Peer-graded Assignment: Course Project 2

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Reproducible Research Course Project 2: Harmful Population Health Impacts and Economic Consequences of US Extreme Weather Events

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Abstract

- In this project, we took data from the Us. National Oceanic and Atmospheric Administration (NOAA) database) that tracks characteristics of major weather events in the United States. Our goal is to determine which types of weather events have the most harmful health impacts to the population and which types of weather events have the greatest economic consequences. Our analysis shows that floods are responsible for the greatest number of fatalities and injuries while hurricanes are responsible for causing the most property damage and crop damage costs.

Introduction

- Storms and other severe weather events can cause both public health and economic problems for communities and municipalities. Many severe events can result in fatalities, injuries, and property damage, and preventing such outcomes to the extent possible is a key concern.
- This project involves exploring the U.S. National Oceanic and Atmospheric Administration's (NOAA) storm database. This database tracks characteristics of major storms and weather events in the United States, including when and where they occur, as well as estimates of any fatalities, injuries, and property damage.

Data

- The data for this assignment come in the form of a comma-separated-value file compressed via the bzip2 algorithm to reduce its size. The data was downloaded using this link from the course website:
  - Storm Data [47Mb]

- There is also some documentation of the database available. Here you will find how some of the variables are constructed/defined.
  - National Weather Service Storm Data Documentation
  - National Climatic Data Center Storm Events FAQ
- The events in the database start in the year 1950 and end in November 2011. In the earlier years of the database there are generally fewer events recorded, most likely due to a lack of good records. More recent years should be considered more complete.

Questions

Our data analysis addresses the following questions:

1. Across the United States, which types of events (as indicated in the EVTYPE variable) are most harmful with respect to population health?
2. Across the United States, which types of events have the greatest economic consequences?

Data Processing

```
library(dplyr)
```

1. Load packages used in this analysis.

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.3.1

## Warning: package 'readr' was built under R version 4.3.1

## Warning: package 'forcats' was built under R version 4.3.1
```

```
## Warning: package 'lubridate' was built under R version 4.3.1

## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v forcats   1.0.0     v readr     2.1.4
## v ggplot2   3.4.2     v stringr   1.5.0
## v lubridate 1.9.2     v tibble    3.2.1
## v purrr     1.0.1     v tidyr     1.3.0

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(ggplot2)
```

2. Load the data

- Download the compressed data file using the URL from the course website. Then use `read.csv` to load the data into our workspace.

```r
dataURL <- "https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2"

download.file("https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2", "StormData.csv

Storm_Data <- read.csv("StormData.csv.bz2", header = TRUE,
                       sep = ",")
```

3. Display dataset summary

- Use `str(Storm_Data)` to display a summary of the dataset. The first line of output shows how many rows and columns this dataset has.

```r
str(Storm_Data)
```

```
## 'data.frame':    902297 obs. of  37 variables:
##  $ STATE__   : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ BGN_DATE  : chr  "4/18/1950 0:00:00" "4/18/1950 0:00:00" "2/20/1951 0:00:00" "6/8/1951 0:00:00" .
##  $ BGN_TIME  : chr  "0130" "0145" "1600" "0900" ...
##  $ TIME_ZONE : chr  "CST" "CST" "CST" "CST" ...
##  $ COUNTY    : num  97 3 57 89 43 77 9 123 125 57 ...
##  $ COUNTYNAME: chr  "MOBILE" "BALDWIN" "FAYETTE" "MADISON" ...
##  $ STATE     : chr  "AL" "AL" "AL" "AL" ...
##  $ EVTYPE    : chr  "TORNADO" "TORNADO" "TORNADO" "TORNADO" ...
##  $ BGN_RANGE : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ BGN_AZI   : chr  "" "" "" "" ...
##  $ BGN_LOCATI: chr  "" "" "" "" ...
##  $ END_DATE  : chr  "" "" "" "" ...
##  $ END_TIME  : chr  "" "" "" "" ...
##  $ COUNTY_END: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ COUNTYENDN: logi  NA NA NA NA NA NA ...
```

