

Assessing Health and Economic Impact of Weather Events

Synopsis of Study Results

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

Wind events, which include tornadoes and hurricanes, are by the far the most harmful in aggregate, causing over 100,000 injuries and 90 deaths over the course of this study. Though less frequent, severe heat events have the highest incidence of deaths and injuries per event. This study finds that severe rain and wind events are by far the most costly in terms of dollars spent to replace property and crop damage.

Questions this study considers

1. Across the United States, which types of events (as indicated in the EVTYPE variable) are most harmful with respect to population health?
2. Across the United States, which types of events have the greatest economic consequences?

Notes about the environment used

This study was done using the following tools, including OS and Programming language versions

The study was conducted on a 64-bit Windows 7 machine with 4 cores.

R language was R version 3.3.3 (2017-03-06)

For publishing to `rpubs.com`, I used RStudio version 0.98.1103

The full project may be found on Github at https://github.com/abarrantesh/Coursera_Reproducible_Research/Week_4

Data Processing

Set libraries used in this analysis

```
library(stringr)
library(lubridate)
library(sqldf)
library(ggplot2)
library(reshape2)
library(gridExtra)
```

Loading the data

```
dseturl <- "https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2"
dsetzip <- "data/StormData.csv.bz2"
dsetrds <- "C:/Users/abarr_000/Desktop/data/StormData.RDS"

if (!file.exists(dsetzip)) {
  download.file(url = dseturl,
               destfile = dsetzip,
               method = "curl")
}

## For faster processing, check for R Data Set save file
## To force data cleaning, delete .RDS file before running/knitting/weaving
RDSloaded <- FALSE
if (!file.exists(dsetrds)) {
  d <- read.csv(file = bzfile(dsetzip), strip.white = TRUE)
} else {
  d <- readRDS(dsetrds)
  RDSloaded <- TRUE
}
```

Cleaning the data

Because we want to determine the most costly disasters, we have to examine the the property damage (`PROPDMG`) and crop damage (`CROPDMG`) values. These are simple integers which must be multiplied by an exponent given in another field (`PROPDMGEXP` and `CROPDMGEXP` respectively. Unfortunately, not all of the exponent values are valid; many appear to be rounding or entry errors from older entry systems.

For the purposes of this study, we accept only the following values for exponent: * H hundred (x100) * K thousand (x1,000) * M million (x1,000,000) * B billion (x1,000,000,000)

```

if(!RDSloaded) {
  calcUSD <- function(dmg, dmgepx) dmg * switch(toupper(dmgepx), H=100, K=1000, M=1000000, B=1000000000, 1)

  d$pdmgUSD <- mapply(calcUSD, d$PROPDMG, d$PROPDMGEXP)
  d$cdmgUSD <- mapply(calcUSD, d$CROPDMG, d$CROPDMGEXP)
}

```

To assist in date analysis, we will convert dates to POSIXct format

```

if(!RDSloaded)
  d$BEGIN_UTC <- mdy(str_extract(d$BGN_DATE, "[^ ]+"))

```

The manual entry nature of the data causes huge difficulties in categorizing the weather events. For example, you will find high wind events entered in completely arbitrary ways, mixing terminology, abbreviations, upper and lower case etc. (thunderstorm, gusty thunderstorm wind, gusty wind/rain, marine tstm wind). We are going to attempt to categorize the most impactful events by looking for common words and abbreviations in a relative handful of weather categories.

```

if (!RDSloaded) {
  generateEvent <- function(evt) {
    evt <- tolower(evt)
    ifelse(grepl("lightning", evt), "lightning",
      ifelse(grepl("hail", evt), "hail",
        ifelse(grepl("rain|flood|wet|fld", evt), "rain",
          ifelse(grepl("snow|winter|wintry|blizzard|sleet|cold|ice|freeze|avalanche|icy", evt), "winter",
            ifelse(grepl("thunder|tstm|tornado|wind|hurricane|funnel|tropical +storm", evt), "wind",
              ifelse(grepl("fire", evt), "fire",
                ifelse(grepl("fog|visibility|dark|dust", evt), "low visibility",
                  ifelse(grepl("surf|surge|tide|tsunami|current", evt), "ocean surge",
                    ifelse(grepl("heat|high +temp|record +temp|warm|dry", evt), "heat",
                      ifelse(grepl("volcan", evt), "volcanic activity",
                        "uncategorized"
                      ))))))))
    }
  }
  d$weatherCategory <- mapply(generateEvent, d$EVTYPE)
}

