Come Hell or High Water: An Analysis of the Impact of State Vulnerability and State Capacity on the Relationship between Climate Change and Terrorism

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An Analysis of the Impact of State Vulnerability and State Capacity on the Relationship between Climate Change and Terrorism

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Table of Contents

1. Abstract

The connection between climate change and violent conflict has received increasing attention, as climate change has made it to the forefront of public debates. With more and more climate hotspots worldwide, that not only experience the pressure from rising temperatures or changes in rainfall patterns, but also increasing levels of violence, it is not a far stretch to assume climate change and conflict might somehow be related. However, there is one specific form of violence that has received less attention in this context: terrorism. Because of that, this thesis tests the relationship between climate change – in the form of rainfall deviation – and terrorism. However, as this relationship is not expected to exist within a vacuum, there is a specific focus on whether state vulnerability, as well as state capacity have an impact on this relationship. The focus of this study are the countries on the African continent within the time frame from 1991 to 2008. The results of this study cannot prove that the assumed relationship between rainfall deviation and terrorism, moderated by state capacity and state vulnerability, exists. However, by looking at the relationship more closely, certain inspirations for future research can be found, as there is a need for research on a larger scale that allows to include more regions of the world.

2. Introduction

2.1. Research Interest and Research Question

Current international debate often circles around two topics: climate change and conflict. While the topic of conflict has been there since people have been on this earth, climate change has entered the centre stage of international political interest at a later point. As this topic is so broad in its consequences, policy makers around the world have to formulate their own corresponding approach on this issue. The impacts of climate change, however, can most intensely already be felt in the so-called climate hotspots of the world and these impacts are manifold (Fan et al. 2021; Giorgi 2006). From the question of existence for island states that have to fight sea level rises, to resource scarcity that stems from a lack of rainfall and to rising temperature that make certain regions in the world uninhabitable in the near future. Climate change will come with a lot of disadvantages and challenges for many people and governments.

However, in many regions of the world that experience climate change very harshly, another component makes mitigating the impact of it even more difficult: violent conflict. An example for a region that experiences both these factors at the same time can be found in the Sahel zone, as it is not only a climate hotspot but also experiences multiple conflict and conflict-involved actors at the same time (Raineri 2020). This begs the question: is it a coincidence that some regions in the world experience these two phenomena at the same time or is there an interaction between the two (Giorgi 2006; Fan et al. 2021)?

While many researchers have tried to link the two in a causal way, the mechanism is not quite as clear, making the relationship between the two far from being deterministic (van Baalen and Mobjörk 2018; Raineri 2020).

The relationship observed can be defined as an indirect one, meaning that climate change is hardly ever the reason for conflict but rather the trigger which leads to intensification of underlying grievances, and in some cases, the transformation from conflict into its violent form.

By oversimplifying this relationship, it can seem as if the two are directly related. What misses the eye, however, are the broader contexts in which this relationship plays out. Otherwise, how would we explain that in some regions climate change has even led to more cooperation within communities, as resources got scarcer and people were more dependent on each other (van Baalen and Mobjörk 2018). This is to show, that it always comes to the people taking agency over the situation they are currently in. And more so, the various context factors that make each case of the assumed climate change-conflict nexus different from the next. Especially the socioeconomic, demographic and political insecurities a region experiences at the time are decisive for a country's adaptive capability (Adano et al. 2012; Koubi 2019).

One example of this can be the economic development of a country. Depending on the development phase a country is in, climate change might has a different impact on the country's coping mechanism and therefore whether a conflict might break out into violence (Koubi 2019). While many outside factors can play a role in how a society adapts to climate change, it is ultimately up to the people that have agency (van Baalen and Mobjörk 2018) .

The focus of this research project will, indeed be along the lines of climate change increasing the risk for violent conflict. What is important to point out, however, is that the two are mutually reinforcing. This means that also violent conflict can further the consequences of climate change (van Baalen and Mobjörk 2018). This may, on the one hand, be by governments not being able to focus their resources towards adapting to and coping with climate change, as they are too occupied dealing with a violent conflict. On the other hand, the fact that violent conflicts also use large amounts of resources, in many instances fossil fuels, can in turn lead to further environmental degradation (Adano et al. 2012).

2.2. Defining Terrorism

There is a lot of research around the connection between climate change and violent conflict. However, what is researched not quite as extensively as the outcome of this relationship is another form of political violence: terrorism.

Not only does climate change interact with all sorts of conflicts that might deteriorate into their violent form but it also often opens up the space for terrorist actors to exploit the vulnerability caused by climate change. There are different mechanisms through which climate change correlates with terrorism but to be able to focus on them, a definition of terrorism has to be established. The search for a definition, however, is complicated. The struggle of how to define terrorism more precisely within academia mirrors the political struggle of agreeing on a definition (Saul 2019). As any terrorism definition is politically charged, the international community has yet to come to an agreement on a common definition. As of now, it is still largely up to the national states to define terrorism within their national legislations (Ramsbotham, Woodhouse, and Hugh 2012; Saul 2019).

Within this research project, terrorism is defined as the use of violence to intimidate a large group of people, beyond the immediately targeted, in the pursuit of a political motive (de la Calle and Sánchez-Cuenca 2011; Kalyvas 2019). The groups associated with terrorism mostly have no territorial control and military capacities (Tilly 2004; de la Calle and Sánchez-Cuenca 2011; Asal et al. 2012). But as specifically Tilly points out, “no useful generalization covers all the different sorts of political interaction for which observers, analysts, and participants sometimes use the term terror, much less for terrorists and terrorism” (2004).

2.3. Structure of the Thesis

After first giving an overview over the main trends within the research on climate change and conflict more broadly, but specifically climate change’s interaction with terrorism, the theoretical framework will be established. The latter allows not only to consider terrorism with its own specifics within the study of climate change but also digs deeper into what moderates this relationship. As already pointed out, the relationship between climate change and political violence is influenced by their contextual factors. This study’s focus will, therefore, be on the moderating effect state vulnerability, as well as state capacity, can have on mitigating climate change’s effect on terrorism. After establishing this relationship, I will go on to describe the way this conceptual framework will be measured and will lay out my research design. Firstly, the main concepts of this research will be operationalised in a way that allows to measure them and eventually run a panel regression on these indicators. Following up on this part will be the description of the chosen research method which is a negative binominal panel regression and the rationale why this research method is considered appropriate for this specific research project. After explaining the research method and the descriptive statistics, the actual analysis will follow with five different regressions run, accounting for the independent and dependent variable, the control variables, as well as the two interaction effects lined out in the literature review: state capacity and state vulnerability. After a discussion of the results follows up on this, the final part discusses the limitations of the research project, as well as pointing out areas for future research, ending in a conclusion to be able to answer the research question:

1. *What is the impact of climate change on terrorism?*
    - 1.1. *What is the impact of climate change on terrorism moderated by state capacity?*
    - 1.2. *What is the impact of climate change on terrorism moderated by state vulnerability?*

2. Literature Review: Different Perspectives on Climate Change and Violent Conflict

While there are many ways to conceptualise the current state of research on the topic, I found two streams within the literature particularly important for this research project: one arguing that climate change can threaten the livelihood of people who would therefore have to fight for their survival. This one can be summarized as the **resource scarcity perspective**. The other one focusing on the tactical considerations taken into account by armed actors. While less obvious, this perspective focusses on the aspect that armed actors can thrive in an environment of insecurity. This means that if climate change puts extra stress on a region and its governing bodies, the attention foremost goes to adapting to climate change and there might be less attention as to how armed actors might exploit the situation. The second one will be considered as the **tactical considerations perspective**.

Geographically, the literature analysing the relationship primarily focusses on East Africa and the Sahel zone, where these phenomena can be observed at the same time (E.g. Nett and Rüttinger 2016; Rüttinger et al. 2015; Brown 2020; Raineri 2020; Hendrix 2014; Hissler 2010). While this allows for a more thorough analysis of the relationship, it is important to point out that the scopes of these studies make them somewhat biased, as they are specifically focusing on a region where they expect a correlation to begin with (Brown 2020; Sakaguchi, Varughese, and Auld 2017; van Baalen and Mobjörk 2018).

2.1. Defining the Resource Scarcity Perspective

The mechanism behind the resource scarcity perspective seems very straight forward. Climate change's impacts, such as droughts or heavy rainfall, lead to a decrease in resources that communities will have to share between them (Koubi 2019). This, for example, can be seen in the herder-farmer conflict in Northern Nigeria, where the fertile land for herders decreases, forcing them to move closer to the farmers' communities, who also have to deal with the aspect of less arable land. Now these two communities not only have to deal with the impacts of climate change, but they have to share their limited resources with a community that is different than theirs and have to find an answer to the question of who deserves the land (Olagunju et al. 2021; Hendrix 2014).

This is where the importance of conflict-solving mechanisms comes in. Resource scarcity has also been seen to bring communities closer together, as they collectively realise that only cooperation will solve this crisis and that violent conflict would additionally drain their already limited capacities. This, however, is only possibly if there are mechanisms in place that allow for a community to find the potential of cooperation, may this be in the form of local institutions that allow for a constructive form of conflict resolution or government regulated distribution mechanisms (Adano et al. 2012).

There are many more examples like this as these cleavages can also take place within communities and in some cases even lead to rising tension that stem from grievances that are much older than tangible impacts of climate change. What this illustrates, however, is that climate change is rarely the underlying reason for a conflict but rather a trigger turning underlying grievances into a form of violence (Asaka 2021).

Furthermore, the resource scarcity might not only lead to violence that might break out between or within different communities and re-activate long-forgotten grievances but it can also be exploited by armed actors that use the resources as weapons of war and use them to extort governments by targeting the population (Nett and Rüttinger 2016).

It is easy to mistake the resource scarcity perspective for only looking at the physiological aspects of climate change, such as land degradation, and the mere fight about who gets to survive on the scarce resources. What leads to violent conflict, however, is how these resources are distributed, who benefits from a lack of them and whether or not there is a legitimate conflict-solving mechanism in place. While not sounding like it, this perspective very much focusses on the social aspect behind the mere question of resources.

2.2. Defining the Tactical Considerations Perspective

The tactical considerations' perspective focusses less on violent conflict breaking out between different communities in a context of extreme pressure to secure their own survival but takes a look at how armed actors of any kind might exploit the physiological aspects of climate change. Through climate change's physiological aspects, there might even be new opportunities that armed actors can exploit. Climate change might thereby not only influence the beginning of a conflict but also the dynamics of a conflict later on (Selby 2014; Adano et al. 2012; Seter 2016; van Baalen and Mobjörk 2018).

One example of this can be the change of vegetation as a consequence of climate change (Gawande, Kapur, and Satyanath 2017). This allows armed actors to move more overtly and to avoid operating in plain sight. Climate change can also have an influence on the infrastructure within a region, making it more difficult for armed actors[1] to command over the territory (Miguel, Satyanath, and Sergenti 2004). However, these tactical considerations highly depend on the nature of the armed actor, as well as the specific kind of climate change impact experienced.

However, the tactical considerations of armed actors go beyond the immediate physiological effects of climate change. Competition, as a result of climate change induced resource scarcity can actually lead to an increase of violence, as armed groups ensure their own access to resources, while local populations increase their efforts to keep the resources to themselves (Bagozzi, Koren, and Mukherjee 2017). The exploitation of an especially vulnerable society can also be seen in the fact that recruitment efforts by armed actors increase in times of extreme suffering from climate change(de la Calle and Sánchez-Cuenca 2011). Local populations may not only depend on the armed actors as a consequence of their resource access but individuals can actually benefit from superior roles in getting access to these resources by being recruited by armed actors. These mechanisms are especially prevalent in areas that heavily rely on agriculture as their main source of income (Vanden Eynde 2018). It comes to show that armed actors can easily profit from changing weather circumstances but that also heavily depends on the kind of armed actor at play.

But even these two strong links, along the lines of resource scarcity or the tactical considerations of armed actors, are often more indirect. Resource scarcity, for example, does not necessarily always lead to conflict in the region that experiences the impacts of climate change. These impacts, however, can force communities to leave their place of residence, as resources get scarcer, leading them to migrate to other more fertile areas. This holds especially for communities depending on agriculture. It, however, increases the stress on the intaking community that now has to share their often limited resources. This increased stress can lead to inter-community tensions that might eventually find their escalation in violent conflict (Olagunju et al. 2021). A similar mechanism can be found in the migration to cities, which are increasingly becoming centres of violent conflict as a result of the close proximity of different

[1] In this context, the term armed actors is used to describe any group of people that uses force to implement their will, these can be governmental, as well as non-governmental groups.

communities and the additional strain on urban infrastructure (van Baalen and Mobjörk 2018; von Uexkull and Buhaug 2021).

2.3. Specific Form of Climate Change: Changes in Rainfall Patterns

The kind of climate change impacts that leads to political violence depends heavily on the coping mechanism of the community and the armed actors involved. It does, however, also depend on the kind of climate change impact a community experiences and how this plays into the considerations of armed actors.

Rainfall deviations is one of the primary methods of measuring climate change. That rainfall – and particularly rainfall deviations which account for wetter and drier years – features prominently in the literature can be explained by the fact that climate change is particularly harsh on communities that depend heavily on rain-fed agriculture (Raleigh and Kniveton 2012). If rainfall deviates strongly, it thereby has a direct impact on these communities. However, the kind of deviation – meaning are wetter or drier years more relevant in this relationship – that stands in relationship with an increase of violence is contested. This can be explained along the lines of resource scarcity caused by climate change or through tactical considerations undertaken by armed actors because of changing climatic conditions. Precipitation levels are an ideal measurement of climate change's impact, as these two strands of research are mirrored in the study of precipitation (Hendrix and Salehyan 2012).

The resource scarcity perspective can be applied especially to extremely dry years, as less arable land leads to a decrease in agricultural production and an increased competition not only over the resources but also the land that can eventually turn into fighting (Olagunju et al. 2021). Dry years have therefore been found to have a correlation with an increase in violence, however, not only because of the scarce resources. Dry years can also be considered an advantage for armed actors that can, along the lines of the tactical consideration's perspective, move more easily in a receding vegetation, making the logistics of violent conflict much easier (van Baalen and Mobjörk 2018). And of course, allowing armed actors to monopolise on already scarce resources, not only making communities dependent on them but also increasing recruiting efforts by exploiting people's desperation.

Wetter years, as would be in line with the resource scarcity perspective, should therefore lead to a decrease in fighting. This, however, is far from being a given. In fact, an overabundance of resources might actually increase fighting (Adano et al. 2012). As opposed to dry seasons, where communities can also come to the realisation that the hardship of resource scarcity is too much of a burden to put additional strains on the people and get involved in fighting, wetter years decrease the need for cooperation (Theisen 2012). Wetter years can also be advantageous for armed actors and their tactical considerations, as wetter years lead to richer vegetation, which perform as ideal hiding spots for armed actors (van Baalen and Mobjörk 2018).

What has not been considered so far is the occurrence of unusual climatic events altogether, not just on the level of yearly deviations. The study of climate variability allows to look at the occurrence of droughts and floods, which again, have a different impact on the outbreak or maintenance of violent conflict. They can lead to a more short-term reaction to the given climatic conditions, that can in turn develop their very own dynamics in human agency (Seter 2016; Theisen 2012; Raleigh and Kniveton 2012).

All this is to show that rainfall deviations matter for the study of violent conflict. However, whether these are positive or negative deviations from the average precipitation is not quite as clear, as both, unusually high, as well as unusually low levels of precipitation have shown to correlate with violent conflict (Hendrix and Salehyan 2012). The focus of this research will therefore not be whether the deviation from the average amount of rainfall is positive or negative but rather whether there is a deviation at all.

2.4. Specific Form of Violent Conflict: Terrorism

While rainfall deviation can explain an increase in violent conflict, its impact highly depends on the kind of actor that acts upon it, as different actors involved in the conflict will make different use of different environmental circumstances. A close look at the actors involved in violent conflict is therefore needed.

In all of the previously cited studies, the measured outcome was some form of violent conflict. Often in form of civil war in countries in Africa, but also civil unrest more generally, violent protests or violence between specific communities, such as the herder-farmer violence in Nigeria. What has not been taken into consideration in this review so far, or at least only as an afterthought, is the connection between climate change and one particular form of violent conflict: terrorism. Terrorism can have the same motivations and even the same triggers as violent conflicts, such as civil war. What is different though, are the resources needed to undertake it. Terrorism is simply cheaper (Findley and Young 2011).

