Analysis of Economic and Population Health Impact of Historical Storm Events

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github repository (https://github.com/scrain/reproducible-research-project-2)

Synopsis

U.S. National Oceanic and Atmospheric Administration's (NOAA) storm database begain tracking a standard set of 48 storm data events in 1996. After analyzing storm data events from 1996 to 2011 it was found that Hurricanes/Typhoons cause the most economic impact in relation to crop and property damage, while Tornados take the most population toll in regards to injuries and fatalities.

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Data Processing

Retrieval and Loading

The compressed data is conditionally downloaded from the source URL if not found locally and then loaded directly via `read.csv`. Before proceeding, some basic validation is done on the file and dataset per some advice found from a course mentor in the discussion forums here (https://www.coursera.org/learn/reproducible-research/discussions/weeks/4/threads/IdtP_JHzEeaePQ71AQUtYw).

```
filename <- 'StormData.csv.bz2'
if (!file.exists(filename)) {
  download.file('https://d396qusza40orc.cloudfront.net/repdata%2Fdata%2FStormData.csv.bz2', filename)
}
storm_data <- read.csv(filename)
# Ensure we got the data downloaded, decompressed and loaded correctly
# by checking filesize and dataset dimemsions
stopifnot(file.size(filename) == 49177144)
stopifnot(dim(storm_data) == c(902297,37))
```

Cleaning and Preparation

After the dataset is loaded, it is cleaned as follows:

1. Given the poor quality of the property and crop damage exponent variables (`PROPDMGEXP` and `CROPDMGEXP`), two variables are added to hold converted multiplier values named `PropDamageMult` and `CropDamageMult` . Again from advice found in the previously mentioned forum post, an approach is used based on the analysis found in the article "How To Handle Exponent Value of PROPDMGEXP and CROPDMGEXP" (https://rstudio-pubs-static.s3.amazonaws.com/58957_37b6723ee52b455990e149edde45e5b6.html). Using this information, the function `convertExponentToMultiplier` is used to convert the original exponent variables into the corresponding multipliers. See appendix A for the result of this exponent to multiplier conversion.

```
convertExponentToMultiplier <- function(exp) {
  ifelse(
    exp == '+', 1,                        # '+' -> 1
    ifelse(
      exp %in% paste(seq(0,8)), 10^1,      # 0-8 -> 10
      ifelse(
        exp %in% c('H', 'h'), 10^2,        # H,h -> 100
        ifelse(
          exp %in% c('K', 'k'), 10^3,      # K,k -> 1,000
          ifelse(
            exp %in% c('M', 'm'), 10^6,    # M,m -> 1,000,000
            ifelse(
              exp %in% c('B', 'b'), 10^9,  # B,b -> 1,000,000,000
              0                            # everything else -> 0
            )
          )
        )
      )
    )
  )
}
storm_data$PropDamageMult <- convertExponentToMultiplier(storm_data$PROPDMGEXP)
storm_data$CropDamageMult <- convertExponentToMultiplier(storm_data$CROPDMGEXP)
```

2. With the mulitplier variables created, `CropDamage` and `PropDamage` variables are added by multiplying them against the corresponding damage variables `PROPDMG` and `CROPDMG` . In addition, a `TotalDamage` variable is also added, using the sum of both the crop and property damage.

```
storm_data$PropDamage  <- storm_data$PROPDMG * storm_data$PropDamageMult
storm_data$CropDamage  <- storm_data$CROPDMG * storm_data$CropDamageMult
storm_data$TotalDamage <- storm_data$PropDamage + storm_data$CropDamage
```

3. For determining the oveall health impact of events, a `PopulationHealthImpact` variable is added using the sum of `FATALITIES` and `INJURIES` variables.

```
storm_data$PopulationHealthImpact <- storm_data$FATALITIES + storm_data$INJURIES
```

4. To make the dataset easier to work with, irrelevant observations are removed. According to the documentation, it was not until 1996 that all event types were being recorded. For that reason, the years from the dataset earlier than that are removed in order to get a fair assessment of all events. Also, since we are answering questions around economic and population health impact, all rows having neither of these are removed as well.

```
storm_data$BeginDate   <- as.Date(storm_data$BGN_DATE, '%m/%d/%Y')
sd <- storm_data[storm_data$BeginDate >= '1996-01-01',]
sd <- sd[sd$TotalDamage > 0 | sd$PopulationHealthImpact  > 0,]
```

5. Looking at the top events with the most `TotalDamage` and `PopulationHealthImpact` showed that there was a least one event that had far more economic impact than any other. Using the NOAA Storm Events Database (https://www.ncdc.noaa.gov/stormevents/choosedates.jsp?statefips=-999%2CALL), it was found that a 2006 flood in Napa County, Califorina (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28Z%29+Flood&beginDate_mm=01&beginDate_dd=01&beginDate_yyyy=2006&endDate_mm=01&endDate_dd=01&endDate_yyyy=2006&cou was mis-entered with a `PROPDMGEXP` of **B**illion instead of **M**illion. The erroneous `PROPDMGEXP` value was then corrected and the `PropDamageMult` , `PropDamage` and `TotalDamage` variables were recalculated. Recalculating the values for the entire dataset was not really necessary, but the code was much simpler.

```
sd$PROPDMGEXP[sd$REFNUM=='605943'] <- 'M'
sd$PropDamageMult <- convertExponentToMultiplier(sd$PROPDMGEXP)
sd$PropDamage  <- sd$PROPDMG * sd$PropDamageMult
sd$TotalDamage <- sd$PropDamage + sd$CropDamage
```

