Technical Paper 5. Conflict and Climate Change in the Lake Chad Region

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6.1 Introduction

Peace and security are basic conditions for economic and social development. Conflict, on the other hand, can reverse years of economic growth and induce long-term harm on almost all aspects of development. For the past decade, the Lake Chad region has been the setting of conflicts between government forces and armed groups, most notably the Boko Haram. Although the intensity of fighting has petered off in recent years, the conflict has spread from Northern Nigeria and now affects all four countries of the region.

Due to the paramount importance of avoiding armed conflict, a large economic literature exists that seeks to find explanations for the onset and prevalence of conflict in developing countries. Blattman and Miguel [2010] list some of the most common theories of conflict including *competition for resources, economic grievances, and the possibility of looting*.

More recently, a strand of literature focuses more on geographic and climatic root causes of conflict. For instance, in a meta-analysis of 55 studies, Burke et al. [2015] find that higher temperatures is the most important climatic factor leading to more interpersonal and intergroup conflict. With a specific focus on civil war in Africa, Burke et al. [2009] warned that projected increases in temperatures could lead to 54 percent increase in armed conflicts by 2030. However, both studies conclude that more research is needed in order to understand the mechanisms behind this relationship as well as investigating the potential adverse effects of climate change. More recently, Eberle et al. [2020] found that a 1 degree increase in temperatures is associated with a 54 percent increase in conflict probability in areas that are home to both herders and farmers and a 17 percent increase in other areas of Africa. A central question is whether the effect goes through an 'income channel' where conflict is ultimately caused by economic downturns due to lower agricultural productivity in periods of warmer temperatures—or whether the effect is somehow physiological, as humans are generally shown, in the medical literature, to be more aggressive when temperatures are higher. Harari and Ferrara [2018] explore the 'income channel' and find that part of the variation in conflict can be explained by a drought index when dis-aggregated to the growing period of the main crops across Africa. However, whether the results would hold without temperatures as an input to the SPEI is unclear.

This paper attempts to shed light on the geographical distribution of conflict and its climatic determinants in the Lake Chad region following a sub-national approach where readily available spatial data is employed at two different units of aggregation: Firstly, 90 second level administrative areas, and secondly, around 5,318 grid cells covering the same region. Exposure to conflict is here defined as the intensity (for districts) or incidence (for cells) of conflict in a given unit in a given year. Parts of the population may not be directly exposed by this definition, but since the units of analysis are relatively small, most will be affected in some ways, for instance by safety concerns when visiting the nearest towns to trade or by the general economic consequences.

The results of the analysis suggest, in line with the literature mentioned above, that temperature anomalies do have a positive impact on conflict across districts, cells and years. It also shows that negative NDVI (Normalised Difference Vegetation Index) anomalies are associated with more conflict—especially in cropland zones and during growing seasons. Rainfall anomalies as well as the SPEI (Standardized Precipitation-Evapotranspiration Index) do not exhibit the same effect on conflict. This could be an indication of measurement errors in these variables—or it could indicate that temperatures and rainfall have different effects on conflict rather than the often-mentioned drought-income channel.

6.2 Data

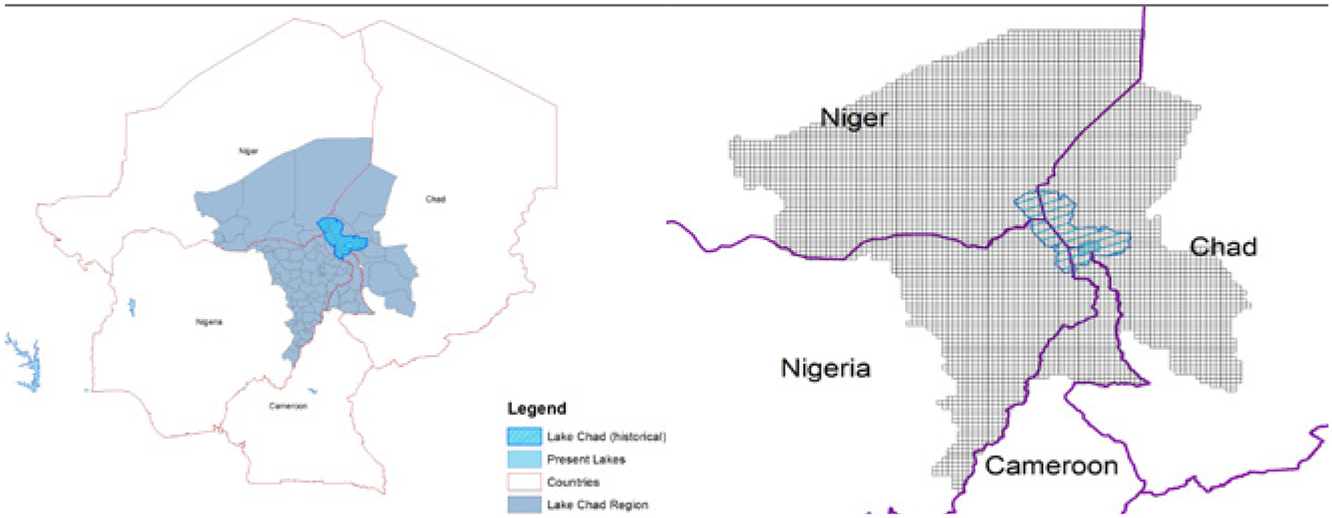
At the core of the analysis lies the geographical delimitation of the Lake Chad region. It comprises 4 countries and a total of 90 districts (2nd level administrative units).

