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Food Security Tipping Points: Using remote sensing to improve famine early warning systems

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Food Security Tipping Points:

Using remote sensing to improve famine early warning systems

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by

Prasanna Krishna Krishnamurthy Reddiar

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ABSTRACT OF THE DISSERTATION

Food Security Tipping Points:

Using remote sensing to improve famine early warning systems

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Doctor of Environment in Environmental Science and Engineering

University of California, Los Angeles 2020

Professor Alan Barreca, Chair

With a growing population and climate-related disasters projected to become more severe, the need to anticipate and better prepare for food crises has never been higher. Status quo early warning systems perform well, by and large, but complex weather phenomena are a major source of uncertainty. In this dissertation, I explore whether statistical diagnostics associated with tipping point theory can be used to improve detection of major crises.

First, the accuracy of early warning systems is evaluated – with a focus on the Greater Horn of Africa. I discuss geographical disparities in early warning skill, and explore the various sources of uncertainty that impact food security projection accuracy. I quantify the contribution of climate forecast skill and conflict events in overall early warning skill to use as a baseline upon which to improve.

Second, the potential applications of tipping point theory are discussed in relation to the use of remotely-sensed environmental variables for food security early warning. I evaluate the different statistical diagnostics that can be applied to identify food security tipping points and the data requirements in terms of spatial and temporal resolutions, data availability, latency and geographic coverage in order to be maximally useful for early warning analysis.

Finally, I test whether statistical diagnostics of tipping points can be used for detection of food security transitions. Through this work, I demonstrate the utility of combining soil moisture measurements from the SMAP mission with food price data for identifying transitions, with a lead time of approximately 3 months. The model presented here was used to detect all major food security transitions (both towards and away from a crisis) in the observational record of soil moisture. Importantly, the diagnostics are also correlated with the magnitude of change in food security conditions which is critical information for food security planning.

Overall, the dissertation advances the science and capabilities of food security early warning, which will lead to an improvement in saving lives and resources.

The dissertation of Prasanna Krishna Krishnamurthy Reddiar is approved.

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2020

DEDICATION

To

Irina

Your patience and belief in me made this possible

My father

For fostering a love for science early on in my life

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Chapter 1

Introduction

1.1. The need for new food security early warning systems

We live in an unprecedented moment in history: commitment to address environmental challenges is increasing (at least in paper) but progress is slower than ever. International leaders have committed to the Sustainable Development Goals, the most ambitious development objectives ever conceived. Of these seventeen objectives, SDG2 – zero hunger by 2030 – seemed like one of the most achievable, with promising decreases in food insecurity occurring continuously since the 1990s (FAO et al., 2010). However, in 2015, a combination of heightened climate risk and protracted conflicts around the world contributed to a reversal in this trend. And indeed, for the past four consecutive years, the number of food insecure people has increased – an unprecedented and worrying trend (FAO et al., 2019).

The implication is simple: we need to do more in order to better understand what drives food insecurity and how the effects of these drivers can be mitigated. Here, early warning systems – integrated systems for hazard prediction and forecasting to enable action that prevents a disaster – offer the solution. One of the earliest food security early warning systems can be traced to the mid-1980s. In 1984, 500,000 people died in Ethiopia alone from one of the largest drought-induced famines in recent history, making international headlines (Webb and Braun, 1994). The realization that droughts can trigger large-scale food crises prompted the humanitarian community to be more proactive by anticipating when such crises might occur. Since then, billions of dollars have gone into developing “early warning systems” designed to provide actionable information about when a crisis might unfold with the intention of preventing the event altogether (Funk et al., 2018).

The value of early warning systems is unquestionable. Issuing a warning with sufficient time to prepare for a crisis can save lives. For instance, in 2017, a combination of robust early warning signals and resilience-building efforts helped mitigate some of the effects of drought in Kenya. According to *ex post* assessments, 500,000 fewer people were in need of humanitarian assistance in 2017 than would be expected based on historical relationships between drought and food assistance needs (Funk et al., 2018).

Yet, nearly four decades later, early warning systems do not always provide adequate signals: in the aftermath of the 2015/2016 El Niño event, major droughts and food shortages in Eastern Africa were missed (FEWS NET, 2017). Part of the problem is due to climate change. Some of the scientific developments made about seasonal teleconnections – and how seasonal patterns affect food security – are based on past climatic trends and they only tell part of the story, or have become less relevant in the current climate. For instance, in Eastern Africa a strong ENSO cycle is typically linked to higher rainfall – but the strong 2015/2016 event resulted in anomalously low seasonal rainfall which existing models could not predict (FEWS NET, 2017). Against this background, how do we improve early warning systems?

1.2. How early warning systems work

Various food security early warning systems exist. Some notable examples include the World Food Programme's Corporate Alert System, which helps determine countries where priority assistance should be targeted, and the Food and Agriculture Organization's Global Information and Early Warning System, which regularly collects information on key food security metrics like prices and production trends to inform interventions. But perhaps the best funded and one of the most influential early warning systems is the United States Agency for International Development (USAID)-funded Famine Early Warning Systems Network (FEWS NET), created in the aftermath of the 1984-1985 famines that devastated much of East Africa (FEWS NET, 2020).

FEWS NET carries out baseline assessments of food security to contextualize when, where and why certain communities are more or less prone to food insecurity. Building on this contextual analysis, regular monitoring and forecasting tools are used to classify food security along a five-phase system called the Integrated Food Security Phase Classification (IPC), with Phase 1 being the least severe and Phase 5 indicating a famine (FEWS NET, 2020; Jones et al., 2007). When a particular area receives a classification of Phase 3 (crisis) or above (emergency or famine), in principle, several mechanisms are triggered to avert a humanitarian crisis – ranging from setting up warehouses, triggering contingency funds, or releasing funds for expanded social protection mechanisms.

Data on conflict, food prices, terms of trade of livestock, migration and seasonal forecasts are therefore all critical to projecting food security and prepare for a crisis. However, these essential information inputs have their own associated uncertainties which early warning analysts need to interpret when an alert is made. For example, climate forecasts can provide critical information about potential crop losses and consequently which groups of people might experience food security as a result – whether it be smallholder farmers who depend on their crops, or communities in other parts of the world who depend on production in the area affected. Climate information comes from various sources – at the regional level, climate outlook forums such as the Greater Horn of Africa Climate Outlook Forum are the dominant source of information. The forums are informed by global, regional and national weather bulletins, but ultimately consensus among meteorologists determines the information provided by the seasonal forecast. As a consequence, the process of projecting food security conditions is often criticized as being a "black box" (Lentz et al., 2019).

1.3. Emerging trends in early warning

The "black box" nature of early warning systems remains a significant criticism of early warning systems. In particular, donors and international agencies often question how accurate an early warning signal really is. A false alarm can result in an expensive operation for a crisis that never unfolds, and thereby limit resources for future emergencies. In response to this criticism, significant effort has focused on developing quantitative metrics to trigger a response in order to move away from a predominantly consensus-based approach.

1.3.1. Forecast-based early warning triggers

Much of the literature has focused on forecast-based early warning, with the idea being that actions to prevent development should happen anyway – but a quantitative threshold triggered by a forecast can help with decisions about how to allocate limited humanitarian resources (Wilkinson et al., 2018). Unlike consensus-based early warning systems that recommend actions based on (potentially subjective) warnings, forecast-based early warning initiatives emphasize decision-making protocols, so actors know when to implement preventive measures, and when and where to invest in risk reduction mechanisms (*ibid.*). Such actions may include, for instance, deployment of humanitarian assets, prepositioning of food, expanding coverage of social protection systems, or distributing cash assistance to affected populations.

By many counts, forecast-based early warning systems are similar in design to conventional early warning. Both use a variety of hazard monitoring tools, ranging from long-term seasonal forecasts to real-time monitoring of environmental conditions (or a combination of these). For drought-related events, because of the slow evolution of drought conditions, real-time monitoring is preferred over long-range forecasting. The datasets used to inform forecast-based early action are similar, with various international, regional, and national forecasting centers providing information. Typically, a combination or international or regional and national forecast data is favored to ensure that national governments trust the triggers and act early on (Wilkinson et al., 2018).

Where forecast-based early warning systems are crucially different is on their use of quantitative triggers (Ruth et al., 2019). Examples include thresholds (which are pre-defined, typically based on historical events), impact models (which are based on models that estimate impacts on poverty rates or agricultural production), and climate sensitivity assessments (which evaluate where climate risk and livelihood risk overlap, and recommends actions based on the idea that preventive action is likely to yield the greatest benefits in these areas). These triggers are automated, rather than subjective, which make them attractive to humanitarian actors who want an objective quantification of the needs in a country affected by food insecurity (Wilkinson et al., 2018).

1.3.2. Multiple triggers, or the defense-in-depth approach

Even with sophisticated triggers, early warning systems can miss a crisis due to the inherent uncertainties of the climate system and the socio-political contexts in which humanitarian agencies operate. To address this, integration of multiple triggers has been proposed: with such approach, uncertainty in the forecast decreases closer to the time, providing a clearer signal for decision-makers (Weingartner and Wilkinson, 2019). The principle is similar to that of defense-in-depth from the cybersecurity philosophy, whereby multiple layers of protection (triggers) ensure that valuable data (food security or other development objectives) are protected (Funk et al., 2019).

With the defense-in-depth approach, uncertainties in key early warning inputs like seasonal forecasts are acknowledged, so decisions are not based solely on a single indicator. Instead, low-cost monitoring and precautionary measures might be implemented. As the season progresses, the likelihood for a food crisis becomes more evident and appropriate interventions are adopted. However, a food crisis might unfold due to unexpected developments like a political crisis or food price surges. As soon as specific thresholds for these indicators are met, the early warning system will trigger action. The result is a more robust system that tracks various drivers of food insecurity and automatically assesses when a specific threshold is met to encourage action (Wilkinson et al., 2018).

1.3.3. Tipping points for food security?

Early analyses on tipping points and regime shifts have tended to focus on ecological applications such as abrupt changes in the thermohaline circulation (Stommel, 1961) and transitions in the earth’s energy balance resulting from changes in solar radiation (Budyko, 1968). The theory of tipping points was explored in ecology by Chant (1961) who studied population collapses resulting predatory/prey relationships, but the concept was more formally developed in ecological thinking by Holling (1973), who described ecosystems as regimes that are susceptible to lower resilience levels as they are exposed to external shocks, until they change abruptly. Interest faded in the 1980s, but the possibility of anthropogenic climate change accelerating sudden changes renewed interest in the mid-1990s and 2000s. This new focus on tipping points has been driven by concern about more intense El Niño events (Trenberth and Hoar, 1997) and thinning of the Arctic ice sheets (Lindsay and Zhang, 2005). Some of these principles might be adopted to social-ecological systems like food security.

The potential effects of these sudden transitions have led to research on the possibility of developing early warning systems for these (e.g., Ditlevsen and Johnsen, 2010; Lenton, 2013). Four key diagnostics have been proposed: increasing autocorrelation (Kuehn, 2011), variance (Dakos et al., 2012), skewness (Golledge et al., 2017) and rate-dependent thresholds (Ashwin et al., 2011). These indicators have been tested for various ecological contexts, including glacier melt, lake eutrophication, and forest mortality – but limited work has been conducted to test the value of these indicators for food security early warning. We test the utility of these diagnostics in this dissertation.

1.3.4. When early warning is not enough

Sometimes state-of-the-art early warning is not enough – the decision to act is arguably the most important indicator of a functioning early warning system. In fact, some scholars even question whether technocratic improvements to early warning systems are even necessary given that governments intervene because of self-interests rather than objective alerts (Whittall, 2010). To illustrate, the most sinister manifestation of this challenge in recent times is perhaps the 2011 famine in Somalia. The crisis unfolded as a result of (1) erratic rainfall in the previous season, (2) cessation of World Food Programme operations due to security concerns, and (3) increasing restrictions on humanitarian presence placed by Al-Shabab (WFP, 2010; FEWS NET and FSNAU, 2011). Prior to the famine, regular warnings of potential drought conditions and an impending crisis were provided for eleven consecutive months. The quality and timeliness of the alerts was unprecedented for the time – and yet the response to the famine only started *after* the famine unfolded. The key challenge in this context was not the lack of information, but the mistrust in the early warning signal (specifically in the reliability of probabilistic seasonal forecasts and the absence of specific mortality estimates) and lack of advocacy efforts which led to a delayed response (Hillbruner and Moloney, 2012). With increasing availability of quantitative early warning analysis approaches, it is expected that decision-makers will trust early warning signal and enable early action – and in fact this has been the source of much research in early warning science. With this dissertation I hope to contribute towards a quantitative approach to increase credibility of early warning systems.

1.4. The potential of remote sensing

Remote sensing products offer an unparalleled opportunity to enhance food security early warning: first, they are globally available (at least for areas where food insecurity tends to be a development challenge); second, they are typically available at low cost; third, they monitor environmental indicators relevant for food security; and fourth, some products are available at sufficient temporal and spatial resolution for food security analysis. These characteristics address the critical challenge of collecting data on a spatial and temporal scale commensurate with food crises through ground-truthing efforts alone (De Sherbinin et al., 2014).

Recent developments in remote sensing science allow for direct observation of drought-related impacts. Several drought-related indicators are already routinely monitored in early warning through satellite observations: precipitation (TRMM/GPM, AghaKouchak et al., 2015), groundwater (GRACE/GRACE-FO)18, soil moisture (SMAP, Velpuri et al., 2016), snow cover (MODIS, Kumar et al., 2014), evapotranspiration (MODIS, ECOSTRESS, Begueria et al., 2014), chlorophyll fluorescence (OCO-2 SIF, Sun et al., 2015) and vegetation health (MODIS, Vrieling et al., 2016) are all indicators derived from satellite imagery that are currently used for drought assessments. And indeed, some of these products are already utilized in early warning systems (e.g., NDVI derived from MODIS is a critical input for global agroecological monitoring in the GIEWS and FEWS NET platforms, while snow cover from MODIS imagery is used for food security planning purposes in Afghanistan by FEWS NET).

However, a key question is whether remotely-sensed data can be used to detect early warning signals for specific drought disasters that lead to a famine. The majority of the indicators mentioned here occur at the appropriate spatial and temporal resolutions to enable detection of droughts, and therefore hold great potential for enhancing early warning. If these indicators can be effectively used, these data could provide an operational platform to prepare for and manage drought risk in a more effective manner. I address this question in this dissertation, with the hope of demonstrating the untapped potential of some remote sensing products that have become available in the recent past.

1.5. Structure of the research

With this dissertation, I evaluate accuracy rates associated with food security early warning and suggest a potential novel approach for enhancing detection of food crises. In Chapter 2 (Krishnamurthy et al., 2020a), I evaluate the accuracy of the Famine Early Warning Systems Network in the Greater Horn of Africa, highlighting major deficiencies in accurately forecasting food security conditions in pastoral and agropastoral regions, areas which tend to be more prone to food insecurity. In Chapter 3 (Krishnamurthy et al., 2020b), I argue that tipping point theory – which has long been tested in ecological applications – could be applied to ever-increasing remotely-sensed products like soil moisture and groundwater to improve early warning signals. In Chapter 4 (Krishnamurthy et al., in review), I show that applying tipping point theory to remotely-sensed datasets offers an approach to improve early detection of impending food crises. In the final Chapter, I discuss how the work presented in the preceding Chapters can help develop the next generation of early warning.

Chapter 2

Dealing with uncertainty in famine predictions: How complex events affect food security early warning skill in the Greater Horn of Africa

Adapted from:

Krishnamurthy R, P.K., Choularton, R.J., and Kareiva, P.M., 2020. Dealing with uncertainty in famine predictions: How complex events affect food security early warning skill in the Greater Horn of Africa. *Global Food Security*, *26*, 100374, doi: 10.1016/j.gfs.2020.100374

2.1. Introduction

The last four years have seen a reversal in decades of progress towards eradicating food insecurity. The latest estimates of global food insecurity suggest that over 821 million people experience food insecurity – compared to 785 million in 2015 (FAO et al., 2019). At the same time, emergency food assistance needs have increased for the fourth consecutive year: over the course of 2020, around 88 million people in 46 countries are projected to require emergency food assistance – representing an increase of 87 percent compared to 2015 (FEWS NET, 2019). This negative trend is primarily the result of protracted conflicts and increased magnitude of extreme weather events (FAO et al., 2019).

The increased risk of severe food insecurity across the world highlights the continued importance of investing in food security early warning systems. Such tools are essential for food assistance and planning, providing actionable information to governments and humanitarian agencies for contingency planning that can ultimately prevent large-scale food crises and human suffering (Brown et al., 2007; Ververs, 2011). Early warning systems develop scenarios based on diverse inputs, ranging from meteorological indicators, seasonal forecasts and agricultural production estimates to food prices, livestock terms of trade, humanitarian assistance plans, and conflict. Given the complexity and uncertainty associated with these data streams, early warning systems can result in incorrect forecasts, which can have serious consequences: on the one hand, overestimating food insecurity leads to inefficient use of limited resources, while on the other, underestimating the severity of food insecurity can lead to humanitarian crises with significant human losses (Heady and Barrett, 2015).

Recent advances in the use of remotely sensed data for agricultural monitoring, improved regional weather forecasts, enhanced approaches for data collection, and the expanding use of mobile technology to collect data in remote areas have all contributed to the improvement of early warning systems. However complex weather phenomena continue to result in prediction errors, as illustrated by the difficulty of forecasting food security trends during the 2015/16 El Niño Southern Oscillation (Choularton & Krishnamurthy, 2019). Improvements have also been made in monitoring socioeconomic trends, such as food prices and conflict intensity – but these still represent a major source of error in forecasting food security. In terms of food security measurements, too, significant progress has been achieved by standardizing tools for quantifying food insecurity through methods like the Integrated Food Security Phase Classification (IPC), which provides a benchmark that allows for inter-comparability of the severity of food insecurity across countries (Schiccitano, 2018).

The standardization of food security metrics, in particular, allows for an unprecedented comparison of the performance of food security early warning systems beyond *ad-hoc* post-crises evaluations. Despite the potential and significance, few evaluations of the accuracy of food security early warning systems have been done, especially at a comparative level across countries. To address this gap, this paper presents a method for assessing the accuracy of the Famine Early Warning System Network (FEWS NET) early warning data during the period January 2011-July 2019, using the Greater Horn of Africa (defined here as Ethiopia, Kenya, Uganda, Somalia, Sudan and South Sudan) as a case study. For the context of this paper, accuracy refers to the ability of food security analysts to project food security by comparing forecasted with actual food security classifications. We envision that this research will provide a more rigorous way to target resources to improve famine and food crisis early warning systems and help identify the specific contextual challenges that most affect early warning including climate prediction (see Coughlan de Perez et al., 2019), market conditions, and conflict.

2.2. Materials and Methods

The method used for this paper consisted of three steps: (1) collection of administrative divisions, livelihood zones, food security classification, seasonal outlook skill, and conflict incidence data, (2) data processing, (3) and an analysis consisting of evaluating differences between forecasted and actual food security classifications, identifying the relationship between accuracy and various sources of error, and a qualitative review of FEWS NET food security assessments to identify factors contributing to discrepancies between outlooks and actual food security classifications (Figure 2.1).

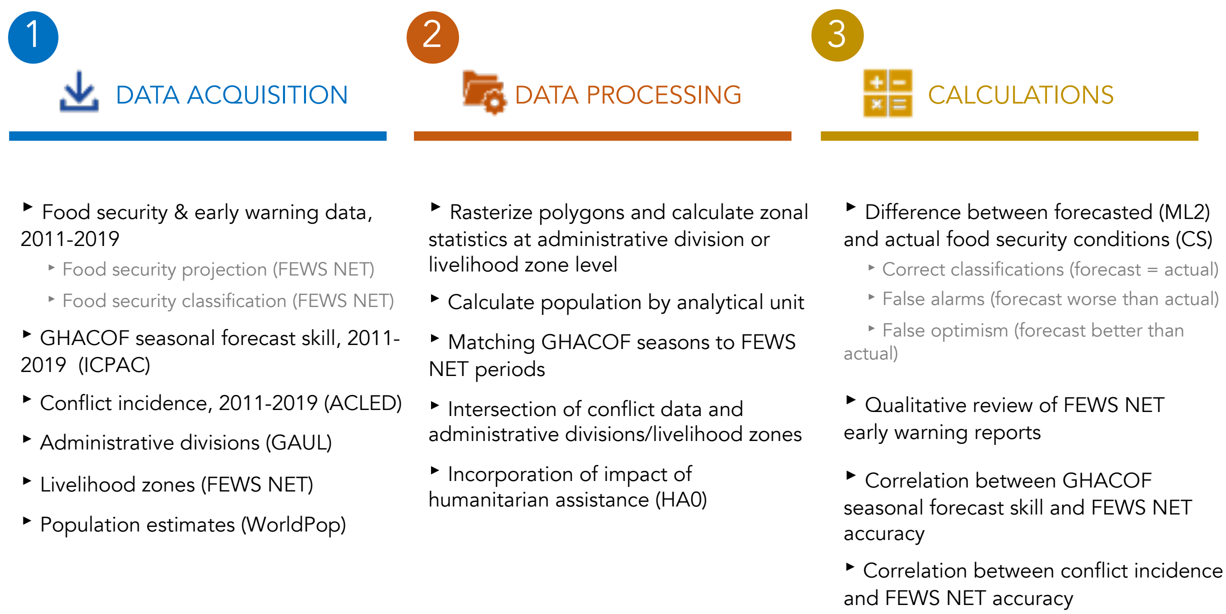

Figure 2.1. Overview of method. The method used for this paper consisted of three major steps.

