CODE DOCUMENTATION

Exploring Predictive Composite Measures for Global Health Facility Disruptions in Conflict Zones

An analysis of Armed Conflict Location and Event Data Project (ACLED) Indicators for Health Facility Disruption Status

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1 DOCUMENTATION MANAGEMENT

1.1 Contributors

Role	Name	Organization
Code designer	Arden Saravis	University of Washington, Department of Epidemiology
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1.2 Version Tracking

Date	Version	Author	Amendment
June 6, 2024	1.0	Arden Saravis	*Initial distribution of code*

1.3 Elements of Git File

File Name	Version/ Date	Purpose of Use
Conflict_Facility_Analysis.R	1	R markdown file for main analysis
Code_Documentation.pdf	1	Document detailing motivation behind the project, elements of the analysis, and code walkthrough

2 INTRODUCTION

2.1 Background & Rationale

In January 2024, one in six people were estimated to have current exposure to political conflict globally[1]. Living in close proximity to armed conflict drastically impacts quality of life, with access to healthcare being an aspect that has long-lasting consequences. Under International Humanitarian Law, it is unlawful to attack health establishments and units[2]. However, incidents of violence against healthcare increased 45% from 2021 to 2022, with 704 instances of health facilities being destroyed or damaged[3]. In addition to direct targeting, health facility damage can also result from indirect explosions, bombings, or crossfire. Beyond the physical destruction of health facilities that impacts care, armed conflict can also affect the delivery of essential supplies, access to health facilities due to road destruction or intimidation, and other infrastructure damages such as lack of electricity or water supply that can hinder care delivery. There is a significant interest in exploring methods to estimate health service availability in conflict zones. This is crucial for governments and humanitarian aid organizations to promptly respond with essential services and enhance the predictive accuracy of health estimation models.

Several qualitative and quantitative studies found a negative association between living near conflict and utilization of routine health services. An observational study in Syria examined conflict event types and found a negative association between bombardments and consultations and antenatal care visits[4]. The vaccine coverage team at IHME has explored spatiotemporal modelling techniques to predict vaccine coverage in conflict zones using household-based surveys from surrounding areas paired with historical trends and spatial covariates in Nigeria[5]. Wigley et. al. used ACLED conflict event data to estimate diphtheria-tetanus-pertussis vaccine coverage among children under the age of one in conflict zones. This study characterized conflict-affected areas as administrative boundaries of the second sub-national level that experienced at least one conflict, with 30 fatalities according to a broad definition and 300 fatalities according to a narrow definition[6]. Vaccine coverage estimates were then summarized in these administrative levels and exhibit the need to expand health service delivery research in areas experiencing conflict. These studies all focused on a specific location and health service, and used Demographic and Health Surveys or patient-level health systems data from medical consultations to assess utilization of health services[4]. Yet, we lack crucial predictive capacities regarding the operational status of health facilities. It would be beneficial to discern global trends in conflict events and health facility disruptions, rather than confining our analysis to specific regions. An example of an organization that has sought to address this gap is the Health Resources and Service Availability Monitoring System (HeRAMS), which is an initiative deployed by the World Health Organization (WHO). This organization gathers real-time information about the availability and accessibility of essential health resources in conflict zones. The goal of this initiative is to have status information ready and accessible to support emergency response efforts, health systems strengthening, and decision making[7]. However, this information is limited to a subset of geographic areas, so worldwide data is not yet accessible with this information.

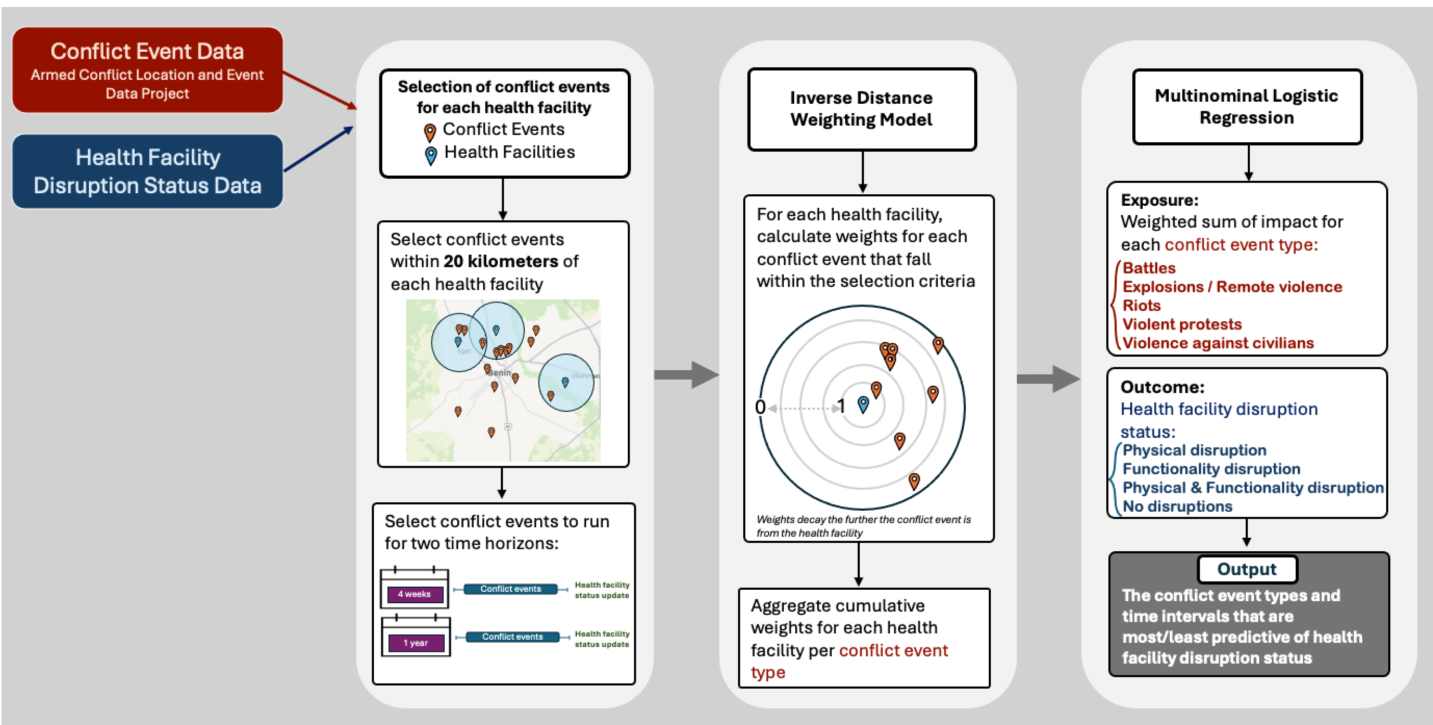
There is a great interest in evaluating techniques to estimate health facility disruptions based on intensity (measured through repeat conflict events in close proximity) and type of conflict events to strengthen public health work in affected areas. It is difficult to source reliable healthcare data in conflict zones, leading to uncertainty in estimates of disease burden and healthcare utilization. Enhanced understanding of the relationships between conflict events and health facility disruptions could provide valuable insights to strengthen estimations for the availability of care in certain settings. For this analysis, we consider health facility disruptions to be any physical damage to the facility or functionality issues (lack of electricity, water, or staff) that hinders the facility from providing care. This can be utilized by healthcare modelers to provide fundamental insights into the relative role that different types of conflict play in service disruptions. Additionally, this can support organizations that track health facility status in identifying regions where facility disruptions are most likely to occur based on conflict events, aiding in the prioritization of areas for data collection where data collection may not yet to be established.

2.2 Purpose of Analysis

Precision of estimates of health service disruption can be improved by using data from the Armed Conflict Location and Event Data Project (ACLED) to explore the combination of indicators (with a focus on conflict type and temporality) that is most predictive of reported health facility disruptions.

Prior quantitative studies focused on health service utilization rather than prediction of health facility disruptions so the methodology used cannot be replicated for this study[4,8–10]. Therefore, new approaches were required for this analysis, and multiple analyses were evaluated to determine the optimal approach.

2.3 Analysis Model



3 METHODOLOGY

3.1 Data - Conflict Events

3.11 ACLED Data Source

The Armed Conflict Location and Event Data Project (ACLED) sources political conflict event data by aggregating reports from international and local news platforms. The data goes through an intercoder reliability process by three coders who cross-reference multiple data sources[11]. The datasets are updated weekly to assure timeliness. Each day of conflict lasting more than 24 hours is recorded as a separate event.