In contrast to the relationship between climate change and violent conflict more broadly, political violence in the form of terrorism can be employed time-efficiently by adapting the employed strategy. This means that terrorist actors can quickly react to changing weather circumstances and might be able to change their strategies much faster than can be accounted for by a yearly analysis (Findley and Young 2012).

There is, however, an understanding that terrorism can be conceptualized in two ways: the actor and the action sense. The actor sense assumes that there are certain armed actors, that operate in clandestinity and without any form of territorial control, and can be defined by these two attributes. Therefore, when these armed actors – defined as terrorists – participate in violence, it can be defined as terrorism (Tilly 2004; Ramsbotham, Woodhouse, and Hugh 2012).

The more prominent one – the action sense – assumes that many different groups can deploy the strategy of terrorism, which is a special form of violence that compensates for its lack of military capacities, which, for example, governments usually have at their disposal. The groups, that deploy terrorism, however, are not terrorists themselves but have merely chosen the strategy of terrorism. According to this definition, all sorts of different actors can choose to adopt this strategy – individuals, groups, movements and in some cases even governments – if it furthers their political motives but they might as well depart from it soon after (de la Calle and Sánchez-Cuenca 2011).

If terrorism is defined as a strategy deployed by various actors in their attempt to further their own motives, it is not much of a stretch to assume that terrorism does not take place within a political vacuum.

2.5. Terrorism & Rainfall

From the tactical considerations' perspective, it becomes very clear why the study of terrorism as correlated with climate change is important. If terrorism is defined as a strategy, rainfall deviations of course have an impact on how this strategy is being adapted to the realities on the ground.

There are three main mechanisms in which climate change – and specifically rainfall deviations – work towards enabling terrorist activities: Firstly, through the concept of fragility. This means that climate change stresses a political system and can exaggerate existing tensions. If the stress on the political system becomes too much and the government loses effective control over its citizens and territory, the state enters a period of fragility. This fragility makes it easier for terrorist organizations to operate if there is a lack of a monopoly of force by the state (Rüttinger et al. 2015). This clearly means that the strategy of terrorism is mainly influenced by whether the state at large is capable of adapting to the impacts of rainfall deviation.

Accordingly, an increase in terrorist attacks, as a result of rainfall deviation, is often expected in an already fragile state that can be easily exploited by terrorist actors. This becomes especially true for countries that heavily on agriculture as a mean of income and employment. They might thereby be especially vulnerable for this mechanism to take place, as the state would have to step in to compensate for the loss in agricultural production. If that is not the case, resource scarcity and human suffering can be the result of it (Gawande, Kapur, and Satyanath 2017).

The second mechanism consists in creating vulnerabilities and exploiting them more directly. As the resource scarcity threatens the livelihood of many people – and the state is not capable of securing their livelihoods – it makes them more vulnerable to recruitment by terrorist groups. This not only further undermines the state but indeed leads to the growth of terrorist organisations. In a way, this mechanism resembles the connection of both the resource scarcity perspective, as well as the tactical consideration perspective (Homer-Dixon 1994; van Baalen and Mobjörk 2018).

The last mechanism through which climate change can exacerbate the playing field for terrorist organizations is again by increasing resource scarcity(Rüttinger et al. 2015). From the tactical considerations' perspective, resource scarcity is indeed an ideal component. As more people suffer from resource scarcity, they might not only be more likely to join terrorist networks, but terrorist actors can increase their influence by making resources even scarcer. Using resources as weapons of war creates a vicious cycle by which terrorist organisations become more powerful while the population that suffers becomes more vulnerable, more likely to join them, more likely also to demand help from a state, that might not be able to provide just that (Nett and Rüttinger 2016; Rüttinger et al. 2015).

All this is to show that these three mechanisms are also all related to each other. Also the resource scarcity and the tactical considerations' perspective often go hand in hand if terrorist actors decide to exploit an already straining situation (Nett and Rüttinger 2016; Asaka 2021).

While these specific mechanisms will not be the main focus of this particular research, they show the importance of making the specific connection between climate change and terrorism . This becomes even more valid as certain environmental circumstances inspire certain kinds of violence (Theisen 2012). With precipitation levels diverging from their mean, small conflicts and terrorist attacks become more likely. This can be partly explained by the fact that terrorist actors have a different physical interaction with their environment as opposed to, for example, military troops. They differ in the "mobility of their forces and material" and the fact that they are less symmetrically structured can be of advantage. They can be deployed more time-efficiently and can often navigate their way even in areas that have become inaccessible for most other military tactics (van Baalen and Mobjörk 2018, 561; Raleigh and Kniveton 2012).

2.6. Mitigating Factors: State Vulnerability & State Capacity

While the literature shows that there is in fact a correlation between climate change and violent conflict and, more precisely, between precipitation and terrorism, there is an overall understanding that these two phenomena do not interact without contextual factors. As climate change has been established as a threat multiplier in many instances, it has also become clear that the biggest risk for climate change to aggravate already pre-existing tensions exists in cases of weak states. It is, therefore, important to consider the climate change-conflict nexus within its political context (Rüttinger et al. 2015; Adano et al. 2012).

As many studies have a limited geographic scope, sometimes focusing only on one state and one conflict in particular, the question remains why some regions are better at handling impacts from climate change, esp. deviations in rainfall, than others.

First of all, countries are exposed differently to the impact of changing rainfall patterns. As already pointed out, climate change and the resulting deviation in rainfall, in some cases leading to droughts or floods, and potential loss of arable land is particularly fatal in societies that primarily depend on agriculture. Strong deviations in rainfall levels are more likely felt immediately in agricultural dependent than in, for example, manufacturing dependent countries. Accordingly, the fact that some states apparently handle climate change better than others, is gravely influenced by how vulnerable a state is to the impacts of climate change in the first place (Scheffran et al. 2012; Jasparro and Taylor 2008; van Baalen and Mobjörk 2018).

This is especially important as the same factors that make communities vulnerable to climate change, can make them vulnerable to terrorism. As previously pointed out, dependency on agriculture can not only make rainfall deviations more noticeable in terms of crop failure but can also be used by terrorist actors through turning these very natural resources into weapons of war.

Looking at these particularly vulnerable countries, it becomes clear that a strong state with hight state capacity is needed to compensate for the eventual losses that rainfall deviation may bring. This also reflects the fragility mechanism portrayed above. The ability to adapt to changing circumstances and mitigating the effects of climate change are extremely important to avoid that terrorist groups can exploit the situation and make an already fragile context even more fragile. State capacity in this context means a state's ability to govern its people and to minimize insecurities within the state, as terrorist actors thrive in insecurity.

All this is to show that rainfall deviation and terrorism can interact very differently in different contexts. First of all, not all states are equally vulnerable to climate change, depending on the importance of agriculture as a means of income for large parts of the population. And second of all, even if a state is particularly vulnerable, it highly depends on the people in power and their capacity whether they can compensate for the losses in agricultural earnings. Only if these two conditions are being taken into consideration, and furthermore, if indeed a country is both vulnerable and its government lacks capacity, can the relationship between rainfall deviation and terrorism play out as expected through one of the three mechanisms.

2.7. Framework and Hypotheses

After carefully considering the existing literature, a lack of research that focusses precisely on the relationship between rainfall deviation and terrorist attacks, moderated by state vulnerability and state capacity can be identified. This research project attempts to fill this gap by focusing on this specific relationship and its interacting factors. However, as the literature on the impact of rainfall deviations is divided, it is important to account for both wetter and drier years, meaning any kind of rainfall deviation from the average will be considered. Accordingly, the following hypotheses will be tested:

Hypothesis 1: The impact of climate change – as measured through rainfall deviation – leads to an increase in terrorist attacks.

H0	Rainfall deviation does not lead to an increase in the number of terrorist attacks.	$\beta = 0$
H1	Rainfall deviation does lead to an increase in the number of terrorist attacks.	$\beta \neq 0$

Hypothesis 2a: The impact of climate change – as measured through rainfall deviation – leads to an increase in terrorist attacks only in countries which are vulnerable.

H0	Rainfall deviation does not lead to an increase in the number of terrorist attacks in countries which are vulnerable.	$\beta = 0$
H1	Rainfall deviation does lead to an increase in the number of terrorist attacks in countries which are vulnerable.	$\beta \neq 0$

Hypothesis 2b: The impact of climate change – as measured through rainfall deviation – leads to an increase in terrorist attacks only in countries which lack state capacity.

H0	Rainfall deviation does not lead to an increase in the number of terrorist attacks in countries which lack state capacity.	$\beta = 0$
H1	Rainfall deviation does lead to an increase in the number of terrorist attacks in countries which lack state capacity.	$\beta \neq 0$

3. Research Design

3.1. Dataset

As already alluded to, in this analysis, climate change will be measured through one of its key variables: rainfall, or more precisely, rainfall deviation. As this research project sets out to do a quantitative analysis of the relationship between rainfall and terrorism, there was a need for a comprehensive dataset that would also be able to take factors outside of this relationship into account. The dataset used for this analysis has been merged out of seven individual datasets: The World Bank Data on the percentage of people employed in the agricultural sector, World Bank Data on the number of youth unemployment and World Bank Data on the GDP per capita (constant 2015 US$), Polity5: Political Regime Characteristics and Transitions Dataset, the Democracy Matrix Dataset, the State Capacity Dataset, the Global Terrorism Database and finally the Hendrix & Salehyan Dataset on precipitation in Africa (World Bank 2022a; 2022c; 2022b; Marshall and Gurr 2020; Lauth and Schlenkrich 2021; Hanson and Sigman 2021; National Consortium for the Study of Terrorism and Responses to Terrorism (START) 2021; Hendrix and Salehyan 2012). Merging different datasets was particularly important to be able to consider control variables. Which variables exactly are of interest will be described later on.

The dataset by Hendrix and Salehyian served as a model for this paper, as they analysed the impact rainfall levels have on the onset of civil wars in Africa, which is why I decided to replicate their analysis with the dependent variable of *Terrorist Attacks* instead of civil war, which is what they had chosen as their dependent variable (2012). Their dataset, however, does not include all of the African countries, which is why this analysis is equally restricted to only 46 of the 54 African states: Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Democratic Republic of the Congo, Egypt, Eritrea, Ethiopia[2], Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Republic of the Congo, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Tanzania, Togo, Tunisia, Uganda, Zambia and Zimbabwe[3].

The time frame of a study on climate change is a very important factor. As research that previously studied this relationship has already pointed out: the time frame has to be able to account for the kind of climate change impacts that are supposed to lead to an increase in a certain kind of violence (van Baalen and Mobjörk 2018; von Uexkull and Buhaug 2021). In this research project, however, the time frame had to be adopted to the data that was at hand. As I am using the Hendrix & Salehyan dataset, their time frame is my main constraint, as they capture data from 1990 till 2008. However, as the data for the control variable *Youth Unemployment*, as well as for the interaction variable *Agriculture Dependency* was only available from 1991 onwards, the time frame has been adapted to account for data from 1991 till 2008.

3.2. Choice and Operationalisation of the Variables

As previously displayed in the literature review, the relationship between rainfall deviation and terrorism is assumed to be moderated by a number of factors. Therefore, not only the dependent

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[2] For Ethiopia, there were two values present for the year 1993, as this was the year Eritrea gained independence from Ethiopia. As this separation, however, took place in April of that year, the data that has been taken into consideration was the later one that only accounted for Ethiopia after Eritrea's independence.

[3] Because of a lack of data for Swaziland in any other dataset than the Hendrix & Salehyan one, this country is also excluded from the analysis.

and independent variable but also the control variables and the variables chosen for the interaction effects will be introduced here.

3.2.1. Dependent Variable: Terrorism

The dependent variables for this analysis is the number of terrorist attacks committed within a year per country: *Terrorist Attacks*. To be able to account for them, the needed data was gained from the Global Terrorism Dataset, which currently provides the most comprehensive data on terrorist attacks worldwide (de la Calle and Sánchez-Cuenca 2011; National Consortium for the Study of Terrorism and Responses to Terrorism (START) 2021).

As one difficulty, however, the dataset does not contain any data for the year 1993 because the collection for that specific year was lost in the process (National Consortium for the Study of Terrorism and Responses to Terrorism (START) 2021). The researchers behind the project did, however, managed to assemble data for some of the countries in a separate dataset that only contains values for 1993, which I merged with the original one. However, as there is quite a high number of missing values within the year 1993, there will be robustness checks later one to be able to determine whether this year potentially has an influence on the regression outcomes. The Global Terrorism Database has one generalized measurement of all terrorist attacks committed within a country-year, which does not differentiate between the different kinds of terrorism that were deployed, which is the measurement I will be using in this analysis, as I want to be able to test my hypotheses on the total number of terrorist attacks, instead of according to certain kinds, such as domestic or transnational terrorism. *Terrorist Attacks* is a count variable and, as will be described in more detail later on in the descriptive statistics, the maximum amount of terrorist attacks a country experienced per year were 344 (National Consortium for the Study of Terrorism and Responses to Terrorism (START) 2021).

3.2.2. Independent Variable: Rainfall Deviation

The independent variable in this research project is how much the yearly rainfall deviates from the mean: *Rainfall Deviation*. As one measurement of the impact of climate change, *Rainfall Deviation* can account for both wetter and drier years, as both have been correlated to an increase in the number of terrorist attacks, as previous studies show (Raleigh and Kniveton 2012; Theisen 2012; Koubi 2019).

The variable is operationalised to account for changes of the level of rainfall from the average. As this variable has been imported from the dataset provided by Hendrix and Salehyan, their operationalisation has been adopted as well. To be able to provide a comprehensive average, they not only took the average of the years analysed in their specific study (1990-2009) but chose the average of the time period of 1979-2008, as the increased number of observations allowed them to reduce the number of outliers that might affect the average deviation of rainfall (Hendrix and Salehyan 2012). This measurement allows to look at the irregularities that might stand in a correlation with the number of terrorist attacks committed per year-country. The deviation is hereby measured in Millimetre.

3.2.3. Independent Variable for Interaction Effect I: Employment Agriculture

State vulnerability will in this research project be accounted for by the percentage of the population that works in the agricultural sector and therefore depends on it for their income: *Employment Agriculture*. The data for this variable comes from the World Bank Development Indicators and is measured in percentage (World Bank 2022). *Employment Agriculture* has been chosen as a measurement for state vulnerability because states that heavily depend on agriculture as a means of income and employment are more vulnerable to changing levels of rainfall but also more vulnerable to terrorism in times of rainfall deviation, as terrorist actors might use scarce natural resources as weapons of war (Sakaguchi, Varughese, and Auld 2017; Nett and Rüttinger 2016).

Therefore, this research sets out to test whether the percentage of the population that works in the agricultural sector (*Employment Agriculture*) in its relationship with the yearly rainfall deviation from the mean rainfall (*Rainfall Deviation*) can lead to a significant increase or decrease in the number of terrorist attacks (*Terrorist Attacks*) a country experiences per year.

However, as *Employment Agriculture* will not only be used as part of the interaction effect but also just as one of the control variable, the more direct relationship with *Terrorist Attacks* would be expected to be along the lines that a country that heavily relies on agriculture would be more vulnerable to terrorism.

3.2.4. Independent Variable for Interaction Effect II: State Capacity

State capacity describes a country's ability to manage and mitigate crises of any kind. To be able to consider state capacity as one of the two interacting variables, I am using the state capacity measurement as proposed by Hanson and Sigman in the "Leviathan's Latent Dimensions: Measuring State Capacity for Comparative Political Research." (2021). Hanson and Sigman define state capacity as a latent concept that measures a state's ability to perform core functions. Their state capacity indicator, therefore, consists of 21 different indicators along the dimensions "Extractive Capacity", mainly focused on the revenues a state gains, "Coercive Capacity", concerned with the state's ability to maintain order within its territory and "Administrative Capacity" that is more focused on the state's ability to provide its citizens with the needed public goods (ibid. 2021, 11 ff.). The state capacity indicator provided in this dataset is chosen because of its more comprehensive approach towards measuring state capacity than any proxy variable could have provided.

As this is one of two interaction effects, the focus will be whether a state's capacity (*State Capacity)* in its relationship with the deviation from the average rainfall level (*Rainfall Deviation)* has a significant impact on the number of terrorist attacks a country experiences per year (*Terrorist Attacks)*.

State Capacity will, however, also be considered as one of the control variables and will hereby be expected to interact with *Terrorist Attacks* more directly. From the literature, the assumption would be that an increase in *State Capacity* would lead to a decrease in *Terrorist Attacks*.

