Weather Event Analysis

Course 5 (Reproducible Research) / Assessment 2

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Synopsis

In this report we aim to identify the weather events in the United States which are most harmful to human health (in terms of fatalities or injuries) and have greatest economic impact (in terms of either crop or property damage). The data used was the NOAA Storm Database from the National Weather Service, for the years 1996-2011. The year 1996 was chosen as starting point for this analysis, as this was the year from which all weather types were recorded, not just tornados. Processing was required on the data to derive the correct amounts based on representation of the data as value/exponent pairs, and to map weather event descriptions in the data to a standardized list of weather events. The key conclusions of this analysis are that the weather events which are most harmful with respect to population health are Tornados, Excessive Heat, Floods and Flash Floods; the events which have the greatest economic impact are Floods, Hurricanes and Storm surge/tide. Of note also were Thunderstorms, which have a very high frequency (>50%) of impactful events, and are the 4th highest contributor to injuries - but relatively low economic impact. A key technical recommendation is for NWS to normalize this data at source to classify weather events against a consistent hierarchy of event types, rather than allowing free-form descriptions (if not already implemented).

Data Loading and Processing

From the National Weather Service (NWS) / National Oceanic and Atmospheric Administration (NOAA) we obtained data on weather events dating from 1950 through 2011. This database tracks characteristics of major storms and weather events in the United States, including when and where they occur, as well as estimates of any fatalities, injuries, and crop/property damage.

National Weather Service Storm Data Documentation: https://d396qusza40orc.cloudfront.net/repdata%2Fpeer2_doc%2Fpd01016005curr.pdf

National Climatic Data Center Storm Events: https://d396qusza40orc.cloudfront.net/repdata%2Fpeer2_doc%2FNCDC%20Storm%20Events-FAQ%20Page.pdf

Dependencies

The code in this analysis requires the following packages to be loaded:

```
library(dplyr)
library(lubridate)
library(tidyr)
library(ggplot2)
library(knitr)
library(kableExtra)
```

Data Loading

We first read the data from the raw text file included in the zip archive.

```
data <- read.csv('repdata-data-StormData.csv')
```

The raw data contains 902297 rows. Note - the data is a simple comma-delimited field-quoted format, but includes carriage returns so the unix line count differs from the true record count in R.

Data Processing

Step 1 - Amounts and Timeframe

For the purposes of this analysis, we are interested in the year, event type, and statistics on fatalities, injuries, and crop/property damage. The columns required for this are first selected into a subset; event types and amount exponents are converted to upper case which also removes factors in these fields, and year is derived from the begin date of the event. A field to map event types is initialized to N/A.

```
datasub <- data[,c(2,8,23:28,37)]
datasub$EVTYPE <- toupper(datasub$EVTYPE)
datasub$CROPDMGEXP <- toupper(datasub$CROPDMGEXP)
datasub$PROPDMGEXP <- toupper(datasub$PROPDMGEXP)
datasub$BGN_DATE <- as.Date(datasub$BGN_DATE,"%m/%d/%Y")
datasub$YEAR <- year(datasub$BGN_DATE)
datasub$EVTYPEMAP <- as.character(NA)
```

The first issue to address is to derive the damage amounts. For both crop and property damage, two fields are presented in the data, a 'DMG' field with a number, and a 'DMGEXP' field with an exponent multiplier. For the DMGEXP values we leveraged earlier work done on analyzing these values vs. other databases (https://rstudio-pubs-static.s3.amazonaws.com/58957_37b6723ee52b455990e149edde45e5b6.html), which can be summarized as follows:

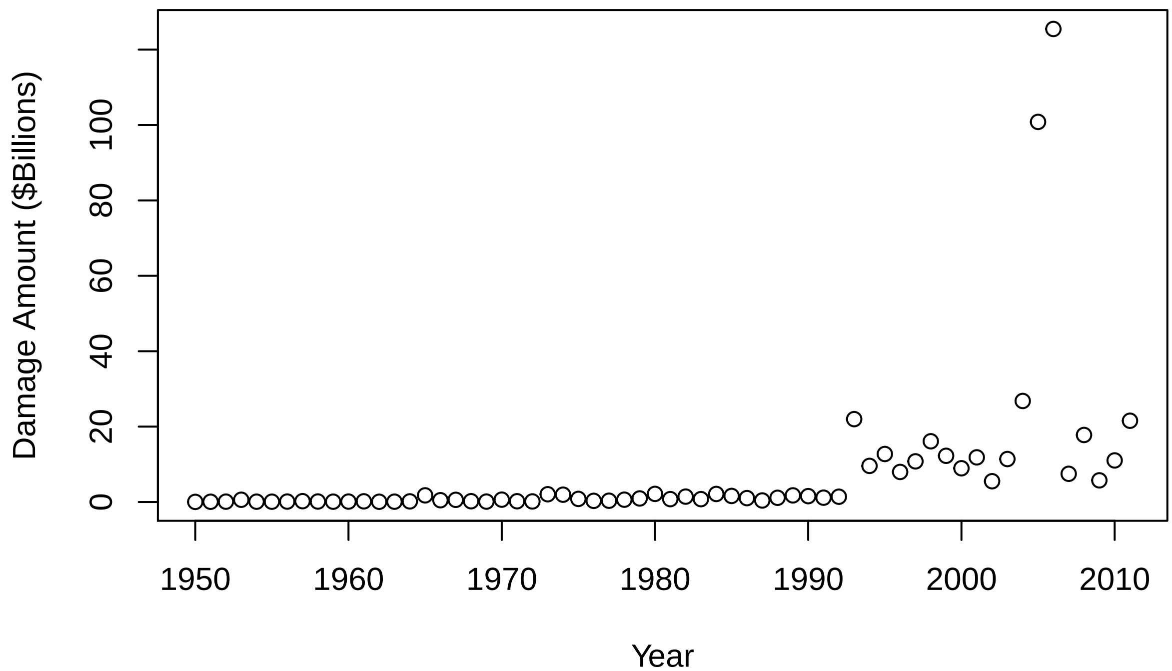
- (-) = 0
- (?) = 0
- black/empty character = 0
- (+) = 1
- numeric 0..8 = 10
- H,h = hundreds = 100
- K,k = kilos = thousands = 1,000
- M,m = millions = 1,000,000
- B,b = billions = 1,000,000,000

A lookup data frame mapping EXP to the multiplier value is constructed and used to derive new 'AMOUNT' fields in our results subset. The final amounts are represented in millions.

```
EXP <- c("","-","?","+","0","1","2","3","4","5","6","7","8","H","K","M","B")
VAL <- c(0,0,0,1,rep(10,9),100,1000,1000000,1000000000)
Lookup <- data.frame(cbind(EXP,VAL))
Lookup$EXP <- as.character(Lookup$EXP)
Lookup$VAL <- as.numeric(as.character(Lookup$VAL))
datasub$CROPFAC <- Lookup[match(datasub$CROPDMGEXP,Lookup$EXP),]$VAL
datasub$PROPFAC <- Lookup[match(datasub$PROPDMGEXP,Lookup$EXP),]$VAL
datasub$CROPAMOUNT <- (datasub$CROPDMG * datasub$CROPFAC)/1000000
datasub$PROPAMOUNT <- (datasub$PROPDMG * datasub$PROPFAC)/1000000
```

The second issue to address is the timeframe of data. Per guidance in the notes on the discussion forum for this course, only Tornados were recorded in earlier years, with a gradual increase in events recorded, but from 1996 onwards the full range of events is recorded. A quick exploratory plot of total damage by year supports this, as it shows a significant uptick in damage amounts starting in the early 1990s.

```
datasub_yearly<-aggregate((datasub$PROPAMOUNT+datasub$CROPAMOUNT)/1000,
                                by=list(datasub$YEAR),FUN="sum")
plot(datasub_yearly,xlab="Year",ylab="Damage Amount ($Billions)")
```



Therefore, in order to provide a consistent dataset for comparison across weather events, we selected only rows for events which began in 1996 onwards. Also, to reduce the dataset for the next step of processing which involves cleaning up event types, we only select 'impactful events' i.e. rows which have non-zero fatalities, injuries or damage:

```
dataevt <- datasub[which((datasub$FATALITIES+datasub$INJURIES
                        +datasub$CROPAMOUNT+datasub$PROPAMOUNT>0)
                        & datasub$YEAR>=1996),]
```

This subset of data for analysis contains 201318 rows/events.