Data source: https://acleddata.com

3.12 Data Dictionary

Variables for analysis	Description
event_id_cnty	Unique ID for each conflict event
event_date	Date that the conflict event occurred. If event occurred over 24 hours, each day will be recorded as a separate event.
event_type	Type of event (battles, riots, etc.)
sub_event_type	A subcategory of event type
region	Region of the world where the event took place (e.g. Eastern Africa)
country	Country or territory in which the event took place
latitude	Latitude of the location in four decimal degrees notation
longitude	Longitude of the location in four decimal degrees notation

Further documentation of event types and their sub-event types:

event_type	Description
Battles	A violent interaction between two organized armed groups at a particular time and location ○ Armed clash ○ Government regains territory ○ Non-state actor overtakes territory
Explosions / Remote Violence	Incidents in which one side uses weapon types that, by nature, are at range and widely destructive ○ Chemical weapon ○ Air/drone strike ○ Suicide bomb ○ Shelling/artillery/missile attack ○ Remote explosive/landmine/IED ○ Grenade
Protests	An in-person public demonstration of three or more participants in which the participants do not engage in violence, though violence may be used against them ○ Excessive force against protesters ○ Protest with intervention *[excluded]* ○ Peaceful protest *[excluded]*

	*** for this analysis, only violent protests are included*
Riots	Violent events where demonstrators or mobs of three or more engage in violent or destructive acts, including but not limited to physical fights, rock throwing, property destruction, etc. o Violent demonstration o Mob violence
Violence Against Civilians	Violent events where an organized armed group inflicts violence upon unarmed non-combatants. The violence is understood to be asymmetric as the perpetrator is assumed to be the only actor capable of using violence in the event o Sexual violence o Attack o Abduction/forced disappearance
Strategic Developments	*[excluded from the analysis due to their non-violent nature]* Captures contextually important information regarding incidents and activities of groups that are not recorded as "Political Violence" or "Demonstrations" events, yet may trigger future events or contribute to political dynamics within and across states o Agreement o Arrests o Change to group/activity o Disrupted weapons use o Headquarters or base established o Looting/property destruction o Non-violent transfer of territory o Other

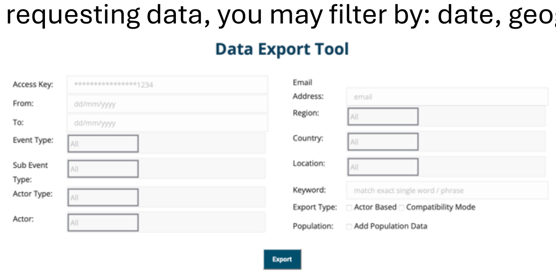
Full ACLED codebook linked here

3.13 Exclusion Criteria

Nonviolent political conflict events will be excluded from this analysis, as the focus is on health facility disruptions. Violent conflicts are expected to have a more direct impact on supply access and cause physical damage compared to nonviolent events.

3.14 Access and Data Download

ACLED data can be accessed and downloaded through their export tool. First, you must register for an account on the ACLED Access Portal to receive a unique access key. When requesting data, you may filter by: date, geographic location, event types, and actor types.



*** For this analysis, the date range was filtered to reflect:*

From: 01/01/2019

To: 01/01/2024

3.2 Data - Health Facility Disruption Data

Health facility disruption data may be sourced from several outlets. For this analysis, mock variables were used that would likely be available in most datasets. For versatility, we provide a generalized overview of how this type of data can be inputted into the analysis. As mentioned before, HeRAMS is an example of a dataset that has information regarding health facility disruptions, and we adapted a dataset with health facility latitude and longitude points to mimic the data we would expect to see in the HeRAMS dataset.

3.21 HeRAMS Data Source (Example)

HeRAMS is one example of a dataset that would fit this analysis. The HeRAMS project gathers facility-level data for a selection of health facilities in conflict zones using a software-based platform[12]. The data is gathered through tele-assessments by data collectors throughout the geographic area. The data is entered periodically into the HeRAMS data portal. Frequency of reporting varies; however most active countries average around six updates per year for each facility[13]. Data collection began in Syria in 2013 and scaled up to 16 countries in Africa, Western Asia, Southern Asia, and Southeastern Asia in 2019[12].

Data source: https://herams.org/session/create

3.21 Health Facility Data Source

To create this analysis, data from the Humanitarian Data Exchange (HDE) was adapted to mimic a dataset that has regular health facility disruption status updates[14]. The dataset includes latitude and longitude points of all health facilities in a country. We created code to generate the following simulated variables: building condition, functionality status, and date of status update.

HDE has health facility datasets by country. To validate code, Nigeria was selected as the example country for this analysis. The dataset used was titled 'NigeriaHealthFacilities.csv'.

Data source: https://data.humdata.org/dataset/nigeria-health-facilities

3.22 Data Dictionary

Proposed structure of dataset for analysis:

Variables for analysis	Description
[latitude]	Latitude of the health facility location in decimal degree notation
[longitude]	Longitude of the health facility location in decimal degree notation
[building_condition]	Current building condition at the time of the update - Not damaged - Partially/fully damaged
[functionality]	Current functionality of the health facility at the time of the update - Fully functioning - Partially /not functioning
[date]	Date of the health facility disruption status update

3.23 Data Access

HDE datasets are open access by selecting the 'Download' button next to the desired dataset. For this analysis, the NigeriaHealthFacilities.csv dataset was used (Modified: 22 June 2021). Code to add the additional variables is included in the data cleaning R script.

3.3 Time & Space

3.31 Consideration of time in analysis

The analysis is conducted considering each health facility disruption status update. The frequency of health facility status updates will depend on the chosen dataset and not all health facilities will be represented at the same points in time. Some health facilities may be assessed more than others depending on the frequency of data collection in the geographic area. For this analysis, we do not account for repeated, dependent observations using longitudinal time varying methods. This is discussed as an area of further exploration in the Moving Forward section.

Temporality will be examined by including conflict events that occurred within four weeks and one year prior to a health facility disruption status update. Due to the long-lasting impacts of conflict events on factors that affect health service delivery, assessing the possible impact of conflict events within a one-year time horizon is vital to evaluate the cumulative impact of conflict. The four-week time horizon allows for the assessment of immediate conflict events.

The data presented in this analysis covers the period from January 2019 to January 2024.

3.32 Consideration of space in analysis

ACLED is a worldwide data project, so data is not restricted to geographic regions. Data on health facility disruption status will likely be limited to certain locations, most often those experiencing humanitarian emergencies, depending on the dataset used. To incorporate as many datapoints as possible, the geographic study area will not initially be restricted. Conflict events impacting each health facility will be chosen based on their proximity to the health facilities included in the health facility dataset of choice. For each health facility, conflict events occurring within a 20-kilometer radius will be identified for this analysis. This radius is selected for computational efficiency and can be adjusted depending on the distance decay parameters that are being assessed. The radius should be set so that conflict event points beyond it have negligible distance weights and, consequently, minimal impact on service delivery. A 20-kilometer radius is selected for this analysis under the assumption that conflict events further than 20 kilometers away would have a negligible effect on the health facility's service delivery.

If a desired analysis includes only a subset of countries/regions, ensure a 50-kilometer buffer around the country/region is created. This accounts for conflict events that may be across a geographic border but still impact health facilities in the bordering country/region when creating the observation window.

3.4 Spatial Interpolation

3.41 Justification of use

For this analysis, spatial interpolation is used to determine the weighted cumulative intensity of conflict for each health facility.
Spatial interpolation provides an estimate of an unknown value of a point given the values of surrounding points within a study area. Local interpolation is the best fit for this analysis over global interpolation since violent conflict tends to have the greatest impact on spaces nearest to the events. Since the conflict event locations are not at random and maintaining precision of these points is vital to the analysis, stochastic interpolation methods (such as Kriging) would not be appropriate for this use case. Deterministic methods are deemed most appropriate for the research question since both datasets are known, and no predictions need to be made based on location[15]. Since we can assume that intensity of conflict events on health facility disruptions diminishes as distance between the two increases, the Inverse Distance Weighting Model is used.

3.42 Inverse Distance Weighting Model

This model estimates values for each health facility point by calculating the distance between the health facility and each conflict event within a 20-kilometer radius and falling within a 1-year and four-week time period before the health facility disruption status update. Each health facility point represents a health facility disruption status update so each health facility will likely be represented multiple times. The closer the conflict event point is to the health facility point, the more 'weight' it will have. This model then separates the conflict events by type (battles, explosions/remote violence, violent protests, violence against citizens, and riots) and sums the weighted conflict event values for each health facility.

