

MIDTERM 615

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1. Flooding data cleaning an EDA

1.1 cleaning and merge two dataset

```
library(tidyverse)
```

```
## —— Attaching core tidyverse packages —— tidyverse 2.0.0 ——
## ✓ dplyr      1.1.3      ✓ readr      2.1.4
## ✓ forcats    1.0.0      ✓ stringr    1.5.0
## ✓ ggplot2    3.4.3      ✓ tibble     3.2.1
## ✓ lubridate  1.9.2      ✓ tidyr      1.3.0
## ✓ purrr      1.0.2
## —— Conflicts ——
——— tidyverse_conflicts() ——
## ✗ dplyr::filter() masks stats::filter()
## ✗ dplyr::lag()     masks stats::lag()
## ⓘ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(readr)
library(lubridate)
library(ggplot2)
```

```
disaster_declarations_df <- read_csv('/Users/xiaoy/Desktop/615 R/midterm/DisasterDeclarationsSummaries.csv')
```

```
## Rows: 64950 Columns: 25
## —— Column specification ——
## Delimiter: ","
## chr  (10): femaDeclarationString, state, declarationType, incidentType, decl...
## dbl  (9): disasterNumber, fyDeclared, ihProgramDeclared, iaProgramDeclared,...
## dtm  (6): declarationDate, incidentBeginDate, incidentEndDate, disasterClos...
## ⓘ Use `spec()` to retrieve the full column specification for this data.
## ⓘ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
fema_web_summaries_df <- read_csv('/Users/xiaoy/Desktop/615 R/midterm/FemaWebDisasterSummaries.csv')
```

```
## Rows: 3588 Columns: 14
## —— Column specification —————
##
## Delimiter: ",",
## chr (2): hash, id
## dbl (9): disasterNumber, totalNumberIaApproved, totalAmountIhpApproved, tot...
## dtm (3): paLoadDate, iaLoadDate, lastRefresh
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
flood_declarations_df <- disaster_declarations_df %>%
  filter(incidentType == 'Flood', fyDeclared %in% c(2020, 2021))

flood_disaster_numbers <- unique(flood_declarations_df$disasterNumber)

## Filter the FEMA web summaries data for the corresponding disaster numbers
flood_financials_df <- fema_web_summaries_df %>%
  filter(disasterNumber %in% flood_disaster_numbers)

## Merge the two datasets on the 'disasterNumber' column
combined_flood_data_df <- inner_join(flood_declarations_df, flood_financials_df, by = 'disaster
Number')

## Group by 'disasterNumber' and aggregate the financial data
combined_flood_data_aggregated <- combined_flood_data_df %>%
  group_by(disasterNumber) %>%
  summarise(
    totalNumberIaApproved = sum(totalNumberIaApproved, na.rm = TRUE),
    totalAmountIhpApproved = sum(totalAmountIhpApproved, na.rm = TRUE),
    totalAmountHaApproved = sum(totalAmountHaApproved, na.rm = TRUE),
    totalAmountOnaApproved = sum(totalAmountOnaApproved, na.rm = TRUE),
    totalObligatedAmountPa = sum(totalObligatedAmountPa, na.rm = TRUE),
    totalObligatedAmountCatAb = sum(totalObligatedAmountCatAb, na.rm = TRUE),
    totalObligatedAmountCatC2g = sum(totalObligatedAmountCatC2g, na.rm = TRUE),
    totalObligatedAmountHmgrp = sum(totalObligatedAmountHmgrp, na.rm = TRUE)
  ) %>%
  ungroup()

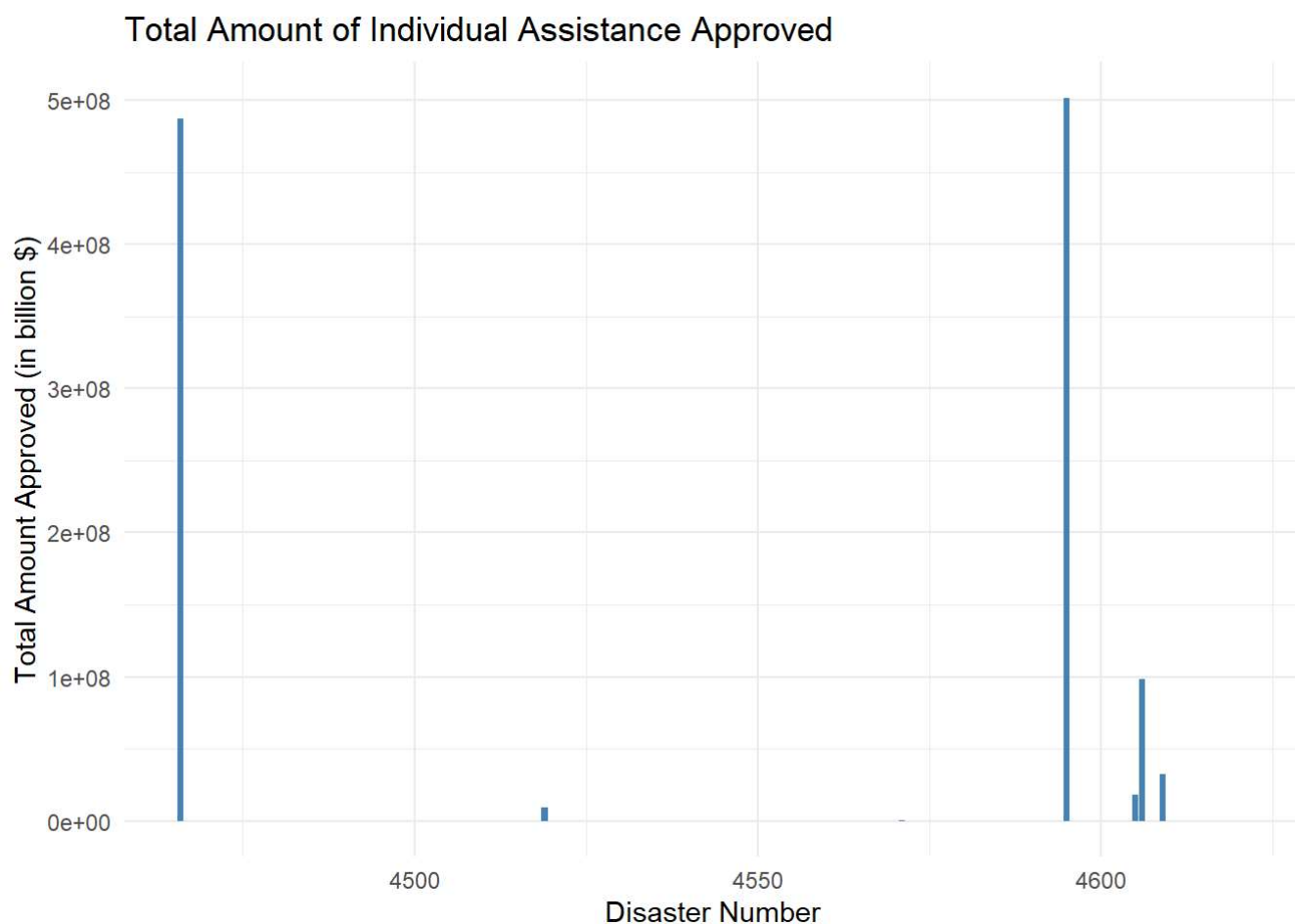
head(combined_flood_data_aggregated)
```

```
## # A tibble: 6 × 9
##   disasterNumber totalNumberIaApproved totalAmountIhpApproved
##           <dbl>           <dbl>           <dbl>
## 1           4466           78554           487195694.
## 2           4475              0              0
## 3           4477              0              0
## 4           4519             660           8969013.
## 5           4539              0              0
## 6           4553              0              0
## # i 6 more variables: totalAmountHaApproved <dbl>,
## #   totalAmountOnaApproved <dbl>, totalObligatedAmountPa <dbl>,
## #   totalObligatedAmountCatAb <dbl>, totalObligatedAmountCatC2g <dbl>,
## #   totalObligatedAmountHmgp <dbl>
```

