Linking water insecurity and social unrest: Investigating the role of perception with survey data in Sub-Saharan Africa

Frieler, Niklas

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Niklas Frieler

s2193639

Supervision: Dr. Babak RezaeeDaryakenari

Co-Reader: Dr. Frits Meijerink

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Institute of Political Science

Leiden University

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Abstract

This study explores the link between water insecurity perception and social unrest. With increasing pressures on water supply due to population growth, especially in Sub-Saharan Africa, individuals will experience increased water stress in the future. While water scarcity is mostly conceptualized in physical terms, the importance of understanding individual perceptions of extreme circumstances, e.g., lacking clean water to maintain livelihoods, cannot be overstated. Building on the theories of grievance emergence and relative deprivation as drivers for increased conflict, the relation between perceived water insecurity and social unrest frequency is analyzed by utilizing survey data from Sub-Saharan Africa between 2011 and 2017. The empirical results suggest a positive effect of water insecurity perception on social unrest, however they are not statistically significant. Nevertheless, they show that water insecurity perception has a social unrest-enhancing effect. The outcome of these results accentuates the difficulty in holistically measuring individual perceptions of water insecurity, highlighting the opportunities for future research. These should include the close investigation of micro-mechanisms influencing the link between perception and social unrest likelihood with sufficient data, as well as a more holistic approach of measuring perception in this context.

Keywords

Water scarcity, perception, social unrest, relative deprivation, grievances, infrastructure availability

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By 2025, it is expected that 1.8 billion people will live in countries or regions with absolute water scarcity (UN Water, 2006). By allocating Sustainable Development Goal (SDG) 6 to the aim of ensuring safe drinking water and sanitation for all, the UN has defined water scarcity as a major challenge of the future. Sub-Saharan Africa is particularly challenged, as 42% of individuals in Sub-Saharan Africa are currently without basic water supply and 95% of cultivated crops in this region are rain-fed (Almer et al., 2017). Also in connection with unprecedented urban growth, which is thought to increase water scarcity, citizens in Sub-Saharan Africa are particularly vulnerable and face increasing risks to their livelihood (Gesellschaft für Internationale Zusammenarbeit (GIZ), 2019).

While the link between resource scarcity and conflict likelihood has been analysed in existing research (Ross, 2004; Magnus Theisen, 2008; Koubi et al., 2012), substantial research demonstrating the specific link between water scarcity and conflict has received increasing attention. Because water may well be the upcoming battleground for countries' political and economic aspirations, its importance has resulted in numerous studies analysing water conflicts (Bernauer & Böhmelt, 2020; Carius et al., 2004; Kreamer, 2013). Previously, however, water scarcity has mostly been conceptualized in physical terms, such as changes in temperature and precipitation (Böhmelt et al., 2014; Bernauer et al., 2014). Thereby, socio-psychological perceptions of water insecurity on an individual level are not adequately addressed. Especially within the resource scarcity- conflict literature, this focus falls short. Thus, this research addresses the question: *To what extent does the individual perception of water insecurity influence the frequency of social unrest in Sub-Saharan Africa?* Connecting this observation to outcomes of individual deprivation (Moore & Jaggers, 1990) and arising grievances from unpleasant livelihood circumstances (Ross, 2004), the link between water

access and social unrest should be highlighted from a different, more individualistic, perspective.

Within the climate conflict literature, the neo-Malthusian camp provides a basic framework by claiming that resource scarcity, through increased population growth, may lead to civil conflict (Böhmelt et al., 2014; Urdal, 2005). While most literature focuses on the likelihood and onset of armed conflict or civil war, the focus on low-level conflict falls short in current research. Thus, the effect of perceived water access on social unrest frequency in Sub-Saharan Africa should receive further attention.

For this, household survey data from the Afrobarometer (Rounds 5-7) is analysed and aggregated to country-year level to understand and quantify individual perceptions of water insecurity, while linking this data to social unrest instances on the basis of Social Conflict Analysis Database (SCAD) data. Hence, I argue that stronger perceptions of water insecurity are associated with a higher frequency of social unrest. The hypothesis is then tested through OLS, negative binomial, and logistic regression analysis which connect the proxy survey question of individual water insecurity perception in 31 countries between 2011 and 2017 to social unrest frequency. The effects across all three models indicate stronger perception of water insecurity to have a conflict-enhancing effect. Yet, the results indicate no significant impact of water insecurity perception on social unrest frequency and incidence in Sub-Saharan Africa.

This research proceeds as follows: The following section focuses on reviewing relevant literature which highlights linkages between water scarcity and perceptions thereof. This is followed by an outline of the theoretical framework on the perception- conflict nexus, building on grievance and relative deprivation literature. Thereafter, in order to gain a deeper understanding of the effect between perceived water insecurity and conflict occurrence, applied data and statistical methods are highlighted. Finally, this study provides a conclusion

to the research question and finishes with a section on recommendations for future research to improve the understanding of individual perception within the environmental conflict literature.

Literature Review

A substantial amount of current conflict literature highlights the debate around the influence of resource scarcities on conflict likelihood (Böhmelt et al., 2014; Gleditsch et al., 2006; Homer-Dixon, 1994; Maxwell & Reuveny, 2000; Ross, 2004). Within this debate, two prevalent camps analyse a possible influence of climate change on conflict: Cornucopians and neo-Malthusians (Ide & Scheffran, 2014). The debate revolves around Malthus' basic claim that the human population growth eventually outpaces available resources, resulting in conflicts over resources (Brown et al., 2014). Simultaneously, cornucopians argue for the possibility of overcoming scarcities through societal adaptivity, thus minimizing conflict risk (Böhmelt et al., 2014; Bernauer et al., 2012). Within this debate, the degree of human vulnerability indicates the chances of conflicts resulting from scarce resources.

Connecting to human vulnerability, even though a number of definitions exist, studies have frequently considered climate change vulnerability as a framework of three concepts: sensitivity, exposure, and adaptive capacity (Adger 2006; Smit and Wandel 2006; Reed et al. 2013). While exposure refers to the level to which a region is disclosed to climate-related events, e.g., drought induced by decreased precipitation or rise in temperature, sensitivity refers to the extent to which a region is affected by the exposure. Adaptive capacity is the ability of a community in the region to resist or recuperate from the effects of the exposure. By focusing on the neo-Malthusian view that environmental changes play a crucial role in the onset and duration of violent conflicts, the question arising in the literature revolves around

which environmental component contributes to the possible conflict link (De Soysa, 2000; Diamond, 2006; Verhoeven, 2011).

Water Conflict

Despite existing ambiguities in regard to the most influential environmental factors on conflict, current research is predominantly supportive of the positive association between water scarcity and conflict onset (Bernauer et al., 2012, Böhmelt et al., 2014; Ohlsson, 2000). Existing research further suggests that water-related conflicts have been consistently increasing for decades, with an amplified increase in the last decade (Gleick & Heberger, 2014; Levy & Sidel, 2011).

Furthermore, it is claimed that most water-related conflicts occur intranationally while being related to subnational disagreements. Causes of this form of conflict are multifold, but revolve around disputes over dams, sociopolitical pressures, and stress over environmental and resource matters (Gleick & Heberger, 2014; Levy, 2019). Whereas many water-related conflicts occur in regions where violence is widespread, only a few have become violent, with the majority of disputes resulting in cooperative attempts between countries (Böhmelt et al., 2014; Levy, 2019). As Almer et al. (2017) claim, case-study accounts of water-related conflicts relate to outbursts of violence between different local communities, i.e. small-scale social conflicts (p. 195).

