CLIMATE CHANGE AND COMMUNAL CONFLICTS

A Disaggregated Study of Sub-Saharan Africa in 1989-2008

Monika Salmivalli

NORWEGIAN UNIVERSITY OF LIFE SCIENCES
Department of International Environment and Development Studies
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monika.salmivalli@gmail.com

Noragric
Department of International Environment and Development Studies
P.O. Box 5003
N-1432 Ås
Norway
Tel.: +47 64 96 52 00
Fax: +47 64 96 52 01
Internet: http://www.umb.no/noragric

Declaration

I, Monika Salmivalli, declare that this thesis is a result of my research investigations and findings. Sources of information other than my own have been acknowledged and a reference list has been appended. This work has not been previously submitted to any other university for award of any type of academic degree.

Signature………………………………..

Date…………………………………………

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Abstract

Does climate change lead to violent conflicts? This question worries world leaders, but research has not yet reached consensus on the topic. Inspired by theories of the Environmental Security School, many studies have been conducted on climate change and conflicts, in particular civil wars. However, this thesis argues that if climate change should lead to conflicts, a more likely outcome may be communal conflicts, on which there are only a few studies. To help fill this knowledge gap, this thesis investigates the relationship between climate change and communal conflicts in Sub-Saharan African in 1989-2008. It employs quantitative method and a disaggregated approach, using grid cells of 0.05˚ x 0.05˚ as units of analysis. Additionally to a regular large-N analysis, this thesis also analyzes climate change and communal conflict in a most likely scenario. Arguably, if climate change and conflicts are related, a relationship should be found where the circumstances for communal conflict, the most likely type of conflict to occur, are most favorable. Yet, this thesis finds no relationship between climate change and communal conflicts. Measured as changes in temperatures and rainfall, climate is not found to explain communal conflict events, not even in the most likely scenario. These results run contradictory to the few other studies which have been conducted on climate change and communal conflicts in Africa.

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1 Introduction

World leaders worry that climate change has been the cause of violent conflict. Amongst others the US President Barack Obama (Obama 2009:1) and the Secretary-General of the United Nations Ban Ki-Moon (Ban 2007) have expressed a clear concern for this. Further, the Norwegian Nobel Committee awarded the Nobel Peace Prize in 2007 to the IPCC and Al Gore for their efforts to collect knowledge of climate change and communicate the severity of it to people worldwide. In the announcement speech, the Chairman of the Committee, Ole Danbolt Mjøs, said:

> *"Unfortunately we can already establish that global warming not only has negative consequences for 'human security', but can also fuel violence and conflict within and between states. (...) The consequences are most obvious, however, among the poorest of the poor, in Darfur and in large sectors of the Sahel belt, where we have already had the first 'climate war'."* (Mjøs 2007:1)

Within International Relations, the Environmental Security School (e.g. Ullman (1983); Homer-Dixon (1999)) argues that resource scarcity, which may be caused by climate change, can worsen livelihoods of people in developing countries and as a consequence, lead to conflicts. However, contrary to these theories and to the worries of world leaders, research has not yet reached consensus on whether climate change and conflicts are correlated or not. Gleditsch (2012:7) summarizes, in a special issue of the Journal of Peace Research, that "on the whole […] it seems fair to say that so far there is not yet much evidence for climate change as an important driver of conflict." The same has been stated in recent reviews by Salehyan (2008) and Bernauer et al. (2012).

However, research on the climate change – conflict relationship has so far focused mainly on studying civil wars. This thesis proposes (as have e.g. Theisen (2008), Hendrix and Salehyan (2012) and Fjelde and Uexkull (2012)) that if climate change and conflicts are associated, an association should be found between climate change and non-state conflicts, in particular communal conflicts, rather than between climate change and civil wars. The threshold for groups to challenge the state (causing a civil war) is arguably much higher than for groups to engage in a violent conflict with each other (defined as a non-state conflict). Furthermore, communal conflict is more likely to be related to climate change than other types of non-state conflicts, as will be argued for in this study.

Some studies have already addressed the relationship between climate change and communal conflicts (e.g. Fjelde and Uexkull (2012) and Raleigh and Kniveton (2012)), and between climate change and non-state conflicts (e.g. Hendrix and Salehyan (2012) and O'Loughlin et al. (2012)). Yet, there are great variations in the results of these studies, possibly because the studies also vary regarding the geographical area studied, the unit of analysis used, the exact definition of conflict used and the conflict data used. Therefore, a lot remains to uncover.

This study will follow the path of focusing on conflicts short of civil war. It will investigate the relationship between climate change and communal conflicts in Sub-Saharan Africa in the years 1989-2008. Its primary contributions to the literature will be to show how the use of both temperature and precipitation as measures of climate change, and the use of grid-cells as disaggregated units of analysis, affects the analysis of climate change and communal conflict.

So far, only few climate-conflict studies have looked at temperature as a measure for climate change. These are O'Loughlin et al. (2012) and Theisen (2012), which study non-state conflicts, and Burke et al. (2009), Buhaug (2010a) and Wischnath and Buhaug (2013)), which focus on climate change and civil wars.

Moreover, the level of analysis chosen may have important consequences on the analysis of climate change and conflicts, as is argued by for instance Buhaug and Lujala (2005) and as will be discussed in this thesis. The analyses in this thesis are conducted on a disaggregated level using grid cells as units of analysis. O'Loughlin et al. (2012) and Theisen (2012) have, similarly to this thesis, used grid cells as units of analysis to study climate change and non-state conflict. However, as O'Loughlin et al. (2012) studies East Africa and Theisen (2012) studies Kenya, this thesis will be the first one to undertake an analysis of climate change and (any type of) non-state conflict in Sub-Saharan Africa using grid cells as units of analysis.

This thesis can thus provide a great opportunity to see whether the use of grid cells affects the results compared to using other disaggregated units. In this sense, the most interesting study to compare to is the study by Fjelde and Uexkull (2012), which uses first-order administrative units to study the same area, Sub-Saharan Africa, and the same type of conflicts, namely communal conflicts, with the same conflict data, the UCDP GED (Melander and Sundberg 2011) and UCDP non-state conflict dataset (Sundberg et al. 2012).

Interestingly, the results of this study indicate that there is no relationship between climate change and communal conflicts: none of the models in which the variables for temperature and rainfall were included were able to better explain communal conflict events than a model where only control variables were included. These results thus contradict the theoretical expectations in this thesis about a relationship between climate change and communal conflicts.

Moreover, this thesis also analyzes climate change and communal conflicts in a most likely scenario. The reason to analyze a most likely scenario is that if climatic changes have the potential to cause conflicts, arguably this will most likely happen in the circumstances described in this scenario. In this study, the most likely scenario is argued to occur in rural areas in Sub-Saharan Africa, characterized by political marginalization and poverty. The most likely scenario is presented in section 3.3.

However, changes in temperature and rainfall proved equally bad at explaining communal conflict events in the most likely scenario. As in the larger models, none of the climatic coefficients helped to explain communal conflict events, compared to models where only control variables were included.

Furthermore, attempt was also made to analyze rainfall and communal conflicts with models as similar as possible to the models used by Fjelde and Uexkull (2012), who have found drought to increase the likelihood of communal conflicts, and whose study differs from this thesis mainly by using first-order administrative units rather than grid cells as disaggregated units of analysis. Still, this thesis did not find any relationship between rainfall and communal conflicts.

Consequently, the results of this thesis run contrary to most other studies on climate change and communal conflicts or non-state conflicts, for instance Fjelde and Uexkull (2012), Raleigh and Kniveton (2012), Hendrix and Salehyan (2012) and O'Loughlin et al. (2012). Especially regarding the difference in results compared to Fjelde and Uexkull (2012), the results of this thesis raise questions about the methodologies applied in studies of climate change and communal conflicts. In particular, the results raise questions about whether grid cells and first-order administrative units capture the relationship between climate change and communal conflicts differently.

This thesis is built up in the following way. In chapter 2, the relevant literature on climate change and conflict will be presented and discussed. In chapter 0, the theoretical arguments underlying and motivating this study are elaborated on. In chapter 4, focus is given on methodological choices and the data used in this study. In chapter 5, the results of this study are presented. In chapter 6, the results are discussed and some ideas for future research are given. Finally, chapter 7 concludes.

1.1 Definitions

1.1.1 Environmental vs. climate change

This thesis studies the relationship between *climate change* and communal conflicts. Climate change is defined as

> *"change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer"* (IPCC 2007:30).[1]

Although climate change is the focus of this thesis, a part of the theoretical arguments in this thesis are based on literature on diverse *environmental changes* and conflict (e.g. Homer-Dixon (1994), Homer-Dixon (1999)). Consequently, the term environmental change is often used in this thesis when referring to relevant literature on *environmental changes* and conflict. This should, however, not be confused with the aim of this thesis, namely to study *climate change* and conflict. The reason why theoretical arguments on environmental changes are

[1] According to the IPCC (2007:30) "this usage differs from that in the United Nations Framework Convention on Climate Change (UNFCCC), where climate change refers to a change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods". Notwithstanding this, the motivation to study the relationship between climate change and conflict is in this study the accelerating tempo in which human-induced climate change is becoming a reality.

used in this study is that climate change[2] is a sub-category of the term environmental changes (Homer-Dixon 1991:88).

1.1.2 Environmental scarcity vs. resource scarcity

The term *environmental scarcity* is often used in the literature on environment and conflict. Homer-Dixon (1999:14-15) defined environmental scarcity as the combination of supply-induced, demand-induced and structural scarcity. Supply-induced scarcity occurs when the availability of necessary renewable resources like land, water or fish decreases. Demand-induced scarcity occurs for example through population growth, when there are more people who need to share the same amount of resources. Structural scarcity on the other hand is a social and political phenomenon: when the access to resources is divided unequally, some groups will face resource scarcity although there might be enough resources for the whole population on a national basis. (Homer-Dixon 1999:14-16)

Several scholars have criticized the term environmental scarcity as being too vague (Gleditsch (1998:388) or to include too many diverse phenomena (Benjaminsen (2009:154). In this study, the term *environmental scarcity* is used where the literature talks about *environmental scarcity*. Yet, the theoretical arguments underlying this study are based on the more specific term *scarcity of renewable resources* such as food and water, originating in supply-induced scarcity. Moreover, scarcity of renewable resource is in this thesis often shortened to *resource scarcity* to make the text more easily readable.

1.1.3 Civil war, non-state conflict and communal conflict

The key difference between a civil war and a non-state conflict is that a civil war occurs between the authorities of a state and between an organized rebel group (Gleditsch et al. 2002:619), while a non-state conflict does not involve the authorities of a state but only more or less organized groups (Sundberg et al. 2012:352-353). Moreover, a communal conflict is a form of non-state conflict and occurs between groups whose members “share a common identification along ethnic, clan, religious, national or tribal lines” (Pettersson 2012:4).

[2] Homer-Dixon (1991) uses the terms green-house warming and climate change interchangeably.

2 Literature review

This chapter will present the literature on climate change and conflict which is relevant for this study. First, a quick overview of the history of environment and conflict research is given (section 2.1), before the key debates in the literature are presented (section 2.2). Thereafter, a brief review is given over the literature on climate change and civil war (section 2.3), before a more extensive review is given over literature on climate change and non-state conflict (section 2.4).

2.1 The history of environment and conflict research

The relationship between environment and conflict has been studied for a few decades. Rønnfeldt (1997) identifies three generations of environmental conflict research. According to Rønnfeldt (1997:473-474), the first generation appeared in the 1980s and argued for taking environmental factors into account in discussions of security (see for instance Ullman (1983), Myers (1989) and Renner (1996)). The first and second generations are often called the "environmental security school". The second generation took the initiative to start empirical studies on the relationship between environmental factors and conflict. It also formalized the hypothesis that environmental scarcity would lead to conflict, discussed already by the first generation. Researchers of the second generation conducted mostly case studies, and through them tried to map exactly how environmental scarcity could lead to conflict (Rønnfeldt 1997:473, 475). Researchers of the second generation include amongst others Homer-Dixon (1991; 1994) and Baechler (1998). The second generation will also be discussed in section 2.2, which outlines the key debates in the literature.

The third generation identified by Rønnfeldt (1997) has criticized a number of the second generations' methodological choices, including failing to study non-conflict cases. This criticism will be elaborated in section 2.2 on key debates in the literature. In addition, the third generation has broadened empirical research on environment and conflict by introducing more environmental variables and more social variables in the research and, according to Rønnfeldt (1997:473,476-477), consequently also connected environment-conflict research to general peace and conflict-research. Although not explicitly mentioned by Rønnfeldt, the third generation also introduced quantitative research on the environment and conflict. Research of the third generation explicitly mentioned by Rønnfeldt (1997) include Gleditsch (1996) and Hauge and Ellingsen (1996), but later the number of researchers affiliated with the third generation's research has increased dramatically (see for instance Nordås and Gleditsch (2007), Raleigh and Urdal (2007), Salehyan (2008), Theisen (2008), Burke et al. (2009), Buhaug (2010a), Bernauer et al. (2012), Hendrix and Salehyan (2012), O'Loughlin et al. (2012) and Fjelde and Uexkull (2012)), as illustrated in the sections on climate change and civil war (2.3) and climate change and non-state conflicts (2.4).

2.2 The key debates

The second generation's concrete hypotheses and empirical studies have arguably been among the most important motivators and sources of disagreement in empirical environment-conflict studies. The second generation's perhaps most prominent scholar has been Thomas Homer-Dixon[3]. Homer-Dixon hypothesized different causal pathways between environmental scarcity and conflict and laid out a plan for empirical research in 1991 (Homer-Dixon 1991). According to him, environmental scarcity might lead to conflict when combined with conflict-risk increasing social, political and economic factors, as discussed in section 3.2.2. Based on empirical case studies conducted by his research group, Homer-Dixon (1994:6) argued in 1994 that many of his hypotheses had proved to be true and that environmental scarcities were already partly responsible for several conflicts in developing countries.

However, these conclusions have later been contested by a number of researchers working with different methods, including researchers affiliated with the third generation. Quantitative researchers have criticized the Environmental Security School amongst other things for selection bias (Gleditsch 1998) and for concluding prematurely that a climate-conflict link exists (e.g. Theisen (2008), Salehyan (2008), Gleditsch (1998)). The selection bias critique concerns that environmental security scholars, including Homer-Dixon (1994), have only studied cases of conflict and have not included in their research cases where environmental problems occur but conflict does not (Gleditsch 1998:391). The consequence of selection bias may be that false conclusions are presented:

[3] In his section on the second generation, Rønnfeldt (1997) discusses only Homer-Dixon and Homer-Dixon's Toronto Group's research due to space constrains. Rønnfeldt explains choosing Homer-Dixon "because of the great frequency by which this group is cited in the literature on this topic" (Rønnfeldt 1997:475). However, as Rønnfeldt notes in note 4 (Rønnfeldt 1997:480), also a number of other researchers are affiliated with the second generation.

"In examining only cases of conflict, one is likely to find at least partial confirmation of whatever one is looking for [...] No society is completely free of environmental degradation, nor is any society completely free of ethnic fragmentation, religious differences, economic inequalities, or problems of governance. From a set of armed conflicts, one may variously conclude that they are all environmental conflicts, ethnic conflicts [...]" (Gleditsch 1998:392)

Furthermore, Gleditsch (1998:392) points out that Homer-Dixon's (1994:6) conclusion about environmental scarcities leading to conflict is not correct. This is according to Gleditsch because Homer-Dixon draws general conclusions based on case-studies. Generalizing results of case studies is violating an important principle in social science research (see for instance Bryman (2008:391)). In addition, Homer-Dixon's conclusions are seen as premature as a number of quantitative large-N studies have failed to find a relationship between environmental factors, including climate change, and conflict (see reviews by Theisen (2008), Salehyan (2008) and Gleditsch (2012)).

Also political ecologists have criticized the environmental security school. Political ecologists have argued the environmental security school does not take enough into account neither context specific factors nor factors of political and economic power, which according to political ecologists are crucial for understanding violent conflicts (see for instance Peluso and Watts (2001), Turner (2004) and Benjaminsen et al. (2009)). To illustrate this, case studies conducted by political ecologists have found underlying social and political explanations to conflicts which on the surface have seemed to be related to environmental degradation. These explanations include political marginalization, corruption and long-term strategies to affect the politics of resource distribution (see Benjaminsen (2008), Benjaminsen et al. (2009) and Turner (2004)).

Moreover, a frequently cited counter-argument to the resource scarcity – conflict thesis is the cornucopian argument. The cornucopians[4] can be characterized as development optimists, because they reject the notion that resource scarcity will necessarily have negative consequences. Instead, they reason that humans are inventive and adaptive, and will therefore find ways to cope with or solve resource scarcity (see for instance Boserup (1965), Simon

[4] Homer-Dixon (1999) talks about economic optimists, which is another term for cornucopians.

(1981) and Ruttan and Hayami (1984)). Although the cornucopian argument dates back to the 1960s-1980s, i.e. to a time before theories on climate change and conflict, the argument's basic idea may be argued to still be relevant today: resource scarcity (be it caused by population growth, climate change or another reason) will not necessarily lead to starvation and social turmoil, because people are adaptive and inventive.

2.3 Climate change and civil war

This section will provide a brief overview of the most important conclusions and dilemmas so far in the quantitative climate change and civil war literature. It will thus not go as much into detail on the different studies as the review on climate change and non-state conflict literature will (section 2.4), as the relationship between climate change and civil war is not the main focus of this study. Nevertheless, the studies of climate change and civil war provide an important background on which the quantitative non-state conflict studies build.

A number of quantitative studies have been conducted on climate change and civil war, but the results have been remain contradictory (see reviews by Gleditsch (2012), Bernauer et al. (2012) and Salehyan (2008)). Changes in rainfall are the most often used proxy for climate change. Studies using it are according to Gleditsch (2012:7) many enough to allow a conclusion: drought and civil war do not seem to be correlated in general. Studies that have not found changes in precipitation and civil wars to be related include Theisen (2008), Koubi et al. (2012) and Theisen et al. (2011).

Gleditsch (2012:7) furthermore points out that studies which use other proxies than changes in rainfall are still too few to allow conclusions. This point applies also to studies on temperature changes and civil war, which are only a few. Of these, the study by Burke et al. (2009) demonstrates a link between temperature increase and civil wars in Africa. However, it has been criticized by Buhaug (2010a) who showed that the findings by Burke et al. (2009) cannot be replicated when some key variables, such as civil war, are operationalized in a theoretically more justifiable way. In sum, the evidence for an overall climate change – civil war link is still highly contradictory and highly contested.

2.4 Climate change and non-state conflicts

In recent years, the focus of quantitative climate-conflict research has started to shift somewhat from studying civil war towards studying different types of conflicts, including non-state conflicts in general and communal conflicts in particular. This section will have its main focus on research on climate change and different types of non-state conflicts, although it also includes results for studies which have not separated between different types of conflicts and thus study for instance civil war and non-state conflicts together.

Research on climate change and non-state conflicts includes global, regional and national quantitative studies as well as qualitative case studies. So far, many of the quantitative studies have found some kind of an association between climate change and non-state conflicts. However, the directions of these associations are not consistent across different studies. Importantly, the number of studies is still too small to draw any conclusions, and more research is needed. The following sections will give an overview of the results of climate change and non-state conflict studies, and Table 1 will provide a summary of them.

2.4.1 Continent-wide and regional quantitative studies of Africa

Studying Sub-Saharan Africa, Fjelde and Uexkull (2012) have found that exceptionally dry years are positively correlated with communal conflicts. This finding supports the environmental scarcity –thesis, which predicts that droughts may lead to resource scarcity, which in turn may lead to conflict (see section 3.2.2). In addition, Fjelde and Uexkull (2012) find some evidence to support their hypothesis that areas characterized by political and economic marginalization see a higher risk for communal violence than other areas in exceptionally dry years. This finding is interesting regarding the most likely scenario tested in this study (see section 3.3). The most likely scenario expects climate-related conflict to have a bigger chance to occur in rural areas characterized by political marginalization and poverty. However, interestingly Fjelde and Uexkull (2012) do not find a higher likelihood for communal conflict in areas characterized by poverty. They speculate that this might be due to their measures of poverty[5], which might not be sufficiently fine-grained to capture the effects of poverty (Fjelde and Uexkull 2012:452). Notably, Fjelde and Uexkull (2012) use conflict data from the Uppsala Conflict Data Program's Geo-referenced Event Dataset (UCDP GED)

[5] based on income per capita in the first-order administrative unit and belonging in the poorer half of the population in Sub-Saharan Africa (Fjelde and Uexkull 2012:452)

(Melander and Sundberg 2011) i.e. the same data which is used in this study. The UCDP GED contains geo-referenced data on events of state-based, non-state and one-sided violence. In addition, Fjelde and Uexkull (2012) have supplemented the UCDP GED data with data from the UCDP non-state conflict dataset (Sundberg et al. 2012) in order to separate between different types of non-state conflicts and have only included communal conflicts in their study, as is also done in this thesis.

Contrary to Fjelde and Uexkull (2012), Hendrix and Salehyan (2012) find that social conflict in Africa including civil war, smaller episodes of violence and non-violent protests are all related to changes in the climate, although in different ways. They find that all types of social conflict (both violent and non-violent) are more likely to occur in years with extreme deviations from average rainfall, i.e. in abnormally dry and wet years. Moreover, they also find that violent events including civil wars, communal violence and riots are most likely in abnormally wet years, while non-violent conflicts like protests and strikes are most likely in abnormally dry years (Hendrix and Salehyan 2012:45-46).

Hendrix and Salehyan (2012) operationalize conflict in six different ways, namely civil conflict onset, total events, non-violent events, violent events, government-targeted events, and non-government targeted events. Notably, none of these categories correspond directly to either communal conflict or non-state conflict in general according to the definitions in this thesis. The conflict data which Hendrix and Salehyan (2012) use is derived from the Social Conflict in Africa Database (SCAD) (Salehyan et al. 2012), which contains geo-referenced data on events of violent and non-violent social and political unrest in Africa. Yet, while the SCAD data is geo-referenced, Hendrix and Salehyan (2012) use countries as their units of analysis.

