Storm Data Analysis

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Synopsis

The National Weather Service collects data regarding major storms and weather events beginning in the year 1950. We have been tasked with summarizing the data from 1950 through November 2011 to determine which type of events are the most harmful with respect to population health as well as have the greatest economic consequences, both across the entire United States.

The top five event types that are most harmful to population health across the United States, when including both fatalities and injuries include (in rank order): tornadoes, excessive heat, thunderstorm winds, flood, and lightening. Looking at fatalities and injuries separately, the rankings fluctuate slightly, but the top five event types remains the same.

In regards to economic consequences related to the top five weather events across the United States, the Total Economic Consequences and Total Property Damage are almost identical, with exception of the 5th ranking. In declining order, they include: Flood, hurricane/typhoon, tornado, storm surge and for total damages, hail, whereas property damage, flash flood. On the other hand, for Total Crop Damages, the number one ranking is drought, followed by flood, river flood, ice storm and hail.

Data Processing

Step 1: Load the data and necessary libraries.

```
library(plyr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:plyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
if(!file.exists("stormdata")){
  dir.create("stormdata")
}
fileUrl<-"https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2"
```

```r
download.file(fileUrl, "stormdata.csv")
stormdata<-read.csv("stormdata.csv")
glimpse(stormdata)
```

```
## Observations: 902,297
## Variables: 37
## $ STATE__    <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ...
## $ BGN_DATE   <fctr> 4/18/1950 0:00:00, 4/18/1950 0:00:00, 2/20/1951 0:...
## $ BGN_TIME   <fctr> 0130, 0145, 1600, 0900, 1500, 2000, 0100, 0900, 20...
## $ TIME_ZONE  <fctr> CST, CST, CST, CST, CST, CST, CST, CST, CST, CST, ...
## $ COUNTY     <dbl> 97, 3, 57, 89, 43, 77, 9, 123, 125, 57, 43, 9, 73, ...
## $ COUNTYNAME <fctr> MOBILE, BALDWIN, FAYETTE, MADISON, CULLMAN, LAUDER...
## $ STATE      <fctr> AL, AL, AL, AL, AL, AL, AL, AL, AL, AL, AL, AL, AL...
## $ EVTYPE     <fctr> TORNADO, TORNADO, TORNADO, TORNADO, TORNADO, TORNA...
## $ BGN_RANGE  <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ BGN_AZI    <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ BGN_LOCATI <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ END_DATE   <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ END_TIME   <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ COUNTY_END <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ COUNTYENDN <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,...
## $ END_RANGE  <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ END_AZI    <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ END_LOCATI <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ LENGTH     <dbl> 14.0, 2.0, 0.1, 0.0, 0.0, 1.5, 1.5, 0.0, 3.3, 2.3, ...
## $ WIDTH      <dbl> 100, 150, 123, 100, 150, 177, 33, 33, 100, 100, 400...
## $ F          <int> 3, 2, 2, 2, 2, 2, 2, 1, 3, 3, 1, 1, 3, 3, 3, 4, 1, ...
## $ MAG        <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ FATALITIES <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 4, 0, ...
## $ INJURIES   <dbl> 15, 0, 2, 2, 2, 6, 1, 0, 14, 0, 3, 3, 26, 12, 6, 50...
## $ PROPDMG    <dbl> 25.0, 2.5, 25.0, 2.5, 2.5, 2.5, 2.5, 2.5, 25.0, 25....
## $ PROPDMGEXP <fctr> K, K, K, K, K, K, K, K, K, K, M, M, K, K, K, K, K,...
## $ CROPDMG    <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ CROPDMGEXP <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ WFO        <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ STATEOFFIC <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ ZONENAMES  <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ LATITUDE   <dbl> 3040, 3042, 3340, 3458, 3412, 3450, 3405, 3255, 333...
## $ LONGITUDE  <dbl> 8812, 8755, 8742, 8626, 8642, 8748, 8631, 8558, 874...
## $ LATITUDE_E <dbl> 3051, 0, 0, 0, 0, 0, 0, 0, 3336, 3337, 3402, 3404, ...
## $ LONGITUDE_ <dbl> 8806, 0, 0, 0, 0, 0, 0, 0, 8738, 8737, 8644, 8640, ...
## $ REMARKS    <fctr> , , , , , , , , , , , , , , , , , , , , , , , ,
## $ REFNUM     <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, ...
```

Step 2: Determine which variable address the assignment criteria. Both questions ask for information 'Across the United States' which eliminates the need to subset or sort information by state, region or county. Therefore, none of those variables are necessary. Both also ask about types of events, so the variable EVTYPE is necessary for both. Neither asks for information regarding parameters of individual events, times, latitude/longitude, magnitude, etc, thereby eliminating the need for any of those variables as well.

