Using self-controlled case series to understand the relationship between conflict and cholera
in Nigeria and the Democratic Republic of Congo

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Abstract

Cholera outbreaks significantly contribute to disease mortality and morbidity in low-income countries. Cholera outbreaks have several social and environmental risk factors and extreme conditions can act as catalysts. A social extreme with known links to infectious disease outbreaks is conflict, causing disruption to services, loss of income and displacement. Here, we used the self-controlled case series method in a novel application and found that conflict increased the risk of cholera in Nigeria by 3.6 times and was attributed to 19.7% of outbreaks. In the Democratic Republic of Congo (DRC) the risk was 2.6 times greater and 12.3% of cholera outbreaks were attributable to conflict. Several states/provinces with the strongest relationship were also areas of high reported conflict. Our results help highlight the importance of rapid and sufficient assistance during social extremes and the need for pre-existing vulnerabilities such as poverty and access to healthcare to be addressed.
Diarrhoal diseases are the eighth leading cause of death worldwide, with cholera contributing significantly, especially in low- and middle-income countries (1). Over 94% of World Health Organization (WHO) reported cholera cases are in Africa and more research is needed to understand cholera dynamics on the continent (2). Previous research has found several environmental and socioeconomic links with cholera, including temperature, precipitation, poverty and water, sanitation, and hygiene (WASH) (3,4,5). Furthermore, extremes of these environmental and social conditions can act as catalysts for outbreaks, such as droughts, floods, and conflicts (6,7,8).

Here, we will focus on the impacts of conflict on cholera outbreaks and compare the results across two countries in Africa, Nigeria and the Democratic Republic of Congo (DRC) in the past 23 years. Several mechanisms have been suggested through which conflict can lead to infectious disease outbreaks (9,10,11,12). During conflicts, services can be disrupted including access to WASH, disruption of disease control programmes and collapse of health systems (e.g., vaccination coverage). Those displaced by conflict may also find it difficult to access healthcare (13,14,15). Populations may not seek medical treatment as they perceive healthcare facilities as unsafe. For example, during the 2018 Ebola outbreak in the DRC healthcare facilities were attacked, dampening efforts to control the virus (16). Conflict can worsen pre-existing vulnerabilities including poverty, as conflicts can cause loss of income, disruption to education, damage to livelihoods and displacement (17).

Nigeria and the DRC share social and environmental similarities, as well as experiencing cholera outbreaks. Both have active conflicts including the Boko Haram Insurgency in northeastern Nigeria (18) and political unrest in the eastern DRC (19). They have the second and third highest numbers of estimated cholera cases per year in Africa, respectively (20), with the Kivu provinces being the most active cholera foci in the world (21). In addition, Nigeria and the DRC have a tropical climate, poor access to WASH and a large proportion of the population living in poverty (<$1.25/day) at 87.7% for the DRC and 62% for Nigeria (22), which are known cholera risk factors.
Few studies have investigated the impacts of conflict on cholera outbreaks, especially quantitatively. Studies have commonly focused on cholera and conflict in Yemen (10,23,24), its effect on vaccination efforts (25) or the impact of conflict on other diseases such as Ebola (16) and COVID-19 (26). Africa is also a chronically understudied continent in relation to cholera, despite reporting a large proportion of global cases (2).

To bridge this research gap, we used the Self-Controlled Case Series (SCCS) method, both nationally and sub-nationally and completed a sensitivity analysis to provide insight into the duration and lag of the effect. The SCCS method is used in a novel application and we aim to understand and promote its use in other contexts (27). Previous uses of the method include testing the effectiveness of drug and vaccine intervention on an individual (28,29) and population level (30). Furthermore, we adapted the recently developed percentage attributable fraction (PAF) equations to the work presented here (30), to understand the proportion of cholera outbreaks attributable to conflict. Based on these results, we suggest mechanisms for which conflict is driving cholera and potential risk factors, building on previous research in this area. We hope this information can be used to strengthen disease prevention in conflict settings and reduce additional mortality and morbidity in conflicts.

Methods

Datasets

Cholera data were compiled from a range of publicly available sources (WHO disease outbreak news, ProMED, ReliefWeb, WHO regional office for Africa weekly outbreak and emergencies, UNICEF cholera platform, EM-DAT, the Nigerian Centre for Disease Control, and a literature search) in both English and French. The full compiled dataset is available in a GitHub repository (https://github.com/GinaCharnley/cholera_data_drc_ngac) and additional information on data collation and validation in a complementary database paper (31). An outbreak was defined by the onset of a cholera case and the case definitions for the two countries are shown in S1 Information. Conflict data were provided by the United Nations Office for the Coordination of
Humanitarian Affairs Humanitarian Data Exchange, which provides data from the Armed Conflict Location & Event Data Project (ACLED) (32). The data included sub-national conflict events, categorised by event type including battles, explosions, protests, riots, strategic developments, and violence against civilians.

