How does climate exacerbate root causes of conflict in Senegal ? 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, nutrition 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 change on food insecurity and local violence in Senegal. The county is highly vulnerable to climate change, particularly floods and droughts (USAID, 2017a; The World Bank Group 2011). Senegal has experienced an average temperature increase of nearly 1°C over the last fifty years, as well as several floods and droughts (USAID, 2017a). Climate trends are expected to become more erratic, with temperatures rising by 1.1 to 3.1 degrees Celsius and rainfall patterns becoming more uncertain over the next forty years (USAID, 2017a; Ministère de l'Environnement et du Développement Durable 2015b). Senegal is highly vulnerable to floods due to its geographical composition and demographic distribution; nearly 70% of the population lives in the urban coastal zone, where even small amounts of rain can cause harmful flooding due to the country's inadequate drainage system (USAID, 2017a). Furthermore, the agricultural sector, which accounts for almost 15% of national GDP, is extremely vulnerable to climate variably because more than 70% of it is rainfed (USAID, 2017a ; Jalloh et al. 2017; Ministère de l'Environnement et du Développement Durable 2015a; 2015b). In the face of future climatic deterioration, this strong reliance on climate could exacerbate the country's food security, which is already stressed by rapid population growth and low yield productivity (USAID, 2017a).

Senegal is considered one of the most stable and peaceful democracy in the African continent (Institute of Economics & Peace 2021; USAID, 2017b). Since its independence in 1960, the country has never had a military coup, and it has gone through three peaceful government transitions (World Bank 2021; BBC 2018 ; USAID, 2017b). Nonetheless, the country is still experiencing a longstanding low-intensity conflict for the independency of the Casamance region that is a driver of instability in the nation (Foucher 2019;USAID, 2017b). The country is also vulnerable to human trafficking and radical Islamism (Kane 2020; USAID, 2017b; Pujol-Mazzini 2018; Counter Extremism Project 2020). These phenomena may have an impact on the country's stability, especially given the country's high prevalence of poverty, which has persisted despite the country's good average economic growth over the last two decades, with nearly forty percent of the population living in poverty (World Food Program, 2021).
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' nutritional security?
II) Does nutrition 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 Senegal 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 change on local vulnerabilities, such as nutrition security, 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. Data and Methods

In order to answer the previous questions this project relies on the following data sources: the Demographic and Health Surveys (DHS) for the socio-economic and food security information (nine rounds - 1997, 2005, 2010, 2012, and from 2014 to 2019); the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (1998-2019) 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 (1998-2020). In the first stage, a probabilistic model is used to quantify the impact of climate variability over the likelihood of having a food insecure children 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 negatively impact households' food and nutritional security?

Table 1 shows the main variable on nutritional security as well as the main predictors of the econometric analysis. The dependent variable is built as a dummy that equals one if the households have at least one malnourished child. Almost a quarter of the households in the sample reported having at least one malnourished child. This share is slightly higher than national statistics, but it is consistent with the rural households reported in the recent literature, which are around 21% (USAID, 2018; World Food Program, 2017). Around 30% of the housheolds are reported to be very poor following the DHS wealth categories.

Table 1: Descriptive Statistics- First stage

Category	Variables	Observations	Mean	Std. Dev.	Min	Max
Nutritional Security Variable	Underweight children	11343	0.28	0.45	0	1
Control Variables	Urban rural	11343	0.34	0.47	0	1
	Household size	11343	11.59	6.53	2	74
	Household head sex	11343	0.77	0.42	0	1
	Household head age	11343	51.03	14.72	15	99
	Number of teen below 16 in the HH	11343	5.96	3.74	0	42
	Very poor households	11343	0.28	0.45	0	1
	HH head with no education	11343	0.76	0.43	0	2
	Livestock, herds and farm animal	9956	0.67	0.47	0	1
	Owns agricultural land	9956	0.49	0.50	0	1
Climate Variables	Rainfall- Anomalies 3 months	11343	-0.004	0.61	-1.37	2.61
	Rainfall- Anomalies 12 months	11343	0.01	0.31	-0.82	1.7
	Temperatures- Anomalies 3 months	11343	0.14	0.58	-1.33	1.33
	Temperatures- Anomalies 12 months	11343	0.02	0.25	-0.67	0.54
	Decreasing rainfall -Lowest extreme 12 months	11343	0.17	0.37	0	1
	Increasing rainfall -Highest extreme 12 months	11343	0.23	0.42	0	1
	Decreasing Max. temp. -Lowest extreme 12 months	11343	0.17	0.37	0	1
	Increasing Max. temp. -Highets extreme 12 months	11343	0.11	0.32	0	1