1.2 Plotting for Visualization

(a) Individual Assistance (IA)

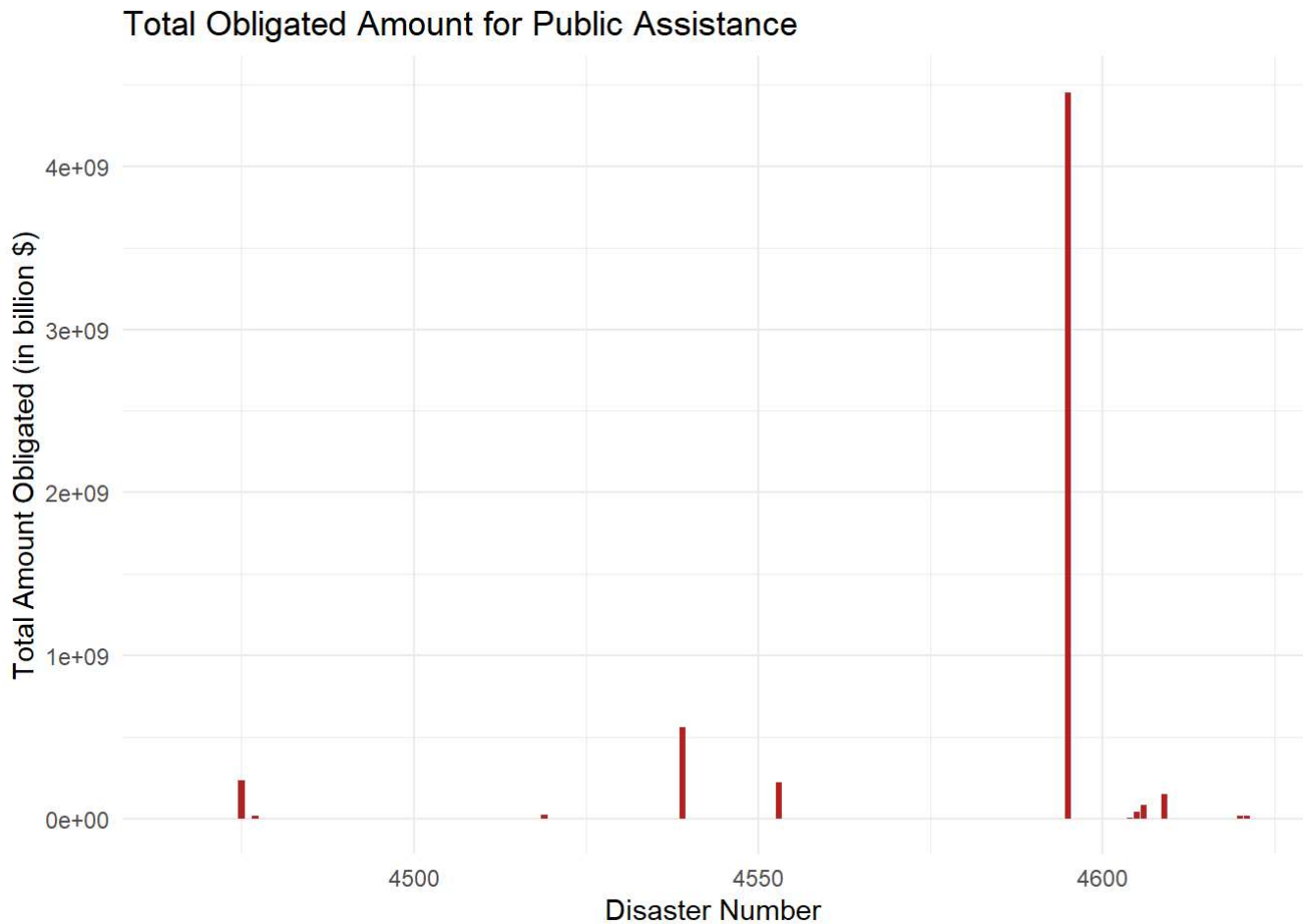
```
ggplot(combined_flood_data_aggregated, aes(x = disasterNumber, y = totalAmountIhpApproved)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  theme_minimal() +
  labs(title = "Total Amount of Individual Assistance Approved", x = "Disaster Number", y = "Total Amount Approved (in billion $)")
```



The first bar chart shows the total amount of Individual Assistance approved for each disaster.

(b) Public Assistance (PA)

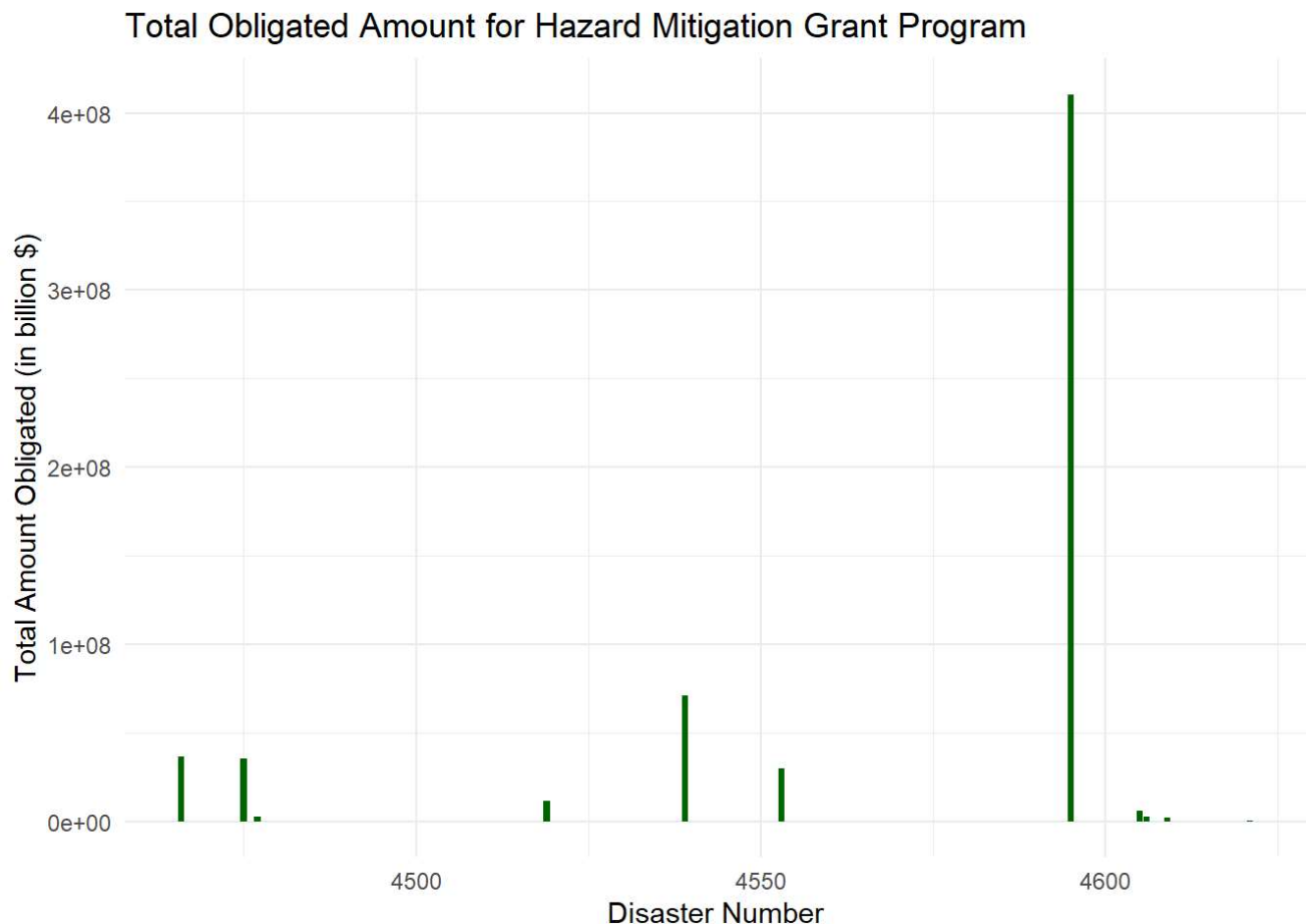
```
ggplot(combined_flood_data_aggregated, aes(x = disasterNumber, y = totalObligatedAmountPa)) +
  geom_bar(stat = "identity", fill = "firebrick") +
  theme_minimal() +
  labs(title = "Total Obligated Amount for Public Assistance", x = "Disaster Number", y = "Total Amount Obligated (in billion $)")
```



