Storm and other weather events: public health and economic impact

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November 19, 2018

Synopsis

In this report we will examine data from the U.S. National Oceanic and Atmospheric Administration's (NOAA) storm database, which tracks the characteristics of major storms and weather events in the US. We will use this data to determine the types of events that, across the United States, are most harmful with respect to population health and the types of events that have the greatest economic consequences. Identifying these types of events allows for more efficient resource allocation to prepare for weather events and minimize their public health and economic impact.

From the data we find that the events with the most significant public health impact are tornado and excessive heat on an aggregate basis (tsunamis, hurricanes/typhoons and excessive heat on a per incident basis), while the types of events that have the largest economic impact and droughts, hurricanes/typhoons and flooding.

The data we will be using can be found here.

Setting up the environment

We begin by installing the necessary packages.

```r
library(lubridate)
library(data.table)
```

Loading and processing the data

Reading the data

```r
URL <- "https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2"
destinationfile <- "repdata%2Fdata%2FStormData.csv.bz2"

if (!file.exists(destinationfile)) {
  download.file(URL, destfile = destinationfile, method = "curl")
}

stormdata <- read.csv("repdata%2Fdata%2FStormData.csv.bz2")
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
## 2 TORNADO         0                                               0
## 3 TORNADO         0                                               0
## 4 TORNADO         0                                               0
## 5 TORNADO         0                                               0
## 6 TORNADO         0                                               0
##   COUNTYENDN END_RANGE END_AZI END_LOCATI LENGTH WIDTH F MAG FATALITIES
## 1         NA         0                      14.0   100 3   0          0
## 2         NA         0                       2.0   150 2   0          0
## 3         NA         0                       0.1   123 2   0          0
## 4         NA         0                       0.0   100 2   0          0
## 5         NA         0                       0.0   150 2   0          0
## 6         NA         0                       1.5   177 2   0          0
##   INJURIES PROPDMG PROPDMGEXP CROPDMG 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
```

```r
dim(stormdata)
```

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

We see that we have 902,297 observations and 37 variables including date, time zone, county ID, county name, state and event type.

```r
str(stormdata, strict.width = 'wrap')
```

```
## '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 3980 3980 ...
## $ BGN_TIME : Factor w/ 3608 levels "00:00:00 AM",..: 272 287 2705 1683
##    2584 3186 242 1683 3186 3186 ...
## $ 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 1873 4598 10592 4372 10094 1973 23873
##    24418 4598 ...
## $ 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 ...
## $ PROPDMG : 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 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 ""," "| __truncated__,..: 1 1 1 1 1 1
##   1 1 1 1 ...
## $ 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 ...
```