```

For purposes of this study, USA is defined as the 50 states in the continental US, plus District of Columbia, Hawaii and Alaska. territories, protectorates, and military regions are excluded

```
if (!RDSloaded)
  d$isUSA <- mapply( function(st) st %in% state.abb, d$STATE )
```

In the interest of performance, we will save the data frame as an R data set (.RDS file). After reading, immediately subset the data to only those records originating in the US.

```
if (!RDSloaded) {
  saveRDS(d, file=dsetrds)
  d <- readRDS(dsetrds)
  RDSloaded <- TRUE
}
## subset to only USA data
d <- d[d$isUSA == TRUE,]
```

Results

Question 1: Across the United States, which types of events (as indicated in the EVTYPE variable) are most harmful with respect to population health?

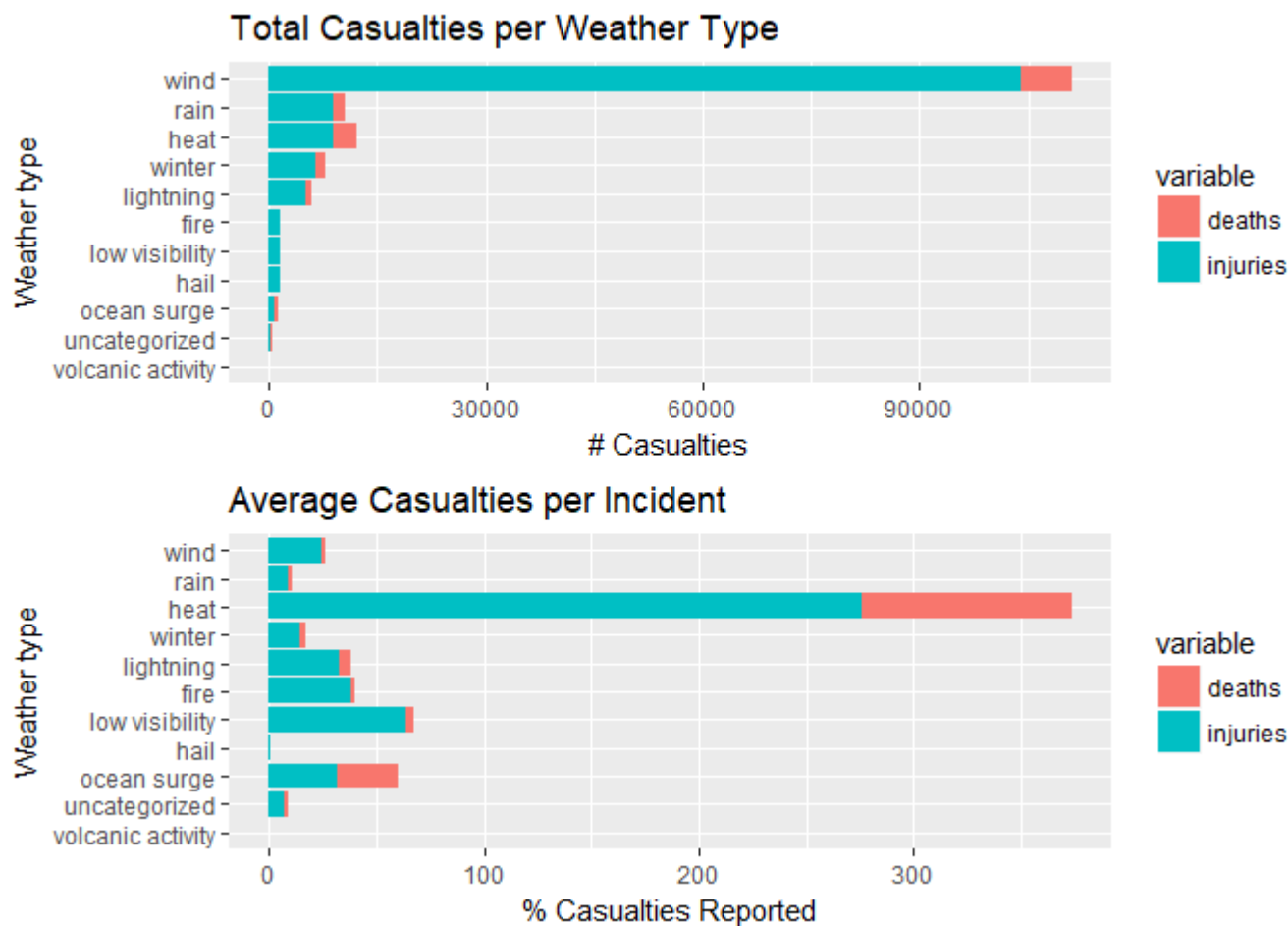
Refer to the result of the query below, which groups US mortalities and injuries by weather category.

```
harm <- sqldf("select sum(FATALITIES) as deaths, sum(INJURIES) as injuries, weatherCategory, count(*) as sumrecs from d group by weatherCategory ")