While the majority of research analyses water-induced armed and transboundary conflicts (Hauge & Ellingsen, 1998; Levy, 2019; Petersen-Perlman et al., 2017; Selby & Hoffmann, 2014), the inclusion of small-scale water-induced conflict is limited. Hence, the current study approaches this shortcoming by analysing social unrest in Sub-Saharan Africa in connection to water scarcity.

Water Scarcity & Social Unrest

The United Nations define water scarcity as "the point at which the aggregate impact of all users impinges on the supply or quality of water under prevailing institutional arrangements to the extent that the demand by all sectors, including the environment, cannot be satisfied fully" (UN Water, 2006, p. 2). Based on this definition, Schewe et al. (2014) add to this by highlighting that changes in temperature affect the earth's hydrological cycle and thus precipitation, which negatively influences local freshwater availability. Moreover, water scarcity adversely affects food security, industrial development and health, majorly impacting individuals in their livelihood (Levy, 2019).

Further recognizing the importance of adequate water availability, Peter Gleick (1999) acknowledges that water can be the cause for development disputes, in which water resources are at the origin of disagreements in the context of social development. This implies inhibited social development of vulnerable individuals due to water insecurity in affected regions and connects to the claim that effects of water scarcity are expected to be felt most on a local level (Almer et al., 2017).

Almer et al. (2017) approach this by providing disaggregated monthly data and customizing their research to the local nature of the phenomenon of water scarcity and its possibility to trigger riots. The authors find a negative association between climatic water balance and riot likelihood in Sub-Saharan Africa while pointing to the specific characteristics of riots being frequent and local. In addition to this, Böhmelt et al. (2014) show that "demand-side drivers" (p. 338) on water, including population pressure, economic activity, and agricultural capacity, have a larger impact on water conflict risk than "supply-side drivers" (p. 338). They define supply-side drivers as climate variability while measuring climate variability as changes in precipitation and temperature (p. 339). This is mentioned

specifically in the current research as their conceptualization highlights a challenge for the holistic understanding of water insecurity and serves as a basis for this study.

As Wolfe and Brooks (2003) show, water scarcity is mostly defined in physical terms, such as gallons per capita, precipitation or temperature. These physical measures, however, do not sufficiently reflect the various impacts water insecurity has on the human perception and comprehension of this phenomenon. Particularly Böhmelt et al. 's (2014) definition of water supply in terms of temperature and precipitation falls short on taking the individually perceived water access on a household level into account when drawing a possible link to conflict. As water insecurity can be viewed as a perceived risk to individuals due to its potential to inflict harm, individuals likely act on this experienced risk in form of mobilization and potential social unrest (Schroeter et al., 2014). Therefore, it becomes apparent that the effect of perceived water insecurity on the individual socio-psychological risk perception has not been adequately included in the water scarcity-conflict literature.

However, the added understanding of individual perception within the water security-conflict nexus is of high importance, as the recognition of vulnerability and risk plays a role in overcoming collective action problems prior to the onset of social unrest. Thus, individual perception plays a crucial role when analysing water-induced unrests and will be touched upon in the following. A comprehensive account of perception in the context of social unrest will follow in the theoretical section.

Perception of water insecurity & social unrest

The question of the extent to which individuals behave consistently across situations has been a central question in personality psychology for many years (Lord, 1982). Whether personality attributes or situational factors determine individuals' behavior has been part of

many debates in the past. A consensus has now emerged, highlighting that it is conditional on the interaction between individual and situation (Lord, 1982, p. 1076).

Moreover, as mentioned by Eveland and Glynn (2012), cultural and socio-environmental factors largely impact human behaviors and attitudes towards a given situation. In these situations, building on the concept of social reality perception, communication between individuals is used to describe events and determine social realities. These realities, in turn, depend on personal communication experiences and differing "maps of social reality" (Eveland & Glynn, 2012). Furthermore, as Linke et al. (2015) call for understanding micro-mechanisms within communities when examining the relationship between environmental variability and violent conflict, this is the focus of the current study.

Based on the above, it becomes apparent that individual perceptions in grave situations need to be regarded in their social and political contexts, while social realities depend on the interaction between members of a community. This is further elaborated on in the following theoretical section.

In line with the literature review, three summarizing shortcomings in existing research should receive attention. First, as mentioned by Böhmelt et al. (2014), much of the literature lacks a more individualistic focus on the interplay between water scarcity and conflict likelihood, disregarding individual dynamics at play. Second, most of the literature is focused on high-level, often armed, conflict (Humphreys, 2005; Lujala et al, 2005; Ross, 2004) which does not take local, non- violent uprisings, such as protests or riots, into account. Last, as previously mentioned, water supply is mostly conceptualized in physical terms, as measured precipitation, drought, and temperature over space and time (Almer et al., 2017; Böhmelt et al., 2014; Bernauer et al., 2014). However, this does not take the individual perception of water supply over the years into account, which is problematic when arguing for individuals overcoming collective action problems to join or initiate social disruptions.

While locating the perception of water insecurity within the social unrest literature, I move beyond the mere physical measurements of water insecurity when analysing causes of social unrest. In accordance with these limitations, the study aims to fill this gap in the literature by highlighting the effect of perceived water insecurity on social unrest frequency in Sub-Saharan Africa, elaborating on the interdisciplinary link between conflict and behavioral psychology.

Theoretical Framework

The theoretical framework of this research builds on the understanding of individual perceptions and resulting behavior in precarious situations and social contexts. Followed by this, the mechanisms of grievance and relative deprivation bridge the gap between negative perceptions due to livelihood insecurities, and social unrest, motivated by increased aggressive behavior. This translates into the hypothesis of this research which is then further examined by including control variables drawn from, e.g., infrastructure availability and food insecurity.

Social & Individual Perception

Bringing human perception into the context of this research, the social perception theory, developed by Dijksterhuis and Bargh (2001), highlights a perception-behavior linkage within which perception induces behavioral output. This psychological theory is built on the finding that imitating behavior among animals is found when exposed to similar situations, underlining the direct link between perception and behavior. Humans, however, possess more flexibility in behavior than animals, where perception most likely is accompanied by determining facilitators, such as motivation, to evoke specific behavior (Dijksterhuis & Bargh, 2001).

In accordance with the suggested connection between "perceptual input and behavioral output" (Dijksterhuis & Bargh, 2001, p. 6), existing studies have found that humans naturally imitate others' perceived behavior (Greenwald, 1970; Wheeler, 1966; Zajonc et al., 1982). In this, perception and imitation of behavior are partly influenced by observables, such as facial expressions, speech patterns, and postures (Dijksterhuis & Bargh, 2001). In addition, Amos et al. (2015) find that socioeconomic characteristics influence risk perception towards climate change (p. 897), while Fothergrill (1996) finds women to be more perceptive of environmental hazards than men. Further developing the socio-psychological understanding of perception in the context of environmental hazards, UN Water highlights the nature of water scarcity to be socially constructed and manifold in scope and risk (UN Water, 2006). The above-mentioned literature reveals the impact of perception on individual behavior, while simultaneously demonstrating the diverse external influences altering individual perceptions of risk situations.

