Food Security (2019) 11:57–68
https://doi.org/10.1007/s12571-018-00885-9

ORIGINAL PAPER

# From rain to famine: assessing the utility of rainfall observations and seasonal forecasts to anticipate food insecurity in East Africa

Erin Coughlan de Perez[1,2,3] · Maarten van Aalst[1,3,4] · Richard Choularton[5] · Bart van den Hurk[3,6] · Simon Mason[2] · Hannah Nissan[2] · Saroja Schwager[2]

Received: 3 May 2018 / Accepted: 25 December 2018 / Published online: 11 February 2019


## Abstract

East Africa experiences chronic food insecurity, with levels varying from year-to-year across the region. Given that much can be done to prevent this level of suffering before it happens, humanitarian agencies monitor early indicators of food insecurity to trigger early action. Forecasts of total seasonal rainfall are one tool used to monitor and anticipate food security outcomes. Factors beyond rainfall, such as conflict, are key determinants of whether lack of rainfall can become a problem. In this paper, we present a quantitative analysis that isolates the value of rainfall information in anticipating food security outcomes across livelihood groups in East Africa. Comparing observed rainfall and temperature with food security classifications, we quantify how much the chance of food insecurity increases when rainfall is low. Results differed dramatically among livelihood groups; pastoralists in East Africa more frequently experience food insecurity than do non-pastoralists, and 12 months of low rainfall greatly increases the chances of "crisis" and "emergency" food security in pastoralist regions. In non-pastoralist regions, the relationship with total rainfall is not as strong. Similar results were obtained for livelihood groups in Kenya and Ethiopia, with slightly differing results in Somalia. Given this, we evaluated the relevance of monitoring and forecasting seasonal total rainfall. Our quantitative results demonstrate that six months of rainfall observations can already indicate a heightened risk of food insecurity, a full six months before conditions deteriorate. Combining rainfall observations with seasonal forecasts can further change the range of possible outcomes to indicate higher or lower risk of food insecurity, but the added value of seasonal forecasts is noticeable only when they show a strong probability of below-normal rainfall.

**Keywords** Drought · Famine · East Africa · Forecasts · Livelihoods · Vulnerability · Precipitation

✉ Erin Coughlan de Perez
coughlan.erin@gmail.com

1 Red Cross Red Crescent Climate Centre, The Hague, The Netherlands

2 International Research Institute for Climate and Society, Columbia University, New York, NY, USA

3 Institute for Environmental Studies, VU University Amsterdam, Amsterdam, The Netherlands

4 Department of Science, Technology, Engineering and Public Policy, University College London, London, UK

5 Tetra Tech, Montpelier, VT, USA

6 Royal Netherlands Meteorological Institute (KNMI), De Bilt, Netherlands

## 1 Introduction

Food insecurity is a recurrent crisis in East Africa. Because impacts happen gradually over many months, humanitarians and government agencies closely monitor warning signs to anticipate impacts. Rainfall is a commonly used early warning indicator because many of the most vulnerable people in the region depend on rainfall for their livelihoods. In particular, forecasts of seasonal rainfall totals are widely disseminated in the region. Some actors rely heavily on these forecasts to anticipate upcoming food security problems, and others disregard them as largely irrelevant given the complexity of food security in the region. Here, we quantify the extent to which rainfall and rainfall forecasts can provide early warning information on potential food insecurity for different vulnerable groups in East Africa.

The link between rainfall deficits and food insecurity involves several intermediate steps, including reduced food production, low livestock prices, high food prices, and ultimately a reduction in food access. In addition to rainfall, the humanitarian system monitors a number of socio-economic factors that are indicators of this chain of problems. Indicators of household stress include decisions to migrate, payment of school fees, distress sale of assets, reduced food consumption, malnutrition, increased morbidity, and livestock mortality (Brown 2008; Cuny and Hill 1999; IPC Global Partners 2012). Food security monitoring services also factor in the impact of changes to terms of trade of staple foods, food transportation networks, as well as local and regional patterns of conflict.

For example, in 2011, East Africa suffered extreme levels of food insecurity that were widely associated with drought conditions. The impact pathway began with low rainfall. While there are a number of different definitions of drought, standardized anomalies of total rainfall have frequently been used in East Africa (Ntale and Gan 2003). Figure 1 shows the Standardized Precipitation Index (SPI)[1] for a 12-month period beginning in May 2010.

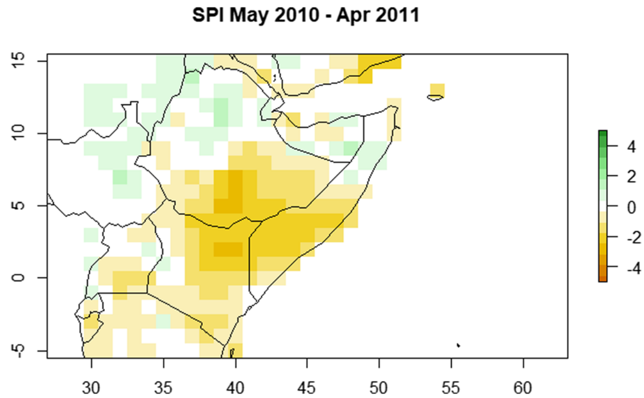


**Fig. 1** Standardized Precipitation Index (SPI) for East Africa during the 2011 drought. Total rainfall amounts between May 2010 and April 2011 were used to calculate a 12-month SPI, showing depressed rainfall over much of the region. Colors represent SPI values, which are the standard deviations from the long-term mean; values of −2 and less are classified as extremely dry and would mean that this year's rainfall was two standard deviations less than the long-term mean. This corresponds to a 1 in 50 year event. Rainfall used to calculate the SPI was CHIRPS from 1981 to 2018 (see methods)

Crop yields in East Africa covary with rainfall (Hansen and Indeje 2004); approximately 50% of the variability in maize yields in Kenya can be explained by interannual temperature and precipitation fluctuations (Iizumi et al. 2013; Ray et al. 2015). The drought of 2011 followed this pattern, and Kenyan regions of marginal agriculture saw harvests of approximately 20% of normal yields (FEWS NET 2011a). Crop yields in southern Somalia were similarly poor, with the lowest production of sorghum and maize in 15 years (FEWS NET 2011b). In pastoralist regions of northern Kenya, 70–80% of livestock migrated out of the region and livestock prices dropped dramatically (FEWS NET 2011c).

Several factors influence whether local food production affects local food prices: especially the ability to trade with other regions; any fluctuations of global food prices; and the level of urbanization of a region (Brown 2014). In 2011, high international prices of wheat and other crops and high costs of fuel and transportation both coincided with the low rainfall conditions in East Africa (FAO 2011, Peri 2017).

Beyond price, actual access to food is mediated by a number of additional factors, such as economic status, livelihood options, conflict, and safety nets (Fraser 2007; Simelton et al. 2012). In conflict situations, damaged infrastructure and outbreaks of violence can reduce access to markets and agricultural lands, and conflict can prevent life-saving access by the international humanitarian system (Maxwell and Hailey 2018). In 2011, Ethiopia's Productive Safety Net Programme increased their feeding program to support people who were otherwise unable to access food. In Somalia, conflict was the major contributor to reduced food access, and it inhibited the delivery of relief food to several regions. Farm laborers who did not have assets or income during the drought period were least able to access food (FSNAU 2011, 20). The food security classifications for East Africa in October 2011 are shown in Fig. 2.