Step 2 - Event Type Mapping

The second major issue to address is normalization of the event types, which is free-form field in the NOAA data. Documentation for the dataset refers to 48 groupings of weather type, which was used as the basis for this analysis, plus an additional "OTHER" category.

The list of events was mapped to these categories using a .csv mapping file consisting of grepl match string (with .* wildcards) and the target category. The code loops through each row of this mapping file in order, and only processes events which have not previously been mapped (mapped event type is still N/A).

Order of processing this file is important in order to classify more specific events before generic ones e.g. "HEAVY RAIN" should be processed before catch-all for anything left-over with "RAIN", otherwise HEAVY RAIN will be mapped to RAIN. The mappings are displayed in the output of the R loop (full evtypemap.csv file can be found at https://github.com/ringspagit/RepData_PeerAssessment2).

Note at this point in the analysis we combined property and crop damage into a singular AMOUNT field. However fatalities and injuries remain separate as combination of this data would obfuscate the impact of fatal weather events.

```
# Gather summary table of events to be mapped, combine property and crop damage amounts
evtypes <- dataevt %>% group_by(EVTYPE) %>%
        summarise(length(unique(REFNUM)),
                sum(CROPAMOUNT+PROPAMOUNT),
                sum(FATALITIES),sum(INJURIES))
colnames(evtypes) <- c('EVTYPE','EVENTS','AMOUNT','FATALITIES','INJURIES')

# Load mapping file and default the EVTYPEMAP field to N/A
evtypemap <- read.csv('evtypemap.csv',comment.char="#")
evtypemap$MAPTO <- as.character(evtypemap$MAPTO)
evtypes$EVTYPEMAP <- as.character(NA)

#Loop thru each mapping row, find subset of matches with grepl
#which still have N/A for EVTYPEMAP and map to new lookup value
for (i in 1:nrow(evtypemap)) {
        repl <- with(evtypes,grepl(evtypemap[i,]$SEARCH,EVTYPE) & is.na(EVTYPEMAP))
        print(paste0('Mapping: ',sum(repl),' rows ',
                     evtypemap[i,]$SEARCH,' to ',evtypemap[i,]$MAPTO))
        if (sum(repl) > 0) {
                evtypes[which(repl),]$EVTYPEMAP <- evtypemap[i,]$MAPTO
        }
}
```

```
## [1] "Mapping: 2 rows NON.*T.*S.*T.*M WIND to HIGH WIND"
## [1] "Mapping: 2 rows MARINE T.*S.*T.*M to MARINE THUNDERSTORM"
## [1] "Mapping: 13 rows TSTM to THUNDERSTORM"
## [1] "Mapping: 3 rows T.*U.*STORM to THUNDERSTORM"
## [1] "Mapping: 0 rows THUNDER to THUNDERSTORM"
## [1] "Mapping: 1 rows MARINE HAIL to MARINE HAIL"
## [1] "Mapping: 3 rows HAIL to HAIL"
## [1] "Mapping: 1 rows MARINE HIGH WIND to MARINE HIGH WIND"
## [1] "Mapping: 3 rows HIGH WIND to HIGH WIND"
## [1] "Mapping: 1 rows MARINE STRONG WIND to MARINE STRONG WIND"
## [1] "Mapping: 2 rows STRONG WIND to STRONG WIND"
## [1] "Mapping: 4 rows COASTAL.*FLOOD to COASTAL FLOOD/EROSION"
## [1] "Mapping: 1 rows COASTAL EROSION to COASTAL FLOOD/EROSION"
## [1] "Mapping: 1 rows BEACH EROSION to COASTAL FLOOD/EROSION"
## [1] "Mapping: 1 rows EROSION/CSTL FLOOD to COASTAL FLOOD/EROSION"
```

```
