NOAA Storm Database - worst cases

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Contents

1 Introduction

In this study we have analysed the NOAA Storm Database in order to determine what are the worst natural catastrophic events, both in terms of public health and in economic impact.

The U.S. National Oceanic and Atmospheric Administration's (NOAA) storm 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 property damage.

The database currently contains data from January 1950 to January 2017, as entered by NOAA's National Weather Service (NWS).

The database can be found on:

https://www.ncdc.noaa.gov/stormevents/ftp.jsp

RPubs version, with fewer plots, for Coursera: http://rpubs.com/erickfis/noaa

2 Objective

The goal of this study is to answer the questions:

1. Across the United States, which types of events were the most harmful with respect to population health ever recorded in a single occurrence?
2. Which types of events caused most harm to population health along all those years?
3. Which types of events had the greatest economic consequences in a single occurrence?
4. Which types of events had the greatest economic consequences along all those years?
5. Which were the places that were subject to the greatest losses, both in terms of human health and economic losses.

3 Methods

To answer each one of those questions, we did a very simple **descriptive analysis** of data.

We used R tools to filter, sort and combine data, so we could get the total sum of fatalities, injuries and economic losses.

4 Data Processing

This code loads the original data and them choose which variables are useful to answer our questions:

```
library(scales)
library(stringr)
library(data.table)
library(chron)
library(dplyr)
library(lubridate)
library(ggplot2)
library(rmarkdown)
library(RColorBrewer)
library(gridExtra)
library(grid)
```

Reading original database:

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

#download.file(fileUrl, "StormData.bz2", method = "curl")

#Full data
dados <- fread(sprintf("bzcat %s | tr -d '\\000'", "StormData.bz2"), na.strings = "")
```

```
##
Read 22.7% of 967216 rows
Read 47.6% of 967216 rows
Read 63.1% of 967216 rows
Read 79.6% of 967216 rows
Read 902297 rows and 37 (of 37) columns from 0.523 GB file in 00:00:07
```

```r
dados <-tbl_df(dados)

# this do a sample data base, with 50000 obs, used for speeding up initial works:
# linhas <- nrow(dados)
# linhas <- sample(linhas,50000)
# dataS <- dados[linhas,]
# write.csv(dataS, "StormData")

# dados <- fread(sprintf("bzcat %s | tr -d '\\000'", "StormData-sample.bz2"))
# dados <-tbl_df(dados)
# dados <- select(dados, -1)



# treating var names
names(dados) <- gsub("_", ".", tolower(names(dados)))
names(dados)
```

```
##  [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"
```

This database has 902297 observations. Each observation corresponds to an event occurrence.

To determine the most harmful events to human health, we will check the variables related to human health, which are "fatalities" and "injuries".

To determine the most harmful events to economy, we will check the variables related to economic measures, from "propdmg" through "cropdmgexp".

Also, in order to analyse various occurrences of the same event, we will measure the duration of the event, its magnitude and where the event occurred (state and county name).

```r
# select desired vars
harm.df <- dados %>% select(evtype, mag, state, countyname, bgn.date, end.date, 23:28)

# treat vars
harm.df <- harm.df %>%
```

```
        mutate(bgn.date = mdy_hms(bgn.date), end.date = mdy_hms(end.date),
               day = as.Date(bgn.date, "%m/%d/%Y"),
               duration = -as.period(interval(end.date, bgn.date)),
               event = tolower(as.character(evtype)),
               countyname =strtrim(countyname,9)) %>%
        select(event, 2, day, duration, 3:4, 7:12)

# fixing exp for economic data
harm.df$propdmgexp[which(harm.df$propdmgexp=="K")] <- as.character(3)
harm.df$propdmgexp[which(harm.df$propdmgexp=="m")] <- as.character(6)
harm.df$propdmgexp[which(harm.df$propdmgexp=="M")] <- as.character(6)
harm.df$propdmgexp[which(harm.df$propdmgexp=="B")] <- as.character(9)
harm.df$propdmgexp <- as.numeric(harm.df$propdmgexp)

harm.df$cropdmgexp[which(harm.df$cropdmgexp=="K")] <- as.character(3)
harm.df$cropdmgexp[which(harm.df$cropdmgexp=="m")] <- as.character(6)
harm.df$cropdmgexp[which(harm.df$cropdmgexp=="M")] <- as.character(6)
harm.df$cropdmgexp[which(harm.df$cropdmgexp=="B")] <- as.character(9)
harm.df$cropdmgexp <- as.numeric(harm.df$cropdmgexp)

harm.df <- mutate(harm.df, prop.ev = propdmg*10^propdmgexp,
                  crop.ev = cropdmg*10^cropdmgexp)
```

This is a really big database which data has been being registered by a lot of different people since 1950. Thus, as expected, there are variations on how people registered events.

For exemple, the string "snow" was used to register a lot of events. They are the same type of event, but count as different:

```
eventos <- grep("snow", harm.df$event, value = TRUE)
eventos <- sort(unique(eventos))
length(eventos)
```

```
## [1] 118
```

```
eventos[1:10]
```

```
##  [1] "accumulated snowfall"            "blizzard and heavy snow"
##  [3] "blizzard/heavy snow"             "blowing snow"
##  [5] "blowing snow & extreme wind ch" "blowing snow- extreme wind chi"
##  [7] "blowing snow/extreme wind chil" "cold and snow"
##  [9] "drifting snow"                   "early snow"
```

This is why we decided to filter those events: we grouped them by its commom strings.

```
# treating event types

eventos <- harm.df$event
# first, need to see what are the event types
contagem <- sort(table(eventos))

# them we create this list of terms

lista.search <- c(
"dry",
"fog",
"wind",
```

```
"winter",
"slide",
"snow",
"flood",
"fld",
"cold|freez",
"hurricane",
"tornado",
"rain|precip",
"hail",
"heat|warm",
"tide",
"storm",
"record",
"blizzard",
"fire",
"funnel",
"surf")

lista.replace <- c(
"drought",
"fog",
"wind",
"winter",
"slide",
"snow",
"flood",
"flood",
"cold",
"hurricane",
"tornado",
"rain",
"hail",
"heat",
"tide",
"storm",
"record temperature",
"blizzard",
"fire",
"funnel",
"surf")


for (i in 1:length(lista.search)) {
        eventos[grepl(lista.search[i], eventos)] <- lista.replace[i]

}

# lets group the events whose count is < 5 and call it "other"
contagem <- sort(table(eventos))
outros <- names(contagem[contagem<5])
eventos[eventos %in% outros] <- "other"
# sort(table(eventos))
```

```
# returning treated events
harm.df$event <- toupper(eventos)
```

```
# Treating County Names
cidades <- toupper(harm.df$countyname)
cidades <- str_trim(cidades)

cidades <- gsub("_| |-", ".", cidades)

cidades[grep("\\.\\.$", cidades)] <- gsub("\\.\\.", "",
                                cidades[grep("\\.\\.$", cidades)]
                                        )

cidades <- sapply(strsplit(cidades, split=">", fixed=TRUE), function(x) (x[1]))
cidades <- sapply(strsplit(cidades, split="(", fixed=TRUE), function(x) (x[1]))
cidades <- sapply(strsplit(cidades, split=",", fixed=TRUE), function(x) (x[1]))

harm.df$countyname <- cidades

rm(dados) # house cleanning
```

5 Human health: the most harmfull events

We have determined what events did more harm to human health.

There were occurrences that caused zero fatalities but a lot of injuries. The inverse is also true, so we did a separate analysis to fatal and non-fatal events.

5.1 Fatal Occurrences

5.1.1 Most fatal in a single occurrence

Most fatal in a single occurrence

In order to determine what were the most fatal events in a single occurrence, we need to see how fatalities are distributed along the occurrences.

```
# subset original data
fatal.df <- harm.df %>%
                filter(!is.na(fatalities)) %>%
                select(1:7)



# quantiles
qt <- quantile(fatal.df$fatalities, probs=seq(.9,1,0.001))

# distribution plot

plt.distr.fatal0 <- ggplot(fatal.df, aes(fatalities))

plt.distr.fatal0 <- plt.distr.fatal0 + geom_density(aes(y=..density..)) + xlim(0,.5) +
        labs(title="All events") +
```

```
        theme(plot.title = element_text(hjust = 0.5))

# display only the qts next to fatal events
qt[(length(qt)-(length(qt[qt>=1])+1)): length(qt)]
```

```
##  99.1%  99.2%  99.3%  99.4%  99.5%  99.6%  99.7%  99.8%  99.9% 100.0%
##      0      0      1      1      1      1      1      2      3    583
```

Looking at this distribution, we can infer that the vast majority of those occurrences were not fatal at all: **99.2% occurrences didn't caused any fatalities.**

On the other hand, fatal occurrences had to have at least 1 fatality.

Now, among the fatal occurrences, we are interested in the ones whose fatalities are beyond the confidence interval, ie. above 99% of the most common values.

```
# subset for fatal events
fatal.df <- filter(fatal.df, fatalities > 0) %>%
                arrange(desc(fatalities)) %>%
                mutate(mean = mean(fatalities),
                median = median(fatalities),
                rank = seq_len(length(event)))



# quantiles, same as
# poisson.test(mean, conf.level = 0.95)

qt <- quantile(fatal.df$fatalities, probs=seq(.999,1,0.005))
qt
```

```
##  99.9%
## 74.027
```

Looking at this distribution, we can infer that **99.8% of the fatal occurrences caused up to 74.027 fattalities**.

Distribution plots

```
# distribution plot

plt.distr.fatal1 <- ggplot(fatal.df, aes(fatalities))

plt.distr.fatal1 <- plt.distr.fatal1 + geom_density(aes(y=..density..)) +
        xlim(0,(qt[1]/10)) +
        labs(title="Fatal events") +
        theme(plot.title = element_text(hjust = 0.5))
```

```
grid.arrange(plt.distr.fatal0, plt.distr.fatal1, nrow=1, ncol=2)
grid.rect(gp=gpar(fill=NA))
```

In this study, we looked on the 1% deadliest occurrences.

```
# subset for 99% CI
fatal95.df <- fatal.df %>% filter(fatalities>qt[1])

# create color pallete for all events
colourCount.fatal.single = length(unique(fatal95.df$event))
getPalette = colorRampPalette(brewer.pal(colourCount.fatal.single, "Set1"))
```

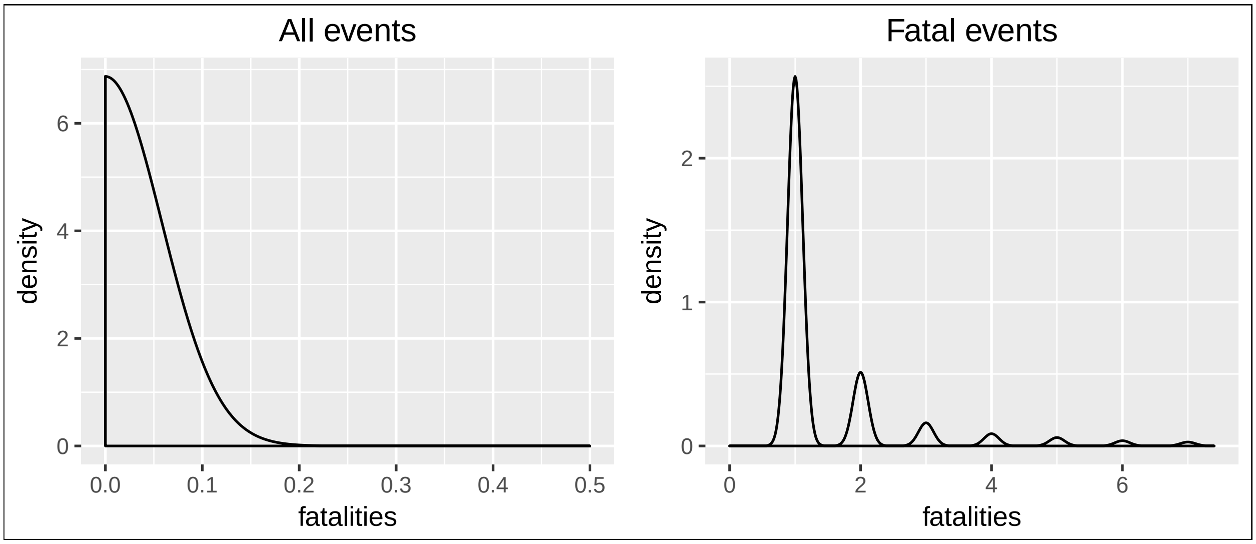

Figure 1: Population distribution for fatalities / occurrences