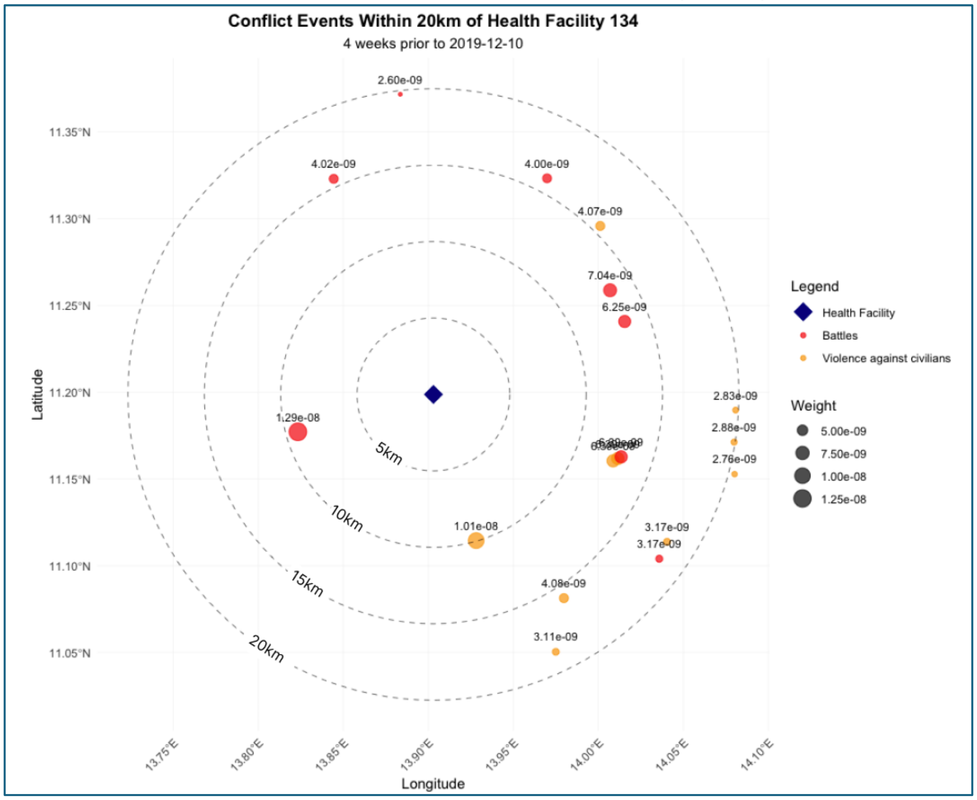
The model equation:

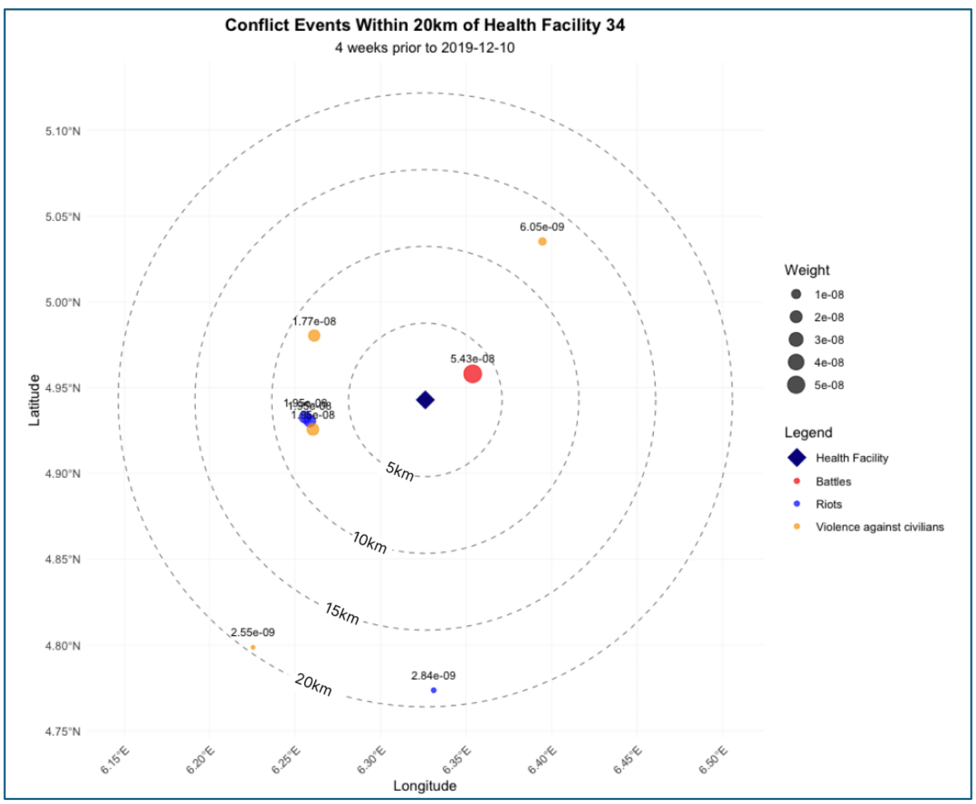
$$x_{f,t} = \Sigma w_{c,f,t} \ \ when \ \ w_{c,f,t} \sim \frac{1}{{d_{c,f,t}}^{a}}$$

Weighted average of all conflict events of a given conflict type

Parameter	Definition
$w_{c,f,t}$	weight (0 to 1) for each conflict event type to each health facility that is within radius *r*
c	conflict event locations (latitude & longitude point data)
$x_{f,t}$	health facility locations (latitude & longitude point data)
t	type of conflict event (battle, riot, etc.)
a	parameter that determines how quickly distance decays as you move away from the health facility
d	distance between each health facility point and conflict event point
r	maximum radius that will determine which conflict events to include for each health facility

Visualizations of the Inverse Distance Weighting Model:





3.5 Regression

3.51 Justification of use

Regression will be used to examine the impact of conflict on health facilities. Conflict event weighted averages by conflict type per facility will be used as covariates. Since our outcome of interest is categorical, independent, and not ordinal, a multinomial logistic regression was determined to be most appropriate for the analysis.

3.52 Study Exposures

The exposure of interest are conflict events, classified as: (i) battles, (ii) explosions/remote violence, (iii) violent protests, (iv) violence against citizens, and (v) riots. These classifications come directly from the ACLED dataset from the variable indicating the *event_type*. Each conflict event causes a disruption, and the effect of that disruption decays over space. The conflict events are quantified by using the weighted sum of impact per event type for each health facility from the inverse distance weighting model. A limitation is that all conflict event types are assumed to have an equal decay rate impacting the health facility. In reality, different event types may have greater impact at greater distances than others. Future work could expand this approach to allow for conflict type-specific decay rates.

3.53 Study Outcomes

The outcome we will examine is health facility disruption, classified as: (i) physical disruption, (ii) functionality disruption, (iii) both physical and functionality disruptions, and (iv) no disruption. The disruption status comes from a combination of two variables assumed to be in a health facility disruption status dataset: 'building_condition' and 'functionality'.

3.54 Model equations and considerations

Run #1: four-week time period

$$Y_{tm} = b_0 + b_1 * \Sigma w_{c,f,t=A} + b_2 * \Sigma w_{c,f,t=B} + b_3 * \Sigma w_{c,f,t=C} + b_4 * \Sigma w_{c,f,t=D} + b_5 * \Sigma w_{c,f,t=E}$$

Run #2: one-year time period

$$Y_{ty} = b_0 + b_1 * \Sigma w_{c,f,t=A} + b_2 * \Sigma w_{c,f,t=B} + b_3 * \Sigma w_{c,f,t=C} + b_4 * \Sigma w_{c,f,t=D} + b_5 * \Sigma w_{c,f,t=E}$$

Conflict event type	
A	Battles
B	Protests
C	Riots
D	Explosions/Remote violence
E	Violence against citizens
Time intervals	
tm	one month interval of time
ty	one year interval of time

** Wald test is necessary to extract p-values for interpretation**

3.55 Interpretation of Results

The multinominal logistic regression output provides coefficients which are the log-odds of the health facility disruption status category compared to the 'no disruption' status by each unit weight increase by conflict event type. The output provides an Akaike Information Criterion which indicates the quality of the model for the data. The Wald test is necessary to extract p-values to test for significance.