The concept of social perception in the context of water insecurity is further highlighted by Murtinho et al. (2013), who posit that water scarcity perception differs between individuals due to different risk reference points, resulting in contrasting perceptions of the same event (p. 670). While showing that long-term climatic changes may be more difficult to perceive than more apparent changes, e.g., deforestation, Murtinho et al. (2013) differentiate between the perception of long-and short-term changes (p. 670).

By building on research which proposes that the perception of the environment is a critical determinant of human behavior (Berkes & Turner, 2006), Murtinho et al. (2013) add to the scarcity perception literature. When relating the insight that environmental perception determines human behavior to water supply, I expect observations to be twofold: On the one hand, water insecurity can result from long-term causes in the past, such as mismanaged water supply or the drying out of wells over time. On the other hand, the perception of water

insecurity on a household level is based on short-term, salient changes that require adaptation on a daily level, e.g. further travel to water collection or limited water availability for cooking and cleaning. These salient changes on a household level may shape individuals' perception of natural resource scarcities and determine their responding behavior to critical circumstances, e.g., in the form of protesting against local water authorities (Nganyanyuka et al., 2018).

Highlighting the link between perception and conflict, Linke et al. (2015) assign the concept of perception a dominant role by observing the mediating effect of social influences on the relationship between environmental variability and violent conflict. Using survey data, they find that community dialogue has pacifying effects on the use of violence in the presence of scarcity (p. 43). However, the question of whether non-violent uprisings show different results remains unanswered.

The insights from the social perception theory give rise to the idea that worsened perception of water security in a region and community leads to grievances and dissatisfaction, which in turn is imitated by community members and peers. If these grievances, due to restricted water security within social and political contexts, are imitated and acted upon as a group, this could result in social unrest. Ross (2004) argues that the link between natural resource wealth and civil war is derived not from a single, but from multiple, mechanisms (p. 62). Therefore, the grievance mechanism could partly contribute to the natural resource-conflict link by explaining that grievances related to water insecurity translate into social unrest. This is elaborated in more detail in the following section.

Given the grave consequences associated with water scarcity, it is likely that exposed individuals perceive these as a threat to their livelihood security, from which particularly strong grievances result (Brauch, 2011, p. 101). As water supply is not only a prerequisite for prosperity, social cohesion and social participation, but also an outcome and indicator of the

social, economic and environmental dimensions of sustainable development, the importance of it to individuals cannot be overstated.

Even though flexibility in imitation exists in humans, as grounded in psychological research, deprivation of resources crucial for survival, e.g. water supply, may lead to less flexibility in imitation. Thus, one can argue that water-deprived individuals embody particularly strong grievances, imitated by close individuals in a similarly water-insecure situation. Such strongly deprived individuals then likely face lower barriers to engage in small-scale social conflict in order to deal with their livelihood insecurity.

Relative deprivation & individual grievances: The link to social unrest

Keeping the previously discussed perception literature in mind, while recalling the research question of the relationship between perceived water insecurity and social unrest, Moore and Jaggers (1990) provide insight into this relationship through a socio-psychological approach. They focus their claim on Gurr's (1972) main argument, who argues that relatively deprived individuals are more likely to engage in political conflict, as feelings of frustration fuel the propensity of aggression (Gurr, 1970, p. 36).

While focusing on an individual level of analysis, Moore and Jaggers (1990) highlight Gurr's (1972) role of appeals, claiming that appealing to an individual's sense of relative deprivation could mobilize individual discontent into rebel movements (p. 22). Further, Moore & Jaggers (1990) hypothesize that prior to individuals collectively joining a larger cause, "appeals must psychologically connect individuals with a larger category of people experiencing similar types and/or levels of deprivation" (p. 35). Extending this theoretical argument to the present research, it can be expected that individuals perceiving themselves as relatively deprived of water access over time have a tendency to show aggressive behavior and are more willing to initiate social unrest.

In relation to the deprivation theory, Ross (2004) builds on a grievance mechanism, spotlighting the possibility that resource extraction creates grievances among local populations, which in turn result in civil war (p. 41). Additionally, grievances among individuals are further caused by temporary inequalities within a country's development process due to different rates of economic progress (Barro, 2000; Humprehys, 2005). Furthermore, grievances are caused by externalities of extraction processes, such as environmental destruction, leading to an impaired access to crucial resources (Humphreys, 2005, p. 512). The mentioned causes of grievances can be related to water supply and perception of water insecurity in two ways and are thus relevant: First, inequalities in a country's development process negatively impact access to basic service infrastructure, including freshwater provision. Second, due to water's nature as a vital resource for survival, particularly salient grievances may arise in the case of perceived insecurity. This results in individuals facing lower barriers to collectively protest or demonstrate to claim water rights.

Based on this insight, the arising question prior to analysing the relationship between perceived water access and conflict likelihood revolves around how individuals collectively organise an uprising in a subjectively deprived situation. As the individual matters largely in overcoming collective action problems and initiate or join a social conflict (Oliver, 1993), this will be discussed briefly.

As Ostrom (2010) highlights in his influential study on collective action, reciprocity, trust, and reputation between individuals play a role in overcoming collective action problems through cooperation (p. 163). The relative presence of these concepts influences the level of cooperation between individuals. Adding to this, Cox (2004) posits that individual behavior in a specific setting "is affected by an individual's initial emotional or normative state and then by direct experience with others in a specific setting" (Ostrom, 2010, p. 161). Resulting from collective action literature, as highlighted by Almer et al. (2017), small-scale

social conflicts are characterized by low requirements regarding organization- contrary to coups or civil wars- which minimizes the barriers to collective action.

Borrowing from the grievance mechanisms in connection with the above-mentioned literature, one can hypothesize a possible link between a perceived lack of water access and experienced grievances due to relative deprivation and environmental degradation. This can result in increased social unrest incidence. Therefore, the arising hypothesis for this research is as follows:

H1: In regions in which individuals perceive water insecurity more strongly, a higher frequency of social unrest is expected.

To conclude the theoretical discussion, the study of perception is relevant within the water insecurity- conflict research due to three dominant reasons: First, it provides a different focus of water conflict and its underlying mechanisms, therefore being a supportive addition to physical measurements of water stress. Second, by drawing from the behavioral psychology theories of perception and resulting behavior, this study contributes to the literature through an interdisciplinary approach, merging psychosocial, environmental, and political competencies regarding water insecurity. Moreover, household perception towards climate and livelihood variability matter in terms of successful climate change adaptation measures, which respectively limit community vulnerability (Amos et al., 2015). In line with this, the multi-faceted nature of water scarcity requires integrated approaches (Liu et al., 2017). This is provided for in this research, while analysing perception of environmental degradation and resulting individual behavior majorly contributes to existing literature.

Hence, measuring perception provides a relevant and influential addition of individual survey data to physically measured data within the water- conflict literature.