The spatial granularity of the analysis was to administrative level 1 (states for Nigeria and provinces for the DRC) and all data points that were reported on a finer spatial scale were aggregated to the upper level. The study period was specified as January 1997 to May 2020, as these were the first and last reports in the conflict data. The temporal scale was set to weekly, with continuous weeks from epidemiological week 1 in 1997 to epidemiological week 20 in 2020 (1-1,220). Continuous weeks was chosen for compatibility with the model and to include periods of conflict that endured from one year into the next. Weeks was chosen, rather than days, to account for reporting lags, as previous work has reported issues in the granularity of data and timeliness of reporting, especially in humanitarian crises due to different sources of data and logistical difficulties (33,34,35). Additional information on the datasets used here are available in S2 Information.

Model Structure and Fitting

The SCCS method investigates the association between an exposure and an outcome event. The aim is to estimate the effect, by comparing the relative incidence of the adverse events (outbreaks) within an exposure period of hypothesised excess risk (conflicts), compared to all other times (peace, according to the dataset used) (36,37,38).

Both the event and exposure were set as binary outcomes, either being present (1) or not (0). The observation period was the full study period (1-1,220). The exposure period was the first week after conflict onset and was reported as multiple onsets, not one long exposure period. The event was defined by the week the cholera outbreaks was reported.

Each event and exposure that occurred in the same state/province were designated an identification number and a pre-exposure, exposure, and post exposure period (see S1 and S2 Tables). The data was fit to conditional logistic regression models (function clogit(), R package
“survival”) (39). The model coefficient values were used to calculate incidence rate ratio (IRR), to understand the magnitude in which conflict increased the risk of cholera outbreaks.

The datasets for each country were then split by state/province and the analysis repeated for each, to understand if the significance of conflict on cholera outbreaks varied by sub-national location and if conflict was more important in some states/provinces compared to others. All statistical analyses were carried out in R version 3.6.2 and the threshold for significance was p<=0.05.

**Percentage Attributable Fraction**

The recently developed percentage attributable fraction (PAF) equations (30) were adapted to the model results found here. The PAF values estimate the percentage of outbreaks that could be attributed to conflict at a national level, using the datasets and the IRR values from the model results (full equations in S3 Information).

**Sensitivity Analysis**

A sensitivity analysis was used to test different methods of defining the exposure end point (set to one week in the main analysis) and to understand the impact this would have on the results. It allowed for further understanding of how long after a conflict event the risk of cholera is heightened. Full information is shown in S4 Information and S1 and S2 Figs.

**Results**

**Conflict and Cholera Occurrence**

The distribution of conflict and cholera in Nigeria and the DRC in the datasets used here is shown temporally and spatially in Figure 1. The data shows an increase in reported conflict and cholera, especially after 2010 (Figure 1a-d) and a large proportion of the cholera cases have been reported in conflict-stricken areas (Figure 1e-f).

The total number of conflicts and outbreaks for each state/province during the study period is shown below in Figure 2 and totaled 4,639 conflict and 396 cholera outbreaks for the DRC and in Nigeria, 8,190 conflicts and 782 cholera outbreaks.
Figure 1. Changes in cholera and conflict for the full datasets for Nigeria (left panel) and the Democratic Republic of Congo (right panel). a, monthly cholera cases and deaths, b, monthly frequency of conflict events and fatalities and c, the number of conflict events and cholera cases as a percentage of the total number of national cases by administrative level 1.
Figure 2. Percentage of events in each dataset including conflict and outbreaks, for a, Nigeria and b, the Democratic Republic of Congo by administrative level 1. FCT - Federal Capital Territory.

To be included in the analysis, the state/province had to report both outbreaks and conflicts during the study period. As such, 22 provinces were included for the DRC and 36 states for Nigeria (states and provinces excluded are shown in S5 Information). The temporal distribution of the
exposure periods and outbreaks included in the SCCS model for each state/province is shown in Figure 3.

