

Analyzing the impacts of Severe Weather Events on Health and Economy from the NOAA dataset

Synopsys

The basic goal of this analysis is to explore the **NOAA Storm Database** and answer some basic questions about severe weather events.

The data analysis will address the following two questions:

- “Across the United States, which types of events (as indicated in the **EVTYPE** variable) are most harmful with respect to population health”. In order to answer this question couple of variables in the dataset will be used to measure the impact of a severe weather event on population health, namely, **INJURIES** and **FATALITIES**. Also, a new derived variable **Health_Hazards** will be created by adding these variables to measure the total impact.
- “Across the United States, which types of events have the greatest economic consequences”. In order to answer this question, again another couple of variables in the dataset will be used to measure the impact of a severe weather event on economy, namely, **PROPDMG** and **CROPDGMG**. Also, a new derived variable **Eco_Hazards** will be created by adding these variables to measure the total impact.

The exploratory data analysis will be done using R and **barplots** will be used to compare the impact of a severe event, both on population health and economy. Two sepearate analysis will be done to answer to two different questions.

As will be seen, **TORNADO** has the highest impact in terms of harmfulness in both the cases.

Data Processing

```
storm <- read.csv(bzfile("repdata-data-StormData.csv.bz2"))
names(storm)
```

```
## [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" "CROPDGMG" "CROPDGMGEXP" "WFO"
"STATEOFFIC"
## [31] "ZONENAMES" "LATITUDE" "LONGITUDE" "LATITUDE_E"
"LONGITUDE_"
## [36] "REMARKS" "REFNUM"
```

```
head(storm)
```

```

##      STATE__      BGN_DATE BGN_TIME TIME_ZONE COUNTY COUNTYNAME
STATE
## 1      1  4/18/1950 0:00:00    0130      CST      97      MOBILE
AL
## 2      1  4/18/1950 0:00:00    0145      CST       3      BALDWIN
AL
## 3      1  2/20/1951 0:00:00    1600      CST      57      FAYETTE
AL
## 4      1   6/8/1951 0:00:00    0900      CST      89      MADISON
AL
## 5      1 11/15/1951 0:00:00    1500      CST      43      CULLMAN
AL
## 6      1 11/15/1951 0:00:00    2000      CST      77 LAUDERDALE
AL
##      EVTYPE BGN_RANGE BGN_AZI BGN_LOCATI END_DATE END_TIME COUNTY_END
## 1 TORNADO          0          0          0          0          0
## 2 TORNADO          0          0          0          0          0
## 3 TORNADO          0          0          0          0          0
## 4 TORNADO          0          0          0          0          0
## 5 TORNADO          0          0          0          0          0
## 6 TORNADO          0          0          0          0          0
##      COUNTYENDN END_RANGE END_AZI END_LOCATI LENGTH WIDTH F MAG
FATALITIES
## 1      NA          0          0          0      14.0   100 3   0
0
## 2      NA          0          0          0       2.0   150 2   0
0
## 3      NA          0          0          0       0.1   123 2   0
0
## 4      NA          0          0          0       0.0   100 2   0
0
## 5      NA          0          0          0       0.0   150 2   0
0
## 6      NA          0          0          0       1.5   177 2   0
0
##      INJURIES PROPDGMG PROPDMGEXP CROPDGMG CROPDMGEXP WFO STATEOFFIC
ZONENAMES
## 1      15      25.0          K          0
## 2       0       2.5          K          0
## 3       2      25.0          K          0
## 4       2       2.5          K          0
## 5       2       2.5          K          0
## 6       6       2.5          K          0
##      LATITUDE LONGITUDE LATITUDE_E LONGITUDE_ REMARKS REFNUM
## 1      3040      8812      3051      8806          1
## 2      3042      8755          0          0          2
## 3      3340      8742          0          0          3
## 4      3458      8626          0          0          4
## 5      3412      8642          0          0          5
## 6      3450      8748          0          0          6

```

```
dim(storm)
```

```
## [1] 902297    37
```

```

loc_vars <- c("STATE", "BGN_DATE", "EVTYPE")
health_vars <- c("FATALITIES", "INJURIES")
prop_vars <- c("PROPDGMG", "CROPDGMG")

```

- As can be seen from above, only the *health_vars* and the *population_vars* are the two sets of variables that will be used to answer question 1 and 2 respectively. The variables from the set *loc_vars*, although never used in current analysis, could be used to analyze location-specific impacts.

