

Severe Weather Events and their effects

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Synopsis

In this report we look at data from the NOAA storm database and answer two questions

- 1) Across the United States, which types of events (as indicated by 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?

Brief description of the database

- 1) The events in the database start in the year 1950 and end in November 2019. 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.
- 2) The data is obtained from the National Weather Service and is published by the National Oceanic and Atmospheric Administration (NOAA) in an attempt to record the occurrence of weather phenomena of sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce

Loading and processing the raw data

The data for this report is a part of the [Storm Events Database] (<https://www.ncdc.noaa.gov/stormevents/>)

The file for our purposes is a comma-separated-value file compressed with bzip2. We will be using the data gathered from 1950 to Nov 2011 for our analysis.

```
library(dplyr)
```

```
##
## 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(ggplot2)
```

```
## Registered S3 methods overwritten by 'ggplot2':
##   method      from
##   [.quosures   rlang
##   c.quosures   rlang
##   print.quosures rlang
```

```
if(!file.exists("StormData.csv.bz2")){
  download.file("https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2",
               "StormData.csv.bz2")
}
```

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

We can now look at the dataset

```
dim(Stormdata)
```

```
## [1] 902297      37
```

```
head(Stormdata)
```

```
##   STATE__      BGN_DATE BGN_TIME TIME_ZONE COUNTY COUNTYNAME STATE
## 1      1 4/18/1950 0:00:00    0130      CST    97    MOBILE    AL
## 2      1 4/18/1950 0:00:00    0145      CST     3    BALDWIN   AL
## 3      1 2/20/1951 0:00:00    1600      CST    57    FAYETTE   AL
## 4      1 6/8/1951 0:00:00    0900      CST    89    MADISON   AL
## 5      1 11/15/1951 0:00:00    1500      CST    43    CULLMAN   AL
## 6      1 11/15/1951 0:00:00    2000      CST    77 LAUDERDALE AL
##   EVTYPE BGN_RANGE BGN_AZI BGN_LOCATI END_DATE END_TIME COUNTY_END
## 1 TORNADO      0          0          0          0          0
## 2 TORNADO      0          0          0          0          0
## 3 TORNADO      0          0          0          0          0
## 4 TORNADO      0          0          0          0          0
## 5 TORNADO      0          0          0          0          0
## 6 TORNADO      0          0          0          0          0
##   COUNTYENDN END_RANGE END_AZI END_LOCATI LENGTH WIDTH F MAG FATALITIES
## 1      NA      0          0          0      14.0  100 3   0          0
## 2      NA      0          0          0       2.0  150 2   0          0
## 3      NA      0          0          0       0.1  123 2   0          0
## 4      NA      0          0          0       0.0  100 2   0          0
## 5      NA      0          0          0       0.0  150 2   0          0
## 6      NA      0          0          0       1.5  177 2   0          0
##   INJURIES PROPDGM PROPDMGEXP CROPDGM CROPDMGEXP WFO STATEOFFIC ZONENAMES
## 1      15     25.0          K      0
## 2       0      2.5          K      0
## 3       2     25.0          K      0
## 4       2      2.5          K      0
## 5       2      2.5          K      0
## 6       6      2.5          K      0
##   LATITUDE LONGITUDE LATITUDE_E LONGITUDE_ REMARKS REFNUM
## 1     3040      8812      3051      8806          1
## 2     3042      8755          0          0          2
## 3     3340      8742          0          0          3
## 4     3458      8626          0          0          4
## 5     3412      8642          0          0          5
## 6     3450      8748          0          0          6
```

```
str(Stormdata)
```

```
## 'data.frame':    902297 obs. of  37 variables:
##  $ STATE__      : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ BGN_DATE      : Factor w/ 16335 levels "1/1/1966 0:00:00",...: 6523 6523 4242 11116 2224 2224 2260 383
##  $ BGN_TIME      : Factor w/ 3608 levels "00:00:00 AM",...: 272 287 2705 1683 2584 3186 242 1683 3186 318
##  $ TIME_ZONE     : Factor w/ 22 levels "ADT","AKS","AST",...: 7 7 7 7 7 7 7 7 7 7 ...
##  $ COUNTY        : num  97 3 57 89 43 77 9 123 125 57 ...
##  $ COUNTYNAME    : Factor w/ 29601 levels "", "5NM E OF MACKINAC BRIDGE TO PRESQUE ISLE LT MI",...: 13513
##  $ STATE         : Factor w/ 72 levels "AK","AL","AM",...: 2 2 2 2 2 2 2 2 2 2 ...
##  $ EVTYPE        : Factor w/ 985 levels " HIGH SURF ADVISORY",...: 834 834 834 834 834 834 834 834 834 834
##  $ BGN_RANGE     : num  0 0 0 0 0 0 0 0 0 0 ...
```

```
## $ BGN_AZI : Factor w/ 35 levels "", " N", " NW",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ BGN_LOCATI: Factor w/ 54429 levels "", "- 1 N Albion",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ END_DATE : Factor w/ 6663 levels "", "1/1/1993 0:00:00",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ END_TIME : Factor w/ 3647 levels "", " 0900CST",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ 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 : Factor w/ 24 levels "", "E", "ENE", "ESE",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ END_LOCATI: Factor w/ 34506 levels "", "- .5 NNW",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ 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 ...
## $ PROPDGMG : num 25 2.5 25 2.5 2.5 2.5 2.5 2.5 25 25 ...
## $ PROPDMGEXP: Factor w/ 19 levels "", "-","?", "+",...: 17 17 17 17 17 17 17 17 17 17 ...
## $ CROPDMG : num 0 0 0 0 0 0 0 0 0 0 ...
## $ CROPDMGEXP: Factor w/ 9 levels "", "?", "0", "2",...: 1 1 1 1 1 1 1 1 1 ...
## $ WFO : Factor w/ 542 levels "", " CI", "$AC",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ STATEOFFIC: Factor w/ 250 levels "", "ALABAMA, Central",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ ZONENAMES : Factor w/ 25112 levels "", "
## $ 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 : Factor w/ 436781 levels "", "-2 at Deer Park\n",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ REFNUM : num 1 2 3 4 5 6 7 8 9 10 ...
```

