How does climate exacerbate root causes of conflict in Zimbabwe? An econometric analysis

1. Objective of the analysis and research questions

Building on previous research taking steps to improve insight into the underlying relationships between climate-induced resource variability, food security, and conflicts (IISD, 2009; Rowani et al., 2011), the two-stage analysis presented in this factsheet was designed to deepen the understanding of the effects of climate on food insecurity and local violence in Zimbabwe. According to The World Bank Group's Climate Risk Profile on Zimbabwe (2021), the country is highly vulnerable to climate extremes and variability. Over the past century, Zimbabwe has been subjected to a variety of natural disasters, including droughts, pandemic diseases, floods, and hurricanes. Because of climate change, the likelihood of these natural hazards will increase (The World Bank Group, 2021). Zimbabwe is expected to suffer from rising temperatures, droughts, increasing rainfall variability, floods, and an increase in storm frequency (Mtisi and Prowse 2012; UNDP 2017; USAID 2019a; Brazier 2015) Rainfall patterns, in particular, are expected to become more erratic, with a more than 20% increase in drought likelihood over the next 30-40 years (The World Bank Group, 2021). Heavy rains and floods are also common in Zimbabwe, and they are also expected to become more frequent in the next future.

Furthermore, the country's socioeconomic and political context is characterized by authoritarian and corrupt governance that is mainly responsible for the low or negative economic growth (Gebremichael and Fitiwi 2018). The government frequently represses demonstrations and arrests human rights activists or opposition members (Transparency International, 2020; USAID, 2019; Brazier, A, 2015; Cain, 2015; Mtisi & Prowse, 2012; UNDP, 2017). The government restrict food distribution and limit access to free or subsidized food for those deemed to be members or supporters of opposition parties, with obvious and direct consequences for their food security (Chamunogwa, 2021). The combination of worsening climatic conditions and authoritarian governance may increase livelihood insecurity, threatening the already weak country's stability. The purpose of this econometric analysis is to provide answers to two major research questions about the indirect relationships among climate, sustainable livelihoods, and conflicts (Couttenier & Soubeyran, 2014; Rowani et al., 2011, IISD, 2009). These questions are:

I) Do extreme climatic events and variability exacerbate households' food insecurity?
II) Does food insecurity, as exacerbated by climate impacts, affect the likelihood and intensity of conflict?

In response to these questions, this study would like to investigate not only how climate-related environmental variability may affect nutrition security in Zimbabwe, but also how nutrition insecurity, in the context of climatic instability may contribute to escalating the intensity of local violence in the latter East African country. Taking into account the impact of climate on local vulnerabilities, such as food insecurity, this econometric analysis attempts to determine to what extent climate may exacerbate the erosion of social order or the state failure resulting in a spiral of violence that undermines local security indirectly (Scheffran et al., 2014).

2. Methods and data

In order to answer the previous questions this study relies on the following data sources: the Demographic and Health Surveys (DHS) for the socio-economic and food security information (four rounds - 1999, 2005, 2010, 2015); the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (1998-2015) for temperature and rainfall data; the Armed Conflict Location & Event Data Project (ACLED) for information on past and on-going conflicts in the area of interest (1998-2016). In the first stage, a probabilistic model is used to quantify the impact of climate variability over the likelihood of having a food insecure child in the household. While in the second stage a fixed effect model is used to assess how climate exacerbated food insecurity could in turn affect the intensity of conflicts.

3. Results

I. Do extreme climatic events and variability exacerbate households' food insecurity?

Table 1 shows the main variable on food security as well as the main predictors of the econometric analysis. The dependent variable is constructed as a dummy that is equal one if the household has at least one food insecure child. Children food insecurity is reported in more than fifty percent of the households that have at least one young child. This share is considerably high but in line with the country statistics reported in the most recent literature (USAID, 2021; WFP, 2021)