Map 6.1 shows the extent of the Lake Chad region within the four countries of Niger, Chad, Nigeria, and Cameroon. It also shows the units of analysis of this study, namely the districts within the lake region on the left panel and the grid cells on the right. These units are chosen from a practical and methodological perspective. Firstly, they are large enough to cover a meaningful number of satellite data pixels, while small enough for the total number of units to be useful in regression analyses. Secondly, many policies are implemented at this level, so policy-makers will be interested in being able to compare distributions of key variables at district level. The grid cell level is chosen to accompany the district level analysis since it allows for much more variation and more observations due to a higher resolution. Furthermore, since the cells represent little squares, there is no concern about endogenous border locations.

Table A6.1 in the appendix contains a list of indicators included in the analysis, their sources, as well as the spatial and temporal resolution of the raw data. Except for conflict, all data sets included here are originally raster format, but are, for the purpose of the analysis, aggregated to the units of analysis, either using the sum (population, conflict event, and fatalities) or mean (Share of cropland, travel time, rainfall, temperatures, and greenness). While NDVI and temperature data is based on pure (processed) satellite images, data on population, travel time, and precipitation are drawn from secondary sources where the pixel values of the raster data sets are generated from combining various sources of raw data. Conflict risk numbers stand out in this list as it is based on geo-referenced point data from the ACLED database and aggregated to the second level administrative units directly from the recorded latitudes and longitudes of the conflict events.

Data on conflict as well as climate come with a time dimension as well. Here, values are summarized to individual calendar years from 2001 to 2018.

Map 6.1: Extent and units of analysis



6.2.1 Conflict

The conflict data used in this study comes from the Armed Conflict Location and Event Database (ACLED). In this database, conflict events are registered based mainly on local media reports, and geo-referenced. It distinguishes between various types of conflict events, most notably *battles*, *riots*, *protests*, and *violence against civilians*. For each conflict event, the number of fatalities is also reported. In this analysis, both the number of events and the number of fatalities by district-year are used. These two measures of conflict exposure are central outcome variables in the regression analyses presented in the next section.

Table 6.1 includes summary statistics of key conflict variables in the Lake Chad region during the years 2001 to 2018. Of conflict events, battles and violence against civilians are the most widespread types. Nigeria has seen by far the largest number of actual battles, and also the largest number of fatalities. Cameroon is in second place in terms of events, but with a distribution of events leaning more towards acts of violence against civilians. Niger is the most peaceful country in the region over the period.

Figure 6.1 shows the development of conflict over time in the entirety of the Lake Chad Region. Of the four conflict event types, battles and violence against civilians have followed a largely similar pattern over the years while riots and protests are not as commonly reported, but still growing in later years. The sum of conflict fatalities in the region is generally high and volatile, but saw a peak around 2014 and 2015 to around 1,000 per year before dropping again later. Note the logarithmic scale of the vertical axis.

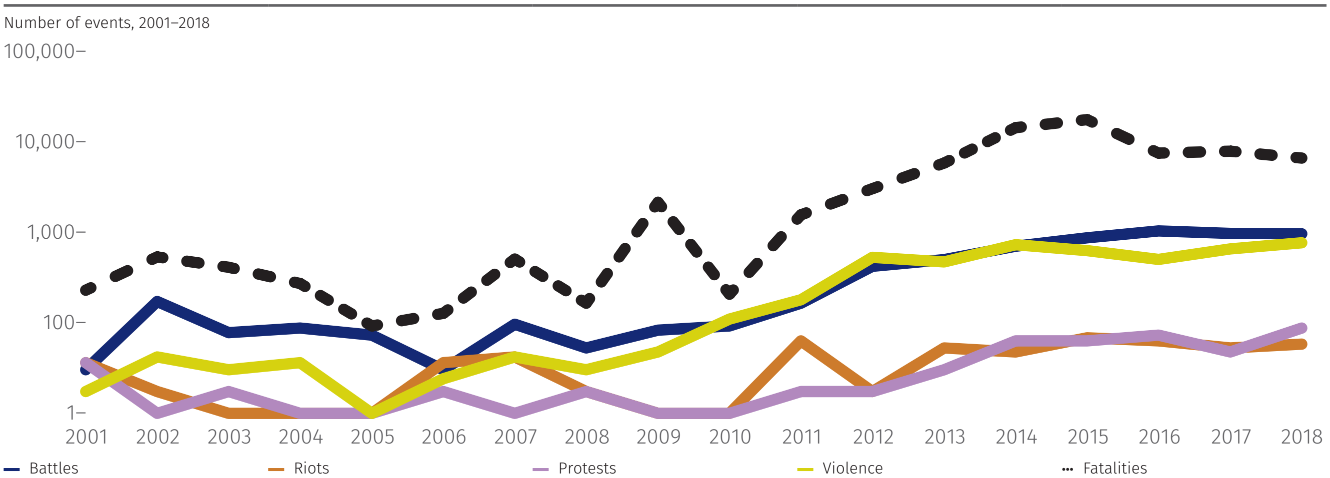
Table 6.1: Number of conflict events and fatalities 2001–2018