2.2.1. Data acquisition

Food security data. The Famine Early Warning System Network (FEWS NET) provides integrated food security phase classification (IPC) data – both forecasted and actual – on a quarterly basis from 2011 until 2015 (January-March, April-June, July-September, October-December) and on a 4-monthly basis from 2016 onwards (February-May, June-September, October-January) in the FEWS NET data portal: http://www.fews.net/fews-data/333. Forecasted IPC classes are provided for the following season (3-4 months ahead). The IPC consists of protocols to classify food insecurity and provide information for decision making according to five categories that are comparable across countries: minimal food insecurity (IPC Phase 1), stressed (Phase 2), emergency (Phase 3), crisis (Phase 4) and famine (Phase 5). Categories are assigned to geographical areas based on consolidated evidence on food-insecure communities to provide information on: (1) the severity of food insecurity, (2) the geographic and socioeconomic distribution of food insecurity, and (3) the reasons for food insecurity (IPC Global Partners, 2012). For an area to be classified in an IPC phase, at least 20 percent of the population in that area must be estimated to be in that phase. Forecasted and actual IPC classes were downloaded for all of the Greater Horn of Africa countries for the period January 2011-October 2019.

The role of humanitarian assistance. Humanitarian assistance affects food security outcomes and influences how accuracy rates are reported. For instance, a region may report differences between projected and actual food security conditions, because humanitarian assistance mitigates the effect of a food crisis. To capture this effect, we identified the areas where humanitarian assistance provision had an impact on the severity of food insecurity, as a response to an alert. Since 2012, FEWS NET IPC data include an exclamation mark to denote areas where food security conditions would be worse without humanitarian assistance. In addition, FEWS NET provides a retrospective account of how much worse (in terms of IPC classes) food security conditions would be in an area (HA0). For instance, if HA0 = 1, food security conditions would likely be worse by 1 IPC class – so if an area is classified as IPC2!, the area would likely be classified as IPC3 in the absence of humanitarian assistance. For locations that were classified with an exclamation mark, we added the HA0 values to represent the food security conditions without humanitarian assistance and thereby remove this effect from our accuracy analysis.

FEWS NET analytical units: administrative divisions and livelihood zones. IPC food security classes are provided at either the administrative level, or at a broader livelihood zone level, depending on the availability of data and to satisfy the requirements of humanitarian planning in specific countries. For the countries in the Greater Horn of Africa, there is a significant difference in the number of analytical units: in Somalia, 19 livelihood zones are used while in Ethiopia, food security conditions are reported for each of 690 *woredas* (third administrative level units). To match the analytical unit of FEWS NET IPC classifications, administrative division layers were downloaded for Ethiopia, Kenya, Uganda, Sudan and South Sudan from the Global Administrative Units Layers (GAUL, http://www.fao.org/geonetwork/srv/en/metadata.show?id=12691) – while for Somalia, livelihood zones from FEWS NET were downloaded.

Population dataset. In order to account for the large differences in population between administrative units, we have downloaded population estimates from the WorldPop database (https://www.worldpop.org/). WorldPop a high spatial resolution raster that relies on a statistically-based weighting layer combined with on ancillary data to spatially disaggregate census counts from administrative census units in an effort to develop higher resolution data products that represent population distribution more accurately (Tatem, 2017). Because WorldPop relies on a modeling approach, the dataset tends to avoid problems of overestimating rural populations – a common problem with unmodeled population estimates like GPW (Leyk et al., 2019).

Predictive skill of seasonal forecasts. Climate information and seasonal forecasts are a major source of information for food security early warning, providing critical predictions about rainfall trends which can ultimately impact agricultural production and translate to food security impact (Funk et al., 2019). One of the predominant seasonal forecasts used for food security projections in the Greater Horn of Africa (GHA) is the GHA Climate Outlook Forum (GHACOF) – a consensus-based service which provides probability distributions to indicate the likelihood of above- (within the wettest third of the climatological record), near- (the third of the recorded rainfall amounts centered on the climatological median), or below-normal rainfall (the driest third of recorded rainfall amounts) over broad geographic zones. Current GHACOF reports include a retrospective analysis of forecast performance using a hit score (available at http://rcc.icpac.net/index.php/long-range-forecast/verification-products) (see also Walker et al., 2019). All available hit scores from January 2011 onwards were downloaded.

Conflict data. The incidence of conflict is a major contributor to food insecurity. Data on conflict incidence were downloaded from the Armed Conflict Location and Evaluation Data Project (ACLED, https://www.acleddata.com/), which records the dates, actors, types of violence, point locations, and fatalities of all reported political violence and protest events. ACLED records are considered to be among the most comprehensive and accurate for conflict analysis.

2.2.2. Data processing

Matching food security data to FEWS NET analytical units. Given slight inconsistencies between administrative layers and the polygons provided by FEWS NET, it was necessary to rasterize the raw shapefiles, and subsequently, extract the majority value for each division. We used the original analytical unit used by FEWS NET in order to maintain the integrity of the analysis.

Calculating population by FEWS NET analytical unit. We used zonal statistics (sum) to estimate the number of people living in each FEWS NET analytical unit. Population estimates were then normalized with the following equation, where pop_i refers to a given population value, pop_{min} is the minimum population value in any analytical unit, and pop_{max} is the maximum population value in the data:

$$pop_{normalized} = \frac{pop_i - pop_{min}}{pop_{max} - pop_{min}}$$

Subsequent results are reported based on these normalized population-based weights.

Matching GHACOF outlooks to FEWS NET seasons. The Greater Horn of Africa Climate Outlook Forum meetings take place three times a year and produce a forecast for the March-May, June-September, and October-December seasons. On the other hand, FEWS NET forecasts are available quarterly between 2011 and 2015, and thereafter for the periods February-June, July-September, October-January. Given these slight differences, the GHACOF verification product was manually matched to the most relevant FEWS NET season.

Number of conflicts per analytical unit. ACLED data on conflict locations are provided as point data. These were matched to the FEWS NET analytical units (using the Intersect tool in QGIS and were later aggregated temporally to match the FEWS NET seasons between 2011 and 2019. For this analysis, we focus on the number of incidents rather than fatalities or number of victims because the latter are incomplete or inaccurate for several events, especially older incidents. As the ACLED database and other conflict databases become increasingly available, we hope that future analysis will provide a more nuanced analysis of the relationship between conflict intensity and early warning accuracy.

2.2.3. Analysis approach

The differences between forecasted and actual IPC classifications were calculated using the following equation:

$$Bias = \frac{\sum_{n=1}^{i}(\hat{y}_n - y_n)}{n}$$

Where $\hat{y}_n$ refers to the nth prediction and y_n is the observed value repeated over *i* observations. This metric is often used in evaluations of accuracy for remote sensing applications (Pan et al., 2016) and model performance (Fratarcangeli et al,. 2016).

The bias calculation provides an estimate of error rates and the direction of error, enabling classification of accuracy according to the following categories:

- correct food security estimate (i.e., the forecast matched the actual IPC category),
- overestimation of food insecurity (i.e., the actual IPC class was lower than anticipated, or false alarm),
- and underestimation of food insecurity (i.e., the actual IPC class was higher than forecasted, or false negative).

These results indicated that significant areas within the region are routinely assessed as being food secure, with no change in food security status over the period of analysis. Therefore, we excluded areas that were assessed as food secure consistently. This allowed for a more specific evaluation of accuracy in the areas facing food insecurity. Final results are presented at the relevant FEWS NET analytical unit, to enable identification of geographic patterns of accuracy.

This information is intended to provide inputs for targeting regions where additional investments in food security monitoring or early warning inputs are required to improve accuracy rates.

Arguably the greatest utility of an early warning system is its ability to detect a major crisis. To do this, we assessed periods where food security conditions deteriorated to at least a crisis situation (IPC 3 or higher), and evaluated whether the transition was forecasted. The analysis of crisis transitions provides further insight into the areas and livelihood groups that are most vulnerable, allowing for targeted early action resources.

To assess sources of uncertainty in food security early warning systems, we reviewed all FEWS NET outlook reports and identified events linked to underestimation and overestimation of food insecurity. Four major types of events were identified through this analysis: droughts and other climate shocks like floods and cyclones, conflicts and political instability, food price volatility, and pest outbreaks – with the first two being the most common sources of error. We then estimated the correlations between food security projections, and GHACOF skill rate (as a proxy for intrinsic uncertainty associated with climate models) as well as conflict incidence (as an indicator of political instability) in order to quantify the contribution of uncertainty in weather forecasts and conflict events on overall early warning accuracy.

2.3. Results

2.3.1. Early warning performance varies by geography

Overall, food security early warning is highly accurate throughout the Greater Horn of Africa, though there is significant variability across countries: South Sudan (80 percent), Ethiopia and Somalia (85 percent), Kenya (92 percent), Sudan (90 percent) and Uganda (95 percent).

Accuracy rates were found to be higher in productive areas, such as the cropping zones of southern Uganda, southwestern Kenya and western Ethiopia – as well as the desert regions of Sudan – where food security early warning projections consistently match the food security situation.

A disaggregation by administrative units (or livelihood zones in the case of Somalia) reveals large variations in accuracy sub-nationally (Figure 2.2). The highest accuracy rates were found in western Ethiopia, southwestern Kenya, southern and northwestern Uganda, and northeastern and southwestern Sudan. All of these regions are predominantly cropping zones, with the notable exception of the northeastern pastoral zone of Sudan.

In contrast, the lowest accuracy rates were reported in central and southern Ethiopia, South Sudan, northeastern Uganda (the Karamoja sub-region), northeastern and southern Kenya, and northern and south-central Somalia. Regions with the lowest early warning accuracy tend to be predominantly pastoral and agropastoral zones.

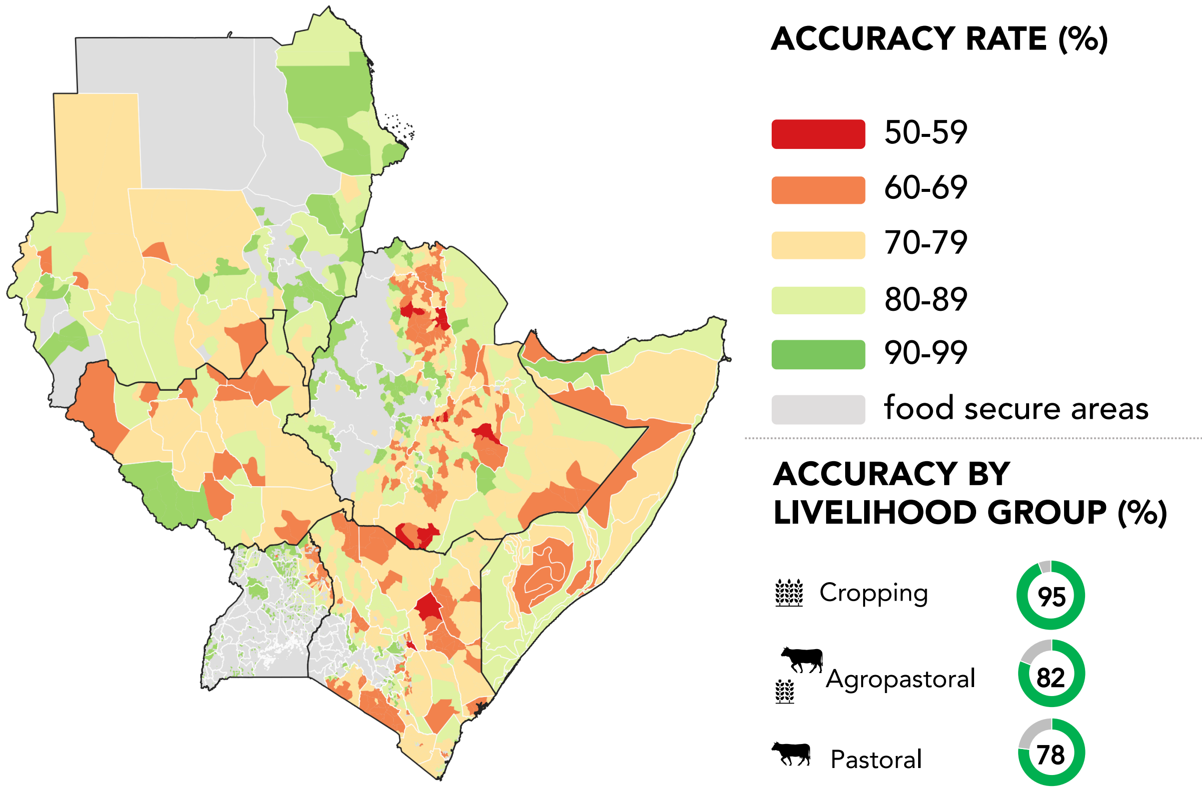

Figure 2.2. Regional accuracy of food security early warning varies significantly in the Greater Horn of Africa. Higher accuracy rates are found in traditionally cropping-based zones of the region, while food security in zones that depend on pastoral and agropastoral livelihoods tends to be less accurately forecasted.

2.3.2. Errors in early warning: false alarms and missed crises

Two types of error occur with early warning analyses: they can either provide an overestimate *or* an underestimate of the severity of food insecurity. The former kind occur when food security conditions (IPC classes) are better than projected. This may be because forecasts do not predict good climatic conditions or because humanitarian assistance is in place to mitigate food insecurity. These errors can be either false alarms or they could be the result of successful early warning prompting an increase in humanitarian assistance. The latter category ('missed crisis' errors) occurs when forecasts miss crises or deteriorations of food security conditions, i.e., the actual IPC category is worse than forecasted.

Overall, errors in early warning are more likely due to underestimates of food insecurity: between 2011 and 2019, 63 percent of errors were missed crisis errors while 37 percent were overestimates or false positives. Further, our analysis reveals that some areas are more prone to overestimates (especially in South Sudan, parts of Sudan, and Somalia) while others are more prone to missed crisis errors (especially in northern, central and eastern Ethiopia, and Kenya). This is further illustrated in Figure 2.3, below, which illustrates the proportion of errors classified as missed crises (0% false negatives (missed crises) = 100% false positives (false alarms)).

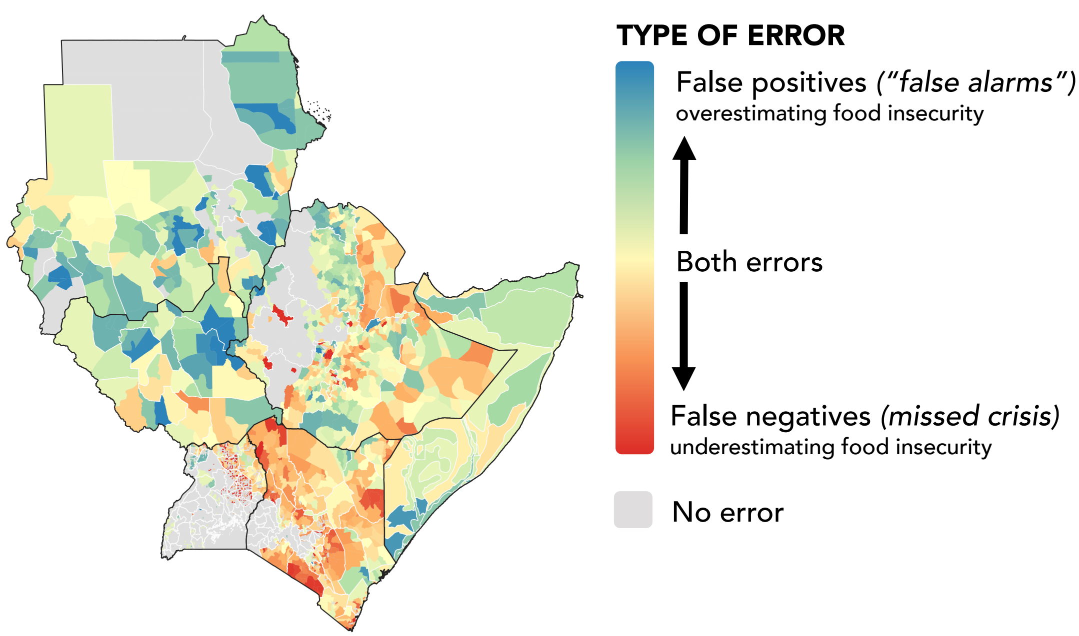

Figure 2.3. Types of errors vary significantly by geography. Darker red areas show locations where early warning underestimates food insecurity, while darker blue areas represent locations where false alarms are more common.

2.3.3. Crisis detection

The greatest contribution of a famine early warning system is its ability to anticipate (and thereby help prepare for) major food crises or serious deteriorations of food insecurity – which we define for this analysis as any increase in IPC category to at least IPC Phase 3. Between 2011 and 2019, 3,014 instances of such transitions occurred – of which 1,949 (65 percent) were correctly identified.

Transitions to crisis or crisis deepening occurred throughout the Greater Horn of Africa, with a larger number of transitions in South Sudan, the central highlands and pastoral lowlands of Ethiopia, the Darfur and Kordofan regions of Sudan, the arid and semi-arid lands of Kenya, south-central Somalia (Figure 2.4). The ability to detect these transitions has a positive correlation with the number of crisis transitions ($R = 0.838$, $p < 0.05$) – in other words, in regions with more frequent transitions, early warning systems tend to project crises more accurately than in areas with infrequent transitions. To illustrate, the northern region of South Sudan experienced the greatest number of crisis transitions but the crisis detection miss rate is less than 20 percent; on the other hand, areas of northern Somalia only experienced one crisis transition which was not forewarned by the early warning analysis.

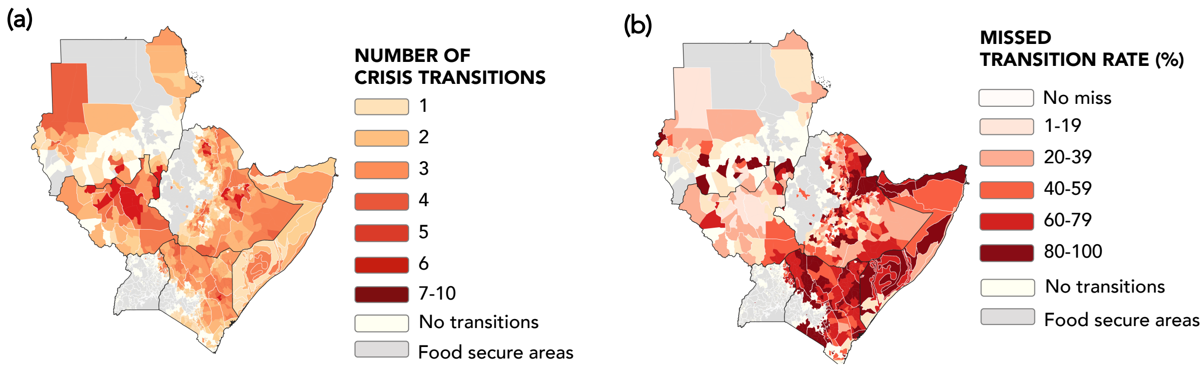

Figure 2.4. (a) Frequency of crisis transitions and (b) rate of missed transitions.

2.3.4. Possible sources or error

The most common sources of error in early warning analysis included limited skill in forecasting climate-related disasters (79 percent of errors in the Greater Horn of Africa were associated with inaccurate drought projections, while an additional 4 percent of errors were due to floods), followed by civil unrest and political conflict (13 percent of errors). The remaining errors were associated food price shocks and pest outbreaks (3 and 1 percent of errors, respectively). Indeed, periods with the highest error rate were also periods with complex weather phenomena which resulted in food security conditions that were challenging to project (Figure 2.5).