```r
# print a table
kable(fatal95.df[, c(10,1:9)], caption="Worst fatal occurrences")
```

Table 1: Worst fatal occurrences

rank	event	mag	day	duration	state	countyname	fatalities	mean	median
1	HEAT	0	1995-07-12	0S	IL	ILZ003	583	2.171638	1
2	TORNADO	0	2011-05-22	0S	MO	JASPER	158	2.171638	1
3	TORNADO	0	1953-06-08	NA	MI	GENESEE	116	2.171638	1
4	TORNADO	0	1953-05-11	NA	TX	MCLENNAN	114	2.171638	1
5	HEAT	0	1999-07-28	0S	IL	ILZ005	99	2.171638	1
6	TORNADO	0	1953-06-09	NA	MA	WORCESTER	90	2.171638	1
7	TORNADO	0	1955-05-25	NA	KS	COWLEY	75	2.171638	1

```r
# prepare text for inline R
worst.fatal.single.ev <- fatal95.df$event[1]
worst.fatal.single.st <- fatal95.df$state[1]
worst.fatal.single.ct <- fatal95.df$countyname[1]
worst.fatal.single.dt <- fatal95.df$day[1]
worst.fatal.single.kill <- fatal95.df$fatalities[1]
```

```r
# the plot
plt.fatal.single <- ggplot(fatal95.df, aes(day, fatalities, colour=event))

plt.fatal.single <- plt.fatal.single + geom_point() +
        geom_text(aes(label=ifelse(rank <= 3,
                 paste0(as.character(day), ": ", fatalities, " killed") ,""),
                hjust=-.03,vjust=0.5)) +

        # geom_hline(aes(yintercept = mean), linetype=2) +
        # geom_hline(aes(yintercept = median), linetype=3) +
        labs(title="Most Fatal",
                  y="", x="") +

        expand_limits(x=as.Date('2017-01-01'))+ #ok
        scale_colour_manual(values = getPalette(colourCount.fatal.single))+
        theme(legend.title=element_blank()) +
        theme(legend.position="bottom") +
        guides(fill=guide_legend(nrow=5, byrow=TRUE)) +
```

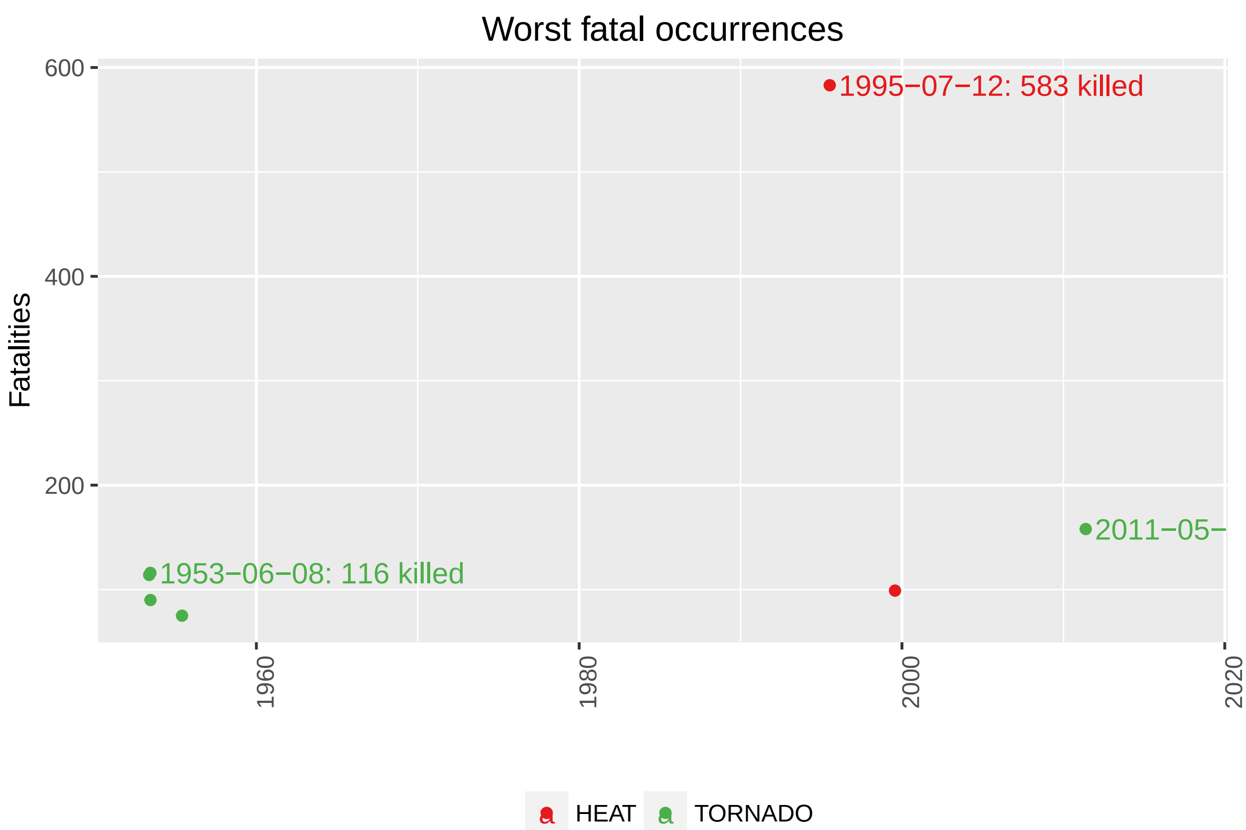

Figure 2: Worst fatal occurrences

5.1.2 Most fatal in all time

Most fatal in all time

Notice that are several occurrences of the same type of event along the time.

Therefore, in order to know which is the worst type of event along all the years, we summed up the fatalities caused by each one of occurrences of this events.

Notice that we are interested only in the worst of them, ie, the ones which are above the mean.

```
# totals per event
fatal.all.df <- fatal.df %>% group_by(event) %>%
        summarise(total = sum(fatalities)) %>% arrange(desc(total)) %>%
        mutate(mean = mean(total), median = median(total),
               rank = seq_len(length(event))) %>%
        filter(total > mean(total))

# create color pallete for all events
colourCount.fatal.all = length(unique(fatal.all.df$event))
getPalette = colorRampPalette(brewer.pal(colourCount.fatal.all, "Set1"))

# prepare text for inline R
worst.fatal.all.ev <- fatal.all.df$event[1]
worst.fatal.all.kill <- fatal.all.df$total[1]

# a table
kable(fatal.all.df[,c(5,1:4)], caption="Total fatalities by event")
```

Table 2: Total fatalities by event

rank	event	total	mean	median
1	TORNADO	5636	398.5526	38.5
2	HEAT	3149	398.5526	38.5
3	FLOOD	1553	398.5526	38.5
4	WIND	1451	398.5526	38.5
5	LIGHTNING	816	398.5526	38.5

```
# the plot
plt.fatal.all <- ggplot(data=fatal.all.df, aes(event, total, fill=event))

plt.fatal.all <- plt.fatal.all + geom_bar(stat="identity") +
        geom_text(aes(label=ifelse(total==max(total),
                paste0(event, ": ", max(total), " killed"),'')),
                hjust=0,vjust=2) +
        geom_hline(aes(yintercept = mean), linetype=1) +
        # geom_hline(aes(yintercept = median), linetype=2) +
        labs(title="All time", y="",
             x="") +

        theme(legend.position="none") +
        scale_colour_manual(values = getPalette(colourCount.fatal.all))+
        theme(legend.title=element_blank()) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
        theme(plot.title = element_text(hjust = 0.5))
```

```r
plt.fatal.all + labs(title="Total Fatalities - All time",
             subtitle="Most fatal events of all time",
                     y="Fatalities", x="")
```

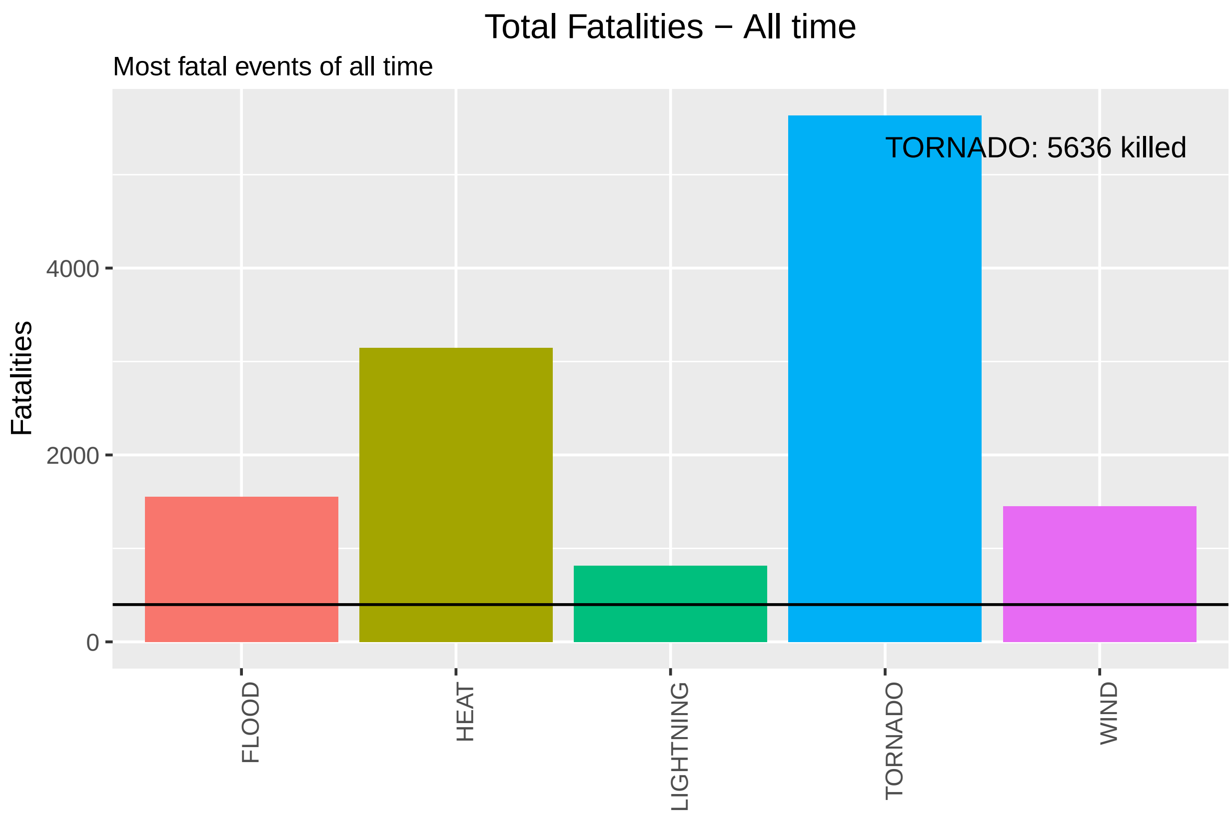

Figure 3: Total fatalities by event

The most fatal event along the time is the **TORNADO. It has killed 5636 people until now.**

5.1.3 Least fatal events

Just for curiosity, these are the less fatal among the fatal events:

```r
# sort for less dangerous, had to subset again due to previous filtering
fatal.all.df <- fatal.df %>% group_by(event) %>%
        summarise(total = sum(fatalities)) %>% arrange(total) %>%
        mutate(mean = mean(total), median = median(total),
               rank = seq(length(event),1, by=-1))

# a table
kable(fatal.all.df[1:10,c(5,1:2)], caption="Least fatal events")
```

Table 3: Least fatal events

rank	event	total
38	BLACK ICE	1
37	FROST	1

rank	event	total
36	HIGH SWELLS	1
35	WINTRY MIX	1
34	DUST DEVIL	2
33	SLEET	2
32	HIGH WATER	3
31	WATERSPOUT	3
30	HIGH SEAS	5
29	ICY ROADS	5

5.2 Injuring Occurrences

5.2.1 Most injuring in a single occurrence

Most injuring in a single occurrence

In order to determine what were the most injuring events in a single occurrence, we need to see how injuries are distributed along the occurrences.

```
rm(fatal.df,fatal.all.df, fatal95.df, qt) # cleannig house


injuring.df <- harm.df %>% filter(!is.na(injuries)) %>%
                select(1:6,8)

# quantiles
qt <- quantile(injuring.df$injuries, probs=seq(.975,1,0.002))

# distribution plot
plt.distr.inj0 <- ggplot(injuring.df, aes(injuries))

plt.distr.inj0 <- plt.distr.inj0 + geom_density(aes(y=..density..)) + xlim(0,0.5) +
        labs(title="All events") +
        theme(plot.title = element_text(hjust = 0.5))


# display only the qts next to injuring events
qt[(length(qt)-(length(qt[qt>=1])+1)): length(qt)]
```

```
## 97.7% 97.9% 98.1% 98.3% 98.5% 98.7% 98.9% 99.1% 99.3% 99.5% 99.7% 99.9%
##     0     0     1     1     1     1     1     2     3     4     8    25
```

Looking at this distribution, we can infer that the vast majority of those occurrences were not injuring at all: **97.9% occurrences didn't caused any injuries**

On the other hand, injuring occurrences had to have at least 1 injury.

Now, among the injuring occurrences, we are interested in the ones whose harm is beyond the confidence interval, ie. above 99% of the most common values.