	Cameroon	*Chad*	*Niger*	*Nigeria*	*Total*
Conflict events	1,861	692	620	12,702	**15,875**
Battles	636	332	256	3,171	**4,395**
Protests	145	56	83	3,101	**3,385**
Riots	87	24	61	1,448	**1,620**
Violence	621	193	133	3,813	**4,760**
Fatalities	6,124	6,234	2,550	60,925	**75,833**

6.2.2 Climate

Climate and climate change are often mentioned among the most important factors for peace and development in the Lake Chad region. For instance, the lake itself has provided livelihoods for the people surrounding it for centuries, but shrank dramatically

Figure 6.1: Conflict events and fatalities over time



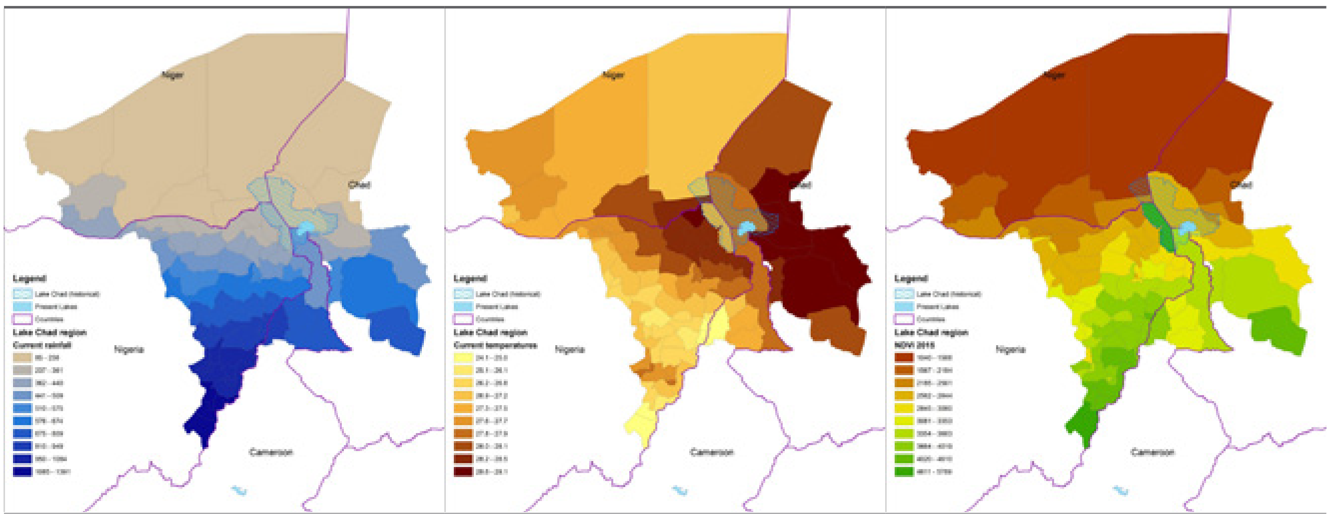
Source: Fisker 2021.

in size during the 1970's and 80's before gradually regenerating in recent decades. It now covers 56 percent of its 1973 extent, although much of the surface is now also covered by vegetation [Vivekananda et al., 2019]. Land-degradation, over-exploitation, and climate change are often mentioned as possible causes for this.

Furthermore, the region around Lake Chad is by no means uniform in terms of climate and weather. To the South, the climate is more humid, and the landscape is greener, whereas the Northern parts are drier, less green, and with a larger difference between day and night-time temperatures. The large areas that were historically submerged by the lake are still greener and cooler than other parts of the region despite relatively low levels of rainfall. Map 6.2 shows the distribution of rainfall, temperatures, and greenness across the 90 sub-national units of the region. While rainfall and greenness show a clear latitudinal gradient, temperatures are also mediated by altitude, and thus generally higher in the Eastern parts of the region.