```

```
## Warning: Quoted identifiers should have class SQL, use DBI::SQL() if the
## caller performs the quoting.
```

```
harm$weatherCategory <- factor(harm$weatherCategory, levels=harm[order(harm$injuries), "weatherCategory"])

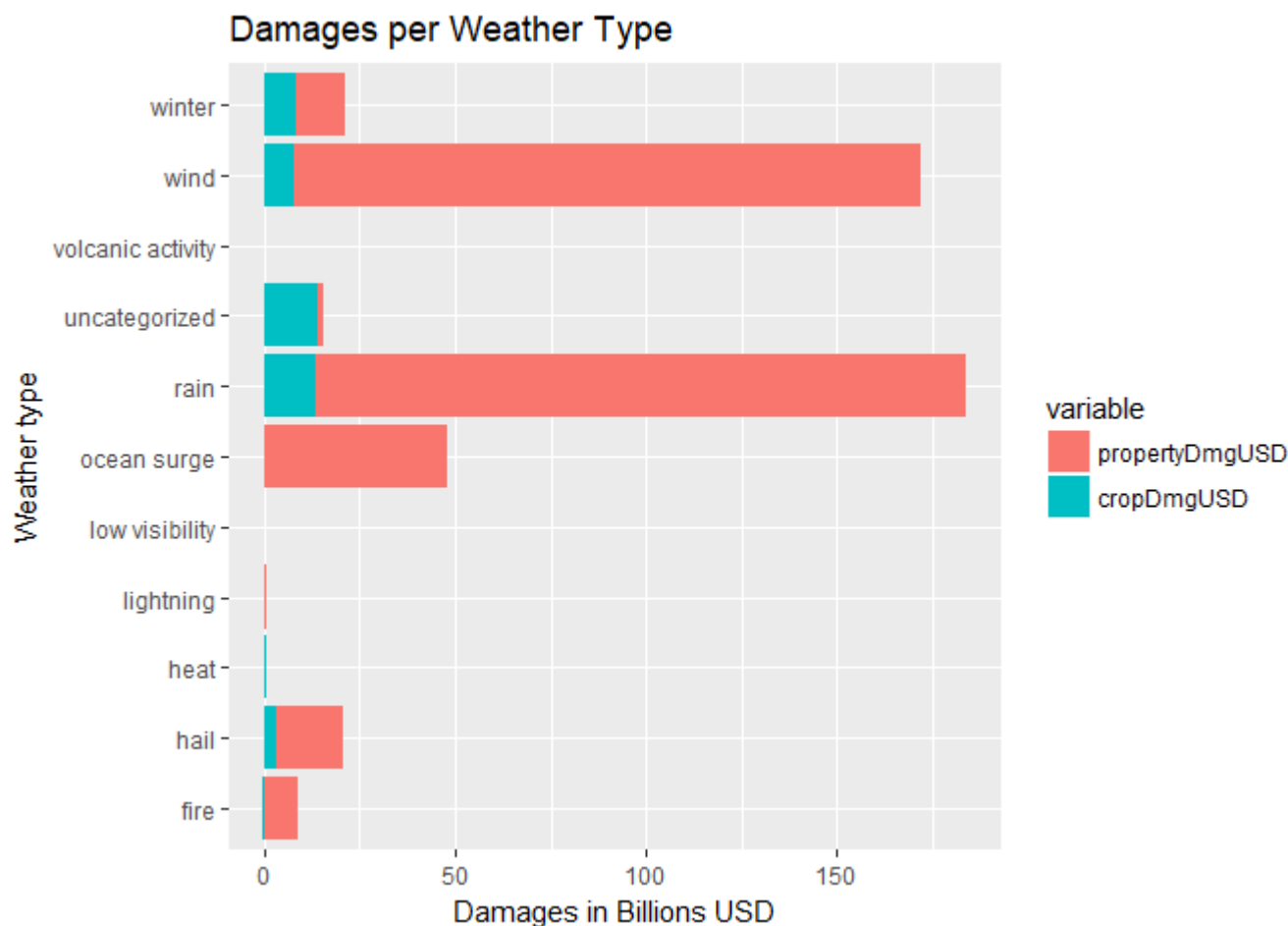
## ggplot Loves Long form, which means a type of normalization using melt()
hdat <- melt(harm, id.vars=c("weatherCategory", "sumrecs"), measure.vars=c("deaths", "injuries"))
hdat <- sqldf("select *,(value/sumrecs)*100 as pctPerEvent from hdat")
plot1 <- ggplot(hdat, aes(x=weatherCategory, y=value, fill=variable)) + geom_bar(stat="identity") + coord_flip() + ggtitle("Total Casualties per Weather Type") + xlab("Weather type") + ylab("# Casualties")
plot2 <- ggplot(hdat, aes(x=weatherCategory, y=pctPerEvent, fill=variable)) + geom_bar(stat="identity") + coord_flip() + ggtitle("Average Casualties per Incident") + xlab("Weather type") + ylab("% Casualties Reported")
grid.arrange(plot1, plot2, ncol = 1)
```