```
##  $ END_RANGE : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ END_AZI   : chr  "" "" "" "" ...
##  $ END_LOCATI: chr  "" "" "" "" ...
##  $ LENGTH    : num  14 2 0.1 0 0 1.5 1.5 0 3.3 2.3 ...
##  $ WIDTH     : num  100 150 123 100 150 177 33 33 100 100 ...
##  $ F         : int  3 2 2 2 2 2 2 1 3 3 ...
##  $ MAG       : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ FATALITIES: num  0 0 0 0 0 0 0 0 1 0 ...
##  $ INJURIES  : num  15 0 2 2 2 6 1 0 14 0 ...
##  $ PROPDMG   : num  25 2.5 25 2.5 2.5 2.5 2.5 2.5 25 25 ...
##  $ PROPDMGEXP: chr  "K" "K" "K" "K" ...
##  $ CROPDMG   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ CROPDMGEXP: chr  "" "" "" "" ...
##  $ WFO       : chr  "" "" "" "" ...
##  $ STATEOFFIC: chr  "" "" "" "" ...
##  $ ZONENAMES : chr  "" "" "" "" ...
##  $ LATITUDE  : num  3040 3042 3340 3458 3412 ...
##  $ LONGITUDE : num  8812 8755 8742 8626 8642 ...
##  $ LATITUDE_E: num  3051 0 0 0 0 ...
##  $ LONGITUDE_: num  8806 0 0 0 0 ...
##  $ REMARKS   : chr  "" "" "" "" ...
##  $ REFNUM    : num  1 2 3 4 5 6 7 8 9 10 ...
```

4. Create Subset of Data

- To answer our questions, we only need columns related to event types and their health and economic impacts, not all 37 columns will be used. Our data analysis will be limited to the following columns. Column name is in bold and description is in normal text. Column descriptions were taken from National Weather Storm Data Documentation.
  - **EVTYPE**: type of weather event
  - **FATALITIES**: fatalities due to weather even
  - **INJURIES**: injuries due to weather event
  - **PROPDMG**: property damage due to weather event
  - **PROPDMGEXP**: multiplier for property damage (B = billions, K = thousands, M = millions)
  - **CROPDMG**: crop damage due to weather event
  - **CROPDMGEXP**: multiplier for crop damage (B = billions, K = thousands, M = millions)

```r
Storm_Data_subset <- c("EVTYPE", "FATALITIES", "INJURIES",
                       "PROPDMG", "PROPDMGEXP", "CROPDMG",
                       "CROPDMGEXP")
Storm_Data2 <- Storm_Data[, Storm_Data_subset]
summary(Storm_Data2)
```

```
##     EVTYPE            FATALITIES          INJURIES            PROPDMG       
##  Length:902297      Min.   :  0.0000   Min.   :   0.0000   Min.   :   0.00  
##  Class :character   1st Qu.:  0.0000   1st Qu.:   0.0000   1st Qu.:   0.00  
##  Mode  :character   Median :  0.0000   Median :   0.0000   Median :   0.00  
##                     Mean   :  0.0168   Mean   :   0.1557   Mean   :  12.06  
##                     3rd Qu.:  0.0000   3rd Qu.:   0.0000   3rd Qu.:   0.50  
##                     Max.   :583.0000   Max.   :1700.0000   Max.   :5000.00  
```

```
##   PROPDMGEXP           CROPDMG         CROPDMGEXP
##  Length:902297      Min.   :  0.000   Length:902297
##  Class :character   1st Qu.:  0.000   Class :character
##  Mode  :character   Median :  0.000   Mode  :character
##                     Mean   :  1.527
##                     3rd Qu.:  0.000
##                     Max.   :990.000
```

- We further subset our data to include only rows where fatalities, injuries, property damages, or crop damages are present.

```
Storm_Data3 <- Storm_Data2 %>%
  filter(FATALITIES > 0, INJURIES > 0, CROPDMG > 0, PROPDMG > 0)
```

5. Determine total costs of property damage and crop damage per event type

- Multiply PROPDMG and CROPDMG by their respective exponent columns to get the cost columns PROPDMG_COST and CROPDMG_COST.