Given the complexity of food security, the link between rainfall and impacts is far from direct. However, there are many preventative actions that can be taken based on forecasted or observed rainfall; therefore it is useful to know how much is worthwhile to implement when rainfall information becomes available. To quantify the effect of a hazard (in this case low rainfall) on societal outcomes (in this case food security), the accepted practice in Catastrophe Risk Modeling, or CAT modeling, is to use a vulnerability function, which plots the relationship between hazard magnitude and potential impact (Pineda-Porras and Ordaz-Schroeder 2003; Porter and White 2016). This relationship can also be called a risk curve (Grunthal et al. 2006), fragility curve (Okuyama and Chang 2004), or damage curve (UNFCCC 2012), and it is commonly used in the design of infrastructure. Because vulnerability varies across people and regions, different vulnerability curves can be developed for different groups.

Here, we focus on isolating the impact of a rainfall hazard on food security conditions. First, we identified different regions of vulnerability in East Africa, based on livelihood groups. Then, we quantified how rainfall affects the types of food security outcomes that could be expected for that population. Lastly, we identified the extent to which observations and forecasts of rainfall can allow these impacts to be anticipated in advance.

We present the methods and results of a quantitative analysis, which compared forecasted rainfall, observed rainfall, and combinations of the two with food insecurity across

[1] http://www.wamis.org/agm/pubs/SPI/WMO_1090_EN.pdf

regions. This quantitative analysis was not intended to provide a method to forecast food insecurity by using rainfall as the only predictor, but rather envisioned as a way to quantify the importance of rainfall in our ability to anticipate food insecurity. The relationship between rainfall and food insecurity can be used by agencies who forecast food insecurity in real-time, in a quantitative or qualitative combination with socio-economic monitoring indicators.

## 2 Methods

Food security outcomes for East Africa have been monitored by the Famine Early Warning Systems Network (FEWS NET) since 2009. In FEWS NET, food security is classified on a scale from 1 (minimal) to 5 (famine), compatible with the Integrated Phase Classification (IPC) (IPC Global Partners 2012).[2] Assessments are released in map form every 3–4 months, and there have been 34 food security updates between 2009 and 2018. There was a change to the FEWS NET classification structure in March 2011, after which the classification system allowed for an overlay showing where food security would likely be worse without current or planned humanitarian assistance. Therefore, this analysis used only the food security outcomes recorded after March 2011, increasing the outcomes by one in the regions where outcomes were judged to be one level worse without current or programmed humanitarian assistance. However, repeating the analysis using the entire dataset to 2009 has results that are broadly similar to those presented here.

FEWS NET also produces shapefiles of the livelihood zones of each country, based on a household economy approach.[3] For the purposes of this analysis, we categorized each livelihood zone based on the extent to which its population relies on animal husbandry and crops, using the following categories: “pastoral”, “agro-pastoral”, “cropping”, and “other”.

[2] Explanation of food security classification system from http://fews.net/IPC.

| | |
|---|---|
| **PHASE 1 Minimal** | More than four in five households (HHs) are able to meet essential food and nonfood needs without engaging in atypical, unsustainable strategies to access food and income. |
| **PHASE 2 Stressed** | Even with any humanitarian assistance at least one in five HHs in the area have the following or worse: Minimally adequate food consumption but are unable to afford some essential non food expenditures without engaging in irreversible coping strategies. |
| **PHASE 3 Crisis** | Even with any humanitarian assistance at least one in five HHs in the area have the following or worse: Food consumption gaps with high or above usual acute malnutrition OR Are marginally able to meet minimum food needs only with accelerated depletion of livelihood assets that will lead to food consumption gaps. |
| **PHASE 4 Emergency** | Even with any humanitarian assistance at least one in five HHs in the area have the following or worse: Large food consumption gaps resulting in very high acute malnutrition and excess mortality OR Extreme loss of livelihood assets that will lead to food consumption gaps in the short term. |
| **PHASE 5 Famine** | Even with any humanitarian assistance at least one in five HHs in the area have an extreme lack of food and other basic needs where starvation, death, and destitution are evident. Evidence for all three criteria (food consumption, acute malnutrition, and mortality) is required to classify Famine. |

[3] http://www.fews.net/livelihoods

In order to characterize the influence of rainfall on food insecurity outcomes across a diverse region, we calculated a standard index of rainfall at each location. For rainfall estimates, we used the Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) dataset, which was developed specifically for drought monitoring and combines satellite observations with available station data (Funk et al. 2014). The timeseries of rainfall is available from 1981 to the present. For temperature data, we used a gridded 2-m temperature dataset from the Global Historical Climatology Network (GHCN) version 2 and the Climate Anomaly Monitoring System (Fan and Van Den Dool 2008). Although the CHIRPS dataset is available at a higher resolution (0.05 degrees), we re-gridded this to 0.5 degrees to match the resolution of the GHCN temperature dataset. However, the results of the analysis using the full 0.05 degree resolution are similar to those presented here at 0.5 degree resolution.

To create a standardized comparable index of “drought” across the entire region, we used the Standardized Precipitation Index (SPI) and the Standardized Precipitation-Evapotranspiration Index (SPEI) for a 12-month period (Vicente-Serrano et al. 2009). While SPI uses only rainfall as an input, SPEI also includes the effect of temperature on water availability through evaporation. For the SPEI calculation, we used the Thornthwaite equation to estimate monthly potential evapotranspiration (Thornthwaite 1948).

We then compared the timeseries of rainfall with the food security outcomes of FEWS NET. We re-gridded the food security data to match 0.5-degree resolution by recording the food security outcome of the center of each 0.5-degree gridpoint. We then calculated the SPI for the 12-month period up until, and including, the month in which FEWS released their food security outcomes (dated from the last day of the month). For each location, we compared its SPI with its food security classification, creating a table of counts indicating the frequency of each type of food security outcome when SPI fell in each of the ranges in Table 1.

We used a chi-squared test for categorical data to estimate the strength of the relationship between ranges of SPI values and the five possible food security outcomes. However, any apparent relationship between the two could be due to random chance because of the large amount of spatial and temporal autocorrelation in the data. To estimate the likelihood of the relationships being due to chance alone, we bootstrapped 500 alternative time series in which we randomized the order in which the rainfall happened while preserving the spatial maps. To account for the temporal autocorrelation, we used a 12-month block bootstrap. For each bootstrapped time series, we calculated the chi-squared statistic, and then counted how many of the randomized replicates have a relationship that is stronger than that found in the original data. If fewer than 2.5% of boostrapped replicates show a stronger