From Table 1 we can also observe that the majority of the reported households are male-headed and live in rural areas. Approximately 60% of households own livestock animals and around fifty percent owns agricultural land. This means that the majority of them are vulnerable to climate change due to their reliance on natural resources (UNDP, 2017; World Bank Group, 2021). Climate variables, are divided in continuous and binary variables. The first category looks at the months specific variability compared to the long run, while dummy variables capture the presence of extreme weather events.

The following correlation analysis was the first approach to understand the link between climate variability and households' nutrition security. Figure 1 panel A & B reports the correlation between the presence of an underweighted children in the household and rainfall anomalies, while Figure 2 Panel A & B the same measure of household malnutrition is analyzed considering temperature anomalies. Figure 1 panel A, despite showing a non-linear relationship, points out a positive correlation between the two variables. Figure 1 panel B and both panel in Figure 2 still depict a nonlinear correlation among the variables of interests but instead do not show a clear pathway.

Figure 1: Correlation Analysis – Underweight child & Rainfall anomalies

Panel A **Panel B**

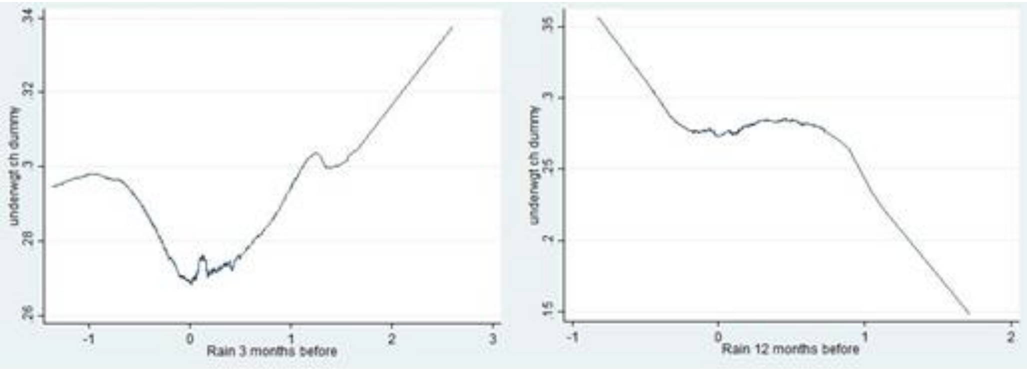
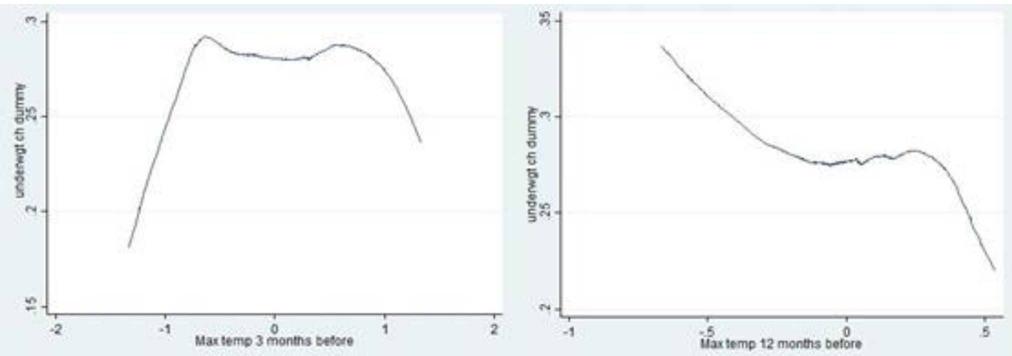


Figure 2: Correlation Analysis – Underweight child & Temperature anomalies

Panel A **Panel B**



To increase the accuracy of the estimate, we develop a more comprehensive model, where other drivers of food and nutrition insecurities 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.