After checking the remaining top 5 by damage and health impact, it was found those are consistent with data available in the NOAA database. See appendix B for more information on the checks of the top individual events. 6. Given the poor consistency of the values found in the `EVTYPE` variable, it was decided to use the list of Event names from Section 2.1.1 of the Storm Data Documentation (https://d396qusza40orc.cloudfront.net/repdata%2Fpeer2_doc%2Fpd01016005curr.pdf). Using various techniques, a new tidy variable named `EventType` was created containing one of these 48 event types or the value `UNCATEGORIZED` indicating the event was not included. All observations start off as `UNCATEGORIZED` and then updated with different approaches with one of the 48 values.

```
eventTypes <- c('Astronomical Low Tide', 'Avalanche', 'Blizzard', 'Coastal Flood', 'Cold/Wind Chill',
                'Debris Flow', 'Dense Fog', 'Dense Smoke', 'Drought', 'Dust Devil', 'Dust Storm',
                'Excessive Heat', 'Extreme Cold/Wind Chill', 'Flash Flood', 'Flood', 'Frost/Freeze',
                'Funnel Cloud', 'Freezing Fog', 'Hail', 'Heat', 'Heavy Rain', 'Heavy Snow', 'High Surf',
                'High Wind', 'Hurricane (Typhoon)', 'Ice Storm', 'Lake-Effect Snow', 'Lakeshore Flood',
                'Lightning', 'Marine Hail', 'Marine High Wind', 'Marine Strong Wind',
                'Marine Thunderstorm Wind', 'Rip Current', 'Seiche', 'Sleet', 'Storm Surge/Tide',
                'Strong Wind', 'Thunderstorm Wind', 'Tornado', 'Tropical Depression', 'Tropical Storm',
                'Tsunami', 'Volcanic Ash', 'Waterspout', 'Wildfire', 'Winter Storm', 'Winter Weather')
sd$EventType <- 'UNCATEGORIZED'  # start all EventTypes off as "Uncategorized"
```

The `EVTYPE` variable was first updated for consistency by removing all whitespace and making all upper case.

```
sd$EVTYPE <- toupper(trimws(sd$EVTYPE))
```

The inital pass of setting `EventType` values from `EVTYPE` data was a simple text matching approach based on: * Ignoring all whitespace and capitalization
* Ignoring all non-alpha characters * Allowing for plural variations (WIND/WIND**S**) * Allowing for verb variations (FLOOD/FLOOD**ING**)

```
regex <- "[^[:alpha:]]" # match all non-alpha
for(eventType in eventTypes) {
  strippedEventType <- toupper(gsub(regex, '', eventType))
  sd$EventType[gsub(regex, '', sd$EVTYPE) == strippedEventType] <- eventType
  sd$EventType[gsub(regex, '', sd$EVTYPE) == paste(strippedEventType, 'S',   sep='')] <- eventType
  sd$EventType[gsub(regex, '', sd$EVTYPE) == paste(strippedEventType, 'ING', sep='')] <- eventType
}
```

The next step of populating `EventType` was a manual mapping using `EVTYPE` values. Some were obvious abbreviations (`TSTM WIND` -> `Thunderstorm Wind`). Other values required reviewing the Storm Data Documentation (https://d396qusza40orc.cloudfront.net/repdata%2Fpeer2_doc%2Fpd01016005curr.pdf) for better understanding. For example `LANDSPOUT` was mapped to `Tornado` and not `Dust Devil` because on page 75 it states:

> Landspouts and cold-air funnels, ultimately meeting the objective tornado criteria listed in Section 7.40.6, will be classified as Tornado events. This manual process was done iteratively while reviewing the damage and health impact totals for the remaining uncategorized `EVTYPE` values until it was determined that further work would not have any meaningful impact to the overall result of this report. See appendix C for the final `EventType` to `EVTYPE` value mappings and appendix D for more information on the `EVTYPE` values that were left uncategorized.

```
coastalFloodAliases <- c('ASTRONOMICAL HIGH TIDE', 'TIDAL FLOODING', 'COASTAL FLOODING/EROSION',
                         'COASTAL  FLOODING/EROSION', 'EROSION/CSTL FLOOD')
sd$EventType[sd$EVTYPE %in% coastalFloodAliases] <- 'Coastal Flood'

winterWeatherAliases <- c('LIGHT FREEZING RAIN', 'ICY ROADS', 'GLAZE', 'FREEZING RAIN',
                          'FREEZING DRIZZLE', 'LIGHT SNOW', 'LIGHT SNOWFALL', 'WINTER WEATHER/MIX',
                          'MIXED PRECIPITATION', 'MIXED PRECIP', 'WINTRY MIX', 'RAIN/SNOW',
                          'WINTER WEATHER MIX')
sd$EventType[sd$EVTYPE %in% winterWeatherAliases] <- 'Winter Weather'
heavySnowAliases <- c('EXCESSIVE SNOW', 'SNOW', 'HEAVY SNOW SHOWER', 'SNOW SQUALL', 'SNOW SQUALLS')
sd$EventType[sd$EVTYPE %in% heavySnowAliases] <- 'Heavy Snow'
highWindAliases <- c('WIND', 'WINDS', 'GUSTY WINDS', 'GUSTY WIND', 'HIGH WIND (G40)',
                     'NON TSTM WIND',  'NON-TSTM WIND', 'WIND DAMAGE', 'NON TSTM WIND',
                     'NON-SEVERE WIND DAMAGE', 'GRADIENT WIND')
sd$EventType[sd$EVTYPE %in% highWindAliases] <- 'High Wind'
freezeAliases <- c('FREEZE', 'DAMAGING FREEZE', 'EARLY FROST', 'FROST', 'AGRICULTURAL FREEZE',
                   'HARD FREEZE', 'UNSEASONABLY COLD', 'UNSEASONABLE COLD')
sd$EventType[sd$EVTYPE %in% freezeAliases] <- 'Frost/Freeze'
extremeColdAliases <- c('EXTREME WINDCHILL', 'EXTREME COLD')
sd$EventType[sd$EVTYPE %in% extremeColdAliases] <- 'Extreme Cold/Wind Chill'
floodAliases <- c('RIVER FLOODING', 'RIVER FLOOD', 'URBAN/SML STREAM FLD', 'URBAN FLOOD')
sd$EventType[sd$EVTYPE %in% floodAliases] <- 'Flood'
flashFloodAliases <- c('FLASH FLOOD/FLOOD', 'FLOOD/FLASH/FLOOD')
sd$EventType[sd$EVTYPE %in% flashFloodAliases] <- 'Flash Flood'
thunderstormAliases <- c('TSTM WIND', 'TSTM WINDS', 'THUNDERSTORM', 'THUNDERSTORMS',
                         'THUNDERSTORM WINDSS', 'THUNDERSTORMS WINDS', 'DRY MICROBURST',
                         'TSTM WIND (G40)', 'THUNDERSTORM WIND/ TREES', 'MICROBURST',
                         'WET MICROBURST', 'THUNDERTORM WINDS', 'THUNDERSTORMS WIND',
                         'SEVERE THUNDERSTORM WINDS', 'TSTM WIND 55', 'THUNDERSTORM WIND 60 MPH',
                         'TSTM WIND (G45)', 'SEVERE THUNDERSTORM', 'THUDERSTORM WINDS',
                         'THUNDEERSTORM WINDS', 'THUNDERESTORM WINDS', 'TSTM WIND 40',
                         'TSTM WIND G45', 'TSTM WIND  (G45)', 'TSTM WIND (41)', 'TSTM WIND 45',
                         'TSTM WIND (G35)', 'TSTM WIND AND LIGHTNING', 'TSTM WIND/HAIL',
                         'THUNDERSTORM WIND (G40)')
sd$EventType[sd$EVTYPE %in% thunderstormAliases] <- 'Thunderstorm Wind'
hailAliases <- c('HAIL DAMAGE', 'SMALL HAIL', 'HAILSTORM')
sd$EventType[sd$EVTYPE %in% hailAliases] <- 'Hail'
hurricaneAliases <- c('HURRICANE', 'TYPHOON', 'HURRICANE OPAL', 'HURRICANE ERIN',
                      'HURRICANE EDOUARD', 'HURRICANE EMILY', 'HURRICANE FELIX',
                      'HURRICANE GORDON', 'HURRICANE OPAL/HIGH WINDS')
sd$EventType[sd$EVTYPE %in% hurricaneAliases] <- 'Hurricane (Typhoon)'
highSurfAliases <- c('HEAVY SURF/HIGH SURF', 'HEAVY SURF', 'HIGH SURF ADVISORY')
sd$EventType[sd$EVTYPE %in% highSurfAliases] <- 'High Surf'
wildfireAliases = c('WILD/FOREST FIRE', 'BRUSH FIRE')
sd$EventType[sd$EVTYPE %in% wildfireAliases] <- 'Wildfire'
heatAliases = c('UNSEASONABLY WARM', 'WARM WEATHER')
sd$EventType[sd$EVTYPE %in% heatAliases] <- 'Heat'
excessiveHeatAliases = c('HEAT WAVE', 'RECORD HEAT')
sd$EventType[sd$EVTYPE %in% excessiveHeatAliases] <- 'Excessive Heat'
heavyRainAliases = c('TORRENTIAL RAINFALL', 'RAIN', 'UNSEASONAL RAIN')
sd$EventType[sd$EVTYPE %in% heavyRainAliases]  <- 'Heavy Rain'
# one-offs
sd$EventType[sd$EVTYPE == 'LANDSPOUT']        <- 'Tornado'
sd$EventType[sd$EVTYPE == 'FOG']              <- 'Dense Fog'
sd$EventType[sd$EVTYPE == 'MARINE TSTM WIND']  <- 'Marine Thunderstorm Wind'
sd$EventType[sd$EVTYPE == 'LANDSLIDE']        <- 'Debris Flow'
sd$EventType[sd$EVTYPE == 'STORM SURGE']      <- 'Storm Surge/Tide'
sd$EventType[sd$EVTYPE == 'COLD']             <- 'Cold/Wind Chill'
```

Results

Event Types Most Harmful to Population Health

```
top_health <- head(
  arrange(
    aggregate(
      cbind(FATALITIES, INJURIES, PopulationHealthImpact) ~ EventType, sd, FUN = sum),
    desc(PopulationHealthImpact)
  ),
  n=5
)
kable(
  top_health,
  caption = 'Top 5 Event Types Most Harmful to Population Health'
)
```