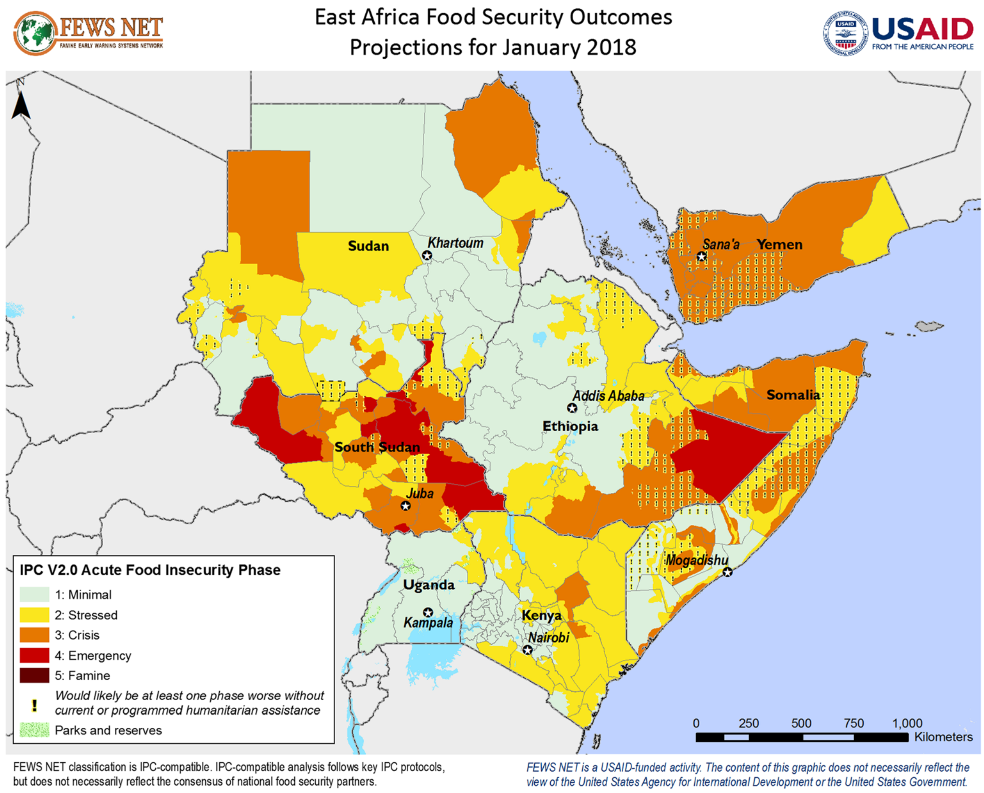



**Fig. 2** Food security classifications in East Africa for October 2011. The categories of food security are: 1-Minimal, 2-Stressed, 3-Crisis, 4-Emergency, and 5-Famine, colored from light to dark on the map. (FEWS-NET)

relationship than the original data, we have confidence that the relationship is not due to random chance.

Lastly, we also investigated the potential for rainfall observations and forecasts to provide an indication of future food insecurity. For this analysis, we focused on the pastoralist regions, most of which have a seasonal cycle with two rainy seasons. Given the observations from a first rainy season (typically March–May), we examined the probability of different food insecurity outcomes for the end of the upcoming, second rainy season. For example, if the March–May rainy season has ended and we have observations from that season, we then estimate the potential food insecurity outcomes for the end of the upcoming October–December rainy season.

In order to be able to compare outcomes across regions, we defined two half-year segments: January–June and July–December, each of which should contain one rainy season and several dry months. For each 6-month observation, we combined it with a set of potential rainfall observations for the following six months, either drawn from climatology or from the forecasted rainfall distribution, and we calculated the SPI of the result.

To create the forecast rainfall distribution, we took 30 samples with replacement of the observed historical rainfall data for the second six months, according to the forecast probabilities of above-normal (top tercile of rainfall), near-normal (middle tercile), and below-normal (bottom tercile). These terciles are the standard format of seasonal rainfall forecasts used across the region. We then combined each resampled timeseries with the timeseries of the first six months, and calculated the SPI. The result was a probability distribution function (pdf) of what the 12-month SPI could look like, given the observed SPI of the first six months. We categorized the SPI of the first six months into different categories, low to high, and fitted a normal distribution of the SPI of 12-month rainfall conditional on the first six months SPI being in that category. We then multiplied the rainfall distribution by the relationship derived between 12-month rainfall and the food security indicator IPC, to estimate the shift in probabilities of IPC outcomes based on this sample of rainfall.

**Table 1** Standardized Precipitation Index (SPI) and Standardized Precipitation-Evapotranspiration Index (SPEI) ranges used in this study, and the frequency of occurrence of each range

| SP(E) I range | Probability of rainfall falling in range |
|---|---|
| Less than −1 | 0.159 |
| −1 to 0 | 0.341 |
| 0 to 1 | 0.341 |
| Greater than 1 | 0.159 |

## 3 Results

Using the livelihood zones from FEWS NET, the majority of East Africa is classified as pastoralist, agro-pastoralist, and agricultural, as seen in Fig. 3a. Food insecurity of IPC 3 or above (stages of crisis, emergency, or famine) is more frequent in pastoralist regions (Fig. 3b).

How often different livelihood classes, “pastoralist”, “agropastoralist”, and “non-pastoralist” experienced different food security outcomes is shown in Fig. 4 (d-f). In pastoralist and agropastoralist areas, IPC phase 2, or “stressed,” was the most common outcome and happened about 50% of the time. Phase 1, “minimal food insecurity,” was observed 5–10% of the time. In contrast, non-pastoralist areas were most commonly classified as “minimal” food insecurity, approximately 50% of the time, and rarely saw an outcome above phase 3.

In pastoralist and agropastoralist areas, rainfall has a strong effect on food security. Low rainfall, an SPI of less than −1, greatly increases the chances of IPC 3 and 4 (darkest brown lines in Fig. 4g-h). Compared to the general outcomes of these groups (black and white plots Fig. 4d-e), the brown lines show a change in the probability of different food security outcomes if we know that there have been 12 months of poor rainfall. Within the probabilities shown here, the actual food security for a specific year will be affected by socio-economic factors mentioned earlier, including those governing food production, food prices, and food access.

Based on the bootstrapped results, we are confident that this relationship between SPI and food security in all three regions was not due to random chance, as the relationship was stronger than 97.5% of all bootstrapped replicates. The relationship between SPEI and outcomes was similar in shape and significance to that of SPI, and we therefore chose to continue the analysis using SPI since it is the simpler index for operational purposes, and SPEI uses temperature data that is likely to be less accurate than the rainfall data used in the SPI.

For non-pastoralist areas, the relationship between rainfall and food security was different from that in pastoralist regions, although there was a change in probabilities of greater food security with greater water availability in these areas. To improve on this analysis, crop models that use daily rainfall observations and specific crop requirements could be explored, instead of the measures of total 12-month rainfall used here (Jayanthi et al. 2014; Quijano et al. 2015).

We repeated this analysis for the three livelihood groups in each individual country in the region (Ethiopia, Kenya, and Somalia), because we wanted to know whether the general relationship was the same across countries, or whether it was different, likely due to differences in regional trade or national policies (Fig. 5). In all three countries, the pastoralist regions showed a strong increase in food insecurity when SPI was less than −1. The similar relationship across national borders likely indicates that food insecurity was localized to the area of low rainfall, although Kenya had an overall lower frequency of ending up in category 4 (Emergency).

Based on the results of the bootstrap analysis (not shown in figure), we were confident that each of these plots was not due to random chance, with the exception of the Kenyan agropastoralists and the Somalian nonpastoralists. The Kenyan agropastoralists did show an increase in food security with low rainfall, but the relationship was not strong enough to be confident it was not random chance. In Somalia, most of the non-pastoralists work in sectors not affected by rainfall (e.g. fishing is prevalent in the north), which is likely to be the reason why these regions did not show sensitivity to rainfall.

In Somalia, when 12-month rainfall was observed to be less than SPI -1, the most probable food security outcome for pastoralists and agropastoralists was “Emergency”, with chances hovering around 50% probability. In Kenya, the chance of non-pastoralists moving from “minimal” food security to “stressed” greatly increases with low rainfall, although in Ethiopia the change was not as large.

