatory variables perform as expected. We find an increase in rCSI to be associated with an increase in maize prices and above average precipitation. We further find that goat prices are negatively associated with the rCSI. An increase in rCSI is associated with a decrease in livestock prices. This result underlines the observation of eroding cereals-livestock terms of trade in case of food crises. In times of increasing food prices, households engage in asset liquidation and small livestock (usually chicken and goats, depending on the area) is among the first assets to be sold to generate income. So in times of crises, particularly small livestock is associated with depletion in prices (Webb et al., 1992; Breisinger et al., 2014). Our findings corroborate this relationship.

Regarding the FCS, we find the relationship between Q1 and FCS to be weaker in the full model. While we still find Q1_1 to be significant in the pooled specifications, Q2 is not statistically significant anymore. Still, this also holds for other explanatory variable, like precipitation and to, some extent, goat prices. We find the strongest association between the FCS and maize prices. We hypothesize that this difficulty in explaining the FCS is driven by a lack of variation in the variable itself, over time as well as well as across districts (see Appendix C, Figure C.10). While we find the inclusion of observations from the local population to improve the model of the coping strategy index, we do not find evidence that this is the case for the FCS.

This limited variation in FCS relates directly to one of the limitations of this study. The validation of data, ideally, requires secondary data that match frequency and spatial detail. By matching the gathered data to available, secondary data, we lose many valuable observations along the frequency domain. Also, given that we had to pool the household data to a pseudo panel data set at the district level, a lot of variation in the main dependent variables was averaged out and many observations were lost. Furthermore, this validation encompassed testing against secondary data and indices, that themselves might suffer from validity problems. Both FCS and rCSI are their associated nutrition and severity weights are relatively new concepts that require further testing and validation. For example, Wiesmann et al. (2009) recommend in their evaluation of the FCS to adjust FCG thresholds (i.e 21 and 35), given that they underestimate the level of food insecurity when compared to calorie consumption per head. Generally it should be considered that the data which is being tested can only perform as good as the secondary data against which it is evaluated.

Furthermore, future research should consider the following aspects: Given that the focus of this empirical evaluation was the validation of information, the added value of the SMS data from a frequency perspective, i.e. the added value of near real-time information, particularly from the perspective of potential end users, could not be assessed. After each round of data elicitation, brief status updates were sent to the partner agencies, NDMA and WHH. Still, given that the frequency domain of information is nevertheless of utmost importance for humanitarian agencies, the usability of information should be explored more thoroughly and systematically in the future.

Moreover, this pilot study covered 8 months, i.e. a relatively short time period. Processes that drive food security outcomes take time to trickle down to household consumption scores. Given a longer time series, it would be of interest to explore the dynamic effects across variables and outcomes in the future. This would also allow for more elaborate estimation techniques that explicitly model the spatial aspect of the data (beyond FE). Recent advances in spatially weighted regression techniques with ordinal and categorical data could be of interest in this regard, e.g. see Dong et al. (2018), as well as outcome predictions based on non-representative samples, see Wang et al. (2015). Furthermore, due to the Kenyan elections in August 2017 and the subsequent annulation of election results, the start of this pilot study had to be postponed to January 2018. That is why the time frame of this pilot study does not cover Kenya's lean season, which usually occurs from August to October (FEWS NET 2018) and only the first couple of months were able to observe the impact the long drought that Kenya experienced during that time. Hence it would be of interest to understand how such a system performs in a slow-onset, drought scenario.

4.8 LESSONS LEARNED

The initial concerns of this pilot study ranged from feasibility issues, to non-response and attrition, lack of capacity to provide valid answers and incentives of the local population to systematically overestimate food security risks. To some extent, it was the objective of this study to provide answers to these challenges. In the following we provide a brief overview over the lessons learned.

With regards to people's capacity to assess the situation correctly, this analysis finds that the local population has the potential to provide valid food security assessments. In this context, particularly Q2, dealing with an approximation of the 5 phase IPC classification, was perceived as too challenging e.g. during a high-level expert workshop in Kenya. This concern may have originated from the fact that IPC analyses are usually compiled in expert consortia, based on different strings of data and quantitative thresholds. Due to the initial worry of participants being unable to understand the phase classification, we dedicated a relatively large time window of the half-day workshop to discuss the different phases, coping and livelihood strategies and had participants consider and discuss real-life examples, e.g which commodities drop first out of their consumption basket, meal preparation in times of crises, and what assets are being sold according to which phase classification. It became clear, even though the terminology was perceived as new, that participants could easily provide examples and relate to all categories from their daily life. Our results show that the local population was able to categorize their food security situation accordingly. Still, undoubtedly IPC analyses can only ever by done according to the protocols and standards under which they were developed. The objective of this study was not to seek a substitute for IPC analyses, but to understand whether the local population could contribute to and be integrated into this process as a complimentary source, with the aim to bridge some of IPC's challenges, e.g. irregularity of reports, time consuming and costly classification processes (see Chapter 2) and to explore the possibility of a continuous, less costly monitoring. This study gives reason to belief that it would be of interest to explore the possibility further.

When considering non-response and attrition rates, we found these to be relatively low. With respect to non-response, the near real-time nature of the SMS system allowed us to follow up with participants as soon as we registered an answer to be missing. In this event, a personalized reminder SMS was sent, which in the majority of cases triggered an answer within hours or the next day. This finding is similar to Dillon (2012), who also reported on the positive aspect of the real-time, interactive participation of the primary researcher. We further observe, that participants usually replied on time (within the same day) once the push-SMS was sent, in some cases even the night before. Particularly during the training workshops, participants voiced that they find the system easy to use, given that it just requires the typing of four digits and a text. The aspect of drop-out and attrition is usually a major concern with studies based on mobile phones and particularly in panel settings i.e. in repeated engagement of participants. For example, Lamanna et al. (2019) argue that two-round surveys are associated with lower attrition rates than panels. Considering attrition rates, we noted two drop-outs, one in Kajiado and one in Makueni, hence, attrition rates were comparatively low. We hypothesize that low attrition rates may stem from a trusting relationship that was built-up during the training workshops, through personalized follow-ups from the primary researcher and through the participants ongoing engagement with NDMA. While we were able to successfully gather a panel data set, our analysis shows that a larger time frame could enable more elaborate econometric analyses, which could further add to understanding the added value of the local population to monitoring systems.