```
Storm_Data3[Storm_Data3 == "B"] <- 10^9
Storm_Data3[Storm_Data3 == "K"] <- 10^3
Storm_Data3[Storm_Data3 == "M"] <- 10^6
Storm_Data3$PROPDMGEXP <- as.numeric(Storm_Data3$PROPDMGEXP)
Storm_Data3$CROPDMGEXP <- as.numeric(Storm_Data3$CROPDMGEXP)

Storm_Data4 <- Storm_Data3 %>%
  mutate(PROPDMG_COST = PROPDMG * PROPDMGEXP) %>%
  mutate(CROPDMG_COST = CROPDMG * CROPDMGEXP)


Storm_Data5 <- Storm_Data4[, c("EVTYPE", "FATALITIES",
                               "INJURIES", "PROPDMG_COST",
                               "CROPDMG_COST")]
```

- Use `group_by()` and `summarize_each()` from the *dplyr* library to find the values for each variable by event type.

```
Storm_Data6 <- Storm_Data5 %>%
  group_by(EVTYPE) %>%
  summarize(across(c(FATALITIES, INJURIES, PROPDMG_COST,
                     CROPDMG_COST), sum))
```

6. Further clean dataset by EVTYPE At this time, our dataset has 23 unique EVTYPEs. A closer look at the EVTYPE column shows that some of our weather event types are still repeated due to slight variations between EVTYPE names (ex. “FLASH FLOOD” and “FLOOD”).

```
unique(Storm_Data6$EVTYPE)
```

```
##  [1] "BLIZZARD"                "EXCESSIVE HEAT"
##  [3] "FLASH FLOOD"             "FLOOD"
```

```
##  [5] "HEAT"                       "HEAT WAVE DROUGHT"
##  [7] "HEAVY SNOW"                 "HIGH WIND"
##  [9] "HIGH WINDS"                 "HURRICANE"
## [11] "HURRICANE/TYPHOON"          "ICE STORM"
## [13] "THUNDERSTORM WIND"          "THUNDERSTORM WINDS"
## [15] "TORNADO"                    "TROPICAL STORM"
## [17] "TROPICAL STORM GORDON"      "TSTM WIND"
## [19] "TSUNAMI"                    "WILDFIRE"
## [21] "WINTER STORM"               "WINTER STORM HIGH WINDS"
## [23] "WINTER STORMS"
```

Similar EVTYPE values were condensed into categories to simplify analysis. This further reduced our unique EVTYPEs from 23 to 10

```r
# Combine similar EVTYPE values
Storm_Data6$EVTYPE <- gsub("BLIZZARD", "WINTER STORM",
                           Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("EXCESSIVE HEAT", "HEAT",
                          Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("FLASH FLOOD", "FLOOD",
                           Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("HEAT WAVE DROUGHT", "HEAT",
                           Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("HEAVY SNOW", "WINTER STORM",
                           Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("HIGH WINDS", "HIGH WIND",
                           Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("HURRICANE/TYPHOON", "HURRICANE",
                           Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("ICE STORM", "WINTER STORM",
                           Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("THUNDERSTORM WINDS", "THUNDERSTORM",                                    Storm_Data6
Storm_Data6$EVTYPE <- gsub("THUNDERSTORM WIND", "THUNDERSTORM",                                   Storm_Data6$
Storm_Data6$EVTYPE <- gsub("TROPICAL STORM GORDON",
                           "TROPICAL STORM", Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("TSTM WIND", "THUNDERSTORM",
                           Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("WINTER STORM HIGH WIND",
                           "WINTER STORM", Storm_Data6$EVTYPE)
Storm_Data6$EVTYPE <- gsub("WINTER STORMS", "WINTER STORM",
                           Storm_Data6$EVTYPE)
```

- Use `group_by()` and `summarize_each()` from the *dplyr* library to find the values for each variable by event type.