Table 1: Descriptive Statistics- First stage

Category	Variables	Observations	Mean	Std. Dev.	Min	Max
Food Security Variable	No minimum meal frequency	4713	0.54	0.5	0	1
Control Variables	Urban rural	4713	0.31	0.46	0	1
	Household size	4713	5.76	2.67	2	27
	Household head sex	4713	0.62	0.49	0	1
	Household head age	4713	39.14	14.56	15	97
	Number of teen below 16 in the HH	4713	3.03	1.79	1	15
	Very poor households	4713	0.22	0.42	0	1
	HH head with no education	4713	0.07	0.26	0	1
	Livestock, herds and farm animal	3883	0.63	0.48	0	1
	Owns agricultural land	3882	0.65	0.48	0	1
Climate Variables	Rainfall- Anomalies 3 months	4713	-0.06	0.5	-1.15	1.23
	Rainfall- Anomalies 12 months	4713	-0.11	0.27	-0.76	0.73
	Temperatures- Anomalies 3 months	4713	-0.06	0.8	-1.63	1.72
	Temperatures- Anomalies 12 months	4713	-0.16	0.52	-1.04	1.17
	Decreasing rainfall -Lowest extreme 12 months	4713	0.28	0.45	0	1
	Increasing rainfall -Highest extreme 12 months	4713	0.13	0.33	0	1
	Decreasing Max. temp. -Lowest extreme 12 months	4713	0.24	0.43	0	1
	Increasing Max. temp. -Highets extreme 12 months	4713	0.16	0.37	0	1

Most of the households in our sample live in rural areas and are mostly male headed. Around sixty percent of the households own both livestock and agricultural land, which makes them highly sensitive to climate variability due to their reliance on natural resources for both agriculture and livestock production (UNDP, 2017; World Bank Group, 2021). Around ten percent of the household head has no education and eighteen percent of them are considered extremely poor following the DHS wealth categories.

[1]Using a correlation analysis approach, we look at the direct link between climate variability and households' food security. Figure 2 and 3 reports the correlation graphs obtained associating children food insecurity with the main climate anomalies measures. Looking at the rainfall anomalies 12 months before the household interview, it appears a positive correlation with the hosehold likelihood of having at least one child that is not fed respecting the minimum meal frequency. The rest of the correlation analysis shows that there exists a clear non-linear relationship between food insecurity and the other dimensions of climate anomalies (Figure 1 – panel A & Figure 2).

[1] Temperature anomalies refer to maximum temperature differences, thus positive and negative deviations in the maximum temperature registered in Kenya in the years before the three DHS rounds. Rainfall anomalies refer to anomalies in the total amount of rainfall (thus positive or negative variations considering the mean) overall the years before the DHS rounds.

Figure 2: Correlation Analysis - Food insecurity & Rainfall anomalies

Panel A ***Panel B***

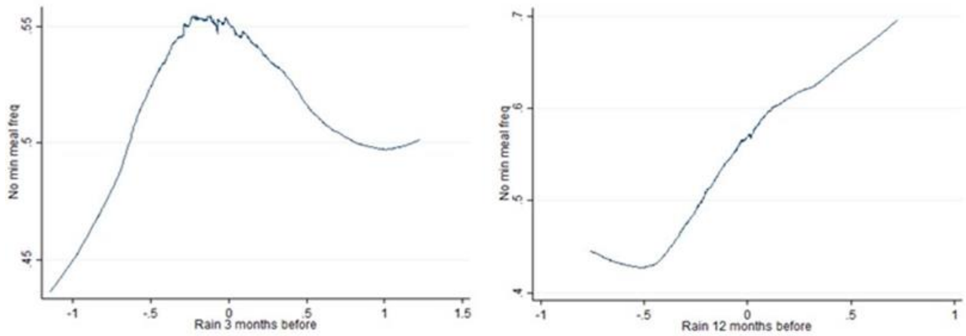
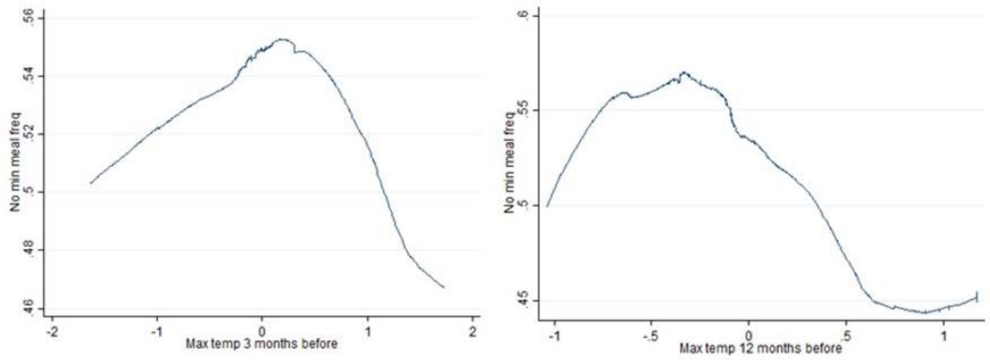