**Figure 3.** Swimmer plots showing the conflict exposure period in the SCCS model (1 week after the onset) and the outbreaks (purple diamond) for each state/province for **a**, Nigeria and **b**, the Democratic Republic of Congo.
**Model Output**

Conflict significantly increased the risk of cholera outbreaks (IRR) in the past 23 years in Nigeria and the DRC. Nigeria showed an effect of greater magnitude, increasing the risk of cholera outbreaks by up to 3.6 times (IRR = 3.6, 95%CI = 3.3-3.9). Whereas for the DRC, the risk was increased by 2.6 times (IRR = 2.6, 95%CI = 2.3-2.9).

Of the 36 Nigerian states included in the analysis, 24 showed significant associations between conflict and cholera outbreaks. The strongest effect was found in Kebbi, Lagos, Osun, Borno and Nasarawa, with IRR values ranging from 6.8 to 6.2 (Figure 4a).

Eleven out of 22 DRC provinces included in the analysis showed a significant relationship between conflict and cholera. Tanganyika, Kasaï-Oriental, Maniema, Nord-Kivu and Kasaï found the strongest values and some were the highest values found in the analysis. In Tanganyika, conflict increased cholera risk by 7.5 times and 3.7 times for Kasaï (Figure 4b).

![Map showing cholera outbreaks in Nigeria and the DRC](image-url)
**Figure 4.** Incidence rate ratio (IRR) for the effect of exposure to conflict within one week of the event and cholera at a sub-national level. For **a**, Nigeria and **b**, the Democratic Republic of Congo. Only results that were significant at the threshold $p<0.05$ are plotted here.

**Percentage Attributable Fraction**

Based on the IRR values from the model results (3.6 for Nigeria and 2.6 for the DRC), the onset of a conflict event was attributable to 19.7% of cholera outbreaks in Nigeria and 12.3% for the DRC.

**Sensitivity Analysis**

The effect of conflict on cholera outbreaks at a national and sub-national level for both Nigeria and the DRC decreased with increasing exposure period. By week 6 the change was minimal and plateaued or increased (full results in S3 and S4 Figs).

**Discussion**
Conflict events in Nigeria increased the risk of cholera outbreaks by 3.6 times and 2.6 times for the DRC. The percentage of cholera outbreaks attributable to the conflicts reported here was 19.7% for Nigeria and 12.3% for the DRC. The states/provinces with the highest increased risk were Kebbi, Nigeria at 6.9 times and Kasaï-Oriental, the DRC at 7.3 times. This showed that in some states/provinces, the effect of conflict was much greater than the national level.

The sensitivity analysis showed a decrease in effect as the weeks progressed, with some states/provinces seeing a plateau or increase around 6 weeks after the event. The decrease with the lag duration may be a “diluting” effect, as the probability of an outbreak will increase across a longer period. The states/provinces that increased after week 6, were often those with the strongest initial effect, especially in the DRC. This larger initial effect may have a longer lasting impact, potentially due to conflict severity.

States/provinces with the greatest increased risk often coincided with areas of high conflict. This provides further evidence to the hypothesis that conflict may be a driver of cholera in Nigeria and the DRC. States/provinces surrounding high conflict areas were also highly significant areas (e.g., Abia, Ogun, Osun, Maniema, and Tanganyika), showing a potential spill-over effect. The states/provinces here were studied independently but a possible explanation may be people fleeing areas of conflict or a cholera outbreak to neighbouring states, as displacement is a known risk factor for disease outbreaks (12). This is especially important for cholera, as a large proportion of people will be asymptomatic but can still shed the pathogen into local reservoirs, which displaced populations may use as drinking water due to a lack of alternatives (40).

Cholera outbreaks can be explosive and self-limiting, due to the high number of asymptomatic individuals, reducing the susceptible pool (40). This potentially explains why the impacts of conflict on cholera was seen just one week after the event. The incubation period of cholera is short (41), making the effect within the first week found here biologically possible for the pathogen and a realistic timeframe for elevated exposure to manifest in cases. Other examples of cholera cases emerging within the first week after an adverse event include Cyclone Thane hitting
the Bay of Bengal (42), water supply interruption in the DRC (43) and Cyclone Aila in West Bengal (44). This provides further evidence of the need for quick and effective aid in humanitarian crisis to avoid outbreaks and reduce mortality (45).

