Severe Weather - Effects and Impact

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Synopsis

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 data analysis involves exploring the U.S. National Oceanic and Atmospheric Administration's (NOAA) storm database from 1950 to 2011. 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.

The data analysis in this report address the following questions:

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

Data Processing

This analysis makes use of dplr, knitr, reshape, xtable and ggplot2 library. Documentation of dplr can be found at http://cran.r-project.org/web/packages/dplR/dplR.pdf

```
# use dplr lib
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(xtable)
library(knitr)
library(reshape)
library(ggplot2)
```

This analysis will use the following original variables:

- EVTYPE: weather event type (i.e. flood, tornado, ...)
- BGN_DATE: beginning date of the event
- STATE: state in which the event occurred
- COUNTY: county in which the event occurred
- FATALITIES: number of human fatalities
- INJURIES: number of human injuries
- PROPDMG: a measure of the property damage
- CROPDMG: a measure of the crop damage

and to compute dollar values for damage PROPDMGEXP and CROPDMGEXP (e.g B for billions, M for millions, etc.)

Load/Retrieve Data

```
# download data
setwd("~/Courses/Data Science/repos/Reproducible
Research/RepData_PeerAssessment2")
dataUrl <-
"https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.b
z2"
dataFile <- "repdata-data-StormData.csv.bz2"

if (!file.exists(dataFile)) {
    download.file(dataUrl, dataFile, method="curl")
}
orgData <- read.csv(bzfile(dataFile))
```

The original data include **902297** records and **37** variables.

```
# select columns needed for this report
data <-
orgData[,c("BGN_DATE","STATE","COUNTY","EVTYPE","FATALITIES","INJURIES"
,"PROPDMG","PROPDMGEXP","CROPDMG","CROPDMGEXP")]
```

Compute dollar amount for property and crop damage

To use data for computation the values DMG columns have to be converted int dollar amounts.

```
# convertToDollar function will convert PROPDMGEXP or CROPDMGEXP
# to the correct dollar amount (i.e. M for millions, B for billions,
etc.)
convertToDollar <- function (x) {
    if (x == "B") {
        1e9
    } else if (x %in% c("m","M")) {
        1e6
    } else if (x %in% c("k", "K")) {
        1e3
    } else if (x %in% c("h", "H")) {
        1e2
    } else if (x %in% c("+", "-", "?")) {
        1
    } else {
        0
    }
}

# Calculate Property and Crop Damage in dollars by converting
xxxxDMGEXP
# to the dollar amount and multiplying its dollar representative
propDamage <- data$PROPDMG * unlist(lapply(data$PROPDMGEXP, function(x)
convertToDollar(x)))
cropDamage <- data$CROPDMG * unlist(lapply(data$CROPDMGEXP, function(x)
convertToDollar(x)))
```

Create Data Frame with columns needed for this analysis

```
# create data frame with  dollar values as number
data <-
cbind(orgData[,c("BGN_DATE","STATE","COUNTY","EVTYPE","FATALITIES","INJ
URIES")], propDamage, cropDamage)
```

Compute per Event Type - Fatalities, Injuries and Damage

1. Total Fatalities, Injuries and Damage

```
totalFatalities <- sum(data$FATALITIES)
totalInjuries <- sum(data$INJURIES)
totalDamage <- sum(data$cropDamage + data$propDamage)
topN_perEvent <- 7
topN_State <- 10
topN_County <- 10
topN_Damage <- 10
```

- total # of fatalities : **1.5145 × 104**
- total # of injuries : **1.4053 × 105**
- total damage amount : **4.7642 × 1011**

2. Top 7 Fatalies per Event Type

```r
dataByEventType <- group_by(data, EVTYPE)

eventDamage <- summarise(dataByEventType,
    fatalities = sum(FATALITIES, na.rm = TRUE),
    injuries   = sum(INJURIES, na.rm = TRUE),
    propDamage = sum(propDamage, na.rm=TRUE),
    cropDamage = sum(cropDamage, na.rm=TRUE),
    totalDmg = sum(propDamage + cropDamage, na.rm=TRUE)
)

fatalitiesIdx <- order(eventDamage$fatalities, decreasing=TRUE)
topFatalities <- eventDamage[fatalitiesIdx[1:topN_perEvent],]
```

3. Top 7 Injuries per Event Type

```r
injuryIdx <- order(eventDamage$injuries, decreasing=TRUE)
topInjury <- eventDamage[injuryIdx[1:topN_perEvent],]
```

Compute per State - Fatalities, Injuries and Damage

An analysis per state was to see the impact on per state level.