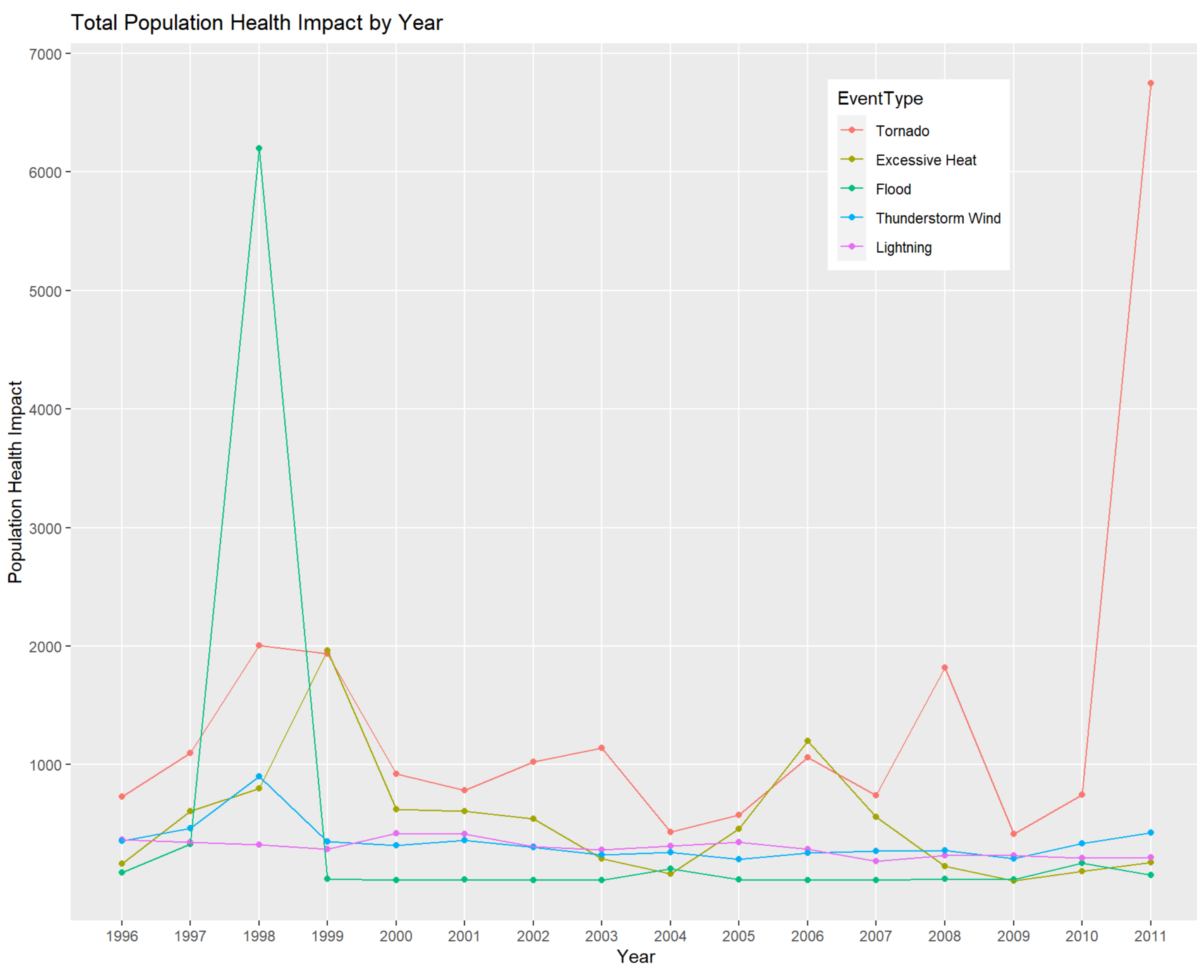
Top 5 Event Types Most Harmful to Population Health

EventType	FATALITIES	INJURIES	PopulationHealthImpact
Tornado	1511	20667	22178
Excessive Heat	1799	6461	8260
Flood	444	6838	7282
Thunderstorm Wind	382	5154	5536
Lightning	651	4141	4792

Tornado events top the list here, with over two and half times the health impact of second place, which is Excessive Heat. Excessive Heat is worth noting however due to the fact that even though it is far behind tornados in total health impact, but has the most fatalities overall.

Next we will look a bit deeper at the data, plotting the yearly total health impact for these top 5.

```
health_by_type_and_year <- aggregate(
  cbind(FATALITIES, INJURIES, PopulationHealthImpact) ~ EventType + year(BeginDate),
  sd,
  FUN=sum
)
names(health_by_type_and_year) <- c('EventType', 'Year', 'Fatalities', 'Injuries', 'PopulationHealthImpact')
health_by_type_and_year <- health_by_type_and_year[health_by_type_and_year$EventType %in% top_health$EventType,]
health_by_type_and_year$EventType <- with(health_by_type_and_year, reorder(EventType, -PopulationHealthImpact))
ggplot(health_by_type_and_year, aes(x=Year, y=PopulationHealthImpact, colour = EventType)) +
  geom_point() + geom_line() +
  scale_x_continuous(breaks = unique(health_by_type_and_year$Year)) +
  scale_y_continuous(
    'Population Health Impact',
    breaks = seq(1000, 7000, by=1000)
  ) +
  ggtitle("Total Population Health Impact by Year") +
  theme(
    legend.position = c(0.75, 0.85),
    panel.grid.minor = element_blank()
  )
```



Here we see two years with significant outliers. In 1998 there was an extremely high health related impact due to flood events. Looking at the NOAA Summary of Natural Hazard Statistics for 1998 (http://www.nws.noaa.gov/om/hazstats/sum98.pdf) shows that a flood in south-central Texas caused over 6,000 injuries accounting for most of that year’s total. The Tornado spike in 2011 can be accounted for due to record breaking spring and summer tornado season according to the NOAA Tornado Annual 2011 Report (https://www.ncdc.noaa.gov/sotc/tornadoes/201113).