Question 1: which types of events are most harmful with respect to population health? The variables pertaining to public health include : According to the National Weather Service Storm Data Documentation (NWCSSDD) - FATALITIES, and INJURIES. This allows for a truncated dataset that includes only 3 variables - EVTYPE, FATALITIES, and INJURIES.

Question 2: which types of events have the greatest economic consequences? Again, according to the NWCSSDD the categories associated with cost(economic consequences) are PROPDMG, PROPDMGEXP, CROPDMG, CROPDMGEXP. This again allows for a truncated dataset that only includes 5 variables - EVTYPE, PROPDMG, PROPDMGEXP, CROPDMG, CROPDMGEXP.

Step 3: Create two data sets using the variables selected in Step 2, one addressing public health and one addressing economic consequences to expedite data processing during analysis.

```
  ## Public health related data
stormdataHealth<-stormdata[, c("EVTYPE", "FATALITIES", "INJURIES")]
str(stormdataHealth)
```

```
## 'data.frame':    902297 obs. of  3 variables:
##  $ EVTYPE    : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 834 834 834 834 834 834 834 834 834 8
##  $ FATALITIES: num  0 0 0 0 0 0 0 0 1 0 ...
##  $ INJURIES  : num  15 0 2 2 2 6 1 0 14 0 ...
```

```
  ## Economic consequences related data
stormdataCost<-stormdata[ ,c("EVTYPE", "PROPDMG", "PROPDMGEXP", "CROPDMG", "CROPDMGEXP")]
str(stormdataCost)
```

```
## 'data.frame':    902297 obs. of  5 variables:
##  $ EVTYPE    : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 834 834 834 834 834 834 834 834 834 8
##  $ 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 ...
```

The *stormdataHealth* dataset is ready for analysis, however the *stormdataCost* dataset requires more processing. The elements of the *PROPDMGEXP* AND *CROPDMGEXP* are multipliers for the numeric amounts of the *PROPDMG* AND *CROPDMG* variables, respectively. Reviewing these, note there are several different multipliers in each variable.

```
unique(stormdataCost$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
```

```
unique(stormdataCost$CROPDMGEXP)
```

```
## [1]   M K m B ? 0 k 2
## Levels:  ? 0 2 B k K m M
```

Notice there is repetition between the two variables. There is no direct explanation as to what the numbers represent, however it is fairly safe to assume they represent exponential multiplicatives. For example, "6" represents ten raised to the power of 6 (10^6) or millions. This exponential should then be multiplied with the corresponding figure in the *PROPDMG* OR *CROPDMG* variable. This assumption is based on the given that according to the NWCSSDD the letters represent the following: "H" or "h" represent hundreds; "K" or "k" represent thousand; "M" or "m" represent millions; and "B" or "b" represent billions. These figures need to be converted to a consistent format in order to use them as multipliers to calculate the economic consequences of each event.

Step 1: create new variables which converts factors in *PROPDMGEXP* and *CROPDMGEXP* to characters.

```
stormdataCost$PROPDMGEXP1<-as.character(stormdataCost$PROPDMGEXP)
stormdataCost$CROPDMGEXP1<-as.character(stormdataCost$CROPDMGEXP)
str(stormdataCost)
```

```
## 'data.frame':    902297 obs. of  7 variables:
##  $ EVTYPE     : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 834 834 834 834 834 834 834 834 834
##  $ 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 ...
##  $ PROPDMGEXP1: chr  "K" "K" "K" "K" ...
##  $ CROPDMGEXP1: chr  "" "" "" "" ...
```