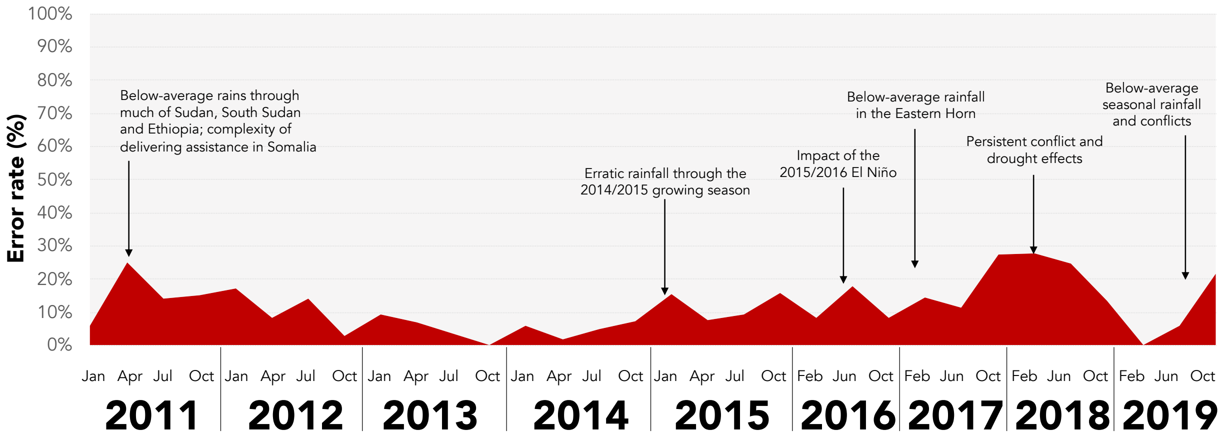

Figure 2.5. Overview of error rates in the Greater Horn of Africa by FEWS NET season. Major events associated with peaks in errors are highlighted though other factors, not listed here, might have also been responsible for errors.

We evaluated the relationship between accuracy rates and the two most common sources of uncertainty (namely, climate forecasts and conflict incidence). As expected for early warning systems that depend on climate forecasts, our analysis suggests seasonal forecast skill is positively correlated with accuracy rates: seasons with more skillful forecasts also translate to accurate food security projections (Figure 2.6). Furthermore, our results indicate a moderately strong relationship between food security predictions and weather forecast skill (R = 0.494, $p < 0.05$). The implication is that complex weather phenomena, which are associated with lower predictive skill, are particularly challenging for early warning analysts. The results also indicate that other factors, beyond climate, affect the accuracy of food security early warning.

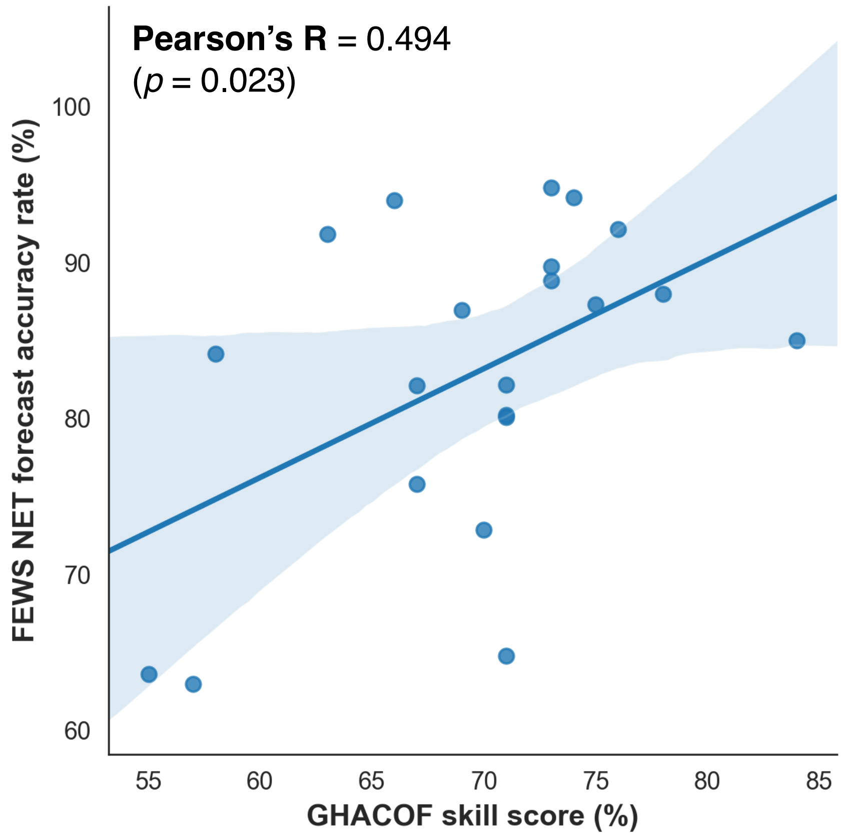

Figure 2.6. Relationship between FEWS NET forecast accuracy and GHACOF skill rate. Higher errors in projecting food security conditions are associated with a higher miss rate in GHACOF outlooks, suggesting that improvements in seasonal forecasts – particularly for complex weather phenomena – will contribute to better food security forecasts.

Conflict also contributes to uncertainty in early warning analysis (Figure 2.7). There is a negative relationship between mean accuracy of FEWS NET projections and the number of conflicts (the R value for accuracy rates and the log value of conflict events is -0.331, indicating that conflict contributes to errors – but it is not the only source of uncertainty). Indeed, every district affected by the civil conflict in South Sudan reports accuracy rates of less than 70 percent with some reporting an accurate projection only on 52 percent of occasions. Similar patterns are found in counties affected by the conflict in the Karamoja sub-region in northeastern Uganda with accuracy rates as low as 50 percent. While overall greater conflict incidence results in lower accuracy rates, the relationship between conflict incidence and accuracy rates is not straightforward. For areas that had between 1 and 49 conflicts as reported by ACLED, higher incidence of conflicts results in lower capacity to project food insecurity. For areas that experienced 50-74 conflicts, accuracy rates were among the highest (on average, 83 percent). Areas with more than 75 conflicts show lower accuracy rates. However, an important caveat should be added here: IPC projections are not spatially independent, thereby decreasing the degrees of freedom in the dataset. Moreover, *t*-tests invalidate the hypotheses that mean accuracy of the 75-99 (*p*-value = 0.3613) and >100 classes (*p*-value = 0.9132) would be greater than that of the 25-49 class. The results of the *t*-tests indicate that the relationship between accuracy and conflict incidence reported here is not statistically meaningful for areas with more than 75 conflicts – and should be considered indicative only.

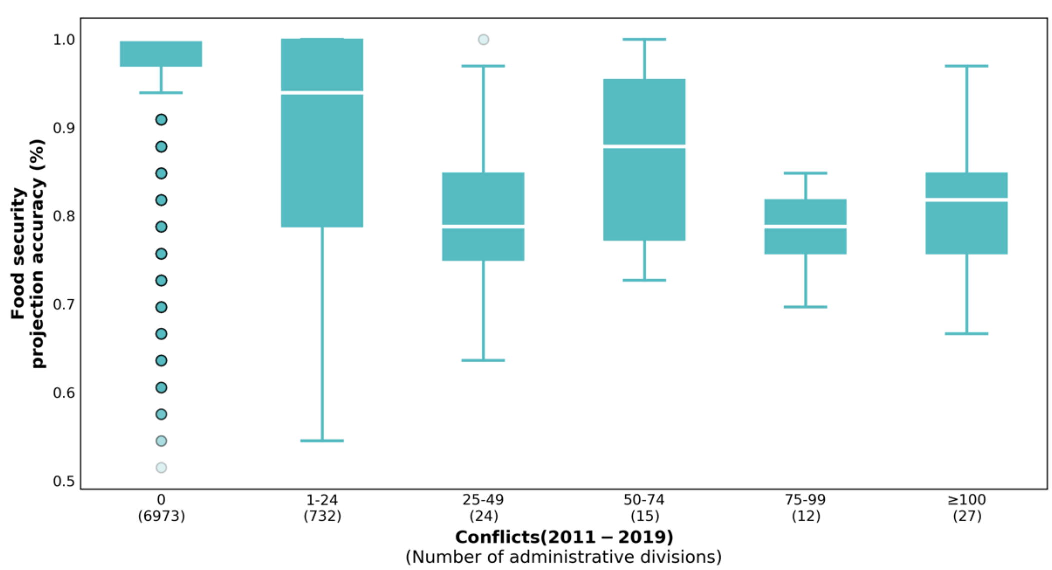

Figure 2.7. In areas with low conflict rates (less than 50 in 2011 and 2018), increasing conflict reduces accuracy rates; whereas areas with more than 50 conflicts show greater projection accuracy. The number of administrative divisions associated with each conflict level is shown in brackets.

2.4. Discussion

2.4.1. Investing in early warning is beneficial – but more work remains to be done

Early warning systems provide alerts that, if heeded adequately, translate to targeted early action that helps save lives and livelihoods for some of the world's most food insecure communities (Drechsler and Soer, 2016). To illustrate, early interventions in the 2016/2017 season in Kenya reduced humanitarian needs. Based on the historical relationships between drought intensity and number of people requiring food assistance, in 2017, 500,000 fewer people required food assistance than expected (Funk et al., 2018). In part, the trend can be attributed to timely early warning alerts feeding into the humanitarian system (Funk et al., 2019), but the effect of long-term livelihood development and the experience of previous droughts arguably play a more significant role in reducing vulnerability (Alinovi, 2010).

Recognizing the value of early warning, substantial investments have been made to global and regional food security (and other) early warning systems over the last four decades – most notably, the Famine Early Warning Systems Network (FEWS NET), the Food and Agriculture Organization's Global Information and Early Warning System (GIEWS), WFP's Corporate Alert System, and the multi-agency Food Security and Nutrition Analysis Unit in Somalia (FSNAU) (e.g., Pulwarty and Sivakumar, 2014). Simultaneously, a lot of work has gone into identifying indicators and triggers that determine when an intervention will take place (Ruth et al., 2017).

Still, early warning systems occasionally overestimate or underestimate the severity of a food crisis, often because of uncertainties associated with seasonal weather forecasts, political instability and other inputs (e.g., Ahmadalipour and Moradkhani, 2017; Thiboult et al., 2017). The costs of over- or underestimating food insecurity can be significant. The former problem can lead to false alarms that can result in setting up an expensive operation for a crisis that is never manifested. Importantly, false alarms can reduce confidence in the quality of early warning alerts among donors – and hence delay action until more severe forms of food insecurity are evident (cf. Tapscott, 1997). On the other hand, underestimating food insecurity can lead to a missed food crisis, with potentially substantial costs on human lives and livelihoods (Braimoh et al., 2018). While both errors are important, the associated costs of missing a crisis have disproportionately negative consequences for the most food insecure populations.

The importance of investing in early warning is now more relevant than ever. A combination of climate-related shocks and protracted conflicts around the world have led to a trend of four consecutive years with increasing numbers of people experiencing food insecurity (FAO et al., 2019; cf. Krishnamurthy et al., 2014). Forecasting where and when vulnerable groups are likely to experience a food crisis is therefore important – but the challenge is translating the uncertainties associated with climate change into seasonal forecasts that feed into early warning. For instance, climate change has been associated with stronger El Niño cycles, and little is known about what more intense ENSO circulations could mean for regional climate, and consequently, what the implications could be food security (Endris et al., 2019).

2.4.2. *Missed crises occur in areas affected by complex climate phenomena while false alarms occur most commonly in conflict zones*

Errors in early warning occur for a variety of reasons. Missed crisis errors typically occur because the seasonal forecasts miss a major anomalous climate phenomenon – and indeed, East Africa is considered the tropical region needing most improvement in seasonal forecasting (Hirpa et al., 2010; Weisheimer and Palmer, 2014). These errors are particularly prominent in pastoral areas where climate variability (and the potential impacts on grazing potential and livestock health) has historically been challenging to forecast (Luseno et al., 2003). However recent work has suggested greater predictability of food security conditions in pastoral and agropastoral areas using a standardized precipitation index, suggesting one way to improve predictive skill in these areas (Coughlan de Perez et all (2019).

Recent examples of this type of error include the 2015/2016 El Niño cycle and the anomalous dry conditions in the first part of 2019. During the 2015/2016 ENSO, forecasts proved very problematic as expectations of normal or above normal rainfall were contrasted by severe droughts in reality. During the 2019 event, below-average rainfall in much of the region did not match the forecast for above normal or near-normal rainfall conditions in the March-May season, leading to crop failures. These two events caused a significant divergence in forecasted food security conditions compared to subsequent actual conditions (Choularton and Krishnamurthy, 2019).

Though our analysis reveals that the majority of missed crises occurred in areas where seasonal forecasts provided inaccurate projections, it would be simplistic to attribute food insecurity solely to rainfall (Sandstrom and Juhola, 2017): sudden conflict, unexpected market conditions or pest outbreaks also affect food security projections. A challenge here is that climate conditions can also influence civil instability, food prices, and pest incidence, and separating the triggers is a complex intellectual problem (cf. Hendrix and Glaser, 2007). At the same time, food security forecasts integrate both probabilistic climate information with a range of quantitative and qualitative information, ultimately relying on expert judgment to construct the most likely food security scenario. Finally, missed errors may also occur because of disruptions in humanitarian or social protection programs – but it is difficult to quantify the effect of these disruptions (FEWS NET, 2019).

Conversely, false alarms are most prominent in areas that are prone to conflict – such as South Sudan. A potential explanation for this is extreme caution from early warning analysts in areas that experience frequent conflict – possibly due to a lack of understanding of how protracted conflict incidence and intensity translates to food security outcomes (Weiss, 2016). In other words, a false alarm may actually be an indicator of a well-functioning humanitarian system whereby an early warning signal triggers a response that is sufficient to mitigate food insecurity. But additional localized information on the effects of humanitarian agencies would be needed to determine where and when this is the case.

In addition to conflict, false pessimism can also be linked to weather events: the above-average 2013/2014 *meher* rains in Ethiopia resulted in an exceptional harvest, with total agricultural production exceeding national projections by 10 percent (FEWS NET, 2014). In these cases, early warning assumptions typically indicate normal precipitation and crop production, in contrast to making an optimistic projection of a better than normal season. While false alarms may have less humanitarian consequences than a missed crisis, these can still have ramifications in terms of decisions made in prioritizing national and international resource allocations to address chronic food insecurity, which often include pockets of more severe food insecurity. They could also limit the ability of decision makers to anticipate surplus food production and plan accordingly. For example, unanticipated high supply levels can result in price drops and reduced income for farmers, even greater challenges with storage and post-harvest losses, and poor import and export planning (Maxwell et al., 2008).

2.4.3. Crisis detection skill needs to improve in areas with fewer transitions

Not all errors are equal. As alluded to earlier, missed crisis errors have a greater humanitarian impact. Within these, missing a transition to a crisis situation or a crisis deepening are arguably the most significant. Our analysis indicates that 65 percent of crisis transitions and crisis deepening instances were detected – illustrating that, though somewhat accurate, there is significant scope for improving skill in crisis detection.

Earlier we highlighted the dominant sources of missed crises: inaccurate seasonal forecasts and conflict. But where does early warning fail to detect a crisis? There appears to be no correlation between missed crisis transitions and livelihood types: the pastoral regions of northern Kenya have high miss rates, but the pastoral regions of Ethiopia have low miss rates. The only trend we identify relates to the number of transitions: in areas with fewer transitions, detection tends to be less skillful. This might be attributable to the fact that in areas with higher frequency of transitions between food security states, analysts learn to identify triggering factors more accurately – whereas in areas where such transitions occur rarely, there is insufficient historical data to estimate how food security trends might change.

This phenomenon may be linked to the atrophy of vigilance hypothesis which posits that in hazardous systems, organizational safeguards against risk in those systems may atrophy over time (Busenberg, 1999; Freudenburg, 1992). For example, the 2007 Global Food Crisis followed decades of neglect of agricultural investment by national governments and development organizations (von Braun, 2008). A similar trend can be seen in Africa's hydrometeorological monitoring capacity. While recent investments in hydrometeorological series in Africa are beginning to reverse the trend, for decades the network of hydrometeorological stations in Africa has been deteriorating, hydrometeorological data are often spotty and inaccurate, and existing stations are often not functioning or fail to communicate with the global meteorological network (Rogers et al., 2019), despite the increasing risks from climate hazards. In the context of the food security early warning in Greater Horn of Africa, a similar "fragmentation of vigilance" seems to be occurring whereby organizational focus is on the most crisis-prone areas, and lower attention (and therefore accuracy in early warning) is found elsewhere. This could represent a particular risk during more severe or large-scale crises where areas unaccustomed to addressing crises may also have less response capacities in the face of shocks and stressors. Investments are therefore needed to understand food security dynamics in areas that do not traditionally experience crises – especially in the context of a changing climate where drought might become more intense and frequent, even in areas that are not currently drought-prone (cf. Sedezcny et al., 2017; Richardson et al., 2018).

2.4.4. Managing uncertainty in early warning

Key sources of error must be further researched in order to adequately address associated uncertainties in early warning systems. Droughts, floods, conflict, food price surges and pest outbreaks are the main sources of uncertainty for projecting food security conditions in the

Greater Horn of Africa. Because forecasting the onset and intensity of these events is challenging, food security early warning systems are intrinsically uncertain. With the understanding that uncertainty can never be fully eliminated, the humanitarian system should interpret these uncertainties in the context of their decision making.

Climate events – and particularly droughts – accounted for the vast majority of missed crises. Our results suggest a medium positive relationship between seasonal forecast skill and food security projection skill, with an association of nearly 50 percent. Part of the challenge is that forecasts provided by the Greater Horn of Africa Climate Outlook Fora (a major source of climate information for FEWS NET projections) offer a probabilistic forecast for rainfall terciles that is overly conservative: probabilities range between 33 and 45 percent (see also Walker et al., 2019). With such probability ranges, it is difficult to make confident projections about food security. This challenge is in turn amplified by the most likely scenario approach taken by FEWS NET analysts which use the most likely tercile as their basis for analysis. More robust seasonal weather forecasts and additional tools are therefore needed for early warning decision making, including for instance, using real-time satellite information in a more seamless manner (Funk and Verdin, 2010), identifying alternative climatic triggers (Coughlan de Perez et al., 2019), or deriving tipping point-derived early warning signals for food security (e.g., Krishnamurthy et al., 2020). Finally, while we note that FEWS NET used a two-tiered scenario approach (most likely and worst-case) until 2009 and moved to a simplified system thereafter, where climate forecast uncertainty is high. Food security analysts could consider creating additional scenarios to inform decision makers.

Conflict is another major source of uncertainty in food security early warning, accounting for nearly one fifth of missed crises since 2011. Food security in areas that experience conflict is generally projected with lower accuracy than those that do not. But the relationship between conflict and food security forecasting skill is not straightforward. For areas that were affected by 50-74 conflicts, accuracy is higher than areas that experienced between 1 and 49 conflicts. In part, this may be because in areas with frequent conflicts, violent events have become part of the baseline and are integrated into food security projections with greater confidence. Incidentally, these areas are also near urban centers where information flows are generally better than in remote rural areas, which may also explain the higher accuracy rates (cf. Moseley, 2001). However, accuracy rates in areas that had over 75 conflicts are lower, illustrating the complexity of integrating conflict analysis into early warning. These results also partially support the notion of atrophy of vigilance in less crisis-prone areas, as discussed earlier in this paper.

Conflict analysis continues to be challenging because of two major issues: data collection in conflict zones is dangerous and often unfeasible, incorporating analysis of conflicts into consensus-based early warning led by governments that are parties to the conflict is impossible (Maxwell, 2019). To address this challenge, much work in the literature on security analysis has recently focused on predicting where and when conflict might take place as well as potential societal impacts (Chafedaux, 2017). Various approaches have been suggested, ranging from expert opinion (Tetlock, 2017) to quantitative methods like autoregressive models (cf., Brandt et al., 2014) and machine learning tools (Colaresi et al., 2017). New technologies like high-resolution satellite imagery to track movement of people or locations of mass graves can also provide additional inputs for early warning, even when certain regions are inaccessible (cf. Witmer, 2015). These methods are relatively novel, and may prove useful in reducing uncertainty for food security early warning analysis. But innovative methods to better understand how conflict affects food crises only represent the first step – after all, the purpose of early warning is to mitigate human suffering. Once a potential crisis has been identified, parties to the conflict (which sometimes include governments) need to agree to enabling the humanitarian system to intervene and avert a large-scale crisis. This, however, is extremely challenging (cf. Maxwell, 2019).

Finally, regardless of the sources of uncertainty an increasing set of tools are available to help decision makers manage uncertainty. These include analytical tools such as near-real time monitoring using mobile and other high frequency data collection techniques (e.g., the World Food Programme's mVAM) as well as information management dashboards speeding up the aggregation and primary analysis of multiple streams of information such as the Somalia Food Security and Nutrition Analysis Unit's (FSNAU) dashboard. These tools allow for more frequent updates of food security forecasts and earlier identification of additional evidence to support decision making. Moreover, approaches to early action including no-regrets early warning (FAO, 2018) and forecast-based early action (Wilkinson et al., 2018) that are grounded in rigorous cost-benefit analyses of the benefits of early action can facilitate earlier decision making to address food crises within larger margins of uncertainty.