Looking at the plot, Tornados have a solid yearly trend despite the record breaking year, so their number one position is not due to that year alone. Flood events however have an overall low yearly trend in comparison to the other top 5 except for 1998. Without this year, flood events would have been in last place instead of third amongst the current top 5. Additional analysis would be needed, but there is good chance it would not have even made the top 5 at all without the 1998 Texas floods.

Event Types with Greatest Economic Consequences

```
top_damage <- head(
  arrange(
    aggregate(
      cbind(CropDamage, PropDamage, TotalDamage) ~ EventType, sd, FUN=sum),
    desc(TotalDamage)
  ),
  n=5
)
kable(
  top_damage,
  format.args = list(big.mark = ","),
  caption = 'Top 5 Event Types with Greatest Economic Consequences'
)
```

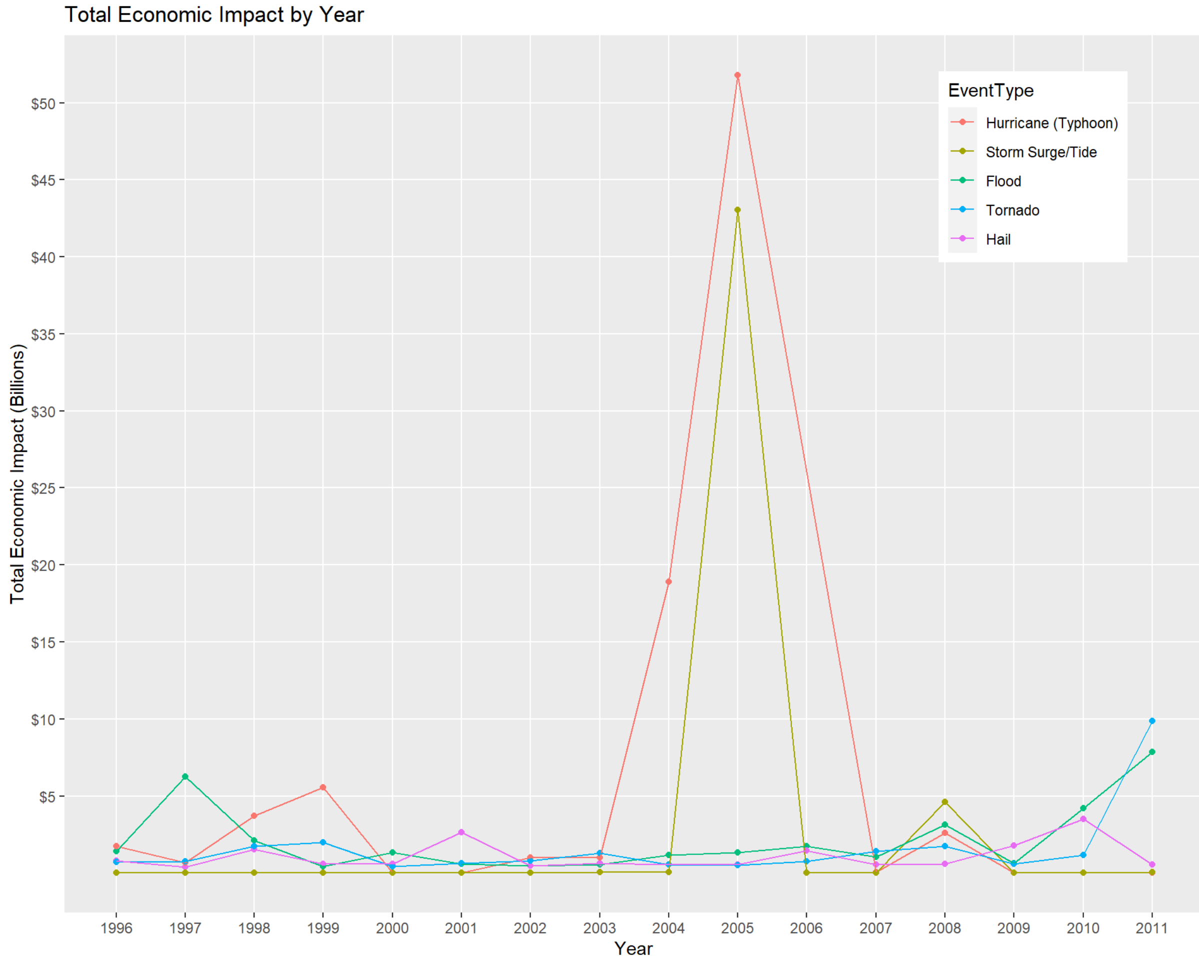
Top 5 Event Types with Greatest Economic Consequences

EventType	CropDamage	PropDamage	TotalDamage
Hurricane (Typhoon)	5,350,107,800	81,718,889,010	87,068,996,810
Storm Surge/Tide	855,000	47,834,724,000	47,835,579,000
Flood	5,013,161,500	29,244,580,200	34,257,741,700
Tornado	283,425,010	24,616,952,710	24,900,377,720
Hail	2,496,822,450	14,595,213,420	17,092,035,870

Here we see that Hurricane (Typhoon) events top the list with $87 billion, which is almost double the next in line which is Storm Surge/Tide events at $47 billion. One interesting note is that Flood events caused almost as much crop damage as hurricanes despite being a distant third place overall.