Regarding the technological aspect of this study, e.g. the SMS system and the encoding of answers, we found both to work surprisingly good during the eight month pilot study. At no point, the system failed from a technological point of view. The information arrived in near real-time and could directly be accessed and processed. This also holds with regards to the encoding, as the vast majority of answers were encoded correctly, such that manual data cleaning could be kept to a minimum. Furthermore, once operational, the system proved to be a cost-effective survey method given costs of around 0.8 US$ per SMS.

Even though this study uses a mobile system for food security assessments, this kind of information gathering could theoretically be used across a large variety of disciplines. It is easily up-scalable, cost effective and has the potential to provide practitioners with near real-time information. As also emphasized by Lamanna et al. (2019), a limitation from a up-scaling perspective is the fact that this system would require people to be literate and to own a mobile phone, hence, introducing certain bias into the data set. Nevertheless, a SMS system can not replace fully-fledged, nationally-representative studies and its scope should be on obtaining near real-time information and on eliciting upon-demand, fast situation assessment.

4.9 conclusions

This study analyzes whether representatives of the local at-risk population can provide valid, rapid food security assessment and whether the inclusion of this kind of information can improve current food security models. Assessments gathered throughout an eight month pilot study from local participants in four Kenyan counties, were tested against standard food security indicators, i.e. FCS, FCG and rCSI.

Across multiple model specifications, this study finds robust results that the gathered food security assessments are in line with existing indicators, as they performs as expected. More specifically, an increase in the FCS is associated with a increase in food availability on the local market and an improvement in the food security classification. Similarly, an increase in the rCSI is associated with a decrease in food availability on the local market an a deterioration of the food security classification. Hence, this study concludes that local knowledge holders can provide valid assessments of their communities' food security situation. Particularly in the case of the rCSI, we further found the inclusion of the SMS data to improve the model fit of models based on general drivers of the food security situation, i.e. crop and livestock prices and weather.

The findings of this study give reason to explore the potential of the at-risk population further, given the large range of advantages associated with the inclusion of the at-risk population into monitoring systems. Future research should consider the incorporation of dynamic effects of food security drivers and the spatial aspect of the data in more detail. Furthermore, the focus of this analysis was on establishing the validity of the information provided, hence the benefit of high-frequency data from the perspective of a humanitarian agency could not be investigated. Hence, it would be of considerable interest to understand the practical advantages of having near real-time information, which facilitates work processes and ultimately, helps to inform operations on the ground. This applies similarly to the experience of the local participants themselves, with regards to having a direct communication channel to monitoring systems.

5

CONCLUSION

This thesis was placed at the intersection of food security monitoring, early warning and big data, and it investigated monitoring systems for food security risks from two perspectives: information content and contribution. Chapter 2 of this thesis focused on the analysis of the information content and gaps of current monitoring systems for food security risks. Chapter 3 and 4 concentrated on ways to contribute to and improve current early warning systems by exploring two new strings of data. If harnessed at their maximum frequency and/or maximum level of spatial disaggregation, both data streams classify as big data and have the ability to surpass currently used information in timeliness, frequency and spatial detail.

In Chapter 2, we developed a theoretical framework of an efficient early warning system (EWS) and used this framework to derive criteria, which we used to test the information provision of the four largest international monitoring system for food security risks. Based on this comparison, we showed that EWSs partially moved towards the diversification of risk monitoring from availability to accessibility indicators, towards the expansion of country coverage and the inclusion of geographically more detailed information. We further found that the majority of information is published at a monthly or less-than-monthly frequency. Also timely information is missing for a number of countries, the information provision is irregular and the geographical coverage of EWSs is smaller than stated. Furthermore, bottom-up information is hardly integrated into EWSs and generally, the population at-risk is still disconnected from monitoring systems, both as an information source as well as a recipient of early warning information. Hence, in Chapter 2 we concluded that monitoring systems fell short of their potential to inform the population about an impending risks to food security.

This thesis subsequently explored two information sources, i.e. the Internet and the at-risk population, and their potential to contribute to food security monitoring systems. In Chapter 3, we investigated the link between GSQ meta data and food prices in Ethiopia, Kenya, Mozambique, Malawi, Rwanda, Tanzania, Uganda, Zambia and Zimbabwe. We found the inclusion of the GSQ keyword *maize* into simple auto-regressive models for maize prices in an in-sample scenario to be significant in four of the analyzed countries. These were Rwanda, Uganda, Zambia and Zimbabwe. Furthermore, a specification in which we included GSQ data as interaction term with a price change dummy, shows a significant and positive relationship, i.e. an increase in maize prices is associated with an increase of the search term *maize*, in all nine countries. In a pseudo-out-of-sample, one-step-ahead forecasting environment, we found that the GSQ-augmented models beat the benchmark model in 8 of the 9 countries included in this study. Zimbabwe was the only country, for which forecasts could not be improved. By including the GSQ data, we reduced the now-casting error of maize prices between 3% and 23%. We achieved the largest improvement of maize price now-casts for Malawi, Kenya, Zambia and Tanzania with improvements larger than 14%. Our results indicated that including contemporaneous search engine data can improve the now-casting capacity of maize price models, which are solely based on past price observations.

In Chapter 4, we further explored how the at-risk population could be directly connected to monitoring systems via their mobile phones and whether representatives of the local, at-risk population can provide valid assessments of their communities' food security situations. In an eight month pilot study, we gathered direct food security assessments via SMS from the at-risk population in three Kenyan counties. To analyze their validity, we tested the food security assessments provided by the at-risk population against standard foods security indicators, i.e. the food consumption score (FCS) and the reduced coping strategy index (rCSI) gathered in face-to-face (F2F) household surveys. Across multiple model specifications, i.e. Pooled Poisson, Negative Binomial and Poisson FE models, we found robust results that the gathered data conforms with existing indicators, i.e. the assessments from the at-risk population perform as theoretically expected. More specifically, we found an increase in FCS to be associated with a increase in food availability on the local market and an improvement in the food security classification, as indicated by local participants. Similarly, an increase in rCSI is associated with a decrease in food availability on the local market and a deterioration of the food security classification. Particularly in the case of the rCSI, we found the inclusion of the SMS data to improve the model fit. Consequently, we concluded that the at-risk population is able to provide valid assessments of their community's food security status.