4 MOVING FORWARD

The next step for this analysis is to access a dataset that has variables related to health facility disruption status to properly run this analysis and identify conflict event types that are most predictive of the health facility disruption status. This analysis could be expanded to many health facility related datasets and the technique could be transferrable to examining impact of armed conflict on other services, with access to disruption data.

The inverse distance decay model could be strengthened by incorporating separate distance decay rates for each conflict event type to enable the model to more accurately reflect how the impact of different conflicts varies with distance and time. This model could also be strengthened by considering each health facility's repeated updates to its disruption status over time. Currently, the precision of the intended results is likely overstated due to the lack of independence of our datapoints. Incorporating a longitudinal mixed-effects analysis could account for this dependence and allow for the examination of within-facility and between-facility variability given our predictors[16].

This analysis could be presented as a tool to make the results approachable to generalized audiences. Conflict event type and number of kilometers away from a health facility could serve as inputs and the tool would output an estimated log odds of disruption value by disruption type. Health facility disruption odds could also be displayed on a map that updates with new conflict events as they become available.

5 CODE USE GUIDE

This part of the document is to provide step-by-step documentation of the code and instructions as to how it functions.

5.1 Data Cleaning

Data Cleaning Code Walkthrough

Arden Saravis

2024-05-19

This code cleans both the conflict event dataset (ACLED) for analysis and creates a dataset to mimic the variables we would expect to see in a dataset documenting health facility disruption status.

```
# Clear environment
rm(list=ls())

# Load libraries for data cleaning
library(tidyverse)

library(dplyr)
```

ACLED Data Cleaning

1) Load ACLED data

Due to the volume of data included in ACLED, data will likely need to be downloaded in sections. Load all sections into R and merge the datasets together.

```
# Read in ACLED data
data <- read.csv("/Users/arden/Desktop/Capstone/Data - Capstone/ACLED_Data_pt1.csv")
data2 <- read.csv("/Users/arden/Desktop/Capstone/Data - Capstone/ACLED_Data_pt2.csv")

# Merge the datasets together (if ACLED is downloaded in sections)
acled <- rbind(data, data2)
```

2) Keep relevant variables for the analysis

- **event_id_cnty :** unique ID for each conflict event
- **event_date :** date that the conflict event occurred. If event occurred over 24 hours, each day will be recorded as a separate event.
- **event_type** : the type of event (battles, riots, etc.)
- **sub_event_type :** a subcategory of event type
- **region :** region of the world where the event took place (e.g. Eastern Africa)
- **country :** the country or territory in which the event took place
- **latitude :** the latitude of the location in four decimal degrees notation
- **longitude :** the longitude of the location in four decimal degrees notation

```
acled <- acled[, c("event_id_cnty", "event_date", "event_type", "sub_event_type",
                   "region", "country", "latitude", "longitude")]
```

3) Filter data by violent event types

- Include all Battles
- Include all Riots

- Include all Explosions/Remote Violence
- Include all Violence Against Civilians
- **Exclude** all Strategic Developments
- For Protests, only include Excessive Force Against Protesters subcategory

```
# Exclude all Strategic Developments
acled <- acled %>% filter(event_type == "Battles" | event_type == "Riots" |
                            event_type == "Explosions/remote violence" |
                            event_type == "Violence against civilians" |
                            event_type == "Protests")

# Only include 'Excessive Force Against Protesters' subcategory in 'Protests'
acled <- acled %>% filter(!(sub_event_type %in% c("Protest with intervention",
                                                    "Peaceful protest")))

head(acled)

##   event_id_cnty      event_date                 event_type sub_event_type
## 1       IRN8160 01 January 2021                    Battles    Armed clash
## 2       PSE8009 01 January 2021                      Riots   Mob violence
## 3       SLV2297 01 January 2021 Violence against civilians         Attack
## 4       SLV2298 01 January 2021 Violence against civilians         Attack
## 5       SLV2299 01 January 2021 Violence against civilians         Attack
## 6        NIC646 01 January 2021 Violence against civilians         Attack
##            region     country latitude longitude
## 1     Middle East        Iran  32.6941   47.2679
## 2     Middle East   Palestine  32.0701   35.2403
## 3 Central America El Salvador  14.0333  -88.9333
## 4 Central America El Salvador  13.3545  -88.9470
## 5 Central America El Salvador  13.3078  -87.8647
## 6 Central America   Nicaragua  12.1973  -86.0971

summary(acled)

##  event_id_cnty       event_date         event_type        sub_event_type
##  Length:262130      Length:262130      Length:262130      Length:262130
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##     region            country            latitude         longitude
##  Length:262130      Length:262130      Min.   :-53.155   Min.   :-172.42
##  Class :character   Class :character   1st Qu.:  7.477   1st Qu.: -43.18
##  Mode  :character   Mode  :character   Median : 19.703   Median :  35.26
##                                        Mean   : 18.702   Mean   :  12.69
##                                        3rd Qu.: 33.842   3rd Qu.:  45.68
##                                        Max.   : 65.317   Max.   : 174.78
```

4) Save the cleaned dataset (acled_clean.csv)

```
write.csv(acled, file = "acled_clean.csv")
```

Health Facility Disruption Dataset Creation/Cleaning

- This code uses data from the Humanitarian Data Exchange (HDE) to mimic a dataset that has regular health facility disruption status updates.
- Variables in the HDE include: ‘X’, ‘latitude’, ‘longitude’

1) Load in relevant HDE dataset(s)

```r
# For code creation, Nigeria is used as the country of interest
nigeria_hf <- read.csv("/Users/arden/Desktop/Capstone/Data - Capstone/nigeria.csv")
```

2) Keep relevant variables for the analysis

- X : the longitude of the health facility
- Y : the latitude of a health facility
- **only keep health facilities where we have latitude and longitude points**

```r
# Subset to only include 'X' and 'Y'
nigeria_hf <- nigeria_hf[, c("X", "Y")]

# Exclude any rows where 'X' or 'Y' is NA
nigeria_hf <- nigeria_hf %>%
  filter(!is.na(X) & !is.na(Y))

# Rename columns X to longitude and Y to latitude
names(nigeria_hf)[names(nigeria_hf) == "X"] <- "longitude"
names(nigeria_hf)[names(nigeria_hf) == "Y"] <- "latitude"
```

3) Create a ‘date’ variable representing the date of a health facility disruption status update.

- Repeat each health facility row three times to represent different dates in time.

```r
# Assuming your dataset is named 'nigeria_hf'
n <- nrow(nigeria_hf)

# Define the dates you want to add
dates <- as.Date(c('2019-12-10', '2021-09-01', '2023-06-27'))

# Replicate each row three times
nigeria_hf <- nigeria_hf[rep(1:n, each = 3), ]

# Add the 'date' variable
nigeria_hf$date <- rep(dates, each = n)
```

4) Add a unique identifier row for each health facility ‘X’

```r
nigeria_hf$X <- 1:nrow(nigeria_hf)
```

5) Create two variables that are descriptors for health facility disruption status

```r
# Define values for 'building_condition'
building_conditions_values <- c('Not damaged', 'Partially/fully damaged')
# Add a new column 'building_condition' with randomized values
nigeria_hf$building_condition <- sample(building_conditions_values,
                                        size = nrow(nigeria_hf),
                                        replace = TRUE)

# Define values for 'functionality'
functionality_values <- c('Fully functioning', 'Partially /not functioning')
# Add a new column 'functionality' with randomized values
nigeria_hf$functionality <- sample(functionality_values, size = nrow(nigeria_hf),
                                   replace = TRUE)
```

6) Save the cleaned dataset (facilities_clean.csv)

```
write.csv(nigeria_hf, file = "facilities_clean.csv")

head(nigeria_hf)

##     longitude  latitude       date X      building_condition
## 1    8.044262 11.496814 2019-12-10 1 Partially/fully damaged
## 1.1  8.044262 11.496814 2019-12-10 2             Not damaged
## 1.2  8.044262 11.496814 2019-12-10 3             Not damaged
## 2    7.179162  9.188441 2019-12-10 4             Not damaged
## 2.1  7.179162  9.188441 2019-12-10 5             Not damaged
## 2.2  7.179162  9.188441 2019-12-10 6             Not damaged
##                 functionality
## 1           Fully functioning
## 1.1 Partially /not functioning
## 1.2         Fully functioning
## 2           Fully functioning
## 2.1 Partially /not functioning
## 2.2         Fully functioning

summary(nigeria_hf)

##    longitude         latitude           date                  X
##  Min.   : 2.732   Min.   : 4.386   Min.   :2019-12-10   Min.   :   1
##  1st Qu.: 5.298   1st Qu.: 7.375   1st Qu.:2019-12-10   1st Qu.:2317
##  Median : 7.320   Median : 9.702   Median :2021-09-01   Median :4632
##  Mean   : 7.654   Mean   : 9.361   Mean   :2021-09-12   Mean   :4632
##  3rd Qu.: 8.892   3rd Qu.:11.511   3rd Qu.:2023-06-27   3rd Qu.:6948
##  Max.   :14.637   Max.   :13.865   Max.   :2023-06-27   Max.   :9264
##  building_condition functionality
##  Length:9264        Length:9264
##  Class :character   Class :character
##  Mode  :character   Mode  :character
##
##
##
```