The results of the probabilistic regressions are summarized in Table 2. Increasing temperature anomalies for both 3 and 12 months are associated with having at least one malnourished child in the household (at the 1% level). Because correlation graphs are only designed to show how two variables move together, it was difficult to see this correlation. Including the previously discussed household socioeconomic characteristics allows for the control of several factors that can influence a child's likelihood of food insecurity. More precisely, a unit increase in the temperature anomalies 3 months correspond to almost 3 percent point[1] increase in the likelihood of having at least on undernourished child. This effect grows considerably when controlling for temperature anomalies 12 months, which a unit increase correspond to 12 percent point increase in the likelihood of child nutritional insecurity.

[1] 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.

Table 2: Summary results - First stage Analysis

VARIABLES	HH has at least one underweight child
Temperatures - Anomalies 3 months	0.099***
	(0.035)
Temperatures - Anomalies 12 months	0.425***
	(0.147)
Rainfall - Anomalies 3 months	0.066*
	(0.037)
Rainfall - Anomalies 12 months	-0.136
	(0.092)
Increasing rainfall -Highest extreme 3 months	0.226***
	(0.053)
Increasing rainfall -Highest extreme 12 months	-0.103*
	(0.058)
Increasing Temperature -Highest extreme 3 months	0.086*
	(0.045)
Increasing Temperature -Highest extreme 12 months	0.085
	(0.068)
Cluster SE	YES
Year FE	YES
District FE	YES
Observations	11,343

This results are consistent with rising temperatures negatively impacting staple crop production such as millet, groundnut and sorghum (Hunter et al. 2020; USAID, 2017a). In Senegal, millet and sorghum are important subsistence crops, while groundnuts is a major cash crop grown on 40% of cultivated land and employ up to one million people. In particular, groundnuts crops are sensitive to both unpredictability of rainfall and higher temperatures, with crop models predicting 5–25 percent production reductions (D'Alessandro et al 2015; USAID, 2017a). Heat stress, in general, can reduce land and livestock productivity, reducing household agricultural income and thus their ability to purchase food (D'Alessandro et al 2015; USAID, 2017a; Swain et al. 2011). Given that nearly 30% of households in the country also rely on livestock, phenomena such as heat stress and high temperature-induced bushfires can have a negative impact on people's livelihoods (D'Alessandro et al. 2015; USAID, 2017a).

Our findings also support a positive and significant (at the 10% level) correlation between 3 month rainfall anomalies and child nutritional security. When controlling for the presence of positive rainfall extremes over three months, which captures heavy rains and floods, the impact is amplified. Households that have experienced a positive rainfall extreme are 6.4 percent points more likely to have an underweight child in the family compared to household that did not experience it. This is consistent with the findings of Akukwe et al. (2020), who discovered that flood-affected households in agrarian communities in southern Nigeria are 2.221 times more likely to be food insecure than non-flooded households. Flooding had a significant impact on household food security, according to their findings, 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 research has found that heavy rains and floods have a negative impact on agricultural production, potentially increasing the severity of food insecurity Pacetti, Caporali, and Rulli, 2017; Devereux 2007).

II. Do food and nutritional insecurities, as exacerbated by climate, affect the likelihood and/or intensity of conflicts?

This analysis estimates the impact of the interaction of nutritional 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. Nutritional insecurity is estimated by the share of household with at least one underweight child in the district. 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 (Battles, riots and strategic developments). 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	Battles 3f	269	0.02	0.12	0	1
	Riots 3f	269	0.07	0.34	0	3.61
	Strategic development 3f	269	0.02	0.1	0	1
	Total conflicts 3f	269	0.24	0.89	0	9.79
	Battles 6f	269	0.1	0.63	0	9
	Riots 6f	269	0.17	0.91	0	10.39
	Strategic development 6f	269	0.04	0.17	0	1.06
	Total conflicts 6f	269	0.64	2.18	0	23.18
	Battles 12f	269	0.21	1.03	0	13
	Riots 12f	269	0.32	1.52	0	17.57
	Strategic development 12f	269	0.08	0.36	0	4
	Total conflicts 12f	269	1.5	4.27	0	41.68
Nutritional Security Variable	Share HH with at least one underwgt children	239	0.29	0.14	0	1
Control Variables	Share of urban HH in the dis.	269	0.34	0.33	0.00	1.00
	Share of working age HH head in the dis.	269	0.80	0.08	0.54	1.00
	Share of Female HH head in the dis.	269	0.21	0.12	0.00	0.49
	Share of poor HH in the dis.	269	0.27	0.23	0.00	1.00
	Share of HH head no education in the dist.	269	0.65	0.28	0.00	1.00
	Share of unemployed women/men in the dis.	269	0.48	0.25	0.00	1.00
	Average HH size in the dis.	269	9.60	1.88	3.33	17.14
	Share of HH owning Ag. Land in the dis.	202	0.57	0.28	0.00	1.00
	Share of Ag. Working women/men in the dis.	269	0.34	0.23	0.00	0.97
	Number of past total conflicts in the dist.	269	0.09	0.33	0.00	2.95
Climate Variables	Rainfall- Anomalies 12 months	269	0.09	0.3	-0.75	1.63
	Temperatures- Anomalies 12 months	269	0.02	0.27	-0.65	0.49
	Temperature -Highest extreme 12 months	269	0.21	0.41	0	1