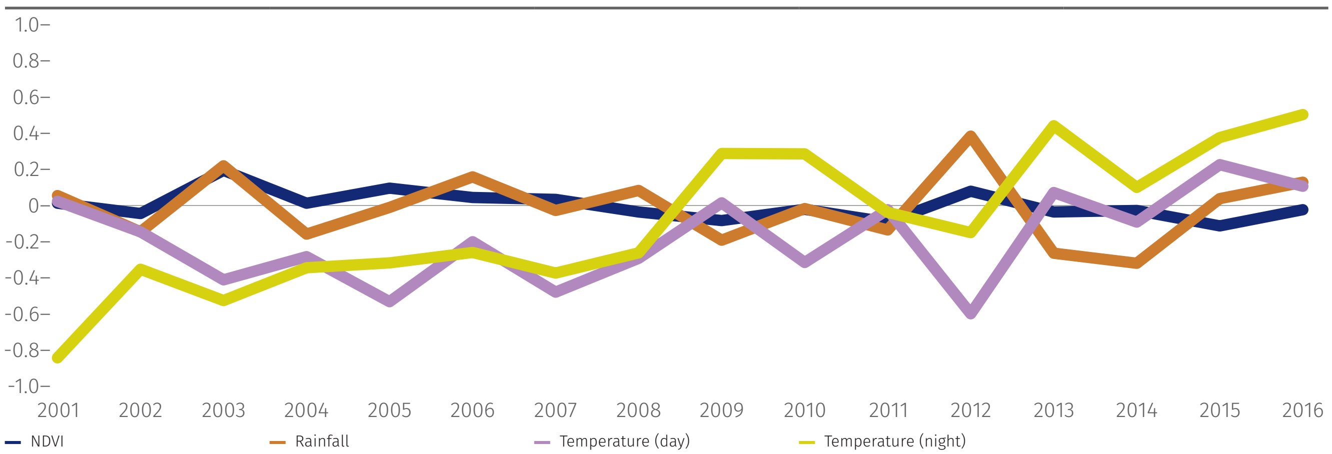
While large geographical variations exist as shown in Map 6.2, another in- teresting perspective is the variation over time. Figure 6.2 demonstrates the district-level average anomalies of NDVI, rainfall, and temperatures over the period 2001–2018. The large positive daytime temperature anomaly towards the end

Map 6.2: Average rainfall, temperatures, and NDVI



Source: Fisker 2021.

Figure 6.2: NDVI, rainfall, and temperature anomalies over time



of the period stands out while two other interesting observations is a general decline in NDVI throughout the period as well as an upward trend in temperatures. Rainfall generally fluctuates around the mean.

In this paper, drought is measured in three different ways: Firstly by anomalies in rainfall and temperatures measured respectively by the Chirps (Climate Hazards Group InfraRed Precipitation with Station) data and Modis Terra, which would correspond to the notion of meteorological droughts; secondly by NDVI anomalies—a more direct proxy for agricultural drought, and finally by the SPEI drought index which combines long time series of rainfall and temperatures to calculate the difference between precipiation and potential evapotransipiration. Despite several shortcomings, the latter is used extensively in the economics literature, for instance by Harari and Ferrara [2018].

6.2.3 Other explanatory factors

Obviously, conflict depends on other factors than the climatic: demographics, infrastructure, and economic development, to mention a few. A larger population density means more potential for disagreement and more competition for limited resources, cf Blattman and Miguel [2010]. On the other hand, a certain population number is probably needed in order for law enforcement and other societal institutions to be efficient. Likewise, infrastructure can be considered to play a roll in the spread of conflict, since an efficient road system allows armed groups to move between locations. Again, more desolate areas may also provide opportunities to hide from government forces, thus enabling local militias to form and grow. Finally, economic activity—often measured by the intensity of night lights—can affect the risk of conflict; either because richer areas contain more opportunity for looting, or because poorer areas may be easier to capture. Map 6.3 displays the distribution by district of the number of conflict fatalities during the period 2015–2019, population in 2020, and average travel time to nearest urban centre in 2015. While the distributions of the latter two indicators look similar, they measure slightly different aspects of economic development: For any given population density, travel time indicates how easy it is to move around the district.

Table 6.2 shows mean values of the different indicators split by country. In terms of average rainfall, the districts of the region belonging to Niger are the driest and Cameroon the wettest. Temperatures are highest in Chad (28.5 degrees Celsius) while the other three countries are all around one degree cooler. The largest increases in temperatures due to climate change are projected to take place in Niger, followed by Chad. Niger is also the country