The results from Chapter 3 and Chapter 4 give reason to assume that signals from the Internet and assessments from the at-risk population have significant potential for early warning systems. Moreover, they emphasize the importance to further investigate the possibilities of including Internet meta-data and the at-risk population into forecasting models and to explore ways to systematically integrate this kind of data into monitoring systems. These results hold exciting prospects for the inclusion of the population, as they enable citizen-science approaches and contribute to the democratization of information. This thesis furthermore illustrates, how two new strings of data can be harnessed at virtually no cost, or in a very cost-effective way. Internet meta-data, in particular GSQ data, is passively produced in any case and readily available free of charge. Also the SMS-system, once operational, gathered data at 0.8 US$ per sent SMS. This is in stark contrast to usually cost-intensive F2F surveys. The Internet and ICTs, hence, offer cost-effective solutions for situation monitoring.

However, we identified various challenges and limitations that arose when working with data derived from the Internet in an environment with low Internet-adoption rates and when including the at-risk population into monitoring systems.

One prevalent issue that we faced is related to the characteristics of secondary data. Secondary data rarely match the frequency and/or spatial detail of newly gathered data. This forces researchers to adopt coarser spatial units and drop observations, and hence limits the capacity to fully validate newly gathered information. Furthermore, results can only be as good as the data against which information is validated and it is not clear, if and to what extend secondary data might be affected by quality issues. Still, the validation of information is critical, particularly when considering the up-scaling of monitoring activities or the automatization of analyses and mapping, given the risks of training algorithms with inconsistent, inaccurate and invalid data (Blumenstock, 2018).

Furthermore, while big data has promising potential, it also requires extensive storage capacities, technical know-how on how to be harnessed and analytic capacities, to be processed and understood. In that regard, Morrow et al. (2016) discuss that more data might be generated when gathering data with mobile phones, but the capacities to handle these data may be not equally advanced. Building the capacities to deal with large and fast amounts of data is, hence, crucial to avoid knowledge concentration and analytical barriers (Hilbert, 2016; Morrow et al., 2016). Another aspect that arises when discussing big data in a developing country context is sample bias and exclusion. Even though increasing Internet and ICT usage enables new pathways to different data, it needs to be considered that this data is associated with a sample bias, given that the majority of the world's population does not have access to the Internet due to accessibility and affordability constraints (World Bank Group, 2016). Also, mobile phones require access to electricity and some degree of literacy. These prerequisites exclude large parts of the population within developing countries and, in particular, the most marginalized people from being represented in new, digital data (Blumenstock, 2018; Rosenstock et al., 2017). Still, given the continuous increase in Internet and mobile phone adoption rates, we expect online signals to gain robustness and the sampling bias to improve in the upcoming years.

While the aforementioned limitations need to be considered, the advancement of early warning and monitoring systems is very relevant to improve predictions, the anticipation of risks to food security, and emerging humanitarian emergencies. Climate change is expected to increase the likelihood of disastrous events, and factors such as conflict and migration are expected to continue to complicate monitoring efforts. This thesis has explored two innovative ways that could contribute to monitoring efforts. Given the results, it would be of interest to explore these pathways further in the future.

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APPENDIX A

Figure A.1: Timing and Frequency of IPC's Acute and Chronic Food Insecurity Assessments.

	2017			2016				2015				2014			
Country	Q3	Q2	Q1	Q4	Q3	Q2	Q1	Q4	Q3	Q2	Q1	Q4	Q3	Q2	Q1
Afghanistan					x			x	x				x		
Bangladesh					o	o		o				o	x		
Botswana															
Burundi		x			xo	x			x					x	
Cambodia															
CAR[1]			x		x			x		x		x		x	
DRC[2]						x	x		x			x		x	
Djibouti								x						x	
El Salvador				x											
Haiti			x	x	x			o				x		x	
Honduras			x	x				x						x	
Kenya			x				x				x		x	x	
Lesotho		x				x									
Madagascar				xx											
Malawi															
Mozambique		x			xx	x									
Nepal												o			
Pakistan												x		x	x
Philippines											o				
Rwanda															
Somalia		x					x				xx				x
South Sudan		x	x		x	xx		x	x	x		x	x	x	
Sudan		x		x		x			x	x			x	x	
Swaziland						x									
Tajikistan						x				x					
Tanzania															
Uganda			xx	x	x		x		x	x	o	x	x		
Yemen			x			x				x			x		
Zimbabwe		x													

Note: Reports published as of July, 20th 2017; [1]CAR: Central African Republic, [2]DRC: Democratic Republic of Congo; the right column reflects the first half and the left column the second half of a year. Acute assessments = x, chronic assessments = o. Source: Own compilation based on content published by IPC.

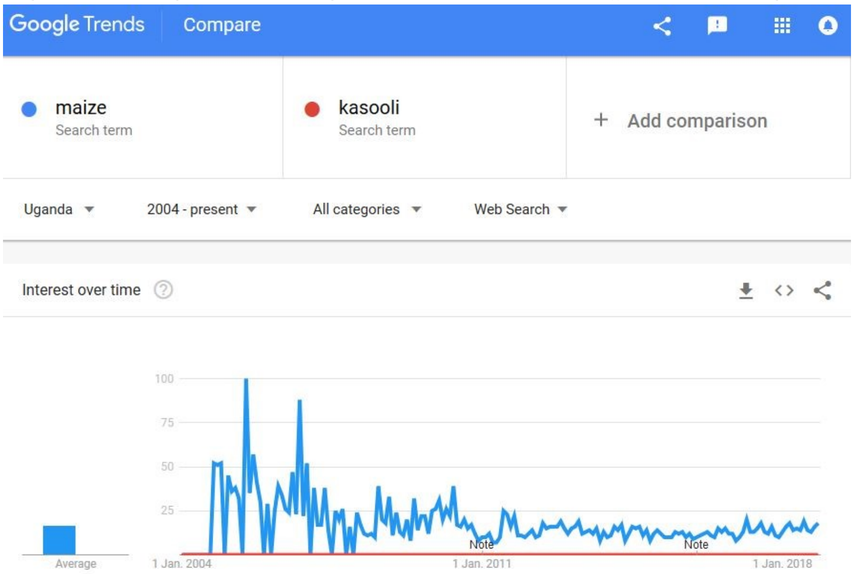
Figure A.2: Reporting Frequency and Timing of WFP's mVAM.

