Missionaries: Catalysts for Aid? Evidence from Africa

Introduction

Aid allocation is ideally based on need, yet often it is influenced by political and strategic considerations. This research investigates how colonial ties, particularly those related to Christian missionaries who preceded modern local-level aid projects and assimilate them in terms of function, impact aid distribution today (Alpino and Hammersmark, 2021).

Data

The data for all aid projects across all 54 countries in Africa was provided by the International Aid Transparency Initiative (IATI) and retrieved from d-portal (link already queries for all 54 countries). In total, 269,058 activities were recorded across 1148 IATI organisations of which 26% had exact geo-locations. Subject to this analysis is the subsample of aid projects that have exact geo-locations, totalling 65521 projects across 278 organisations.

Missionary data comes from Hedde - von Westernhagen and Becker (2022) and is retrieved from Harvard Dataverse. To date, this is the most extensive colonial missionary dataset on Africa, surpassing Nunn (2010) whose data is often used for similar studies in terms of coverage.

Country boundaries and sub-national boundaries are retrieved from GADM (see "whole world" and "whole world as six separate layers") and ArcGis. Boundaries on climate zones come from Regional Centre for Mapping of Resource for Development.

```
## Warning: package 'sf' was built under R version 4.2.3

## Warning: package 'openxlsx' was built under R version 4.2.3

## Warning: package 'zoo' was built under R version 4.2.3

## Warning: package 'ggplot2' was built under R version 4.2.3

## Warning: package 'spatstat' was built under R version 4.2.3

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## Warning: package 'spatstat.explore' was built under R version 4.2.3

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```

```
## Warning: package 'spatstat.linnet' was built under R version 4.2.3

## Warning: package 'terra' was built under R version 4.2.3

## Warning: package 'tmap' was built under R version 4.2.3

## Warning: package 'spatialreg' was built under R version 4.2.3

## Warning: package 'spData' was built under R version 4.2.3

## Warning: package 'Matrix' was built under R version 4.2.3

## Warning: package 'spdep' was built under R version 4.2.3
```

Loading Aid Data

The downloaded aid data from the link above is loaded and converted into a spatial data frame.

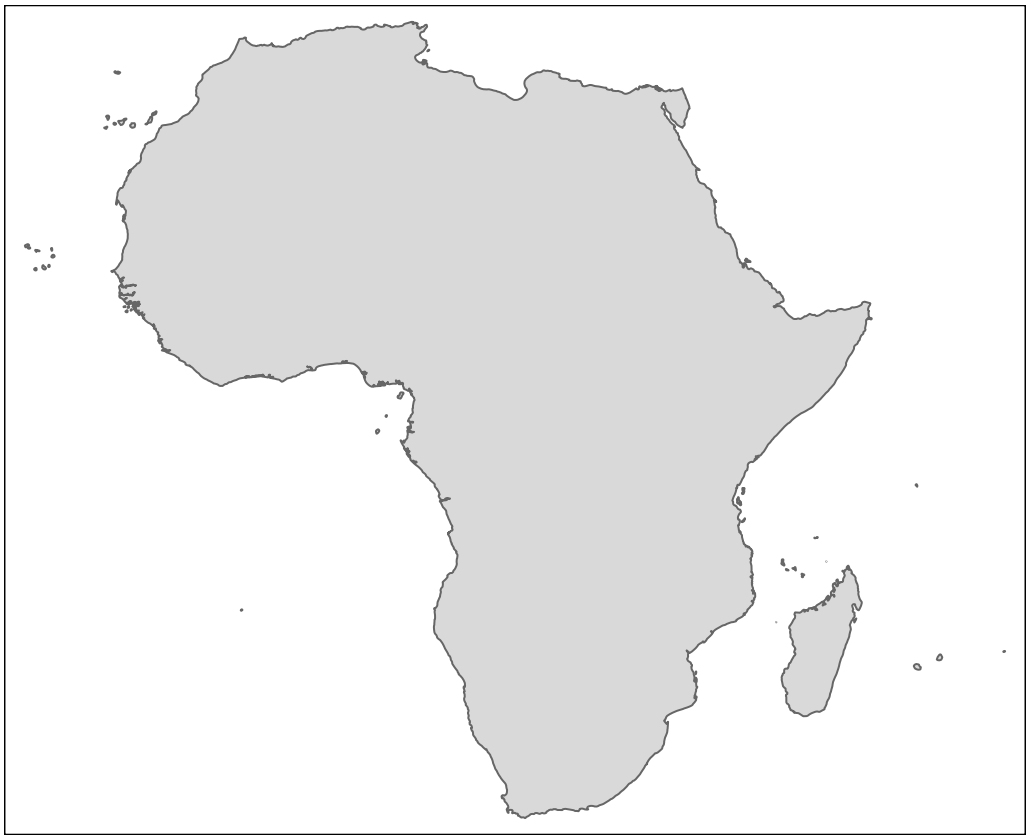
```
aiddata <- read.csv("data/dportal_map_activities.csv")
aiddata$day_start <- ymd(aiddata$day_start)  # using lubridate's ymd function to parse dates
aiddata_sf <- st_as_sf(aiddata, coords = c("location_longitude", "location_latitude"), crs = 4326)
```

Loading Africa boundaries

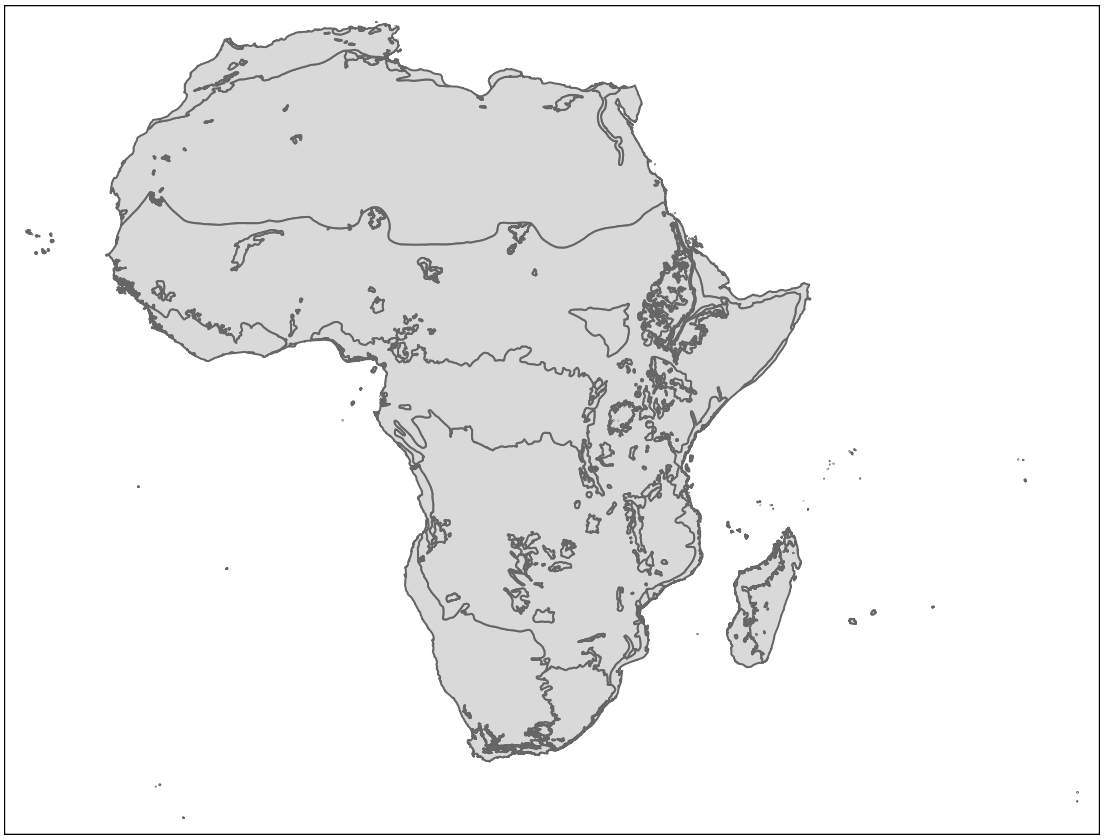
The sub-national, district boundaries at level 1 are loaded from GADM and filtered for African countries only. The code checks if boundaries for all countries was found. GADAM provided level 1-4. Here, level 1 is chosen because it has Africa-wide coverage, while more granular levels are not available for all African countries.

Furthermore, a shape file for the whole African continent is loaded, and the areas that are desert are subtracted. The remaining area can be considered the habitable land in Africa and is used later on to filter out raster cells that are located in inhabitable land when running spatial regressions.

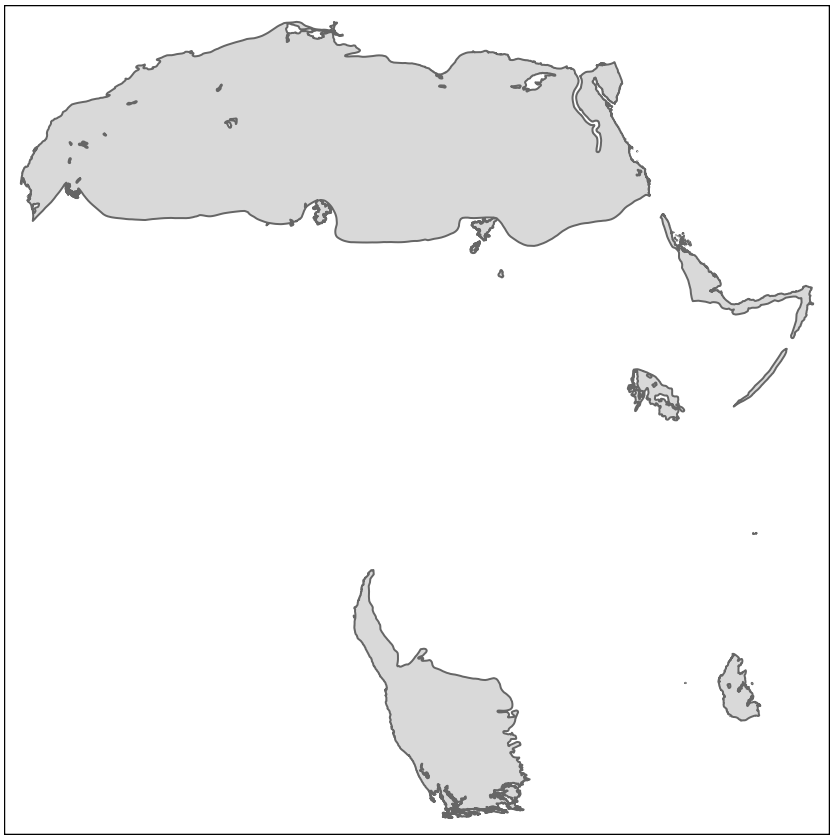
```
#Level 1 boundaries
boundaries <- st_read("data/gadm404-levels.gpkg",layer = "level1")
africa_boundaries <- boundaries[boundaries$COUNTRY %in% africa_countries,]

found <- unique(africa_boundaries$COUNTRY)
missing_countries <- setdiff(africa_countries, found)
print(missing_countries)

# Country boundaries
boundaries_ctr <- st_read("data/Africa_Boundaries.shp")
#crs_info <- st_crs(boundaries_ctr)
#print(crs_info)

#Continent boundaries
continents <- st_read("data/World_continents.shp")
african_continent <- continents[continents$CONTINENT == "Africa",]
qtm(african_continent)
```



```
biomes <- st_read("data/Africa_Biomes_Dataset.shp")
biomes <- st_transform(biomes, crs = 4326)
qtm(biomes)
```



```
desert <- biomes[biomes$FID == 1,]
qtm(desert)
```



```
#subtract desert from continent
habitableAfrica <- st_difference(african_continent, desert)



#st_write(habitableAfrica, "data/habitableAfrica.shp")



rm(boundaries, found, crs_info, missing_countries, continents, biomes)
gc()
```

Loading Missionary Data

Next the the data on the location of missions is loaded. In total 2278 missions are recorded.