```
# subset for harm events
injuring.df <- injuring.df %>% filter(injuries > 0) %>%
                arrange(desc(injuries)) %>%
                mutate(mean = mean(injuries),
                median = median(injuries),
```

```
                rank = seq_len(length(event)))

# quantiles, same as
# poisson.test(mean, conf.level = 0.95)

qt <- quantile(injuring.df$injuries, probs=seq(.999,1,0.005))
qt
```

```
## 99.9%
##   500
```

Looking at this distribution, we can infer that **99.8% of the injuring occurrences caused up to 500 injuries**.

Distribution plots

```
# distribution plot
plt.distr.inj1 <- ggplot(injuring.df, aes(injuries))

plt.distr.inj1 <- plt.distr.inj1 + geom_density(aes(y=..density..)) + xlim(0,(qt[1]/20)) +
        labs(title="Injuring events") +
        theme(plot.title = element_text(hjust = 0.5))
```

```
grid.arrange(plt.distr.inj0, plt.distr.inj1,
             nrow=1, ncol=2)
grid.rect(gp=gpar(fill=NA))
```

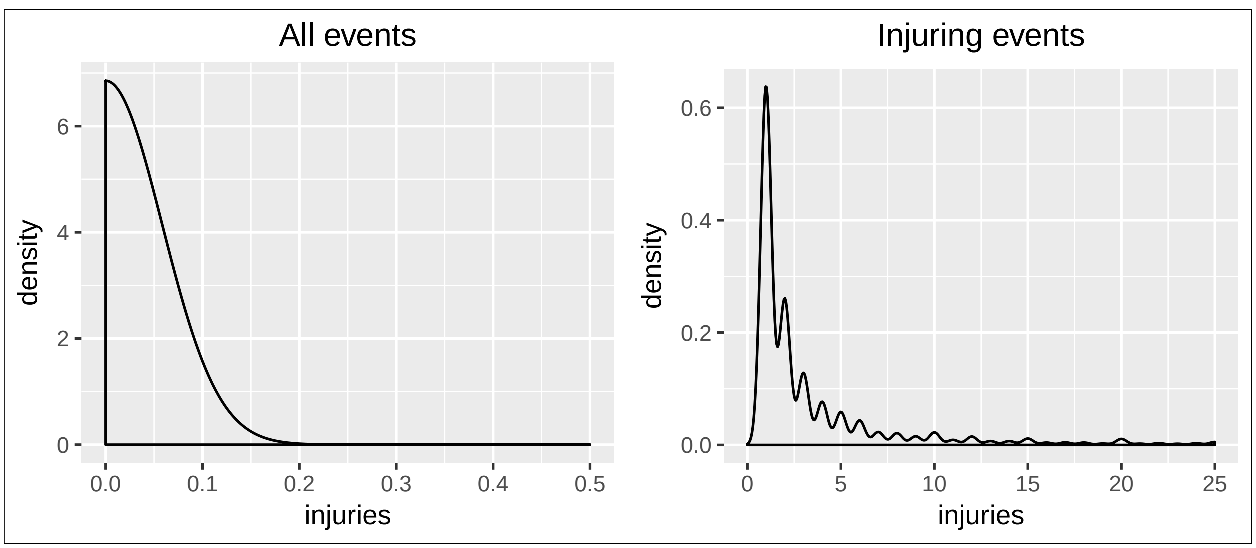

Figure 4: Population distribution for Injuries / occurrences

In this study, we looked on the 1% most injuring occurrences.

```
# subset for 99% CI
injuring95.df <- filter(injuring.df, injuries>qt[1])

# create color pallete for all events
colourCount.inj.single = length(unique(injuring95.df$event))
getPalette = colorRampPalette(brewer.pal(colourCount.inj.single, "Set1"))
```

```r
# print a table
kable(injuring95.df[,c(10,1:9)], caption="Worst injuring occurrences")
```

Table 4: Worst injuring occurrences

rank	event	mag	day	duration	state	countyname	injuries	mean	median
1	TORNADO	0	1979-04-10	NA	TX	WICHITA	1700	7.982731	2
2	STORM	0	1994-02-08	0S	OH	OHZ42	1568	7.982731	2
3	TORNADO	0	1953-06-09	NA	MA	WORCESTER	1228	7.982731	2
4	TORNADO	0	1974-04-03	NA	OH	GREENE	1150	7.982731	2
5	TORNADO	0	2011-05-22	0S	MO	JASPER	1150	7.982731	2
6	FLOOD	0	1998-10-17	0S	TX	COMAL	800	7.982731	2
7	TORNADO	0	2011-04-27	0S	AL	TUSCALOOS	800	7.982731	2
8	TORNADO	0	1953-06-08	NA	MI	GENESEE	785	7.982731	2
9	HURRICANE	0	2004-08-13	0S	FL	FLZ055	780	7.982731	2
10	FLOOD	0	1998-10-17	0S	TX	TXZ206	750	7.982731	2
11	TORNADO	0	2011-04-27	0S	AL	JEFFERSON	700	7.982731	2
12	FLOOD	0	1998-10-17	0S	TX	BEXAR	600	7.982731	2
13	TORNADO	0	1953-05-11	NA	TX	MCLENNAN	597	7.982731	2
14	TORNADO	0	1965-04-11	NA	IN	HOWARD	560	7.982731	2
15	FLOOD	0	1998-10-17	0S	TX	TXZ205	550	7.982731	2
16	HEAT	0	2007-08-04	0S	MO	MOZ061	519	7.982731	2
17	TORNADO	0	1966-03-03	NA	MS	HINDS	504	7.982731	2

```r
# prepare text for inline R
worst.injuring.single.ev <- injuring95.df$event[1]
worst.injuring.single.st <- injuring95.df$state[1]
worst.injuring.single.ct <- injuring95.df$countyname[1]
worst.injuring.single.dt <- injuring95.df$day[1]
worst.injuring.single.inj <- injuring95.df$injuries[1]
```

```r
# the plot
plt.inj.single <- ggplot(injuring95.df, aes(day, injuries, colour=event))

plt.inj.single <- plt.inj.single + geom_point() +
        geom_text(aes(label=ifelse(rank <= 3,
                 paste0(as.character(day), ": ", injuries, " injuried") ,""),
                hjust=-.03,vjust=0.5)) +

        # geom_hline(aes(yintercept = mean), linetype=2) +
        # geom_hline(aes(yintercept = median), linetype=3) +
        labs(title="Most Injuring",
                   y="", x="") +

        expand_limits(x=as.Date('2017-01-01'))+ #ok
        scale_colour_manual(values = getPalette(colourCount.inj.single))+
        theme(legend.title=element_blank()) +
        theme(legend.position="bottom") +
        guides(fill=guide_legend(nrow=5, byrow=TRUE)) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
        theme(plot.title = element_text(hjust = 0.5))
```

```r
        # scale_y_continuous(expand = c(0, 0)) +
        # geom_hline(aes(yintercept = mean), linetype=2) +
        # geom_hline(aes(yintercept = median), linetype=3)
plt.inj.single + labs(title="Worst injuring occurrences",
                      y="Injuries", x="")
```

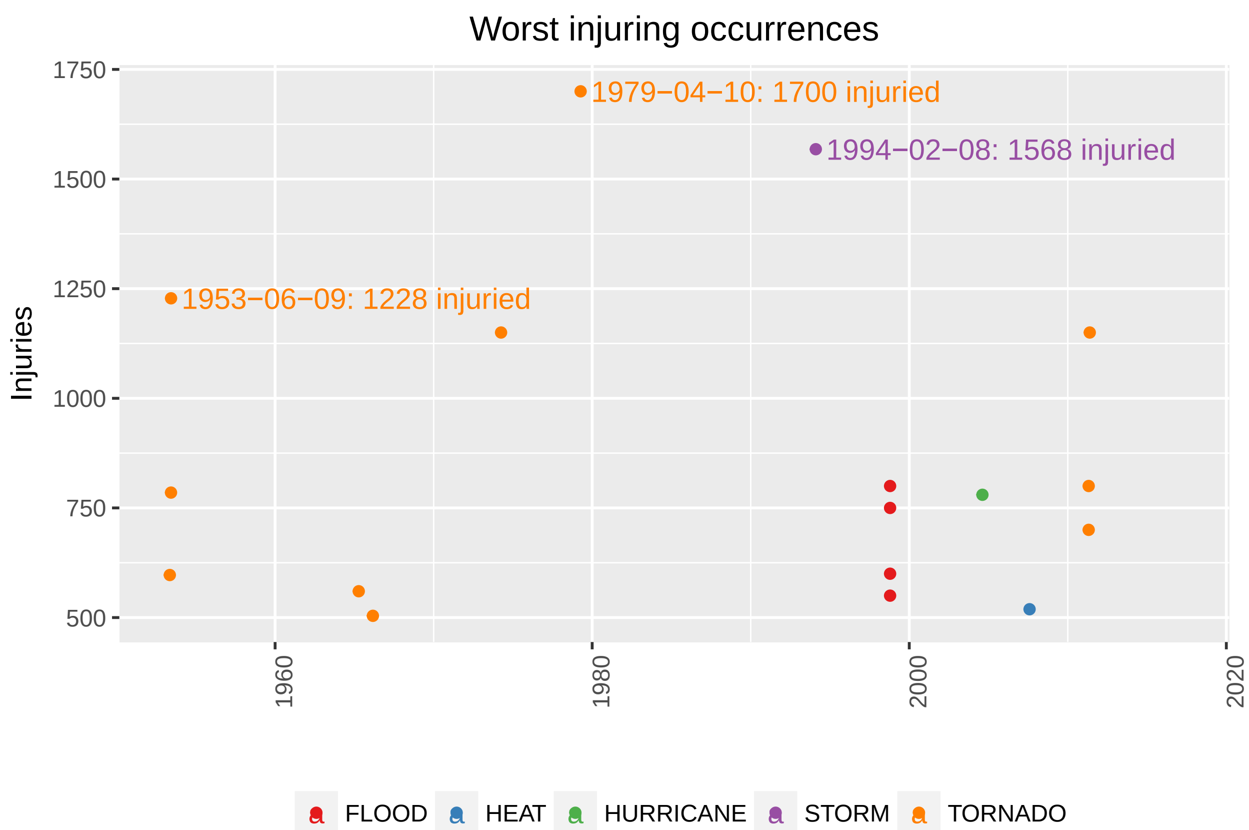

Figure 5: Worst injuring occurrences

The single most injuring event was a **TORNADO, that occurred in TX, WICHITA, on 1979-04-10, injuring 1700 people.**

However, if we compare this single awful event to the mean of injuries caused, we see that this is very unlikely to happen.

5.2.2 Most injuring in all time

Most injuring in all time

Notice that are several occurrences of the same type of event along the time.

Therefore, in order to know which is the worst type of event along all the years, we summed up the injuries caused by each one of occurrences of this events.

Notice that we are interested only in the worst of them, ie, the ones which are above the mean.