	2017							2016												2015											
Country	7	6	5	4	3	2	1	12	11	10	9	8	7	6	5	4	3	2	1	12	11	10	9	8	7	6	5	4	3	2	1
Afghanistan		xx	xx	x	x	x	x	xx																							
Burundi			xx	x	x	x	x	xx	x	x																					
Cameroon																			x	x											
CAR			x		x		x	x			x																				
Chad					x			x	x	x	x	x	xx												x	x	x				
DRC				x	x	x	x	x	x	x	x	x	x																		
Guinea, Liberia, SL*							x											x	x	x	x	x	x	x	x	x	x				
Haiti														x																	
Honduras				x			x	x																							
Iraq						x	x		x	x	x	x	x		x	x	x														
Lesotho			x	x	x	x	x	x	x	x	x	x																			
Madagascar				x	x								x	x	x		x														
Malawi			x		x	x	x	x	x	x	x	x	x																		
Mali								x				x																			
Mozambique				x	x	x	x	x	x	x	x		x																		
Myanmar								x	x																						
Niger			x		x			x	x	x														xx	x				x	x	
Nigeria						x		x		x		x	x		x																
Papa New Guinea								x									x														
Somalia																xxx	x	x													
South Sudan																x	x														
Swaziland					x	x	x																								
Syria			x	x	x	x	x	x	x		x	x	x																		
Uganda					x		x		x		x	x		x																	
Ukraine														x							x										
Yemen			x	x	x	x	x	x	x	x	x	x																			
Zambia			x	x	x	x		x	x	x	x	x	x																		
Zimbabwe			x	x	x	x	x	x	x	x		x		x																	

Note: Remaining frequency reports for FEWS NET available upon request. Source: Source: Own compilation based on reports published until July, 4th 2017.

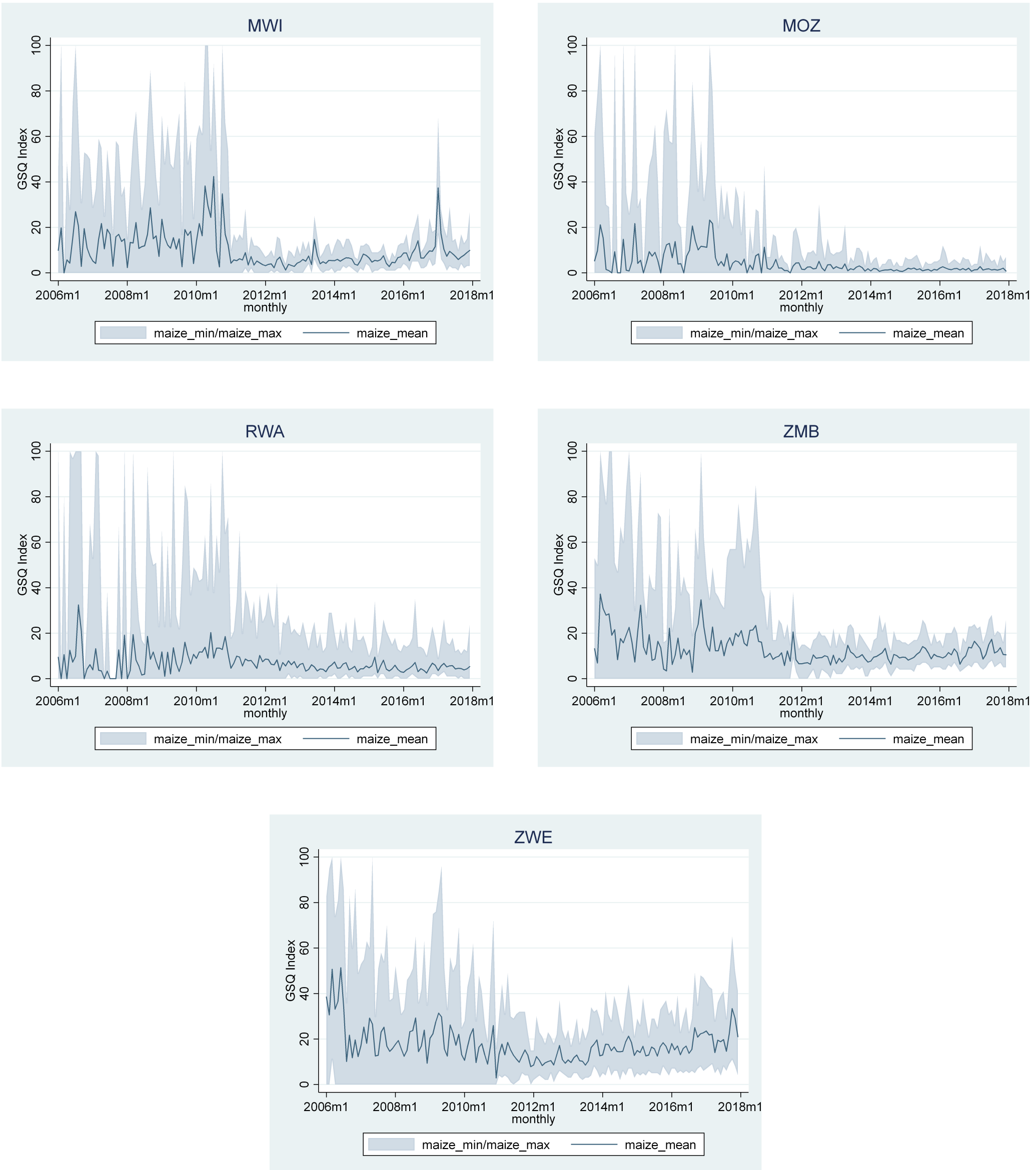
APPENDIX B

Figure B.3: Luganda vs. English: Search-Term Comparison for Uganda.