We can now subset the table with the parameters that we would like to look at. EVTYPE,F,MAG,FATALITIES,INJURIES,PRO and CROPDMGEXP

```
Stormdata_subset <- Stormdata[,c("EVTYPE", "F", "MAG", "FATALITIES", "INJURIES",
                                "PROPDMG", "PROPDMGEXP", "CROPDMG", "CROPDMGEXP")]
```

As mentioned in [National Weather Service Storm Data Documentation] (https://d396qusza40orc.cloudfront.net/repdata%2Fpeer2_doc%2Fpd01016005curr.pdf) the value K corresponds to thousand, M for a million and B for a billion and these valid qualifiers are found in PROPDMGEXP and CROPDMGEXP. To make it less confusing and for initial analysis, we have created a new column total damage with the crop and property damage added and listed together. This was done by creating a function total damage which takes as its arguments PROPDMG,PROPDMGEXP, CROPDMG and CROPDMGEXP.

```
total_damage <- function(prop_dmg,prop_exp,crop_dmg,crop_exp){
  propdam <- 0
  cropdam <- 0

  if (prop_dmg > 0){
    if (tolower(prop_exp) == "h")
      propdam <- prop_dmg * 0
    if (tolower(prop_exp) == "k")
      propdam <- prop_dmg * 1000
    if (tolower(prop_exp) == "m")
      propdam <- prop_dmg * 1000000
    if (tolower(prop_exp) == "b")
      propdam <- prop_dmg * 1000000000
  }
}
```

```

if (crop_dmg > 0){
  if (tolower(crop_exp) == "h")
    propdam <- crop_dmg * 0
  if (tolower(crop_exp) == "k")
    propdam <- crop_dmg * 1000
  if (tolower(crop_exp) == "m")
    propdam <- crop_dmg * 1000000
  if (tolower(crop_exp) == "b")
    propdam <- crop_dmg * 1000000000
}
return(propdam+cropdam)
}
Stormdata_subset$Totaldam <- mapply(total_damage,Stormdata_subset$PROPDMG,Stormdata_subset$PROPDMGEXP,
                                     Stormdata_subset$CROPDMG,Stormdata_subset$CROPDMGEXP)

```

Results

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

To do this, we first subset the data based on weather pattern and then calculate the sum of injuries/fatalities for the respective patterns. This is put forth in the form of a table and figure for the 10 most harmful weather patterns (since there is too many to show them all).

```

injuries <- Stormdata_subset %>% group_by(EVTYPE)%>%
  summarise(injuries = sum(INJURIES,na.rm = TRUE)) %>% as.data.frame() %>% rename(Weather_pattern=EVTYPE)
top_ten_i <- head(subset(injuries[order(injuries$injury_count,decreasing = TRUE),]),10)
top_ten_i

