Overwheming destructive force of Tornados from 1950-2011

Synopsis

In an effort to better prepare for natural disasters in the United States, we've aggregated disaster reports from the U.S. National Oceanic and Atmospheric Administration's (NOAA) storm database (1950-2011) to look for events that are most harmful financially and physically. The findings indicate that tornadoes are the combined worst natural disasters we face. Not only do they cause the most harm to human beings, they are top five worst in financial burden and top five most frequently occurring.

Data Processing

```
stormData <- read.csv("StormData.bz2")
```

Since we're going to be focused on analyzing the event type's (EVTYPE) impact against health and economic livelihood of the population, we can start by checking to make sure we have the columns properly named and typed.

```
colnames(stormData)
```

```
##  [1] "STATE__"    "BGN_DATE"   "BGN_TIME"   "TIME_ZONE"
"COUNTY"
##  [6] "COUNTYNAME" "STATE"      "EVTYPE"     "BGN_RANGE"
"BGN_AZI"
## [11] "BGN_LOCATI" "END_DATE"   "END_TIME"   "COUNTY_END"
"COUNTYENDN"
## [16] "END_RANGE"  "END_AZI"    "END_LOCATI" "LENGTH"
"WIDTH"
## [21] "F"          "MAG"        "FATALITIES" "INJURIES"
"PROPDMG"
## [26] "PROPDMGEXP" "CROPDMG"    "CROPDMGEXP" "WFO"
"STATEOFFIC"
## [31] "ZONENAMES"  "LATITUDE"   "LONGITUDE"  "LATITUDE_E"
"LONGITUDE_"
## [36] "REMARKS"    "REFNUM"
```

Health impact would likely be measured best in number of fatalities and injuries (FATALITIES and INJURIES as the respective column names).

For the economic analysis we have PROPDMG and CROPDMG and their exp values in PROPDMGEXP and CROPDMGEXP

```
unique(stormData$PROPDMGEXP)
```

```
##  [1] K M   B m + 0 5 6 ? 4 2 3 h 7 H - 1 8
## Levels:  - ? + 0 1 2 3 4 5 6 7 8 B h H K m M
```

Since the values have ranges from K, M, B to 1-9, we can assume K, M, B for thousand, million, billion and 1-9 as $10^{n.}$ Now subset the columns we are taking to be relevant to the investigation, get rid of any zero values that we don't need.

```
st <- subset(stormData, FATALITIES > 0 | INJURIES > 0 |
PROPDMG > 0 | CROPDMG >
    0, select = c("STATE__", "BGN_DATE", "END_DATE",
"EVTYPE", "FATALITIES",
    "INJURIES", "PROPDMG", "PROPDMGEXP", "CROPDMG",
"CROPDMGEXP"))
```

Let's total up the fatalities and injuries

```
st$totalHealth <- st$FATALITIES + st$INJURIES
```

Now convert the dollar amounts for crop and property damage.

```
st$propdamage <- st$PROPDMG
st$PROPDMGEXP <- as.character(st$PROPDMGEXP)
st$PROPDMGEXP[tolower(st$PROPDMGEXP) == "h"] <- "2"
st$PROPDMGEXP[tolower(st$PROPDMGEXP) == "k"] <- "3"
st$PROPDMGEXP[tolower(st$PROPDMGEXP) == "m"] <- "6"
st$PROPDMGEXP[tolower(st$PROPDMGEXP) == "b"] <- "9"
st$PROPDMGEXP[st$PROPDMGEXP == "" | st$PROPDMGEXP == "-" |
st$PROPDMGEXP ==
    "?" | st$PROPDMGEXP == "+"] <- "0"
st$PROPDMGEXP <- as.numeric(st$PROPDMGEXP)
st$propdamage <- (10^st$PROPDMGEXP) * st$PROPDMG
```

```
st$cropdamage <- st$CROPDMG
st$CROPDMGEXP <- as.character(st$CROPDMGEXP)
st$CROPDMGEXP[tolower(st$CROPDMGEXP) == "h"] <- "2"
st$CROPDMGEXP[tolower(st$CROPDMGEXP) == "k"] <- "3"
st$CROPDMGEXP[tolower(st$CROPDMGEXP) == "m"] <- "6"
st$CROPDMGEXP[tolower(st$CROPDMGEXP) == "b"] <- "9"
st$CROPDMGEXP[st$CROPDMGEXP == "" | st$CROPDMGEXP == "-" |
st$CROPDMGEXP ==
    "?" | st$CROPDMGEXP == "+"] <- "0"
st$CROPDMGEXP <- as.numeric(st$CROPDMGEXP)
st$cropdamage <- (10^st$CROPDMGEXP) * st$CROPDMG
```

Let's also total up the damage amounts

```
st$totalDamage <- st$cropdamage + st$propdamage
```