```r
# totals per event
injuring.all.df <- injuring.df %>% group_by(event) %>%
        summarise(total = sum(injuries)) %>%
```

```r
        arrange(desc(total)) %>%
        mutate(mean = mean(total), median = median(total),
               rank = seq_len(length(event)))  %>%
        filter(total >= mean(total))

# create color pallete for all events
colourCount.inj.all = length(unique(injuring.all.df$event))
getPalette = colorRampPalette(brewer.pal(colourCount.inj.all, "Set1"))

# prepare text for inline R
worst.injuring.all.ev <- injuring.all.df$event[1]
worst.injuring.all.inj <- injuring.all.df$total[1]

# a table
kable(injuring.all.df[,c(5,1:4)], caption="Total injuries by event")
```

Table 5: Total injuries by event

rank	event	total	mean	median
1	TORNADO	91407	4015.086	232
2	WIND	11497	4015.086	232
3	HEAT	9243	4015.086	232
4	FLOOD	8683	4015.086	232
5	LIGHTNING	5230	4015.086	232

The most injuring event along the time is the **TORNADO. It has injuried 91407 people until now.**

```r
# the plot
plt.inj.all <- ggplot(data=injuring.all.df, aes(event, total, fill=event))

plt.inj.all <- plt.inj.all + geom_bar(stat="identity") +
        geom_text(aes(label=ifelse(total==max(total),
                paste0(event, ": ", max(total), " injuried"),'')),
                hjust=0,vjust=2) +
        geom_hline(aes(yintercept = mean), linetype=1) +
        # geom_hline(aes(yintercept = median), linetype=2) +
        labs(title="All time",
             y="", x="") +

        theme(legend.position="none") +
        scale_colour_manual(values = getPalette(colourCount.inj.all))+
        theme(legend.title=element_blank()) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
        theme(plot.title = element_text(hjust = 0.5))


plt.inj.all  + labs(title="Total Injuries - All time",
             subtitle="Most injuring events of all time",
                     y="Injuries", x="")
```

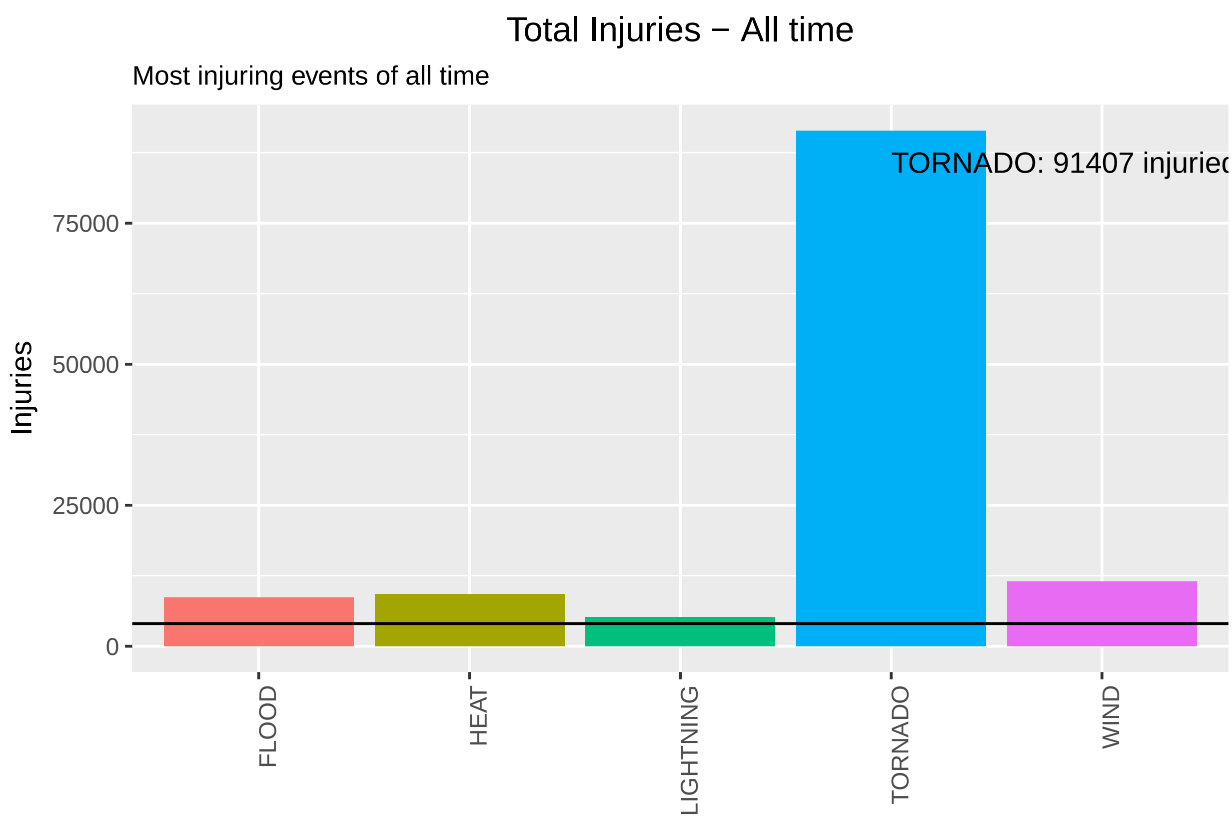

Figure 6: Total Injuries by event

5.2.3 Least injuring events

Just for curiosity, lets show now what are the less injuring among the injuring events:

```
# sort for less dangerous, had to subset again due to previous filtering
injuring.all.df <- injuring.df %>% group_by(event) %>%
        summarise(total = sum(injuries)) %>% arrange(total) %>%
        mutate(mean = mean(total), median = median(total),
               rank = seq(length(event),1, by=-1))

# a table
kable(injuring.all.df[1:10,c(5,1:2)], caption="Least injuring events")
```

Table 6: Least injuring events

rank	event	total
35	FROST	3
34	FUNNEL	3
33	TIDE	5
32	TYPHOON	5
31	HIGH SEAS	8
30	OTHER	21
29	BLACK ICE	24
28	WATERSPOUT	29
27	ICY ROADS	31

rank	event	total
26	DROUGHT	33

6 Economy: the the most harmfull events

We have determined what events did more harm to economy, both in terms of property and crops damage.

There were events that causes zero property damage but a lot of crop damage. The inverse is also true, so we did a separate analysis to property VS crop damaging events.

6.1 Property losses

6.1.1 Most Property Damaging event in a single occurrence

In order to determine what were the most property damaging events in a single occurrence, we need to see how damages are distributed along the occurrences.

```
# property damages
rm(injuring.df, injuring.all.df, injuring95.df) # cleannig house

prop.df <- harm.df %>% filter(!is.na(prop.ev)) %>%
                        select(1:6,13)


# quantiles
qt <- quantile(prop.df$prop.ev, probs=seq(.999,1,0.002))

# distribution plot
plt.distr.prop0 <- ggplot(prop.df, aes(log(prop.ev)))

plt.distr.prop0 <- plt.distr.prop0 + geom_density(aes(y=..density..)) + #xlim(0,.5) +
        labs(title="All events", x="log(amount $)") +
        theme(plot.title = element_text(hjust = 0.5))


# display only the qts next to harmfull events
qt
```

```
##    99.9%
## 53931800
```

Looking at this distribution, we can infer that 99.8% of the occurrences caused less than **$53,931,800 in losses**.

On the other hand, damaging occurrences had to have damages above zero.

Now, among the damaging occurrences, we are interested in the ones whose damages are above 99.8% of the most common values.

```
# subset for harm events
prop.df <- prop.df %>% filter(prop.ev > 0) %>%
                arrange(desc(prop.ev)) %>%
                mutate(value = dollar(prop.ev),
                        media.raw = mean(prop.ev),
```

```
                        mediana.raw = median(prop.ev),
                        mean = dollar(media.raw),
                        median = dollar(mediana.raw),
                        rank = seq_len(length(event)))
# quantiles, same as

qt <- quantile(prop.df$prop.ev, probs=seq(.999,1,0.002))
qt
```

```
##     99.9%
## 120000000
```

Looking at this distribution, we can infer that **99.8% of the damaging occurrences caused up to $120,000,000 in losses**.

Distribution plots

```
# distribution plot
plt.distr.prop1 <- ggplot(prop.df, aes(log(prop.ev)))

plt.distr.prop1 <- plt.distr.prop1 + geom_density(aes(y=..density..)) + #xlim(0,100) +
        labs(title="Damaging events", x="log(amount $)") +
        theme(plot.title = element_text(hjust = 0.5))
```

```
grid.arrange(plt.distr.prop0, plt.distr.prop1, nrow=1, ncol=2)
grid.rect(gp=gpar(fill=NA))
```

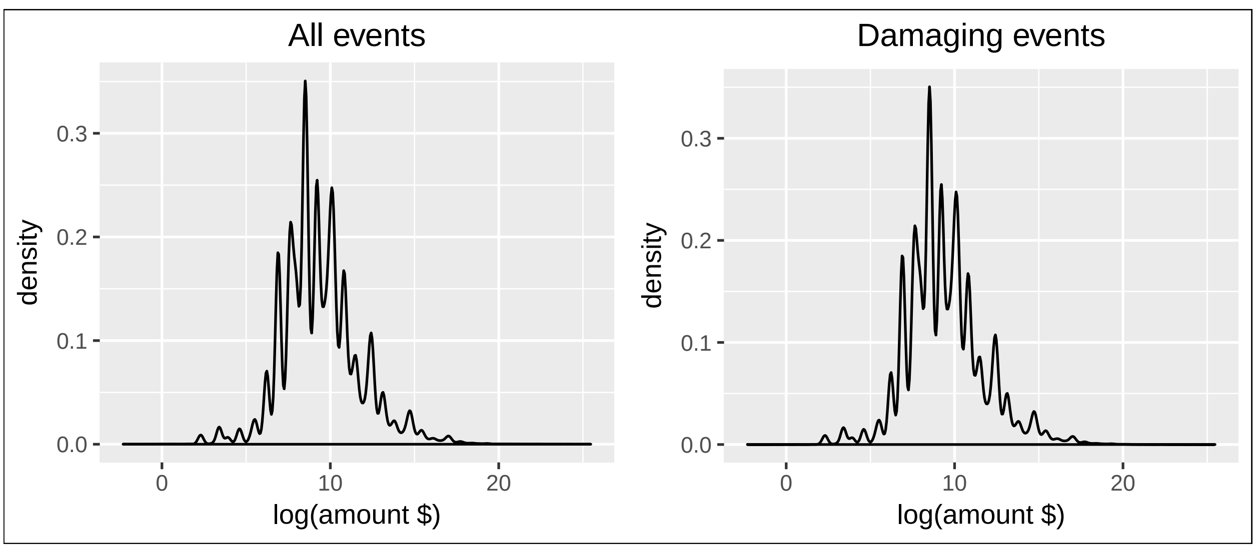

Figure 7: Population distribution for losses / occurrences

In this study, we looked on the 1% most harmful occurrences.

```
# subset for 99% CI
prop95.df <- filter(prop.df, prop.ev>qt[1])

# create color pallete for all events
colourCount.prop.single = length(unique(prop95.df$event))
getPalette = colorRampPalette(brewer.pal(colourCount.prop.single, "Set1"))
```

```
# prepare text for inline R
worst.prop.single.ev <- prop95.df$event[1]
worst.prop.single.st <- prop95.df$state[1]
worst.prop.single.ct <- prop95.df$countyname[1]
worst.prop.single.dt <- prop95.df$day[1]
worst.prop.single.value <- prop95.df$value[1]
worst.prop.single.mean <- prop95.df$mean[1]
worst.prop.single.median <- prop95.df$median[1]
```

```
# print a table
#
# pander(prop95.df[1:20,c(13,1:6,8,11:12)], caption="Worst property damaging occurrences - pander",  sp

kable(prop95.df[1:20,c(13,1:6,8)],
      caption=paste("Worst property damaging occurrences, mean = ",
                    worst.prop.single.mean, " and median = ",
                    worst.prop.single.median))
```

Table 7: Worst property damaging occurrences, mean = \$1,791,099 and median = \$10,000

rank	event	mag	day	duration	state	countyname	value
1	FLOOD	0	2006-01-01	0S	CA	NAPA	\$115,000,000,000
2	STORM	0	2005-08-29	0S	LA	LAZ040	\$31,300,000,000
3	HURRICANE	0	2005-08-28	0S	LA	LAZ034	\$16,930,000,000
4	STORM	0	2005-08-29	0S	MS	MSZ080	\$11,260,000,000
5	HURRICANE	0	2005-10-24	0S	FL	FLZ068	\$10,000,000,000
6	HURRICANE	0	2005-08-28	0S	MS	MSZ068	\$7,350,000,000
7	HURRICANE	0	2005-08-29	0S	MS	MSZ018	\$5,880,000,000
8	HURRICANE	0	2004-08-13	0S	FL	FLZ055	\$5,420,000,000
9	STORM	0	2001-06-05	0S	TX	TXZ163	\$5,150,000,000
10	WINTER	0	1993-03-12	0S	AL	ALZ001	\$5,000,000,000
11	FLOOD	0	1993-08-31	NA	IL	ADAMS	\$5,000,000,000
12	HURRICANE	0	2004-09-04	0S	FL	FLZ041	\$4,830,000,000
13	HURRICANE	0	2004-09-13	0S	FL	FLZ001	\$4,000,000,000
14	HURRICANE	0	2005-09-23	0S	LA	LAZ027	\$4,000,000,000
15	TIDE	0	2008-09-12	0S	TX	TXZ213	\$4,000,000,000
16	FLOOD	0	1997-04-18	0S	ND	NDZ027	\$3,000,000,000
17	HURRICANE	0	1999-09-15	0S	NC	NCZ007	\$3,000,000,000
18	TORNADO	0	2011-05-22	0S	MO	JASPER	\$2,800,000,000
19	RAIN	0	1995-05-08	0S	LA	LAFOURCHE	\$2,500,000,000
20	HURRICANE	0	2004-09-13	0S	AL	ALZ051	\$2,500,000,000