3.2.5. Control Variables

As a control variable, *GDP per capita* has been introduced into this research project because of the fact that resource scarcity is felt extremely in countries with a very low *GDP per Capita* (Adano et al. 2012), as resource scarcity can be one potential outcome of *Rainfall Deviation* that might lead to increased vulnerability in the society and might even provide incentives for recruitment by terrorist actors (Nett and Rüttinger 2016). The assumption is that if the country has a comparatively high *GDP per Capita*, this resources scarcity could be compensated for, thereby decreasing the vulnerability to *Terrorist Attacks*. Therefore, if the *GDP per capita* is comparatively low in a country, it could potentially have a positive effect on *Terrorist Attacks*.

As previous research has shown, there is a correlation between regime types and the likelihood of experiencing terrorist attacks, with a broad understanding that democracies are more likely to experience terrorist activities than autocracies (Eubank and Weinberg 1994). This can partly be understood by the fact that the risks, as well as the costs are lower for terrorist actors in democracies (Chenoweth 2013; Li 2005). Therefore, the control variable *Democracy Level* is being introduced into the regression. Scaled from 1 to 20, with 1 being a totalitarian regime and 20 an advanced democracy, an increase on the scale would be expected to go hand in hand with an increase in *Terrorist Attacks*. The scale has been adopted from the Polity V dataset and then recoded from an original -10 to 10, to a scale from 1 to 20 for interpretation reasons (Marshall and Gurr 2020).

In previous analyses that focussed on the relationship between state capacity and political violence, the coherence of a regime was detrimental in determining how vulnerable a state was to outside harm (Gates et al. 2006; Jones, Mattiacci, and Braumoeller 2017). The relationship between the two has proven to be somewhat of a U-shape, with forms of political violence being least likely in highly authoritarian regimes and in full democracies (Hendrix and Salehyan 2012; Gates et al. 2006).

The assumption from this is, that coherent autocracies and coherent democracies would be better in mitigating harm than mixed-type systems, such as a deficient democracy, a moderate autocracy or a hybrid regime (Gates et al. 2006, 907). Building on this argument, the variable *Institutional Coherence* was chosen as one of the control variables. Based on the literature, an increase in *Institutional Coherence*, regardless of being coherently autocratic or coherently democratic, would lead to a decrease in *Terrorist Attacks.*

The dataset Democracy Matrix by the University of Würzburg clustered regime types according to a number of procedures and regulations within a state, such as procedures of decision, regulation of intermediate sphere, public communication, guarantee of rights and rules of settlement and implementation. Along these different indicators, they came up with five different regime types: Working Democracy, Deficient Democracy, Hybrid Regime, Moderate Autocracy and Hard Autocracy (Lauth and Schlenkrich 2021). Due to the importance of institutional coherence, the variable is coded as a dummy variable equalling 1 for a working democracy or a hard autocracy and equalling 0 for a deficient democracy, a hybrid regime or a moderate autocracy.

Civil war and terrorism often go hand in hand in reinforcing each other. Research has found there to be a correlation between ongoing civil wars and a rise in numbers of terrorist attacks, however, as especially the post-conflict phase is extremely vulnerable and can be exploited by terrorist actors (van Baalen and Mobjörk 2018). This research project therefore takes into account the duration of peace years the country has experienced from civil war, introducing the control variable *Peace Years*. Accordingly, a high number of *Peace Years* would be expected to lead to a decrease in *Terrorist Attacks*. The variable *Peace Years* counts the number of years a country has lived free from civil wars and has been adopted from Hendrix and Salehyan's dataset and is considered to be an important control variable in this research project (2012).

Youth Unemployment is introduced as a control variable for the percentage of young people – between 15 and 24 – that are unemployed. While the relationship between terrorism and youth unemployment is not one-dimensional, previous research has found there to be a correlation between the number of young unemployed people and a rise in the number, especially of domestic terrorism. This can be explained by the fact that the grievances that come with a high youth unemployment rate might make people more prone to recruitment efforts undertaken by terrorist actors (Adelaja and George 2020). Assumably, an increase in *Youth Unemployment* would go hand in hand with an Increase in *Terrorist Attacks*.

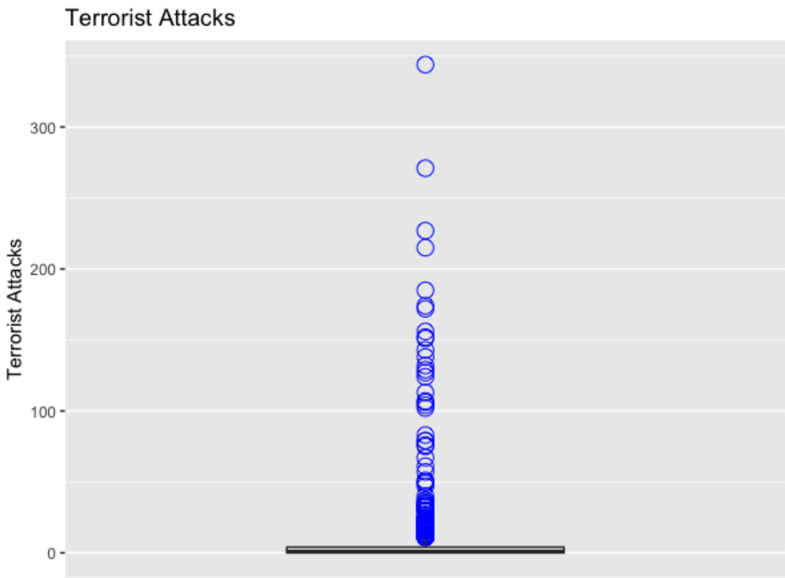
All the control variables in this dataset have been coded as numeric variables for computational reasons, except the binary variable *Regime Coherence*.

3.3. Descriptive Statistics

Statistics	N	Mean	St. Dev	Min	Pctl (25)	Median	Pctl (75)	Max
Terrorist Attacks	795	8.27	28.67	0	0	1	4	344
Rainfall Deviation	826	0.06	1.01	-3.73	-0.61	0.03	0.73	3.91
Employment Agriculture	828	56.30	21.65	5.60	41.60	56.95	74.20	92.40
State Capacity	826	-0.27	0.62	-2.31	-0.63	-0.24	0.09	1.50
Democracy Level	822	10.06	5.22	1	5	9	15	20
Peace Years	826	14.52	14.89	0	1	10	27	57
Youth Unemployment	828	16.11	14.39	0.45	5.62	9.64	26.35	60.43
Regime Coherence	799	0.22	0.41	0	0	0	0	1
GDP per Capita	792	27,588,102,210	52,781,283,218	631,345,665	3,358,433,943	7,757,469,949	23,424,143,690	326,504,898,642

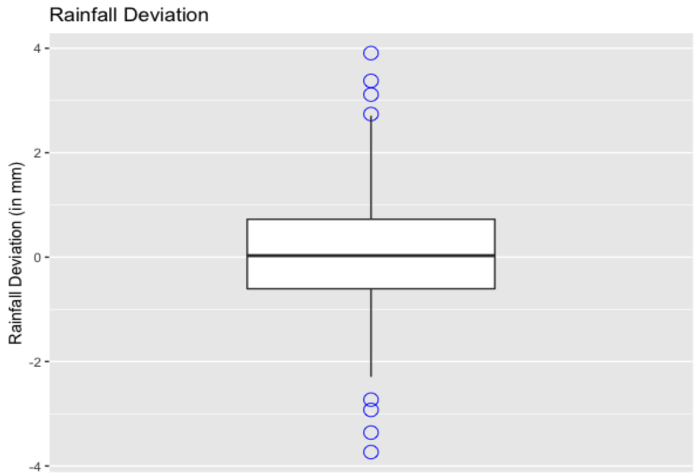
Descriptive Statistics Table

The descriptive statistics as portrayed in the Descriptive Statistics Table above, are important to understand the dataset. As my dependent variable is *Terrorist Attacks*, I am particularly interested in its distribution. What comes to mind first, is that this variable has a lot of missing values. As previously mentioned, this can be explained by the fact that the Global Terrorism Database unfortunately lost most of the country data for the year 1993, leading to a high number of NAs in this year (National Consortium for the Study of Terrorism and Responses to Terrorism (START) 2021). This should be taken into consideration and will be subject to a robustness check later on to make sure that the analysis is not flawed by this circumstance. Furthermore, when looking at the ratio of the mean to the standard deviation, it can be observed that the standard deviation (28.67) is much higher than the mean, which is 8.27. This implies that the data is over-dispersed – which is the case if the standard deviation is higher than the mean. Due to this and the fact that the dependent variable is count data, in this thesis a negative binominal regression is used (Cameron and Trivedi 1998). Looking at the 75th percentile, it becomes clear, that while the maximum of terrorist attacks per year per country is 344, 75% of the countries in the dataset experience 4 or less terrorist attacks per year, meaning that the data on terrorism is right-skewed and has a very high number of outliers as can be seen in the Boxplot Terrorist Attacks Outliers. This means that a large number of countries only experiences very few, if any, terrorist attacks within one year, while there is a very small number of countries that experience a high number of terrorist attacks per year.



Boxplot Terrorist Attacks Outliers

The independent variable of interest *Rainfall Deviation* is measured in the deviation of rainfall per year per country in millimetre. As mean and median are both close to zero, it seems that this variable has less variance and outliers, which can in fact be seen in the Boxplot Rainfall Deviation Outliers, as there are only eight outliers identified. According to the 75th percentile, 75% of the countries in this dataset experienced 3.73 to 0.73 mm of rainfall deviation per year.



Boxplot Rainfall Deviation Outliers

Employment Agriculture looks at the percentage of the population in a given country-year that works in the agricultural sector. Looking at the data's distribution leads to the assumption that on average around 56% of the people in the countries under consideration work in the agricultural sector. This is additionally very close to the median being around 57%, with seemingly little outliers. However, the high standard deviation of 21.65 paints a different picture, as there seems to be a high variance within the data. According to the 75th percentile, 75 % of the data have a share of population of up to 74% that are working in the agricultural sector. As already described, in this thesis, state vulnerability is operationalised as *Employment Agriculture*. For now, there is of course no relationship between climate change and state vulnerability established or tested, which is something I will have to focus on within the regression but it is already interesting to see that in my dataset within the countries considered a lot of people rely on agriculture as a means of income and employment, making these countries potentially more vulnerable to climate change, as well as terrorism.

The variable *State Capacity*, as in direct comparison to the *Employment Agriculture*, is not a percentage but a scale composed of several different indicators measuring different dimension of state capacity, making the data slightly more difficult to interpret. The scale is from -2.31 to 1.49. The mean of the data is at -0.27, with the median at -0.24. However, the standard deviation of 0.62 indicates that there seems to be a high variance within the data. The 75th percentile is at 0.09, leading to the assumption that around 75% of the cases in this dataset seem to be on the lower end of the state capacity scale, meaning the corresponding states are less capable of maintaining order within their territories and providing basic goods to their population.

The *Democracy Level* variable is a scale coded from 1 to 20. While originally coded from -10 to 10, the recoding was undertaken in an attempt to make the interpretation easier. The mean of the variable is at 10.6, with the median at 9, portraying that there must be some outliers that are indeed a lower than 10.6. The high standard deviation of 5.22 portraying a range within the data. With the 75th Percentile showing that 75% of the countries in the dataset are at 15 or lower of the scale, and the 25th percentile showing that only 25 % of the countries within the dataset score a really low number on the democracy scale of 5 or less, most countries seem to be somewhere in the middle of being fully democratic or fully autocratic.

The variable *Peace Years* measuring the number of years since the last active civil war shows that the countries in this dataset have experienced an average of around 15 years of peace since the last civil war. However, this number should be treated with caution, as the standard deviation is higher than the mean at 14.9, and a median of 10, leading to the conclusion that there must be a lot of outliers that have experienced much less than the average 15 years. The 25th percentile shows that only 25% of the countries in this data set have experienced one year or less of peace, while the 75th percentile shows that most of the cases in this analysis, have experienced 27 years of peace or less. This further confirms the variance, both by their values and being present within the interquartile range. This means that there aren't just extreme outliers, but large variation even within the 25th and 75th quartiles.

The data on the variable *Youth Unemployment* is given as a percentage of how many people between the ages of 15 to 24 are unemployed per country. The mean here is 16.11, however, as the median is at 9.64 and there is a relatively high standard deviation of 14.39, there seem to be quite a lot of outliers that have less than 16.11% of young people unemployed. The 25th percentile shows that 25% of countries have an unemployment rate of 5.62% or lower, while 75% of the cases have an unemployment rate of maximum 26.35%. With a maximum percentage of 60.43%, and the majority being found around 26.35%, this data can be considered right-skewed.

The *GDP per Capita* has a mean at approximately 28 billion US$, however with a very high standard deviation of around 53 billion US$, showing a very high range within the variable, with the median being actually at around 8 billion US$ so much lower than the mean, leading to the assumption that there are a lot of countries in this dataset that are falling below the mean *GDP per Capita*. While the max is at around US$327 billion, 75% of the countries have a *GDP per Capita* that is at US$23 billion or below, especially showing that this data contains a lot of very high outliers which lead to the fact that the mean is actually higher than the 75th percentile. This variable's data is right-skewed, meaning that there are some countries with an extremely high GDP per Capita, however, 75% of the countries have a GDP per Capita of US$23billion or less.

3.4. Chosen Method

The focus of this analysis is to observe the relationship between *Rainfall Deviation* and *Terrorist Attacks* over time. To be able to do so, the dataset used is a panel dataset that allows me to observe this relationship per country-year. As climate change is a process that takes place over time and cannot easily be observed over a short period of time, it becomes clear that this phenomenon has to be observed over a longer period – or as in this scenario over 18 years.

To be able to choose a method, the dependent variable is of importance. The dependent variable in this analysis is the incidents of terrorist activities per country-year. This kind of data can also be called "count-data". Looking at the descriptive statistics, it becomes clear that the dependent variable is over-dispersed, meaning that the variance is higher than the mean. As already described, in case of an over-dispersed dependent count-variable, the best choice of a regression is the so-called negative binominal regression (Cameron and Trivedi 1998).

3.5. Multicollinearity

Variable	Employment Agriculture	Regime Coherence	Rainfall Deviation	Democracy Level	State Capacity	Peace Years	GDP per Capita	Youth Unemployment
Employment Agriculture								
Regime Coherence	-.01							
Rainfall Deviation	.01	-.08						
Democracy Level	-.06	-.01	-.01					
State Capacity	-.19	-.09	.03	.22				
Peace Years	-.20	-.30	-.02	.15	.09			
GDP per Capita	-.44	.15	.03	.01	.13	-.06		
Youth Unemployment	-.64	-.05	-.04	.09	.06	.17	.35	

Multicollinearity Table

To make sure that the variables in this analysis are not measuring some of the same aspects by being related to each other, a test for multicollinearity has been conducted as a precursor to the panel regressions. However, as can be seen in the table above, the values are all rather low indicating that the variables are not critically related to each other in a way that would cause their exclusion in the regression models. The only two variables that are slightly more related are *Youth Unemployment* and *Employment Agriculture*.

4. Statistical Analysis

4.1. Regression I: Terrorism & Rainfall

Regression I only includes the independent and the dependent variable of this analysis: *Rainfall Deviation* and *Terrorist Attacks* to establish whether there is any significant relationship between the two variables, without taking into consideration any other outside factors. In this output, however, what becomes very clear is that there is no significant relationship between the two. Additionally, the coefficient is so close to zero that the two graphs are rather parallel than related to each other. However, this would only be relevant if the relationship was significant. Log likelihood, which calculates how well the model fits the data, is currently at -1,861.149 becomes smaller negative number as I incorporate the control variables. Theta, the dispersion parameter, measures how well the model fits the dependent variable's skewed distribution on a scale from 0 to 1 and will hopefully increase in the following regressions.

	Terrorist Attacks
	Regression I
Rainfall Deviation	-0.003
	(0.974)
Constant	2.115***
	(<2e-16 ***)
Observations	793
Log Likelihood	-1,861.149
Theta	0.164***
Standard Error	(0.010)

p-Values: '***' 0.001 '**' 0.01 '*' 0.05

Table Regression I

4.2. Regression II: Terrorism & Rainfall + Control Variables

Regression II includes, the independent, the dependent and all control variables, as well as the two constituent variables that will be used to create an interaction effect later on. However, within this analysis, they are merely control variables. Compared to the first model, it becomes clear that the log likelihood increases. This shows that the regression with all the control variables is already a better fit, as the log likelihood increases from -1,861.149 to -1,501.832. Also, the value of the dispersion parameter theta increases. This value increases from 0.164 to

0.302 and is highly significant. Taken together with log likelihood, this shows that this model's configuration is already a better fit for the data. Additionally, although there is still no statistical significance for the independent variable *Rainfall Deviation,* some of the control variables have a significant influence on the dependent variable *Terrorist Attacks*. *GDP per Capita,* while being highly significant, has such a small coefficient that interpretation will not go any further than pointing out that the relationship is slightly positive.