Studying East Africa, O'Loughlin et al. (2012) find that abnormally wet years are more peaceful than years with average rainfall, whereas abnormally dry years are not related to conflict. These results stands in contrast to the continent-wide studies by both Hendrix and Salehyan (2012) and Fjelde and Uexkull (2012). Notably, O'Loughlin et al. (2012) do not differentiate between civil wars, non-state violence and one-sided violence, but include all types of violent conflict under "conflict". Moreover, they also use temperature as a climatic variable, and find that warm years see more violence than years with average temperature.

Abnormally cold years are not related to conflict. However, O'Loughlin et al. (2012) note that although these findings are significant, the effect of the climatic variables on conflict is modest compared to effects of political, economic and physical geographic factors. O'Loughlin et al. use conflict data from the Armed Conflict Location and Event Dataset (ACLED) (Raleigh et al. 2010), which contains geo-referenced data on both violent and non-violent conflict events. ACLED also assigns each conflict event to specific conflict parties.

Contrary to O'Loughlin et al. (2012), Raleigh and Kniveton (2012) find that violent events connected to civil wars and communal conflict in East Africa are more frequent both in times of drought and in times of excessive rain. Yet, civil war events are most likely during droughts whereas communal conflict events are most likely in times of abundant rainfall (Raleigh and Kniveton 2012:62). This difference between the findings of O'Loughlin et al. (2012) and Raleigh and Kniveton (2012) is puzzling, as both use conflict data from ACLED. In other words, Raleigh and Kniveton (2012) and O'Loughlin et al. (2012) use the same conflict data to study the same region, but get different results. A possible explanation might be that O'Loughlin et al. (2012) analyze civil war, non-state conflict and one-sided violence together without differentiating between the conflict types, whereas Raleigh and Kniveton (2012) run separate analyses for civil war and communal violence. Another possible explanation is that the time periods studied do not overlap entirely: O'Loughlin et al. (2012) use conflict data for 1990-2009, while Raleigh and Kniveton (2012) only use data for 1997-2009. Thirdly, while O'Loughlin et al. (2012) use grid cells as their units of analysis, Raleigh and Kniveton (2012) use conflict locations, which also might affect the results.

Furthermore, the results which Raleigh and Kniveton (2012) get are also interesting compared to Hendrix and Salehyan (2012) and Fjelde and Uexkull (2012). While Hendrix & Salehyan find both government-targeted (e.g. civil war) and non-government targeted (e.g. non-state conflict) events to be most likely in wet years, Raleigh and Kniveton (2012) find civil war events to be most likely in dry years and communal violence most likely in wet years. Contrary to both of them, Fjelde and Uexkull (2012) find communal violence to be most likely in dry years.

There are several possible explanations for these different findings. For instance, an explanation may lie in the study area: Hendrix and Salehyan (2012) study Africa and Fjelde and Uexkull (2012) study Sub-Saharan Africa, while O'Loughlin et al. (2012) and Raleigh and Kniveton (2012) study East Africa. Moreover, an explanation may lie in the lack of conflict specification. Namely, Hendrix and Salehyan (2012) and O'Loughlin et al. (2012) do not show separate results for communal conflicts or even non-state conflicts in general, making it hard to directly compare their results to the communal conflict results by Fjelde and Uexkull (2012) and Raleigh and Kniveton (2012)).

Another possible explanation may lie in the conflict data used by the different studies: Fjelde and Uexkull (2012) have used data from UCDP GED (Melander and Sundberg 2011), Hendrix and Salehyan (2012) have used data from SCAD (Salehyan et al. 2012), and O'Loughlin et al. (2012) and Raleigh and Kniveton (2012) have used data from ACLED (Raleigh et al. 2010). Concerning the data, there are a few points that are worth discussing. Firstly, different datasets are likely to contain partly different data even when trying to capture the same phenomena, if they are based on different sources and compiled by different coders. In this case, the different datasets have used different combinations of sources, although all have relied at least partly on media sources (see Salehyan et al. (2012:505), Raleigh et al. (2010:656), Sundberg et al. (2012:353-354)). Secondly, ACLED has been criticized for poor coding quality compared to UCDP GED. According to Eck (2012:131-132), there are many errors in the ACLED data including errors in coding of conflict locations. Eck also argues that ACLED is very likely to give a false impression of how secure its data on event locations is. While UCDP GED reports being very confident on 29% of the event locations it reports, ACLED reports being very confident in 77% of the event locations. Yet, conflict locations ought to be equally difficult for coders behind ACLED and UCDP GED to identify (Eck 2012:133-134). These problems with the ACLED data may in the worst case lead to researchers using ACLED, such as O'Loughlin et al. (2012) and Raleigh and Kniveton (2012), to get misleading results.

2.4.2 Local quantitative studies

Studying drylands of Northern Kenya, Witsenburg and Adano (2009) have found there to be more violent incidents related to so called cattle raiding, i.e. pastoralists stealing cattle from other pastoralists, in Northern Kenya during times of abundant rainfall. They note that the environment in years with abundant rainfall makes raiding easier, for instance as there is better access for water during raiding trips (Witsenburg and Adano 2009:529,531). On the contrary, in times of scarce rainfall and consequently scarce resources the pastoralists do not have resources to spend on raiding (Witsenburg and Adano 2009:531).

Looking at different types of violent conflicts short of civil war in Kenya, Theisen (2012) finds that dry years and especially years following dry years see less conflicts compared to years with average or abundant rainfall. This finding matches the finding of Witsenburg and Adano (2009), as most of the conflicts that occurred in the time period and area of Theisen's study are pastoral conflicts (Theisen 2012:93).

Meier et al. (2007) study whether cattle raiding in the Horn of Africa is linked to precipitation, vegetation and forestry. They do not get a significant result for precipitation and forestry, but find a positive relationship between vegetation and cattle raiding. They argue this positive relation to be fairly logical, as high grass allows raiders to hide more easily both before and after raids (Meier et al. 2007:731).

2.4.3 Qualitative case studies

Qualitative case studies give varying results. Turner (2004) finds some pastoral conflicts in the Sahel to be related to herders' access to resources, but he shows that these conflicts are not spontaneous actions driven by herders' sudden scarcity of resources during hard times. Rather, these conflicts are part of herder groups' long-term strategies to gain access to resources. Thus Turner's study does not lend support to the resource scarcity-hypothesis.

Benjaminsen (2009) studies a conflict between herders and farmers in Tanzania, but he finds the political marginalization of pastoralists and the effects of corruption to be the most important explanations for the conflict. In contrast, scarcity of resources is not seen to have much explanatory power.

Eaton (2008) studies cattle raiding in Kenya and similarly to Witsenburg and Adano (2009) and Theisen (2012), finds cattle raiding to be more frequent in wet than dry periods (Eaton 2008:100-101). He also clearly contests the notion that cattle raiding would be a consequence of poverty, since raiders many times make fortunes through raiding (Eaton 2008:101-102). If raiding is not a consequence of poverty, it logically follows that it cannot occur as a survival strategy when facing acute resource scarcity.

2.4.4 Overview of quantitative studies

Table 1 below will give an overview of the quantitative climate change and non-state conflict studies, which were presented above, and their key differences.

Table 1 Overview of quantitative non-state conflict results.

Study	Area	Proxy for climate change	Type of conflict	Unit of analysis[6]	Onset or event	Result	Important control results?
Fjelde & Uexkull (2012)	Sub-Saharan Africa	Rainfall deviations	Communal violence	Disggregated: First order administrative units within countries	Events	Dry years see more communal violence	Marginalization possibly related to conflict; poverty not
Hendrix & Salehyan (2012)	Africa	Rainfall deviations	Social conflict including civil war, communal conflict, non-violent protests etc.	Aggregated: Countries	Events	Wet years see more violent conflict, dry years see more non-violent conflict	
O'Loughlin et al. (2012)	East Africa	Rainfall and temperature deviations	Violent conflict including civil wars, non-state conflict and one-sided violence	Disaggregated: Grid cells	Events	Wet years see less conflicts, warm years see more conflict. Dry and cold years are not correlated to conflict.	Political, economic and physical geographic factors have a stronger relationship to conflict than climate
Raleigh & Kniveton[7] (2012)	East Africa	Rainfall deviations	Civil war and communal violence	Disaggregated: Conflict location	Events	Wet and dry years see more of both types of conflict than average years, but civil war is most likely in dry years and communal violence in wet years	
Witsenburg and Adano (2009)	Northern Kenya	Rainfall deviations	Cattle raiding between pastoralist groups	Regional: One district	Events and intensity	Wet years see more cattle raiding	
Theisen (2012)	Kenya	Rainfall and temperature deviations	Conflicts short of civil war, mostly pastoral conflicts	Disaggregated: grid cells	Occurrence and events	Dry years and years following dry years see less conflict	
Meier et al. (2007)	Horn of Africa	Rainfall, forestry and vegetation	Cattle raiding between pastoralist groups	Disaggregation: first order administrative units	Events	Vegetation increases risk of conflict	Vegetation result: the effect is stronger when coupled with disturbing behavior and lack of peace efforts

[6] The units of analysis are discussed more in-depth in section 4.3.
[7] Uses months instead of years as units.

3 Theory

This chapter will present and discuss relevant theoretical arguments underlying and motivating this study. In figure 1, an overview is given of how climate change is expected to lead to communal conflict. The remaining sections in this chapter will explain this chain of thought, and also present the concrete hypotheses of this study.

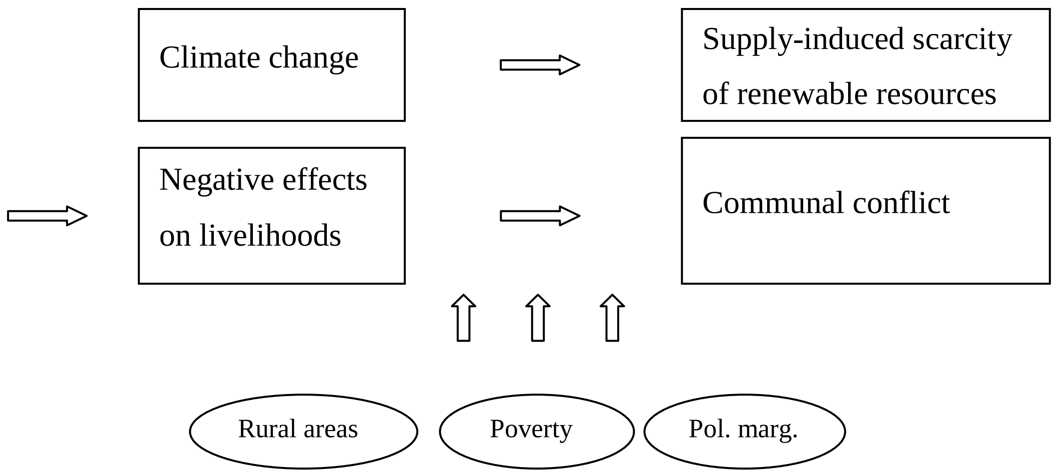

Figure 1 : This model visualizes how climate change, including changes in temperature and rainfall, will lead to supply-induced scarcity of renewable resources, in particular negative effects on agriculture and drinking water. This scarcity in turn will worsen people's livelihoods by affecting their access to food and water, and by affecting the earnings they receive from agriculture. Especially when this occurs to poor and politically marginalized groups, groups may have few options for how to cope with resource scarcity and may therefore engage in communal conflict.

In the first section (3.1), it will be explained what kind of climatic changes are expected to occur in Africa and consequently, how African livelihoods are expected to be impacted. This is important background information for the sections that follow, because if climate change could lead to conflicts, it is expected to do so by affecting the livelihoods of people, as is shown in Figure 1. In the second section (3.2), it will be discussed how and why effects on livelihoods could lead to conflict, and why non-state conflicts, in particular communal conflicts, are a more likely result of climatic changes than civil wars. In this section, hypotheses for the larger models of this study will be presented. In the third section (3.3), a most likely scenario will be outlined, explaining in which circumstances climate-related conflict is most likely to occur. Hypotheses for the most likely scenario are also presented. Finally, in the fourth section (3.4), all the hypotheses tested in this study will be summarized.

3.1 Impact on livelihoods in Sub-Saharan Africa

Climate change is found to impact Africa in a variety of ways. According to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), Africa will likely experience higher temperatures, less rain in some regions, more rain in other regions, more extreme events (such as storms, sustained droughts and floods) as well as ecosystem changes (such as increasing of arid- and semiarid lands and sea level rise) (Boko et al. 2007). These effects are, in their turn, likely to impact livelihoods of people.

As temperature and rainfall are used as proxies of climate change in this study, a brief overview will now be given of how the changes in temperature and rainfall will differ across different regions in Africa. All across Africa, in all seasons, temperatures are very likely to increase between 3˚C-4˚C during the next century (Christensen et al. 2007:867). These rises are higher than the global average of approximately 2˚C (ibid). Dry subtropical regions, in particular the western part of the Sahara, will see the highest increases (around 4˚C), while coastal areas and moister tropics such as equatorial areas will see increases of approximately 3˚C (Christensen et al. 2007:866-867). Compared to temperature, changes in rainfall will vary more across different regions in Africa. North Africa including Northern Sahara will see considerably less rainfall (Christensen et al. 2007:868). Also the extreme southwest of Africa is very likely to see less rainfall in winter (Christensen et al. 2007:868). On the other hand, East Africa is likely to see increased rainfall (Christensen et al. 2007:869). Notably, changes in rainfall in the Sahel, Southern Sahara and the Guinean cost are still unknown (Christensen et al. 2007:850, 869-871).

The Fourth Assessment Report lists examples of how the livelihoods of people may be impacted. For instance, droughts and higher temperatures may in many cases decrease agricultural productivity (Boko et al. 2007:439, 447-448), which in turn means less food and earnings for farmers and herders. However, in some regions agricultural production may also increase as a consequence of higher temperatures (Boko et al. 2007:447-448). The effects on agricultural production are important as the portion of GDP that agriculture contributes with varies between 10-70% across African countries (Boko et al. 2007:439). Higher temperatures, together with other effects of climate change such as changes in freshwater flows, may also decrease fish stocks, although this is likely to depend on human management of the water resources (Boko et al. 2007:448). If fish stocks decrease, it will mean less food and earnings for fishers. Furthermore, climate change is likely to increase water stress in Northern and Southern Africa, while East and West Africa may see increased water availability (Boko et al. 2007:444-445). On the other hand, extreme weather events may cause shocks for populations across the continent for instance by damaging infrastructure (Boko et al. 2007:439-440, 450). Ecosystem changes like sea level rise may amongst other things decrease fish stocks (Boko et al. 2007:449-450), meaning less food and earnings for fishers. Sea level rise may also threaten populations living in coastal cities in Africa, most notably poor populations (Boko et al. 2007:450). Finally, all the effects on livelihoods may lead to migration (Boko et al. 2007:450). In sum, climate change will mostly impact livelihoods through water availability and food production, and maybe also some through effects on infrastructure and migration.

It is important to note, however, that there are also a number of uncertainties related to both the predicted effects of climate change and the predicted effects on African livelihoods. For instance, temperature predictions vary between different estimations (Boko et al. 2007:443), precipitation predictions are relatively uncertain for the whole of Africa (Boko et al. 2007:443), and the development of agricultural production is hard to predict even without climate change (Boko et al. 2007:448). Despite these uncertainties in magnitude, Africa is very likely to see climatic changes (see summary by Christensen et al. (2007:4)) and there is a good possibility that African livelihoods will be impacted by these changes (Boko et al. 2007:450).

Furthermore, Africa is also considered especially vulnerable to climate change because of a range of social, political and economic factors that affect the livelihoods and adaptation capacities of the African societies (Boko et al. 2007:454). For example poverty can limit people’s coping strategies, such as their possibilities to change income source as a response to environmental stress (Adger and Kelly 1999:258-260). Consequently in Africa, due to widespread poverty, many poor farmers whose crops are not resilient to climate change may not have the capacity to change the crops they grow to more heat or drought tolerant crops, or to seek employment in other sectors outside agriculture. Moreover, herders, whose cattle may suffer from decreasing amounts of grazing land and drinking water, may also be likely to have few options to seek alternative employment.

3.2 Violent conflict

In this section, it will be discussed how changes in livelihoods caused by climate change, especially resource scarcity, may lead to conflict, and what type of conflict is most likely to occur. This discussion firstly looks at the sources of scarcity (section 3.2.1) and thereafter on the consequences of scarcity (section 3.2.2). Next, section 3.2.3 argues for why communal conflict is the most likely type of conflict to occur as a consequence of resource scarcity. Finally, section 3.2.4 presents hypotheses for this study.

3.2.1 Sources of scarcity

Ullman (1983) was one of the first scholars to address the issue of resource scarcity leading to increased insecurity, and was thus one of the key scholars behind the term "environmental security". He argued that especially population growth would lead to resource scarcity, which again would constitute a security threat. Ullman also discussed scarcity in the supply of resources, which originated amongst other things from the overuse of certain resources like forests, fish, and seed crops (Ullman 1983:143-145).

Moreover, Thomas Homer-Dixon and his research group at the University of Toronto were among the first to study environmental security empirically (see literature review in Chapter 2). Homer-Dixon defined three sources of environmental scarcity: supply-induced scarcity, demand-induced scarcity and structural scarcity (Homer-Dixon 1999:14-16). These terms were explained in section 1.1.2. For the framework of this study, supply-induced scarcity is of core interest. Many of the effects of climatic changes on African livelihoods, including negative effects on agricultural production and water supplies, diminish the supply of critical renewable resources. However, demand-induced and structural scarcities are also taken into account in this study through trying to control for their effects by using control variables such as population and politically and economically marginalized groups.

It is also important to note, that Homer-Dixon (1994:7-8) argued primarily for environmental changes such as "degradation and depletion of agricultural land, forests, water and fish" to be related to conflict, and stated that climate change was not among the phenomena most likely to cause conflict. This statement was based on the argument that the effects of climate change would not be felt for decades, and its effects would "most likely operate not as individual environmental stresses, but in interaction with other, long-present resource, demographic, and economic pressures that have gradually eroded the buffering capacity of some societies" (Homer-Dixon 1994:7-8).

However, the study presented in this thesis is based on the logic that by studying climatic changes in the past it will be possible to understand climatic changes' potential to cause conflict also in the future, when the effects of anthropogenic climate change will become most clearly visible[8]. Furthermore, it is argued that effects of climate change, such as temperature and precipitation changes, may indeed act as "individual environmental stresses" through their effects on livelihoods, at least to the same degree that Homer-Dixon argues that scarcities of agricultural land, forests, water and fish act (see section 3.2.2). Thus Homer-Dixon's theoretical arguments are seen to speak in favor of also climatic changes leading to conflict.

3.2.2 Consequences of scarcity

On way scarcity of renewable resources may lead to conflict, is if groups start fighting over scarce resources, or access to scarce resources. Several conflicts in developing countries, including conflicts between pastoralists and between pastoralists and farmers, have been described as conflicts over scarce resources such as land and water (see for instance Homer-Dixon (1994), Bächler (1998), Kahl (2006), Suliman (1999)). For instance, Suliman (1999:34) argues that the conflicts in Darfur in western Sudan can be explained as a result of resource competition between farmers and herders. He notes that the droughts in 1983-1984 led herders to use the land of farmers to a much higher extent than before, and this eventually led to conflict between the groups. Moreover, Kahl (1998) argues that the ethnic violence in Kenya in 1991-1993 was possible due to scarcity of crop land. According to Kahl, the ethnic clashes were arranged by President Moi and his allies, who felt threatened by an ethnically united opposition which demanded increased democratization. To arrange the clashes, the authorities played on the lack of good-quality crop land and old grievances relating to the division of crop land.

[8] See section 4.9 for a discussion on this logic.

Another way scarcity of renewable resources may lead to conflict is that groups may also wish to change national or local laws and regulations in order to get a better long term access to resources. In that case, groups would arguably need to direct their demands towards local or national authorities. Homer-Dixon (1994:24) notes, that frustration over lack of resources may breed willingness among groups to challenge the state. Therefore, if non-violent means of trying to impact laws and regulations regarding for instance land ownership prove ineffective, groups may arguably rebel. However, challenging the state is very costly, and in section 3.2.3 it will be discussed more in detail under which circumstances rebellion against the state would be possible, and why groups suffering from resource scarcity are more likely to challenge other groups than to challenge the state.

Furthermore, negative economic effects due to degradation of the environment can lead to increased poverty. These negative effects can occur for instance when increases in temperature or decreases in rainfall decrease agricultural productivity, as explained in section 3.1, and thus also decrease the income and nutrition that households gain from farming. Facing increased poverty may in turn increase the willingness of a group to fight the state. Poverty, measured by low per capita income and low economic growth rates, has been found to be robustly correlated to the onset of civil war (Hegre and Sambanis 2006). However, it can be argued that increased poverty may also increase a group's willingness to fight other groups, if other groups have better access to resources and fewer restraints on food production. It has been noted, namely, that in addition to absolute scarcity, i.e. lacking resources that one needs, also relative scarcity may increase the risk of conflict (see Fjelde and Uexkull (2012:446-447) and Raleigh (2010:79)).

Both absolute and relative scarcity can be classified as grievance-based potential reasons for conflict. The question of whether greed or grievance causes conflict is extensively researched in relation to civil war (see for instance (Gurr 1970), (Collier and Hoeffler 2004) and (Regan and Norton 2005)). Yet, the discussion is arguably equally relevant when studying non-state conflicts, such as communal conflicts. Notably, the arguments presented in this chapter are supportive of grievance, rather than greed, explaining climate change –induced conflict.

Resource scarcity has also been argued to lead to conflict through migration. As the renewable resources which are necessary for maintaining a livelihood, including water and yields from agriculture, get too scarce, people will migrate into areas with more resources. According to Homer-Dixon (1994:20), when groups, who suffer from environmental scarcity, migrate to new areas to get better access to resources, this migration can result in conflicts between the migrating group and groups who already live in the new area. However, in this thesis, the issue of scarcity-caused migration leading to conflict is not addressed explicitly. Doing so would require analyzing quantitative data which already follows a potential causal path from resource scarcity to migration and further to conflict, and this kind of an analysis was beyond the capacity of this study[9].

