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Vegetation Wars: Effects of Long-term Climate Change on Violent Intergroup Conflict in the Sahel Region 2010–2016

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Abstract

There is a widely held belief that global climate change will lead to several adverse consequences, one of them being an increased likelihood of violence on the African continent. This study investigates these claims by studying the links between climate change and violent intergroup conflict in the Sahel region 2010–2016. Using high-resolution satellite data, the incidence and intensity of violence in the area of study is analyzed with an unprecedented degree of spatial accuracy. After controlling for various variables thought to influence the outbreak of conflict, as well as employing a number of robustness checks, the results indicate that areas more severely affected by long-term decreases in average vegetative conditions were more likely to experience violent events in the studied time period. On average, an absolute 20-year decrease in the five-year mean of the Normalized Difference Vegetation Index (NDVI) of 10% corresponded to an increase of the likelihood of violence erupting in a particular area with around 1.3% in the main model. The results are in line with previous research linking worsening environmental conditions to violent intergroup conflict, strengthening the case that the security aspects of global climate change should be highly prioritized in the future in both research and policymaking.

Keywords: climate change, conflict, Sahel, Africa, long term, NDVI

JEL: F59, O13, Q51, Q54

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TABLE OF CONTENTS

List of figures and tables

Figures

Tables

I. Introduction

Few events have had such a fundamental impact on human societies as that of global climate change. The former Secretary-General of the United Nations, Ban Ki-moon, eloquently summarized that "ours is the first generation with the potential to end poverty – and the last to act to avoid the worst effects of climate change" (Ban, 2015). It is a common conception that climate change is a great threat to security, and there is no doubt that the phenomenon will grow even further in importance over the coming decades. Aggregate economic losses are said to accelerate with increasing temperatures, and the effects of climate change are projected to slow down economic growth, erode food security, and increase the displacement of people (IPCC, 2014, p. 20).

One of the major consequences of climate change is believed to be that of an increased occurrence of violent conflict on certain parts of the African continent, where environmental exposure is high and political institutions are weak. The relationship between environmental pressures and violent conflict is currently poorly understood, and there is a pressing need for an understanding of the conflict potential of climate change in order to accurately assess the impact of a changing environment on human societies. To address this, the purpose of this thesis will be to examine the connection between climate change and violent intergroup conflict in the Sahel region, an area plagued by long-lasting conflicts, weak political institutions and socio-economic stagnation, in the time period 2010–2016.

Scholars have long been concerned with the relationship between worsening climate conditions and the occurrence of violent conflict. Although the study of how humans cope with resource scarcity can be traced back to well-known historical thinkers such as Malthus, (and even Hobbes), more recently the field of climate security takes its starting point in the highly influential work of Thomas Homer-Dixon (1994, 1999). Most of this work has been of a qualitative nature, focusing on detailed studies of specific cases. The past decade has, however, seen a dramatic increase in the number of quantitative studies examining this relationship, leading to a large amount of existing social science research on the subject of climate security.

This voluminous field of research has as of yet failed to produce definitive conclusions regarding the links between climate change and violent conflict. Quite puzzlingly, the existing body of research is more or less split down the middle, with some studies claiming to show the existence of a relationship between the two phenomena, and others alleging to prove the exact opposite. A recent review of quantitative studies on the topic found that there does not exist sufficient evidence to assert the presence of a link between climate change and violent conflict (Koubi et al., 2014). But just one year later, another review using a different sample of quantitative studies reached the conclusion that the evidence, albeit somewhat inconclusive, still indicates the existence of a link between the two phenomena, showing that the average effect from increasing temperature by one standard deviation was an increase in the probability of intergroup conflict of 11.3% (Burke et al., 2015).

Given the divisiveness of the results from quantitative studies, it is clear that researchers have failed to adopt a satisfactory methodology in the study of climate security. Several methodological aspects of the existing research can be called into question. First, almost all studies fail to take into account the often extensive temporal scope of the impacts of climate change, focusing on short-term climate variability (e.g. weather fluctuations) instead of actual climate change (van Baalen and Mobjörk, 2016, p. 4). Second, many studies make use of the UCDP/PRIO Armed Conflict Dataset, which requires the presence of a government actor on either side of the conflict in order for the event to be reported. Since climate change may be assumed to affect different types of conflict between a multitude of actors other than the government, the use of this dataset may provide misleading results (Meierding, 2013, p. 190). Finally, the scale and detail of the data analyzed in existing studies are often unnecessarily limited, with the most common spatial units being administrative regions such as countries, states and provinces. Although some studies take into account the spatial distribution of violence on a finer level (e.g. Harari and La Ferrara, 2013; O'Loughlin et al., 2012; Theisen et al., 2011), very few studies combine this approach with the use of high resolution satellite data (see De Juan (2015) for an excellent exception).

This study will attempt to address these methodological limitations in the existing body of research by making use of the Armed Conflict Location and Event Data Project (ACLED), which employs a less limited definition of violent conflict, in combination with high resolution satellite imagery to provide a comprehensive analysis of the links between long-term climate change and the spatial distribution of violent conflict in the Sahel region in the time period 2010–2016. The contributions of this study to the existing literature will be threefold. First, it adopts an approach that has, to the authors' knowledge, previously only been used on a limited case study basis, providing a new method for large-scale climate-security analysis. Second, it studies the links between climate change and violent conflict with an unprecedented level of detail, providing a solid foundation from which to evaluate the presence of a link between the two phenomena. Finally, it contributes to the long-standing debate within the field of climate security, providing one small step closer to answering the question of whether climate change causes violent conflict.

Before proceeding any further, certain concepts of central importance to this study will need to be defined. More specifically, the terms *climate change* and *violent intergroup conflict* are in need of clarification. *Climate change* is defined by the United Nations Intergovernmental Panel on Climate Change (IPCC) as "a change in the state of the climate […] that persists for an extended period, typically decades or longer" (IPCC, 2014, p. 5). In other words, climate change denotes extended changes of environmental conditions. Existing climate-security studies, however, often focus on *climate variability* (i.e. short-term climate fluctuations). By using long-term changes in the 5-year means of the Normalized Difference Vegetation Index (NDVI) as an explanatory variable, this study will attempt to assess the impact of long-term changes in the climate on violent intergroup conflict, offering an alternative to the climate variables more commonly used in the field (i.e. rainfall and temperature deviations).

Violent intergroup conflict is an often-recurring concept in conflict studies in general, and climate-security studies in particular. One important distinction to be made is that between *interpersonal* (i.e. violent crime, for example murder) and *intergroup* (organized) conflicts. Although there does exist a substantial body of research on the effects of climate change on interpersonal conflicts (e.g. Ranson, 2014; Iyer and Topalova, 2014), the major focus of the field is instead on that of organized violence between groups, and this will also be the area of interest for this study. Several definitions of intergroup conflict exist. However, many scholars have argued that one of the most probable responses to the onset of climate change-induced resource scarcity is small-scale, communal conflict, rather than large-scale civil war or rebellion (Fjelde and von Uexkull, 2012, p. 446). This argument is rather intuitive, since the use of violent means to alleviate existing conditions related to resource scarcity would, in the presence of a weak state, in all likelihood be targeted towards neighboring groups rather than state representatives. Since the African continent is characterized by fragile states with limited power (Raleigh, 2010), conflict involving other actors than the state is likely to occur. To take this into account, this study will use a wide interpretation of the term conflict, mirroring the definition made by van Baalen and Mobjörk (2016, p. 8), who define violent intergroup conflict as "deliberate violent acts perpetrated by a government or organized or semi-organized group against state forces, other organized or semi-organized groups or civilians"

Given the definitions above, the purpose of this study, to investigate the connection between climate change and violent intergroup conflict in the Sahel region, can be further specified into the following hypotheses:

H1: Long-term changes in climatic conditions increase the probability of violent intergroup conflict occurring in the Sahel region in 2010–2016.

H2: Long-term changes in climatic conditions increase the number of fatalities of violent intergroup conflict occurring in the Sahel region in 2010–2016.

In order to validate these hypotheses, this study will proceed in the following manner. The next section will provide a thorough review of previous climate-security research. Due to the interdisciplinary nature of the subject, studies from a variety of fields will be included, but the main focus will naturally be on economic research. Following this, the theoretical framework used in this study will be presented. The section after this will present the data and methods applied in the study, followed by a section devoted to an analysis of the data. After the analysis, the results will be discussed, and finally a concluding section regarding the main findings of this study will be presented, together with a discussion regarding implications for future research.