5.2 Data Analysis

Data Analysis Code Walkthrough

Arden Saravis

2024-05-19

Document Setup

1. Clear environment
2. Load libraries

```
# Clear environment
rm(list=ls())

# Load libraries for analysis
library(ggplot2)
```

```r
library(mapdata)
library(spatstat) # Geospatial library
library(sf) # Geospatial library
library(nnet) # multinominal logistic regression
```

1) Read in datasets

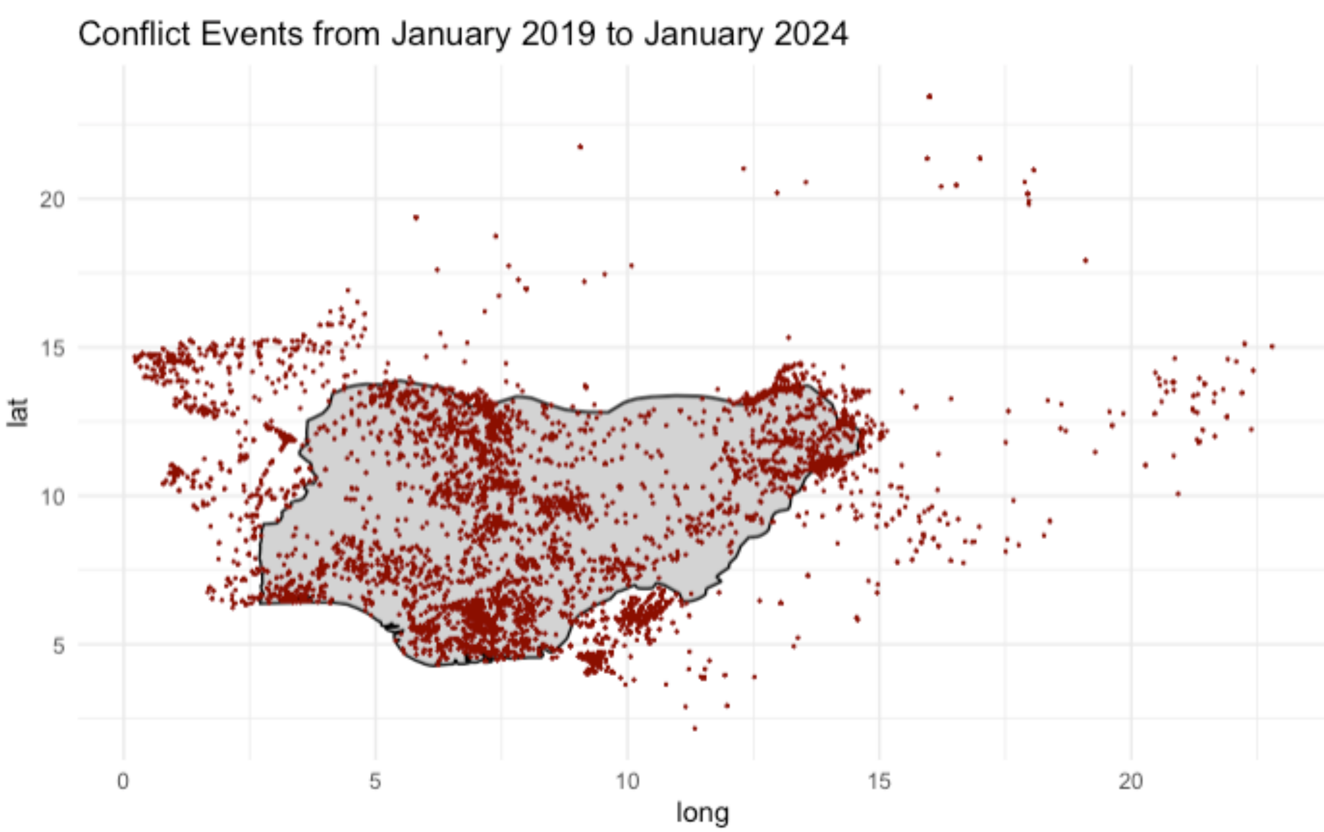
- **ACLED** - Armed Conflict Location and Event Data Project (provides point data of armed conflict events worldwide)
- **HeRAMS** - Health Resources and Service Availability Monitoring System (provides point data of health facilities in conflict zones along with its functionality status)

```r
# Load ACLED dataset into environment
acled <- read.csv("/Users/arden/Desktop/Capstone/Data - Capstone/acled.csv")

# Show a summary of the dataset
summary(acled)

##        X           event_id_cnty       event_date         event_type
##  Min.   :     1   Length:262130      Length:262130      Length:262130
##  1st Qu.: 65533   Class :character   Class :character   Class :character
##  Median :131066   Mode  :character   Mode  :character   Mode  :character
##  Mean   :131066
##  3rd Qu.:196598
##  Max.   :262130
##  sub_event_type        region            country            latitude
##  Length:262130      Length:262130      Length:262130      Min.   :-53.155
##  Class :character   Class :character   Class :character   1st Qu.:  7.477
##  Mode  :character   Mode  :character   Mode  :character   Median : 19.703
##                                                           Mean   : 18.702
##                                                           3rd Qu.: 33.842
##                                                           Max.   : 65.317
##    longitude       geo_precision     fatalities
##  Min.   :-172.42   Min.   :1.000   Min.   :  0.000
##  1st Qu.: -43.18   1st Qu.:1.000   1st Qu.:  0.000
##  Median :  35.26   Median :1.000   Median :  0.000
##  Mean   :  12.69   Mean   :1.394   Mean   :  1.306
##  3rd Qu.:  45.68   3rd Qu.:2.000   3rd Qu.:  1.000
##  Max.   : 174.78   Max.   :3.000   Max.   :600.000


# Load health facilities (nigeria_clean) dataset into environment
    # Dataset can be changed according to region of interest or with a valid dataset
facilities <- read.csv("/Users/arden/facilities_clean.csv")

# Show a summary of the dataset
summary(facilities)

##       X.1            longitude         latitude          date
##  Min.   :   1.0   Min.   : 2.732   Min.   : 4.386   Length:9264
##  1st Qu.: 772.8   1st Qu.: 5.298   1st Qu.: 7.375   Class :character
##  Median :1544.6   Median : 7.320   Median : 9.702   Mode  :character
##  Mean   :1544.6   Mean   : 7.654   Mean   : 9.361
##  3rd Qu.:2316.4   3rd Qu.: 8.892   3rd Qu.:11.511
##  Max.   :3088.2   Max.   :14.637   Max.   :13.865
##        X         building_condition functionality
##  Min.   :   1   Length:9264        Length:9264
```

```
##  1st Qu.:2317   Class :character   Class :character
##  Median :4632   Mode  :character   Mode  :character
##  Mean   :4632
##  3rd Qu.:6948
##  Max.   :9264
```

