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Food, Drought and Conflict

Evidence from a Case-Study on Somalia

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Abstract:

Recent evidence points at the importance of childhood aspirations for our understanding of poverty and development. But how are these affected by the exposure to violence? This paper employs a logistic framework to study that question for Burundi, a conflict-affected, fragile state. Using data from a new nationwide survey with a panel component we distinguish between armed violence, domestic violence, violence at school and participation in violence. We find that (i) aspiring a job in the public sector is popular regardless of the type of violence; (ii) Children exposed to armed conflict have higher aspirations, defined as wishing to be employed outside of agriculture. Our results also show that these children, as well as children exposed to domestic violence, have a lower probability to fulfill their aspirations; (iii) children exposed to violence at school or children who perpetrated violence do not aspire to leave agriculture, making that their outcomes are closer to their aspirations, (iv) the differences between aspirations and outcomes for the four types of violence have a

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1 Introduction

Food insecurity can both be a cause and a consequence of conflict. Not only is food insecurity a consequence of conflict, but it can also fuel and drive conflicts. Another important factor affecting this relationship is the level of drought experienced in a certain geographic area of the country within a given timeframe. Extreme weather events have become more frequent over the past decades. By consequence, taking into account how drought affects the relationship between food security and conflict is paramount. Drought has been found to trigger conflict by various authors. In addition, its effect on the state of food security has been documented as well.

Moreover, not only drought is likely to affect food security, but excessive rainfall as well. Both for very low levels of drought (with a lot of rainfall), and for very high levels of drought, there may be a deterioration of an individual's food security status. Therefore, the relationship between drought and food security indicators might be of a quadratic (U-shaped) nature. Maertens (2016) finds a similar U-shaped relationship between rainfall (very low and high levels of rainfall) and conflict risk.

Furthermore, excessive rain may not only impact nutrition outcomes directly, but will have an influence on health outcomes (eg waterborne diseases) as well. At the same time, health outcomes are also closely linked with nutrition outcomes. Therefore, both nutrition and health (and education) are considered as key determinants of food security. When an individual's health is deficient, this will inevitably determine the uptake of nutrients. Vice versa, lack of access to adequate food, both qualitatively as quantitatively, will deteriorate an individual's health condition.

In this paper, we contribute to the literature by looking at the impact of conflict on food security in the presence of drought. A few studies argue that food prices affect outbreaks of conflict, or serve as a channel through which drought affects conflict. However, there is little evidence in the reverse direction, where the effect of conflict on food security is studied in drought affected areas. Moreover, this analysis is conducted at various levels of aggregation and for different population groups (for instance rural versus urban livelihoods, urban versus pastoral, agro-pastoral or riverine livelihoods). Findings that are not visible or averaged out at higher levels of aggregation may be revealed at lower levels of aggregation or that only hold for certain specific livelihoods. This is important, since it may increase the insight in the linkages between conflict, food security and drought and their spatial distribution. In turn, this may better inform policymakers when designing policies and development programs that aim at targeting vulnerable populations. Finally, this study uses a broad set of food security indicators; both anthropometric measures and price indicators, contributing to the richness of this analysis. Likewise, various conflict typologies (one-sided conflict, intrastate, internationalized, and low-intensity conflict) are employed, since this may affect the way conflict affects food security.

Somalia serves as a particularly interesting region to examine this complex relationship between drought, conflict, and food security, given the protracted and complex crises experienced by Somalia in the past decades and the high percentage of food insecure people. Since 1991, Most of Somalia's armed clashes since 1991 have been fought in the name of clan and violent conflicts have erupted more frequently since 2002 in Somalia (ACLED, 2014). Moreover, Somalia has witnessed a steady increase in drought intensity over the past decades. Due to its geographic location and fragile environments, Somalia is highly vulnerable to weather shocks - particularly droughts (FSNAU, 2011). In 2011, Somalia experienced one of the most severe droughts since 50 years (Maxwell and Fitzpatrick, 2012). Therefore, studying the link between conflict, and food security in Somalia is of primary interest.

This paper is structured as follows. Section 2 provides descriptive evidence on the context of our study. Section 3 starts with a review of the existing literature on the relation between conflict, drought and food security. Section 4 elaborates on the empirical methodology and describes the dataset used for the empirical analysis, and sets out the empirical strategy. Finally, Section 5 discusses the regression results and Section 6 formulates conclusions and implications.

2 Study context

Over the past decades, the state of certain food security indicators has vastly improved in Somalia, whilst less progress has been booked on others. Figure 1 shows the evolution of a few food security indicators for Somalia over time, spanning the time period between 1990-2013. Prevalence of anemia among 5 year old children seems to be overall declining, while access to water has improved significantly as well.

Per capita food production variability and mostly cereal import dependency ratio don't follow such a clear downward trend and seem to be responding more to external shocks like political instability, conflict, etc.

Figure 1: Evolution of food security indicators over time, 1990-2013. Data are collected from the FAO set of food security indicators database (2016).

Intrastate and Internationalized Intrastate typologies of conflict correspond to the definitions used in the UCDP/PRIO Armed Conflict Dataset (Pettersson and Wallensteen, 2015). One-sided conflict events are events where civilians are targeted. Figure 2 depicts the trends for these conflict typologies. There seems to be an upward trend for one-sided, intrastate, as well as internationalized intrastate events. One-sided events and intrastate conflict events are most prevalent, even though internationalized intrastate conflict has risen sharply.

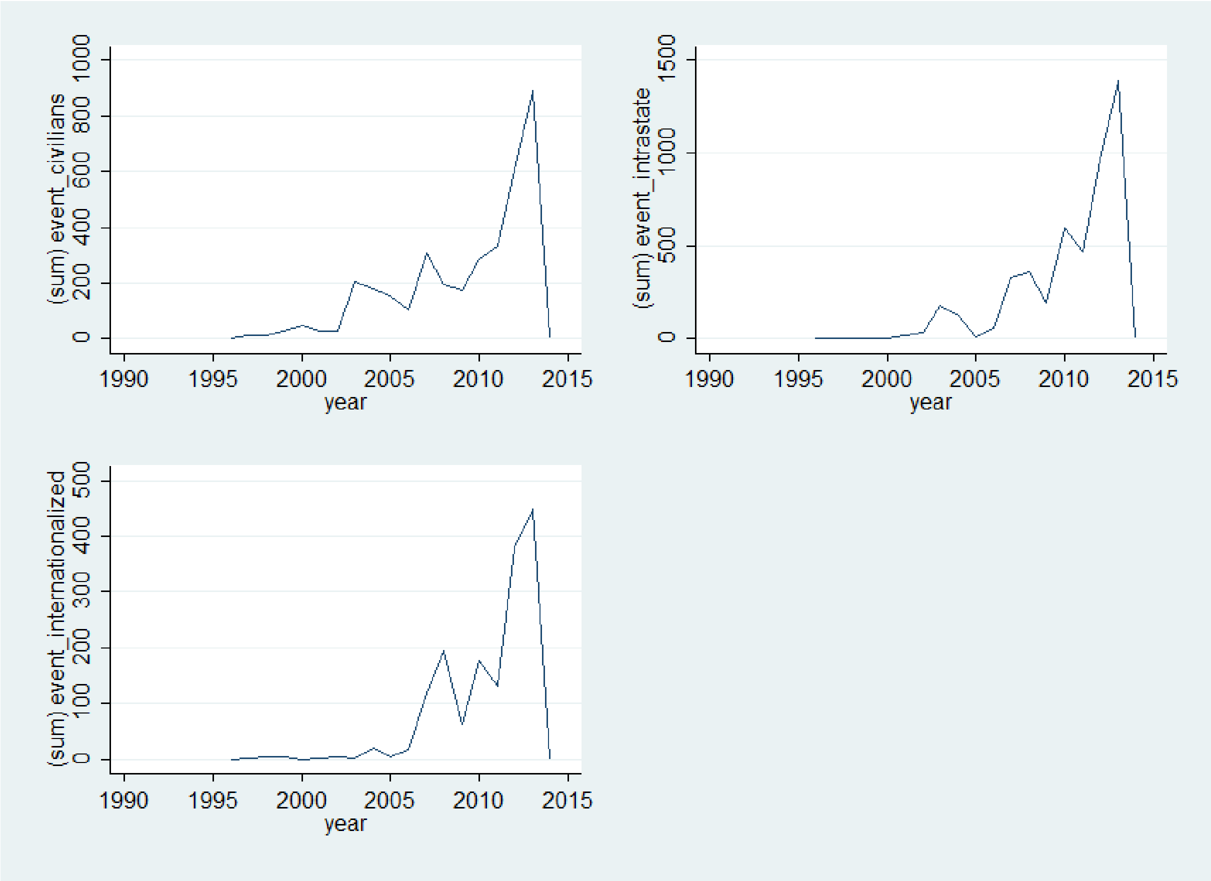

Figure 2: One-sided and intrastate conflict, by district and year (1997-2013), ACLED-PRIO, 2016.

Figure 3 depicts the intrastate and one-sided conflict events by district. Clearly, there is a large variation among districts. Most of the violent conflicts are taking place in the Banadir district/region due to the presence of the capital. Figure 4 depicts local district prices of for 1kg of white maize and 1 kg of red sorghum. Local district prices seem to vary in terms of volatility. The observed variation in conflict intensity and food prices (and other food security indicators) among districts and regions makes it worthwhile to study the relationship between conflict and food security on different levels of aggregation.

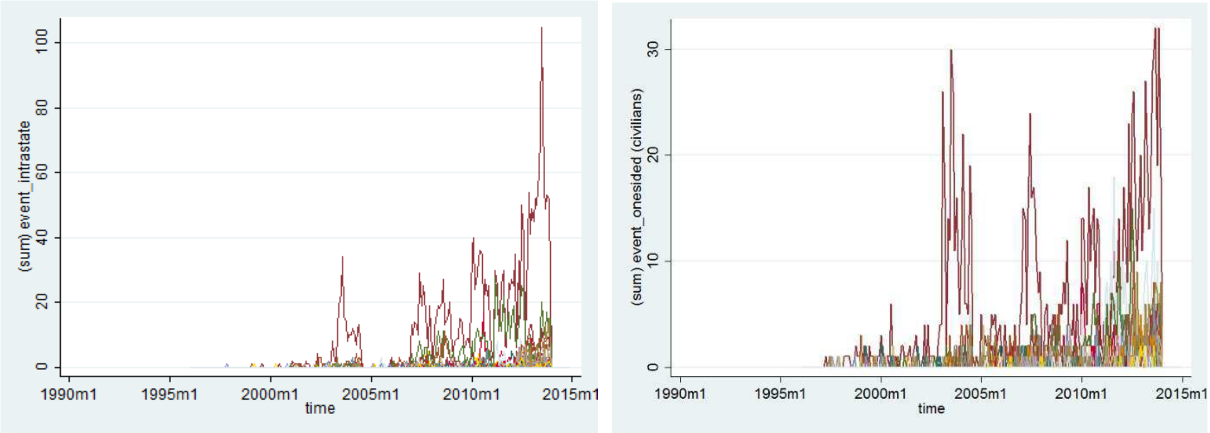

Figure 3: Onesided and intrastate conflict, by district and year (1997-2013), ACLED-PRIO, 2016.

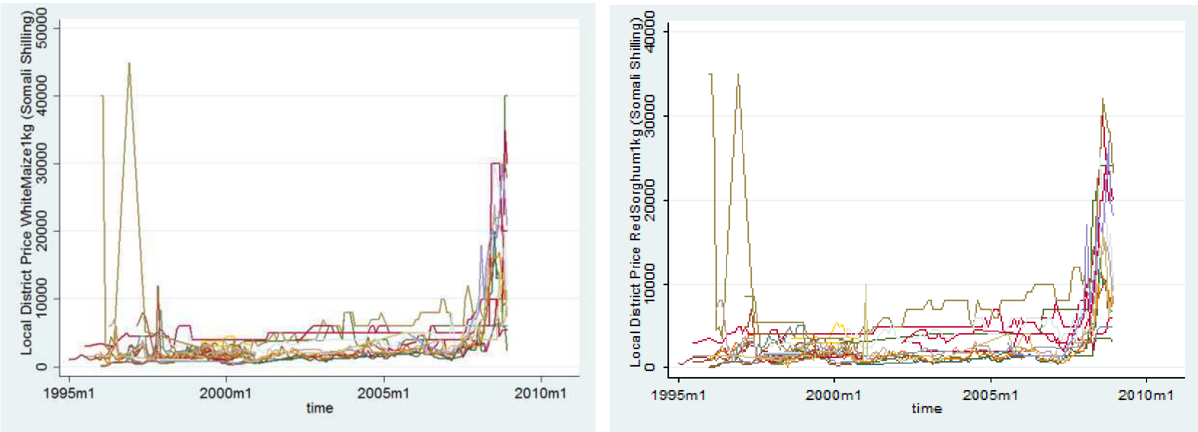

Figure 4: Local district prices for 1kg of white maize and 1 kg of red sorghum, 1996-2008. FNSAU, 2016.

Figure 5 depict the distribution of violent events (left map of Somalia) and fatalities, within the regions of Somalia. Violent events and fatalities seem to be more concentrated in the South and South-West of the country, and alongside the border with Ethiopia. We will study the impact of conflict and drought on food security outcomes, both on the district level as well as the household level. Our data on the district level is spread over the districts (and regions) of the entire country, whilst the household level data are restricted to the districts of Bosasso and Iskushuban in the northeastern Bari Region (Puntland) and Burao and Odweyne districts in the northwestern region of Toghdeer (Somaliland).