```
missions <- st_read("data/bj_missions.shp")
```

```
## Reading layer 'bj_missions' from data source
##   'C:\Users\kaius\OneDrive - Hertie School\MSc Data Science for Public Policy\Semester_4\Geospatial
##   using driver 'ESRI Shapefile'
## Simple feature collection with 2278 features and 4 fields
## Geometry type: POINT
```

```
## Dimension:     XY
## Bounding box:  xmin: -17.20426 ymin: -34.52016 xmax: 50.1411 ymax: 36.89282
## Geodetic CRS:  WGS 84
```

```
str(missions)
```

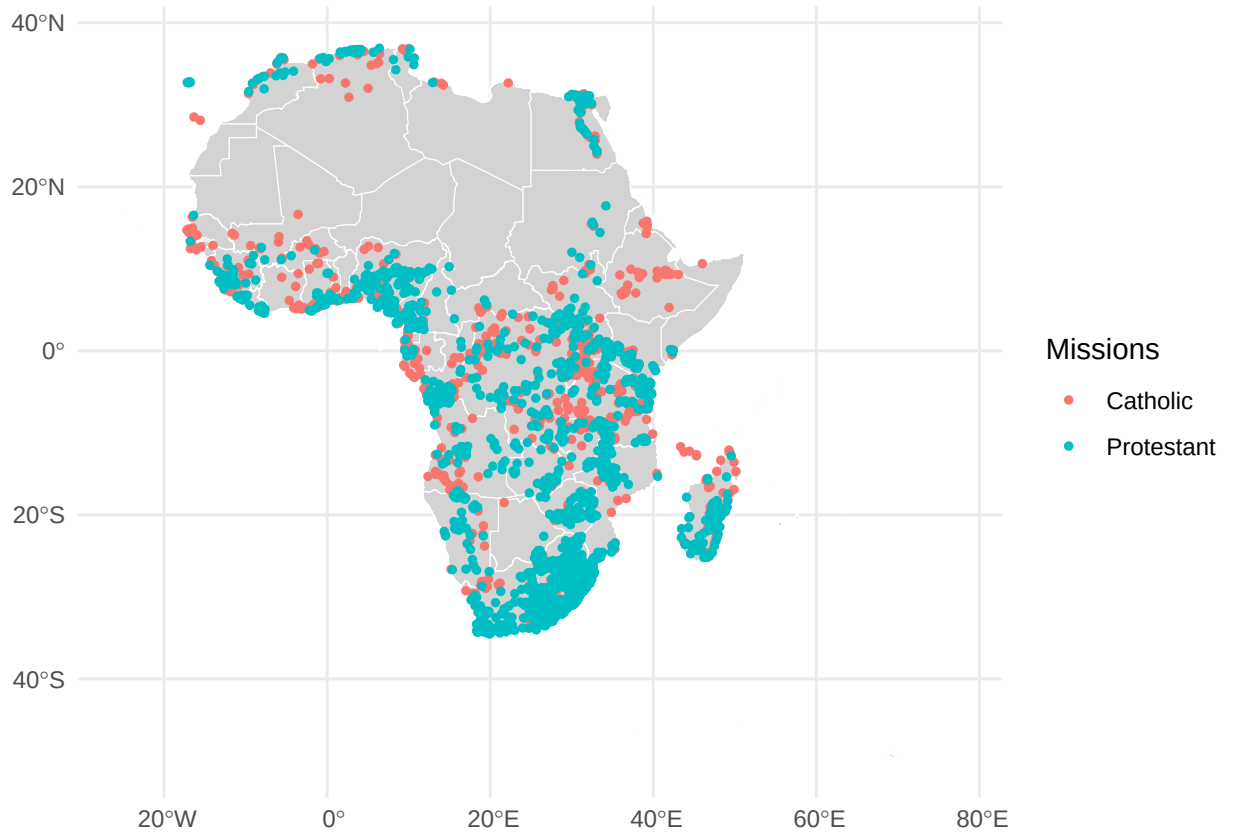
```
## Classes 'sf' and 'data.frame':   2278 obs. of  5 variables:
##  $ xcoord  : num  -5.29 -5.79 -6.18 -6.96 -7.91 ...
##  $ ycoord  : num  35.5 35.6 35 33.9 33.4 ...
##  $ denom   : chr  "Catholic" "Catholic" "Catholic" "Catholic" ...
##  $ vacated : chr  "no" "no" "no" "no" ...
##  $ geometry:sfc_POINT of length 2278; first list element:  'XY' num  -5.29 35.49
##  - attr(*, "sf_column")= chr "geometry"
##  - attr(*, "agr")= Factor w/ 3 levels "constant","aggregate",..: NA NA NA NA
##   ..- attr(*, "names")= chr [1:4] "xcoord" "ycoord" "denom" "vacated"
```

Summary statistics

Mapping missionary data

This map displays mission locations by denomination on a map of national boundaries.

```
missions_plot <- ggplot() +
  geom_sf(data = boundaries_ctr, fill = "lightgray", color = "white") +
  geom_sf(data = missions, aes(color = denom), size = 1) +
  labs(color = "Missions" ) +
  theme_minimal()

print(missions_plot)
```




```
ggsave("output/missions.png", missions_plot,  width = 10, height = 7)
rm(missions_plot)
```

Mapping missionary data against aid projects

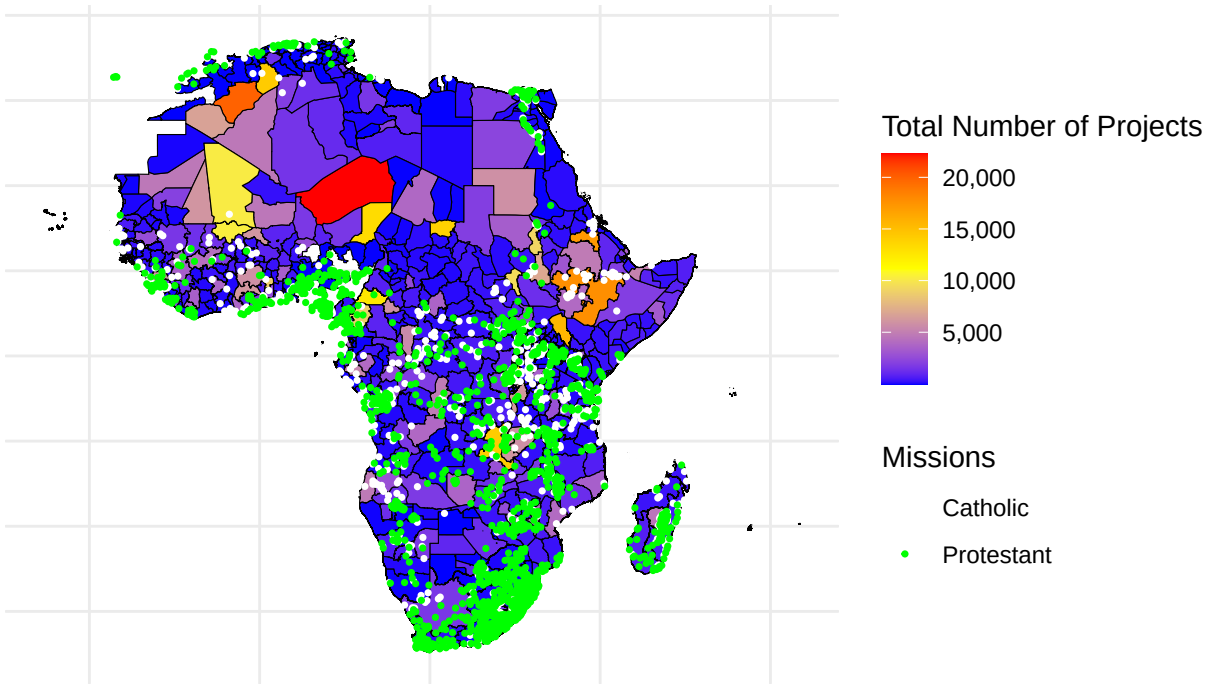
The line of code below performs a spatial join between the aid data and the African district boundaries by merging point location of the aid projects with polygons indicating the district boundaries, specifically where the points intersect the polygons. This operation creates a new dataset that add district names and and further district information to the aid projects.

```
master <- st_join(aiddata_sf, africa_boundaries, join = st_intersects)
```

This plot shows the location point of missions and number of aid projects by level 1 boundary. To do so, a new dataset was created with the number of aid projects by level 1 district. This dataset was merged with the level 1 boundary dataset to create a spatial dataframe including the polygons of the districts and the number of projects in each district. This data is plotted along side the point locations of missions, where mission points are coloured by their denomination.

A caveat of this map is that larger districts in terms of area tend to have more projects and therefore show up in brighter colour. In order to address this issue, the concentration of aid project is revisisted in the analysis section by plotting the number of aid projects and missions on grid cells of 0.5x0.5 degrees (approximately 55kmx55km) following Alpino and Hammersmark (2021).