The second chart illustrates the total obligated amount for Public Assistance for each disaster, also in billions of dollars.

(c) Hazard Mitigation Grant Program (HMGP)

```
ggplot(combined_flood_data_aggregated, aes(x = disasterNumber, y = totalObligatedAmountHmgs)) +
  geom_bar(stat = "identity", fill = "darkgreen") +
  theme_minimal() +
  labs(title = "Total Obligated Amount for Hazard Mitigation Grant Program", x = "Disaster Number", y = "Total Amount Obligated (in billion $)")
```



The third chart presents the total obligated amount for the Hazard Mitigation Grant Program for each disaster, in billions of dollars.

From these charts, we can observe significant differences in the financial assistance provided by different disaster events. Some disasters have a much greater financial impact and require more assistance than others.

2. explore Top 10 States by Disaster Counts recent 10 years

2.1 initial question

- How does the number of disasters change over time?
- And what are the change curves of the ten continents that have received the most disasters in the past 10 years?
- What does this indicate or reflect?

2.2 EDA and Solution

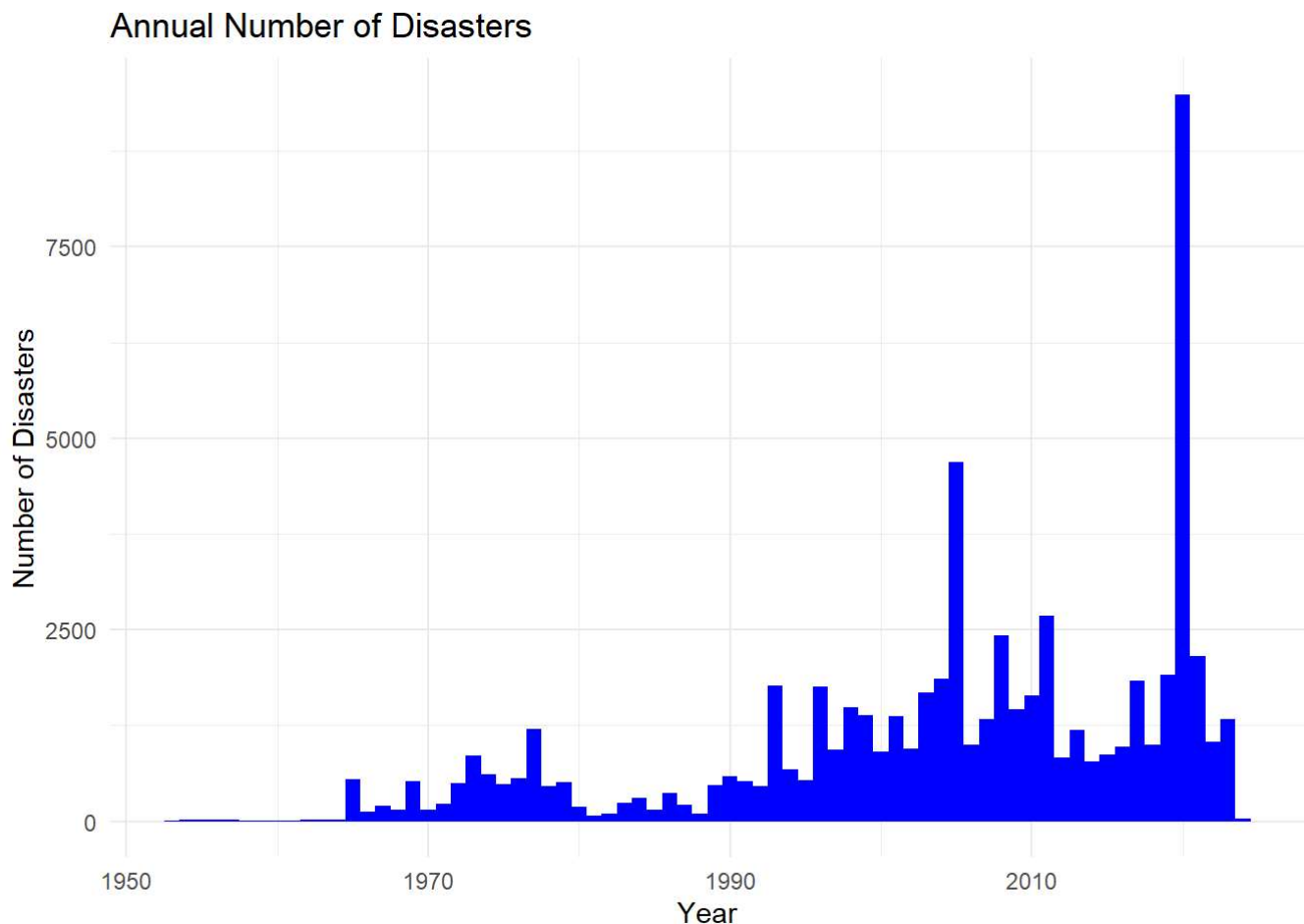
(a) Overall bar chart of disasters over time

```
# Descriptive statistics analysis
disaster_annual_summary <- disaster_declarations_df %>%
  group_by(fyDeclared) %>%
  summarise(
    totalDisasters = n(),
    disasterTypes = list(unique(incidentType))
  )

# Print the number and types of disasters for different years
print(disaster_annual_summary)
```

```
## # A tibble: 72 × 3
##   fyDeclared totalDisasters disasterTypes
##   <dbl>         <int> <list>
## 1     1953             10 <chr [3]>
## 2     1954             14 <chr [5]>
## 3     1955             20 <chr [5]>
## 4     1956             18 <chr [5]>
## 5     1957             18 <chr [5]>
## 6     1958              5 <chr [2]>
## 7     1959              8 <chr [2]>
## 8     1960             13 <chr [7]>
## 9     1961             11 <chr [2]>
## 10    1962             16 <chr [2]>
## # i 62 more rows
```

```
# plot for change of disasters per year
ggplot(disaster_declarations_df, aes(x = fyDeclared)) +
  geom_histogram(binwidth = 1, fill = "blue") +
  theme_minimal() +
  labs(title = "Annual Number of Disasters", x = "Year", y = "Number of Disasters")
```



According to the graph, it can be observed that the distribution of disasters is random and seems to have little to do with the year. However, compared to before and after 1950, the overall trend is still on the rise.