Furthermore, it is important to note, that environmental factors are never likely to be the only explanatory factors for conflict, as emphasized by Homer-Dixon. Rather, environmental scarcity combined with a range of social, political and economic factors could lead to conflict (Homer-Dixon 1999:16). Despite the importance of social, political and economic factors, Homer-Dixon still saw that environmental factors can be independent triggers of conflict. To find out whether environmental factors can be seen as independent triggers of conflict, as Homer-Dixon argues, this study will test whether climatic changes correlate with communal conflict when several social, political and economic variables are controlled for. All of the control variables will be presented and discussed in chapter 4.

3.2.3 Communal conflict vs. civil war

There are good reasons to expect that if a link between climate change and conflict exists, it is to be found between climate change and communal conflicts rather than between climate change and civil wars. In section 3.2.2 different climate change –induced reasons for engaging in violent conflict were discussed, and these included gaining access to scarce resources which another group holds, and changes in national or local laws and regulations in order to improve a group’s access to scarce resources. Thus this section will concentrate on discussing firstly, why civil wars are a less likely consequence of climate change than non-state conflicts (section 3.2.3.1) and secondly, why communal conflict is the most likely type of non-state conflict to occur (section 3.2.3.2).

[9] Reuveny (2007) has done a qualitative variant of this kind of study by studying cases of environmental migration and whether they led to conflict in the migrant-receiving area.

3.2.3.1 Non-state conflict vs. civil war

As Hendrix and Salehyan (2012:37) argue, referring to Maxwell and Reuveny (2000), civil war does not lead to an increase in the absolute amount of resources a state has. Therefore, what a civil war can affect is the distribution of resources. Hendrix and Salehyan continue by arguing that this means that engaging in war against the government is not logical for a group suffering from resource scarcity. They write that "often times, groups will find neighboring communities, rather than the government, the most appropriate target for making demands; this is especially true if the state is known to be unwilling or unable to redistribute resources in a society" (Hendrix and Salehyan 2012:37). This can be seen as a feasible argument if the state is unable to redistribute resources. However, the state's unwillingness to distribute resources is something that a suffering group in theory could try to affect, even through war if negotiations or other peaceful means prove insufficient. Next it will be discussed a bit deeper why the state's unwillingness to distribute resources nevertheless unlikely would lead to civil war.

As Raleigh and Kniveton (2012:53) point out, groups that engage in civil war want to overthrow the current regime. Groups that suffer from resource scarcity, on the other hand, will not necessarily want to overthrow the regime, but only improve their own livelihoods. Simultaneously, one can imagine that overthrowing the government and taking power of the whole state would enable scarcity affected groups to change laws and regulations for their own benefit. Thus engaging in civil war could be a viable option. However, this is where the conditions for a conflict become important and help explaining why scarcity-affected groups are more likely to fight other groups, i.e. engage in non-state conflict, than to engage in civil war.

First off, it is very costly for any group to engage in a civil war because the government is likely to have a relatively strong military force (Hendrix and Salehyan 2012:37). Thus only strong groups have the possibility to start a civil war, and not the weak groups that are the most likely to suffer from resource scarcity (see for instance Raleigh (2010)). Also, it is not just the strength of the government's forces that is important in determining the cost of engaging in civil war. Militias fighting the state also need to be able to provide protection to the individuals and groups who participate in the insurgency (Regan and Norton 2005:324). In addition, they also need to afford to pay the warriors participating in the insurgency.

According to Regan and Norton (2005:324), common people are highly unlikely to participate in civil war only out of a moral conviction for the cause. This point reflects the emerging consensus in the literature on causes of civil wars that grievances alone cannot explain civil wars (Hendrix and Salehyan 2012:37). The costs for people to participate are so high (e.g. threats from government forces) that they will need to be paid well by the militias in order to keep them fighting (Regan and Norton 2005:323). Thus only relatively wealthy groups can have the capability to engage in civil wars.

On the other hand, for less strong groups suffering from resource scarcity, smaller forms of conflict may be an option. The cost of fighting another group of people (e.g. a pastoralist group fighting farmers over access to land and water) is arguably lower. According to Regan and Norton (2005:324), when the costs are lower, experienced grievances (e.g. a discrimination in division of resources) may be a sufficient reason for starting a conflict. However, Regan and Norton talk about nonviolent forms of protest as conflicts with low costs and civil wars as conflicts with high costs. Thus it is unsure where non-state conflicts would be placed on Regan and Norton's threshold for greed/grievance motivated conflicts, i.e. whether they believe grievances would be enough to cause non-state conflicts.

Yet, reflecting on points made earlier in this section, good arguments can be presented for why grievances could be enough to cause non-state violence. Firstly, the costs for individuals engaging in non-state violence are likely to be lower than when participating in civil war, as the counterpart (the group that one fights against) most often will be much less strong than government forces. Thus the individuals are not likely to feel a similar need for protection as when participating in civil war. Secondly, when the individuals do not feel a similar need for protection, the leaders of a fighting group do not have the same need to get access to resources, e.g. diamonds, to finance their soldiers. Thus the economic threshold for starting a conflict is lower for non-state conflicts than for civil wars.

It is time to return to the question over who groups will fight if they find violence necessary to ease their resource scarcity. Looking at the purpose of a conflict, groups could gain from both fighting the state and fighting other groups. However, looking at the conditions for a conflict, fighting other groups is likely to be the only executable option. As the discussion above has shown, "for most aggrieved actors, most of the time, rebellion is not a viable option" (Hendrix and Salehyan 2012:37). Therefore, if climate change –caused resource scarcity will lead to violent conflicts, these conflicts are more likely to be non-state conflicts than civil wars.

3.2.3.2 Communal conflict vs. other types of non-state conflicts

Non-state conflicts can occur between very different types of groups and for different reasons, including resource scarcity. This thesis argues that communal conflict is the most likely type of non-state conflict to occur as a result of climate change –induced resource scarcity. This is because other types of non-state conflicts are probably better explained by other factors, as also argued by Fjelde and Uexkull (2012:447).

The UCDP non-state conflict database which is used in this study to separate between different types of non-state conflicts has separated between three types according to the conflicting parties levels of organization. The first type of non-state conflict is conflict between "highly organized rebel groups" (Pettersson 2012:4). The second type is between "groups composed of supporters and affiliates to political parties and candidates", and "captures fighting between political parties/candidates and lethal electoral violence" (Pettersson 2012:4). The third type, which is referred to as communal conflict, is conflict between "groups that share a common identification along ethnic, clan, religious, national or tribal lines" (Pettersson 2012:4).

Violence between rebel groups is argued to occur as a way for the groups to become more powerful in their struggle against the government (Fjelde and Nilsson 2012). Moreover, having a highly organized rebel organization requires large resources, as was argued for in the previous section (3.2.3.1). Poor and marginalized groups, who are argued in this thesis (section 3.3) to be most likely to suffer from resource scarcity, often do not have such resources. Therefore, they are unlikely to be represented by highly organized rebel groups and consequently unlikely to engage in fighting with another rebel group in order to ease their resource scarcity.

Electoral violence, in turn, may occur either because groups are against elections in general, because groups are against the electoral system which is applied, or because groups wish to affect the results of the elections (Höglund 2009:415-416). In relation to resource scarcity, electoral violence could occur because groups wish to affect results of elections, e.g. to change the parties in power into parties that promise changes in distribution of necessary renewable resources. However, those groups which this thesis proposes to be most likely to suffer highest from resource scarcity are politically marginalized and therefore least likely to be able to affect national politics. Therefore, those groups do not have a purpose to use resources for trying to affect the outcome of national elections. Thus electoral violence is not seen as the most likely type of violent conflict to occur as a consequence of resource scarcity. Instead, communal conflicts may occur between groups who are marginalized and poor, as none of the groups participating in communal conflicts will by definition[10] have highly organized fighting organizations, and because groups may see a realistic chance to improve their situation regarding scarce resources by fighting another group. Therefore, the arguments presented in this thesis for how climate change could lead to conflict, fit best for communal conflict.

3.2.4 Hypotheses

Based on the discussions above, four hypotheses will be tested. The first hypothesis is based on the notion that higher temperatures may lead to negative consequences for agriculture, as noted in section 3.1, which again can lead to conflict, as discussed in section 3.2.2:

H1a: Higher temperatures in one year will increase the likelihood of communal conflict events in the same year

However, the negative consequences of higher temperatures on agricultural production will not be felt immediately. It takes some months for agricultural crops to grow and produce yield, and thus farmers need to store food from one yield to the next. Following this logic, the following hypothesis is added:

H1b: Higher temperatures in one year will increase the likelihood of communal conflict events in the following year

[10] The following is noted in Pettersson (2012:4) about groups participating in communal conflicts: “These are not groups that are permanently organized for combat, but who at times organize themselves along said lines to engage in fighting”.

Yet, bearing this logic in mind, what might make a conflict start in the same year that scarcity occurs, is people's awareness of the coming resource scarcity. Thus it is meaningful to statistically analyze the effects of climatic changes both on communal conflicts in the same year and in the next year, as reflected in the hypotheses above. This logic also applies to the hypotheses below.

Moreover, also too little rainfall may have negative effects for agriculture and for livestock keeping, as noted in section 3.1. These negative effects can again lead to conflict, as discussed in section 3.2.2. Consequently, the following hypothesis is developed:

> *H2a: Lower rainfall will increase the likelihood of communal conflict events in the same year*

However, neither negative consequences of low rainfall on agriculture will be felt immediately, for the same reasons as explained regarding temperature changes. Thus the following hypothesis is added:

> *H2b: Lower rainfall will increase the likelihood of communal conflict events in the following year*

3.3 Most likely scenario

In this section, a most likely scenario for a climate change induced communal conflict will be described. The idea behind designing a most likely case is that if climatic changes have the potential to cause conflicts, this will most likely happen in the circumstances described in this scenario. These circumstances are when people belong to social or ethnic groups, which are politically marginalized, when poverty is widespread, and when people live in rural areas.

The basis for this most likely scenario resembles the arguments by Fjelde and Uexkull (2012), who study rainfall and communal conflict in Sub-Saharan Africa. Fjelde and Uexkull expect the possibility of communal conflict to increase with the presence of marginalized groups and poverty. However, what makes the study of this thesis different is that instead of only controlling for marginalized groups and poverty, as Fjelde and Uexkull, the most likely scenario in this study is designed so that only grid cells, where a marginalized group and poverty are present, and which are considered to be in rural areas, are included in the analysis. This way the effects of climatic changes on communal conflict should, if they exist, not be overshadowed by grid cells where climate change –induced communal conflict is highly unlikely. These include grid cells over urban areas and grid cells over desert and other non-populated areas.

3.3.1 Marginalized groups

According to Raleigh (2010:70), politically and economically marginalized groups facing resource scarcity may have few other options to improve their situation than to fight against other groups to get more resources. On the other hand, groups who have more influence over politics or are seen by the government as more important, get more help from the government when facing resource scarcity than marginalized groups (Raleigh 2010:70) and will thus likely not consider violence an option to cope with resource scarcity. Thus, following this logic, it is not resource scarcity per se that may make people fight, but their lack of other options to cope with scarcity.

In addition, marginalized people often live in areas which are poor and have few public services and where living environments are challenging, for example arid- and semi-arid lands (Raleigh 2010:73,77). These areas are also expected to be hardest hit by climate change and disasters (Raleigh 2010:73). These facts can make marginalized groups under increased conflict risk, as it is widely noted in the literature that groups suffering from a combination of physical and social vulnerability are more prone to conflict (Raleigh 2010:71).

3.3.2 Poverty

Poverty is found to robustly increase the risk of civil war (Hegre and Sambanis 2006). Yet, it may also be likely to increase the risk of communal conflicts, as discussed in section 3.2.2. The poor are also likely to be hardest hit by climatic changes (Raleigh 2010:72) and they often also have the lowest capacity to adapt to the changes (Adger and Kelly 1999). Furthermore, the poor are argued to have least to lose by engaging in violent conflict, making violent conflict more likely where there is poverty (Fjelde and Uexkull (2012)). In addition, Fjelde and Østby (2012) have found that economic inequality increases the risk of non-state conflicts. However, it is important not to mix poverty with economic inequality, as poverty refers to poverty in absolute terms, i.e. living under a certain poverty limit or lacking necessary resources, while economic inequality means that some groups are poor compared to other groups. Thus the finding by Fjelde and Østby (2012) does not illuminate whether poor groups, who live in an area where other groups are relatively poor as well, are any more likely to engage in non-state conflict than richer people are. However, for reasons outlined above, it is reasonable to expect that they are.

3.3.3 Rural areas

Climate change –induced conflict is also more likely in rural than urban areas. According to Raleigh (2010:76), government's are more likely to react to urban trouble than rural, such as food shortages, because urban populations are often seen as politically more relevant than rural populations. Rural populations are easier to ignore than urban population, because riots or violence in urban areas are seen to be more threatening to the elites than rural unrest (Raleigh 2010:76). Consequently, being ignored by the state, rural groups are often marginalized and, facing resource scarcity, may have few other options than to engage in violent conflict in order to improve their situation, in the same way as marginalized groups, as pointed out in section 3.3.1.

Secondly, rural populations in Sub-Saharan Africa are often highly dependent on income from agriculture (Chauvin et al. 2012). As urban populations have different and more varied income sources, lower agricultural productivity and water shortages are arguably likely to impact rural populations harder and earlier than urban populations. Urban populations may also suffer as a consequence of declining agricultural production when food prices increase (Hendrix and Salehyan 2012:38), but they are still likely to be effected later than rural people and, as noted above, to be protected better by the state than rural people (Raleigh 2010:76).

3.3.4 Hypotheses for the most likely scenario

Based on the discussion above, the following hypotheses are added:

H3a: Higher temperatures in one year will increase the likelihood of communal conflict events in the same year in rural grid cells hosting marginalized groups where the level of poverty is high

H3b: Higher temperatures in one year will increase the likelihood of communal conflict events in the next year in rural grid cells hosting marginalized groups where the level of poverty is high

H4a: Lower precipitation in one year will increase the likelihood of communal conflict events in the same year in rural grid cells hosting marginalized groups where the level of poverty is high

H4b: Lower precipitation in one year will increase the likelihood of communal conflict events in the next year in rural grid cells hosting marginalized groups where the level of poverty is high

3.4 Summary of hypotheses

Larger models:

H1a: Higher temperatures in one year will increase the likelihood of communal conflict events in the same year

H1b: Higher temperatures in one year will increase the likelihood of communal conflict events in the following year

H2a: Lower precipitation will increase the likelihood of communal conflict events in the same year

H2b: Lower precipitation will increase the likelihood of communal conflict events in the following year

Most likely scenario:

H3a: Higher temperatures in one year will increase the likelihood of conflicts in the same year in rural grid cells hosting marginalized groups where the level of poverty is high

H3b: Higher temperatures in one year will increase the likelihood of conflicts in the next year in rural grid cells hosting marginalized groups where the level of poverty is high

H4a: Lower precipitation in one year will increase the likelihood of conflicts in the same year in rural grid cells hosting marginalized groups where the level of poverty is high

H4b: Lower precipitation in one year will increase the likelihood of conflicts in the next year in rural grid cells hosting marginalized groups where the level of poverty is high

4 Methods

4.1 Introduction

This chapter will present and discuss the methodological choices of this study. Methodological choices are important because they determine what kind of information it is possible to retrieve from a study. For example, the use of qualitative method allows the researcher to study details of a phenomenon deeply and try to understand the views of the people he/she studies. On the other hand, quantitative method, which is utilized in this study, allows the researcher to study for example the opinions of thousands of people and to generalize from the results. (Bryman 2008)

More specific methodological choice, such as which statistical methods to use, which control variables to use and how to measure the dependent and independent variable are also very important. They determine whether a researcher succeeds in measuring exactly what he/she aims to measure, and whether he/she has taken relevant alternative explanations into account. For example, in quantitative climate change and conflict studies, discussions of methodological choices have revealed premature conclusions. This is illustrated by the debate between Homer-Dixon (1994) and Gleditsch (1998), and between Burke et al. (2009); (2010) and Buhaug (2010a); (2010b) (both debates are discussed in chapter 2). Discussions of methodological choices have also helped to bring studies on climate change and conflict forward, for instance by introducing disaggregation of the unit of analysis, which is discussed in section 4.3 in this chapter.

This chapter will proceed in the following way. First it will discuss why quantitative method is used instead of qualitative in this study (section 4.2). Next, it will discuss why the analyses are disaggregated, and why a grid cells structure is used (section 4.3). Thereafter, it will present the data structure which is used (section 4.4) and the sampling which is conducted (section 4.5) before presenting which variables are chosen and how they are operationalized (section 4.6). Furthermore, it will explain why logistic regression is chosen as the specific tool for conducting the analyses (section 4.7), and also which methodological challenges the study faces (section 4.8). Finally, it will discuss a few limitations related to the study (section 4.9).

4.2 Quantitative vs. qualitative method

US President Barack Obama has said that "more frequent droughts and crop failures breed hunger and conflict" (Obama 2009:1). His statement illustrates a popular narrative[11] according to which climate change causes conflicts. Scientific research, however, has not yet found enough robust evidence to back this claim (see Gleditsch (2012:7), Salehyan (2008) and Bernauer et al. (2012)). For studying the claim scientifically, it is meaningful to start with looking at whether climate change and conflicts are associated on a wider scale. This study aims to contribute to the knowledge on whether there is a general association between climate change and conflict in Sub-Saharan Africa, and therefore quantitative research method is the appropriate choice.

Quantitative method has the advantage of enabling the study of phenomena in a highly consistent manner. More precisely, it allows researchers to make sure they measure and analyze phenomena in the same way across studies conducted by different researchers and in different points in time (Bryman 2008:144). This consistency is arguably important in order to compare results of different studies and to draw conclusions based on them**.** In addition, quantitative method enables researchers to detect "fine differences" (Bryman 2008:144). For instance, in conflict research quantitative studies can compare the intensity of conflicts by measuring the amount of battle-related deaths between conflicts. Furthermore, quantitative method also enables researchers to make "more precise estimates of the degree of relationship between concepts" (Bryman 2008:144). In climate change and conflict studies this means that it is possible to conduct statistical analyses on data about climate and conflicts and to see whether and to what degree changes in climate and conflict are related. Notably, it is also possible to check whether a possible correlation between climate variables and conflict is caused or affected by a third variable, i.e. a spurious effect.

Finally, quantitative method allows researchers to generalize conclusions from a sample, given that proper sampling criteria have been followed (Bryman 2008:156). This means that it is not necessary to gather data on for instance all of the African population on the variables of interest to say something about the whole of Africa. Instead, it is sufficient to gather information on a representative sample of the African population and to generalize the results from the sample to the whole population. In this study, random sampling was done when a

[11] See for example Benjaminsen (2009) for an overview

subset of grid cells without communal conflict events was chosen, as will be explained in section 4.5.

Qualitative method has also been useful in studying the climate-conflict relationship, but it cannot illuminate the issue on an equally large scale since a qualitative study often cannot be generalized beyond the particular case studied (see Bryman (2008:391-392)). So far, qualitative case studies have been successfully used to give indications on whether and how climate and conflict may be related in certain places, and what other factors affect the climate-conflict relationship (examples of case studies are presented in sections 2.4.3 and 3.2.2). Despite varying results, case studies have informed quantitative studies for instance by inspiring hypotheses (e.g. Homer-Dixon (1994)) and giving ideas for control variables, in addition to providing thorough analyses on the particular cases studied. Yet, as this study looks for a general pattern between climate change and conflict, qualitative method including case study is not the appropriate choice.

4.3 Disaggregation using a grid cells structure

In this study, the relationship between climate change and communal conflicts will be studied on a disaggregated level, i.e. on a lower geographical level than the nation state. This section will discuss the role of disaggregation in the conflict literature, the benefits of disaggregation and the benefits of using grid cells as a tool for disaggregation.

4.3.1 Benefits of disaggregation

In the study of conflicts, the focus has in recent years moved from using whole countries to using smaller geographical areas as the units of analysis (Tollefsen et al. 2012:363-364). Studies have used several different types of units including first order administrative entities within countries, i.e. provinces and districts (e.g. Fjelde and Uexkull (2012), Østby et al. (2009), Rustad et al. (2011), Urdal (2008)), conflict zones (e.g. Buhaug and Gates (2002)), social groups (e.g. Buhaug et al. (2008)), and grid-cells (e.g. Buhaug and Rød (2006), Raleigh and Urdal (2007), and Theisen (2012)).

Disaggregation has at least two important benefits over country-level analysis. Firstly, disaggregation allows studies to focus on those geographical areas where conflicts actually are fought. “Fighting rarely spans entire countries”, as noted by Buhaug and Lujala

(2005:403) regarding civil wars. Furthermore, it is typical for civil conflicts to be fought in remote rural areas, close to borders with other countries (Rustad et al. 2011:19). Secondly, conflict areas seldom have the same characteristics as the country on average. Thus, if one tries to find out which social, political, economic, demographic or geographic factors are related to a conflict that is limited in geographic scope, but one studies the national averages of these factors, the results are likely to be misleading (Buhaug and Lujala 2005:404). Instead, using disaggregated data on both conflicts and different explanatory and control variables makes it possible to better capture the variables that correlate with conflict.

These arguments can be illustrated with an example provided by Buhaug and Lujala (2005:404). They write that none of the conflicts that India has seen since 1990 have taken place on more than 5% of the country's total area. Using country-level variables (i.e. national averages of the level of economic development, geographical terrain, changes in temperature etc.) do not make it possible to understand differences between these conflicts. Consequently, a study of these Indian conflicts and possible explanatory variables needs to occur on a lower geographical level than the entire nation state to provide some explanations. These arguments are equally relevant, if not even more relevant when studying communal conflicts, as communal conflicts are likely to be fairly local phenomena. Many countries have also experienced several communal conflicts (see Sundberg et al. (2012)).