Q1: Across the United States, which types of events (as indicated in the EVTYPE variable) are most harmful with respect to population health?

- In order to answer this question, couple of variables in the dataset will be used to measure the impact of a severe weather event on population health, namely, **INJURIES** and **FATALITIES**.
- A new derived variable **Health_Hazards** is created by adding these two variables (**Health_Hazards = INJURIES + FATALITIES**) to measure the total impact.

Results of Analysis

```
storm1 <- storm[c(loc_vars, health_vars)]
storm1$Health_Hazards <- storm1$FATALITIES + storm1$INJURIES
fatalities <- sort(tapply(storm1$FATALITIES, storm1$EVTYPE, sum),
decreasing=TRUE)
injuries <- sort(tapply(storm1$INJURIES, storm1$EVTYPE, sum),
decreasing=TRUE)
hazards <- sort(tapply(storm1$Health_Hazards, storm1$EVTYPE, sum),
decreasing=TRUE)
n <- 20 # top 20 harmful events
fatalities <- head(fatalities, n) #f[f > 0]
injuries <- head(injuries, n) #i[i > 0]
hazards <- head(hazards, n) #h[h > 0]
fatalities <- as.data.frame(cbind(event=names(fatalities),
count=fatalities, type="Fatalities"))
injuries <- as.data.frame(cbind(event=names(injuries), count=injuries,
type="Injuries"))
hazards <- as.data.frame(cbind(event=names(hazards), count=hazards,
type="Health Hazard"))
d <- rbind(fatalities, injuries, hazards)
d$count <- as.integer(as.character(d$count))
d <- transform(d, event = reorder(event, -count))
hazards$count <- as.integer(as.character(hazards$count))
tblHealth <- cbind(fatalities[1:2], injuries[1:2])
names(tblHealth) <- c("Events", "Fatalities", "Events", "Injuries")
print(tblHealth, row.names=FALSE)
```

