Regional Environmental Change (2020) 20: 129
https://doi.org/10.1007/s10113-020-01713-7

ORIGINAL ARTICLE

Water scarcity, climate adaptation, and armed conflict: insights from Africa

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Received: 23 October 2019 / Accepted: 12 October 2020 / Published online: 13 November 2020

Abstract
The dynamic relationships between climate change and armed conflict have been discussed at length, but there have been few studies that integrate dimensions of climate adaptation into the processes linking climate change to armed conflict. By using geospatial grids for climate change and armed conflict, and country-level climate vulnerability measures of sensitivity and adaptive capacity, we empirically examine the effects of climatic and non-climatic conditions on the probability of armed conflict in Africa. Results suggest that there are close links between climate drivers and armed conflict. Importantly, greater levels of adaptive capacity lead to a lower likelihood of armed conflict. From a policy perspective, our results suggest that enhancing adaptive capacity under conditions of climate pressure will reduce the probability of people taking up arms in response to water scarcity.

Keywords Adaptive capacity · Africa · Climate change · Sensitivity · Water scarcity

Introduction

Understanding climate change requires that we understand the social consequences that can result. Recent evidence links water scarcity driven by climate change to the civil war in Syria (Kelley et al. 2015) and to the war and genocide in Darfur, Sudan (UNEP 2007). Droughts contribute to the stability risk of agriculturally dependent and politically excluded groups (von Uexkull et al. 2016), and more generally, climate-driven extreme weather disasters or mass displacement by natural disasters have been linked to armed conflict (Ghimire et al. 2015; Schleussner et al. 2016).

There have been contentious arguments about the relationship between climatic pressures and armed conflict (e.g., Schweizer 2019; Theisen 2017; van Weezel 2019). Burke et al. (2009) and Hsiang et al. (2013) demonstrate that temperature increases are linked to the onset of armed conflict, but this is challenged by Buhaug et al. (2014). Scarcity tied to water resources forms the core theoretical explanation in nearly all arguments, but not all research finds that water deficits increase conflict (Selby 2019; Selby et al. 2017). Salehyan and Hendrix (2014) demonstrate, for example, that increases in rainfall are associated with increased armed conflict. Intuition, conventional wisdom, and contemporary policy do not always comport with empirical evidence (e.g., the US DoD 2011). The empirical relationships or the conditions under which they hold can have profound political consequences.

As noted by Hendrix (2017), African countries pose difficult problems for understanding the relationship between climate and conflict because of physical, economic, and social impacts along with vulnerabilities like agricultural livelihoods, economic development, and limited resources or investment for adaptation to climate change. The complexity of the African environment makes it important to understand the effects of climatic and non-climatic conditions on the likelihood of armed conflict and the role of climate adaptation in reducing the propensity for armed responses to climatic stress. Based on prior theoretical argument and empirical evidence on states' capacity to repress violence, Koubi (2017) posited that there has been considerable evidence that climate-driven

Communicated by Chinwe Ifejika Speranza

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economic conditions coupled with political factors contribute to conflicts within agriculturally dependent countries.

Important for our understanding of the relationship between climate pressures and conflict is that contemporary change can be quite small yet aggregate over time. Precipitation or temperature anomalies in any given month would be unlikely to act as a catalytic condition for armed conflict. This temporal effect can be moderated by the social ability to adapt to reductions in precipitation or soil moisture, for example, by irrigation systems. If the rate of change in climate-driven pressures is slower than the ability to adapt, communities may adapt in ways that minimize the effect of climate pressures on resources. This would suggest that even in the face of declining resources, scarcity would be muted. To the extent that states have developed their adaptive capacity, social resilience will be strengthened (Kim and Marcouiller 2020) and conflict minimized. Functionally, this suggests that models of climate-induced armed conflict should include capacities to offset the effects of climate through adaptive responses.

Little empirical research, however, has modeled the role of adaptive capacity and climate sensitivity in the climate-conflict nexus, in spite of the recognition that adaptation may be a critical factor (Feitelson and Tubi 2017; Gemenne et al. 2014; Schleussner et al. 2016; Theisen 2017). If communities are perfectly able to adapt to contemporary climate conditions, there will be few climate-driven stressors on the social environment. Our work accounts for two research questions. First, how do climate change drivers contribute to the likelihood of armed conflict in the African context?, and second, what is the role of climate change adaptation in moderating the probability of armed conflict?

This paper examines the relationship between multiple types of climate anomalies and the likelihoods of armed conflict in Africa, drawing upon georeferenced conflict records, high-resolution climate data, and other spatially-explicit data for covariates. We advance scholarship by using geospatial grids to capture climate pressures and armed conflict and incorporating climate sensitivity and adaptive capacity in our models. Our results support the notion that national level adaptive capacity reduces the effects of climate pressures on armed conflict.

Water scarcity, climate adaptation, and armed conflict

Schleussner et al. (2016) linked climate-generated disasters to armed conflict through ethnic tensions. Through meta-analysis, Hsiang and Burke (2014) demonstrate that there are causal associations between climatological changes and various forms of socio-political stability. Burke et al. (2009, 2015) frame arguments in terms of water scarcity that results from increasing temperature and precipitation anomalies. As temperature rises, agricultural and water scarcity issues generate social tension that can lead to armed conflict. The US DoD (2011) addresses a similar concern regarding water scarcity issues and unrest on the African continent.

If drought leads to water scarcity, the mechanism in part runs through the ability of agricultural land and industrial capacity to remain productive. Lesk et al. (2016) demonstrate that sustained drought and extreme heat reduce crop yields by up to 10%. A 1-year short fall in precipitation may lead to near-term productivity declines, but drought captures more than precipitation deficits (Dai et al. 2004). Moreover, soil productivity can recover from short-term deficits, and if the community is capable of adapting, its effects can be minimized by recourse to irrigation, among other adaptive strategies. Recent research demonstrates the ameliorating effect of agricultural adaptive capacity on crop yields under conditions of climate stress (Regan et al. 2019). We posit that if communities reliant on agricultural economies have low adaptive capacities in the context of climate change, they will have increased difficulties in maintaining agricultural productivity.

