

Title: Reproducible Research: Peer Assessment Two

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Summary

It is common knowledge that storms and severe weather conditions have a serious impact on public health and the economy. There is a general consensus that the utilisation of data will help to inform and prioritise decisions about if and when they could occur, including estimates of potential fatalities, injury and damage to property. This report draws the readers attention to this fact and presents quantitative evidence based on a storm database collected from the U.S. Oceanic and Atmospheric Administration (NOAA) from 1950-2011.

Synopsis

The results in this report present us with some interesting results. From the first set of results we find that tornados have accounted for the number of deaths since recordings began in 1950, with 5633 recorded fatalities. This was followed by excessive heat with 1903 recordings and the lowest end of the scale 224 of deaths caused by Avalanche. In terms of injury again we find that tornados account for most recorded incidences with 91346 recordings since 1950. At the lower end of the top ten events we are interested in in this report we find that 1361 injuries were recorded. Looking at the economic burden severe weather conditions has on the economy we find that floods account for the main cause of damage to property at a total cost of 115 billion since 1950 with hurricane/typhoon, and storm surge accounting for 58 billion and 31 billion respectively. (the results here are problematic because of duplication in the records). In terms of the costs caused by damage to crops we find that river floods and ice storms account for the most economic costs, costing 5, 5, and 1.5 billion respectively.

Load Libraries and Perform Initial Setup

```
#Load Libraries
```

```
library(ggplot2)
```

```
library(plyr)
```

```
#This allows the reader to examine the software environment
```

```
sessionInfo()
```

```
## R version 3.0.2 (2013-09-25)
## Platform: x86_64-pc-linux-gnu (64-bit)
##
## locale:
## [1] LC_CTYPE=en_GB.UTF-8    LC_NUMERIC=C
## [3] LC_TIME=en_GB.UTF-8    LC_COLLATE=en_GB.UTF-8
## [5] LC_MONETARY=en_GB.UTF-8 LC_MESSAGES=en_GB.UTF-8
## [7] LC_PAPER=en_GB.UTF-8   LC_NAME=C
## [9] LC_ADDRESS=C           LC_TELEPHONE=C
## [11] LC_MEASUREMENT=en_GB.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] stats    graphics grDevices utils    datasets methods  base
##
## other attached packages:
## [1] plyr_1.8.1  ggplot2_1.0.0
##
## loaded via a namespace (and not attached):
## [1] colorspace_1.2-4 digest_0.6.4  evaluate_0.5.5 formatR_1.0
## [5] grid_3.0.2    gtable_0.1.2  htmltools_0.2.6 knitr_1.7
## [9] MASS_7.3-29   munsell_0.4.2 proto_0.3-10  Rcpp_0.11.2
## [13] reshape2_1.4  rmarkdown_0.2.68 scales_0.2.4  stringr_0.6.2
## [17] tools_3.0.2   yaml_2.1.13
```

Load Data

```
if(!file.exists("./data/repdata-data-StormData.csv")){
  dataset <- read.table(
    bzfile("./data/repdata-data-StormData.csv.bz2",
      "repdata-data-StormData.csv"), sep=";", header=T, na.string="NA")
}
```

Check that we have data

At this stage we just want to check that we have loaded some data.

```
head(dataset, n=1)

## STATE__      BGN_DATE BGN_TIME TIME_ZONE COUNTY COUNTYNAME
STATE
## 1      1 4/18/1950 0:00:00 0130    CST   97   MOBILE   AL
## EVTYPE BGN_RANGE BGN_AZI BGN_LOCATI END_DATE END_TIME
COUNTY_END
## 1 TORNADO      0              0
## COUNTYENDN END_RANGE END_AZI END_LOCATI LENGTH WIDTH F MAG
FATALITIES
## 1      NA      0              14 100 3 0      0
## INJURIES PROPDMG PROPDMGEXP CROPDMG CROPDMGEXP WFO
STATEOFFIC ZONENAMES
## 1      15      25      K      0
```

```
## LATITUDE LONGITUDE LATITUDE_E LONGITUDE_ REMARKS REFNUM
## 1 3040 8812 3051 8806 1
```

Data Preprocessing

I left completing this assignment far too late. I would have liked to have cleaned the data more than I have. In particular, the final set of results caused problems because of duplicate EVTYPE data values - please see the numeric values - I should have dealt with these values in the preprocessing stage, but have not due to time constraints.