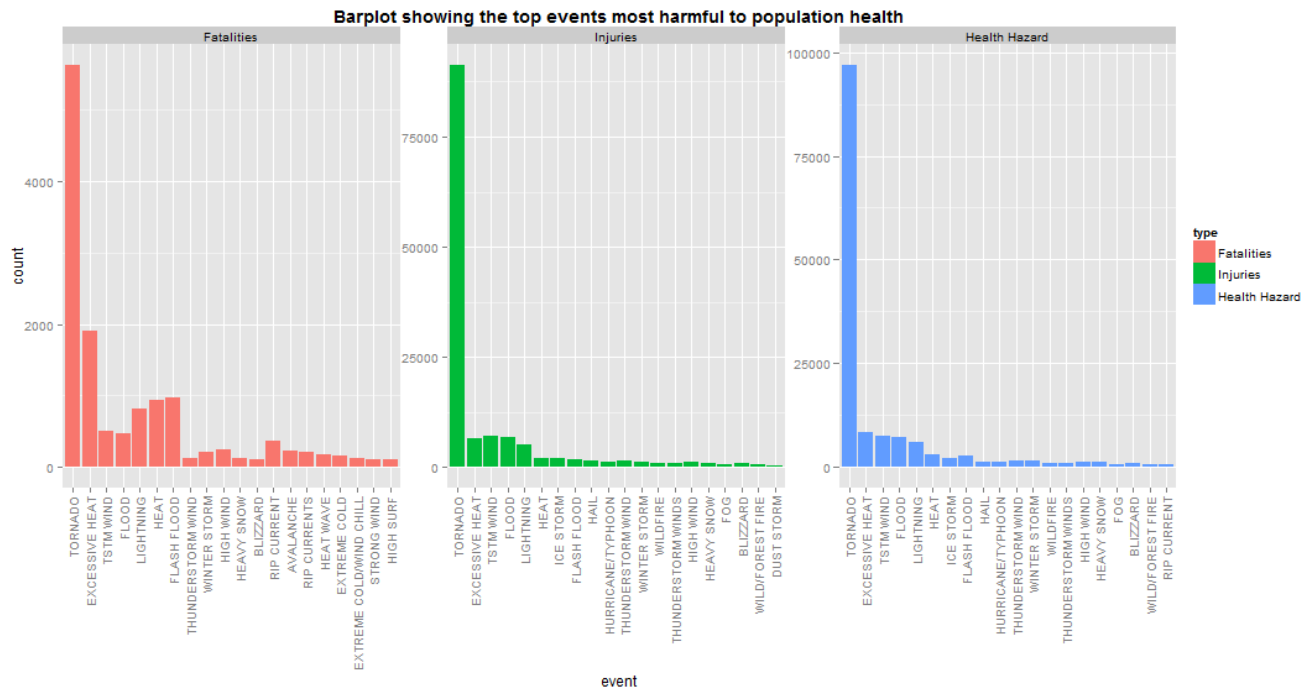
##	Events	Fatalities	Events	Injuries
##	TORNADO	5633	TORNADO	91346
##	EXCESSIVE HEAT	1903	TSTM WIND	6957
##	FLASH FLOOD	978	FLOOD	6789
##	HEAT	937	EXCESSIVE HEAT	6525
##	LIGHTNING	816	LIGHTNING	5230
##	TSTM WIND	504	HEAT	2100
##	FLOOD	470	ICE STORM	1975
##	RIP CURRENT	368	FLASH FLOOD	1777
##	HIGH WIND	248	THUNDERSTORM WIND	1488
##	AVALANCHE	224	HAIL	1361
##	WINTER STORM	206	WINTER STORM	1321
##	RIP CURRENTS	204	HURRICANE/TYPHOON	1275
##	HEAT WAVE	172	HIGH WIND	1137
##	EXTREME COLD	160	HEAVY SNOW	1021
##	THUNDERSTORM WIND	133	WILDFIRE	911
##	HEAVY SNOW	127	THUNDERSTORM WINDS	908
##	EXTREME COLD/WIND CHILL	125	BLIZZARD	805
##	STRONG WIND	103	FOG	734
##	BLIZZARD	101	WILD/FOREST FIRE	545
##	HIGH SURF	101	DUST STORM	440

```
tblHealth <- cbind(hazards[1:2], round(100*hazards[2] /
sum(hazards[2]),2))
names(tblHealth) <- c("Events", "Total.Health.Hazards",
"Percent.Total.Health.Hazards")
print(tblHealth, row.names=FALSE)
```