II. Literature Review

The economic analysis of conflict has long constituted a rather small part of the larger field of economics, but research of major importance has still been conducted during the previous decades. Beginning with the work of Haavelmo (1954), a substantial research body has been built up within the field often referred to as "defense economics." Scholars within this field attempt to study human conflict from an economic point of view, including work on such diverse topics as civil war, terrorism, peacekeeping and arms races.[1] The existing theoretical foundations regarding the links between climate change and conflict are, unfortunately, quite limited. Economic theory has not yet caught up with the developments in this area, severely hampering any attempts to explicitly link the empirical findings of economic research in this field to an established theoretical framework.

Economic study of climate-related security concerns, or simply climate security, constitutes a relatively new addition to defense economics. The following segment will consist of a comprehensive review of the existing literature within this field, exploring the links between climate change and violent intergroup conflict. As has been previously concluded, the effects of changing climate conditions on intergroup conflict are more probable to be of a large magnitude in areas where states and institutions are already weak. This leads to a natural focus on conflicts on the African continent, which will be the geographical area studied in the majority of the research presented below.

One of the most common independent variables used in quantitative climate-security studies is rainfall. Negative shocks in annual rainfall at the country level have been found to increase the likelihood of violent conflict on the African continent (Miguel et al., 2004). At a finer level of spatial and temporal disaggregation, positive deviations from the precipitation norms have been found to decrease the probability of violence in East Africa (O'Loughlin et al., 2012). Links between extreme deviations from precipitation norms, both positive and negative, and social conflict (e.g. demonstrations, strikes, riots etc.) have also been identified (Hendrix and Salehyan, 2012). Apart from rainfall, the explanatory variable most commonly used is temperature. Existing evidence links higher temperatures to increased likelihood of war (Burke et al., 2009). This can to

[1] For an excellent introduction to the field of defense economics, *Handbook of Defense Economics* vol. 2*: Defense in a Globalized World* (Sandler and Hartley, 2007) is highly recommended.

a certain extent be explained by the increased occurrence of droughts in warmer years, which have been found to cause an increase in the risk of conflict (Maystadt and Ecker, 2014; Maystadt et al., 2015).

However, these results are not conclusive. Some argue that meteorological phenomena do not affect violence, and that socio-political and geographical factors are the main causes of violent conflict (e.g. Buhaug, 2010; Theisen et al., 2011). Others argue that temperature and rainfall are imperfect indicators of climate change, instead using other proxies including land degradation and cropland pressure, which have not been proven to affect the occurrence of conflict (Hendrix and Glaser, 2007; Theisen, 2012).

In recent years, the increased availability of satellite data, as well as better access to substantial processing power, have made the use of remote-sensing methods in economic research far easier than in the past. As has been previously mentioned, few researchers have as of yet adopted this approach to climate-security studies. In his study of the spatial distribution of violence in the Darfur conflict in 2005–2006, Alexander De Juan utilizes this technique, using high-resolution satellite data in combination with geo-coded data on violent conflict to evaluate the existence of a causal chain between climate change and conflict which had previously been established by qualitative research. Using this novel approach, a link between the two phenomena is identified (De Juan, 2015).

Even though the results of quantitative studies in the field remain somewhat inconclusive, a growing amount of evidence suggests that there does in fact exist some kind of link between climate change and violent conflict. What these studies fail to do, however, is provide a comprehensive explanation as to exactly *how* this connection arises. That is, through which causal mechanisms does climate change affect the occurrence of violent conflict? A substantial body of qualitative research has attempted to address this issue, and several qualitative studies have been able to identify a number of links between climate change and violent conflict on the African continent.

The term *ecoviolence* has been used to describe conflicts directly related to environmental factors, of which the bloody wars in Somalia and Rwanda after the end of the Cold War are considered to be examples (Homer-Dixon and Blitt, 1998). The struggle to acquire a diminishing amount of crucial resources (such as water, farmland etc.) has been identified as a major cause for the long-lasting civil war in Sudan, which ravaged the now-divided country for decades (Suliman, 1997). These conflicts primarily take place on a local, community level, but are often escalated by state policies (Assal, 2006). Pastoralist groups in East Africa have been found to be particularly sensitive to deteriorating climate conditions, with recurrent droughts being one of the major causes for increased eruptions of violent conflict among these groups (Hundie, 2010; Schilling et al., 2012).[2] Climate change has also been found to cause malnutrition, which in turn is related to violent conflict (Rowhani et al., 2011). In other words, increasing scarceness of resources vital for human societies due to deteriorating climatic conditions leads to a heightened level of resource competition between groups, increasing the likelihood of violent conflict.

Another relationship between climate change and violent conflict that has been identified is that of climate-related migration. People choose to migrate for many different reasons, which are split into so-called push and pull forces (e.g. Portes and Böröcz, 1989). These forces consist of, among other things, high unemployment and economic underdevelopment (e.g. Lucas, 2006). Climate change is believed to result in both push and pull effects (e.g. McLeman and Hunter, 2010; Gleditsch et al., 2007). Simply put, worsening climate conditions in one geographical location may cause parts of the population to migrate to more fertile lands somewhere else. This in turn intensifies ethnic and other intergroup tensions in the targets of these migrations, increasing the risk of violent conflict in those areas (De Juan, 2015; Mohammed, 2004). Increased migration due to climate change thus constitutes a mechanism working in the opposite direction of conflicts related to resource scarcity; instead of increasing the risk of conflict in areas that have experienced a decline in available resources (i.e. resource conflicts), this mechanism causes conflict to occur in areas where resources are relatively plentiful, as people tend to migrate to areas where climatic conditions are more favorable.

[2] Worth noting, however, is that a multitude of factors other than those directly related to a change in existing resource conditions due to changing climate conditions are identified, for instance proliferation of small arms and the presence of illicit trade.

The identified effects of climate change and climate variability on violent conflict are highly dependent on existing contextual factors, most importantly so-called negative othering[3] and recent political changes (Ide, 2015). In addition, changing climatic conditions are almost never the main cause of a conflict, instead serving as an accelerator of existing grievances (Seter et al., 2016). Climate change is widely believed to have a negative effect on agricultural production in sub-Saharan Africa (Exenberger and Pondorfer, 2013). This, in combination with other factors, lead certain scholars to conclude that the Sahel region will be especially vulnerable to security risks caused by global warming (Scheffran and Battaglini, 2011). These arguments strengthen the case that the Sahel region, with its high levels of political uncertainty and environmental exposure, as well as a presence of traditional sources of conflict (e.g. political, ethnic and religious turmoil), constitutes an area that is highly likely to exhibit connections between climate change and violent intergroup conflict.

III. Theoretical Framework and Empirical Model

As can be concluded by the research presented above, the connection between climate change and violent intergroup conflict on the African continent is highly complex. This demands that great care be taken to the theoretical framework applied in studies such as this, to ensure that the causal mechanisms remain well identified. Based on previous research, this study assumes the presence of two main pathways between climate change and violent intergroup conflict. This highly simplified theoretical model differs from other frameworks used in the field, which often are of a much more complex character.[4] A major drawback when using these kinds of models is the difficulty to prove the existence of a separate causal link. In order to address this, the theoretical framework used in this study will focus on the fundamental mechanisms to create a model that is more suitable for evaluation using quantitative methods.

[3] I.e. the identification of other groups as existential threats and/or of a lower value.
[4] See for instance the work of Homer-Dixon (1999) or van Baalen and Mobjörk (2016) for great examples of these types of complex causal models.

The following model is proposed to explain the occurrence of violent intergroup conflict in a specific geographical area at a certain point in time:

$$Y_{i,t} = \beta_1 X_{i,t} + \beta_2 m_{i,t} + \beta_3 c_{i,t} + \beta_4 \Delta c_{i,t} + \mu_{i,t} \quad (1)$$

where $Y_{i,t}$ denotes some conflict variable (e.g. the incidence or intensity of violent intergroup conflict) in area i at time t. "Traditional" causes of conflict (e.g. political or ethnic grievances) are represented by the first term, $X_{i,t}$. The second term, $m_{i,t}$, denotes the effects from migration on area i. Since an increased inflow of people is assumed to increase the likelihood of conflict, the coefficient is hypothesized to be positive. Migration to a specific area may occur for many different reasons, climate change is merely one of them. As previous research has shown, migration in the region of study tends to occur to areas that have seen relatively favorable developments of environmental conditions. This means that climate-related migration has an opposite effect to that of other resource-related conflicts believed to be caused by climate change (which are thought to occur in areas where environmental conditions have deteriorated). By separating this link in the model above, the effects from climate-migration can to some extent be controlled for using changes in census data, thus addressing a major concern regarding causality when studying the connection between climate change and violent intergroup conflict.