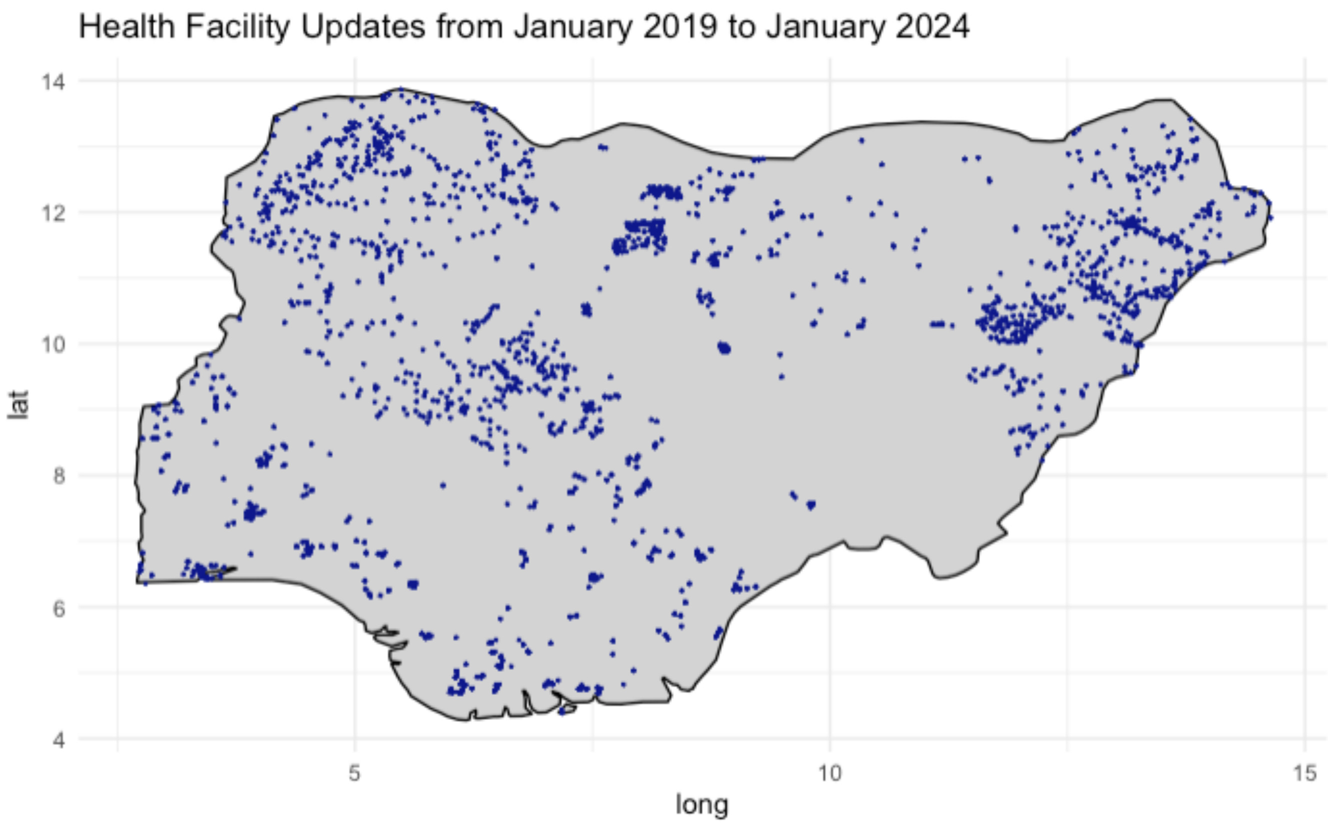
2) Visualize point data of conflict events and health facilities

```
# Get world map data and subset to only include Nigeria
    # region = "Nigeria" - can be substituted for another country/region of interest or del
eted for a world map
world_map <- map_data("world", region = "Nigeria")

# Plot conflict events on the map of Nigeria
ggplot() +
  geom_map(data = world_map, map = world_map,
           aes(x = long, y = lat, map_id = region),
           fill = "lightgray", color = "black") +
  geom_point(data = acled,
             aes(x = longitude, y = latitude),
             color = "darkred", size = 0.1) +
  labs(title = "Conflict Events from January 2019 to January 2024") +
  theme_minimal()
```




```
# Get world map data and subset to only include Nigeria
    # region = "Nigeria" - can be substituted for another country/region of interest or del
eted for a world map
world_map <- map_data("world", region = "Nigeria")

# Plot health facilities
```

```r
ggplot() +
  geom_map(data = world_map, map = world_map,
           aes(x = long, y = lat, map_id = region),
           fill = "lightgray", color = "black") +
  geom_point(data = facilities,
             aes(x = longitude, y = latitude),
             color = "darkblue", size = 0.1) +
  labs(title = "Health Facility Updates from January 2019 to January 2024") +
  theme_minimal()
```



3) Create an observation window for the analysis

- **This selects the data that falls into the geographic area of interest**
- For this test analysis, the observation window is Nigeria plus a 50km buffer around the border. The purpose of this expansion is to include data points that may lay in bordering countries that could affect health facility functionality that would be excluded by restricting to data only in Nigeria.

```r
#### Create an observation window for analysis (restricting to Nigeria) ####

# Coordinates for Nigeria
nigeria_coords <- list(
  x = c(3.5, 14, 14, 3.5, 3.5),
  y = c(4, 4, 13.9, 13.9, 4)
)

# Create an owin object for Nigeria
    ## This restricts the analysis to run solely for data points laying in Nigeria
nigeria_owin <- owin(poly = nigeria_coords)

# Expand the window by 50km in each direction
```

```
nigeria_owin_buffer <- owin(c(nigeria_coords$x[1] - 0.45, nigeria_coords$x[3] + 0.45),
                             c(nigeria_coords$y[1] - 0.45, nigeria_coords$y[3] + 0.45))
```

4) Make conversions to variables to appropriate formats for the analysis

- Convert the latitude and longitude points of 'facilities' and 'acled' to an sf object
    - *this converts it to a spatial geometry and projects the data on a coordinate referencing system in point form so spatial functions can be performed*
- Convert the 'date' variable to a usable form
- Calculate 4 weeks prior to the health facility status update to use later in the analysis
- Calculate 1 year prior to the health facility status update to use later in the analysis

```
# Convert 'facilities' and 'acled' to sf object
    ## This converts latitude and longitude points into geospatial marks for analysis using
the WGS84 projection
facilities_sf <- st_as_sf(facilities, coords = c("longitude", "latitude"), crs = "+proj=lon
glat +datum=WGS84", agr = "constant")

acled_sf <- st_as_sf(acled, coords = c("longitude", "latitude"), crs = "+proj=longlat +datu
m=WGS84", agr = "constant")

# Convert date variables to class "Date" to make it usable for analysis
facilities_sf$date <- as.Date(facilities_sf$date)
acled_sf$event_date <- dmy(acled_sf$event_date)

# Calculate 4 weeks prior to the health facility status update
    ## This prepares the data to only capture conflict events that occurred within the four
-week time period before the update
facilities_sf$four_weeks <- facilities_sf$date - weeks(4)

# Calculate 1 year prior to the health facility status update
    ## This prepares the data to only capture conflict events that occurred within the one-
year time period before the update
facilities_sf$one_year <- facilities_sf$date - weeks(52)
```

5) Run the Inverse Distance Weighting function for the 4-week time horizon

Function steps for each health facility:

1. Subsets data to include conflict events that occurred within 4 weeks prior to the health facility update

2. Calculate the distance between the health facility and each conflict event point

3. Select conflict events that fall within 20km of the health facility

4. Calculate the inverse distance weights following the defined equation and value for 'p' (power)

5. Aggregate weighted values per event type (i) battles, (ii) explosions/remote violence, (iii) violent protests, (iv) violence against citizens, (v) riots, and (vi) violent strategic developments)