Figure 3: Correlation Analysis - Food insecurity & Temperature anomalies

Panel A ***Panel B***



To increase the accuracy of the estimate, we develop a more comprehensive model, where other drivers of food insecurity are considered, for example gender, age and education of the head of the household and other household context specific characteristics that could confound the impact of climate on our variable of interest. We also control for unobservable context specific with the use of time and district fixed effects. Furthermore, we also address potential serial autocorrelation of climate and other time-varying variables by using year and location clustered standard errors (Table 2).

Contrary to what we observed in the one-to-one correlation analysis, Table 2 shows that increasing temperature anomalies have a positive and significant (at 5 percent level) correlation with food insecurity at household level. This correlation was difficult to be observed from the correlation graphs since they are designed only to capture how two variables move together. Adding confounding socio-economic characteristics allows to control for several factors that can shape the children likelihood of being food insecure. More precisely, after the implementation of the probit model we find that a unit increase of temperature anomalies corresponds to almost six percent points[2] increase in the likelihood of household level food insecurity. This result is consistent with the literature that shows how rising temperatures can negatively impact staple crop production such as maize, beans, groundnut, and sorghum (Hunter et al. 2020). Heat stress can reduce land productivity which in turn decrease household agricultural income, reducing their ability to purchase food (Hunter et al. 2020; Chanza and Gundu-Jakarasi 2020; Swain et al. 2011). The livestock sector in Zimbabwe is also impacted by rising temperatures, heavy rainfall events, and frequent droughts. Heat stress can harm

[2] Percent points increase were obtained by computing the average marginal effects of the climate variables over the nutritional insecurity level. That is, taking the value of the derivative of our variable of interests.

livestock directly, as well as indirectly through reduced pasture and water availability, as well as disease and pests brought on by climate change (USAID 2019a; Kandji, Verchot, and Mackensen 2006).

Results for rainfall anomalies confirm our preliminary correlation analysis, that is, rainfall anomalies increase food insecurity. More specifically, a unit increase in rainfall anomalies in the past 12 months, increase the likelihood of a household having a food insecure child by sixteen percent points. This considerable impact can be explained by the fact that heavy rains and floods have a disruptive effect, and not only on the agricultural and livestock productivity but also on disease outbreaks and have catastrophic consequences on households' properties, health facilities as well as schools and road infrastructures (IFRC, 2019; Bola, G. et al. 2014; Oluoko-Odingo, A. A. 2011). In Zimbabwe, the Cyclone Idai, which created multiple floods and landslides, triggered a humanitarian crisis affecting over 270,000 people, and displacing 17,608 families (IFRC, 2019). And the occurrence of these events is increasing with time. Bola, G. et al. (2014) found that flooding in Zimbabwe has been more common in the last two decades. Extreme events as the ones mentioned above clearly have dramatic effects over household livelihood stability and food security levels. For example, Akukwe, et al. (2020) found that flood-affected households in agrarian communities in South-eastern Nigeria are 2.221 times more likely to be food insecure than non-flooded households. According to their findings, flooding had a significant impact on household food security, with only 7.2 percent of households in their sample being food secure after flooding, compared to 33.3 percent of households being food secure prior to flooding (Akukwe, Oluoko-Odingo, and Krhoda 2020). Other studies have shown that heavy rains and floods have a negative impact on agricultural production, which could lead to an increase in the severity of food insecurity (Pacetti, Caporali, and Rulli, 2017; Devereux 2007).

Table 2: Summary results - First stage Analysis

VARIABLES	**HH has at least one young child(6-24 months) that is not feeded respecting the minimum meal frequency**
Temperatures - Anomalies 3 months	0.159**
	(0.076)
Temperatures - Anomalies 12 months	-0.187
	(0.177)
Rainfall - Anomalies 3 months	-0.018
	(0.067)
Rainfall - Anomalies 12 months	0.441***
	(0.134)
	(0.090)
Decreasing rainfall -Lowest extreme 12 months	-0.077
	(0.057)
Increasing rainfall -Highest extreme 12 months	0.231***
	(0.083)
Cluster SE	YES
Year FE	YES
District FE	YES
Observations	4,713