```r
# Create a dataset with number of projects by level 1 district
regional_projects <- master %>%
  group_by(NAME_1) %>%
  summarise(Num_Projects = n()) %>%
  st_set_geometry(NULL)  # Remove geometry for non-spatial summary

# Merge number of aid project by district with district polygons
map_data <- merge(africa_boundaries, regional_projects, by = "NAME_1")

# Ensure the merged data is still an sf object
map_data <- st_as_sf(map_data)

# Plotting the map with ggplot2
missionandaid <- ggplot(data = map_data) +
  geom_sf(aes(fill = Num_Projects), color = "black", size = 0.5) +
  geom_sf(data = missions, aes(color = denom), size = 0.6) +
  scale_fill_gradientn(colors = c("blue", "yellow", "red"),
                       values = scales::rescale(c(0, 10000, 20000)),
                       labels = comma,
                       guide = "colourbar") +
  scale_color_manual(values = c("Catholic" = "white", "Protestant" = "green"),
                     labels = c("Catholic", "Protestant")) +
  labs(fill = "Total Number of Projects",
       color = "Missions" ) +
  theme_minimal() +
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        axis.title.x = element_blank(),
        axis.title.y = element_blank(),
        panel.background = element_blank())

#title = "Missions and Aid Projects by Region in Africa",

print(missionandaid)
```




```
ggsave("output/missionsandaid.png", missionandaid,  width = 10, height = 7)
rm(missionandaid)
```

Summary statistics on the aid data

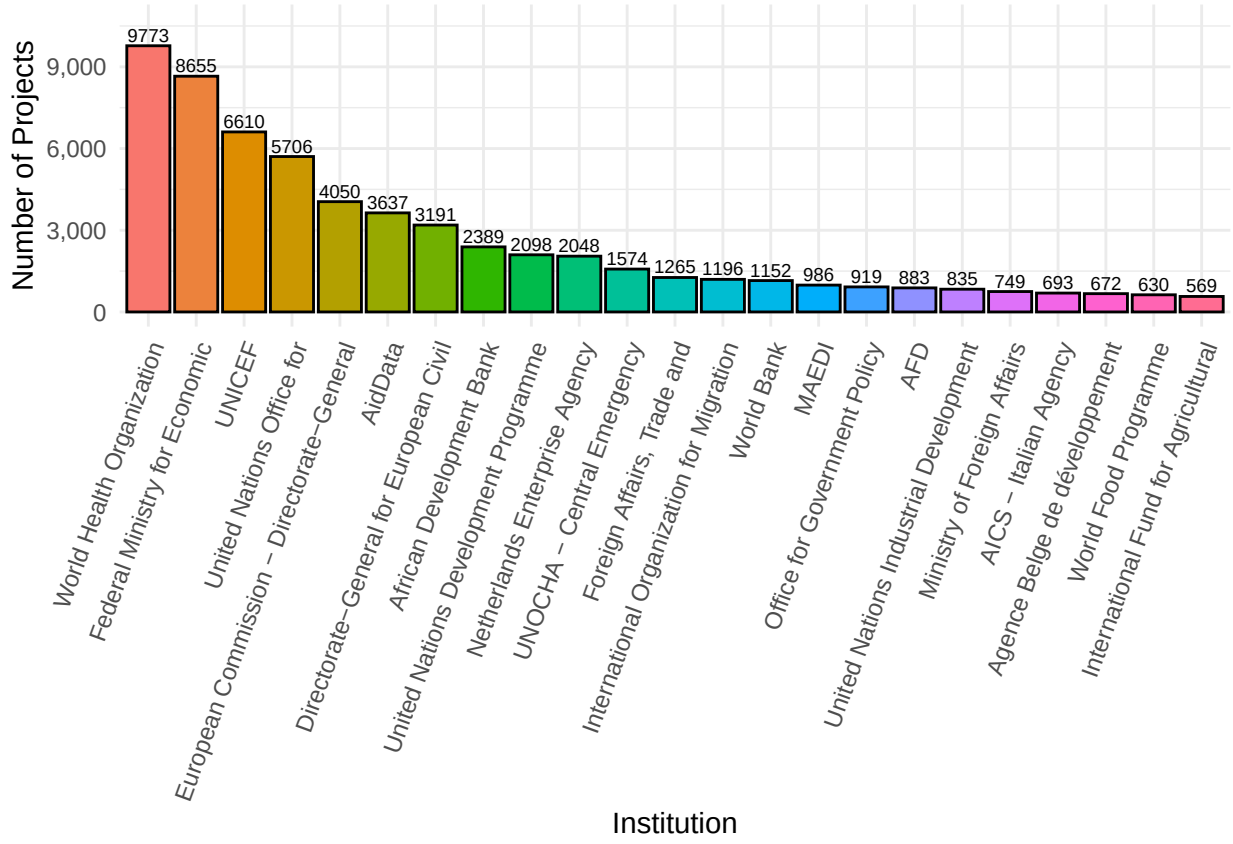
Graph 1: Number of project by institution where institution names are cut to the first four words and institutions with less than 500 projects are filtered out. One can observe that international organisations and bilateral donors have the highest number of reported geo-tagged projects in Africa. The organisation AidData is not a donor, but a data provider for geo-tagged aid projects.

This reporting error brings to light a more fundamental issue with the data. The dataset classifies the agency that reports the data to IATI as donor, regardless of the implementing organisation. This means, that that projects could be double counted if the reporting agency, e.g. Agence Française de Développement, reports projects that finance multi-lateral organisations, e.g. UNICEF, who in turn report the project, given they implement it.

For the Federal Ministry of Economics Cooperation and Development (the organisation with the second most projects in this dataset) (BMZ), the universe of aid projects financed by the ministry was sourced from BMZ. For the BMZ, I found that close to all projects are reported in my data, and that the data includes only bilateral aid, i.e. it excludes funding to other international organisations. For other donors similar research could be conducted to refine the understanding about the quality of data provided here.

```
# Summarize data to count number of projects per reporting institution
project_counts <- aiddata %>%
  mutate(reporting = sapply(str_split(reporting, " "), function(x) paste(x[1:min(length(x), 4)], collaps
  group_by(reporting) %>%
```

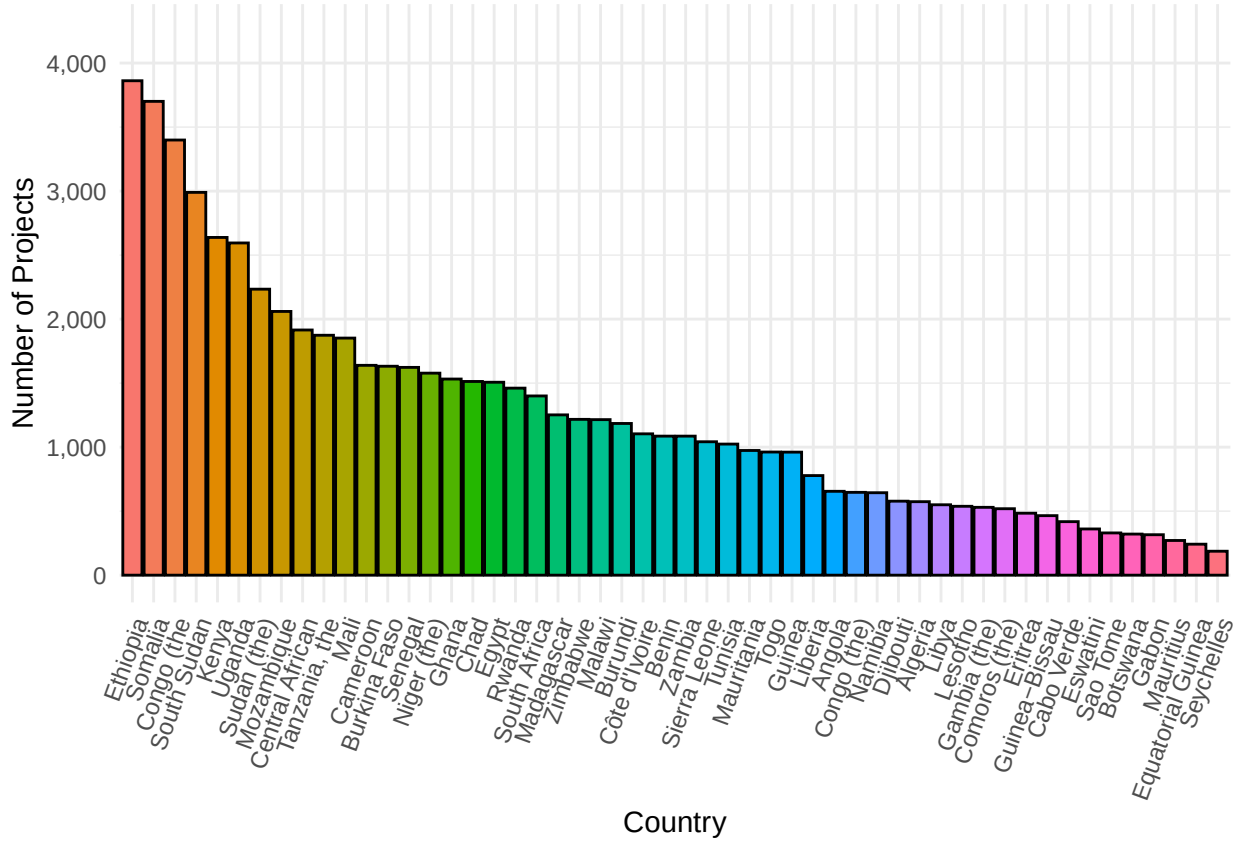
```
  summarise(Number_of_Projects = n_distinct(aid), .groups = 'drop') %>%
  filter(Number_of_Projects >= 500)  #

prepared_data <- project_counts %>%
  mutate(reporting = factor(reporting, levels = project_counts$reporting[order(-project_counts$Number_o

# Create the plot
projectByInstitution <- ggplot(prepared_data, aes(x = reporting, y = Number_of_Projects, fill = reporti
  geom_bar(stat = "identity", color = "black") +  # Create the bars
  geom_text(aes(label = Number_of_Projects), vjust = -0.3, color = "black", size = 2.3) +  # Add text l
  theme_minimal() +
  labs(x = "Institution",
       y = "Number of Projects") +
  theme(axis.text.x = element_text(angle = 70, hjust = 1)) +  # Rotate x-axis labels for better readabi
  guides(fill = FALSE) +  # Suppress the legend
  scale_y_continuous(labels = label_comma(), limits = c(NA, max(prepared_data$Number_of_Projects) * 1.1