Data processing

To prepare data for analysis, we will convert date colums and explicitly state property and crop damage figures, given that these are included in text form (for instance, we need to convert damage estimates from 10K to 10,000). Additionally, we note that some event types are duplicated due to small differences in character strings (e.g. FLOODING and FLOOD), so we will also correct some of these issues.

```
stormdata$BGN_DATE <- mdy_hms(stormdata$BGN_DATE)
stormdata$EVTYPE <- as.character(stormdata$EVTYPE)
stormdata$EVTYPE <- toupper(stormdata$EVTYPE)
```

```r
for (i in 1:902297) {
  if (stormdata$EVTYPE[i] == "GUSTY WIND") {
    stormdata$EVTYPE[i]<- "GUSTY WINDS"
  } else if (stormdata$EVTYPE[i] == "FLASH FLOOD") {
    stormdata$EVTYPE[i]<- "FLASH FLOODING"
  } else if (stormdata$EVTYPE[i] == "FLOOD") {
    stormdata$EVTYPE[i]<- "FLOODING"
  } else if (stormdata$EVTYPE[i] == "HIGH WIND") {
    stormdata$EVTYPE[i]<- "HIGH WINDS"
  } else if (stormdata$EVTYPE[i] == "LANDSLIDE") {
    stormdata$EVTYPE[i]<- "LANDSLIDES"
  } else if (stormdata$EVTYPE[i] == "RIP CURRENTS") {
    stormdata$EVTYPE[i]<- "RIP CURRENT"
  } else if (stormdata$EVTYPE[i] == "RIVER FLOOD") {
    stormdata$EVTYPE[i]<- "RIVER FLOODING"
  } else if (stormdata$EVTYPE[i] == "STRONG WIND") {
    stormdata$EVTYPE[i]<- "STRONG WINDS"
  } else if (stormdata$EVTYPE[i] == "THUNDERSTORM WIND") {
    stormdata$EVTYPE[i]<- "THUNDERSTORM WINDS"
  } else if (stormdata$EVTYPE[i] == "WILD FIRES") {
    stormdata$EVTYPE[i]<- "WILDFIRE"
  } else if (stormdata$EVTYPE[i] == "WIND") {
    stormdata$EVTYPE[i]<- "WINDS"
  } else {
  }
}
```

```r
PropertyDamage <- as.numeric(0)
for (i in 1:902297) {
  if (stormdata$PROPDMGEXP[i] == "K") {
    PropertyDamage[i] <- (stormdata$PROPDMG[i] * 1000)
  } else if (stormdata$PROPDMGEXP[i] == "M") {
    PropertyDamage[i] <- (stormdata$PROPDMG[i] * 1000000)
  } else if (stormdata$PROPDMGEXP[i] == "B") {
    PropertyDamage[i] <- (stormdata$PROPDMG[i] * 1000000000)
  } else {
    PropertyDamage[i]<- 0
  }
}
stormdata$PropertyDamage <- PropertyDamage

CropDamage <- as.numeric(0)
for (i in 1:902297) {
  if (stormdata$CROPDMGEXP[i] == "K") {
    CropDamage[i]<- (stormdata$CROPDMG[i] * 1000)
  } else if (stormdata$CROPDMGEXP[i] == "M") {
    CropDamage[i]<- (stormdata$CROPDMG[i] * 1000000)
  } else if (stormdata$CROPDMGEXP[i] == "B") {
    CropDamage[i]<- (stormdata$CROPDMG[i] * 1000000000)
  } else {
    CropDamage[i]<- 0
  }
}
```

```r
stormdata$CropDamage <- CropDamage
head(stormdata)
```

```
##   STATE__   BGN_DATE BGN_TIME TIME_ZONE COUNTY COUNTYNAME STATE  EVTYPE
## 1       1 1950-04-18     0130       CST     97     MOBILE    AL TORNADO
## 2       1 1950-04-18     0145       CST      3    BALDWIN    AL TORNADO
## 3       1 1951-02-20     1600       CST     57    FAYETTE    AL TORNADO
## 4       1 1951-06-08     0900       CST     89    MADISON    AL TORNADO
## 5       1 1951-11-15     1500       CST     43    CULLMAN    AL TORNADO
## 6       1 1951-11-15     2000       CST     77 LAUDERDALE    AL TORNADO
##   BGN_RANGE BGN_AZI BGN_LOCATI END_DATE END_TIME COUNTY_END COUNTYENDN
## 1         0                                               0         NA
## 2         0                                               0         NA
## 3         0                                               0         NA
## 4         0                                               0         NA
## 5         0                                               0         NA
## 6         0                                               0         NA
##   END_RANGE END_AZI END_LOCATI LENGTH WIDTH F MAG FATALITIES INJURIES
## 1         0                      14.0   100 3   0          0       15
## 2         0                       2.0   150 2   0          0        0
## 3         0                       0.1   123 2   0          0        2
## 4         0                       0.0   100 2   0          0        2
## 5         0                       0.0   150 2   0          0        2
## 6         0                       1.5   177 2   0          0        6
##   PROPDMG PROPDMGEXP CROPDMG CROPDMGEXP WFO STATEOFFIC ZONENAMES LATITUDE
## 1    25.0          K       0                                       3040
## 2     2.5          K       0                                       3042
## 3    25.0          K       0                                       3340
## 4     2.5          K       0                                       3458
## 5     2.5          K       0                                       3412
## 6     2.5          K       0                                       3450
##   LONGITUDE LATITUDE_E LONGITUDE_ REMARKS REFNUM PropertyDamage CropDamage
## 1      8812       3051       8806              1          25000          0
## 2      8755          0          0              2           2500          0
## 3      8742          0          0              3          25000          0
## 4      8626          0          0              4           2500          0
## 5      8642          0          0              5           2500          0
## 6      8748          0          0              6           2500          0
```