I. Do extreme climatic events and variability exacerbate households' food insecurity?

This analysis estimates the impact of the interaction of food insecurity and climate on the likelihood and intensity of conflict. Table 3 reports the variables that are included in the second stage of the analysis. This analysis is run at district level. Food insecurity is estimated by the total number of households in the district that have at least one food insecure child. Climate variables are estimated as before, as rainfall and temperature anomalies, following Maystadt and Ecker

(2014). Conflict is measured as total number of conflicts and total number of the different types of conflict reported in ACLED (riots, protests, explosion, and remote violence). We estimated the model across three main temporal lags, 3, 6 and 12 months after data on food security was collected. Past total conflict is added to the analysis to control for spatial and temporal autocorrelation, that is, places that in the past have experienced conflict are believed to be more likely to experience it again.

Table 3: Descriptive Statistics - Second stage

Category	Variable	Obs.	Mean	Std. Dev.	Min	Max
Conflict Variables	Explosions remote violence 3f	200	0.00	0.00	0	0.02
	Protests 3f	200	0.13	0.7	0	6.97
	Riots 3f	200	0.12	0.62	0	7.48
	Total conflicts 3f	200	0.64	2.47	0	19.85
	Explosions remote violence 6f	200	0.01	0.12	0	1.44
	Protests 6f	200	0.27	1.47	0	16.56
	Riots 6f	200	0.18	0.92	0	11.59
	Total conflicts 6f	200	1.67	5.52	0	44.01
	Explosions remote violence 12f	200	0.03	0.29	0	3.86
	Protests 12f	200	0.63	3.72	0	45.96
	Riots 12f	200	0.36	2.09	0	27.66
	Total conflicts 12f	200	3.8	11.85	0	102.47
Food Security Variable	Tot HH no min meal freq.	200	12.61	10.97	0	95
Control Variables	Urban rural	200	0.18	0.25	0.00	1.00
	HH head age	200	45.47	4.09	36.06	56.26
	Tot poor HH dis.	200	53.30	31.90	0.00	165.00
	Tot men/women no education dis.	200	6.00	6.63	0.00	36.00
	% HH owns land	200	0.55	0.36	0.00	1.00
	Tot men/women unemployed dis.	200	114.84	124.56	9.00	907.00
	Total conflicts	200	0.23	0.80	0.00	7.81
	UN population density	200	219.99	468.77	8.02	2985.26
	% Ag. working men dis.	200	0.12	0.16	0.00	0.75
Climate Variables	Rainfall- Anomalies 3 months	200	-0.05	0.43	-0.97	1.12
	Temperatures- Anomalies 3 months	200	-0.15	0.78	-1.52	1.59
	Rainfall- Anomalies 12 months	200	-0.1	0.27	-0.76	0.64
	Temperatures- Anomalies 12 months	200	-0.17	0.54	-1.04	1.12

Table 4 & 5 reports the summary results for this analysis. The results show that increasing food insecurity is significantly and positively correlated with the higher presence of riots in the district for all the three future conflict specifications. A hundred more food insecure households in the district, for example, corresponds to 2.3 more riots in the three months after. This effect appears to be stronger six and twelve months later, with an increase of 3.3 and 7.6 more riots associated with the same increase in household food insecurity. Similarly, an increase of one hundred food insecure households corresponds to 1.9 and 6.3 more protests in the next 6 and 12 months, respectively. From Table 4 we also observe a positive correlation between food insecurity and explosion/remote violence but with less magnitude and significance level compared to riots and protests.

Our results also show that climate exacerbated food insecurity could lead to an increase in political tension in Zimbabwe. To understand whether climate exacerbate the impact of food insecurity on conflict we interact climate anomalies with our variables of food insecurity. Table 4 reports the results of the interaction with climate anomalies occurring 3 months before, while table 5 with climate anomalies occurring 12 months before. Our results show that increasing temperature anomalies together with increasing food insecurity are positively correlated to future riots and protests occurring 6 and 12 months after and with riots and total number of conflicts occurring 3 months after. More specifically, we find that an increase of 100 food insecure households in the district combined with increasing temperature anomalies in the previous three months leads to an increase of 2.9 riots and 3.7 total conflict in the next three months, but also to 3.6 and 11.8 protests and 3.1 and 4.8 riots in the six and twelve months after, respectively. Similarly, the interaction between temperature anomalies 12 months and food insecurity is positively and significant correlated with the future riots (3 months after) and future protest (6 months after).
Table 5 shows that increasing rainfall anomalies occurring 12 months begore combined with increasing food insecurity, is positively correlated with future explosions and remote violence (6 and 12 months later). We find that an increase of one hundred food insecure households in the district combined with increasing rainfall anomalies in the previous 12 months leads to an increase of 1.2 and 2.7 explosion and remote violence events in the district 6 and 12 months later. Our findings also show that increased food insecurity and rainfall anomalies, as well as temperature anomalies combined with food insecurity, reduce the intensity of future explosions (6 and 12 months).