# Display the plot
print(projectByInstitution)
```



Graph2: This figure shows the number of aid projects across countries. Given we are not working with a sample of aid data, it is important to understand where aid projects in the data are concentrated. It seems that Ethopia, Somalia, Congo and South Sudan have many projects which surprised the author.

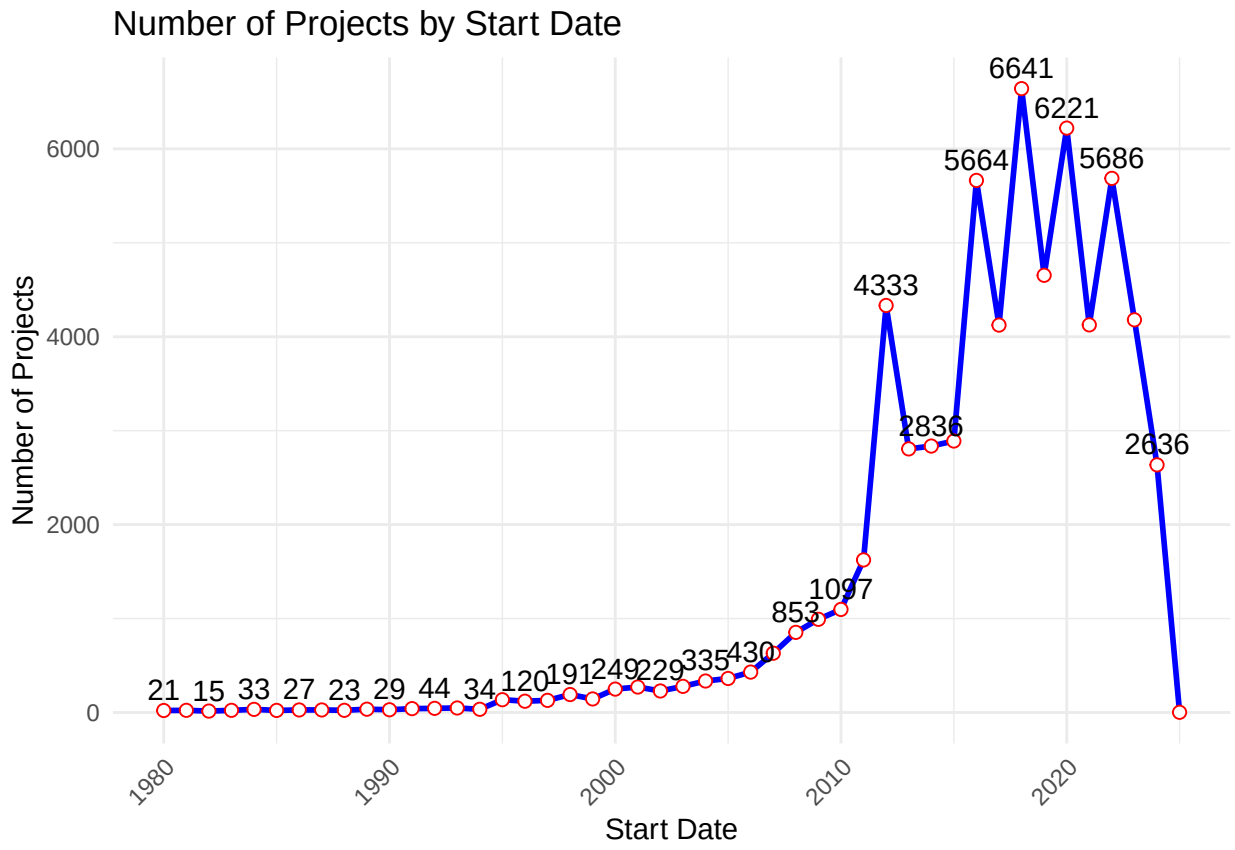
```
# Summarize data to count number of projects per reporting institution
project_counts <- aiddata %>%
```

```
  mutate(country_code = sapply(str_split(country_code, " "), function(x) paste(x[1:min(length(x), 2)], c
  group_by(country_code) %>%
  summarise(Number_of_Projects = n_distinct(aid), .groups = 'drop')

prepared_data <- project_counts %>%
  mutate(country = factor(country_code, levels = project_counts$country_code[order(-project_counts$Numbe


# Create the plot
projectByInstitution <- ggplot(prepared_data, aes(x = country, y = Number_of_Projects, fill = country))
  geom_bar(stat = "identity", color = "black") +  # Create the bars
  theme_minimal() +
  labs(x = "Country",
       y = "Number of Projects") +
  theme(axis.text.x = element_text(angle = 70, hjust = 1)) +  # Rotate x-axis labels for better readabi
  guides(fill = FALSE) +  # Suppress the legend
  scale_y_continuous(labels = label_comma(), limits = c(NA, max(prepared_data$Number_of_Projects) * 1.1

# Display the plot
print(projectByInstitution)
```



Graph3: This graph plots the number of project by start date in order to better understand the temporal dimension of the data. The large increase in projects after 2010 suggests that many more projects with geotags were reported to IATI, albeit it stays unclear whether this is due to an increase in aid projects or an improvement in project reporting.

```r
# Summarize data to count the number of projects starting each day
daily_projects <- aiddata %>%
  mutate(year = year(day_start))%>%
  group_by(year) %>%
  summarise(Number_of_Projects = n_distinct(aid), .groups = 'drop') %>%
  arrange(year) %>% # Ensure data is in chronological order for plotting
  filter(year >= 1980)


# Create the line chart
line_chart <- ggplot(daily_projects, aes(x = year, y = Number_of_Projects)) +
  geom_line(group = 1, color = "blue", size = 1) +  # Draw the line
  geom_point(color = "red", size = 2, shape = 21, fill = "white") +  # Add points to the line
  geom_text(data = filter(daily_projects, year %% 2 == 0), aes(label = Number_of_Projects), vjust = -0.5
  labs(title = "Number of Projects by Start Date",
       x = "Start Date",
       y = "Number of Projects") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))  # Rotate x-axis labels for better readabili

# Display the plot
print(line_chart)
```

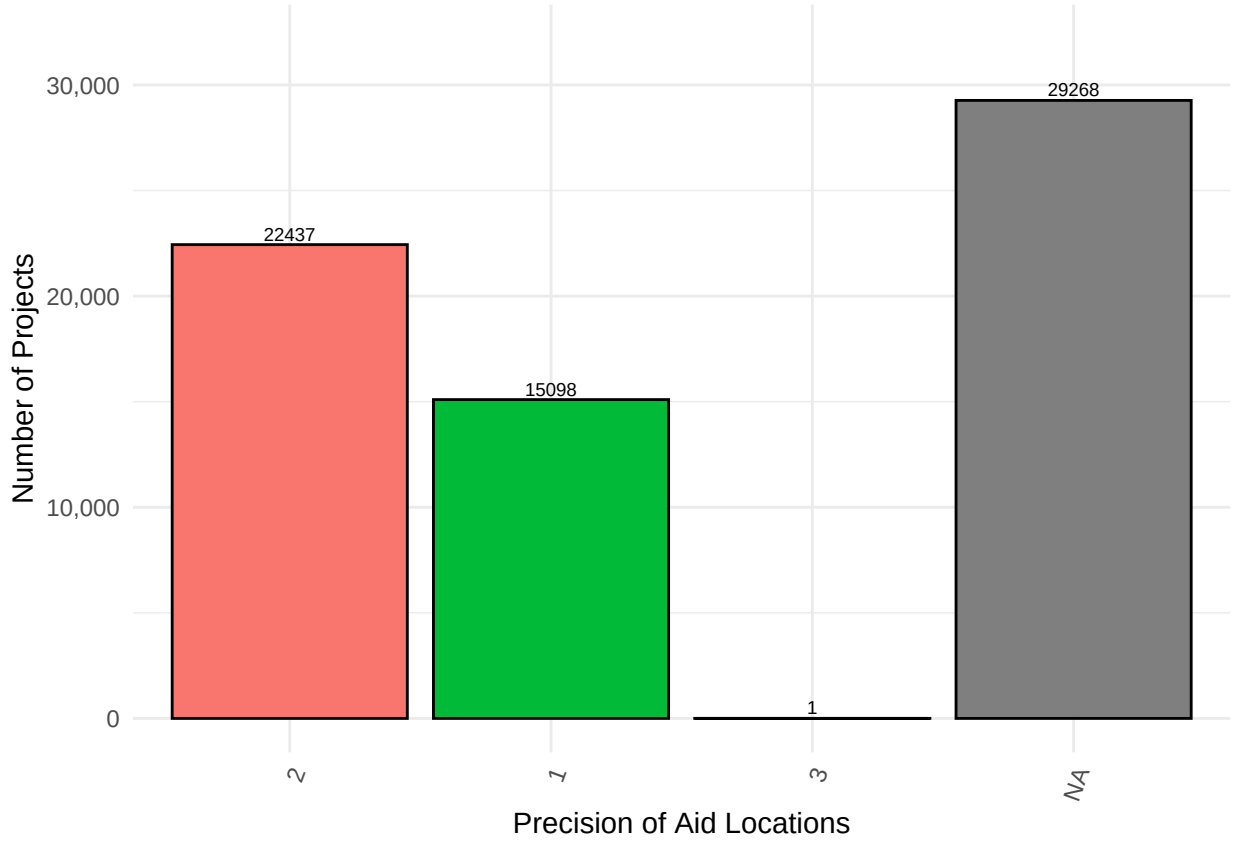


Graph4: Next, the quality of the geotags are evaluated. As explained by Alpino and Hammersmark (2021), the variable "location_precision" ranges from level 1-8, where 1 signifies a exact location specification, and 2 signifies a location accuracy up to 25km of the project location. All other precision levels are more coarse

or not suited for geospatial analysis, and therefore projects with other precision levels are not reported with geo-tags in d-portal.

Given this context, we can observe from Graph4 that about half of the projects have a precision level of 1 or 2 and the rest has no reported precision level.