What has been done is to convert the alpha values that represent thousands, millions and billions into numerical equivalents so that we can calculate the property and crop damage. For this project I have capped the number of events that we are interested in to the top ten as these account for most of the damage and costs.

During this stage we also work out which weather event causes the most loss of life and injury and which of the weather events recorded has the most significant economic impact on property and crops

```
#PROPDMGEXP
```

```
#Convert the exponential to a numeric value that we can work with.
```

```
dataset$PROPDMGEXP <- as.character(dataset$PROPDMGEXP)
```

```
## Warning: closing unused connection 5
```

```
## (./data/repdata-data-StormData.csv.bz2)
```

```
dataset$PROPDMGEXP[grep("K", dataset$PROPDMGEXP)] <- "1000"
```

```
dataset$PROPDMGEXP[grep("k", dataset$PROPDMGEXP)] <- "1000"
```

```
dataset$PROPDMGEXP[grep("M", dataset$PROPDMGEXP)] <- "1000000"
```

```
dataset$PROPDMGEXP[grep("m", dataset$PROPDMGEXP)] <- "1000000"
```

```
dataset$PROPDMGEXP[grep("B", dataset$PROPDMGEXP)] <- "1000000000"
```

```
dataset$PROPDMGEXP[grep("b", dataset$PROPDMGEXP)] <- "1000000000"
```

```
#Set all other characters to 1 - we consider this to be noise in the data.
```

```
to.be.one <- dataset$PROPDMGEXP %in% c("1000", "1000000",
```

```
"1000000000") == F
```

```
dataset$PROPDMGEXP[to.be.one == TRUE] <- "1"
```

```
#Change the variable to numeric so that we can perform the calculations
```

```
dataset$PROPDMGEXP <- as.numeric(dataset$PROPDMGEXP)
```

```
#CROPDMGEXP
```

```
#Convert the exponential to a numeric value that we can work with.
```

```
dataset$CROPDMGEXP <- as.character(dataset$CROPDMGEXP)
```

```
dataset$CROPDMGEXP[grep("K", dataset$CROPDMGEXP)] <- "1000"
```

```
dataset$CROPDMGEXP[grep("k", dataset$CROPDMGEXP)] <- "1000"
```

```
dataset$CROPDMGEXP[grep("M", dataset$CROPDMGEXP)] <- "1000000"
```

```
dataset$CROPDMGEXP[grep("m", dataset$CROPDMGEXP)] <- "1000000"
```

```
dataset$CROPDMGEXP[grep("B", dataset$CROPDMGEXP)] <- "1000000000"
```

```
dataset$CROPDMGEXP[grep("b", dataset$CROPDMGEXP)] <- "1000000000"
```

```

#Set all other characters to 1 - we consider this to be noise in the data.
to.be.one <- dataset$CROPDMGEXP %in% c("1000", "1000000",
"1000000000") == F
dataset$CROPDMGEXP[to.be.one == TRUE] <- "1"
#Change the variable to numeric so that we can perform the calculations
dataset$CROPDMGEXP <- as.numeric(dataset$CROPDMGEXP)

#Calculate the costs
dataset$prop.damage <- dataset$PROPDMG * dataset$PROPDMGEXP
dataset$crop.damage <- dataset$CROPDMG * dataset$CROPDMGEXP

#Extract the top 10 most
top.ten.prop <- head(dataset[order(dataset$prop.damage,
decreasing=TRUE),], 10)
top.ten.crop <- head(dataset[order(dataset$crop.damage,
decreasing=TRUE),], 10)

#First of all summarise all the fatalities and injuries for all of the event types in the dataset.
casulties <- ddply(dataset, .(EVTYPE), summarize,
  fatalities = sum(FATALITIES),
  injuries = sum(INJURIES))

#Get the top 10 event types that cause fatality.
top.ten.fatalities <- head(casulties[order(casulties$fatalities,
decreasing=TRUE), ], 10)

#Get the top 10 event types that cause fatality.
top.ten.injuries <- head(casulties[order(casulties$injuries, decreasing=TRUE),
], 10)

```

Results

Question One: Across the United States, which types of events (as indicated in the EVTYPE variable) are most harmful with respect to population health

We are not interested in every event type, only the ones that cause the most harm. For the purposes of this study we are only interested in the top 10 Event Types that cause the most harm to the population (although this could be changed to suite specific needs).