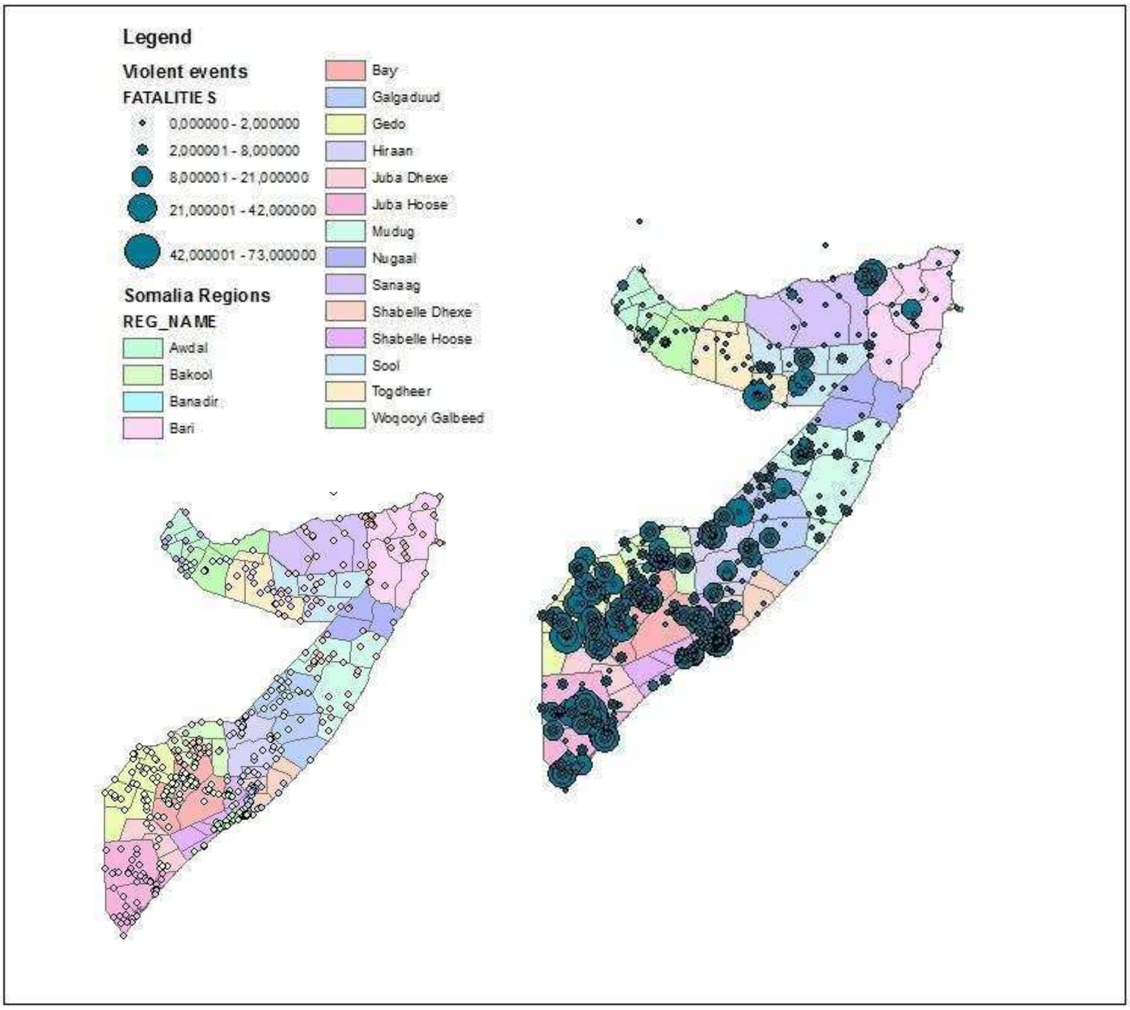

Figure 5: Distribution of violent events (left) and fatalities (right) in the regions of Somalia. Author's calculation based on ACLED-PRIOGRID data (1997-2014).

3 Literature

A vast amount of literature has identified food insecurity to be an important threat to violent conflict (Pinstrup-Andersen and Shimokawa, 2008; Breisinger, Ecker, and Al-Riffai 2011; Brinkman and Hendrix, 2011; Breisinger et al. 2012; Maystadt et al., 2014), especially in the presence of unstable political regimes, slow or falling economic growth, and high between-group inequality. Particularly, rising food prices have been found to increase the risk of political unrest and conflicts (Arezki and Brückner, 2011; Bellemare, 2011).

At the same time, conflict also poses a threat to food security, both directly and indirectly. For example, conflicts may destroy transportation infrastructure or diminish productive assets which could lead to income losses (Deininger and Castagnini 2006; Devereux, 2006; Verpoorten, 2009). Conflict may also indirectly affect food security through its effect on local food prices. These negative effects on food availability will impact household-level food security. More specifically, key determinants of food insecurity such as nutrition, health, and education will be affected by conflict. Akresh, Verwimp, and Bundervoet (2010) find that the Rwandan genocide had negative effects on child stunting, while Bundervoet, Verwimp, and Akresh (2009) show that in Burundi an additional month of war exposure decreases children's height-for-age z-scores by 0.047 standard deviations, compared with non-exposed children. Minoiu and Shemyakina (2012) found that children in Côte d'Ivoire conflict exposure in utero or during early life experienced health setbacks, compared to those born in non-affected regions during the same period. Furthermore, D'Souza and Jolliffe (2013) show that in Afghanistan levels of conflict and food security measured by insufficient calorie intake or real food consumption are negatively correlated (after controlling for household characteristics and key commodity prices) when faced with food price spikes. They did not find overall higher food insecurity levels in conflict affected areas as compared to non-affected areas, but based on a multivariate analysis, they do find that conflict may negatively affects household coping strategies when faced with food prices spikes.

Alongside of the literature linking conflict and food security, the relationship between drought and conflict has been examined as well in a number of studies. Based on the economic theory that links changes in opportunity costs to conflict participation (Collier and Hoeffler, 1998; 2004), extreme weather conditions have been linked to increased conflict events, assuming causal relationship between weather shocks and adverse economic conditions (Kurukalasuriya et al., 2006; Schlenker and Lobell, 2010; Dell, Jones, and Olken, 2012). Burke et al. (2009) show that a rise in temperature of 1 degree Celsius increases the incidence of internal armed conflict in Sub Sahara African countries by 4.5 percent in the same year and 0.9 percent in the next year. Hsiang, et al. (2011) found that the probability of conflict outbreaks arising throughout the tropics doubles during El Niño years relative to La Niña years, while O'Loughlin et al. (2012) find that abnormally high temperatures and low rainfall increased the risk of violent conflict in East Africa over the past two decades.

The combined effect of drought and conflict on food security outcomes has received less attention in the literature. Maystadt and Ecker (2014) find that drought triggers conflict through decreased livestock prices in Somalia. Raleigh et al. (2015) find that a positive feedback exists between food price and violence – higher food prices increase conflict rates within markets and conflict increases food prices, based on data from 113 African markets between 1997 and 2010. At the same time, they also find that anomalously dry conditions are associated with increased frequencies of conflict. However, there is little evidence in the reverse direction, where the effect of conflict on food security is studied in drought affected areas. Furthermore, it should also be noted that the effect of conflict on food prices is ambiguous since it depends on the category of food that is being examined (prices of livestock versus prices of agricultural products). In addition, depending on the net food consumption or production status of a household, the effect of increasing prices may have either an unfavorable or either beneficial effect on a household's poverty status (and thus affect consumption in a different way). Overall, urban households tend to be net consumers of food, while rural households tend to be net producers of food. Therefore, it is recommendable to not only look at various food security indicators, but also at various levels of aggregation and population groups when studying the link between conflict, drought, and food security.

4 Methodology and data

4.1 District and regional level

4.1.1 Empirical strategy

In this section, we will examine the impact of conflict and drought on food security at the district level. Both drought and conflict are expected to have a negative effect on food security outcomes. In addition, drought is likely to affect conflict, according to the literature (Maystadt and Ecker, 2014; Raleigh et al., 2015). Therefore, the link between conflict and drought may be a potential confounding factor affecting the links between conflict and food security and drought and food security, and should not be ignored.

For our analysis, we will use various food security variables, both anthropometric measures and price indicators, spanning different time periods. Likewise, we will look at various conflict typologies: violence against civilians (onesided), intrastate violence, internationalized violence, as well as 'low-intensity' conflict where a low threshold of 5 battle deaths per month is used, and up to a maximum of 100 battle deaths per month. It should be noted however that data limitations is a key issue in this study. E.g. anthropometric indicators of food security – such as the prevalence of stunted and underweight individuals, etc. – are not available on a yearly basis over a long time period. Therefore, the choice of the food security indicators in this study has been based on the availability of data with a reasonable time and spatial coverage. Nevertheless, most of the food security variables used span a relatively short time period.

Furthermore, the link between food-security and conflict is likely to suffer from reverse causality as the main source of endogeneity. To account for endogeneity due to simultaneity bias, we lag the conflict variables over one time period. Furthermore, we account for the history of violent conflict events, given its significant impact on ongoing conflict.

Besides conflict, according to the literature, there are several variables that can affect the food security situation of our unit of analysis (districts – households). In this study, several additional district-specific control variables are used, obtained from combining geospatial datasets. More detailed information on control variables and data is described in the next section. We start by examine the effect of drought on both conflict and food security outcomes in separate bivariate regressions. Then we will run the full model including all relevant control variables.

$$FoodSecurity_{it} = \alpha + \beta_1 Drought_{it-1} + \beta_2 X_{it} + \mu_i + \eta_t + \epsilon_{it}, \quad (1)$$

$$Conflict_{it} = \alpha + \beta_1 Drought_{it-1} + \beta_2 X_{it} + \mu_i + \eta_t + \epsilon_{it}, \quad (2)$$

We expect to find a positive triggering effect of drought on conflict. Drought can thus be considered as an endogenous control variable. Besides from a study by Lerchner (2008) which is specifically focused on matching methods, there is no clear answer in the literature on how to tackle the issue of endogenous controls. Omitting the endogenous control variable could lead to omitted variable bias, whilst including the variable could lead to inconsistent estimates due to endogeneity. Therefore, I start by excluding the drought variable from the following equation, which measures the impact of conflict on food security:

$$FoodSecurity_{it} = \alpha + \beta_1 Conflict_{it-1} + \beta_2 X_{it} + \mu_i + \eta_t + \epsilon_{it}, \tag{3}$$

In a next set of regressions, the drought variable will be included which allows us to compare the results. To avoid simultaneity bias between the conflict variables and drought, the former are lagged one time-period, unlike the drought variable:

$$FoodSecurity_{it} = \alpha + \beta_1 Conflict_{it-1} + \beta_2 Drought_{it} + \beta_3 X_{it} + \mu_i + \eta_t + \epsilon_{it}, \tag{4}$$

The subscripts i=1,...,C and t=1,...,T denote district and time (monthly level), respectively, $\textit{FoodSecurity}_{i}$ the food security indicator; $\textit{Conflict}_{it}$ is the conflict variable, $\textit{Drought}_{it}$ the drought variable, X_{it} is a vector of controls, μ_{i} and η_{t} are district (or region) and year fixed effects, respectively, and ε_{it} is the error term.

By controlling for district-fixed and time-fixed effects in all regressions we address the potential problem of omitted/unobserved variables in a general manner. The district-fixed effects variables pick up time-constant, unobserved heterogeneity across districts, for instance ethnic composition of the population. The time-fixed effects variables control for external shocks that affect all of Somalia similarly. In a few bivariate regressions, we leave out the time and district dummies and add them in a later stage. All regressions are run using clustered standard errors at the district level (or regional level for the regressions including anthropometric food security variables).

As a robustness check, we adjust error terms for spatial and time dependency since there may be not enough district units in our dataset for clustering standard errors. To adjust standard errors for spatial and temporal correlation, we adopt Hsiang's (2010) procedure. We allow for a time dependency of up to three months, and a distance cutoff point of 160 kilometers, which is the average distance between the centers of neighboring districts. Using standard errors adjusted for spatial and temporal correlation is appropriate in cases in which spatial correlation is present in the error term (spatial error model), and has been performed in a vast amount of literature when using geo-referenced data. However it does not address the issue of how to explicitly model spatial dependence in the process itself (conflict and drought spillovers).

4.1.2 Data

Estimations are based on monthly panel data at the district level. Somalia has 18 administrative regions and 74 districts, and the time frame of our analysis ranges from January 1997 to December 2013 (with exception of some regressions). Since we use various food security indicators throughout the analysis, the number of observations differs depending on which indicator is used.

As anthropometric measures of food security, we use district (and region, livelihood) specific data on the percentage of the population that is underweight and/or stunted, from the Food Security and Nutrition Analysis Unit, Somalia (FSNAU) Integrated Database System. This data is available for both rainy seasons *Deyr* and *Gu*, covering a limited time-span of 5 years between 2009-2014. The data is derived from the Nutrition Datasets. Since stunting is a long-term measure of food security, and is highly likely to be correlated with stunting in previous time periods. To account for the dynamics of the model, we will take into account past observations of the stunting variable. In particular, we will include the 3-month lag of the stunting variable in the regressions equation. An individual (children aged between 6-59 months for the FSNAU data) is stunted whenever the "height for age" value is two standard deviations below the WHO Child Growth Standards median. In the regressions where the stunting variable is the dependent variable, 3-month lags of the conflict and drought variables will be used, to take into account the time needed for stunting to become apparent.

Furthermore, we use local district monthly price data from the FNSAU Integrated Market Database System as a basis to build additional food security indicators. More specifically, we construct a normalized price index of maize and sorghum – two major food crops in Somalia – using local district prices for 1k white maize, yellow maize, white sorghum and yellow sorghum. To control for price inflation, prices are normalized by dividing them by the price of imported red rice, which doesn't lead to biased estimates according to Maystadt and Ecker (2014), who apply a similar normalization procedure. A final indicator is the price volatility of the combined maize-sorghum price. The price volatility is calculated using the following volatility measure, based on the variance of log returns (Gilbert and Morgan, 2010):

$$Vol = Var\left[\log\left(\frac{p_t}{p_{t-1}}\right)\right]$$

These food security measures are complemented with data on the number of urban and rural individuals in stressed (*AFLC_urban* and *AFLC_rural*), crisis (*HE_urban* and *HE_rural*), or emergency food security situations (*famine_urban* and *famine_rural*). This data is obtained from the Integrated Food Security Phase Classification (IPC, 2016), which is measured twice a year since 2010 in the case of Somalia. IPC uses a set of standardized tools that aims at providing a 'common currency' for classifying the severity and magnitude of food insecurity. When combining these data with interpolated and extrapolated UNDP data on the rural and urban populations by region, we can obtain the share of the urban and rural population in stresses, crisis, or emergency food security situations.