The third and fourth terms denote variables related to changes in the climate where the first, $c_{i,t}$, represents long-term changes. More specifically, $c_{i,t}$ captures the absolute change in some environmental measure between periods z and t, where $z < t$. The relationship between $c_{i,t}$ and the coefficient will naturally vary depending on the measure used. In this case the main measurement of environmental conditions will be average vegetation, and thus a positive value for $c_{i,t}$ indicates an improvement of the climate (which is believed to lower the probability of conflict), resulting in a negative value for the coefficient β_3.

Finally, $\Delta c_{i,t}$ captures the effect from climate variability. Variance of the climate is not in itself a cause of conflict. Rather, short-term shocks due to increased variability have different effects depending on the nature of the shock. For instance, large deviations in rainfall may have either positive or negative effects on violence depending on whether the shock itself was positive or negative, as can be seen in the research presented in Section II. To capture this effect, the measurement of climate variability is defined as deviations from average climate conditions. In other words, by subtracting the long-term average value of some climate variable, e.g. vegetation, from the value for an individual year, the result will denote the deviation in the measurement, and thus capture short-term shocks in the climate (assuming positive values for positive shocks and vice versa). Once again, the sign of the coefficient will depend on the climate variable studied. In the case of vegetation, positive yearly deviations from the long-term average is assumed to have a negative effect on the outbreak of conflict, indicating that the coefficient should be negative. In addition, there is cause to believe that climate shocks have temporally lagged effects on the incidence and intensity of conflict. To take this into account, the model is altered to include values for climate variability in the two preceding periods. $\mu_{i,t}$ denotes the error term.

$$Y_{i,t} = \beta_1 X_{i,t} + \beta_2 m_{i,t} + \beta_3 c_{i,t} + \beta_4 \Delta c_{i,t} + \beta_5 \Delta c_{i,t-1} + \beta_6 \Delta c_{i,t-2} + \mu_{i,t} \qquad (2)$$

By obtaining suitable controls for $X_{i,t}$, $m_{i,t}$ and $\Delta c_{i,t}$, this study will be able to focus on the effects from long-term climate change on the incidence and intensity of violent intergroup conflict. However, this simplified model will still be of limited explanatory power to a certain extent. Long-term deterioration of environmental conditions affects the occurrence of conflict in different ways, and has different impacts depending on socio-political factors that are difficult to account for in a study such as this. By grouping the effects of climate change together in the somewhat blunt category of “intensified resource competition”, this study will at least be able to say something regarding the connection between the two phenomena. For a more complete evaluation of the causal chain, in-depth case studies will be a necessary complement.

IV. Data and Methods

In order to investigate the validity of the hypotheses postulated in the introductory section, this study will make use of spatially distributed data on vegetation and violence in the Sahel region. The analyzed region will be divided into grid cells measuring roughly 8x8 km. Determining the optimal cell size is a highly delicate endeavor. On the one hand, using too large cells decreases the possibility of capturing variations in spatial distribution, implying that the resolution should be kept at the highest possible level of disaggregation. On the other hand, uncertainty regarding the accuracy in the georeferencing of certain variables (e.g. violent acts) indicate that too small grid cells would fail to correctly pinpoint data to the correct region, distorting the results of the analysis. In this case, the 8x8km structure is inherited from the satellite data used, and this size is also determined to be an acceptable trade-off between high resolution and geographic certainty. Since the size of the grid cells may influence the outcome, the primary model is supplemented by an analysis using a cell size of 16x16km (i.e., 4 times the size of the original grid cells) as a robustness check in order to limit the impact on the results of the scale used in the analysis, which constitutes one of the two parts of the so-called Modifiable Areal Unit Problem (MAUP).[5]

Usage of grid cells as the primary unit of analysis is not new to the field of climate-security research, but most studies use a much coarser resolution. As a result of the high resolution in this study, the number of grid cells analyzed will be around 124 000, placing great demands on the collection and analysis of data. To determine the presence of a link between the two phenomena, this study will make use of a cross-section approach, where violent intergroup events in the period 2010–2016 constitute the dependent variable, and the long-term change in average vegetation makes up the main explanatory variable. Using violent events occurring in the seven years from 2010 through 2016 ensures that the data studied is as recent as possible, without expanding the temporal delimitation too far.

Turning to the geographical demarcation, countries whose territories are covered by the Sahel to a greater extent are included, resulting in the selection of Burkina Faso, Chad, Eritrea, Mali, Mauritania, Niger, Senegal and the Sudans.[6] Including the entirety of the countries, instead of just the core Sahel areas, increases the area of study, providing more data for the analysis. These countries have all been subject to violent intergroup conflict during the period of study. Crises related to political turmoil, ethnical and religious grievances, poverty and malnutrition have plagued the area, resulting in a large number of violent events. Infamous conflicts include the

[5] The second being issues related to the choice of zones applied in the analysis. For a detailed explanation of the MAUP, see for instance Openshaw (1984).
[6] Nigeria and Algeria are thus excluded, even though the Sahel region is included within their boundaries. This exclusion is made due to the fact that this area constitutes a minimal part of both countries.

Tuareg rebellion in Northern Mali 2012, the Boko Haram insurgency[7] and the ongoing civil conflict in the Sudans (Batten Carew and Dowd, 2015; Dowd, 2013; Daoust, 2015). Including the countries in their entirety (even the parts that are not directly covered by the Sahel), may lead to the inclusion of certain areas that are unaffected by environmental changes in the Sahel. But since the Sahel covers major parts of all countries included in the study, and can be assumed to affect the developments in these nations to a large extent, this is a minor issue.

Figure 1. *The Sahel region (authors' own illustrations)*

[7] Although violence perpetrated by Boko Haram is primarily located in Nigeria, the insurgency has also spilled over to the neighboring Sahel countries.

Normalized Difference Vegetation Index

A suitable proxy for studying the spatial distribution and development of vegetation is the Normalized Difference Vegetation Index. Satellites orbiting Earth provide data on visible and near-infrared light, using the following formula to calculate an index that ranges from -1 to +1:

$$NDVI = (NIR - VIS) / (NIR + VIS) \tag{3}$$

Where NIR is the near-infrared radiation and VIS is equal to the visible radiation (Weier and Herring, 2000). Since healthy vegetation absorbs incoming red light while reflecting infrared radiation to a greater extent than senescent vegetation, the calculated value represents the level of vegetation in each tile (Pettorelli, 2013, pp. 30–31). In practice, the index assumes values between 0 and 1 for land mass, where values close to 0 indicate barren areas (e.g. deserts) and higher values indicate increasing levels of vegetation (dense rainforest areas, for instance, have an NDVI value of around 0.9) (Pettorelli, 2013, pp. 31–32).

The index has been shown to be highly correlated with various aspects of vegetation, including photosynthetic capacity, carbon assimilation and evapotranspiration (Pettorelli, 2013, p. 32). Given the proven robustness of the index, it is no surprise that it is widely used in a variety of research areas, ranging from meteorology and biology to economics. Climate-security studies have also made use of the index to a certain extent, with varying methodological approaches (e.g. Brown, 2010; Olsson and Siba, 2013). This study, however, will adopt a method that closely resembles that used by Alexander De Juan in his study of the links between long-term climate change and the spatial distribution of violence in the Darfur conflict (De Juan, 2015). By using yearly deviations of the NDVI from the 5-year means, as well as the 20-year changes of the 5-year means for each grid cell, this study will be able to take both short-term climate variability and long-term climate change into account.

Data used in the analysis will be acquired from two datasets, both using partly the same satellite data. The first dataset makes use of the Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectrometer (MODIS) instruments onboard NASA satellites orbiting Earth to calculate a global measurement of the NDVI using 8x8km grid cells, encompassing the time period 1981–2006 (Tucker et al., 2005). The second dataset also uses the MODIS instruments, but offers a much higher spatial resolution of 250x250m, dramatically increasing the size of the data. This dataset offers data from 2000 and onwards (Huete et al., 2002). Both datasets are included in order to maximize the time period analyzed, leading to high resolution satellite data being available from 1981 through 2016. The data is accessed through the online database provided by the International Research Institute for Climate and Society (IRI) at Columbia University.[8] Expanding the temporal scale even further would of course have provided even greater insight into the effects of changing environmental conditions over long periods of time, but given the limited availability of the satellite data required, the inclusion of a larger historical period is simply impossible. This limits the analysis somewhat, since trends of greater scope than two decades, (not entirely uncommon for climate patterns), are not included in the model.