Overall, the results of these analyses suggest that food insecurity and climate anomalies matter in explaining the occurrence and intensity of future conflicts which is consistent with previous research indicating that climate change indirectly leads to increased conflict occurrence (Crost et al., 2018; Fjelde, 2015; Mach et al., 2019). However, the role of climate as threat multiplier differs for different types of conflict. In Zimbabwe protest and riots have increased considerably in the last 10 years due to events such as the economic and political crisis in 2015 and the government military assisted transition in 2017 leading to more violent episodes (Wigmore-Shepherd, 2016; Morris, 2018).
In a country already affected by high level of political insecurity, the combined effect of climate variability and food insecurity on conflict could exacerbate social and political polarization, potentially leading to more violent clashes between government and opposition supporters (Swain et al. 2011).

Table 4: Summary results- Second stage of the analysis with Climate anomalies 3 months

Variables	**3 months after**							
	Explosions/remote violence	Explosions/remote violence	Protest	Protest	Riots	Riots	Total Conflict	Total Conflict
Tot. HH no min meal Freq.	-0.000*	-0.000*	-0.003	-0.003	0.026***	0.023***	-0.011	-0.015
	(0.000)	(0.000)	(0.005)	(0.005)	(0.006)	(0.005)	(0.011)	(0.011)
Rainfall - Anomaly 3 months # Tot. HH no min meal Freq.		0.000		-0.009		0.002		0.003
		(0.000)		(0.006)		(0.007)		(0.014)
Temperature - Anomaly 3 months # Tot. HH no min meal Freq.		0.000**		-0.001		0.029***		0.037***
		(0.000)		(0.004)		(0.004)		(0.009)
Variables	**6 months after**							
	Explosions/remote violence	Explosions/remote violence	Protest	Protest	Riots	Riots	Total Conflict	Total Conflict
Tot. HH no min meal Freq.	0.003**	0.004***	0.023***	0.019**	0.036***	0.033***	-0.026	-0.032
	(0.001)	(0.001)	(0.008)	(0.008)	(0.007)	(0.007)	(0.044)	(0.045)
Rainfall - Anomaly 3 months # Tot. HH no min meal Freq.		0.001		0.007		-0.009		0.061
		(0.002)		(0.010)		(0.009)		(0.060)
Temperature - Anomaly 3 months # Tot. HH no min meal Freq.		-0.007***		0.036***		0.031***		0.046
		(0.001)		(0.007)		(0.006)		(0.039)
Variables	**12 months after**							
	Explosions/remote violence	Explosions/remote violence	Protest	Protest	Riots	Riots	Total Conflict	Total Conflict
Tot. HH no min meal Freq.	0.007**	0.008***	0.073***	0.063***	0.080***	0.076***	0.061	0.059
	(0.003)	(0.003)	(0.024)	(0.020)	(0.015)	(0.014)	(0.074)	(0.075)
Rainfall - Anomaly 3 months # Tot. HH no min meal Freq.		0.003		-0.069**		-0.028		-0.008
		(0.003)		(0.027)		(0.019)		(0.101)
Temperature - Anomaly 3 months # Tot. HH no min meal Freq.		-0.017***		0.118***		0.048***		0.025
		(0.002)		(0.018)		(0.012)		(0.065)
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	200	200	200	200	200	200	200	200

Table 5: Summary results- Second stage of the analysis with Climate anomalies 12 months