When an agrarian society can no longer remain agriculturally viable, migration can be one result. At the community level, a dramatic decline in resources requires either the ability to adapt or suggests the possibility of conflict (Yang and Choi 2007). Consistent with this, Hsiang et al. (2013) find that warmer temperatures and lower rainfall predict an increase in communal violence. von Uexkull et al. (2016) argue that drought can be linked to the increased likelihood of conflict under agricultural dependency with politically excluded groups in poor countries. However, Salehyan and Hendrix (2014) demonstrate that water scarcity has at best a tenuous relationship to armed conflict, and they see water abundance as a potentially larger problem. The abundance-leads-to-conflict argument is contested by Fjelde and von Uexkull (2012).

Evidence suggests, therefore, that excessive precipitation or drought can cause the types of scarcity that might generate social unrest, but the difference between drought and extreme precipitation can be one of temporal scaling. Both could generate conditions of scarcity, but drought would take longer to root and impose longer-term consequences. Excess precipitation could cause short-term flooding and associated dislocations, but its effects are remediated relatively quickly. Seasonality of weather-related scarcity might also drive the climate-conflict nexus (Landis 2014).

Country and time fixed effects, instrumenting variables, and functional form all can influence the direction of the estimated relationships (O'Loughlin et al. 2014). We posit that temporal and spatial aggregation are critical to the processes by which climate pressures might cause conflict and are critical to empirically estimating those relationships (Fjelde and von Uexkull 2012; Landis 2014; O'Loughlin et al. 2012).

Moreover, human social and physical adaptation intervenes between climate-driven pressures and armed conflict.

While the direct evidence of the climate-causes-conflict thesis is somewhat ambiguous (Ide 2018), the more robust specifications see climate change as something of a facilitator given other underlying conditions, such as agricultural dependency, migration, land use change, food price, or ethnic tensions (e.g., Kelley et al. 2015; Landholm et al. 2019; Raleigh et al. 2015; von Uexkull et al. 2016; Theisen et al. 2011/12). A recent expert survey in nature comes to a similar conclusion about the complexity of the process that links climate stress to armed conflict (Mach et al. 2019). We accept those underlying political and social tensions and emphasize the role of state resources in confronting climate change so as to reduce this added pressure of one more stress point at local communities.

Spatial and temporal aggregation and climate adaptation

Water is a resource for which we have a reasonably strong empirical foundation to link to armed conflict and cooperation (e.g., Water Conflict Chronology Database) or interstate conflict over water (e.g., Tir and Stinnett 2012). If water scarcity decreases crop yields (Lesk et al. 2016; Yang and Choi 2007) and food security is one element that can put populations at risk, recurring drought conditions that are partly a function of temperature and precipitation deficits will increase the risk of conflict (Brown and Funk 2008; Lobell et al. 2008). Most African agriculture relies on rain-fed irrigation and estimates put the amount of groundwater irrigation in Africa at just 6% (You et al. 2010). Given human social ability to adapt, sustained drought conditions could generate either adaptation to the drier conditions or a reduction in crop yields; one might generate cooperation, the other conflict.

Outcomes tied to climate change are in part a function of the sensitivity and capacity to adapt to climate hazards, such that high sensitivity and low capacity leave a country more vulnerable to climate change. Brooks et al. (2005) define vulnerability in terms of state level susceptibility to injury or damage from climate events. Based on Intergovernmental Panel on Climate Change (IPCC)'s multi-dimensional vulnerability as an interaction of adaptive capacity, sensitivity, and exposure, Busby et al. (2014) conceptualize and quantify environmental vulnerability in Africa by including physical exposure to climate related hazard, population, household and community resilience, and governance and political violence.

Climate change adaptation can be related to responses to climate impacts and represent social efforts to reduce the climate risks (Moser and Boykoff 2013). Smit and Wandel (2006, 282) argued that adaptation in numerous social science domains has been regarded as "responses to risks associated with the interaction of environmental hazards and human vulnerability or adaptive capacity." Numerous recent studies related to climate adaptation policy (e.g., Adger 2006; Füssel and Klein 2006; Smit and Wandel 2006; Thomas et al. 2019) used vulnerability metrics composed of exposure, sensitivity, and adaptive capacity in the context of quantitative and qualitative methods.

At the community or regional level, adaptation is made more efficient to the extent that national-level preparedness is in place (Brooks et al. 2005). Preparedness is driven by the values at risk and the structural ability to adapt. We view the risks from climate change in terms of national-level sensitivity, that is, what is at risk and in what sectors, and the underlying capacity to adapt to those changing conditions that put value at risk. Adaptation is also context-specific and national-level adaptive strategies that do not take local political and socio-economic or ecological factors into account can sometimes lead to conflict in the face of water scarcity. In this sense, our work focuses on the role of national level—as opposed to local-level adaptation and the observed propensity for armed conflict. This is a critical link in armed conflict in the context of climate change induced water scarcity.

In addition, comparing two countries facing the same climate stressors, we would expect the one least able to adapt to suffer greater consequences, whether that be lower crop yields or a greater propensity for armed conflict. When the outcome involves armed conflict, the national government has a strong interest in providing adaptive resources, if it is able to do so.

Climate modeling, regional variation, and armed conflict

Climate modeling forecasts dramatic regional variation in temperature and precipitation anomalies as a result of changing pressures on weather systems (Hamlet 2011; Hansen et al. 2012; IPCC 2014; US DoD 2011). Within geographically expansive countries, the variation is expected to be large (Hamlet 2011). For example, on the African continent, a 2.5° square grid generates 42 separate grids incorporating the Democratic Republic of Congo, with each grid comprising a land area of approximately 270 by 270 km; there are 495 grids on the African continent. Variation in temperature and precipitation is not uniform across the 42 grids in the Congo, even though smaller countries, such as Togo with four grids, might have more uniform anomalies. There is no theoretical reason to observe social consequences resulting from national-level variation rather than local temperature and precipitation anomalies, particularly when much of the armed conflict is local (e.g., Salehyan and Hendrix 2014). There is no expectation in the climate modeling that the land that loses its productive capacity will be contiguous, or confined within geopolitical borders, so attention to spatial distributions is important. In short, where the deficit occurs will be as important as that it occurs.