	Terrorist Attacks	
	Regression I	Regression II
Rainfall Deviation	-0.003	0.055
	(0.974)	(0.4582)
State Capacity		-0.189
		(0.1547)
Employment Agriculture		0.023***
		(1.7 e-05)***
Peace Years		-0.049***
		(<2e-16)***
Youth Unemployment		0.012
		(0.1250)
GDP per Capita		2.721e-11***
		(<2e-16)***
Regime Coherence		0.337
		(0.0696)
Democracy Level		-0.076***
		(7.90e-07)***
Constant	2.115***	0.176
	(<2e-16 ***)	(0.6866)
Observations	793	727
Log Likelihood	-1,861.149	-1,501.832
Theta	0.164***	0.302***
Standard Error	(0.010)	(0.022)

p-Values: '***' 0.001 '**' 0.01 '*' 0.05

Table Regression I+ II

The effect of *Employment Agriculture* is highly significant, as can be seen in Table Regression I + II, at a 99.9% confidence. To be able to interpret the coefficients impact on Terrorist Attacks, however, the exponential of the coefficient has to be taken into consideration. What already becomes clear is, that according to the coefficient of 0.023, there is a positive relationship *between Employment Agriculture* and *Terrorist Attacks*. The exponential of 0.0023 is 1.023. This means that a one percentage point increase in *Employment Agriculture* leads to an increase in Terrorist Attacks by 2.3%.[4]

However, as *Employment Agriculture* was chosen in this analysis for its interaction with *Rainfall Deviation*, its interpretation will become increasingly interesting, when it is modelled in an interaction effect. *Peace Years* has a highly significant negative relationship with the dependent variable at the 99.9% confidence. An increase in *Peace Years* by one year thereby leads to a decrease in *Terrorist Attacks* by 4.8%. *Democracy Level* has a highly significant negative relationship with *Terrorist Attacks* at the 99.9% confidence. The *Democracy Level* variable is coded as a scale from 0-20 with 20 being the most democratic. Considering this, an increase of 1 point on the scale towards more democratic would lead to a decrease in *Terrorist Attacks* of around 7.3%. However, it would be impossible to have an increase above the level of 20, where the scale ends.[5]

Finally, of the control variables, only *Youth Unemployment*, *Regime Coherence* and *State Capacity* have no significant impact on the dependent variable.

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[4] To be able to interpret the coefficients of all significant variables in the regression models, all of the coefficients' exponentials will be interpreted without specifically describing the displayed way from coefficient to exponential for each variable.

[5] For computational reasons, *Democracy Level* has been coded as a numeric variable instead of a factorial variable to account for even small changes on the scale.

4.3. Regression III: Terrorism & Rainfall + Control Variables + Interaction Effect I

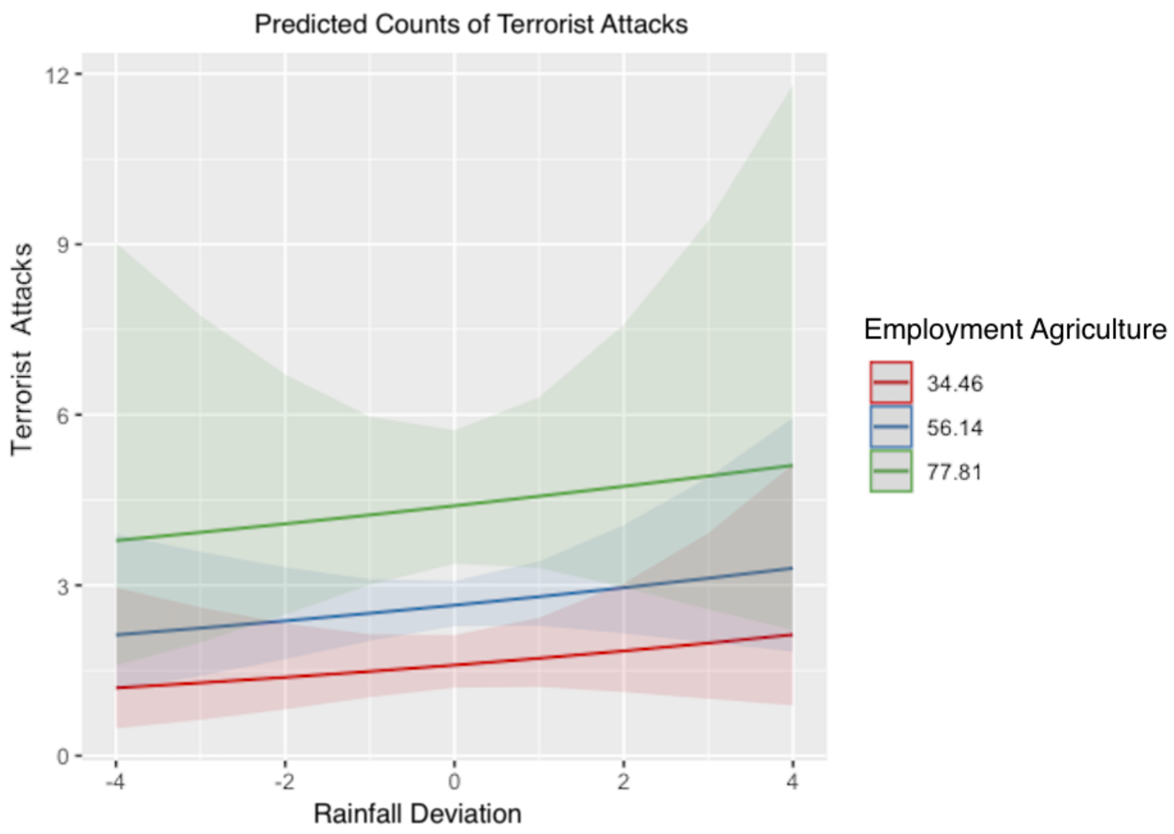
	Terrorist Attacks			
	Regression I	Regression II	Regression III	Regression IV
Rainfall Deviation	-0.003	0.055	0.100	0.032
	(0.974)	(0.4582)	(0.636)	(0.680)
State Capacity		-0.189	-0.185	-0.177
		(0.1547)	(0.164)	(0.1867)
Employment		0.023***	0.023***	0.023***
Agriculture		(1.7 e-05)***	(1.79e-05)***	(1.81e-05)***
Peace Years		-0.049***	-0.050***	-0.049***
		(<2e-16)***	(<2e-16)***	(<2e-16)***
Youth Unemployment		0.012	0.012	0.011
		(0.1250)	(0.126)	(0.1409)
GDP per Capita		2.721e-11***	2.722e-11***	2.722e-11***
		(<2e-16)***	(<2e-16)***	(<2e-16)***
Regime Coherence		0.337	0.339	0.339
		(0.0696)	(0.068)	(0.0686)
Democracy Level		-0.076***	-0.076***	-0.076***
		(7.90e-07)***	(7.54e-07)***	(7.67e-07)***
Interaction Effect I			-0.001	
			(0.817)	
Interaction Effect II				-0.086
				(0.4909)
Constant	2.115***	0.176	0.178	0.189
	(<2e-16 ***)	(0.6866)	(0.686)	(0.6671)
Observations	793	727	727	727
Log Likelihood	-1,861.149	-1,501.832	-1,501.800	-1,501.630
Theta	0.164***	0.302***	0.302***	0.302***
Standard Error	(0.010)	(0.022)	(0.022)	(0.022)

p-Values: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05

Table Regression III + IV

Regression III includes the Interaction Effect I between *Rainfall Deviation* and *Employment Agriculture* on *Terrorist Attacks*, as well as the control variables. As, however, portrayed in Table Regression III, there is no significant effect of the relationship between *Rainfall Deviation* and *Employment Agriculture* on *Terrorist Attacks*. Apart from that, all other significances are the same as in Regression II. The factor for *Rainfall Deviation* increases slightly, but can still not be considered, as it remains insignificant. The only significant coefficient that changes slightly is the one for *Peace Years*, as it increases slightly from -0.049 to -0.050. This means that an increase by one year in *Peace Years* leads to a decrease in *Terrorist Attacks* of 4.9% instead of 4.8% in the previous regression.

As log likelihood increases very slightly from -1.501,832 to -1,501.800, while theta stays exactly the same, it has to be assumed that incorporating Interaction Effect I has not made this model a better fit for the data at hand.



Plot Interaction Effect I

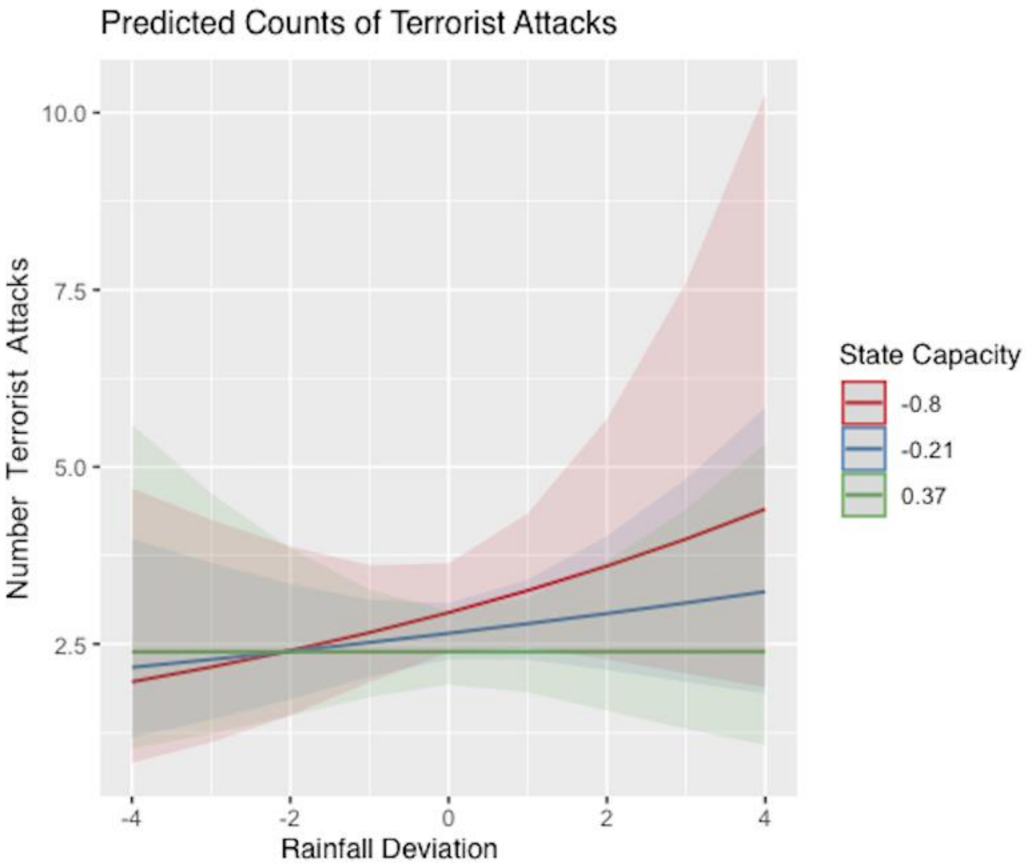
While the Interaction Effect I, which was introduced into this model does not have a significant relationship with *Terrorist Attacks*, it is still wort looking at how *Rainfall Deviation* and *Employment Agriculture* interact with each other and what their impact on *Terrorist Attacks* was, if it was significant. What can be seen in Plot Interaction Effect I, however, is, that apparently there is no interaction at all. An interaction can be observed when the lines are nonparallel. However, in this plot the lines are parallel, meaning that there does not seem to be any – if even insignificant – interaction effect.

4.4. Regression IV: Terrorism & Rainfall + Control Variables + Interaction Effect II

Regression IV includes the Interaction Effect II on the relationship between *Rainfall Deviation* and *State Capacity* and its impact on the dependent variable *Terrorist Attacks*. As can be seen in Regression IV in Table Regression III + IV, also Interaction Effect II does not have a significant impact on *Terrorist Attacks*. Considering the other variables in the regression, all the significances stay exactly the same as in the previous regression, as well as the significant coefficients, apart from *Peace Years* which slightly changes.

This means that in the final regression in this research project, *Employment Agriculture* has a highly significant positive relationship with *Terrorist Attacks* at the 99.9% confidence. Furthermore, an increase in *Employment Agriculture* by one percentage point leads to a 2.3% increase in *Terrorist Attacks*. *Peace Years* also has a highly significant relationship with *Terrorist Attacks*, also at 99.9% confidence. However, this relationship is negative and an increase in *Peace Years* by one year leads to a decrease in *Terrorist Attacks* by 4.8% as opposed to 4.9% in Regression III. Democracy Level, finally, also continues to have a highly significant negative relationship with the dependent variable at 99.9% confidence. A one step increase in Democracy Level, therefore, leads to a decrease in *Terrorist Attacks* by 7.3%. *GDP per Capita* continues to have a very slightly positive relationship with Terrorist Attacks at the 99.9% confidence, which, however, is too small to properly interpret.

The log likelihood again has very slightly increased from -1,501.800 to -1.501.630, with theta remaining exactly the same at a value of 0.302. Considering the only slight increase in log likelihood and the fact that theta has not changed throughout Regression II, III and IV and has always remained highly significant at the 99.9% confidence, also Regression IV does not seem to be a better fit for the data. Therefore, including the Interaction Effect II has not improved this model's fit to the data.



Plot Interaction Effect II

Different from the Interaction Effect I, in Plot Interaction Effect II, the lines are nonparallel. And while the Interaction Effect II is again not significant, in Interaction Effect II there is an actual interaction between the three variables, that apparently has its peak at a Rainfall Deviation of -2.

4.5. Robustness Checks

As previously mentioned, the Global Terrorism Database only contains a very limited number of observations for the year 1993. To make sure that the regressions that have been considered so far are not constrained because of this particular year and the lack of observations, two robustness checks have been carried out. The first one considers the entire time frame, however, excludes the year 1993, while the second one only takes into account the years after 1993, limiting the analysis to the timeframe 1994-2008.

As can be seen in the two tables in the appendix, the results for both robustness checks – whether only 1993 was excluded or whether 1991, 1992 and 1993 were excluded – turned out to be identical. Both robustness checks did not show any change of the significance levels of the coefficients in any of the four regression and only slightly altered the values of the coefficients for the statistically significant control variables. Most importantly, neither the independent, nor the two interaction effects have become significant by limiting the timeframe.

The log likelihood is slightly higher in the two identical robustness checks compared to our regressions: -1,812.844 (Regression I), -1,466.285 (Regression II), -1,466.222 (Regression III) and -1,466.073 (Regression IV). In comparison, the original regressions including 1993 have log likelihoods of -1,861.149 (Regression I), -1,501.832 (Regression II), -1,501.800 (Regression III) and -1,501.630 (Regression IV). Pointing at the fact that the two models might be a slightly better fit for the data without 1993. However, the picture is slightly different when it comes to the theta values. For the two models without 1993, they are all highly significant at the 99.1% confidence and take the following values: 0.160 (Regression I), 0.296 (Regression II), 0.296 (Regression III) and 0.296 (Regression IV). In this comparison, the original models considering 1993 are actually closer to a perfect fit than the ones without 1993: 0.164 (Regression I), 0.302 (Regression II), 0.302 (Regression III) and 0.302 (Regression IV), while also all being highly statistically significant at the 99.9% confidence.

In summary, it seems as if the chosen models including the year 1993 did not lead to any distortions. The significance levels are exactly the same as the ones for the models that leave out 1993 and the model fit to the data is also almost the same. This leads to the assumption, that the data chosen for this analysis did not flaw the outcome or even the interpretation.

5. Discussion

5.1. Answering the Research Question

This research project set out to answer the broad question of what the impact of climate change – in this study operationalised as rainfall deviation – on terrorism is. More specifically, the objective was to determine whether there is a moderating effect of state vulnerability and state capacity respectively on rainfall deviation. Therefore, Hypothesis 1 focussed on the relationship without any moderating factors, while Hypothesis 2a and 2b considered the two different moderations separately.