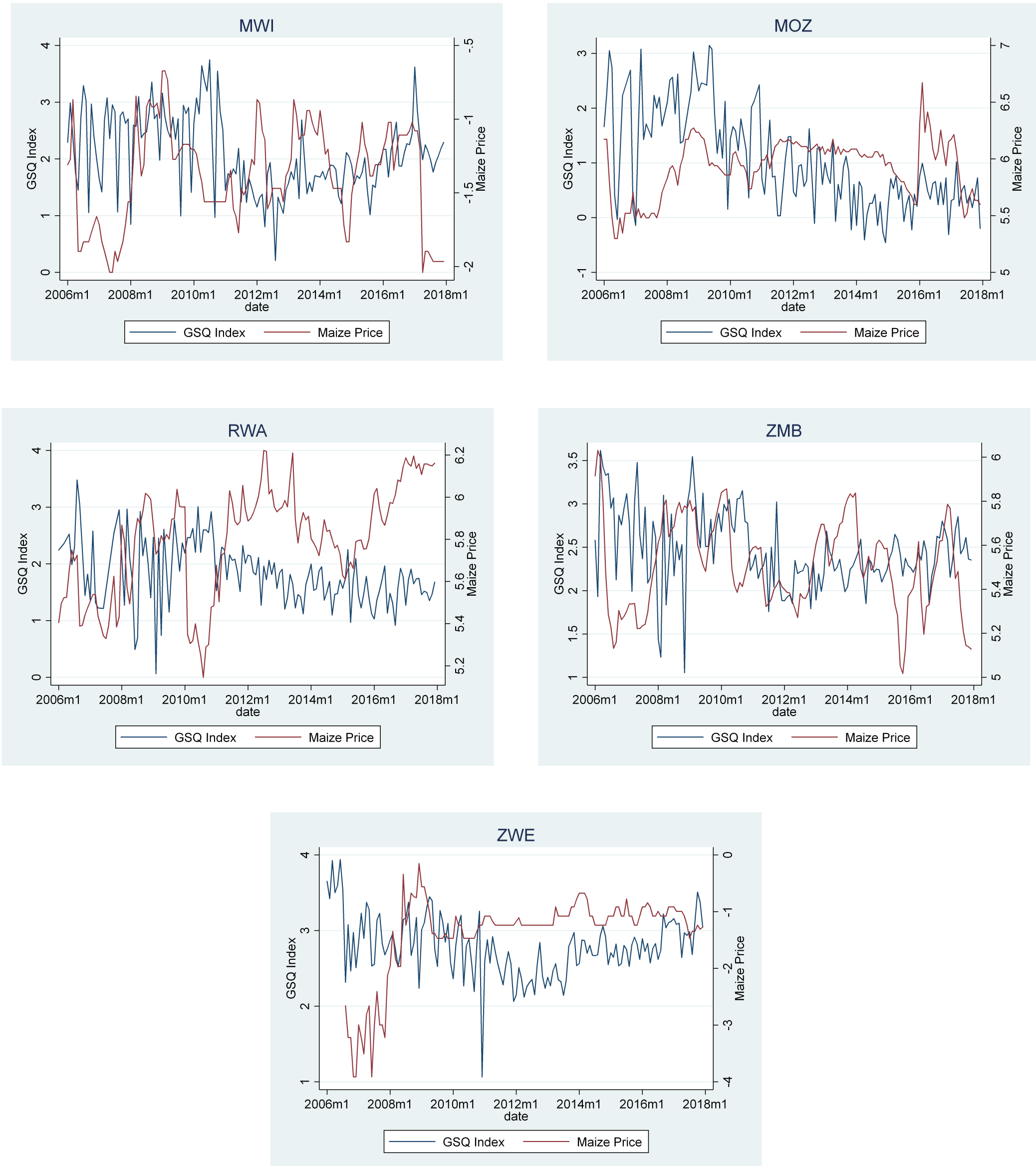
Source: Screenshot taken from https://trends.google.com on Nov, 11th 2018.

Figure B.4: Sampling Noise of GSQ Data for the Term *maize* in Malawi, Mozambique, Rwanda, Zambia, Zimbabwe.



Source: Own compilation based on data extracted from www.google.de/trends, sampled over a period of 30 days.

Figure B.5: Maize Prices and GSQ Data for the Term *maize* in Malawi, Mozambique, Rwanda, Zambia, Zimbabwe



Source: Own compilation.

Table B.1: Philipps-Perron Unit Root Test Statistic.

Country	Variable	P-Perron Statistic	P-Perron Lags	Order of Integration
ETH	maize ln	-4.904684*** (0.00)	4	I(0)
ETH	maize usd ln	-2.704097* (0.07)	4	I(0)
KEN	maize ln	-6.431211*** (0.00)	4	I(0)
KEN	maize usd ln	-2.470026 (0.122)	4	
KEN	maize d1	-18.15845*** (0.00)	4	
KEN	maize usd d1	-9.468563*** (0.00)	4	I(1)
MOZ	maize ln	-4.860092*** (0.00)	4	I(0)
MOZ	maize usd ln	-3.165808** (0.02)	4	I(0)
MWI	maize ln	-7.32375*** (0.00)	4	I(0)
MWI	maize usd ln	-2.916184** (0.04)	4	I(0)
RWA	maize ln	-8.677816*** (0.00)	4	I(0)
RWA	maize usd ln	-2.604109** (0.09)	4	I(0)
TZA	maize ln	-6.34058*** (0.00)	4	I(0)
TZA	maize usd ln	-2.52525* (0.10)	4	I(0)
UGA	maize ln	-8.609276*** (0.00)	4	I(0)
UGA	maize usd ln	-3.169517** (0.02)	4	I(0)
ZMB	maize ln	-8.130215*** (0.00)	4	I(0)
ZMB	maize usd ln	-3.444542*** (0.01)	4	I(0)
ZWE	maize ln	-7.265877*** (0.00)	4	I(0)
ZWE	maize usd ln	-2.492414 (0.12)	4	
ZWE	maize d1	-22.87312*** (0.00)	4	
ZWE	maize usd d1	-16.5487*** (0.00)	4	I(1)