Here we demonstrated a relationship between rainfall over a 12-month period with food insecurity, and we then attempted to determine whether or not it was possible to anticipate food security outcomes halfway through the 12-month period. A longer window of anticipation could provide additional time for people to react before the food insecurity happens. Therefore, we estimated how much can be known about

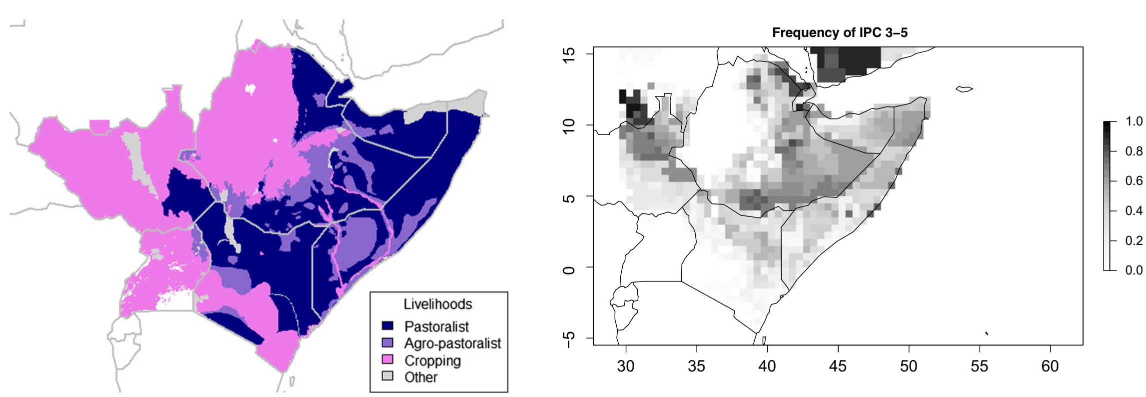



**Fig. 3** (**a**) Livelihood zones of East Africa, with pastoralist regions in dark blue, agro-pastoralist regions in light purple, and cropping regions in pink. Regions that do not fall in these categories are in grey. (**b**) How often each location has experienced food security classifications of “crisis” or higher (numbers 3–5) between 2011 and 2018. Note that Yemen was only classified starting in Oct 2014 ($n = 13$), all others have approximately 27 observations

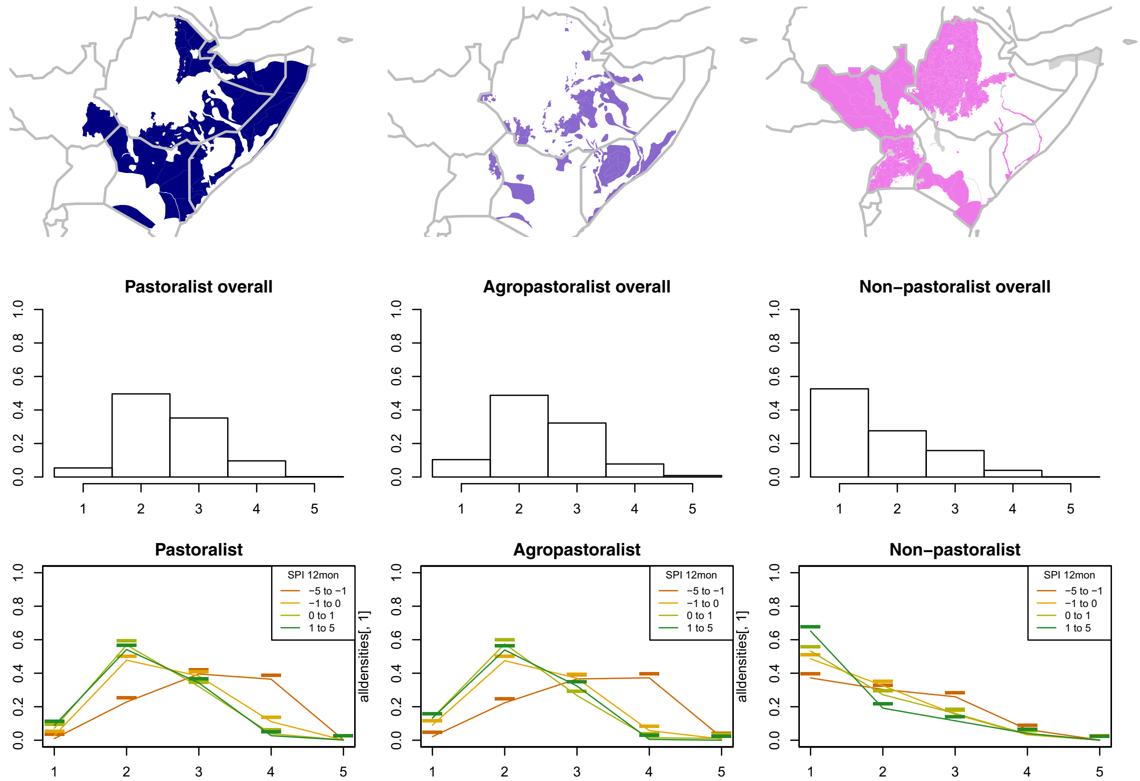



**Fig. 4** Regions that are (**a**) pastoralist (**b**) agropastoralist, and (**c**) non-pastoralist. The middle row shows, for each livelihood group, the aggregate food security outcomes between 2011 and 2018. The x-axis is food security outcomes and the y-axis is the frequency of experiencing each type of outcome. The bottom row shows, for each region, the distribution of food security outcomes contingent on SPI. The x-axis is food security outcomes, and the y-axis is the frequency of experiencing each type of outcome. Each color represents a probability distribution function of food insecurity outcomes, showing the probability of having an outcome of 1–5 conditional on that SPI category. (**g**) For pastoral regions, when SPI is observed to be in in one of 4 different color-coded bins, the probability of food security outcomes 1–5 are shown in each color, and connected with a line of that color. (**h-i**) Same as in (**g**), but for agropastoral and non-pastoral regions

12-month SPI in advance by only observing one rainy and dry season in one half of the year and then forecasting the results of the next rainy season in order to ultimately estimate the 12-month rainfall for the end of that year.

First, given the observed six months of rainfall, including one rainy season, the possible outcomes for the total rainfall for the end of 12 months (six months observed plus six months unknown) is shown in Fig. 6a. Results were generated by combining the observed rainfall with a random sample of historical observations for the second half of the year. For example, we started with a 6-month observed rainfall total and combined this with a randomly selected rainfall total for the second half of the year, and then repeated, combining it with a number of random samples from the historical distribution to see what the total 12-month rainfall might look like, given the observed 6-month rainfall at the beginning. In the case where the observed 6-month total was very high (green line in Fig. 6a), the range of potential outcomes for 12-month rainfall would be on the wet side, even if the rest of the year was rather dry.

Knowing this range of possible outcomes, we could then estimate the possible food security outcomes for the end of the 12-month period (Fig. 6b). For example, if we had experienced that the first six months of a year were very wet, then the probability of pastoralist regions being in IPC 2 by the end of the year would be almost 80%. This outcome is affected not only by the rainfall of the upcoming season but also by socio-economic factors governing food access, which can themselves be exacerbated by drought.

Figure 6a-b uses the climatological probability of possible rainfall amounts, which assumes that there is no information about what the upcoming rainy season will be like (probability of rainfall is equally distributed over lower, medium and higher terciles). However, seasonal forecasts are available in East Africa, and can provide an early indication of potential rainfall before the season starts. Figure 6 also shows the potential rainfall outcomes that would result from a combination of observed 6-month rainfall and forecast seasonal rainfall. Figure 6c shows a forecast of a 100% chance of below-normal tercile of rainfall, and 6e shows 100% chance of above-normal tercile of rainfall. Figure 6g and i provide more common seasonal forecasts, with the highest probability being 50% chance below-normal or above-normal rainfall.