6. Add the facility identifier 'X' back into the dataset

7. lapply() then applies the steps above to each facility in the defined dataset

8. Combine all the results from each facility into a single dataset

```
# Create function to process each health facility
facility_run <- function(i, p=2) {    # Define the power parameter for IDW (decay rate)
```

```
  # Subset the data to only include conflict events that occurred within 4 weeks prior to t
he health facility update
  acled_sf_4wk <- acled_sf[acled_sf$event_date >= facilities_sf[i, ]$four_weeks & acled_sf$
event_date <= facilities_sf[i, ]$date, ]

  # Calculate the distance between the health facility and each conflict event
  acled_sf_4wk$dist <- as.vector(st_distance(facilities_sf[i, ], acled_sf_4wk))

   # Select conflict events that fall within 20km of the health facility **distance in mete
rs (20 km = 20,000 meters)
      ## This selects conflict events that would be relevant for the analysis assuming that
health facilities over 20km away would have minimal effect on health facility functionality
  acled_sf_4wk <- acled_sf_4wk[acled_sf_4wk$dist <= 20000, ]

  # Check if the subset is empty
      ## This allows for a health facility to not have any proximal conflict events by retu
rning 0
  if (nrow(acled_sf_4wk) == 0) {
    return(data.frame(event_type = 'no_event', weights = 0, facility = facilities_sf$X[i]))
  }

  # Compute inverse distance weights for each conflict event
  acled_sf_4wk$weights <- 1 / (acled_sf_4wk$dist^p)

  # Aggregate weighted values per event type
  aggregate_values <- aggregate(weights ~ event_type, data = acled_sf_4wk, FUN = sum)

  # Add 'X' (facility) identifier to the aggregated values
  aggregate_values$facility <- facilities_sf$X[i]

  # Return the aggregate values
  return(aggregate_values)
}

# Use lapply to apply the function to each row/facility in facilities_sf dataset
aggregate_results <- lapply(1:nrow(facilities_sf), function(n) {
   facility_run(i=n, p=2) # nests of loops of functions for p values
})

# Combine all results into a single dataframe
idw_results_4wk <- do.call(rbind, aggregate_results)

glimpse(idw_results_4wk)

## Rows: 10,158
## Columns: 3
## $ event_type <chr> "no_event", "no_event", "no_event", "no_event", "no_event",…
## $ weights    <dbl> 0.000000e+00, 0.000000e+00, 0.000000e+00, 0.000000e+00, 0.0…
## $ facility   <int> 1, 2, 3, 4, 5, 6, 7, 7, 8, 8, 9, 9, 10, 11, 12, 13, 14, 15,…

# Create function to process each health facility
facility_run <- function(i, p=2) {    # Define the power parameter for IDW (decay rate)

  # Subset the data to only include conflict events that occurred within 4 weeks prior to t
he health facility update
  acled_sf_1yr <- acled_sf[acled_sf$event_date >= facilities_sf[i, ]$one_year & acled_sf$ev
```

```
ent_date <= facilities_sf[i, ]$date, ]

  # Calculate the distance between the health facility and each conflict event
  acled_sf_1yr$dist <- as.vector(st_distance(facilities_sf[i, ], acled_sf_1yr))

   # Select conflict events that fall within 20km of the health facility **distance in mete
rs (20 km = 20,000 meters)
      ## This selects conflict events that would be relevant for the analysis assuming that
health facilities over 20km away would have minimal effect on health facility functionality
  acled_sf_1yr <- acled_sf_1yr[acled_sf_1yr$dist <= 20000, ]

  # Check if the subset is empty
      ## This allows for a health facility to not have any proximal conflict events by retu
rning 0
  if (nrow(acled_sf_1yr) == 0) {
    return(data.frame(event_type = 'no_event', weights = 0, facility = facilities_sf$X[i]))
  }

  # Compute inverse distance weights for each conflict event
  acled_sf_1yr$weights <- 1 / (acled_sf_1yr$dist^p)

  # Aggregate weighted values per event type
  aggregate_values <- aggregate(weights ~ event_type, data = acled_sf_1yr, FUN = sum)

  # Add 'X' (facility) identifier to the aggregated values
  aggregate_values$facility <- facilities_sf$X[i]

  # Return the aggregate values
  return(aggregate_values)
}

# Use lapply to apply the function to each row/facility in facilities_sf dataset
aggregate_results <- lapply(1:nrow(facilities_sf), function(n) {
   facility_run(i=n, p=2) # nests of loops of functions for p values
})

# Combine all results into a single dataframe
idw_results_1yr <- do.call(rbind, aggregate_results)

glimpse(idw_results_1yr)

## Rows: 14,963
## Columns: 3
## $ event_type <chr> "no_event", "no_event", "no_event", "Violence against civil…
## $ weights    <dbl> 0.000000e+00, 0.000000e+00, 0.000000e+00, 2.910771e-09, 2.9…
## $ facility   <int> 1, 2, 3, 4, 5, 6, 7, 7, 7, 7, 8, 8, 8, 8, 9, 9, 9, 9, 10, 1…
```

OPTIONAL: Plot one health facility and its associated conflict events to visualize the IDW model

This is an example of what the IDW function is executing in the above code.

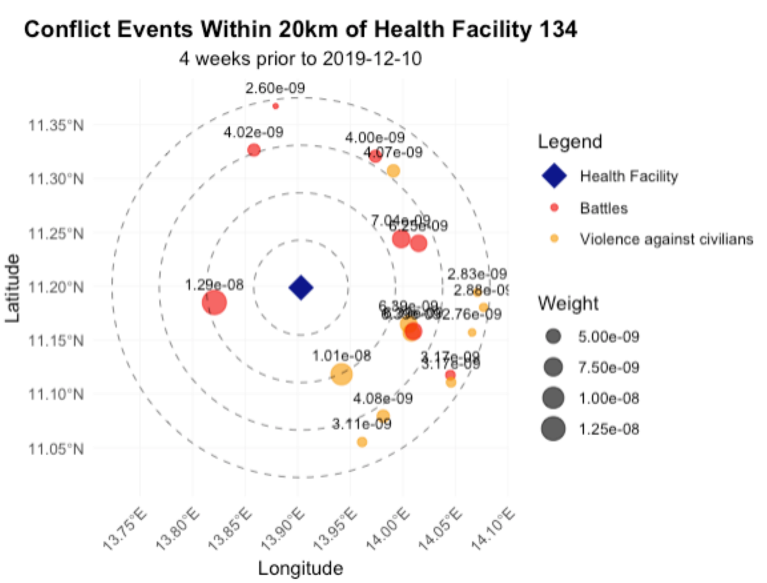
*** if there are no conflict events within 20 kilometers of the specified health facility, a plot will still appear with the information listed.*

```
# Visualization function for a selected health facility to show IDW
visualize_idw <- function(facility, p=2) {
```

