

Impact of sever weather events on public health and economic of the U. S. between 1950 and 2011

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Synopsis

The report gives brief summary on impact of sever weather events on public and economic of the U. S. between 1950 and 2011. From the public health perspective of view, heat-related sever weather events become a significant problem. On the other hand, floods cost a lot and kill quite a lot of people.

Data processing

The data was obtained from the U.S. National Oceanic and Atmospheric Administration's (NOAA) storm database (<https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2>)

```
stormZip <- "storm.bz2"
if (file.access(stormZip, 4))
{
  stormUrl <-
    "http://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2"
  download.file(stormUrl, stormZip)
}
storm <- read.csv(stormZip, stringsAsFactors = F)
```

The total number of observations in the set is

```
nrow(storm)
```

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

According to NWS Directive 10-1605 (<http://www.ncdc.noaa.gov/stormevents/pd01016005curr.pdf>) any event must fall into one of following categories

```
eventTypes <-
  c("ASTRONOMICAL LOW TIDE", "AVALANCHE",
    "BLIZZARD",
    "COASTAL FLOOD", "COLD/WIND CHILL", "DEBRIS FLOW",
    "DENSE FOG", "DENSE SMOKE", "DROUGHT", "DUST DEVIL", "DUST STORM",
    "EXCESSIVE HEAT", "EXTREME COLD/WIND CHILL",
    "FLASH FLOOD", "FLOOD", "FROST/FREEZE", "FUNNEL CLOUD", "FREEZING FOG",
    "HAIL", "HEAT", "HEAVY RAIN", "HEAVY SNOW", "HIGH SURF", "HIGH WIND", "HURRIC
ANE/TYPHOON",
    "ICE STORM",
    "LAKE-EFFECT SNOW", "LAKESHORE FLOOD", "LIGHTNING",
    "MARINE HAIL", "MARINE HIGH WIND", "MARINE STRONG WIND", "MARINE THUNDERSTORM
WIND",
    "RIP CURRENT",
    "SEICHE", "SLEET", "STORM SURGE/TIDE", "STRONG WIND",
    "THUNDERSTORM WIND", "TORNADO", "TROPICAL DEPRESSION", "TROPICAL STORM", "TSU
NAMI",
    "VOLCANIC ASH",
    "WATERSPOUT", "WILDFIRE", "WINTER STORM", "WINTER WEATHER")
```

The proportion of properly marked observations in the set is

```
storm$EVTYPE <- toupper(storm$EVTYPE)
properlyMarked <- storm$EVTYPE %in% eventTypes
sum(properlyMarked) / length(storm$EVTYPE) * 100
```

```
## [1] 70.42459
```

Following events either aren't represented in the set or improperly marked

```
eventTypes[!(eventTypes %in% storm$EVTYPE)]
```

```
## [1] "DEBRIS FLOW"
```

The proportion of partially marked observations in the set is

```
partiallyMarked <- storm$EVTYPE %in%
  grep(paste(eventTypes, collapse = "|"),
       unique(storm$EVTYPE[!properlyMarked]), value = T)
sum(partiallyMarked) / length(storm$EVTYPE) * 100
```

```
## [1] 3.195954
```