Healthcare facilities can suffer in periods of conflict and cholera outbreaks can overwhelm systems, a potential cause of the relationship between conflict and cholera shown here. Care can be inaccessible because of direct infrastructure damage or difficulties getting to the facilities due to impromptu roadblocks (46). Supplies may be stolen and/or unable to be delivered, including oral rehydration solution (ORS), pathogen-sensitive antibiotics and oral cholera vaccines, which are important for cholera outbreak control and mortality (47). Finally, safety is a serious issue, both for healthcare workers and patients and non-governmental (NGO) organisations can withdraw from these areas, citing an inability to ensure the safety of their staff (48). Steps need to be taken globally to reduce this violence, such as using active clinical management for all patients to enhance the acceptance of pathogen-specific treatment centres (49).

Conflict has the potential to worsen pre-existing vulnerabilities, which can exacerbate poverty, another potential cause of the effect of conflict on cholera. The impacts of poverty can be far reaching and is a known risk factor for cholera (5,50), along with other diseases (51). For example, poor urban settlements have faced the brunt of outbreaks including Zika, Ebola, typhoid, and cholera, due to crowding and poor access to WASH (52). Those in poorer communities may also have more contacts and greater transmission, creating a vicious cycle (51). Conflict can result in loss of possessions, habitual residence, and an inability to find employment, reducing income generation, savings and financial backstops (17). In times of worsening poverty, people may not be able to afford healthcare and basic medical supplies, especially in vulnerable groups. This disruption to daily life can cause many more deaths than direct battlefield fatalities and leads to stagnation in development (53).

A lack of WASH facilities is likely to have contributed to the positive relationship between cholera and conflict found here. Although WASH and poverty were not directly evaluated, their
effects are likely to have been important. Conflict events can lead to disruption in sanitation and hygiene and adverse events can act as catalysts in the interaction of contaminated water and the human populations (54). Displacement from conflict can cause issues in accessing WASH (e.g., latrine access, soap availability) and several displacement camps have seen rapid cholera outbreaks, including the DRC after the Rwandan genocide in 1994 (2). If people are displaced due to conflict, this may result in the use of water contaminated with toxigenic strains of *Vibrio cholerae* because alternatives are lacking, leading to outbreaks.

A potential limitation of this analysis is the confounding effect of waterbodies in the most significant states/provinces including the Lake Chad basin in Nigeria and the African Great Lakes Region in the DRC. Water is considered fundamental in cholera transmission (55), although no study has yet demonstrated a long-term persistence of toxigenic *Vibrio cholerae* in African lakes (56). Understanding these additional environmental factors including seasonal weather changes and the pre-existing vulnerabilities discussed, is very important as these are known to impact disaster-related outbreaks and multi-disaster events (13, 54). Although beyond the scope of the methods used here, as conflict was investigated in isolation, this is an important area of future research.

Several reporting issues are likely to have affected the data used here, including underreporting, overreporting and a reporting lag. Underreporting is a significant issue in global cholera and conflict estimates, due to asymptomatic cases, disincentives to report and logistical issues (35,57). Cholera surveillance is difficult in conflicts, due to displaced populations and security issues. Alternatively, during times of conflict health surveillance can be enhanced by the government and/or NGOs (34). Reporting delay is another potential problem and some national reporting delays, have been found to range from 12 days for meningococcal disease to 40 days for pertussis (34). Conflict severity is complex, far-reaching and challenging to measure. Making assessments and assumptions of how a conflict event impacts a health outcome is difficult and involve assumptions and oversimplifications. Although beyond the scope of this work, it is an
important area of future qualitative research with those working in a variety of different organizations in the conflict-affected areas.

Despite the limitations of conflict and cholera data, the data used here are to the highest standard currently available and has been used by several other studies, making the research comparable \((11,14,16)\). Creating partnerships with those working on the ground and exploring more sensitive data options is an area of future research \((58)\). Additional methods to account for data limitations included setting both the event and the exposure to a binary outcome to reduce the impacts of severity and using a weekly instead of daily temporal scale to account for delays. Additionally, several methods of validating the cholera data were used \((31)\) and the sensitivity analysis helped highlight the duration of the effect and possible lag effects of the conflict data.

In summary, our analysis shows a clear relationship between cholera and conflict in both Nigeria and the DRC at both a national and sub-national level. Conflict increased the risk of cholera outbreaks by up to 7.3 times in some states/provinces and almost 20\% of cholera outbreaks being attributable to conflict in Nigeria. This finding potentially holds in other countries and diseases and highlights how the SCCS methodology could be used in different contexts. Cholera risks are likely multi-factorial in both northeastern Nigeria and eastern DRC and several conditions need to be met for emergencies to lead to cholera outbreaks. Sufficient and rapid support, along with enhanced efforts to build community trust can reduce this access risk. Finding conflict resolution should be the main priority in fragile states and pre-existing vulnerabilities need to be addressed, such as poverty, expansion of affordable healthcare and improvements in WASH. By reducing these vulnerabilities, communities will have greater resources to adapt to social extremes and could help to reduce vulnerabilities both in times of conflict and peace.