The conflict variables (one-sided, intrastate, and internationalized) are constructed as the sum of respectively one-sided (against civilians), intrastate, and internationalized violent conflict events in each administrative unit per month, using the combined PRIO-ACLED dataset (2016). The dataset reports 12,287 conflict events in Somalia between 1997 and 2013, of which the majority were violent (including battles between conflict groups and violence against civilians). In addition, a dummy variable *lowintensity* is constructed, taking on value 1 whenever the threshold of 5 battle deaths per time period is reached, with a maximum of 25 battle deaths. Because we look at monthly data instead of yearly data, the threshold of the *lowintensity* variable is set lower than the threshold used by PRIO/UCPD where a minimum of 25 battle deaths per time period is needed, because the latter is measured in one year while our dataset is on a monthly basis.

This dataset is spatially merged using the geostatistical software ARCGIS to the PRIOGRID database, which contains a range of grid-cell specific data on socio-economic conditions, ethnic groups, climatic conditions, etc. For the regressions at the district level, this spatial data is averaged over the grid cells of the country's district. Spatial information on the district (and regional) border within the country is derived from the GADM database of Global Administrative Areas, version 2.8, 2015.

The variable *drought* captures the severity of drought measured at the grid cell's level, in a given month. The severity value is the SPEI1 value, obtained from the Standardized Precipitation and Evapotranspiration Index SPEI1 from the SPEI Global Drought Monitor. The values are standardized where deviation estimates less than 1 standard deviation indicate near normal rainfall. The monthly SPEI1 index measures deviation from long-term normal rainfall for that month (Begueria et al., 2014). In this study, the deviation values (anomalies) should be interpreted as follows: months that are drier than normal have a positive precipitation anomaly and months that are wetter than normal have a negative precipitation anomaly. In some of the bivariate regressions, we also look at temperature (*temp*) instead of drought. This variable gives the yearly mean temperature (in degrees Celsius) in the grid cell, based on monthly meteorological statistics from GHCN/CAMS, developed at the Climate Prediction Center, NOAA/National Weather Service (Fan and van den Dool, 2008).

In addition to drought, other variables from the PRIOGRID database are added to the regression equation. *capdist* captures the distance to the nearest national capital from the centroid of the grid cell, indicating the remoteness of the district (Weidmann et al., 2010). Even though this data is time varying, the variation over time is small and therefore this variable will only be included when no district (or regional) dummies are added to the regression. This is however an important control variable, since nowadays the majority of poor and food insecure people still live in remote areas. *lnpop* measures the grid-specific population, taken from the 'Gridded Population of the World', version 3. Population estimates are available for 1990, 1995, 2000, and 2005. The remaining data points are calculated based on interpolation. Finally, we control for history of conflict by taking into account the total number of violent events, lagged by 2 years.

Furthermore, since food security outcomes (especially the price variable) are likely to be influenced by the amount of food aid received, we also take into account the amount of food aid (*food aid*) received, measured in actual tons. However, food aid does not only have a direct effect on food security outcomes. Conflict is likely to attract more food aid to the country, so one has to take into account potential endogeneity when interpreting the estimation results of the impact of conflict on food security, when adding food aid to the regression.

Finally, we extend the analysis by looking at the effect of excessive rainfall (or low levels of drought) on waterborne diseases (results will be shown in the Appendix). More specifically, we look at under-5-mortality (children between one and 59 months of age), caused by diarrhoea and malaria - water plays a role in the development of the disease transmitter. As a comparison, we compare these results with one's for lower respiratory diseases, which are transmitted via the air. Note that all disease variables are measured at the country level (not on the district level), on a yearly basis. Data are obtained from the Word Health Organization datasets. Below, Table 1 summarizes the descriptive statistics of the regression variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
pcunderweight (%)	377	23,421	12,748	2,600	61,800
pcstunting (%)	375	21,079	12,513	0,400	48,700
nprice_maizesorghum index	5438	0,467	0,242	0,023	3,333
volatility	4080	0,182	0,198	0,002	3,202
AFLC_urban (share of urban population)	235	0,146	0,340	0,000	3,090
AFLC_rural (share of rural population)	224	0,196	0,138	0,000	0,756
HE_urban (share of urban population)	235	0,027	0,044	0,000	0,193
HE_rural (share of rural population)	224	0,103	0,212	0,000	1,631
famine_urban (share of urban population)	180	0,020	0,068	0,000	0,617
famine_urban (share of rural population)	190	0,003	0,017	0,000	0,189
onesided events	16872	0,211	1,254	0,000	32,000
intrastate events	16872	0,280	2,376	0,000	105,000
internationalized events	16872	0,092	0,677	0,000	16,000
lowintensity events	22242	0,024	0,152	0,000	1,000
drought	8600	0,250	1,011	-5,206	5,832
temp	21036	29,571	3,110	21,486	38,137
diarrhoea (1-59m, thousands)	16	21,381	2,796	17,100	26,200
malaria (1-59m, thousands)	16	1,469	0,796	0,400	3,500
lower respiratory infection (1-59m)	16	27,213	4,006	20,400	33,500
Food aid (Emergency, Tons)	25	114871,100	98990,840	4853,200	364507,800
Food aid (Project, Tons)	25	2782,721	4517,435	0,000	17274,450
log population	21012	11,565	1,767	0,000	21,084
capital distance	21036	532,197	322,569	24,070	1252,423
events history	22052	29,958	181,662	0,000	4167,000

Table 1. Descriptive statistics – district level

4.2 Household level

At the household level – in line with the analysis at the district level – we look at the impact of conflict exposure and drought on the various food security measures. Firstly, we examine the effect on the food consumption score (*fcs*) of the household. The food consumption score captures the dietary diversity and nutrient value of food consumed by households. It is calculated from the types of foods and the frequency with which they are consumed over a seven day period (FAO, 2016), reported by the respondent. The threshold for being considered as food secure it set at 28. Below this threshold, a household is considered as food insecure.

Furthermore, we examine the effect of conflict exposure and drought on food expenditures (*food_exp*) of the household and non-food expenditures (*nonfood_exp*). The amount a household spends on food is an indicator for household food security. However, in times of distress, the household will more likely cut down on the expenses on non-food items first, since food consumption is a more basic need than non-food consumption. Therefore, it is interesting to look at how both variables behave under conflict and drought exposure.

To measure the household's conflict exposure, we use information on the threat of conflict (none, low, medium, high) between clans in daily life. This *conflict* variable is reported by the household and can be interpreted as a perception of conflict threat (or lack thereof). Ideally, we would like to have information on conflict shocks, to avoid simultaneity bias.

All the household data are derived from a household level survey, conducted in June 2014, in various districts and regions in both Somaliland and Puntland. This survey is part of the Impact Evaluation of the Joint Resilience Strategy of FAO, UNICEF and WFP in Somalia. The survey sample in Puntland consisted of 809 households: 297 in Bossaso and 512 in the Iskushuban district. The total number of individuals covered by the survey was 5,228 of which 1,993 were in Bossaso, and 3,235 in Iskushuban, comprising 49.9% females and 51.1% males. The sample in Somaliland included 802 households: 368 in Burao and 434 in Odweyne district, 74.2% of the total were male-headed households and 25.8% were female-headed households. The total number of individuals covered by the survey was 4 696; 2160 in Burao, and 2 536 in Odweyne. The largest group of household livelihoods in Puntland is urban (29%), followed by Internally Displaced Persons (IDPs) with 28%. The pastoralists make up 15% of households, the fishing community are 13.6%; farmers 7% and agro pastoralists are 6.5% of households. In contrast, in Somaliland the households interviewed were mainly pastoral (75%), followed by agro-pastoralist (almost 21% of the households). Urban (together with IDPs and farming livelihoods) represent less than 5% of the livelihoods in Somaliland (FAO, 2016a; 2016b).

Below, Table 2 summarizes the descriptive statistics of the regression variables. Interestingly, urban households have a higher food consumption score (about 18%) compared to pastoral households. At the same time, urban households seem to have reported lower threats of conflict (12% lower) between clans than pastoral households. Thus, living in urban areas seems to be associated with higher food consumption scores, but at the same time lower reported threats of conflict, when compared to pastoral households. This result may be driven by differences in household income, market access, food prices, etc. Controlling for these factors will be essential in determining the causal relationship between conflict and food consumption scores at the household level.

Variable	Obs	Mean	Std. Dev.	Min	Max
fcs	1568	55,756	18,838	0,000	112,000
fcs_urban	315	61,561	20,024	0,000	107,333
fcs_pastoral	690,000	52,253	15,552	0,000	112,000
log food_exp	1595,000	13,220	3,279	0,000	17,016
log nonfood_exp	1595,000	12,919	1,760	0,000	15,396
conflict	1573,000	0,240	0,730	0,000	3,000
conflict_urban	313,000	0,291	0,837	0,000	3,000
conflict_pastoral	701,000	0,331	0,841	0,000	3,000
drought	1591	0,873	1,241	-0,542	2,270
log formal_transfer	1595,000	3,113	5,531	0,000	16,148
log informal_transfer	1595,000	2,048	4,856	0,000	17,687
femhead	1595,000	0,246	0,431	0,000	1,000
hhsize	1595,000	6,238	2,726	1,000	17,000
educhead	1421,000	2,080	3,368	0,000	13,000
log totincome	1503	11,445	4,726	-0,021	17,759
urban	1595	0,197	0,398	0,000	1,000
distance_market	1581	-18,774	23,726	-130,000	0,000
shagr_wge	1466	0,003	0,050	-0,063	0,979
shnonagr_wge	1466	0,226	0,392	-0,776	1,500
shcrop	1466	0,026	0,160	-0,787	2,737
shlivestock	1466	0,453	0,477	-1,532	2,723
shselfemp	1466	0,154	0,384	-2,227	2,698
shtransfer	1466	0,097	0,258	-1,526	1,625
shother	1466	0,041	0,164	-0,136	1,535
diarrhoea	1547	0,076	0,081	0,000	1,000
typhoid	1547	0,050	0,069	0,000	1,000

Table 2. Descriptive statistics – household level

The survey data are combined with monthly varying spatial drought data from the SPEI Global Drought Monitor. This information is merged to the household-level data, based on information on the district location of the household. Unfortunately, there is no information on the exact location of the household given that the spatial coordinates of the household are not available.

In more general terms - similar to the district level but with a different set of control variables - we run the following regressions:

$$FoodSecurity_i = \alpha + \beta_1 Drought_{it-1} + \beta_2 X_i + \mu_i + \epsilon_i, \tag{5}$$

to measure the effect of drought on food security. We also examine the effect of drought on conflict and the effect of conflict on food security:

$$Conflict_i = \alpha + \beta_1 Drought_{it-1} + \beta_2 X_i + \mu_i + \epsilon_i, \tag{6}$$

$$FoodSecurity_i = \alpha + \beta_1 Conflict_i + \beta_2 X_i + \mu_i + \epsilon_i, \tag{7}$$

Finally, we look at the effect of conflict on food security when drought is added as a control variable:

$$FoodSecurity_i = \alpha + \beta_1 Conflict_i + \beta_2 Drought_i + \beta_3 X_i + \mu_i + \epsilon_i, \tag{8}$$

where the subscripts i=1,...,C denote the household; *FoodSecurity*_{i} the food security indicator; *Conflict*_{i}is the conflict variable, *Drought*_{i} the drought variable; *Conflict*Drought*_{i} the interaction term, X_{i} is a vector of controls, and ε_{i} is the error term. Regressions are run using ols regression and standard errors are clustered at the district level.

In line with the previous section, we add the following set of control variables measured at the district level: drought (interacted with the conflict variable), the log of the district population, distance to the capital and history of conflict events. We also control for a number of control variables measured at the household level, since they may affect a household's food security situation as well: household size (*hhsize*), the log of monthly household income (*loghhincome*), the distance to the nearest market – an indicator of market access, and a set of variables depicting the percentage of total household income derived from agricultural wage or non-agricultural wage employment, crop or livestock production, transfers, and self-employed activities (*shagrwage, shnonagrwage, shcrop, shlivestock, shselfemp, shtransfer*). We also include information on the distance to the nearest market and health facility. This information could also a serve as a measure of proximity to urban areas. Furthermore, a dummy variable indicating whether the household is headed by a female (*femhead*) is added to the regression. The latter is an important determinant of household wealth, given the fact that female headed households are comparatively income-poor (Buvinic and Gupta, 1997; Fafchamps and Quisumbing, 2002). Finally, education of the household head is taken into account (*educhead*). Education is an important tool to reduce poverty and to fight food insecurity, as it creates better future income opportunities by targeting illiteracy and the lack of numeracy.

Finally, to corroborate our findings, we will supplement the analysis with data from a household panel dataset. This household panel dataset is the result of an impact evaluation, carried out in April 2013 (baseline) and April 2015 (midline). The impact evaluation was set up to evaluate and improve the conditions of households in Somalia[2]. Households in the Doolow district received the treatment in 2013, while households in the Luuq district did not (control group). In this analysis the dataset is limited to the set of control households in Luuq, which didn't receive a treatment, to avoid confounding the analysis by the program treatment effect. However, due to a lack of reliable conflict data that contain enough variation, we will not be able to include a conflict variable in the analysis. We do look at the effect of drought on food security outcomes, namely the food consumption score (*fcs*), food expenditures

[2] To build household resilience, a JRS program was adopted jointly by FAO, WFP, and UNICEF. One of the program's main purposes was to improve household income generating capacity through a set of interventions.