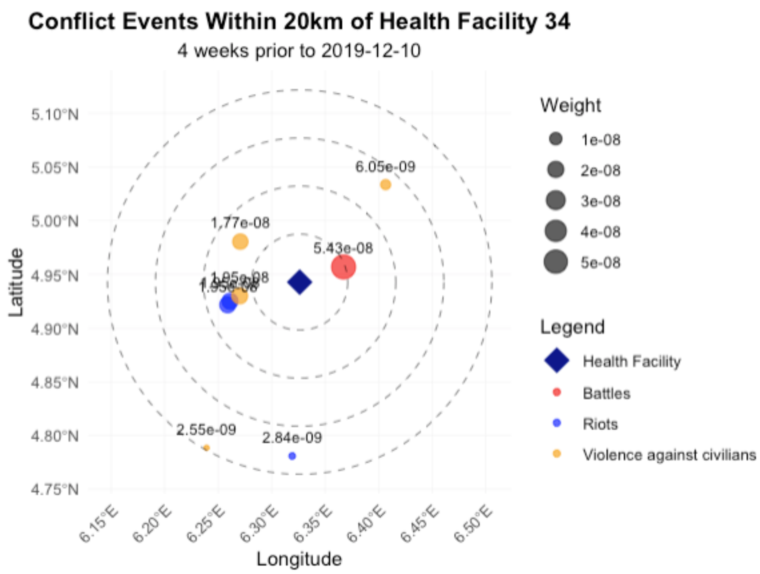
```
  selected_facility <- facilities_sf[facility, ]
  acled_sf_4wk <- acled_sf[acled_sf$event_date >= selected_facility$four_weeks & ac
led_sf$event_date <= selected_facility$date, ]
  acled_sf_4wk$dist <- as.vector(st_distance(selected_facility, acled_sf_4wk))
  acled_sf_4wk <- acled_sf_4wk[acled_sf_4wk$dist <= 20000, ]

  # Create buffer circles around the health facility
    buffer_20km <- st_buffer(selected_facility, dist = 20000)
    buffer_15km <- st_buffer(selected_facility, dist = 15000)
    buffer_10km <- st_buffer(selected_facility, dist = 10000)
    buffer_5km <- st_buffer(selected_facility, dist = 5000)

  # Calculate the bounding box for the plot
  bbox <- st_bbox(selected_facility)
  range <- 20000  # Define a range around the facility to ensure it is centered


# Check if the subset is empty and if so, output a plot that states there are no
surrounding conflict types during a certain time period
if (nrow(acled_sf_4wk) == 0) {
  return(ggplot() +
           geom_sf(data = selected_facility, aes(color = "Health Facility"), size =
6.5, shape = 18) +
           geom_sf(data = buffer_20km, fill = NA, color = "black", linetype = "dash
ed") +  # Add the buffer circle
           geom_sf(data = buffer_15km, fill = NA, color = "black", linetype = "dash
ed") +  # Add the buffer circle
           geom_sf(data = buffer_10km, fill = NA, color = "black", linetype = "dash
ed") +  # Add the buffer circle
           geom_sf(data = buffer_5km, fill = NA, color = "black", linetype = "dashe
d") +  # Add the buffer circle
           labs(title = paste("No Conflict Events Within 20km of Health Facility",
facilities_sf$X[facility]),
                subtitle = paste("4 weeks prior to", selected_facility$date),
                color = "Event Type",
                x = "Longitude",
                y = "Latitude") +
           coord_sf(xlim = c(bbox$xmin - range, bbox$xmax + range), ylim = c(bbox$y
min - range, bbox$ymax + range)) +
           scale_color_manual(name = "Legend",
                              values = c("Health Facility" = "darkblue"),
                              labels = c("Health Facility"),
                              breaks = "Health Facility") +
           theme_minimal() +
           theme(plot.title = element_text(hjust = 0.5, face = "bold"),  # Center a
nd bold the title
                 plot.subtitle = element_text(hjust = 0.5),
                 panel.grid.major = element_line(color = 'gray95', size = 0.2),
                 panel.grid.minor = element_line(color = 'gray95', size = 0.2),
                 axis.text.x = element_text(angle = 45, hjust = 1)  # Slant the Lon
gitude points
           )
```

```
  )
}

  # Compute inverse distance weights for each conflict event
  acled_sf_4wk$weights <- 1 / (acled_sf_4wk$dist^p)

  # Transform both datasets to the same CRS
  selected_facility_transformed <- st_transform(selected_facility, crs = 3857)
  acled_sf_4wk_transformed <- st_transform(acled_sf_4wk, crs = 3857)

  # Jitter the conflict events
  acled_sf_4wk_transformed <- st_jitter(acled_sf_4wk_transformed, amount = 1000)

  # Round all numeric columns to 3 significant figures
  acled_sf_4wk_transformed[] <- lapply(acled_sf_4wk_transformed, function(x) {
    if (is.numeric(x)) signif(x, 3) else x
  })

  # Create buffer circles around the health facility
    buffer_20km <- st_buffer(selected_facility_transformed, dist = 20000)
    buffer_15km <- st_buffer(selected_facility_transformed, dist = 15000)
    buffer_10km <- st_buffer(selected_facility_transformed, dist = 10000)
    buffer_5km <- st_buffer(selected_facility_transformed, dist = 5000)


  # Define a scale of colors for event_type
  event_type_colors <- c("Battles" = "red",
                         "Riots" = "blue",
                         "Protests" = "green",
                         "Violence against civilians" = "orange",
                         "Explosions/remote violence" = "purple")

  # Calculate the bounding box for the plot
  bbox <- st_bbox(selected_facility_transformed)
  range <- 20000  # Define a range around the facility to ensure it's centered


# Plot for health facilities that have surrounding conflict events:
  ggplot() +
    geom_sf(data = acled_sf_4wk_transformed, aes(color = event_type, size = weights
            ), alpha = 0.7) +  # Updated to include size aesthetic
    geom_sf(data = selected_facility_transformed, aes(color = "Health Facility"),
            size = 6.5, shape = 18) +
    geom_sf(data = buffer_20km, fill = NA, color = "black", linetype = "dashed") +
            # Add the buffer circle
    geom_sf(data = buffer_15km, fill = NA, color = "black", linetype = "dashed") +
            # Add the buffer circle
    geom_sf(data = buffer_10km, fill = NA, color = "black", linetype = "dashed") +
            # Add the buffer circle
    geom_sf(data = buffer_5km, fill = NA, color = "black", linetype = "dashed") +
            # Add the buffer circle
    geom_sf_text(data = acled_sf_4wk_transformed,
```

```
                 aes(label = format(weights, scientific = TRUE)),
                 nudge_y = 1000,    # Adjust vertical position
                 nudge_x = 0,       # Adjust horizontal position if needed
                 size = 3) +        # Adjust text size
    labs(title = paste("Conflict Events Within 20km of Health Facility",
            facilities_sf$X[facility]),
            subtitle = paste("4 weeks prior to", selected_facility$date),
            color = "Event Type",
            size = "Weight",        # Add a label for the size legend
            x = "Longitude",
            y = "Latitude") +
    coord_sf(xlim = c(bbox$xmin - range, bbox$xmax + range), ylim = c(bbox$ymin -
            range, bbox$ymax + range)) +
    scale_color_manual(name = "Legend",
                       values = c("Health Facility" = "darkblue",
                                  event_type_colors),
                       labels = c("Health Facility", names(event_type_colors)),
                       breaks = c("Health Facility", names(event_type_colors))) +
    theme_minimal() +
    theme(plot.title = element_text(hjust = 0.5, face = "bold"),
          plot.subtitle = element_text(hjust = 0.5),
          panel.grid.major = element_line(color = 'gray95', size = 0.2),
          panel.grid.minor = element_line(color = 'gray95', size = 0.2),
          axis.text.x = element_text(angle = 45, hjust = 1)  # Slant the longitude
points
            )  }

# Visualize for a specific facility with labels in exponential format (e.g., facili
ty with ID 34)
visualize_idw(134)
```




```
visualize_idw(34)
```




```
visualize_idw(2)
```

6) Reformat the idw_results data frame for regression analysis

- Reshape the data to a wide format
- Merge health facility functionality information

```
# Reshape data to wide format
idw_results_regress_4wk <- idw_results_4wk %>% pivot_wider(names_from = event_type, values_
from = weights, values_fill = 0) %>% select(-no_event)# four-week
idw_results_regress_1yr <- idw_results_1yr %>% pivot_wider(names_from = event_type, values_
from = weights, values_fill = 0) %>% select(-no_event) # one-year

# Merge health facility disruption status information from 'facilities'
idw_results_regress_4wk <- left_join(idw_results_regress_4wk, facilities, by = c("facility"
= "X")) %>%
  select(-X.1, -longitude, -latitude, -date)

idw_results_regress_1yr <- left_join(idw_results_regress_1yr, facilities, by = c("facility"
```

```
= "X")) %>%
  select(-X.1, -longitude, -latitude, -date)

# Create one 'disruption' column for 4 week data
idw_results_regress_4wk <- idw_results_regress_4wk %>% mutate(disruption = case_when(
  building_condition == 'Partially/fully damaged' & functionality == 'Fully functioning' ~
'Physical',
  building_condition == 'Not damaged' & functionality == 'Partially /not functioning' ~ 'Fu
nctional',
  building_condition == 'Partially/fully damaged' & functionality == 'Partially /not functi
oning' ~ 'Physical & Functional',
  building_condition == 'Not damaged' & functionality == 'Fully functioning' ~ 'No disrupti
ons'))

# Create one 'disruption' column for 1 year
idw_results_regress_1yr <- idw_results_regress_1yr %>% mutate(disruption = case_when(
  building_condition == 'Partially/fully damaged' & functionality == 'Fully functioning' ~
'Physical',
  building_condition == 'Not damaged' & functionality == 'Partially /not functioning' ~ 'Fu
nctional',
  building_condition == 'Partially/fully damaged' & functionality == 'Partially /not functi
oning' ~ 'Physical & Functional',
  building_condition == 'Not damaged' & functionality == 'Fully functioning' ~ 'No disrupti
ons'))
```

facility	Battles	Explosions	Protests	Violence against civilians	Riots	disruption
1	*[weight]*	*[weight]*	*[weight]*	*[weight]*	*[weight]*	*[disruption type]*
2	*[weight]*	*[weight]*	*[weight]*	*[weight]*	*[weight]*	*[disruption type]*
…	*[weight]*	*[weight]*	*[weight]*	*[weight]*	*[weight]*	*[disruption type]*

7) Run regression models to assess associations between conflict event types and functionality status.

- Use **multinomial regression** since the outcome is categorical and unordered
- Use **Wald Test** to extract p-values for the analysis results

```
# Fit multinomial logistic regression model
model_4wk <- multinom(disruption ~ Battles + Explosions + Protests + Violence against civil
ians + Riots, data = idw_results_regress_4wk)
# Print model summary
summary(model_4wk)

# Calculate p-values using the Wald Test
z <- summary(model_4wk)$coefficients / summary(model_4wk)$standard.errors
p <- 2 * (1 - pnorm(abs(z)))
p

# Fit multinomial logistic regression model
model_1yr <- multinom(disruption ~ battles + explosions + protests + v_civilians + riots, d
ata = idw_results_regress_1yr)
# Print model summary
summary(model_1yr)

# Calculate p-values using the Wald Test
z <- summary(model_1yr)$coefficients / summary(model_1yr)$standard.errors
```

```r
p <- 2 * (1 - pnorm(abs(z)))
p
```

6 CITATIONS

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