Because data demonstrate considerable regional variation in global temperature and precipitation anomalies, expectations for social or political consequences should be attentive to local and temporal variation (e.g., O'Loughlin et al. 2012). For example, the mean temperature changes in Rwanda in the 19 years from 1980 through 1999 (0.09 °C) versus the 12 years in the twenty-first century (0.38 °C) increased by a factor of four. Sorting out discordant results has turned to the specification of the research design, statistical estimation, spatial scaling (Adams et al. 2018; Detges 2016; Hsiang and Meng 2014; O'Loughlin et al. 2014; Schleussner et al. 2016), and sampling bias (von Uexkull et al. 2016).

Climate change and armed conflict: theoretical links and hypotheses

The theoretical mechanisms translate climate pressures into the incentives for groups to take up arms against their state work through the effect of climate on hydrology and ecology (Műller et al. 2016; Nijssen et al. 2001; Theisen et al. 2011/12). As climate restricts access by some to resources required for production or subsistence, we would anticipate that those denied access have increased incentives to demand changes to the patterns of distribution (Brown and Funk 2008; Exenberger and Pondorfer 2013; Regan and Norton 2005; Scheffran et al. 2012). Yang and Choi (2007) demonstrate that rainfall serves as a proxy for local wealth–through the mechanism of crop yields—in the Philippines and when wealth is constrained conflict increases. Moreover, Benjaminsen et al. (2012), Hendrix and Salehyan (2012), Raleigh and Kniveton (2012), Theisen et al. (2011/12), and others use rainfall patterns in Africa to model conflict at the local level. Water deficits in regions with low levels of irrigation have an immediate impact on the production of crops, altering the ability of many regions to provide sustenance and tradable goods.

A common metric for describing climate change is the change in global temperature, or the anomaly, from a baseline (Hsiang et al. 2013; NOAA 2014). The effect of temperature on hydrological cycles is driven, at least partially, by the temperature's effect on evapotranspiration. Higher temperatures can increase the rate at which soil loses its moisture, and with the loss of moisture comes a reduction in crop yield productivity (Ochsner et al. 2013). One would have expected that increases in precipitation and soil moisture would reduce the likelihood of conflicts in rain-fed dependent systems. However, such temperature's influence on soil moisture is not necessarily immediate. This interaction between temperature and precipitation as they work through soil moisture levels suggests that the effects of climate on conflict might not be direct.

We frame hydrologic processes relating to local water scarcity in terms of multi-year patterns, focusing on physical changes rather than immediate triggers such as weather (Gleditsch 2012). Contemporary scholarship sometimes argues that climate change must work through intervening processes (e.g., Exenberger and Pondorfer 2013). We expect that the effects of climate will, over time, impact soil moisture and/or drought conditions. Low or declining levels of soil moisture can reflect systematic patterns in climatic variability and over temporal ranges of years can lead to conditions of water insecurity. The contemporary example of note is the climate-induced conflict in Sudan where pastoralists and sedentary farmers shared a common resource for generations. As drought reduced, the productivity of the land the motivation for conflict increased (UNEP 2007). A similar argument was recently made with regard to the conflict in Syria (Kelley et al. 2015).

When soil moisture in specific regions drops to levels that are unsustainable, there will be direct impacts on ground and subterranean water access, as well as reductions in river discharge rates (Nijssen et al. 2001; Ochsner et al. 2013). We argue that increasing temperatures and declining precipitation decrease soil moisture content, which in turn affects the ability to produce crop yields consistent with population needs. This impact on soil moisture also reflects declining access to water for drinking and industrial production. As water in a community becomes increasingly scarce and the adaptive capacity strained, we are more likely to observe armed conflict.

> Hypothesis 1: local increases in temperature or a decrease in soil moisture will contribute to increase the likelihood of observing armed conflict.
> Hypothesis 2: excessive localized rainfall (precipitation) will increase the likelihood of observing armed conflict

Climatic stress can be associated with vulnerability in the context of climate change. Climatic pressures on a local environment provide incentives for both conflict and cooperation. When national-level sensitivity or exposure as a form of vulnerability to climate change is high, the likelihood of armed conflict will increase under increasing pressures from the climate. On the other hand, if the national-level adaptive capacity is high, the likelihood of armed conflict will be lower.

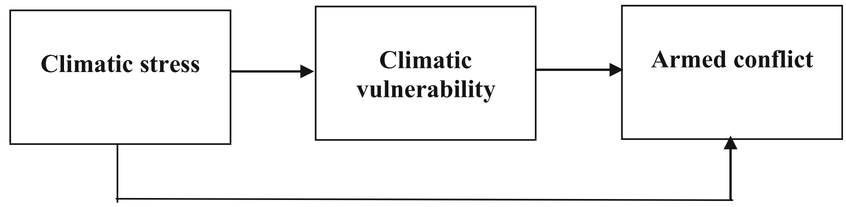
> Hypothesis 3: higher levels of adaptive capacity or lower levels of climate sensitivity will reduce the likelihood of armed conflict under conditions of climate stress.

Research design and methods

Analytical framework and variables

Our analytical framework is described in Fig. 1. The framework delineates the relationships between climatic stress and

Fig. 1 Analytical framework



armed conflict as mediated by climatic vulnerability. We assume the levels of vulnerability (i.e., adaptive capacity, sensitivity, exposure) will be affected by climatic stress and influence the likelihood of armed conflict. Our expectations are that the physical changes in conditions related to hydrology as a result of climate change will increase the risk of armed conflict when those changes are in the direction of hotter and drier conditions. That is, as temperature increases, and soil moisture or precipitation decreases (as drought conditions increase), we expect to observe a greater likelihood of armed conflict.

We test expectations on a spatial and temporal domain that incorporates the African continent 1980–2013. The temporal period changes to 1995–2013 when we include country-level adaptive capacity and sensitivity attributes to the model. We divide our geographical sample into 2.5° × 2.5° grids within 53 African countries. Our outcome variable is the grid-month based, binary indicator, of an ongoing armed conflict. We test robustness with a count indicator of the number of armed battles in proximity to the initial onset of an armed conflict. The conflict data comes from the Uppsala Conflict Data Project (UCDP).