(*foodexp*), and non-food expenditures (*nonfood_exp*). Drought is measured at the start of the rainy season (before the interviews took place), and is obtained from the Standardized Precipitation and Evapotranspiration Index SPEI1 from the SPEI Global Drought Monitor (Bergueria et al., 2014).

5 Discussion of results

We perform our analysis on different aggregation levels, namely the district level and the household level. The advantage of lower aggregation levels is that certain effects that may cancel out on a higher aggregation level (even on the district level), can be picked up on in lower aggregation level analysis. We also exploit the available information on the type of livelihood to complement our analysis to see whether the type of livelihood matters for the obtained results (both on the regional and household level). In addition, the household level analysis offers more details on household characteristics, health outcomes, direct and indirect transfers received, etc., which we can account for.

We start our analysis by running a set of bivariate regressions of the drought variable on the number of urban and rural individuals in stressed (*AFLC*), crisis (*HE*), and emergency (*famine*) situations, expressed as a ratio of respectively the total urban and rural population (the 'IPC classification variables', in Table 3, Table 4). As a comparison, we also examine the effect of temperature on the abovementioned dependent variables. We expect to find positive effects of conflict on anthropometric measures of food security (percentage underweight and stunted individuals), as well as on the IPC classification variables. (The effect on prices and volatility is less clear.) Overall, in Table 3 we find a small but significant effect of drought on the ratio of stressed individuals (*AFLC_rural*) in rural areas, as well as the ratio of individuals in emergency (*famine*) situations. Interestingly, we do not find such effect in urban areas. This indicates that people living in rural areas seem to be more affected by excessive drought than people living in urban areas. Adding temperature and later the food aid received to the regression does not alter these results (Table 4). Temperature does have a positive significant effect on the ratio of urban individuals in crisis or famine, whilst no significant effect is measured on rural individuals. However, adding food aid to the regression alters the latter finding.

	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_drought	0.007	0.002	0.000	0.018**	0.000	0.005*	0.007	0.003	0.000	0.019**	0.001	0.005*
	(0.022)	(0.002)	(0.000)	(0.007)	(0.009)	(0.002)	(0.023)	(0.002)	(0.000)	(0.007)	(0.008)	(0.003)
lag_drought_sq							0.001	-0.002	-0.001	-0.003	-0.012	-0.003
							(0.006)	(0.001)	(0.000)	(0.005)	(0.007)	(0.002)
_cons	0.152**	0.026***	0.003*	0.190***	0.101***	0.018**	0.151**	0.030***	0.004*	0.195***	0.122***	0.025**
	(0.053)	(0.005)	(0.002)	(0.021)	(0.025)	(0.006)	(0.058)	(0.006)	(0.002)	(0.025)	(0.034)	(0.009)
Pseudo R-squared	0.001	0.004	0.000	0.031	0.000	0.011	0.001	0.017	0.010	0.033	0.014	0.022
N	216	216	175	205	205	165	216	216	175	205	205	165

Table 3: Dep var: urban and rural people in stressed, crisis, and emergency (famine) situations, as a ratio of respectively the total urban and rural population. Regressions are run without time and district dummies, using ols regression with standard errors clustered at the district level. The drought variables are lagged one time period.

	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_drought	0.014	0.003	0.000	0.023*	0.002	0.009*	0.008	-0.004	-0.000	0.045**	-0.047	0.063
	(0.013)	(0.003)	(0.001)	(0.011)	(0.011)	(0.005)	(0.013)	(0.004)	(0.004)	(0.016)	(0.030)	(0.045)
lag_drought_sq	0.008	-0.000	-0.001	-0.002	-0.010	-0.002	-0.001	-0.001	-0.002	-0.013	-0.009	-0.015
	(0.007)	(0.002)	(0.001)	(0.006)	(0.008)	(0.003)	(0.005)	(0.002)	(0.002)	(0.009)	(0.015)	(0.013)
temp	-0.002	0.005***	0.002**	0.007	0.018	0.006	-0.015	0.002	0.058	-0.030**	-0.038*	0.118
	(0.008)	(0.002)	(0.001)	(0.011)	(0.012)	(0.003)	(0.011)	(0.005)	(0.059)	(0.013)	(0.019)	(0.242)
foodaid_total							0.000	0.000*	-0.000	0.000	0.000	0.000
							(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	0.153	-0.128**	-0.056**	-0.016	-0.375	-0.149	0.456	-0.114	-1.769	0.889**	1.150*	-3.912
	(0.245)	(0.046)	(0.024)	(0.328)	(0.346)	(0.097)	(0.328)	(0.151)	(1.803)	(0.396)	(0.552)	(7.697)
Pseudo R-squared	0.031	0.069	0.050	0.054	0.042	0.056	0.446	0.628	0.466	0.463	0.484	0.390
N	156	156	115	149	149	109	97	97	56	94	94	54
district and time dummies	no	no	no	no	no	no	yes	yes	yes	yes	yes	yes

Table 4: Dep var: urban and rural people in stressed, crisis, and emergency (famine) situations, as a ratio of respectively the total urban and rural population. Regressions are run without and with time and district dummies as indicated, using ols regression with standard errors clustered at the district level. The drought variables are lagged one time period.

We do the same for the percentage underweight individuals and stunted individuals (Table 5, Table 6). The analysis is first done for all livelihoods together (5), and then separately for pastoral, riverine, and urban livelihoods (6). The results in Table 5 show no immediate effect of drought, but when looking at the livelihoods separately, drought seems to have an increasing linear effect on the percentage underweight individuals for pastoral livelihoods. As a robustness check, we also include the quadratic term of the drought variable. This doesn't seem to alter the analysis. However, for riverine households, the relationship between drought and percentage stunted individuals is likely to be quadratic (U-shaped). This suggests a U-shaped relationship between drought and stunted individuals. Both for very low levels of drought (or a lot of rainfall), and for very high levels of drought, there will be an increase in the percentage of stunted individuals. In contrast, the relationship between drought and both underweight and stunted individuals is also quadratic, but 'hump-shaped'. Even though some caution is due here when interpreting the results given the low number of observations for this group, the results seem to indicate an opposite effect as for riverine households. This could be explained by the fact that riverine households are located in the proximity of rivers, and thus excessive rainfall (as well as excessive drought) may have a bigger deteriorating effect on the percentage of underweight and stunted individuals. Urban households on the contrary tend to be net food buyers, so they will likely profit from lower livestock prices, as a consequence of drought. At the same time, pastoral livelihoods – which are mainly livestock herders – face an increasing effect on the percentage stunted individuals when faced with drought. This may equally be explained by the price effect, since drought has a decreasing effect on livestock prices (Maystadt and Ecker, 2014). In all regressions (Table 5), temperature seems to have a strong positive effect on both stunting and percentage underweight individuals.

	pcunderweight est1 b/se	pcstunting est2 b/se	pcunderweight est3 b/se	pcstunting est4 b/se	pcunderweight est5 b/se	pcstunting est6 b/se	pcunderweight est7 b/se	pcstunting est8 b/se
lag_drought	1.500	-0.180	2.669	1.770			1.654	-0.926
	(1.695)	(1.073)	(1.843)	(1.695)			(2.004)	(2.518)
lag_drought_sq			-1.031	-0.829			-0.136	0.307
			(1.225)	(0.734)			(0.876)	(0.851)
lag_stunting		0.778***		0.772***		0.478***		0.540*
		(0.123)		(0.108)		(0.085)		(0.198)
temp					2.565***	2.536***	2.270**	2.789**
					(0.755)	(0.592)	(0.825)	(0.675)
foodaid_total							-0.000	0.000
							(0.000)	(0.000)
_cons	22.441***	2.562	23.287***	2.485	-54.896**	-70.311**	-32.829	-84.380***
	(4.048)	(3.657)	(4.269)	(3.042)	(23.462)	(17.698)	(28.375)	(14.571)
Pseudo R-sq	0.014	0.558	0.027	0.564	0.236	0.579	0.327	0.641
N	324	158	324	158	377	179	208	88

Table 5: Dep var: percentage underweight individuals and stunted individuals. Regressions are run without time and district dummies, using ols regression with standard errors clustered at the district level. The drought variables are lagged one to three time periods, the variable *lag_stunting* is lagged 12 time periods.

	pcunderweight	pcstunting	pcunderweight	pcstunting	pcunderweight	pcstunting	pcunderweight	pcstunting	pcunderweight	pcstunting	pcunderweight	pcstunting
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_drought	1.498	1.970	3.789***	12.699*	2.200**	0.327	2.219**	1.089	-3.257	-0.716	-7.064	-10.443***
	(1.536)	(2.515)	(0.271)	(3.833)	(0.484)	(1.346)	(0.687)	(2.126)	(4.144)	(2.609)	(3.342)	(0.939)
lag_stunting		0.609		0.589		1.068*		1.060*		0.446		0.431
		(0.277)		(0.210)		(0.288)		(0.279)		(0.216)		(0.217)
drought_sq			-2.705*	-5.422**			-0.025	-0.412			1.832	3.767**
			(0.795)	(1.192)			(0.858)	(0.760)			(0.972)	(0.428)
_cons	14.484	4.349	17.254*	1.304	15.484***	-3.594	15.511**	-3.337	32.336**	13.839***	32.819**	16.760**
	(5.555)	(6.668)	(4.061)	(5.775)	(3.233)	(2.329)	(4.076)	(2.144)	(7.511)	(0.175)	(6.935)	(1.953)
Pseudo R-sq	0.049	0.438	0.338	0.526	0.062	0.659	0.062	0.662	0.043	0.215	0.066	0.371
N	45	16	45	16	107	59	107	59	67	37	67	37
Livelihood	urban	urban	urban	urban	pastoral	pastoral	pastoral	pastoral	riverine	riverine	riverine	riverine

Table 6: Dep var: percentage underweight individuals and stunted individuals. Results are depicted by livelihood (urban, pastoral, and riverine). Regressions are run without time and district dummies, using ols regression with standard errors clustered at the district level. The drought variables are lagged one to three time periods, the variable *lag_stunting* is lagged 12 time periods.

To extend the analysis, we also examine the effect of drought on the prevalence of waterborne diseases. Interestingly, the results in Table 7 (see Appendix) show a positive rainfall effect (or a negative drought effect) on under-5-mortality caused by diarrhoea, when adding control variables to the regression. We find no such effect for malaria nor for lower respiratory infections. This confirms the hypothesis that excessive rainfall leads to more deaths caused by waterborne diseases. This finding is important, since diarrhoea remains one of the most important causes of under-5-mortality in Somalia. Battling this disease, especially in riverine regions, is of great importance.

Table 8 and Table 9 show the effect of the conflict variables (one-sided, intrastate, internationalized, and low intensity conflict) on the percentage underweight and stunted individuals, respectively. One-sided conflict, intrastate and low intensity conflict seem to have a significant increasing effect on the percentage underweight individuals. Adjusting standard errors for spatial and temporal correlation as a robustness check doesn't seem to alter these findings, except for the effect of the low intensity variable, which becomes insignificant (Table 9, results shown in the Appendix).

	pcunderweight	pcstunting	pcunderweight	pcstunting	pcunderweight	pcunderweight	pcstunting	pcunderweight	pcstunting
	est1	est2	est3	est4	est5	est6	est7	est8	est9
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	3.298***	1.025							
	(0.907)	(0.830)							
lag_intrastate			4.444***	-0.491					
			(1.317)	(1.243)					
lag_internationalized					-0.241	-2.992*	-1.377		
					(1.055)	(1.404)	(1.067)		
lag_lowintensity								2.109*	-0.423
								(0.959)	(1.024)
lag12_stunting		0.268		0.270			0.269		0.268
		(0.223)		(0.219)			(0.223)		(0.223)
events_history	-0.105	0.088	-0.136	0.108	-0.075	-0.075	0.117	-0.102	0.100
	(0.094)	(0.134)	(0.085)	(0.130)	(0.050)	(0.090)	(0.132)	(0.095)	(0.134)
lnpop	-7.719*	11.696**	-9.485**	12.272**	-1.326	-6.777	12.138***	-7.432*	12.151***
	(3.813)	(2.706)	(3.948)	(2.538)	(2.491)	(4.090)	(2.716)	(3.965)	(2.473)
capdist	-0.406	1.186	-0.372	1.129	0.003	-0.416	1.190	-0.440	1.148
	(0.396)	(0.675)	(0.389)	(0.686)	(0.143)	(0.389)	(0.657)	(0.395)	(0.662)
foodaid_total	-0.000**	0.000	-0.000**	0.000		-0.000**	0.000	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
_cons	453.508	-1043.031	448.198	-1007.779	22.772	448.279	-1052.191	476.317	-1020.000
	(352.319)	(545.820)	(344.110)	(550.353)	(103.090)	(347.106)	(533.268)	(351.509)	(533.875)
Pseudo R-squared	0.758	0.862	0.764	0.862	0.790	0.758	0.863	0.756	0.862
N	232	98	232	98	362	232	98	232	98
district and time dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 8 Dep var: percentage underweight individuals and stunted individuals Regressions are run with time and district dummies, using ols regression with standard errors clustered at the regional level. The variable *lag_stunting* is lagged 12 time periods.

Table 10 and 11 show the equivalent outcomes for the IPC classification variables (percentage of the population in stressed (*AFLC*), crisis (*HE*), and emergency (*famine*) situations). Here the results are mixed. Table 10 reveals a small positive effect of one-sided and internationalized conflict on the percentage of populations experiencing famine. However, when adjusting the standard errors for spatial and temporal correlations as a robustness check (Table 11, results are shown in the Appendix), we find a small positive effect of one-sided and internationalized conflict on the ratio of urban individuals in crisis, a negative effect of one-sided and internationalized conflict on rural individuals in stress, and a negative effect of one-sided and intrastate conflict on the ratio of urban individuals in emergency situations (famine). The mixed effects may be explained by the important effect of food aid on the outcome variables in case of emergency situations. Even though we control for the amount of food aid received, as mentioned before, there may be reversed causality between conflict and food aid, which could bias our estimates.