Research Design

Level of Analysis & Sample Selection

A sample of household surveys, derived in 465 Sub-Saharan African first-level administrative regions from Afrobarometer survey data and aggregated to country level, is utilized. The aggregation to country-year level results in acquired cases from 31 countries (*n 90)* across Sub-Saharan Africa (Figure 1). Country-year constitutes the appropriate level of analysis to assess the link between the perception of water insecurity and the incidence of social unrest events as it allows for applications across countries. As Africa's population is projected to nearly triple by 2050 (Cartwright, 2015), individuals relying on natural resources, including freshwater, are particularly at risk. Thus, specifically Sub-Saharan Africa is considered to be particularly vulnerable to both quantitative and qualitative water risk (World Bank, 2004, p. 113), referring to the possibility of experiencing both, droughts as well as lacking water-related infrastructure.

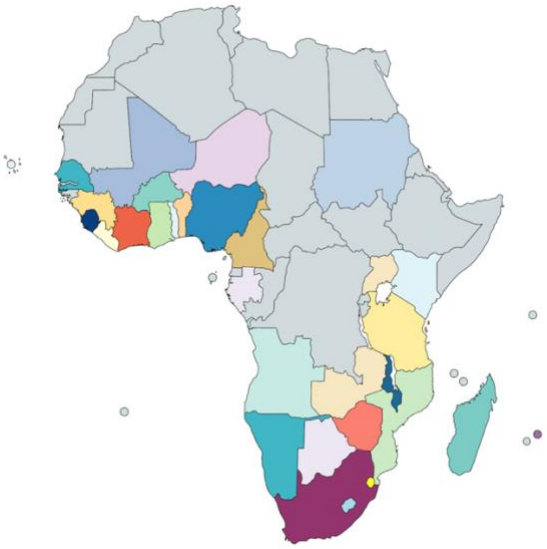
Moreover, Bernstein and Crosby (1980) highlight that the relative deprivation theory shows that anger and dissatisfaction differ with the subjective evaluation of one's status. Thus, when applying this theoretical insight to a hypothetical scenario of water-deprived individuals in Sub-Saharan Africa, individuals are likely to evaluate their status subjectively differently, even if external circumstances are more or less identical. Individual activity, e.g., joining a small-scale social conflict in response to limited water access, therefore depends on the subjective assessment of that individual's status and less on objective reality. Hence, survey data is appropriate to include an individual's subjective assessment of the situation in the research.

As the Afrobarometer survey data is collected in temporal survey rounds between 2011 and 2017, not all regions in which the survey was conducted over a period of seven years are included equally (Han, 2020). Thus, the mean per country and year is included for

variables derived from the survey (*water insecurity perception, food insecurity, and perceived infrastructure availability*). The *social unrest frequency* data is then matched with the average country-year data of *water insecurity perception* to test the developed hypothesis.

Figure 1

Sample of 31 Sub-Saharan African countries included in the analysis



Dependent Variables: Social Unrest Frequency & Incidence

Data on the dependent variables, *Social Unrest frequency and incidence,* is derived from the Social Conflict Analysis Database (SCAD), compiled by Salehyan et al. (2012). The SCAD includes a broad spectrum of events embodying numerous types of social conflict, including organized and spontaneous demonstrations, organized and spontaneous riots, general and limited strikes, pro-government violence, anti-government violence, extra-government-violence, and intra-government violence. Most events are recorded at the town and day levels. The database includes data on social unrest events in all countries with a population of at least 1,000,000 between 1990 and 2017, while it relies on reports by the *Associated Press* (AP), *Agence France Presse* (AFP) as well as non-governmental organizations (NGOs).

SCAD focuses on social conflict incidences, while it excludes data on armed conflict such as organized rebellions, civil wars and international war. It attributes specific issues as causes of tension to each event, indicating the nature of each conflict incidence. For the purpose of this research, a variable utilizing *social unrest frequency* per country and year is computed and includes all above-mentioned event types. Due to inadequate data availability to holistically understand the effect of water insecurity perception on social unrest, all event types are included in the analysis. Further, due to the yet unfamiliar impact of perception on social unrest, including a more diverse set of social unrest events is appropriate for this research. Thus, the dependent variable *social unrest frequency* measures the number of reported social unrests in a particular country-year. The variable *social unrest incidence* is coded as a dummy variable, which takes the value of 1 if at least one conflict occurred in a coded country-year, and the value of 0 if no event occurred. Including a dummy variable and estimating a binary logistic regression model strengthens the robustness of the linear regression and shines light on the more general link between social unrest occurrence and water insecurity perception (Field, 2013).

Independent Variable: Perception of Water Insecurity

Data on the perception of water insecurity is derived from household survey data in 465 first-level administrative regions in 31 Sub-Saharan countries between 2011 and 2017 (Figure 1). It is then aggregated at the country-year level and includes 90 cases in the mentioned time frame (2011-2017) (see Appendix A for a full list of countries involved). To construct real-time indicators of perceived water insecurity, the independent variable is based on the Afrobarometer survey question: *Over the past year, how often, if ever, have you or anyone in your family: Gone without enough clean water for home use?* (Han, 2020, p. 14). Respondents chose between the options *Never, Just Once or Twice, Several Times, Many*

Times, and *Always*, with the value 0=*Never* and 4=*Always.* Following, the data is aggregated to country-year level to receive an average perception of water insecurity for each country and year in which the survey was conducted. A higher average of individuals indicating no clean water access for home use therefore implies a more acute perception of water insecurity in a specific country.

Koren et al. (2021) have measured the link between water insecurity and social unrest using Twitter data. They operationalize water insecurity as "instances where any persons or groups lack some level of physical, social, or eco- nomic access to sufficient and safe levels of water for consumption or crops, via either (i) barriers in access to water or (ii) the actual unavailability of sufficient water." (p. 74). Based upon similar employment of the independent variable *water insecurity*, this operationalization is appropriate to generalize the understanding of this concept in the current study. Since the independent variable of water insecurity perception is positively skewed, it is log-transformed in this study to create a more normal distribution and increase the models' robustness (Field, 2013, p. 373).

Control Variables

To mitigate omitted variable bias (OVB), control variables are added to the included models. As suggested by Noemdoe et al. (2006) and Rijsberman (2006), one can expect that the degree of available infrastructure influences the perception of water insecurity. An individual who perceives to have access to roads and available transport to travel for water may therefore perceive water (in)security less prevalent than a household lacking transport or infrastructure to collect water. Therefore, the effect of available infrastructure likely impacts the perception of water insecurity. In line with Rijsberman's recommendation (2006), the *perceived degree of available infrastructure* is controlled for in perceived water scarcity research. The data for the variable is derived from the Afrobarometer Rounds 5-7 data

(Afrobarometer, 2011-2019), asking individuals about how they perceive the availability of electricity, intact roads and bridges, and sanitation services (Han, 2020)[1]. The mean answers from the Afrobarometer survey waves between 2011 and 2017 are then utilized per country and year.

(Log)GDP per capita is treated as a proxy for a country's economic development and is expected to limit water scarcity and thus the connected individual perceptions thereof. Economic development is an important control variable within conflict literature and correlates with lower levels of conflict (Collier & Hoeffler, 2004; Hegre & Sambanis, 2006). Interestingly, however, Böhmelt et al. (2014) find a positive correlation between economic development and water-conflict, hence why GDP per capita will be controlled for. The World Bank indicator GDP per capita is measured in US dollars and is included using a log-transformed value to account for skewness and expected non-linear effects (Böhmelt et al., 2014, p. 342).