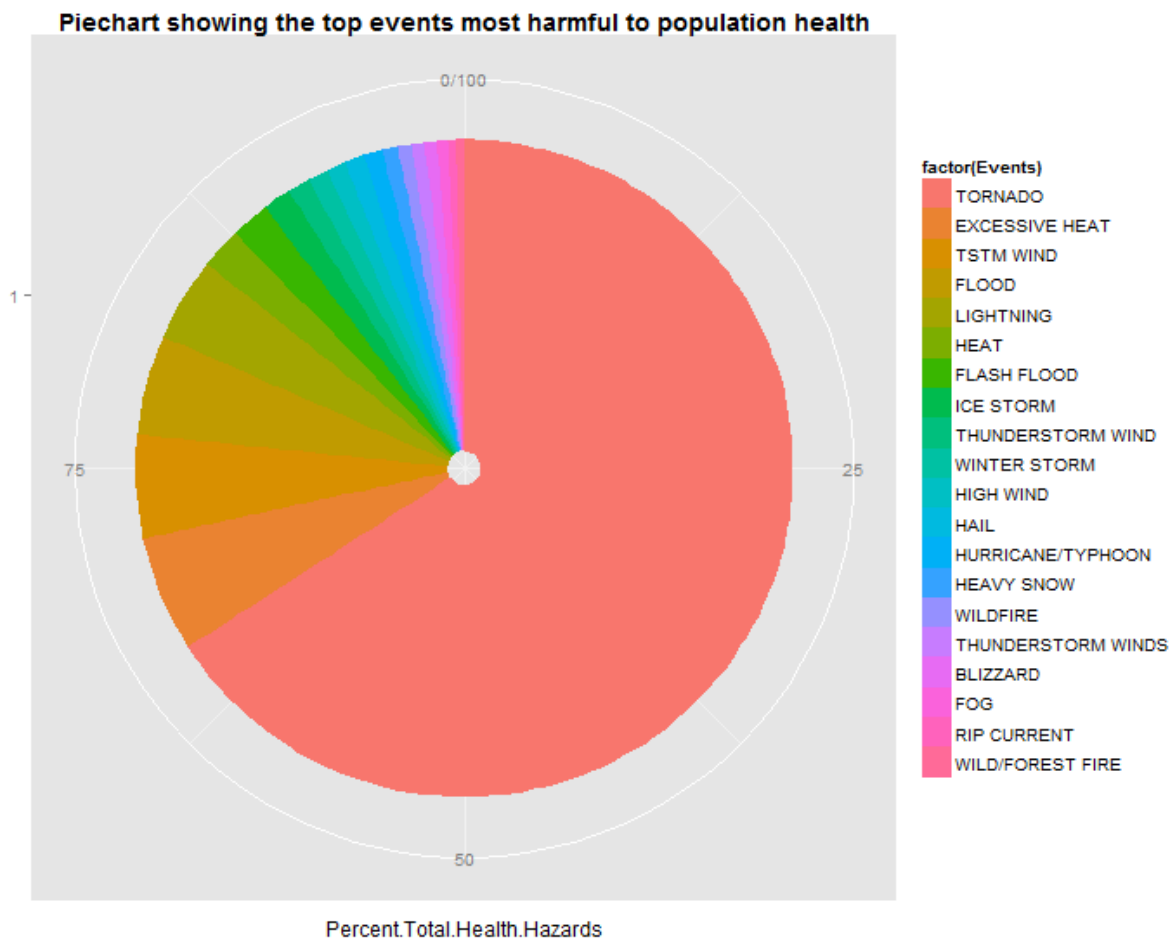
##	Events	Total.Health.Hazards
Percent.Total.Health.Hazards		
##	TORNADO	96979
65.86		
##	EXCESSIVE HEAT	8428
5.72		
##	TSTM WIND	7461
5.07		
##	FLOOD	7259
4.93		
##	LIGHTNING	6046
4.11		
##	HEAT	3037
2.06		
##	FLASH FLOOD	2755
1.87		
##	ICE STORM	2064
1.40		
##	THUNDERSTORM WIND	1621
1.10		
##	WINTER STORM	1527
1.04		
##	HIGH WIND	1385
0.94		
##	HAIL	1376
0.93		
##	HURRICANE/TYPHOON	1339
0.91		
##	HEAVY SNOW	1148
0.78		
##	WILDFIRE	986
0.67		
##	THUNDERSTORM WINDS	972
0.66		
##	BLIZZARD	906
0.62		
##	FOG	796
0.54		
##	RIP CURRENT	600
0.41		
##	WILD/FOREST FIRE	557
0.38		

- As can be seen from above, **TORNADO, EXCESSIVE HEAT, TSTM WIND, FLOOD, LIGHTNING** are the top events that are most harmful to population health, causing 65.86%, 5.72%, 5.07%, 4.93%, 4.11% and 2.06% of health hazards respectively. The barplot and the pie charts below pictorially show the same result.

```
library(ggplot2)
ggplot(d, aes(x=event, y=count, fill=type)) +
  geom_bar(stat="identity") +
  facet_wrap(~type, scales = "free") +
  ggtitle("Barplot showing the top events most harmful to population health") +
  theme(axis.text.x=element_text(angle=90,hjust=1,vjust=0.5),
        plot.title = element_text(lineheight=.8, face="bold"))
```



```
tblHealth <- transform(tblHealth, Events = reorder(Events, -
Percent.Total.Health.Hazards))
p <- ggplot(data=tblHealth,
  aes(x=factor(1),
    y=Percent.Total.Health.Hazards,
    fill = factor(Events))
)
p <- p + geom_bar(stat = "identity") + xlab("")
p + coord_polar(theta="y") +
  ggtitle("Piechart showing the top events most harmful to population
health") +
  theme(plot.title = element_text(lineheight=.8, face="bold"))
```



Q2: Across the United States, which types of events have the greatest economic

consequences?

- In order to answer this question, again another couple of variables in the dataset are used to measure the impact of a severe weather event on economy, namely, **PROPDMG** and **CROPDMG**.
- Also, a new derived variable **Eco_Hazards** is created by adding these variables (**Eco_Hazards = PROPDMG + CROPDMG**) to measure the total impact.