1. Total Fatalities, Injuries and Damage by State

```r
by_state <- group_by(data, STATE)
state_damage <- summarise(by_state,
    fatalities = sum(FATALITIES, na.rm=TRUE),
    injuries = sum(INJURIES, na.rm=TRUE),
    propDamage  = sum(propDamage, na.rm=TRUE),
    cropDamage  = sum(cropDamage, na.rm=TRUE),
    totalDmg = sum(propDamage + cropDamage, na.rm=TRUE)
)
```

2. Top 10 Fatalies per State

```r
fatalStateIdx <- order(state_damage$fatalities, decreasing=TRUE)
topFatalState <- state_damage[fatalStateIdx[1:topN_State],]
```

3. Top 10 Damage in dollar per State

```r
dmgStateIdx <- order(state_damage$totalDmg, decreasing=TRUE)
topDmgState <- state_damage[dmgStateIdx[1:topN_State],]
```

Compute Events with Top Damage

```
damageIdx <- order((eventDamage$cropDamage + eventDamage$propDamage),
decreasing=TRUE)
topDollarDmg <- eventDamage[damageIdx[1:topN_Damage],]
```

Results

Analysis per Event Type

Top Fatalities by Event Type

```
print(topFatalities[,1:2], floating=FALSE)

## Source: local data frame [7 x 2]
##
##              EVTYPE fatalities
## 834         TORNADO       5633
## 130  EXCESSIVE HEAT       1903
## 153     FLASH FLOOD        978
## 275            HEAT        937
## 464       LIGHTNING        816
## 856       TSTM WIND        504
## 170           FLOOD        470
```

Top Injuries by Event Type

```
print(topInjury[,c(1,3)])

## Source: local data frame [7 x 2]
##
##              EVTYPE injuries
## 834         TORNADO    91346
## 856       TSTM WIND     6957
## 170           FLOOD     6789
## 130  EXCESSIVE HEAT     6525
## 464       LIGHTNING     5230
## 275            HEAT     2100
## 427       ICE STORM     1975

#kable(head(topInjury[,1:3]), format = "markdown")
```

Top Economic Damage by Event Type

```
X <- topDollarDmg[,c(1,4:6)]
X[,c(2:4)] <- X[,c(2:4)] / 1000000000
print(X)

## Source: local data frame [10 x 4]
##
```

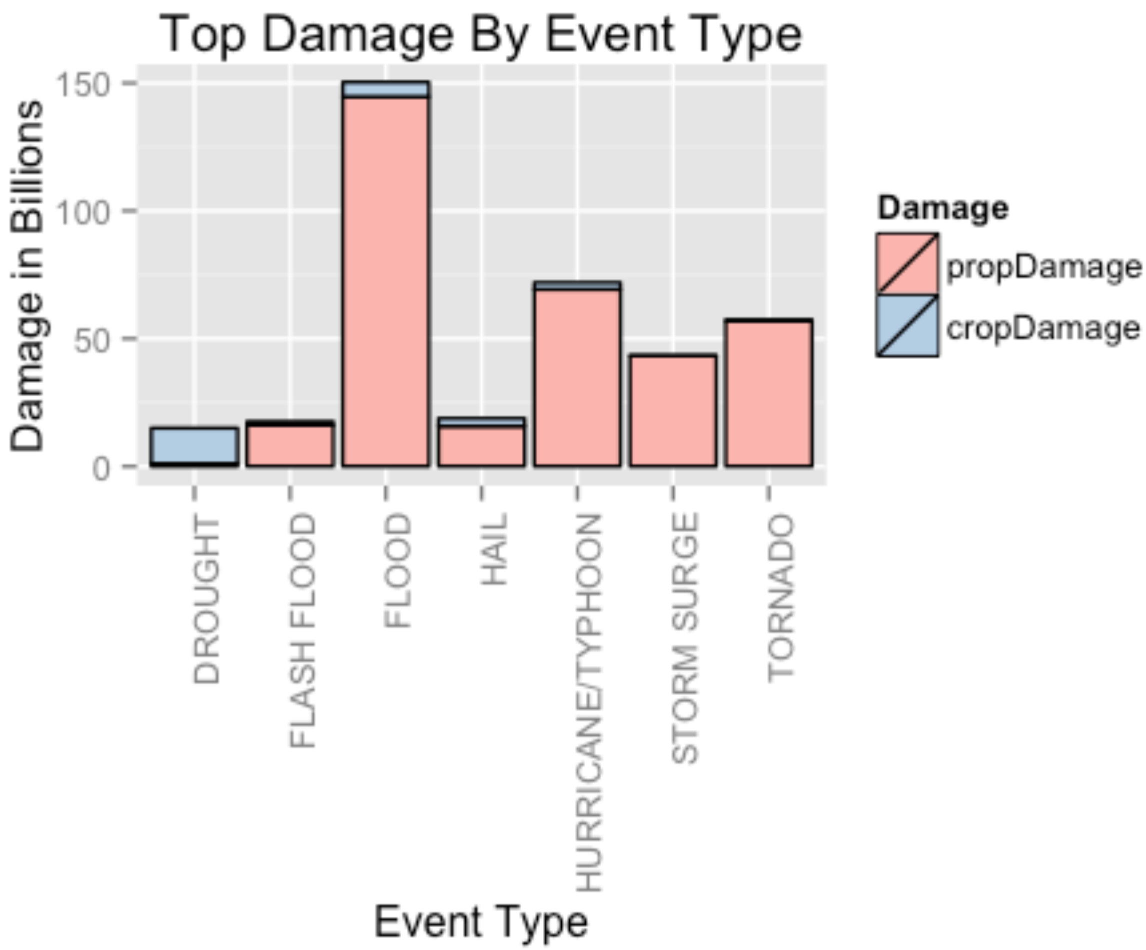
```
##                 EVTYPE propDamage cropDamage totalDmg
## 170              FLOOD    144.658   5.661968  150.320
## 411 HURRICANE/TYPHOON      69.306   2.607873   71.914
## 834            TORNADO     56.937   0.414953   57.352
## 670        STORM SURGE     43.324   0.000005   43.324
## 244               HAIL     15.732   3.025954   18.758
## 153        FLASH FLOOD     16.141   1.421317   17.562
## 95             DROUGHT      1.046  13.972566   15.019
## 402          HURRICANE     11.868   2.741910   14.610
## 590        RIVER FLOOD      5.119   5.029459   10.148
## 427          ICE STORM      3.945   5.022113    8.967

#kable(head(X), format = "markdown")
```