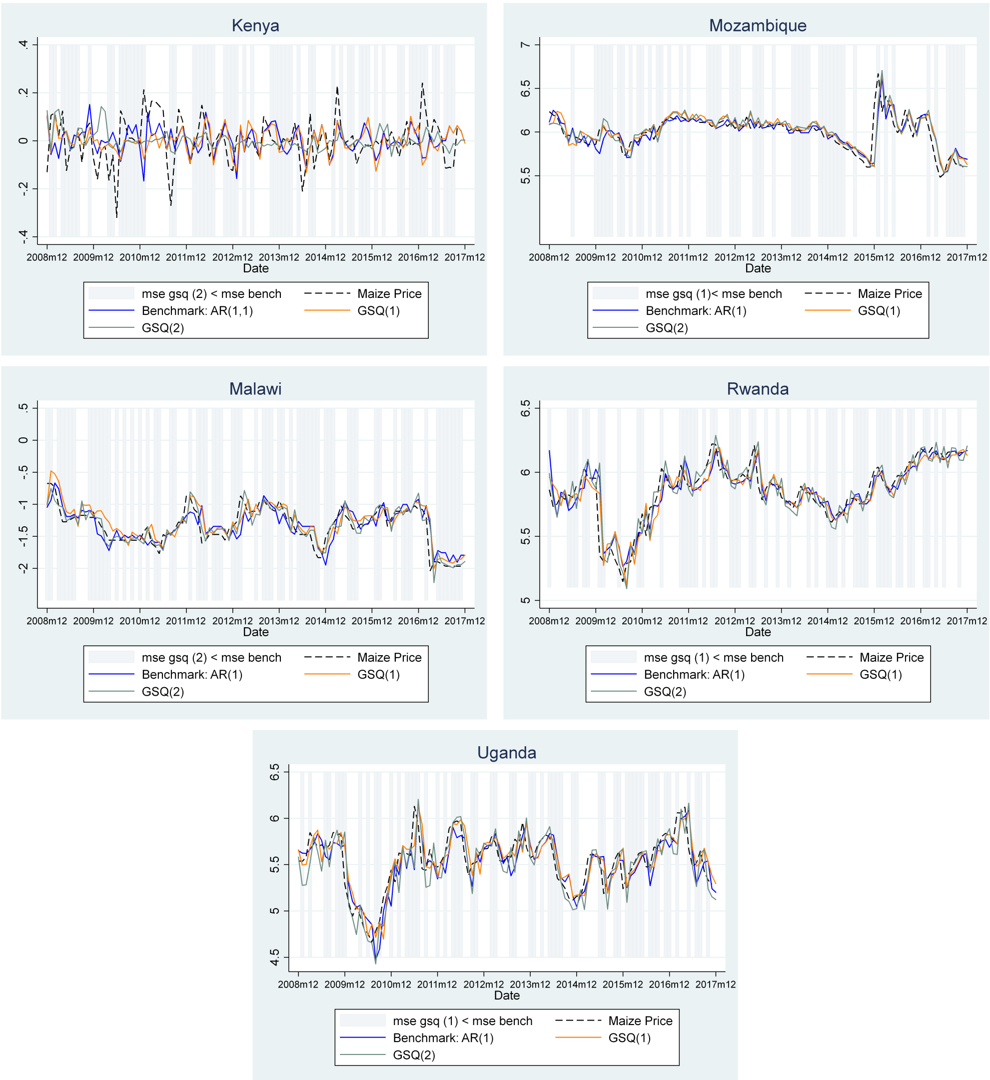
Source: Own estimation. Note: maize ln = GSQ search term *maize*, maize usd ln = local maize prices in USD, d1 = first differences, p-values in parentheses.

Table B.2: Lag-Order Selection Statistics.

Country	Lags	LL	LR	P-Value	SBIC
ETH	0	-22.230			0.36
	1	120.284	285.03	0.00	-1.70
	2	127.406	14.24*	0.00	-1.77*
KEN	0	133.677			-1.90
	1	136.566	5.78*	0.02	-1.91*
MOZ	0	2.550			0.00
	1	108.051	211.00*	0.00	-1.49*
MWI	0	-45.007			0.69
	1	65.392	220.80*	0.00	-0.88*
RWA	0	-5.470			0.11
	1	111.394	233.73*	0.00	-1.54*
TZA	0	-55.493			0.84
	1	86.046	283.08*	0.00	-1.18*
UGA	0	-46.221			0.71
	1	55.093	202.63*	0.00	-0.73*
ZMB	0	29.229			-0.39
	1	153.266	248.07	0.00	-2.15
	2	164.714	22.90*	0.00	-2.28*
ZWE	0	-29.159			0.48
	1	-23.402	11.52	0.00	0.43
	2	-16.778	13.25*	0.00	0.37*

Source: Own estimation. LL=log likelihood, LR=likelihood ratio, SBIC=Schwarz's Bayesian Information Criterion, maximum number of 6 lags included.

Figure B.6: Benchmark vs. GSQ-Augmented Out-Of-Sample Forecasts.



Note: In-sample training period (01.2006 - 12.2018) not displayed. Source: Own estimation.

APPENDIX C

Figure C.7: Participant's Manual, Page 2: Question 2, Which Signals to Watch.

Participant's Manual: Question 2

Which signals to watch for your assessment?

You should base your food security assessments on observations related to agricultural and livestock markets, the political and economics contexts, diets, anthropometry, coping and livelihood strategies.

- **Agricultural markets:** development of food prices, quality of harvest, pests, unusual weather, droughts, livestock prices
- **Political and economic context:** social conflict, do people have work?
- **Changing diets:** Quantity and quality of food consumed
- **Coping strategies:** Substitution of food with cheaper alternatives, skipping meals (who is skipping meals? Adults or children? Stronger risk if children skip meals), consumption of unusual food (e.g. termites), begging and looting
- **Livelihood strategies:** selling cattle, selling assets, migration (indicates stress in region where people are migrating from, as well as stress in regions where people are migrating to)
- **Anthropometry**: are people skinnier than usual, are adults underweight, are children dying?

Classification of Question 2:

Phase 1: None / minimal food insecurity	Phase 2: Stressed	Phase 3: Crisis	Phase 4: Emergency	Phase 5: Famine
More than 4 in 5 households are able to meet essential food and non-food needs without engaging in atypical, unsustainable strategies to access food and income, including any reliance on humanitarian assistance.	Even with any humanitarian assistance, at least 1 in 5 households in the area have the following or worse: Minimally adequate food consumption but are unable to afford some essential non-food expenditures without engaging in irreversible coping strategies.	Even with any humanitarian assistance, at least 1 in 5 households in the area have the following or worse: Food consumption gaps with high or above usual malnutrition Or Are marginally able to meet minimum food needs only with accelerated depletion of livelihood assets that will lead to food consumption gaps.	Even with any humanitarian assistance at least 1 in five households in the are have the following or worse: Large food consumption gaps resulting in very high acute malnutrition and excess mortality Or Extreme loss of livelihood assets that will lead to food consumption gaps in the short term.	Even with any humanitarian assistance, at least 1 in 5 households in the area have an extreme lack of food and other basic needs where starvation, death and destitution are evident.

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Source: Own design.

Table C.3: FCS, Composition and Weighting.