## [1] "Mapping: 3 rows FLASH FLOOD to FLASH FLOOD"
## [1] "Mapping: 1 rows LAKESHORE FLOOD to LAKESHORE FLOOD"
## [1] "Mapping: 6 rows FLOOD to FLOOD"
## [1] "Mapping: 1 rows URBAN.*SM.*L.* to FLOOD"
## [1] "Mapping: 1 rows HIGH WATER to FLOOD"
## [1] "Mapping: 2 rows ASTRONOMICAL to ASTRONOMICAL LOW/HIGH TIDE"
## [1] "Mapping: 1 rows FUNNEL CLOUD to FUNNEL CLOUD"
## [1] "Mapping: 8 rows SURF to HIGH SURF"
## [1] "Mapping: 2 rows RIP CURRENT to RIP CURRENT"
## [1] "Mapping: 1 rows SEICHE to SEICHE"
## [1] "Mapping: 2 rows STORM SURGE to STORM SURGE/TIDE"
## [1] "Mapping: 2 rows COASTAL.*STORM to STORM SURGE/TIDE"
## [1] "Mapping: 1 rows TSUNAMI to TSUNAMI"
## [1] "Mapping: 1 rows WATERSPOUT to WATERSPOUT"
## [1] "Mapping: 1 rows EXCESSIVE HEAT to EXCESSIVE HEAT"
## [1] "Mapping: 3 rows HEAT to HEAT"
## [1] "Mapping: 1 rows DROUGHT to DROUGHT"
## [1] "Mapping: 1 rows DUST DEVIL to DUST DEVIL"
## [1] "Mapping: 1 rows DUST STORM to DUST STORM"
## [1] "Mapping: 1 rows DUST to DUST STORM"
## [1] "Mapping: 2 rows WARM to HEAT"
## [1] "Mapping: 1 rows LIGHTNING to LIGHTNING"
## [1] "Mapping: 1 rows HEAVY RAIN to HEAVY RAIN"
## [1] "Mapping: 3 rows HURRICANE to HURRICANE/TYPHOON"
## [1] "Mapping: 1 rows TYPHOON to HURRICANE/TYPHOON"
## [1] "Mapping: 1 rows TORNADO to TORNADO"
## [1] "Mapping: 4 rows BURST to STRONG WIND"
## [1] "Mapping: 1 rows LANDSPOUT to STRONG WIND"
## [1] "Mapping: 1 rows TROPICAL DEPRESSION to TROPICAL DEPRESSION"
## [1] "Mapping: 1 rows TROPICAL STORM to TROPICAL STORM"
## [1] "Mapping: 2 rows PRECIP to HEAVY RAIN"
## [1] "Mapping: 8 rows RAIN to HEAVY RAIN"
## [1] "Mapping: 1 rows WILDFIRE to WILDFIRE"
## [1] "Mapping: 1 rows DENSE SMOKE to DENSE SMOKE"
## [1] "Mapping: 2 rows FIRE to WILDFIRE"
## [1] "Mapping: 1 rows AVALANCHE to AVALANCHE"
## [1] "Mapping: 1 rows BLIZZARD to BLIZZARD"
## [1] "Mapping: 1 rows DENSE FOG to DENSE FOG"
## [1] "Mapping: 1 rows FREEZING FOG to FREEZING FOG"
## [1] "Mapping: 1 rows FOG to DENSE FOG"
## [1] "Mapping: 1 rows FROST/FREEZE to FROST/FREEZE"
## [1] "Mapping: 2 rows FROST to FROST/FREEZE"
## [1] "Mapping: 6 rows FREEZ to FROST/FREEZE"
## [1] "Mapping: 2 rows HEAVY SNOW to HEAVY SNOW"
## [1] "Mapping: 1 rows ICE STORM to ICE STORM"
## [1] "Mapping: 2 rows LAKE.*EFFECT SNOW to LAKE-EFFECT SNOW"
## [1] "Mapping: 0 rows SLEET to SLEET"
## [1] "Mapping: 3 rows WINTER WEATHER to WINTER WEATHER"
## [1] "Mapping: 1 rows WINTER STORM to WINTER STORM"
## [1] "Mapping: 1 rows WINTRY to WINTER WEATHER"
## [1] "Mapping: 5 rows ICE to WINTER WEATHER"
## [1] "Mapping: 1 rows ICY to WINTER WEATHER"
## [1] "Mapping: 9 rows SNOW to WINTER WEATHER"
## [1] "Mapping: 2 rows EXTREME COLD to EXTREME COLD/WIND CHILL"
```

```
## [1] "Mapping: 1 rows EXTREME WIND.*CHILL to EXTREME COLD/WIND CHILL"
## [1] "Mapping: 7 rows COLD to COLD/WIND CHILL"
## [1] "Mapping: 2 rows EXPOSURE to COLD/WIND CHILL"
## [1] "Mapping: 9 rows WIND to HIGH WIND"
## [1] "Mapping: 0 rows DEBRIS FLOW to DEBRIS FLOW/LANDSLIDE"
## [1] "Mapping: 3 rows LANDSL.* to DEBRIS FLOW/LANDSLIDE"
## [1] "Mapping: 3 rows MUD.*SL to DEBRIS FLOW/LANDSLIDE"
## [1] "Mapping: 1 rows ROCK SLIDE to DEBRIS FLOW/LANDSLIDE"
## [1] "Mapping: 1 rows DAM BREAK to DEBRIS FLOW/LANDSLIDE"
## [1] "Mapping: 1 rows VOLCANIC ASH to VOLCANIC ASH"
## [1] "Mapping: 1 rows SWELLS to OTHER"
## [1] "Mapping: 1 rows WAVE to OTHER"
## [1] "Mapping: 1 rows MARINE to OTHER"
## [1] "Mapping: 3 rows SEAS to OTHER"
## [1] "Mapping: 1 rows DROWNING to OTHER"
## [1] "Mapping: 1 rows OTHER to OTHER"
## [1] "Mapping: 1 rows GLAZE to OTHER"
```

```r
# Print final summary
print(paste(sum(!is.na(evtypes$EVTYPEMAP)),' mapped'))
```

```
## [1] "186  mapped"
```

```r
print(paste(sum(is.na(evtypes$EVTYPEMAP)),' unmapped'))
```

```
## [1] "0  unmapped"
```