Table 10 Dep var: urban and rural people in stressed, crisis, and emergency (famine) situations, as a ratio of respectively the total urban and rural population. Regressions are run without and with time and district dummies as indicated, using ols regression with standard errors clustered at the district level. The conflict variables (one-sided, intrastate, and internationalized conflict) are lagged one time period.

	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12	est13	est14	est15	est16	est17	est18
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	-0.003	0.003*	-0.005	-0.069	-0.051	0.052*												
	(0.006)	(0.002)	(0.005)	(0.050)	(0.065)	(0.031)												
lag_intrastate							0.000	0.001	-0.004	0.078***	0.028	-0.018						
							(0.002)	(0.002)	(0.003)	(0.026)	(0.052)	(0.024)						
lag_internationalized													-0.014	0.006*	0.001	-0.071*	-0.057	0.045*
													(0.016)	(0.003)	(0.008)	(0.037)	(0.062)	(0.028)
events history	0.001***	-0.000**	-0.000	0.001	0.001	-0.004	0.001***	-0.000	-0.000	-0.002	-0.001	-0.002	0.001***	-0.000**	-0.001***	0.001	0.001	-0.003
	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	(0.003)	(0.000)	(0.000)	(0.000)	(0.002)	(0.005)	(0.003)	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)	(0.003)
lnpop	0.029	-0.007	0.004	0.151**	0.022	-0.146***	0.028	-0.007	0.004	0.125**	0.009	-0.128**	0.032	-0.008	0.002	0.155**	0.026	-0.146***
	(0.034)	(0.011)	(0.005)	(0.066)	(0.060)	(0.034)	(0.034)	(0.011)	(0.004)	(0.058)	(0.067)	(0.049)	(0.033)	(0.011)	(0.005)	(0.060)	(0.061)	(0.034)
capdist	0.004**	0.000	-0.000	-0.002	0.006	-0.001	0.004**	0.000	-0.000	-0.003	0.006	-0.001	0.004**	0.000	-0.000	-0.002	0.006	-0.001
	(0.002)	(0.001)	(0.000)	(0.003)	(0.005)	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)	(0.005)	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)	(0.005)	(0.002)
foodaid_total	-0.000**	0.000**	-0.000	-0.000	0.000*	-0.000***	-0.000**	0.000**	-0.000	0.000	0.000*	-0.000**	-0.000**	0.000**	-0.000**	-0.000	0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	-3.795**	-0.035	0.422	0.262	-6.024	3.413*	-3.798**	-0.006	0.267	1.117	-5.810	3.217*	-3.756**	-0.046	0.469	0.182	-6.074	3.826*
	(1.609)	(0.706)	(0.360)	(1.959)	(5.176)	(1.601)	(1.611)	(0.709)	(0.484)	(1.744)	(5.470)	(1.775)	(1.581)	(0.704)	(0.366)	(1.747)	(4.929)	(1.951)
Pseudo R-squared	0.557	0.635	0.834	0.547	0.449	0.468	0.557	0.634	0.834	0.566	0.448	0.448	0.559	0.636	0.830	0.557	0.451	0.465
N	107	107	62	104	104	60	107	107	62	104	104	60	107	107	62	104	104	60
district and time dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Examining the regression results at the district (not livelihood) level (Table 12, 13), we do not find evidence for an effect of drought on most of the conflict variables. Temperature seems to affect low intensity and internationalized conflict positively. Adding time and district dummies to the regression in Table 13, cancels out the effect of temperature on conflict. However, drought is more than just heat or absence of rainfall (what our drought variable measures), it is the combination of high temperatures and low rainfall. When including both drought and temperature in the regression, the drought variable becomes significant.

	onesided	**intrastate**	**internat**	**lowintens**	**onesided**	**intrastate**	**internat**	**lowintens**	**onesided**	**intrastate**	**internat**	**lowintens**
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_drought	0.121	0.110	-0.006	0.012	0.101	0.100	-0.004	0.009				
	(0.087)	(0.110)	(0.025)	(0.008)	(0.085)	(0.115)	(0.029)	(0.007)				
lag_drought_sq					0.031	0.016	-0.004	0.005				
					(0.023)	(0.023)	(0.009)	(0.003)				
temp									0.008	0.019	0.013***	0.002*
									(0.010)	(0.015)	(0.005)	(0.001)
_cons	0.335**	0.443	0.152**	0.038***	0.307*	0.429	0.155**	0.033***	-0.012	-0.277	-0.299**	-0.024
	(0.149)	(0.269)	(0.061)	(0.009)	(0.156)	(0.281)	(0.067)	(0.009)	(0.239)	(0.326)	(0.118)	(0.025)
Pseudo R-squared	0.005	0.001	0.000	0.004	0.006	0.001	0.000	0.006	0.000	0.001	0.004	0.001
N	7656	7656	7656	8566	7656	7656	7656	8566	16068	16068	16068	21036

Table 12: Dep var: conflict indicators. Regressions are run without time and district dummies, using ols regression with standard errors clustered at the district level.

Table 13: Dep var: conflict indicators. Regressions are run with time and district dummies, using ols regression with standard errors clustered at the district level.

	onesided	**intrastate**	**internat**	**lowintens**	**onesided**	**intrastate**	**internat**	**lowintens**	**onesided**	**intrastate**	**internat**	**lowintens**	**onesided**	**intrastate**	**internat**	**lowintens**
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12	est13	est14	est15	est16
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_drought	0.093	0.037	-0.022	0.008	0.105	0.089	-0.003	0.009					0.082*	0.090	0.002	0.009*
	(0.060)	(0.057)	(0.025)	(0.007)	(0.064)	(0.084)	(0.026)	(0.006)					(0.048)	(0.080)	(0.018)	(0.005)
lag_drought_sq					-0.017	-0.074	-0.028	-0.002					-0.016	-0.076	-0.029	-0.003
					(0.028)	(0.068)	(0.017)	(0.002)					(0.028)	(0.070)	(0.017)	(0.003)
temp									0.028	-0.020	-0.017	0.002	0.065	0.021	-0.007	0.008
									(0.035)	(0.026)	(0.015)	(0.005)	(0.058)	(0.045)	(0.023)	(0.007)
_cons	1.145***	1.656**	0.724***	-0.044***	-0.031	0.001	-0.013	-0.040***	-0.655	0.868	0.561	-0.083	-2.221	-0.871	0.344	-0.214
	(0.389)	(0.772)	(0.220)	(0.012)	(0.104)	(0.084)	(0.026)	(0.013)	(1.188)	(0.905)	(0.499)	(0.159)	(1.700)	(1.344)	(0.679)	(0.210)
Pseudo R-squared	0.355	0.304	0.221	0.213	0.356	0.306	0.224	0.213	0.330	0.287	0.199	0.161	0.358	0.307	0.225	0.221
N	7656	7656	7656	8566	7656	7656	7656	8566	16068	16068	16068	21036	7308	7308	7308	7660
district and time dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 14 shows the results of the effect of conflict on the IPC food security indicators (percentage of the population in stressed (*AFLC*), crisis (*HE*), and emergency (*famine*) situations) when including the drought variable in the regression, while the regressions displayed in Table 15 do this for the percentage underweight and stunted individuals. Overall, the results remain largely the same for the IPC classification indicators when including drought as a control variable (Table 14), as compared to Table 10, showing the results without the drought variable. Again, we find a small positive effect of one-sided and internationalized conflict on the percentage of populations experiencing famine. For the anthropometric measures of food insecurity, adding drought to the equation doesn't alter the results found in Table 8 (without the drought variable), except for the disappearing of the significant negative effect of internationalized conflict on the percentage underweight individuals when controlling for food aid, as was displayed in Table 8.

Table 14: Dep var: urban and rural people in stressed, crisis, and emergency (famine) situations, as a ratio of respectively the total urban and rural population. The drought variable is included in the model. Regressions are run without and with time and district dummies as indicated, using ols regression with standard errors clustered at the district level. The conflict variables (one-sided, intrastate, and internationalized conflict) are lagged one time period.

	AFLC_urban	HE_urban	famine_urbar	AFLC_rural	HE_rural	famine_rural	AFLC_urban	HE_urban	famine_urbar	AFLC_rural	HE_rural	famine_rural	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12	est13	est14	est15	est16	est17	est18
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	-0.004	0.003*	-0.004	-0.073	-0.042	0.058*												
	(0.007)	(0.002)	(0.006)	(0.050)	(0.070)	(0.029)												
lag_intrastate							0.000	0.001	-0.003	0.080**	0.042	-0.027						
							(0.002)	(0.002)	(0.004)	(0.028)	(0.059)	(0.033)						
lag_internationalized													-0.014	0.005*	0.003	-0.080**	-0.054	0.053**
													(0.016)	(0.003)	(0.010)	(0.035)	(0.056)	(0.023)
drought	0.003	-0.007	-0.002	-0.014	-0.076*	0.001	0.003	-0.007	-0.002	-0.016	-0.078*	0.013	0.003	-0.007	-0.003	-0.013	-0.075*	0.003
	(0.009)	(0.007)	(0.003)	(0.020)	(0.044)	(0.012)	(0.009)	(0.007)	(0.003)	(0.018)	(0.043)	(0.018)	(0.008)	(0.007)	(0.003)	(0.018)	(0.044)	(0.009)
events history	0.001***	-0.000**	-0.001	0.001	0.001	-0.005	0.001***	-0.000	-0.000	-0.002	-0.001	-0.002	0.001***	-0.000**	-0.001**	0.000	0.000	-0.004
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)	(0.003)	(0.000)	(0.000)	(0.000)	(0.002)	(0.005)	(0.004)	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)	(0.003)
lnpop	0.044	-0.001	0.002	0.174**	0.017	-0.153***	0.043	-0.001	0.002	0.140*	-0.002	-0.124*	0.047	-0.002	-0.000	0.176**	0.020	-0.150***
	(0.035)	(0.011)	(0.007)	(0.076)	(0.066)	(0.046)	(0.034)	(0.011)	(0.006)	(0.070)	(0.073)	(0.071)	(0.035)	(0.011)	(0.006)	(0.070)	(0.067)	(0.046)
capdist	0.004**	0.000	-0.000*	-0.002	0.005	-0.001	0.004**	0.000	-0.000	-0.003	0.004	-0.000	0.004**	0.000	-0.000*	-0.002	0.005	-0.001
	(0.002)	(0.001)	(0.000)	(0.002)	(0.005)	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)	(0.005)	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)	(0.005)	(0.002)
foodaid_total	-0.000*	0.000**	-0.000	-0.000	0.000	-0.000**	-0.000*	0.000**	-0.000	0.000	0.000*	-0.000*	-0.000*	0.000**	-0.000*	-0.000	0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	-4.467**	-0.099	0.547*	-0.521	-4.770	3.692*	-4.467**	-0.072	0.424	0.554	-4.213	2.726	-4.419**	-0.115	0.628*	-0.419	-4.691	3.863*
	(1.626)	(0.794)	(0.355)	(1.658)	(5.285)	(1.858)	(1.629)	(0.797)	(0.507)	(1.452)	(5.601)	(2.161)	(1.589)	(0.797)	(0.345)	(1.516)	(5.063)	(2.134)
Pseudo R-squared	0.560	0.633	0.837	0.546	0.478	0.483	0.559	0.631	0.837	0.564	0.479	0.460	0.562	0.633	0.836	0.558	0.480	0.479
N	95	95	55	92	92	53	95	95	55	92	92	53	95	95	55	92	92	53
district and time dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

	pcunderweight	pcstunting	pcunderweight	pcstunting	pcunderweight	pcunderweight	pcstunting	pcunderweight	pcstunting
	est1	est2	est3	est4	est5	est6	est7	est8	est9
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	3.526***	0.918							
	(0.861)	(0.749)							
lag_intrastate			4.252***	-0.528					
			(1.027)	(1.283)					
lag_internationalized					-0.141	-2.567	-1.720		
					(1.073)	(1.426)	(1.359)		
lag_lowintensity								2.413*	-0.561
								(1.261)	(1.145)
drought	0.192	0.227	0.117	0.275	0.124	0.229	0.334	0.081	0.308
	(0.809)	(1.157)	(0.745)	(1.090)	(0.629)	(0.903)	(1.204)	(0.842)	(1.032)
lag12_stunting		0.285		0.285			0.284		0.284
		(0.229)		(0.226)			(0.228)		(0.229)
events_history	-0.159*	0.094	-0.187**	0.115	-0.100*	-0.136	0.127	-0.159*	0.106
	(0.078)	(0.152)	(0.066)	(0.144)	(0.047)	(0.083)	(0.154)	(0.084)	(0.150)
lnpop	-8.882*	11.330	-10.581**	12.418*	-0.662	-7.700	11.980*	-8.408*	11.659
	(4.362)	(5.513)	(4.133)	(4.616)	(2.466)	(4.811)	(5.419)	(4.588)	(5.763)
capdist	-0.759	1.143	-0.719	1.161	-0.113	-0.751	1.188	-0.781	1.086
	(0.509)	(0.953)	(0.478)	(0.925)	(0.137)	(0.513)	(0.940)	(0.509)	(1.057)
foodaid_total	-0.000**	0.000	-0.000**	0.000		-0.000**	0.000	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
_cons	757.751	-1006.352	746.197	-1034.401	107.383	735.049	-1048.895	768.161	-967.575
	(458.049)	(791.029)	(430.471)	(756.860)	(107.360)	(462.518)	(780.393)	(459.318)	(873.665)
Pseudo R-squared	0.777	0.830	0.782	0.830	0.799	0.776	0.831	0.776	0.830
N	208	88	208	88	324	208	88	208	88
district and time dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 15: Dep var: percentage underweight individuals and stunted individuals. The drought variable is included in the model. Regressions are run with time and regional dummies, using ols regression with standard errors clustered at the district level. The variable *lag_stunting* is lagged 12 time periods.