As Hendrix and Haggard (2015) highlight in their influential study, democratic regimes are more prone to urban unrest than autocracies (p. 154). Also Dalton et al. (2005) highlight that individuals protest because they are able to and expect governments to respond to their claims. Based on this finding, one can expect that regime type influences the frequency of protests. Thus, *regime type* is controlled for in the analysis. The variable is derived from the polity2 index from the Polity5 project (Marshall & Gurr, 2020), which distinguishes between democracies, hybrid regimes, and authoritarian regimes along a categorical 21-point scale. For the analysis, values between 5 to -5 are coded as hybrid regimes, and values between -6 and -10 as authoritarian regimes (Center for Systemic Peace, 2020).

[1] The questions asked to individuals in the Afrobarometer surveys include: *How well or badly would you say the current government is handling the following matters: Maintaining roads and bridges? / Providing a reliable supply of electricity? / Handling providing water and sanitation services?*. The answer options are coded as follows: 1= Very Badly; 2= Fairly Badly; 3= Fairly Well; 4= Very well; 5= Don't Know.

Moreover, household water insecurity fundamentally drives household food insecurity (Brewis et al., 2019). While the link between food insecurity and conflict has been analysed extensively in conflict literature (Hendrix & Haggard, 2015; Rezaeedaryakenari et al., 2020), the coexistence of both concepts should be emphasized. Due to the close correlation between water- and food insecurity, individuals might be unable to distinguish between food- and water insecurity. This could result in individuals indicating experienced food insecurity, while disregarding water scarcity's influence on food insecurity. Thus, as brought forward by Koren et al. (2021), *food insecurity* should be controlled for when analysing the effect of water insecurity on social unrest (p. 72). The variable utilized for this is the mean of perceived food insecurity, based on the question how often individuals have gone without enough food to eat in the past year. Last, the control variable *(log)population size* is derived from the Penn World Table, Version 10 (Feenstra et al., 2015) and log-transformed to account for national distinctions. Literature suggests that a larger population size increasingly strains scarce resources, thereby increasing conflict risk (Homer-Dixon, 1994). Further, larger populations indicate more chances for individuals to experience and perceive water insecurity and a higher number of individuals potentially joining social unrest events.

Preliminary Analysis

Checking for assumptions of linear regression, a number of methods are utilized, the outcome of which can be found in Appendix A. First, checking for the independence of observations within the dependent variable, the Durbin Watson test has shown that autocorrelation between observations is not found (Durbin Watson 1.85). Second, as indicated by the Shapiro Wilk and Kolmogorov-Smirnov tests, the assumption of normality is violated. Thus, to account for this violation, a negative binomial regression is included in the analysis (White & Bennetts, 1996). Overdispersion of the dependent variable *social unrest frequency* confirms

the use of a negative binomial regression (Gardner et al., 1995). Third, when checking for linearity between the independent and dependent variable, this assumption appears to be violated (Appendix C). Fourth, the assumption of homoscedasticity is violated, as seen when plotting standard residuals against their fitted values (Appendix C). To account for this, country-fixed effects as well as robust standard errors are included in the OLS regression and negative binomial respectively.

Estimation Model

Research regarding conflict studies argues that intrastate conflict, especially low-intensity events of social unrest, occur locally (Böhmelt et al., 2014; Ross, 2004). Thus, household survey data is utilized to measure the effect of water insecurity perceptions on social unrest in this research. For this analysis, as mentioned above, the survey data is aggregated and means per country-year are derived. Limitations of this approach are mentioned in the concluding section.

First, a longitudinal country-year level analysis (2011-2017) is conducted through an OLS linear regression model to test the continuous variables of perceived water insecurity and social unrest frequency (Model I). As highlighted above, numerous assumptions of the model are violated, resulting in likely misleading results (Casson & Farmer, 2014).

Therefore, a negative binomial regression is utilized and added to the analysis (Model II) to account for overdispersion of the dependent variable as well as for the violation of normality in the linear model (Alexander et al., 2000) (see Appendix C). As negative binomial regression accounts for overdispersion of count data, as is the case in *social unrest frequency*, its utilization is appropriate in this study (Hilbe, 2014). The negative binomial regression (Model II) is estimated including robust standard errors to improve the robustness

of found effects. Country-fixed effects, with Benin as the reference category, are included in the OLS regression model (Appendix D) to improve its robustness.

Last, as further robustness checks of the found effects in Model I and II, a binary logistic regression with the dichotomous dependent variable of *social unrest incidence* is conducted (Model III). For this, as mentioned above, the main dependent variable of *social unrest frequency* is recoded in a dichotomous variable with 0 indicating no incidence and 1 found incidence of at least one social unrest event in a country-year. The software used for this analysis is the Statistical Package for the Social Sciences (SPSS) Version 27.0.1.0.

Results

Table 1 displays the main results from the OLS, negative binomial, and logistic regression. For the OLS regression model (Model I), the model fit explains 23.7% of the variance in social unrest frequency. In the negative binomial regression (Model II), the Akaike's Information Criterium (AIC) amounts to 707.35 in the negative binomial model, including controls. The AIC is a measure indicating the goodness-of-fit in maximum likelihood estimation, with lower values corresponding to a comparatively better fit (Bozdogan, 1987, p. 347). The explanatory power of the logit model (Model III) is 11%, according to Nagelkerke's S Square.

The hypothesis of the current study suggests that higher water insecurity perception increases the incidence of social unrest in Sub-Saharan Africa. Assessing the coefficients associated with *water insecurity perception* in all models (I, II, III), the effect direction is in line with this research's hypothesis, yet not significant. The OLS regression (Model I) indicates *water insecurity perception* to have a positive and insignificant impact on social unrest frequency (b= 3.052; p= 0.704). A one-unit increase (i.e., 10% increase) in water

insecurity perception is thus associated with a 0.03 increase in social unrest frequency, *ceteris paribus.* This outcome is in line with the hypothesis of this research.

In the negative binomial model, increased *water insecurity perception* also appears to have a social unrest-enhancing effect, however the result remains insignificant (b= 0.113; *p*= 0.770). The logistic regression model (Model III) highlights a similar positive effect between *water insecurity perception* and *social unrest incidence* (b= 0.054; p= 0.948). As these results do not offer support for the hypothesis of this study, they have to be interpreted with caution due to the lack of significance in all models.

Looking at the control variables in the OLS and negative binomial model, *perceived infrastructure availability* is significant and negatively correlated with social unrest frequency in Model II (b= -0.071; *p*< 0.001). This means that a 1-unit increase in reported perception of infrastructure availability decreases social unrest frequency by the factor of 0.27. It also has a negative, yet insignificant, effect in Model I (b= -0.270, *p*= 0.283). Due to research highlighting the limiting effects adequate infrastructure has on water scarcity (Noemdoe et al., 2006; Rijsberman, 2006), in connection with research highlighting lacking infrastructure to increase developmental unrest (Kelley at al., 2015), this finding has been expected.

Food insecurity has a negative effect on social unrest frequency in all models, though this relation is insignificant. For *(log)GDP per capita*, every 1-unit increase (i.e., 10% increase) in the log-transformed variable increases social unrest incidence by 0.034 units, however this parameter is insignificant (b= 0.341; *p*= 0.267). While scholars, such as Sánchez and Namhata (2019), show the conflict-limiting effect of higher GDP, others (Dalton et al., 2010, p. 58; Korotayev et al., 2017) question this finding by highlighting the relation between increased income and higher protest likelihood.