Map 6.3: Conflict intensity, population density and travel time

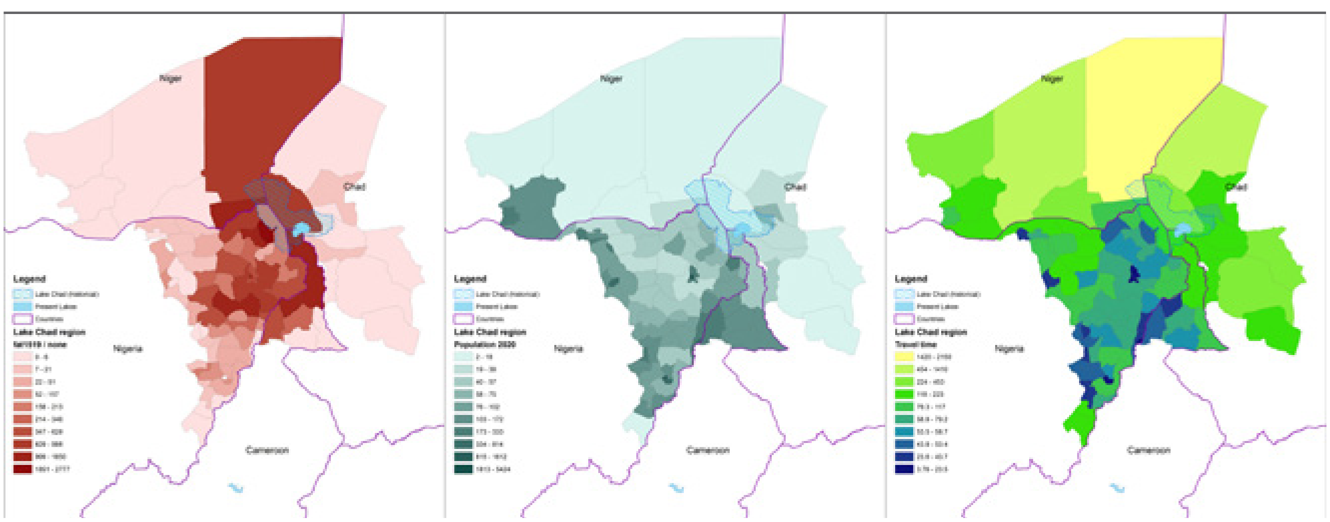


Table 6.2: Summary statistics: Mean values of climate and control variables

	Cameroon	*Chad*	*Niger*	*Nigeria*	*Total*
NDVI	0.360	0.287	0.189	0.347	0.327
Temp. (daytime)	15.42	15.51	15.48	15.40	15.42
Temp. (nighttime)	14.69	14.69	14.61	14.66	14.66
Rainfall (chirps)	61.45	36.75	24.39	63.39	56.84
Projected rainfall change	22.00	30.44	30.90	22.63	24.19
Projected temp. change	6.045	6.430	7.498	6.364	6.451
Population 2000 (1000s)	443.6	142.3	290.6	121.3	160.2
Population 2020 (1000s)	788.2	276.4	769.5	228.0	318.8
Travel time	73.27	282.1	603.4	73.19	143.5
Distance to border	25.98	96.79	97.96	72.79	74.57

with the lowest projected increase in rainfall, pointing towards even more difficult conditions for farmers and pastoralists there. NDVI values are generally much larger in Cameroon and Nigeria, and lower in Niger.

Average population numbers for districts vary between 228,000 (Nigeria) and 788,000 (Cameroon), with the districts belonging to Niger having seen the largest percentage increase between 2000 and 2020.

Travel times to urban areas are generally low in Nigeria and Cameroon, while large distances exist in Niger and to a lesser extent in Chad, the main reason being that districts in these countries stretch far into desert areas. Average distance to an international border is by far lowest in Cameroon.

6.2.4 Correlations

In order to provide an overview of how conflict incidence and intensity is correlated with the factors that form part of the analysis, Table 6.3 consists of pairwise correlations between conflict and each of the other variables when all cross-sections that form the panel are pooled.

While the effects of the climatic variables are studied in more detail in the next section, it is interesting to note here that conflict is more likely in areas with larger populations, smaller travel times to urban centres, and also in areas with a larger share of cropland areas. Regarding the latter two indicators, the correlations are reversed when observing districts compared to cells. This is likely caused by the fact that some districts are geographically large (especially in Niger and Chad) and these have lower shares of cropland area as well as larger travel distances while also less conflict.

Table 6.3: Pairwise correlations between conflict and explanatory variables in pooled data

	Any event (cells)	*log(events) (districts)*
Temp anom.	0.0873	0.241
Rainfall anom	0.0171	0.0345
NDVI anom	-0.0822	-0.1697
SPEI	0.0912	0.1496
log(population)	0.1409	0.5557
log(travel time)	-0.1648	0.0057
Cropland share	0.1278	-0.0598
Observations	96,642	1,692

6.3 Empirical strategy

This section lays out the approach to analysing the climatic determinants of conflict in the Lake Chad region. The analysis investigates the effects of climate on conflict from various perspectives: in the main specification, district-year conflict intensity and cell-year conflict incidence are explained by anomalies (z-scores calculated each month in the 19-year period where the value represents standard deviations from the long-term mean within the unit and month) in temperature, rainfall, and greenness as well as a 6-month SPEI drought index in a fixed effects set-up. Since both conflict and climate are spatially dynamic processes, the regressions are based upon assumptions of spatially correlated error terms, and in some specifications including a spatially lagged dependent variable. This takes into account the fact that conflict events tend to spread from a point of origin to neighboring areas.

Due to the differences in size between second-level administrative units and cells of approx. 10 km * 10 km, two different dependent variables are considered, that best exploit the variation in the data: the former case employs the logarithm of the number of conflict events (i.e. the intensity of conflict) while in the latter case, a dummy variable indicating whether a conflict event has taken place in a given cell in a given year is used (i.e. incidence of conflict).