Hypothesis 1 tests whether rainfall deviation leads to an increase in terrorist attacks. Looking at Regression IV, which includes all control variables, as well as an interaction effect, it becomes clear that no statistical significance could be found between the independent and the dependent variable. Therefore, for Hypothesis 1, we cannot reject H0. This relationship could not be proven to be significant. Hypotheses 2a and 2b are the reasons for the interaction effects to be included in Regression III and IV. However, neither of the interaction effects proved to have a significant relationship on the dependent variable. Therefore, we cannot reject H0, neither for Hypothesis 2a nor for Hypothesis 2b. For Hypothesis 2a, this means that in this study it could not be proven that the number of terrorist attacks depends on the relationship between the deviation in rainfall and state vulnerability, which was operationalized by the percentage of people employment in the agricultural sector. For Hypothesis 2b, the result is similar. The number of terrorist attacks a country experienced within a year does not depend on the interaction between the deviation in rainfall and state capacity of that specific state.

Accordingly, within the limited framework of this specific research project, climate change – operationalized as deviation in rainfall – does not have any impact on terrorism. More specifically, even under conditions of a vulnerable state or a state lacking state capacity, climate change could not be proven to have a significant impact on terrorism.

While the main concepts of this research project could not be proven to impact each other, there are, however, other conclusions that can be drawn from the control variables' impact on the dependent variable. Three control variables continued to have highly significant impacts on the number of terrorist attacks throughout all four regression, with only minor changes in the coefficients. These are the following:

The percentage of people employed in the agricultural sector does indeed on its own, without being part of an interaction effect, have a highly significant impact on the number of terrorist attacks a country experiences in a year. This relationship is positive and an increase by one percentage point in this control variable lead to an increase in the number of terrorist attacks by 2.3% in all three regression it was included in. Based on the literature, this kind of relationship has been anticipated between the two variables, as countries that are highly dependent on agriculture as a means of income and employment are more likely to fall victim to terrorism. This can partly be explained by the fact that, especially in times of resource scarcity, terrorist actors can easily exploit this dependence on agriculture. They do so by using resources as weapons of war and increasing vulnerability even further within the population.

Another control variable that turned out to have a highly significant negative relationship with the number of terrorist attacks throughout all three regressions it was included in, is the level of democracy. This means that a one-step increase on the democracy scale, which is coded from 0 to 20, leads to a decrease in terrorist attacks by 7.3%. Looking at the literature, this relationship would have been expected to lead to the opposite outcome. While the literature on the impact of democracy on terrorism is contested and there is not yet one final answer as how these two interact, a positive relationship would have been expected. The literature assumes that the more democratic a country is, the more likely it is to experience terrorist attacks. However, in this research, the opposite statement is true: the more democratic a country is, the less terrorist attacks it experiences.

What would have been expected from the literature, however, is that the longer a country's population has lived in peace from civil war, the fewer terrorist attacks it experiences. Indeed, this relationship turned out be highly significant in this research project. Living in peace for one more year leads to a decrease in the number of terrorist attacks of 4.8-4.9 %.

Finally, the GDP per Capita remained highly significant throughout all regressions, as well, however, showing only a very slightly positive relationship. This, if the factor was high enough to properly interpret it, means that an increase of GDP per Capita would go hand in hand with an increase in the number of terrorist attacks. However, this relationship should be interpreted with caution.

5.2. Limitations of the Research Project and Perspectives for Future Research

While this research project was able to shed light on the relationship between climate change and terrorism, mitigated by state vulnerability and state capacity, there are a couple of limitations this research has faced. These could potentially be taken into consideration in future research projects for an even more comprehensive analysis of the relationship in question.

5.2.1. Timeframe and Scope of the Research Project

In this thesis, a yearly analysis was chosen, partly because of time constraints, as well as the dependency on the dataset by Hendrix and Salehyan. However, a lot of the literature suggests that a monthly analysis would be more informative, as this would allow to account for sudden weather changes and would allow for a more thorough analysis for the specific mechanism employed by groups using terrorism. One of the main specifics that differentiate the relationship of climate change and terrorism from climate change and violent conflict more broadly, is that the strategy of terrorism can be employed time-efficiently, meaning that terrorist actors can quickly react to changing weather circumstances and might be able to change their strategies much faster than can be accounted for by a yearly analysis.

Long term climate change will hardly be accounted for in the time span of 17 years and should be analysed in much broader terms, spanning longer periods than undertaken in this analysis. However, choosing a relatively short time span can also mean that tactical considerations by armed actors will be observed rather than long-term grievances. Therefore, it very clearly depends on the specific research project's objective (van Baalen and Mobjörk 2018). Studying shorter time periods, however, assumes persistent change within weather patterns. This can lead to a bias from the beginning (Sakaguchi, Varughese, and Auld 2017).

But not only the unit of time could have been chosen more fine-grained but also the unit of analysis. While a country-level analysis made sense to be able to compare differences on a large scale, terrorism often operates in specific regions within a country and very rarely in the entirety of it. Especially in countries that have grave differences, e.g. in infrastructure development between periphery and urban centres, a more fine-grained analysis of the different regions within a country might have been more informative. Pressure stemming from migration caused by climate change is particularly visible in urban centres, while rural areas are often less well-connected to the centre making it more vulnerable to terrorist groups to find a standing, with the government being less able to interfere quickly (van Baalen and Mobjörk 2018; von Uexkull and Buhaug 2021). On top of these considerations, weather patterns can also differ within countries, and a state-level analysis can simply not account for these differences.

Terrorism, however, is a concept that spans state borders and often operates in border regions that are out of sight of the central government's view. Therefore, while there is also clear need for a smaller unit of analysis, it would be important for future research to focus on an entire region, such as the Sahel zone, instead of specific countries. This is something that has largely been undertaken in researching the relationship between climate change and other political violence, less so, however, for terrorism. Climate change, as well as terrorism, are concepts that know no border, which is something that should be taken into consideration in the future.

However, to be able to have a comparatively large case number and span an entire continent in one research project, a state-level, yearly analysis seemed appropriate for this specific research project. In terms of measuring terrorist attacks, the outcome variable of this research project only took the existence of terrorist attacks into consideration. However, previous studies on slightly different topics have shown that the operationalisation of the outcome variable could have been much more advanced, incorporating aspects, such as domestic/transnational terrorism, outbreak of violence, intensity, longevity but could also extend to variables, such as rebel recruitment, which has been seen to be a particularly important aspect in how terrorist actors use climate change for their advantage.

Many studies about the relationship between climate change and violent conflict in general and terrorism more specifically have focussed specifically on countries or regions that show signs of both occurrences. While this allows for a thorough analysis of the interaction, it also comes with an inherent bias, as only regions or countries are taken into consideration, where one expects a certain relationship to be manifest. This study, while broadening its scope to the entire continent of Africa, partly faces this bias, as well. While not all African countries face violent conflict or terrorism, there is a higher likeliness for these two occurrences to interact than in other parts of the world, as parts of Africa, e.g. the Sahel zone, are so called climate hotspots, that "are specifically responsive to global warming" and that are specifically affected by its consequences (Fan et al. 2021, 2; Giorgi 2006).

5.2.2. Operationalisation of the Independent and the Dependent Variable

This research project only focused on the rainfall deviations from the mean, however, it could not take climate disasters, such as floods or droughts, that are inherently different in how they affect a region and a population. Future research could potentially focus on the relationship between climatic events and the recruitment for terrorist organisations. Even worse, using only the deviation from the mean might actually mask events such as droughts, as it cannot take into consideration how the level of precipitation was distributed over time (Theisen 2012). These weather events are only becoming more likely because of climate change and should accordingly be considered more within the study on terrorism and climate change.

But not only the way the independent variable is conceptualized limits this particular research project. The research on terrorism more broadly is limited by the fact that there is no agreement on a common definition of what the term terrorism actually entails. As long as this is the case, researchers that undertake data collection efforts themselves have to come to an agreement which cases to consider and which to leave out, depending on the definition they chose.

Building on this, research that use the data collections on terrorism are restricted to the definition of the data they are using for their analysis. This also the case in this research project. While, the Global Terrorism Database is the most comprehensive collection on terrorist incidents worldwide and the data collection is very thorough, research projects that use their data have to also their definition of what terrorism is. Accordingly, a common definition of the term terrorism is needed and could also be itself the subject of future research.

What becomes clear, finally, is that a quantitative approach is appropriate to demonstrate a relationship between climate change and terrorism on a large scale. However, while control variables have been taken into consideration to account for potential external explanations besides the dependent and independent variable, the mechanisms that lead to an increase in the dependent variable cannot be properly taken into account in this kind of study. For this reason, future research could not only operate within different time scales or different unit of analysis but might also considering combining a strictly quantitative approach with a qualitative method that would allow to draw conclusion on the causalities behind this relationship.

6. Conclusion

As pointed out in the introduction, there are indeed many regions in the world that experience violent conflict and climate change at the same time, which suggests the assumption that the two might actually be related to one another or even reinforce each other. Indeed, plenty of research has found an interaction between the two, pointing mostly at the fact that climate change is rarely the reason for conflict but should be understood as a trigger that makes an already tense situation escalate.

However, climate change does not always lead to violent conflict, begging the question of whether some regions that experience climate change are just not characterized by underlying tensions or grievances or whether there are other mechanisms that moderate this relationship.

This research was set out to look at the relationship between climate change and violence and in order to find out whether there are outside factors that trigger an escalation into violence. However, not any kind of violence was meant here but specifically terrorism. While the literature has investigated the relationship between climate change and violent conflict manifoldly, there is still not as much research on the connection between climate change and terrorism.

By laying out a research design that specifically focussed on the impact that rainfall deviation can have on the number of terrorist attacks a country experiences within a year, this research project's focus was particularly on the factors that might be able to determine this relationship: state vulnerability and state capacity. The assumption behind this approach is that if a state is particularly vulnerable to climate change by for example heavily relying on agriculture as a means of income and employment, this would make it more likely to also be vulnerable to terrorism. Not only because terrorist actors might exploit this situation and the people in it but also because some governments might simply not be able to compensate the losses. This would not only further deteriorate the population's situation but might make them also more vulnerable to recruitment efforts by terrorist actors.

This is why state capacity was assumed to be an important determinant. Additionally, all of these mechanisms take place in countries that lack state capacity. The relationship is rather straightforward: if a country is under increased stress by climate change, making it vulnerable, it is up to a state's government to compensate for these stresses, to reassure its citizens and to decrease incentives that might push them into the arms of terrorist actors. Also, if the state can ensure its population access to resources no matter what, the room for terrorist actors to monopolise on them becomes smaller. Accordingly. this research project's focus was on proving that both state capacity and state vulnerability are important in the study of climate change and terrorism. However, for this relationship to be tested, an impact of climate change – operationalised as rainfall deviation – had to be tested first. In a next step the interaction between rainfall deviation and state vulnerability on terrorism, as well, as the interaction between rainfall deviation and state capacity on terrorism had to be tested.

In this particular research project, under the limitations that have already been described, in this time frame and in the context of only African countries, neither of these relationships could be proven to be significant. This is not to say that a relationship between rainfall deviation and the number of terrorist attacks, and more broadly climate change on terrorism, is not existent. But, if existent, with this study's framework it could not be captured. Also, the lack of significance for impact of state capacity and state vulnerability does not mean that these are not important determinants but maybe that in this specific project they were either not sufficiently captured or other context variables were simply more important.

While no significant relationship between the main concepts of interest could be found, there were other factors that seem to be important in the study of terrorism and also showed an effect in this research project: the number of people that work in the agriculture sector, the level of democracy a country has and finally the number of years a country has remained peaceful since the last civil war. All three of them had a significant impact on whether the number of terrorist attacks rose or declined and should be part of future research on terrorism.

If this research project has one contribution to make, it is its display of how little we actually know about the interaction between climate change and terrorist attacks. While there are some mechanisms that have found to be in place in certain examples, such as land degradation leading to an increase in tensions between herders and farmers in Nigeria or the use of resources as weapons of war in some parts of the Sahel zone, there are still many research puzzles out there when it comes to climate change and conflict. This is even more true for the relationship between climate change and terrorism, leaving room for a lot of new research to come.

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Appendix 1: Tables Robustness Check

Table Robustness Check I: Exclusion of the Year 1993

	Number_Terrorist_Attacks			
	I	II	III	IV
Precipitation_Deviation	-0.005	0.057	0.121	0.033
	(0.089)	(0.075)	(0.215)	(0.079)
State_Capacity		-0.184	-0.178	-0.171
		(0.135)	(0.135)	(0.136)
Employment_Agriculture		0.023***	0.023***	0.023***
		(0.006)	(0.006)	(0.006)
Years_in_Peace		-0.051***	-0.051***	-0.051***
		(0.006)	(0.006)	(0.006)
Youth_Unemployment		0.012	0.012	0.012
		(0.008)	(0.008)	(0.008)
GDP_per_Capita		0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)
Regime_Coherence_Dummy		0.350*	0.353*	0.352*
		(0.189)	(0.190)	(0.190)
Level_of_Democracy		-0.074***	-0.074***	-0.074***
		(0.016)	(0.016)	(0.016)
Precipitation_Deviation:Employment_Agriculture			-0.001	
			(0.004)	
Precipitation_Deviation:State_Capacity				-0.090
				(0.127)
Constant	2.113***	0.205	0.208	0.219
	(0.091)	(0.447)	(0.447)	(0.446)
Observations	779	715	715	715
Log Likelihood	-1,812.844	-1,466.285	-1,466.222	-1,466.073
theta	0.160*** (0.010)	0.296*** (0.022)	0.296*** (0.022)	0.296*** (0.022)

*p<0.1; **p<0.05; ***p<0.01

Table Robustness Check II: Exclusion of Years 1991, 1992, 1993

	Number_Terrorist_Attacks			
	I	II	III	IV
Precipitation_Deviation	-0.005 (0.089)	0.057 (0.075)	0.121 (0.215)	0.033 (0.079)
State_Capacity		-0.184 (0.135)	-0.178 (0.135)	-0.171 (0.136)
Employment_Agriculture		0.023*** (0.006)	0.023*** (0.006)	0.023*** (0.006)
Years_in_Peace		-0.051*** (0.006)	-0.051*** (0.006)	-0.051*** (0.006)
Youth_Unemployment		0.012 (0.008)	0.012 (0.008)	0.012 (0.008)
GDP_per_Capita		0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Regime_Coherence_Dummy		0.350* (0.189)	0.353* (0.190)	0.352* (0.190)
Level_of_Democracy		-0.074*** (0.016)	-0.074*** (0.016)	-0.074*** (0.016)
Precipitation_Deviation:Employment_Agriculture			-0.001 (0.004)	
Precipitation_Deviation:State_Capacity				-0.090 (0.127)
Constant	2.113*** (0.091)	0.205 (0.447)	0.208 (0.447)	0.219 (0.446)
Observations	779	715	715	715
Log Likelihood	-1,812.844	-1,466.285	-1,466.222	-1,466.073
theta	0.160*** (0.010)	0.296*** (0.022)	0.296*** (0.022)	0.296*** (0.022)
Note:				*p<0.1; **p<0.05; ***p<0.01