Step 2: convert the letters, "H", "h", "K", "k", "M", "m" and "B" to their corresponding exponents, 2,3,6 & 9, respectively, for both property and crop damage exponents. For the unknown factors, "", "=", "+", "-" and "?", just replace with zero for simplicity.

```
 ## property damages
stormdataCost$PROPDMGEXP1[stormdataCost$PROPDMGEXP1 %in% c("B")]="9"
stormdataCost$PROPDMGEXP1[stormdataCost$PROPDMGEXP1 %in% c("","=", "+", "-","?")]="0"
stormdataCost$PROPDMGEXP1[stormdataCost$PROPDMGEXP1 %in% c("H", "h")]="2"
stormdataCost$PROPDMGEXP1[stormdataCost$PROPDMGEXP1 %in% c("K", "k")]="3"
stormdataCost$PROPDMGEXP1[stormdataCost$PROPDMGEXP1 %in% c("M", "m")]="6"
stormdataCost$PROPDMGEXP1[stormdataCost$PROPDMGEXP1 %in% c("0")]="3"

 ## crop damages
stormdataCost$CROPDMGEXP1[stormdataCost$CROPDMGEXP1 %in% c("?", "")]="0"
stormdataCost$CROPDMGEXP1[stormdataCost$CROPDMGEXP1 %in% c("B")]="9"
stormdataCost$CROPDMGEXP1[stormdataCost$CROPDMGEXP1 %in% c("M","m")]="6"
stormdataCost$CROPDMGEXP1[stormdataCost$CROPDMGEXP1 %in% c("K","k")] = "3"
str(stormdataCost)
```

```
## 'data.frame':    902297 obs. of  7 variables:
##  $ EVTYPE     : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 834 834 834 834 834 834 834 834 834
##  $ 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 ...
##  $ PROPDMGEXP1: chr  "3" "3" "3" "3" ...
##  $ CROPDMGEXP1: chr  "0" "0" "0" "0" ...
```

Step 3: Calculate the total property and crop damage individually, then combine them for a cumulative total.

```
 ## total property damage
stormdataCost$TotPropDmg<-stormdataCost$PROPDMG*10^as.numeric(stormdataCost$PROPDMGEXP1)
 ## total crop damage
stormdataCost$TotCropDmg<-stormdataCost$CROPDMG*10^as.numeric(stormdataCost$CROPDMGEXP1)
 ## total cummulative damage
stormdataCost$totalDamage<-stormdataCost$TotPropDmg + stormdataCost$TotCropDmg
str(stormdataCost)
```

```
## 'data.frame':    902297 obs. of  10 variables:
```

```
##  $ EVTYPE     : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 834 834 834 834 834 834 834 834 834
##  $ 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 ...
##  $ PROPDMGEXP1: chr  "3" "3" "3" "3" ...
##  $ CROPDMGEXP1: chr  "0" "0" "0" "0" ...
##  $ TotPropDmg : num  25000 2500 25000 2500 2500 2500 2500 2500 25000 25000 ...
##  $ TotCropDmg : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ totalDamage: num  25000 2500 25000 2500 2500 2500 2500 2500 25000 25000 ...
```

Analysis

Question 1 event types most harmful to population health:

A truncated dataset has already been created, *stormdataHealth*, it now needs to be summarized by EVTYPE, or event type.

```
totHealth<- stormdataHealth %>% group_by(EVTYPE) %>%
  summarise_each(funs(sum))
str(totHealth)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    985 obs. of  3 variables:
##  $ EVTYPE    : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 1 2 3 4 5 6 7 8 9 10 ...
##  $ FATALITIES: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ INJURIES  : num  0 0 0 0 0 0 0 0 0 0 ...
```

Next, add a new variable to represent the combined total of fatalities and injuries.

```
totHealth$totFI<-totHealth$FATALITIES+totHealth$INJURIES
str(totHealth)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    985 obs. of  4 variables:
##  $ EVTYPE    : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 1 2 3 4 5 6 7 8 9 10 ...
##  $ FATALITIES: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ INJURIES  : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ totFI     : num  0 0 0 0 0 0 0 0 0 0 ...
```

Rearrange the dataset to sort our total fatalities and injuries from highest to lowest numbers to determine those events most harmful to the population's health.

```
totHealth1<-arrange(totHealth, desc(totFI))
head(totHealth1)
```

```
## # A tibble: 6 × 4
##           EVTYPE FATALITIES INJURIES totFI
##           <fctr>      <dbl>    <dbl> <dbl>
## 1        TORNADO       5633    91346 96979
## 2 EXCESSIVE HEAT       1903     6525  8428
## 3      TSTM WIND        504     6957  7461
## 4          FLOOD        470     6789  7259
## 5      LIGHTNING        816     5230  6046
## 6           HEAT        937     2100  3037
```