(b) Top 10 States

```
# Financial impact analysis - Distribution of financial assistance by year
financial_annual_summary <- combined_flood_data_aggregated %>%
  left_join(disaster_declarations_df %>% select(disasterNumber, fyDeclared), by = "disasterNumber") %>%
  group_by(fyDeclared) %>%
  summarise(
    totalIhpApproved = sum(totalAmountIhpApproved, na.rm = TRUE),
    totalPaObligated = sum(totalObligatedAmountPa, na.rm = TRUE),
    totalHmgpObligated = sum(totalObligatedAmountHmgp, na.rm = TRUE)
  )

print(financial_annual_summary)
```

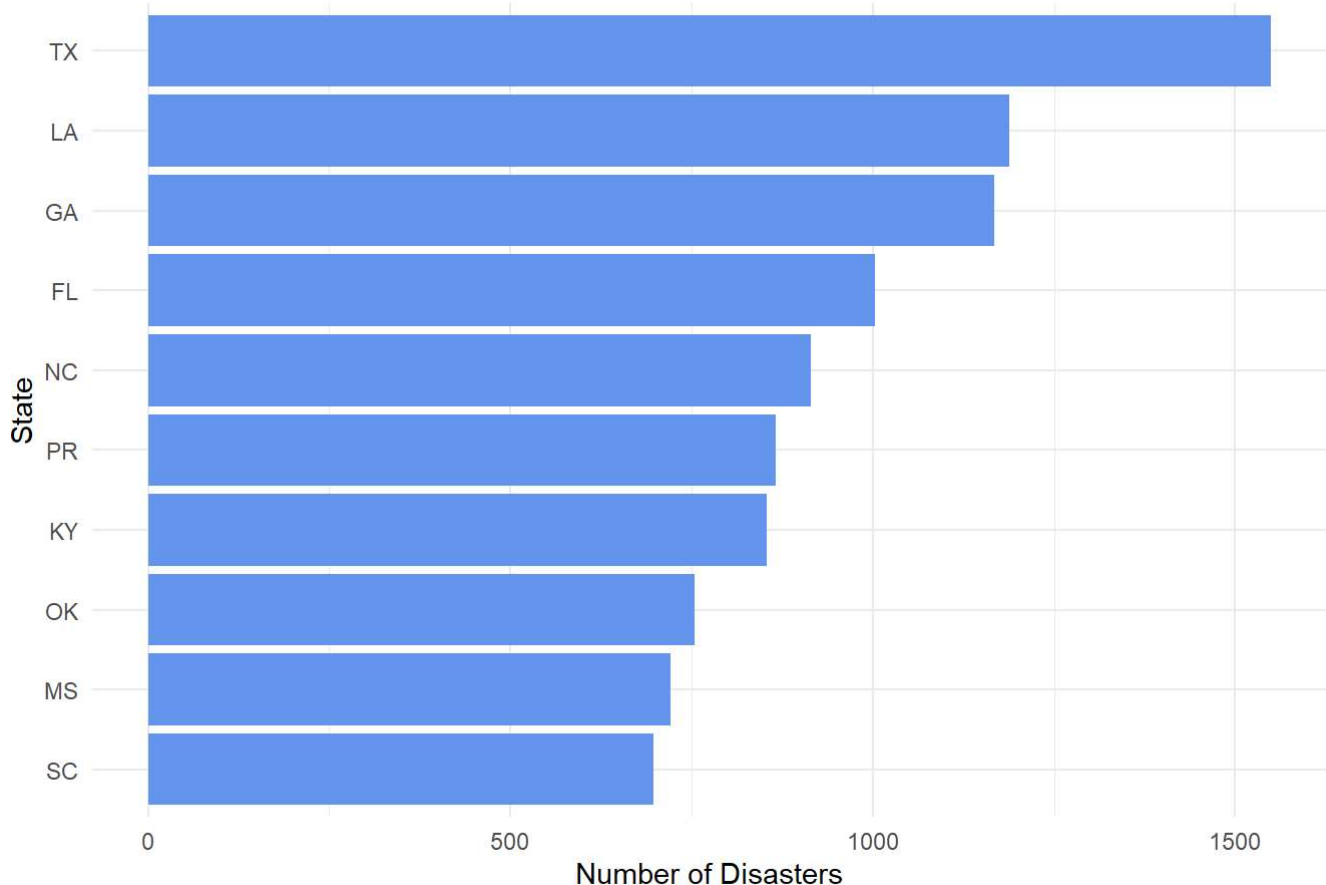
```
## # A tibble: 2 × 4
##   fyDeclared totalIhpApproved totalPaObligated totalHmgpObligated
##   <dbl>         <dbl>         <dbl>         <dbl>
## 1    2020      3446245911.      17056452040.      2601485703.
## 2    2021      26038765454.      224272604234.      20592840986.
```

```
disasters_2014_2024 <- disaster_declarations_df %>%  
  filter(fyDeclared >= 2014, fyDeclared <= 2024)  
  
# Count the number of disasters by state  
state_disaster_counts <- disasters_2014_2024 %>%  
  count(state, sort = TRUE)  
  
top10_states_disasters <- head(state_disaster_counts, 10)  
top10_states_disasters
```

```
## # A tibble: 10 × 2  
##   state      n  
##   <chr> <int>  
## 1 TX      1549  
## 2 LA      1188  
## 3 GA      1168  
## 4 FL      1003  
## 5 NC       914  
## 6 PR       866  
## 7 KY       854  
## 8 OK       754  
## 9 MS       721  
## 10 SC      697
```

```
# Create a bar chart to display the number of disasters for the top 10 states  
ggplot(top10_states_disasters, aes(x = reorder(state, n), y = n)) +  
  geom_bar(stat = "identity", fill = "cornflowerblue") +  
  coord_flip() + # For horizontal bars  
  theme_minimal() +  
  labs(title = "Top 10 States by Disaster Counts (2014-2024)", x = "State", y = "Number of Disasters")
```


Top 10 States by Disaster Counts (2014-2024)



We can obtain the ten continents with the highest number of disasters, which have been presented in the code and table. We can see that the continent with the most disasters in the past decade has been Texas($n=1549$).

(c) Conclusion

This means that these ten continents have the highest number of disasters, and they should strengthen their disaster prevention measures and have increased their financial expenditure on disasters.