Exploratory analysis

Let us group weather events by state and by event type to get a clearer picture on the distribution of these instances.

```r
## Group by state
stormdata <- as.data.table(stormdata)
grouped_state <- stormdata[, list(count = .N, property_damage = sum(PROPDMG),
                          fatalities = sum(FATALITIES), injuries = sum(INJURIES)),
                     by = list(state = STATE)]
grouped_state
```

```
##     state count property_damage fatalities injuries
```

```
##  1:    AL 22739      363606.66        784     8742
##  2:    AZ  6156       83046.67        208      968
##  3:    AR 27102      361121.58        530     5550
##  4:    CA 10780      203598.79        550     3278
##  5:    CO 20473       81496.79        163     1004
##  6:    CT  3294       29155.17         41      897
##  7:    DE  1913       18304.17         30      338
##  8:    DC   437        3568.50         31      383
##  9:    FL 22124      374427.95        746     5918
## 10:    GA 25259      485873.68        327     5061
## 11:    HI  2547       11688.61         44       95
## 12:    ID  4767       41538.09         58      273
## 13:    IL 28488      357624.15       1421     5563
## 14:    IN 21506      260225.49        391     4720
## 15:    IA 31069      685487.35        140     2892
## 16:    KS 53440      387183.80        356     3449
## 17:    KY 22092      242190.66        239     3480
## 18:    LA 17323      294074.96        310     3215
## 19:    ME  4524       65171.45         25      177
## 20:    MD  8185       89255.86        162     1537
## 21:    MA  5652       78400.37        140     2121
## 22:    MI 17910      225030.23        398     4586
## 23:    MN 23609      194999.27        168     2282
## 24:    MS 22192      481811.85        555     6675
## 25:    MO 35648      329207.32        754     8998
## 26:    MT 14695       60102.11         58      181
## 27:    NE 30271      318614.86        102     1471
## 28:    NV  3139       30711.75        105      232
## 29:    NH  3022       51667.49         32      195
## 30:    NJ  8075       70504.77        180     1152
## 31:    NM  7129       54619.96         72      385
## 32:    NY 21058      373109.42        342     1340
## 33:    NC 25351      255058.55        398     3415
## 34:    ND 14632      163863.13         69      608
## 35:    OH 24922      559834.39        403     7112
## 36:    OK 46802      347294.00        458     5710
## 37:    OR  4821       22832.59         75      225
## 38:    PA 22226      288611.06        846     3223
## 39:    RI   839       10880.90          7       48
## 40:    SC 17126      151890.23        221     1786
## 41:    SD 21727      132139.08         61      868
## 42:    TN 21721      272126.78        521     5202
## 43:    TX 83728      937137.98       1366    17667
## 44:    UT  4135       45664.33        136     1070
## 45:    VT  3871       97582.57         23       71
## 46:    VA 21189      206132.30        174     1703
## 47:    WA  3312       81090.72        146      753
## 48:    WV  9099      163223.28         92      363
## 49:    WI 19781      311608.66        279     2309
## 50:    WY  7332       37172.20         56      432
## 51:    PR  3015       35223.79        115       52
## 52:    AK  4391       33995.51         74      112
## 53:    ST     1           0.00          0        0
## 54:    AS   257        2954.50         41      164
```

```
## 55:    GU   306          9440.34         81      416
## 56:    MH     1             5.00          0        1
## 57:    VI   338          2509.40          7        2
## 58:    AM  1879          5653.80         10       30
## 59:    LC   274             0.00          0        0
## 60:    PH    28             0.00          1        0
## 61:    GM  5337           606.04          1        0
## 62:    PZ    96            76.00          5        3
## 63:    AN  3250           294.00         12       23
## 64:    LH   654             0.00          0        0
## 65:    LM  1347          1633.10          4        2
## 66:    LE  1526            30.00          0        0
## 67:    LS   262           400.00          1        0
## 68:    SL     7            15.00          0        0
## 69:    LO    70            70.00          0        0
## 70:    PM     1             0.00          0        0
## 71:    PK    23            31.00          0        0
## 72:    XX     2             0.00          0        0
##     state count property_damage fatalities injuries
```