After reviewing *totHealth1*, it is obvious that only the top 5 are significant in relation to overall total fatalities and injuries.

```
totHealth1<-totHealth1 [1:5,]
totHealth1
```

```
## # A tibble: 5 × 4
##            EVTYPE FATALITIES INJURIES totFI
##            <fctr>      <dbl>    <dbl> <dbl>
## 1         TORNADO       5633    91346 96979
## 2 EXCESSIVE HEAT       1903     6525  8428
## 3       TSTM WIND        504     6957  7461
## 4           FLOOD        470     6789  7259
## 5       LIGHTNING        816     5230  6046
```

It would also be interesting to review the order of event types in relation to fatalities and injuries separately, to see which comprises more occurrences per event type, fatalities or injuries. Therefore, re-order the dataset, *totHealth1* by each fatalities and injuries, rather than the total combined. See Figure 1 under results for graphics.

```
arrange(totHealth1, desc(FATALITIES))
```

```
## # A tibble: 5 × 4
##            EVTYPE FATALITIES INJURIES totFI
##            <fctr>      <dbl>    <dbl> <dbl>
## 1         TORNADO       5633    91346 96979
## 2 EXCESSIVE HEAT       1903     6525  8428
## 3       LIGHTNING        816     5230  6046
## 4       TSTM WIND        504     6957  7461
## 5           FLOOD        470     6789  7259
```

```
arrange(totHealth1, desc(INJURIES))
```

```
## # A tibble: 5 × 4
##            EVTYPE FATALITIES INJURIES totFI
##            <fctr>      <dbl>    <dbl> <dbl>
## 1         TORNADO       5633    91346 96979
## 2       TSTM WIND        504     6957  7461
## 3           FLOOD        470     6789  7259
## 4 EXCESSIVE HEAT       1903     6525  8428
## 5       LIGHTNING        816     5230  6046
```

The number one event type to harm to population health is consistently tornadoes, but the other event types fluctuate some in the individual categories.

Question 2 Event types with greatest economic consequences:

Because total figures for property damage, crop damage and cumulative damage were calculated during data processing, create a new dataset including only those variables as well as *EVTYPE*.

```
stormdataCost1<-stormdataCost[c("EVTYPE", "TotPropDmg", "TotCropDmg", "totalDamage")]
str(stormdataCost1)
```

```
## 'data.frame':    902297 obs. of  4 variables:
##  $ EVTYPE     : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 834 834 834 834 834 834 834 834 834
##  $ TotPropDmg : num  25000 2500 25000 2500 2500 2500 2500 2500 25000 25000 ...
##  $ TotCropDmg : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ totalDamage: num  25000 2500 25000 2500 2500 2500 2500 2500 25000 25000 ...
```

Next, summarize the new dataset, *stormdataCost1* by event type.

```
totCost<-stormdataCost1%>%group_by(EVTYPE)%>% summarise_each(funs(sum))
str(totCost)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    985 obs. of  4 variables:
##  $ EVTYPE     : Factor w/ 985 levels "   HIGH SURF ADVISORY",..: 1 2 3 4 5 6 7 8 9 10 ...
##  $ TotPropDmg : num  200000 0 50000 0 8100000 8000 0 0 5000 0 ...
##  $ TotCropDmg : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ totalDamage: num  200000 0 50000 0 8100000 8000 0 0 5000 0 ...
```

Rearrange the dataset from highest to lowest dollar amounts to determine which events with the greatest economic consequences.

```
totCost<-arrange(totCost, desc(totalDamage))
totCost1<-totCost[1:5,]
totCost1
```

```
## # A tibble: 5 × 4
##              EVTYPE   TotPropDmg TotCropDmg  totalDamage
##              <fctr>        <dbl>      <dbl>        <dbl>
## 1             FLOOD 144657716800 5661968450 150319685250
## 2 HURRICANE/TYPHOON  69305840000 2607872800  71913712800
## 3           TORNADO  56947576980  414953270  57362530250
## 4       STORM SURGE  43323536000       5000  43323541000
## 5              HAIL  15735559920 3025954473  18761514393
```