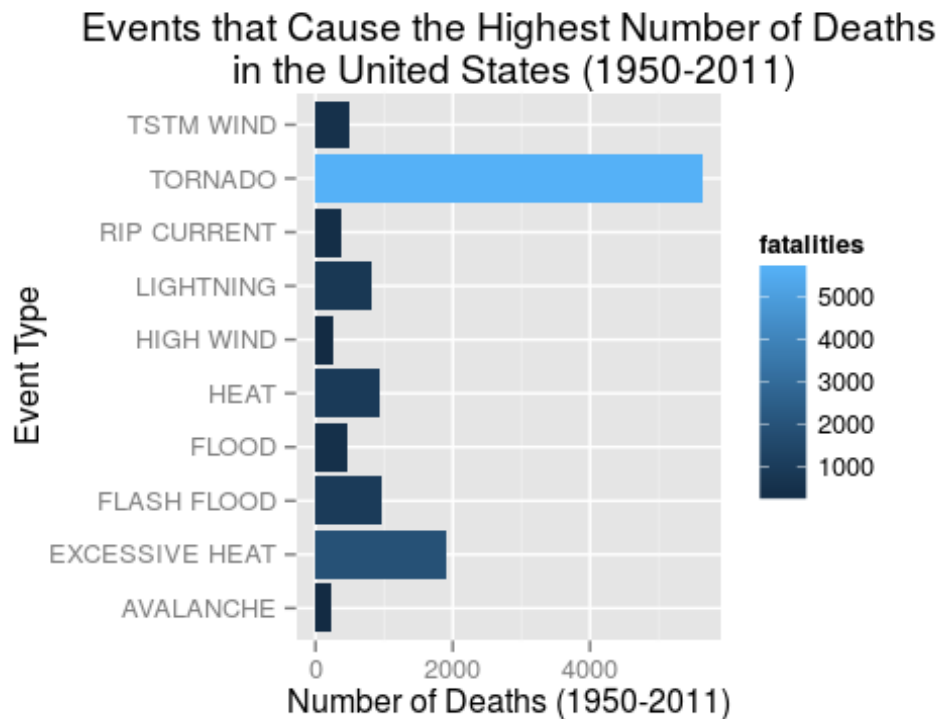
The results below show the top ten number of fatalities and injuries categorised by event type

```

##Top 10 Events that Caused the Highest Number of Deaths
#Plot top ten fatalities by event type
library(ggplot2)
ggplot(top.ten.fatalities, aes(EVTYPE, fatalities, fill=fatalities)) +

```

```
geom_bar(stat="identity") + coord_flip() +
stat_summary(fun.y = median, geom="bar") +
labs(x="Event Type", y="Number of Deaths (1950-2011)",
title="Events that Cause the Highest Number of Deaths\n in the United States (1950-2011)")
```



#Display the top 10 fatalities
top.ten.fatalities[,c("EVTYPE", "fatalities")]

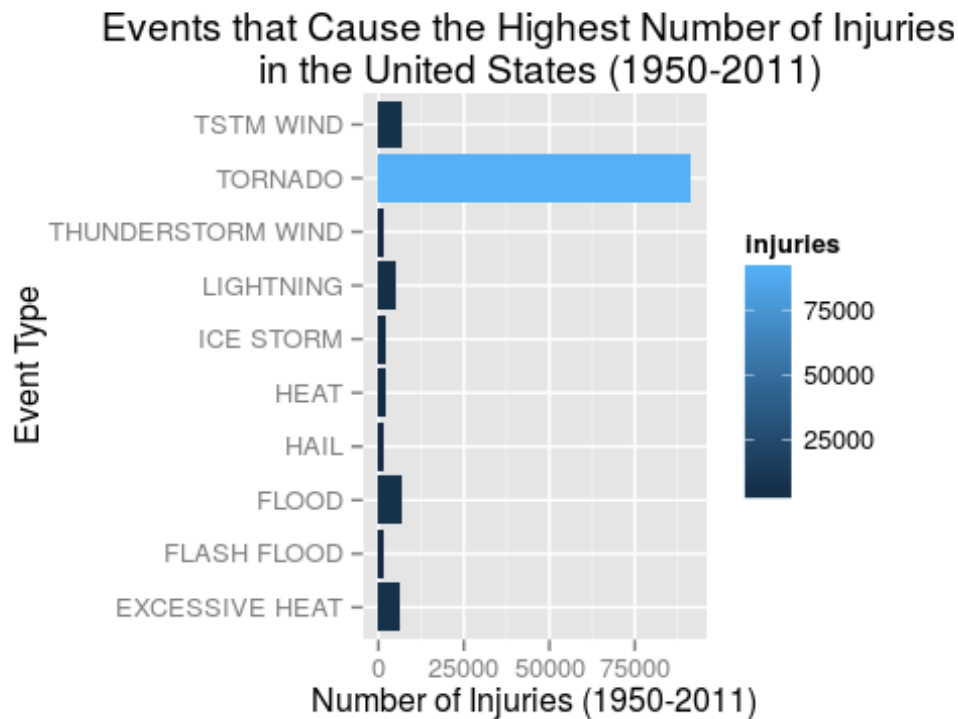
```
##      EVTYPE fatalities
## 830   TORNADO      5633
## 123 EXCESSIVE HEAT    1903
## 147  FLASH FLOOD     978
## 269    HEAT         937
## 452  LIGHTNING       816
## 854   TSTM WIND      504
## 164    FLOOD        470
## 581  RIP CURRENT     368
## 354   HIGH WIND      248
## 11   AVALANCHE      224
```

