Public Health and Economic Impact of Weather events in the US

Synopsis

Here

Data Processing

1. **Note 1:** Dependencies: no
2. **Note 2:** The source documentation for this analysis is given in NWSI

For out analysis, we are going to use the NOAA Storm Database. So first we need to download it to a temporal file, expand it and put it in a data frame called weather_dataset:

```
filename = "http://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2"
tempfile <- tempfile()
download.file(filename, tempfile)
weather_dataset = read.csv(bzfile(tempfile), sep=",", header=T)
unlink(tempfile)
```

With the following function lets check if there are any NA's in the dataset:

```
nacols <- function(df) {
    colnames(df)[unlist(lapply(df, function(x) any(is.na(x))))]
}
na_cols = nacols(weather_dataset)
na_cols
```

```
## [1] "COUNTYENDN" "F"          "LATITUDE"   "LATITUDE_E"
```

As we can see there are 4 columns that contain NA values. So lets keep in mind this just in case we have to use them.

We will also check the number of rows with NA's, to have an idea of the completeness of our dataset:

```
ok = complete.cases(weather_dataset)
na_rows = sum(!ok)
na_rows
```

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

As we can see, there are a lot (902297) of missing values in this dataset.

Lets get to know a bit out dataset. These are the fields:

```
str(weather_dataset)
```

```
## '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 ...
```

This are the field names:

```
colnames(weather_dataset)
```

```
##  [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"
```