Appendix II: R Code

```
setwd("~/Library/Mobile Documents/com~apple~CloudDocs/MIRD/Literatur/Data")
Sys.setenv(LANG = "en")
#install.packages("readxl")
library(readxl)
#install.packages("readr")
library(readr)
#install.packages("tidyverse")
library(tidyverse)
#install.packages("haven")
library(haven)
#install.packages("stargazer")
library(stargazer)
#install.packages("tidyr")
library(tidyr)
#install.packages("dplyr")
library (dplyr)
#install.packages("compare")
library(compare)
#install.packages("errorlocate")
library(errorlocate)
#install.packages("plyr")
library(plyr)
#install.packages("writexl")
library(writexl)
#install.packages("plm")
library(plm)
#install.packages("foreign")
```

```
library(foreign)

#install.packages("ggplot2")

library(ggplot2)

#install.packages("MASS")

library(MASS)

#install.packages("car")

library(car)

#install.packages("ggplot", dependencies = TRUE, respos = "hhtp://cran.us.r-project.org")

library(ggplot2)

#install.packages("skimr")

library(skimr)

#install.packages("panelr")

library(panelr)

#install.packages("pglm")

library(pglm)

#install.packages("xtable")

library(xtable)

#############################################################################################################
#Two Main Variables: Dependent Variable: Terrorism, Main Independent Variable: Precipitation

##############################################################################################################
#TERRORISM

#Importing the Global Terrorism Database

#Restructure and remodel dataset to only include categories I need for my analysis

terrorism_data <- read_excel("Global Terrorism Data_cut.xlsx")

View(terrorism_data)

terrorist_attacks <- ftable(terrorism_data$iyear, terrorism_data$country_txt)

View(terrorist_attacks)

terrorism<-as.data.frame(terrorist_attacks)

View(terrorism)
```

```
terrorism_1 <- terrorism[terrorism$Var1 %in% c("1991", "1992", "1993", "1994",
                                              "1995", "1996", "1997", "1998", "1999", "2000",
                                              "2001", "2002", "2003", "2004", "2005", "2006",
                                              "2007", "2008"), ]

View(terrorism_1)

terrorism_1$Var2

terrorism_2 <- terrorism_1[terrorism_1$Var2 %in% c("Algeria", "Angola", "Benin", "Botswana", "Burkina
Faso", "Burundi",
                                                    "Cameroon", "Central African Republic", "Chad", "Ivory Coast",
                                                    "Democratic Republic of the Congo", "Egypt", "Eritrea", "Ethiopia",
                                                    "Gabon", "Gambia", "Ghana", "Guinea", "Guinea-Bissau", "Kenya",
                                                    "Lesotho", "Liberia", "Libya", "Madagascar", "Malawi", "Mali",
"Mauritania",
                                                    "Mauritius", "Morocco", "Mozambique", "Namibia", "Niger",
"Nigeria",
                                                    "People's Republic of the Congo", "Rwanda", "Senegal", "Sierra
Leone", "Somalia",
                                                    "South Africa", "Sudan", "Tanzania", "Togo", "Tunisia",
                                                    "Uganda", "Zambia", "Zimbabwe"),]


View(terrorism_2)

#Number of Rows 782

colnames(terrorism_2) <- c("Year","Country","Number_Terrorist_Attacks")

View(terrorism_2)

terrorism_sorted <- terrorism_2[order(terrorism_2$Country), ]

View(terrorism_sorted)


#The GTD does not have any data for the 1993, because of the data getting lost in the process

#this led the organisation to creating a specific dataset for 1993, which accordingly now

#has to be added to the dataframe


terrorism_1993 <- read_excel("GTD_1993.xlsx")
```

```
view(terrorism_1993)

terrorism_1993_1 <- ftable(terrorism_1993$iyear, terrorism_1993$country_txt)

View(terrorism_1993_1)

terrorism_1993_2<-as.data.frame(terrorism_1993_1)

view(terrorism_1993_2)

terrorism_1993_3 <- terrorism_1993_2[terrorism_1993_2$Var2 %in% c("Algeria", "Angola", "Benin",
"Botswana", "Burkina Faso", "Burundi",

                                        "Cameroon", "Central African Republic", "Chad", "Ivory Coast",

                                        "Democratic Republic of the Congo", "Egypt", "Eritrea", "Ethiopia",

                                        "Gabon", "Gambia", "Ghana", "Guinea", "Guinea-Bissau", "Kenya",

                                        "Lesotho", "Liberia", "Libya", "Madagascar", "Malawi", "Mali",
"Mauritania",

                                        "Mauritius", "Morocco", "Mozambique", "Namibia", "Niger",
"Nigeria",

                                        "People's Republic of the Congo", "Rwanda", "Senegal", "Sierra
Leone", "Somalia",

                                        "South Africa", "Sudan", "Tanzania", "Togo", "Tunisia",

                                        "Uganda", "Zambia", "Zimbabwe"),]


View(terrorism_1993_3)

colnames(terrorism_1993_3) <- c("Year","Country","Number_Terrorist_Attacks")

View(terrorism_1993_3)

rownames(terrorism_1993_3) <- 1:nrow(terrorism_1993_3)

View(terrorism_1993_3)

#Add rows with missing values for the countries that did not report any terrorist attacks in 1993, to get to the
needed number of rows

class(terrorism_1993_3$Country)

#the column listing the countries is defined as a factor, which doesn't allow me to enter the name of the country

#therefore, I transform it into a character vector


terrorism_1993_3$Country <- as.character(terrorism_1993_3$Country)
```

```
#Coding the missing country rows with "NA"

row_benin <- c(1993, "Benin", NA)

row_botswana <- c(1993, "Botswana", NA)

row_burkina <- c(1993, "Burkina Faso", NA)

row_burundi <- c(1993, "Burundi", NA)

row_cameroon <- c(1993, "Cameroon", NA)

row_CAR <- c(1993, "Central African Republic", NA)

row_chad <- c(1993, "Chad", NA)

row_DRC <- c(1993, "Democratic Republic of the Congo", NA)

row_eritrea <- c(1993, "Eritrea", NA)

row_gabon <- c(1993, "Gabon", NA)

row_gambia <- c(1993, "Gambia", NA)

row_ghana <- c(1993, "Ghana", NA)

row_guinea <- c(1993, "Guinea", NA)

row_guinea_bissau <- c(1993, "Guinea-Bissau", NA)

row_ivory_coast <- c(1993, "Ivory Coast", NA)

row_kenya <- c(1993, "Kenya", NA)

row_lesotho <- c(1993, "Lesotho", NA)

row_liberia <- c(1993, "Liberia", NA)

row_libya <- c(1993, "Libya", NA)

row_madagascar <- c(1993, "Madagascar", NA)

row_malawi <- c(1993, "Malawi", NA)

row_mali <- c(1993, "Mali", NA)

row_mauritania <- c(1993, "Mauritania", NA)

row_mauritius <- c(1993, "Mauritius", NA)

row_morocco <- c(1993, "Morocco", NA)

row_mozambique <- c(1993, "Mozambique", NA)

row_namibia <- c(1993, "Namibia", NA)

row_nigeria <- c(1993, "Nigeria", NA)

row_roc <- c(1993, "Republic of the Congo", NA)
```

```
row_senegal <- c(1993, "Senegal", NA)
row_sudan <- c(1993, "Sudan", NA)
row_zambia <- c(1993, "Zambia",  NA)
row_zimbabwe <- c(1993, "Zimbabwe", NA)

#Inserting the different country rows
view(terrorism_1993_3)

terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_benin
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_botswana
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_burkina
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_burundi
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_cameroon
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_CAR
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_chad
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_DRC
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_eritrea
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_gabon
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_gambia
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_ghana
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_guinea
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_guinea_bissau
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_ivory_coast
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_kenya
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_lesotho
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_liberia
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_libya
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_madagascar
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_malawi
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_mali
```

```
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_mauritania
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_mauritius
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_morocco
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_mozambique
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_namibia
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_nigeria
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_roc
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_senegal
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_sudan
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_zambia
terrorism_1993_3[nrow(terrorism_1993_3) + 1,] <- row_zimbabwe

view(terrorism_1993_3)
terrorism_1993_sorted <- terrorism_1993_3[order(terrorism_1993_3$Country), ]
rownames(terrorism_1993_sorted) <- 1:nrow(terrorism_1993_sorted)
view(terrorism_1993_sorted)
write.csv(terrorism_1993_sorted,"Terrorism Dataframe 1993", row.names = FALSE)
#Combining the two dataframes to have complete data from 1991 to 2008
terrorism_total <- rbind(terrorism_sorted, terrorism_1993_3)
view(terrorism_total)
class(terrorism_sorted$Year)
class(terrorism_1993_3$Year)
#Transform the Year Column into a Character Vector to be able to sort by years
class(terrorism_total$Year)
terrorism_total$Year <- as.character(terrorism_total$Year)
view(terrorism_total)
#Order the terrorism data according to year and country
terrorism_total1 <- terrorism_total[order(terrorism_total$Year), ]
terrorism_final <- terrorism_total1[order(terrorism_total1$Country), ]
view(terrorism_total1)
```

```
view(terrorism_final)


#Assign the right row names to the dataset
rownames(terrorism_final) <- 1:nrow(terrorism_final)
view(terrorism_final)


#Renaming Columns
names(terrorism_final)[names(terrorism_final) == "Year"] <- "Year_Terrorism"
names(terrorism_final)[names(terrorism_final) == "Country"] <- "Country_Terrorism"


View(terrorism_final)
write_xlsx(terrorism_final, "Complete_Terrorism_Data")


##############################################################################################
#############
#PRECIPITATION
#Transform Precipiation Data from Salehyan & Hendrix
#to only include the precipiation deviation and one control variable that
#also works in the context of terrorism: time since last active conflict


#Upload Precipiation Dataset, as assembled by Hendrix & Salehyan for independent variable
precipitation_data <- read_dta("Replication_Revised.dta")
View(precipitation_data)
precipitation_data$country


precipitation<-as.data.frame(precipitation_data)
view(precipitation)
head(precipitation)
precipitation_cut <- precipitation[,c("country", "year",
                                      "GPCP_precip_mm_deviation_sd",
```

```
                            "GPCP_precip_mm_deviation_sd_l", "peaceyears")]

view(precipitation_cut)


precipitation_adapted <- precipitation_cut[precipitation_cut$year %in% c("1991", "1992", "1993", "1994",
                                          "1995", "1996", "1997", "1998", "1999", "2000",
                                          "2001", "2002", "2003", "2004", "2005", "2006",
                                          "2007", "2008"), ]

view(precipitation_adapted)

precipitation_adapted$country

precipitation_adapted1 <- precipitation_adapted[precipitation_adapted$country %in% c ("Algeria", "Angola",
"Benin", "Botswana", "Burkina Faso", "Burundi",
                                              "Cameroon", "Central African Republic", "Chad", "Ivory
Coast",
                                              "Democratic Republic of Congo", "Egypt", "Eritrea",
"Ethiopia",
                                              "Gabon", "Gambia", "Ghana", "Guinea", "Guinea-Bissau",
"Kenya",
                                              "Lesotho", "Liberia", "Libya", "Madagascar", "Malawi",
"Mali", "Mauritania",
                                              "Mauritius", "Morocco", "Mozambique", "Namibia", "Niger",
"Nigeria",
                                              "Republic of Congo", "Rwanda", "Senegal", "Sierra Leone",
"Somalia",
                                              "South Africa", "Sudan", "Tanzania", "Togo", "Tunisia",
                                              "Uganda", "Zambia", "Zimbabwe"),]


view(precipitation_adapted1)

#There are two rows missing in the dataset, which would make merging it with  other dataframes impossible

#therefore I am looking for the missing rows

ftable(precipitation_adapted1$year)


#The rows missing are the years 1991 and 1992 for Eritrea, I will therefor add two additional rows with N.A.s to
get to the needed number

#of rows to be able to merge the dataframes
```

```
#Renaming

precipitation_adapted1$country[precipitation_adapted1$country=="Democratic Republic of Congo"] <- "Democratic Republic of the Congo"

precipitation_adapted1$country[precipitation_adapted1$country=="Republic of Congo"] <- "Republic of the Congo"



#sorting the data according to country column

precipitation_final <- precipitation_adapted1[order(precipitation_adapted1$country), ]



#Change Row Names, starting from 1:nrow

rownames(precipitation_final) <- 1:nrow(precipitation_final)



#Add new rows

Eritrea_precip_91 <- c("Eritrea", "1991", NA, NA, NA)

Eritrea_precip_92 <- c("Eritrea", "1992", NA, NA, NA)



precipitation_final <- rbind(precipitation_final[1:198,],Eritrea_precip_91,precipitation_final[-(1:198),])

precipitation_final <- rbind(precipitation_final[1:199,],Eritrea_precip_92,precipitation_final[-(1:199),])



#Change column names

names(precipitation_final)[names(precipitation_final) == "country"] <- "Country_Precipitation"

names(precipitation_final)[names(precipitation_final) == "year"] <- "Year_Precipitation"

View(precipitation_final)



write_xlsx(precipitation_final, "Complete_Precipitation_Data.xlsx")

####################################################################################################################

#Variables for Interaction Effect

####################################################################################################################

#DEPENDENCE ON AGRICULTURE
```

```
#Import Dataset

agriculture <- read.csv("Dependency_on_Agriculture.csv")

View(agriculture)

head(agriculture)

agriculture_cut <- agriculture[ , c('Year', 'Area', 'Value')]

View(agriculture_cut)


#Rename Column Name

names(agriculture_cut)

names(agriculture_cut)[names(agriculture_cut) == "employment_agriculture"] <- "Employment_Agriculture"

view(agriculture_cut)

agriculture_cut_2 <- agriculture_cut[agriculture_cut$Area %in% c ("Algeria", "Angola", "Benin", "Botswana",
"Burkina Faso", "Burundi",
                                              "Cameroon", "Central African Republic", "Chad", "C?te d'Ivoire",
                                              "Democratic Republic of the Congo", "Egypt", "Eritrea", "Ethiopia",
                                              "Gabon", "Gambia", "Ghana", "Guinea", "Guinea-Bissau", "Kenya",
                                              "Lesotho", "Liberia", "Libya", "Madagascar", "Malawi", "Mali",
"Mauritania",
                                              "Mauritius", "Morocco", "Mozambique", "Namibia", "Niger",
"Nigeria",
                                              "Congo", "Rwanda", "Senegal", "Sierra Leone", "Somalia",
                                              "South Africa", "Sudan (former)", "United Republic of Tanzania",
"Togo", "Tunisia",
                                              "Uganda", "Zambia", "Zimbabwe"),]


agriculture_cut_3 <- agriculture_cut_2[agriculture_cut_2$Year %in% c("1991", "1992", "1993", "1994",
"1995", "1996", "1997", "1998", "1999", "2000",
                                                "2001", "2002", "2003", "2004", "2005", "2006",
                                                "2007", "2008"), ]


ftable(agriculture_cut_3$Year)

ftable(agriculture_cut_3$Area)
```

```
view(agriculture_cut_3)

#Rename Observations

agriculture_cut_3$Area[agriculture_cut_3$Area=="C?te d'Ivoire"] <- "Ivory Coast"

agriculture_cut_3$Area[agriculture_cut_3$Area=="Congo"] <- "Republic of the Congo"