Our primary predictor variables capture climate conditions at the grid level and national-level adaptive capacity and sensitivity. We rely on National Oceanic and Atmospheric Administration (NOAA) for data on temperature, soil moisture, and precipitation anomalies. Soil moisture and precipitation data are recorded in terms of the contemporary values, and then, we generate an anomaly from a 1948–1980 baseline. This approach makes the anomalies consistent across the various data sets. Each data series is normalized to zero and negative or positive values express the month-on-month changes. The climate data for this project required processing to standardized temporal and spatial resolutions. In all cases, the spatial processing was done first. The final spatial grid of data points was set at a 2.5° interval. Soil moisture and temperature anomalies required down-sampling the original data to a lower resolution. To obtain temperature anomalies, we used a nearest neighbor algorithm except in those cases where the central points of more than one of the original 2° grid cells fell within a single new 2.5° cell. In these cases, the average value was assigned to the new cell. All of the variables were already at a monthly interval, so temporal aggregation was not necessary. In all of the down-sampled data, maximum and minimum values were maintained along with the mean value.

After the data were processed to a temporal and spatial resolution with an average value for each month/grid cell, these grid cells were then coordinated with georeferenced conflict data within countries to generate a database with a dichotomous coding for whether or not there was an armed conflict in a particular cell for a particular month. Political boundaries often cross the borders of individual grid cells. In these cases, climate data are duplicated for each specific country, although the country designation for each conflict is retained. Data preparation was done primarily in R using bindings for the Geospatial Data Abstraction Library with some additional processing and visualization in ESRI ArcGIS. All code is available upon request.

To account for a non-instantaneous effect between climate change and conflict, we create 30-month moving averages for each of our climate conditions. The choice of 30 months is not capricious. Two and a half years of increasingly hotter temperatures or declining precipitation would generate cumulative stress on a community; we test alternatives by way of checking the robustness of our results. We use the mean values for each grid-month to create our moving averages. Our moving average approach helps to move the causal processes away from short-term climate variability or seasonal variation. An increasing or decreasing trend over 2.5 years reflects more closely climate imposed stress (Kelley et al. 2015).

The temperature models created by NOAA are based on individual readings and generally unrelated to geopolitical boundaries, leaving some locations with data that are counted in cells that cover parts of two (or more) countries. For example, a recording station within a short distance of a political border can cover a cell in two countries and there is no expectation that the temperature variation is a function of those political boundaries. In these instances, we count the cell as part of both adjoining countries. The number of monthly observations per grid cell is 408 if a grid is contained within one country. If a grid crosses national boundaries, there will be multiples of 408 observations for that grid. In the extreme, one grid encompasses five different countries.

Duplicating grid cell data to include all relevant data at the state level could lead to two potential problems. First, there are issues with artificially increasing the sample size with inaccurate data and potentially obscuring viable patterns. Second, because the boundaries of an individual grid can contain data from multiple states, there also remains the potential for the modifiable areal unit problem (Jelinski and Wu 1996). To overcome this, we also ran our models without those grids that overlap multiple states (264 grids cross country boundaries, 231 are within one country). Our analysis uses hierarchical modeling which allows for controls at grid and national levels.

We use data from the Uppsala Conflict Data Project (UCDP) to record the existence of an armed conflict in a country-grid. UCDP records three types of armed conflict: (1) those involving the state, (2) those between groups, and (3) mass killings of civilians. To be included, a conflict event must meet the conditions for an armed conflict, which requires having at least 25 battle fatalities within a given year. The data are recorded at the level of the battle, and by the geo-coordinates of the location of a battle. We adopt these geo-located battles to aggregate to conflict months within our 2.5° square grids (Sundberg and Melander 2013). Our outcome variable used in the empirical analyses reflects the existence of an armed action within a grid which forms all or part of a broader armed conflict that kills at least 25 people. The dependent variable represents civil conflicts between rebel movements and government and communal conflict between groups. Twenty-five battle fatalities provide a threshold that is low enough to capture armed conflict in localized areas but also high enough to require organized efforts to achieve this threshold.

Because our grids impose artificial boundaries over the political and social dynamics of a potential armed conflict, we account for conflicts in immediately adjoining grids that could be part of the same conflict process across our grids. If there is a conflict in the same country in an adjacent grid that starts within 1 year of the neighboring grid and if the conflict in a grid does not have a battle, then both grids are coded ongoing conflict. For example, if a grid has a conflict that starts in January and ends in March (3-month-coded ongoing) but a contiguous grid has a conflict that starts in March and runs through July (5-month-coded ongoing) then both are considered to have 8 months of ongoing conflict. If the two grids have a gap between ongoing conflicts of less than 1 year, both are considered one conflict for that entire duration. A gap of 1 year starts a new conflict. This is consistent with the UCDP criterion and it minimizes our breaking up of cultural groups based on a climate-determined grid structure. We test robustness on different specifications.

Table 1 describes our control variables, including the percentage of rural population (rural population), mortality rate (mortality rate), political regime type (polity), and economic wealth (per capita GDP) as country-level non-climatic conditions. Those variables were derived from the UN and World Bank, and the POLITY IV project; we use annual observations. Given the number of observations reported in Table 1, there are missing data for grid-level and country-level climate and non-climate conditions. In order to control for the underlying environmental conditions in each locale, we generate a climate classification as a structural indicator of the amount of rainfall in each grid. This climate classification was created from a digitized version of a standard Arid Zones of Africa Map (McCarthy et al. 2001, 518). Grid cells containing multiple zones were given a characterization of the dominant value. We generate six categories reflecting arid, hyperarid, semi-arid, dry-subhumid, mostly-subhumid, and humid conditions; we collapse these six categories into three that reflect the degree of aridity in a country-grid, with arid and hyperarid, semi-arid and dry sub-humid, and most subhumid and humid comprising the three categories.

To capture country-level adaptive capacity, exposure, and climate sensitivity, we rely on data from the Notre Dame Global Adaptation Index (ND-GAIN) project (https://index.gain.org). Three vulnerability components and specific indicators used in our work are summarized in Appendix Table 3. Under the six sectors composed of food, water, health, ecosystem services, human habitat, and infrastructure, each component as a composite indicator was transformed into standardized scales (see Chen et al. 2015).