Again, we will look at the yearly trend for these top five.

```
damage_by_type_and_year <-  aggregate(
  cbind(CropDamage,PropDamage,TotalDamage)~EventType+year(BeginDate),
  sd,
  FUN=sum
)
names(damage_by_type_and_year) <- c('EventType', 'Year', 'CropDamage', 'PropDamage', 'TotalDamage')
sd_dmg_yearly <- damage_by_type_and_year[damage_by_type_and_year$EventType %in% top_damage$EventType,]
sd_dmg_yearly$EventType <- with(sd_dmg_yearly, reorder(EventType, -TotalDamage))
ggplot(sd_dmg_yearly, aes(Year, TotalDamage / 10^9, colour = EventType)) +
  geom_point() + geom_line() +
  scale_x_continuous(breaks = unique(damage_by_type_and_year$Year)) +
  scale_y_continuous(
    'Total Economic Impact (Billions)',
    labels = scales::dollar,
    breaks = seq(5,50, by=5)
  ) +
  ggtitle('Total Economic Impact by Year') +
  theme(
    legend.position = c(0.85, 0.85),
    panel.grid.minor = element_blank()
  )
```



Like in the previous yearly trend, we see a couple of significant outliers, but this time they both occur in the same year of 2005 with Hurricane (Typhoon) and Storm Surge/Tide events. The significant Hurricane event for 2005 was Hurricane Katrina according to the NOAA 2005 Summary of Natural Hazard Statistics (http://www.nws.noaa.gov/om/hazstats/sum05.pdf) where it is noted that Katrina had an estimated $93 billion in claims. While Storm Surge/Tide events are not called out in the NOAA summary, the $93 billion seems to correlate with the combined values of Hurricanes and Storm surges for that year.

Similarly, as with the top five events for population health impact, the top five event list might look different if it were not for this year with the significant outliers. Additional analysis would be needed, but hurricane event's number one position could be in jeopardy without 2005 and storm surge might not have even made the list at all without it.

Appendices

Appendix A - Exponent to Multiplier Conversion Result

Below is a table showing the resulting mappings of the different exponent values found in `PROPDMGEXP` and `CROPDMGEXP` to the corresponding multipliers used in `PropDamageMult` and `CropDamageMult` .

```
prop_exp_mult <- unique(subset(storm_data, select=c('PROPDMGEXP','PropDamageMult')))
crop_exp_mult <- unique(subset(storm_data, select=c('CROPDMGEXP','CropDamageMult')))
names(prop_exp_mult) <- c('EXP Value', 'Converted Multiplier')
names(crop_exp_mult) <- c('EXP Value', 'Converted Multiplier')
exp_mult <- unique(rbind(prop_exp_mult, crop_exp_mult))
exp_mult <- exp_mult[order(exp_mult$`Converted Multiplier`, exp_mult$`EXP Value`),]
exp_mult$`EXP Value` <- as.character(exp_mult$`EXP Value`)
exp_mult$`EXP Value`[exp_mult$`EXP Value` == ''] <- "&lt;blank&gt;"
kable(
  exp_mult,
  row.names = FALSE,
  align=c('c','l'),
  caption = 'Final mapping of the EXP values to Damage Multiplier'
)
```

Final mapping of the EXP values to Damage Multiplier

EXP Value	Converted Multiplier
<blank>	0e+00

EXP Value	Converted Multiplier
-	0e+00
?	0e+00
+	1e+00
0	1e+01
1	1e+01
2	1e+01
3	1e+01
4	1e+01
5	1e+01
6	1e+01
7	1e+01
8	1e+01
h	1e+02
H	1e+02
K	1e+03
k	1e+03
m	1e+06
M	1e+06
B	1e+09

Appendix B - Review of Top Individual Events During Data Preparation

During data preparation the list of top 5 individual events by total damage and population health impact were reviewed and checked for consistency against the NOAA Storm Events Database (https://www.ncdc.noaa.gov/stormevents/choosedates.jsp?statefips=-999%2CALL).

Top Individual Events By Total Damage

```
top_events_by_total_damage <- subset(storm_data, BeginDate  >= '1996-01-01')
top_events_by_total_damage <-top_events_by_total_damage [
  order(-top_events_by_total_damage$TotalDamage, top_events_by_total_damage$EVTYPE),
  c('REFNUM', 'STATE', 'BeginDate', 'EVTYPE', 'CROPDMG', 'CROPDMGEXP', 'PROPDMG', 'PROPDMGEXP', 'TotalDamage')
]
kable(
  head(
    top_events_by_total_damage,
    n =5
    ),
  row.names = FALSE,
  caption = 'Top Five Individual Events by Total Economic Damage (prior to data correction)'
)
```

Top Five Individual Events by Total Economic Damage (prior to data correction)

REFNUM	STATE	BeginDate	EVTYPE	CROPDMG	CROPDMGEXP	PROPDMG	PROPDMGEXP	TotalDamage
605943	CA	2006-01-01	FLOOD	32.5	M	115.00	B	115032500000
577616	LA	2005-08-29	STORM SURGE	0.0		31.30	B	31300000000
577615	LA	2005-08-28	HURRICANE/TYPHOON	0.0		16.93	B	16930000000
581535	MS	2005-08-29	STORM SURGE	0.0		11.26	B	11260000000
569288	FL	2005-10-24	HURRICANE/TYPHOON	0.0		10.00	B	10000000000

- REFNUM 605943: NOAA link 1/1/2006, CA, Napa County, Flood (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28Z%29+Flood&beginDate_mm=01&beginDate_dd=01&beginDate_yyyy=2006&endDate_mm=01&endDate_dd=01&endDate_yyyy=2006&cou This was determined to be an erroniously entered PROMDMGEXP value.
- REFNUM 577616: NOAA link 8/29/2005, LA, Storm Surge (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28Z%29+Storm+Surge%2FTide&beginDate_mm=08&beginDate_dd=29&beginDate_yyyy=2005&endDate_mm=08&endDate_dd=29&endDate_ This entry appears to be consistent with NOAA data and correlates with some significant storm surge activity from Katrina.
- REFNUM 577615: 8/28/2005, LA, Hurricane (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28Z%29+Hurricane+%28Typhoon%29&beginDate_mm=08&beginDate_dd=28&beginDate_yyyy=2005&endDate_mm=08&endDate_dd=28&en Also Hurricane Katrina related, this data was also determined to be consistent with the NOAA database.