It can be observed that the number of rows surpasses the number of US states; were we to dive into an analysis of events per state we would have to take a closer look at this issue with the data. At first glance, we can easily see that there are some event instances with 'XX' as the state, potentially indicating missing data.

```
## Group by event type
stormdata <- as.data.table(stormdata)
grouped_etype <- stormdata[, list(count = .N, property_damage = sum(PROPDMG),
                            fatalities = sum(FATALITIES), injuries = sum(INJURIES)),
                     by = list(event_type = EVTYPE)]
grouped_etype
```

```
##                    event_type  count property_damage fatalities injuries
##   1:                  TORNADO  60652      3212258.16       5633    91346
##   2:                TSTM WIND 219942      1335995.61        504     6957
##   3:                     HAIL 288661       688693.38         15     1361
##   4:            FREEZING RAIN    260         2951.70          7       23
##   5:                     SNOW    617         3069.32          5       31
##  ---
## 883:          LAKESHORE FLOOD     23           47.50          0        0
## 884: MARINE THUNDERSTORM WIND   5812          436.40         10       26
## 885:       MARINE STRONG WIND     48          418.33         14       22
## 886:    ASTRONOMICAL LOW TIDE    174          320.00          0        0
## 887:        VOLCANIC ASHFALL      3            0.00          0        0
```

Data Analysis

1. Impact: Population health

To determine the type of event that has the largest impact on population health, we will look at the Fatalities and Injuries variables for each event type.