```
# Summarize data to count number of projects by location predicsion
project_counts <- aiddata %>%
  group_by(location_precision) %>%
  summarise(Number_of_Projects = n_distinct(aid), .groups = 'drop')

prepared_data <- project_counts %>%
  mutate(location_precision = factor(location_precision, levels = project_counts$location_precision[ord

# Create the plot
precision <- ggplot(prepared_data, aes(x = location_precision, y = Number_of_Projects, fill = location_
  geom_bar(stat = "identity", color = "black") +  # Create the bars
  geom_text(aes(label = Number_of_Projects), vjust = -0.3, color = "black", size = 2.3) +  # Add text l
  theme_minimal() +
  labs(x = "Precision of Aid Locations",
       y = "Number of Projects") +
  theme(axis.text.x = element_text(angle = 70, hjust = 1)) +  # Rotate x-axis labels for better readabi
  guides(fill = FALSE) +  # Suppress the legend
  scale_y_continuous(labels = label_comma(), limits = c(NA, max(prepared_data$Number_of_Projects) * 1.1

# Display the plot
print(precision)
```

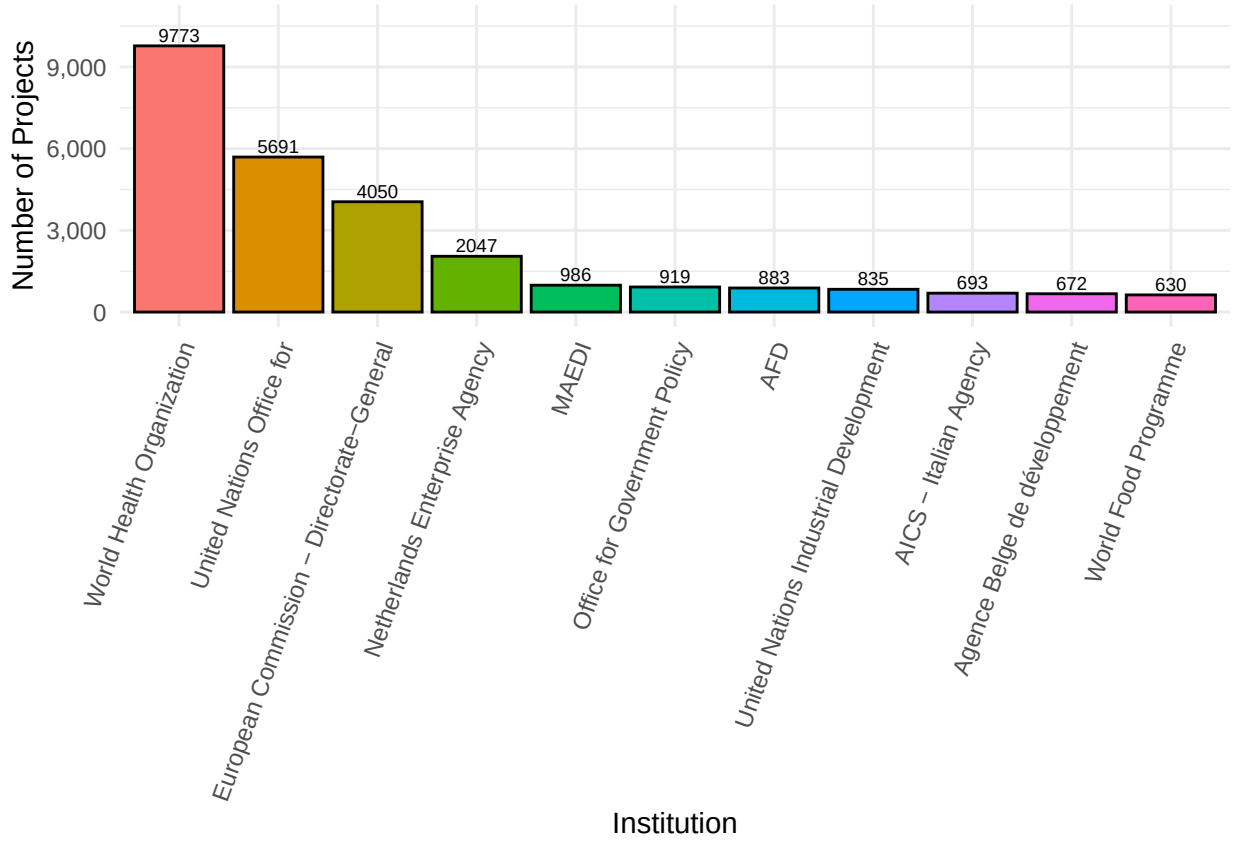


```
rm(precision)
```

Graph5 and 6 reports the number of projects by institution that have no reported precision levels against those that do (Graph6). Comparing Graph5 to Graph6, we can observe that donors either report their project locations using the location_precision variable, or they do not. For example, WHO which was ranked largest donor in Graph1 has no project with location_precision specified. In contrast, all BMZ projects consistently come with a location precision.

These findings could provoke future researcher to focus on donors that report precision levels and/or have high reporting coverage of their projects like the BMZ. Since reducing the scope of aid projects to a single donor comes with the drawback that it likely represents the population of aid project even less, this project sticks with using the entire data.

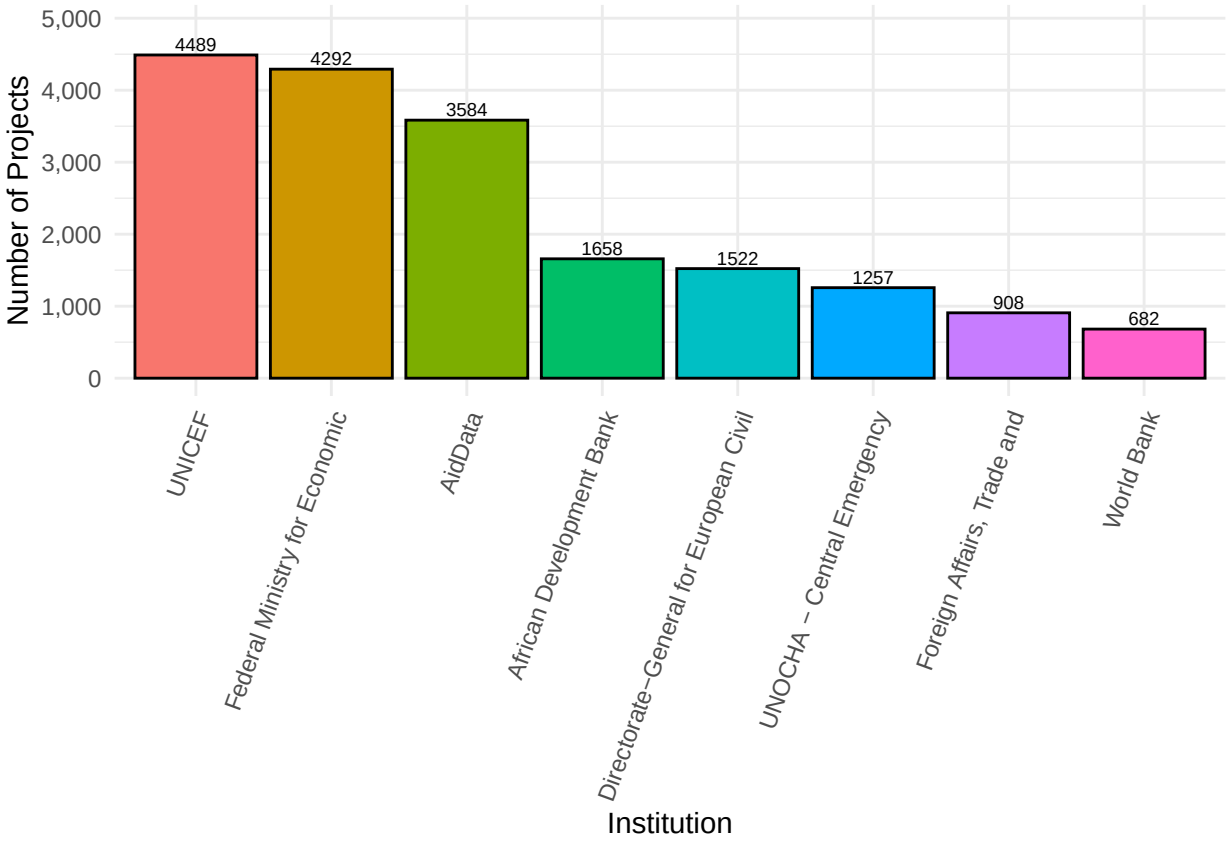
```
# Filter data to include only rows where location_precision is NA
filtered_data <- aiddata %>%
  filter(is.na(location_precision))

# Summarize filtered data to count number of projects by institution
project_counts <- filtered_data %>%
  mutate(reporting = sapply(str_split(reporting, " "), function(x) paste(x[1:min(length(x), 4)], collaps
  group_by(reporting) %>%
  summarise(Number_of_Projects = n_distinct(aid), .groups = 'drop')%>%
  filter(Number_of_Projects >= 500)  #

prepared_data <- project_counts %>%
  mutate(reporting = factor(reporting, levels = project_counts$reporting[order(-project_counts$Number_o

# Create the plot
institution_plot <- ggplot(prepared_data, aes(x = reporting, y = Number_of_Projects, fill = reporting))
  geom_bar(stat = "identity", color = "black") +  # Create the bars
  geom_text(aes(label = Number_of_Projects), vjust = -0.3, color = "black", size = 2.3) +  # Add text l
  theme_minimal() +
  labs(x = "Institution",
       y = "Number of Projects") +
  theme(axis.text.x = element_text(angle = 70, hjust = 1)) +  # Rotate x-axis labels for better readabi
  guides(fill = FALSE) +  # Suppress the legend
  scale_y_continuous(labels = label_comma(), limits = c(NA, max(prepared_data$Number_of_Projects) * 1.1

# Display the plot
print(institution_plot)
```




```
rm(institution_plot)
```

```
# Filter data to include only rows where location_precision is NA
filtered_data <- aiddata %>%
  filter(!is.na(location_precision))

# Summarize filtered data to count number of projects by institution
project_counts <- filtered_data %>%
  mutate(reporting = sapply(str_split(reporting, " "), function(x) paste(x[1:min(length(x), 4)], collaps
  mutate(year = year(day_start))%>%
  filter(year<=2016)%>%
  group_by(reporting) %>%
  summarise(Number_of_Projects = n_distinct(aid), .groups = 'drop')%>%
  filter(Number_of_Projects >= 500)  #

prepared_data <- project_counts %>%
  mutate(reporting = factor(reporting, levels = project_counts$reporting[order(-project_counts$Number_o

# Create the plot
institution_plot <- ggplot(prepared_data, aes(x = reporting, y = Number_of_Projects, fill = reporting))
  geom_bar(stat = "identity", color = "black") +  # Create the bars
  geom_text(aes(label = Number_of_Projects), vjust = -0.3, color = "black", size = 2.3) +  # Add text l
  theme_minimal() +
  labs(x = "Institution",
       y = "Number of Projects") +
  theme(axis.text.x = element_text(angle = 70, hjust = 1)) +  # Rotate x-axis labels for better readabi
```

```
  guides(fill = FALSE) +  # Suppress the legend
  scale_y_continuous(labels = label_comma(), limits = c(NA, max(prepared_data$Number_of_Projects) * 1.1)