	Food Items (examples)	Food Groups (definitive)	Weight (definitive)
1	Maize, maize porridge, rice, sorghum, millet, pasta, bread, other cereals, cassava, potatoes and sweet potatoes, other tubers, plantains	Main Staples	2
2	Beans, peas, groundnuts, cashew-nuts	Pulses	3
3	Vegetables, leaves	Vegetables	1
4	Fruits	Fruit	1
5	Beef, goat, poultry, pork, eggs, fish	Meat and fish	4
6	Milk yogurt, other dairy	Milk	4
7	Sugar, sugar products, honey	Sugar	0.5
8	Oils, fats and butter	Oil	0.5
9	Spices, tea, coffee, salt, fish powder, small amounts of milk for tea	Condiments	0

Source: WFP (2008).

Table C.4: rCSI, Composition and Weighting.

In the past 7 days, if there have been times when you did not have enough food or money to buy food, how often had your household had to	Universal severity weight
Relative frequency score	
a. Rely on less preferred food and less expensive food?	1
b. Borrow food, or rely on help from a friend or relative?	2
c. Limit portion sized at meal times?	1
d. Restrict consumption by adults so that small children can eat?	3
e. Reduce the number of meals eaten in a day?	1

Source: WFP (2008).

Table C.5: Mean and Variance of FCS and rCSI.

	Mean	Variance
FCS	39.37	221.97
rCSI	10.7	153.47

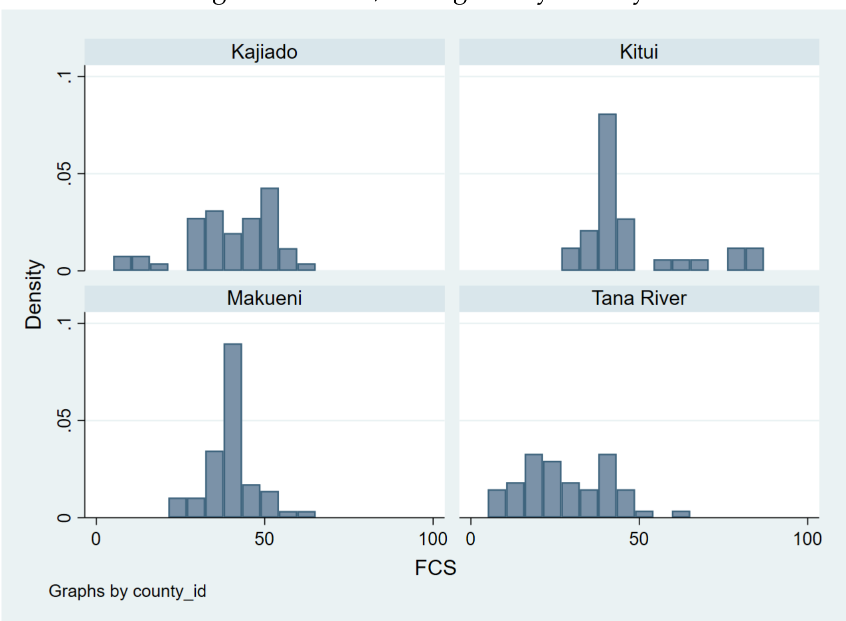
Source: Own calculation.

Table C.6: Secondary Data, Time Period: Jan - Aug 2018.

Source	Type	Spatial Unit
NDMA	Drought Early Warning and Monitoring: Monthly Household Questionnaire	Household Level
NDMA	Monthly Staple and Livestock Prices	County Level
NASA	Daily Cumulative Precipitation	Downloaded based on Geo-Information at the District Level

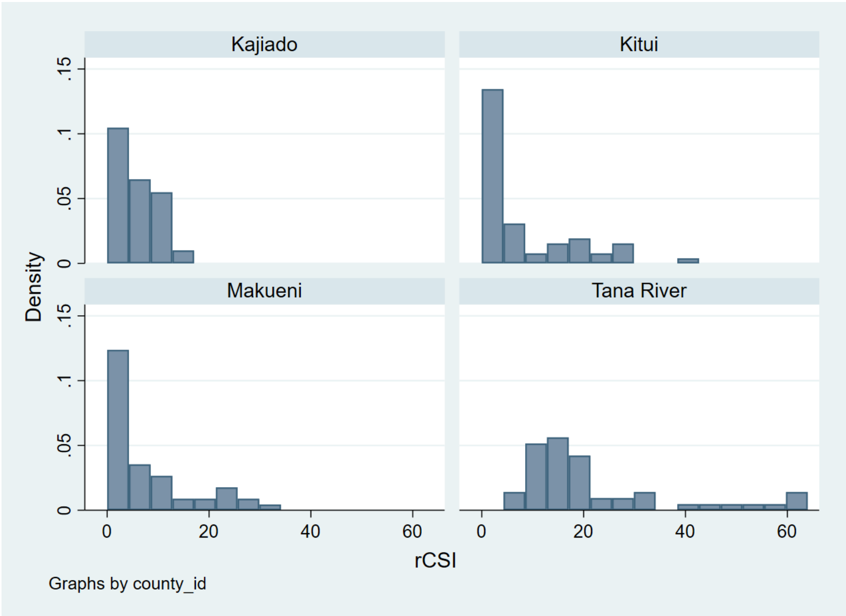
Source: Own calculation.

Figure C.8: FCS, Histogram by County.



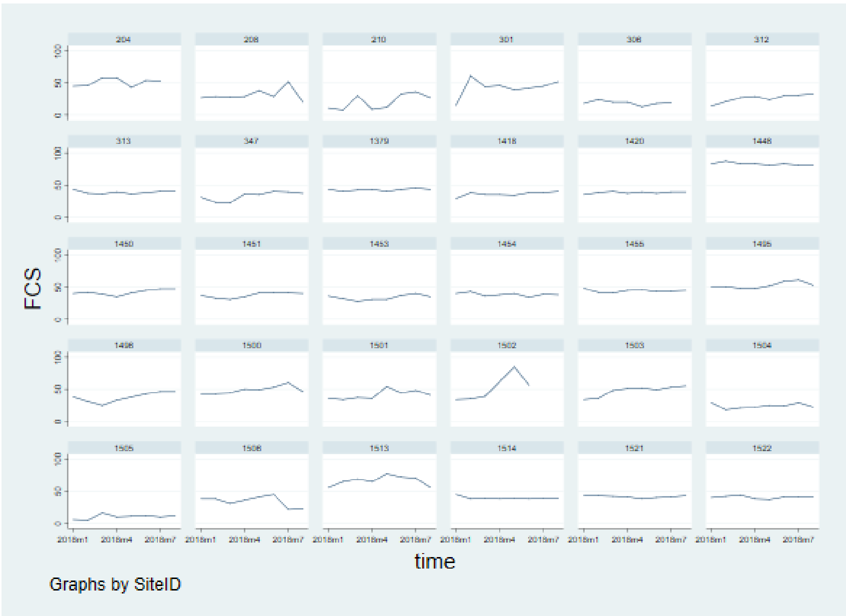
Source: Own compilation based on NDMA household data.