Looking into the effect of drought on the normalized maize-sorghum price index (Table 16), after introducing time and district fixed effects and other control variables, we find a very small positive price effect as expected for agricultural crops. Temperature has a small negative effect on prices, and a small positive one on volatility. However, these effects disappears when controlling for time and district fixed effects, while the effect of drought on the normalized prices remains. This may be due to the fact that the temperature variable measures yearly mean temperature, rather than temperature anomalies, and may therefore not display enough variation.

Table 16: Dep var food security indicators: the normalized maize-sorghum price index and volatility measure. Regressions are run without time and district dummies as indicated, using ols regression with standard errors clustered at the district level.

	price	price	volatility	volatility	price	volatility	price	price	price	price	volatility	volatility	volatility	volatility
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12	est13	est14
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_drought	-0.026**	-0.027**	-0.003	0.003			0.022**		0.023**		0.009		0.003	
	(0.012)	(0.013)	(0.006)	(0.006)			(0.009)		(0.009)		(0.006)		(0.004)	
lag_drought_sq		0.002		-0.005**			-0.009***		-0.010***				0.000	
		(0.005)		(0.002)			(0.003)		(0.003)				(0.001)	
temp					-0.022**	0.008***		0.013		0.011		0.006		0.004
					(0.009)	(0.002)		(0.013)		(0.014)		(0.005)		(0.006)
lnpop									-0.007	-0.006			0.009	0.011
									(0.009)	(0.008)			(0.008)	(0.006)
capdist									0.003	0.002			0.001	0.000
									(0.003)	(0.002)			(0.001)	(0.001)
foodaid_total									-0.000	-0.000			-0.000	-0.000
									(0.000)	(0.000)			(0.000)	(0.000)
_cons	0.487***	0.486***	0.189***	0.192***	1.150***	-0.081	0.880***	0.653**	-2.260	-1.171	0.150***	0.042	-0.525	0.081
	(0.032)	(0.033)	(0.015)	(0.015)	(0.253)	(0.070)	(0.025)	(0.305)	(2.791)	(1.876)	(0.052)	(0.124)	(1.072)	(0.218)
Pseudo R-sq	0.009	0.009	0.000	0.002	0.081	0.054	0.518	0.522	0.527	0.527	0.325	0.497	0.504	0.506
N	4720	4720	3557	3557	5219	3960	4720	5219	4128	4710	3557	3960	3048	3444
district and time dummies	no	no	no	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes

	price	volatility	price	volatility	price	volatility	price	volatility
	est1	est2	est3	est4	est5	est6	est7	est8
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	-0.001	-0.000						
	(0.003)	(0.002)						
lag_intrastate			-0.003	-0.000				
			(0.004)	(0.002)				
lag_internationalized					-0.001	-0.003*		
					(0.005)	(0.002)		
lag_lowintensity							-0.014	-0.007
							(0.015)	(0.009)
events_history	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnpop	-0.009	0.007	-0.008	0.007	-0.009	0.007	-0.009	0.007
	(0.008)	(0.005)	(0.008)	(0.006)	(0.008)	(0.005)	(0.008)	(0.005)
capdist	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
_cons	-0.414	-0.208	-0.425	-0.206	-0.410	-0.202	-0.531	-0.411
	(1.286)	(0.718)	(1.272)	(0.717)	(1.290)	(0.713)	(1.369)	(0.704)
Pseudo R-squared	0.527	0.489	0.527	0.489	0.527	0.489	0.525	0.497
N	5155	3878	5155	3878	5155	3878	5195	3936
district and time dummies	no	no	no	no	no	no	yes	yes

Table 17: Dep var food security indicators: the normalized maize-sorghum price index and volatility measure. Regressions are run without and with time and district dummies as indicated, using ols regression with standard errors clustered at the district level.

Table 17 displays the results of the regressions of the conflict variables on the price variables. Whilst there is evidence for a very small negative effect (almost zero) from internationalized conflict, using adjusted error terms for spatial and temporal correlation as a robustness check (Table 19, see Appendix)) slightly alters the estimation results of the model. Internationalize conflict has a very small, near zero, positive effect and low intensity conflict affects the price variables (price and volatility respectively) negatively. Controlling for the amount of food aid received does not alter the regression results. Overall, the effect of the conflict variables on the price variables is very small (Table 18).

	price	volatility	price	volatility	price	volatility	price	volatility
	est1	est2	est3	est4	est5	est6	est7	est8
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	0.002	0.002						
	(0.003)	(0.002)						
lag_intrastate			0.002	-0.001				
			(0.007)	(0.001)				
lag_internationalized					0.003	-0.004**		
					(0.006)	(0.002)		
lag_lowintensity							0.001	-0.005
							(0.018)	(0.005)
events_history	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnpop	-0.005	0.005	-0.005	0.006	-0.005	0.006	-0.005	0.007
	(0.008)	(0.005)	(0.008)	(0.005)	(0.008)	(0.005)	(0.008)	(0.005)
capdist	0.002	0.001	0.002	0.001	0.002	0.000	0.002	0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
foodaid_total	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	-0.754	0.087	-0.755	0.079	-0.765	0.079	-0.894	0.058
	(1.538)	(0.103)	(1.530)	(0.105)	(1.545)	(0.101)	(1.640)	(0.106)
Pseudo R-squared	0.529	0.425	0.529	0.425	0.529	0.426	0.527	0.429
N	4670	3386	4670	3386	4670	3386	4710	3444
district and time dummies	yes	yes	yes	yes	yes	yes	yes	yes

Table 18: Dep var food security indicators: the normalized maize-sorghum price index and volatility measure. Regressions are run with time and district dummies, using ols regression with standard errors clustered at the district level.

Table 20 shows the results of the effect of conflict on the price indicators (the maize-sorghum price index and the volatility measure) when including the drought variable in the regression. Again, adding drought as a control variable doesn’t seem to alter the regression results, suggesting that the estimates of the model measuring the effect of conflict on food security indicators (IPC indicators in Table 14, anthropometric measures in Table 15, and price variables in Table 20) are unbiased, even in the presence of a potential endogenous regression variable. This may be explained by the fact that the conflict variables are lagged one time period, unlike the drought variable in these regressions, and thus simultaneity bias may be avoided.

	price	price	price	price	volatility	volatility	volatility	volatility
	est1	est2	est3	est4	est5	est6	est7	est8
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	0.001	0.002						
	(0.004)	(0.002)						
lag_intrastate			0.005	-0.001				
			(0.008)	(0.001)				
lag_internationalized					0.007	-0.003*		
					(0.007)	(0.002)		
lag_lowintensity							0.012	-0.003
							(0.022)	(0.006)
drought	0.012	0.004	0.012	0.004	0.012	0.004	0.012	0.004
	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)	(0.002)	(0.008)	(0.002)
events_history	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnpop	-0.005	0.005	-0.006	0.006	-0.005	0.006	-0.006	0.007
	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)	(0.009)	(0.006)
capdist	0.003	0.001	0.003	0.001	0.003	0.001	0.003	0.001
	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
foodaid_total	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	-2.048	0.086	-2.046	0.076	-2.085	0.078	-2.299	0.053
	(2.626)	(0.117)	(2.617)	(0.119)	(2.645)	(0.116)	(2.791)	(0.120)
Pseudo R-squared	0.525	0.425	0.526	0.425	0.526	0.425	0.524	0.429
N	4087	2992	4087	2992	4087	2992	4127	3050
district and time dummies	yes	yes	yes	yes	yes	yes	yes	yes

Table 20: Dep var food security indicators: the normalized maize-sorghum price index and volatility measure. Regressions are run with time and district dummies, using ols regression with standard errors clustered at the district level.

On the household level, we use different food security outcomes, namely the imputed food consumption score, based on food consumption measured over 7 days prior to the interview, food expenditures, and non-food expenditures. These variables are directly related to food prices, since prices will determine the household purchasing power. As mentioned before, studying expenditures on non-food items may be interesting, because cutting expenses on non-food items may serve as a household coping strategy in times of hardships (Christiaensen and Sarris, 2007; D'Souza and Jolliffe, 2012). Reducing expenditure on non-food items is a less costly coping mechanism and therefore likely to be preferred by households who can afford it than reducing food expenditures (Christiaensen and Sarris, 2007). The household dataset allows us to distinguish between urban and pastoral households (the biggest groups in the dataset). Since urban households tend to be net food buyers, they will likely profit from lower food prices, while pastoralists may suffer more from it or profit from it, depending on their net food production status (pastoralists are traditionally livestock herders). As such, we may find a differential effect of drought or conflict on the food security score for both livelihoods.

Table 21 show the results of bivariate regressions of drought (and/or temperature) on food security outcomes and conflict. Table 21 shows that drought seems to have a positive effect on all food security outcomes, whilst temperature has a negative one. When including both rainfall-based drought and temperature in the regression equation, the signs remain the same, but the temperature effect seems bigger than the rainfall-based drought effect. From Table 22, we learn that drought has a positive triggering effect on conflict exposure, as experienced by the household. At the household level, we do not include the quadratic drought term, because of collinearity with the drought variable.

	fcs	food_exp	nonfood_exp	fcs	food_exp	nonfood_exp	fcs	food_exp	nonfood_exp	fcs	food_exp	nonfood_exp
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
drought	7.066***	0.707***	0.341***				4.072***	0.189***	0.282***	4.482***	0.142	0.235***
	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)	(0.367)	(0.074)	(0.035)
temp				-8.342***	-1.229***	-0.540***	-6.274***	-1.085***	-0.124***	-4.584***	-0.832***	0.094
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.707)	(0.128)	(0.068)
log_formal_transfer										0.053	0.005	-0.027
										(0.067)	(0.030)	(0.022)
log_informal_transfer										-0.130	-0.033	-0.010
										(0.153)	(0.028)	(0.006)
femhead										-0.084	-0.314	-0.452**
										(0.217)	(0.652)	(0.116)
hhsize										0.199	0.048**	0.047***
										(0.253)	(0.012)	(0.008)
educhead										0.363	-0.025	-0.001
										(0.301)	(0.032)	(0.023)
log hh income										0.287	0.103	0.189**
										(0.355)	(0.083)	(0.056)
distance_market										0.027	0.010*	0.001
										(0.019)	(0.003)	(0.001)
distance_health										-0.002	-0.001	-0.000
										(0.005)	(0.001)	(0.000)
shagr_wge										2.510	0.544	0.326
										(11.048)	(0.284)	(0.591)
shnonagr_wge										0.438	-0.606*	-0.048
										(4.472)	(0.239)	(0.072)
shcrop										-6.240***	-0.935	-0.743*
										(1.000)	(0.583)	(0.258)
shlivestock										1.599	-1.502*	-0.738
										(2.291)	(0.541)	(0.321)
shselfemp										-3.313	-1.116	-0.273
										(2.649)	(0.729)	(0.203)
shtransfer										-2.929	0.520	1.499
										(2.450)	(0.829)	(0.650)
_cons	47.761***	12.175***	12.543***	279.033***	46.433***	27.574***	222.964***	42.485***	15.997***	171.707***	35.195***	7.959**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(19.975)	(3.958)	(2.370)
Pseudo R-squared	0.159	0.065	0.060	0.159	0.065	0.060	0.159	0.065	0.060	0.182	0.084	0.149
N	1564	1591	1591	1564	1591	1591	1564	1591	1591	1195	1212	1212
district FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 21: Dep var imputed food security score, food expenditures, and non-food expenditures. Regressions are run with district dummies, using ols regression with standard errors clustered at the district level.

	conflict	conflict	conflict	conflict	conflict
	est1	est2	est3	est4	est5
	b/se	b/se	b/se	b/se	b/se
drought	0.105		0.140***		0.133***
	(0.045)		(0.000)		(0.000)
temp		-0.084		0.000***	-0.015***
		(0.107)		(0.000)	(0.000)
_cons	0.148**	2.521	0.171***	0.093***	0.592***
	(0.031)	(2.975)	(0.000)	(0.000)	(0.000)
Pseudo R-	0.032	0.005	0.057	0.057	0.057
N	1570	1570	1570	1570	1570
district FE	no	no	yes	yes	yes

Table 22: Dep var conflict exposure. Regressions are run with and without district dummies (as indicated), using ols regression with standard errors clustered at the district level.

In line with the analysis extension on the district level discussed above, we also examine the effect of drought on waterborne diseases (malaria, typhoid) at the household level (results shown in the Appendix). Again, we find a negative drought effect (or a positive rainfall) on both malaria and typhoid (Table 23, and Table 24 including all control variables, see Appendix).