and this is a simple summary:

```
summary(weather_dataset)
```

```
##     STATE__                  BGN_DATE              BGN_TIME
```

```
##  Min.   : 1.0   5/25/2011 0:00:00:  1202   12:00:00 AM: 10163
##  1st Qu.:19.0   4/27/2011 0:00:00:  1193   06:00:00 PM:  7350
##  Median :30.0   6/9/2011 0:00:00 :  1030   04:00:00 PM:  7261
##  Mean   :31.2   5/30/2004 0:00:00:  1016   05:00:00 PM:  6891
##  3rd Qu.:45.0   4/4/2011 0:00:00 :  1009   12:00:00 PM:  6703
##  Max.   :95.0   4/2/2006 0:00:00 :   981   03:00:00 PM:  6700
##                 (Other)          :895866   (Other)    :857229
##    TIME_ZONE          COUNTY           COUNTYNAME          STATE
##  CST    :547493   Min.   :  0   JEFFERSON :  7840   TX     : 83728
##  EST    :245558   1st Qu.: 31   WASHINGTON:  7603   KS     : 53440
##  MST    : 68390   Median : 75   JACKSON   :  6660   OK     : 46802
##  PST    : 28302   Mean   :101   FRANKLIN  :  6256   MO     : 35648
##  AST    :  6360   3rd Qu.:131   LINCOLN   :  5937   IA     : 31069
##  HST    :  2563   Max.   :873   MADISON   :  5632   NE     : 30271
##  (Other):  3631                 (Other)   :862369   (Other):621339
##               EVTYPE          BGN_RANGE        BGN_AZI
##  HAIL             :288661   Min.   :   0          :547332
##  TSTM WIND        :219940   1st Qu.:   0   N      : 86752
##  THUNDERSTORM WIND: 82563   Median :   0   W      : 38446
##  TORNADO          : 60652   Mean   :   1   S      : 37558
##  FLASH FLOOD      : 54277   3rd Qu.:   1   E      : 33178
##  FLOOD            : 25326   Max.   :3749   NW     : 24041
##  (Other)          :170878                  (Other):134990
##          BGN_LOCATI                  END_DATE             END_TIME
##               :287743                    :243411               :238978
##  COUNTYWIDE   : 19680   4/27/2011 0:00:00:  1214   06:00:00 PM:  9802
##  Countywide   :   993   5/25/2011 0:00:00:  1196   05:00:00 PM:  8314
##  SPRINGFIELD  :   843   6/9/2011 0:00:00 :  1021   04:00:00 PM:  8104
##  SOUTH PORTION:   810   4/4/2011 0:00:00 :  1007   12:00:00 PM:  7483
##  NORTH PORTION:   784   5/30/2004 0:00:00:   998   11:59:00 PM:  7184
##  (Other)      :591444   (Other)          :653450   (Other)    :622432
##    COUNTY_END COUNTYENDN       END_RANGE      END_AZI
##  Min.   :0    Mode:logical   Min.   :  0          :724837
##  1st Qu.:0    NA's:902297    1st Qu.:  0   N      : 28082
##  Median :0                   Median :  0   S      : 22510
##  Mean   :0                   Mean   :  1   W      : 20119
##  3rd Qu.:0                   3rd Qu.:  0   E      : 20047
##  Max.   :0                   Max.   :925   NE     : 14606
##                                            (Other): 72096
##            END_LOCATI         LENGTH           WIDTH            F
```

```
##                 :499225   Min.   :   0.0   Min.   :   0   Min.   :0
##  COUNTYWIDE     : 19731   1st Qu.:   0.0   1st Qu.:   0   1st Qu.:0
##  SOUTH PORTION  :   833   Median :   0.0   Median :   0   Median :1
##  NORTH PORTION  :   780   Mean   :   0.2   Mean   :   8   Mean   :1
##  CENTRAL PORTION:   617   3rd Qu.:   0.0   3rd Qu.:   0   3rd Qu.:1
##  SPRINGFIELD    :   575   Max.   :2315.0   Max.   :4400   Max.   :5
##  (Other)        :380536                                   NA's   :843563
##       MAG            FATALITIES     INJURIES         PROPDMG
##  Min.   :    0   Min.   :  0   Min.   :   0.0   Min.   :   0
##  1st Qu.:    0   1st Qu.:  0   1st Qu.:   0.0   1st Qu.:   0
##  Median :   50   Median :  0   Median :   0.0   Median :   0
##  Mean   :   47   Mean   :  0   Mean   :   0.2   Mean   :  12
##  3rd Qu.:   75   3rd Qu.:  0   3rd Qu.:   0.0   3rd Qu.:   0
##  Max.   :22000   Max.   :583   Max.   :1700.0   Max.   :5000
##
##    PROPDMGEXP        CROPDMG        CROPDMGEXP          WFO
##         :465934   Min.   :  0.0          :618413          :142069
##  K      :424665   1st Qu.:  0.0   K      :281832   OUN    : 17393
##  M      : 11330   Median :  0.0   M      :  1994   JAN    : 13889
##  0      :   216   Mean   :  1.5   k      :    21   LWX    : 13174
##  B      :    40   3rd Qu.:  0.0   0      :    19   PHI    : 12551
##  5      :    28   Max.   :990.0   B      :     9   TSA    : 12483
##  (Other):    84                   (Other):     9   (Other):690738
##                                STATEOFFIC
##                                     :248769
##  TEXAS, North                       : 12193
##  ARKANSAS, Central and North Central: 11738
##  IOWA, Central                      : 11345
##  KANSAS, Southwest                  : 11212
##  GEORGIA, North and Central         : 11120
##  (Other)                            :595920
##
ZONENAMES
##
:594029
##
:205988
##  GREATER RENO / CARSON CITY / M - GREATER RENO / CARSON CITY / M
:   639
##  GREATER LAKE TAHOE AREA - GREATER LAKE TAHOE AREA
```

```
:   592
##  JEFFERSON - JEFFERSON
:   303
##  MADISON - MADISON
:   302
##  (Other)
:100444
##     LATITUDE      LONGITUDE        LATITUDE_E     LONGITUDE_
##  Min.   :   0   Min.   :-14451   Min.   :   0   Min.   :-14455
##  1st Qu.:2802   1st Qu.:  7247   1st Qu.:   0   1st Qu.:     0
##  Median :3540   Median :  8707   Median :   0   Median :     0
##  Mean   :2875   Mean   :  6940   Mean   :1452   Mean   :  3509
##  3rd Qu.:4019   3rd Qu.:  9605   3rd Qu.:3549   3rd Qu.:  8735
##  Max.   :9706   Max.   : 17124   Max.   :9706   Max.   :106220
##  NA's   :47                      NA's   :40
##                                            REMARKS           REFNUM
##                                                :287433   Min.   :     1
##                                                : 24013   1st Qu.:225575
##  Trees down.\n                                 :  1110   Median :451149
##  Several trees were blown down.\n              :   568   Mean   :451149
##  Trees were downed.\n                          :   446   3rd Qu.:676723
##  Large trees and power lines were blown down.\n:   432   Max.   :902297
##  (Other)                                       :588295
```