This data is then re-summarized based on the mapped event types

```r
evsum <- as.data.frame(evtypes %>% group_by(EVTYPEMAP) %>%
                summarise(sum(EVENTS),sum(AMOUNT),sum(FATALITIES),sum(INJURIES)))
colnames(evsum) <- c('EVTYPE_MAPPED','EVENTS','AMOUNT','FATALITIES','INJURIES')
```

This summary dataset consists of 48 rows corresponding to 201318 events (control total compare to original subset of event level detail which had 201318 rows).

Notes:

- Summary table of all mapped event types is provided in the Results section.
- The summarized data set does not contain all 49 events (the NOAA 48 event types, plus 'OTHER') because there was no data directly corresponding to SLEET.
- There is an element of subjectivity in the mapping, and further higher grouping which could be performed at this point. For example, is there an important distinction between different densities of hazardous FOG, or different types of winter weather. This was beyond the scope of this analysis, and does not appear to be material to the main conclusions, but something for further consideration if deeper analysis required.
- The mapping csv file was constructed by starting with the 48 event types provided in the NWS document, then iteratively updating the file for additional patterns by observing remaining events to be mapped, and re-running the assignment process, until all of the event types in the dataset were mapped. Sanity checks were performed by listing the original and mapped event types in order of mapping to see that similar events (e.g. various types of wind) were mapped consistently. The following R code was useful for this (output not shown here):

```r
as.data.frame(evtypes[order(evtypes$EVTYPEMAP,evtypes$EVTYPE),])
```

Step 3 - Selecting the Most Impactful Events

Next, this event level data was re-cast as percentages of the impact totals, to help visualize the relative impact of an event between health and economy on a consistent scale.

```
evsum_pct <- cbind(
        evsum[1],
        round(prop.table(evsum[2])*100,1),
        round(prop.table(evsum[3])*100,1),
        round(prop.table(evsum[4])*100,1),
        round(prop.table(evsum[5])*100,1))
```

In order to see which of the 48 events have the biggest impact on health and economy, the data set was reduced to a superset of events containing the top 5 most impactful events for each of fatalities, injuries and damage amount, along with a normalized form of this data to support plotting.

```
evsum_pct$TOP <- FALSE
evsum_pct[order(-evsum_pct$AMOUNT),][c(1:5),]$TOP <- TRUE
evsum_pct[order(-evsum_pct$FATALITIES),][c(1:5),]$TOP <- TRUE
evsum_pct[order(-evsum_pct$INJURIES),][c(1:5),]$TOP <- TRUE

evtop<-evsum_pct[which(evsum_pct$TOP),]

# Normalize data into rows for plotting
evtopnorm<-as.data.frame(evtop[c(1,3:5)] %>% gather(IMPACT,COUNT,-EVTYPE_MAPPED))
```