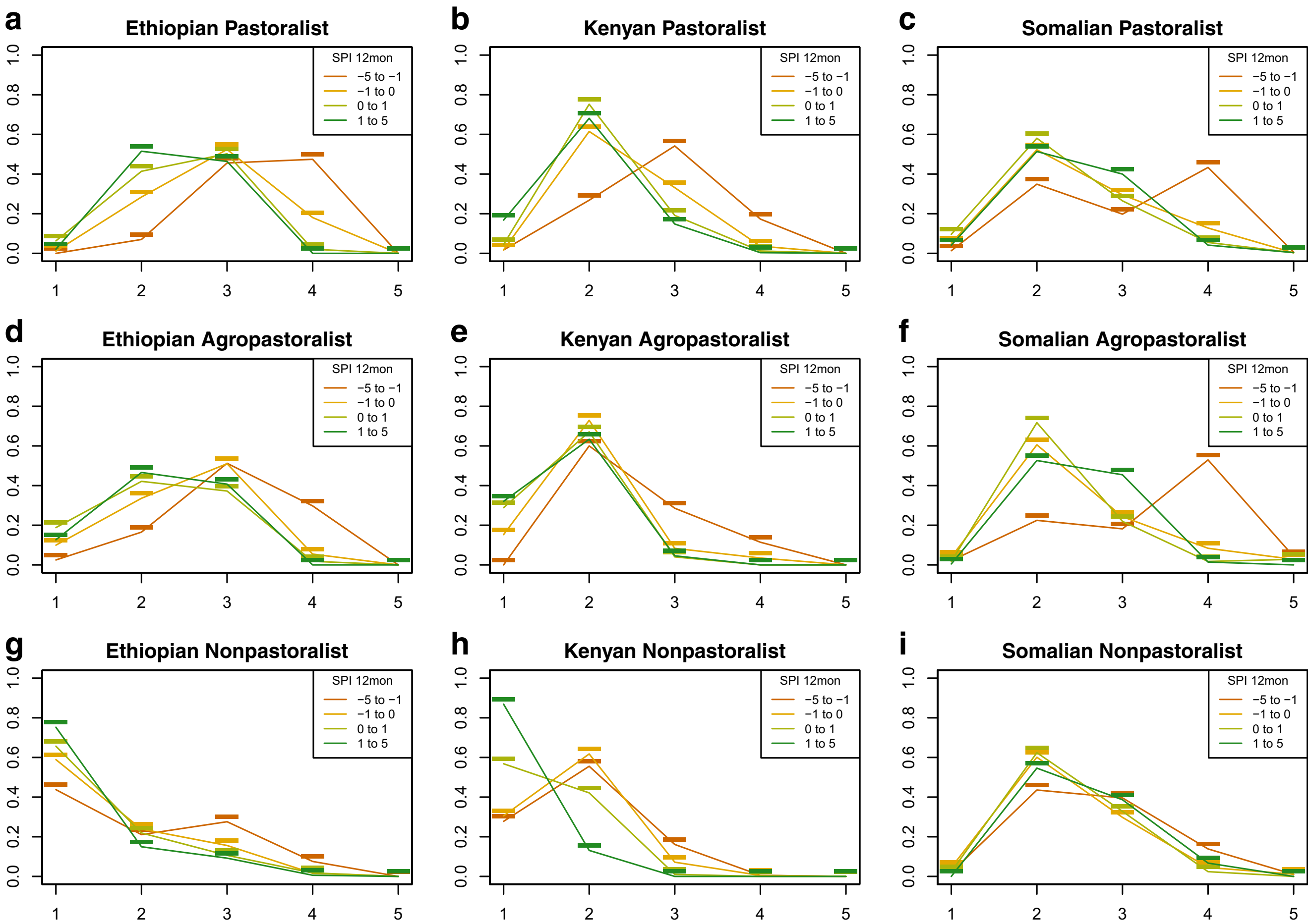



**Fig. 5** As in the third row of Fig. 4, but for each livelihood group in Ethiopia (**a**, **d**, **g**), Kenya (**b**, **e**, **h**), and Somalia (**c**, **f**, **i**). Each plot shows the distribution of food security outcomes contingent on SPI. The x-axis is food security outcomes, and the y-axis is the frequency of experiencing each type of outcome. Each color represents a probability distribution function of food insecurity outcomes, showing the probability of having an outcome of 1–5 conditional on that SPI category

In the right column of Fig. 6 the distribution of possible food security outcomes for pastoralist regions based on this combination of rainfall and forecast is noticeably different for forecasts of 100% below/above-normal rainfall (compare second and third row of Fig. 6), but nearly indistinguishable for forecasts of 50% chance below/above-normal rainfall (compare fourth and fifth row of Fig. 6). In all cases, food insecurity is affected by factors other than rainfall, and therefore there is still a wide distribution of possible outcomes.

## 4 Discussion

In East Africa, food insecurity outcomes differ dramatically between different pastoralist and non-pastoralist livelihood zones. Pastoral and agro-pastoral populations are chronically food insecure, and investment in these regions should address long-term food insecurity as well as periods of increased food stress. Somalia is the only region that has seen instances of IPC 5 famine in the last ten years (in agropastoral regions).

In cropping regions of Kenya and Ethiopia, "minimal" food insecurity is the most common outcome, and cumulative 12-month rainfall only slightly shifts the probability towards greater food insecurity. Tailored crop models are likely to be more useful to anticipate food production in these regions because they can model cultivars and requirements for rainfall at critical moments in the growing cycle (Jayanthi et al. 2014; Quijano et al. 2015). In the non-pastoralist regions of Somalia, total rainfall amounts are unlikely to have any bearing on food security outcomes.

In pastoralist and agro-pastoralist regions of all three countries, however, total rainfall amounts are indeed related to outcomes and consequently can provide a significant source of information for anticipating crises. For example, the long-term frequency of "Emergency" food insecurity in pastoralist regions is about 13% (Fig. 4d), but if 12-month rainfall SPI is below −1, then the probability of "Emergency" triples to about 36% (Fig. 4e).