We have to provide a unique standard unit for the values of crop damage and property damage. I choose K (thousand's of $)

```
# provide a unique standard unit for prop damage
standarizePropDmgUnit = function(propDmg, propDmgExp) {
  if(propDmgExp=="b") {#billion
    propDmg * 1000 * 1000

  } else if(propDmgExp=="M") {#million
    propDmg * 1000
  } else if(propDmgExp=="m") {#Thousandth
    propDmg / (1000^6)
  } else if(propDmgExp=="H") {#hundred
    propDmg / 1000
  } else {# fr K and all other values, return as is
    #Note: its very obscure the symbol h and the numbers,
    # -, + and ?
```

```
    # I just keep it as is
    propDmg
  }
}

# provides a unique standard unit for
# crop damage values
standarizeCropDmgUnit = function(cropDmg, cropDmgExp) {
  if(cropDmgExp=="b") {#billion
    cropDmg * 1000 * 1000
  } else if(cropDmgExp=="M") {#million
    cropDmg * 1000
  } else if(cropDmgExp=="m") {#Thousandth
    cropDmg / (1000^6)
  } else if(cropDmgExp=="H") {#hundred
    cropDmg / 1000
  } else {# fr K and all other values, return as is
    #Note: its very obscure the symbol h and the numbers,
    # -, + and ?
    # I just keep it as is
    cropDmg
  }
}

#remove entries with 0 fatalities (harmless)
weather_dataset = weather_dataset[weather_dataset$FATALITIES != 0,]

#remove entries with no injuries (harmless)
weather_dataset = weather_dataset[weather_dataset$INJURIES != 0,]

#remove entries with no prop damage expenditures
weather_dataset = weather_dataset[weather_dataset$PROPDMG != 0,]

#remove entries with no crop damage expenditures
weather_dataset = weather_dataset[weather_dataset$CROPDMG != 0,]

for(i in 1:nrow(weather_dataset)) {
    propDmg = weather_dataset[i,"PROPDMG"]
    propDmgExp = weather_dataset[i,"PROPDMGEXP"]
    cropDmg = weather_dataset[i,"CROPDMG"]
```

```
    cropDmgExp = weather_dataset[i,"CROPDMGEXP"]

    weather_dataset[i,"PROPDMG"] = standarizePropDmgUnit(
      propDmg, propDmgExp)
    weather_dataset[i,"CROPDMG"] = standarizeCropDmgUnit(
      cropDmg, cropDmgExp)
    # do stuff with row
}


# IMPORTANT: please not I didn't "clean" the fields in the sense
# that I didn't merge fields together like others did.
# I tihink that for doing that, one should have more info
# on why those fields that look the same should be merged
# with confidence. else one may be twisting results
```

Results

We want to answer the following 2 fundamental questions:

1. Across the United States, which types of events are most harmful with respect to population health?
2. Across the United States, which types of events have the greatest economic consequences?

Most harmful events for population health

The field for the event types is EVTYPE. Lets take a look at some event types:

```
str(weather_dataset$EVTYPE)
```

```
##  Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 834 834 972 973 976 851 170 30 786 30 ...
```

In section 7 of the NWSI reference document ([NWSI]) we can inspect the different types of events in detail. For example From that document we can see that Excessive Heat (Z) event type is used for reporting fatalities (directly-related) or major impacts to human health occurring during excessive heat; Here is the quote: **Excessive Heat (Z) Fatalities (directly-related) or major impacts to human health occurring during excessive heat warning conditions are reported using this event category.**

coming back to our question, We need a meassure of the impact of each of these event types to public health. From the doc and the dataset, that impact should be given by two fields: FATALITIES (death cases) and INJURIES.