```r
Storm_Data7 <- Storm_Data6 %>%
  group_by(EVTYPE) %>%
  summarize(across(c(FATALITIES, INJURIES, PROPDMG_COST,
                     CROPDMG_COST), sum))
```

ANALYSIS

1. Estimate the total health impact (fatalities and injuries) of each event type

- For each event type, find the sum of fatalities and injuries to find the total health impact on the population. Sort the results in descending order by total health impact.

```
Storm_Data8 <- Storm_Data7 %>%
  mutate(TotalHealthImpact = FATALITIES + INJURIES)


Storm_Data_Health <- Storm_Data8[, c("EVTYPE", "FATALITIES",
                                     "INJURIES",
                                     "TotalHealthImpact")] %>%
  arrange(desc(TotalHealthImpact))
```

2. Estimate the total economic cost (property and crop damage) of each event type

- For each event type, find the sum of property and crop damage to find the total economic cost. Sort the results in descending order by total economic cost.

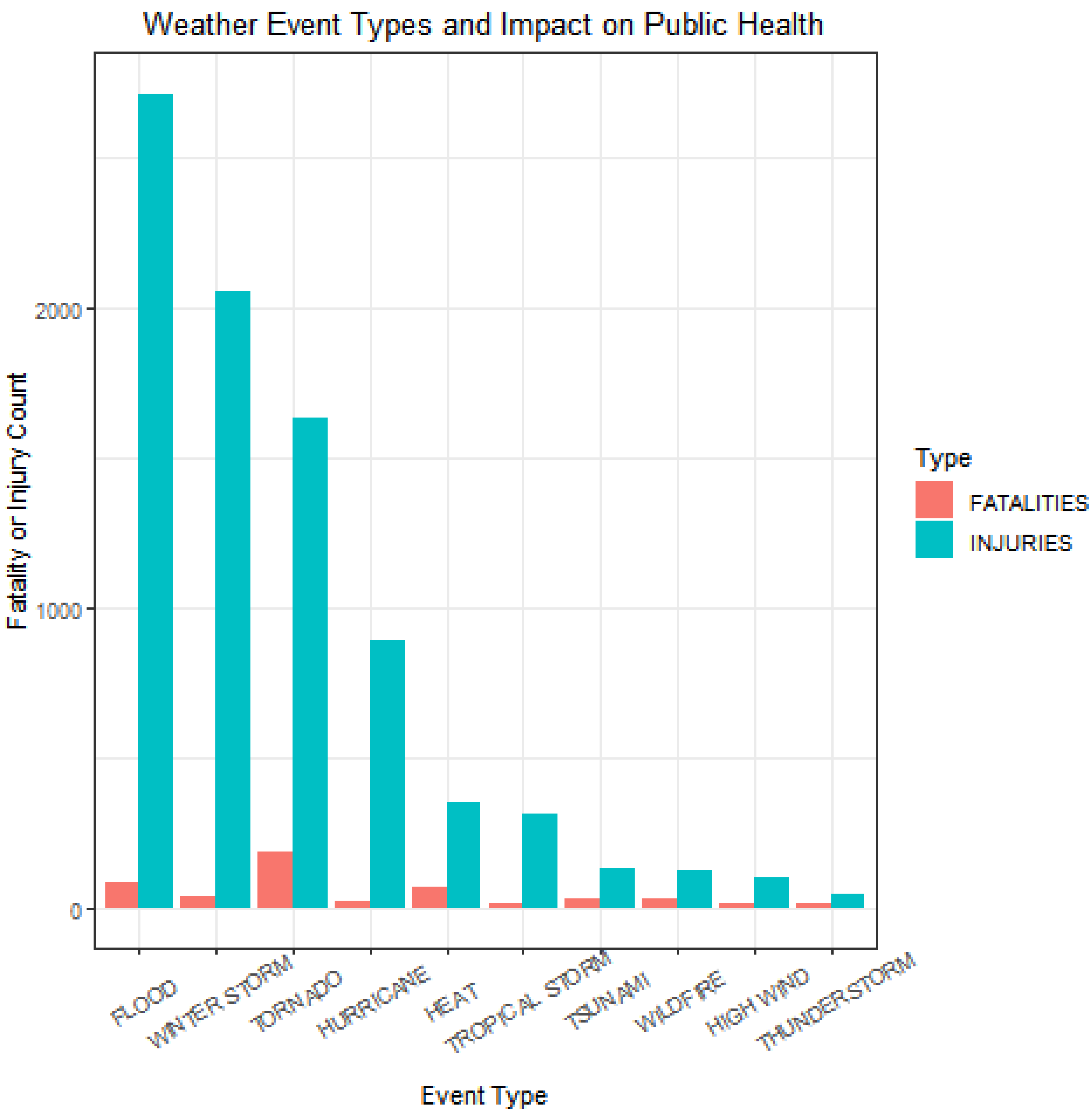
```
Storm_Data9 <- Storm_Data7 %>%
  mutate(TotalEconomicCost = PROPDMG_COST + CROPDMG_COST)