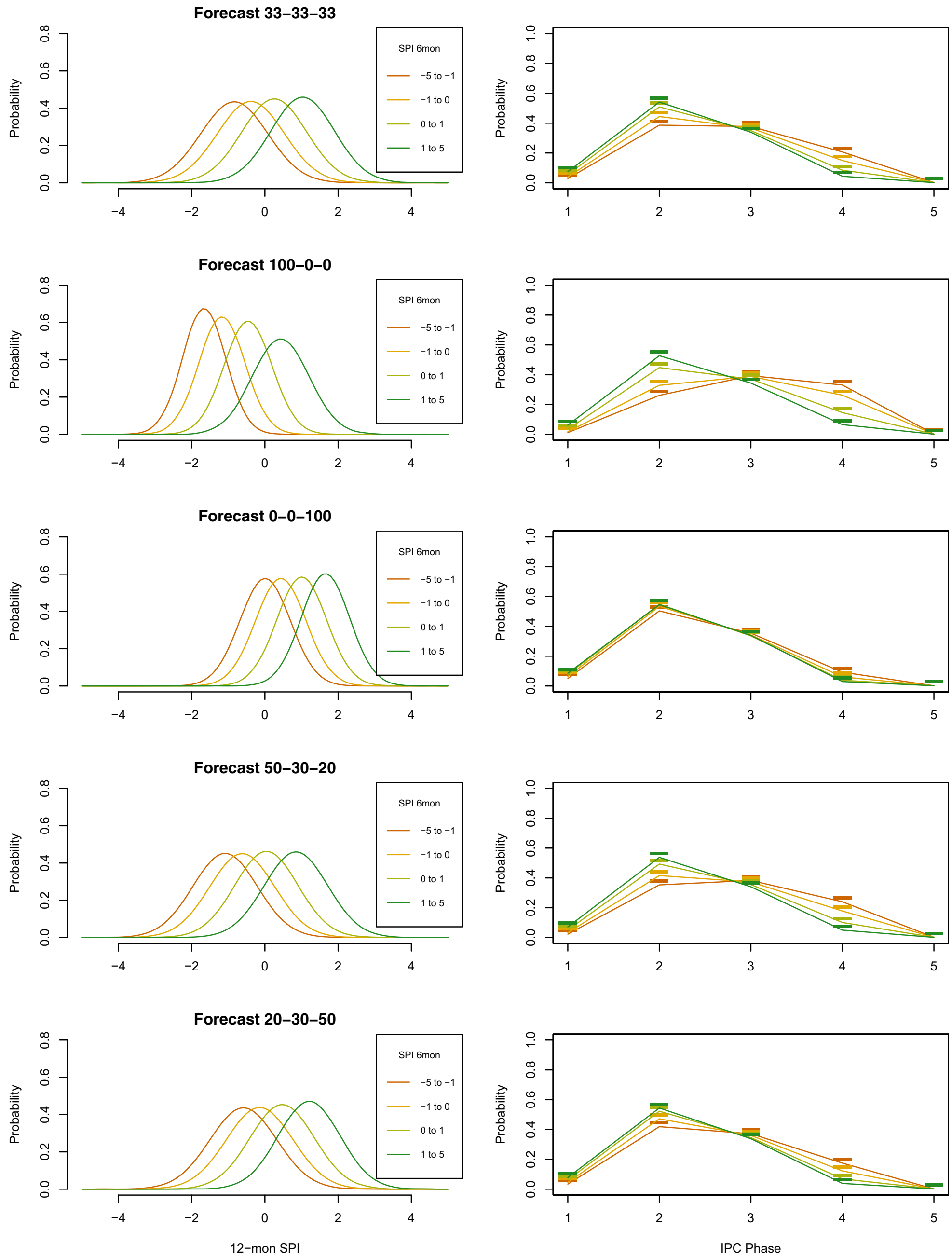



**Fig. 6** Left column shows how likely it is to experience different SPIs of 12-month rainfall, if the first 6 months had already been experienced. Each color represents a probability distribution function of 12-month rainfall outcomes, showing the probability of having SPI values from −4 to 4, conditional on observed SPI values for the first six months in combination with a perfectly reliable seasonal forecast for the upcoming six months. Each row represents a different seasonal forecast. A forecast of climatology (**a**, **b**), a forecast of 100% chance of below-normal (**c**, **d**), 100% chance of above-normal (**e**, **f**), 50% chance of below normal (**g**, **h**), and 50% chance of above-normal (**i**, **j**). The rows are labeled with three numbers, which are the probability of the lower, middle, and upper rainfall tercile occurring in the upcoming six months. Right column shows the IPC food security outcomes for pastoralist regions that could be expected in each case, at the end of the 12-month season (using relationship from Fig. 4e)

Vulnerability to shocks is high in pastoralist regions, and periods of increased food insecurity are strongly associated with 12-month periods of low rainfall. This paper provides a quantitative estimate of how much the probability of adverse outcomes increases as rainfall decreases. To achieve the best forecast of food insecurity, this rainfall information should be integrated qualitatively or quantitatively with indicators of prices, conflict, trade, and negative coping mechanisms. Currently, this is a task that is carried out by teams within FEWS NET. Given the distribution of potential outcomes based on the rainfall, these additional socio-economic factors can be used to narrow the range of possible outcomes.

The vulnerability relationships presented here for both pastoralists and non-pastoralists represent a historical snapshot of vulnerability for this region in the past 10 years. Both these relationships and the reliance on rainfall-changes with time should be continually updated with new information on livelihoods and vulnerability. Such vulnerability relationships also do not adequately characterize possible outcomes from shocks that were not experienced in the past 10 years, and therefore are outside the data sample used here. It would be ideal to further refine the categories of livelihood zones, to develop clearer relationships for specific groups of people across East Africa. Similarly, further refining food security outcomes could help better anticipate and prevent impacts.

However, these quantitative relationships between rainfall and food insecurity show promise in supporting early warning systems in East Africa, for example to be incorporated into the Famine Early Warning System forecasts (FEWS). With the observations from only one rainy season, there is already a good indication of the range of possible food security outcomes that could be expected by the end of the following rainy season. Using these observations allows for six months of lead-time, without waiting for the second rainy season to fail. For example, if 6-month rainfall SPI in a pastoralist region is observed to be below −1, then the probability of "Emergency" food insecurity doubles.

Seasonal forecasts, in combination with the observed rainfall information from the past season, can help constrain this space of probability, showing higher probabilities for certain outcomes. The skill of seasonal rainfall forecasts in East Africa is stronger than in many other regions of the world, because East African rainfall is influenced by the El Niño Southern Oscillation and the Indian Ocean Dipole (Gitau et al. 2015; Manzanas et al. 2014). The reliability of seasonal rainfall forecasts from the European Centre for Medium Range Weather Forecasts was categorized as "marginally" or "still useful" in most of the year for East Africa (Weisheimer and Palmer 2014), and the forecasts from the International Research Institute for Climate and Society show similar results (Barnston et al. 2010). Therefore, seasonal forecasts only provide a small amount of information to help indicate what kind of food insecurity could be expected, and should not be over-emphasized when trying to anticipate upcoming disasters.

However, because most seasonal forecasts are not very "sharp", meaning that they do not have very strong probabilities for what will happen in the upcoming season, they are unlikely to make a meaningful difference in the probability of food insecurity outcomes. In the past 20 years of IRI forecasts, more than one-quarter of calendar years did not have a single location in East Africa with a strong forecast of 50% chance or higher. Statistical models developed for this specific region, however, are likely to be able to produce stronger forecasts (Funk 2016). Work being done on predicting the drought effects of back-to-back La Niñas in this region could also help improve the skill of these forecasts (Funk et al. 2018).

Ultimately, observed rainfall should be used as a basic input to predict potential food insecurity outcomes, and little weight should be given to seasonal forecasts unless they show extremely high probabilities of specific outcomes. During El Niño and La Niña years, seasonal forecasts can provide much sharper probabilities, especially for the October–December rainy season (Barnston et al. 2010).

## 5 Conclusions

In the pastoralist and agropastoralist regions of East Africa, low rainfall over two rainy seasons is strongly related to a decrease in food security, and this rainfall can be used to support early warnings in advance of major shocks. With six months of lead-time, many actions can be taken to prepare for potential food insecurity. These actions can include scaling up of social protection systems, as done in Ethiopia in 2011, to respond to a potentially deteriorating food security situation in the coming months. Actions can also include water rationing, rehabilitation of water resources, stockpiling of livestock feed, and preparation for scaling up of temporary assistance, such as school feeding programs. These results can also encourage practitioners not to "over-interpret" rainfall forecasts, because even with perfect knowledge of rainfall, the range of food security outcomes is still very wide. For example, the probability distribution function of food security outcomes is only slightly changed when there is a forecast of 50% chance of below-normal rainfall (see Fig. 6).