Table 25 shows the result of the regressions of the conflict exposure measures on the food security outcomes. We find a positive effect on the food consumption score. When looking at food and non-food expenditures, we see a negative effect of conflict exposure on consumption of non-food items. This is in line with the 'non-food coping strategy hypothesis', where households experiencing shocks lower their consumption of non-food items as a coping mechanism (amongst other possible coping mechanisms) (Christiaensen and Sarris, 2007; D'Souza and Jolliffe, 2012). Table 26 shows the results by livelihood. Interestingly, we find that the effect on food-expenditures is now negative and significant for pastoral households, while positive and significant for urban households. This shows that pastoral (rural) households, who are net producers of food, are more likely to become more food insecure when exposed to conflict than urban households, who are net buyers of food.

	fcs	food_exp	nonfood_exp
	est1	est2	est3
	b/se	b/se	b/se
conflict	3.053*	0.162	-0.144***
	(1.033)	(0.100)	(0.024)
log formal transfer	-0.000	0.000	-0.000**
	(0.000)	(0.000)	(0.000)
log informal transfer	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)
femhead	0.234	-0.294	-0.445**
	(0.164)	(0.652)	(0.107)
hhsize	0.180	0.046*	0.050**
	(0.256)	(0.015)	(0.010)
educhead	0.381	-0.027	-0.002
	(0.308)	(0.035)	(0.024)
log hh income	0.247	0.096	0.170**
	(0.350)	(0.070)	(0.052)
distance_market	0.024	0.010*	0.001
	(0.019)	(0.004)	(0.001)
distance_health	-0.001	-0.001	-0.000
	(0.005)	(0.001)	(0.000)
shagr_wge	2.497	0.481	0.402
	(11.504)	(0.413)	(0.471)
shnonagr_wge	1.290	-0.528	0.063
	(4.202)	(0.296)	(0.082)
shcrop	-5.289**	-0.833	-0.729*
	(1.475)	(0.578)	(0.234)
shlivestock	2.089	-1.464*	-0.680
	(1.941)	(0.613)	(0.317)
shselfemp	-2.588	-1.029	-0.233
	(2.295)	(0.718)	(0.203)
shtransfer	-4.241	0.186	1.088*
	(5.060)	(0.579)	(0.449)
_cons	39.675***	11.624***	10.658***
	(2.881)	(1.375)	(0.582)
Pseudo R-squared	0.194	0.085	0.149
N	1180	1196	1196
district FE	yes	yes	yes

Table 25: Dep var imputed food security score, food expenditures, and non-food expenditures. Regressions are run with district dummies, using ols regression with standard errors clustered at the district level.

	fcs	food_exp	nonfood_exp	fcs	food_exp	nonfood_exp
	est1	est2	est3	est1	est2	est3
	b/se	b/se	b/se	b/se	b/se	b/se
conflict	5.034***	0.334***	-0.087**	1.932	-0.159**	-0.230***
	(0.034)	(0.003)	(0.020)	(1.051)	(0.044)	(0.021)
log formal transfer	0.000***	-0.000***	-0.000***	-0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log informal transfer	0.000***	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
femhead	2.805***	-0.069	-0.723*	0.862	-0.754	-0.229
	(0.339)	(0.223)	(0.231)	(0.691)	(1.055)	(0.131)
hhsize	-0.138**	0.010	-0.002	0.100	0.106**	0.044*
	(0.036)	(0.018)	(0.013)	(0.143)	(0.028)	(0.019)
educhead	0.304***	0.003	0.004	0.425	-0.061	0.039*
	(0.008)	(0.004)	(0.004)	(0.282)	(0.040)	(0.014)
log hh income	0.021	0.213***	0.326***	1.181***	-0.008	0.093
	(0.103)	(0.015)	(0.013)	(0.177)	(0.150)	(0.048)
distance_market	0.136***	0.021**	0.015**	0.005	0.015*	0.000
	(0.018)	(0.005)	(0.004)	(0.010)	(0.006)	(0.002)
distance_health	-0.046	-0.003	-0.004	-0.002	-0.001	-0.000***
	(0.046)	(0.008)	(0.013)	(0.008)	(0.001)	(0.000)
shagr_wge	-4.229***	0.335*	0.361**	13.552	0.103	1.126*
	(0.501)	(0.121)	(0.081)	(15.527)	(1.085)	(0.370)
shnonagr_wge	2.448*	0.617***	0.525***	-1.949	-1.089	-0.482
	(0.917)	(0.049)	(0.069)	(7.441)	(0.586)	(0.276)
shcrop	-70.359**	-9.676	-0.289	5.235	1.135	0.039
	(21.079)	(5.338)	(6.236)	(4.333)	(0.995)	(0.495)
shlivestock	2.083	0.288	-0.188	3.617	-2.060	-0.858*
	(1.128)	(0.259)	(0.206)	(4.275)	(0.929)	(0.310)
shselfemp	-2.408*	0.396***	0.746***	-4.033	-2.076	-0.685**
	(0.769)	(0.025)	(0.017)	(5.996)	(0.971)	(0.150)
shtransfer	-11.428***	2.036***	3.632***	9.479	-0.082	-0.150
	(1.191)	(0.167)	(0.156)	(4.832)	(1.230)	(0.552)
_cons	36.416***	10.146***	8.244***	26.864**	13.470**	11.773***
	(0.949)	(0.183)	(0.213)	(5.535)	(2.711)	(0.315)
Pseudo R-squared	0.153	0.166	0.312	0.308	0.105	0.097
N	212	212	212	550	561	561
district FE	yes	yes	yes	yes	yes	yes
Livelihood	urban	urban	urban	pastoral	pastoral	pastoral

Table 26: Dep var imputed food security score, food expenditures, and non-food expenditures. Results are depicted by livelihood (urban and pastoral livelihoods). Regressions are run with district dummies, using ols regression with standard errors clustered at the district level.

Below, Table 27 shows the results of the effect of conflict on the food security indicators, when including the drought variable in the model. The results remain largely the same as in Table 25, without including the drought variable.

	fcs	food_exp	nonfood_exp
	est1	est2	est3
	b/se	b/se	b/se
conflict	3.053*	0.162	-0.144***
	(1.033)	(0.100)	(0.024)
drought	6.311***	0.542***	0.183**
	(0.497)	(0.035)	(0.046)
log formal transfer	-0.000	0.000	-0.000**
	(0.000)	(0.000)	(0.000)
log informal transfer	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)
femhead	0.234	-0.294	-0.445**
	(0.164)	(0.652)	(0.107)
hhsize	0.180	0.046*	0.050**
	(0.256)	(0.015)	(0.010)
educhead	0.381	-0.027	-0.002
	(0.308)	(0.035)	(0.024)
totincome1	0.247	0.096	0.170**
	(0.350)	(0.070)	(0.052)
distance_market	0.024	0.010*	0.001
	(0.019)	(0.004)	(0.001)
distance_health	-0.001	-0.001	-0.000
	(0.005)	(0.001)	(0.000)
shagr_wge	2.497	0.481	0.402
	(11.504)	(0.413)	(0.471)
shnonagr_wge	1.290	-0.528	0.063
	(4.202)	(0.296)	(0.082)
shcrop	-5.289**	-0.833	-0.729*
	(1.475)	(0.578)	(0.234)
shlivestock	2.089	-1.464*	-0.680
	(1.941)	(0.613)	(0.317)
shselfemp	-2.588	-1.029	-0.233
	(2.295)	(0.718)	(0.203)
shtransfer	-4.241	0.186	1.088*
	(5.060)	(0.579)	(0.449)
_cons	43.093***	11.918***	10.757***
	(2.962)	(1.374)	(0.589)
Pseudo R-squared	0.194	0.085	0.149
N	1180	1196	1196
district FE	yes	yes	yes

Table 27: Dep var imputed food security score, food expenditures, and non-food expenditures. The drought variable is included in the model. Regressions are run with district dummies, using ols regression with standard errors clustered at the district level.

Finally, Table 28 displays the results of the estimation of the effect of drought on food security outcomes. The positive drought effect on the food consumption score (*fcs*) disappears, while the effect on non-food expenditures (*nonfood_exp*) becomes apparent, again in accordance with the non-food coping strategy hypothesis. This finding corresponds to our expectations, and in contrast with the counter-intuitive positive drought effect found in Table 21. The latter could be explained by the use of a panel dataset (a two year panel) for the results shown in Table 28, which us allows to control for unobserved household heterogeneity, as opposed to the cross-sectional analysis of the Somaliland and Puntland survey data (Table 21).

	fcs	food_exp	nonfood_exp	fcs	food_exp	nonfood_exp
	est1	est2	est3	est4	est5	est6
	b/se	b/se	b/se	b/se	b/se	b/se
drought_start	-4.129***	-0.009	-1.283***	-2.041	0.003	-1.225***
	(1.204)	(0.066)	(0.065)	(1.256)	(0.066)	(0.066)
femhead				6.988**	0.329***	0.260**
				(2.932)	(0.120)	(0.116)
hhsize				1.427**	0.086**	0.121***
				(0.551)	(0.035)	(0.034)
educhead				-0.039	0.025	0.053*
				(0.718)	(0.025)	(0.028)
totincome1				0.001	0.000	-0.000
				(0.001)	(0.000)	(0.000)
distance_market				9.720***	0.007	0.155
				(3.086)	(0.158)	(0.190)
distance_health				6.183**	0.275**	0.542***
				(2.912)	(0.136)	(0.193)
shagr_wge				7.025	0.190	0.837***
				(9.833)	(0.307)	(0.308)
shnonagr_wge				0.092	0.000	-0.003
				(0.058)	(0.002)	(0.005)
shcrop				-7.378	-0.400	-0.257
				(6.554)	(0.415)	(0.255)
shlivestock				-5.710	0.052	-0.271
				(3.706)	(0.252)	(0.201)
shselfemp				6.267**	0.118	0.247
				(2.640)	(0.099)	(0.190)
_cons	68.550***	7.232***	6.195***	42.469***	6.323***	4.780***
	(2.080)	(0.111)	(0.114)	(5.362)	(0.317)	(0.306)
Pseudo R-squared	0.033	0.000	0.534	0.243	0.084	0.695
N	342	342	342	272	272	272
district and year dummies	no	no	no	no	no	no

Table 28: Dep var imputed food security score, food expenditures, and non-food expenditures. Regressions are run using the difference-in-difference approach, with standard errors clustered at the district level.

6 Conclusion

Overall, the results of this analysis show that it is valuable to study the relationship between conflict, drought and food security on different levels of aggregation, because this reveals findings that are not visible at higher levels of aggregation. Moreover, by distinguishing between different livelihoods – for instance urban vs rural, or urban vs pastoral, agro-pastoral, riverine – we can draw conclusions that hold for certain livelihoods while not for others due to a difference in livelihood-specific characteristics.

We find a positive effect of drought on the percentage underweight individuals for pastoral livelihoods on the regional level. Interestingly, our results reveal a U-shaped relationship between drought and both the percentage underweight and stunted individuals for riverine livelihoods, suggesting that for these livelihoods, who are located in the proximity of rivers, both excessive rainfall as well as excessive drought have a deteriorating effect on the percentage of underweight and stunted individuals. We also find that drought seems to have a small increasing effect on the ratio of rural populations in stressed, crisis, and emergency food security situations, while there seems to be no significant effect for urban populations. On the household level, based on evidence from a Somaliland and Puntland survey, we find a positive effect of rainfall-based drought on food security outcomes. However, using a panel dataset obtained from a household survey that took place in Doolow (Gedo region), a negative effect of drought on non-food expenditures is found, affirming the hypothesis that the households in our analysis will buy less non-food items when confronted with distressing situations.

Our results – both on the regional and household level - confirm the hypothesis that more than average rainfall leads to a higher incidence of under-5 deaths caused by waterborne diseases (diarrhoea and typhoid). The finding that excessive rainfall also leads to poorer food security outcomes, confirms the close link between food security and health outcomes. Waterborne disease infection could be a channel through which rainfall affects food security in an indirect way, while poor food security outcomes will inevitably result in poorer resistance to infections. The policy implication of this finding is that battling and preventing these diseases, especially in riverine regions, is of great importance. This holds even stronger in the case of diarrhoea, which remains one of the most important causes of under-5-mortality in Somalia.

On the district level, we do not find substantial evidence that drought triggers conflict. In contrast, on the household level we do find strong evidence for this, suggesting that conflict analysis at a lower aggregation level does reveal some findings that we may not pick up on when running the analysis at a higher aggregation level.

Finally, we find an increasing effect of one-sided, intrastate, and internationalized conflict on the percentage underweight individuals on the district level. On the household level, there is strong evidence for a negative effect of conflict on non-food expenditures, which also confirms the household non-food coping strategy hypothesis. In addition, there is evidence of a negative effect of conflict exposure on food expenditures for pastoral (rural) households, in contrast with urban households. This emphasizes the fact that conflict has a more profound effect on the food security of rural households, notwithstanding their functions as food producers.

7 References

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8 Appendix

	diarrhoea	malaria	respiratory	diarrhoea	malaria	respiratory	diarrhoea	malaria	respiratory	diarrhoea	malaria	respiratory
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
drought	-8.313	-2.470	-5.221	-16.352	-2.999	-10.889	-17.752*	-3.218	-10.520	-15.219*	-2.057	-11.817
	(6.501)	(3.326)	(8.904)	(10.964)	(4.602)	(15.904)	(10.485)	(3.852)	(14.929)	(7.160)	(4.235)	(10.951)
drought_sq	9.274	2.808	0.024	12.583	3.256	5.160	14.485	0.281	17.567	-27.930	-4.331	-42.676
	(11.131)	(4.271)	(13.843)	(11.857)	(5.062)	(16.901)	(10.597)	(5.192)	(14.124)	(18.241)	(6.776)	(28.550)
temp				4.277	0.197	1.983	7.122*	0.557	1.572	18.255**	1.550	22.560**
				(3.151)	(0.934)	(5.504)	(3.669)	(0.961)	(6.060)	(4.231)	(2.992)	(6.282)
lnpop							-0.753	-0.354*	1.129	1.048	0.066	2.331
							(0.757)	(0.214)	(1.142)	(1.106)	(0.280)	(1.740)
capdist							-0.942	0.075	-0.629	-1.083	-0.229	-1.581*
							(0.946)	(0.157)	(1.306)	(0.630)	(0.217)	(0.831)
nlights_mean										-231.726**	-40.848*	-224.095*
										(65.620)	(20.455)	(97.973)
Food aid (Emergency)										0.000	-0.000	0.000
										(0.000)	(0.000)	(0.000)
Food aid (Project)										0.000	-0.000	0.000
										(0.000)	(0.000)	(0.000)
_cons	22.430**	1.773***	28.651***	-103.842	-4.059	-30.102	316.643	-46.566	286.597	38.164	76.888	147.825
	(0.921)	(0.505)	(1.081)	(93.170)	(27.373)	(162.428)	(473.947)	(82.297)	(662.086)	(291.173)	(139.707)	(446.277)
Pseudo R-squared	0.102	0.108	0.105	0.203	0.116	0.116	0.312	0.417	0.293	0.792	0.669	0.823
N	16	16	16	15	15	15	15	15	15	13	13	13

Table 7: Dep var: waterborne diseases (diarrhoea and malaria) and lower respiratory infections. Regressions are run without time and district dummies, using ols regression with standard errors clustered at the district level.

	pcunderweight	pcstunting	pcunderweight	pcstunting	pcunderweight	pcstunting	pcunderweight	pcstunting
	est1	est2	est3	est4	est5	est6	est7	est8
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	2.963*				-0.346			
	(2.036)				(2.352)			
lag_intrastate		5.138***				-1.316		
		(1.506)				(1.207)		
lag_internationalized			-2.118				-2.487	
			(1.781)				(2.227)	
lag_lowintensity				4.361				-0.262
				(3.338)				(1.618)
lag_stunting					0.529**	0.510**	0.551***	0.530**
					(0.212)	(0.214)	(0.207)	(0.208)
events_history	-0.134**	-0.168**	-0.121**	-0.113**	-0.042	-0.033	-0.023	-0.043
	(0.055)	(0.054)	(0.056)	(0.057)	(0.035)	(0.037)	(0.044)	(0.036)
lnpop	-1.340	-4.007**	-0.594	-1.356	6.145**	6.665***	5.552**	6.001**
	(1.311)	(1.390)	(1.333)	(1.488)	(2.769)	(2.483)	(2.353)	(2.767)
capdist	-0.481***	-0.449**	-0.493***	-0.565**	-0.224*	-0.296**	-0.283**	-0.227*
	(0.180)	(0.170)	(0.180)	(0.167)	(0.140)	(0.116)	(0.140)	(0.132)
foodaid_total	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	0.000	-0.000
	(146.543)	(129.795)	(149.818)	(138.764)	(10.035)	(9.871)	(11.342)	(9.719)
Pseudo R-squared	0.098	0.167	0.092	0.114	0.252	0.256	0.261	0.252
N	154	154	154	154	99	99	99	99

Table 9: Dep var: percentage underweight individuals and stunted individuals. Regressions are run using ols regression with standard errors adjusted for spatial and temporal correlation. The variable *lag_stunting* is lagged 12 time periods.