Table 4 reports the summary results for this analysis. The results did not show any positive and significant correlation between nutritional insecurity and conflict. From Table 4 it appears that conflict are not explained only by controlling for the share of households with at least one underweight children.

To understand whether climate exacerbate the impact of food insecurity on conflict we interact climate anomalies with our variables of nutritional insecurity. Table 4 also reports the results of the interaction with climate anomalies occurring 3 and 12 months before. When nutritional insecurity is combined with rainfall anomalies over a 12-month period, there is a positive and significant (at 10% level) correlation with the presence of riots three and six months after the interview. More specifically, a one-percentage-point increase in the proportion of households with a nutritionally insecure child associated with increasing rainfall anomalies corresponds to an increase of 1.5 and 3.6 riots in the following three and six months, respectively. The same interaction has a positive and significant correlation with the total number of conflict 6 and 12 months after the interview, with an increase of 5 and 10 total conflict led by a 1% increase in nutritionally insecure households associated with increasing rainfall anomalies 12 months. This positive and significant relationship is also present when nutritional insecurity is combined with a 3 month period of high rainfall. It appears that a 1% increase in the share of nutritionally insecure households that have experienced extreme rainfall anomalies in the previous three months corresponds to 1.8, 5.7, and 4.7 more riots in the following three, six, and twelve months, respectively, when compared to households that have not experienced any extreme rainfall episodes. Furthermore, the same interaction, correspond to 1.6 and 11.4 more total conflict in the following 3 and 12 months.

Table 4 also shows that nutritional insecurity, combined with increasing temperature anomalies, has a positive and significant correlation with the future presence of strategic developments. Following ACLED guidelines strategic developments' are useful for understanding the context of disorder because they capture key developments that go beyond both physical violence directed at individuals or armed groups and demonstrations involving the physical gathering of people (ACLED, 2018). In general, a one percent rise in nutritional insecurity mixed with rising temperature anomalies is associated with a one percent increase in strategic development over the next six to twelve months. Our findings also show an interaction between increasing nutritional insecurity and positive temperature extremes in the 12 months preceding the interview. It appears that a 10% increase in the share of nutritionally insecure households that experienced extreme temperature anomalies resulted in 9 more riots three months later and 5.8 more battles in the following year when compared to households that did not experience these temperature extremes. This interaction also demonstrates that a 1% increase in nutritional insecurity for households experiencing extreme temperature anomalies is significantly (at a 10% level) correlated with 4 additional battles in the following 12 months. This results are consistent with Burke, et al (2009) findings, which points out a positive correlation between increasing temperatures and civil conflict in Africa.

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 (Burke, et al., 2009; Crost et al., 2018; Fjelde, 2015; Mach et al., 2019). Despite being consistent with previous studies, these findings are surprising, especially given the country's stable and mostly peaceful situation.