- Note: The numbers of damage are in billions.

```
X <- topDollarDmg[1:7,c(1,4:5)]
X1 <- melt(X, id=(c("EVTYPE")))
colnames(X1) <-  c("EventType","Damage","Value")
X1$Value = X1$Value / 1000000000

ggplot(X1, aes(x=EventType,y=Value, fill=Damage)) +
    geom_bar(stat="identity", colour="black") +
    ggtitle("Top Damage By Event Type") +
    ylab("Damage in Billions") + xlab("Event Type") +
    scale_fill_brewer(palette="Pastel1") +
    theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



Note: The numbers of propDamage and cropDamage are in billions.

Observations:

- Tornates caused the most fatalities (over 5,000) and injuries (over 91,000).
- Floods caused the most monitary damage, over $150 billion total wtih over $144 billion by property damage.
- Droughts have the most negative impact on crop damage.

Analysis per State

Top Fatalities by State

```
topFatalState[,1:3]

## Source: local data frame [10 x 3]
##
##    STATE fatalities injuries
## 20    IL       1421     5563
## 63    TX       1366    17667
```

```
## 51     PA         846      3223
## 2      AL         784      8742
## 37     MO         754      8998
## 13     FL         746      5918
## 38     MS         555      6675
## 8      CA         550      3278
## 5      AR         530      5550
## 62     TN         521      5202
```

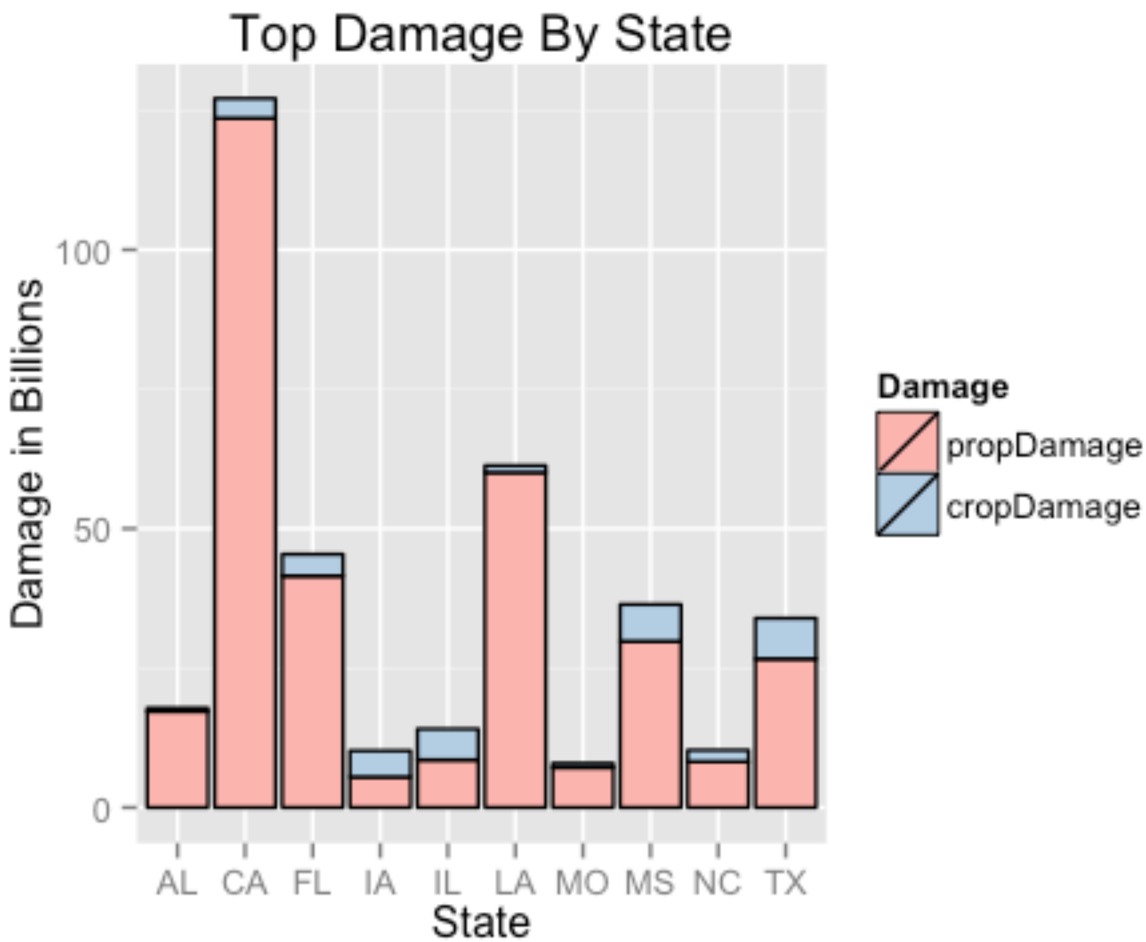
Top Economic Damage by State

```
kable(head(topDmgState[,c(1,4:6)]), format = "markdown")