##Top 10 Events that Caused the Highest Number of Injuries

#Plot top ten injuries by event type

```
ggplot(top.ten.injuries, aes(EVTYPE, injuries, fill=injuries)) +
geom_bar(stat="identity") + coord_flip() +
stat_summary(fun.y = median, geom="bar") +
labs(x="Event Type", y="Number of Injuries (1950-2011)",
```

title="Events that Cause the Highest Number of Injuries \n in the United States (1950-2011)")



#Display the top 10 fatalities
top.ten.injuries[,c("EVTYPE", "injuries")]

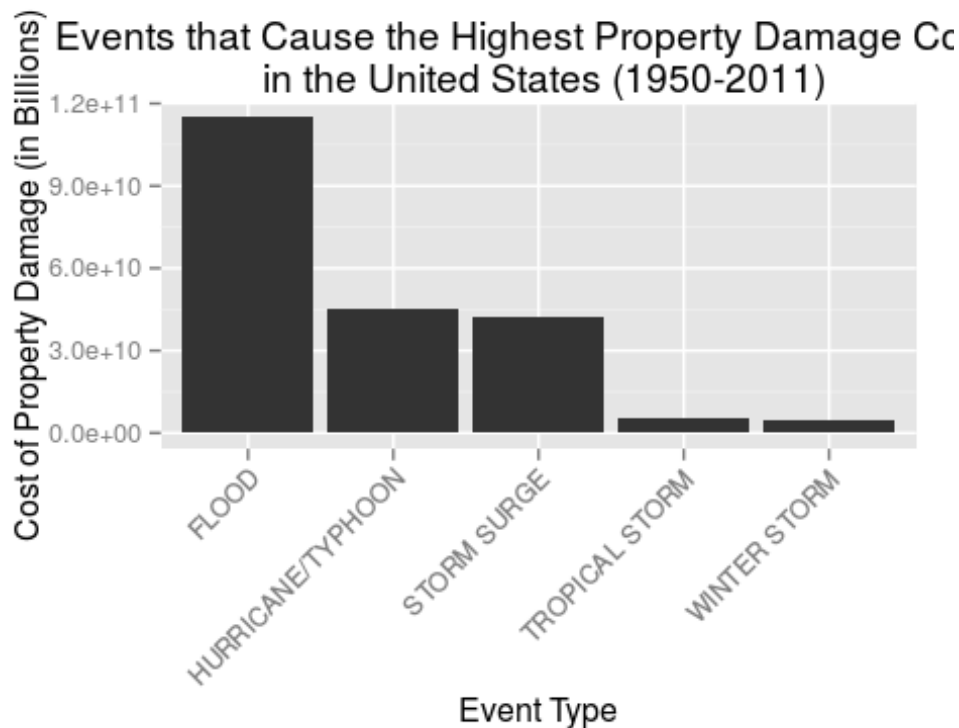
```
##      EVTYPE injuries
## 830   TORNADO   91346
## 854   TSTM WIND   6957
## 164    FLOOD    6789
## 123 EXCESSIVE HEAT  6525
## 452    LIGHTNING  5230
## 269     HEAT    2100
## 424    ICE STORM  1975
## 147  FLASH FLOOD  1777
## 759 THUNDERSTORM WIND 1488
## 238     HAIL    1361
```

Question Two: Across the United States, which types of events have the greatest economic consequences?

As with question one we are not interested in every event type, only the ones that have the greatest economical costs. For the purposes of this study we are only interested in the top 10 Event Types that cost the economy the most (although this could be changed to suite specific needs).