```
plt.prop.single <- ggplot(prop95.df, aes(day, prop.ev, colour=event))

plt.prop.single <- plt.prop.single + geom_point() +
        geom_text(aes(label=ifelse(rank <= 3,
                as.character(day),""),
                hjust=-.03,vjust=0.5)) +
        # geom_hline(aes(yintercept = media.raw), linetype=2) +
```

```
         # geom_hline(aes(yintercept = mediana.raw), linetype=3) +
        labs(title="Property Dammaging",
                    y="", x="") +

        expand_limits(x=as.Date('2017-01-01'))+ #ok
        scale_y_continuous(labels = dollar)+

        scale_colour_manual(values = getPalette(colourCount.prop.single))+
        theme(legend.title=element_blank()) +
        theme(legend.position="bottom") +
        guides(fill=guide_legend(nrow=5, byrow=TRUE)) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
        theme(plot.title = element_text(hjust = 0.5))

plt.prop.single + labs(title="Worst property damaging occurrences",
                    y="Losses", x="")
```

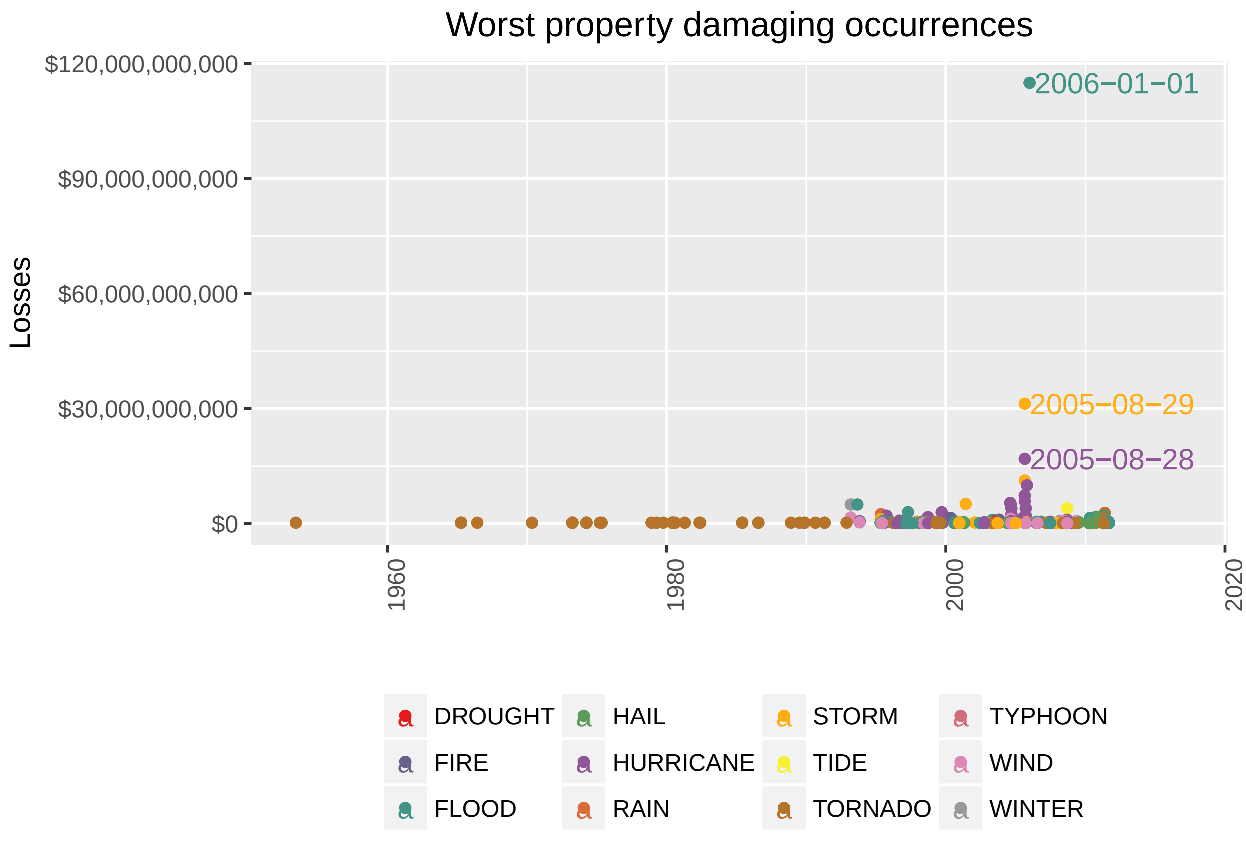

Figure 8: Worst property damaging occurrences

The single most economic damaging event to properties was a **FLOOD, that occurred in CA, NAPA, on 2006-01-01, causing U$ $115,000,000,000 in losses**.

6.1.2 Most Property Damaging event in all time

Most Property Damaging event in all time

Notice that are several occurrences of the same type of event along the time.

Therefore, in order to know which is the worst type of event along all the years, we summed up the losses caused by each one of occurrences of this events.

Notice that we are interested only in the worst of them, ie, the ones which are above the mean.

```r
# totals per event
prop.all.df <- prop.df %>% group_by(event) %>%
                summarise(total.raw = sum(prop.ev)) %>%
                arrange(desc(total.raw)) %>%
                mutate(media.raw = mean(total.raw),
                       mediana.raw = median(total.raw),
                       total = dollar(total.raw),
                       mean = dollar(media.raw),
                       median = dollar(mediana.raw),
                       rank = seq_len(length(event))) %>%
                filter(total.raw > mean(total.raw))

# create color pallete for all events
colourCount.prop.all = length(unique(prop.all.df$event))
getPalette = colorRampPalette(brewer.pal(colourCount.prop.all, "Set1"))

# prepare text for inline R
worst.prop.all.ev <- prop.all.df$event[1]
worst.prop.total <- prop.all.df$total[1]
```

```r
# a table
kable(prop.all.df[, c(8,1,5:7)], caption="Total losses by event")
```

Table 8: Total losses by event

rank	event	total	mean	median
1	FLOOD	$168,258,894,238	$9,309,236,205	$6,537,750
2	HURRICANE	$84,656,180,010	$9,309,236,205	$6,537,750
3	TORNADO	$57,003,317,814	$9,309,236,205	$6,537,750
4	STORM	$56,197,366,960	$9,309,236,205	$6,537,750
5	WIND	$17,951,211,793	$9,309,236,205	$6,537,750
6	HAIL	$15,977,047,956	$9,309,236,205	$6,537,750

```r
plt.prop.all <- ggplot(data=prop.all.df, aes(event, total.raw, fill=event))

plt.prop.all <- plt.prop.all + geom_bar(stat="identity") +

        geom_text(aes(label=ifelse(total.raw==max(total.raw),
                paste(event, dollar(max(total.raw)), sep=": "),'')),
                hjust=0,vjust=2) +
        geom_hline(aes(yintercept = media.raw), linetype=1) +
        # geom_hline(aes(yintercept = mediana.raw), linetype=2) +
        labs(title="All time", y="", x="") +

        scale_y_continuous(labels = dollar)+

        theme(legend.position="none") +
        scale_colour_manual(values = getPalette(colourCount.prop.all))+
        theme(legend.title=element_blank()) +
```

```
        theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
        theme(plot.title = element_text(hjust = 0.5))

plt.prop.all + labs(title="Total Damages - All time",
             subtitle="Most property damaging events of all time",
                     y="Losses", x="")
```

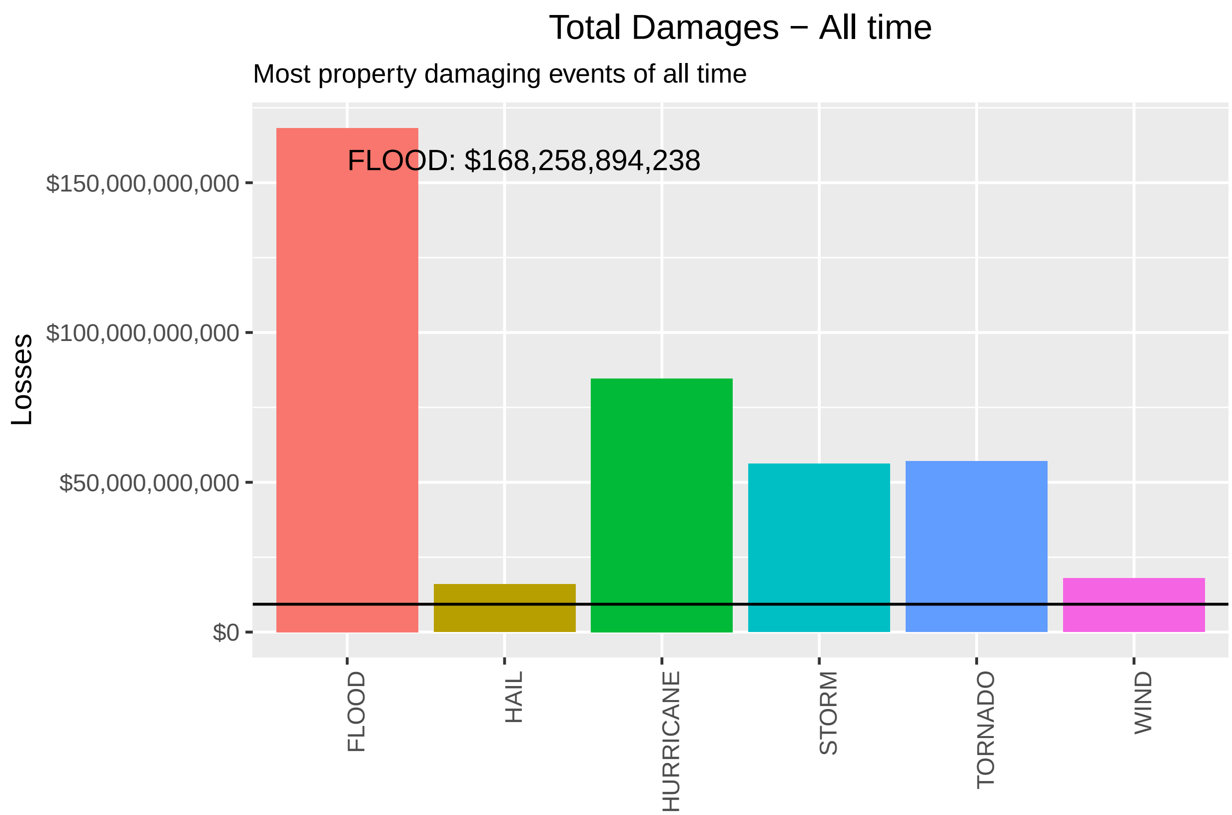

Figure 9: Total Property Damages by event

The most property damaging event along the time is the **FLOOD. It has caused $168,258,894,238 in losses.**

6.1.3 Least property damaging events

Just for curiosity, these are the less damaging events:

```
prop.all.df <- prop.df %>% group_by(event) %>%
                summarise(total.raw = sum(prop.ev)) %>%
                arrange(total.raw) %>%
                mutate(media.raw = mean(total.raw),
                        mediana.raw = median(total.raw),
                        total = dollar(total.raw),
                        mean = dollar(media.raw),
                        median = dollar(mediana.raw),
                        rank = seq(length(event),1, by=-1))
```

```r
kable(prop.all.df[1:10, c(8,1,5)], caption="Least property damaging events")
```

Table 9: Least property damaging events

rank	event	total
46	RIP CURRENT	$1,000
45	HIGH SWELLS	$5,000
44	URBAN/SMALL STREAM	$5,000
43	WINTRY MIX	$12,500
42	FROST	$15,000
41	HIGH SEAS	$15,500
40	WET MICROBURST	$35,000
39	MICROBURST	$80,000
38	DENSE SMOKE	$100,000
37	GUSTNADO	$102,050

6.2 Crop losses

6.2.1 Most Crop Damaging event in a single occurrence

In order to determine what were the most crop damaging events in a single occurrence, we need to see how damages are distributed along the occurrences.

```r
# crop damages
rm(prop.df, prop.all.df, prop95.df) # cleannig house

crop.df <- harm.df %>% filter(!is.na(crop.ev)) %>%
                select(1:6,14)


# quantiles
qt <- quantile(crop.df$crop.ev, probs=seq(.998,1,0.002))

# distribution plot
plt.distr.crop0 <- ggplot(crop.df, aes(log(crop.ev)))

plt.distr.crop0 <- plt.distr.crop0 + geom_density(aes(y=..density..)) + #xlim(0,.5) +
        labs(title="All events", x="log(amount $)") +
        theme(plot.title = element_text(hjust = 0.5))


# display only the qts next to harmfull events
qt
```

```
##       99.8%        100%
##    7000000 5000000000
```

Looking at this distribution, we can infer that 99% of the occurrences caused less than **$7,000,000 in losses**.

On the other hand, damaging occurrences had to have damages above zero.

Now, among the damaging occurrences, we are interested in the ones whose damages are above 99% of the most common values.