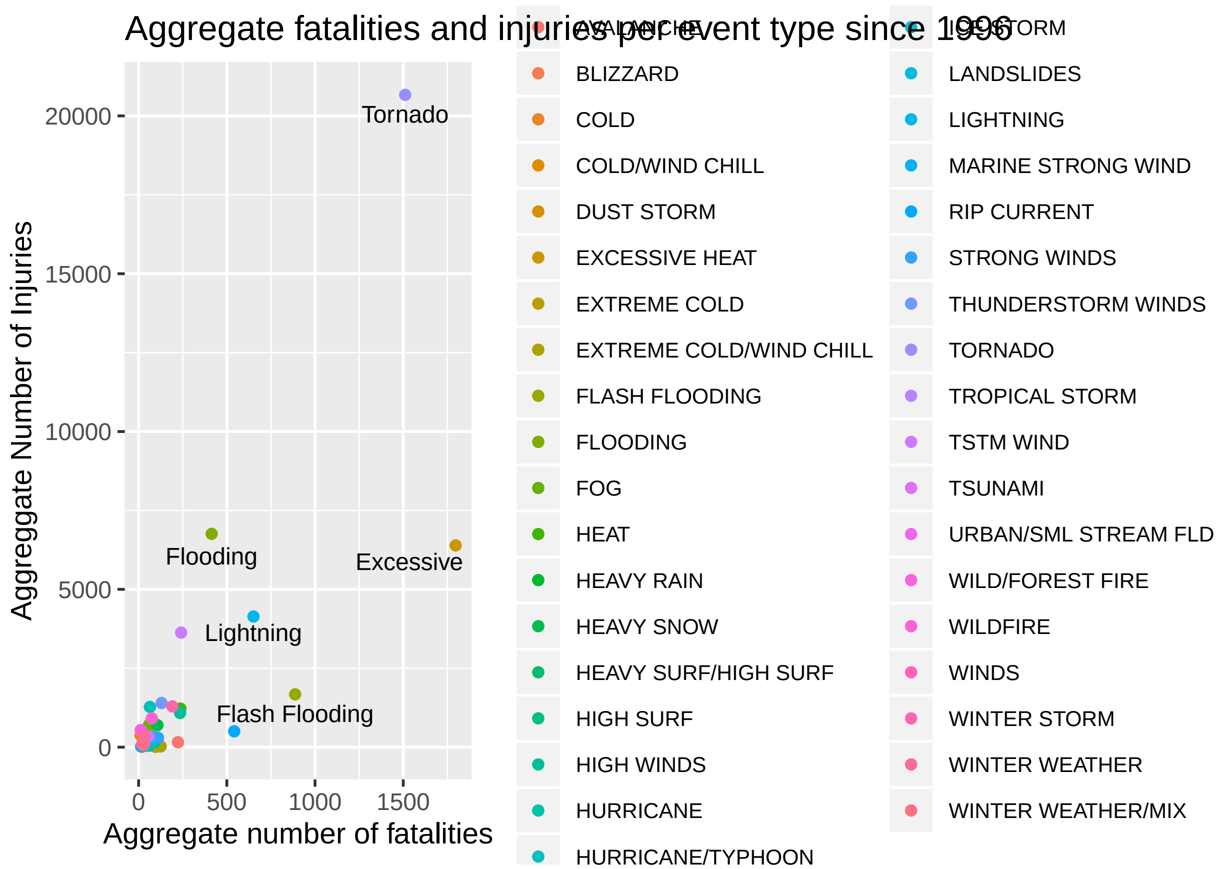
We will look at two different measures to determine which types of events have the most relevant impact on public health: 1) Aggregate injuries and fatalities per event type and 2) Average injuries and fatalities per type of event.

We start off by aggregating the number of fatalities and injuries per event type as follows. We remove event types with fewer than 10 injuries and fewer than 10 fatalities to facilitate analysis. We note that we will only look at aggregate figures since 1996 given that it is when all event types began to be included in the database.

```
subsetstormdata <- subset(stormdata, year(stormdata$BGN_DATE) > 1995)
injuries <- with(subsetstormdata, tapply(INJURIES, EVTYPE, sum))
fatalities <- with(subsetstormdata, tapply(FATALITIES, EVTYPE, sum))
fatalities <- as.data.frame(fatalities)
injuries <- as.data.frame(injuries)
a <- rownames(fatalities)
fatalities$EventType <- a
a <- rownames(injuries)
injuries$EventType <- a
merged <- merge(fatalities, injuries, by.x = "EventType", by.y ="EventType")
merged <- subset(merged, fatalities> 10 & injuries> 10)
```

We now graph aggregate fatalities and injuries per event type.

```
library(ggplot2)
g <- ggplot(merged, aes(fatalities, injuries))
g <- g +
  geom_point(aes(color = EventType)) +
  labs(x = "Aggregate number of fatalities", y = "Aggreggate Number of Injuries") +
  ggtitle("Aggregate fatalities and injuries per event type since 1996") +
  theme(legend.position="right") + theme(legend.text = element_text(size=8)) +
  annotate("text", x = 1511, y = 20067, label = "Tornado", size = 3) +
  annotate("text", x = 1697, y = 5891, label = "Excessive Heat", size = 3) +
  annotate("text", x = 414, y = 6058, label = "Flooding", size = 3) +
  annotate("text", x = 651, y = 3641, label = "Lightning", size = 3) +
  annotate("text", x = 887, y = 1074, label = "Flash Flooding", size = 3)
print(g)
```