# Display the plot
print(institution_plot)
```




```
rm(institution_plot)
```

Method

Two methods are used to assess the spatial correlation between colonial mission stations and contemporary aid projects.

First, a Cross K-Function is used. This function evaluates if two sets of points, A and B, are clustered or dispersed. At radius r, it compares the clustering of A and B to a random distribution of B (Gelb (2023). "Network k Functions").

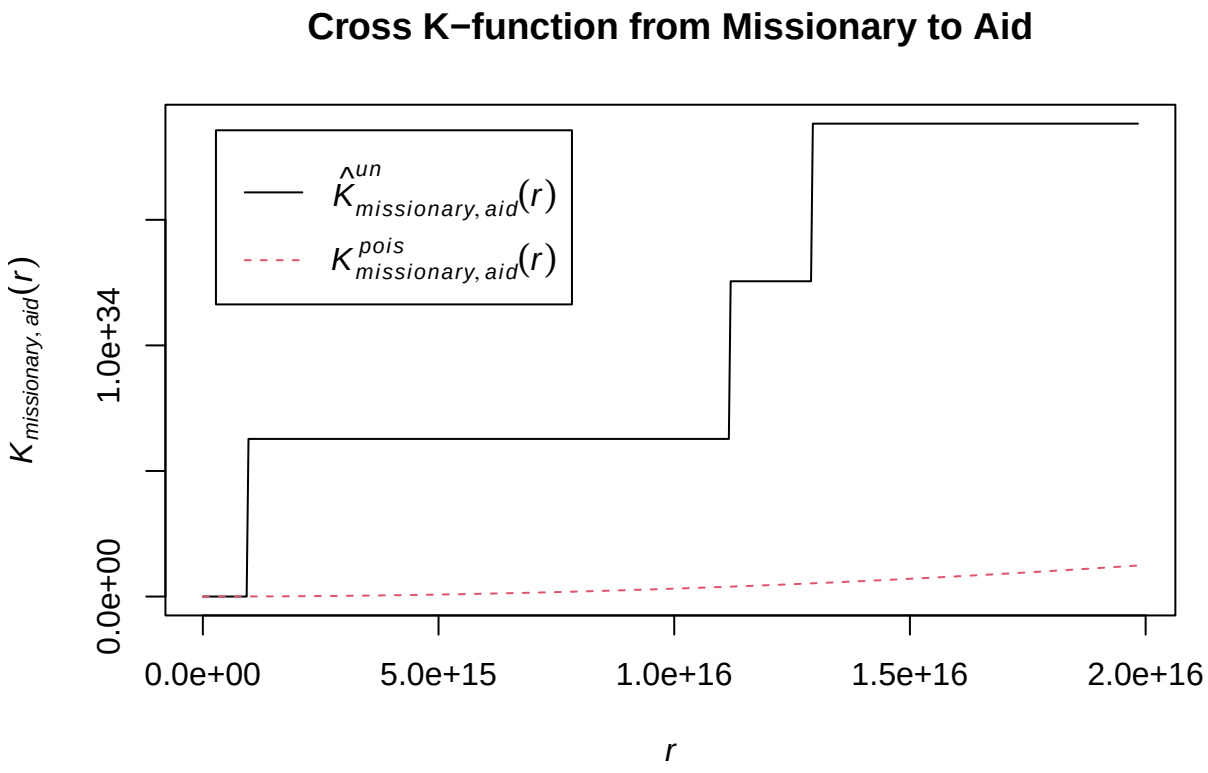
Second, regression and spatial regression is used. To use regressions, the aid projects and missions have to be mapped to grid cells as explained in the analysis section.

Analysis

Analysis using Cross K-function

The plot below represents the baseline (red, dotted line) which represents the how K would look like if the data was distributed according to a Poision distribution, against the sample K. Because K(un), the cross-K function of missions to aid projects, is above K(pois), the random baseline, we can infer that aid projects tend to be clustered around missions by more than we would expect at random.

```
aid_points <- ppp(aiddata$location_longitude, aiddata$location_latitude, window=owin(range(aiddata$loca
missionary_points <- ppp(missions$xcoord, missions$ycoord, window=owin(range(missions$xcoord), range(mi

aid_points$marks <- "aid"
missionary_points$marks <- "missionary"
combined_points <- superimpose(aid=aid_points, missionary=missionary_points)

combined_points$marks <- as.character(unlist(combined_points$marks))
combined_points$marks <- factor(combined_points$marks)

# Cross K-function
cross_k <- Kcross(combined_points, i="missionary", j="aid", correction="none")

# Plotting the cross K-function
plot(cross_k, main="Cross K-function from Missionary to Aid")
```



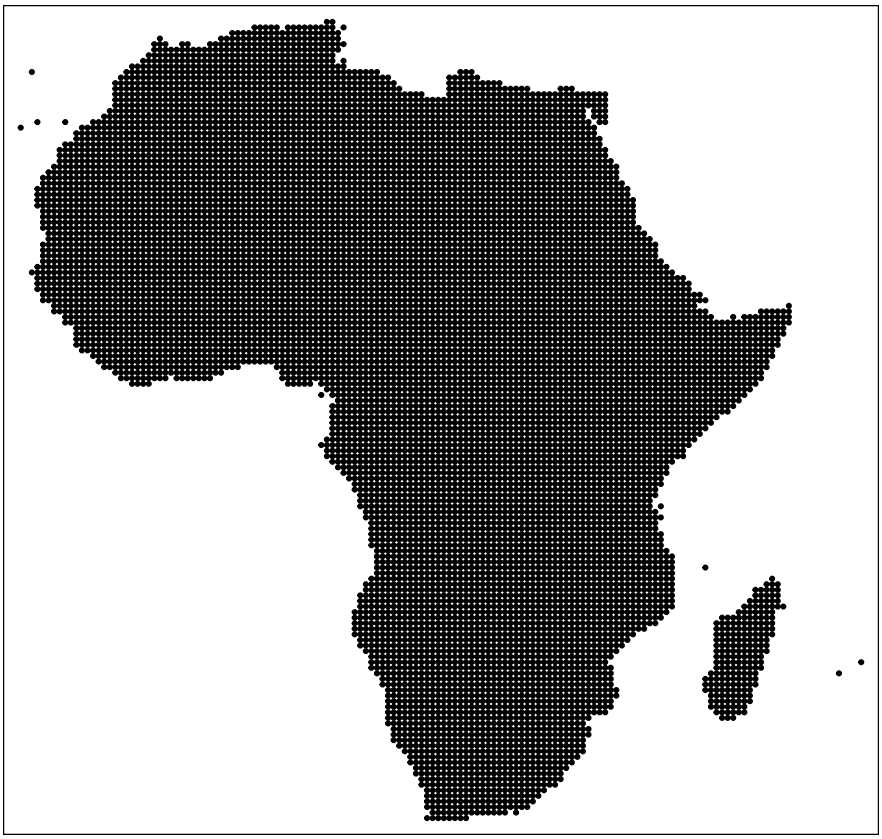
Analysis using regression analysis

In order to run regression analysis, I aggregate the number of aid projects and missions on a grid cell level, where one grid cell has the size 0.5x0.5 degrees (approximately 55km x 55km). To achieve this, I create a raster with grid cells of the resolution 0.5x0.5 degrees bounded by the area of Africa. The cordinates were retrieved from the shape file with the African continent.

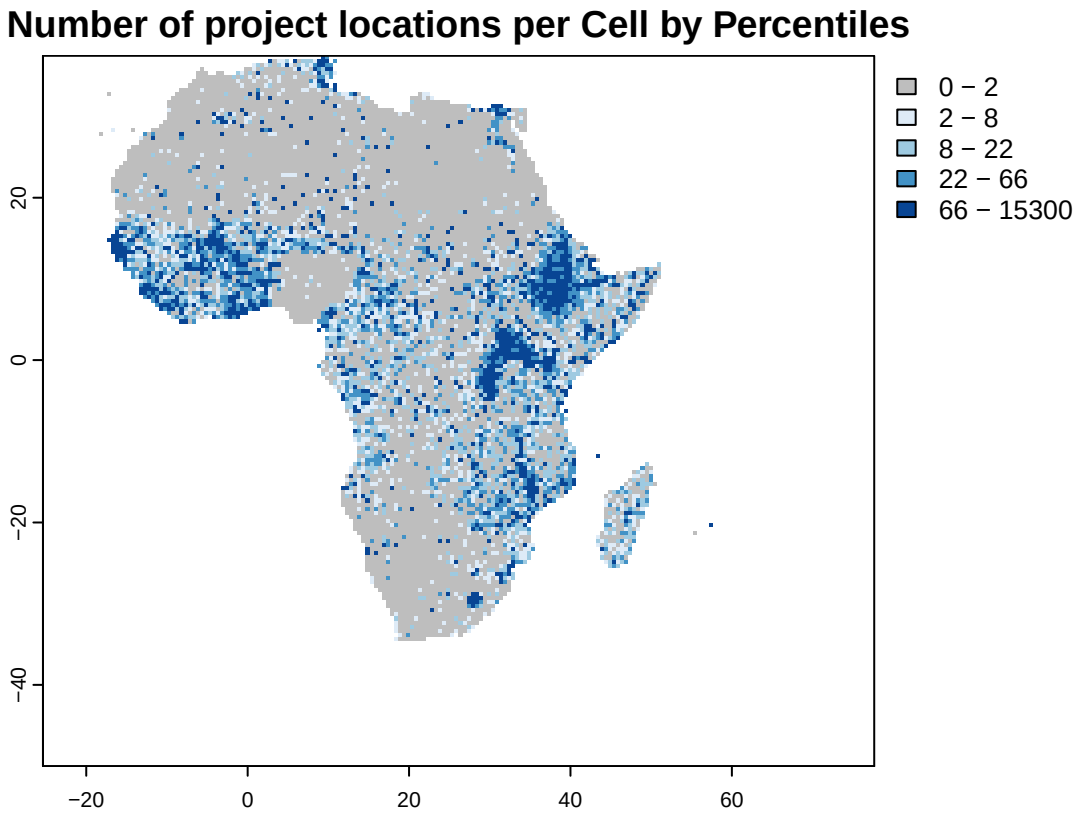
Next, the raster is mapped on the Africa shape file and the raster cells are cropped out that cover Africa. Aid data is then rasterised on this raster and the resulting plot shows the concentration of aid projects on a grid cell level over Africa.

Distributing aid projects into grid cells

```
# Creating a raster
# Define the extent using the bounding box coordinates
xmin <- -25.3618
xmax <- 77.60327
ymin <- -50.01889
ymax <- 37.55986

# Create a raster with a 0.5 degree resolution and map it on Africa
raster_05deg <- rast(xmin=xmin, xmax=xmax, ymin=ymin, ymax=ymax, resolution=0.5)
xy <- xyFromCell(raster_05deg, 1:ncell(raster_05deg))
coop <- st_as_sf(as.data.frame(xy), coords = c("x", "y"),
                 crs = st_crs(african_continent))
coop <- st_filter(coop, african_continent)
coop2 <- st_filter(coop, habitableAfrica)
coop_rast <- rasterize(coop, raster_05deg, field=1, fun='count')
coop_rast2 <- rasterize(coop2, raster_05deg, field=1, fun='count')
qtm(coop)
```