Variables	3 months after							
	Explosions/remote violence	Explosions/remote violence	Protest	Protest	Riots	Riots	Total Conflict	Total Conflict
Tot. HH no min meal Freq.	-0.000	-0.000	-0.004	-0.004	0.028***	0.030***	-0.017	-0.012
	(0.000)	(0.000)	(0.005)	(0.005)	(0.005)	(0.006)	(0.012)	(0.013)
Rainfall - Anomaly 12 months # Tot. HH no min meal Freq.		0.000		-0.026**		-0.045***		-0.005
		(0.000)		(0.013)		(0.015)		(0.035)
Temperature - Anomaly 12 months # Tot. HH no min meal Freq.		-0.000		0.004		0.016*		0.033
		(0.000)		(0.008)		(0.009)		(0.020)
Variables	**6 months after**							
	Explosions/remote violence	Explosions/remote violence	Protest	Protest	Riots	Riots	Total Conflict	Total Conflict
Tot. HH no min meal Freq.	0.002	0.002	0.024***	0.030***	0.039***	0.037***	-0.016	-0.000
	(0.001)	(0.001)	(0.008)	(0.008)	(0.007)	(0.007)	(0.051)	(0.055)
Rainfall - Anomaly 12 months # Tot. HH no min meal Freq.		0.012***		-0.064***		-0.084***		0.090
		(0.004)		(0.022)		(0.020)		(0.148)
Temperature - Anomaly 12 months # Tot. HH no min meal Freq.		-0.005**		0.034**		0.003		0.072
		(0.002)		(0.013)		(0.012)		(0.085)
Variables	**12 months after**							
	Explosions/remote violence	Explosions/remote violence	Protest	Protest	Riots	Riots	Total Conflict	Total Conflict
Tot. HH no min meal Freq.	0.005*	0.003	0.081***	0.077***	0.084***	0.074***	0.040	0.033
	(0.003)	(0.003)	(0.023)	(0.021)	(0.015)	(0.015)	(0.085)	(0.091)
Rainfall - Anomaly 12 months # Tot. HH no min meal Freq.		0.027***		-0.368***		-0.191***		-0.186
		(0.007)		(0.056)		(0.040)		(0.245)
Temperature - Anomaly 12 months # Tot. HH no min meal Freq.		-0.013***		0.032		-0.019		-0.009
		(0.004)		(0.034)		(0.024)		(0.141)
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	200	200	200	200	200	200	200	200

3 Conclusions

The aim of this analysis was to demonstrate how climate change does exacerbate root causes of conflict. The results of the first and second analysis shows the linkages between these three dimensions. In the first stage of the analysis a positive correlation between climate anomalies and household food insecurity has been established. In particular, the probability of having a food insecure child in the household significantly increases when temperature increases 3 months before the data collection but also in case of extreme positive rainfall variability 12 months before the interview. This suggest that household and in particular children are considerably vulnerable to different kind of climate anomalies. In the second stage the analysis, that was aggregated at district level, results show a positive significant correlation between increasing level of food insecurity and higher intensity of conflict, more specifically protest and riots. This correlation is also present when food insecurity is interacted with the presence of higher temperature anomalies. We also find that the combination of food insecurity and temperature anomalies increases the total number of conflict 3 months after the household interview. To conclude, our results also point out that the combination of rainfall anomalies and food insecurity exacerbate the risks of explosions and remote violence in the country.

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ANNEX

a. Data and Methods

The two-stage analysis presented in this factsheet is based on data from four rounds of the Zimbabwe Demographic and Health Surveys - 1999, 2005, 2010, 2015. (DHS). Individual data on women was extracted in order to define the main variable of interest for measuring food insecurity at the household and sub-county levels, the presence of at a least one child in the household that is not fed respecting the minimum meal frequency. This variable is created following precisely Croft, T. et al (2018) guide to DHS statistics and takes into account also the differences among breastfed and non-breastfed children.

Data from the DHS have also been used to create household and sub-county control variables based on the characteristics of the household heads, poverty status, educational level, employment, and land ownership. These predictors were chosen based on previous empirical studies (Arene et al., 2010; Beyene et al., 2010; Aidoo et al., 2013), as well as other factors such as information availability.