The exposure variable reflects the extent to which a system is exposed to significant climate change or climate hazards. To measure exposure, our work adopts 12 sub-indicators such as projected change of deaths from climate change induced diseases and projected change of marine biodiversity. The sensitivity variable represents social, political, and physical risks posed by climate pressures and includes 12 sub-indictors such as food import dependency and water dependency ratio (Chen et al. 2018; Regan et al. 2019). The adaptive capacity variable reflects social, political, and economic infrastructure that can respond to the physical and social consequences of climate change and is also a composite indicator composed of 12 sub-indicators such as access to reliable drinking water and agriculture capacity (Chen et al. 2018; Regan et al. 2019). From the suite of 24 sensitivity and adaptive capacity as part of vulnerability described in ND-GAIN, we isolate two specific indicators of sensitivity (water dependency) and adaptive capacity (drinking water access) because they represent primary structural conditions where climate-driven water scarcity can have its most dramatic effect (Műller et al. 2016).

Methods

We specify empirical models that include country-level non-climatic variables, grid level climatic variables, and a grid level indicator of armed conflict (see Table 1). To account for the different spatial levels and unobserved effects and endogeneity, we use multi-stage panel logistic regression with ongoing conflict as our outcome variable (model I of Table 2). The models are specified to “take account of the variability concerned about each level of nesting” (Snijders and Bosker 1999, 1) and adjust for the lack of independence within the spatial clusters (Raudenbush and Bryk 2002). A multi-level panel logistic regression model is appropriate to estimate the spatial cross-level effects of country-level non-climatic

Table 1 Descriptive statistics

Variable name		Number of observations	Mean	SD	Range
Grid-level climatic stress variables					
Temperature anomaly		305,125	0.567	0.689	− 4.662–5.264
Soil moisture anomaly		300,627	− 23.004	61.853	− 461.22–663.44
Precipitation anomaly		284,340	− 0.395	3.423	− 40.466–79.453
Arid effect		359,032	0.397	0.489	0–1
Arid and humid effect		359,032	0.308	0.461	0–1
Humid effect		359,032	0.293	0.455	0–1
Country-level non-climatic condition variables					
Polity		332,200	− 1.587	5.659	− 10–10
Per capita GDP		311,212	1354.04	2017.92	64.81–24,035.71
Mortality rate		335,404	133.358	69.188	13.10–334.50
Rural population		335,956	63.425	17.099	13.542–95.661
Water dependency		185,636	0.461	0.394	0–1
Drinking water access		185,612	0.728	0.322	0.002–1
Country-level vulnerability condition variables					
Exposure		168,693	0.566	0.093	0.34–0.75
Sensitivity		193,353	0.414	0.101	0.101–0.656
Adaptive capacity		193,353	0.270	0.150	0.042–0.703
Grid-level armed conflict variables					
Ongoing conflict	1 = yes	40,889	0.111	0.314	0–1
	0 = no	325,973			
Onset conflict	1 = yes	15,249	0.041	0.199	0–1
	0 = no	351,613			

conditions and grid-level climatic conditions on the likelihood of armed conflicts. Additionally, we use a multilevel negative binomial regression to test the effect of climate and adaptation on the number of battles associated with a conflict (see model II of Table 2).

Next, we use an instrumental variable estimation with two-step probit endogenous regressors to account for an underlying process by which water scarcity persists. This accounts for unobserved effects and endogeneity in one or more time-varying explanatory variables. We treat the soil moisture anomaly as endogenous and model it using several variables including 4-month-lagged climatic conditions (temperature anomaly, precipitation anomaly, soil moisture anomaly) and components of country-level sensitivity (water dependency) and adaptive capacity conditions (drinking water access) as instruments variables (see model III, Table 2). For water dependency, low is better and for water access, high is better.

Results

Climate change and armed conflicts

Our results suggest that increases in temperature and precipitation at the grid level increase the likelihood of observing armed conflicts in that grid ($\beta = 0.163$, $\sigma = 0.008$; $\beta = 0.004$, $\sigma = 0.002$, model I(1), Table 2); increases in soil moisture are associated with a decrease in the likelihood of observing conflict ($\beta = -0.003$, $\sigma = 0.00009$). This supports the general inference that climate change leads to increased armed conflict.

We expand these grid-based models to include country-level socio-economic and political conditions along with adaptive capacity (drinking water access) and climate sensitivity (water dependency) attributes reflecting water resources as conditions of vulnerability, using a two-stage panel logistic regression (Table 2, model I (2)). The results continue to support the argument that warmer and drier conditions are associated with an increased observation of armed conflict under the grid level climatic stress conditions ($\beta = 0.043$, $\sigma = 0.013$; $\beta = -0.002$, $\sigma = 0.0001$). The country-level adaptive capacity attribute (e.g., drinking water access) is not associated with armed conflict, but the country-level climate sensitivity attribute (e.g., water dependency ratio) is associated with an increase in the probability of observing armed conflict in a particular grid. This result can be supported by model I (3) and (4) that show the positive role of general adaptive capacity attributes in decreasing the likelihood of conflict. With more attention to country-level vulnerability conditions, model I (3) and (4) integrate three vulnerability components (exposure, sensitivity, adaptive capacity) derived from composite

Table 2 The effect of climatic stress and non-climatic conditions on armed conflict