Given the availability of high quality satellite data over a long period of time, several NDVI values can be assigned to each grid cell. First, the 5-year mean NDVI value for each cell in the year 2010 is used to indicate average vegetation, capturing existing climatic conditions. Second, the 20-year change in average NDVI at the beginning of the time period is calculated by subtracting the 5-year mean of 1990 from the 5-year mean of 2010, resulting in a measurement of long-term changes in vegetative conditions (and thus, climate change). Third, in order to include a measurement for climate variability, the difference between the yearly NDVI and the 5-year mean for the years 2008, 2009 and 2010 are calculated (positive values indicate above mean vegetation for that specific year). By including the three consecutive years preceding the studied period, potential temporal delays are captured by the model, thus controlling for various possible effects from climate variability.[9] As a final modification, grid cells containing large amounts of water (i.e. major lakes) are excluded in order to avoid misleading values of the NDVI.

[8] The complete database can be accessed at IRI (2017).
[9] The definition of climate variability being short-term deviations from average environmental conditions.

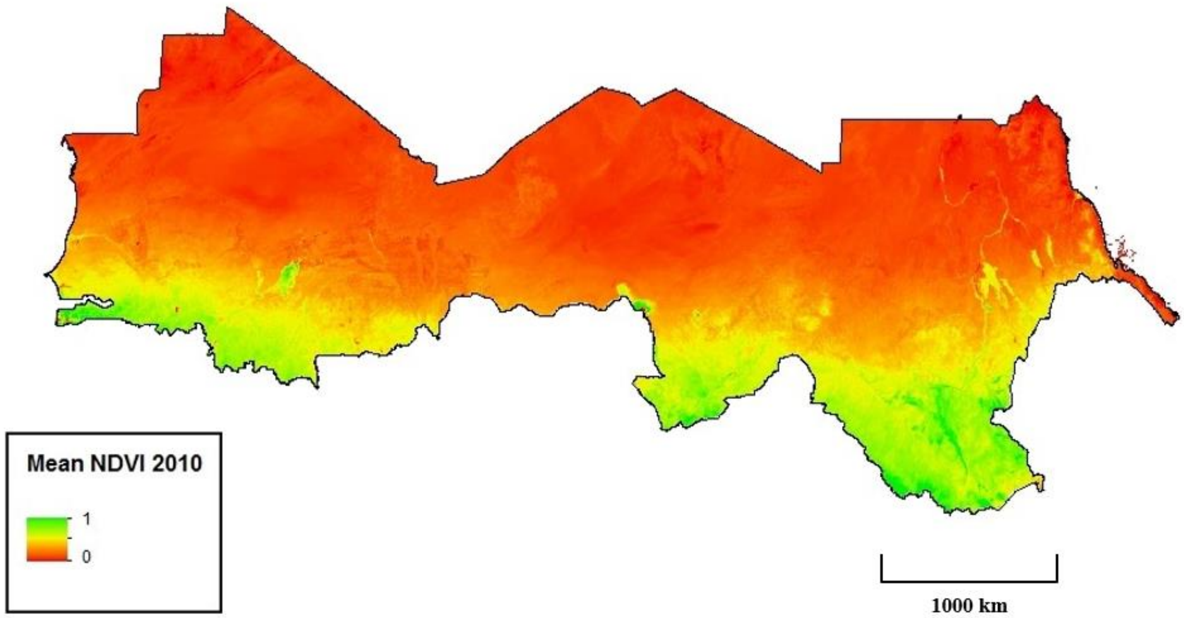

Figure 2. *Average vegetation (5-year mean NDVI) in the Sahel region 2010 (authors' own illustrations based on own calculations from satellite data provided by the International Research Institute for Climate and Society of Columbia University (IRI)).*

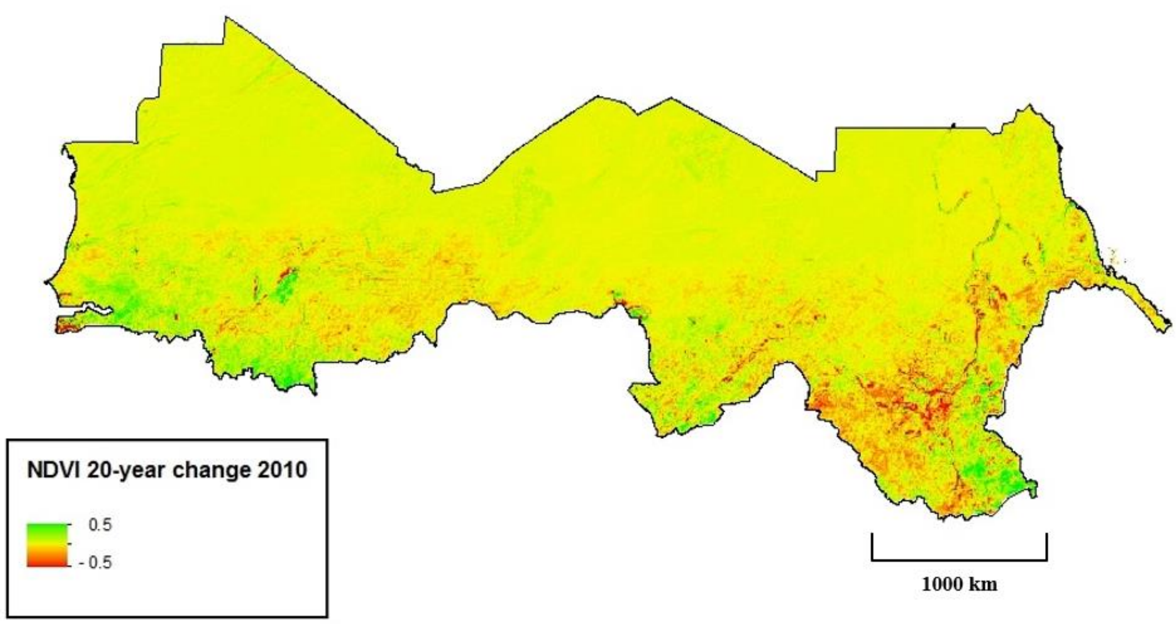

Figure 3. *20-year change in average vegetation in the Sahel region 2010 (authors' own illustrations based on own calculations from satellite data provided by the International Research Institute for Climate and Society of Columbia University (IRI)).*

As can be seen in figure 2, vegetative conditions in the studied area are far from favorable. The northern parts of these countries border, and to a certain extent include, the Sahara Desert, leading to very low values of the NDVI. Contrary to popular belief, the countries immediately bordering the southern parts of the Sahara Desert have, on average, seen a slight increase in vegetative conditions during the period 1990–2010. However, the changes in average vegetative conditions have varied greatly within the region, where some parts have seen drastically increased vegetation, and others have seen the exact opposite, with a slight increase being the most normal development (figure 3).

Violent conflict

For the assessment of the incidence and intensity of conflicts in the Sahel region, this study will make use of the Armed Conflict Location and Event data project (ACLED), which offers a thorough compilation of violent acts committed by rebels, governments and militias within over 50 unstable countries from 1997 to 2016 (Raleigh et al., 2010). This dataset has made a tremendous contribution to the advancement of conflict studies, albeit with certain flaws. Concerns have been raised regarding the quality of the underlying data stemming from uneven control issues (Eck, 2012). The only comparable dataset is the Uppsala Conflict Data Program (UCDP). Several fundamental differences exist between the two, the biggest being the inclusion of non-fatal conflicts in the ACLED, contrary to the UCDP, which only includes conflicts that result in at least one fatality. Based on ACLED data, grids are assigned two values measuring conflict incidence and intensity, respectively.[10] The incidence measure is a dummy variable equaling 1 if a violent conflict was reported in the area in the studied time period. Conflict intensity is measured as the number of conflict-related fatalities in each grid cell.

[10] The ACLED contains certain non-violent events (e.g. the establishment of militia HQ:s). These events are excluded from the analysis.

According to the ACLED dataset, 1 489 of the 123 739 grid cells included in the analysis experienced an act of violence during the time period. In 966 of these cells people were killed as a result of the reported conflicts, causing a total of 55 227 fatalities.