To include local measures of climate variability and violence, external datasets have been merged into the DHS.
Temperature and precipitation anomalies[3] at the sub-county level have been created as standard indicators to account for spatial and temporal variations in maximum temperature and rainfall amounts using the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) data (Maystadt et al., 2014). These indicators are designed to detect abnormal deviations from the mean of the maximum temperature and precipitation in the Zimbabwe sub-counties. Climate anomalies have been divided into quintiles (Q1-Q5) to capture small and extreme climatic changes in order to improve understanding of abnormal climatic conditions (Cooper et al., 2019; Mueller et al., 2014). This procedure allows the extreme positive and negative quintiles to control for abundant/high and scarce/low rainfall and maximum temperature.
Data from the Armed Conflict Location & Event Data Project (ACLED) at the sub-county level has then been used to gather information on local conflicts. The ACLED dataset on Zimbabwe, in particular, has been used to define the various types of conflicts that occur on a regular basis in Zimbabwe numerous sub-counties.

These three datasets on socioeconomic, climate, and conflict variables were combined based on the dates of the DHS interviews. Thus, using the DHS questionnaire's months, years, and sub-counties, data on climate and local violence have been aligned with socioeconomic variables. Furthermore, climate and conflict lag variables have been created to capture past extreme climatic changes (3-12 months prior to the interview) as well as future violent events (3-6-12 months after the interview).

The analysis has been divided into two different stages linked by the nutrition security variable. The first stage aims at evaluating the potential links between climate variability and nutrition security by examining how extreme weather conditions may increase the likelihood of reporting the presence of an underweight female member in the household. A non-linear probit model has been used to investigate how climate variability at time $t-1$ (S_{dt-1}) may be associated with a change in the probability of having food insecure child within the household at time t (Y_{jdt}). The latter, thus the main variable of interest, is a dummy variable that takes the value 1 if the household reports the presence of at least one food insecure child. Climate variables, on the other hand, are defined as continuous deviations from the mean as well as dummy variables in the case of extreme weather conditions. The model has been defined as follow:

$$P\left(Y_{jdt} = 1 \middle| S_{dt-1}, T_{dt-1}, X_{jdt}\right) = \Phi(\beta_0 + \beta_1 S_{dt-1} + \beta_2 T_{dt-1} + \beta_3 X_{jdt} + \alpha_t + \gamma_r + u_{jdt})$$

[3] Temperature anomalies refer to maximum temperature differences, thus positive and negative deviations in the maximum temperature registered in Senegal in the years before the three DHS rounds. Rainfall anomalies refer to anomalies in the total amount of rainfall (thus positive or negative variations considering the mean) overall the years before the DHS rounds.

In addition to the main variables, T_{dt-1} is a dummy based on past violent conflicts (12 months before the DHS interview) that controls for the impact that local violence within sub-counties may have on food security. Moreover, a set of socio-economic predictors at the household level (X_{jdt}) has been included controlling for critical determinants of the households' well-being (Arene et al., 2010; Beyene et al., 2010; Aidoo et al., 2013). Controls include characteristics of the heads of households (gender, age, educational level), household size, rural or urban environment, poverty level, and agricultural land ownership. Finally, α_t and γ_r are time and sub-county fixed effects to capture for unobservable characteristics while u_{jdt} is the error term. All the models tested have been weighted using the cluster weights given by the DHS.

The second stage of the analysis aims to answer the second research question of this factsheet by considering how climate variability exacerbate nutrition insecurity can lead to higher intensity of conflict. To proceed with the analysis, the original household level DHS has been collapsed at the sub-county level to capture the number of conflicts that have occurred by year and location. A simple panel data fixed-effects model has been defined using a panel regression analysis approach to understand to what extent increasing levels of nutrition insecurity within sub-counties may contribute to exacerbate local violence. The following variables of interest are included in the model:

$$C_{dt+1} = \beta_0 + \beta_1 I_{dt} + \beta_2 K_{dt} + \beta_3 P_{dt} + \alpha_t + \gamma_c + u_{dct}$$

C_{dt+1} is the dependent variable on predicted future local tensions (3, 6, and 12 months after the DHS interviews) that captures the intensity of several conflict types within Zimbabwe sub-counties. This model primarily analyses non-state conflicts such as protest, riots, remote violence/explosions, and total number of conflict. These types of events were chosen based on their local relevance in increasing the frequency, intensity, and gravity of violence. In addition to the conflict variables, I_{dt} measures the sub-counties' nutritional status by counting the share of households with at least one underweight child . K_{dt} and P_{dt} take into account local conflict predictors such as poverty, unemployment, and education, as well as the presence of on-going conflicts at time t. α_t and γ_c are time and county fixed effects, respectively, and u_{dct} is the error term.