Storm_Data_Economic <- Storm_Data9[, c("EVTYPE",
                                       "CROPDMG_COST",
                                       "PROPDMG_COST",
                                       "TotalEconomicCost")] %>%
  arrange(desc(TotalEconomicCost))
```

Results

1. Event Types Most Harmful to Population Health

- The results below show the 10 most harmful weather events in terms of population health in the U.S., as measured by fatalities and injuries. **FLOOD events show the greatest health impact.**




```
# Transform EVTYPE to a factor variable
Storm_Data_Health$EVTYPE <- as.factor(Storm_Data_Health$EVTYPE)

Storm_Data_Health2 <- Storm_Data_Health %>%
  gather(Type, value = Impact, 2:3)


png("health_plot.png")
health_plot <- ggplot(Storm_Data_Health2,
                      aes(x = reorder(EVTYPE,
                                      -TotalHealthImpact),
                          y = TotalHealthImpact,
                          fill = Type)) +
  geom_col(aes(x = reorder(EVTYPE, -TotalHealthImpact),
               y = Impact), position = "dodge") +
```

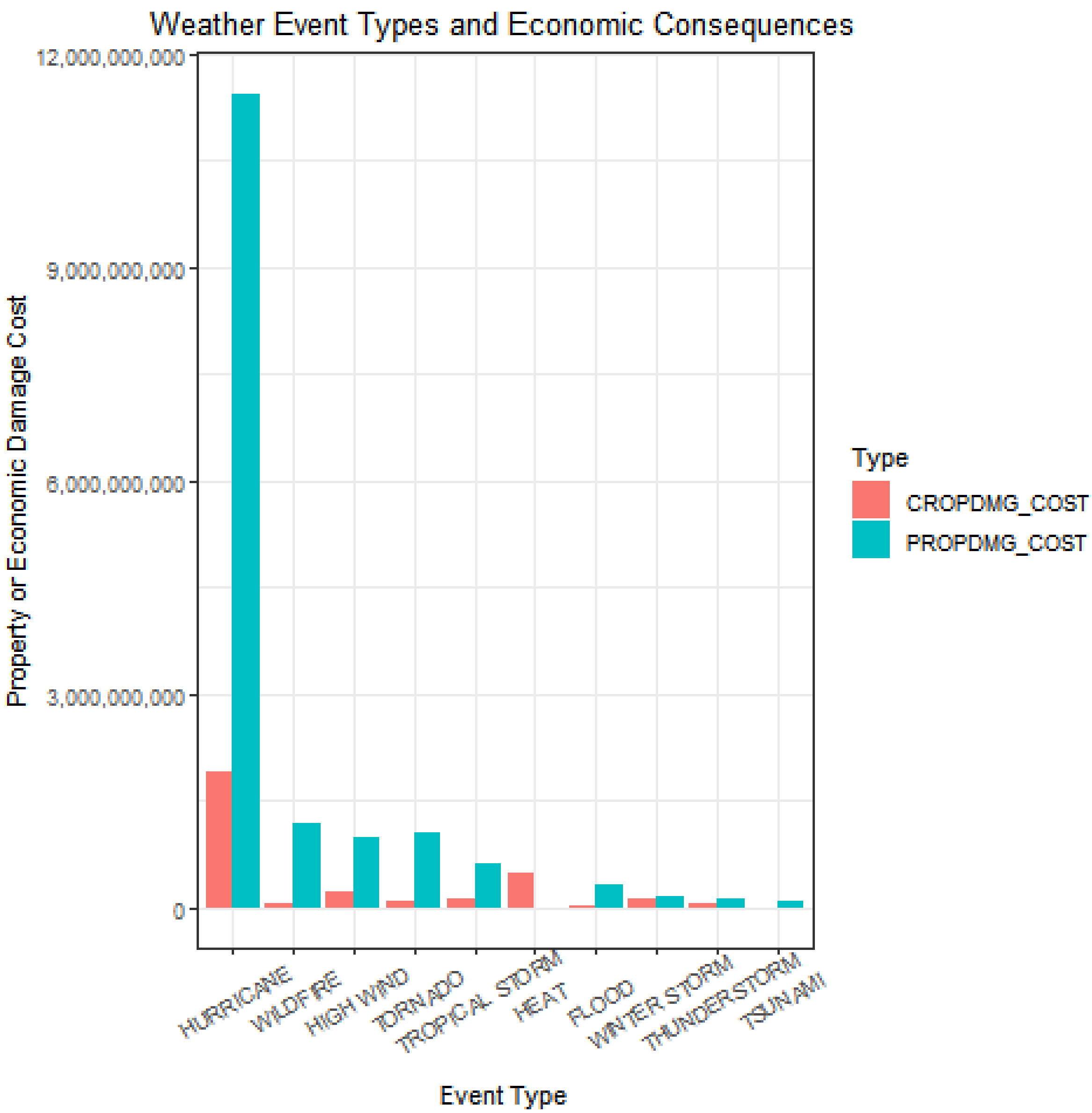
```
  labs(x= "Event Type", y = "Fatality or Injury Count") +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 30, vjust=0.7)) +
  ggtitle("Weather Event Types and Impact on Public Health") +
  theme(plot.title = element_text(hjust = 0.5))