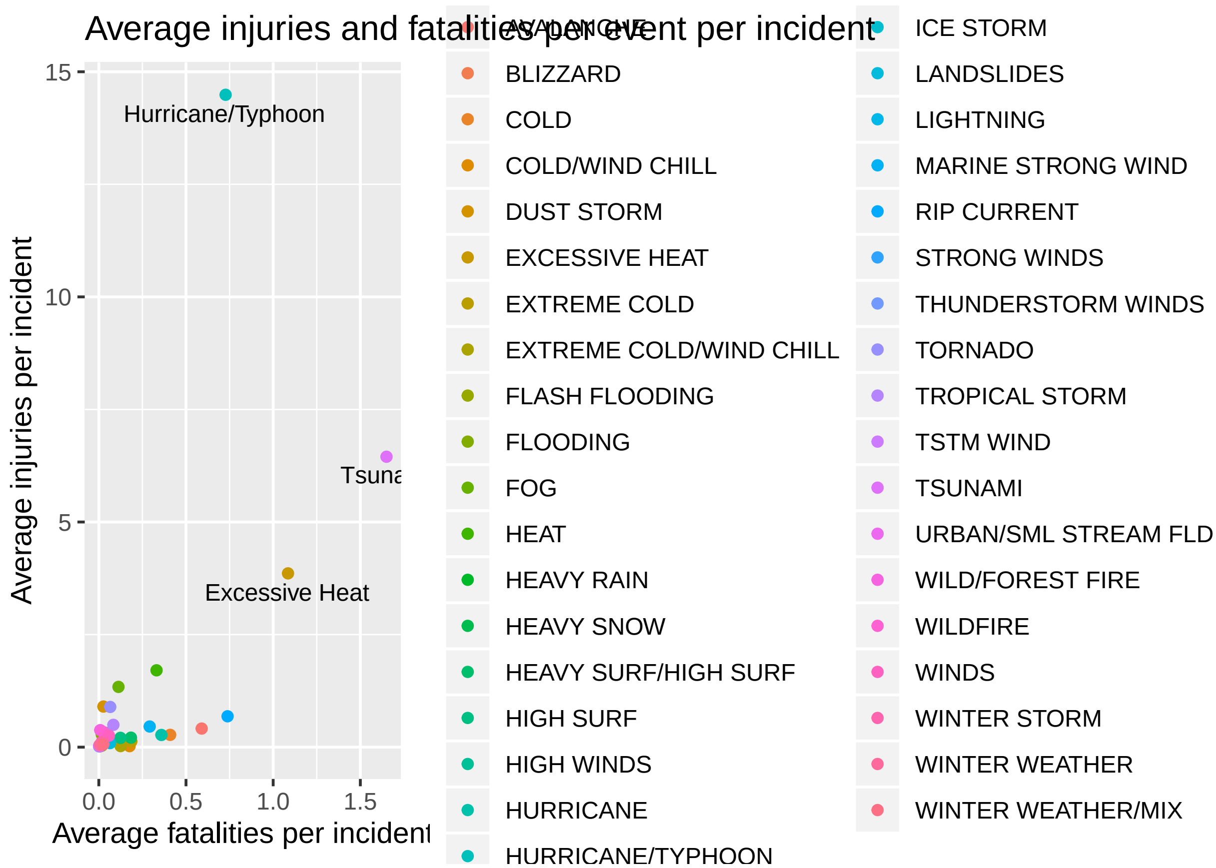


From this graph we can see that the types of events that have the most significant public health impact are: the tornado by number of injuries and excessive heat by number of fatalities. Other important events include flooding, lightning and flash flooding. We see that the majority of the other events are largely concentrated closer to the origin, within a range of 0-2,500 average injuries, and within a range of 0-500 fatalities. That is, there is a clear distinction between the events that have the most significant impact and other events. Among the other events which could be expected to cause a significant health impact are hurricanes and typhoons.