For the purpose of the analysis improperly marked observations are grouped under "ANY" section. The impact on public health is judged based on numbers of killed **FATALITIES** and injured **INJURIES** people. The economic impact - on property damage **PROPDMG** and crop damage **CROPDMG** in billions of U. S. \$.

```
library(dplyr)
```

```
storm <- storm %>% select(EVTYPE, FATALITIES, INJURIES, PROPDMG, PROPDMGEXP, CROP  
DMG, CROPDMGEXP)  
for (i in 1:length(eventTypes))  
{  
  storm$EVTYPE[grepl(paste0("^", eventTypes[i], "$"), storm$EVTYPE)] <- eventTypes[i]  
}  
storm$EVTYPE[!(storm$EVTYPE %in% eventTypes)] <- "ANY"  
  
storm$PROPDMG[storm$PROPDMGEXP == "K"] <- storm$PROPDMG[storm$PROPDMGEXP == "K"]  
* (10^3)  
storm$PROPDMG[storm$PROPDMGEXP == "M"] <- storm$PROPDMG[storm$PROPDMGEXP == "M"]  
* (10^6)  
storm$PROPDMG[storm$PROPDMGEXP == "B"] <- storm$PROPDMG[storm$PROPDMGEXP == "B"]  
* (10^9)  
storm$PROPDMG <- storm$PROPDMG / (10^9)  
  
storm$CROPDMG[storm$CROPDMGEXP == "K"] <- storm$CROPDMG[storm$CROPDMGEXP == "K"]  
* (10^3)  
storm$CROPDMG[storm$CROPDMGEXP == "M"] <- storm$CROPDMG[storm$CROPDMGEXP == "M"]  
* (10^6)  
storm$CROPDMG[storm$CROPDMGEXP == "B"] <- storm$CROPDMG[storm$CROPDMGEXP == "B"]  
* (10^9)  
storm$CROPDMG <- storm$CROPDMG / (10^9)  
  
storm <- storm %>% select(EVTYPE, FATALITIES, INJURIES, PROPDMG, CROPDMG)  
  
sum(storm$EVTYPE == "ANY") / length(storm$EVTYPE) * 100
```

```
## [1] 29.57541
```

```
sum(storm$EVTYPE %in% eventTypes) / length(storm$EVTYPE) * 100
```

```
## [1] 70.42459
```

Results

Event types ordered by total number of people killed

```
healthImpact <- storm %>%
  group_by(EVTYPE) %>%
  rename(Type = EVTYPE) %>%
  summarise(Killed = sum(FATALITIES),
            Injured = sum(INJURIES)) %>%
  arrange(desc(Killed), desc(Injured))

healthImpact
```

```
## Source: local data frame [48 x 3]
##
##           Type Killed Injured
## 1      TORNADO   5633   91346
## 2         ANY    2023   12558
## 3 EXCESSIVE HEAT   1903    6525
## 4  FLASH FLOOD    978    1777
## 5         HEAT    937    2100
## 6  LIGHTNING    816    5230
## 7        FLOOD    470    6789
## 8  RIP CURRENT    368     232
## 9   HIGH WIND    248    1137
## 10 AVALANCHE    224     170
## ..          ...      ...      ...
```

Even though tornado's impact on public health have been recorded for more than 60 years, just 15 years of collecting data on the heat-related events shows that this is quite serious problem. It probably was overlooked in the past due to inability to effectively collect data.

Event types ordered by the total property damage in billions of U. S. dollars

```
economicImpact <- storm %>%
  group_by(EVTYPE) %>%
  rename(Type = EVTYPE) %>%
  summarise(Property = sum(PROPDMG),
            Crop = sum(CROPDMG)) %>%
  arrange(desc(Property), desc(Crop))

economicImpact
```

```
## Source: local data frame [48 x 3]
##
##           Type      Property      Crop
## 1      FLOOD 144.657710  5.6619684
## 2      ANY  82.959535 11.8483725
## 3 HURRICANE/TYPHOON 69.305840  2.6078728
## 4      TORNADO 56.925661  0.4149533
## 5    FLASH FLOOD 16.140812  1.4213171
## 6      HAIL  15.727367  3.0255379
## 7    TROPICAL STORM  7.703891  0.6783460
## 8    WINTER STORM  6.688497  0.0269440
## 9      HIGH WIND  5.270046  0.6385713
## 10     WILDFIRE  4.765114  0.2954728
## ..      ...      ...      ...
```

Just 15 years of observations shows that floods entail the largest economic consequences. They also kill significant number of people.