```
# Number of project by raster
aiddata_sf <- st_transform(aiddata_sf, crs(raster_05deg))
aiddata_vect <- vect(aiddata_sf)
aid_raster <- rasterize(aiddata_vect, raster_05deg, fun="count")
aid_raster[is.na(aid_raster)] <- 0
aid_raster <- mask(aid_raster, coop_rast, maskvalue=NA, updatevalue=NA)
aid_raster2 <- mask(aid_raster, coop_rast2, maskvalue=NA, updatevalue=NA)

# Calculate the percentile breaks
percentiles <- seq(0, 100, by = 10)  # Adjust this as needed
breaks <- quantile(values(aid_raster), probs = percentiles / 100, na.rm = TRUE)

# Ensure breaks are unique and sorted (adding minimum for zero coverage)
breaks <- c(min(values(aid_raster), na.rm = TRUE), unique(sort(breaks)))

# Ensure breaks are unique in case of duplicate percentile values
breaks <- unique(breaks)

# Define a color palette including 'gray' for NA values
colors <- c("gray", brewer.pal(8, "Blues"))

# Plot the raster with custom color for NA
plot(aid_raster, breaks=breaks, col=colors, main="Number of project locations per Cell by Percentiles")
```




```
rm(invalid_geometry)
gc()
```

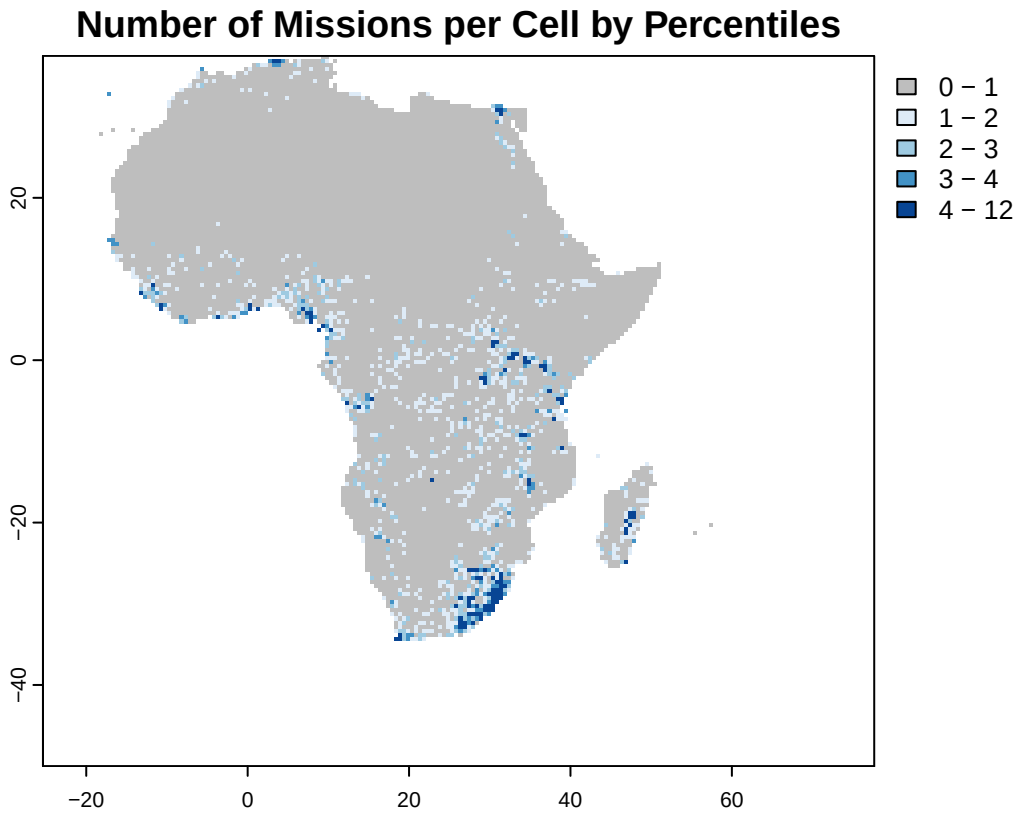
```
##             used  (Mb) gc trigger   (Mb)  max used   (Mb)
## Ncells   9643401 515.1   19161698 1023.4  19161698 1023.4
## Vcells 118712038 905.8  187408234 1429.9 234178957 1786.7
```

Add missions to raster data

The same excercise is repeated for the missions data.

```
# rasterise mission data
# Number of project by raster
missions <- st_transform(missions, crs(raster_05deg))
missions_vect <- vect(missions)
mission_raster <- rasterize(missions_vect, raster_05deg, fun="count")
mission_raster[is.na(mission_raster)] <- 0
mission_raster <- mask(mission_raster, coop_rast, maskvalue=NA, updatevalue=NA)
mission_raster2 <- mask(mission_raster, coop_rast2, maskvalue=NA, updatevalue=NA)

# Calculate the percentile breaks
percentiles <- seq(0, 100, by = 1)  # Adjust this as needed
breaks <- quantile(values(mission_raster), probs = percentiles / 100, na.rm = TRUE)
```

```r
# Ensure breaks are unique and sorted (adding minimum for zero coverage)
breaks <- c(min(values(mission_raster), na.rm = TRUE), unique(sort(breaks)))

# Ensure breaks are unique in case of duplicate percentile values
breaks <- unique(breaks)

# Define a color palette including 'gray' for NA values
colors <- c("gray", brewer.pal(8, "Blues"))
plot(mission_raster, breaks=breaks, col=colors, main="Number of Missions per Cell by Percentiles")
```




```r
# merge data
# Extract raster values to data frames
aid_values <- values(aid_raster)
aid_data <- data.frame(x = xy[,1], y = xy[,2], aid_projects = aid_values)
colnames(aid_data)[3] <- "NumAid"

mission_values <- values(mission_raster)
missions_data <- data.frame(x = xy[,1], y = xy[,2], missions = mission_values)
colnames(missions_data)[3] <- "NumMissions"


# Merge the data frames by coordinates
regression_data <- merge(aid_data, missions_data, by=c("x", "y"))

# Remove NA values which may complicate the analysis
```

```r
regression_data <- na.omit(regression_data)

rm(aiddata_vect, missions_vect, aid_values, mission_values, missions_data, aid_data)
gc()
```

```
##             used  (Mb) gc trigger   (Mb)  max used   (Mb)
## Ncells   9644184 515.1   19161698 1023.4  19161698 1023.4
## Vcells 118584809 904.8  187408234 1429.9 234178957 1786.7
```

```r
gc()
```

```
##             used  (Mb) gc trigger   (Mb)  max used   (Mb)
## Ncells   9641280 514.9   19161698 1023.4  19161698 1023.4
## Vcells 118583535 904.8  187408234 1429.9 234178957 1786.7
```

Regressions

As a initial step, a normal regression is run with the number of aid projects per cell as dependent variable and the number of missions per cell as the treatment variable. A moran's test is conducted and the residuals plotted. The Moran I test shows that the data is spatially correlated, as can also be visually inspected in the plot of residuals against lagged residuals.

```r
# Linear regression model
formula <- formula(NumAid ~ NumMissions)
model <- lm(formula = formula, data=regression_data)
summary(model)
```

```
##
## Call:
## lm(formula = formula, data = regression_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -369.1   -60.3   -60.3   -51.3 15218.7
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   60.254      5.294  11.382  < 2e-16 ***
## NumMissions   34.312      6.901   4.972 6.73e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 514.7 on 10230 degrees of freedom
## Multiple R-squared:  0.002411,   Adjusted R-squared:  0.002313
## F-statistic: 24.72 on 1 and 10230 DF,  p-value: 6.73e-07
```

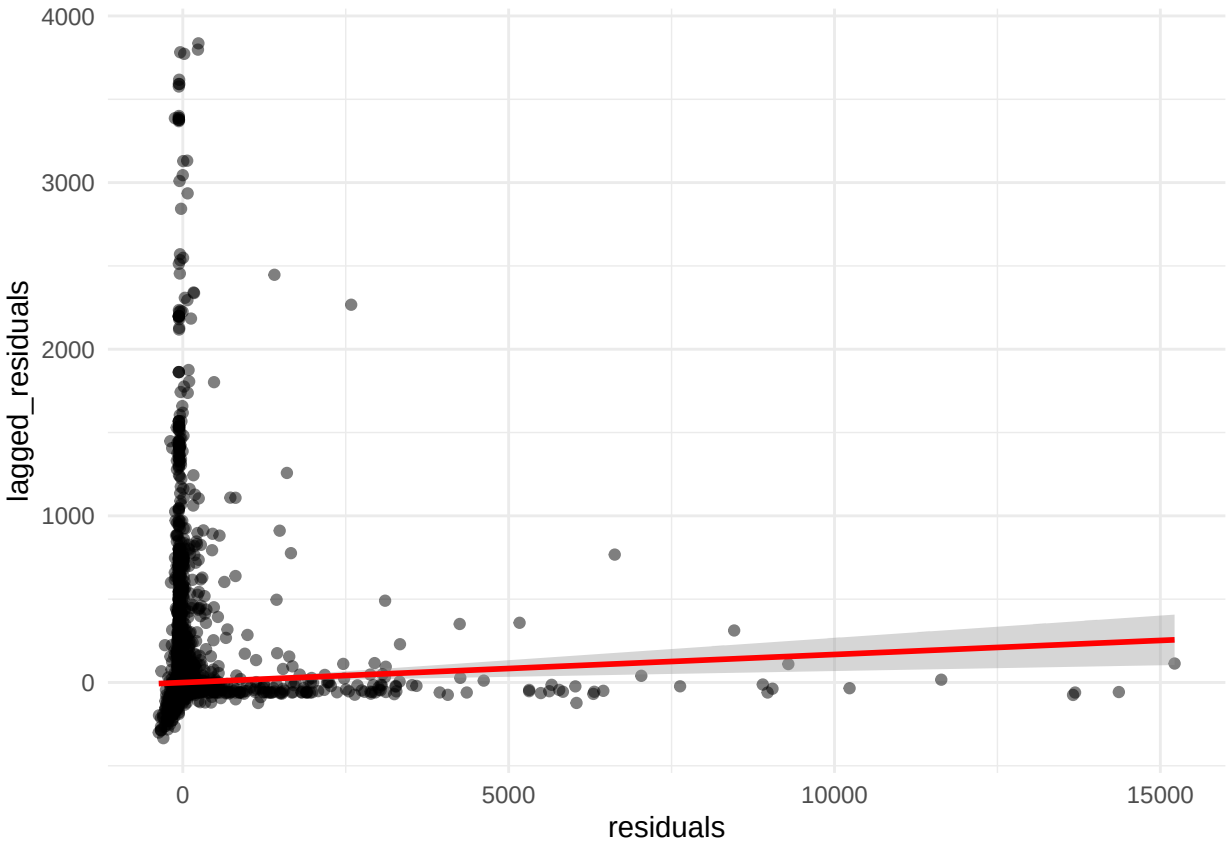
```r
#Analysing correlation in error term