Equation 1 describes the fixed effects model of conflict intensity/incidence and its climatic predictors at the district/cell level:

$$Conflict_{it} = \beta_1 C_{it} + \beta_2 W * conflict_{it} + \varepsilon_{it} \qquad (1)$$

where $Conflict$ is either the logarithm of the number of conflict events in a district (i) or an indicator of the presence of conflict in a cell (also i) in given year (t). C is a vector of climate anomalies observed in unit i in year t: rainfall as well as daytime temperature in the first model, NDVI (greenness) in the second, and the 6-month SPEI index in the third. In the analysis, these three models are used because they represent three different ways of measuring climatic impacts. The first model, which includes rainfall and temperature anomalies, is the most direct way of linking climate shocks to conflict intensity/incidence. The second model (with NDVI anomalies) compares the outcome of climate variations (i.e. the conditions of the vegetation) to conflict, while the third approach refers to a drought index (SPEI) that combines rainfall and temperatures into a measure that informs about agricultural potential.

$W * conflict_{it}$ is the spatial lag of the dependent variable. It measures the average number of conflict events or fatalities in neighboring districts in the same year, i.e. districts or cells that share a border with the unit in question. It does not distinguish between within-country borders and country borders in this set-up. This term is included separately as a check to whether controlling for the auto-regressive nature of conflict alters the results. ε is the random error term that allows for spatial correlation.

The climatic variables included in the baseline specification described by equation 1 are all averages for full calendar years. However, as argued by Harari and Ferrara [2018] among others, if the mechanism that links climate anomalies and conflict is economic hardship induced by agricultural drought, only the anomalies observed during the agricultural growing season should matter.

A related concern is that not all units of observation are areas of agricultural activity. If a drought-income-conflict relationship is expected, it is likely to be more directly impacting cropland areas than desert or pastoral areas. In order to capture the differential effect of climate anomalies on conflict, in equation 2, each climate variable in C is therefore interacted with the share of cropland in each unit of observation. Another potential source of heterogeneity in impacts is the population of a given unit. More people means more potential for conflict and thus a larger effect of climate shocks could be expected. Equation 2 describes the model with heterogeneous effects, which is similar to equation 1 in all other aspects:

$$Conflict_{it} = \beta_1 C(GP)_{it} + \beta_2 C(GP)_{it} * X_i + \beta_3 W * conflict_{it} + \varepsilon_{it} \qquad (2)$$

where $C(GP)_{it}$ is a vector of climate anomalies calculated only for the growing period months i the specific locations before aggregating to years, districts and cells and X is the share of cropland in cell/district i in the year 2000.

Finally, in order to test whether the relationships depend on population density, a model is run at the cell level where conflict incidence is interacted with a dummy variable taking the value one if a cell belongs to the upper half of the population distribution.

6.4 Results

6.4.1 Baseline results

Table 6.4 includes the results of applying a fixed effects estimator to equation 1 where the units of observation are districts and the dependent variable the logarithm of conflict events in a given year. Column 1–3 contain the results of regressions where the error terms are assumed to be spatially correlated whereas column 4–6 assume spatial auto-correlation and thus include a spatially lagged dependent variable.

Each column represents a specific way of measuring impacts of climate variation: Column 1 and 4 focus on the direct relationship between weather anomalies (rainfall and temperature) and conflict intensity. Column 2 and 5 use the observed NDVI-anomalies as an observable proxy for drought conditions whereas column 3 and 6 show the effects of a common drought-index that combines long-term information on rainfall and temperatures, namely the 6-month SPEI.

The results for districts and cells are qualitatively comparable: Temperature anomalies (both daytime and night-time) show a positive effect on conflict intensity and incidence. In other words, in hotter-than-usual years, districts or cells are more likely to experience conflict activity. Furthermore, and perhaps surprisingly, positive rainfall anomalies, i.e. years where rainfall levels are above the mean are also associated with more conflict measured at both district and cells. Turning to measures of drought, NDVI anomalies have the expected sign, meaning that worse growing conditions are correlated with more conflict. The SPEI, on the other hand, shows the opposite correlation, namely that drought-years (a negative value by this measure) tend to be aligned with less widespread conflict.

Adding numbers to the results, a positive temperature anomaly of one standard deviation is associated with a 17.6 percentage points increase in the yearly number of conflict events taking place in a given district. At the cell level, a similar temperature anomaly adds 0.8 percentage points to the likelihood of a cell experiencing any conflict events in that year. A *negative* NDVI anomaly of one standard deviation leads to an increase in the number of conflict events of 8.9 percentage points at the district level whereas the likelihood of experiencing a conflict at the cell level increases by 0.7 percentage points.

Table 6.4: Baseline results, Districts

	(1)	(2)	(3)	(4)	(5)	(6)
Temp.	0.176*** (0.028)			0.099*** 0.015)		
Rainfall	0.011 (0.027)			0.013 (0.014)		
NDVI		-0.089*** (0.028)			-0.057*** (0.014)	
SPEI			0.165*** (0.048)			0.080*** (0.022)
Spat. lag Conf. events				0.784*** (0.020)	0.796*** (0.020)	0.811*** (0.019)
N	1,692	1,598	1,692	1,692	1,598	1,692
Pseudo-r2	0.059	0.029	0.022	0.067	0.037	0.028

Note: Spatially correlated standard errors in parentheses. Fixed effects. Z-scores. * p<0.10, ** p<0.05, *** p<0.01