agriculture_cut_3$Area[agriculture_cut_3$Area=="Sudan (former)"] <- "Sudan"

agriculture_cut_3$Area[agriculture_cut_3$Area=="United Republic of Tanzania"] <- "Tanzania"


names(agriculture_cut_3)[names(agriculture_cut_3) == "Area"] <- "Country_Agri"

names(agriculture_cut_3)[names(agriculture_cut_3) == "Year"] <- "Year_Agri"

names(agriculture_cut_3)[names(agriculture_cut_3) == "Value"] <- "Employment_Agriculture"


view(agriculture_cut_3)



agriculture_cut_4 <- agriculture_cut_3[order(agriculture_cut_3$Year_Agri), ]

agriculture_final <- agriculture_cut_4[order(agriculture_cut_4$Country_Agri), ]

view(agriculture_cut_4)

view(agriculture_final)


#Assign the right row names to the dataset

rownames(agriculture_final) <- 1:nrow(agriculture_final)

view(agriculture_final)


##########################################################################################
########################

#STATE CAPACITY

data_state_capacity <- read_dta("StateCapacityDataset_v1.dta")

View(data_state_capacity)
```

```
head(data_state_capacity)

state_capacity1 <- data_state_capacity[ , c('country', 'year', 'Capacity')]

view(state_capacity1)

state_capacity2 <- state_capacity1[state_capacity1$country %in% c ("Algeria", "Angola", "Benin", "Botswana", "Burkina Faso", "Burundi",
                                   "Cameroon", "Central African Rep.", "Chad", "Cote d'Ivoire",
                                   "Congo, Dem Rep", "Egypt", "Eritrea", "Ethiopia",
                                   "Gabon", "Gambia", "Ghana", "Guinea", "Guinea-Bissau", "Kenya",
                                   "Lesotho", "Liberia", "Libya", "Madagascar", "Malawi", "Mali", "Mauritania",
                                   "Mauritius", "Morocco", "Mozambique", "Namibia", "Niger", "Nigeria",
                                   "Congo, Rep.", "Rwanda", "Senegal", "Sierra Leone", "Somalia",
                                   "South Africa", "Sudan", "Tanzania", "Togo", "Tunisia",
                                   "Uganda", "Zambia", "Zimbabwe"),]

view(state_capacity2)

state_capacity3 <- state_capacity2[state_capacity2$year %in% c("1991", "1992", "1993", "1994",
                                  "1995", "1996", "1997", "1998", "1999", "2000",
                                  "2001", "2002", "2003", "2004", "2005", "2006",
                                  "2007", "2008"), ]

View(state_capacity3)

state_capacity <- as.data.frame(state_capacity3)

#adding missing rows, in order to get to the same number of observations

row_Eritrea_cap_1991 <- c("Eritrea", 1991, NA)
```

```
row_Eritrea_cap_1992 <- c("Eritrea", 1992, NA)


#add rows to dataset

state_capacity[nrow(state_capacity) + 1,] <- row_Eritrea_cap_1991

state_capacity[nrow(state_capacity) + 1,] <- row_Eritrea_cap_1992

view(state_capacity)


#order dataframe

state_cap1 <- state_capacity[order(state_capacity$year), ]

state_cap_final <- state_cap1[order(state_cap1$country), ]


view(state_cap_final)


#Assign the right row names to the dataset

rownames(state_cap_final) <- 1:nrow(state_cap_final)

View(state_cap_final)


#############################################################################################################################

#Transform Control Variables

#############################################################################################################################

#INSTITUTIONAL COHERENCE

#Clean and Transform Control Variable Institutional Coherence

coherence <- read.csv("DemocracyMatrix_v4.csv")

View(coherence)

head(coherence)

coherence$country

coherence$year

coherence$decision_freedom_context

coherence$classification_context
```

```
#creating new datasets, using only columns we need from coherence

coherence_2 <- coherence[ , c('country', 'year', 'classification_context')]

View(coherence_2)


#Checking what type of variable it its

is.numeric(coherence$classification_context)

is.factor(coherence$classification_context)

is.character(coherence$classification_context)

is.character(coherence_2$classification_context)

#creating a dummy variable

coherence_2$classification_context <- ifelse(coherence_2$classification_context == "Hard Autocracy" |
coherence_2$classification_context == "Working Democracy", 1, 0)

View(coherence_2)

#Adapting the dataset to only include the countries and years

#that are in the original precipiation dataframe, as well as renaming countries

#that were named differently


Coherence_cut <- coherence_2[coherence_2$country %in% c ("Algeria", "Angola", "Benin", "Botswana",
"Burkina Faso", "Burundi",

                    "Cameroon", "Central African Republic", "Chad", "Ivory Coast",

                    "Democratic Republic of Congo", "Egypt", "Eritrea", "Ethiopia",

                    "Gabon", "The Gambia", "Ghana", "Guinea", "Guinea-Bissau", "Kenya",

                    "Lesotho", "Liberia", "Libya", "Madagascar", "Malawi", "Mali", "Mauritania",

                    "Mauritius", "Morocco", "Mozambique", "Namibia", "Niger", "Nigeria",

                    "Republic of the Congo", "Rwanda", "Senegal", "Sierra Leone", "Somalia",

                    "South Africa", "Sudan", "Tanzania", "Togo", "Tunisia",

                    "Uganda", "Zambia", "Zimbabwe"),]

Coherence_Dummy <- Coherence_cut[Coherence_cut$year %in% c ("1991", "1992", "1993", "1994",

             "1995", "1996", "1997", "1998", "1999", "2000",

             "2001", "2002", "2003", "2004", "2005", "2006",
```

```
"2007", "2008"),]


View(Coherence_Dummy)

Coherence_Dummy$country[Coherence_Dummy$country=="Cote D'Ivoire"] <- "Ivory Coast"

Coherence_Dummy$country[Coherence_Dummy$country=="Democratic Republic of Congo"]<- "Democratic Republic of the Congo"


names(Coherence_Dummy)

View(Coherence_Dummy)

#Sort the dataframe according to year and country

Coherence_Dummy_1 <- Coherence_Dummy[order(Coherence_Dummy$year), ]

Coherence_Dummy_Final <- Coherence_Dummy[order(Coherence_Dummy$country), ]

view(Coherence_Dummy_1)

View(Coherence_Dummy_Final)


#Assign the right row names to the dataset

rownames(Coherence_Dummy_Final) <- 1:nrow(Coherence_Dummy_Final)

#Change column names

view(Coherence_Dummy_Final)

names(Coherence_Dummy_Final)[names(Coherence_Dummy_Final) == "year"] <- "Year_Coherence"

names(Coherence_Dummy_Final)[names(Coherence_Dummy_Final) == "country"] <- "Country_Coherence"

names(Coherence_Dummy_Final)[names(Coherence_Dummy_Final) == "regime_coherence"] <- "Regime_Coherence"


View(Coherence_Dummy_Final)


###########################################################################################################################

#GDP_PER_CAPITA

#Importing and transforming GDP Data

#Constant 2015 US $
```

```
GDP_per_Capita <- read.csv("WB_GDP_per_Capita.csv")

View(GDP_per_Capita)

head(GDP_per_Capita)


GDP_flipped<- pivot_longer (GDP_per_Capita, cols= X1989..YR1989.:X2010..YR2010.,

                            names_to = "Year", values_to = "GDP")

View(GDP_flipped)


GDP_cut<- subset(GDP_flipped,Series.Name=="GDP (constant 2015 US$)")

View(GDP_cut)


GDP_cut$Year[GDP_cut$Year=="X1989..YR1989."] <- "1989"

GDP_cut$Year[GDP_cut$Year=="X1990..YR1990."] <- "1990"

GDP_cut$Year[GDP_cut$Year=="X1991..YR1991."] <- "1991"

GDP_cut$Year[GDP_cut$Year=="X1992..YR1992."] <- "1992"

GDP_cut$Year[GDP_cut$Year=="X1993..YR1993."] <- "1993"

GDP_cut$Year[GDP_cut$Year=="X1994..YR1994."] <- "1994"

GDP_cut$Year[GDP_cut$Year=="X1995..YR1995."] <- "1995"

GDP_cut$Year[GDP_cut$Year=="X1996..YR1996."] <- "1996"

GDP_cut$Year[GDP_cut$Year=="X1997..YR1997."] <- "1997"

GDP_cut$Year[GDP_cut$Year=="X1998..YR1998."] <- "1998"

GDP_cut$Year[GDP_cut$Year=="X1999..YR1999."] <- "1999"

GDP_cut$Year[GDP_cut$Year=="X2000..YR2000."] <- "2000"

GDP_cut$Year[GDP_cut$Year=="X2001..YR2001."] <- "2001"

GDP_cut$Year[GDP_cut$Year=="X2002..YR2002."] <- "2002"

GDP_cut$Year[GDP_cut$Year=="X2003..YR2003."] <- "2003"

GDP_cut$Year[GDP_cut$Year=="X2004..YR2004."] <- "2004"

GDP_cut$Year[GDP_cut$Year=="X2005..YR2005."] <- "2005"

GDP_cut$Year[GDP_cut$Year=="X2006..YR2006."] <- "2006"

GDP_cut$Year[GDP_cut$Year=="X2007..YR2007."] <- "2007"
```

```
GDP_cut$Year[GDP_cut$Year=="X2008..YR2008."] <- "2008"

GDP_cut$Year[GDP_cut$Year=="X2009..YR2009."] <- "2009"

GDP_cut$Year[GDP_cut$Year=="X2010..YR2010."] <- "2010"


View(GDP_cut)


#Rename Columns

names(GDP_cut)[names(GDP_cut) == "GDP"] <- "GDP (constant 2015 US$)"

names(GDP_cut)[names(GDP_cut) == "Country.Name"] <- "Country"


GDP_sorted <- GDP_cut[GDP_cut$Year %in% c("1991", "1992", "1993", "1994", "1995", "1996", "1997",
"1998", "1999", "2000",

                                          "2001", "2002", "2003", "2004", "2005", "2006",

                                          "2007", "2008"), ]

view(GDP_sorted)


GDP <- GDP_sorted[ , c('Country', 'Year', 'GDP (constant 2015 US$)')]

view(GDP)


#Change Column Names

names(GDP)[names(GDP) == "Year"] <- "Year_GDP"

names(GDP)[names(GDP) == "Country"] <- "Country_GDP"


view(GDP)


#Change Country Names

GDP$Country_GDP[GDP$Country_GDP=="Cote d'Ivoire"] <- "Ivory Coast"

GDP$Country_GDP[GDP$Country_GDP=="Congo, Rep."] <- "Republic of the Congo"

GDP$Country_GDP[GDP$Country_GDP=="Congo, Dem. Rep."] <- "Democratic Republic of the Congo"

GDP$Country_GDP[GDP$Country_GDP=="Egypt, Arab Rep."] <- "Egypt"
```

```
view(GDP)


#Order according to year and country

GDP_1 <- GDP[order(GDP$Year_GDP), ]

GDP_2 <- GDP_1[order(GDP_1$Country_GDP), ]


#Save GDP as Dataframe

GDP_Final<-as.data.frame(GDP_2)

#Assign the right row names to the dataset

rownames(GDP_Final) <- 1:nrow(GDP_Final)

View(GDP_Final)


##############################################################################################
#################################

#YOUTH UNEMPLOYMENT RATE

#Transforming the Data

unemployment <- read.csv("ILO Youth Unemployment.csv")

View(unemployment)

head(unemployment)


# Turning year columns into rows

head(unemployment)

unemployment_flipped<- pivot_longer (unemployment, cols= X1991..YR1991.:X2011..YR2011.,

                              names_to = "Year", values_to = "Percentage")

View(unemployment_flipped)


#Subsetting the dataset to only include the needed columns

youth_unemployment <- unemployment_flipped[ , c('Country.Name', 'Year', 'Percentage')]

view(youth_unemployment)
```

```
#Renaming the observations in the year column

youth_unemployment$Year[youth_unemployment$Year=="X1991..YR1991."] <- "1991"
youth_unemployment$Year[youth_unemployment$Year=="X1992..YR1992."] <- "1992"
youth_unemployment$Year[youth_unemployment$Year=="X1993..YR1993."] <- "1993"
youth_unemployment$Year[youth_unemployment$Year=="X1994..YR1994."] <- "1994"
youth_unemployment$Year[youth_unemployment$Year=="X1995..YR1995."] <- "1995"
youth_unemployment$Year[youth_unemployment$Year=="X1996..YR1996."] <- "1996"
youth_unemployment$Year[youth_unemployment$Year=="X1997..YR1997."] <- "1997"
youth_unemployment$Year[youth_unemployment$Year=="X1998..YR1998."] <- "1998"
youth_unemployment$Year[youth_unemployment$Year=="X1999..YR1999."] <- "1999"
youth_unemployment$Year[youth_unemployment$Year=="X2000..YR2000."] <- "2000"
youth_unemployment$Year[youth_unemployment$Year=="X2001..YR2001."] <- "2001"
youth_unemployment$Year[youth_unemployment$Year=="X2002..YR2002."] <- "2002"
youth_unemployment$Year[youth_unemployment$Year=="X2003..YR2003."] <- "2003"
youth_unemployment$Year[youth_unemployment$Year=="X2004..YR2004."] <- "2004"
youth_unemployment$Year[youth_unemployment$Year=="X2005..YR2005."] <- "2005"
youth_unemployment$Year[youth_unemployment$Year=="X2006..YR2006."] <- "2006"
youth_unemployment$Year[youth_unemployment$Year=="X2007..YR2007."] <- "2007"
youth_unemployment$Year[youth_unemployment$Year=="X2008..YR2008."] <- "2008"
youth_unemployment$Year[youth_unemployment$Year=="X2009..YR2009."] <- "2009"
youth_unemployment$Year[youth_unemployment$Year=="X2010..YR2010."] <- "2010"
youth_unemployment$Year[youth_unemployment$Year=="X2011..YR2011."] <- "2011"

view(youth_unemployment)

#Cutting out empty rows from the dataset that are not assigned to any year or country

youth_unemployment_cut1 <- youth_unemployment[-c(1051:1155), ]

##Making sure all of the datasets have the same amount of rows prior to merging them
```

```
#Sorting the rows according to the column country alphabetically

unemployment_cut2 <- youth_unemployment_cut1[youth_unemployment_cut1$Year %in% c("1991", "1992",
"1993", "1994",

                                             "1995", "1996", "1997", "1998", "1999", "2000",

                                             "2001", "2002", "2003", "2004", "2005", "2006",

                                             "2007", "2008"), ]



names(unemployment_cut2)[names(unemployment_cut2) == "Country.Name"] <- "Country"

view(unemployment_cut2)

unemployment_cut3 <- unemployment_cut2[unemployment_cut2$Country %in% c ("Algeria", "Angola",
"Benin", "Botswana", "Burkina Faso", "Burundi",

                               "Cameroon", "Central African Republic", "Chad", "Cote d'Ivoire",

                               "Congo, Dem. Rep.", "Egypt, Arab Rep.", "Eritrea", "Ethiopia",

                               "Gabon", "Gambia, The", "Ghana", "Guinea", "Guinea-Bissau", "Kenya",

                               "Lesotho", "Liberia", "Libya", "Madagascar", "Malawi", "Mali",
"Mauritania",

                               "Mauritius", "Morocco", "Mozambique", "Namibia", "Niger", "Nigeria",

                               "Congo, Rep.", "Rwanda", "Senegal", "Sierra Leone", "Somalia",

                               "South Africa", "Sudan", "Tanzania", "Togo", "Tunisia",

                               "Uganda", "Zambia", "Zimbabwe"),]



unemployment_cut3$Country[unemployment_cut3$Country=="Cote d'Ivoire"] <- "Ivory Coast"

unemployment_cut3$Country[unemployment_cut3$Country=="Congo, Rep."] <- "Republic of the Congo"

unemployment_cut3$Country[unemployment_cut3$Country=="Congo, Dem. Rep."] <- "Democratic Republic
of the Congo"

unemployment_cut3$Country[unemployment_cut3$Country=="Egypt, Arab Rep."] <- "Egypt"

unemployment_cut3$Country[unemployment_cut3$Country=="Gambia, The"] <- "Gambia"


view(unemployment_cut2)


#Change Column Names
```

```
names(unemployment_cut3)[names(unemployment_cut3) == "Year"] <- "Year_Unemployed"

names(unemployment_cut3)[names(unemployment_cut3) == "Country"] <- "Country_Unemployed"

names(unemployment_cut3)[names(unemployment_cut3) == "Percentage"] <- "Percentage_Unemployed"


#Order according to year and country

unemployment_1 <- unemployment_cut3[order(unemployment_cut3$Year_Unemployed), ]

unemployment_2 <- unemployment_1[order(unemployment_1$Country_Unemployed), ]


#Save Unemployment_sorted as Dataframe

Unemployment_Final<-as.data.frame(unemployment_2)

#Assign the right row names to the dataset

rownames(Unemployment_Final) <- 1:nrow(Unemployment_Final)

View(Unemployment_Final)


###########################################################################################################

#LEVEL OF DEMOCRACY

#Importing the Polity V Dataset to be able to measure the level of democracy

polity_dataset <- read_excel("p5v2018.xls")

View(polity_dataset)


polity_cut1 <- polity_dataset[,c("country", "year",

                          "polity2")]


#recode dataframe to have a scale from 0-20, rather than from -10 to 10

polity_cut1$polity2[polity_cut1$polity2=="10"] <- "20"

polity_cut1$polity2[polity_cut1$polity2=="9"] <- "19"

polity_cut1$polity2[polity_cut1$polity2=="8"] <- "18"

polity_cut1$polity2[polity_cut1$polity2=="7"] <- "17"

polity_cut1$polity2[polity_cut1$polity2=="6"] <- "16"
```

```
polity_cut1$polity2[polity_cut1$polity2=="5"] <- "15"

polity_cut1$polity2[polity_cut1$polity2=="4"] <- "14"

polity_cut1$polity2[polity_cut1$polity2=="3"] <- "13"

polity_cut1$polity2[polity_cut1$polity2=="2"] <- "12"

polity_cut1$polity2[polity_cut1$polity2=="1"] <- "11"

polity_cut1$polity2[polity_cut1$polity2=="0"] <- "10"

polity_cut1$polity2[polity_cut1$polity2=="-1"] <- "9"

polity_cut1$polity2[polity_cut1$polity2=="-2"] <- "8"

polity_cut1$polity2[polity_cut1$polity2=="-3"] <- "7"

polity_cut1$polity2[polity_cut1$polity2=="-4"] <- "6"

polity_cut1$polity2[polity_cut1$polity2=="-5"] <- "5"

polity_cut1$polity2[polity_cut1$polity2=="-6"] <- "4"

polity_cut1$polity2[polity_cut1$polity2=="-7"] <- "3"

polity_cut1$polity2[polity_cut1$polity2=="-8"] <- "2"

polity_cut1$polity2[polity_cut1$polity2=="-9"] <- "1"

polity_cut1$polity2[polity_cut1$polity2=="-10"] <- "0"


View(polity_cut1)


#include only countries and years needed for this analysis