Wind events – including tornadoes and hurricanes – have the highest impact on health in terms of absolute numbers reported. Heat events – including fires and heat waves – show the highest percentage of casualties per event.

Question 2: Across the United States, which types of events have the greatest economic consequences?

```
crop <- sqldf("select sum(pdmgUSD) as propertyDmgUSD, sum(cdmgUSD) as cropDmgUSD, count(*) as sumrecs, weatherCategory from d group by weatherCategory")
crop <- sqldf("select *, propertyDmgUSD + cropDmgUSD as totalCost from crop")
## create long form on crop vs property damage columns
cdat <- melt(crop, id.vars=c("weatherCategory", "sumrecs", "totalCost"), measure.vars=c("propertyDmgUSD", "cropDmgUSD"))
cdat <- sqldf("select *, (value/sumrecs) as costPerEvent from cdat")
plot3 <- ggplot(cdat, aes(x=weatherCategory, y=value/1000000000, fill=variable)) + geom_bar(stat="identity") + coord_flip() + ggtitle("Damages per Weather Type") + xlab("Weather type") + ylab("Damages in Billions USD")
grid.arrange(plot3, ncol=1)
```



Rain and wind events are the most costly weather types, both in terms of property and damage to crops. There is a very significant crop damage cost in the “uncategorized” weather events. This bears examination, and possibly some re-evaluation of the categorization used in this study.

Appendix

Utility functions

Some functions not used in the published analysis that may be useful

```
## timeconv() is used to take inconsistent times and convert them to a standard format
## times will either be 24-hour HHMM ("1330") or 12-hour strings with AM/PM ("01:30:00 PM")
## functions returns format of 24-hour HH:MM:SS ("13:30:00")
timeconv <- function(x) {
  if (nchar(x) == 4) {
    paste(substr(x,1,2), substr(x,3,4), "00", sep=":")
  } else {
    timeadd <- 1
    if (substr(x,nchar(x)-1,nchar(x)) == "PM") timeadd <- 12
    paste0(
      formatC(as.integer(substr(x,1,2)) + timeadd, width=2, format="d", flag="0"),
      substr(x,3,nchar(x)-3))
  }
}
```