Table 6.5: Baseline results, Cells

	(1)	(2)	(3)	(4)	(5)	(6)
Temp.	0.008*** (0.001)			0.006*** (0.000)		
Rainfall	0.002*** (0.001)			0.001*** (0.000)		
NDVI		-0.007*** (0.001)			-0.005*** (0.000)	
SPEI			0.011*** (0.001)			0.006*** (0.001)
Sp_lag				0.443*** (0.005)	0.446*** (0.005)	0.450*** (0.005)
N	91,273	91,273	91,273	91,273	91,273	91,273
psudo-r2	0.01	0.01	0.01	0.01	0.01	0.01

Note: Spatially correlated standard errors in parentheses. Fixed effects. Z-scores. * p<0.10, ** p<0.05, *** p<0.01

All results are robust to controlling for the geographical spillover of conflicts. Column 4–6 of Table 6.4 and 6.5 add a spatially lagged version of the dependent variable that measures the average conflict incidence or number of conflict events in neighboring units (i.e. districts or cells that share a border with the district or cell in question). This variable generally has a large contribution to explaining conflict intensity while point estimates on the explanatory variables tend to drop slightly.

Table A6.2 and A6.3 in the appendix show results of estimating a model including temporal lags of the explanatory variables. It is demonstrated that temperature anomalies are significant predictors of the number of conflict events at the district level up to three years into the future. NDVI anomalies, on the other hand, only predict conflict with statistical significance in the same year as the conflicts. This fits well with the notion of NDVI anomalies being a more direct proxy of vegetation conditions on the ground than other climatic variables.

6.4.2 Exploring heterogeneous effects

A central question that remains to be addressed is whether the results found in table 6.4 and 6.5 are caused by a drought-income-channel where conflict is more likely in places where farmers are suffering from economic hardship. In order to investigate that, the next set of results will include climate anomalies calculated on basis of growing season months only, and further introduce interaction terms between each variable and the share of cropland within a unit of observation. This largely follows the approach of Harari and Ferrara [2018] who found an effect growing season SPEI on conflict incidence across all of Sub-Saharan Africa, albeit with much larger units of observations.

Table 6.6 and 6.7 show the effects of growing season-specific climate anomalies on conflict in districts and cells respectively. Both tables further include interactions between these and the share of cropland within each unit.

Temperature anomalies are still positively associated with conflict; especially in areas with more cropland.

For drought measured by NDVI anomalies, the negative effect observed in the baseline model also persists. Additionally it should be noted that the effect is weaker in areas of no cropland and larger, the larger the share of a unit is considered cropland. This is in line with expectations that bad harvests can lead to more conflict through an income channel.

Turning to rainfall and SPEI—the two variables where results opposite to the expectations were found in the baseline analysis, a few interesting observations are

Table 6.6: Heterogeneous effects, Districts

	(1)	(2)	(3)
GP Temp. anom.	0.021 (0.047)		
GP Rainfall anom.	0.002 (0.043)		
Cropland*GP Temp. anom.	0.478*** (0.112)		
GP NDVI anom.		-0.086* (0.051)	
Cropland*GP NDVI anom.		-0.219* (0.117)	
GP SPEI			-0.173** (0.070)
Cropland*GP SPEI			0.464*** (0.159)
N	1,692	1,692	1,692
pseudo-r2	0.07	0.05	0.01

Note: Standard errors in parentheses. * *p*<0.10, ** *p*<0.05, *** *p*<0.01

noted: Firstly, the positive correlation between rainfall and conflict disappears when only considering the growing seasons. The same is true for SPEI, however, when focusing on the agricultural areas, the positive (and somewhat contradictory) relationship re-emerges.

Another potential mediating factor is population density. In Table 6.8, *Urban* refers to a situation where the population of a cell is larger than the median of the distribution, which serves as a crude way of distinguishing between urban and rural areas. What is evident is that the effects of climate anomalies on conflict events are largely driven by areas witha population density above the median. In all cases the point estimates retain their direction, but become much more significant (statistically and economically) when adding the urban interaction terms.

Results including heterogeneous effects related to market access (travel time to nearest urban area) are not included as they are similar to those where population is used as interaction term.

Table 6.7: Heterogeneous croplands effects, Cells

	(1)	(2)	(3)
GP Temp. anom.	0.002* (0.001)		
GP Rainfall anom.	0.001 (0.001)		
Cropland*GP Temp. anom.	0.046*** (0.001)		
Cropland*GP Rainfall anom.	0.004 (0.003)		
GP NDVI anom.		-0.001 (0.001)	
Cropland*GP NDVI anom.		-0.036*** (0.003)	
GP SPEI			0.001 (0.002)
Cropland*GP SPEI			0.025*** (0.004)
N	61,013	61,013	61,013
pseudo-r2	0.02	0.01	0.00

Note: Standard errors in parentheses. * *p*<0.10, ** *p*<0.05, *** *p*<0.01

Table 6.8: Heterogeneous population effects, Cells

	(1)	(2)	(3)
Temp. anom.	0.002*** (0.001)		
Rainfall anom.	0.000 (0.001)		
Temp. anom. (day)*Urban	1.288*** (0.095)		
Rainfall anom*Urban	0.385*** (0.095)		
NDVI anom.		-0.002*** (0.001)	
NDVI anom*Urban		-1.251*** (0.093)	
SPEI			0.003** (0.001)
SPEI*Urban			1.404*** (0.165)
N	91,273	91,273	91,273
pseudo-r2	0.01	0.01	0.00

Note: Standard errors in parentheses. * *p*<0.10, ** *p*<0.05, *** *p*<0.01

6.5 Conclusion

In conclusion, this study finds that the distribution of conflict events across time and space in the Lake Chad region is correlated with climatic factors.