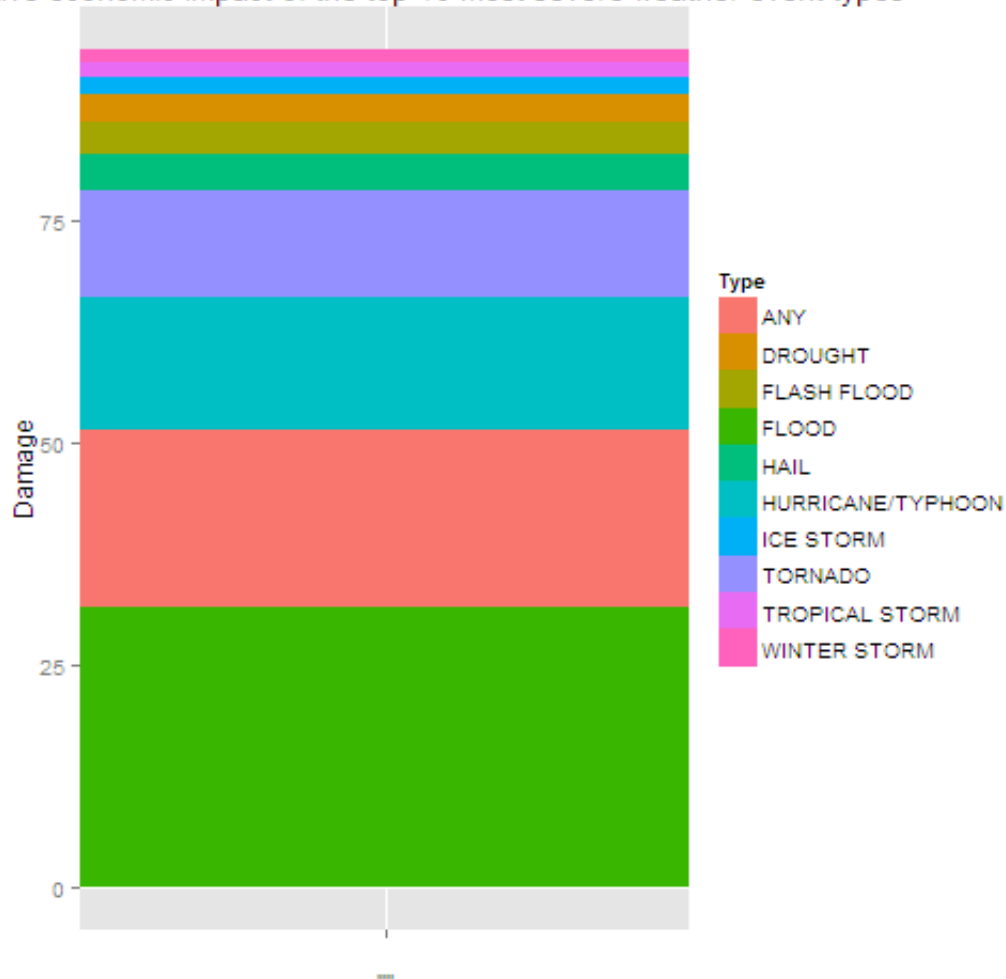
The figure below summarize total economic impact of the top 10 most sever weather event types

```
library(ggplot2)

totalDamage <- sum(storm$PROPDMG) + sum(storm$CROPDMG)
relativeEconomicImpact <- storm %>%
  group_by(EVTYPE) %>%
  rename(Type = EVTYPE) %>%
  summarise(Damage = sum(PROPDMG) + sum(CROPDMG)) %>%
  top_n(10, Damage) %>%
  arrange(desc(Damage))
relativeEconomicImpact$Damage <- relativeEconomicImpact$Damage / totalDamage * 100

g <- ggplot(relativeEconomicImpact, aes(x = "", y = Damage, fill = Type)) +
  geom_bar(width = 1, stat = "identity") +
  ggtitle("Total relative economic impact of the top 10 most severe weather event types")
print(g)
```

itive economic impact of the top 10 most severe weather event types



Further work

One may notice that improperly marked events (“ANY”) killed quite a few people and caused significant amount of damage, so more effort should be made to properly classify observations in NOAA’s set. This work is planned for the future versions of the report.