The amount of rainfall required to sustain livelihoods varies across local populations. While in pastoralist regions, total accumulated rainfall is an indicator of potential food insecurity, the relationship is not as strong in agricultural areas. For these regions, crop models can be used to anticipate harvest outcomes, based on the exact rainfall requirements of the crop planted in a specific location as well as early-season assessments of crop status. Financial mechanisms have also been developed to deliver humanitarian finance before expected negative outcomes of a failed crop (Kehinde 2014).

Ultimately, reducing the spatial extent of this analysis to create very local models focused on indicators for specific groups can improve our ability to predict impacts. This can incorporate information on the specific rainfall requirements for that group and include interaction effects with socio-economic variables related to food access.

While the bulk of forecasting for food security is focused on avoiding negative outcomes, this analysis has shown that observations of high rainfall can also provide a slightly increased probability of a good year. Humanitarians and governments working in these regions can explore opportunities to take advantage of such food security forecasts based on observed rainfall to support socio-economic growth and agricultural productivity in wet years.

To facilitate the use of rainfall for food security forecasts, climate service providers should consider methods to provide combined observed and forecasted rainfall to decision-makers in the region. In many cases, using only observed data can give a strong indication of potential food insecurity outcomes, and in years where forecasts present an unusually strong signal, such as El Niño or La Niña years, rainfall forecasts can be combined with the observed data to improve predictions of food insecurity. Some products already exist to begin to provide this analysis, including a combination of rainfall observations and climatology (USGS and USAID n.d.), as well as a site that combines observations with forecasts to highlight areas of concern (IRI n.d.). Presenting this information as a change in the range of potential food insecurity outcomes can help humanitarians combine such findings with other relevant factors for food security and further narrow the range of possible outcomes.

Advances in impact forecasting, such as the probability distribution functions of different outcomes based on a forecast (e.g. Fig 6), can help estimate possible outcomes for different groups of people and provide tailored forecasts for particularly vulnerable populations. Because different livelihood zones have dramatically different relationships to rainfall, further understanding of differential vulnerability across livelihood zones and socio-economic groups can allow for tailored support to those who are most likely to be impacted by a particular hazard.

**Acknowledgements** The authors would like to acknowledge the humanitarian practitioners who have piloted Forecast-based Financing around the world, and who have asked the questions that have led to this research. In particular, the German Federal Foreign Office has developed an action plan for humanitarian adaptation to climate change (Rüth 2015), which has spurred investment in early action plans around the world. Funding for this work also comes from the IKEA Foundation, who are supporting Forecast-based Financing in East Africa. Mason was funded by grant/cooperative agreement NA13OAR4310184 from the U.S. National Oceanic and Atmospheric Administration (NOAA). The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its sub-agencies.

## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.



## References

Barnston, A. G., Li, S., Mason, S. J., Dewitt, D. G., Goddard, L., & Gong, X. (2010). Verification of the first 11 years of IRI's seasonal climate forecasts. *Journal of Applied Meteorology and Climatology, 49*(3), 493–520.

Brown, M. E. (2008). *Famine Early Warning Systems and remote sensing data*. Berlin: Springer.

Brown, M. (2014). *Food security, food prices, and climate variability*. Oxford: Routledge.

Cuny, F. C., & Hill, R. B. (1999). *Famine, conflict, and response: A basic guide*. West Hartford: Kumarian Press.

Famine Early Warning Systems Network (FEWS NET). (2011a). Special report Kenya food security. *USAID*. Retrieved from http://www.fews.net/sites/default/files/documents/reports/Kenya_Special_Report_2011_06_final.pdf

Famine Early Warning Systems Network (FEWS NET). (2011b). Somalia Price bulletin. *USAID*. Retrieved from http://www.fews.net/sites/default/files/documents/reports/Somalia_2011_12_grains.pdf

Famine Early Warning Systems Network (FEWS NET). (2011c). Kenya Dekadal food security monitoring. *USAID*. Retrieved from http://www.fews.net/sites/default/files/documents/reports/KE_Dekadal_Report_2011_09_15_final.pdf.

Fan, Y., & Van Den Dool, H. (2008). A global monthly land surface air temperature analysis for 1948 – Present. *Journal of Geophysical Research, 113*, 1–18.

FAO (2011). Drought-related food insecurity: a focus on the Horn of Africa. Paper presented at the Ministerial-level Meeting: Drought Emergency, Rome, IT. https://reliefweb.int/report/somalia/drought%E2%80%90related-food-insecurity-focus-horn-africa. Accessed 23 Jan 2019.

Fraser, E. D. G. (2007). Travelling in antique lands : Using past famines to develop an adaptability / resilience framework to identify food systems vulnerable to climate change. *Climatic Change, 83*, 495–514.

Funk, C. (2016). Concerns about the Kenya/Somalia short rains. *Climate Hazards Group Blog*. http://blog.chg.ucsb.edu/?m=201610

Funk, C. C., Peterson, P. J., Landsfeld, M. F., Pedereros, D. H., Verdin, J. P., Rowland, J. D., et al. (2014). A Quasi-Global Precipitation Time Series for Drought Monitoring: U.S. Geological Survey Data Series 832. https://doi.org/10.3133/ds832

Funk, C., Galu, G., Hillbruner, C., Harrison, L., Korecha, D., Eilerts, G., et al. (2018). Examining the role of unusually warm indo-Pacific Sea-surface temperatures in recent African droughts. *Quarterly Journal of the Royal Meteorological Society*, (February), 1–24. https://doi.org/10.1002/qj.3266.

Gitau, W., Camberlin, P., & Okoola, R. (2015). Oceanic and atmospheric linkages with short rainfall season intraseasonal statistics over. *Equatorial Eastern Africa., 2399*(August 2014), 2382–2399. https://doi.org/10.1002/joc.4131.

Grunthal, G., Thieken, A. H., Schwarz, J., Radtke, K. S., Smolka, A., & Merz, B. (2006). Comparative risk assessments for the city of Cologne – Storms, floods, earthquakes. *Natural Hazards, 38*, 21–44.

Hansen, J., & Indeje, M. (2004). Linking dynamic seasonal climate forecasts with crop simulation for maize yield prediction in semi-arid Kenya. *Agricultural and Forest Meteorology, 125*, 143–157.

Iizumi, T., Sakuma, H., Yokozawa, M., Luo, J., Challinor, A. J., Brown, M. E., et al. (2013). Prediction of seasonal climate-induced variations in global food production. *Nature Climate Change, 3*(10), 904–908.

IPC Global Partners. (2012). *IPC integrated food security phase classification technical manual version 2.0 evidence and standards for better food security decisions*. Rome: FAO http://www.fews.net/sites/default/files/uploads/IPC-Manual-2-Interactive.pdf.

Jayanthi, H., Husak, G. J., Funk, C., Magadzire, T., Chavula, A., & Verdin, J. P. (2014). Modeling rain-fed maize vulnerability to droughts using the standardized precipitation index from satellite estimated rainfall — Southern Malawi case study. *International Journal of Disaster Risk Reduction, 10*, 1–11.

Kehinde, B. (2014). Applicability of risk transfer tools to manage loss and damage from slow-onset climatic risks. *Procedia Economics and Finance, 18*, 710–717.

Manzanas, R., Frías, M. D., Cofiño, A. S., & Gutiérrez, J. M. (2014). Validation of 40 year multimodel seasonal precipitation forecasts : The role of ENSO on the global skill. *Journal of Geophysical Research: Atmospheres, 119*, 1–12.