2.5. Conclusions

The value of food security early warning systems is undeniable: being able to forecast when and where a crisis might unfold can help minimize food security impacts. Investments in early warning have led to improvements in the way that food security analysis is conducted – from standardizing food security measurements to understanding teleconnections between global climate process and seasonal rainfall patterns. Despite this progress, climate change and protracted conflicts in various regions of the world highlight the need to update our current early warning systems.

Building on the framework developed by Choularton and Krishnamurthy (2019), here we present an analysis of limitations associated with early warning projections and possible sources of uncertainty that could be addressed with continued investment in the Greater Horn of Africa. Our analysis highlights that projections of food security in pastoralist and agropastoralist areas are less accurate – and additional work to understand food security dynamics among these livelihood groups is needed. Further, our findings suggest that errors in seasonal forecasts and the difficulty of predicting conflicts (and associated food security consequences) are among the most significant challenges in food security early warning analysis. Improving skill in these two streams of work will likely improve the accuracy of food security projections.

Finally, the analysis presented here can the foundation of a quality assurance and continuous improvement process for this kind of early warning analysis. We also hope that by measuring the reliability of these systems, we can increase the confidence of decision makers to act early to mitigate the growing risks posed by hunger and famine.

Chapter 3

Applying tipping point theory to remote sensing science to improve early warning drought signals for food security

Adapted from:

Krishnamurthy R, P.K., Fisher, J.B., Schimel, D.S. and Kareiva, P.M., 2020. Applying Tipping Point Theory to Remote Sensing Science to Improve Early Warning Drought Signals for Food Security. *Earth's Future*, *8*(3), p.e2019EF001456.

3.1. Introduction

Droughts have always been part of human history, and when combined with social or political failures they have been linked to civil unrest, famines and even the collapse of civilizations. Droughts occur in many parts of the world, often with disproportionate impacts on the most vulnerable populations (Schlenker and Lobell, 2010; Diffenbaugh et al., 2015; Lesk et al., 2016; Richardson et al., 2018). Most importantly, as a result of climate change, droughts are projected to become more frequent and intense globally (Cook et al., 2018). As drought becomes more common and harsher, society's ability to mobilize relief efforts will be stressed, and the premium of effective early warning systems will be heightened.

Clearly famine has many causes of which drought is only one factor (FAO et al., 2019). But in many places in the world characterized by poor food distribution systems and vulnerable populations, drought tends to be one of the most common instigators of famine (cf. Funk et al., 2019). Famine has many causes, and can occur without any climate drivers. This is particularly true in areas where communities depend on rainfed agriculture or traditional livestock rearing for their livelihood (cf. Brown and Brickley, 2012). These regions are primarily located in sub-Saharan Africa, South and Southeast Asia, and Latin America – all regions that are particularly susceptible to shifts in climatic conditions such as a delay in the onset of the rainy season, or interruptions to the rainy season (Verdin et al., 2005). In these regions, monitoring climatic indicators can offer an opportunity to anticipate and prepare for food crises (Brown and Brickley, 2012; de Perez et al., 2019). This does not mean that a severe drought necessarily must lead to famine – since poor governance, lack of technical capacity or relief capacity, and conflict can exacerbate the impact of a minor drought that might otherwise not result in a crisis (Devereux, 2019; Glantz, 2019). Nonetheless, the nexus of climate change enhancing drought severity and famine poses one of the greatest global challenges we face today.

Existing early warning systems for famine tend to rely on community and household data that can be aggregated up to larger scales, or crop assessments on the scale of kilometers or hectares (e.g., Funk and Verdin, 2010; MAF Timor-Leste, 2016; MDM Sri Lanka and WFP, 2017) . In fact, globally standardized classifications of food insecurity are expressed in terms of "*1 in 5 households*" or *"4 in 5 households"* (see Table 2). This makes sense because suffering occurs at the household level. However, this does not mean that early warning data needs to be restricted to the household level or farm field-level. Drought and food security crises can strike at much larger scales – at hundreds or thousands of square kilometers, and even at the scale of nations (Verdin et al., 2005). Collecting data on a spatial scale commensurate with large-scale drought and famine is a challenge from the perspective of cost and sampling design (see de Sherbinin et al., 2014). Here, the advent of remote sensing instruments offers a possible cost-effective solution – these data provide large areal coverage and can be made available at no (or low) cost to international agencies and scientists (Kogan, 2000).

Although remotely-sensed data currently provide input into drought and food security analysis, their use at the global level is not systematic, partly due to insufficient consideration of end-user needs and technical capacities (Purdy et al., 2019), and partly because in some contexts, climate data are deemed irrelevant given the complexity of food security challenges (de Perez et al., 2019). In an effort to improve this situation, scientists have begun to offer suggestions for how satellite data might be used as an input into early warning decision-making (e.g., Verdin et al., 2005; Brown, 2011; de Perez et al., 2019). There is evidence that rainfall data over a 12-month period can anticipate drought risks in East Africa as much as six months in advance (de Perez et al., 2019). Here we build off that recent work and develop an additional dimension to the use of satellite data in early warning systems: the theory of tipping points in dynamic systems. Unlike household surveys, or even crop field assessments, data streams from satellites can provide a richness of dynamics, and temporal variability that lends itself to dynamic systems theory (e.g., van Nes et al., 2014; Reyer et al., 2015; Dakos et al., 2019). After summarizing the types of pertinent data available from satellites and existing classifications of food insecurity, we explore "tipping point theory" as a possible framework that could enrich the value of satellite data. More specifically, when the data records are sufficiently long, one might be able to take advantage of changing statistical attributes of environmental time series beyond the 12-month or within-year analyses that have recently shown so much promise (de Perez et al., 2019).

3.2. The satellite data revolution

Remotely-sensed environmental data are already being used for drought and food security assessments, though their use is still relatively limited. To date these applications of remotely sensed data have been restricted to rainfall or vegetation indices (USGS 2017; NOAA 2017; Rojas et al. 2011, WFP et al. 2014, Otkin et al. 2015), and have tended to focus on the relationship between what has happened in the last twelve months and what might be expected in the upcoming growing season. When these climate data are used, it is widely appreciated that climate data are only part of the picture – there are numerous social, political and economic factors that can determine whether or not a famine occurs, and sometimes over-ride recent precipitation or temperature regimes. However, there is general agreement that rainfall and other climatic factors are an important contributor to food crises, at least in some regions of sub-Saharan Africa, Asia and Latin America (e.g., Verdin et al., 2005; Haile, 2005; Brown and Brickley, 2012).

The ideal or optimal remotely sensed data for early warning systems would: 1) be global in coverage, or at least cover all areas of the globe where drought is likely to be an issue, 2) have sufficient spatial resolution to be relevant to the administrative units responsible for food security and famine relief, 3) have intervals between data collection events short enough that the chance to respond to a food crisis has not passed, 4.) be available at near-real-time so that they can be operational and useful for humanitarian planning, and 5) represent data that are ecologically or environmentally salient to crop or livestock failure.

In Table 1 we identify the satellite sensors for hydrological and vegetation indicators that best meet most of the above criteria. For the purpose of famine and food production, all of the data sources in Table 2 are effectively global in coverage. In terms of spatial resolution – administrative units relevant for food security range from 1,500 m^2 (densely populated areas near urban centers) to 2,100 km^2 (scarcely populated regions in desert regions), with the mean size being 150 km^2 or ~12 km pixels (derived using data from FEWS NET, 2018). Nine of the fifteen satellite data sets have a resolution of 12 km pixels or better, and thus are at a scale that is commensurate with administrative units. Responses to major drought-induced food crises take on average three to four weeks to reach maximum operational capacity (IASC, 2014). This means that the temporal resolution of environmental data similarly needs to be on the order of three to four weeks. Examining the satellite data in Table 3.1, thirteen of the fifteen data sets are collected at intervals less than three weeks. Finally, more than half of the remote sensing products examined here are available in near-real-time. In comparison, the availability of household or crop assessment data depends on the time required to conduct fieldwork, and record and clean the data. Minimally this requires weeks, and usually longer than a month (De Sherbinin et al., 2014).

Table 3.1 Remotely-sensed environmental indicators that could be related to droughts or the impacts of droughts on food insecurity.

INDICATOR	REGIONAL UTILITY FOR FOOD SECURITY	SENSOR	PRODUCT	NOMINAL SPATIAL RESOLUTION	TEMPORAL RESOLUTION	AVAILABILITY OF DATA
Precipitation	Areas that depend on rainfed agriculture	TRMM/GPM	Rainfall rate	30 km	3 hours	1997-present
Groundwater	Regions with limited rainfall that extract groundwater for irrigation	GRACE/ GRACE-FO	Total water storage	300 km	1 month	2002-2017, GRACE-FO: 2018
Snowpack	Areas that depend on snowmelt for agricultural water	MODIS	MOD10 snow cover area	500 m	8 days	2000-present
		MODIS	MOD10 snow water equivalent	25 km	8 days	2000- 2008
		MODIS	MOD10 snow depth	24 km	daily	2000- 2017
Soil moisture	Arid and semi-arid areas with limited rainfall	SMAP	Soil moisture	36 km	50 hours	2015-present
		SMOS	Soil moisture	35-50 km	23 days	2009-present
		Sentinel-1	Soil moisture	500 m	6-12 days	2015-present
Evapotranspiration		MODIS	MOD16 ET	500 m	8 days	2000-present

	Agricultural regions, particularly irrigated crop land	ECOSTRESS	L3 ET_PT-JPL	70 m	3-5 days	2018-present
NDVI		Landsat	Landsat NDVI	30 m	16 days	Landsat 5- 8: 1984-present
		AVHRR	AVHRR NDVI	1 km	daily	AVHRR-3: 1998-present
		MODIS	MOD13	250 m	16 days	1999-present
		SPOT	SPOT-VGT	1 km	10 days	1998-present
Fluorescence		OCO-2	SIF	~2 km	16 days	2014-present

3.3. "Tipping point theory" as a framework applied to droughts and food security

Tipping point theory emerges from the analysis on nonlinear dynamic systems and hence tends to be highly abstract and mathematical (Dakos et al., 2019). Tipping points occur in nonlinear dynamic systems where an incremental change in a variable can lead to a completely different state: a system moves from one equilibrium state to a fundamentally different equilibrium state. These jumps to a new regime can happen because one of the state variables is perturbed, or because a particular input or stress is gradually and incrementally altered (Lenton, 2011). In its simplest form, the idea of a tipping point can be captured by the game "Jenga", whereby wooden blocks are stacked on top of each other, and players take turns to remove a block and place it on top of the tower. The probability of a player's turn resulting in the collapse of the block tower is low, though the probability increases with each turn. These gradual changes (removal of blocks) inexorably make the structure unstable, until part (or all) of it collapses – game over. In tipping point theory, systems can behave in a similar way, with each day of accumulated environmental stress pushing the system closer to when it all tumbles down.

Because climate and food systems are highly nonlinear, there is merit in asking if tipping point theory might provide ideas for how to analyze remotely sensed datasets. Without any theory, it is obvious that simple increasing or decreasing trends can signal changes in the risk regime. However, droughts and famine need not just be the result of gradual deterioration – they could be dramatic flips in a food system. In particular, there is historical evidence that droughts have triggered abrupt food security crises (Fei and Zhou, 2016; Gupta et al., 2019). In this regard, flash droughts are especially notable: they occur over shorter periods than seasonal forecasts can anticipate (typically weeks) and can have severe effects on crop yields and grazing lands (e.g., Otkin et al., 2016; Xiong et al., 2018). And even for droughts that develop gradually over seasonal or annual scales, food security impact may manifest abruptly; for instance, the 2011 famine in Eastern Africa occurred after several months of below-average rainfall in the region rather than during the entire period of drought (Ververs, 2011). In such instances, framing impacts as tipping points offers a quantitative approach for early warning analysis.

3.3.1. Droughts as tipping points

What might a famine tipping point look like? An example of a state-variable perturbation that could cause such a tipping point is the addition of too many grazers to a grazer-pasture system. With the addition of too many livestock, intense grazing might degrade the pasture and cause massive soil erosion, which means the livestock cause even more damage because there is less forage, and ultimately a new state is reached that entails semi-arid shrubland or desert as opposed to a fertile pasture (Fleischer, 1994; Ellis and Swift, 1998). In this example, as forage stock is depleted vegetation health indices (such as the Normalized Difference Vegetation Index) would detect lower inter-annual variability in NDVI conditions signaling a transition to a landscape dominated by barren land or shrubs. Another major type of tipping point entails a regime shift that occurs because some climatic stress or input is gradually increased. For instance, the absence of rainfall during the rainy season could trigger a major crop failure and would represent a regime shift.

Currently, the leading metric used in famine early warning is the Integrated Food Security Phase Classification (IPC; see IPC Global Partners, 2012). The IPC approach consists of collecting data on agricultural production, food prices, nutrition rates, weather patterns, and other variables to determine the general food security situation in an area based on five classes (Table 3.2). The IPC framework was introduced in 2007 and later refined in 2011 and is now used in more than fifty countries to compare food security in a standardized manner (IPC Global Partners, 2012). The standardization of food security measurement provided a breakthrough in famine early warning systems because data quantifying food stress were sufficiently standard that they can now be used to test retroactively whether or not any proposed early warning system has merit. Indeed, leading food security early warning systems – such as the USAID-funded Famine Early Warning System Network (FEWS NET) and the FAO's Global Information and Early Warning System (GIEWS) – rely on the IPC classification system to trigger humanitarian responses. An analogous approach, adjusted to crop patterns rather than food security conditions *per se*, is that of the GEOGLAM Crop Monitor which is also based on a five-class system ranging from exceptional to favorable, watch, poor and failure (see Whitcraft et al., 2015)

Table 3.2 Integrated Food Security Phase Classification (IPC). IPC phases are defined based on the classification criteria below (adapted from IPC Global Partners, 2012).

IPC CLASS	FOOD INSECURITY CLASSIFICATION	CRITERIA
Phase 1	Minimal	At least four out of every five households are able to meet food security needs without resorting to atypical coping strategies.
Phase 2	Stressed	At least one in five households is able to maintain adequate food security but resorts to atypical coping strategies (such as selling livestock or assets) to afford essential nonfood items.
Phase 3	Crisis	At least one in five households have food consumption gaps with high acute malnutrition or are marginally able to maintain adequate food consumption only with sell of assets that will lead to food gaps. **National drought response.**
Phase 4	Emergency	At least one in five households have large food consumption gaps resulting in very high acute malnutrition or mortality, or resort to coping strategies that will result in large consumption gaps. **International drought response.**
Phase 5	Famine	At least one in five households have an extreme lack of food or other basic needs. Starvation, death and destitution are evident. **International drought response.**

With this framework, a tipping point in a food system can be thought of as a shift between periods with minimal food insecurity or mildly stressed food security (IPC 1 or 2) to a food crisis (IPC 3 or higher) in the following year (see Figure 3.1 for an illustration of this concept). We adopt this between-year filter to distinguish from seasonal trends that happen every year (such as drying out through the growing season). An example of a tipping point using the IPC categories is found in East Africa after the 2015/2016 El Niño episode. Usually El Niño events yield extended autumn rains in East Africa, which is good for livestock grazing (Korecha and Barnston, 2007). This was not the case for the 2015/2016 event, which instead was characterized by extremely low rainfall in both the summer and autumns. This trend, combined with insufficient drought preparedness, resulted in crop failures and livestock mortality – and consequently a depletion of livelihood assets and food stocks. As a result, food security conditions deteriorated in large parts of northern and central Ethiopia (see Figure 3.1), the arid and semi-arid areas of northern Kenya, central Somalia and the Karamoja sub-region of Uganda (FEWS NET, 2017).

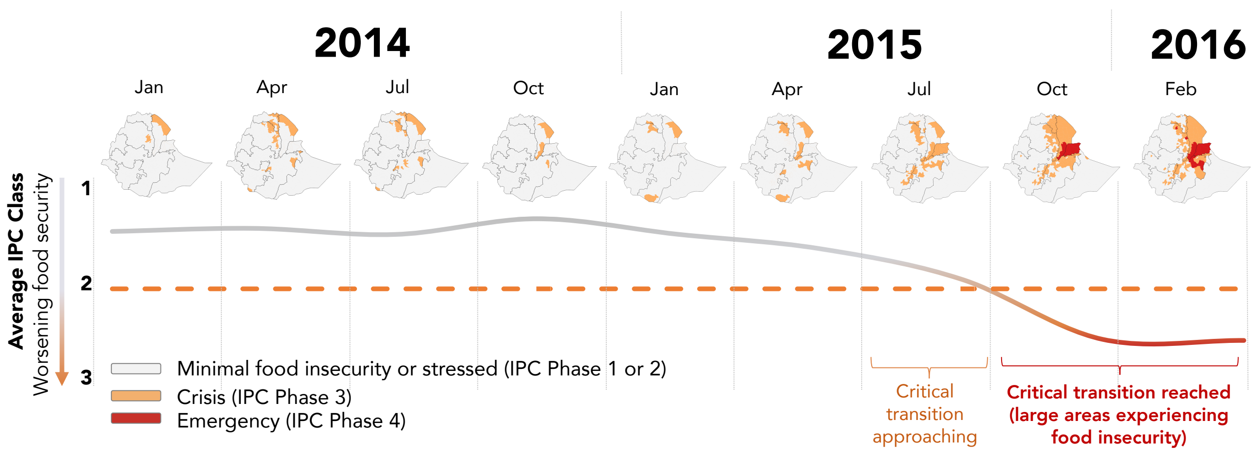

Figure 3.1. IPC classes provide an opportunity to identify drought tipping points that result in a food crisis. Application of IPC metrics to identify tipping points, showing the transition from stable food security conditions to a food crisis resulting from drought in Ethiopia (derived using FEWS NET, 2018).

Early warning systems that incorporate climatic indicators have some record of success in mitigating major food crises. In June of 2015, for instance, seasonal forecasts suggested that southern Africa would experience drier-than-normal conditions during the rainy season that typically occurs between November and March. Responding to these warnings, several governments pre-positioned food stocks and imported food. By January, data indicated that the region was indeed experiencing its driest rainy season in over 35 years – but effective integration of early warning and early interventions helped avert a far larger crisis. Similarly, predictions of below-average rainfall in parts of Eastern Africa during the 2017 season were instrumental in triggering a multi-agency humanitarian response. Despite the severity of the 2017 drought, relatively few deaths were reported (FEWS NET, 2017). Even in cases where drought is not the main contributor to a food crisis, monitoring climatic indicators can provide useful information on the likelihood of potential changes in food prices, conflict, migration and other socioeconomic information that might trigger a crisis as environmental and socioeconomic indicators are intricately inter-connected (e.g., de Perez et al., 2019).

3.3.2. Early warning of tipping points

Tipping point theory has identified four major statistical diagnostics that might be used as early warning signals of an impending tipping point (e.g., Lenton, 2011):

Autocorrelation: In tipping point theory, dynamical systems that are approaching a transition typically exhibit 'critical slowing down' (Lenton, 2011), which statistically would be manifested as increased autocorrelation. Detection of tipping points through analysis of autocorrelation has been conducted for long-term processes occurring at decadal to century scales, such as the end of glacial phases or desertification of North Africa (Dakos et al., 2008; Figure 3.2(a)). Decadal and century timeframes are far too long to be useful for early warning of famine, which occurs on sub-annual scales that might not be preceded by critical slowing down signals (cf. Boettiger et al., 2013). However, examples from the ecological equilibrium field have shown that regime changes can be detected through autocorrelation metrics on annual timescales for collapse of quail populations (Hefley et al., 2013), on the scale of months in phytoplankton cycles (Batt et al., 2013), and on the scale of days for plankton populations (Veraart et al., 2012).

Skewness: Some disturbances push a system closer to the boundary of an alternative state, which statistically can be manifested as an increase in skewness and a decrease in the "normalcy" of a data series. (Guttal and Jayaprakash, 2008). Golledge et al. (2017) detected a tipping point in East Antarctic ice-sheet mass during the Pliocene era through increasing skewness. As with autocorrelation analysis, skewness requires consistent data points for long timeseries (Figure 3.2(b)).

Increased variance: A system characterized by noise, such as a climate system, could exhibit flickering: this is the condition whereby strong disturbances push the system across boundaries of alternative states (Scheffer et al., 2009; Dakos et al., 2012). Flickering and critical slowing down correspond to higher variance prior to a complete transition as shown by increases in standard deviation or amplitude of a particular variable (Figure 3.2(c)). Using variance, Carpenter and Brock (2006) identified tipping points in eutrophication rates due to phosphorus fertilization, and Takimoto (2009) found transitions in demographic shifts among invasive species.