3. Population for whom poverty status is determined date cleaning and EDA

3.1 data cleaning and merge the data from 2020 and 2021

```
# Load necessary libraries
library(readr)
library(dplyr)
library(ggplot2)

# Load the 2020 data
data_2020 <- read_csv("/Users/xiaoy/Desktop/615 R/midterm/S1701/ACSST5Y2020.S1701-Data.csv")
```

```
## New names:
## Rows: 3222 Columns: 735
## --- Column specification
## -----
## ----- Delimiter: ", " chr
## (734): GEO_ID, NAME, S1701_C01_001E, S1701_C01_001M, S1701_C01_001MA, S1... 1gl
## (1): ...735
## i Use `spec()` to retrieve the full column specification for this data. i
## Specify the column types or set `show_col_types = FALSE` to quiet this message.
## • `` -> `...735`
```

```
# Select columns and rename for clarity
gender_poverty_2020 <- data_2020 %>%
  select(
    NAME,
    Total_Male_Population = S1701_C01_011E,
    Male_Population_Below_Poverty = S1701_C02_011E,
    Percent_Male_Population_Below_Poverty = S1701_C03_011E,
    Total_Female_Population = S1701_C01_012E,
    Female_Population_Below_Poverty = S1701_C02_012E,
    Percent_Female_Population_Below_Poverty = S1701_C03_012E
  ) %>%
  mutate(
    Total_Male_Population = as.numeric(Total_Male_Population),
    Male_Population_Below_Poverty = as.numeric(Male_Population_Below_Poverty),
    Total_Female_Population = as.numeric(Total_Female_Population),
    Female_Population_Below_Poverty = as.numeric(Female_Population_Below_Poverty)
  ) %>%
  mutate(
    Male_Poverty_Rate = Male_Population_Below_Poverty / Total_Male_Population,
    Female_Poverty_Rate = Female_Population_Below_Poverty / Total_Female_Population
  ) %>%
  na.omit()
```

```
## Warning: There were 4 warnings in `mutate()`.
## The first warning was:
## i In argument: `Total_Male_Population = as.numeric(Total_Male_Population)`.
## Caused by warning:
## ! 强制改变过程中产生了NA
## i Run `dplyr::last_dplyr_warnings()` to see the 3 remaining warnings.
```

```
data_2021 <- read_csv("/Users/xiaoy/Desktop/615 R/midterm/S1701/ACSST5Y2021.S1701-Data.csv")
```

```
## New names:
## Rows: 3222 Columns: 747
## --- Column specification
## -----
## ----- Delimiter: ", " chr
## (746): GEO_ID, NAME, S1701_C01_001E, S1701_C01_001EA, S1701_C01_001M, S1... 1gl
## (1): ...747
## ⓘ Use `spec()` to retrieve the full column specification for this data. ⓘ
## Specify the column types or set `show_col_types = FALSE` to quiet this message.
## • `` -> `...747`
```

```
# Repeat the process for 2021 data
gender_poverty_2021 <- data_2021 %>%
  select(
    NAME,
    Total_Male_Population = S1701_C01_011E,
    Male_Population_Below_Poverty = S1701_C02_011E,
    Percent_Male_Population_Below_Poverty = S1701_C03_011E,
    Total_Female_Population = S1701_C01_012E,
    Female_Population_Below_Poverty = S1701_C02_012E,
    Percent_Female_Population_Below_Poverty = S1701_C03_012E
  ) %>%
  mutate(
    Total_Male_Population = as.numeric(Total_Male_Population),
    Male_Population_Below_Poverty = as.numeric(Male_Population_Below_Poverty),
    Total_Female_Population = as.numeric(Total_Female_Population),
    Female_Population_Below_Poverty = as.numeric(Female_Population_Below_Poverty)
  ) %>%
  mutate(
    Male_Poverty_Rate = Male_Population_Below_Poverty / Total_Male_Population,
    Female_Poverty_Rate = Female_Population_Below_Poverty / Total_Female_Population
  ) %>%
  na.omit()
```

```
## Warning: There were 4 warnings in `mutate()`.
## The first warning was:
## ⓘ In argument: `Total_Male_Population = as.numeric(Total_Male_Population)`.
## Caused by warning:
## ⓘ 强制改变过程中产生了NA
## ⓘ Run `dplyr::last_dplyr_warnings()` to see the 3 remaining warnings.
```

```
# Merge the datasets by NAME
merged_poverty <- left_join(gender_poverty_2020, gender_poverty_2021, by = "NAME", suffix = c(
  "_2020", "_2021"))

head(merged_poverty)
```

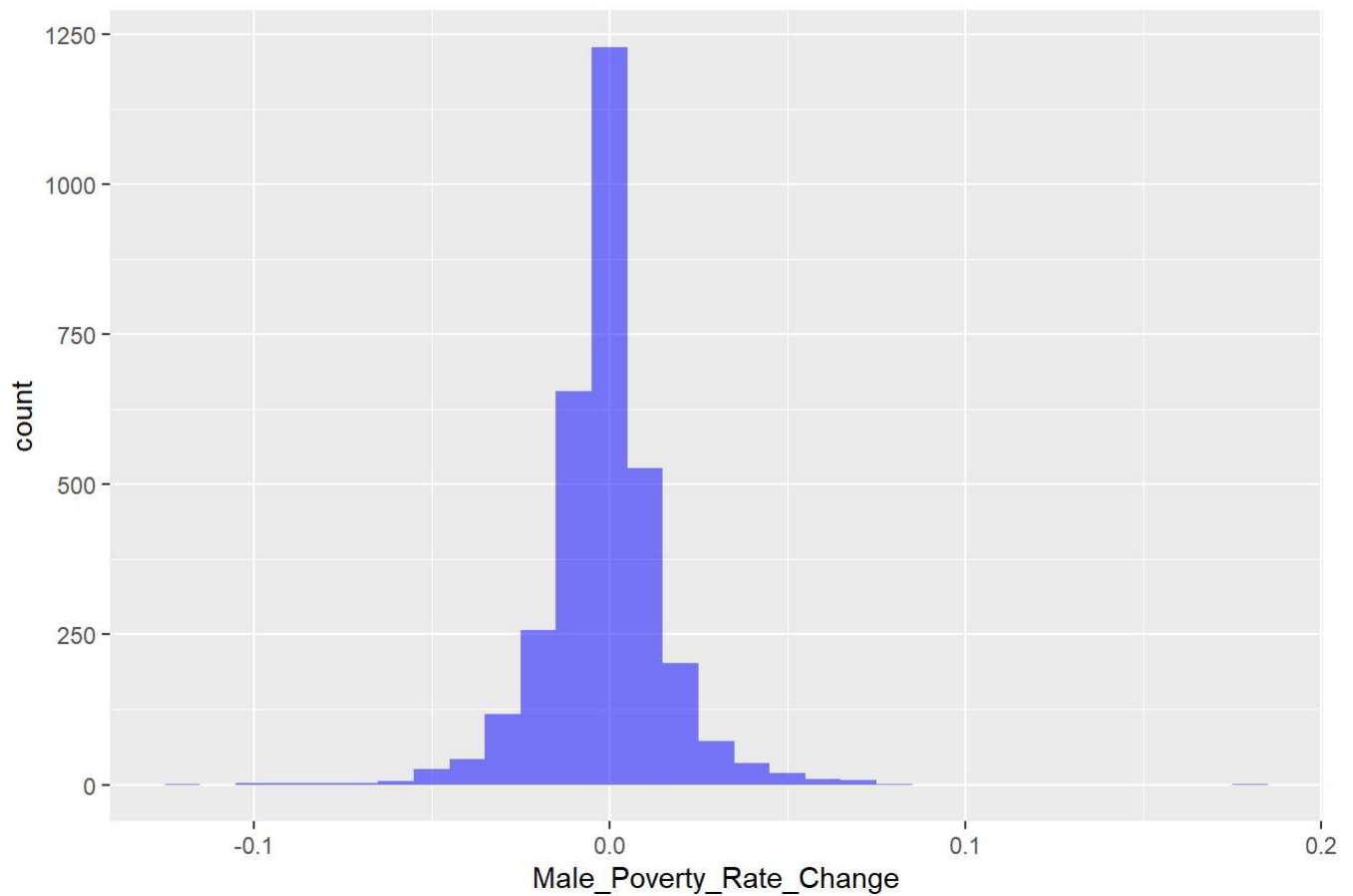
```
## # A tibble: 6 × 17
##   NAME      Total_Male_Population_20201 Male_Population_Below_Poverty_20202 Percent_Male_Population_Below_Poverty_20203
##   <chr>      <dbl>                                <dbl> <chr>
## 1 Autauga    26781                                3417 12.8
## 2 Baldwin  103832                               7803 7.5
## 3 Barbour   10346                                2509 24.3
## 4 Bibb Cou  10507                                1865 17.8
## 5 Blount C   28261                                3278 11.6
## 6 Bullock   5242                                 1355 25.8
## # i abbreviated names: 1Total_Male_Population_2020,
## # 2Male_Population_Below_Poverty_2020,
## # 3Percent_Male_Population_Below_Poverty_2020
## # i 13 more variables: Total_Female_Population_2020 <dbl>,
## #   Female_Population_Below_Poverty_2020 <dbl>,
## #   Percent_Female_Population_Below_Poverty_2020 <chr>,
## #   Male_Poverty_Rate_2020 <dbl>, Female_Poverty_Rate_2020 <dbl>, ...
```