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**Author Bio**

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Supporting information

S1 Information. Cholera case definitions according to the Nigerian Centre for Disease Control and the Ministère de la Santé Publique de la République démocratique du Congo.

NCDC:
Suspected case: Severe dehydration or death from acute watery diarrhoea in a patient aged 5 years or more. In an epidemic situation: A suspected case in any person aged 5 years or more with acute watery diarrhoea with or without vomiting.
Confirmed case: A suspected case in which Vibrio cholerae O1 or O139 has been isolated in the stool.

RDC Ministère de la Santé:
Suspected case: Severe dehydration or death following acute watery diarrhoea in a patient aged 5 years or more. In an epidemic situation: Acute watery diarrhoea with or without vomiting in a patient aged 1 year or more.
S2 Information. Dataset information.

Cholera data was compiled from a range of publicly available sources (WHO’s disease outbreak news, ProMED, ReliefWeb, WHO’s regional office for Africa weekly outbreak and emergencies, UNICEF cholera platform, EM-DAT, the Nigerian CDC and a literature search) in both English and French. A data charting form was used to enable a dynamic data entry process and collected data on date, geographic location, cases, deaths, hospitalisations, fatality rates, gender, age, oral cholera vaccinations, risk factors, aid and the source of the report. Data spanned from 1971-2021 for Nigeria and 1978-2021 for the DRC on a daily temporal scale and was provided at the finest spatial scale possible.

Conflict data was provided by the United Nations Office for the Coordination of Humanitarian Affairs’s Humanitarian Data Exchange (HDX, 2020). The data included sub-national conflict events for both countries on a fine spatial scale, given to the exact location in longitude/latitude. This was reported on a daily temporal scale and spanned from 1997 to 2020. The data was also categorised by event type which included battles, explosions, protests, riots, strategic developments and violence against civilians. This was further sub-categorised within these groups and reported number of fatalities.

The study period was selected as Jan 1997 to May 2020, as these were the first and last reports in the conflict data. The spatial granularity of the analysis was to administrative level 1 (states for Nigeria and provinces for the DRC) and all data points that were reported on a finer spatial scale were attributed to the upper level. To be included in the analysis, the state/province had to report both outbreaks and conflicts during the study period, therefore 22 provinces were included for the DRC and 36 states for Nigeria.
S3 Information. Percentage attributable fraction (PAF) equations.

Estimate the number of outbreaks attributable to conflicts, $A_i$, for each province $i$. Using the formula:

$$A_i = \lambda_i d_i^{E+}(IRR - 1) \quad (1)$$

Where $d_i^{E+}$ is the total duration of conflict exposure for the province $i$ (if no conflict in province $i$, thus $d_i^{E+} = 0$), $\lambda_i$ is the rate of outbreak occurrence in a Poisson process in the absence of conflict, and IRR is the incidence rate ratio associated with exposure to conflict. With $N_i^{E-}$ being the number of outbreaks observed in the province $i$ during the un-exposed period and $T$ being the total period of observation, an estimator of $\lambda_i$ is $\hat{\lambda}_i = N_i^{E-} / (T - d_i^{E+})$, which leads to:

$$\hat{A} = \sum_i N_i^{E-} d_i^{E+} (\hat{IRR} - 1) / (T - d_i^{E+}) \quad (2)$$

Based on $\hat{A}$ and $N$, the total number of outbreaks observed, we can easily obtain the equivalent of the population attributable fraction, $PAF$, which corresponds to the proportion of the total number of outbreaks in both countries that are attributable to conflicts (this is equivalent to the PAF obtained in classical epidemiological studies, but here population refers to the “population of provinces”):

$$PAF = \frac{\hat{A}}{N} \quad (3)$$
S4 Information. Sensitivity analysis. Alternative exposure end points to identify the effect of lag.