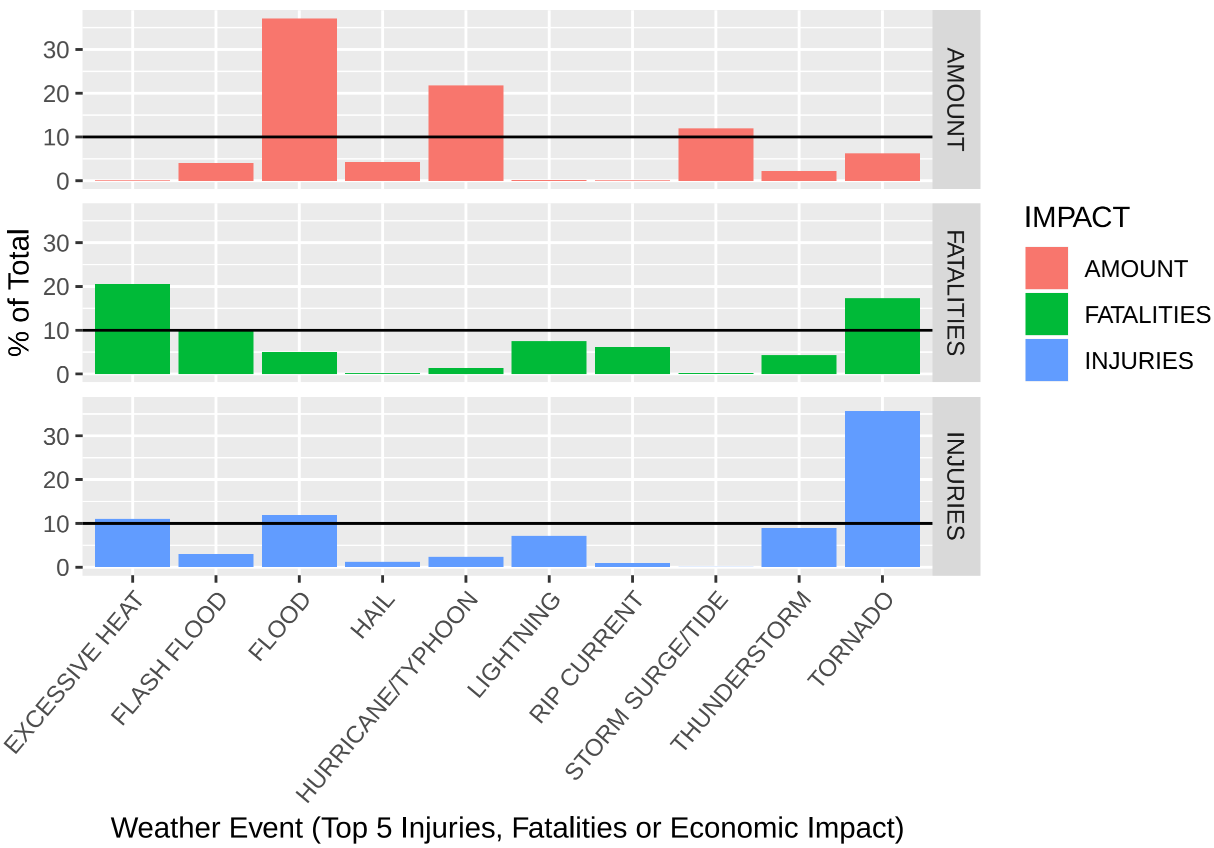
This results in a population of 10 key events for final analysis

Results

Plotting the percentages of these 10 key events illustrates the finding in the data, narrowing down to the Top 3, with emphasis at 10% or higher:

- The weather events which have the greatest **population health** (fatalities or injuries) impact are **Tornados, Excessive Heat, Floods and Flash Floods**.
- The weather events which have the greatest **economic** consequences are **Floods, Hurricanes and Storm surge/tide**.
- Of additional note in the data are **Thunderstorms** which have a very high frequency (>50%) of impactful events, and the 4th highest impactful to health via injury, though present a low economic impact.

```
g <- ggplot(evtopnorm,aes(x=EVTYPE_MAPPED,y=COUNT,fill=IMPACT))
g <- g + geom_bar(stat="identity")
g <- g + facet_grid(rows = vars(IMPACT))
g <- g + labs(x="Weather Event (Top 5 Injuries, Fatalities or Economic Impact)",y="% of Total")
g <- g + theme(axis.text.x = element_text(angle = 50, hjust = 1))
g <- g + geom_hline(yintercept=10)
print(g)
```