We will now sum up all relevant columns that are necessary to determine the worst disasters.

```
onlySums <- st[, c("EVTYPE", "FATALITIES", "INJURIES",
"propdamage", "cropdamage",
    "totalDamage", "totalHealth")]
agged <- aggregate(. ~ EVTYPE, onlySums, sum)
```

Results

Health Impact

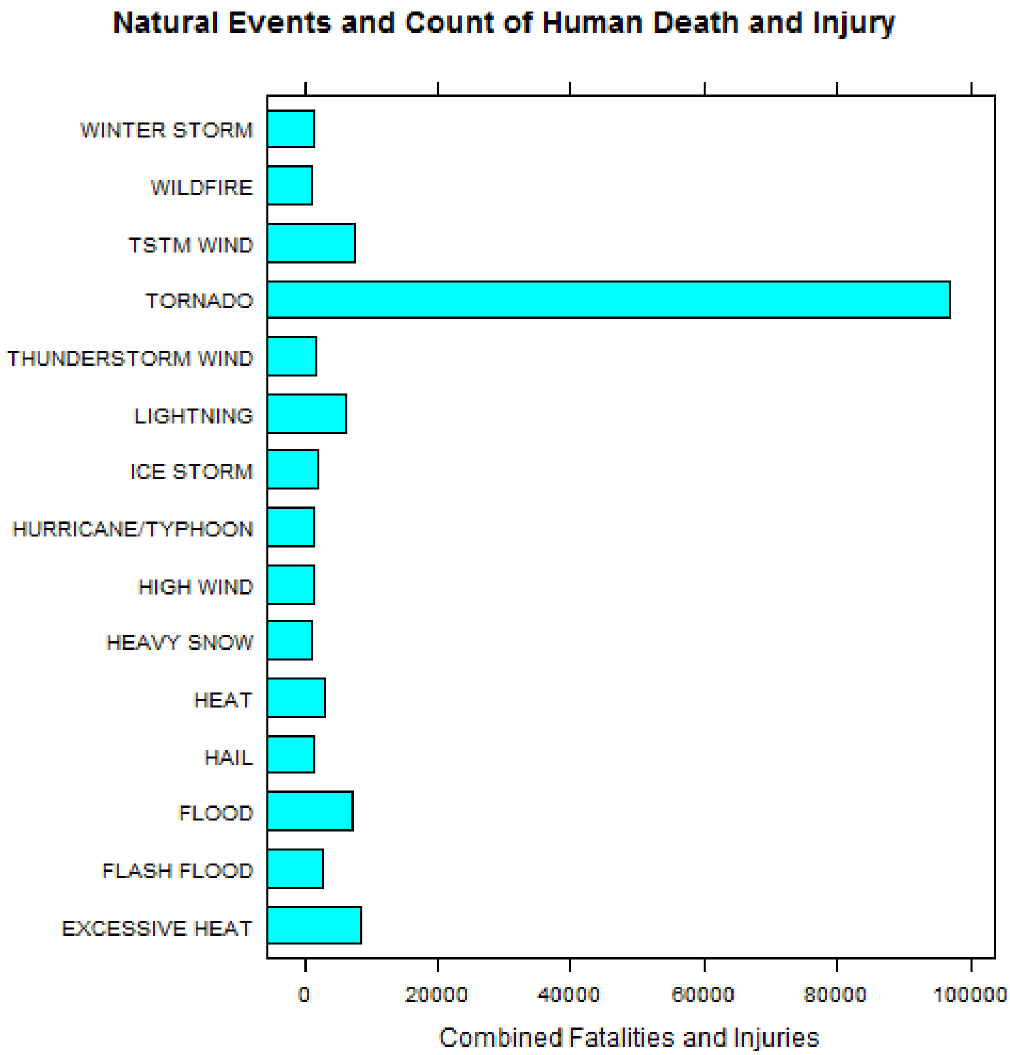
Now we can begin to look at the health impact by environmental disaster.

```
topFifteen <- head(agged[order(-agged$totalHealth),
c("EVTYPE", "totalHealth")],
    15)
topFifteen
```

```
##                EVTYPE totalHealth
## 407           TORNADO       96979
## 61     EXCESSIVE HEAT        8428
## 423         TSTM WIND        7461
## 86              FLOOD        7259
## 258         LIGHTNING        6046
## 151              HEAT        3037
## 73        FLASH FLOOD        2755
## 238         ICE STORM        2064
## 364 THUNDERSTORM WIND        1621
## 481      WINTER STORM        1527
## 200         HIGH WIND        1385
## 134              HAIL        1376
## 224 HURRICANE/TYPHOON        1339
## 170        HEAVY SNOW        1148
## 471          WILDFIRE         986
```