```r
# subset for harm events
crop.df <- crop.df %>% filter(crop.ev > 0) %>%
                arrange(desc(crop.ev)) %>%
                mutate(value = dollar(crop.ev),
                        media.raw = mean(crop.ev),
                        mediana.raw = median(crop.ev),
                        mean = dollar(media.raw),
                        median = dollar(mediana.raw),
                        rank = seq_len(length(event)))

# quantiles, same as
# poisson.test(mean, conf.level = 0.95)

qt <- quantile(crop.df$crop.ev, probs=seq(.999,1,0.005))
qt
```

```
##     99.9%
## 336111520
```

Looking at this distribution, we can infer that **99.8% of the damaging occurrences caused up to $336,111,520 in losses.**

Distribution plots

```r
# distribution plot
plt.distr.crop1 <- ggplot(crop.df, aes(log(crop.ev)))

plt.distr.crop1 <- plt.distr.crop1 + geom_density(aes(y=..density..)) + #xlim(0,qt[1]) +
        labs(title="Damaging events", x="log(amount $)") +
        # scale_x_continuous(labels = dollar)+
        # theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
        theme(plot.title = element_text(hjust = 0.5))
```

```r
grid.arrange(plt.distr.crop0, plt.distr.crop1,
             nrow=1, ncol=2)
grid.rect(gp=gpar(fill=NA))
```

In this study, we looked on the 1% most harmful occurrences.

```r
# subset for 99% CI
crop95.df <- filter(crop.df, crop.ev>qt[1])

# create color pallete for all events
colourCount.crop.single = length(unique(crop95.df$event))
getPalette = colorRampPalette(brewer.pal(colourCount.crop.single, "Set1"))

worst.crop.single.ev <- crop95.df$event[1]
worst.crop.single.st <- crop95.df$state[1]
worst.crop.single.ct <- crop95.df$countyname[1]
worst.crop.single.dt <- crop95.df$day[1]
worst.crop.single.value <- crop95.df$value[1]
worst.crop.single.mean <- crop95.df$mean[1]
worst.crop.single.median <- crop95.df$median[1]


# print a table
```

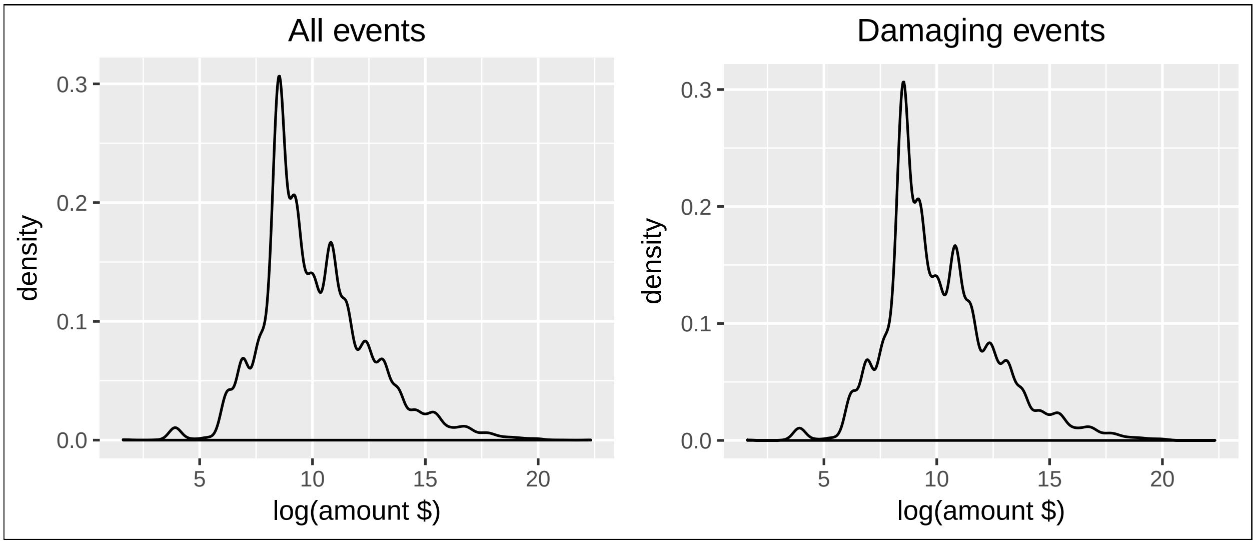

Figure 10: Population distribution for losses / occurrences

```
kable(crop95.df[1:20,c(13,1:6,8)],
      caption=paste("Worst crops damaging occurrences, mean = ",
                    worst.crop.single.mean, " and median = ",
                    worst.crop.single.median))
```

Table 10: Worst crops damaging occurrences, mean = $2,224,406 and median = $15,000

rank	event	mag	day	duration	state	countyname	value
1	FLOOD	0	1993-08-31	NA	IL	ADAMS	$5,000,000,000
2	STORM	0	1994-02-09	0S	MS	MSZ001	$5,000,000,000
3	HURRICANE	0	2005-08-29	0S	MS	MSZ018	$1,510,000,000
4	DROUGHT	0	2006-01-01	0S	TX	TXZ091	$1,000,000,000
5	COLD	0	1998-12-20	0S	CA	CAZ020	$596,000,000
6	DROUGHT	0	2001-08-01	0S	IA	IAZ004	$578,850,000
7	DROUGHT	0	2000-11-01	0S	TX	TXZ021	$515,000,000
8	DROUGHT	0	1995-08-01	0S	IA	IAZ004	$500,000,000
9	DROUGHT	0	1998-07-06	0S	OK	OKZ049	$500,000,000
10	HURRICANE	0	1999-09-15	0S	NC	NCZ007	$500,000,000
11	DROUGHT	0	1999-07-01	0S	PA	PAZ006	$500,000,000
12	FLOOD	0	2000-10-03	0S	FL	FLZ072	$500,000,000
13	FLOOD	0	2007-07-01	0S	MO	HENRY	$500,000,000
14	HEAT	0	2006-07-16	0S	CA	CAZ089	$492,400,000
15	DROUGHT	0	2002-12-01	0S	NE	NEZ039	$480,000,000
16	DROUGHT	0	1998-12-01	0S	TX	TXZ021	$450,000,000
17	HURRICANE	0	2005-08-25	0S	FL	FLZ068	$423,000,000
18	DROUGHT	0	2001-12-01	0S	TX	TXZ021	$420,000,000
19	HURRICANE	0	1999-09-14	0S	NC	NCZ029	$413,600,000
20	HEAT	0	1995-08-20	NA	AL	TALLADEGA	$400,000,000

```
plt.crop.single <- ggplot(crop95.df, aes(day, crop.ev, colour=event))

plt.crop.single <- plt.crop.single + geom_point() +
        geom_text(aes(label=ifelse(rank <= 3,
                as.character(day),""),
                hjust=-.03,vjust=0.5)) +
        # geom_hline(aes(yintercept = media.raw), linetype=2) +
        # geom_hline(aes(yintercept = mediana.raw), linetype=3) +
        labs(title="Crop Damaging"
```

```r
                    y="Losses", x="")
```

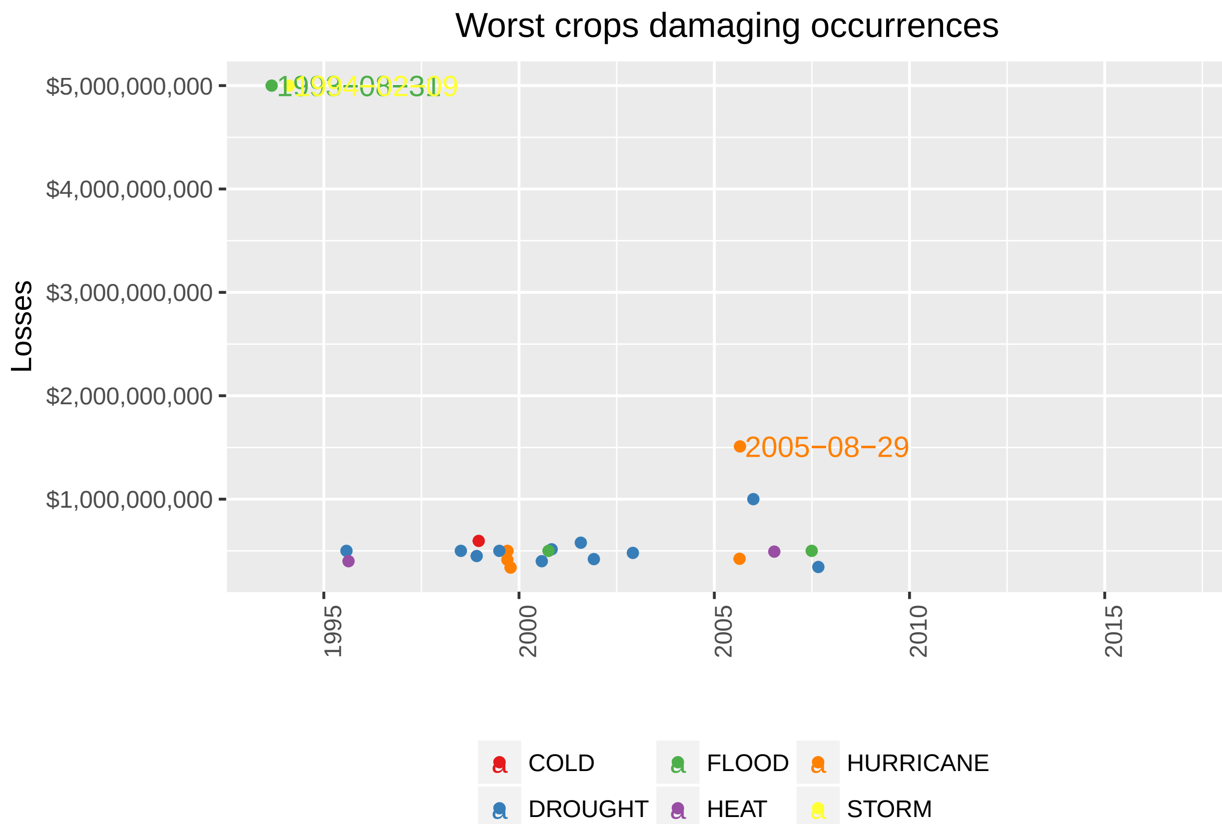

Figure 11: Worst crops damaging occurrences

The single most economic damaging event to crops was a **FLOOD, that occurred in IL, ADAMS, on 1993-08-31, causing U$ $5,000,000,000 in losses.**

6.2.2 Most Crop Damaging event in all time

Most Crop Damaging event in all time

Notice that are several occurrences of the same type of event along the time.

Therefore, in order to know which is the worst type of event along all the years, we summed up the losses caused by each one of occurrences of this events.

Notice that we are interested only in the worst of them, ie, the ones which are above the mean.