Summary of impact (%) for key events:

```
evtop[c(1:5)] %>% kable() %>% kable_styling()
```

	EVTYPE_MAPPED	EVENTS	AMOUNT	FATALITIES	INJURIES
12	EXCESSIVE HEAT	0.3	0.1	20.6	11.0
14	FLASH FLOOD	9.4	4.1	10.2	2.9
15	FLOOD	5.1	37.1	5.1	11.8
19	HAIL	11.3	4.3	0.1	1.2
25	HURRICANE/TYPHOON	0.1	21.7	1.4	2.3
29	LIGHTNING	5.5	0.2	7.5	7.1
35	RIP CURRENT	0.3	0.0	6.2	0.9
37	STORM SURGE/TIDE	0.1	11.9	0.2	0.1
39	THUNDERSTORM	52.3	2.2	4.3	8.8
40	TORNADO	6.1	6.2	17.3	35.6

Summary of impact ($MM/count) for key events:

```
evsum[which(evsum_pct$TOP),][c(1:5)] %>% kable() %>% kable_styling()
```

	EVTYPE_MAPPED	EVENTS	AMOUNT	FATALITIES	INJURIES
12	EXCESSIVE HEAT	685	500.1257	1797	6391
14	FLASH FLOOD	19013	16557.1606	887	1674
15	FLOOD	10309	149142.7657	447	6839
19	HAIL	22691	17092.0559	7	723
25	HURRICANE/TYPHOON	208	87068.9968	125	1328
29	LIGHTNING	11152	749.9755	651	4141
35	RIP CURRENT	603	0.1630	542	503
37	STORM SURGE/TIDE	221	47835.6290	17	44
39	THUNDERSTORM	105372	8930.4985	379	5129
40	TORNADO	12366	24900.3707	1511	20667

Summary of impact (%) for all events:

```
evsum_pct %>% kable() %>% kable_styling()
```

EVTYPE_MAPPED	EVENTS	AMOUNT	FATALITIES	INJURIES	TOP
ASTRONOMICAL LOW/HIGH TIDE	0.0	0.0	0.0	0.0	FALSE
AVALANCHE	0.1	0.0	2.6	0.3	FALSE
BLIZZARD	0.1	0.1	0.8	0.7	FALSE
COASTAL FLOOD/EROSION	0.1	0.1	0.1	0.0	FALSE
COLD/WIND CHILL	0.1	0.0	1.4	0.0	FALSE
DEBRIS FLOW/LANDSLIDE	0.1	0.1	0.5	0.1	FALSE
DENSE FOG	0.1	0.0	0.8	1.5	FALSE
DENSE SMOKE	0.0	0.0	0.0	0.0	FALSE
DROUGHT	0.1	3.6	0.0	0.0	FALSE
DUST DEVIL	0.0	0.0	0.0	0.1	FALSE
DUST STORM	0.0	0.0	0.1	0.6	FALSE
EXCESSIVE HEAT	0.3	0.1	20.6	11.0	TRUE
EXTREME COLD/WIND CHILL	0.1	0.3	2.9	0.2	FALSE
FLASH FLOOD	9.4	4.1	10.2	2.9	TRUE
FLOOD	5.1	37.1	5.1	11.8	TRUE
FREEZING FOG	0.0	0.0	0.0	0.0	FALSE
FROST/FREEZE	0.1	0.3	0.0	0.0	FALSE
FUNNEL CLOUD	0.0	0.0	0.0	0.0	FALSE
HAIL	11.3	4.3	0.1	1.2	TRUE
HEAT	0.1	0.0	2.7	2.3	FALSE
HEAVY RAIN	0.6	0.3	1.2	0.5	FALSE
HEAVY SNOW	0.5	0.2	1.2	1.2	FALSE
HIGH SURF	0.1	0.0	1.7	0.4	FALSE
HIGH WIND	2.7	1.5	3.0	2.0	FALSE
HURRICANE/TYPHOON	0.1	21.7	1.4	2.3	TRUE
ICE STORM	0.3	0.9	0.9	0.5	FALSE
LAKE-EFFECT SNOW	0.1	0.0	0.0	0.0	FALSE
LAKESHORE FLOOD	0.0	0.0	0.0	0.0	FALSE
LIGHTNING	5.5	0.2	7.5	7.1	TRUE
MARINE HAIL	0.0	0.0	0.0	0.0	FALSE
MARINE HIGH WIND	0.0	0.0	0.0	0.0	FALSE
MARINE STRONG WIND	0.0	0.0	0.2	0.0	FALSE
MARINE THUNDERSTORM	0.1	0.0	0.2	0.1	FALSE
OTHER	0.0	0.0	0.2	0.4	FALSE
RIP CURRENT	0.3	0.0	6.2	0.9	TRUE
SEICHE	0.0	0.0	0.0	0.0	FALSE
STORM SURGE/TIDE	0.1	11.9	0.2	0.1	TRUE
STRONG WIND	1.7	0.1	1.3	0.6	FALSE
THUNDERSTORM	52.3	2.2	4.3	8.8	TRUE
TORNADO	6.1	6.2	17.3	35.6	TRUE
TROPICAL DEPRESSION	0.0	0.0	0.0	0.0	FALSE
TROPICAL STORM	0.2	2.1	0.7	0.6	FALSE
TSUNAMI	0.0	0.0	0.4	0.2	FALSE
VOLCANIC ASH	0.0	0.0	0.0	0.0	FALSE
WATERSPOUT	0.0	0.0	0.0	0.0	FALSE
WILDFIRE	0.6	2.0	1.0	2.5	FALSE
WINTER STORM	0.7	0.4	2.2	2.2	FALSE
WINTER WEATHER	0.4	0.0	1.0	1.1	FALSE