Based on the total counts above, tornadoes have the worst impact on human life when combining injury and fatalities. Let's plot the event types out to get a better sense of scale.

```
library(lattice)
barchart(data = topFifteen, EVTYPE ~ totalHealth, xlab = "Combined Fatalities and Injuries",
    main = "Natural Events and Count of Human Death and Injury")
```



To make sure the top fifteen results aren't getting skewed by either the injury or fatality counts, lets order by both measureables and compare the top fifteen.

```
head(agged[order(-agged$FATALITIES), c("EVTYPE",
"FATALITIES")], 15)
```

```
##                 EVTYPE FATALITIES
## 407            TORNADO       5633
## 61      EXCESSIVE HEAT       1903
## 73         FLASH FLOOD        978
## 151               HEAT        937
## 258          LIGHTNING        816
## 423          TSTM WIND        504
## 86               FLOOD        470
## 306        RIP CURRENT        368
## 200          HIGH WIND        248
## 11           AVALANCHE        224
## 481       WINTER STORM        206
## 307       RIP CURRENTS        204
## 153          HEAT WAVE        172
## 67        EXTREME COLD        160
## 364  THUNDERSTORM WIND        133
```

```
head(agged[order(-agged$INJURIES), c("EVTYPE",
"INJURIES")], 15)
```

```
##                 EVTYPE INJURIES
## 407            TORNADO    91346
## 423          TSTM WIND     6957
## 86               FLOOD     6789
## 61      EXCESSIVE HEAT     6525
## 258          LIGHTNING     5230
## 151               HEAT     2100
## 238          ICE STORM     1975
## 73         FLASH FLOOD     1777
## 364  THUNDERSTORM WIND     1488
## 134               HAIL     1361
## 481       WINTER STORM     1321
## 224  HURRICANE/TYPHOON     1275
## 200          HIGH WIND     1137
## 170         HEAVY SNOW     1021
## 471           WILDFIRE      911
```

In both cases tornadoes were clearly more destructive.

Let's also check out the frequency of these disasters.

```
freqs <- as.data.frame(with(onlySums, table(EVTYPE)))
head(freqs[order(-freqs$Freq), c("EVTYPE", "Freq")], 15)
```

```
##                  EVTYPE  Freq
## 856             TSTM WIND 63234
## 760  THUNDERSTORM WIND 43655
## 834               TORNADO 39944
## 244                  HAIL 26130
## 153          FLASH FLOOD 20967
## 464            LIGHTNING 13293
## 786 THUNDERSTORM WINDS 12086
## 170                 FLOOD 10175
## 359             HIGH WIND  5522
## 676           STRONG WIND  3370
## 972         WINTER STORM  1508
## 310           HEAVY SNOW  1342
## 290           HEAVY RAIN  1105
## 957             WILDFIRE   857
## 427            ICE STORM   708
```