Figure C.9: rCSI, Histogram by County.



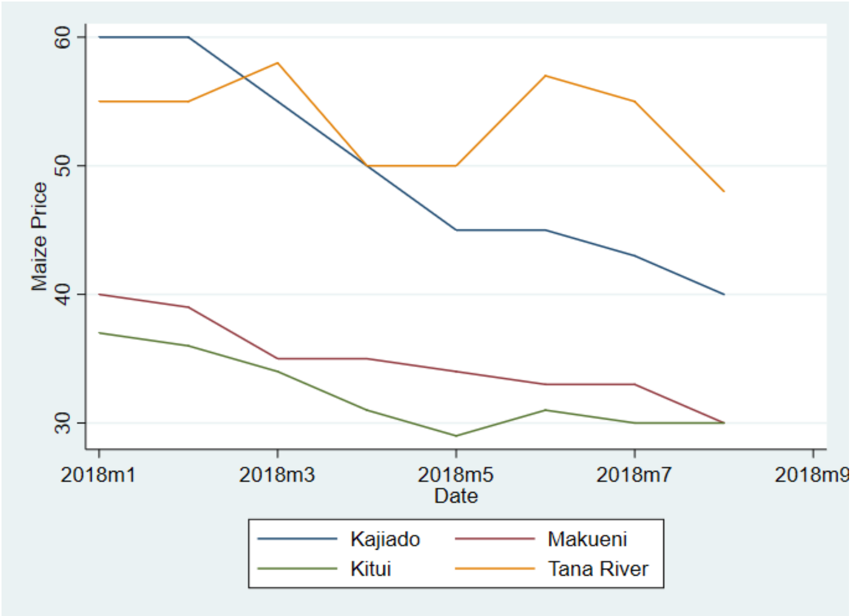
Source: Own compilation based on NDMA household data.

Figure C.10: FCS, at the District Level.



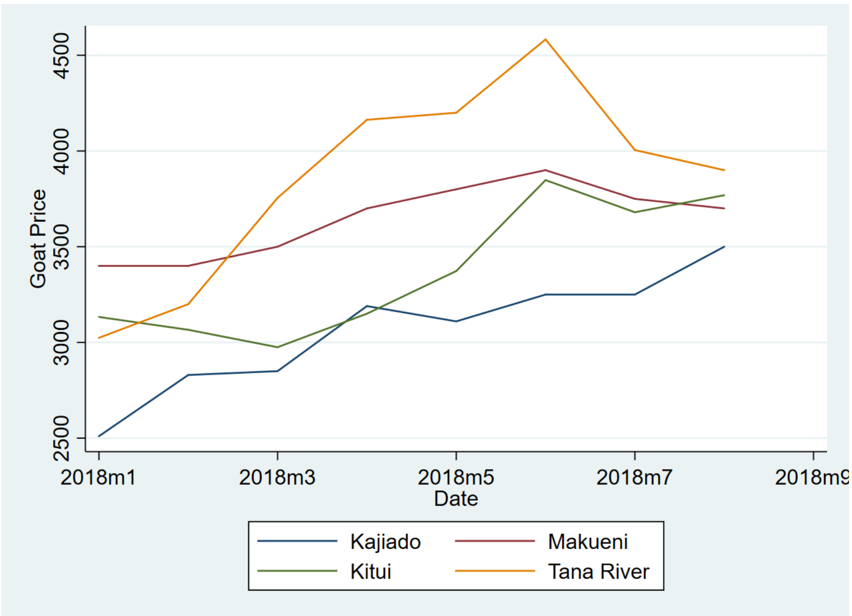
Note: SiteID refers to the different districts /geo-locations. Source: Own compilation based on NDMA household data.

Figure C.11: Maize Price, by County.



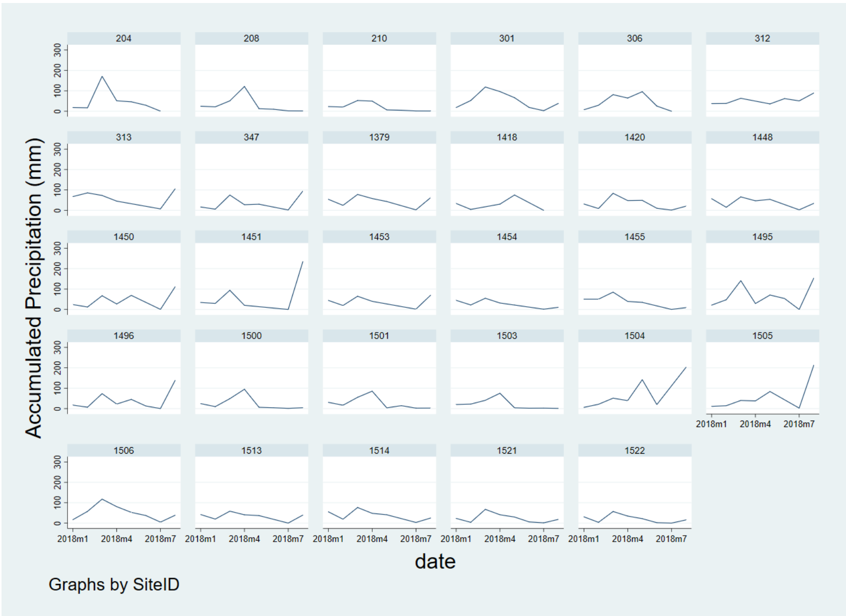
Source: Own compilation based on NDMA price data.

Figure C.12: Goat Price, by County.



Source: Own compilation based on NDMA price data.

Figure C.13: Accumulated Precipitation.



Note: SiteID refers to the different districts /geo-locations. Source: Own compilation. The area-averaged of daily accumulated precipitation was produced with the Giovanni online data system, developed and maintained by the NASA Goddard Earth Sciences Data and Information Services Center.