Thresholds: A fourth methodological approach which holds potential for the identification of tipping points is based on the idea of rate-dependent tipping, whereby the forcing has to exceed a threshold to result in a critical transition (Ashwin et al., 2012; Siteur et al., 2016; Figure 3.2(d)). In the context of drought and food security, rate-dependent tipping may be quantified as, for instance, the number of days with below-average precipitation during the initial phase of the rainy season, triggering a drought tipping. Rate-dependent tipping is a relatively novel concept and much work is yet to be conducted to determine whether threshold analysis can provide meaningful early warning signals. A working example that has been identified in the literature is that of 'compost bomb instability', whereby there is an explosive release of soil carbon from peatlands after a critical rate of global warming is reached (Wieczorek et al., 2011). As with other diagnostic approaches, rate-dependent tipping requires highly dense timeseries.

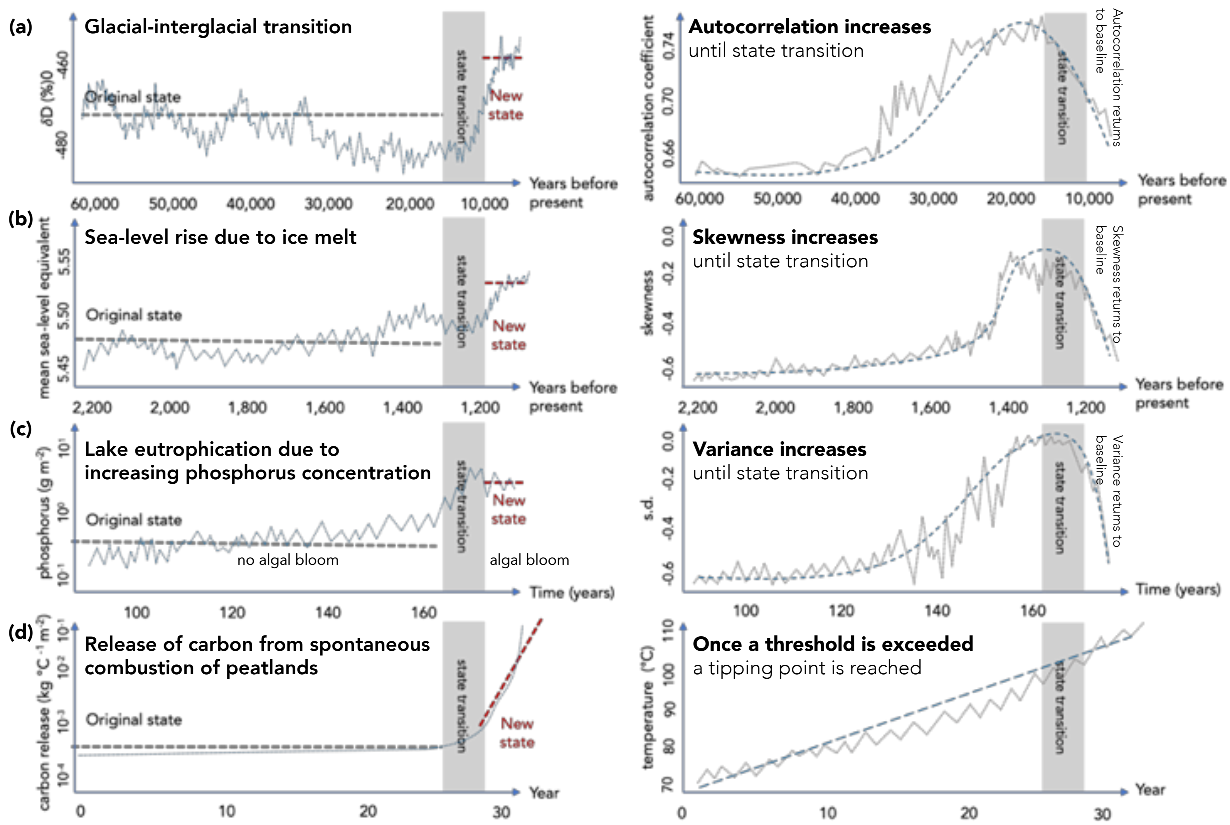

Figure 3.2. Four main tipping point characteristics may be identified for early warning signals. The examples illustrate an early warning signal identified by (a) autocorrelation towards the end of a glacial period (Dakos et al., 2008), (b) skewness associated with ice melt (Golledge et al., 2017), (c) increased variance with eutrophication (Carpenter and

Brock, 2006), and (d) a theoretical example of a rate-dependent threshold for modelled carbon release from peatlands as a temperature threshold is reached.

3.3.3. Operationalizing tipping point diagnostics for famine early warning signals: Combining IPC metrics, satellite-derived environmental variables and tipping point theory

The four statistical diagnostics – namely, autocorrelation, skewness, variance and threshold exceedance – offer an opportunity to operationalize an early warning system that detects transitions from one state of food security conditions (e.g., minimal food insecurity, or IPC Phase 1) to a state of a food crisis (e.g., IPC Phase 3). In such a system specific diagnostic associated with an environmental variable would be monitored, and when specific thresholds are met, a famine warning would be triggered (Figure 3.3).

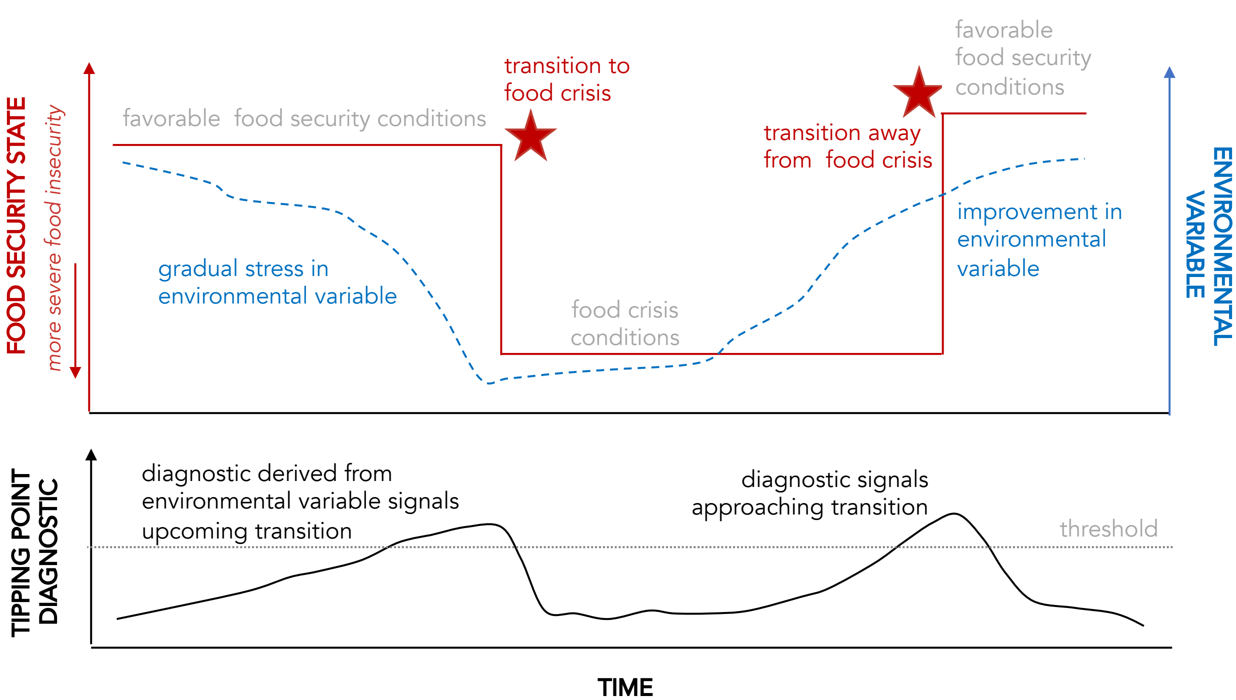

Figure 3.3. In our conceptual model, the transition of interest is the regime shift from favorable food security conditions into a food crisis, and vice versa. Favorable conditions might include by sufficient (or surplus) food, while a crisis might be characterized by depletion of food stocks or loss of livelihoods. Environmental indicators derived from satellite observations might enable early detection of such transitions through specific statistical diagnostics, such as increasing autocorrelation, allowing governments and the humanitarian system to prepare for food crises.

3.4. Potential remotely-sensed indicators of tipping points

Given the range of hydrological and vegetation indicators available, a key question is which environmental indicators (or combination of indicators) are best-suited for early warning. Below we highlight the utility of the various indicators for drought and food security analysis, and discuss their promise for future analyses.

3.4.1. Hydrological indicators

Precipitation: In rainfed agricultural systems, which dominate in much of sub-Saharan Africa, South Asia and Latin America, the main source of water for agriculture is seasonal precipitation and droughts are often associated with below-average rainfall levels (Salmon et al., 2015; Senay et al., 2015). Rainfall monitoring is one of the most direct and simplest methods to assess potential critical transitions. In the context of rainfall, a tipping point might be thought of as a transition towards more variable seasonal rainfall resulting in more extreme rainfall extremes (both high and low) and subsequent crop losses during the agricultural season (cf. Trenberth, 2011). Satellite products, such as those from the Global Precipitation Measurement constellation, offer data at the global level and are useful for identifying such tipping points. The long-term historical dataset available from GPM measurements as well as the high temporal resolution are significant advantages for early warning analysis. But the relatively low spatial resolution (30 km) is likely to limit early detection of tipping points to droughts covering a large geographical area – and decisions based on precipitation data would have to take place at regional scales rather than at the subnational level.

Groundwater: In addition to rainfall, groundwater is a major source of agricultural water. Groundwater extraction is both a response to dry conditions, and a contributing factor to more intense drought (Zaveri et al., 2016). Abrupt decreases in groundwater availability (for instance, through a severe drought) would result in a lower water table, to a point at which water pumps may not be economically or physically feasible (van Lanen and Peters, 2000). Such tipping points would have significant effects not only on seasonal agriculture but on long-term water availability. GRACE/GRACE-FO observations offer estimates of total water storage that can be used as a proxy of groundwater levels, providing unprecedented potential to measure groundwater globally and detect the point at which groundwater shortage may reach the tipping points highlighted here. Droughts associated with groundwater shortages occur over large geographic areas and at seasonal or longer timescales (Li and Rodell, 2015). GRACE/GRACE-FO data have the lowest resolution of all sensors evaluated here – which will pose a challenge for analysis at geographic scales that are relevant for government planning. In addition, temporal resolutions of monthly intervals of remotely-sensed groundwater data (Swenson et al., 2003) do not allow for timely preparedness. However, initial work has shown that assimilation of

GRACE/GRACE-FO data into land surface models (e.g. Zaitchik et al., 2008; Girotto et al., 2016) can enhance spatial and temporal resolution, which may prove useful for early detection.

Snowpack: Snow behaves as a natural reservoir for water, particularly in mountainous environments (Belmeccheri et al., 2016). Monitoring snow is essential for drought assessment, particularly in mountainous environments where snow melt provides the main source of water for agricultural livelihoods (AghaKouchak et al., 2015). A tipping point in snowpack could be linked to rising temperatures. As mountain regions reach temperatures over 0 degrees Celsius earlier in the season, accelerated snowmelt may limit the amount of water available during the agricultural season (Molden et al., 2016). A related but more extreme tipping point is the potential for total loss of snowpack (e.g., Fyfe et al., 2017), which could result in a food security tipping point by reducing availability of water for crops such as paddy and wheat in mountainous regions where no alternative irrigation sources exist – such as in the high mountains of Nepal (Krishnamurthy et al., 2013). The use of snow data for drought assessment is less developed compared to other hyrdological products; in part, this is attributable to the lag between snowmelt and the change in water availability (AghaKouchak et al., 2015). This time lag is a benefit for early warning and identification of tipping points over longer timescales (e.g. Huang et al., 2015), and temporal resolutions of 1-2 weeks is sufficient to detect potential tipping points. However, the lag between snowfall, melt and runoff varies significantly by region and season, so careful analysis is required to translate this lag into meaningful tipping points.

Soil moisture: Soil moisture is a critical element of the hydrological cycle that directly affects plant water availability, overall plant productivity and crop yields – especially in arid and semiarid areas with limited water and marginal agricultural lands (Martinez-Fernandez et al., 2016; Wang et al., 2016; Sietz et al., 2017). In such regions, a tipping point may result from the depletion of soil moisture that in turn places plants under stress, and can even lead to plant mortality (Tietjen et al., 2017). Consequently, measurements of soil moisture through SMAP, SMOS and Sentinel-1 are critical for assessment of drought tipping points, particularly in environments prone to food insecurity (cf. Sohrabi et al., 2015; Cleverly et al., 2016). While soil moisture data are promising for tipping point analysis, the extent of historical satellite measurements is currently too limited to provide baseline dynamics against which a tipping point might be detected. In addition, as with rainfall measurements, soil moisture data are reported at relatively low resolutions (36 km), limiting their utility to regional or large-scale droughts.

3.4.2. Vegetation indicators

Vegetation health (NDVI): Vegetation indices such as the normalized difference vegetation index (NDVI; Tucker, 1978; Vrieling et al., 2016) and the vegetation health index (VHI; Rojas et al., 2011) are routinely assessed to determine drought impacts on food security (Enenkel et al., 2015; Brown, 2016), particularly in regions with simple topography and well-defined rainfall seasonality (Karnieli et al., 2010). A tipping point measured by **NDVI** (or related vegetation indices) may be identified through a sharp decrease in greenness before the end of the agricultural season (e.g. Zhou et al., 2017). NDVI calculations from Landsat, AVHRR, MODIS and SPOT-VGT observations have been successfully used to monitor drought (and translate drought to food security impact). However, when NDVI anomalies have been detected, they are typically detected while a drought is occurring, which might be too late to be much use in terms of early warning. .But NDVI could confirm a tipping point anticipated by analyses of other data streams.

Chlorophyll fluorescence: Solar-induced chlorophyll fluorescence (SIF) is a relatively novel indicator used to monitor drought dynamics. Fluorescence measures the biochemical, physical and metabolic functions of plants, including photosynthesis, and can be used to assess changes in these functions during a drought event (Sun et al., 2017). A reduction in photosynthesis (as expected in drought conditions) would translate to lower fluorescence yield (Daumard et al., 2010) and could potentially be linked to drought tipping. The application of SIF from OCO-2 observations on drought assessment has been relatively limited given its novelty; however, initial analyses suggest that fluorescence anomalies are closely related to drought intensity and soil moisture in Texas and the US Mid-West (Sun et al., 2015). However, as with NDVI, metabolic functions of plants are likely to show the characteristics of a transition *after* a tipping point, and hence may be more useful for confirming rather than forecasting a drought.

Evapotranspiration (ET): ET is a major component of terrestrial ecosystems that links the water, energy and carbon cycles, representing the exchange of water and energy between ecosystems and the atmosphere (Chen et al., 2014). Increased ET rates are linked to higher water stress and therefore reduced net primary productivity and agricultural yield. Monitoring of ET rates has been used in drought assessments (Begueria et al., 2014) and has accurately identified the magnitude of drought events in situations where stand-alone precipitation measurements failed to reflect the extent or seriousness of the drought (Dubrovsky et al., 2009). This is because ET represents the demand for water rather than the supply (for instance, precipitation, snow, groundwater and soil moisture are useful measurements of supply), and an increasing demand for water at the global level necessitates greater consideration of both sides of the supply-demand equation (Fisher et al., 2017). In the context of ET, a tipping point can be thought of as the moment when stomata close to limit water loss through transpiration, stopping carbon uptake. ET measurements are available from Landsat, MODIS and the recently launched ECOSTRESS mission, and provide data to evaluate the risk of drought tipping points in near-real-time. ET measurements occur at the appropriate temporal and spatial resolutions for food security-relevant early warning systems, and moreover link hydrology to vegetation. Therefore, ET is likely to prove an extremely valuable indicator for identifying tipping points.

3.5. Limitations – Yes, but too much potential to ignore

In agricultural and livestock systems, tipping point research has been limited by data – the absence of long time series of data at the needed temporal scale and spatial scales. Several of the satellite instruments used for drought assessment have only started collecting data within the last decade, with merely a handful of measurements (primarily precipitation- and vegetation-based) available for more than 20 years. Some of the more recent sensors for soil moisture (SMAP) and fluorescence (OCO-2 SIF) provide time-series data for fewer than 5 years. In addition, efforts such as the NASA MEaSUREs (Making Earth System Data Records for Use in Research Environments) program, which aims to create long-term records by combining data from different missions, will accelerate progress. Moreover, in its 2017-2027 Decadal Strategy, the US National Academies of Sciences, Engineering and Mathematics highlighted the importance of enhancing applications of remote sensing data for water resource management while also stressing the relevance of vegetation stress information for a variety of applications including ecosystem health and agriculture (NASEM, 2018). As such, the remote sensing data highlighted in this paper will be prioritized and will likely continue to be available, either with existing or upcoming missions (NASEM, 2018).

Though we argue that remote sensing holds great potential for improving early warning systems, this is not to say that the use of remote sensing data is without limits. Remote sensing data are subject to error, largely due to cloud cover, atmospheric interference, geometric distortions and sensor degradation (which can include scanline problems) (Campbell and Wynne, 2011). These errors could lead to inaccurate interpretations of signals Various efforts have attempted to quantify error rates through different approaches – including accuracy rates comparing satellite and ground measurements (measured in percentages, bias, or root mean square error) and uncertainty ranges (measured in the unit of measurement of the satellite). The nature of these errors is different for each measurement. In mountainous regions of Ethiopia, for instance, remote sensors underestimate rainfall (Romilly and Gebremichael, 2011) while MODIS products tend to underestimate snow cover in heavily clouded regions and in areas with thin snow (Hall and Riggs, 2007). Measurements of error suggest high accuracy for SMAP (0.04 cm^3 cm^{-3}, Das et al., 2015), GRACE (8 mm per season, Strassberg et al., 2007), TRMM (84%, Hirpa et al., 2010), and MODIS snow (93%, Hall and Riggs, 2007), NDVI (88%, Lunetta et al., 2006) and ET (70-85%, Velpuri et al., 2013). The relatively high accuracy indicate that the data have utility for detection of tipping points (and other applications); still, taking inaccuracies into account is important when interpreting data and translating them into early warning signals.

Assuming there are sufficiently long-terms and fine scale data, it is not clear that remote sensing data can, in fact, be used to *forecast* a tipping point (cf. Andreadis et al., 2017). Each drought is different. Traditional definitions of drought center around intensity and impacts, ranging from meteorological (based on anomalies from average precipitation) to hydrological (where there is persistently low water availability), agricultural (where there is insufficient water for crops) and socioeconomic drought (when societal demand for water exceeds supply, leading to reduced hydropower and municipal water supply) (Fisher and Andreadis, 2014; Wilhite, 2016). The heterogeneity of droughts means that not every drought will lead to a food crisis: there are years during which the conditions for agricultural drought are met, but there is no food security impact, and conversely there are years during which a less severe meteorological drought results in food scarcity (cf. Lewis, 2017). A fundamental task is therefore identifying the subtle differences in system dynamics that occur prior to a major food crisis triggered by drought compared to other events. In other words, the challenge is whether remote sensing indicators can be used effectively to detect abrupt transitions towards food insecurity rather than simply seasonal trends or inter-annual variability.

A final limitation entails the reality of political and social factors. A variety of famine early warning tools are already in existence (e.g., the USAID Famine Early Warning System, FAO's Global Information and Early Warning System, and WFP's Corporate Alert System). Yet, food crises still occur. In part, this discrepancy arises when the alerts generated by early warning systems are not credible, either because the quality of inputs is questionable or because the different warning systems provide conflicting messages (Lautze et al., 2012). At the same time, early warning systems are political tools and depend on agreement that there is a problem, that it is urgent and that a solution is feasible (Zschau and Kuppers, 2013). It is easy to understand why governments may either not want to admit there is a crisis, or – conversely – claim a crisis that was in fact not a crisis (Maxwell and Fitzpatrick, 2011; Hillbruner and Moloney, 2012). That said, any methodological improvements in the effectiveness and credibility of early warning metrics can only help governments make better decisions (Choularton and Krishnamurthy, 2019).

Satellite data are unique in being global, georeferenced, available soon after measurement, and generally inexpensive to end users (Kogan, 2000). Moreover, they record a wide variety of attributes—from soil moisture to snowpack. Satellite data will always need ground-truthing, but given the expected increase in droughts, with all the human tragedy these droughts can create, satellite data warrant our attention. In particular, because satellite data are only going to improve, and because we will have an increasing number of droughts for which we also have satellite data with a long lead time – a high priority for research should be testing different ways of processing these data to generate an early warning for droughts that can trigger food crises. Tipping point theory is one possible framework because it generates diagnostics that generate a signal of impending crisis conditions *before* as opposed to during the event. Practical application of tipping point theory requires dense data streams (in time and space) and this is exactly what satellite remote sensing provides. The next step is comprehensive analyses of several droughts around the world along with the time series of remotely sensed data that preceded these events.