print(health_plot)
dev.off()
```

```
## pdf
##   2
```

2. Event Types with the Greatest Economic Consequences

- The results below show the 10 weather events with the greatest economic consequences events in the U.S., as measured by crop damage costs (CROPDMG_COST) and property damage costs (PROPDMG_COST). **Hurricane events show the greatest cost in both categories.**




```r
# Transform EVTYPE to a factor variable
Storm_Data_Economic$EVTYPE <- as.factor(
  Storm_Data_Economic$EVTYPE)

Storm_Data_Economic2 <- Storm_Data_Economic %>%
  gather(Type, value = Cost, 2:3)


png("economic_plot.png")
economic_plot <- ggplot(Storm_Data_Economic2,
                      aes(x = reorder(EVTYPE,
                                      -TotalEconomicCost),
                          y = TotalEconomicCost,
                          fill = Type)) +
  geom_col(aes(x = reorder(EVTYPE, -TotalEconomicCost),
```

```
                y = Cost), position = "dodge") +
  labs(x= "Event Type",
       y = "Property or Economic Damage Cost") +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 30, vjust=0.7)) +
  ggtitle("Weather Event Types and Economic Consequences") +
  theme(plot.title = element_text(hjust = 0.5)) +
  scale_y_continuous(labels = scales::comma)

print(economic_plot)
dev.off()
```

```
## pdf
##   2
```

Conclusion

Based on the evidence demonstrated in this analysis and supported by the included data and graphs, the following conclusions can be drawn:

1. **Across the United States, which types of events (as indicated in the EVTYPE variable) are most harmful with respect to population health?**

    - Floods are responsible for the greatest number of fatalities and injuries.

2. **Across the United States, which types of events have the greatest economic consequences?**

    - Hurricanes are responsible for causing the most property damage and crop damage costs.