	Multilevel model										Instrumental model	
	Model I: ongoing conflict					Model II: onset conflict					Model III: ongoing conflict	
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)
Grid-level climatic stress conditions												
Temperature anomaly (TA)	0.163***	0.043**	0.005	0.114***	0.009	0.119***	− 0.027	− 0.058**	0.094**	− 0.007	− 0.001	− 0.080***
	(0.008)	(0.013)	(0.013)	(0.027)	(0.026)	(0.013)	(0.021)	(0.020)	(0.044)	(0.042)	(0.005)	(0.010)
Soil moisture anomaly (SA)	− 0.003***	− 0.002***	− 0.002***	− 0.002***	− 0.002***	− 0.003***	− 0.002***	− 0.002***	− 0.0002	0.0003	− 0.010***	− 0.012***
	(0.00009)	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0006)	(0.0005)	(0.0002)	(0.0005)
Precipitation anomaly (PA)	0.004**	− 0.002	− 0.002	0.0001	− 0.010	0.004	− 0.001	− 0.0006	− 0.036**	− 0.047**	0.017***	0.016***
	(0.002)	(0.003)	(0.004)	(0.010)	(0.010)	(0.003)	(0.005)	(0.005)	(0.015)	(0.015)	(0.001)	(0.002)
TA*PA	0.011***	0.010**	0.002	0.055***	0.042**	0.004	0.001	− 0.001	0.095***	0.092***	0.009***	0.012***
	(0.003)	(0.004)	(0.005)	(0.012)	(0.013)	(0.005)	(0.007)	(0.007)	(0.018)	(0.019)	(0.001)	(0.002)
Country-level non-climatic conditions												
Polity		0.009**		0.009**			0.009*		0.009*			− 0.039***
		(0.003)		(0.003)			(0.005)		(0.005)			(0.001)
Per capita GDP		− 0.0001***		− 0.0001***			− 0.0001***		− 0.0001***			− 0.00004***
		(0.00001)		(0.00001)			(0.00002)		(0.00002)			(4.43e-06)
Mortality rate		0.003***		0.003***			0.004***		0.004***			− 0.002***
		(0.0006)		(0.0006)			(0.0009)		(0.0009)			(0.0001)
Rural population		0.042***		0.041***			0.051***		0.049***			− 0.00003
		(0.004)		(0.004)			(0.006)		(0.006)			(0.0006)
Water dependency		0.236*		0.213*			0.660*		0.595*			0.715***
		(0.258)		(0.257)			(0.432)		(0.431)			(0.019)
Drinking water access		0.036		0.030			0.388*		0.427**			− 0.061*
		(0.141)		(0.142)			(0.215)		(0.216)			(0.035)
Country-level vulnerability conditions												
Exposure			1.395*		1.422*			2.180*		2.316**		0.701***
			(0.808)		(0.810)			(1.169)		(1.170)		(0.113)
Sensitivity			2.857***		2.870***			4.273***		4.264***		2.317***
			(0.396)		(0.396)			(0.582)		(0.582)		(0.114)
Adaptive capacity (AC)			− 16.315***		− 16.422***			− 16.855***		− 17.075***		− 0.586***
			(0.574)		(0.585)			(0.891)		(0.906)		(0.070)
Interaction effect												
TA*AC				− 0.268**	− 0.015				− 0.459**	− 0.204		
				(0.089)	(0.086)				(0.144)	(0.137)		
SA *AC				− 0.0002	− 0.001				− 0.009***	− 0.013***		
				(0.001)	(0.001)				(0.002)	(0.002)		
PA*AC				− 0.016	0.027				0.142**	0.187**		
				(0.043)	(0.041)				(0.061)	(0.060)		
TA*PA*AC				− 0.186***	− 0.162**				− 0.388***	− 0.376***		
				(0.049)	(0.048)				(0.069)	(0.069)		

Table 2 (continued)

	Multilevel model										Instrumental model	
	Model I: ongoing conflict					Model II: onset conflict					Model III: ongoing conflict	
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)
Constant	− 2.137***	− 5.252***	− 0.014	− 5.184***	− 0.013	− 3.189***	− 7.639***	− 2.174**	− 7.545***	− 2.211**	− 1.386***	− 1.704***
	(0.008)	(0.458)	(0.636)	(0.458)	(0.637)	(0.012)	(0.631)	(0.877)	(0.629)	(0.876)	(0.006)	(0.090)
Country characteristic level		1.859	2.439	1.856	2.443		2.008	2.590	1.999	2.585		
		(0.238)	(0.292)	(0.238)	(0.293)		(0.267)	(0.316)	(0.265)	(0.315)		
N of observations	284,068	113,498	131,536	113,498	131,536	284,068	113,498	131,536	113,498	131,536	281,968	103,234
Log likelihood	− 105,701.59	− 43,937.33	− 46,256.45	− 43,916.49	− 46,245.78	− 52,806.47	− 23,105.57	− 24,116.65	− 23,078.30	− 24,086.62		
Wald Chi-square		965.56***	1265.08***	1005.42***	1283.56***		508.59***	618.45***	562.56***	673.56***	1793.37***	3891.56***

*,**,*** $P < 0.1$, $P < 0.05$, $P < 0.001$, standard error in parentheses

indicators and the grid level climatic stress condition. In addition, the interaction between climatic stress (particularly in temperature and precipitation) and adaptive capacity demonstrate the positive role of adaptive capacity in reducing the likelihood of armed conflict at the grid level in the face of localized climate stress (Table 2, model I (4)).

Following the specification in model I (Table 2), we examine the relationship with monthly battle occurrences (onset conflict) associated with an armed conflict. The core results hold with an increase in temperature and a decline in soil moisture being associated with the likelihood of battles ($\beta = 0.11$, $\sigma = 0.01$; $\beta = -0.003$, $\sigma = 0.0001$; model II (1)). We see the results for battles as a confirmation that our dichotomous coding of an ongoing conflict does not bias results; however, we have no theoretical foundation to think that climate anomalies directly affect the number of individual battles.

Our instrumental variable model confirms the results of our multilevel models. Our instrumental specification directly tests the underlying argument about water scarcity on conflict by treating long term trends in soil moisture as endogenous. The overall grid climatic stress conditions are also influential in the likelihood of armed conflict, while country-level vulnerability conditions remain significant and in the expected direction (model III (2)). In this sense, we can conclude that increases in temperature and soil moisture or decreases in precipitation as a function of climatic stress are related to the increase in the likelihood of observing armed conflict.

The role of climate adaptation in armed conflicts

Furthermore, we examine the relationship between the probability of armed conflict and country-level vulnerability conditions (exposure, sensitivity, adaptive capacity) by the climatic classifications (i.e., arid, arid and humid, and humid regions) and six African divisions (northern, southern, eastern, western, middle, sub-Saharan). As depicted in Fig. 2, each bar generated from model I (5) of Table 2 presents standard coefficient values by vulnerability components. The results show that negative associations exist between adaptive capacity and the likelihood of armed conflicts under three types of climate conditions and six country divisions within Africa. In particular, the positive role adaptive capacity played in reducing the probability of armed conflict within humid regions.