Table 11: Dep var: urban and rural people in stressed, crisis, and emergency (famine) situations, as a ratio of respectively the total urban and rural population. Regressions are run using ols regression with standard errors adjusted for spatial and temporal correlation. The conflict variables are lagged one time period.

	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural	AFLC_urban	HE_urban	famine_urban	AFLC_rural	HE_rural	famine_rural
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12	est13	est14	est15	est16	est17	est18
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	-0.004	0.003**	-0.006**	-0.085*	-0.073	0.041												
	(0.008)	(0.002)	(0.003)	(0.051)	(0.088)	(0.035)												
lag_intrastate							0.000	0.002	-0.004**	0.069**	0.046	-0.064**						
							(0.006)	(0.002)	(0.002)	(0.029)	(0.058)	(0.027)						
lag_internationalized													-0.013	0.007**	-0.002	-0.064**	-0.049	0.046*
													(0.011)	(0.003)	(0.002)	(0.021)	(0.044)	(0.030)
events history	0.001***	-0.000**	-0.000**	0.001	-0.002	-0.003	0.001**	-0.000*	-0.000**	-0.002*	-0.004	0.002	0.001***	-0.000**	-0.001***	0.000	-0.003	-0.002
	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.002)
lnpop	0.040	-0.011	0.003*	0.173**	-0.028	-0.142*	0.039	-0.011	0.003*	0.144***	-0.051	-0.108*	0.042*	-0.012	0.001	0.170**	-0.032	-0.144*
	(0.029)	(0.012)	(0.002)	(0.043)	(0.078)	(0.071)	(0.029)	(0.013)	(0.002)	(0.046)	(0.071)	(0.063)	(0.028)	(0.013)	(0.001)	(0.043)	(0.077)	(0.072)
capdist	0.003***	0.000	-0.000***	-0.002	0.006*	-0.000	0.003***	0.000	-0.000	-0.003	0.006	0.001	0.003***	0.000	-0.000***	-0.002	0.006*	-0.000
	(0.001)	(0.001)	(0.000)	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)	(0.004)	(0.003)
foodaid_total	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	0.000
	(5.068)	(2.735)	(8.523)	(7.617)	(7.944)	(7.944)	(5.075)	(2.738)	(8.929)	(8.136)	(7.318)	(7.318)	(5.017)	(2.703)	(9.115)	(7.589)	(7.709)	(7.709)
Pseudo R-squared	0.224	0.036	0.939	0.266	0.067	0.252	0.223	0.033	0.933	0.262	0.062	0.280	0.227	0.043	0.928	0.257	0.063	0.262
N	91	91	55	88	88	53	91	91	55	88	88	53	91	91	55	88	88	53

	price	price	price	price	volatility	volatility	volatility	volatility
	est1	est2	est3	est4	est5	est6	est7	est8
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
lag_onesided	-0.000				-0.000			
	(0.003)				(0.001)			
lag_intrastate		0.001				-0.000		
		(0.003)				(0.001)		
lag_internationalized			-0.001				0.001**	
			(0.002)				(0.000)	
lag_lowintensity				-0.026***				0.001
				(0.009)				(0.003)
events_history	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnpop	-0.001	-0.001	-0.001	-0.000	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)
capdist	-0.001*	-0.001*	-0.001*	-0.001**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
foodaid_total	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000
	(0.088)	(0.088)	(0.088)	(0.088)	(0.029)	(0.029)	(0.029)	(0.029)
Pseudo R-squared	0.004	0.004	0.004	0.008	0.003	0.003	0.004	0.003
N	1093	1093	1093	1093	820	820	820	820

Table 19: Dep var food security indicators: the normalized maize-sorghum price index and volatility measure. Regressions are run using ols regression with standard errors adjusted for spatial and temporal correlation.

	diarrhoea	typhoid	diarrhoea	typhoid	diarrhoea	typhoid	diarrhoea	typhoid
	est1	est2	est3	est4	est5	est6	est7	est8
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
drought	-0.004***	0.003***			-0.029**	-0.027*		
	(0.000)	(0.000)			(0.006)	(0.009)		
temp			-0.029***	-0.037***			0.030*	0.030
			(0.000)	(0.000)			(0.010)	(0.022)
log_formal_transfer					0.001	0.002	0.001	0.002
					(0.001)	(0.001)	(0.001)	(0.001)
log_informal_transfer					0.001	-0.005**	0.001	-0.005**
					(0.001)	(0.001)	(0.001)	(0.001)
femhead					0.014	-0.005	0.014	-0.005
					(0.025)	(0.033)	(0.025)	(0.033)
hhsize					0.130***	0.138***	0.130***	0.138***
					(0.009)	(0.008)	(0.009)	(0.008)
educhead					0.006	0.005*	0.006	0.005*
					(0.004)	(0.002)	(0.004)	(0.002)
log hhincome					-0.002	0.002	-0.002	0.002
					(0.003)	(0.004)	(0.003)	(0.004)
distance_market					0.001**	0.000	0.001**	0.000
					(0.000)	(0.000)	(0.000)	(0.000)
distance_health					0.000	-0.000	0.000	-0.000
					(0.000)	(0.000)	(0.000)	(0.000)
shagr_wge					-0.119**	-0.151	-0.119**	-0.151
					(0.036)	(0.123)	(0.036)	(0.123)
shnonagr_wge					0.087**	0.028	0.087**	0.028
					(0.025)	(0.037)	(0.025)	(0.037)
shcrop					0.122	0.008	0.122	0.008
					(0.092)	(0.058)	(0.092)	(0.058)
shlivestock					0.123	0.038	0.123	0.038
					(0.057)	(0.053)	(0.057)	(0.053)
shselfemp					0.108**	0.030	0.108**	0.030
					(0.030)	(0.022)	(0.030)	(0.022)
shtransfer					0.021	0.123***	0.021	0.123***
					(0.076)	(0.014)	(0.076)	(0.014)
_cons	0.567***	0.412***	1.388***	1.443***	-0.276**	-0.472***	-1.094**	-1.308
	(0.000)	(0.000)	(0.000)	(0.000)	(0.079)	(0.041)	(0.288)	(0.631)
Pseudo R-squared	0.003	0.005	0.003	0.005	0.491	0.562	0.491	0.562
N	1543	1543	1543	1543	1175	1175	1175	1175
district dummies	yes	yes	yes	yes	yes	yes	yes	yes

Table 23: Dep var waterborne diseases (diarrhea, typhoid/parathypoid). Regressions are run with district dummies, using ols regression with standard errors clustered at the district level.

	diarrhoea	typhoid	diarrhoea	typhoid	diarrhoea	typhoid	diarrhoea	typhoid	diarrhoea	typhoid	diarrhoea	typhoid
	est1	est2	est3	est4	est5	est6	est7	est8	est9	est10	est11	est12
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
drought	-0.108***	-0.168***	-0.040***	-0.045***	0.020	-0.011	-0.084	-0.157**	0.003	-0.012*	-0.025	-0.017
	(0.005)	(0.005)	(0.000)	(0.005)	(0.011)	(0.006)	(0.051)	(0.047)	(0.012)	(0.004)	(0.029)	(0.029)
temp							0.049	0.023	0.090**	0.068***	-0.094	-0.012
							(0.118)	(0.110)	(0.026)	(0.002)	(0.055)	(0.056)
log_formal_transfer	0.003**	0.003**	0.003	0.001	-0.001	0.005	0.003**	0.003**	0.003	0.001	-0.001	0.005
	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)	(0.005)	(0.001)	(0.001)	(0.003)	(0.004)	(0.004)	(0.005)
log_informal_transfer	-0.011***	-0.008*	0.007**	-0.003	0.007	-0.005	-0.011***	-0.008*	0.007**	-0.003	0.007	-0.005
	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)	(0.005)	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)	(0.005)
femhead	-0.019	-0.080**	0.027	0.012	-0.012	-0.072	-0.019	-0.080**	0.027	0.012	-0.012	-0.072
	(0.014)	(0.015)	(0.013)	(0.026)	(0.102)	(0.059)	(0.014)	(0.015)	(0.013)	(0.026)	(0.102)	(0.059)
hhsize	0.109***	0.119***	0.141***	0.148***	0.137***	0.141***	0.109***	0.119***	0.141***	0.148***	0.137***	0.141***
	(0.002)	(0.002)	(0.010)	(0.008)	(0.012)	(0.009)	(0.002)	(0.002)	(0.010)	(0.008)	(0.012)	(0.009)
educhead	0.003***	-0.002	0.008	0.005	0.011*	0.017***	0.003***	-0.002	0.008	0.005	0.011*	0.017***
	(0.001)	(0.001)	(0.003)	(0.005)	(0.004)	(0.003)	(0.001)	(0.001)	(0.003)	(0.005)	(0.004)	(0.003)
log hhincome	0.005*	0.006*	-0.007	-0.001	-0.008	-0.010	0.005*	0.006*	-0.007	-0.001	-0.008	-0.010
	(0.002)	(0.002)	(0.007)	(0.014)	(0.009)	(0.010)	(0.002)	(0.002)	(0.007)	(0.014)	(0.009)	(0.010)
distance_market	0.002	0.001	0.001*	0.000	0.001**	0.001	0.002	0.001	0.001*	0.000	0.001**	0.001
	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)
distance_health	0.003*	0.003***	0.000	-0.000***	0.000	-0.000	0.003*	0.003***	0.000	-0.000***	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
shagr_wge	-0.470***	-0.350***	0.348	-0.043	-0.562**	0.102	-0.470***	-0.350***	0.348	-0.043	-0.562**	0.102
	(0.025)	(0.046)	(0.259)	(0.234)	(0.169)	(0.341)	(0.025)	(0.046)	(0.259)	(0.234)	(0.169)	(0.341)
shnonagr_wge	0.090***	0.014***	0.187*	0.029	-0.270***	0.014	0.090***	0.014***	0.187*	0.029	-0.270***	0.014
	(0.006)	(0.002)	(0.073)	(0.037)	(0.040)	(0.283)	(0.006)	(0.002)	(0.073)	(0.037)	(0.040)	(0.283)
shcrop	4.072***	4.224***	0.510	-0.518**	-0.175	-0.083	4.072***	4.224***	0.510	-0.518**	-0.175	-0.083
	(0.315)	(0.608)	(0.608)	(0.157)	(0.155)	(0.222)	(0.315)	(0.608)	(0.608)	(0.157)	(0.155)	(0.222)
shlivestock	0.177***	0.103**	0.155	-0.019	-0.197**	-0.033	0.177***	0.103**	0.155	-0.019	-0.197**	-0.033
	(0.026)	(0.027)	(0.075)	(0.015)	(0.047)	(0.224)	(0.026)	(0.027)	(0.075)	(0.015)	(0.047)	(0.224)
shselfemp	0.057	0.041	0.244**	0.046*	-0.090	-0.079	0.057	0.041	0.244**	0.046*	-0.090	-0.079
	(0.046)	(0.048)	(0.061)	(0.019)	(0.121)	(0.247)	(0.046)	(0.048)	(0.061)	(0.019)	(0.121)	(0.247)
shtransfer	0.142**	0.291***	-0.011	0.104	-0.466	-0.186	0.142**	0.291***	-0.011	0.104	-0.466	-0.186
	(0.030)	(0.047)	(0.097)	(0.054)	(0.265)	(0.365)	(0.030)	(0.047)	(0.097)	(0.054)	(0.265)	(0.365)
_cons	0.012	-0.044***	-0.335**	-0.473*	-0.044	-0.331	-1.367	-0.675	-2.857**	-2.377***	2.576	-0.006
	(0.012)	(0.006)	(0.094)	(0.167)	(0.171)	(0.204)	(3.298)	(3.064)	(0.638)	(0.123)	(1.549)	(1.452)
Pseudo R-squared	0.457	0.558	0.560	0.614	0.600	0.669	0.457	0.558	0.560	0.614	0.600	0.669
N	209	209	548	548	162	162	209	209	548	548	162	162
district dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 24: Dep var waterborne diseases (diarrhea, typhoid/parathypoid). Results are depicted by livelihood (urban, pastoral, agropastoral). Regressions are run with district dummies, using ols regression with standard errors clustered at the district level.