Results of Analysis

```

storm2 <- storm[c(loc_vars, prop_vars)]
storm2$PROPDGM <- as.numeric(as.character(storm2$PROPDGM))
storm2$CROPDMG <- as.numeric(as.character(storm2$CROPDMG))
storm2$Eco_Hazards <- storm2$PROPDGM + storm2$CROPDMG
hazards <- sort(tapply(storm2$Eco_Hazards, storm2$EVTYPE, sum),
decreasing=TRUE)
prop <- sort(tapply(storm2$PROPDGM, storm2$EVTYPE, sum),
decreasing=TRUE)
crop <- sort(tapply(storm2$CROPDMG, storm2$EVTYPE, sum),
decreasing=TRUE)
n <- 20 # top 20 harmful
prop <- head(prop, n)
crop <- head(crop, n)
hazards <- head(hazards, n)
hazards <- as.data.frame(cbind(event=names(hazards), count=hazards,
type="Eco Hazard"))
prop <- as.data.frame(cbind(event=names(prop), count=prop, type="Prop
Dmg"))
crop <- as.data.frame(cbind(event=names(crop), count=crop, type="Crop
Dmg"))
d <- rbind(hazards, prop, crop)
d$count <- as.numeric(as.character(d$count))
d <- transform(d, event = reorder(event, -count))
hazards$count <- as.numeric(as.character(hazards$count))
tblHealth <- cbind(prop[1:2], crop[1:2])
names(tblHealth) <- c("Events", "PropDmg", "Events", "CropDmg")
print(tblHealth, row.names=FALSE)

```

##	Events	PropDmg	Events	CropDmg
##	TORNADO	3212258.16	HAIL	579596.28
##	FLASH FLOOD	1420124.59	FLASH FLOOD	179200.46
##	TSTM WIND	1335965.61	FLOOD	168037.88
##	FLOOD	899938.48	TSTM WIND	109202.6
##	THUNDERSTORM WIND	876844.17	TORNADO	100018.52
##	HAIL	688693.38	THUNDERSTORM WIND	66791.45
##	LIGHTNING	603351.78	DROUGHT	33898.62
##	THUNDERSTORM WINDS	446293.18	THUNDERSTORM WINDS	18684.93
##	HIGH WIND	324731.56	HIGH WIND	17283.21
##	WINTER STORM	132720.59	HEAVY RAIN	11122.8
##	HEAVY SNOW	122251.99	FROST/FREEZE	7034.14
##	WILDFIRE	84459.34	EXTREME COLD	6121.14
##	ICE STORM	66000.67	TROPICAL STORM	5899.12
##	STRONG WIND	62993.81	HURRICANE	5339.31
##	HIGH WINDS	55625	FLASH FLOODING	5126.05
##	HEAVY RAIN	50842.14	HURRICANE/TYPHOON	4798.48
##	TROPICAL STORM	48423.68	WILDFIRE	4364.2
##	WILD/FOREST FIRE	39344.95	TSTM WIND/HAIL	4356.65
##	FLASH FLOODING	28497.15	WILD/FOREST FIRE	4189.54
##	URBAN/SML STREAM FLD	26051.94	LIGHTNING	3580.61

```

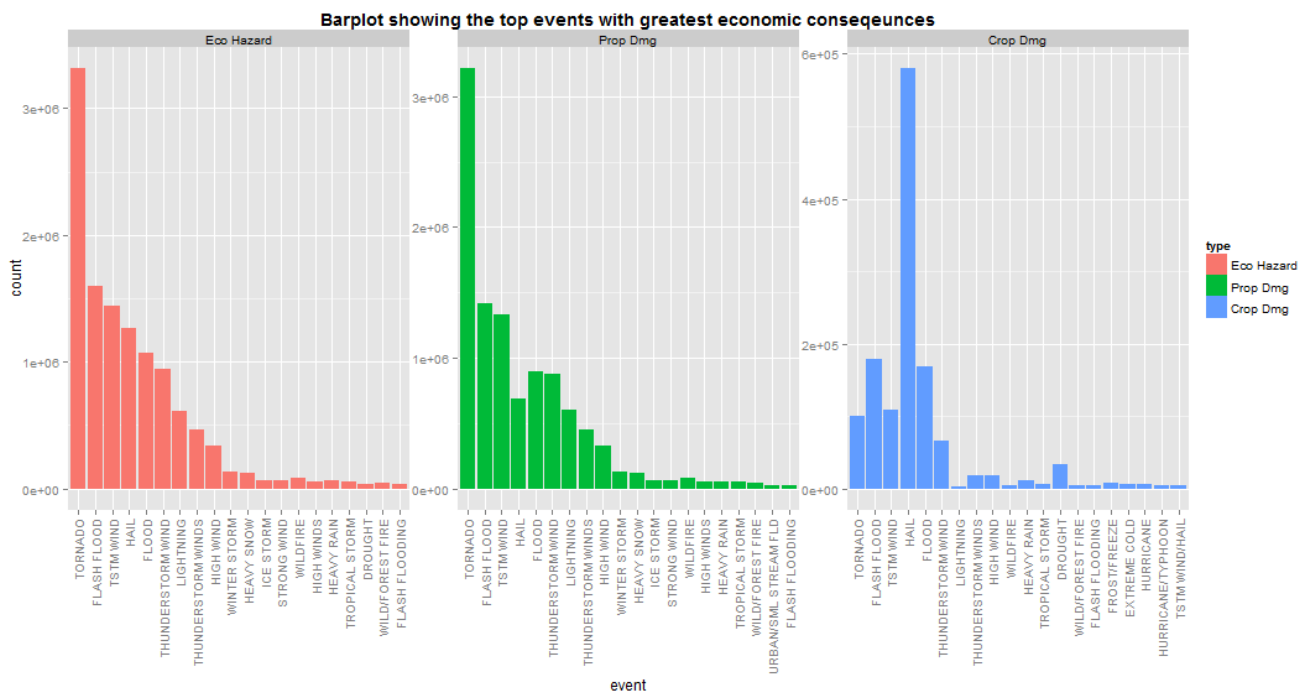
tblHealth <- cbind(hazards[1:2], round(100*hazards[2] /
sum(hazards[2]),2))
names(tblHealth) <- c("Events", "Total.Eco.Hazards",
"Percent.Total.Eco.Hazards")
print(tblHealth, row.names=FALSE)