- REFNUM 581535: NOAA link 8/29/2005, MS, Storm Surge (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28Z%29+Storm+Surge%2FTide&beginDate_mm=08&beginDate_dd=29&beginDate_yyyy=2005&endDate_mm=08&endDate_dd=29&endDate_ Another Katrina related event found to be consistent with NOAA data.
- REFNUM 569288: NOAA link 10/24/2005, FL, Palm Beach, Hurricane (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28Z%29+Hurricane+%28Typhoon%29&beginDate_mm=10&beginDate_dd=24&beginDate_yyyy=2005&endDate_mm=10&endDate_dd=24&en This event due to Hurricane Wilma and was found to be consistent with information in the NOAA database.

Top Individual Events By Population Health Impact

The same review of the top 5 individual events for total population health impact was also done and all were found to be in line with the current NOAA data.

```
top_events_by_health_impact <- subset(storm_data, BeginDate  >= '1996-01-01')
top_events_by_health_impact <-top_events_by_health_impact [
  order(-top_events_by_health_impact$PopulationHealthImpact, top_events_by_health_impact$EVTYPE),
 c('REFNUM', 'STATE', 'BeginDate', 'EVTYPE', 'INJURIES', 'FATALITIES', 'PopulationHealthImpact')
]
kable(
  head(
    top_events_by_health_impact,
    n =5
    ),
  row.names = FALSE,
  caption = 'Top Five Individual Events by Population Health Impact'
)
```

Top Five Individual Events by Population Health Impact

REFNUM	STATE	BeginDate	EVTYPE	INJURIES	FATALITIES	PopulationHealthImpact
862563	MO	2011-05-22	TORNADO	1150	158	1308
860355	AL	2011-04-27	TORNADO	800	44	844
344098	TX	1998-10-17	FLOOD	800	2	802
529299	FL	2004-08-13	HURRICANE/TYPHOON	780	7	787
344117	TX	1998-10-17	FLOOD	750	0	750

- REFNUM 862563: NOAA link 5/22/2011, MO, Jasper, Tornado (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28C%29+Tornado&beginDate_mm=05&beginDate_dd=22&beginDate_yyyy=2011&endDate_mm=05&endDate_dd=22&endDate_yyyy=2011&c
- REFNUM 860355: NOAA link 4/27/2011, AL, Tuscaloosa, Tornado (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28C%29+Tornado&beginDate_mm=04&beginDate_dd=27&beginDate_yyyy=2011&endDate_mm=04&endDate_dd=27&endDate_yyyy=2011&c
- REFNUM 344098: NOAA link 10/17/1998, TX, Comal, Flood (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=ALL&beginDate_mm=10&beginDate_dd=17&beginDate_yyyy=1998&endDate_mm=10&endDate_dd=17&endDate_yyyy=1998&county=COMAL%
- REFNUM 529299: NOAA link 8/13/2004, FL, Hurricane (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28Z%29+Hurricane+%28Typhoon%29&beginDate_mm=08&beginDate_dd=13&beginDate_yyyy=2004&endDate_mm=08&endDate_dd=13&en
- REFNUM 344117: NOAA link 10/17/1998, TX, Flood (https://www.ncdc.noaa.gov/stormevents/listevents.jsp?eventType=%28C%29+Flash+Flood&eventType=%28Z%29+Flood&beginDate_mm=10&beginDate_dd=17&beginDate_yyyy=1998&endDate_mm=10&endD

Appendix C - EVTYPE to EventType Translation Results

Below shows each `EventType` that had multiple `EVTYPE` values grouped into it as a result of the translation process along with each of those `EVTYPE` values. `EventType` values with just a single `EVTYPE` were omitted here because they were simply the upper case equivalent.

```
eventType_by_EVTYPE <- unique(subset(sd[sd$EventType != 'UNCATEGORIZED',], select=c(EventType, EVTYPE)))
eventType_by_EVTYPE <- eventType_by_EVTYPE[order(eventType_by_EVTYPE$EventType, eventType_by_EVTYPE$EVTYPE),]
for (eventType in unique(eventType_by_EVTYPE$EventType)) {
  if(length(eventType_by_EVTYPE$EVTYPE[eventType_by_EVTYPE$EventType==eventType]) > 1) {
    k <- kable(
      eventType_by_EVTYPE$EVTYPE[eventType_by_EVTYPE$EventType==eventType],
      row.names = FALSE,
      col.names = eventType
    )
    print(k)
  }
}
```

Coastal Flood
ASTRONOMICAL HIGH TIDE
COASTAL FLOODING/EROSION
COASTAL FLOOD

Coastal Flood
COASTAL FLOODING
COASTAL FLOODING/EROSION
EROSION/CSTL FLOOD
TIDAL FLOODING

Cold/Wind Chill
COLD
COLD/WIND CHILL

Dense Fog
DENSE FOG
FOG

Excessive Heat
EXCESSIVE HEAT
HEAT WAVE
RECORD HEAT

Extreme Cold/Wind Chill
EXTREME COLD
EXTREME COLD/WIND CHILL
EXTREME WINDCHILL

Flash Flood
FLASH FLOOD
FLASH FLOOD/FLOOD
FLOOD/FLASH/FLOOD

Flood
FLOOD
RIVER FLOOD
RIVER FLOODING
URBAN/SML STREAM FLD

Frost/Freeze
AGRICULTURAL FREEZE
DAMAGING FREEZE
EARLY FROST
FREEZE
FROST
FROST/FREEZE
HARD FREEZE
UNSEASONABLE COLD
UNSEASONABLY COLD