3.2 Explore the sex and year for the poor people distribution

```
# Calculate the change in poverty rate
merged_poverty <- merged_poverty %>%
  mutate(
    Male_Poverty_Rate_Change = Male_Poverty_Rate_2021 - Male_Poverty_Rate_2020,
    Female_Poverty_Rate_Change = Female_Poverty_Rate_2021 - Female_Poverty_Rate_2020
  )

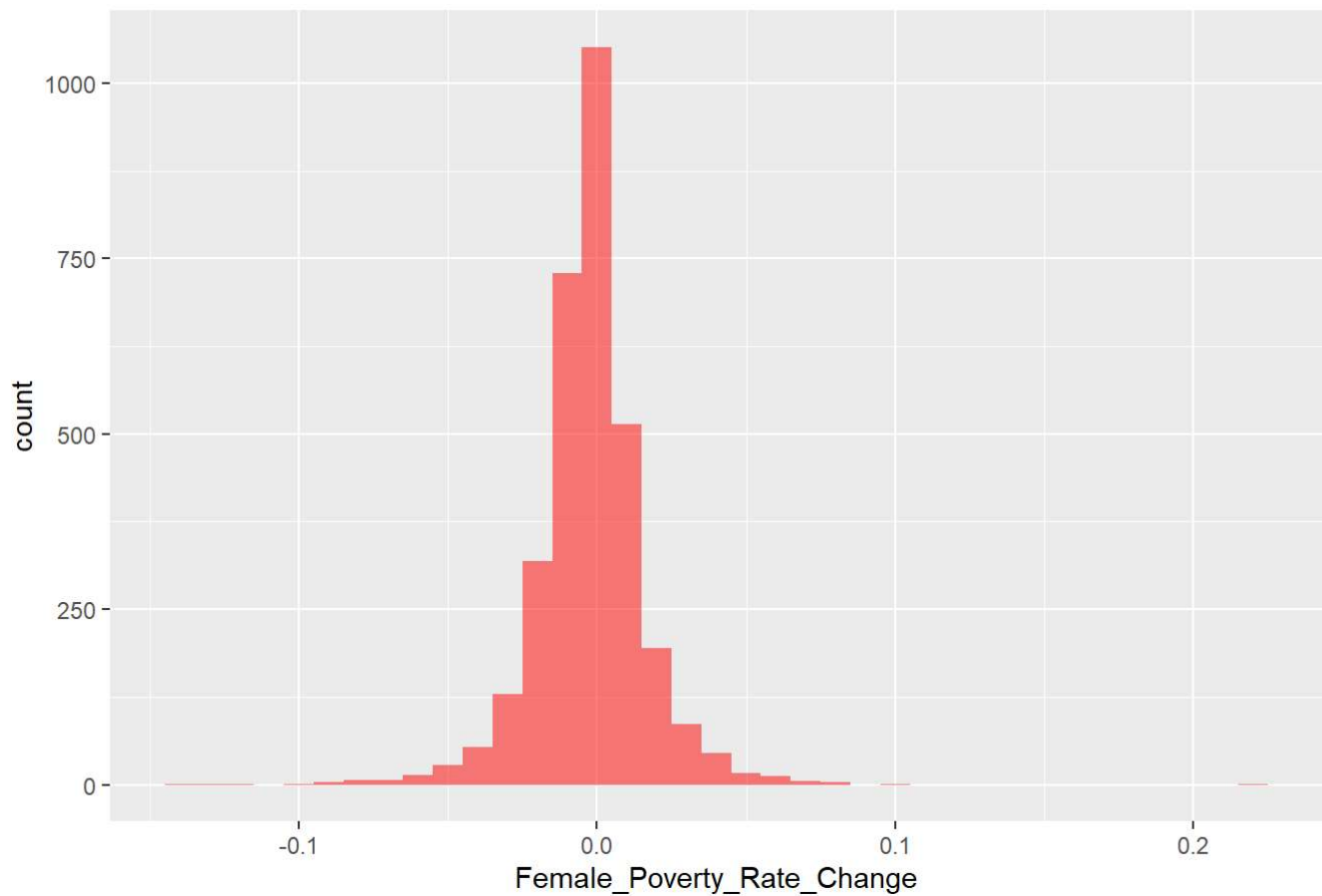
# Histogram of poverty rate change
ggplot(merged_poverty, aes(x = Male_Poverty_Rate_Change)) +
  geom_histogram(binwidth = 0.01, fill = "blue", alpha = 0.5) +
  labs(title = "Histogram of Male Poverty Rate Change 2020-2021")
```