```

| ## | Weather_pattern | injury_count |
|--------|-------------------|--------------|
| ## 834 | TORNADO | 91346 |
| ## 856 | TSTM WIND | 6957 |
| ## 170 | FLOOD | 6789 |
| ## 130 | EXCESSIVE HEAT | 6525 |
| ## 464 | LIGHTNING | 5230 |
| ## 275 | HEAT | 2100 |
| ## 427 | ICE STORM | 1975 |
| ## 153 | FLASH FLOOD | 1777 |
| ## 760 | THUNDERSTORM WIND | 1488 |
| ## 244 | HAIL | 1361 |

```

fatalities <- Stormdata_subset %>% group_by(EVTYPE)%>%
  summarise(fatalities = sum(FATALITIES,na.rm = TRUE)) %>% as.data.frame() %>% rename(Weather_pattern=EVTYPE)
top_ten_f <- head(subset(fatalities[order(fatalities$fatality_count,decreasing=TRUE),]),10)
top_ten_f

```

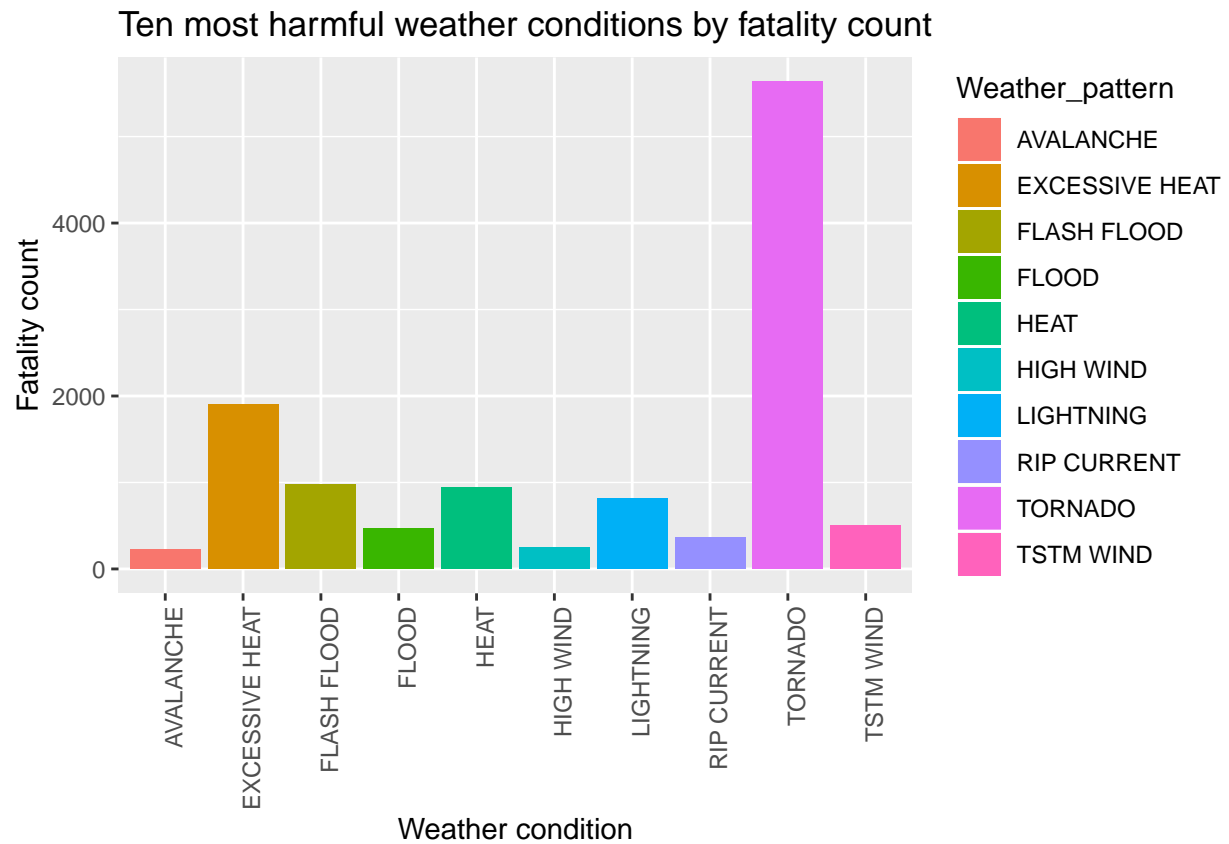