We should treat these 2 in a separate way as they are not the same. But we can “join” them together to see the overall “health impact” as this is what we want to answer

Total deaths per event type (first 10 greatest by # of deaths):

```
deathsPerEvtyp = aggregate(weather_dataset['FATALITIES'],
  by=list(event = weather_dataset$EVTYPE), FUN=sum)
# order the results
deathsPerEvtyp = deathsPerEvtyp[with(deathsPerEvtyp, order(-FATALITIES)), ]

top10Fatalities = head(deathsPerEvtyp, n=10)
top10Fatalities
```

```
##                 event FATALITIES
## 15            TORNADO        190
## 4               FLOOD         58
## 2      EXCESSIVE HEAT         46
## 19            TSUNAMI         32
## 20           WILDFIRE         31
## 3         FLASH FLOOD         23
## 5                HEAT         22
## 11 HURRICANE/TYPHOON         22
## 8           HIGH WIND         15
## 1            BLIZZARD         14
```

Those are the top-10 most deathful events. As we can see, tornados and excessive heat are the most fatal events by far, with 5633 and 1903 number of deaths respectively.

Total injuries per event type (first 10 greatest by # of injuries):

```
injPerEvtyp = aggregate(weather_dataset['INJURIES'],
  by=list(event = weather_dataset$EVTYPE), FUN=sum)
# order the results
injPerEvtyp = injPerEvtyp[with(injPerEvtyp, order(-INJURIES)), ]

top10Injuries = head(injPerEvtyp, n=10)
```