Histogram of Male Poverty Rate Change 2020-2021



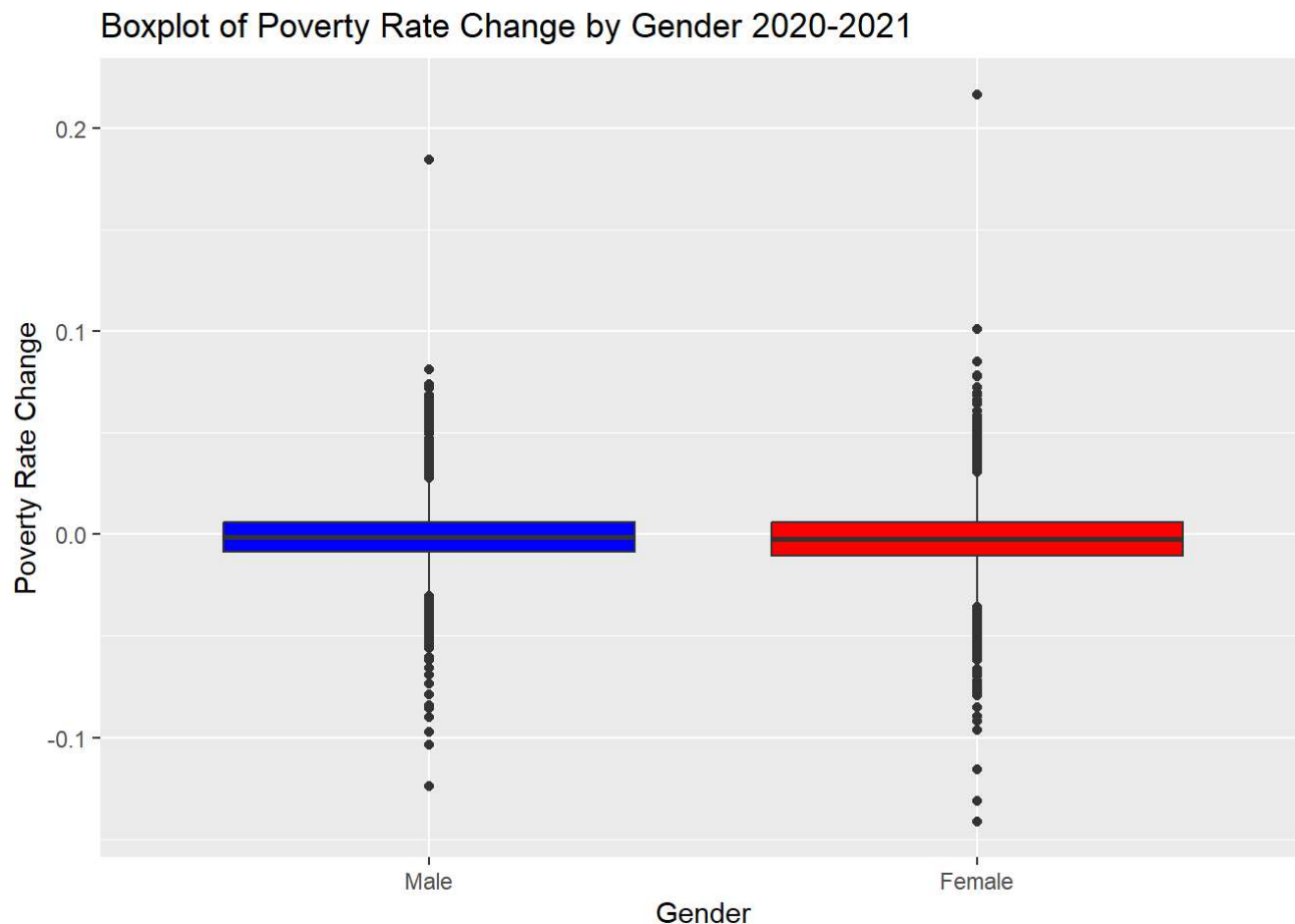
```
ggplot(merged_poverty, aes(x = Female_Poverty_Rate_Change)) +  
  geom_histogram(binwidth = 0.01, fill = "red", alpha = 0.5) +  
  labs(title = "Histogram of Female Poverty Rate Change 2020-2021")
```

Histogram of Female Poverty Rate Change 2020-2021



The histogram shows the distribution of changes in male and female poverty rates from 2020 to 2021.

```
# Boxplot of poverty rate change
ggplot(merged_poverty) +
  geom_boxplot(aes(x = factor(0), y = Male_Poverty_Rate_Change), fill = "blue") +
  geom_boxplot(aes(x = factor(1), y = Female_Poverty_Rate_Change), fill = "red") +
  labs(title = "Boxplot of Poverty Rate Change by Gender 2020-2021") +
  xlab("Gender") +
  ylab("Poverty Rate Change") +
  scale_x_discrete(labels = c("Male", "Female"))
```



The box plot provides more detailed information about the distribution of changes.

3.3 Conclusion

- 1.The histogram of the change in male poverty rate shows that most values are concentrated near zero, which means that for many regions, there is no significant change in male poverty rate.
- 2.The histogram of the change in female poverty rate also shows a similar pattern, but overall, it appears that the downward trend in female poverty rate is more pronounced.
- 3.The median change for both genders is close to zero, indicating that over half of the regions have experienced very small changes in poverty rates.
- 4.The quartile range for women is slightly wider than that for men, indicating that changes in female poverty rates are more dispersed across regions.

4. combine Population for whom poverty and

flooding

4.1 data merge and organization

```
library(tidyverse)
library(readr)

poverty_data_2020_df <- data_2020

# Filter out flood disasters
flood_disasters <- filter(disaster_declarations_df, incidentType == 'Flood')

columns_to_use <- c('NAME', 'S1701_C01_011E', 'S1701_C02_011E', 'S1701_C01_012E', 'S1701_C02_012E')
column_renames <- c('NAME', 'Total_Male_Population', 'Male_Population_Below_Poverty',
                    'Total_Female_Population', 'Female_Population_Below_Poverty')

gender_poverty_df <- poverty_data_2020_df %>%
  select(all_of(columns_to_use)) %>%
  rename_with(~ column_renames) %>%
  drop_na()

# Convert columns to numeric
for (col in column_renames[-1]) {
  gender_poverty_df[[col]] <- as.numeric(gender_poverty_df[[col]])
}
```

```
## Warning: 强制改变过程中产生了NA
```

```
## Warning: 强制改变过程中产生了NA
```

```
## Warning: 强制改变过程中产生了NA
```

```
## Warning: 强制改变过程中产生了NA
```

```
flood_disasters <- flood_disasters %>%
  mutate(County = str_replace(designatedArea, '\\(County\\)', ''),
         State = state)

gender_poverty_df <- gender_poverty_df %>%
  separate(NAME, into = c('County', 'State'), sep = ',', extra = 'merge') %>%
  mutate(County = str_replace(County, ' County', ''))
```

```
## Warning: Expected 2 pieces. Missing pieces filled with `NA` in 1 rows [1].
```



```

# A lookup table for state abbreviations and their full names
state_name_mapping <- data.frame(
  Abbreviation = c("AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DE", "FL", "GA",
    "HI", "ID", "IL", "IN", "IA", "KS", "KY", "LA", "ME", "MD",
    "MA", "MI", "MN", "MS", "MO", "MT", "NE", "NV", "NH", "NJ",
    "NM", "NY", "NC", "ND", "OH", "OK", "OR", "PA", "RI", "SC",
    "SD", "TN", "TX", "UT", "VT", "VA", "WA", "WV", "WI", "WY"),
  FullName = c("Alabama", "Alaska", "Arizona", "Arkansas", "California", "Colorado",
    "Connecticut", "Delaware", "Florida", "Georgia",
    "Hawaii", "Idaho", "Illinois", "Indiana", "Iowa", "Kansas", "Kentucky",
    "Louisiana", "Maine", "Maryland", "Massachusetts", "Michigan", "Minnesota",
    "Mississippi", "Missouri", "Montana", "Nebraska", "Nevada", "New Hampshire",
    "New Jersey", "New Mexico", "New York", "North Carolina", "North Dakota",
    "Ohio", "Oklahoma", "Oregon", "Pennsylvania", "Rhode Island", "South Carolina",
    "South Dakota", "Tennessee", "Texas", "Utah", "Vermont", "Virginia",
    "Washington", "West Virginia", "Wisconsin", "Wyoming")
)

# Assuming flood_disasters is your dataframe and it has a column 'state' with state abbreviations
flood_disasters <- flood_disasters %>%
  left_join(state_name_mapping, by = c("state" = "Abbreviation")) %>%
  select(-state) %>%
  rename(state = FullName)

## Remove the na
gender_poverty_df <- gender_poverty_df[-1, ]
flood_disasters <- flood_disasters[-1, ]

# Merge the datasets

merged_data <- merge(flood_disasters, gender_poverty_df, by.x = c("state", "County"), by.y = c(
  "State", "County"), all.x = TRUE)
## select the cols we need

merged_data <- merged_data %>%
  select(
    County ,
    state,
    Total_Female_Population,
    Total_Male_Population,
    Male_Population_Below_Poverty,
    Female_Population_Below_Poverty
  )

# remove the na
merged_data <- na.omit(merged_data)

head(merged_data)