However, counter-arguments have also been presented. Hendrix and Salehyan (2012:38) argue for the benefits of country-level analysis, rather than disaggregation, in studies of climate change and conflict, because "many of the most significant effects are likely to be felt across the country". Examples of such effects are droughts that cause people to migrate from rural areas to the cities. Notwithstanding these remarks, disaggregation is in this study judged to have most arguments in favor when studying communal conflicts.

4.3.2 Benefits of grid cells

Using grid cells also has several benefits compared to other types of disaggregation. Grid cells are artificially constructed units (section 4.4 will describe this more in detail). They are all of equal sizes, they are apolitical and they are not determined by any specific social, demographic, or geographic characteristic (Tollefsen et al. 2012:365). Thus they may be used without taking any of the above mentioned characteristics into account (Rustad et al.

2011:25). This implies that the units of analysis are fully independent on any characteristics, such as demography, that one may wish to use as independent variables (Tollefsen et al. 2012:365). In addition, their sizes can be changed depending on the researcher's needs (Tollefsen et al. 2012). Furthermore, as Theisen (2012:87) points out, it is easier to "model dependence between observations" when the cells are of identical sizes.

Other ways of disaggregation are less beneficial for this study for reasons presented below. First-order administrative units, such as provinces and districts, vary in form and political function between countries and between different points in time. Thus it may be hard for the researcher to stay on track of all of these differences (Tollefsen et al. 2012:365). It may also be hard to get information on how the administrative units have changed over time (Rustad et al. 2011:25). Moreover, first-order administrative units are can be of highly varying sizes. As a consequence, the analysis of for instance climate and conflict within these units will be disaggregated to different degrees: in administrative units that encompass a small surface area the spatial resolution for variables will be high, whereas in administrative units with a large surface area the spatial resolution will be much lower.

Furthermore, using conflict zones as units of analysis was not possible in this study, because using conflict zones as the unit of analysis means that no areas without conflict are included in the analysis. In studies where one is interested for instance to study the duration of conflicts on a disaggregated level, it may be beneficial to use conflict zones as units of analysis (see for instance Rustad et al. (2008)). However, this was not the case for this study and therefore conflict zones were not an option.

Using social groups as units of analysis firstly suffers from the lack of disaggregated data on other types of groups than ethnic groups (Rustad et al. 2011:25). Secondly, using social groups would mean concentrating the analysis on previously known groups (such as ethnic and religious groups). This would in turn imply that one would effectively rule out the possibility to grasp correlations between climatic changes and communal violence between new forms of groups, for example groups with mixed ethnic and religious characteristics. Buhaug et al. (2008) use ethnic groups as their units of analysis, but in their study it makes sense because they expect ethnic group characteristics to largely explain the occurrence of civil conflict, and ethnic groups are consequently also chosen as their independent variable.

However, in this study the independent variables are changes in climatic effects such as precipitation and temperature. Therefore using social groups as units of analysis might limit the validity of the analysis for the reasons mentioned above.

Using grid cells have also been noted to suffer from some limitations. Since the grid cells are apolitical and independent from all other kinds of social factors, they ignore "important societal cleavages that follow sub-national boundaries" which might be a problem for grasping conflict dynamics in some cases (Rustad et al. 2011:25). However, this limitation is in this study attempted to be overcome by using different group characteristics and cleavages as control variables, such as income level and marginalized groups. Moreover, despite their limitations, grid cells are still viewed to be the best of the options available based on the discussion above.

4.4 Data structure

In order to analyze variables on a disaggregated level using grid cells, this study utilizes the PRIO-GRID unified spatial data structure (Tollefsen et al. 2012)[12]. The PRIO-GRID divides the world into grid cells based on longitudes and latitudes, and there are several cells within each country. The cells are sized 0.05˚ x 0.05˚ degrees, corresponding to 55km x 55km at the equator. Furthermore, the cells give information on specific variables (e.g. whether a conflict occurred or not) for one year at the time. Thus the structure of PRIO-GRID is a year – grid cell structure. (Tollefsen et al. 2012)

Moreover, the PRIO-GRID contains data on many variables, such as temperature and rainfall values (the independent variables of this study) and several variables which are used as control variables in this study. The data for these variables is given per grid cell. However, as PRIO-GRID does not contain data on all the variables used in this study, a new dataset was created by expanding the PRIO-GRID with data on communal conflict events (the dependent variable of this study) and several control variables. Some of these variables have data on a disaggregated level, while data for other variables was only available on a country level. More information on this will be given when the specific variables are discussed (see section 4.6). Furthermore, the new dataset has excluded grid cells outside Sub-Saharan Africa and years

[12] http://www.prio.no/Data/PRIO-GRID/

before 1989, because the data on communal conflict events that is used in this study is available only from 1989. To see which countries are counted as part of Sub-Saharan Africa, see Appendix A.

4.5 Sampling

In this study, sampling was conducted for grid cells in which there were no communal conflict events. The sample was taken from the full dataset which includes all grid cells in Sub-Saharan Africa. A sample was taken from the full dataset in order to deal with the problem of spatial correlation and to reduce the number of observations (grid cells) without communal conflict events.

Spatial correlation occurs when units of analysis (here grid cells) which are close to each other contain information on different variables which is not entirely independent from information of the same variables in neighboring units. If uncorrected, spatial correlation may cause “underestimated standard errors and inefficient coefficient estimates” (Buhaug et al. 2011:825). A way to reduces the problem with spatial correlation between units is to use only a subset of units for the analyses (see for instance Buhaug et al. (2011); Wischnath and Buhaug (2013)). In this study, the subset is constituted of the sample of grid cells without conflict events and all grid cells with conflict events. When using a subset, the likelihood of units being geographically close to each other and thus potentially being spatially correlated, becomes quite small.

Secondly, reducing the amount of grid cells without conflict events increases the percentage of grid cells with conflict events in the total amount of observations. In the dataset used in this study, the amount of grid cells is very high, approximately 160000, and only 368 (0.2%) of these contain communal conflict events. Using all grid cells, the effects of different variables on conflict events could easily drown in the huge amount of grid cells without conflict events. Therefore, using only a subset of grid cells makes the effects of different variables on conflict events become more visible. Using a subset of units is one of the solutions that King and Zeng (2001) provide to a rare events problem.

In this thesis, a subset of grid cells is chosen by letting STATA choose a random sample of 5% of all grid cells without conflict events. In addition, all grid cells with communal conflict events are included into the subset. In total the subset includes 8001 grid cells without conflict events, and 368 grid cells with communal conflict events. Consequently, the percentage of grid cells with communal conflict events is 4.4 % of all grid cells in the subset.

Moreover, because the grid cells without communal conflict events are chosen by random sampling, the results of the analysis can be generalized on all grid cells in Sub-Saharan Africa (King and Zeng 2001:139,142). Therefore using a subset of grid cells instead of all grid cells does not limit the amount of observations on which the results of the analyses are applied on. Instead, it only makes a possible correlation between temperature and rainfall on communal conflict events more clearly visible than the correlation would be if all grid cells were included in the analysis.

4.6 Variables and their operationalizations

4.6.1 Dependent variable

The dependent variable is in this study "communal conflict event", indicating whether or not there has been a communal conflict event in a particular grid cell in a particular year. The dependent variable is operationalized as a dummy variable, taking the value 1 for every calendar year a grid-cell has seen a communal conflict event and 0 otherwise.

The data for communal conflict events is derived from a combination of two datasets. The UCDP Geo-referenced Event Dataset (GED) (Melander and Sundberg 2011; Sundberg et al. 2010) contains information on non-state conflict events in grid cells. A non-state conflict event is defined in the UCDP GED as

> *"The incidence of the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death in either the best, low or high estimate categories at a specific location and for a specific temporal duration."* (Sundberg et al. 2010:4)

However, the UCDP GED does not provide information on what type of non-state conflicts the events are part of. Therefore the UCDP GED is in this study supplied with information from the UCDP non-state conflict dataset (Sundberg et al. 2012), which provides information on what type of non-state conflicts the conflicts are. The UCDP non-state conflict dataset has categorized non-state conflicts into three types: conflicts between highly organized rebel groups; conflicts between supporters of political parties or candidates; and communal conflicts, which occur between

> *"Groups that share a common identification along ethnic, clan, religious, national or tribal lines. These are not groups that are permanently organized for combat, but who at times organize themselves along said lines to engage in fighting. This level of organization captures aspects of what is commonly referred to as 'communal conflicts', in that conflict stands along lines of communal identity."* (Pettersson 2012:4)

Non-state conflicts of the two first types are not included in this study for reasons explained in section 3.2.3.2. The UCDP GED and UCDP non-state conflict dataset were combined using a few variables they have in common, namely year, conflict ID, side A ID and side B ID, to obtain information on which grid cells have seen communal conflict events. The information from the two UCDP datasets were further included in the PRIO-GRID based dataset used in this study by converting the excel files into STATA files and thereafter using the merge-command in STATA.

In principle, no sampling lies behind the data on communal conflict events, as both the UCDP GED and the UCDP non-state conflict dataset have attempted to collect information on all non-state conflicts, including communal conflicts, for the study period and area of this study, namely Sub-Saharan Africa in 1989-2008. However, it is vital to note that the UCDP non-state conflict dataset does not contain information on all non-state conflict events which are included in the UCDP GED. This became visible when combining the two datasets, as only 740 of the total 1130 non-state conflict events in UCDP GED received information on the type of non-state conflict. When this was investigated further, it was found that several conflict IDs which were included in the UCDP GED were not found in the UCDP non-state conflict dataset. As a consequence, not all communal conflict events in Sub-Saharan African in 1989-2008 which are included in the UCDP GED are included in this study. It was a trade-off between the number of non-state conflict events and the ability to identify which type of non-state conflict the conflict events were part of. The theoretical arguments of this study support mainly the idea of events of communal conflict (rather than all three types of non-state conflict) being related to climate change. Therefore, a smaller but more precisely defined amount of observations was chosen over a larger but less precisely defined amount. In other words, 368 observations on communal conflicts were chosen over 1130 observations of non-state conflicts.

Moreover, it is good to bear in mind that although datasets like the UCDP GED and the UCDP non-state conflict dataset attempt to contain information on all observations of conflict, it is not certain that they succeed in their task. These two datasets, as many other datasets on conflicts, rely on both media and expert sources (Sundberg et al. 2012:353-354). However, there is always a possibility that some conflict events go unnoticed by the media or even by experts, especially if they occur in peripheral, difficultly accessible places.

4.6.2 Independent variables

The independent variables are two effects of climate change, namely temperature and rainfall. Temperature is operationalized as deviation from the average temperature for the time period 1989-2008 for each grid cell. Rainfall is operationalized through two different variables: precipitation and drought. Like temperature, precipitation is operationalized as deviation from the average precipitation for the time period 1989-2008 for each grid cell. This operationalization is done following the example of Hendrix and Salehyan (2012:41), who argue that measuring deviations from the long-term average better captures the actual climatic realities for farmers and herders than measuring deviations from the previous year, as is done in many climate-conflict studies (e.g. Hendrix and Glaser (2007); Miguel et al. (2004)). This is because a high rise in for instance precipitation from the previous year does not necessarily imply a wet year, if the previous year was exceptionally dry (Hendrix and Salehyan 2012:41). Furthermore, the yearly means for temperature and precipitation are based on monthly statistics.

Drought, on the other hand, is operationalized as four categories indicating different degrees of drought within a year: These categories are “no drought”, which has the value 0 and which means that a grid cell did not see any drought events within a year; “moderate drought”, which has the value 1 and which means that a grid cell had three or more consecutive months with moderate drought; “severe drought”, which has the value 1.5 and which means that a grid cell had at least two consecutive months with severe drought; and “extreme drought”, which has the value 2.5 and which means that a grid cell fits in both the category “moderate drought” and “severe drought” (Tollefsen 2012:10). These values are based on the Standardized Precipitation Index (Rudolf et al. 2010), which gives standardized measures for deviations from normal rainfall patterns compared to the long-term averages in the preceding six months, based on monthly data. These values are coded as annual values by the authors of PRIO-GRID.

Data for temperature and rainfall changes are incorporated into the original version of PRIO-GRID, and are thus already given for each grid cell. The data for temperature and precipitation are derived from the University of Delaware (NOOA 2011), while the data for drought are derived from the Global Precipitation Climatology Center (Rudolf et al. 2010).

4.6.3 Control variables

Control variables are used to check whether other factors than the independent variables influence the dependent variable. In this study, control variables are used to develop a baseline model, i.e. a model consisting of variables which are known to best explain conflict, and climatic variables are thereafter added to this model to test the explanatory power of the climatic variables. See a presentation and discussion of the baseline model in section 5.1.2. Although this procedure differs from how control variables are used in many other studies, the role of control variables remains the same, i.e. to check whether and in which way they affect the relationship between the dependent and independent variables.

In this section, the control variables are presented which are used in the baseline model, namely population per grid cell; gross cell product per capita; infant mortality rate per grid cell; regime type; spatial lag of conflict; and time lag of conflict. In addition is also those control variables are presented which are used to define the most likely scenario, namely (in addition to infant mortality rate) distance from nearest city of 50000 inhabitants and politically marginalized groups. When the baseline model was developed all the control variables mentioned above were tested, in addition to distance from capital. However, as the distance from capital -variable was not included in either the baseline model or to define the most likely scenario, it is presented briefly in Appendix C**,** which also presents the development of the baseline model.

4.6.3.1 Population per grid cell

High population is argued to be positively linked to conflict (Fearon and Laitin 2003), and population is a standard control variable in the literature (Fjelde and Uexkull 2012:449). In this study, population is operationalized as population per grid cell. The data for population was incorporated into the original version of PRIO-GRID, and is derived from Gridded Population of the World, version 3 (CIESIN Center for International Earth Science Information Network Columbia University 2005). As the data for population was available only for the years 1990, 1995, 2000 and 2005, population for the years in between has been interpolated from those years for which there was data, and extrapolated for the years before and after years for which there was data. Also, the values for the population variable are not used as such, but rather the natural logarithm of the variable is used. This is because the relationship between population and communal conflicts is expected to be logarithmic rather than linear. Moreover, as population is found in the literature to be related to conflict, high population is in this study expected to increase the risk of communal conflicts. Furthermore, the variable population is included in the baseline model.

4.6.3.2 Poverty

Poverty is found to be one of the key factors to explain and predict civil conflict (see Fearon and Laitin (2003); Hegre and Sambanis (2006)). There are also many arguments for why poor regions are more likely to see communal conflicts induced by climate change, as is discussed in section 3.3.2. In this study, poverty is operationalized as two different variables: gross cell product per capita (GDP PC) and infant mortality rate per grid cell (IMR). Gross domestic product per capita is a standard control variable in the literature (see e.g. Hegre and Sambanis (2006)), but it has been criticized frequently for not necessarily reflecting the real level of development and human well-being in a society, for instance if there are great economic cleavages within the society (Fleurbaey 2009). It is nevertheless included in this study, partly because it is a standard control variable and partly because it was available on a disaggregated level (GCP PC), which may increase its representativeness. However, like GDP PC, also GCP

PC may be unable to reflect the real level of development in a grid cell, if there are great economic cleavages within the grid cell. Another indicator for poverty is infant mortality rate (IMR), which may better capture the level of development and human well-being than GCP PC. IMR is found to reflect the health of entire populations, which again is related to the general level of development and human well-being (Reidpath and Allotey 2003).

The data for both GCP PC and IMR were incorporated into the original version of PRIO-GRID. The data for GCP PC is derived from the G-Econ dataset (Nordhaus 2006), which has released the data at a lower resolution than the PRIO-GRID, namely at 0.1˚ x 0.1˚. Thus the GCP PC data is not on an equally disaggregated level as the units of analysis in this study. The GCP PC data is also only available for the years 1990, 1995, 2000 and 2005, so the data has been interpolated for the years in between and extrapolated for the years before and after those years for which there is data. On the other hand, the data for IMR is derived from raster data in the SEDAC Global Poverty Mapping project (Storeygard et al. 2008), and the values of IMR mean the number of children who die before the age of one year. The data for IMR are only available for the year 2000, and therefore the value for year 2000 is given for each year in the dataset. Moreover, the values for GCP PC and IMR are not used as such in the baseline model, but rather the natural logarithm of the variables is used. This is because the relationship between GCP PC and IMR respectively and communal conflicts is expected to be logarithmic rather than linear. However, when defining the most likely scenario, IMR is used as such rather than the natural logarithm of IMR. Furthermore, low values on GCP PC and high values on IMR are in this study expected to increase the risk of communal conflicts for the reasons mentioned above. GCP PC and IMR are included in the baseline model, and IMR is also used to define the most likely scenario.

4.6.3.3 Regime type

A country's regime type is good to control for since there is found to be a difference in the level of unrest in countries depending on the regime type: highly democratic and highly authoritarian countries are found to be most stable, whereas countries in between see most unrest (e.g. Hegre et al. (2001)). Operationalization of regime type uses the 'polityII' variable, where the scale of regime type ranges from -10 to 10 (full autocracies – full democracies). The polityII –variable data are derived from the Polity IV project at the Center for Systemic Peace (Marshall 2011). It is important to note that the polityII -variable is a country-level variable, and thus every grid cell within a country has the same value for regime type. The polityII -variable was incorporated to the dataset used in this study by using the variables year and gwno, which are used in both the PRIO-GRID (Tollefsen et al. 2012) and the Polity IV dataset (Marshall 2011). The gwno-variable is a country code assigned by Gleditsch and Ward (1999), and the year variable identifies the calendar year in question. The regime type variable is used in the baseline model to ease comparison with regime type squared, which is presented next.

4.6.3.4 Regime type squared

The relationship between regime type and conflict is found to have an inverted u-shape (Hegre et al. 2001), as was described above. The regime type variable was in this study squared in order to achieve two things: firstly, to create a regime type variable that has a linear relationship with conflict, and secondly, to give both observations of full autocracies and observations of full democracies low values on the regime type variable, and observations with a regime type halfway between full democracy and full autocracy high values on the regime type variable. The regime type squared variable is used in the baseline model, and low values on the variable are expected to increase the likelihood of communal conflict events.

4.6.3.5 Politically marginalized groups

Politically marginalized groups are potentially more likely to engage in communal violence than less marginal groups, as Raleigh (2010) has thoroughly argued for and as is discussed in the theory chapter of this thesis. Thus politically marginalized groups are controlled for in this study. The variable for politically marginalized groups is a dummy variable which indicates whether or not at least one politically marginalized group lives in a grid cell. The variable takes the value 1 if at least one politically marginalized group lives in a grid cell, and 0 otherwise. The data for politically marginalized groups is derived from the Ethnic Power Relations Dataset (EPR) v.1.1 (Cederman et al. (2009-05-01); Wimmer et al. (2009)). The exclusion-variable from the EPR was merged with a PRIO-GRID file containing information from the Geo-referenced Ethnic Power Relations Dataset (Geo-EPR) (Wucherpfennig et al. (2010-02-12); Wucherpfennig et al. (2011)), which the PRIO-GRID had already given grid cell identifications. In this way a dummy variable containing information on politically marginalized groups in grid cells was created.

However, it is important to note that the EPR dataset only contains data for the political status of groups in countries with surface area of minimum 500000 square kilometers and a population of minimum one million as of year 2005 (Wimmer et al. 2009:325, footnote 11). This leads the variable for politically marginalized groups to suffer from a form of selection bias, which will be discussed in section 4.8.6. Moreover, the variable political marginalization was in this thesis tested for the baseline model, but as it did not contribute significantly to it, it was not included. However, the variable is used to define the most likely scenario.

4.6.3.6 City distance

City distance is included to control for how urban/rural a grid cell is. Controlling for whether an area is urban or rural is interesting since urban and rural areas can be expected to see different types of conflict. While for instance food riots may be more likely in urban areas, in this study communal conflicts motivated by resource scarcity are expected to most likely occur in rural areas (see 3.3.3). Moreover, while communal conflicts for other reasons may occur also in urban societies, the risk for communal conflicts in urban areas might decrease since governments can be expected to act faster to stop urban unrest, which is seen as constituting a greater threat towards the government than rural unrest (Raleigh 2010:76). Thus communal conflict is in this study expected to occur more frequently in rural areas.

The variable city distance is operationalized as the within grid cell-average distance to the nearest city of 50 000 inhabitants, in minutes by land transportation. The data were incorporated in the PRIO-GRID and are derived from a high-resolution raster map of accessibility by Nelson (2008). Higher city distance is in this thesis expected to increase the risk of communal conflicts. Moreover, the values for city distance were not used as such when the variable was tested for the baseline model, but rather the natural logarithm of the variable was used. This is because the relationship between city distance and communal conflicts is expected to be logarithmic rather than linear. However, because the variable did not contribute to the baseline model, it is not included in the baseline model. However, when defining the most likely scenario, city distance is used as such rather than the natural logarithm of the city distance.

4.6.3.7 Spatial and temporal lag of conflict

Spatial lag of conflict is important to control for, since conflicts may spread to neighboring countries or areas (see e.g. Hegre and Sambanis (2006); Buhaug and Gleditsch (2008)). Furthermore, a conflict may be the continuation of another conflict instead of actually connected to a new exogenous event like climate. Therefore, time lag of conflict is also controlled for. Consequently, it is expected in this study that spatial and time lag of conflict will increase the risk of communal conflict events. The spatial lag of conflict -variable checks whether there is a communal conflict event in a neighboring grid cell, and gives a grid cell the value 1 if there is a communal conflict event in a neighboring grid cell in the same year, and 0 otherwise. Notably, this variable only checks the grid cells directly above and below and directly to the left and right of a grid cell. Thus it does not check for those grid cells which are diagonal neighbors to a grid cell, because this was technically too difficult to do with the statistical software used in this study, namely STATA 9. As a consequence, the diagonally neighboring cells are left unchecked for conflict, which may be a limitation for this study. On the other hand, the time lag for conflict –variable checks whether there was a communal conflict event in a grid cell in the previous year and takes the value 1 if there was, and 0 otherwise.