To further describe the effects of national-level adaptive capacity on armed conflict within a grid, we present several graphs generated from model I (5). As illustrated in Fig. 3, each graph reflects the impact of high or low national-level adaptive capacity under different climatic conditions. High and low conditions of adaptive capacity are determined relative to the global mean level of adaptive capacity. At a glance, in Fig. 3a, as the temperature increases, the likelihood of armed conflict in a grid increases in high adaptive capacity

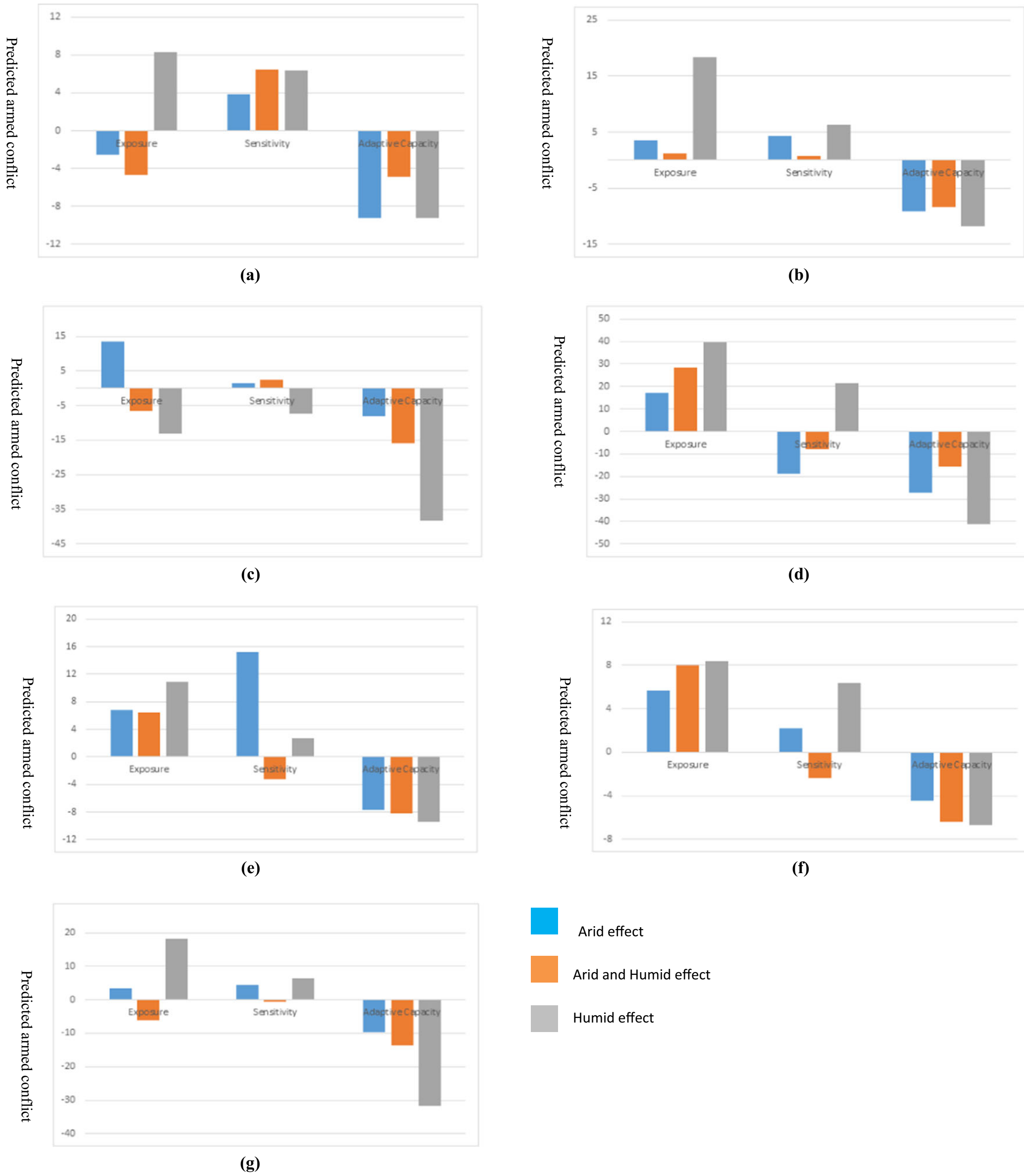


Fig. 2 Relationship between vulnerability component (exposure, sensitivity, adaptive capacity) and predicted armed conflict under arid or humid effect. **a** Northern region, **b** southern region, **c** eastern region, **d** western region, **e** middle region, **f** sub-Saharan region, **g** entire region

countries but declines in low capacity countries. However, the underlying probability of observing a conflict, given climate-driven stress, is higher and the slope is steeper in low adaptive capacity countries. When controlling for country-level characteristics, as the soil moisture content increases, the probability of observing an armed conflict decreases, but does so from a higher initial position in low capacity countries relative to high capacity countries (Fig. 3b). In this context, we draw the conclusion that higher levels of adaptive capacity or lower levels of climate sensitivity lead to a decrease in the likelihood of observing armed conflict.

Discussions and conclusions

Scholarly debate about the role of climate change in armed conflict has generated divergent outcomes (e.g., Buhaug et al. 2014; Burke et al. 2015; Salehyan and Hendrix 2014), with specific cases presenting hard to refute evidence (Kelley et al. 2015) and with confounding conditions accelerating the influence of climate drivers (Schleussner et al. 2016). Our results help to clarify and extend this debate in important ways. By narrowing the spatial focus to a 2.5° square grid, we isolate more local climatic conditions and link them more closely to

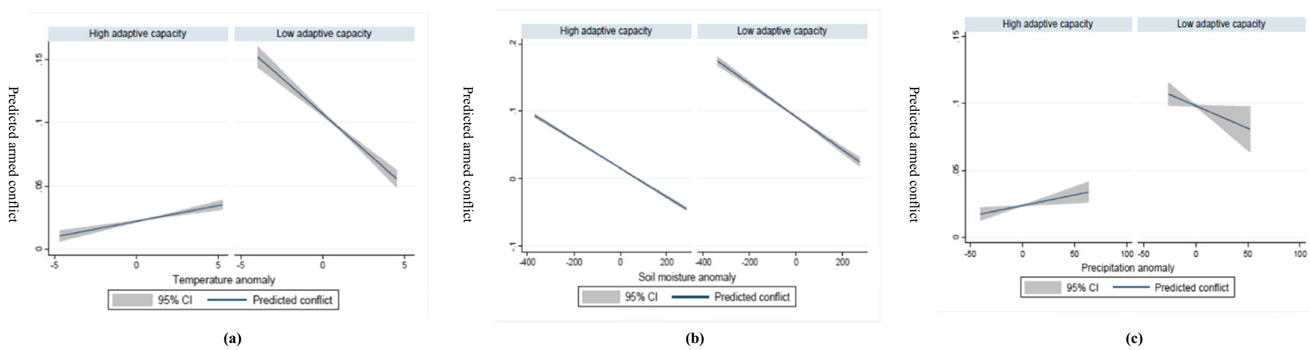


Fig. 3 Predicted armed conflict and climatic conditions by adaptive capacity level. **a** Temperature anomaly, **b** soil moisture anomaly, **c** precipitation anomaly

local conflict events. Furthermore, our methodology changes climate drivers from short-term fluctuations over a month into longer term trends that reflect the cumulative influence of climate on conflict. There should be little expectation that short-term variation in climate (averaged at the year or recorded at the month) would compel something as complex as armed conflict.