Chapter 4

Detecting food security tipping points

4.1. Introduction

Trigger thresholds are a common component of many early warning systems (Mathys, 2007). In the context of famine or food insecurity early warning, a trigger threshold, such as below-average seasonal precipitation during the agricultural growing period, can signal the need for emergency food assistance (Wilkinson et al., 2018). Of the various triggers for impending food crises, those that relate to drought are in the greatest need of refinement because droughts are associated with more than two thirds of the food insecurity crises that are not anticipated in East Africa alone (Krishnamurthy and Choularton, 2020). Improving the performance of such thresholds is therefore critically important. If a trigger indicator warns of an impending crisis when there is none (false positive), this misdirects limited resources; conversely, if a trigger indicator fails to anticipate a food crisis that does occur (false negative), people will unnecessarily suffer (Choularton and Krishnamurthy, 2019).

Current famine early warning systems rely heavily on consensus-based probabilistic seasonal forecasts that primarily translate rainfall patterns into food security outcomes (Ogallo et al., 2008). While substantial work has been done to improve seasonal forecasts, complex weather phenomena continue to hinder food security projections. To address this challenge, near real-time remote sensing data are increasingly used, especially to fill data gaps for areas of the world that have limited *in situ* environmental data (Funk and Verdin, 2010). For example, vegetation indices such as the normalized difference vegetation index have been used to monitor crop health and thereby estimate drought impact (Becker-Reshef et al., 2010). Rainfall anomalies have also been used to assess the severity of drought (Husak et al., 2013). A new generation of satellite-based indicators may provide additional improvements in early warning systems, with soil moisture from the Soil Moisture Active Passive (SMAP) mission, showing particular promise as a potential predictor of food crises (Cleverly et al., 2016; Fritz et al., 2019).

New remote sensing data alone are not enough to enhance our capabilities for early warnings. We also need analytical frameworks for the analyses of these new data. The most straightforward approach would be to look for simple increasing or decreasing trends in environmental indicators associated with food security and use a detected trend as a trigger for action. However, food crises can occur abruptly (Gupta et al., 2019), without any lead-up of a prolonged environmental trend. For abrupt shocks to food systems, an analytical framework based on tipping point theory is promising (Krishnamurthy et al., 2020).

Applications of tipping point theory in ecological systems and climate conditions have shown that lag-1 autocorrelations can be used to detect a critical slowing down prior to major transitions (Scheffer et al., 2009; Dakos et al., 2015). Here, we investigate lag-1 autocorrelation as a possible predictor of transitions in food security conditions, soil moisture, and food price data to anticipate food security tipping points. We tested the approach across all drought-induced food crises that occurred since 2015, when soil moisture records began. The food crises took place in Guatemala, Kenya, Uganda, Somalia, Ethiopia, Sudan, Zimbabwe, Mozambique, Malawi and Cambodia. Following the approach taken in previous applications of tipping point theory, we first ask if the autocorrelation diagnostic can predict the onset of a food crisis using the SMAP soil moisture record. We also provide the first empirical documentation of a link between the magnitude of the autocorrelation change and the severity of the ensuing transition. Finally, because state transitions need not be irreversible, we also asked if the autocorrelation could be used to predict exiting from a food crisis. This is the first paper investigating how tipping point theory can detect transitions to a new state, and then transitions back to the original (or an improved) state in the context of food security.

To identify food security tipping points, we use the Integrated Food Security Phase Classifications (IPC) (see Methods). The IPC is an approach to standardize food security metrics (IPC Global Partners, 2019), classifying the severity of food insecurity according to a five-class system (1-minimal insecurity, 2-stressed, 3-crisis, 4-emergency, 5-famine). IPC classes are reported every three months (every four months since 2016) for the smallest administrative division, or at the livelihood zone level in the case of Somalia and Mali (the average size of these analytical units is 150 km^2). For our analysis we do not focus solely on transitions to crisis conditions (IPC 3 or higher); instead we define a food security tipping point as a prolonged period, i.e., > 6 months, of food security conditions that change by more than 0.5 in IPC classes (Baro and Deubel, 2006).

4.2. Early warning model

We detect food security tipping points by calculating lag-1 autocorrelation values (AR(1)) associated with SMAP soil moisture data (SMAP Level 3 Radiometer Global Daily 36 km EASE-Grid Soil Moisture Version 6) (Figure 4.1). In some situations, soil moisture data alone might be sufficient to predict oncoming food crises. However, major changes in food prices are known to contribute to food crises. The Soil Moisture Auto-Regressive Threshold (SMART) allows soil moisture autocorrelation to be sensitive to price changes. We calculated the food security tipping point threshold by adding half of the difference between the first and maximum SMART values across the record to the first AR(1) using a rolling window of at least one full rainy season (for SMAP, 100 observations). Once the threshold is exceeded by at least 60 days a transition is predicted to occur. Food security tipping points occur in both directions – deterioration or improvement in food security conditions (Srokosz and Bryden, 2015). The direction of change is determined by the direction of the rolling average statistic. We applied the SMART model to all major food crises in the SMAP record (a total of thirteen since 2015). Across all case studies, SMART values increased significantly prior to a shift in IPC class (Kendall's $\tau > 0.5$; $p<0.05$).

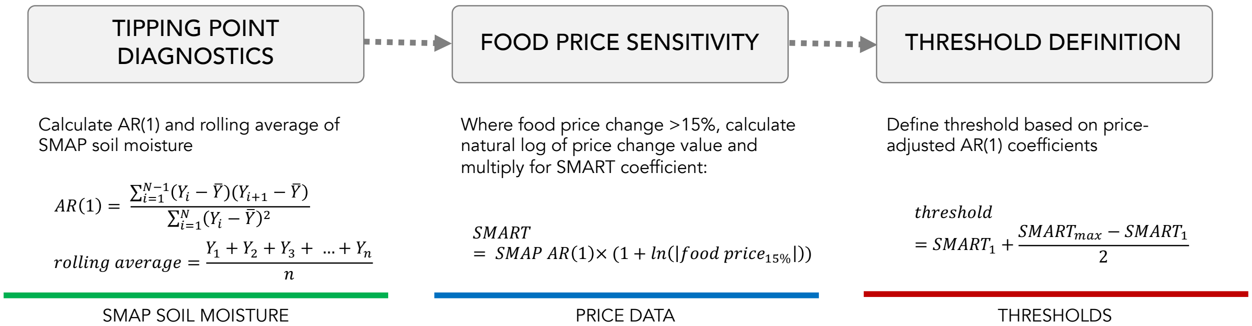

Figure 4.1. The Soil Moisture Auto-Regressive Transition (SMART) model integrates tipping point theory and remotely sensed soil moisture to predict food security tipping points. Autocorrelation coefficients and rolling averages for Soil Moisture Active Passive (SMAP) values are calculated, using a moving window of full rainy season (100 SMAP observations). Extreme price swings (>15% in either direction, relative to the previous month) are then incorporated into the autocorrelation coefficient. Finally, the threshold that indicates an approaching transition is defined using the first and the maximum SMART values. The model is applied to every case study without individual calibration for specific cases, allowing for universal replication in other contexts.

4.3. Methods

The method used for this analysis consisted of three steps (Figure 4.2):

1. The first step consisted of downloading food security trend data for locations where major crises occurred, retrieving food price data for the major food staples, and downloading remotely-sensed data (see Remotely Sensed Data).

2. The second step consisted of calculating tipping point diagnostics associated with each remotely-sensed variable and defining thresholds. Food price data were used to refine the diagnostics and the associated thresholds.
3. The final step involved determining logic rules to quantify what constitutes a tipping point and a trigger in order to perform further assessment of early warning skill.

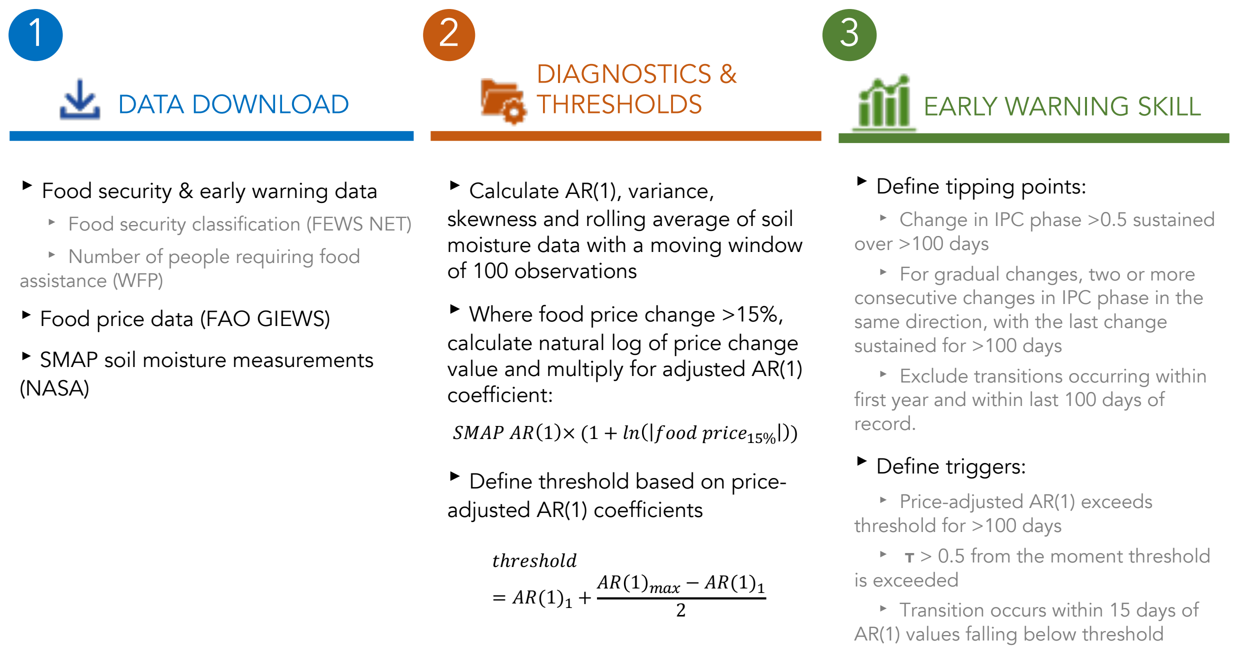

Figure 4.2. Detailed overview of the method undertaken for this analysis. The method used for this paper consisted of three major steps: data download, defining diagnostics and thresholds, and defining tipping points and triggers to enable analysis of early warning skill.

The analysis was then conducted for all major droughts since 2015 as defined by the World Food Programme and the Food and Agriculture Organization for which food security metrics since 2015 were available. For this analysis we therefore included ten case studies (Figure 4.3).

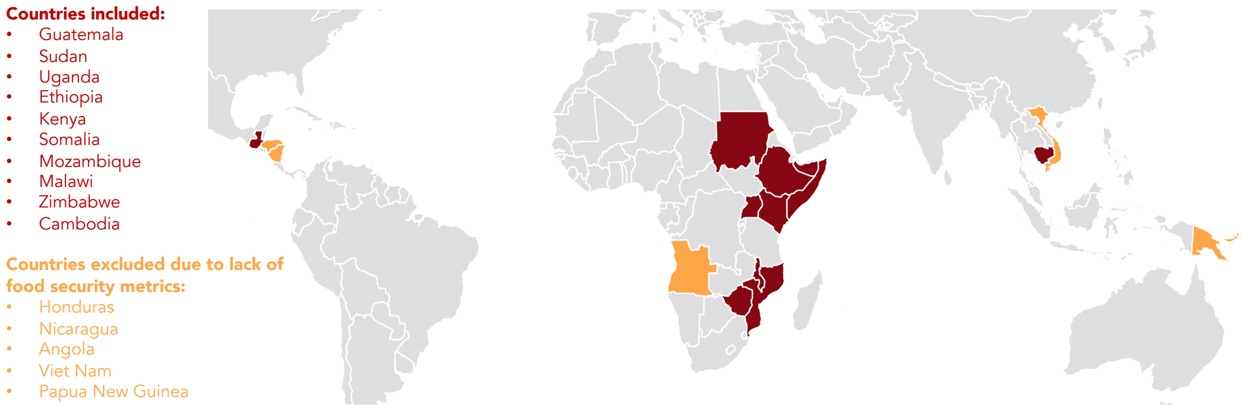

Figure 4.3. Major crises induced primarily by drought were identified in sixteen countries since April 2015. Of these, ten (Guatemala, Sudan, Uganda, Kenya, Ethiopia, Somalia, Malawi, Zimbabwe, Mozambique and Cambodia) were included for this analysis due to the availability of food security metrics.

4.3.1. Data sources

Food crises. The regime shift of interest is the transition between a stable state of minimal food insecurity to a prolonged period with heightened food insecurity. All of the major food crises triggered by drought, identified jointly by the Food and Agriculture Organization (FAO) and the World Food Programme, (WFP) since 2015, and for which food security metrics were available (see below) were included in this analysis. The countries included for this work are: Cambodia, Ethiopia, Guatemala, Kenya, Malawi, Mozambique, Somalia, Sudan, Uganda and Zimbabwe.

Food security metrics. Food security metrics are available through the Integrated Food Security Phase Classification (IPC) approach, which consists of protocols to classify food insecurity and provide information for decision making according to five categories that are comparable across countries: minimal food insecurity, stressed, emergency, crisis and famine (Phases 1 through 5 respectively). Phases are assigned to administrative units or livelihood zones based on consolidated evidence on food-insecure communities to provide information on: (1) the severity of food insecurity, (2) the distribution of food insecurity, and (3) the factors contributing to food insecurity (IPC Global Partners, 2019). Food security classifications for countries that experienced drought-induced food crises were downloaded from the FEWS NET Data Portal (https://fews.net/data). For Cambodia, FEWS NET does not provide food security analyses so the number of people receiving food assistance from the World Food Programme (WFP) was used as a proxy for the severity of food insecurity. Data were retrieved from WFP's standard project and annual country reports (https://www.wfp.org/operations).

Remotely-sensed data. For each of the identified case studies, we used area-averaged time series from the following datasets:

- Surface soil moisture derived from the SMAP Level 3 Radiometer Global Daily 36 km EASE-Grid Soil Moisture Version 6, available from April 2015 onwards (https://nsidc.org/data/SPL3SMP/versions/6). The dataset provides global coverage every 2.5 days. The SMAP mission built on the experience and lessons from previous soil moisture remote sensing missions such as Soil Moisture and Ocean Salinity (SMOS) to detect and mitigate the effect of radio frequency interference in order to provide continuous global high-quality soil moisture data (Oliva et al., 2012). Soil moisture data are filtered to exclude observations in urban areas, areas with high surface water content, and areas impacted by radio frequencies in the same micro-wave wavelengths as SMAP – all of which are known to affect the quality of SMAP data (Reichle et al., 2017).

- Precipitation derived from the TRMM and GPM missions Level 3 0.25° gridded products, available from 1998 until April 2015 (TRMM) and from February 2014 onwards (GPM) (https://pmm.nasa.gov/data-access/downloads/gpm). GPM is an advanced successor of TRMM with additional channels on the dual-frequency precipitation radar (DPR) and on the GPM Microwave Imager (GMI) to enable detection of light precipitation and snowfall (Skofronick-Jackson et al., 2017). Because the two datasets are inter-comparable, a long-term dataset starting in 1998 is available (Stocker et al., 2018).
- Evapotranspiration from the MODIS Level 4 500 m Version 6 product (MOD16A2), available from January 2001 until present (https://modis.ornl.gov/cgi-bin/MODIS/global/subset.pl). Pixels are screened for cloud and aerosol cover to provide more accurate estimates of evapotranspiration rates (USGS, 2020). ET pixel values are the sum of all eight days within the composite period.
- Normalized difference vegetation index values from the MODIS Level 3 250 m Version 6 product (MOD13Q1), available from January 2001 until present (https://modis.ornl.gov/cgi-bin/MODIS/global/subset.pl). Imagery is available for every 16-day period using the two 8-day composite surface reflectance granules (MOD09A1) in the 16-day period. The imagery is filtered for water bodies to improve accuracy of NDVI estimates (USGS, 2020).

- Equivalent water heights from processed GRACE/GRACE-FO data, available from March 2002 until October 2017 (GRACE) and from May 2018 until present (GRACE-FO). Monthly mass grids are processed by the CNES/GRGS group and provided as 1° ×1° grids through the GRACE-plotter (http://thegraceplotter.com/; Lemoine et al., 2018). Unfortunately, there are continuity issues given that no measurements were obtained from October 2017 until May 2018, which limits the skill of GRACE measurements for detecting food security transitions.

Our analysis revealed that soil moisture was the indicator with most promise for detecting drought-induced food crises through tipping point diagnostics.

Food prices. Prices of the dominant food staple in the nearest market were retrieved from the Food and Agriculture Organization's Global Information and Early Warning System food price monitoring tool (http://www.fao.org/giews/food-prices/tool/public/#/home). Price data were downloaded in the local currency for a kilogram of the selected staple.

4.3.2. Tipping point early warning signals: diagnostics and thresholds

Previous studies have demonstrated the utility of using at least four diagnostics for detecting sudden transitions in systems (Krishnamurthy et al., 2020): increasing lag-1 autocorrelation (e.g, Dakos et al., 2008), increasing variance (Takimoto, 2009), increasing skewness (Golledge et al., 2017), and threshold exceedance (Wieczorek et al., 2011). The literature recommends defining the rolling window based on the number of observations before the transition occurs (usually half of the observations) (see Dakos et al., 2012; 2013; Scheffer et al., 2013). This approach is preferred when the timing of the transition is known. For our analysis, we tested the predictive ability of our model and assumed that the timing of the crisis transition is not known. We used a consistent rolling window equivalent to at least one rainy period in every country (250 days, or 100 SMAP observations). While a larger window size would be preferred, transitions occurring in 2016 would have been missed.

After evaluating the skill associated with each diagnostic, we focused the analysis on lag-1 autocorrelation (AR(1)) coefficients and rolling averages associated with SMAP measurements. The AR(1) coefficient provides an indication that a transition is likely to occur, but does not indicate the direction of change. A similar trend was found elsewhere in climatological applications of tipping point theory (Dakos et al., 2008). In our analysis, the rolling average diagnostic indicates the direction of change and therefore is a useful metric for early warning protocols. Lag-1 autocorrelation is calculated using the following equation:

$$Eq. 1$$

$$AR(1) = \frac{\sum_{i=1}^{N-1}(Y_i - \bar{Y})(Y_{i+1} - \bar{Y})}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2}$$

Where Y_i refers to the ith observation of soil moisture, $\bar{Y}$ is the average soil moisture value, and N refers to the number of observations.

The initial analysis revealed that some crises were missed by soil moisture measurements alone, and that sudden food price increases were implicated. Our analysis revealed that difference in food prices of at least 15% relative to the previous month preceded a transition in IPC classes. However, food prices have non-linear effects on food security, with higher increases in food prices resulting in exponentially more severe food security consequences (Kalkuhl et al., 2016). To account for this relationship, the natural log of prices was calculated. Where food prices changes exceeded the 15% threshold, the log- transformed absolute value of the transformed food price change was multiplied with soil moisture AR(1) and rolling average values according to the following equation to adjust the diagnostics:

$$Eq. 2$$

$$SMART = SMAP\ AR(1) \times \ (1 + \ln(|food\ price_{15\%}|))$$

In studies for detection of major climatic shifts such as glaciations (Dakos et al., 2008) the threshold is defined based on the initial AR(1) value, which in turn is based on the rolling window size – with an increase in autocorrelation after this baseline indicating an approaching tipping point (Scheffer et al., 2009). We build on this foundation and apply a threshold based on the difference between the initial and maximum SMART, as shown in Equation 3:

$$Eq. 3$$

$$threshold = SMART_1 + \frac{SMART_{max} - SMART_1}{2}$$

Theoretically, the maximum SMART value can increase over time due to changing environmental conditions or more severe price swings. As such the threshold can therefore be adjusted to such changes in environmental and market variables.

This threshold is applied to all cases without calibration for individual cases, making this approach applicable for every location where a food crisis unfolded in our study. The threshold also eliminated all false alarms that would otherwise be identified with a threshold based solely on the initial autocorrelation coefficient. The advantage of defining thresholds through an equation is the possibility of simplifying the analysis of threshold levels, while also taking into account the local context (initial and maximum SMART values are different for each of the case studies examined here).

4.3.3. Operationalizing the early warning system model

A set of logic rules were developed to identify tipping points and triggers. A **tipping point** is considered where there is a change in IPC class in either direction that is greater than 0.5 that is sustained for at least 100 days, resulting in two types of regime shifts – entering a crisis, and exiting a crisis. In other words, short-term fluctuations in food security are not considered regime shifts. For instances where food security conditions changed gradually, a regime shift is defined as two or more consecutive changes in IPC class in the same direction if the change is greater than 0.5 IPC classes since the first transition and is sustained by at least 100 days. In the latter case a tipping point begins at the first change in IPC conditions. For our analysis, we exclude transitions that occurred within the first year of the observational record of SMAP (because of insufficient historical measurements to establish a threshold) and those transitions occurring within 100 days of the end of the record (due to the absence of food security data to validate the transition).