Table 1

Main Regression Results

Variables	(Model I) OLS	(Model II) Negative Binomial	(Model III) Logit
(Constant)	-42.893*** (60.211)	-1.917*** (2.793)	6.374*** (6.336)
Water Insecurity Perception (log)[a]	3.052 (8.003)	0.113 (0.384)	0.054 (0.819)
Infrastructure Availability[a]	-0.270 (0.250)	-0.071*** (0.015)	-0.044 (0.064)
Food Insecurity[a]	-8.613 (9.144)	-0.523 (0.335)	-0.229 (0.908)
GDP/ capita (log)	4.027 (5.114)	0.341 (0.238)	-0.215 (0.528)
Regime Type	0.778 (0.553)	0.057* (0.027)	0.102 (0.055)
Population (log)	3.741 (4.315)	0.272 (0.185)	-0.484 (0.462)
N	90	90	90
R^2	0.056		
AIC		707.351	
Cox & Snell R Square			0.075
Nagelkerke S Square			0.110

Note. Standard Errors in Parentheses. ***p < 0.001, **p<0.01, *p<0.05

[a] Based on the mean per country-year.

As social unrest in this research encompasses many different event types, the mixed effects of GDP on social unrest frequency are expected, as GDP per capita could have pacifying effects on some event types, while not on others. *(Log)Population size* has a

positive effect on social unrest incidence in the OLS regression (b= 3.741; *p*= 0.388) and negative binomial model (Model II: b= 0.272; *p*= 0.143), while it has a conflict-reducing effect in the logistic regression model (b= -0.484; *p*= 0.755). All effects are insignificant.

Last, the control variable of *regime type* is significant in Model II and produces a positive effect on social unrest incidence, as a one-unit increase in regime type corresponds with a 0.057 increase in social unrest frequency (b= 0.057; *p*= 0.039). Furthermore, Model I shows a positive effect of regime type on social unrest frequency, however not significant (b= 0.778; *p*= 0.163). This finding lends careful support that democracies could show a higher incidence of low-level conflict, compared to autocracies, as discussed by Böhmelt et al. (2014).

Robustness Checks

To improve the robustness of the negative binomial model, *robust standard errors* were included in the baseline model. Further, to mitigate omitted variable bias in the OLS model, *country-fixed effects* were added (see Online Appendix D) (Vogelsang, 2012). No major changes in effects between independent and dependent variables have been found, with a continuing positive and insignificant effect between water insecurity perception and social unrest frequency (b= 0.037; *p*= 0.997).

(Log)GDP per capita changes its effect direction and shows a negative effect, indicating that every one-unit increase in logged GDP (i.e., 10% increase) decreases the frequency of social unrest by 0.0037. The variable of *perceived infrastructure availability* remains significant in the negative binomial model (Model II) and has a negative effect on social unrest frequency (b= -0.793; *p*= 0.22). The effects of food insecurity and regime type on social unrest incidence remain similar to the model excluding country-fixed effects.

As mentioned above, to improve robustness of the effect between water insecurity perception and social unrest, a dichotomous variable of *social unrest incidence* is computed, with 0 indicating no unrest and 1 indicating unrest in a country-year. Following this, a binary logistic regression is included in the analysis (Table 1, Model III) to provide further insight into the relationship analyzed in this research (Field, 2013). While the model produces similar effect findings as Models I and II, *(log)GDP per capita* changes its effect direction, however, remains insignificant (b= -0.215; *p*= 0.684). Similarly, the log-transformed variable *(log)population size* also changes effect direction, indicating that a one-unit increase (i.e., 10% increase) in population size decreases social unrest incidence by 4.8 units.

Last, since survey data on water insecurity perception, infrastructure availability perception, and food insecurity perception is not available for every year between 2011-2017, missing values were linearly interpolated to increase the sample size to *n* 215 (Appendix B, Table 4). This is appropriate, as one can expect water insecurity perception to have a low variability from year to year (Noor et al., 2015). However, the interpolated results do not differ drastically from the main regression results (Table 1) and show the same positive, insignificant effect direction between *water insecurity perception* and *social unrest frequency*. In general, the utilized models do not find a significant effect between water insecurity perception and social unrest. Implications and limitations of these findings will be considered in the following.

Conclusion

This study aimed to highlight the role of individual perception of water insecurity within the water-conflict research by asking whether unfavorable perceptions of water insecurity increase social unrest frequency in Sub-Saharan Africa. Based on theories of ‘grievance mechanisms’ and ‘relative deprivation’, individuals were expected to develop grievances due

to individual livelihood deprivation, eventually translating into forms of social unrest. Based on this, the hypothesis of this research presupposed that increased perceptions of water insecurity coincide with higher social unrest frequency.

The empirical results of this research show the impact of *water insecurity perception* to have a positive effect on *social unrest frequency*, though the results are insignificant. Looking at *social unrest incidence* as the dependent variable (Model III), results are similar to *social unrest frequency*, with insignificant results indicating a positive effect between *water insecurity perception* and *social unrest incidence*. Across all tested models, the effect of *water insecurity perception* on *social unrest* remains positive and insignificant, also when including robustness checks.

Prior to highlighting future research opportunities, the limitations of the current study are discussed. First, the proxy question for perceived water insecurity focuses on water scarcity incidence, however, lacks taking other indicators of water scarcity into account, e.g., duration of experienced water scarcity. This does not encompass a holistic understanding of the impact water scarcity has on the survey respondents. Differences in arising deprivation and grievances, while resulting in differences of likelihood for individuals to engage in low-level conflict, should be scrutinized further. As White (2012) indicates, relying on a single indicator to analyze water scarcity likely provides deceiving conceptions of this concept (p. 164). Hence, attention should be given to interconnected criterions to arrive at a deeper understanding of the importance of, e.g., freshwater storage (Damkjaer & Taylor, 2017) or water use (Liu et al., 2017) on the perception of water insecurity.

Moreover, as the data on water insecurity perception was derived from household surveys, generalizability of given answers proves difficult, even when aggregated to country-level. As respondents were retrospectively asked how often they dealt without clean water for home use in the past year, even similar answers to the question indicate differences in

perception of water insecurity owing to individual reference points (Murtinho et al., 2013). Due to proxying water insecurity perception, based on the survey question asking individuals how often they have gone without clean water for home use (Han, 2020), the indicator is imperfect in capturing perception of water insecurity entirely. As risk perception depends on "public awareness, [and] coping capacities of communities […]" (UNESCO World Water Assessment Programme, 2006, p. 31), modeling perception of water insecurity should also include, but not be limited to, the above factors. This likely explains the mixed result outcome between *water insecurity perception* and *social unrest frequency*, depending on the inclusion of control variables.

Furthermore, mean values of water insecurity perception are derived per country and year for this study as perception data is not extensive. As means of further research, the focus should lie on analyzing local data to improve the understanding of immediate micro-mechanisms at play between perception of water insecurity and overcoming the barrier of engaging in social unrest. Koren et al.'s (2021) research on analysing Twitter data to highlight the instant effect of environmental stresses on social conflict could serve as a starting point when aiming to understand these active micro-mechanisms.