Higher-than-usual temperatures leads to an increase in conflict activity both measured at the district level and the more detailed grid cell level. The same is true for observed greenness anomalies, an effect that becomes stronger when focusing on anomalies during the growing season in cropland areas. However, rainfall (CHIRPS) and SPEI are not showing similar relationships with conflict. Two possible explanations for these apparently contradictory findings stand out: The first possibility is that conflict in the Lake Chad region is, in fact, affected much more by temperature anomalies than rainfall anomalies. This would be in line with the hypothesis that there the channel through which the relationship operates is more physiological than depending on agricultural income. A second possible explanation for the seemingly opposite results could simply be measurement errors in the SPEI and CHIRPS data sets. Both of these data sources are (partly) interpolated from weather station observations, and the distance to the nearest weather station is sometimes large. Figure A.1 in the appendix shows the distribution of weather stations used by CHIRPS and CRU (the database behind SPEI) respectively in the Lake Chad Region. There are around 12 (CHIRPS in 2010) and 7 (CRU in all years 2000-2014) weather stations in the region with observations that feed into the Chirps and SPEI data sets. This compares to 90 districts and 5,369 cells. So for a large majority of the observations in this analysis, rainfall and the SPEI will be based entirely on interpolations. On the contrary, the spatial resolution of NDVI and Temperatures is higher than the cells used, so in that case, the observed values are more valid. Likewise, conflict data is aggregated from high precision geographical coordinates, so there is also high confidence that the conflicts actually took place in the recorded locations.

Based on this it is therefore not possible to conclude which of the explanations is more likely. The fact that NDVI anomalies show expected signs and the effect is more pronounced in croplands during growing season points toward the measurement error explanation. However, this relation could to some extent also be spuriously driven by temperatures affecting both NDVI and conflict. More precise rainfall data, for instance from the Global Precipitation Measurement Mission (GPM) might shed more light on this puzzle.

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Appendix

Table A6.1: Data sources

	Indicators	Data format	Spatial resolution	Temporal coverage	Source
Population	Number of people per cell	Raster (tiff)	30 arc seconds (~1 km)	2000, 2020	World Pop
Infrastructure	Intensity of Night-time lights (average radiance)	Raster (tiff)	500 m pixels	Monthly - here April 2012 (earliest available) and April 2019	Visible Infrared Imaging Radiometer Suite (VIIRS)
	Accessibility to cities (travel time to nearest urban center)	Raster (tiff)	1 km	2015 (update and improvement to 2000 dataset)	Malaria Atlas Project
Climate	Precipitation	Raster (tiff)	2.5 arc minutes (~4 km)	Monthly, 2000–2018	Chirps
	Greenness (NDV) and temperature	Raster (HDF)	0.05 degrees (~5 km)	Monthly, 2000–2018	Modis Terra, mod13c2
Climate Change	Projected temperature and precipitation (CMIP6, SSP2.5)	Raster (tiff)	2.5 arc minute (~4 km)	2014–2060	Worldclim
Conflict	Number of events + Fatalities (Battles, protests, riots, violence against civilians)	Geo-referenced event (point) data	GPS points aggregated to district level	2015–2019 and change between 1014 and 1519	ACLED

Table A6.2: Baseline results with time lags, district level

	(1)
Temp. anom. (day)	0.192*** (0.034)
L.Temp. anom. (day)	0.132*** (0.031)
L2.Temp. anom. (day)	0.201*** (0.047)
L3.Temp. anom. (day)	0.065* (0.038)
Rainfall anom.	-0.022 (0.026)
L.Rainfall anom.	-0.080*** (0.027)
L2.Rainfall anom.	-0.018 (0.026)
L3.Rainfall anom.	-0.086*** (0.030)
Constant	0.769*** (0.028)
N	1410
r2	0.17

Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A6.3: Baseline results with time lags, district level

	(1)	(2)
NDVI anom.	-0.168*** (0.025)	
L.NDVI anom.	-0.055 (0.067)	
L2.NDVI anom.	-0.058 (0.048)	
L3.NDVI anom.	-0.118 (0.076)	
(mean) spei06		0.321*** (0.043)
L.(mean) spei06		0.206*** (0.034)
L2.(mean) spei06		0.206*** (0.030)
L3.(mean) spei06		0.110** (0.045)
Constant	0.673*** (0.032)	0.942*** (0.044)
N	1,316	1,410
r2	0.06	0.11

Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Figure A6.1: Distribution of weather stations in the Lake Chad region