The **trigger** is important for signaling when an intervention should take place, and is therefore an essential element of quality and skill. In our analysis, the trigger is activated when the following three conditions are met:

- diagnostic exceeds threshold for >60 days
- $\tau > 0.5$ from the moment threshold is exceeded
- tipping point occurs within 15 days of diagnostic values decreasing below threshold levels

These definitions yielded three sets of triggers: true positives (a transition is forecasted, and it does indeed occur), false positives (a transition is forecasted but food security conditions remain unchanged), and false negatives (no transition is forecasted but food security conditions experience a shift).

4.4. Results

For each case study, tipping point diagnostics and thresholds are shown through a 'dashboard' (Figure 4.4). In the upper panel, food security conditions (IPC) are denoted by the solid grey line, while soil moisture values (SMAP) are shown by the solid blue line and food price changes (relative to the previous month) (FAO GIEWS) are shown by the dotted blue line. The period of interest is the prolonged shift in food security conditions (a change in IPC class of at least 0.5 sustained for at least six months following a minimum baseline of one rainy season), denoted by the red bar at the top of the plot. The period starts with a transition toward deteriorating food security conditions (at the beginning of the bar) and improvement in conditions (at the end of the bar). In the case of Kenya, for example, a food crisis began in June 2016 and lasted over 18 months following a prolonged period of below-average rainfall (FEWS NET, 2017). Over 1.3 million people were affected. Food security conditions improved in December 2017 and continued to improve. Minor fluctuations in 2018 are not considered tipping points as food security conditions were not sustained for at least six months. In the lower panel, the SMART indicator (thick solid black line) exceeds the threshold by at least three months prior to the crisis transition and then stabilizes below the threshold during the crisis. During periods of extreme price changes, the AR(1) also changes – this is illustrated by the blue outline – although in this case the prices did not affect the trigger as it had already been exceeded. Before exiting the crisis, the SMART indicator again exceeded the threshold by at least three months signaling a potential upcoming shift. The rolling average, shown at the bottom by red (negative rolling average) and blue (positive) bars indicate the direction of transition.

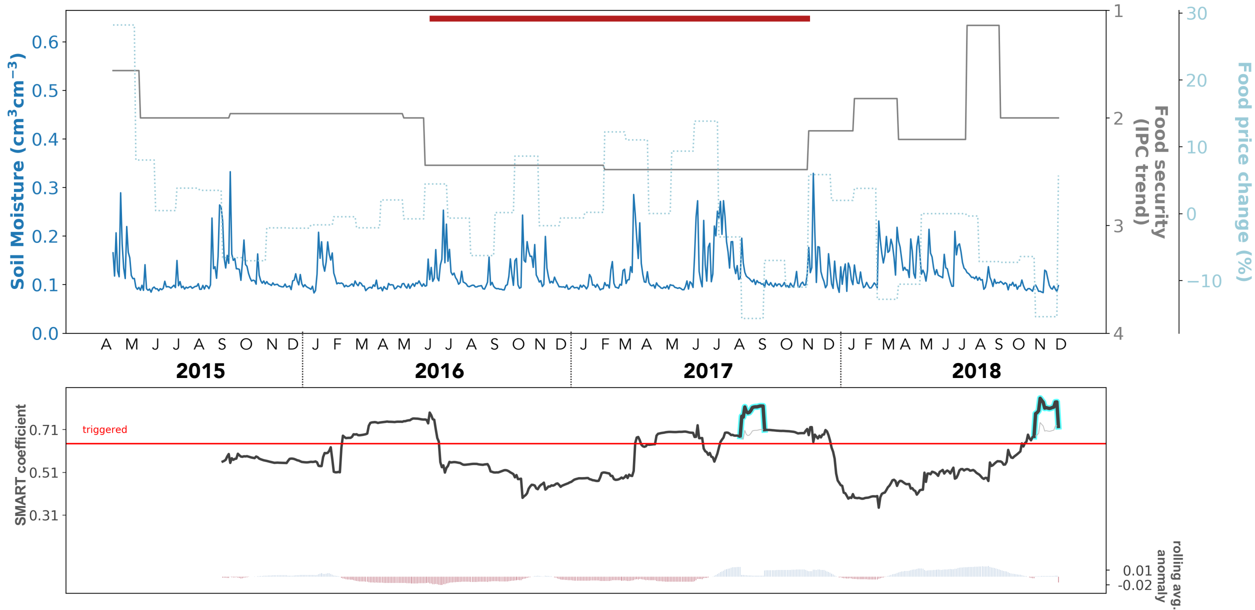

Figure 4.4. Food security tipping points detected by tipping point statistics. Top panel: Integrated Food Security Phase Classification (IPC) (gray line), remotely sensed soil moisture (solid blue line), and food price anomalies (dashed blue line). Bottom panel: Soil Moisture Auto-Regressive Threshold (SMART) indicator (black line, with blue highlight when price-influenced), trigger threshold (red line), and soil moisture rolling average (red/blue bars). When the SMART indicator exceeds the triggered threshold, a food security tipping point is forecasted; the indicator provides skill of up to three months lead time. The period of state change is indicated by the maroon bar in the top panel. The example shown above is for the northeastern region of Kenya; the other case studies are shown in the Supplemental Material.

Across all case studies, we found that the SMART, once triggered, provides a lead time of no less than three months before a major transition both toward a food crisis or away from a crisis.

As the lead time to a transition decreases, the signal becomes stronger, providing greater confidence that a transition is increasingly likely. In contrast, during periods of no transition ("baseline"), SMART values are lower (*p*<0.05) (Figure 4.5). These results suggest that the SMART indicator is a useful metric for predicting when a major transition will occur as well as when conditions are likely to be stable.

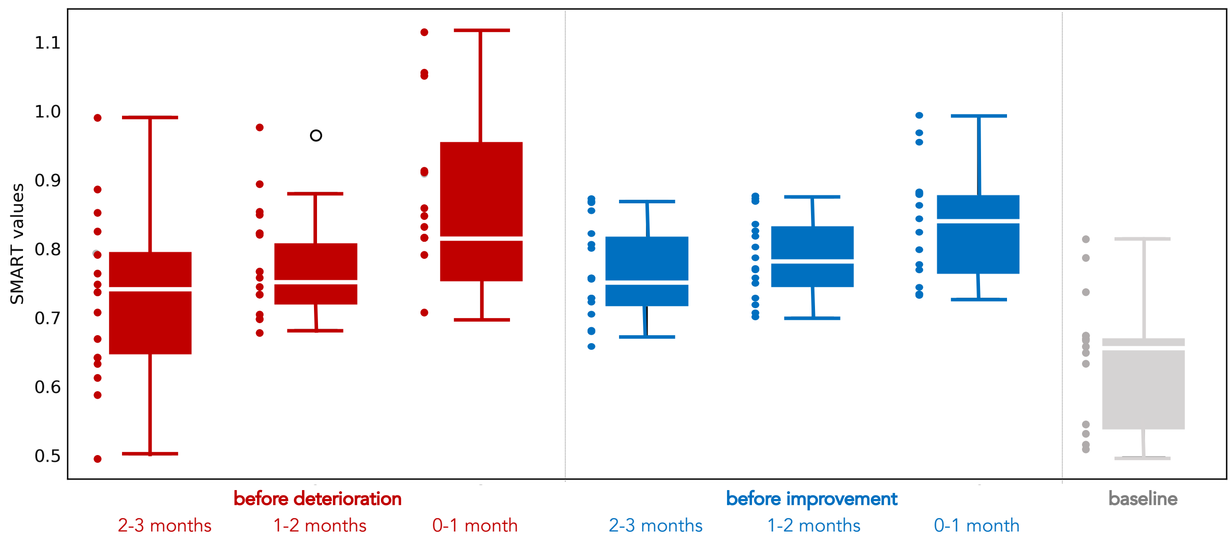

Figure 4.5. Sustained periods of Soil Moisture Auto-Regressive Threshold (SMART) values are indicative of a potential food security state shift. As the transition approaches, SMART values increase, providing greater certainty about impending shifts in food security conditions. Baseline SMART values are significantly lower than the values associated with periods prior to transitions (p<0.05).

In addition to enabling forecasts of when a transition might occur, SMART values predict the magnitude of the food security shift, i.e., the change in food security conditions as measured by IPC classes (Figure 4.6). The implication is that the SMART indicator not only indicates when a deterioration or alleviation is likely to occur, but also provides a quantitative indication of how large the shift in food security conditions is likely to be. The median values of SMART in the three months preceding a transition are strongly correlated with the change in IPC classes, with a larger SMART value indicating a larger transition. The predictive skill is nearly equal for exits ($R^2 = 0.83$, $p<0.05$) and for transitions towards crises ($R^2 = 0.81$, $p<0.05$).

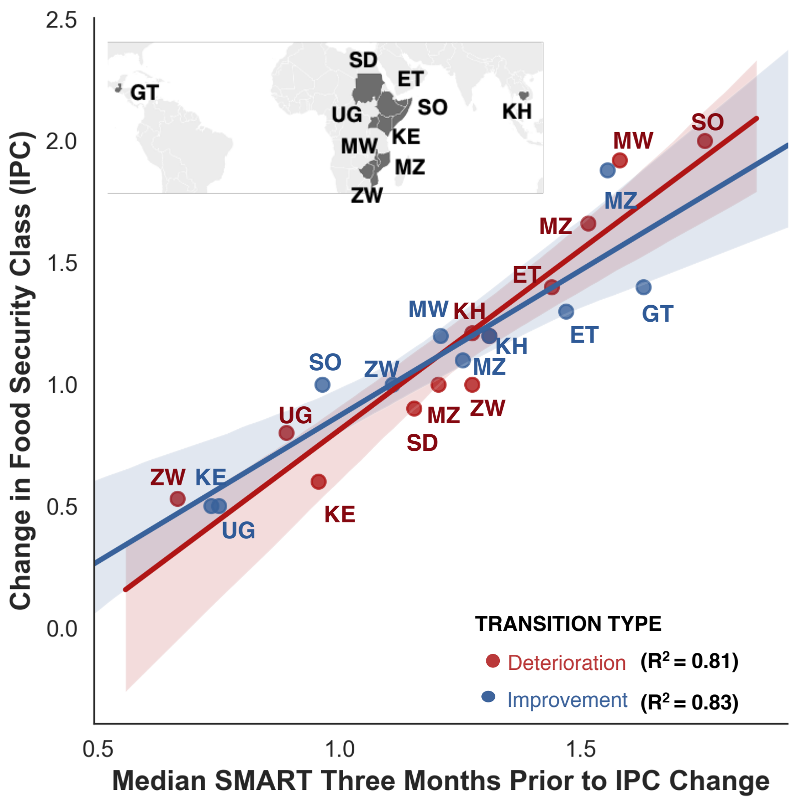

Figure 4.6. The 3-month median Soil Moisture Auto-Regressive (SMART) values forecast the size of the transition for both crises and exits. Data include all major drought-induced food crises over the soil moisture satellite record.

4.5. Not all remote sensing products are created equal

Existing early warning systems rely on consensus-based seasonal forecasts, which tend to perform with lower accuracy in periods with complex climate phenomena. During El Niño years, for example, the hit rate of seasonal forecasts is 55-58% compared to the average hit rate of 69-72% (ICPAC, 2019). Consequently, food security forecasting skill (i.e., the ability to successfully predict IPC categories) is lower in years with strong ENSO cycles (64%) compared to years without a strong ENSO signal (84%) (Krishnamurthy and Choularton, 2020). Part of the challenge has to do with the need for updating forecasts. Platforms like the Climate Outlook Forums, whereby analysts interpret information from a range of national, regional and international seasonal forecasts are expensive and therefore meet infrequently, e.g., 3-4 times per year (Walker et al., 2019).

To address this challenge, Earth observation data are increasingly being used to provide regular monitoring updates and develop automatic triggers that activate funding mechanisms and famine prevention activities (Jjemba et al., 2018). Remote sensing products have different characteristics in terms of the types of variables they measure, temporal and spatial resolutions, historical availability, spatial coverage and accuracy (Krishnamurthy et al., 2020). Near-real-time monitoring of vegetation health (Meroni et al., 2019) and rainfall anomalies (Funk and Verdin, 2010) has already proven to be valuable in improving responses to drought through signals for early warning (e.g., Rojas et al., 2011). Initially, we tested tipping point diagnostics on a broad suite of remote sensing products for hydrology and vegetation health, including soil moisture, NDVI, rainfall anomalies, and evapotranspiration (Krishnamurthy et al., 2020). A key question is which of these characteristics is the most relevant for detecting food security transitions. In terms of type of measurement, it is important for indicators to be predictive. Vegetation health indicators often lag in terms of detecting vegetation stress (and, ultimately, a food crisis), unlike hydrological indicators like soil moisture, which anticipate stress (e.g., Enenkel et al., 2015). In our analysis, vegetation indicators like NDVI and evapotranspiration only detect 33-66% of transitions. However, not all hydrological indicators perform with higher accuracy – GRACE groundwater measurements detected 0-57% of transitions, largely due to the limited temporal resolution. In comparison, our analysis using soil moisture was able to detect all transitions (Figure 4.7).

Remotely-sensed soil moisture is a relatively novel indicator, available operationally only since 2010 (through the Soil Moisture and Ocean Salinity mission) (Kerr et al., 2012) and 2015 (through the Soil Moisture Active-Passive mission) (Entekhabi et al., 2010). Here we focus on SMAP observations, which generally have a higher spatial resolution (36 km for SMAP radiometer compared to 35-50 km for SMOS). SMAP also has a slightly higher temporal resolution (2.5 days) than SMOS (3 days). SMAP measurements are more accurate (global correlation with in situ soil moisture measurements of 0.76) than SMOS measurements (global correlation of 0.66), especially in areas of the world that tend to be more vulnerable to food crises (Chen et al., 2018). SMART detected all 25 major food security transitions in 10 countries – on average one transition every two years. In contrast, the SMART forecast using SMOS data identified only 72% of transitions in the same period (Figure 4.7). In our study, the ability to detect changes over time was more important for tipping point detection than spatial resolution. This is consistent with other applications of tipping point theory (Livina and Lenton, 2012). In terms of measurement accuracy, SMAP was adequate for timely detection of food security transitions.

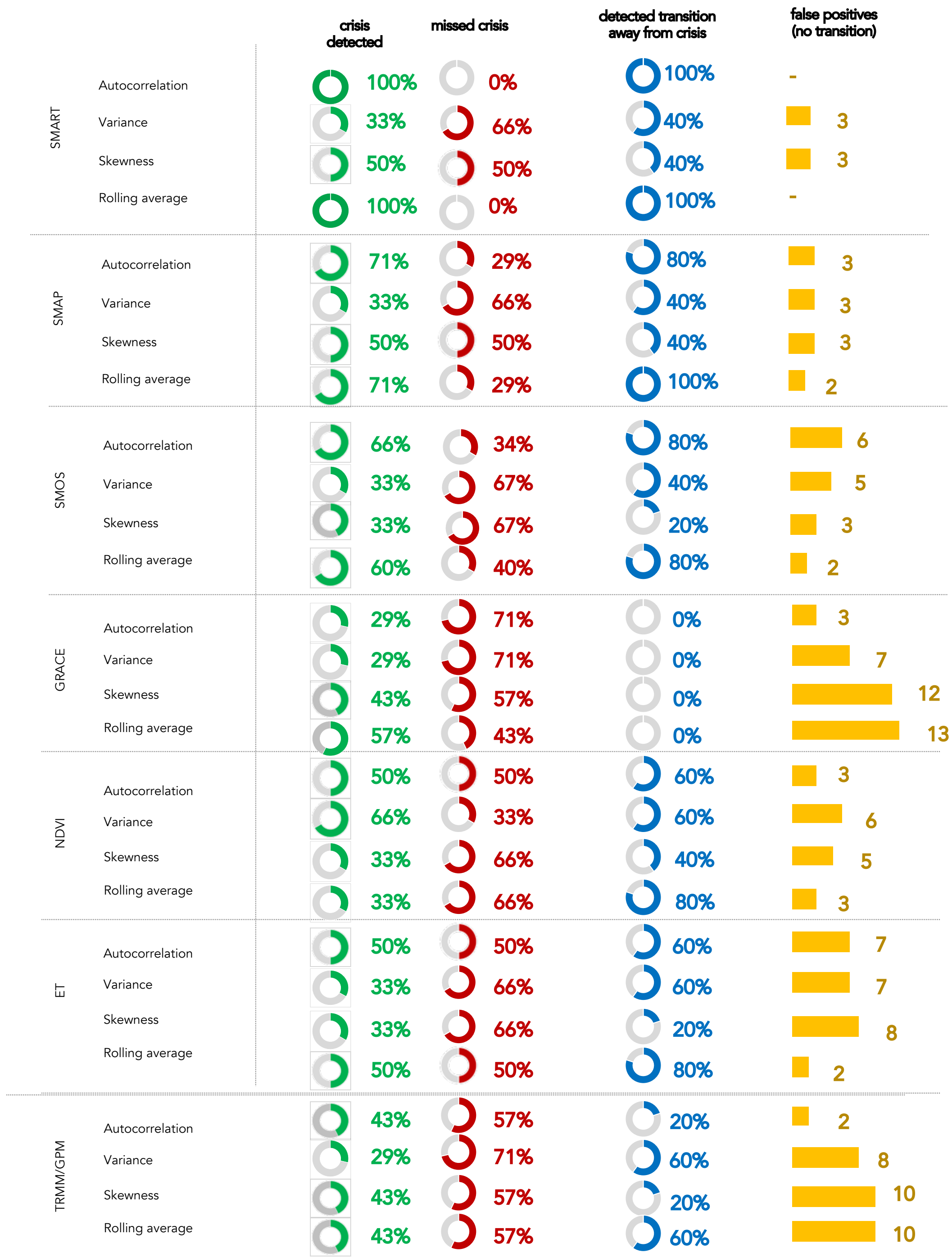

Figure 4.7. Certain diagnostic approaches and remotely-sensed datasets are more accurate in identifying transitions to food crises than others. The combination of rolling averages

and autocorrelation in soil moisture measurements perform well in detecting deteriorations and improvements of food security trends.

Across our case studies, food security transitions are more sensitive to soil moisture trends than to food prices: 70 percent of transitions can be predicted with soil moisture autocorrelation triggers alone. But, incorporating food prices raises predictive skill to 100%, especially in Southern African and Asian countries where extreme food price changes are a major trigger of food insecurity. The result of combining the two indicators may allow improved detection of the incubation of a food crisis when food price signals begin to worsen or improve synchronously with potential drought stress, especially in countries where rainfed agriculture and livestock production are predominant sources of livelihoods and food security (Turner, 1997).

Table 4.1. Food price swings contributed, partly or primarily, to food security transitions in some of the case studies examined here. In such instances, a food price change of at least 15 percent relative to the previous month, in either direction (increase or decrease) was noted in the month prior to a transition.

Food price swing (% relative to previous month)	IPC change at transition	Transition type	Country	Food prices played a role
15.2	-	Crisis	Cambodia	x
31.5	-	Crisis	Cambodia	x
15.9	1.2	Crisis	Guatemala	x
18.1	1.4	Crisis	Malawi	x
21.9	1	Crisis	Mozambique	x
42.3	1.86	Crisis	Mozambique	x
48.8	2	Crisis	Somalia	x
42.1	1.5	Crisis	Sudan	x

42.5	0.5	Crisis	Zimbabwe	x
18.7	1	Crisis	Zimbabwe	x
0	0.67	Crisis	Ethiopia	
0.7	0.5	Crisis	Kenya	
11.2	1	Crisis	Sudan	
4.7	0.8	Crisis	Uganda	
-25.5	1	Exit	Ethiopia	x
-29.5	0.5	Exit	Guatemala	x
-18.1	0.9	Exit	Malawi	x
-16.5	0.7	Exit	Malawi	x
-72.72	2.8	Exit	Mozambique	x
-18.1	0.5	Exit	Uganda	x
-1.1	-	Exit	Cambodia	
-2.9	1	Exit	Guatemala	
-1.9	0.62	Exit	Kenya	
-2.6	0.5	Exit	Somalia	
-0.6	1.88	Exit	Sudan	
-1.7	1	Exit	Zimbabwe	

Our results also indicate an empirical relationship between the magnitude of median autocorrelation metrics and the change in food security conditions. To our knowledge, this is the first documented analysis of a relationship between tipping point metrics and the magnitude of change in the system. If this relationship between magnitude of autocorrelation metrics and magnitude of change in food security holds up in future crises, it would be have huge value in responding to food crises – the response could be scaled to the size of the crisis. A humanitarian operation that does not match the scale of the crisis either squanders resources, or fails to protect lives. Currently, analysts rely on metrics of malnutrition and precipitation anomalies to make assumptions about the number of people who will require humanitarian assistance (Funk et al.,

2019) – but the SMART model might provide an additional layer of information to anticipate humanitarian needs.