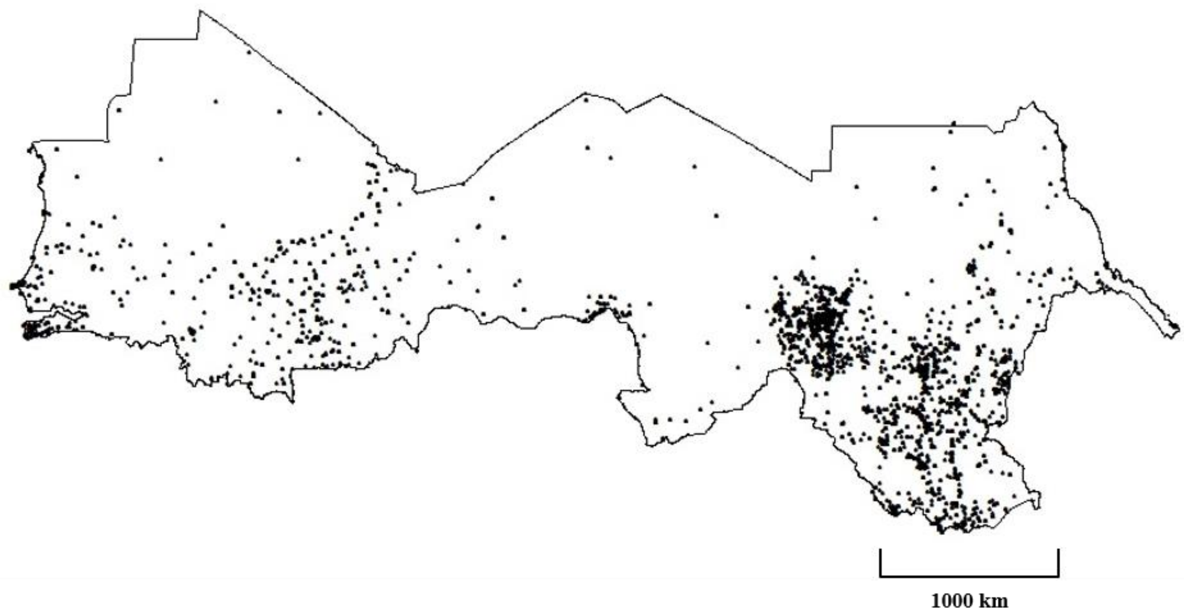

Figure 4. *Spatial distribution of intergroup violence in the Sahel region 2010–2016 (authors' own illustrations based on data provided by the ACLED dataset)*.

It is clear from the data that the largest cluster of violent acts committed over the years 2010–2016 is located in the southeastern parts of the region, which constitutes the location of the Sudans (figure 4). This comes as no surprise, given the ongoing conflict in the region. The two Sudans, however, are far from alone, as many more acts of violence have been reported in other countries in the region during the studied time period. In addition, an initial visual inspection of the violence data overlaid with 20-year changes in mean NDVI seems to indicate that violence is indeed more likely to take place in areas where vegetative conditions have deteriorated and/or stagnated (figure 5), but a further analysis is needed to discern the true nature of these connections.

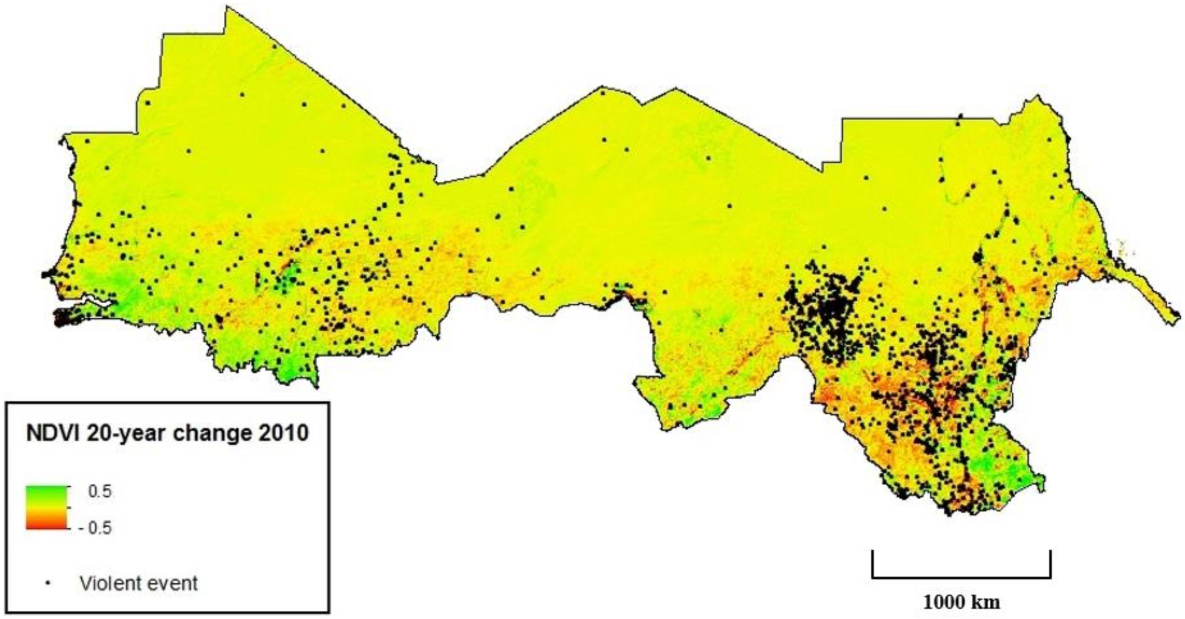

Figure 5. *Spatial distribution of intergroup violence in the Sahel region 2010–2016, overlaid with 20-year change in vegetation (authors' own illustrations based on data provided by the ACLED dataset and own calculations from satellite data provided by the IRI).*

Control variables

Apart from climatic conditions, a number of variables can be assumed to have an effect on the presence of violent conflict. The number of people living in a certain grid cell would naturally have an effect; as was previously stipulated in the theoretical discussion above, increasing the amount of people in a specific location also increases the probability that a violent act is to occur (De Juan, 2015). Thus, the population density for each grid cell as of the year 2010 is included in the analysis. In order to control for the effects of climate-related migration on the likelihood of conflict, the 10-year population change is calculated for every cell. In other words, by subtracting the population level of 2000 from the population of 2010, the net change in population density can be controlled for. By controlling for net migration, one of the two main effects of climate change on violent conflict is partly removed, leaving the effects of changing resource conditions on local disputes and grievances, i.e. resource conflicts, as the main link.

Both population variables are based on data from the Gridded Population of the World dataset (GPW), provided by the Center for International Earth Science Information Network (CIESIN) at Columbia University, which offers a georeferenced, gridded dataset on global population density (CIESIN, 2016). This data is not as spatially accurate as the satellite imagery used to capture climate conditions, leading to a degree of uncertainty regarding the true population density of each grid cell. In addition, the GPW in all likelihood fails to account for the large number of internally displaced people in the Sahel, since some of them probably fail to register in national census data. Regardless, the GPW constitutes the most advanced source for the spatial distribution of population that is currently available (Doxsey-Whitfield et al., 2015).

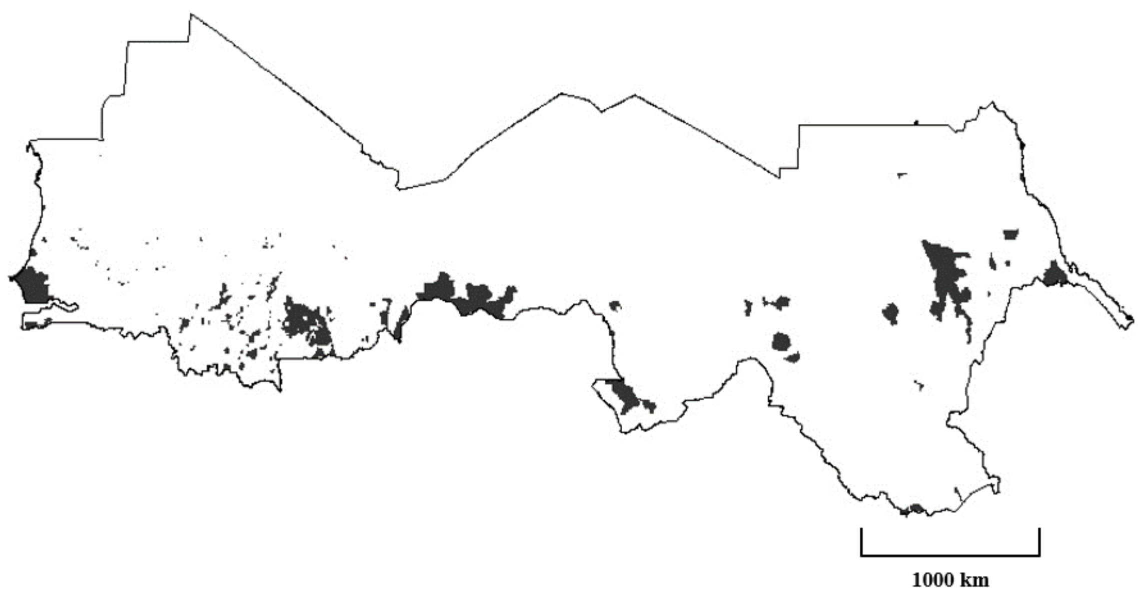

Figure 6. *Major population clusters in the Sahel region 2010 (authors' own illustrations based on the GPW UN-adjusted population count for 2010 provided by the Socioeconomic Data and Applications Center, NASA).*

It is widely believed that socioeconomic factors influence violence patterns, especially in the less developed areas of the world (e.g. Collier and Hoefller, 2004). As a proxy for societal welfare, the infant mortality rate (IMR, i.e. the number of children who die before their first birthday for every 1 000 births), as provided by the Global Poverty Mapping Project at CIESIN is employed (CIESIN, 2005). This dataset includes the IMR on a subnational, administrative district level as of the year

2000.[11]

In addition to socioeconomic factors, the presence of natural resources may serve as a catalyst of conflict (e.g. Ross, 2004; Humphreys, 2005). Using the datasets on diamond resources and petroleum provided by the Peace Research Institute Oslo (PRIO) in combination with the MRDS dataset on minerals from the United States Geological Survey, three dummy variables indicating the presence of diamonds, oil or minerals are coded (Gilmore et al., 2005; Lujala, et al., 2007; U.S. Geological Survey, 2005).