Table 4 : Summary results – Second stage of the analysis

Variables	3 months after							
	Battles	Battles	Riots	Riots	Strategic developments	Strategic developments	Total Conflict	Total Conflict
Share HH with at least one underwgt child	-0.045	-0.009	-0.163	-0.284*	-0.046	-0.062	-0.192	-0.292
	(0.104)	(0.103)	(0.122)	(0.150)	(0.052)	(0.059)	(0.260)	(0.337)
Rainfall - Anomaly 12 months # Share HH with at least one underwgt child		-0.016		1.529*		0.255		0.908
		(0.235)		(0.773)		(0.222)		(1.022)
Temperature - Anomaly 12 months # Share HH with at least one underwgt child		0.411		0.193		0.074		2.370
		(0.351)		(0.312)		(0.170)		(1.797)
Rainfall- Highest extreme 3 moths # Share HH with at least one underwgt child		-0.071		1.869***		-0.156		1.627**
		(0.095)		(0.541)		(0.107)		(0.689)
Temperature -Highest extreme 12 months # Share HH with at least one underwgt child		-0.096		0.942**		0.089		0.545
		(0.136)		(0.387)		(0.137)		(0.385)
Variables	**6 months after**							
	Battles	Battles	Riots	Riots	Strategic developments	Strategic developments	Total Conflict	Total Conflict
Share HH with at least one underwgt child	-0.229	-0.146	-0.671	-0.904*	-0.122	-0.128	-0.961	-1.287
	(0.231)	(0.201)	(0.447)	(0.503)	(0.138)	(0.121)	(0.836)	(0.905)
Rainfall - Anomaly 12 months # Share HH with at least one underwgt child		0.234		3.589*		0.960		5.284*
		(0.652)		(1.895)		(0.652)		(2.761)
Temperature - Anomaly 12 months # Share HH with at least one underwgt child		1.234		1.040		0.944*		1.726
		(1.011)		(0.786)		(0.547)		(3.079)
Rainfall- Highest extreme 3 moths # Share HH with at least one underwgt child		0.309		5.748*		0.751		0.309
		(0.315)		(3.180)		(0.530)		(0.315)
Temperature -Highest extreme 12 months # Share HH with at least one underwgt child		0.147		2.401		0.369		1.801
		(0.204)		(1.471)		(0.426)		(1.234)
Variables	**12 months after**							
	Battles	Battles	Riots	Riots	Strategic developments	Strategic developments	Total Conflict	Total Conflict
Share HH with at least one underwgt child	-0.513	-0.442	-1.126	-1.471*	-0.215	-0.187	-3.097	-4.038*
	(0.417)	(0.387)	(0.800)	(0.871)	(0.279)	(0.233)	(1.885)	(2.128)
Rainfall - Anomaly 12 months # Share HH with at least one underwgt child		0.204		5.715		0.734		10.212**
		(0.632)		(3.416)		(1.010)		(5.008)
Temperature - Anomaly 12 months # Share HH with at least one underwgt child		1.052		1.965		1.107*		-0.336
		(0.927)		(1.932)		(0.562)		(3.752)
Rainfall- Highest extreme 3 moths # Share HH with at least one underwgt child		0.353		4.795*		0.925		11.420*
		(0.487)		(2.370)		(0.597)		(6.075)
Temperature -Highest extreme 12 months # Share HH with at least one underwgt child		0.581*		3.806		0.395		4.029*
		(0.337)		(2.483)		(0.475)		(2.376)
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

4. 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 nutritional insecurity has been established. In particular, the probability of having an underweight child in the household significantly increases when temperature increases 3 and 12 months before the data collection but also in case of extreme positive rainfall variability 3 months before the interview. This suggest that household and in particular children are considerably vulnerable to different kind of climate anomalies. The results of the second stage of the analysis, which was aggregated at the district level, show a positive significant correlation between increasing levels of nutritional insecurity combined with increasing rainfall and temperature anomalies and higher intensity of conflict, specifically with riots and the total number of conflicts. When nutritional insecurity is examined separately from climate anomalies, this correlation does not appear. We also discovered that the combination of nutritional insecurity and temperature fluctuations increases the number of battles 12 months after the household interview. Finally, our findings show that the combination of 12 months of temperature anomalies and nutritional insecurity raises the level of strategic developments 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 ten rounds of the Senegal Demographic and Health Surveys from 1997 to 2019. (DHS). Individual data on women was extracted in order to define the main variable of interest for measuring nutrition insecurity at the household and sub-county levels, the presence of at a least one underweights child in the household.

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[2] 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 Senegal 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 Senegal, in particular, has been used to define the various types of conflicts that occur on a regular basis in Senegal 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 malnourished women 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

[2] 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.

one underweight 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:

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

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 nutrition 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 Senegal sub-counties. This model primarily analyses non-state conflicts such as battles, riots, strategic developments, 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. Indeed, common examples of low-intensity persistent violent episodes reported across the country include frequent violent attacks, livestock raids, communal conflicts and ethnic clashes, youth recruitment, and gender-based violence (Seter, 2016; Witsenburg et al., 2009; Kumssa et al., 2014). 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 ongoing conflicts at time t. α_t and γ_c are time and county fixed effects, respectively, and u_{dct} is the error term.