As with population health, it is interesting to look at how the top five event types vary contingent on only property and crop damages.

```
 ## property damages
totCost2<-arrange(totCost, desc(TotPropDmg))
totCost2<-totCost2[1:5,]
totCost2
```

```
## # A tibble: 5 × 4
##              EVTYPE   TotPropDmg TotCropDmg  totalDamage
##              <fctr>        <dbl>      <dbl>        <dbl>
## 1             FLOOD 144657716800 5661968450 150319685250
## 2 HURRICANE/TYPHOON  69305840000 2607872800  71913712800
## 3           TORNADO  56947576980  414953270  57362530250
## 4       STORM SURGE  43323536000       5000  43323541000
## 5       FLASH FLOOD  16823142010 1421317100  18244459110
```

```r
 ## crop damages
totCost3<-arrange(totCost, desc(TotCropDmg))
totCost3<-totCost3[1:5,]
totCost3
```

```
## # A tibble: 5 × 4
##        EVTYPE   TotPropDmg  TotCropDmg  totalDamage
##        <fctr>        <dbl>       <dbl>        <dbl>
## 1     DROUGHT   1046106000 13972566000  15018672000
## 2       FLOOD 144657716800  5661968450 150319685250
## 3 RIVER FLOOD   5118945500  5029459000  10148404500
## 4   ICE STORM   3944977810  5022113500   8967091310
## 5        HAIL  15735559920  3025954473  18761514393
```

While there are almost no differences in the top five event types total combined damages and total property damages, there is a major difference with total crop damages. Drought is not included in the top five (or ten either) for either property or total damages, yet it is the number one event type causing the most economic consequences for crops. See Figure 2 for graphics.

Results

Figure 1

Below are barplots of the top five event types that are most harmful to population health across the United States. Notice that the allocation is slightly different for fatalities in respect to both the combined numbers and injuries by themselves. There are also much less fatalities than injuries, as noted in the bar plots with counts in the 100's for fatalities as opposed to counts in the 1000's for injuries.

```r
par(mfrow = c(1,3))
bp<-barplot(totHealth1$totFI/1000,
    main = "Total Combined Fatalities and Injuries",
    xlab = "", ylab = "Total (in thousands)", col = "red",
    ylim = c(1, 100), names.arg = totHealth1$EVTYPE, las=2)
text(bp, 0, totHealth1$totFI, cex = 1, pos = 3 )
bp1<-barplot(totHealth1$FATALITIES/100,
            main = "Tota Fatalities",
            xlab = "", ylab = "Total (in hundreds)",
            col = "orange",
            ylim = c(1, 60), names.arg = totHealth1$EVTYPE,
            las=2)
text(bp1, 0, totHealth1$FATALITIES, cex = 1, pos = 3 )
bp2<-barplot(totHealth1$INJURIES/1000,
             main = "Total Injuries", xlab = "",
             ylab = "Total (in thoursands)" , col = "yellow",
             ylim = c(1, 100), names.arg = totHealth1$EVTYPE,
             las=2)
text(bp2, 0, totHealth1$INJURIES, cex = 1, pos = 3 )
```