```r
# totals per event
crop.all.df <- crop.df %>% group_by(event) %>%
                summarise(total.raw = sum(crop.ev)) %>%
                arrange(desc(total.raw)) %>%
                mutate(media.raw = mean(total.raw),
                       mediana.raw = median(total.raw),
                       total = dollar(total.raw),
                       mean = dollar(media.raw),
                       median = dollar(mediana.raw),
                       rank = seq_len(length(event))) %>%
```

```
                filter(total.raw > mean(total.raw))

# create color pallete for all events
colourCount.crop.all = length(unique(crop.all.df$event))
getPalette = colorRampPalette(brewer.pal(colourCount.crop.all, "Set1"))

# prepare text for inline R
worst.crop.all.ev <- crop.all.df$event[1]
worst.crop.total <- crop.all.df$total[1]

# a table
kable(crop.all.df[, c(8,1,5:7)], caption="Total losses by event")
```

Table 11: Total losses by event

rank	event	total	mean	median
1	DROUGHT	$13,972,581,000	$2,231,988,917	$296,658,415
2	FLOOD	$12,275,737,200	$2,231,988,917	$296,658,415
3	STORM	$5,738,319,500	$2,231,988,917	$296,658,415
4	HURRICANE	$5,505,292,800	$2,231,988,917	$296,658,415
5	COLD	$3,298,176,550	$2,231,988,917	$296,658,415
6	HAIL	$3,046,470,470	$2,231,988,917	$296,658,415

```
plt.crop.all <- ggplot(data=crop.all.df, aes(event, total.raw, fill=event))

plt.crop.all <- plt.crop.all + geom_bar(stat="identity") +

        geom_text(aes(label=ifelse(total.raw==max(total.raw),
                paste(event, dollar(max(total.raw)), sep=": "),'')),
                hjust=0,vjust=2) +
        geom_hline(aes(yintercept = media.raw), linetype=1) +
        # geom_hline(aes(yintercept = mediana.raw), linetype=2) +
        labs(title="All time", y="", x="") +

        scale_y_continuous(labels = dollar)+

        theme(legend.position="none") +
        scale_colour_manual(values = getPalette(colourCount.crop.all))+
        theme(legend.title=element_blank()) +
        theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
        theme(plot.title = element_text(hjust = 0.5))

plt.crop.all + labs(title="Total Damages - All time",
             subtitle="Most crops damaging events of all time",
                     y="Losses", x="")
```

The most crop damaging event along the time is the **DROUGHT. It has caused $13,972,581,000 in losses.**

6.2.3 Least crops damaging events

Just for curiosity, lets show now what are the less damaging among the events:

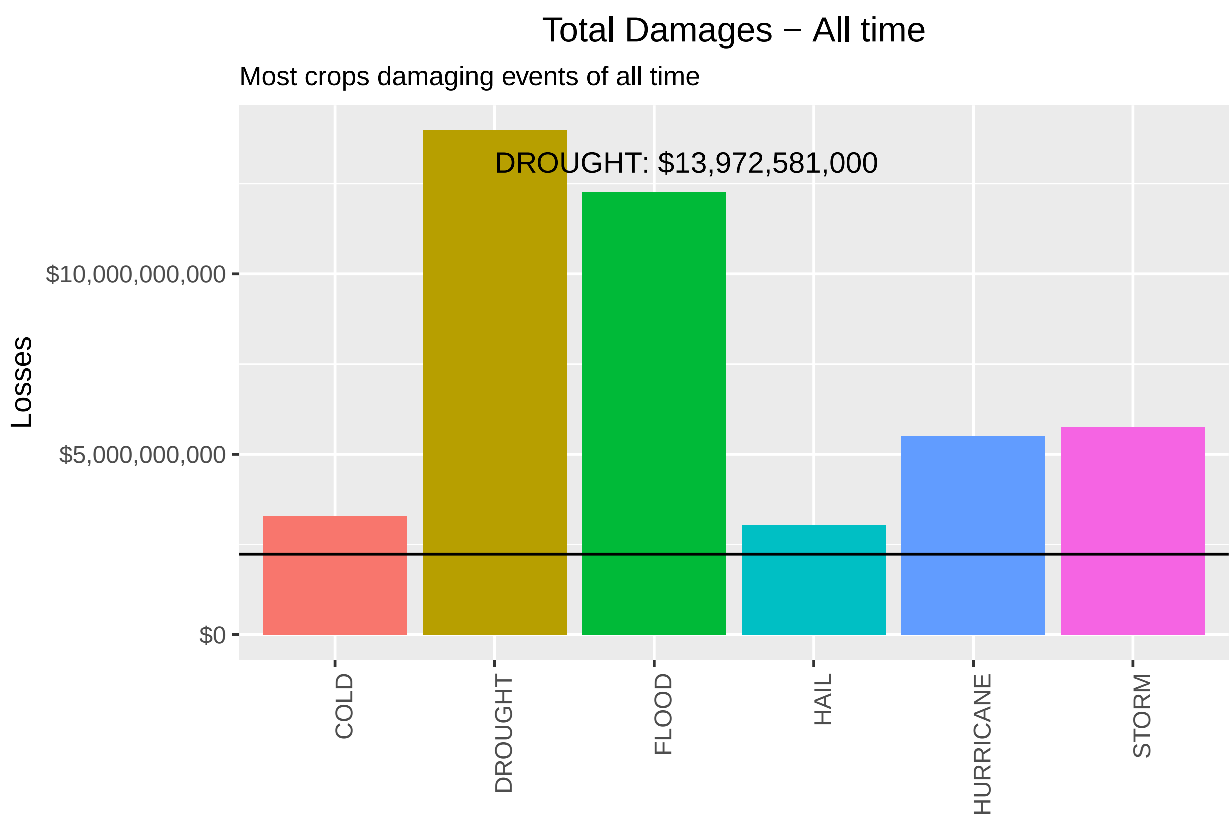

Figure 12: Total Crop Damages by event

```r
crop.all.df <- crop.df %>% group_by(event) %>%
                summarise(total.raw = sum(crop.ev)) %>%
                arrange(total.raw) %>%
                mutate(media.raw = mean(total.raw),
                       mediana.raw = median(total.raw),
                       total = dollar(total.raw),
                       mean = dollar(media.raw),
                       median = dollar(mediana.raw),
                       rank = seq(length(event),1, by=-1))



kable(crop.all.df[1:10, c(8,1,5)], caption="Least crops damaging events")
```

Table 12: Least crops damaging events

rank	event	total
22	GUSTNADO	$1,550
21	TSUNAMI	$20,000
20	TYPHOON	$825,000
19	TIDE	$850,000
18	LIGHTNING	$12,092,090
17	SLIDE	$20,017,000
16	WINTER	$42,444,000

rank	event	total
15	FROST	$66,000,000
14	BLIZZARD	$112,060,000
13	SNOW	$134,663,100

7 Most aflicted locations

We have determined what locations had the worst outcome from those events, both in terms of human health and economic losses.

Unfortunatelly, these has been the worst counties for living in:

```
# subset original data
cities.df <- harm.df %>%
                filter(!(is.na(countyname) | is.na(state))) %>%
                select(6,5,7:14) %>%
                group_by(state, countyname) %>%
                summarise(fatalities = sum(fatalities, na.rm=TRUE),
                        injuries = sum(injuries, na.rm=TRUE),
                        prop.dmg = sum(prop.ev, na.rm=TRUE),
                        crop.dmg = sum(crop.ev, na.rm=TRUE)
                )
```

7.1 Worst fatality count

```
cities.fatal.df <- arrange(cities.df, desc(fatalities)) %>% ungroup(state, countyname) %>%
      mutate(rank = seq_len(length(fatalities)),
                prop.dmg = dollar(prop.dmg),
                crop.dmg = dollar(crop.dmg)
             )

kable(cities.fatal.df[1:10, c(7,1:6)], caption="Total fatalities by county")
```

Table 13: Total fatalities by county

rank	state	countyname	fatalities	injuries	prop.dmg	crop.dmg
1	IL	ILZ003	605	14	$429,000	$0
2	IL	ILZ014	300	22	$2,321,000	$0
3	PA	PAZ054	174	295	$124,701,980	$25,000,000
4	MO	JASPER	165	1271	$2,858,007,330	$5,500
5	MI	GENESEE	121	925	$87,108,750	$5,000,000
6	TX	MCLENNAN	117	635	$63,071,100	$4,000
7	TX	TXZ163	116	3	$6,131,681,000	$270,200,000
8	IL	ILZ005	114	0	$277,000	$0
9	AL	JEFFERSON	110	1576	$2,024,930,600	$2,254,000
10	PA	PAZ037	107	0	$0	$0

```
worst.fatal.city.county <- cities.fatal.df$countyname[1]
worst.fatal.city.st <- cities.fatal.df$state[1]
```

```
worst.fatal.city.count <- cities.fatal.df$fatalities[1]
```

The county with the biggest fatality count is **ILZ003, in IL, with 605 people killed.**

7.2 Worst injuries count

```
rm(cities.fatal.df) # house cleanning
cities.inj.df <- arrange(cities.df, desc(injuries)) %>% ungroup(state, countyname) %>%
      mutate(rank = seq_len(length(injuries)),
                prop.dmg = dollar(prop.dmg),
                crop.dmg = dollar(crop.dmg)
             )

kable(cities.inj.df[1:10, c(7,1:6)], caption="Total injuries by county")
```

Table 14: Total injuries by county

rank	state	countyname	fatalities	injuries	prop.dmg	crop.dmg
1	TX	WICHITA	51	1852	$310,139,880	$0
2	AL	JEFFERSON	110	1576	$2,024,930,600	$2,254,000
3	OH	OHZ42	1	1568	$50,000,000	$5,000,000
4	MA	WORCESTER	96	1289	$284,569,630	$0
5	OH	GREENE	37	1275	$269,935,250	$0
6	MO	JASPER	165	1271	$2,858,007,330	$5,500
7	MO	MOZ061	9	1133	$1,000	$0
8	AL	TUSCALOOS	60	1103	$1,604,059,750	$725,000
9	MO	MOZ009	73	978	$3,225,050	$23,649,200
10	MI	GENESEE	121	925	$87,108,750	$5,000,000

```
worst.inj.city.county <- cities.inj.df$countyname[1]
worst.inj.city.st <- cities.inj.df$state[1]
worst.inj.city.count <- cities.inj.df$injuries[1]
```

The county with the biggest injuries count is **WICHITA, in TX, with 1852 people injuried.**

7.3 Worst property losses

```
rm(cities.inj.df) # house cleanning

cities.prop.df <- arrange(cities.df, desc(prop.dmg)) %>% ungroup(state, countyname) %>%
      mutate(rank = seq_len(length(prop.dmg)),
                prop.dmg = dollar(prop.dmg),
                crop.dmg = dollar(crop.dmg)
      )

kable(cities.prop.df[1:10, c(7,1:6)], caption="Total property losses by county")
```

Table 15: Total property losses by county

rank	state	countyname	fatalities	injuries	prop.dmg	crop.dmg
1	CA	NAPA	1	0	$115,116,385,000	$66,900,000
2	LA	LAZ040	0	0	$31,316,850,000	$0
3	LA	LAZ034	1	0	$17,152,118,400	$178,330,000
4	MS	MSZ080	0	1	$11,264,195,000	$0
5	FL	FLZ068	19	16	$10,367,010,000	$1,047,000,000
6	FL	FLZ001	33	0	$9,686,320,000	$87,800,000
7	MS	MSZ068	1	0	$7,375,405,000	$0
8	TX	TXZ163	116	3	$6,131,681,000	$270,200,000
9	MS	MSZ018	17	104	$5,908,768,000	$1,514,706,500
10	FL	FLZ055	9	786	$5,424,027,000	$292,000,000

```
worst.prop.city.county <- cities.prop.df$countyname[1]
worst.prop.city.st <- cities.prop.df$state[1]
worst.prop.city.count <- cities.prop.df$prop.dmg[1]
```

The county with the biggest property losses is **NAPA, in CA, with $115,116,385,000 in losses.**

7.4 Worst crops losses

```
rm(cities.prop.df) # house cleanning


cities.crop.df <- arrange(cities.df, desc(crop.dmg)) %>% ungroup(state, countyname) %>%
      mutate(rank = seq_len(length(crop.dmg)),
             prop.dmg = dollar(prop.dmg),
             crop.dmg = dollar(crop.dmg)
      )

kable(cities.crop.df[1:10, c(7,1:6)], caption="Total crops losses by county")
```

Table 16: Total crops losses by county

rank	state	countyname	fatalities	injuries	prop.dmg	crop.dmg
1	IL	ADAMS	0	23	$5,009,087,550	$5,000,084,000
2	MS	MSZ001	4	5	$2,643,000	$5,000,000,000
3	TX	TXZ091	69	224	$182,509,000	$2,422,471,000
4	TX	TXZ021	2	4	$12,450,000	$1,845,050,000
5	IA	IAZ004	10	9	$737,543,460	$1,579,805,100
6	MS	MSZ018	17	104	$5,908,768,000	$1,514,706,500
7	FL	FLZ068	19	16	$10,367,010,000	$1,047,000,000
8	GA	GAZ001	20	29	$158,011,850	$926,260,000
9	NE	NEZ039	4	14	$22,057,020	$771,550,000
10	NC	NCZ029	29	201	$1,940,635,500	$768,600,000

```
worst.crop.city.county <- cities.crop.df$countyname[1]
worst.crop.city.st <- cities.crop.df$state[1]
worst.crop.city.count <- cities.crop.df$crop.dmg[1]
```

The county with the biggest croperty losses is **ADAMS, in IL, with $5,000,084,000 in losses.**

8 Results

8.1 Population Health

```
# plist <- list(plt.fatal.single, plt.fatal.all, plt.inj.single, plt.inj.all)
# n <- length(plist)
# nCol <- floor(sqrt(n))
# do.call("grid.arrange", c(plist, ncol=nCol))

grid.arrange(plt.fatal.single, plt.fatal.all, plt.inj.single, plt.inj.all,
             nrow=2, ncol=2)
grid.rect(gp=gpar(fill=NA))
```

The single most fatal event was a **HEAT, that occurred in IL, ILZ003, on 1995-07-12, killing 583 people.**

The most fatal event along the time is the **TORNADO. It has killed 5636 people until now.**

The single most injuring event was a **TORNADO, that occurred in TX, WICHITA, on 1979-04-10, injuring 1700 people.**

The most injuring event along the time is the **TORNADO. It has injuried 91407 people until now.**

8.2 Economic Damages