4.7 Logistic regression

Out of several quantitative methods, logistic regression has been chosen to analyze all data in this study. This is because the dependent variable (whether there is a communal conflict event or not) is a dichotomous variable, and logistic regression is a good analysis tool when working with dichotomous variables. Using linear regression, e.g. ordinary least squares regression, requires that the relationship between the variables is expected to be linear. However, with a dichotomous variable, one cannot get a linear relationship, and therefore one of the central assumptions of linear regression, linearity, cannot be fulfilled (Field 2009:265-267). In comparison, logistic regression deals with this problem by converting the non-linear relationships, which one gets when using dichotomous variables, to linear relationships (Field 2009:265-267).

Technically, this is done by converting shares into *logits* (Skog 2010:355). Firstly, the *odds* are calculated:

$$Odds = \frac{\tilde{Y}}{1-\tilde{Y}} \qquad \textbf{Equation 1}$$

Odds represent the likelihood for an event occurring ($\tilde{Y}$) versus the event not occurring (1-$\tilde{Y}$). For instance, if there is a 60% chance that it will rain tomorrow, and a 40% chance that it will not, the equation 0.60/(1-0.60)=1.5 shows that it is 1.5 times more likely that it will rain than not rain tomorrow.

Secondly, logits are obtained from the logarithm of odds:

$$Logit\ (\tilde{Y}) = \log \frac{\tilde{Y}}{1-\tilde{Y}} \qquad \textbf{Equation 2}$$

Using logits, a linear regression model can be created from logistic regression (Skog 2010:357):

$$Logit\ (Y) = \alpha + \beta 1(\mathrm{X}) \qquad \textbf{Equation 3}$$

In this equation, α is the constant which tells how much the logit of Y (the dependent variable) is when X (the independent variable) is zero. Furthermore, β_1 is the regression parameter, which tells how much the logit of Y increases when X increases with 1 (Skog 2010:357). Based on this, the logit model used in this study can be exemplified by the following model:

Communal conflict events = α + (β_1 *Temperature deviation*)$_i$ + (β_2 *Population*)$_i$ + (β_3 *Infant mortality rate*)$_i$ + (β_4 *Gross cell product per capita*)$_i$ + (β_5 *Regime type*)$_j$ + (β_6 *Regime type squared*)$_j$ + (β_7 *Spatial lag of conflict*)$_i$ + (β_8 *Time lag of conflict*)$_i$ + e_i

where $_i$ is the grid cell, $_j$ is the country and e_i is the error term for the grid cell in question.

When the relationship between variables is shown in the logit-format, the interpretation of results is not as straightforward as when using linear regression. In order to obtain a substantial interpretation, i.e. to say for instance how many percentages the risk for a conflict event increases with a specific increase in the independent variable, one needs to calculate the *odds* and *oddsratios* (Skog 2010:361-363). However, in this thesis odds and oddsratios are not used. Instead, interpretations of the results are given only based on the output of logit. Therefore, the interpretations given in this thesis are technical in nature. It means that the significance and direction of the coefficients are commented on, as well as the different models' fit to the data.

A model's fit to the data is in this study analyzed by comparing the log likelihoods of the different models. Log likelihood is the result of estimation done by the maximum likelihood –method (Skog 2010:375). Lower log likelihood indicates a better fit of the model to the data (Skog 2010:368). However, as log likelihoods almost automatically decrease for each variable which is added to the dataset, one cannot compare the log likelihoods of two models simply by looking at which model has smaller log likelihood. Therefore likelihood ratio (LR) tests are conducted to see whether a difference between the log likelihoods of two models is statistically significant, controlling for the difference in the number of variables in a model (Skog 2010:375). A statistically significant difference is found by looking at whether the difference in log likelihoods receives the following result from the LR test: the result needs to be more than the chi-square value for the amount of degrees of freedom which is equal to the difference in the amount of variables in the model (Skog 2010:375-376). In other words, if model A has 6 variables and model B has 5 variables, the degrees of freedom between the models is 1. Therefore a significant difference in the log likelihoods of the two models needs to be at least the chi-square value for 1 degrees of freedom.

In this study, the statistical software STATA 9.0 is used to conduct the analyses. With the command "logit", STATA reports amongst other things the regression parameters (β_1), the constant (α), the standard errors and the p-values for the variables in question. STATA also reports the log likelihoods for each model.

4.8 Methodological challenges

4.8.1 Multicollinearity

In statistics, multicollinearity may be a problem. Multicollinearity means that two or more independent variables correlate to a high degree, and it may lead to negative consequences for both the estimated coefficients and their standard errors (Chen et al. 2003). It is possible to check whether a model suffers from multicollinearity in several ways. In this thesis, pairwise correlations between the variable were conducted, and these correlations are shown in correlation matrices. In addition, variance inflation factor (VIF) -tests were conducted.

4.8.2 Omitted variable bias

It is also possible that the relationship between the dependent and independent variable is explained by a third variable, which affects them both. This third variable, if not controlled for, could cause a spurious relationship between the dependent and independent variable. The chance to see a spurious relationship is reduced by adding those variables to a model which can be expected to influence both the dependent and independent variable. These are so called control variables, and they are used also in this study. Furthermore, there is always a chance that a relevant control variable has not been included into the model. In this case, the analyses suffer from omitted variable bias. To minimize the chance for omitted variable bias, control variables should be chosen through carefully reviewing the literature. (Skog 2010:41-45) This was done also in this thesis.

4.8.3 Outliers

Observations, which have values that deviate a lot from the average values, are called outliers and may influence the regression results. There are several ways of dealing with outliers. In this study, two tests are used to check the effects of outliers in the models. The first one is Pregibon’s (1981) delta-beta test, which identifies the effect that the removal of one observation has on the whole model, including on all coefficients. The delta-beta test resembles the Cook’s D in ordinary least squares regression, and like with Cook’s D, observations which have a delta-beta -value higher than 1 should be investigated further (Chen et al. (2013); Field (2000:124)). The second test is Pregibon’s (1981) leverage test, which identifies the leverage, or effect, of a specific observation on the predicted outcome of the model. If any observations have leverage values which are higher than two or three times the average leverage values, these observations should be investigated further (Field 2000:124-125). The results of these tests are commented on in section 5.4.2.

4.8.4 Rare events

Only 0.2% of all grid cells in Sub-Saharan African in 1989-2008 have seen a communal conflict event. This makes the occurrence of a communal conflict event a very rare phenomenon, which in turn may cause problems for the analysis of them. The effects of rare events may namely be underestimated by regular logit analysis (King and Zeng 2001).

In this study, the problem of rare events was attempted to be overcome by running the analyses on a subset of observations, i.e. on grid cells with communal conflict events and on a random sample of 5% of all grid cells without conflict events (see section 4.5 for a description of the subset). Consequently, the number of grid cells with communal conflict events rose to 4.4 % of the total amount of grid cells studied. However, King and Zeng (2001), who suggest to use this method, also argue that it should be used with "appropriate statistical corrections" (King and Zeng 2001:143). Unfortunately, due to time constraints, this was not done in this thesis. In principle, this may cause the results to be misleading, as the results are not corrected for the actual ratio between observations with and without communal conflict events in the full dataset. However, this may in practice not be of great concern for the results of this study, as this study found no significant results. Thus the results should not suffer from the fact that the effect from communal conflict events in the results could be higher than it would be if corrected for the true ratio between observations with and without conflict.

Moreover, King and Zeng (2001) suggest a limit for when it is appropriate to use the rare events logit method for conducting analyses. They argue that the advantages of using rare events logit are highest when the sample size is less than "a few thousand" and when there are less than "5% or so" events in the total sample (King and Zeng 2001:157). In this study, the sample size (size of the subset) is in total 8369 observations, being a little higher than the sample size which would benefit most of rare events logit, and the number of events is 4.4%, which is only a little less than the 5% limit which King and Zeng suggest. Therefore, rare events logit was not chosen as the primary type of regression to be used in this study. It would have been interesting, however, to compare the results of this study to the same analyses conducted with rare events logit. Unfortunately, due to time constraints this was not possible to do in this thesis.

4.8.5 Time dependency and spatial dependency

Spatial and time dependencies of conflicts are likely to cause problems in quantitative conflict research: as discussed in section 4.6.3.7, earlier and nearby incidences of conflict are strong predictors of conflict. In this study, spatial and time dependency are tried to control for by the time lag of communal conflict and spatial lag of communal conflict variables. However, as discussed in section 4.6.3.7, these variables are not able to capture all incidents of earlier and nearby communal conflicts. Therefore, some time and spatial dependencies of conflict might remain unseen in this study.

4.8.6 Missing data and selection bias

Missing data may be a problem in quantitative studies. In this study, many variables lack data on some observations, because these data points do not exist in the available datasets. The variables population, infant mortality rate and gross cell product per capita did not have data for all years, and the available data were therefore interpolated/extrapolated to those years which lacked data, as described in section 4.6.3. A consequence of this is that the data for these three variables do not necessarily reflect the real values for all years. However, this is seen as a better option than lacking data for many years.

When the interpolated and extrapolated values are included in the dataset, the total number of observations with missing data is small[13] for most variables. A notable exception is the variable political marginalization, for which one-third of all grid cells in the dataset lack information. This has some consequences especially for the most likely scenario analyses (which among other things only include grid cells in which politically marginalized groups live). Notably, 76 out of 169 grid cells with communal conflict events in the most likely scenario lack information on marginalized groups. Consequently, this lack of data further limits the number of grid cells with communal conflict events and marginalized groups in the most likely scenario.

[13] 4.5% at the highest.

One reason for the lack of data on marginalized groups is that the EPR dataset (Wimmer et al. 2009), from which the information on the political status of groups is derived, only includes data on groups which live in countries with an area of minimum 500,000 square kilometers and with a population of minimum 1 million as of year 2005 (Wimmer et al. 2009:325, footnote 11). Thus only those 19 countries[14] in Sub-Saharan Africa which fulfill these criteria have information about marginalized groups in the dataset used in this study. Consequently, the most likely scenario used in this study suffers from a selection bias, which is that only observations from relatively big countries are included. Yet, as this is the only data available, not much could be done to correct this selection bias.

However, there are also grid cells within these 19 countries that lack data on marginalized groups[15]. The reason for this is unknown. If there is a systematic pattern in which grid cells have information on marginalized groups and which do not, the data on marginalized groups may suffer from another selection bias.

Furthermore, the most important problem with missing data in this thesis is arguably the fact that not all communal conflict events in Sub-Saharan Africa in the study period could be included in this study, for the reasons explained in section 4.6.1. This may also lead to a selection bias for the dependent variable, if there is a systematic pattern in which communal conflicts were included and which were not. However, the author of this thesis is not aware of any such pattern.

4.9 Limitations

In addition to the methodological challenges discussed in section 4.8, there are a few limitations to the research conducted in this thesis. The first is that the data which is used is data on past events, while, as is generally known, effects of anthropogenic climate change are not expected to occur until a little into the future. However, it is reasonable to look at how the effects of climatic changes (e.g. temperature rise) have correlated with conflict in the past. Although temperature rise would be natural in the time period studied in this thesis, a temperature rise of for instance two degrees is still likely to affect (or not affect) societies and

[14] A list of which countries this includes is available in Appendix B.
[15] The dataset used in this study includes in total 133428 grid cells which are part of those 19 countries included in the EPR dataset, and 52161 of those grid cells lack information on the variable political marginalization.

livelihoods in the same ways regardless of whether it is caused by anthropogenic climate change or not.

Secondly, the time period of this study is relatively short. This study will look at temperature and rainfall changes over 20 years (1989-2008), but it could be that this is a too short period to reveal changes that are comparable to changes caused by anthropogenic climate change. However, this is the time period for which the UCDP GED (Melander and Sundberg 2011) and the UCDP non-state conflict database (Sundberg et al. 2012) provide data on communal conflict events. In addition, the time period used in this study might still reveal if small changes in temperature or rainfall correlate with communal conflict events.

5 Results

In this chapter, the results of the study are presented. First, the results for the larger models are presented (section 5.1). This presentation includes some descriptive statistics, a presentation of the baseline model and finally the multivariate analyses. Thereafter, the results for the most likely scenario are presented (section 5.2). This presentation includes the same elements as the presentation of the larger models. Section 5.3 gives a summary of all the results. Finally, section 5.4 presents the results of relevant statistical tests.

Based on the discussion in section 4.5, all analyses in this thesis are based on a subset of grid cells, i.e. only grid cells with communal conflict events and a random sample of 5% of grid cells without conflict events. Moreover, all analyses are conducted using logistic regression, because the dependent variable is a dichotomous variable, taking the value 1 if a communal conflict event has occurred and 0 if not. For a presentation and discussion on methodological choices in this study, see chapter 4.

Furthermore, bivariate analyses were also conducted for all hypotheses. Although the results of bivariate analyses provide a good start, they need to be controlled for a number of other possible explanatory factors, so called control variables. Moreover, analyses including control variables, so called multivariate analyses, are seen in this study to be of higher importance than bivariate analyses. Because of this, and due to space constraints, the results of the bivariate analyses are reported in Appendix D.

5.1 Large-model analyses

In this section, analyses for the large models are presented. First, some descriptive statistics are provided (section 5.1.1). Thereafter, the baseline model for the large-model analyses is presented (section 5.1.2), before the multivariate analyses are reported and the hypotheses 1 and 2 are discussed based on the multivariate results (section 5.1.3).

5.1.1 Descriptive statistics

Table 2 presents some descriptive statistics for the variables used in this study. These results are based on the subset of grid cells.

Table 2 Descriptive statistics for the larger models

Variable	Mean	Std.dev.	Min	Max	N
Dependent variable					
Communal confl.event	0.044	0.205	0	1	8369
Independent variables					
Temp.dev.	-0.004	0.467	-2.021	3.176	8036
Prec.dev.	0.646	124.980	-1270.7	1302.113	8036
Drought	0.306	0.749	0	2.5	8320
Control variables					
Population (ln)	9.908	1.991	1.386	15.350	8356
IMR (ln)	6.872	0.400	4.605	7.527	8178
GCP PC (ln)	7.014	0.952	5.293	12.202	7944
Regime type	-0.227	5.437	-10	10	8034
Regime type (sq)	29.613	23.859	0	100	8034
Spatial lag	0.028	0.165	0	1	8369
Time lag	0.007	0.086	0	1	8369

5.1.2 Baseline model for the multivariate analyses

This section will present a baseline model which is used for the multivariate analyses. A baseline model is a model consisting of variables which represent our "best guess of the outcome" (Field 2009:268). Often the baseline model only consists of the constant (α) to the dependent variable (Field 2009:268). However, for the multivariate analyses in this study a baseline model is constructed of variables which are known to be good predictors of conflict and which also contribute to explaining communal conflicts in this study.

The reason to use a baseline model is to study the effect of adding or removing one specific variable from a model. To do this, one needs to look at how well the baseline model explains the data compared to how well an alternative model explains the data. An alternative model consists of the baseline model and independent variables of interest, in this case climatic variables. How well a model explains the data is measured by a model's goodness of fit – indicator. In this study where logistic regression is used, this means that the log likelihood of a baseline model is compared to the log likelihood of an alternative model to see whether or not the alternative model explains the data better than the baseline model. (Field 2009:267-268)

The following variables were tested when the baseline model was developed: spatial lag of communal conflict; time lag of communal conflict; population per grid cell; infant mortality rate per grid cell; gross cell product per capita; regime type of the country; regime type of the country, squared; political marginalization; distance to capital; and distance to nearest city of 50000 inhabitants. The baseline model was developed by adding all the variables to one model, and then comparing the log likelihood of that model to alternative models where one variable at the time were removed. When a variable was removed and the log likelihood of the alternative model became significantly worse compared to the full model, the variable in question was included in the baseline model. To see the results of the development of the baseline model, see Appendix C.

The baseline model which was chosen for the multivariate analyses in this study consists of the following variables: spatial lag of communal conflict, time lag of communal conflict, population per grid cell, infant mortality rate per grid cell, gross cell product per capita, regime type of the country and regime type of the country, squared. The baseline model is presented in Table 3.

Table 3 The baseline model

VARIABLES	(Baseline model) Confl.events
Population (ln)	0.517***
	(0.059)
IMR (ln)	-1.571***
	(0.244)
GCP PC (ln)	-0.537***
	(0.131)
Regime type	-0.006
	(0.019)
Regime type (sq)	-0.014***
	(0.004)
Spatial lag	4.519***
	(0.236)
Time lag	5.123***
	(0.775)
Constant	5.037**
	(2.277)
Degrees of freedom	7
LR chi2(x)	960.51
Log likelihood	-565.414
Observations	7,411

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 3, the values which are given for the variables are the regression coefficients, and stars indicate their significance levels. Below the coefficients, in parentheses, are the coefficients' standard errors. Moreover, the log likelihood, likelihood ratio test score (abbreviated as LRchi2(x)) and the degrees of freedom compared to the baseline model (in this case compared to a model where only the constant is included) are given in the bottom of the table. Log likelihood is a goodness-of-fit indicator, and was discussed in section 4.7, and LR tests and degrees of freedom are explained below.

In Table 3, the total amount of observations for the baseline model is 7411. Looking at the different variables, it is visible firstly that the coefficient for population is positive. This result means that for every one unit increase in population (ln), the risk of communal conflict events increases with 0.517 on the logit scale. In order to interpret for instance the percentages that

0.517 on the logit scale indicates, one would need to calculate the odds and odds ratio for the value. However, as noted in section 4.7, odds and odds ratios are not calculated in this study, and therefore no substantial interpretations will be given. Instead, technical interpretations are given[16]. Regarding the coefficient for population in the baseline model, it can therefore be interpreted here as showing that higher population increases the risk of communal conflict events. This result was as expected (see a discussion on control variables and expectations to them in section 4.6.3). Moreover, the coefficient for population is statistically significant on a 0.01 level. This means that there is a 99% chance that the coefficient for temperature actually is 0.517 according to the data, and that it is not 0.517 only by coincidence.

Table 3 further shows that the regression coefficients for the variables in the baseline model are all significant on a 0.01 level, except for regime type, which is included only to ease comparison with regime type squared. Moreover, grid cells with lower infant mortality rates significantly increase the risk of communal conflict events, according to the result of the baseline model. This result is surprising and runs contrary to what was expected. On the other hand, lower gross cell product per capita significantly increases conflict risk. This result is as expected, but it is contradictory to the result of IMR, as high IMR and low GCP PC are expected to indicate poverty. Furthermore, the coefficient for regime type is negative, indicating that low levels of democracy are related to communal conflict. However, this result is insignificant and therefore cannot be trusted with minimum 90% certainty (corresponding to significance on a 0.1 level). On the other hand, a low value on the regime type squared – variable increases the likelihood of communal conflict events, meaning that countries with a regime type which is somewhere halfway between full democracy and full dictatorship run the highest risk of witnessing communal conflict events. This result is significant and was as expected. Finally, spatial lag of conflict, i.e. that a communal conflict event has occurred in a neighboring cell, as well as time lag of conflict, i.e. that a communal conflict event has occurred in the same cell in the previous year, significantly increase the risk of a communal conflict events. These results are as expected.

[16] The software CLARIFY could also have been used to ease the substantial interpretation of coefficients. However, as none of climatic coefficients in the multivariate results in this thesis helped to explain communal conflict events, the use of CLARIFY was not seen as giving the interpretations any additional value.

Moreover, the baseline model does significantly better at explaining communal conflict events than a model where only the constant is included[17]. This is visible from the likelihood ratio (LR) test. The LR test shows whether there is a statistically significant difference between the log likelihoods of two models (Skog 2010:375). Log likelihood here tells how well a model explains communal conflict events. The difference between two log likelihoods is statistically significant when the score of the LR test is similar or higher than the chi-square distributed value for that amount of degrees of freedom which corresponds to the difference in the number of variables between the models (Skog 2010:375-376). The chi-square distributed values are obtained from a chi-square table[18]. Regarding the baseline model which is presented in Table 3, the LR test for the difference between the log likelihood of the baseline model, compared to a model where only the constant is included, is higher than the chi-square distributed value for 1 degree of freedom. Thus it may be concluded that the log likelihood of the baseline model is significantly better than the log likelihood of a model where only the constant is included.

5.1.3 Multivariate analyses with climatic variables

In this section, the hypotheses 1 and 2 are tested by adding climatic variables to the baseline model. These climatic variables are deviation from yearly average temperature, deviation from yearly average precipitation, and the degree of drought. As temperature can also be affected by rainfall, temperature is also tested together with precipitation and drought. Precipitation and drought are, however, not included in the same model, as they measure the same phenomena, namely rainfall, although with different techniques (see section 4.6 for a presentation of the variables).

5.1.3.1 Hypotheses 1a and 2a

Firstly, hypotheses 1a and 2a are tested. These hypotheses expect higher temperatures and lower rainfall respectively to increase the risk of communal conflict in the same year. The results for the analysis are presented in Table 4.