Next, we calculate the average injuries and fatalities per event to examine the weather events with the highest public health impact per instance. We continue to use the subseted data from 1996 and thereafter.

```r
A <- table(subsetstormdata$EVTYPE)
A <- as.data.frame(A)
merged <- merge(merged, A, by.x = "EventType", by.y = "Var1")
average <- merged
average$AverageFatalities <- average$fatalities / average$Freq
average$AverageInjuries <- average$injuries / average$Freq

g <- ggplot(average, aes(AverageFatalities, AverageInjuries))
g <- g + geom_point(aes(color = EventType)) +
  labs(x = "Average fatalities per incident", y = "Average injuries per incident") +
  ggtitle("Average injuries and fatalities per event per incident") +
  annotate("text", x = 1.65, y = 6.05, label = "Tsunami", size = 3) +
  annotate("text", x = 1.08, y = 3.45, label = "Excessive Heat", size = 3) +
  annotate("text", x = 0.72, y = 14.08, label = "Hurricane/Typhoon", size = 3)
print(g)
```



We can observe from this graph that the events with the most significant impact per incident on average are tsunamis, hurricanes and typhoons, and excessive heat. In response to our previously held expectation related to hurricanes, we can see that these do not occur as often as other events such as tornados, and thus their presence in the first graph was not very noticeable. However, on a per instance basis, in this graph we can appreciate how distant they are from other event types in terms of their public impact.

2. Impact: Economic

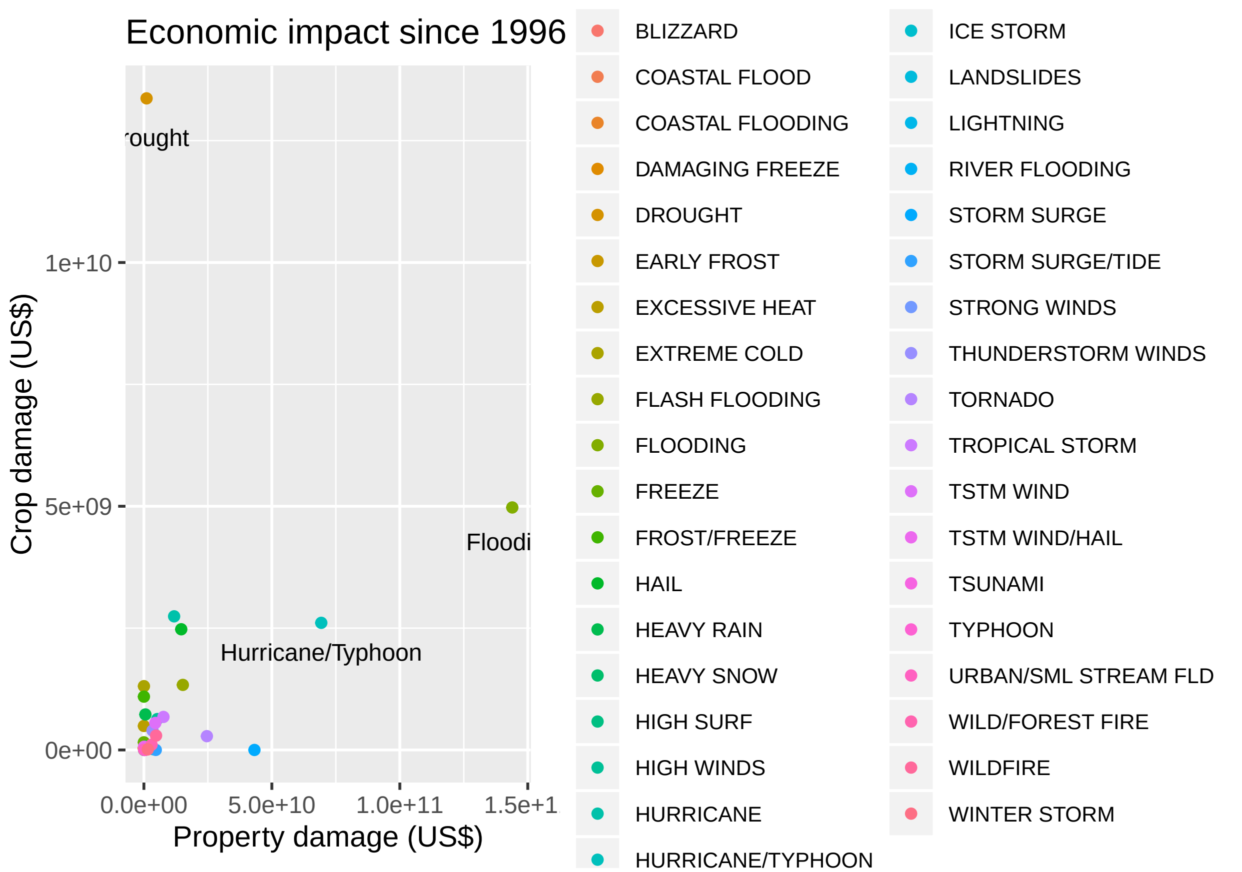
To measure the economic impact, we will also use the subseted data from 1996 and thereafter and look at the magnitude of the damage on property and crops.