Realizing the above-mentioned limitations, future research pathways are explored on in the following. As Murtinho et al. (2013) highlight, individuals have different reference points which result in variability of reported perception concerning similar events. While this insight partly explains the mixed results of this study, future research should aim to establish generalizable measurements of perception in cooperation with psychological research. A promising alternative could include asking survey respondents about certain events not in retrospect, but instead providing an option to report on the experience concerning water-scarcity events instantly. Twitter data or data from other social networks, as mentioned above

in connection with analyzing local micro-mechanisms, could be analyzed in certain regions to model near-immediate effects of environmental strain on social conflict.

In addition, future research should tie to differentiating between population groups which may vary in water insecurity perceptions (Quinn et al., 2003), e.g., women being more perceptive of environmental hazards than men (Fothergrill, 1996). This will provide an insight into the perceptions of different groups while adding to a more holistic conceptualization of resource scarcity perception. Further, while this research explored the link of perception and social conflict through grievance and individual deprivation mechanisms, measurement of these was not possible in the scope of this thesis. Future work should thus scrutinize the link between water insecurity perception and social unrest further by including a mediation analysis with the above-mentioned mechanisms to inspect present micro-mechanisms further.

To adequately acknowledge and avert the possibility that water insecurity could increasingly become a destabilizing geopolitical power (Hendrix & Haggard, 2015), policymakers require a scientific understanding of the mechanisms at play between water insecurity and conflict. Highlighting this, not only from physical measurements of water insecurity and arriving at conclusions about general impact, but from a more socio-psychological viewpoint, is crucial. The perceptions of individuals play an important role in understanding micro-mechanisms underlying conflict dynamics. While analyzing survey data is only the beginning in modeling perceptions more holistically, it is important to acknowledge individuals in order to draft effective policies and produce more person-centered research in the future.

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Appendix A: Descriptive Statistics

Table 2

Descriptive Statistics

Variable	*N*	*M*	*SD*
Social Unrest Frequency	90	18.29	22.71
Water Perception (country mean)[a]	90	1.11	0.48
GDP per capita[a]	90	9.46	0.48
Infrastructure availability (country mean)	90	3.55	10.18
Food Insecurity (country mean)	90	1.05	0.41
Regime Type	90	4.45	4.40
Population Size[a]	90	7.01	0.58

Note. *N* = Sample Size. *M* = Mean. *SD* = Standard Deviation.
[a] Log-transformed variable

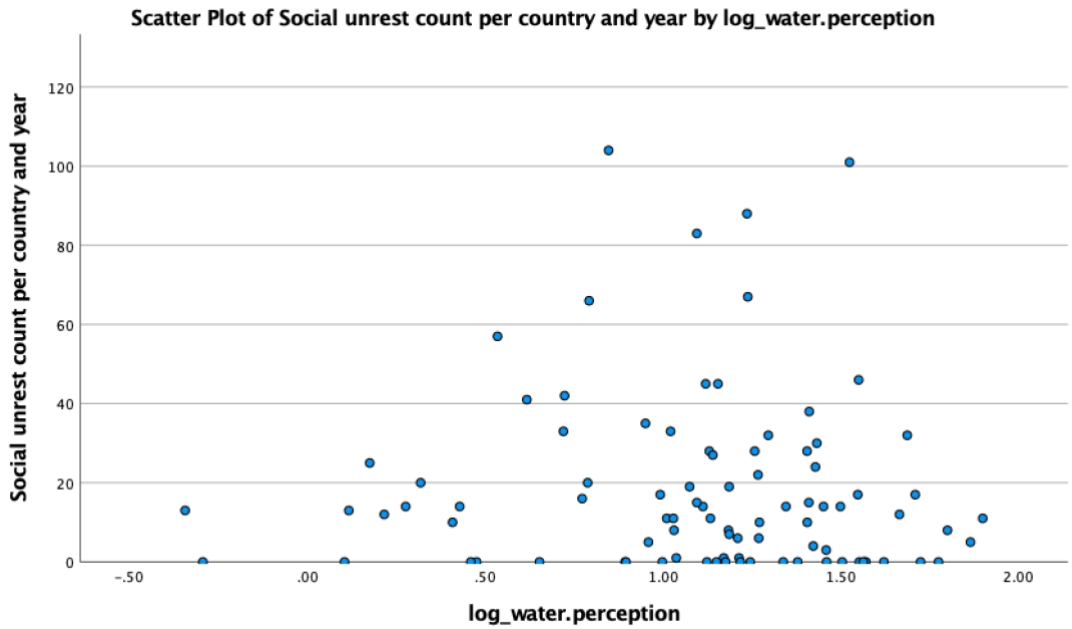
Table 3

Included countries in the analysis, based on the World Bank country list of Sub-Saharan African region and their respective unrest counts

Country	Social Unrest Frequency (2011-2017)	Country	Social Unrest Frequency (2011-2017)
Benin	63	Mozambique	31
Botswana	144	Namibia	27
Burkina Faso	130	Niger	33
Cameroon	68	Nigeria	54
Cape Verde	110	Senegal	64
Cote d'Ivoire	43	Sierra Leone	0
Gabon	6	South Africa	0
Gambia	26	Sudan	0
Ghana	23	Swaziland	4
Guinea	33	Tanzania	67
Kenya	174	Togo	17
Lesotho	30	Uganda	123
Liberia	48	Zambia	15
Madagascar	6	Zimbabwe	10
Malawi	134		
Mali	62		
Mauritius	74		

Graph 1

Scatterplot indicating the direct relation between the log transformed water insecurity perception variable (IV) and social unrest frequency (DV).



Appendix B: Linear Interpolation

Linearly interpolated results of included models

Table 4
Linearly interpolated regression results

	(Model IV)	**(Model V)**	**(Model VI)**
Variables	**OLS** (interpol.)	**Negative Binomial** (interpol.)	**Logit** (interpol.)
(Constant)	-32.806 (2.564)	0.761 (1.779)	5.868 (3.182)
Water Perception (log)[a]	2.564 (7.407)	0.810 (0.715)	1.455 (1.306)
Infrastructure Availability[a]	-0.261 (0.233)	-0.126 (0.170)	-0.055 (0.064)
Food Insecurity[a]	-8.070 (8.481)	-0.521 (0.327)	0.075 (0.712)
GDP/ capita (log)	3.476 (4.265)	0.042 (0.136)	-0.372 (0.258)
Regime Type	0.769 (0.438)	0.054** (0.027)	0.084 (0.033)
Population (log)	3.333 (3.586)	0.235 (0.126)	-0.412 (0.280)
N	215	215	215
R^2	0.497		
AIC		1635.382	
Cox & Snell R Square			0.091
Nagelkerke S Square			0.128

Note. Standard Errors in Parentheses. ***p < 0.001, **p<0.01, *p<0.05

[a] Based on the mean per country-year.

Appendix C: Assumption Testing

Assumptions for linear regression (Models II, IV, & VII)

A simple linear regression with country-fixed effects (Benin as reference category) has been conducted (Model II & VII). A linearly interpolated OLS regression model has also been included to expand the sample size $n = 90$ to $n = 215$ (Model IV). A positive effect between water insecurity perception and social unrest is suggested in all models, yet the results are insignificant. The Durbin Watson test indicates no autocorrelation to be found between the employed variables (Durbin Watson = 1.46). Further, the multicollinearity assumption, with a VIF = 1.05, is also not violated. However, a variety of linear regression assumptions are violated: The normality assumption of the dependent variable, as well as the linearity assumption between independent and dependent variable, are violated. Further, the scatterplot of standardized residuals shows that the assumption of homoscedasticity is violated and heteroskedasticity of the variance is found. Therefore, the simple linear regression model has been ruled out and a negative binomial regression has been used.