Other geographical factors that could influence the incidence and intensity of conflict are included. First, the elevation of a particular region (measured in meters above sea level), has been argued to have an effect on violent conflict, and is thus added to the model (Fearon and Laitin, 2003). Second, the distance of a certain area to government strongholds is also believed to influence the dynamics of violent conflict (Buhaug et al., 2009). To control for this, the distances to both regional and country capitals are computed for each grid cell. Finally, country dummies are added to control for any structural differences between the states studied.

[11] Data is missing for South Sudan in the original dataset, supplemented with national data from the World Bank.

Table 1.
Summary statistics for variables included in the main model

VARIABLES	N	Mean	SD	Min	Max
Conflict incidence	123 739	0.012	0.109	0	1
Conflict fatalities	123 739	0.446	20.896	0	4634
NDVI 20-year change	123 739	0.076	0.026	-0.45	0.424
NDVI mean 2010	123 739	0.324	0.102	0.163	0.855
NDVI deviation 2008	123 739	-0.002	0.012	-0.155	0.135
NDVI deviation 2009	123 739	-0.006	-0.017	-0.246	0.08
NDVI deviation 2010	123 739	0.005	0.015	-0.15	0.133
Population 2010 (log)	123 739	5.176	2.349	-1.219	13.514
Population change 2000–2010	123 739	0.316	1.941	-4.981	336.101
Diamonds	123 739	0.0001	0.01	0	1
Oil	123 739	0.007	0.084	0	1
Minerals	123 739	0.0007	0.026	0	1
Distance to country capital	123 739	5.265	2.729	0	12.898
Distance to district capital	123 739	2.531	1.821	0	8.556
Infant mortality	123 739	112.523	37.12	17	203.1
Elevation	123 739	463.763	268.61	0	3368

Model specification

Combining the data specification with the theoretical framework presented above, the equation used for the regression analysis takes on the following form:

$$Y_{i,j} = \beta_0 + \beta_1 NDVI\_Change_{1990-2010_i} + \beta_2 NDVI\_Deviation_{2008_i} + \beta_3 NDVI\_Deviation_{2009_i} + \beta_4 NDVI\_Deviation_{2010_i} + \beta_5 NDVI\_5yr\_Mean_{2010_i} + \beta_6 \log\left(Population_{2010_i}\right) + \beta_7 Population\_Change_{2000-2010_i} + \beta_8 Infant\_Mortality_{2000_i} + \beta_9 Diamonds_i + \beta_{10} Oil_i + \beta_{11} Minerals_i + \beta_{12} Distance\_to\_Country\_Capital_i + \beta_{13} Distance\_to\_District\_Capital_i + \beta_{14} Elevation_i + \beta_{15} Country_j + u_i \quad (4)$$

where $Y_{i,j}$ denotes the conflict variable for grid i in country j over the time period 2010–2016, taking on the form of a dummy variable for measuring conflict incidence and an integer for the measurement of intensity. The first term of the equation after the constant represents c in the initial framework, capturing long-term changes in the NDVI. Climate variability, Δc, is picked up by the second through fourth terms, with the remaining terms serving as an estimation of other conflict effects, X_i (as well as country level dummy variables).

V. Analysis

Main results

The results of the main model for the incidence of conflict is presented in Table 2. After the inclusion of control variables and country dummies, the coefficient for 20-year changes of the NDVI takes on the value -0.130 (Model IV below). This result confirms the initial hypothesis of a connection between long-term changes in environmental conditions and violent intergroup conflict. The coefficient indicates that an absolute increase in the NDVI of 10% between 1990 and 2010 in a certain area decreases the likelihood of that area experiencing violent intergroup conflict in the period 2010–2016 by 1.3%. In other words, a negative change in the NDVI increases the likelihood of conflict, indicating a link between climate change-induced resource scarcity and violent intergroup conflict. Since the Sahel region on average experienced a positive change in vegetation during the time period, the results could also be interpreted as improving resource conditions alleviating scarcity-related grievances, thus decreasing the likelihood of conflict. Nevertheless, the results are robust and statistically significant on a >99% confidence level after the introduction of all control variables, providing solid evidence for the connection between climate change and conflict incidence.

Table 2.

Conflict incidence, main model

VARIABLES	Model I	Model II	Model III	Model IV[1]
NDVI 20-year change	-0.199***	-0.201***	-0.138***	-0.130***
	(0.0210)	(0.0221)	(0.0224)	(0.0231)
NDVI mean 2010		0.110***	0.0668***	0.0436***
		(0.00443)	(0.00574)	(0.00763)
NDVI deviation 2008		-0.00260	0.0121	-0.0167
		(0.0393)	(0.0396)	(0.0401)
NDVI deviation 2009		-0.158***	-0.126***	-0.129***
		(0.0274)	(0.0273)	(0.0312)
NDVI deviation 2010		-0.135***	-0.0606**	-0.0252
		(0.0261)	(0.0269)	(0.0292)
Population 2010 (log)			0.00437***	0.00527***
			(0.000375)	(0.000444)
Population change 2000–2010			0.00302***	0.00291***
			(0.00102)	(0.00100)
Diamonds			0.0631	0.0622
			(0.0734)	(0.0734)
Oil			0.00217	0.00863
			(0.00557)	(0.00558)
Minerals			0.100***	0.0975***
			(0.0354)	(0.0353)
Distance to country capital			0.00344***	0.00378***
			(0.000252)	(0.000275)
Distance to district capital			-0.000392*	-0.00119***
			(0.000223)	(0.000309)
Infant mortality			-8.94e-05***	3.10e-05
			(1.05e-05)	(2.32e-05)
Elevation			7.33e-06***	1.87e-05***
			(1.76e-06)	(2.11e-06)
Constant	0.0272***	0.00869***	-0.0336***	-0.0655***
	(0.00170)	(0.00189)	(0.00311)	(0.00436)
Observations	123,739	123,739	123,739	123,739
R-squared	0.002	0.014	0.026	0.030

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[1] Including country dummies

Several aspects of the results are worth highlighting. As can be seen in the table above, a number of variables influence the likelihood of a certain grid cell experiencing an eruption of violence. Both the number of people living in an area, as well as the net change in the population level, have positive effects on violent conflict. After controlling for population, areas with more favorable vegetative conditions are also less likely to be the site of a violent event. This could be due to the fact that these areas on average have a larger resource surplus, meaning that the need to fight in order to acquire resources is less than in other areas. Positive deviations of the NDVI also have a negative effect on the likelihood of conflict, with deviations in the year 2009 having the most significant effect.

The introduction of 10-year population changes decreases the effects from long-term NDVI changes, but only slightly. This could be due to the fact that the climate-migration link is not as active as previous research might suggest. However, as has been previously stated in the discussion regarding data and methodology above, 10-year changes in the GPW constitutes an imperfect measure of migration since it fails to take all kinds of migration (e.g. IDP's not registered in census data) into account. Since this variable is almost impossible to measure at the scale and spatial accuracy required, the effects from climate-migration cannot be completely removed from the model. This indicates that the effects from long-term changes in the NDVI on resource-related conflicts could be even higher than indicated by the results presented above.

Several geographical variables are also of importance when explaining the outbreak of violent conflict. The distance to country capitals and average elevation were both found to increase the likelihood of violent conflict. An antagonistic effect is identified regarding the distance to the district capital, with cells closer to the district capitals being more likely to experience conflict. Quite interestingly, the presence of minerals in a certain grid cell drastically increases the likelihood of conflict, with the total effect in the main model being over 9%. This is in line with previously held beliefs in conflict studies, and is connected to the so-called resource curse that is thought to plague the African continent (e.g. Bannon and Collier, 2003; Mehlum et al., 2006).