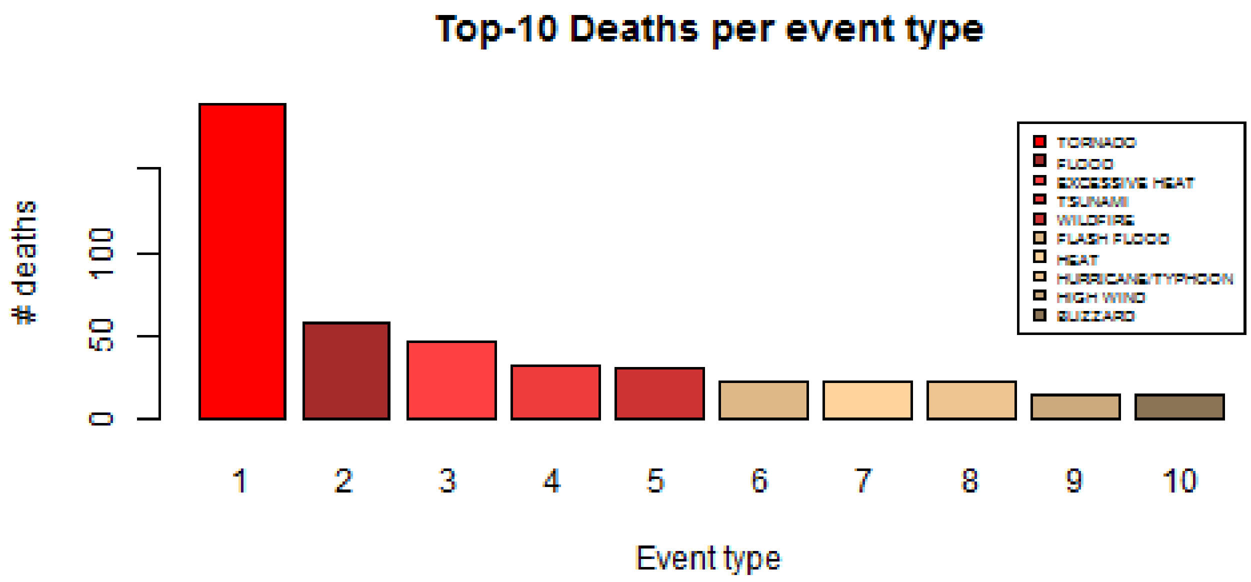
```
top10Injuries
```

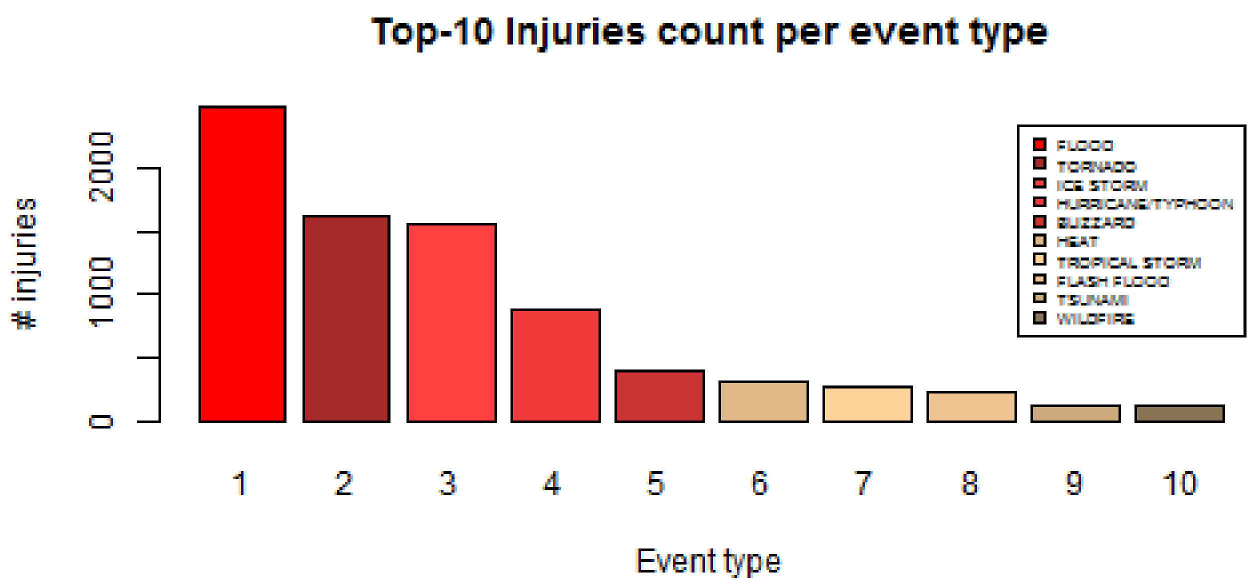
```
##                event INJURIES
## 4              FLOOD     2495
## 15           TORNADO     1630
## 12         ICE STORM     1568
## 11 HURRICANE/TYPHOON      884
## 1           BLIZZARD      402
## 5               HEAT      320
## 16    TROPICAL STORM      267
## 3        FLASH FLOOD      220
## 19           TSUNAMI      129
## 20          WILDFIRE      124
```

Those are the top-10 most harmful (only injuries) events, with tornados been the most harmful (91346 injurie cases) events by far.

The following is a graph (bar plot) of the top-10 most harmful events in each case (death and injuries):

```
par(mfrow = c(2, 1))
# deaths plot
barplot(top10Fatalities$FATALITIES,main="Top-10 Deaths per event type", xlab="Event type", ylab="# deaths",col=c("red", "brown","brown1","brown2", "brown3","burlywood","burlywood1","burlywood2", "burlywood3","burlywood4"), names.arg=1:10, legend=top10Fatalities[,"event"], args.legend=c(cex=0.5))
#args.legend=c(cex=0.4))
# and this is the injuries plot
barplot(top10Injuries$INJURIES,main="Top-10 Injuries count per event type",
    xlab="Event type", ylab="# injuries",col=c("red", "brown","brown1","brown2",
"brown3","burlywood","burlywood1","burlywood2", "burlywood3","burlywood4"), names.arg=1:10,
legend=top10Injuries[,"event"], args.legend=c(cex=0.5))
```