We begin by aggregating per event type over property and crop damage. We subset for events with an impact of more than US44mm in property damage or US30mm in crop damage for analytical purposes.

```
property <- with(subsetstormdata, tapply(PropertyDamage, EVTYPE, sum))
crop <- with(subsetstormdata, tapply(CropDamage, EVTYPE, sum))
property <- as.data.frame(property)
crop <- as.data.frame(crop)
a <- rownames(property)
property$EventType <- a
a <- rownames(crop)
crop$EventType <- a
mergeddamage <- merge(property, crop, by.x = "EventType", by.y ="EventType")
mergeddamage <- subset(mergeddamage, property > 44000000 | crop > 30000000)
```

In the following graph, we observe that the events with the largest economic impact since 1996 have been droughts, floods and hurricanes/typhoons, which is in line with expectations given that these types of events have a much more significant impact on germane factors to the economy such as infrastructure and overall transportation, agriculture and in the case of hurricanes and floods even an absolute standstill of the economic activity in the area as communities need to abandon their homes.

```
g <- ggplot(mergeddamage, aes(property, crop))
g <- g + geom_point(aes(color = EventType)) +
  labs(x = "Property damage (US$)", y = "Crop damage (US$)") +
  ggtitle("Economic impact since 1996") + theme(legend.position="right") +
  theme(legend.text = element_text(size=8)) +
  annotate("text", x = 1046101000, y = 12567566000, label = "Drought", size = 3) +
  annotate("text", x = 143944833550, y = 4274778400, label = "Flooding", size = 3) +
  annotate("text", x = 69305840000, y = 2007872800, label = "Hurricane/Typhoon", size = 3)
print(g)
```



3. Conclusions

We have identified that the weather events with the most significant public health impact since 1996 have been the tornado and excessive heat, while the events with the most significant impact on a per instance basis have been the hurricane, typhoon, tsunami and also excessive heat. When looking at the economic impact of these events, once again the hurricane and typhoon post significant figures, while the drought and flooding events prove to be those with the highest impact as measured by crop and property damage.

An interesting way to further pursue this analysis is to gather data on economic activity per state, such as agriculture, and match it to the overall economic impact of these events to examine whether or not these have historically affected regions that are highly dependent on an economic activity particularly susceptible to certain types of events.