Turning to conflict intensity, the relationship is not as clear as for that of incidence. The main model shows a weak positive effect on conflict fatalities from long-term decreases in the NDVI. However, the introduction of all controls limit the significance of this variable. The coefficient is small, with an absolute decrease in the NDVI of 10% leading to less than one extra fatality per grid cell. This small effect, in combination with the relatively limited statistical significance, leads to the conclusion that the second hypothesis of this study, that long-term climate change increases the number of fatalities of violent intergroup conflict, is not supported by the results of the analysis.[12]

[12] When employing the robustness checks used for incidence on conflict intensity statistical significance deteriorates even further, strengthening this conclusion.

Table 3.

Conflict intensity, main model

VARIABLES	Model I	Model II	Model III[1]	Model IV[2]
NDVI 20-year change	12.37***	11.61***	-10.29***	-8.205**
	(3.812)	(3.928)	(3.945)	(4.025)
NDVI mean 2010		4.834***	4.219***	0.644
		(0.825)	(1.143)	(1.356)
NDVI deviation 2008		9.782	11.48	11.23
		(12.55)	(12.68)	(12.76)
NDVI deviation 2009		-21.35**	-19.02**	-9.966
		(8.323)	(7.965)	(6.894)
NDVI deviation 2010		-6.146	-1.276	4.456
		(4.348)	(4.718)	(5.223)
Population 2010 (log)			0.0709	0.185***
			(0.0523)	(0.0568)
Population change 2000–2010			0.0418	0.0395
			(0.0277)	(0.0273)
Diamonds			0.227	0.287
			(0.540)	(0.539)
Oil			2.843	3.040
			(2.577)	(2.597)
Minerals			0.961	1.026
			(1.233)	(1.231)
Distance to country capital			0.0666	0.0800
			(0.0483)	(0.0550)
Distance to district capital			0.0399	0.0198
			(0.0529)	(0.0698)
Infant mortality			-0.00280**	0.00739**
			(0.00120)	(0.00340)
Elevation			0.000653**	0.000958***
			(0.000284)	(0.000366)
Constant	1.386***	-0.317	-1.065**	-2.503***
	(0.310)	(0.349)	(0.418)	(0.573)
Observations	123,739	123,739	123,739	123,739
R-squared	0.000	0.001	0.002	0.002

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Including all control variables
[2] Including country dummies

Robustness checks

In order to evaluate the robustness of the results, several checks are introduced. Since the connection between climate change and conflict intensity was discarded in the main model, these checks are only used on the analysis of conflict incidence. As a first robustness check, two additional models supplement the analysis. The first model introduces dummies for the 145 administrative districts in the region (see Model I below). It could be argued that several structural effects not active on the country level instead show up at the district level, for instance local ethnic or political turmoil, which motivates the addition of this layer to the analysis. This decreases the effects from NDVI changes by roughly one third, but the connection is still highly active. Interestingly enough, the effects from both existing vegetation as well as NDVI deviation lose their statistical significance, indicating a high degree of uncertainty regarding whether these two measures have any effect at all on the likelihood of conflict.

The second model switches from a linear probability regression to a probit model, which is commonly used to estimate probabilities. A probit estimation differs from a linear probability model, as it assumes a non-linear relationship between the dependent and independent variables. When interpreting the coefficients of a probit model, they should be read as the marginal effect on the dependent variable from a change in one variable, conditional on the values for all other variables, leading to different impacts from the variable of study depending on what values the other variables assume. As can be seen in the results of the probit model below (Model II), the negative effects on conflict incidence from long-term increases in the NDVI are present also when using a probit model, and the statistical significance remains at >99%.

Table 4.

Conflict incidence, including administrative district dummies and probit model

VARIABLES	Model I[1]	Model II[2]
NDVI 20-year change	-0.0843***	-1.977***
	(0.0241)	(0.338)
NDVI mean 2010	0.0225	1.647***
	(0.0153)	(0.109)
NDVI deviation 2008	0.0139	-0.182
	(0.0443)	(0.636)
NDVI deviation 2009	0.00478	-1.521***
	(0.0375)	(0.421)
NDVI deviation 2010	-0.0194	-0.0615
	(0.0332)	(0.505)
Population 2010 (log)	0.00685***	0.253***
	(0.000526)	(0.0103)
Population change 2000–2010	0.00212**	0.00742**
	(0.00100)	(0.00295)
Diamonds	0.0624	0.800
	(0.0721)	(0.538)
Oil	0.00345	0.0182
	(0.00545)	(0.0918)
Minerals	0.0937***	0.827***
	(0.0353)	(0.205)
Distance to country capital	0.00163***	0.0848***
	(0.000358)	(0.00541)
Distance to district capital	-5.19e-05	0.0303***
	(0.000422)	(0.0114)
Infant mortality	-0.000115***	-0.00298***
	(3.45e-05)	(0.000415)
Elevation	1.73e-05***	0.000246***
	(2.27e-06)	(3.38e-05)
Constant	-0.0340***	-4.686***
	(0.00635)	(0.118)
Observations	123,739	123,739
R-squared	0.049	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[1] Including administrative district dummies

[2] Probit model

A major concern when analyzing spatial data is that of the Modifiable Areal Unit Problem (MAUP). This problem arises when the shape and size of the areal units used to analyze spatially distributed data influence the outcome of the analysis itself (Dark and Bram, 2007). To make certain that the results are not simply an effect of the manner by which the data has been processed, (i.e. due to the scale problems associated with the MAUP), the same analysis as in the main model is conducted using grid cells measuring 16x16 km. When expanding the size of the grid cells, the effect from 20-year changes in the NDVI increases dramatically, strengthening the findings of the main analysis. This is the case when controlling for country as well as administrative districts (Models I and II below). Note once again that the effects from vegetation deviations lose their significance when controlling for administrative dummies, strengthening the assumption above that this variable is a poor predictor for conflict.

Table 5.

Conflict incidence, 16x16 km grid cells, including country and administrative district dummies

VARIABLES	Model I[1]	Model II[2]
NDVI 20-year change	-0.542***	-0.357***
	(0.0879)	(0.0948)
NDVI mean 2010	0.164***	0.131**
	(0.0259)	(0.0517)
NDVI deviation 2008	-0.0219	0.0863
	(0.156)	(0.175)
NDVI deviation 2009	-0.457***	0.0690
	(0.122)	(0.155)
NDVI deviation 2010	-0.103	0.0724
	(0.115)	(0.135)
Population 2010 (log)	0.0151***	0.0187***
	(0.00127)	(0.00153)
Population change 2000–2010	0.00281***	0.00296***
	(0.000465)	(0.000637)
Diamonds	0.0381	0.0331
	(0.0712)	(0.0662)
Oil	0.0332*	0.0199
	(0.0174)	(0.0170)
Minerals	0.110***	0.0933**
	(0.0417)	(0.0402)
Distance to country capital	0.0121***	0.00690***
	(0.000851)	(0.00123)
Distance to district capital	-0.00475***	-0.00261*
	(0.00103)	(0.00147)
Infant mortality	2.33e-05***	3.35e-05***
	(3.58e-06)	(4.51e-06)
Elevation	4.55e-05***	3.21e-05***
	(4.82e-06)	(4.93e-06)
Constant	-0.199***	-0.170***
	(0.0132)	(0.0182)
Observations	31,302	31,302
R-squared	0.097	0.141

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[1] Including country dummies

[2] Including administrative district dummies

Finally, the issue of spatial autocorrelation needs to be addressed. It may be plausible to assume that the outbreak of violence in one grid cell influences neighboring grid cells, increasing the likelihood of violence erupting in these locations as well. A visual inspection strengthens this assumption, since violent events seem to be heavily clustered around certain areas (figure 4, above). This initial assumption is confirmed by the calculation of the global Moran's I, which is a measure of spatial autocorrelation for the entire dataset. The statistic indicates a high probability of clustering, which means that this phenomenon must be controlled for. By including the distance to the nearest violent event for each individual grid cell, the effects from neighboring areas experiencing violence can be included in the model. As can be seen by the results (Models I and II below), there does indeed seem to exist a connection between the distances to violent events and the likelihood of conflict, where areas further from locations stricken by violence are less likely to experience violent events themselves. An interesting observation is that the addition of this measure removes the effects observed from distance to closest district capital that was observed in the main model. This may indicate that the previously identified effect from the distance to the closest district capital was present due to the fact that these administrative centers often, but not always, are at the center of clusters of violent events. However, the effects from changes in the NDVI are only slightly mitigated, showing that the link between climate change and violent conflict is present even after the spatial autocorrelation of violence is taken into consideration.