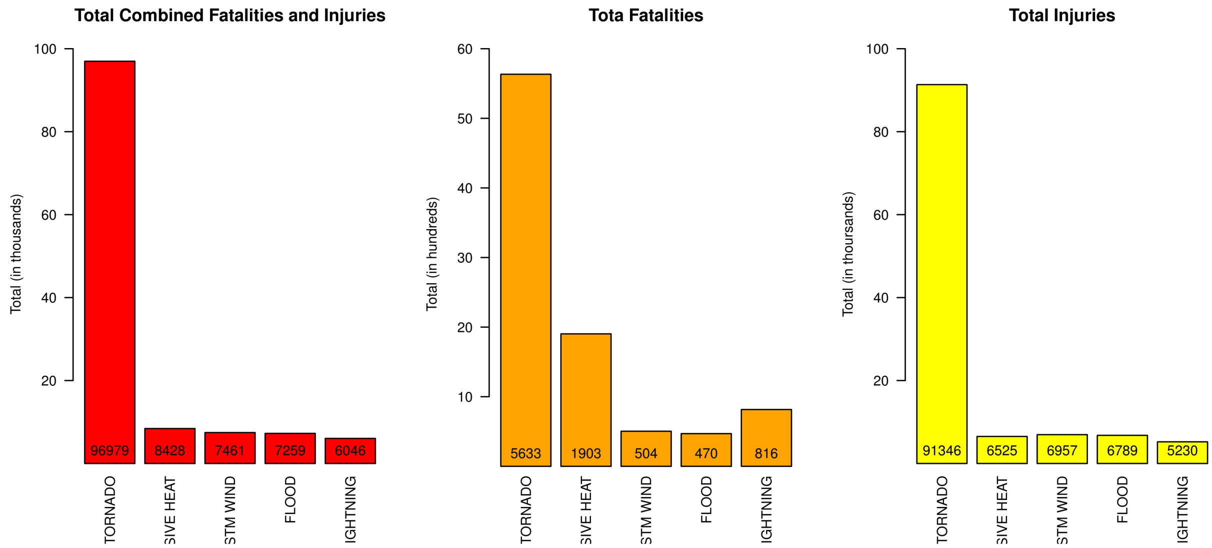
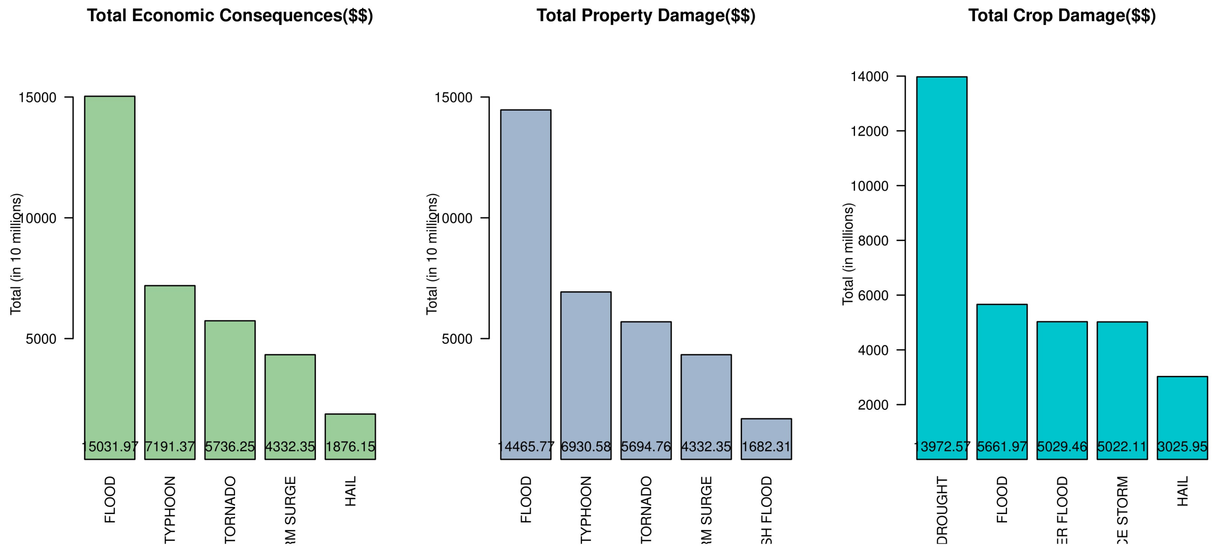


Figure 2

Below are the barplots of the top five event types that subject the most severe economic consequences across the United States, based on dollar amounts. Because of the large dollar amounts (combined flood damages exceed $150 BILLION) for simplicity of the graphs, the total figures for both Total Consequences and Total Property Damages have been divided by ten million dollars, or in the case of Crop Damage, one million dollars.

```r
par(mfrow = c(1,3))
cp<-barplot(totCost1$totalDamage/10^7,
  main = "Total Economic Consequences($$)", xlab = "",
  ylab = "Total (in 10 millions)", ylim=c(1, 17000),
  col = "darkseagreen3", names.arg = totCost1$EVTYPE, las = 2)
text(cp, 0, round(totCost1$totalDamage/10^7,2), cex = 1, pos = 3)
cp1<-barplot(totCost2$TotPropDmg/10^7,
  main = "Total Property Damage($$)", xlab = "",
  ylab = "Total (in 10 millions)", ylim=c(1, 17000),
  col = "lightsteelblue3", names.arg = totCost2$EVTYPE, las = 2)
text(cp1, 0, round(totCost2$TotPropDmg/10^7,2), cex = 1, pos = 3)
cp2<-barplot(totCost3$TotCropDmg/10^6,
  main = "Total Crop Damage($$)", xlab = "",
  ylab = "Total (in millions)", ylim=c(1, 15000),
  col = "turquoise3", names.arg = totCost3$EVTYPE, las = 2)
text(cp2, 0, round(totCost3$TotCropDmg/10^6,2), cex = 1, pos = 3)
```



Notice, with the exception of position five, Total Economic Consequences and Total Property Damages have the same rankings and are both figures in tens of millions of dollars. However, while Total Crop Damage in only in millions of dollars, Flood is bumped out of first position by drought. This is completely reasonable considering crops must have precipitation and/or irrigation to survive, drought conditions greatly hinder both those requirements hence causing loss of crops.