| ## | Weather_pattern | fatality_count |
|--------|-----------------|----------------|
| ## 834 | TORNADO | 5633 |
| ## 130 | EXCESSIVE HEAT | 1903 |
| ## 153 | FLASH FLOOD | 978 |
| ## 275 | HEAT | 937 |
| ## 464 | LIGHTNING | 816 |
| ## 856 | TSTM WIND | 504 |
| ## 170 | FLOOD | 470 |
| ## 585 | RIP CURRENT | 368 |

```
## 359      HIGH WIND      248
## 19      AVALANCHE      224

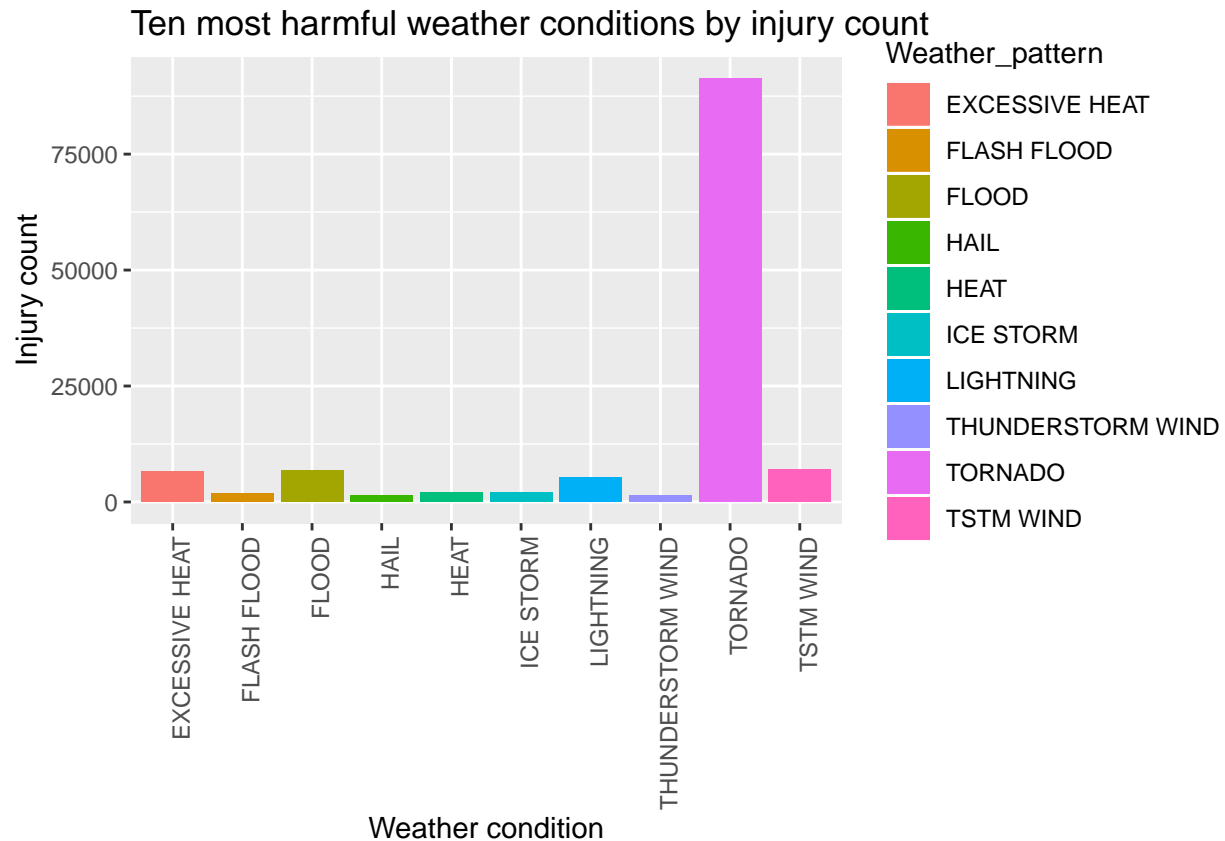
most_injuries <- ggplot(top_ten_i, aes(Weather_pattern,injury_count)) +geom_col(aes(fill=Weather_pattern))

most_fatalities<- ggplot(top_ten_f, aes(Weather_pattern,fatality_count)) +geom_col(aes(fill=Weather_pattern))

most_fatalities
```



```
most_injuries
```