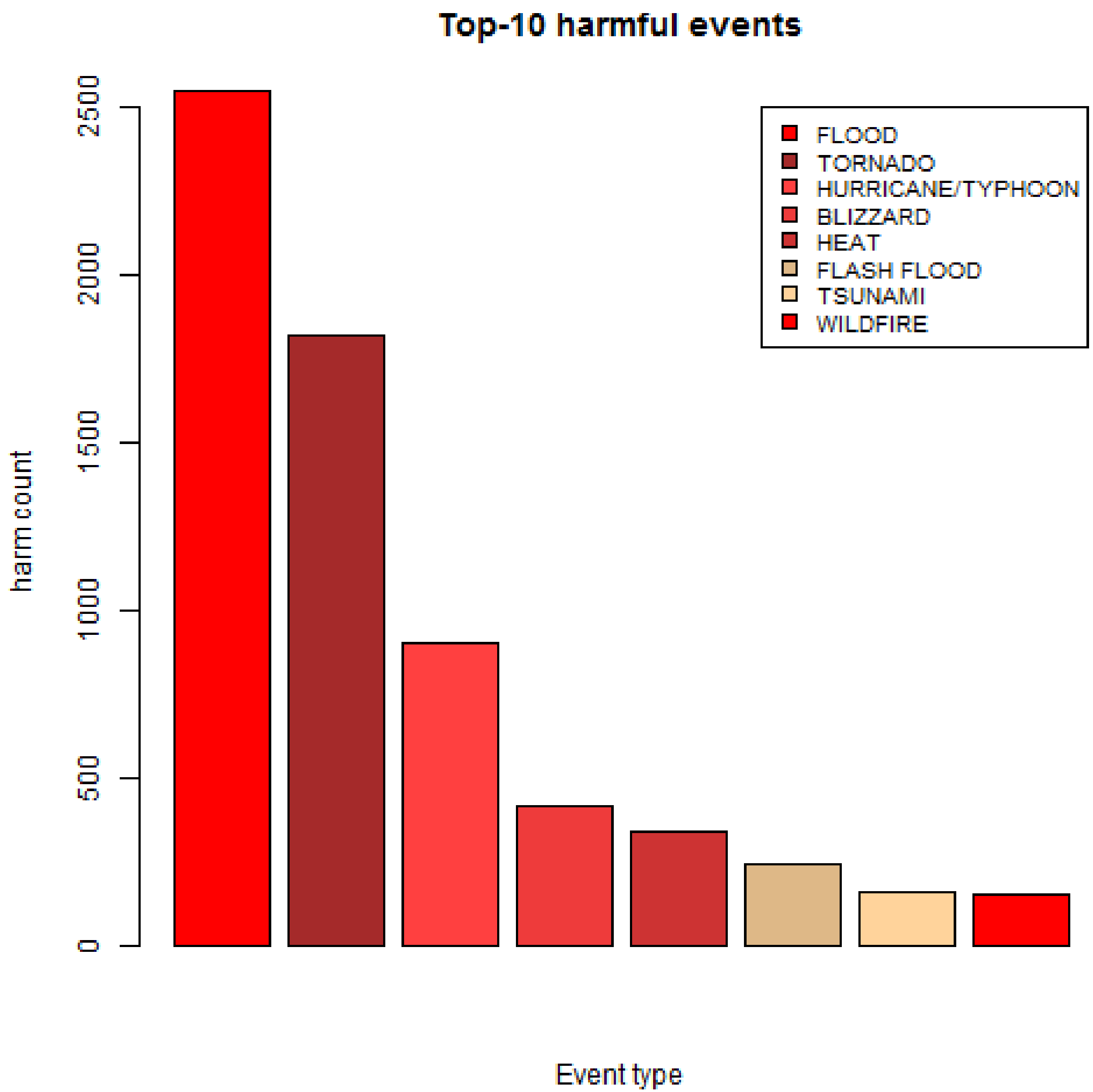




And lets see the overall harm (deaths + injuries)

```
# first lets merge the 2 datasets
```

```r
harmPerEvtyp = merge(top10Fatalities,top10Injuries)
harmPerEvtyp$HARM = harmPerEvtyp$FATALITIES + harmPerEvtyp$INJURIES
# order the results
harmPerEvtyp = harmPerEvtyp[with(harmPerEvtyp, order(-HARM)), ]

barplot(harmPerEvtyp$HARM,main="Top-10 harmful events",
    xlab="Event type",ylab="harm count", col=c("red", "brown","brown1","brown2",
"brown3","burlywood","burlywood1"), legend=harmPerEvtyp[,"event"],
    args.legend=c(cex=0.8))
```



As we can see, overall, the 10-most harmful event is the tornado, following is excessive heat, wind, flood, lightening, heat and flash flood.

We should take very special care regarding tornados!!!