[17] Often a model, where only the constant is included, is called a baseline model, as was explained in section 5.1.2. However, in this thesis the term ”baseline model” refers to the model presented in Table 3.
[18] See for instance Skog (2010:193)

Table 4 Results for hypotheses 1a and 2a

VARIABLES	(Baseline model) Confl.events	(10) Confl.events	(11) Confl.events	(12) Confl.events	(13) Confl.events	(14) Confl.events
Temp.dev.		0.185			0.194	0.181
		(0.212)			(0.214)	(0.212)
Prec.dev.			0.000		0.000	
			(0.000)		(0.000)	
Drought				0.094		0.067
				(0.109)		(0.112)
Population (ln)	0.517***	0.504***	0.504***	0.519***	0.504***	0.506***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
IMR (ln)	-1.571***	-1.782***	-1.772***	-1.565***	-1.777***	-1.776***
	(0.244)	(0.253)	(0.255)	(0.244)	(0.254)	(0.254)
GCP PC (ln)	-0.537***	-0.547***	-0.551***	-0.528***	-0.545***	-0.542***
	(0.131)	(0.133)	(0.133)	(0.131)	(0.133)	(0.133)
Regime type	-0.006	0.002	-0.001	-0.005	0.002	0.003
	(0.019)	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)
Regime type (sq)	-0.014***	-0.015***	-0.014***	-0.014***	-0.015***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Spatial lag	4.519***	4.568***	4.551***	4.522***	4.571***	4.570***
	(0.236)	(0.240)	(0.239)	(0.236)	(0.241)	(0.240)
Time lag	5.123***	5.099***	5.092***	5.062***	5.091***	5.057***
	(0.775)	(0.777)	(0.778)	(0.777)	(0.778)	(0.780)
Constant	5.037**	6.727***	6.665***	4.885**	6.673***	6.596***
	(2.277)	(2.304)	(2.312)	(2.291)	(2.310)	(2.321)
Degrees of freedom		1	1	1	2	2
LR chi2(x)		0.75	0.05	0.73	0.87	1.11
Log likelihood	-565.414	-549.340	-549.694	-564.492	-549.284	-548.972
Observations	7,411	7,120	7,120	7,374	7,120	7,113

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 4, the baseline model from Table 3 is included in order to ease comparison between the models. In Model 10, temperature was added to the baseline model to test the effect of temperature on the model's explanatory power over communal conflict events. As Table 4 shows, the coefficient for temperature is positive but not statistically significant. Therefore the analysis points to higher temperature increasing the risk of communal conflict events, but it cannot tell with a high enough certainty if this really is a true result or if it is just based on coincidence. Moreover, the log likelihood of Model 10 was compared to the log likelihood of the baseline model by conducting a likelihood ratio (LR) test. As the LR between the models is less than the chi-square value with one degree of freedom, the difference between the log likelihoods of the baseline model and Model 10 is not statistically significant. This means that adding temperature to the baseline model does not improve the model’s capacity to explain the data.

Model 11 tests the effect of adding precipitation to the model. The coefficient for precipitation is zero, meaning that higher or lower precipitation does not affect the risk of communal conflict events. However, as the coefficient is insignificant, the result cannot be guaranteed with at least 90% certainty to not be caused by chance. Thus it is not possible to say with high enough certainty how precipitation affects communal conflict events. Furthermore, the LR test between Model 11 and the baseline model revealed that there is no significant difference in how well the two models explain the data. Consequently, precipitation does not seem to help explain communal conflict events.

Model 12 uses another indicator for rainfall, namely drought. The coefficient for drought is positive but not significant, thus pointing to lower rainfall increasing conflict risk but with less than 90% certainty. Furthermore, the LR test between Model 12 and the baseline model also proved that adding drought does not improve the model’s capacity to explain the communal conflict events.

In Model 13, temperature and precipitation were tested together. This is done in order to see whether the coefficients for temperature and precipitation change when tested together, as precipitation may affect temperature. However, neither of the coefficients has become significant, and they have approximately the same size and direction as in Models 10 and 11 where temperature and precipitation respectively were tested alone. Moreover, due to the coefficients’ lack of significance these results are less than 90% certain. A LR test further reveals that adding both temperature and precipitation to the model does not improve the models explanatory power compared to the baseline model.

In Model 14, temperature and drought are tested together. Neither of them is significant, and they have the same directions as in Models 10 and 12 when they were tested alone. The coefficient for temperature has also approximately the same size as in Model 10, but the coefficient for drought has decreased some in size compared to Model 12, suggesting that part of the effect of drought is explained by temperature, although due to insignificance this cannot be verified by minimum 90% certainty. Furthermore, like the previous models, a LR test reveals that Model 14 does no better in explaining communal conflict events than the baseline model.

Based on the results for Models 10-14, hypotheses 1a and 2a are rejected in this study. Hypothesis 1a expects higher temperature to increase the risk of communal conflict events, while hypothesis 2a expects lower levels of rainfall to increase conflict risk. The coefficient for temperature pointed in the same direction as was anticipated by hypothesis 1a, suggesting that hypothesis 1a could be correct. Simultaneously, the coefficient for drought also pointed to the same direction as anticipated by hypothesis 2a, while the coefficient for precipitation was zero, pointing to no relationship between rainfall and conflict. The results for drought and precipitation are therefore somewhat contradictory. However, none of the three coefficients were statistically significant, and therefore none of the results for the climatic variables can be trusted with minimum 90% certainty. In addition, and most importantly, none of models with climatic variables contributed significantly to explain the data, compared to the baseline model. Thus climatic variables, controlled for the variables in the baseline model, did not help to explain communal conflict events in this study. Hypotheses 1a and 2a are thus discarded in this study.

5.1.3.2 Hypotheses 1b and 2b

The hypotheses 1b and 2b expect changes in temperature and rainfall respectively in one year to increase communal conflict risk the following year. These hypotheses are tested by changing the Models 10-12 by including values for the climatic variables for the previous year relative to the values for all the other variables. This change is reflected in Models 15-17. The results for the analyses are presented in Table 5.

Table 5 Results for hypotheses 1b and 2b

VARIABLES	(Baseline model) Confl.events	(15) Confl.events	(16) Confl.events	(17) Confl.events
Temp.dev. t-1		-0.382*		
		(0.216)		
Prec.dev. t-1			0.000	
			(0.000)	
Drought				-0.091
				(0.115)
Population (ln)	0.517***	0.509***	0.506***	0.519***
	(0.059)	(0.061)	(0.061)	(0.060)
IMR (ln)	-1.571***	-1.688***	-1.688***	-1.493***
	(0.244)	(0.264)	(0.262)	(0.250)
GCP PC (ln)	-0.537***	-0.510***	-0.497***	-0.485***
	(0.131)	(0.134)	(0.134)	(0.132)
Regime type	-0.006	-0.007	0.001	-0.001
	(0.019)	(0.020)	(0.020)	(0.020)
Regime type (sq)	-0.014***	-0.013***	-0.015***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Spatial lag	4.519***	4.530***	4.551***	4.521***
	(0.236)	(0.239)	(0.240)	(0.237)
Time lag	5.123***	5.158***	5.125***	5.128***
	(0.775)	(0.777)	(0.779)	(0.775)
Constant	5.037**	5.729**	5.719**	4.200*
	(2.277)	(2.368)	(2.364)	(2.328)
Degrees of freedom		1	1	1
LR chi2(x)		3.12	0.32	0.65
Log likelihood	-565.414	-530.498	-531.901	-546.528
Observations	7,411	6,757	6,757	6,998

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 5, the baseline model is again included to ease the comparison. In Model 15, temperature for the previous year is added to the baseline model. The coefficient for temperature is negative, meaning that lower temperatures increasing the risk of conflict, and significant on a 0.1 level. However, a LR test shows that Model 15 does not have a significantly better log likelihood than the baseline model. Thus, despite a significant coefficient, adding temperature for the previous year to the baseline model does not improve the model's capacity to explain communal conflict events.

Model 16 tests the effect of precipitation in the previous year on communal conflict events in a current year. The coefficient is zero, indicating that changes in precipitation are not related to increases the risk of communal conflict events. However, the coefficient is not significant, meaning that the results of Model 16 cannot be trusted with minimum 90% certainty. Moreover, a LR test between the log likelihoods of Model 16 and the baseline model shows that the log likelihoods are not significantly different. Consequently Model 16, where precipitation for the previous year is tested, is not able to explain communal conflict events any better than the baseline model is.

In Model 17, the effect of drought in the previous year is tested on communal conflict events in the current year. The coefficient for drought is negative, indicating that lower levels of drought increase the risk of communal conflict events. However, the coefficient is not significant, and thus the results cannot be trusted with minimum 90% certainty. Furthermore, the difference in the explanatory power of Model 17 is not significantly different from the baseline model, meaning that drought in the previous year cannot help to explain communal conflict events any better than the baseline model.

In the same way as in models 13-14 in Table 4, temperature for the previous year was also analyzed together with the coefficients for precipitation and drought in the previous year. However, as the results of these analyses did not differ significantly from the results of Models 15-17, the results for them are not reported.

Consequently, the results for Models 15-17 show that both hypothesis 1b and 2b are rejected in this study. Hypothesis 1b expects higher temperatures in one year to increase the risk of communal conflicts in the following year, while hypothesis 2b expects lower levels of rainfall in one year to increase the risk of communal conflicts in the following year. Firstly, all the climatic coefficients pointed in different directions than what was anticipated by the hypotheses. Secondly, only the coefficient for temperature was statistically significant. Thirdly, and most importantly, none of the models, not even Model 15 with the significant coefficient for temperature, had significantly higher log likelihood than the baseline model. This means that none of the climatic coefficients improved the baseline model's capacity to explain communal conflict events. As a result, hypotheses 1b and 2b are rejected in this study.

5.1.3.3 Model specification á la Fjelde and Uexkull (2012)

This section presents an analysis of the effects of rainfall on communal conflict events, using model specifications as similar as possible to Fjelde and Uexkull (2012). The reason to do this is to see if the different results obtained in this study and in the study by Fjelde and Uexkull (2012) can be explained by differences in model specifications. Table 6 below will present two models, which are specified to be as similar as possible to models 1 and 4 presented by Fjelde and Uexkull (2012:450).

Table 6 Results for larger models á la Fjelde and Uexkull (2012)

VARIABLES	(Baseline F&U 2012) Confl.events	(18) Confl.events	(19) Confl.events
Prec.dev.		0.000	
		(0.000)	
Drought			0.058
			(0.083)
Population (ln)	0.562***	0.549***	0.563***
	(0.045)	(0.045)	(0.045)
GCP PC t-1 (ln)	-0.286***	-0.294***	-0.281***
	(0.092)	(0.093)	(0.091)
Com.confl.spatial lag t-1	2.406***	2.401***	2.398***
	(0.271)	(0.271)	(0.271)
Com.confl.time lag	4.055***	4.042***	4.041***
	(0.482)	(0.481)	(0.482)
War spatial lag t-1	0.682***	0.678***	0.683***
	(0.142)	(0.142)	(0.142)
Constant	-7.787***	-7.571***	-7.843***
	(0.806)	(0.817)	(0.809)
Df		1	1
LR chi2(x)		0.32	0.47
Log likelihood	-952.079	-939.493	-951.320
Observations	7,534	7,259	7,498

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 6, the first model is a baseline model, which includes the same control variables as were used by Fjelde and Uexkull (2012) in their models 1 and 4. Four of these variables, namely population, GCP PC, spatial lag and conflict lag correspond to the variables used in the multivariate analyses of this study. However, GCP PC and spatial lag have received values for the previous year, following the example of Fjelde and Uexkull (2012). Also, the variables GCP PC, spatial lag and time lag are operationalized a little differently by Fjelde and Uexkull (2012) than they are in the models in Table 6 and in this thesis in general. Nevertheless, these variables, including population, are based on the same data in this thesis and in Fjelde and Uexkull (2012). The variable war spatial lag for the previous year, on the other hand, is not used in other analyses in this thesis, and it measures the spatial lag of civil war (corresponding to conflict types 3 and 4 in UCDP/PRIO Armed Conflict Dataset (Themnér and Wallensteen 2012)). In this thesis, it is operationalized in the same way as spatial lag of conflict, while it is operationalized a little differently in Fjelde and Uexkull (2012). Furthermore, of the independent variables drought is based on the same data and operationalized in the same way in both studies, while precipitation is in this thesis based on data derived from a different source than in Fjelde and Uexkull (2012), but it is operationalized in a similar way.

The results of the models in Table 6 show that the coefficient for precipitation in Model 18 is zero and the coefficient for drought in Model 19 is positive, just like in models 10 and 12 in this thesis. Moreover, none of the coefficients are significant, and none of the models have significantly higher log likelihood than the baseline model. Consequently, also these models reject hypothesis 2a, which expects lower rainfall to increase the risk of communal conflict events. Thus the results of this study remain contradictory to the results of Fjelde and Uexkull (2012), even when the models are specified to be as similar as possible. Chapter 6 will discuss possible reasons for this.

5.2 Most likely scenario

The results presented in this section are based on analyses in a most likely scenario for resource scarcity –induced conflict. The argument for using a most likely scenario is that if resource scarcity caused by climate change is related to conflict, this relationship should as a minimum be found where the conditions for climate change induced conflict are most favorable. Moreover, no other study to date has analyzed communal conflict or non-state conflicts of any kind in a similar way (however, Wischnath and Buhaug (2013) have used a most likely scenario to study climate and civil wars in Asia). The most likely scenario is argued in this thesis to be a rural area, where politically marginalized groups live and where the level of poverty is relatively high. For a presentation and discussion of the scenario, see section 3.3.

Technically, the most likely scenario is based on grid cells which include communal conflict events and a random sample of 5% of grid cells without events, as in most analyses presented earlier. In addition, only grid cells which include at least one marginalized group, where infant mortality rate is above the 50^{th} percentile for the whole of Sub-Saharan Africa, and where distance to the nearest city with 50 000 inhabitants is more than 120 minutes, are included in the scenario. Based on the criteria above, in total 1450 grid cells are included in the most likely scenario. Out of these, 3.4% , i.e. 50 grid cells, have seen a communal conflict event.

5.2.1 Descriptive statistics

Table 7 will provide some descriptive statistics for the variables in the most likely scenario.

Table 7 Descriptive statistics for the most likely scenario

Variable	**Mean**	**Std.dev.**	**Min**	**Max**	**N**
Dependent variable					
Communal confl.event	.034	.182	0	1	1450
Independent variables					
Temp.dev.	.0217	.430	-1.367	1.688	1429
Prec.dev.	9.420	126.231	-507.04	578.762	1429
Drought	.415	.865	0	2.5	1449
Control variables					
Population (ln)	9.959	1.670	2.639	14.261	1449
GCP PC (ln)	6.529	.843	5.293	12.202	1448
IMR (ln)	7.163	.105	7.013	7.527	1294
Regime type	-2.413	3.778	-9	8	1368
Regime type (sq)	20.090	23.262	0	81	1368
Spatial lag	.031	.175	0	1	1450
Time lag	.009	.097	0	1	1450
Variables which define the most likely scenario					
IMR	1299.561	146.255	1111	1858	1294
Politically marginalized groups	1	0	1	1	1450
City distance	673.385	591.333	125	5794	1450

5.2.2 Multivariate analyses

The following section will report the results for the multivariate analyses in the most likely scenario. However, one thing needs to be noted first concerning the baseline model. The baseline model, which was developed for the larger models, is also used as a baseline model for the most likely scenario. A baseline model was also developed separately for the most likely scenario, testing which variables improved the model's explanatory power under the conditions defined for the most likely scenario. However, only three variables contributed to explain communal conflict events. These variables were population, time lag of conflict and spatial lag of conflict, of which STATA dropped time lag of conflict due to its capacity to predict observations perfectly. Based on these results, a baseline model for the communal conflict would have included only two variables. This was seen as a quite thin baseline model, and therefore it was chosen that the baseline model which was developed for the larger models should also be used for the most likely scenario analyses.

5.2.2.1 Hypotheses 3a and 4a

Hypotheses 3a and 4a expect higher temperatures and less rainfall respectively to increase the risk of communal conflict events. The results for the analyses are presented in Table 8.

Table 8 Results for hypotheses 3a and 4a

VARIABLES	(Baseline most likely scenario) Confl.events	(20) Confl.events	(21) Confl.events	(22) Confl.events
Temp.dev.		0.702		
		(1.920)		
Prec.dev.			-0.002	
			(0.004)	
Drought				-1.686
				(2.858)
Population (ln)	1.603**	1.588**	1.590**	1.563**
	(0.659)	(0.657)	(0.663)	(0.630)
IMR (ln)	5.310	5.945	4.049	5.013
	(9.11)	(9.28)	(9.16)	(8.92)
GCP PC (ln)	-1.380	-1.310	-1.108	-1.436
	(1.699)	(1.715)	(1.706)	(1.660)
Regime type	0.014	0.064	0.094	0.029
	(0.451)	(0.458)	(0.467)	(0.428)
Regime type (sq)	-0.055	-0.048	-0.053	-0.053
	(0.070)	(0.070)	(0.070)	(0.066)
Spatial lag	8.541***	8.643***	8.610***	8.284***
	(2.020)	(2.038)	(2.091)	(1.953)
Constant	-53.69	-58.56	-46.09	-50.47
	(65.64)	(66.65)	(65.85)	(64.70)
Degrees of freedom		1	1	1
LR chi2(x)		0.14	0.33	0.98
Log likelihood	-12.878	-12.801	-12.705	-12.389
Observations	1,198	1,179	1,179	1,198

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 8, the first model is the baseline model for the most likely scenario. It includes the same variables as the baseline model in Table 4 and Table 5, but it differs by being based on the most likely scenario selection of grid cells. However, when running all the models in Table 8, STATA (the statistical software used in this study) found the variable time lag of conflict to predict the results perfectly, and thus dropped the variable along with 13 perfectly predicted observations. Due to this, alternative model specifications were tried, including dropping entirely the variable time lag of conflict, but the results did not change significantly. For this reason, all the models in Table 8 are without the variable time lag for conflict.

Furthermore, the results for the variables in the baseline model have changed some compared to the large-N analyses, and are therefore worth commenting on. The coefficient for population has increased in size, but is significant only on 0.05 level compared to 0.01 in the larger models. Moreover, the coefficient for IMR has seized to be significant. Interestingly, the coefficient for IMR has shifted from being negative in the larger models to become positive in the most likely scenario models. As a consequence, IMR now reflects the theoretical expectations for it, which were presented in section 4.6.3.2. GCP PC has also seized to be significant, but has increased in size and remained negative. Furthermore, regime type is still insignificant, but is positive in all models in Table 8, while it varied between positive and negative in the larger models. Regime type squared, on the other hand, has seized to be significant but remained negative as in the large-N models. Finally, the coefficient for spatial lag of conflict has increased in size, and remains significant on a 0.01 level. These changes for the control variables are reflected in all models in Table 8.

In Model 20, temperature is added to the most likely scenario baseline model and the coefficient for temperature is positive. This result suggests that studying a most likely scenario for climate change –induced communal conflict, higher temperature may increase the risk of communal conflicts. It is moreover visible in Model 21 that lower precipitation seems to increase the risk of communal conflicts, as the coefficient for precipitation is negative, while the coefficient for drought in Model 22 is also negative, suggesting that lower levels of drought increase the risk of communal conflict. The results for precipitation and drought are therefore contradictory. However, none of the coefficients for climatic variables are statistically significant, making it impossible to accept them as true with minimum 90% certainty. Furthermore, none of the models which include climatic variables are able to explain communal conflict events better than the baseline model, as is reflected in the LR tests.

Temperature was also tested together with precipitation and drought in a most likely scenario, but the results did not differ significantly from the results presented in Table 8. Therefore they are not reported.

Based on these results, hypotheses 3a and 4a are both rejected in this study. Hypothesis 3a expects higher temperatures to increase the risk of communal conflicts in a most likely scenario. Although the coefficient for temperature points in the same direction as is anticipated by the hypothesis, the coefficient is not statistically significant, and most importantly, Model 20 which includes temperature is not able to explain communal conflict events in a most likely scenario any better than the baseline model. Hypothesis 4a, on the other hand, expects lower levels of rainfall to increase the risk of communal conflicts in a most likely scenario. The results for precipitation and drought point in opposite directions, and none of the coefficients are significant in any models. Most importantly, neither Model 21 nor Model 22, which include precipitation and drought respectively, help to explain communal conflict events, compared to the baseline model.

5.2.2.2 Hypotheses 3b and 4b

Hypotheses 3b and 4b expect higher temperatures and lower rainfall respectively in the previous year to increase the risk of communal conflict events in a current year. The results for the analyses are presented in Table 9.

Table 9 Results for hypotheses 3b and 4b

VARIABLES	(Baseline most likely scenario) Confl.events	(23) Confl.events	(24) Confl.events	(25) Confl.events
Temp.dev. t-1		-2.003		
		(1.972)		
Prec.dev. t-1			0.002	
			(0.002)	
Drought t-1				-0.549
				(0.800)
Population (ln)	1.603**	1.763**	1.576**	1.665**
	(0.659)	(0.744)	(0.653)	(0.670)
IMR (ln)	5.310	3.098	6.120	4.861
	(9.11)	(8.98)	(9.89)	(9.07)
GCP PC (ln)	-1.380	-1.336	-1.945	-1.594
	(1.699)	(1.713)	(2.051)	(1.737)
Regime type	0.014	-0.028	-0.193	0.010
	(0.451)	(0.492)	(0.587)	(0.415)
Regime type (sq)	-0.055	-0.075	-0.073	-0.042
	(0.070)	(0.077)	(0.082)	(0.066)
Spatial lag	8.541***	8.170***	8.724***	8.543***
	(2.020)	(2.144)	(2.093)	(1.973)
Constant	-53.69	-39.91	-55.95	-49.75
	(65.64)	(64.69)	(70.60)	(65.83)
Degrees of freedom		1	1	1
LR chi2(x)		1.02	0.73	0.55
Log likelihood	-12.878	-12.361	-12.507	-12.600
Observations	1,198	1,099	1,099	1,117

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Like the models in Table 8, also the models in Table 9 are without the control variable time lag for conflict, because STATA found the variable to predict the results perfectly and consequently dropped the variable along with 13 perfectly predicted observations. Moreover, the rest of the variables constituting the baseline model for the most likely scenario, i.e. spatial lag of conflict, population, IMR and regime type, behave in all models in Table 9 approximately in the same way as in Table 8.

In Models 23-25 climatic variables are added to the baseline model. In Model 23, the coefficient for temperature is negative suggesting that lower temperature in one year increases the risk of communal conflicts in the following year in a most likely scenario. Moreover, in

Model 24 the coefficient for precipitation is positive and in Model 25 the coefficient for drought is negative, suggesting that higher levels of rainfall increase the risk of communal conflicts. However, none of the climatic coefficients are significant in any of the models. This means that it is not possible to trust the results for the climatic variables with minimum 90% certainty. Furthermore, the LR tests between Models 23-25 and the baseline model show that none of the models where climatic variables are included are able to explain communal conflict events better than the baseline model in a most likely scenario.