# Assuming each point corresponds to the center of a raster cell
coords <- regression_data[c("x", "y")]
```

```r
# Create neighbors based on a distance threshold
# Calculate the appropriate distance threshold based on the raster resolution
dist_threshold <- 0.5 # Adjust 0.5 to your raster's resolution if different

# Create neighbors
nb <- dnearneigh(coords, 0, dist_threshold, longlat = FALSE)

# Convert neighbors to weights
wts <- nb2listw(nb, style="W", zero.policy=TRUE)
moran.test(model$residuals, listw=wts)
```

```
##
##  Moran I test under randomisation
##
## data:  model$residuals
## weights: wts
## n reduced by no-neighbour observations
##
## Moran I statistic standard deviate = 2.4322, p-value = 0.007504
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##      1.684219e-02     -9.783778e-05      4.851126e-05
```

```r
residuals_model <- residuals(model)
lagged_residuals_model <- lag.listw(wts, residuals_model)

res <- data.frame("lagged_residuals"=lagged_residuals_model, "residuals"=residuals_model)

ggplot(res, aes(x = residuals, y = lagged_residuals)) +
  theme_minimal() +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", color = "red")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



Spatial regression

Next, we create a lagged missions variable using weights estimated using neighbours up to a distance of 0.5 degrees. This should result in a weight that reflects only the number of missions in the direct neighboring grid cells. The lagged treatment variable was manually constructed because using inbuilt functions led to issues in calculating weights due to most cells reporting neither aid projects or missions.

Two specifications are tested: First the lagged treatment variable is added to the initial specification. In a second model, the interaction between the missions and lagged missions is also added.

```
regression_data$lag_NumMissions <- lag.listw(wts, regression_data$NumMissions, zero.policy = TRUE)



# Summary to check for NA or extreme values
summary(regression_data$lag_NumMissions)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.2079  0.2500  8.0000
```

```
# Linear model with spatial lag variable
model_with_lag <- lm(NumAid ~ NumMissions + lag_NumMissions, data = regression_data)
summary(model_with_lag)
```

```
##
```

```
## Call:
## lm(formula = NumAid ~ NumMissions + lag_NumMissions, data = regression_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -368.8   -60.3   -60.3   -51.2 15218.8
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      60.2671     5.4360  11.087  < 2e-16 ***
## NumMissions      34.3813     9.6053   3.579 0.000346 ***
## lag_NumMissions  -0.1323    12.7334  -0.010 0.991713
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 514.8 on 10229 degrees of freedom
## Multiple R-squared:  0.002411,   Adjusted R-squared:  0.002216
## F-statistic: 12.36 on 2 and 10229 DF,  p-value: 4.352e-06
```

```
# Linear model including main effects and interaction term
model_with_interaction <- lm(NumAid ~ NumMissions * lag_NumMissions, data = regression_data)
summary(model_with_interaction)
```

```
##
## Call:
## lm(formula = NumAid ~ NumMissions * lag_NumMissions, data = regression_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -352.6   -55.8   -55.8   -48.8 15217.7
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    55.831      5.617   9.939  < 2e-16 ***
## NumMissions                    52.986     11.307   4.686 2.82e-06 ***
## lag_NumMissions                21.937     14.566   1.506  0.13210
## NumMissions:lag_NumMissions  -12.404      3.981  -3.116  0.00184 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 514.5 on 10228 degrees of freedom
## Multiple R-squared:  0.003357,   Adjusted R-squared:  0.003064
## F-statistic: 11.48 on 3 and 10228 DF,  p-value: 1.638e-07
```

Spatial regression removing cells without any aid

In a final step, the same spatial regressions are run with the data restricted to cells that had at least one aid project to restrict the sample to habitable areas in Africa. However, this restriction is not without problems because aid project might not go to areas of need. Therefore, this restriction strategy is likely to give biased results.

```r
# Assuming 'NumAid' is your variable of interest
moran.test(regression_data$NumAid, listw=wts)
```

```
##
##  Moran I test under randomisation
##
## data:  regression_data$NumAid
## weights: wts
## n reduced by no-neighbour observations
##
## Moran I statistic standard deviate = 2.599, p-value = 0.004675
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##      1.800519e-02     -9.783778e-05      4.851833e-05
```

```r
# Removing zeros
data_no_zeros <- regression_data[regression_data$NumAid > 0, ]
coords2 <- data_no_zeros[c("x", "y")]
nb2 <- dnearneigh(coords2, 0, dist_threshold, longlat = FALSE)
listw_no_zeros <- nb2listw(nb2, style="W", zero.policy=TRUE)

moran.test(data_no_zeros$NumAid, listw=listw_no_zeros)
```

```
##
##  Moran I test under randomisation
##
## data:  data_no_zeros$NumAid
## weights: listw_no_zeros
## n reduced by no-neighbour observations
##
## Moran I statistic standard deviate = 0.32423, p-value = 0.3729
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##      0.0041221894     -0.0002334267      0.0001804643
```

```r
data_no_zeros$lag_NumMissions <- lag.listw(listw_no_zeros, data_no_zeros$NumMissions, zero.policy = TRU



# Summary to check for NA or extreme values
summary(data_no_zeros$lag_NumMissions)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.3187  0.3333  8.0000
```

```r
# Linear model with spatial lag variable
model_with_lag <- lm(NumAid ~ NumMissions + lag_NumMissions, data = data_no_zeros)
summary(model_with_lag)
```

```
##
## Call:
## lm(formula = NumAid ~ NumMissions + lag_NumMissions, data = data_no_zeros)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -445.3  -139.4  -127.4   -90.6 15138.7
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      142.410     12.482  11.409   <2e-16 ***
## NumMissions       34.099     15.521   2.197   0.0281 *
## lag_NumMissions   -8.552     20.492  -0.417   0.6765
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 761.7 on 4578 degrees of freedom
## Multiple R-squared:  0.001314,   Adjusted R-squared:  0.0008775
## F-statistic: 3.011 on 2 and 4578 DF,  p-value: 0.04932
```

```
# Linear model including main effects and interaction term
model_with_interaction <- lm(NumAid ~ NumMissions * lag_NumMissions, data = data_no_zeros)
summary(model_with_interaction)
```

```
##
## Call:
## lm(formula = NumAid ~ NumMissions * lag_NumMissions, data = data_no_zeros)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -497.1  -137.4  -127.4   -90.4 15139.1
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  140.394     13.053  10.756   <2e-16 ***
## NumMissions                   40.080     19.211   2.086    0.037 *
## lag_NumMissions               -2.071     23.882  -0.087    0.931
## NumMissions:lag_NumMissions   -4.285      8.108  -0.528    0.597
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 761.8 on 4577 degrees of freedom
## Multiple R-squared:  0.001375,   Adjusted R-squared:  0.0007202
## F-statistic:   2.1 on 3 and 4577 DF,  p-value: 0.09801
```

Spatial regression restricted to habitable

To resolve this issue, a final specification the same two spatial regressions are run on those grid cells that were located in habitable Africa - parts of the continent excluding desert and bodies of water (see Data Section on how this was constructed).

```r
# Extract raster values to data frames
aid_values <- values(aid_raster2)
aid_data <- data.frame(x = xy[,1], y = xy[,2], aid_projects = aid_values)
colnames(aid_data)[3] <- "NumAid"

mission_values <- values(mission_raster2)
missions_data <- data.frame(x = xy[,1], y = xy[,2], missions = mission_values)
colnames(missions_data)[3] <- "NumMissions"


# Merge the data frames by coordinates
regression_data_habitable <- merge(aid_data, missions_data, by=c("x", "y"))

# Remove NA values which may complicate the analysis
regression_data_habitable <- na.omit(regression_data)

regression_data_habitable$lag_NumMissions <- lag.listw(wts, regression_data_habitable$NumMissions, zero



# Summary to check for NA or extreme values
summary(regression_data_habitable$lag_NumMissions)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.2079  0.2500  8.0000
```

```r
# Linear model with spatial lag variable
model_with_lag <- lm(NumAid ~ NumMissions + lag_NumMissions, data = regression_data_habitable)
summary(model_with_lag)
```

```
##
## Call:
## lm(formula = NumAid ~ NumMissions + lag_NumMissions, data = regression_data_habitable)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -368.8   -60.3   -60.3   -51.2 15218.8
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      60.2671     5.4360  11.087  < 2e-16 ***
## NumMissions      34.3813     9.6053   3.579 0.000346 ***
## lag_NumMissions  -0.1323    12.7334  -0.010 0.991713
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 514.8 on 10229 degrees of freedom
## Multiple R-squared:  0.002411,   Adjusted R-squared:  0.002216
## F-statistic: 12.36 on 2 and 10229 DF,  p-value: 4.352e-06
```

```r
# Linear model including main effects and interaction term
model_with_interaction <- lm(NumAid ~ NumMissions * lag_NumMissions, data = regression_data_habitable)
summary(model_with_interaction)
```

```
##
## Call:
## lm(formula = NumAid ~ NumMissions * lag_NumMissions, data = regression_data_habitable)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
##  -352.6   -55.8   -55.8   -48.8 15217.7
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    55.831      5.617   9.939  < 2e-16 ***
## NumMissions                    52.986     11.307   4.686 2.82e-06 ***
## lag_NumMissions                21.937     14.566   1.506  0.13210
## NumMissions:lag_NumMissions  -12.404      3.981  -3.116  0.00184 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 514.5 on 10228 degrees of freedom
## Multiple R-squared:  0.003357,   Adjusted R-squared:  0.003064
## F-statistic: 11.48 on 3 and 10228 DF,  p-value: 1.638e-07
```

Discussion

Future research could add more covariates to control for other factors that predict both missions and aid projects and could bias the results. Furthermore, uninhabitable areas could have included lakes and other bodies of water or dense forest area, as well as national parks.

Conclusion

This research project analysed the spatial correlation betweeen colonial missions and contemporary aid projects in Africa. It found that there seems to be a correlation between the two that persists over different specifications and methods.

References

Matteo Alpino and Eivind Moe Hammersmark (2021). "The Role of Historical Christian Missions in the Location of World Bank Aid in Africa", World Bank Policy Research Working Paper, 9146 Christine Heddevon Westernhagen and Bastian Becker (2022). "Mapping Missions: New Data for the Study of African History", Research Data Journal for the Humanities and Social Sciences, 7(1) Nathan Nunn (2010). Religious conversion in colonial Africa. American Economic Review: Papers & Proceedings, 100 (2), 147–152. Gelb (2023). "Network k Functions"