Events with greatest economic consequences

Now lets see what happens with the economic aspect. The question is: **Across the United States, which types of events have the greatest economic consequences?** Let's see for each economic factor in each own:

The fields we are interested in are:

1.“PROPDMG” (property damage)
2.“CROPDMG” (crop damage)

with corresponding units: “PROPDMGEXP” (unit for property damage) “CROPDMGEXP” (unit for crop damage)

So this is the property damage per event type:

```
propDmgPerEvtyp = aggregate(weather_dataset['PROPDMG'],
  by=list(event = weather_dataset$EVTYPE), FUN=sum)

# order the results
propDmgPerEvtyp = propDmgPerEvtyp[with(propDmgPerEvtyp, order(-PROPDMG)), ]
top10propDmg = head(propDmgPerEvtyp, n=10)
top10propDmg
```

```
##                        event PROPDMG
## 15                   TORNADO 1051902
## 8                  HIGH WIND  948690
## 16            TROPICAL STORM  628520
## 4                      FLOOD  221000
## 10                 HURRICANE  140250
## 20                  WILDFIRE  125121
## 3                FLASH FLOOD   97712
## 19                   TSUNAMI   81000
## 14        THUNDERSTORM WINDS   75680
## 22 WINTER STORM HIGH WINDS   60000
```

As we can see, the tornado and flash wind are the events whith the greatest damage

Lets see what about the crop damage

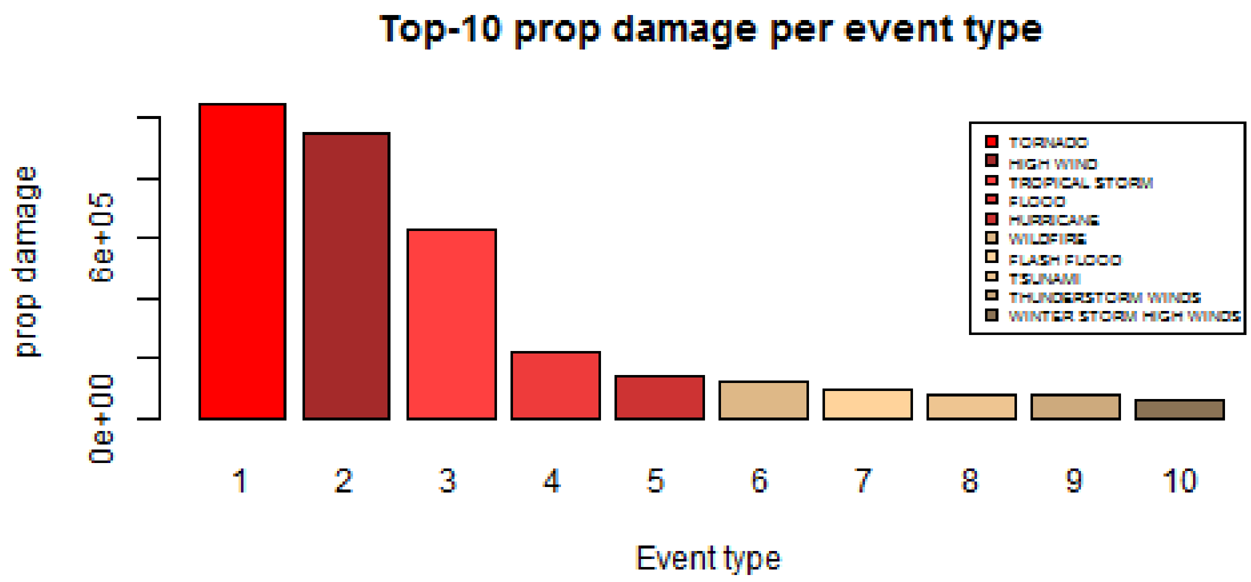
```
cropDmgPerEvtyp = aggregate(weather_dataset['CROPDMG'],
  by=list(event = weather_dataset$EVTYPE), FUN=sum)

# order the results
cropDmgPerEvtyp = cropDmgPerEvtyp[with(cropDmgPerEvtyp, order(-CROPDMG)), ]

top10cropDmg = head(cropDmgPerEvtyp, n=10)
top10cropDmg
```