Our results demonstrate that at the country-grid level of observation, climate drivers of water scarcity are associated with an increased likelihood of armed conflict, and that national-level adaptive capacity under conditions of climate stress can reduce that probability. The role of adaptive capacity in moderating armed conflict under conditions of climate-driven scarcity provides policy suggestions. Our work relies on the assumption that the country-level adaptive capacity is crucial. There could be a major gap between a state/country-level indicator and individual or community level motivations for participating in conflict, yet in many regions such as Northern Kenya, South Sudan, or Eastern Congo, the country is unable or unwilling to provide aid, and there is important subnational variation that is lost by looking at the country-level adaptive capacity. National-level adaptive capacity can act in ways to moderate the effect of climate on the choice sets of people facing increasingly harsh conditions. In this sense, the state can take steps that reduce the marginal impact of climatic changes and in doing so provide local level respite from the conditions that nature is envisaging on a local region. Although we have yet to see this in the literature, facilitating—or bolstering—a country's adaptive capacity may be a form of external intervention into countries that are potentially at risk of armed conflict (Regan and Meachum 2014). The US DoD (2011) estimates that by 2060 nearly 600,000 km^2 of currently arable land in Africa will become non-productive because of climate imposed scarcity. Our evidence suggests that investing in the adaptive capacity of African countries can reduce the propensity for people to take up arms as they confront recurring water scarcity. Governments and aid agencies may be well placed to facilitate movements toward more prepared countries.

Our work addresses the links between climate, adaptation, and conflict in Africa. However, some of the most important aspects of adaptation can be that (1) people are already engaged in extensive adaptation activities, including circular migration, and (2) most adaptation is determined by families and communities without programs from the national level. Future research should expand our focus on national-level capacity and categorize the diverse factors that might account for local level adaptive efforts. Beyond the linear relationship between climate change and armed conflict in this research, it would be worthwhile to delineate how drier climates link declining crop yields to the increased likelihood of armed conflict by utilizing a structural equation modeling to capture the complex causal process and further address the impacts of violent conflict on food security and household resilience (e.g., Brück et al. 2019). As described by Raleigh and Kniveton (2012), our study needs to redefine the dependent variable, conflict types to reflect different processes and causal expectations for the role of climate change on different conflict types.

Moreover, our African focus could be expanded globally to address sampling bias in climate-conflict research (Adams et al. 2018; Hendrix 2017). In effect, all countries experience climate change and choosing a continent more prone to conflict may obscure a different underlying relationship, but evidence is accumulating that climate stress is one driver of armed conflict in other regions as well. Future research also needs to address the dynamics of armed conflicts as suggested by Theisen (2017) along with regional and ethnic oppositional zones and various battle types like group-group, state-group, and mass killing.

To reflect spatial and temporal conflicts, our work relied on 2.5 × 2.5° grids at monthly intervals and attempted to address neighboring effects of conflicts. Such measures can reveal a limit to fully account for spill over conflict in partially filled grids. In addition to the necessity to measure the various conflict types, future study needs to address the spatial effects by defining spill over conflicts. Our models support the inference that 2.5-year moving averages of temperature, precipitation, and soil moisture are strong predictors of armed conflict within country-grids. These results confirm many of the findings in the literature, albeit with nuances. Increases in temperatures within a grid that are sustained over a 30-month period are associated with increases in armed conflict; increases in soil moisture decrease conflict. At the same time, increases in precipitation over a 30-month period are associated with an increased likelihood of armed conflict in a grid, which is consistent with the results of Salehyan and Hendrix (2014), but seems to run counter to others (e.g., Fjelde and von Uexkull 2012).

The use of national-level cross-sectional measures of adaptive capacity (and sensitivity) can be a major limitation of this paper. Supported by Schultz and Mankin (2019), we need to consider the possibility that temperature data might have some omissions. Given that our evidence points to rather strong links between climate drivers and armed conflict, our results also suggest that the greater the level of adaptive capacity of a country, the less likely they are to observe conflict in one of their grids. Furthermore, our use of different level predictor variables reveals a limitation to fully reflect the role of political (or power) relations in shaping communities' adaptive capacities and distributive effects of climatic effects. This result remains robust to model specification.

We are, however, under no illusions that climate alone will lead groups to take up arms against their government. Others have demonstrated the import of extant political and social conditions on the ground climate stress takes root. We accept and demonstrate that climate-driven water scarcity helps generate the condition conducive for armed conflict, and importantly, that state-level capacity to confront the pressures from climate change can reduce the impact of this "additional" stress to local environments.

Appendix

Table 3 Vulnerability components and sub-indicators under six sectors

Food	Water	Health	Ecosystem services	Human habitat	Infrastructure
Exposure (12)					
Projected change of cereal yields	Projected change of annual runoff	Projected change of deaths from climate change induced diseases	Projected change of biome distribution	Projected change of warm period	Projected change of hydropower generation capacity
Projected population change	Projected change of annual groundwater recharge	Projected change of length of transmission season of vector-borne diseases	Projected change of marine biodiversity	Projected change of flood hazard	Projection of sea level rise impacts
Sensitivity (12)					
Food import dependency	Fresh water withdrawal rate	Slum population	Dependency on natural capital	Urban concentration	Dependency on imported energy
Rural population	Water dependency ratio	Dependency on external resource for health services	Ecological footprint	Age dependency ratio	Population living under 5 m above sea level
Adaptive capacity (12)					
Agriculture capacity	Access to reliable drinking water	Medical staffs	Protected biomes	Quality of trade and transport-related infrastructure	Electricity access
Child malnutrition	Dam capacity	Access to improved sanitation facilities	Engagement in international environmental conventions	Paved roads	Disaster preparedness

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