Five alternative exposure periods were tested from the original exposure period (1 week after the onset of exposure, lag 1) and were named lag periods due to the potential lag effect from conflict onset to cholera outbreaks, these included:

1. Lag 2 - Week of conflict onset + 2 weeks
2. Lag 4 - Week of conflict onset + 4 weeks
3. Lag 6 - Week of conflict onset + 6 weeks
4. Lag 8 - Week of conflict onset + 8 weeks
5. Lag 10 - Week of conflict onset + 10 weeks

The sensitivity analysis was run on both a national and sub-national level and S1 and S2 Figs show additional swimmer plots of lag 10 and line plots of the temporal trends.
S5 Information. Excluded events. States/provinces removed as they did not report conflict and cholera in the study period (1997-2020).

Democratic Republic of Congo:
- Haut-Uele - 629 conflict events removed
- Kasai-Central - 234 conflict events removed
- Lomani - 101 conflict events removed
- Tshuapa - 70 conflict events removed

Nigeria:
- Imo - 239 conflict events removed
S1 Table. The layout of the data frame used to create the pseudo-dataset for the model. Each new ‘end’ period represents a different sensitivity analysis and each event and exposure are given a reference number (indiv). The example shown here is for the Democratic Republic of Congo Conflict dataset.

| province | exday | eventday | start | end | start 1 | end 0 | end 1 | end 2 | end 4 | end 6 | end 8 | end 10 | indiv |
|----------|-------|----------|-------|-----|---------|------|------|------|-----|-----|-----|------|-------|
| Bas-Uele | 3     | 374      | 1     | 54  | 3       | 3    | 4    | 5    | 7   | 9   | 11  | 13    | 1     |
| Bas-Uele | 4     | 374      | 1     | 54  | 4       | 4    | 5    | 6    | 8   | 10  | 12  | 14    | 2     |
| Bas-Uele | 6     | 374      | 1     | 54  | 6       | 6    | 7    | 8    | 10  | 12  | 14  | 16    | 3     |
| Bas-Uele | 7     | 374      | 1     | 54  | 7       | 7    | 8    | 9    | 11  | 13  | 15  | 17    | 4     |
| Bas-Uele | 9     | 374      | 1     | 54  | 9       | 9    | 10   | 11   | 13  | 15  | 17  | 19    | 5     |

S2 Table. The pseudo-dataset created from the data in S1 Table for the first two reference numbers. This data can then be fit to the model (conditional logistic regression).

| indiv | exday | eventday | start | end | event | exgr  | interval | loginterval |
|-------|-------|----------|-------|-----|-------|-------|----------|-------------|
| 1     | 3     | 374      | 1     | 3   | 0     | 0     | 2        | 0.693147180559945 |
| 1     | 3     | 374      | 3     | 13  | 0     | 1     | 10       | 2.30258509299405  |
| 1     | 3     | 374      | 13    | 54  | 1     | 0     | 529      | 6.2709884318583    |
| 2     | 4     | 374      | 1     | 4   | 0     | 0     | 3        | 1.09861228866811   |
| 2     | 4     | 374      | 4     | 14  | 0     | 1     | 10       | 2.30258509299405  |
| 2     | 4     | 374      | 14    | 54  | 1     | 0     | 528      | 6.26909628370626   |
S1 Figure. Swimmer plots showing the conflict dataset for lag 10 in the sensitivity analysis. In relation to outbreaks (black triangles) for Nigeria (NGA) and the Democratic Republic of Congo (COD).
S2 Figure. Number of outbreak (orange) and conflict (purple) events by year in Nigeria and the Democratic Republic of Congo over the full study period.
S3 Figure. Results of national sensitivity analysis. Incidence rate ratio (IRR) for the effect of exposure to conflict within 1, 2, 4, 6, 8 and 10 weeks of the event and cholera for a, Nigeria and b, the Democratic Republic of Congo. Only results that were significant at the threshold p=<0.05 are plotted here. From week 1 to week 10 the risk decreased from 3.6 to 2.08 for Nigeria and from 2.6 to 1.5 for the DRC. This suggests that the risk of conflict on cholera is highest soon after the event but remains a detectable association albeit at a lower level for potentially a long period of time after the event.
**S4 Figure. Results of subnational sensitivity analysis.** Incidence rate ratio (IRR) for the effect of exposure to conflict within 1, 2, 4, 6, 8 and 10 weeks of the event and cholera at administrative level 1. For a, Nigeria and b, the Democratic Republic of Congo. Only results that were significant at the threshold \( p<0.05 \) are plotted here. Thirty Nigerian states and 13 DRC provinces were found to be significant for at least one of the lag periods and the most significant states predominately followed the trends of the national analysis. Values ranged from Kebbi at 6.9 to 4.0 times increased risk of cholera, to Gombe at 2.4 to 1.5 (Fig 6a).