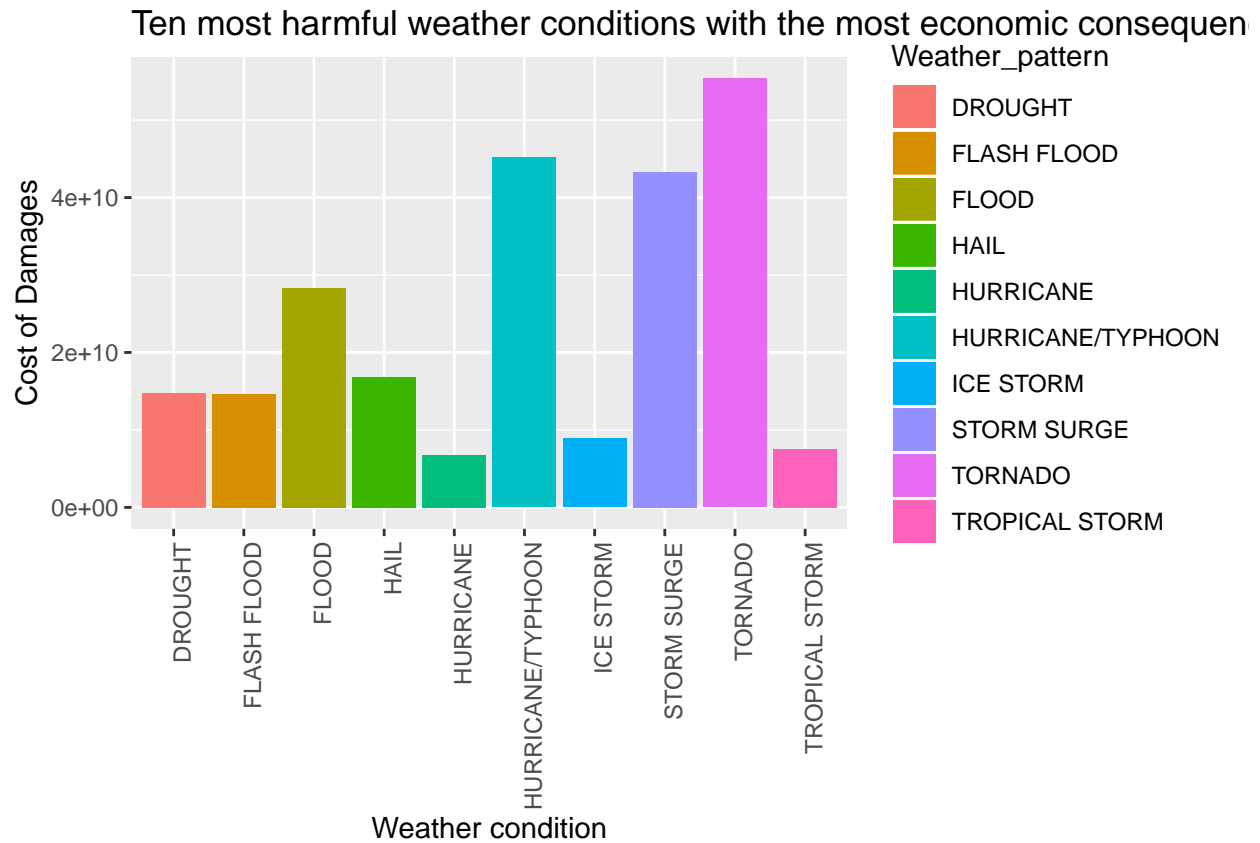
2) Across the United States, which types of events have the greatest economic consequences?

Using the total damage data that we have already calculated and introduced as a separate column. We now subset the data by weather pattern again and calculate the sum of economic damage for the top 10 weather patterns

```
Economic_damage <- Stormdata_subset %>% group_by(EVTYPE)%>%
  summarise(Economic_dmg =sum(Totaldam,na.rm = TRUE)) %>% as.data.frame() %>% rename(Weather_pattern=EVTYPE)
top_ten_E <- head(subset(Economic_damage[order(Economic_damage$Economic_dmg,decreasing = TRUE),]),10)
top_ten_E
```

```
##      Weather_pattern Economic_dmg
## 834      TORNADO      55365052590
## 411 HURRICANE/TYPHOON 45173417800
## 670    STORM SURGE    43321941000
## 170      FLOOD      28348588200
## 244      HAIL      16797832730
## 95      DROUGHT      14785940000
## 153    FLASH FLOOD    14635147600
## 427    ICE STORM      8880537310
## 848    TROPICAL STORM 7518856150
## 402    HURRICANE      6800951010
```

```
most_Economics<- ggplot(top_ten_E, aes(Weather_pattern,Economic_dmg)) +geom_col(aes(fill=Weather_pattern))
most_Economics
```



##Conclusions The report concludes three plots and tables with information about the top 10 most destructive weather patterns with most injuries, fatalities, and economic consequences.