```
grid.arrange(plt.prop.single, plt.prop.all,
             plt.crop.single, plt.crop.all,
             nrow=2, ncol=2)
grid.rect(gp=gpar(fill=NA))
```

The single most economic damaging event to properties was a **FLOOD, that occurred in CA, NAPA, on 2006-01-01, causing U$ $115,000,000,000 in losses**.

The most property damaging event along the time is the **FLOOD. It has caused $168,258,894,238 in losses.**

The single most economic damaging event to crops was a **FLOOD, that occurred in IL, ADAMS, on 1993-08-31, causing U$ $5,000,000,000 in losses**.

The most crop damaging event along the time is the **DROUGHT. It has caused $13,972,581,000 in losses.**

8.3 Most aflicted locations

The county with the biggest fatality count is **ILZ003, in IL, with 605 people killed.**

The county with the biggest injuries count is **WICHITA, in TX, with 1852 people injuried.**

The county with the biggest property losses is **NAPA, in CA, with $115,116,385,000 in losses.**

The county with the biggest croperty losses is **ADAMS, in IL, with $5,000,084,000 in losses.**

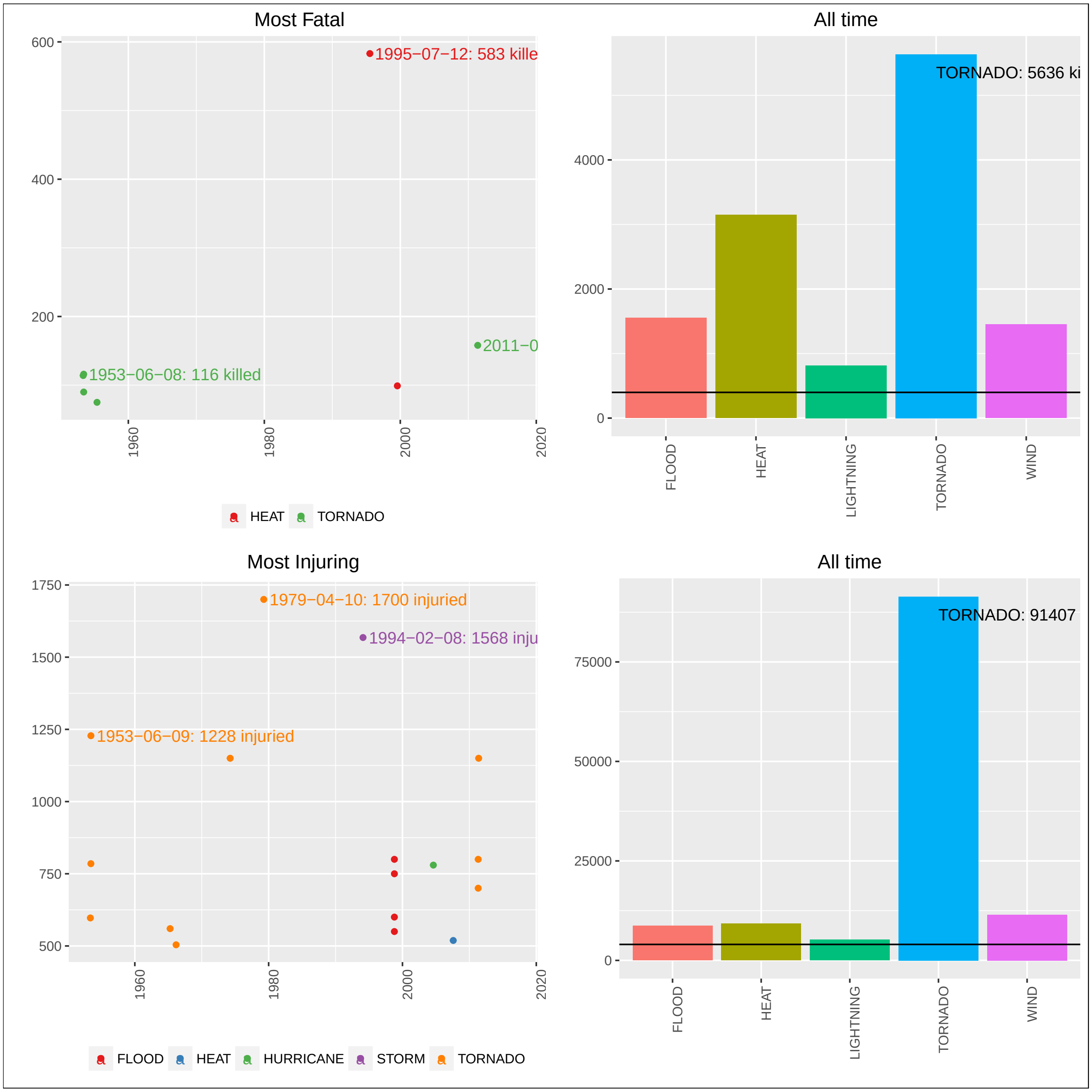

Figure 13: Population Health: fatalities and injuries

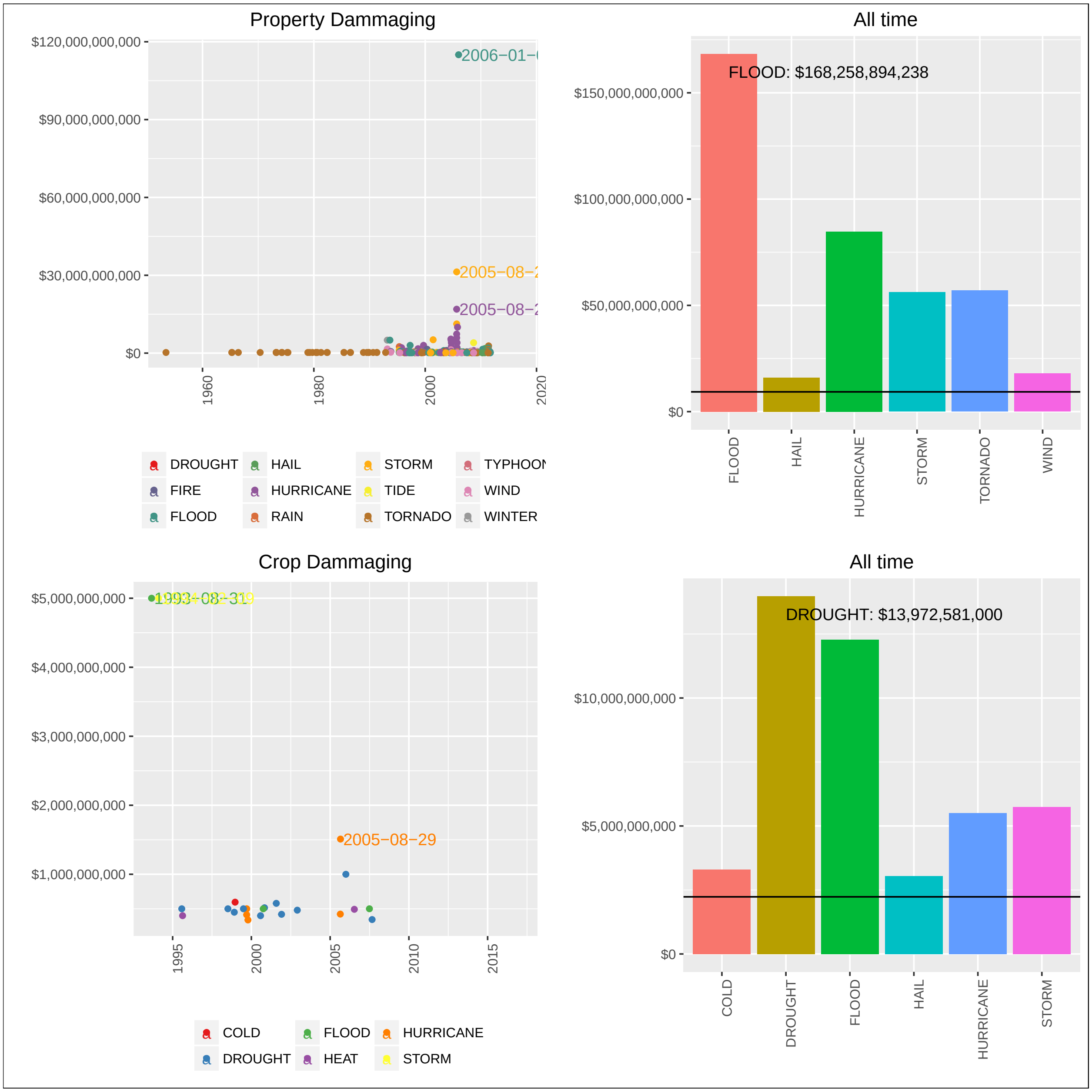

Figure 14: Economic Damages: property and crops

8.4 Distribution of data

```
grid.arrange(plt.distr.fatal0, plt.distr.fatal1, plt.distr.inj0, plt.distr.inj1,
             nrow=1, ncol=4,
             bottom="Fatalities and injuries")
grid.rect(gp=gpar(fill=NA))
```

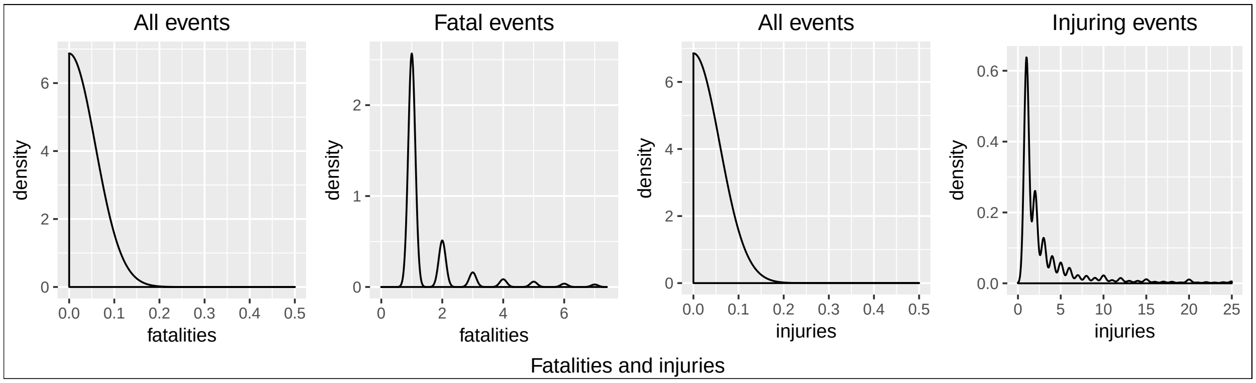

Figure 15: Population distribution

```
grid.arrange(plt.distr.prop0, plt.distr.prop1, plt.distr.crop0, plt.distr.crop1,
             nrow=1, ncol=4,
             bottom="Property and crops losses")
grid.rect(gp=gpar(fill=NA))
```

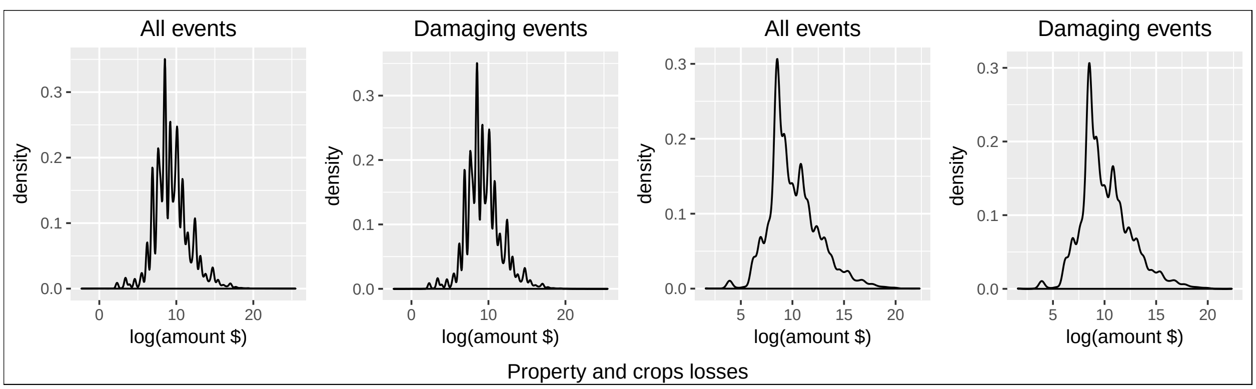

Figure 16: Population distribution