Maxwell, D., & Hailey, P. (2018). Dan Maxwell and Peter Hailey Commentary: Evidence, Analysis, and the Politics of Declaring Famine. http://fic.tufts.edu/newsroom/dan-maxwell-and-peter-hailey-commentary-evidence-analysis-and-the-politics-of-declaring-famine/. Accessed 11 April 2018.

Ntale, H. K., & Gan, T. Y. (2003). Drought indices and their application to East Africa. *International Journal of Climatology, 23*, 1335–1357.

Okuyama, Y., & Chang, S. (Eds.). (2004). Modeling Spatial and Economic Impacts of Disasters.

Peri, M. (2017). Climate variability and the volatility of global maize and soybean prices. *Food Security, 9*(4), 673–683.

Pineda-Porras, O., & Ordaz-Schroeder, M. (2003). Seismic vulnerability function for high-diameter buried pipelines: Mexico City's primary water system case. *Pipelines*.

Porter, C., & White, E. (2016). Potential for application of a probabilistic catastrophe risk modelling framework to poverty outcomes: General form vulnerability functions relating household poverty outcomes to Hazard intensity in Ethiopia. *World Bank Policy Research Working Paper*, (June).

Quijano, J. A., Jaimes, M. A., Torres, M. A., Reinoso, E., Castellanos, L., Escamilla, J., & Ordaz, M. (2015). Event-based approach for probabilistic agricultural drought risk assessment under rainfed conditions. *Natural Hazards, 76*, 1297–1318.

Ray, D. K., Gerber, J. S., Macdonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nature Communications, 6, 5989*.

Rüth, A. (2015). *Framework: Action plan of the Federal Foreign Office for humanitarian adaptation to climate change*. Berlin: Germany http://www.drk.de/fileadmin/Presse/Downloads/Bild/Ausland/GRC__2015__FFO_Action_Plan_CCA.pdf.

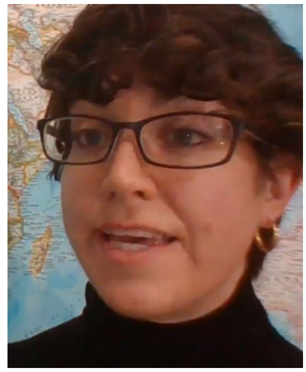
Simelton, E., Fraser, E. D. G., Termansen, M., Benton, T. G., Gosling, S. N., South, A., Arnell, N. W., Challinor, A. J., Dougill, A. J., & Forster, P. M. (2012). The socioeconomics of food crop production and climate change vulnerability : A global scale quantitative analysis of how grain crops are sensitive to drought. *Food Security, 4*(2), 163–179.

Thornthwaite, C. W. (1948). An approach toward a rational classification of climate. *American Geographical Society, 38*(1), 55–94.

UNFCCC. (2012). Current knowledge on relevant methodologies and data requirements as well as lessons learned and gaps identified at different levels, in assessing the risk of loss and damage associated with the adverse effects of climate change. https://unfccc.int/resource/docs/2012/tp/01.pdf

Vicente-Serrano, S. M., Begueria, S., & Lopez-Moreno, J. (2009). A multiscalar drought index sensitive to global warming : The standardized precipitation evapotranspiration index. *Journal of Climate, 23*, 1696–1718.

Weisheimer, A., & Palmer, T. N. (2014). On the reliability of seasonal climate forecasts. *Journal of the Royal Society, Interface, 11, 20131162*.



**Erin Coughlan de Perez** is the manager of the climate science team at the Red Cross / Red Crescent Climate Centre and an associate at Columbia University. She manages innovative pilots of Forecast-based financing systems in more than 10 countries around the world, which integrate new funding mechanisms with early action protocols to prevent and prepare for the impacts of extreme events. Erin's research links the statistics of extreme climate events with thresholds for preventative action in the humanitarian and development sectors. She is a Lead Author in the upcoming IPCC 6th Assessment Report.

**Maarten van Aalst** has been involved with the Red Cross / Red Crescent Climate Centre since 2006. He coordinates support to climate risk management across the Red Cross Red Crescent Movement, and links with scientific and policy communities on climate change, disaster risk management and development planning. Maarten was Coordinating Lead Author for the IPCC special report on extremes and a Lead Author for the IPCC Fifth Assessment Report. He holds adjunct appointments at the International Research Institute for Climate and Society at Columbia University, and at the Department of Science, Technology, Engineering and Public Policy at University College London. Since completing a PhD in atmospheric science, Maarten has also worked on climate change adaptation and disaster risk management with organisations such as the World Bank, several regional development banks, OECD, UNDP and several governments.

**Richard Choularton** is a senior associate focused on food security and climate resilience with Tetra Tech International Development Services. As the former Chief of the World Food Programme's Climate and Disaster Risk Reduction Unit, he is a recognized, world-renowned expert in climate change adaptation and risk mitigation, resilience, food security, emergency preparedness, and early warning systems. Richard previously served as director of the Office of Humanitarian Assistance at CHF International. He was also the decision and planning support advisor for the Famine Early Warning Systems Network (FEWS NET), a leading provider of early warning and analysis on acute food insecurity that was created by the U.S. Agency for International Development (USAID) in 1985.

**Bart van den Hurk** has a PhD in land surface modelling, obtained in Wageningen in 1996. Since then he has developed a scientific career at the Royal Netherlands Meteorological Institute (KNMI) as researcher, involved in studies addressing modelling land surface processes in regional and global climate models, data assimilation of soil moisture, and constructing regional climate change scenarios. Since 2005 he has been part-time professor "Regional Climate Analysis" at IMAU at the Utrecht University. From 2014 onwards he occupies the chair "Climate Interactions with the Socio-Ecological System" at IVM at Amsterdam Vrije Universiteit. Between 2007 and 2010 he was chair of the WCRP-panel GLASS, and member of the Netherlands Climate Changes Spatial Planning program. Since 2008 he has been a member of the board of NWO-ALW. He is convenor of a range of conferences and HESSD editor. At KNMI he was a member of the Institute Reorganisation group (2013), and now leads the R&D section on weather/climate modelling.

**Simon Mason** is Chief Climate Scientist at the IRI and a Senior Research Scientist of Columbia University, New York, USA. His work is focused on developing climate services at National Meteorological and Hydrological Services around the world. He was a lead author of the Global Framework for the Climate Services Implementation Plan.

**Hannah Nissan** is an Associate Research Scientist at the IRI; she joined in 2015 as an Earth Institute Fellow and a Fullbright Scholar, working in partnership with the Red Cross Red Crescent Climate Centre. Hannah studied physics at the University of Bristol in the UK, and holds a Postgraduate Diploma in Economics from the University of Cambridge and a PhD in Regional Climate Modeling from Imperial College London. Her doctoral thesis explored the role of atmospheric aerosols in modulating soil erosion. She has since worked on South Asian weather and climate variability. Prior to joining the IRI Hannah worked at the International Energy Agency and the Scottish Government. Her current research is focused on understanding the characteristics and changing risks of heat waves in Bangladesh and their health impacts. She also conducts training for health and meteorology professionals in South Asia and the Caribbean on heat early warning systems and climate-health relationships.

**Saroja Schwager** is currently completing her Master of Arts in Climate and Society at Columbia University. She received her Bachelor of Arts from New York University, where she studied foreign relations and environmental policy. Her current research interests include the climate and security nexus and how policy, governance and socio-economic factors interact with and even exacerbate climate risks, especially in the Middle East and the Horn of Africa. She does research for the Red Cross Red Crescent Climate Centre.