Based on these results, hypotheses 4a and 4b are rejected in this study. Hypothesis 4a expects higher temperature in one year to increase the risk of communal conflicts in the following year in a most likely scenario, but in Model 23 the coefficient for temperature suggests that instead lower temperature increases conflict risk. Moreover, as the coefficient for temperature is not significant, and as Model 23 does not explain communal conflicts any better than the baseline model, hypothesis 4a is rejected. On the other hand, hypothesis 4b expects that lower levels of rainfall increase the risk of communal conflicts in a most likely scenario. However, the coefficients for precipitation and drought in Models 24 and 25 respectively point to an opposite relationship between rainfall and conflict, but none of the coefficients are significant. Moreover, most importantly, none of the models with precipitation or drought are better able to explain communal conflict events than the baseline model is. Therefore, also hypothesis 4b is rejected in this study.

5.2.2.3 Model specification á la Fjelde and Uexkull (2012)

This section presents models for the most likely scenario which are specified to be as similar as possible to models 1 and 4 in Fjelde and Uexkull (2012:450). The reason to do this here in addition to section 5.1.3.3 is to see whether the relationship between drought and communal conflict which Fjelde and Uexkull (2012) found will become visible in this thesis when the conditions for communal conflicts are as favorable as possible. Table 10 presents the results.

Table 10 Results for most likely scenario models á la Fjelde and Uexkull (2012)

VARIABLES	(Baseline F&U 2012) Confl.events	(25) Confl.events	(26) Confl.events
Prec.dev.		-0.000	
		(0.001)	
Drought			-0.923**
			(0.425)
Population (ln)	0.966***	0.966***	0.958***
	(0.148)	(0.148)	(0.148)
GCP PC t-1 (ln)	-0.954***	-0.934***	-1.008***
	(0.356)	(0.357)	(0.369)
Com.confl.spatial lag t-1	2.478***	2.487***	2.487***
	(0.628)	(0.631)	(0.644)
Com.confl.time lag	2.571*	2.542*	2.653**
	(1.369)	(1.376)	(1.337)
War spatial lag t-1	0.913**	0.895**	0.832**
	(0.401)	(0.404)	(0.407)
Constant	-8.965***	-9.063***	-8.286***
	(2.685)	(2.694)	(2.755)
Df		1	1
LR chi2(x)		0.08	7.95
Log likelihood	-118.110	-117.914	-114.136
Observations	1,358	1,340	1,358

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the model 25 in Table 10, precipitation is zero and insignificant, just like in earlier models. Moreover, the log likelihood of model 25 is not significantly different from the log likelihood of the baseline model, meaning that precipitation does not help to explain communal conflict events. On the other hand, the coefficient for drought has become significant in model 26, and it is negative, indicating that lower levels of drought (i.e. higher levels of rainfall) are related to communal conflicts. A LR test further shows that model 26 is able to explain communal conflict events significantly better than the baseline model. It is therefore visible that rainfall, measured as precipitation, cannot help explain communal conflict events in a most likely scenario, while rainfall measured as drought can contribute to explaining communal conflict events in the scenario. However, this relationship runs contrary to what was expected by hypothesis 4a, which expected lower levels of rainfall to increase the risk of communal conflict events in a most likely scenario. Consequently, also when analyzing the relationship between rainfall and communal conflict events in a most likely scenario, even when the models are specified as similarly as possible to the models by Fjelde and Uexkull (2012), this study finds different results than their study.

5.3 Summary of all results

In this study, the effects of temperature, precipitation and drought were tested on communal conflict events. In the bivariate analyses (reported in Appendix D), temperature was significant and improved the model's log likelihood in all the bivariate large-N analyses, while precipitation and drought were insignificant and did not contribute significantly to the model's log likelihood in the same analyses. In the bivariate analyses for the most likely scenario, temperature was significant in all models and improved the model's log likelihood in most models, while precipitation and drought were significant in most models and improved the model's log likelihood in some models.

However, when control variables are added to the models in the multivariate section, the majority of the climatic coefficients become insignificant. Only temperature for the previous year is significant in Model 15. Moreover, and most importantly, none of the multivariate models where climatic coefficients are included have a better log likelihood than the baseline model. This means that the climatic variables which were tested in this study do not help to explain communal conflict events in Sub-Saharan Africa in 1989-2008, not even when tested in a most likely scenario for climate change induced conflict. An attempt was further made to specify the models as similarly as possible to Fjelde and Uexkull (2012), who found drought to increase the risk of communal conflict events using first-order administrative units as units of analysis. However, the results remained approximately the same. Consequently, all the hypotheses of this study are rejected.

5.4 Statistical tests

In this study, some statistical tests have been conducted in order to control for possible methodological challenges, which were described in section 4.8.

5.4.1 Multicollinearity

The multivariate models presented in this study were tested for multicollinearity by conducting pairwise correlations and VIF-tests. The results show that the models do not suffer from multicollinearity between independent variables. Only spatial lag of communal conflict vs. communal conflict events gets a correlation value which is above 0.7, but this is not a multicollinearity problem since communal conflict events is the dependent variable. Instead, the result only shows that spatial lag of communal conflict is highly correlated with communal conflict, as was theoretically expected and as is visible from the regression coefficients for spatial lag of communal conflict in the multivariate analyses in this study.

5.4.2 Extreme and influential observations

The multivariate models were also tested for extreme and influential observations by conducting Pregibon's leverage and delta-beta tests. The results of these tests show a few things. Firstly, the delta-beta tests of the larger models show that there are no observations which exercise a high influence on the larger models. Secondly, the delta-beta tests show that there are three observations which affect the most likely scenario-models considerably. The most likely scenario models were ran without these three observations, but this resulted in STATA not conducting the regression because the variable spatial lag of conflict predicted the remaining observations perfectly. An attempt was further made at removing spatial lag of conflict from the analysis (time lag of conflict was removed by STATA automatically for the same reason, as explained in section 5.2). Thus results were obtained for a model without the variables spatial lag of conflict and time lag of conflict (the models are not reported here). In these models, some climatic variables became significant, and some models with climatic variables received a better log likelihood than the baseline model. Yet, these results are arguably of little substantial interest, as they suffer from omitted variable bias after the removal of the spatial and time lag of conflict –variables. What the consequences of the delta-beta test on the most likely scenario models show, on the other hand, is that the study of climate change and communal conflict should perhaps study communal conflict onsets instead of communal conflict events, in order to avoid spatial and time lag of conflict events to explain such a big part of the conflict observations and to get a better possibility to see which independent variables actually explain communal conflict onsets.

The results for the leverage tests for both the large-N models and the most likely scenario models show that all models have a high number of observations which affect the outcome of the model to a much higher degree than the average observation. In statistics, observations like these are seen as outliers and therefore as problematic observations, which should be investigated. However, this was difficult to do in this study, as the number of observations with high leverage values was so high (390 observations in the larger models, and around 62 observations in the most likely scenario models).

6 Discussion

This chapter discusses all the results of this study in relation to the literature. As was presented in chapter 5, the results from both the analyses of the larger models and the most likely scenario –models reject all the hypotheses of this study. These results run contrary to most results of the quantitative studies on climate change and non-state conflicts presented in section 2.4. Where for instance Fjelde and Uexkull (2012) find that communal conflict is more frequent in dry years; Raleigh and Kniveton (2012) that communal conflict occurs more often in wet years; and Hendrix and Salehyan (2012) that violent conflict in general is more likely in wet years; this study finds no relationship between rainfall and communal conflicts, not even when analyzing a most likely scenario. The results of this study are more in line with O'Loughlin et al. (2012), who do not find dry years to be correlated to conflict. However, O'Loughlin et al. (2012) instead find that wet years decrease the risk of conflict compared to years with normal levels of rainfall. In contrast, the results of this study do not find any such effect.

Moreover, where O'Loughlin et al. (2012) find warmer than average years to increase the risk of conflicts, including non-state conflict, this study does not find any significant effect of temperature on communal conflict events. Although the coefficient for temperature was significant in one model, the coefficient was negative, indicating that colder than average years are related to conflict. Also, the model did not explain communal conflict events any better than a model with the same control variables but without the coefficient for temperature, i.e. the baseline model.

What is especially interesting about the findings in this thesis is that climatic coefficients were not found to affect the risk of communal conflict events even in a most likely scenario. The most likely scenario was argued in this thesis to be rural areas where politically marginalized groups live and where the level of poverty is high. Theory suggests that these are the circumstances were climate change induced conflict is most likely to occur. Yet, neither changes in temperature nor rainfall were found to increase the risk of communal conflict events in these circumstances.

There are many possible reasons for the different results between this study and other studies on climate change and non-state conflicts, including communal conflicts. As was discussed in section 2.5, the climate change – non-state conflict studies (including this study) differ in terms of how they define conflict, which area and time period they study, which conflict data they use and what they use as their units of analysis. In addition, the specific models which are used in the different studies also differ.

In order to explain these differences, systematic comparisons may be in order. Firstly, more studies are needed on climate change and communal conflicts. There are only a few studies to date which explicitly look at communal conflicts and climate change, although communal conflicts are arguably the most likely form of climate change -induced conflict. Moreover, some of the current studies which use non-state conflicts in general have combined non-state conflicts into a variable ‘conflict’ or ‘violent conflict’, which also includes civil war and one-sided violence. In these cases, the effects of climate on non-state conflicts may be overshadowed by the effects, or lack of effects, of climate on the other types of violence, which are not as likely to be related to climate as non-state conflicts are. Hence, this thesis argues that the most useful conflicts to study related to climate change are communal conflicts. However, already separating non-state conflicts in general from civil war and one-sided violence could help researchers get closer to analyzing the most likely type of conflict to potentially occur as a result of climate change.

Moreover, it would be useful to compare whether different datasets on non-state or communal conflict events give different results. In order to compare them systematically, researchers would need to use a concise definition of conflict, preferably communal conflict, and they would need to study the same areas and time periods. Preferably these areas and time periods would be as large and long as possible. In order to reduce the risk of studying too many irrelevant places, one possible approach is to narrow down the amount of observations by conducting analyses on a subset of disaggregated units, as was done in this study. Furthermore, in order to eliminate the possibility of small differences in model specifications causing differences in results, the same models should be tried on the different datasets.

Methodologically, the most interesting finding of this study is that using grid cells as units of analysis (as is done in this study) yields different results than using first-order administrative units as units of analysis, as is done in the study by Fjelde and Uexkull (2012). Both this study and the study by Fjelde and Uexkull (2012) analyze the relationship between climate change and communal conflicts in Sub-Saharan African in 1989-2008, i.e. the two studies analyze the same type of conflicts in the same area and in the same time period, and use the same data on communal conflicts, namely UCDP GED (Melander and Sundberg (2011); Sundberg et al. (2010)). An attempt was even made in this study to analyze models which were specified as similarly as possible to the models by Fjelde and Uexkull (2012) (see sections 5.1.3.3 and 5.2.2.3). Yet, the results differ.

Therefore, it is possible that grid cells and first-order administrative units differ in how they capture relationships between for instance rainfall and communal conflict. However, it is not possible to state definitively that the difference in results is caused by the difference in the unit of analysis, as the attempt to analyze similarly specified models in this thesis was not an exact replication of the study by Fjelde and Uexkull (2012). Thus it may be that very small differences in the operationalizations of some variables are the reasons for the differences. However, this does not seem very likely, as the remaining differences are quite small. Finding out whether this is the case is important not only for research on climate change and communal conflicts, but also for other disaggregated studies of conflict.

Also more generally, more studies are needed on climate change and communal conflicts in order to establish whether communal conflicts can occur as a consequence of climate change. Future studies could make use of comparing different regions within Africa to see whether the likelihood of climate change –induced communal conflicts differs between the regions. For instance, no study to date has looked at climate change and communal conflicts in West Africa, while a few studied different regions in East Africa. Moreover, future studies could also do wisely in trying to study communal conflict onset rather than events of communal conflicts. This could improve the possibility to see whether climate change acts as a trigger for communal conflicts. Studying conflict onset could namely help to overcome the problem of communal conflict events being perfectly predicted by conflict events which have occurred nearby or in the previous year, as partly happened in the most likely scenario of this thesis (as discussed in section 5.4.2). In this way, studying communal conflict onsets could illuminate which factors make a communal conflict start. However, for this to be possible, geo-coded data on communal conflict onsets is needed.

7 Conclusion

Theories of the Environmental Security School have inspired a number of studies on climate change and violent conflict. However, no consensus has yet been reached on whether climate change affects violent conflict. Simultaneously, only a few studies have been conducted on climate change and communal conflicts, which is arguably the most likely type of conflict to occur as a result of climate change. This thesis has contributed to fill this gap by studying the relationship between climate change and communal conflicts in Sub-Saharan Africa in the years 1989-2008. It has studied this relationship using quantitative method, more specifically logistic regression, and by using grid cells of 0.05˚ x 0.05˚ as disaggregated units of analysis. Both temperature and precipitation have been used as measures of climate change. This thesis has also studied climate change and communal conflict in a most likely scenario, arguing that if climate change and communal conflicts are related, a relationship should be found in this scenario. This scenario is argued to be rural areas, where politically marginalized groups live and where the level of poverty is high.

Yet, this thesis finds no relationship between climate change and communal conflicts. Neither temperature nor rainfall contributed to explain communal conflicts in any of the models used in this study, and therefore all the hypotheses of this study are rejected. A relationship between climate change and communal conflicts was thus not found even where the circumstances for climate change –induced communal conflict were most favorable, i.e. in the most likely scenario.

These results differ from the results of other studies on climate change and communal conflicts (e.g. Fjelde and Uexkull (2012) and Raleigh and Kniveton (2012)), and climate change and non-state conflicts (e.g. Hendrix and Salehyan (2012) and O'Loughlin et al. (2012)). Most interestingly, the results of this thesis differ from the results of Fjelde and Uexkull (2012), who found drought to increase the likelihood of communal conflicts. The study by Fjelde and Uexkull (2012) is very similar to this thesis, except regarding the choice of disaggregated units of analysis: while this thesis uses grid cells, Fjelde and Uexkull (2012) use first-order administrative units. As the results in this thesis differed from Fjelde and Uexkull (2012) even when models were specified as similarly as possible, there is a possibility that the unit of analysis used affects the results.

8 References

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Appendix A Countries in Sub-Saharan Africa

Countries counted as belonging to Sub-Saharan Africa in this thesis:
Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Republic of Congo (Brazzaville), Democratic Republic of Congo (Kinshasa), Cote D'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, The Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe.

This list of countries is based on the listing by UN (2013), where Sub-Saharan Africa is said to include all countries in Africa expect for countries which are part of Northern Africa. However, the Sudan, which is also part of Northern Africa, is also counted as Sub-Saharan Africa. Moreover, in this thesis two Sub-Saharan countries are excluded from the study. These are Seychelles and Sao Tome & Principe, and they are excluded because they have not been given a *gwno*-number in Gleditsch and Ward (1999), which was in this thesis necessary for countries to have in order to combine data for the countries on different variables.

Appendix B Countries in the EPR dataset

These are countries included in the EPR dataset (Wimmer et al. 2009).

Country	Population year 2005	Area in km year 2005
Angola	16489021	1246700
Botswana	1875673	566730
Central African Republic	4017880	622980
Chad	9785902	1259200
Democratic Republic of Congo (Kinshasa)	57420522	2267050
Ethiopia	74263861	1000000
Kenya	35614576	569140
Madagascar	17885967	581540
Mali	13176642	1220190
Mauritania	3047249	1030700
Mozambique	20770013	786380
Namibia	2079951	823290
Niger	12993884	1266700
Nigeria	139823340	910770
Somalia	8359859	627340
South Africa	47198469	1214470
The Sudan	38410320	2376000
Tanzania	38831024	885800
Zambia	11462365	743390

As is visible in the table, these countries fulfill the criteria of being included in the EPR dataset, which are “states with a population of at least 1 million and a surfare area of at least 500,000 square kilometers as of 2005” (Wimmer et al. 2009:325, footnote 11).

Appendix C Baseline model

Table S- 1 presents the results of the development of the baseline model. In Table S- 1, it is visible that models 2-4, 6, and 10-11 are have a significantly worse log likelihood compared to model 1. This means that the variables, which were omitted from the model these models did contribute significantly to the models log likelihood, i.e. the models explanatory power. Therefore these variables qualify to be included in the baseline model.

Capital distance

The variable capital distance is presented here, as it was tested for the baseline model but was not included in it. Distance from capital is included to control for how politically peripheral a grid cell is expected to be. Distance from capital is operationalized as distance in kilometers from the center of a grid cell to the national capital. The data were incorporated into the original version of PRIO-GRID, and have been calculated based on geographical coordinates for national capitals derived from the cShapes dataset (Weidmann et al. 2008). In this study, distance from capital is also log transformed. High distance from capital is furthermore expected to increase the risk of communal conflicts.

Table S- 1 Development of the baseline model

VARIABLES	(1) C.Events	(2) C.Events	(3) C.Events	(4) C.Events	(5) C.Events	(6) C.Events	(7) C.Events	(8) C.Events	(9) C.Events	(10) C.Events	(11) C.Events
Population (ln)	0.600***		0.589***	0.613***	0.602***	0.641***	0.510***	0.592***	0.611***	0.845***	0.611***
	(0.096)		(0.096)	(0.094)	(0.095)	(0.094)	(0.076)	(0.094)	(0.076)	(0.083)	(0.092)
IMR (ln)	-1.316***	-1.142***		-0.972***	-1.297***	-1.146***	-1.587***	-1.324***	-1.325***	-1.241***	-1.431***
	(0.294)	(0.286)		(0.259)	(0.293)	(0.295)	(0.249)	(0.296)	(0.291)	(0.260)	(0.279)
GCP PC (ln)	-0.363**	-0.372**	-0.158		-0.395**	-0.567***	-0.558***	-0.380**	-0.364**	-0.252*	-0.365**
	(0.160)	(0.153)	(0.157)		(0.159)	(0.156)	(0.134)	(0.155)	(0.160)	(0.139)	(0.154)
Regime type	-0.029	-0.036	-0.023	-0.033		-0.013	-0.003	-0.026	-0.029	-0.054**	-0.035
	(0.027)	(0.026)	(0.026)	(0.026)		(0.023)	(0.0194)	(0.026)	(0.027)	(0.024)	(0.026)
Regime type (sq)	-0.022***	-0.0270***	-0.0195***	-0.026***	-0.021***		-0.0144***	-0.0225***	-0.022***	-0.028***	-0.025***
	(0.006)	(0.005)	(0.005)	(0.0058)	(0.005)		(0.004)	(0.006)	(0.005)	(0.005)	(0.005)
Pol.marginal.	-0.121	-0.119	-0.184	-0.168	-0.057	-0.055		-0.095	-0.124	0.122	-0.091
	(0.231)	(0.225)	(0.229)	(0.228)	(0.223)	(0.234)		(0.222)	(0.230)	(0.194)	(0.221)
Cap.dist.	0.000	-0.000	8.98e-05	0.000	3.63e-05	9.77e-05	-0.000		0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
City dist.	-0.000	-0.002***	-0.000	-2.61e-05	-0.000	3.15e-05	4.24e-05	-0.000		0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Spatial lag	3.999***	4.476***	4.013***	4.029***	4.028***	4.143***	4.526***	4.008***	3.995***		4.032***
	(0.281)	(0.275)	(0.276)	(0.281)	(0.280)	(0.278)	(0.238)	(0.280)	(0.280)		(0.274)
Time lag	4.834***	5.003***	5.133***	4.944***	4.862***	5.035***	5.112***	4.818***	4.837***	4.790***	
	(0.795)	(0.811)	(0.797)	(0.799)	(0.794)	(0.789)	(0.776)	(0.793)	(0.795)	(0.760)	
Constant	1.460	8.228***	-8.757***	-3.612*	1.540	0.616	5.452**	1.767	1.352	-2.484	2.313
	(2.848)	(2.584)	(1.667)	(2.084)	(2.859)	(2.863)	(2.422)	(2.754)	(2.793)	(2.551)	(2.737)
Degr.fr.	1										
LR chi2(x)		41.50	17.53	5,34	1,17	15.76	0.28	0.17	0.04	221.93	59.90
Log likelihood	-377.332	-398.149	-392.899	-383.327	-377.917	-385.213	-565.131	-377.415	-377.352	-488.296	-407.281
Observations	4,588	4,591	4,744	4,706	4,588	4,588	7,411	4,588	4,588	4,588	4,588

Standard errors in parentheses

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

Appendix D Bivariate results

Table S-2 Bivariate results for hypotheses 1a and 2a

VARIABLES	(4) Confl.events	(5) Confl.events	(6) Confl.events	(7) Confl.events	(8) Confl.events
Temp.dev.	-0.458***			-0.456***	-0.457***
	(0.117)			(0.119)	(0.117)
Prec.dev.		0.000		0.000	
		(0.000)		(0.000)	
Drought			0.031		0.024
			(0.069)		(0.070)
Constant	-3.074***	-3.052***	-3.083***	-3.074***	-3.079***
	(0.054)	(0.053)	(0.057)	(0.054)	(0.059)
Degrees of freedom	1	1	1	2	2
LR chi2(x)	15.45	0.53	0.20	15.46	15.55
Log likelihood	-1471.2662	-1478.7241	-1507.1856	-1471.2609	-1470.6601
Observations	8,036	8,036	8,320	8,036	8,024

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table S-3 Bivariate results for hypotheses 1b and 2b

VARIABLES	(1) Confl.events	(2) Confl.events	(3) Confl.events	(4) Confl.events	(5) Confl.events
Temp.dev. t-1	-0.574***			-0.563***	-0.574***
	(0.117)			(0.119)	(0.117)
Prec.dev. t-1		0.000545		0.000230	
		(0.000414)		(0.000420)	
Drought t-1			-0.0174		-0.0198
			(0.0705)		(0.0707)
Constant	-3.044***	-3.013***	-3.027***	-3.044***	-3.036***
	(0.0558)	(0.0542)	(0.0581)	(0.0558)	(0.0602)
Degrees of freedom	1	1	1	2	2
LR chi2(x)	24.13	1.72	0.06	3.23	3.41
Log likelihood	-1436.5593	-1447.7627	-1476.4968	-1435.916	-1436.408
Observations	7,649	7,649	7,918	7,649	7,637

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table S-4 Bivariate results for hypotheses 3a and 4a

VARIABLES	(1) Confl.events	(2) Confl.events	(3) Confl.events	(4) Confl.events	(5) Confl.events
Temp.dev.	-0.580*			-0.753**	-0.580*
	(0.332)			(0.350)	(0.325)
Prec.dev.		-0.002*		-0.002**	
		(0.001)		(0.001)	
Drought			-0.731**		-0.738**
			(0.317)		(0.317)
Constant	-3.334***	-3.328***	-3.160***	-3.353***	-3.159***
	(0.146)	(0.146)	(0.149)	(0.150)	(0.151)
Degrees of freedom	1	1	1	2	2
LR chi2(x)	3.04	3.08	8.85	7.72	12.08
Log likelihood	-215.23136	-215.21124	-213.03471	-212.88833	-210.70861
Observations	1,429	1,429	1,449	1,429	1,429

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table S-5 Bivariate results for hypotheses 3b and 4b

VARIABLES	(1) Confl.events	(2) Confl.events	(3) Confl.events	(4) Confl.events	(5) Confl.events
Temp.dev. t-1	-1.299***			-1.468***	-1.304***
	(0.374)			(0.389)	(0.373)
Prec.dev. t-1		-0.001		-0.002**	
		(0.001)		(0.001)	
Drought t-1			-0.180		-0.198
			(0.181)		(0.181)
Constant	-3.309***	-3.266***	-3.192***	-3.344***	-3.229***
	(0.154)	(0.147)	(0.157)	(0.159)	(0.166)
Degrees of freedom	1	1	1	2	2
LR chi2(x)	12.58	2.67	1.09	17.68	13.91
Log likelihood	-207.18779	-212.13814	-213.64671	-204.63774	-206.52108
Observations	1,340	1,340	1,359	1,340	1,340

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E Robustness tests for the baseline model

The baseline model includes the following variables: communal conflict events (dep.var.), population per grid cell (ln), infant mortality rate per grid cell (ln), gross cell product per grid cell (ln), regime type, regime type squared, spatial lag of communal conflict, time lag of communal conflict.