4.5.1. Global application of the model

Research has shown that investment in early warning systems is highly valuable, with some estimates suggesting that a dollar invested in early warning saves up to 100 dollars in response (*48*). However, setting up early warning systems can be expensive and are therefore difficult to replicate globally across all locations. Typically, such early warning systems are only set up for priority countries. However, there are a number of cases where food security crises can still occur – and yet limited food security monitoring capacity exists.

The model we propose here, based on price-sensitive soil moisture autocorrelation, is based on universalizable criteria applied to open-source information and can be replicated across all geographies. The main data sources, SMAP soil moisture and food prices are collected regularly through existing systems. At the same time, the thresholds utilized for the triggers are based on the context-specific characteristics of soil moisture dynamics (the maximum and initial values). The advantage of defining thresholds through a universal equation is the possibility of simplifying the analysis of threshold levels, while also taking into account the local context.

The model we present here is universal and can be applied in any geography. In countries where no early warning systems are in place, it can signal an emerging crisis. And in countries with existing systems, our approach can provide increased confidence about the accuracy of signals detected through other indicators.

4.5.2. Data length requirements

In the absence of historical data, interpreting tipping point diagnostics is a complicated task. The length of the historical baseline influences the size of the rolling window, i.e., the subset of the data used to calculate diagnostics: a shorter window size is more likely to provide unclear signals while a longer rolling window offers a longer-term baseline for reducing the effects of large noise, identifying anomalies and potential tipping points (Rogers and Tsirkunov, 2011).

The rolling window size also determines the initial and maximum autocorrelation values (and therefore influences the accuracy of the threshold). A small window is likely to hide seasonal trends, whereas a very large window size will hide some seasonal variability – both examples result in an inaccurate initial autocorrelation value (Livina and Lenton, 2012). In addition, a small window size could result in an artificially high maximum SMART value because short periods will be associated with soil moisture values that are very similar to each other. Conversely, a large window size would hide sub-seasonal trends, potentially resulting in a smaller maximum SMART value. As a result, the threshold level will be set too low and false positives will be triggered (Dakos et al., 2012).

As the foregoing discussion illustrates, determining the size of the rolling window is essential for accurate early warning – yet the appropriate size of the rolling window is heavily contested. In applications for climate tipping points, the rolling window size is equivalent to 50 percent of the data series prior to the regime shift when the timing of the transition is known, with the idea being that signals identified in the first half of the dataseries represent baseline conditions that change as the transition is being reached (Dakos et al., 2008). Other authors suggest rolling window sizes based on time. In ecological studies of whale populations, a data period of twenty years proved to be the minimally sufficient timeframe to detect inflections in population numbers (Clements et al., 2017). Recent work has suggested that the size of the rolling window depends on the frequency of data points, with datasets available at high temporal resolution recommended (Livina and Lenton, 2012).

Ultimately the size of the rolling window depends on the time scales at which the tipping point is expected to occur. For process occurring on millennial scales – such as glaciations, the collapse of the thermohaline circulation, or the desertification of North Africa – window sizes of 2,500 years, 20,000 years and 1,500 years respectively provide early warning signals based on increasing autocorrelation (Dakos et al., 2008). For food security applications, the relevant timescale is at the sub-annual (seasonal scale) scale – and at sub-annual scales high temporal resolutions allow for estimation of autocorrelation (Takimoto, 2009).

For the purposes of this work, we tested the applicability of a universal window size assuming the beginning of the transition phase is not known, and used a rolling window size of 100 SMAP observations (at least 250 days) to capture seasonal variability during the length of at least one rainy season across all case studies. The window size of 100 was kept constant to account for missing records or days with cloud cover. The window size also used to allow for detection of transitions starting in 2016. Even without a long historical record (records began on April 2015), accuracy rates for crisis detection are promising. In part, this might be attributed to the high temporal resolution of the data (2.5 days). That SMAP measurements performed well even with a relatively short data record bodes well for its future usability in early warning. As the data record expands, we will be able to test the utility of larger window sizes for predicting future food security transitions.

4.5.3. Tipping point thresholds

There is an inherent difficulty in forecasting when a crisis will begin: a declaration of famine or food crisis is not only based on deteriorating food security conditions but also on political consensus that a crisis is indeed unfolding (Seal et al., 2017). By contrast, it is easier to predict when a food crisis will end for two reasons. First, declaring that a food crisis has ended is politically desirable (Kenneally, 2011). Second, climatological and environmental thresholds of improving conditions – though less studied— are less politically sensitive than those associated with food crises (Zschau and Küppers, 2013). Having said that, anecdotal evidence suggests that current early warning systems may be conservative in predicting recovery from major food crises, especially in conflict settings (Choularton and Krishnamurthy, 2019). Our approach provides an additional objective layer of information for determining when a crisis is approaching or likely to end with a three-month lead for both types of transition. Given that a large-scale humanitarian operation takes at least six weeks to mount (IASC, 2015), the three-month lead provides time to avert a crisis.

Setting the right threshold level is key for automatic trigger-based early warning systems and disaster risk finance mechanisms, providing information about when certain activities are needed to avert a crisis (Wilkinson et al., 2018). A low threshold is likely to result in too many false alarms being issued (and thereby reduce the credibility of the system). Conversely, a high threshold level would miss crises (Choularton and Krishnamurthy, 2019). Setting the threshold correctly therefore has implications for effective early warning, and disaster risk finance. In contrast, improving the performance of these systems can build confidence to take action and to trigger disaster risk finance where reducing basis risk is critical.

Here we use a universal threshold based on the initial and maximum SMART values, making it applicable to any geographic context without requiring further calibration; the threshold eliminated all false positives and false negatives in our case studies. But two important challenges remain. First, there is no guarantee that the approach will work for future drought-related crises or in wealthier economies with different food systems. However, that our analysis worked for all case studies across various geographical contexts is highly promising but further replication exercises are required test the validity of the approach. Second, the threshold is dependent on the maximum SMART value. With changing environmental (e.g., soil moisture) and social (e.g., food prices) conditions, the maximum AR(1) coefficient could drastically change with implications on where the threshold is set. Here, too, additional work with a focus on future droughts will provide further clarity on this.

Given the utility of SMAP data for food security early warning, can the humanitarian and science communities can continue to rely on the mission's continuation? The active radar has already broken, and the mission is past its three-year nominal duration. On top of this, the mission cost nearly US$1 billion (NASA, 2015). Soil moisture has not been explicitly prioritized as a key indicator to monitor in the US National Academies of Sciences, Engineering and Mathematics 2017-2027 Decadal Survey for Earth Science. However, as SMAP has shown to be very valuable for food crisis early warning, collection of these data has enormous societal value. The fact that continued collection of soil moisture data might not continue in the long run – both because of technical issues (broken sensors) and competing scientific priorities – is a disturbing possibility. On the basis of our promising results, we strongly recommend prioritizing soil moisture measurements with characteristics analogous to SMAP in future satellite missions.

4.6. The unexplored promise of tipping point theory in combination with environmental indicators

Food crises depend on multiple factors such as availability of crops and grazing land, food prices, governance regimes, health conditions and conflict – so even if an early warning correctly predicts that some thresholds (e.g., sufficient food) are not met, a crisis can still unfold because another event triggered it (e.g., political instability) (Ross et al., 2009). On top of this, there are a multitude of factors that early warning systems are not meant to capture: governance structures, legal frameworks, feasibility of providing humanitarian assistance, or the effects of pandemics (Walker, 2013). To address this challenge, a layered early warning system with multiple data streams providing information at different times can reduce uncertainty about the intensity and timing of food crises: for instance, seasonal forecasts might not suggest deteriorating trends, but monitoring of political stability might suggest an impending crisis (Funk et al., 2019). Conversely, an early warning signal might trigger early assistance and thereby preventing a crisis – in such cases, additional calibration might be needed to ensure the model adequately captures the effects of assistance.

Our results show the significant opportunities for integrating tipping point theory to complement triggers that feed into existing early warning systems – such as seasonal forecasts (available at least 3-4 months before a potential crisis), vegetation and drought impact models (constantly being updated), and real-time monitoring. With food security challenges increasing due to climate-related events and conflict incidence (FAO et al., 2019), our approach offers an additional layer of prediction prior to a major food security tipping point. When all triggers indicate an upcoming crisis, the autocorrelation values can help enhance early interventions by providing greater confidence about the signal and by informing on the severity of the crisis. On the other hand, when all other triggers fail to predict an unfolding crisis, the tipping points framework offers a warning signal with a three-month lead-time to enable early action.

The remote sensing tipping point approach we present here provides a potential step-change in food security early warning, given the temporal associations between detected early warning signals and the timing and intensity of food security transitions. The lead time of the signal will allow governments and the humanitarian community to prepare for a crisis, and potentially avert it. At the same time, the SMART indicator provides an indication of the severity of food security transitions – another piece of critical information for reducing humanitarian impacts.

Chapter 5

Conclusions

5.1. Summary of results

Food security early warning systems are of paramount importance to achieving the global objective of eradicating hunger. The principal contribution of my research is demonstrating that the mathematical underpinnings of tipping point theory can be applied to food security early warning and thereby provide early warning of impending transitions. To accomplish this research, I relied on publicly available datasets from global efforts such as the Famine Early Warning Systems Network (FEWS NET), the Food and Agriculture Organization's Global Information Early Warning System (GIEWS), and various satellite missions. My efforts contribute to the overall advancement in early warning capabilities, with a specific focus on long-term shifts in food security conditions of at least six months in duration.

Chapter 2, published in *Global Food Security* (Krishnamurthy et al., 2020a), provides a baseline for understanding the state of current early warning systems, and includes an in-depth overview of where and why early warning systems fail to anticipate food crises. Early warning data are now available for over a decade, enabling a systematic analysis of how accurately early warning forecasts predict actual food security conditions. Yet, despite the potential, Chapter 2 is the first study to carry out such an analysis at a regional scale. Four major findings emerge from this research.

First, early warning skill varies significantly by geography. In general, areas that are traditionally more food secure (such as the highly productive highlands of Western Ethiopia) have higher accuracy rates than areas that experience food insecurity on a seasonal basis. In contrast, areas that exhibit lower early warning skill rates are associated with complex topography, such as the transition between mountains and plains in central Ethiopia, areas with frequent conflict such as in South Sudan, and pastoral regions such as in the arid and semi-arid lands of Kenya. One of the key contributions of this work is providing a spatially explicit overview of early warning accuracy rates to enable targeted investment of resources for enhanced data collection and future analysis in these locations.

The second key finding of Chapter 2 is that not all errors are the same. Some regions are more prone to overpredicting food insecurity (false alarms) while others experience the opposite scenario (false negatives, or missed crises). The implications of both errors are significant, both in terms of resources and human lives. A false alarm can trigger a large-scale humanitarian response that is not needed, thereby limiting resources for future responses in other locations. Another important but unquantified impact of false alarms is the reduced confidence of donors in early warning systems resulting from frequent false alarms. This problem is perhaps best exemplified in the children's fable "The Boy Who Cried Wolf" in which a boy repeatedly tricks the villagers into believing that a wolf is approaching. Later, when a wolf actually comes to the village, the villagers do not heed the boy's warnings and the town's sheep are ultimately eaten by the wolf. With a system that produces false alarms on a consistent basis, there is a serious risk that the donors ("the villagers") will not respond to the warning of an approaching crisis ("the wolf"). My analysis revealed that this type of error is most common in areas with high conflict, possibly because food security analysts are being overly cautious in interpreting trends. The other type of error, false negatives (or missed crises), are arguably more costly from a humanitarian perspective. Failing to anticipate and respond to a crisis can result in millions of lives lost, and even for survivors, the implications of destroyed livelihoods can be significant. My analysis indicates that this type of error is more common in areas with complex climates, indicating that weather forecasting skill is still in need of additional improvement. The results are again shown in a spatial map to support decision makers in interpreting uncertainties associated with early warning forecasts.

The third key finding of Chapter 2 concerns the ability of early warning systems to anticipate transitions to crisis situations – in other words, how well do early warning systems predict that a given area will transition from a state of acceptable food security conditions to a crisis situation? The somewhat surprising result of this enquiry is that areas that experience fewer crises are more prone to error. This is, in part, because in areas that are less prone to crises, there are less resources available to forecast food insecurity. Yet, a crisis can occur anywhere – even in places that do not traditionally experience them – and successfully preparing for such a situation is essential if we are to save lives.

Finally, in Chapter 2 I also reviewed the key sources of uncertainty associated with early warning systems. It is well known that the major sources of error are linked to the ability to forecast climatic conditions (droughts, floods, and tropical storms) and socioeconomic variables (conflict intensity, price volatility). My research provides the first quantification of the contribution of each of these variables to early warning skill. The research also shows that climate forecast skill is twice as important as conflict frequency in determining successful food security forecasts.

In all, Chapter 2 provides a baseline for understanding the status quo of early warning systems, which rely heavily on consensus-base seasonal climate analysis. With the increasing availability of remote sensing products that monitor environmental variables on a global scale, there is a case to be made for testing whether incorporating these satellite-derived datasets into early warning. In the last decade, satellite missions aimed at measuring soil moisture (SMOS, SMAP), groundwater (GRACE and GRACE-FO), chlorophyll fluorescence (OCO-2 SIF) and evapotranspiration (ECOSTRESS) have become available, opening up possibilities for more sophisticated analysis and inputs into early warning. By design, these products have different characteristics and spatial and temporal resolutions. With so many different products, the question is then how to integrate the various products more systematically into an early warning platform. Chapter 3, published in *Earth's Future* (Krishnamurthy et al., 2020b), addresses this critical question by arguing that tipping point theory offers an overarching framework for such integration. In so doing, the research defines what a food security tipping point might look like, and how it might differ from tipping points explored in the ecological literature. The research also offers a meta-analysis of the utility of various remotely-sensed environmental datasets on vegetation health and hydrology for detecting tipping points. Here I also explore the different statistics that could be used to provide actionable early warning signals of impending tipping points: increasing autocorrelation, increasing variance, increasing skewness and threshold exceedance. The ability to detect any of these diagnostics prior to food security tipping points would have implications for early warning capabilities.

The theoretical underpinnings of tipping point theory that originated in the research of Holling (1973) offer exciting opportunities for applications in early warning. But to date, research in the field has focused on large-scale ecological transitions such as the collapse of the North Atlantic Oscillation, the disappearance of glaciers, or the loss of forests. These are all events that are difficult to reverse. In food systems, such transitions do not exist because the implication would be a permanent state of famine. So, with that in mind, how realistic is the application of these principles to seasonal processes that influence food security trends?

Chapter 4 is the culmination of the previous Chapters: if Chapter 2 provides a baseline for understanding where and why early warning needs improvement and Chapter 3 provides a framework for potentially improving integration of new remote sensing products into early warning systems, Chapter 4 then explores the feasibility of applying tipping point theory to the detection of food security transitions. The research in Chapter 4 combines two diagnostics from tipping point theory (namely, autocorrelation and rolling averages) with food price data to provide a tool for detecting food security tipping point. The approach is applied to all major food crises in the record of the SMAP mission (April 2015-present). Three key findings emerge from this work.

The first major result of Chapter 4 (Krishnamurthy et al., in review) is that the combination of soil moisture autocorrelation and food price statistics detected all transitions – both deterioration and improvement of food security conditions – in the SMAP record, including those that were not identified by status quo early warning systems. Although the SMAP record is relatively recent, the ability to detect all transitions for all major food crises, which included 25 transitions, is encouraging and illustrates the potential for including remotely sensed soil moisture in tipping point analysis for predictive food security early warning. This finding also adds credibility to the argument that tipping points might be reversible, at least in food security systems, and that the statistics used to detect a shift between one state, and another could also be used to detect a shift in the opposite direction. From an operational standpoint, the finding is useful because it provides information that can inform how long a humanitarian operation should last.

The second key finding of the research is that the signal provided by soil moisture and price statistics lasts between three and six months. A longer lead time is of course ideal, but the ability to provide signals even three months prior to a crisis is beneficial for staging a humanitarian operation. The research also shows that the autocorrelation statistics associated with the signal increase as the crisis is approaching, thereby providing increasing confidence that a transition is likely to occur shortly.

The final and perhaps the most surprising finding in Chapter 4 is that the magnitude of autocorrelation is linked to the size of change in food security conditions. To my knowledge, this research is the first to identify a quantifiable relationship between a tipping diagnostic and the size of the regime shift. This is a finding that is fascinating from a theoretical perspective, yet more work is needed to better understand why the diagnostic and the magnitude of change in the system are related. From a practical standpoint, however, the implication is significant: the ability to predict how significantly food security conditions will change can help ensure that the scale of the operation matches the scale of the problem.

A word of humility is warranted here. The work conducted for Chapter 4 is based on historical cases and there is no guarantee that future food crises will be successfully anticipated using the principles and approaches proposed here. After all, the past is not always a good predictor of the future. The findings are, however, promising and deserve further attention moving forward.

Ultimately, the decision to act on an early warning signal is not purely a scientific one. There is a great deal of subjective decision-making that takes place before a drought or a food crisis is declared. Even if there is evidence of an impending crisis, it may take months for a response to be mounted. A key challenge is ensuring that all relevant stakeholders agree that there is a problem, that it is a serious one, and that it should be addressed. It is my hope that the research developed for my dissertation contributes to an objective decision-making process anchored in publicly available datasets.

5.2. Future directions

The advent of remote sensing of environmental variables has greatly contributed to food security early warning systems since the 1980s. Since 2010, a new suite of vegetation and hydrological products have become available to enable further improvements to early warning capabilities. In this dissertation, I showed that SMAP soil moisture data can contribute significantly to anticipating when food security tipping points induced by drought events might unfold – and the implications for food security and humanitarian interventions are far-reaching. But this research is only the first step towards improving detection of food security tipping points. From a scientific perspective, there are still various questions that deserve further exploration. While from an operational angle, there is still work to be done.

Moving forward past the doctoral dissertation, a key priority will be operationalizing the SMART analysis (Chapter 4) into a practical and functional tool that serves the humanitarian community and vulnerable populations in tandem and in support of existing early warning systems. Such an operational tool might be in the form of a dynamic near real-time map interface and tool that receives soil moisture measurements and food price information as inputs, and highlights where the SMART threshold has been exceeded by a given number of days. The information would then be validated through other sources of information, such as additional remote sensing analysis of vegetation anomalies or food security surveys, and ultimately provide some basis for scaling up humanitarian assistance.

The issue of data integration into the SMART model is also one that requires further investigation. In Chapter 4, I demonstrated the utility of SMAP soil moisture and food prices as predictors of impending food security transitions. In part, the datasets were selected because of their availability in areas where food insecurity is a development challenge. However, data availability moving forward is likely to be a concern. For instance, the active sensor of SMAP has already broken, and the nominal length of the SMAP mission has been exceeded. To what extent the international community can continue to rely on SMAP (or SMAP-like) soil moisture measurements is a key question. Food price data at the market level are collected and stored routinely by the Food and Agriculture Organization, and the near-global collection of these data is likely to continue for the foreseeable future. But future research might show that other indicators, such as fuel prices or metrics of market openness may prove to be better predictors of food insecurity. If such relationships are identified, a case could be made for investing in curating other datasets.

Drought is a key contributing factor to food insecurity but not the only reason behind food crises (Chapter 2). Future work should focus on testing whether the tipping point detection approach can be applied to rapid onset hazards such as floods and storms. By their very nature, rapid-onset disasters do not exhibit critical slowing down expected before a tipping point (Chapter 3), but some of the principles developed for the SMART model might be applicable to these climate events (Chapter 4).

A final question, and perhaps the topic that deserves another dedicated dissertation is whether tipping point diagnostics can be applied to conflicts. In Chapter 4, initial analysis showed that there is no straightforward relationship between soil moisture metrics and conflict – in some cases (e.g,, Yemen) soil moisture and conflict intensity appear to follow a similar trajectory while in others (e.g., northeastern Nigeria) there is no immediately discernible correlation between the two variables. But if future research is able to provide early warning signals for conflict outbreaks and intensity, the contributions to food security, humanitarian and peacekeeping operations will be invaluable.

The work presented in my dissertation contributes to the advancement of early warning systems by applying principles of tipping point theory to food systems – a connection that has, to date, not been explicitly made. In the future, I hope that the findings of this research contribute to global food security interventions and I would also like to continue applying the skills and knowledge I have gained these last four years to continue addressing questions of global importance.

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