```

##	Events	Total.Eco.Hazards	Percent.Total.Eco.Hazards
##	TORNADO	3312277	28.02
##	FLASH FLOOD	1599325	13.53
##	TSTM WIND	1445168	12.23
##	HAIL	1268290	10.73
##	FLOOD	1067976	9.04
##	THUNDERSTORM WIND	943636	7.98
##	LIGHTNING	606932	5.13
##	THUNDERSTORM WINDS	464978	3.93
##	HIGH WIND	342015	2.89
##	WINTER STORM	134700	1.14
##	HEAVY SNOW	124418	1.05
##	WILDFIRE	88824	0.75
##	ICE STORM	67690	0.57
##	STRONG WIND	64611	0.55
##	HEAVY RAIN	61965	0.52
##	HIGH WINDS	57385	0.49
##	TROPICAL STORM	54323	0.46
##	WILD/FOREST FIRE	43534	0.37
##	DROUGHT	37998	0.32
##	FLASH FLOODING	33623	0.28

- As can be seen from above, **TORNADO, FLASH FLOOD, TSTM WIND, HAIL, FLOOD, THUNDERSTORM WIND** are the top events that have greatest economic consequences, causing 28.02%, 13.53%, 12.23%, 10.73%, 9.04% and 7.98% of economic hazards respectively. The barplot below pictorially shows the same result.

```
ggplot(d, aes(x=event, y=count, fill=type)) +
  geom_bar(stat="identity") + facet_wrap(~type, scales = "free") +
  ggtitle("Barplot showing the top events with greatest economic
  consequences") +
  theme(axis.text.x=element_text(angle=90,hjust=1,vjust=0.5),
        plot.title = element_text(lineheight=.8, face="bold"))
```



Data Transformation

- As can be seen from the above analysis, the only data transformation used was to convert the absolute values of the health / economic hazards to corresponding percentage values, since proportions (relative to all the hazards) give better insights.