The baseline model was clustered by grid cells in the robustness tests below.

<u>Pregibon's leverage:</u>

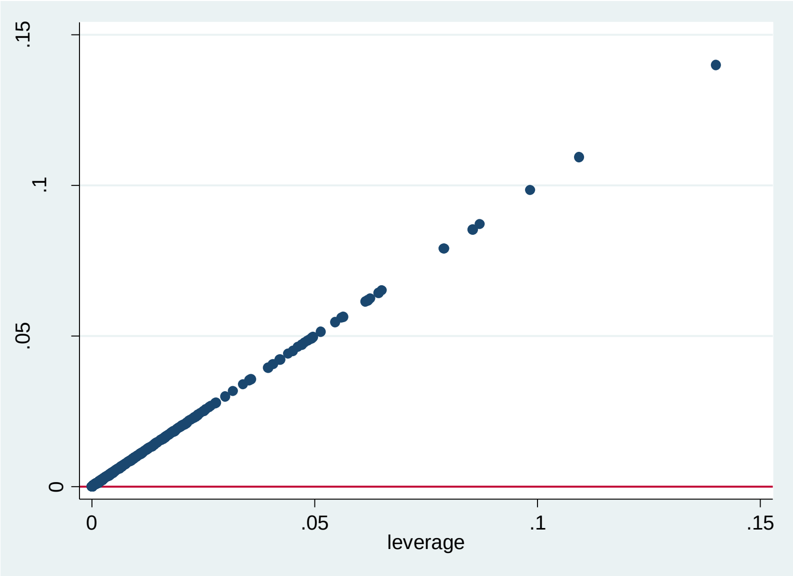

Figure S- 1 presents the results of a Pregibon's leverage test on the baseline model. Mean leverage value: 0.0014. Number of observations with leverage value >(0.0014 x 3): 395.

Pregibon’s delta-beta:

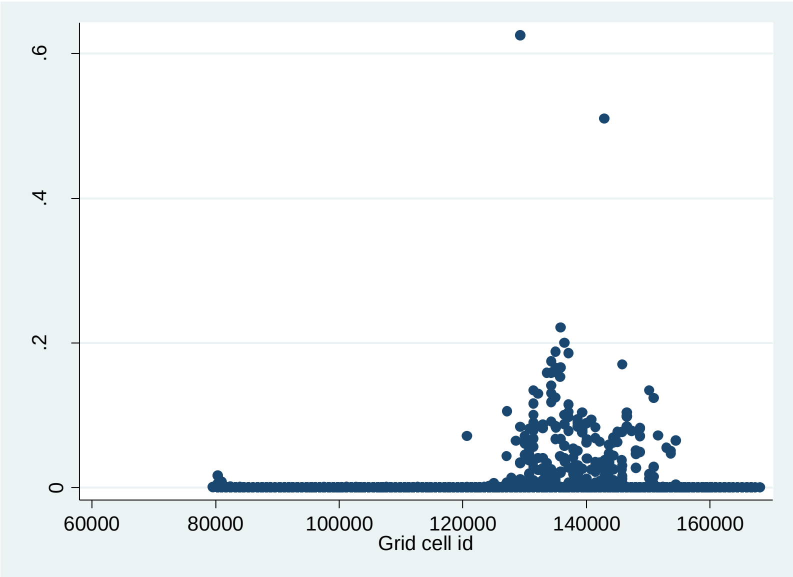

Figure S- 2 presents the results of Pregibon’s delta-beta test on the baseline model. Number of observations: 7411. Number of observations with a delta-beta value <1: 7411.

VIF-test and correlation matrix:

See Appendix F Robustness tests. The results of the VIF-tests and pairwise correlations for the baseline model are the same as the results for the baseline model -variables in the VIF-tests and pairwise correlations for the larger models (hypotheses 1-2).

Appendix F Robustness tests

Hypotheses 1a & 2a

Pregibon's delta-beta:

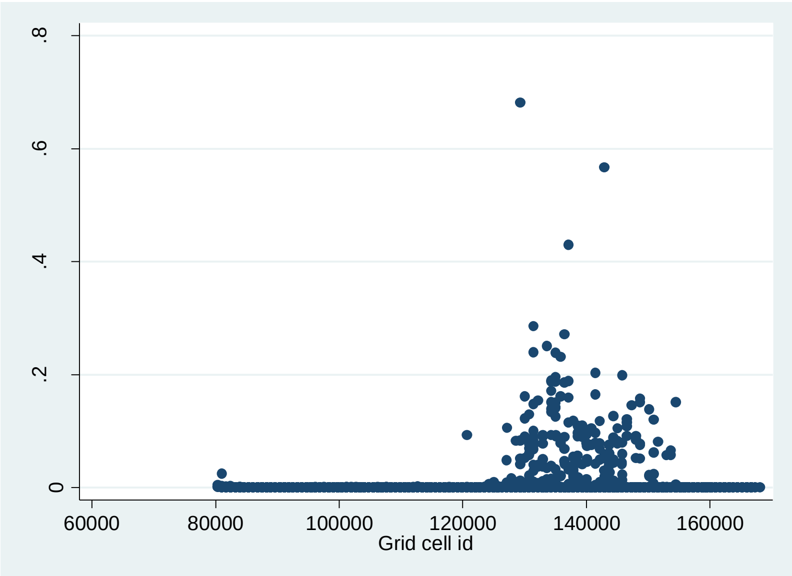

Figure S- 3 presents the results of Pregibon's delta-beta test on the variables included in the multivariate models testing hypotheses 1a and 2a. Number of observations: 7113. Number of observations with delta-beta values<1: 7113.

Pregibon's leverage:

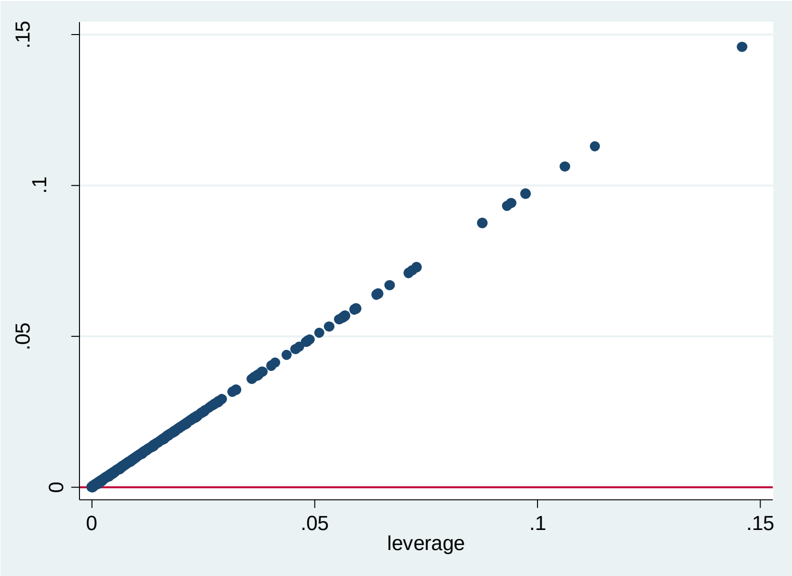

Figure S- 4 presents the results of Pregibon's leverage test on the variables included in the multivariate models testing hypotheses 1a and 2a. Mean of leverage values: 0.0019. Number of observations with leverage values >(0.0019 x 3): 390.

VIF-tests:

Table S-6 VIF-tests for variables included in hypotheses 1a and 2a.

Variable	**VIF**	**1/VIF**
Population (ln)	1.96	0.511066
City distance	1.90	0.525263
GCP PC (ln)	1.64	0.611556
IMR (ln)	1.61	0.620244
Regime type (sq)	1.33	0.751549
Regime type	1.26	0.794885
Temp.deviation	1.10	0.908025
Prec.deviation	1.08	0.929023
Political marginalization	1.07	0.932326
Drought	1.05	0.950560
Mean VIF	1.40	

Correlation matrix:

Table S-7 Correlation matrix for variables included in hypotheses 1a and 2a.

	Confl.events	Temp.dev.	Prec.dev.	Drought	Popul. (ln)	IMR (ln)	GCP PC (ln)	Regime type	Reg type (sq)	Spatial lag	Time lag
Confl.events	1.0000										
Temp.dev.	-0.0435*	1.0000									
Prec.dev.	0.0081*	-0.1504*	1.0000								
Drought	0.0050	-0.0177*	0.1731*	1.0000							
Population (ln)	0.1654*	-0.0444*	0.0001	0.0069	1.0000						
IMR (ln)	0.0126*	-0.0023	-0.0227*	-0.0124*	0.0462*	1.0000					
GCP PC (ln)	-0.0854*	-0.0388*	-0.0072	-0.0168*	-0.2797*	-0.4944*	1.0000				
Regime type	-0.0102*	-0.1618*	0.0026	0.0048	-0.0399*	-0.1951*	0.2096*	1.0000			
Regime type (sq)	-0.1196*	0.1140*	-0.0113*	-0.0357*	-0.1583*	-0.4087*	0.3117*	0.1812*	1.0000		
Spatial lag	0.5760*	-0.0465*	-0.0045	0.0027	0.1365*	0.0252*	-0.0798*	-0.0104*	-0.0977*	1.0000	
Time lag	0.3589*	-0.0278*	-0.0063	0.0152*	0.0609*	0.0136*	-0.0492*	-0.0091*	-0.0696*	0.2357*	1.0000

Hypotheses 1b & 2b

Pregibon's delta-beta: No result, because delta-beta tests cannot be conducted on time series operators (here temperature, precipitation and drought in the previous year).

Pregibon's leverage: No result, because leverage tests cannot be conducted on time series operators (here temperature, precipitation and drought in the previous year).

VIF-tests:

Table S- 8 VIF-tests for variables included in hypotheses 1b and 2b.

Variable	**VIF**	**1/VIF**
Population (ln)	1.96	0.509604
City distance	1.91	0.523005
GCP PC (ln)	1.66	0.603330
IMR (ln)	1.64	0.608907
Regime type (sq)	1.47	0.678745
Regime type	1.24	0.804607
Political marginalization	1.09	0.920957
Temp.deviation (t-1)	1.08	0.923696
Prec.deviation (t-1)	1.06	0.942792
Drought (t-1)	1.05	0.950929
Mean VIF	1.42	

Correlation matrix:

Table S- 9 Correlation matrix for variables included in hypotheses 1b and 2b.

	Confl events	Temp.dev. (t-1)	Prec.dev. (t-1)	Drought (t-1)	Popul. (ln)	IMR (ln)	GCP PC (ln)	Regime type	Reg type (sq)	Spatial lag	Time lag
Confl.events	1.0000										
Temp.dev. (t-1)	-0.0558*	1.0000									
Prec.dev. (t-1)	0.0150*	-0.1455*	1.0000								
Drought (t-1)	-0.0028	-0.0193*	0.1728*	1.0000							
Population (ln)	0.1654*	-0.0361*	-0.0016	0.0376*	1.0000						
IMR (ln)	0.0126*	-0.0319*	0.0101*	-0.0177*	0.0462*	1.0000					
GCP PC (ln)	-0.0854*	-0.0313*	-0.0146*	-0.0212*	-0.2797*	-0.4944*	1.0000				
Regime type	-0.0102*	-0.1543*	0.0136*	0.0273*	-0.0399*	-0.1951*	0.2096*	1.0000			
Regime type (sq)	-0.1196*	0.1136*	0.0003	-0.0256*	-0.1583*	-0.4087*	0.3117*	0.1812*	1.0000		
Spatial lag	0.5760*	-0.0494*	0.0201*	0.0037	0.1365*	0.0252*	-0.0798*	-0.0104*	-0.0977*	1.0000	
Time lag	0.3589*	-0.0269*	0.0016	0.0053	0.0609*	0.0136*	-0.0492*	-0.0091*	-0.0696*	0.2357*	1.0000

Hypotheses 3a & 4a

Pregibon's delta-beta:

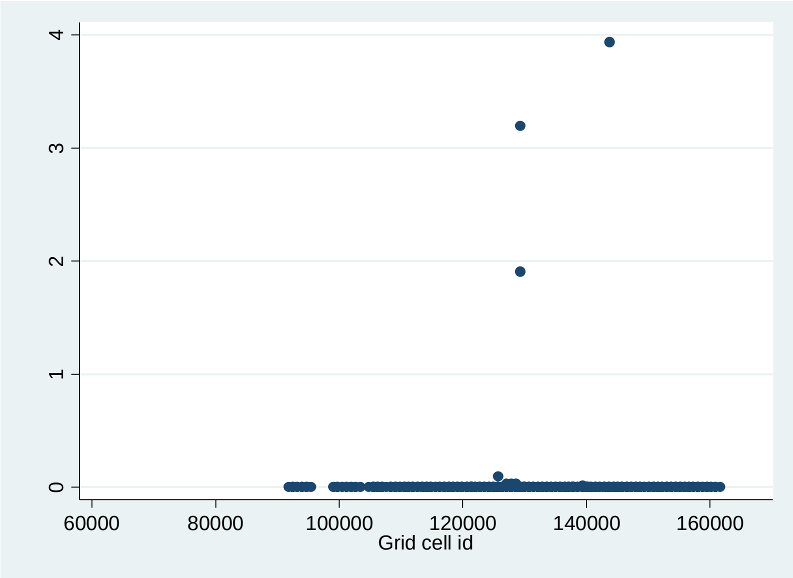

Figure S- 5 presents results of Pregibon's delta-beta test on the variables included in the multivariate models testing hypotheses 3a and 4a. Number of observations: 1179. Number of observations with delta-beta<1: 1176.

Pregibon's leverage:

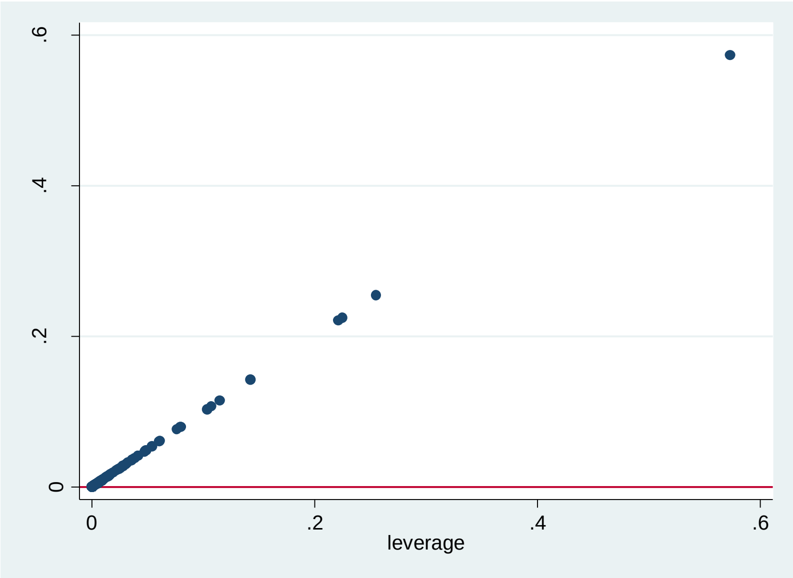

Figure S- 6 presents results of Pregibon's leverage test on the variables included in the multivariate models testing hypotheses 3a and 4a. Mean of leverage values: 0.0036. Number of observations with leverage-values >(00.36 x 3): 62.

VIF-tests:

Table S-10 VIF-tests for variables included in hypotheses 3a and 4a.

Variable	**VIF**	**1/VIF**
Spatial lag	1.89	0.529035
Time lag	1.80	0.556428
Regime type	1.47	0.681994
Regime type (sq)	1.45	0.688544
GCP PC (ln)	1.41	0.710792
IMR (ln)	1.28	0.781744
Population (ln)	1.17	0.856374
Temperature deviation	1.12	0.889859
Precipitation deviation	1.09	0.920454
Drought	1.06	0.943502
Mean VIF	**1.37**	

Correlation matrix:

Table S- 11 Correlation matrix for variables included in hypotheses 3a and 4a.

	Confl events	Temp.dev.	Prec.dev.	Drought	Popul. (ln)	IMR (ln)	GCP PC (ln)	Regime type	Regime type (sq)	Spatial lag	Time lag
Confl.events	1.0000										
Temp.dev.	-0.0462*	1.0000									
Prec.dev.	-0.0463*	-0.1856*	1.0000								
Drought	-0.0668*	-0.0325*	0.1783*	1.0000							
Population (ln)	0.2442*	-0.0402*	0.0111	0.0438*	1.0000						
IMR (ln)	-0.1042*	-0.0185	0.0262*	0.0914*	0.0115	1.0000					
GCP PC (ln)	-0.1538*	-0.0835*	-0.0378*	-0.0747*	-0.2676*	0.3869*	1.0000				
Regime type	0.0778*	-0.1984*	0.0780*	0.0474*	-0.0261*	-0.0062	-0.1593*	1.0000			
Regime type (sq)	-0.1022*	0.1454*	-0.0521*	-0.0860*	-0.0231*	-0.1007*	0.1476*	-0.5919*	1.0000		
Spatial lag	0.7853*	-0.0487*	-0.0384*	-0.0552*	0.2381*	-0.1007*	-0.1513*	0.0732*	-0.0987*	1.0000	
Time lag	0.4838*	-0.0244*	-0.0731*	-0.0271*	0.1424*	-0.0574*	-0.1233*	0.0726*	-0.0830*	0.5053*	1.0000

Hypotheses 3b & 4b

Pregibon's delta-beta: No result, because delta-beta tests cannot be conducted on time series operators (here temperature, precipitation and drought in the previous year).

Pregibon's leverage: No result, because leverage tests cannot be conducted on time series operators (here temperature, precipitation and drought in the previous year).

VIF-tests:

Table S- 12 VIF-test for variables included in hypotheses 3b and 4b.

Variable	VIF	1/VIF
Spatial lag	1.90	0.525399
Time lag	1.80	0.555756
GCP PC (ln)	1.44	0.693909
IMR (ln)	1.29	0.774237
Regime type (sq)	1.27	0.789471
Regime type	1.21	0.825225
Population (ln)	1.18	0.845096
Temperature deviation (t-1)	1.12	0.895243
Precipitation deviation (t-1)	1.07	0.936497
Drought (t-1)	1.06	0.946179
Mean VIF	**1.33**	

Correlation matrix:

Table S- 13 Correlation matrix for variables included in hypotheses 3b and 4b.

	Confl.events	Temp.dev.	Prec.dev.	Drought	Popul. (ln)	IMR (ln)	GCP PC (ln)	Regime type	Regime type (sq)	Spatial lag	Time lag
Confl.events	1.0000										
Temp.dev. (t-1)	-0.0952*	1.0000									
Prec.dev. (t-1)	-0.0429*	-0.1375*	1.0000								
Drought (t-1)	-0.0272*	-0.0329*	0.1474*	1.0000							
Population (ln)	0.2442*	-0.0414*	0.0206*	0.0773*	1.0000						
IMR (ln)	-0.1042*	-0.0714*	0.0416*	0.0518*	0.0115	1.0000					
GCP PC (ln)	-0.1538*	-0.0952*	-0.0011	-0.1072*	-0.2676*	0.3869*	1.0000				
Regime type	0.0778*	-0.1726*	0.0663*	0.1153*	-0.0261*	-0.0062	-0.1593*	1.0000			
Regime type (sq)	-0.1022*	0.1601*	0.0245*	-0.1327*	-0.0231*	-0.1007*	0.1476*	-0.5919*	1.0000		
Spatial lag	0.7853*	-0.1109*	-0.0428*	-0.0200*	0.2381*	-0.1007*	-0.1513*	0.0732*	-0.0987*	1.0000	
Time lag	0.4838*	-0.0733*	-0.0689*	-0.0243*	0.1424*	-0.0574*	-0.1233*	0.0726*	-0.0830*	0.5053*	1.0000