Summary of impact ($MM/count) for all events:

```
evsum %>% kable() %>% kable_styling()
```

EVTYPE_MAPPED	EVENTS	AMOUNT	FATALITIES	INJURIES
ASTRONOMICAL LOW/HIGH TIDE	10	9.74500	0	0
AVALANCHE	264	3.71180	223	156
BLIZZARD	228	532.71895	70	385
COASTAL FLOOD/EROSION	196	407.30556	6	7
COLD/WIND CHILL	125	33.38650	126	24
DEBRIS FLOW/LANDSLIDE	203	347.64710	43	55
DENSE FOG	159	20.46450	69	855
DENSE SMOKE	1	0.10000	0	0
DROUGHT	258	14413.66700	0	4
DUST DEVIL	84	0.66363	2	39
DUST STORM	97	8.59400	11	376
EXCESSIVE HEAT	685	500.12570	1797	6391
EXTREME COLD/WIND CHILL	296	1355.18640	257	108
FLASH FLOOD	19013	16557.16061	887	1674
FLOOD	10309	149142.76570	447	6839
FREEZING FOG	7	2.18200	0	0
FROST/FREEZE	146	1387.56100	4	16
FUNNEL CLOUD	9	0.13410	0	1
HAIL	22691	17092.05587	7	723
HEAT	172	1.70650	239	1311
HEAVY RAIN	1112	1325.45524	102	262
HEAVY SNOW	1030	705.54964	107	700
HIGH SURF	213	110.37450	145	240
HIGH WIND	5530	5887.47916	259	1187
HURRICANE/TYPHOON	208	87068.99681	125	1328
ICE STORM	631	3657.90881	82	318
LAKE-EFFECT SNOW	198	40.18200	0	0
LAKESHORE FLOOD	5	7.54000	0	0
LIGHTNING	11152	749.97552	651	4141
MARINE HAIL	2	0.00400	0	0
MARINE HIGH WIND	19	1.29701	1	1
MARINE STRONG WIND	46	0.41833	14	22
MARINE THUNDERSTORM	142	5.90740	19	34
OTHER	65	1.30990	16	232
RIP CURRENT	603	0.16300	542	503
SEICHE	9	0.98000	0	0
STORM SURGE/TIDE	221	47835.62900	17	44
STRONG WIND	3496	243.75934	113	324
THUNDERSTORM	105372	8930.49848	379	5129
TORNADO	12366	24900.37072	1511	20667
TROPICAL DEPRESSION	35	1.73700	0	0
TROPICAL STORM	410	8320.18655	57	338
TSUNAMI	14	144.08200	33	129
VOLCANIC ASH	2	0.50000	0	0
WATERSPOUT	27	5.73020	2	2
WILDFIRE	1229	8162.70463	87	1458
WINTER STORM	1460	1544.68725	191	1292
WINTER WEATHER	768	50.03570	91	660