polity_cut2 <- polity_cut1[polity_cut1$country %in% c ("Algeria", "Angola", "Benin", "Botswana", "Burkina Faso", "Burundi",

                                                       "Cameroon", "Central African Republic", "Chad", "Cote D'Ivoire",

                                                       "Congo-Brazzaville", "Egypt", "Eritrea", "Ethiopia",

                                                       "Gabon", "Gambia", "Ghana", "Guinea", "Guinea-Bissau", "Kenya",

                                                       "Lesotho", "Liberia", "Libya", "Madagascar", "Malawi", "Mali", "Mauritania",

                                                       "Mauritius", "Morocco", "Mozambique", "Namibia", "Niger", "Nigeria", "Congo Kinshasa",

                                                       "Rwanda", "Senegal", "Sierra Leone", "Somalia",

                                                       "South Africa", "Sudan", "Tanzania", "Togo", "Tunisia",

                                                       "Uganda", "Zambia", "Zimbabwe"),]
```

```
polity <- polity_cut2[polity_cut2$year %in% c("1991", "1992", "1993", "1994",
                                               "1995", "1996", "1997", "1998", "1999", "2000",
                                               "2001", "2002", "2003", "2004", "2005", "2006",
                                               "2007", "2008"), ]

View(polity)



ftable(polity$year)
#After realising that the number of rows (and therefore observations was less than expected for a time span of
#18 years and 46 countries (=828), I was looking into the yearly distributions with ftable and could find that for Ethiopia
#two values were recorded for the year 1993. This can be explained by the fact that Eritrea gained indepenced from Ethiopia
#in 1993 and therefore Ethiopia with Eritrea was counted for 1993, as well as Ethiopia without Eritrea in 1993. This can
#also be seen in the country codes changing from ETH to ETI. Considering that the split from Eritrea happened in April of 1993,
#I will take the observation only accounting for Ethiopia into consideration and will delete the other one
#in order to get to the correct number of rows.)

polity<- polity[-213,]
View(polity)
#Observation missing for Eritrea in 1991, 1992
#Observation missing for Congo-Brazzaville in 2005, 2006, 2007, 2008

polity_1<-as.data.frame(polity)


#creating rows with NAs for the missing observations
row_eritrea_1991_pol <- c("Eritrea", 1991,  NA)
row_eritrea_1992_pol <- c("Eritrea", 1992, NA)
```

```
row_congo_b_2005_pol <- c("Congo-Brazzaville", 2005, NA)
row_congo_b_2006_pol <- c("Congo-Brazzaville", 2006, NA)
row_congo_b_2007_pol <- c("Congo-Brazzaville", 2007, NA)
row_congo_b_2008_pol <- c("Congo-Brazzaville", 2008, NA)

#inserting the rows into the dataframe
polity_1[nrow(polity_1) + 1,] <- row_eritrea_1991_pol
polity_1[nrow(polity_1) + 1,] <- row_eritrea_1992_pol
polity_1[nrow(polity_1) + 1,] <- row_congo_b_2005_pol
polity_1[nrow(polity_1) + 1,] <- row_congo_b_2006_pol
polity_1[nrow(polity_1) + 1,] <- row_congo_b_2007_pol
polity_1[nrow(polity_1) + 1,] <- row_congo_b_2008_pol

View(polity_1)

polity_1$country[polity_1$country=="Congo Kinshasa"] <- "Democratic Republic of the Congo"
polity_1$country[polity_1$country=="Congo-Brazzaville"] <- "Republic of the Congo"
polity_1$country[polity_1$country=="Cote D'Ivoire"] <- "Ivory Coast"

#Sort the dataframe according to year and country
Polity_Final <- polity_1[order(polity_1$country), ]
view(Polity_Final)

#Assign the right row names to the dataset
rownames(Polity_Final) <- 1:nrow(Polity_Final)
View(Polity_Final)

#Change Column Names
names(Polity_Final)[names(Polity_Final) == "year"] <- "Year_Democracy"
```

```
names(Polity_Final)[names(Polity_Final) == "country"] <- "Country_Democracy"

names(Polity_Final)[names(Polity_Final) == "polity2"] <- "Level_of_Democracy"

view(Polity_Final)

View(Thesis_Panel)

##########################################################################################
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#Merging the 8 different dataframes into a single one

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##############

#MERGING DATAFRAMES PRECIPITATION AND TERRORISM

view(precipitation_sorted)

view(terrorism_final)

DV_IV <- cbind(precipitation_final, terrorism_final)

View(DV_IV)

##########################################################################################
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#Adding the other datasets

merge_agriculture <- cbind(DV_IV, agriculture_final)

View(merge_agriculture)


merge_unemployment <- cbind(merge_agriculture, Unemployment_Final)

View(merge_unemployment)


merge_GDP <- cbind(merge_unemployment, GDP_Final)

View(merge_GDP)


merge_coherence <- cbind(merge_GDP, Coherence_Dummy_Final)

View(merge_coherence)


merge_democracy <- cbind(merge_coherence, Polity_Final)

view(merge_democracy)
```

```
Final_Data <- cbind(merge_democracy, state_cap_final)


write_xlsx(Final_Data, "Complete_22.05.2022.xlsx")


##############################################################################################
##############

#Transform Final Dataset

Thesis_Data <- Final_Data[ , c('Country_Precipitation', 'Year_Precipitation', 'GPCP_precip_mm_deviation_sd',
'peaceyears', 'Number_Terrorist_Attacks',

                         'Employment_Agriculture', 'Percentage_Unemployed', 'GDP (constant 2015 US$)',

                         'classification_context', 'Level_of_Democracy', 'Capacity')]

View(Thesis_Data)


names(Thesis_Data)[names(Thesis_Data) == "Country_Precipitation"] <- "Country"

names(Thesis_Data)[names(Thesis_Data) == "Year_Precipitation"] <- "Year"

names(Thesis_Data)[names(Thesis_Data) == "GPCP_precip_mm_deviation_sd"] <- "Precipitation_Deviation"

names(Thesis_Data)[names(Thesis_Data) == "peaceyears"] <- "Years_in_Peace"

names(Thesis_Data)[names(Thesis_Data) == "Percentage_Unemployed"] <- "Youth_Unemployment"

names(Thesis_Data)[names(Thesis_Data) == "GDP (constant 2015 US$)"] <- "GDP_per_Capita"

names(Thesis_Data)[names(Thesis_Data) == "classification_context"] <- "Regime_Coherence_Dummy"

names(Thesis_Data)[names(Thesis_Data) == "Capacity"] <- "State_Capacity"

names(Thesis_Data)[names(Thesis_Data) == "Employment_Agriculture_State_Vulnerability"] <-
"Employment_Agriculture"


View(Thesis_Data)

write_xlsx(Thesis_Data, "Thesis_Data_PK.xlsx")


##############################################################################################
##############
```

```
#Preparing the Regression

#Making sure the variables have the right class

class(Thesis_Data$Precipitation_Deviation_SD) #character -> numeric

class(Thesis_Data$Precipitation_Deviation_SD_L) #character -> numeric

class(Thesis_Data$Years_in_Peace) #character -> numeric

class(Thesis_Data$GDP_per_Capita) #character -> numeric

class(Thesis_Data$Number_Terrorist_Attacks) #character -> numeric

class(Thesis_Data$Regime_Coherence_Dummy) #numeric -> factor

class(Thesis_Data$Employment_Agriculture) #numeric stays as numeric

class(Thesis_Data$Level_of_Democracy) #character -> factor

class(Thesis_Data$Youth_Unemployment) #numeric stays as numeric

class(Thesis_Data$State_Capacity) #character -> numeric



Thesis_Data$Precipitation_Deviation <- as.numeric(Thesis_Data$Precipitation_Deviation)

Thesis_Data$Years_in_Peace <- as.numeric(Thesis_Data$Years_in_Peace)

Thesis_Data$GDP_per_Capita <- as.numeric(Thesis_Data$GDP_per_Capita)

Thesis_Data$Number_Terrorist_Attacks <- as.numeric(Thesis_Data$Number_Terrorist_Attacks)


Thesis_Data$Level_of_Democracy <- as.numeric(Thesis_Data$Level_of_Democracy)

Thesis_Data$State_Capacity <- as.numeric(Thesis_Data$State_Capacity)


View(Thesis_Data)

Thesis_Panel <- pdata.frame  (Thesis_Data, index =c("Country", "Year"))

class(Thesis_Panel$Regime_Coherence_Dummy)

View(Thesis_Panel)
```

```
###########################################################################################
###########

#Descricptive Statistics

stargazer((Thesis_Panel),

          type = "text",

          title = "Descriptive Statistics",

          style = "qje",

          out = "Final_Descriptive_Statistics.doc",

          digits = 2,

          median = TRUE,

          iqr = TRUE)


#Boxplot

library(ggplot2)

boxplot(Thesis_Panel$Precipitation_Deviation)

boxplot(Thesis_Panel$Youth_Unemployment)


ggplot(Thesis_Panel, aes(x = Thesis_Panel$Precipitation_Deviation)) +

  geom_boxplot()


p <- ggplot(Thesis_Panel, aes(x=Precipitation_Deviation, y=Number_Terrorist_Attacks)) +

  geom_boxplot()


ggplot(data = Thesis_Data, aes(y = Precipitation_Deviation)) +

  geom_boxplot() +

  scale_x_discrete() +

  labs(title = "Distribution of the Rainfall Deviation Data",

       y = "Rainfall Deviation (in mm)")


ggplot(Thesis_Data, aes( y=Number_Terrorist_Attacks)) +
```

```
  geom_boxplot(outlier.colour="blue", outlier.shape=1,
               outlier.size=4)+
  scale_x_discrete() +
  labs(title = "Terrorist Attacks",
       y = "Terrorist Attacks")

exp(-1.249)

ggplot(Thesis_Panel, aes(x=Precipitation_Deviation, y=Number_Terrorist_Attacks)) +
  geom_boxplot(outlier.colour="red", outlier.shape=8,
               outlier.size=4)

ggplot(Thesis_Data) +
  geom_point(aes(y = Precipitation_Deviation)) +
  theme_bw() +
ylab ("Rainfall Deviation") +
  geom_smooth(aes( x = Precipitation_Deviation), method = "glm",
              method.args = list(family = "binomial")) +
  geom_jitter(aes( x = Precipitation_Deviation), color = "maroon",
              width = 0.25, height = 0.1, alpha = 0.3)
#Mullticollinarity
correlation <- Thesis_Panel %>%
  select(Number_Terrorist_Attacks,
    Precipitation_Deviation,
         State_Capacity,
         Employment_Agriculture,
         GDP_per_Capita,
         Level_of_Democracy,
         Years_in_Peace,
         Youth_Unemployment,
```

```
        Regime_Coherence_Dummy) %>%
  correlate() %>%
  rearrange()%>%
  shave()

fashion(correlation)
correlation %>% fashion() %>% write_xlsx("Multicollinarity_all.xlsx")
stargazer(correlation, type = "text",
          out = "Correlation")

write.table(correlation, file = "Correlation.xlxs")

##################################################################################################################
###ANALYSIS
##################################################################################################################

#Regression_1: only including the dependent and the main independent variable


Regression_1 <- glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation, data = Thesis_Panel)

summary(Regression_1)

stargazer(Regression_1, type = "text",
          out = "Regression_I_Final.doc")


############################################################################################################
```

```
#Regression 2: including all of the control variables, as well as state capacity

#and state vulnerability but without an interaction effect


Regression_2 <-  glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation + State_Capacity

                        + Employment_Agriculture + Years_in_Peace + Youth_Unemployment

                        + GDP_per_Capita + Regime_Coherence_Dummy

                        + Level_of_Democracy,  data = Thesis_Panel)

summary(Regression_2)


stargazer(Regression_1, Regression_2, type = "text",

          out = "Regression_II_Final.doc")




###########################################################################################

#Regression 3: Full Regression with Interaction Effect between Precipitation_Deviation and
Employment_Agriculture

Regression_3 <-  glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation*Employment_Agriculture

                        + State_Capacity + Years_in_Peace + Youth_Unemployment

                        + GDP_per_Capita + Regime_Coherence_Dummy

                        + Level_of_Democracy,  data = Thesis_Panel)


summary(Regression_3)


stargazer(Regression_1, Regression_2, Regression_3, type = "text",

          out = "Regression_III_Final.doc")


#Plotting the Interaction Effect I

library(sjPlot)

library(sjmisc)

library(ggplot2)
```

```
plot_model(Regression_3, type = "pred", terms = c("Precipitation_Deviation", "Employment_Agriculture"))


##########################################################################
#Regression 4: Full Regression with Interaction Effect between Precipitation_Deviation and State_Capacity


Regression_4 <- glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation*State_Capacity
            +Employment_Agriculture +Years_in_Peace + Youth_Unemployment
            +GDP_per_Capita + Regime_Coherence_Dummy
            +Level_of_Democracy, data = Thesis_Panel)

summary(Regression_4)

stargazer(Regression_1, Regression_2, Regression_3, Regression_4, type = "text",
     out = "Regression_IV_Final_Final.doc")

plot_model(Regression_4, type = "pred", terms = c("Precipitation_Deviation", "State_Capacity",
                   xlab = "Rainfall Deviation",
                   trace.label = "State Capacity" ))



##################################################################################
#Robustness Check 1
#Only excluding 1993 because of the small numbers of observations for this particular year due to the GTD
view(Thesis_Data)
Robustness <- Thesis_Data[Thesis_Data$Year %in% c("1991", "1992", "1994",
                  "1995", "1996", "1997", "1998", "1999", "2000",
                  "2001", "2002", "2003", "2004", "2005", "2006",
```

```
                              "2007", "2008"), ]

Robustness_Panel <- pdata.frame  (Robustness, index =c("Country", "Year"))


view(Robustness)


Regression_1_Robust <- glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation, data =
Robustness_Panel)




Regression_2_Robust <-  glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation + State_Capacity

          + Employment_Agriculture + Years_in_Peace + Youth_Unemployment

          + GDP_per_Capita + Regime_Coherence_Dummy

          + Level_of_Democracy,  data = Robustness_Panel)


Regression_3_Robust <-  glm.nb(Number_Terrorist_Attacks ~
Precipitation_Deviation*Employment_Agriculture

          + State_Capacity + Years_in_Peace + Youth_Unemployment

          + GDP_per_Capita + Regime_Coherence_Dummy

          + Level_of_Democracy,  data = Robustness_Panel)




Regression_4_Robust <- glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation*State_Capacity

          +Employment_Agriculture +Years_in_Peace + Youth_Unemployment

          +GDP_per_Capita + Regime_Coherence_Dummy

          +Level_of_Democracy, data = Robustness_Panel)


summary(Regression_3)


stargazer(Regression_1_Robust, Regression_2_Robust, Regression_3_Robust, Regression_4_Robust, type =
"text",

    out = "Regression_Robust.doc")
```

```
#####################################################################################

#Robustness Check 2

#Looking at the years 1994-2008

view(Thesis_Data)

Robustness_2 <- Thesis_Data[Thesis_Data$Year %in% c("1994",

                                 "1995", "1996", "1997", "1998", "1999", "2000",

                                 "2001", "2002", "2003", "2004", "2005", "2006",

                                 "2007", "2008"), ]

Robustness_Panel_2 <- pdata.frame  (Robustness, index =c("Country", "Year"))


view(Robustness_2)


Regression_1_Robust_2 <- glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation, data =
Robustness_Panel_2)


Regression_2_Robust_2 <-  glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation + State_Capacity

                    + Employment_Agriculture + Years_in_Peace + Youth_Unemployment

                    + GDP_per_Capita + Regime_Coherence_Dummy

                    + Level_of_Democracy,  data = Robustness_Panel_2)


Regression_3_Robust_2 <-  glm.nb(Number_Terrorist_Attacks ~
Precipitation_Deviation*Employment_Agriculture

                    + State_Capacity + Years_in_Peace + Youth_Unemployment

                    + GDP_per_Capita + Regime_Coherence_Dummy

                    + Level_of_Democracy,  data = Robustness_Panel_2)


Regression_4_Robust_2 <- glm.nb(Number_Terrorist_Attacks ~ Precipitation_Deviation*State_Capacity
```

```
+Employment_Agriculture +Years_in_Peace + Youth_Unemployment

+GDP_per_Capita + Regime_Coherence_Dummy

+Level_of_Democracy, data = Robustness_Panel_2)
```

```
stargazer(Regression_1_Robust_2, Regression_2_Robust_2, Regression_3_Robust_2, Regression_4_Robust_2, type = "text",

    out = "Regression_Robust_2.doc")
```