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

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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

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.

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

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\(^1\) 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). 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 system 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. 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".

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 bootstrapped replicates show a stronger

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**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.

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

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

| 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 Somali 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

![Image](image-url)

**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.
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.
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).
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 (Barstorn 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.

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Compliance with ethical standards

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

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