1. **Normality of the dependent variable assumption:**

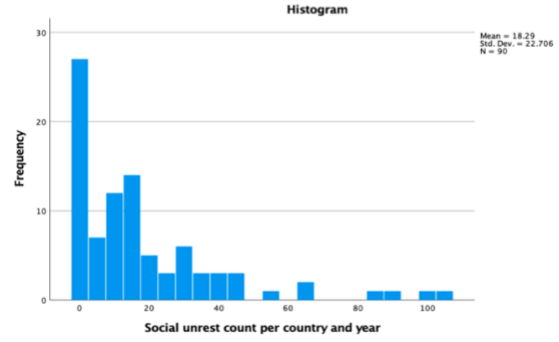
   Assumption is violated.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Social unrest count per country and year	.210	90	<.001	.767	90	<.001

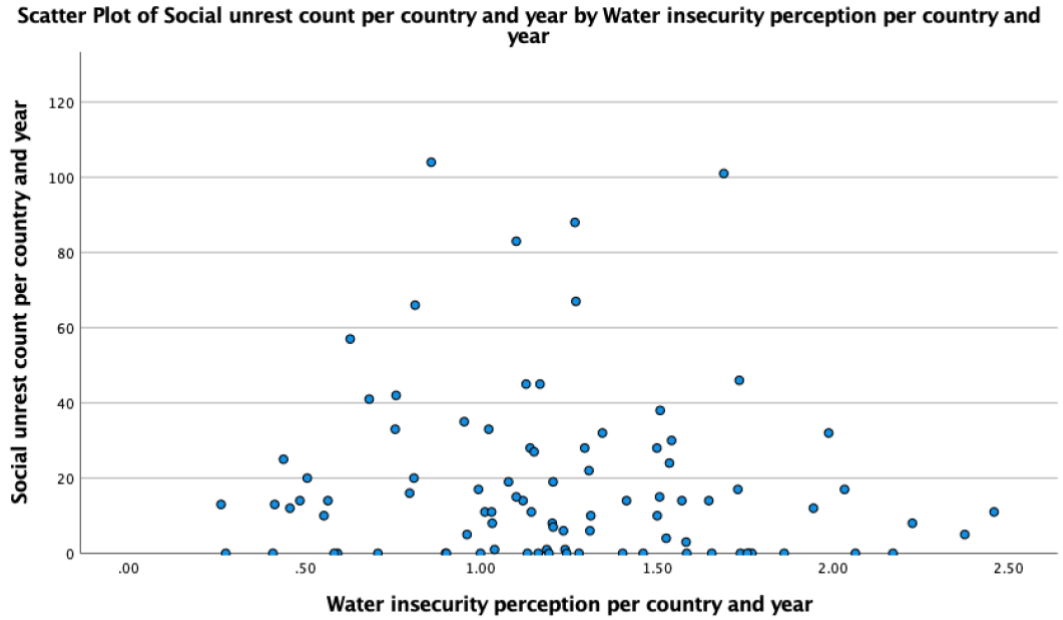
a. Lilliefors Significance Correction

Social unrest count per country and year



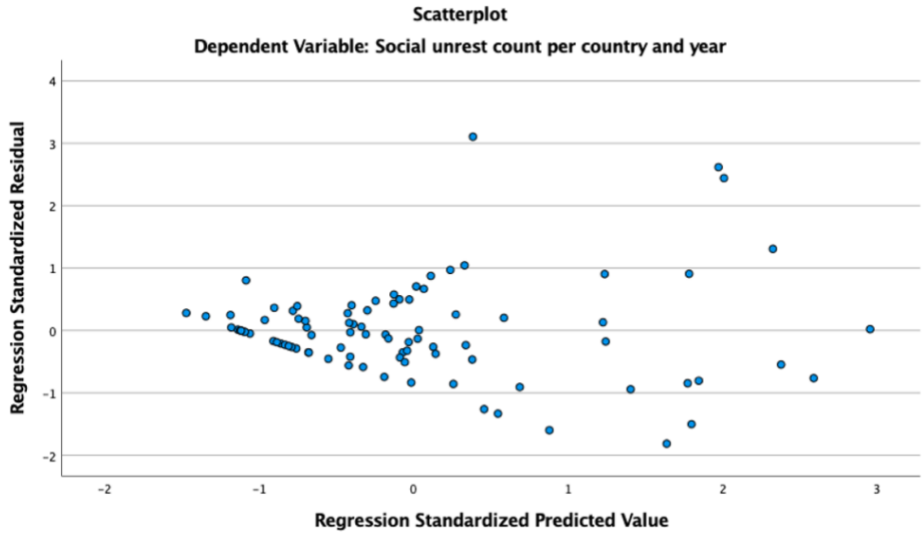
2. **Linearity assumption of the relationship between dependent and independent variable (mean):**

   Assumption is violated.



3. **Standardized Residuals checking for homoskedasticity:**

   Assumption is violated.



4. **Multicollinearity assumption:**

   Estimating a simple linear regression model, including all control variables, suggests the assumption of multicollinearity not to be violated, as VIF = 1.048.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	Social unrest count per country and year	1.000	1.000
2	Social unrest count per country and year	.954	1.048
	Polity2 Index	.952	1.050
	log_GDP	.969	1.032
	log_population	.898	1.113
	Available infrastructure: Mean from Q56I, Q56L, Q56M	.928	1.078
	Food Insecurity mean	.883	1.132

a. Dependent Variable: log_water.perception

5. **Overdispersion check:**

Due to the fact that the mean and variance of the dependent variable (social unrest frequency) show a large difference from each other, overdispersion can be assumed. Negative Binomial Regression accounts for this.

Descriptive Statistics

Social unrest count per country and year

N	Valid	216
	Missing	0
Mean		16.79
Std. Deviation		21.919
Variance		480.435
Range		130

Appendix D: Robustness Checks

Table 5
OLS Regression Models with and without country-fixed effects

	(Model VII)	**(Model VIII)**
Variables	OLS with fixed effects	OLS without fixed effects
(Constant)	1383.325 (874.946)	-42.893 (60.211)
Water Perception (log)[a]	0.037 (9.628)	3.052 (8.003)
Infrastructure Availability[a]	-0.739* (0.313)	-0.270 (0.250)
Food Insecurity[a]	-4.431 (10.75)	-8.613 (9.144)
GDP/ capita (log)	-0.493 (7.168)	4.027 (5.114)
Regime Type	2.666 (1.592)	0.778 (0.553)
Population (log)	-188.399 (122.010)	3.741 (4.315)
N	90	90
R^2	0.518	0.056
Adj. R^2	0.190	-0.012

Note. Standard Errors in Parentheses. ***p < 0.001, **p<0.01, *p<0.05

[a] Based on the mean per country-year.

Online Appendix

Data for the replication of the employed models is found in the Online Appendix. The utilized dataset as well as the SPSS outputs and syntaxes of Models I to VIII are available at https://drive.google.com/drive/folders/1et4TUSw1eg8Uni-zZVJuQvN9Gr9X9PPt .