The results below show the top ten highest economical costs for prop and crop for the severest weather categorised by event type.

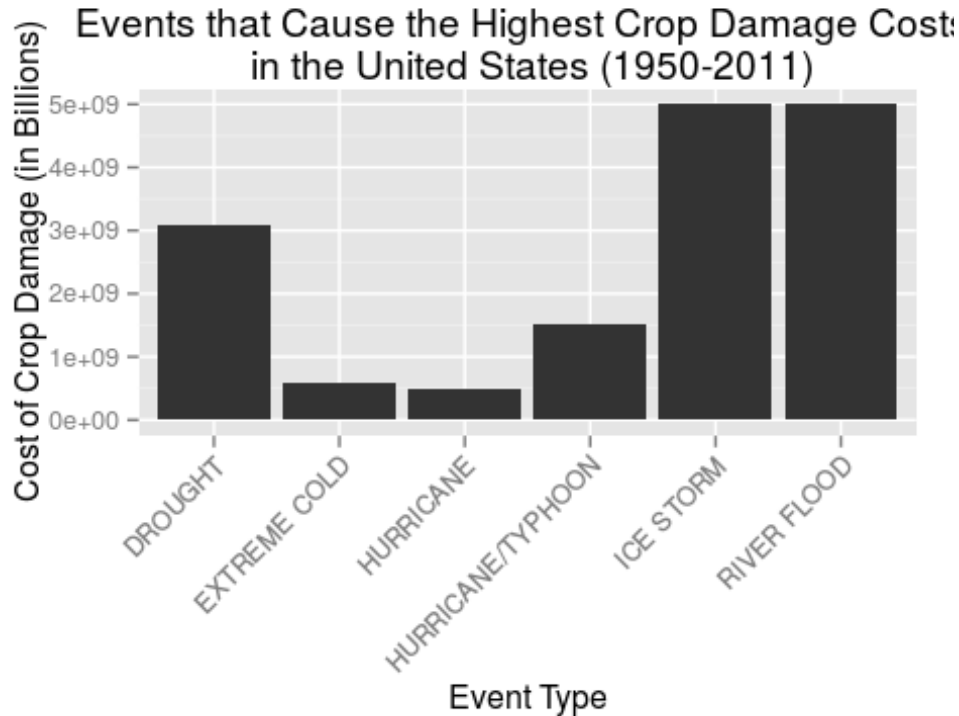
```
#Plot the top 10 economic prop damages
ggplot(top.ten.prop, aes(EVTYPE, prop.damage)) +
  geom_bar(stat="identity") +
  stat_summary(fun.y = median, geom="bar") +
  labs(x="Event Type", y="Cost of Property Damage (in Billions)",
       title="Events that Cause the Highest Property Damage Costs \n in the
United States (1950-2011)") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



```
#Display the top 10 prop damage
top.ten.prop[,c("EVTYPE", "prop.damage")]

##          EVTYPE prop.damage
## 605953      FLOOD  1.150e+11
## 577676  STORM SURGE  3.130e+10
## 577675 HURRICANE/TYPHOON  1.693e+10
## 581535  STORM SURGE  1.126e+10
## 569308 HURRICANE/TYPHOON  1.000e+10
## 581533 HURRICANE/TYPHOON  7.350e+09
## 581537 HURRICANE/TYPHOON  5.880e+09
## 529351 HURRICANE/TYPHOON  5.420e+09
## 443782  TROPICAL STORM  5.150e+09
## 187564   WINTER STORM  5.000e+09
```

```
#Plot the top 10 economic crop damages
ggplot(top.ten.crop, aes(EVTYPE, crop.damage)) +
  geom_bar(stat="identity") +
  stat_summary(fun.y = median, geom="bar") +
  labs(x="Event Type", y="Cost of Crop Damage (in Billions)",
       title="Events that Cause the Highest Crop Damage Costs \n in the United States (1950-2011)") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



```
#Display the top 10 crop damage
top.ten.crop[,c("EVTYPE", "crop.damage")]

##          EVTYPE crop.damage
## 198389  RIVER FLOOD 5000000000
## 211900   ICE STORM 5000000000
## 581537 HURRICANE/TYPHOON 1510000000
## 639347   DROUGHT 1000000000
## 312986  EXTREME COLD  596000000
## 422676   DROUGHT  578850000
## 410175   DROUGHT  515000000
## 199733   DROUGHT  500000000
## 337008   DROUGHT  500000000
## 366694   HURRICANE  500000000
```