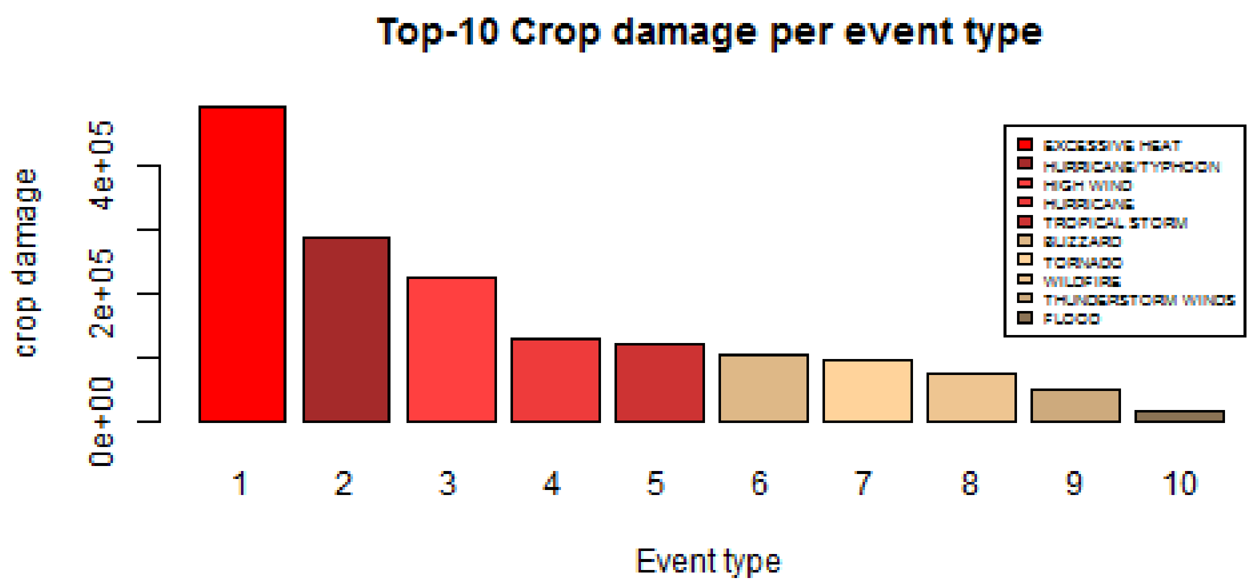
```
##                  event CROPDMG
## 2       EXCESSIVE HEAT  492400
## 11   HURRICANE/TYPHOON  285002
## 8            HIGH WIND  222935
## 10           HURRICANE  127000
## 16      TROPICAL STORM  121695
## 1             BLIZZARD  105000
## 15             TORNADO   93525
## 20            WILDFIRE   75150
## 14 THUNDERSTORM WINDS   50016
## 4                FLOOD   17731
```

And we can see that Hail is the event with the greatest damage, following is flsh flood, wind, tornado, etc.

Let see a plot of all this:

```
par(mfrow = c(2, 1))
# prop plot
barplot(top10propDmg$PROPDMG,main="Top-10 prop damage per event type",
    xlab="Event type", ylab="prop damage",col=c("red", "brown","brown1","brown2",
"brown3","burlywood","burlywood1","burlywood2", "burlywood3","burlywood4"), names.arg=1:10,
legend=top10propDmg[,"event"],args.legend=c(cex=0.5))
# and this is the crop plot
barplot(top10cropDmg$CROPDMG,main="Top-10 Crop damage per event type",
    xlab="Event type", ylab="crop damage",col=c("red", "brown","brown1","brown2",
"brown3","burlywood","burlywood1","burlywood2", "burlywood3","burlywood4"), names.arg=1:10,
legend=top10cropDmg[,"event"],args.legend=c(cex=0.5))
```


Top-10 prop damage per event type
prop damage
0e+00
6e+05
1
2
3
4
5
6
7
8
9
10
Event type
TORNADO
HIGH WIND
TROPICAL STORM
FLOOD
HURRICANE
WILDFIRE
FLASH FLOOD
TSUNAMI
THUNDERSTORM WINDS
WINTER STORM HIGH WINDS


Top-10 Crop damage per event type
crop damage
0e+00
2e+05
4e+05
1
2
3
4
5
6
7
8
9
10
Event type
EXCESSIVE HEAT
HURRICANE/TYPHOON
HIGH WIND
HURRICANE
TROPICAL STORM
BLIZZARD
TORNADO
WILDFIRE
THUNDERSTORM WINDS
FLOOD