```

##	County	state	Total_Female_Population	Total_Male_Population
## 2001	Carroll	Iowa	9876	9885
## 2070	Clinton	Iowa	23248	22358
## 3790	Baltimore	Maryland	424925	382754
## 3791	Baltimore	Maryland	424925	382754
## 3792	Baltimore	Maryland	424925	382754
## 5299	St. Louis	Missouri	512126	462482
##	Male_Population_Below_Poverty		Female_Population_Below_Poverty	
## 2001			725	743
## 2070			2719	3512
## 3790			33086	41858
## 3791			33086	41858
## 3792			33086	41858
## 5299			38585	52052

4.2 initial question

What conclusion can you draw by comparing the poverty rate in flood affected areas with the national average poverty rate and the average poverty rate in each state.

4.3 EDA and Solution

```
# Add the total columns to the gender_poverty_df
gender_poverty_df <- gender_poverty_df %>%
  mutate(Total_Population = Total_Male_Population + Total_Female_Population,
         Total_Population_Below_Poverty = Male_Population_Below_Poverty + Female_Population_Below_Poverty)

# Calculate the poverty rate for each county affected by floods
merged_data <- merged_data %>%
  mutate(Total_Population = Total_Male_Population + Total_Female_Population,
         Total_Population_Below_Poverty = Male_Population_Below_Poverty + Female_Population_Below_Poverty,
         Poverty_Rate = Total_Population_Below_Poverty / Total_Population)

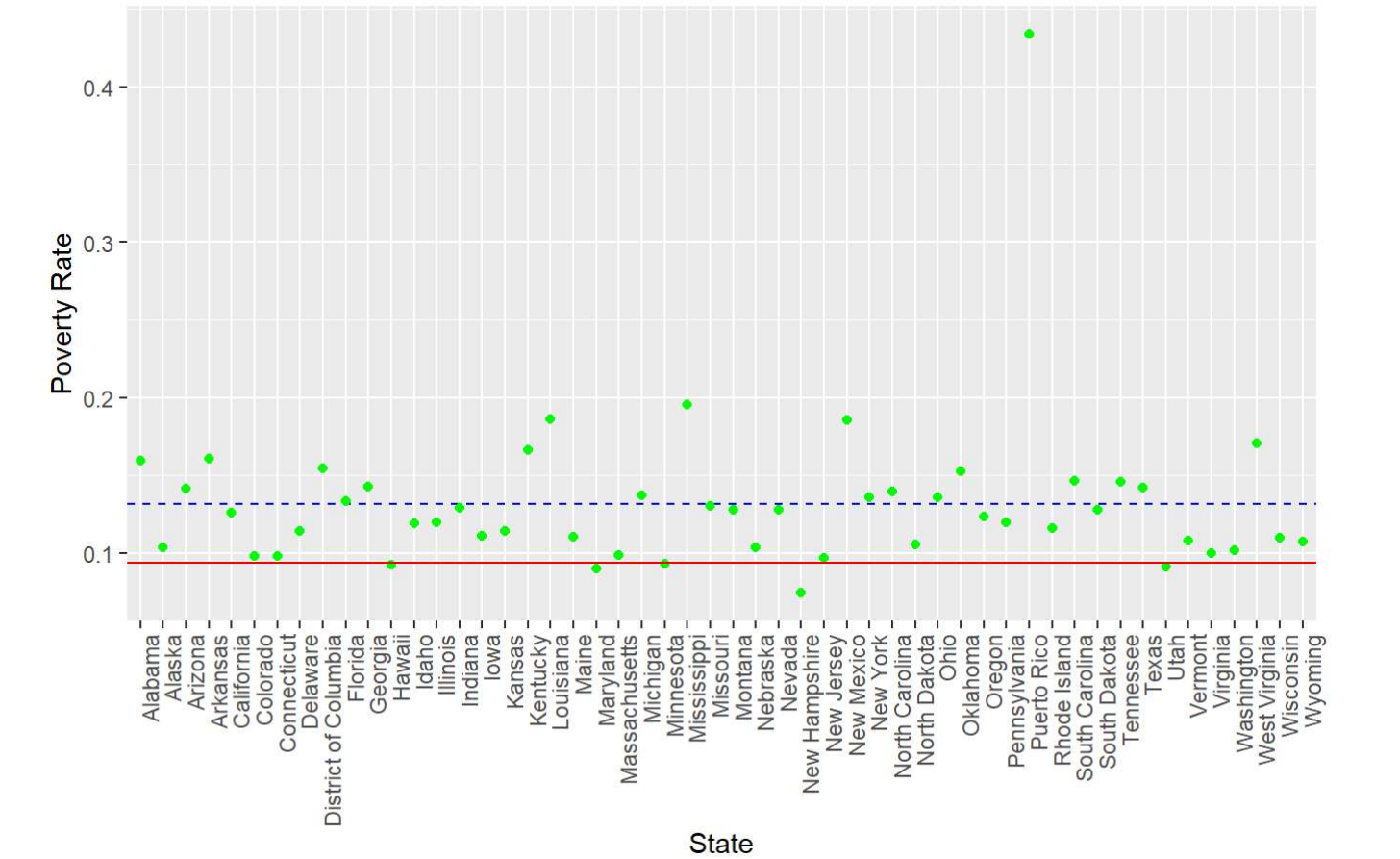
national_average_poverty_rate <- sum(gender_poverty_df$Total_Population_Below_Poverty) /
  sum(gender_poverty_df$Total_Population)

# Calculate the average poverty rate for each state
state_average_poverty_rates <- gender_poverty_df %>%
  group_by(State) %>%
  summarise(Total_Population_Below_Poverty = sum(Total_Population_Below_Poverty),
            Total_Population = sum(Total_Population)) %>%
  mutate(Poverty_Rate = Total_Population_Below_Poverty / Total_Population)

# Calculate the average poverty rate for counties affected by floods
average_poverty_rate_flood_affected <- mean(merged_data$Poverty_Rate)

# Plotting the average poverty rates for comparison
ggplot() +
  geom_hline(yintercept = national_average_poverty_rate, color = 'blue', linetype = 'dashed') +
  geom_point(data = state_average_poverty_rates, aes(x = State, y = Poverty_Rate), color = 'green') +
  geom_hline(yintercept = average_poverty_rate_flood_affected, color = 'red') +
  labs(x = 'State', y = 'Poverty Rate', title = 'Comparison of Poverty Rates: National, State, and Flood Affected Counties') +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```

Comparison of Poverty Rates: National, State, and Flood Affected Counties



In this chart, we can see the following content: 1.The blue dashed line represents the national average poverty rate.

2.The green dots represent the average poverty rate for each state.

3.The solid red line represents the average poverty rate of counties affected by floods.

Conclusion:

We can see that some states have poverty rates far above the national average, while the average poverty rate in flood affected areas is slightly higher than the national average.