##
##
## |   |STATE |  propDamage|  cropDamage|   totalDmg|
## |:--|:-----|----------:|----------:|---------:|
## |8  |CA    |   1.236e+11|   3.528e+09| 1.271e+11|
## |24 |LA    |   6.007e+10|   1.229e+09| 6.130e+10|
## |13 |FL    |   4.151e+10|   3.903e+09| 4.541e+10|
## |38 |MS    |   2.981e+10|   6.610e+09| 3.642e+10|
## |63 |TX    |   2.664e+10|   7.301e+09| 3.394e+10|
## |2  |AL    |   1.724e+10|   6.068e+08| 1.785e+10|

X <- topDmgState[,c(1,4:5)]
X <- melt(X, id=(c("STATE")))
colnames(X) <-  c("State","Damage","Value")
X$Value = X$Value / 1000000000

ggplot(X, aes(x=State,y=Value, fill=Damage)) +
    geom_bar(stat="identity", colour="black") +
    ggtitle("Top Damage By State") +
    ylab("Damage in Billions") + xlab("State") +
    scale_fill_brewer(palette="Pastel1")
```




```
kable(head(topDmgState[,c(1,6)]), format = "markdown")
```

```
##
##
## |   |STATE |   totalDmg|
## |:--|:-----|----------:|
## |8  |CA    |  1.271e+11|
## |24 |LA    |  6.130e+10|
## |13 |FL    |  4.541e+10|
## |38 |MS    |  3.642e+10|
## |63 |TX    |  3.394e+10|
## |2  |AL    |  1.785e+10|
```

Note: The numbers of propDamage and cropDamage are in billions.

Observations:

- California has the highest damage from all states (over $127 billion), followed by Lousiana and Florida. In each case, the biggest bulk came from property damage.

- The top states for human fatalities and injuries are Illinois, Texas, Pennsylvania, Alabama and Missouri.

Conclusion

The data analysis address the following questions:

- which types of events (as indicated in the EVTYPE variable) are most harmful with respect to population health across the United States.
- which types of events have the greatest economic consequences across the United States.