Economic Impact

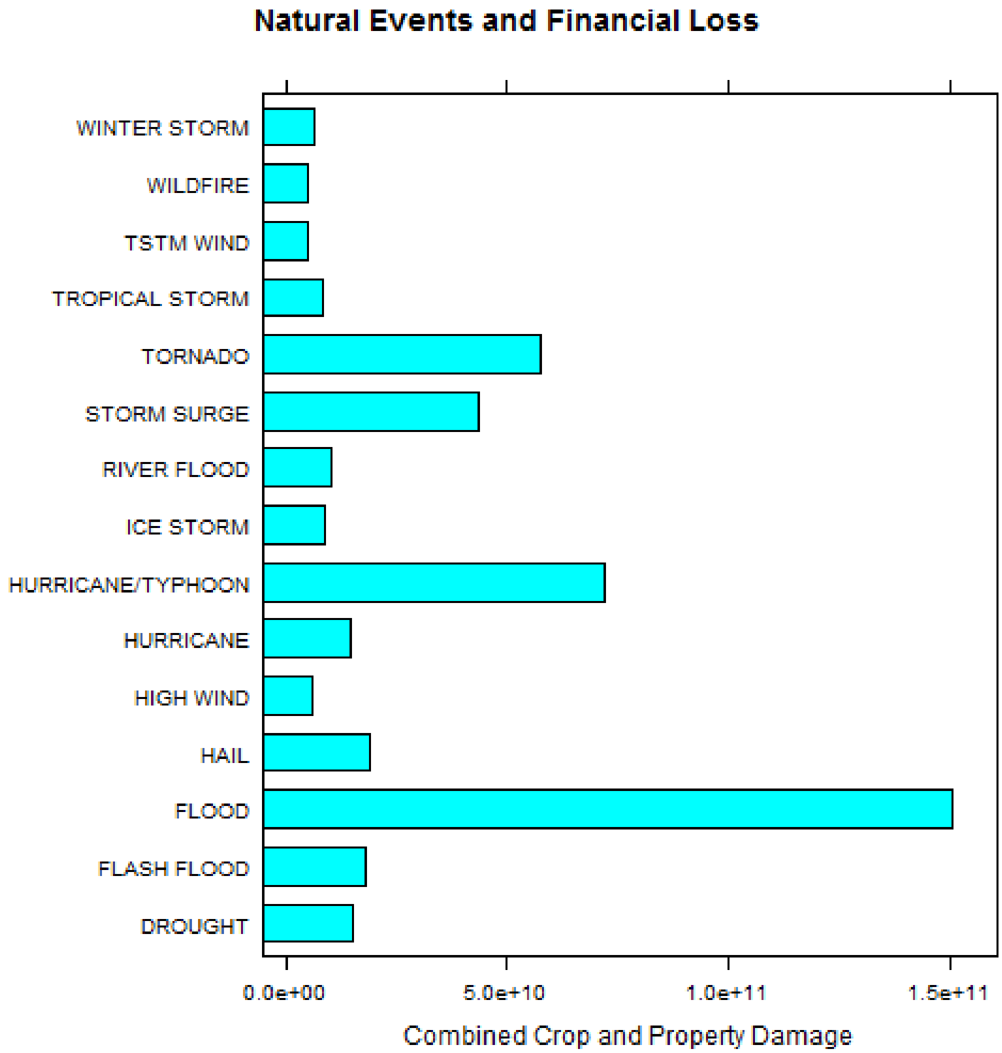
We already have all of the event types aggregated, so we can take a look at the top fifteen worst disasters by economic impact (the combined dollar amount of estimated crop and property damage).

```
topFifteenProp <- head(agged[order(-agged$totalDamage),
c("EVTYPE", "totalDamage")],
    15)
topFifteenProp
```

```
##                 EVTYPE totalDamage
## 86                FLOOD   1.503e+11
## 224 HURRICANE/TYPHOON   7.191e+10
## 407             TORNADO   5.736e+10
## 350         STORM SURGE   4.332e+10
## 134                HAIL   1.876e+10
## 73          FLASH FLOOD   1.824e+10
## 49              DROUGHT   1.502e+10
## 215           HURRICANE   1.461e+10
## 310         RIVER FLOOD   1.015e+10
## 238           ICE STORM   8.967e+09
## 417      TROPICAL STORM   8.382e+09
## 481        WINTER STORM   6.715e+09
## 200           HIGH WIND   5.909e+09
## 471            WILDFIRE   5.061e+09
## 423           TSTM WIND   5.039e+09
```

Flooding ranks highest on the total financial damage list. Again, we can plot this information to get a sense of how much more destructive floods were than any other disaster.

```
barchart(data = topFifteenProp, EVTYPE ~ totalDamage, xlab
= "Combined Crop and Property Damage",
    main = "Natural Events and Financial Loss")
```



Based on this information, floods have cost roughly 6 billion dollars more than the next leading disaster candidate, hurricanes.

To get a better sense of the types of events that impact property vs crop damage, let's sort the list by each damage type.

```
head(agged[order(-agged$cropdamage), c("EVTYPE",
"cropdamage")], 15)
```

```
##                 EVTYPE cropdamage
## 49             DROUGHT  1.397e+10
## 86               FLOOD  5.662e+09
## 310        RIVER FLOOD  5.029e+09
## 238          ICE STORM  5.022e+09
## 134               HAIL  3.026e+09
## 215          HURRICANE  2.742e+09
## 224 HURRICANE/TYPHOON  2.608e+09
## 73         FLASH FLOOD  1.421e+09
## 67        EXTREME COLD  1.293e+09
## 114       FROST/FREEZE  1.094e+09
## 159         HEAVY RAIN  7.334e+08
## 417     TROPICAL STORM  6.783e+08
## 200          HIGH WIND  6.386e+08
## 423          TSTM WIND  5.540e+08
## 61      EXCESSIVE HEAT  4.924e+08
```

```
head(agged[order(-agged$propdamage), c("EVTYPE",
"propdamage")], 15)
```

```
##                 EVTYPE propdamage
## 86               FLOOD  1.447e+11
## 224 HURRICANE/TYPHOON  6.931e+10
## 407            TORNADO  5.695e+10
## 350        STORM SURGE  4.332e+10
## 73         FLASH FLOOD  1.682e+10
## 134               HAIL  1.574e+10
## 215          HURRICANE  1.187e+10
## 417     TROPICAL STORM  7.704e+09
## 481       WINTER STORM  6.688e+09
## 200          HIGH WIND  5.270e+09
## 310        RIVER FLOOD  5.119e+09
## 471           WILDFIRE  4.765e+09
## 351  STORM SURGE/TIDE  4.641e+09
## 423          TSTM WIND  4.485e+09
## 238          ICE STORM  3.945e+09
```

Not surprisingly, drought was the worst killer of crops with flooding close behind.