As can be seen in the maps of violent events presented above, a large number of violent events are clustered in the Sudan region. To ensure that this is not a main driver of the result, the main model is run without observations from the two Sudans. This does not affect the results regarding the long-term changes in the NDVI.

Table 6.

Conflict incidence controlled for spatial autocorrelation, including country and administrative district dummies

VARIABLES	Model I[1]	Model II[2]
NDVI 20-year change	-0.118***	-0.0773***
	(0.0231)	(0.0241)
NDVI mean 2010	0.0294***	0.00584
	(0.00763)	(0.0154)
NDVI deviation 2008	-0.0112	0.00180
	(0.0400)	(0.0442)
NDVI deviation 2009	-0.103***	0.0104
	(0.0311)	(0.0374)
NDVI deviation 2010	-0.0390	-0.0295
	(0.0292)	(0.0331)
Population 2010 (log)	0.00353***	0.00522***
	(0.000440)	(0.000520)
Population change 2000–2010	0.00297***	0.00214**
	(0.00101)	(0.00101)
Diamonds	0.0652	0.0649
	(0.0729)	(0.0718)
Oil	0.00556	0.00116
	(0.00559)	(0.00544)
Minerals	0.0965***	0.0925***
	(0.0353)	(0.0352)
Distance to country capital	0.00379***	0.00182***
	(0.000275)	(0.000358)
Distance to district capital	-0.000515*	0.000595
	(0.000306)	(0.000420)
Infant mortality	2.76e-05	-0.000104***
	(2.31e-05)	(3.44e-05)
Elevation	1.54e-05***	1.36e-05***
	(2.11e-06)	(2.29e-06)
Distance to violence	-0.0123***	-0.0120***
	(0.000450)	(0.000467)
Constant	-0.0346***	-0.00411
	(0.00434)	(0.00650)
Observations	123,739	123,739
R-squared	0.034	0.052

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Including country dummies
[2] Including administrative district dummies

VI. Discussion

The results of this study point to a number of interesting topics worth mentioning. To begin with, the key finding of this study is that there does indeed seem to exist a connection between long-term climate change and violent intergroup conflict. After controlling for a multitude of variables believed to influence the outbreak of conflict, as well as employing numerous robustness checks, the results remain solid. Areas that saw relative decreases in vegetation between 1990 and 2010 were also, on average, more likely to experience violent conflict during the time period 2010–2016. The effect estimated by the main model from an absolute decrease of the NDVI by 10% was an increased likelihood of conflict by 1.3%. Since this effect is valid for such a large geographical area, this increased likelihood of violence due to deteriorating vegetative conditions may have adverse consequences for the region as a whole. Consider the example of the Sahel region experiencing a decline of average vegetation of 10% over the next 20 years. Not a far-fetched guess, given the current development of global climate patterns. This 10% decrease would thus increase conflict probability by 1.3% for almost 124,000 grid cells, which could result in thousands of new conflict events as a direct result of climate change.

This finding, however, is not as gruesome as might first be assumed. First, climate change constitutes only one of many factors that influence the incidence of violent intergroup conflict. Climate change on its own does not seem to cause conflict, implying that deteriorating resource conditions may be countered by the improvement of other factors, such as political institutions. Second, and most importantly, the Sahel as a whole saw an increase of average vegetation between 1990–2010, meaning that the likelihood of conflict decreased due to increased climate favorability. If this pattern were to hold in the future, climate change would actually lead to a decrease in violence. This, however, requires the assumption that the effects of global warming as a whole will have a positive impact on vegetative conditions in the Sahel region in the coming decades.

A few words also need to be said regarding climate-related migration as a link between climate change and violent intergroup conflict. Since 10-year changes in census data is an imperfect measure of migration patterns, the complete separation of this link is in all likelihood not possible to achieve in a quantitative study. However, the results from this study clearly indicate that for the Sahel region during the time period 2010–2016, resource-related factors were a more active link than climate-migration. The reason that this can be stated with such certainty is simple; since long-term increases in the NDVI decreased the likelihood of conflict even when certain elements of the climate-migration link remain in the estimation, (which should have a completely opposite effect on conflict probability), this link must have a larger impact than migration in this particular region.

The effects from climate variability (measured as yearly deviations from average vegetation) are more difficult to interpret. A negative relationship between vegetation deviations and the incidence of violent conflict was identified in the main model. However, this result failed to pass the robustness checks employed. This indicates a high degree of uncertainty regarding the explanatory power of this variable. Based only on this result, it is not possible to draw any major conclusions regarding the effects of climate fluctuations on the occurrence of violent intergroup conflict. Different measurements and definitions for climate variability are used in different studies, and there may be alternative ways to study the effects of this phenomenon. However, since the main area of interest for this study is the effects of long-term climate change, a further exploration of the effects of climate variability will not be undertaken.

Contrary to the relationships observed between climate change and the incidence of violence, this study did not manage to discern the existence of a link between climate change and the intensity of violent intergroup conflict. This seems plausible, since resource scarcity alone should not lead to a larger number of fatalitites per violent event. The result could have occurred due to the measurement of intensity used, i.e. fatalities. If some other measurement, for instance the number of conflict events per grid cell, had been used, the results may have been different.

The methodology employed by this study is not without flaws, and a number of limitations to the results arise because of this. First, the theoretical framework is relatively simplified. Using only two major pathways between changing environmental conditions and violent intergroup conflict simplifies the analysis, but also limits the conclusions that can be drawn. Evidence has been uncovered suggesting the existence of a link between climate change-induced resource scarcity and violent intergroup conflict, but a deeper explanation regarding what this link looks like in practice, and through which pathways this phenomenon affects human societies, lies beyond the scope of the model used in this study. Second, the model fails to take into account certain spatial dimensions of climate change. For instance, the effects of climate-related migration may be considerable in geographical areas beyond the scope of this analysis, due to the incredibly vast and complex effects from climate change on human societies. Finally, using remote sensing as an analytical tool is a highly delicate endeavor. As can be seen in the section above, the sizes of the coefficients increase dramatically by simply expanding the size of the grid cells. It is clear that identified spatial patterns to a certain extent depend on the method of analysis employed. However, through the utilization of robustness checks such as varying the size of the grid cells, this study has hopefully been able to counter at least some of these problems.

VII. Conclusions

The purpose of this study was to examine the connection between climate change and violent intergroup conflict in the Sahel region 2010–2016. Results from the analysis conducted above seem to confirm the first of the two hypotheses proposed in the introductory section, namely that long-term changes in climatic conditions increase the probability of violent intergroup conflict occurring in the Sahel region in 2010–2016. The size of the effect varies depending on the model used, with the results of the main model indicating an average increase in the probability of violent conflict of 1.3% when the NDVI experiences an absolute decrease of 10%. No apparent link was identified between long-term climate change and the intensity of violent conflict (measured by the number of fatalities), leading to the conclusion that the results are unable to prove the second hypothesis, that long-term changes in climatic conditions increase the number of fatalities of violent intergroup conflict occurring in the Sahel region 2010–2016.

Using the findings of this study as a starting point, several areas of interest for future research can be identified. First, and most importantly, the use of remote sensing should be supplemented by detailed field studies to confirm, and evaluate, the connections identified by quantitative analysis. By using the results from remote sensing as a way to identify potential hotspots where the climate-conflict link should be of major importance, field studies could further explore these results on the ground. Second, studying other areas than the Sahel using methods similar to those used in this study would be highly interesting, since a comparison of the results may yield some insight regarding the generalizability of the results. The external validity of the findings is currently quite limited, with small opportunities to apply the results to other geographical areas than the Sahel. Finally, different approaches to the measurement of environmental conditions should be considered. By adding other variables of interest to the analysis, such as land degradation or other environmental measures, the complex nature of climate change may be taken into account in a more satisfactory manner.

There is no doubt that the changing environmental conditions of our planet are having a substantial effect on human societies around the world. The results of this study strengthen the argument that these effects have implications for human security on the African continent, adding to the growing body of evidence suggesting the presence of a link between climate change and violent conflict. In order to mitigate these effects it is of utmost importance that scholars and policymakers alike pursue the matter further. It is the responsibility of the global community to make certain that appropriate measures are taken to counter the inevitable side-effects of a warming planet on societies around the world. This study identifies one of these side-effects to be an increased likelihood of violent intergroup conflict on the African continent. Combating global warming is thus not something to be undertaken merely for the sake of maintaining environmental stability; it will also, quite literally, save lives.

VIII. References

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