Hail
HAIL
SMALL HAIL

Heat
HEAT
UNSEASONABLY WARM
WARM WEATHER

Heavy Rain
HEAVY RAIN
RAIN
TORRENTIAL RAINFALL
UNSEASONAL RAIN

Heavy Snow
EXCESSIVE SNOW
HEAVY SNOW
HEAVY SNOW SHOWER
SNOW
SNOW SQUALL
SNOW SQUALLS

High Surf
HEAVY SURF
HEAVY SURF/HIGH SURF
HIGH SURF
HIGH SURF ADVISORY

High Wind
GRADIENT WIND
GUSTY WIND
GUSTY WINDS
HIGH WIND
HIGH WIND (G40)
HIGH WINDS
NON-SEVERE WIND DAMAGE
NON-TSTM WIND
NON TSTM WIND
WIND
WIND DAMAGE
WINDS

Hurricane (Typhoon)
HURRICANE
HURRICANE EDOUARD
HURRICANE/TYPHOON
TYPHOON

Lake-Effect Snow
LAKE-EFFECT SNOW
LAKE EFFECT SNOW

Marine Thunderstorm Wind
MARINE THUNDERSTORM WIND
MARINE TSTM WIND

Rip Current
RIP CURRENT
RIP CURRENTS

Storm Surge/Tide
STORM SURGE
STORM SURGE/TIDE

Strong Wind
STRONG WIND
STRONG WINDS

Thunderstorm Wind
DRY MICROBURST
MICROBURST
THUNDERSTORM
THUNDERSTORM WIND
THUNDERSTORM WIND (G40)
TSTM WIND
TSTM WIND (G45)
TSTM WIND (41)
TSTM WIND (G35)
TSTM WIND (G40)
TSTM WIND (G45)
TSTM WIND 40
TSTM WIND 45
TSTM WIND AND LIGHTNING
TSTM WIND G45
TSTM WIND/HAIL
WET MICROBURST

Tornado
LANDSPOUT
TORNADO

Wildfire
BRUSH FIRE
WILD/FOREST FIRE
WILDFIRE

Winter Weather
FREEZING DRIZZLE
FREEZING RAIN
GLAZE
ICY ROADS

Winter Weather
LIGHT FREEZING RAIN
LIGHT SNOW
LIGHT SNOWFALL
MIXED PRECIP
MIXED PRECIPITATION
RAIN/SNOW
WINTER WEATHER
WINTER WEATHER MIX
WINTER WEATHER/MIX
WINTRY MIX

Appendix D - Uncategorized EVTYPE Values

Here is the list of `EVTYPE` values not translated and left with an `EventType` value of `UNCATEGORIZED`. Also included are the sum of the calculated `TotalDamage` and `PopulationHealthImpact` totals. These were omitted due to a proper `EventType` value not being obvious. These include values like `OTHER` with no obvious match as well as `GUSTY WIND/HVY RAIN` which matches potentially to more than one `EventType`. Given the realitively low amountof damage and health impact values for these remaining types, omitting them would have no impact to the overall result of the analysis.

```
uc <- sd[sd$EventType=='UNCATEGORIZED',]
kable(
  arrange(aggregate(cbind(TotalDamage,PopulationHealthImpact) ~ EVTYPE, uc, FUN=sum),EVTYPE),
  row.names = FALSE
)
```

EVTYPE	TotalDamage	PopulationHealthImpact
BEACH EROSION	100000	0
BLACK ICE	0	25
BLOWING DUST	20000	0
BLOWING SNOW	15000	2
COASTAL EROSION	766000	0
COASTAL STORM	50000	5
COASTALSTORM	0	1
COLD AND SNOW	0	14
COLD TEMPERATURE	0	2
COLD WEATHER	0	2
DAM BREAK	1002000	0
DOWNBURST	2000	0
DROWNING	0	1
EXTENDED COLD	100000	1
FALLING SNOW/ICE	0	2
FREEZING SPRAY	0	1
GUSTY WIND/HAIL	20000	0
GUSTY WIND/HVY RAIN	2000	0
GUSTY WIND/RAIN	2000	0
HAZARDOUS SURF	0	1
HEAVY RAIN/HIGH SURF	15000000	0
HEAVY SEAS	0	1
HEAVY SURF AND WIND	0	3
HIGH SEAS	15000	10
HIGH SWELLS	5000	1
HIGH WATER	0	3

EVTYPE	TotalDamage	PopulationHealthImpact
HYPERTHERMIA/EXPOSURE	0	1
HYPOTHERMIA/EXPOSURE	0	7
ICE JAM FLOOD (MINOR	1000	0
ICE ON ROAD	0	1
ICE ROADS	12000	1
LANDSLIDES	5000	2
LANDSLUMP	570000	0
LATE SEASON SNOW	180000	0
MARINE ACCIDENT	50000	3
MUD SLIDE	100100	0
MUDSLIDE	1225000	6
MUDSLIDES	0	1
OTHER	1089900	4
ROCK SLIDE	150000	0
ROGUE WAVE	0	2
ROUGH SEAS	0	13
ROUGH SURF	10000	5
SNOW AND ICE	0	1
WHIRLWIND	12000	1
WIND AND WAVE	1000000	0