Vignette

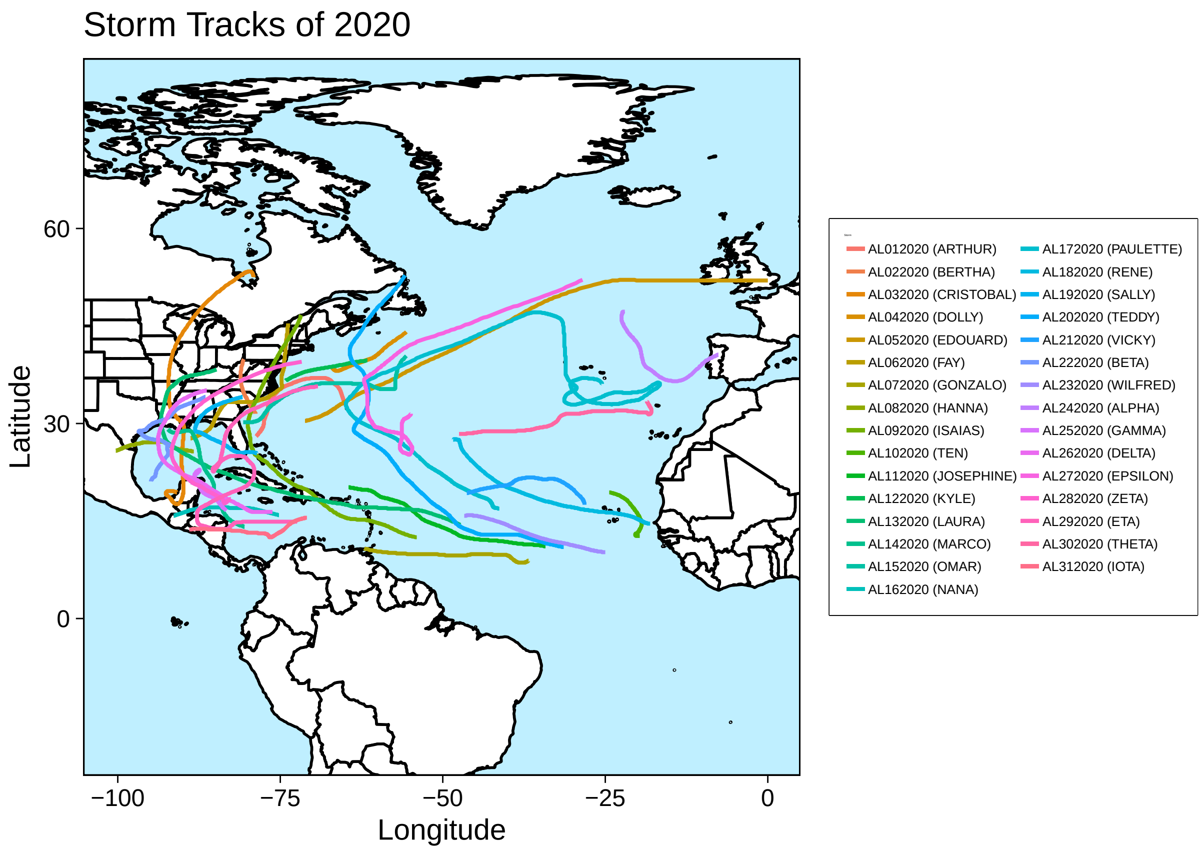
```
library(hurricane)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

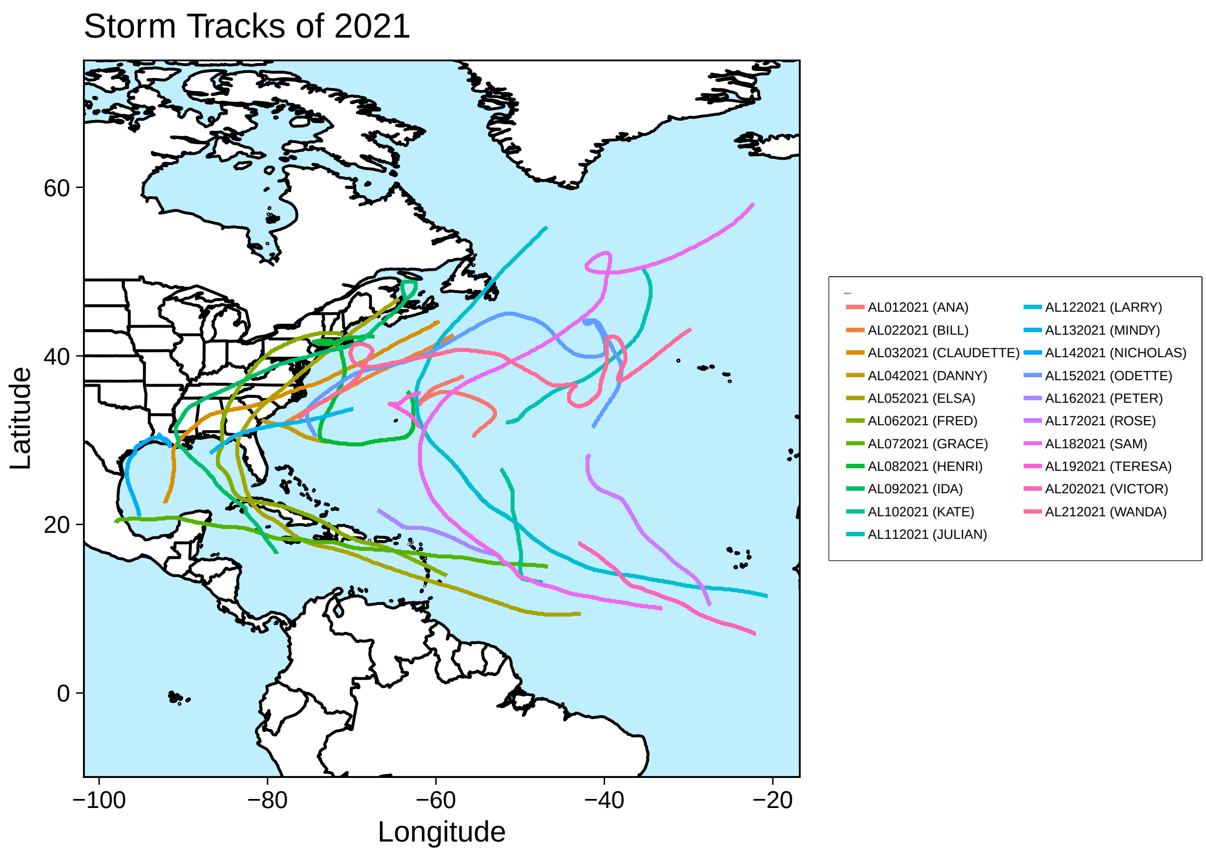
```
library(ggplot2)
```

Track of all storms in 2020, 2021, and 2022.

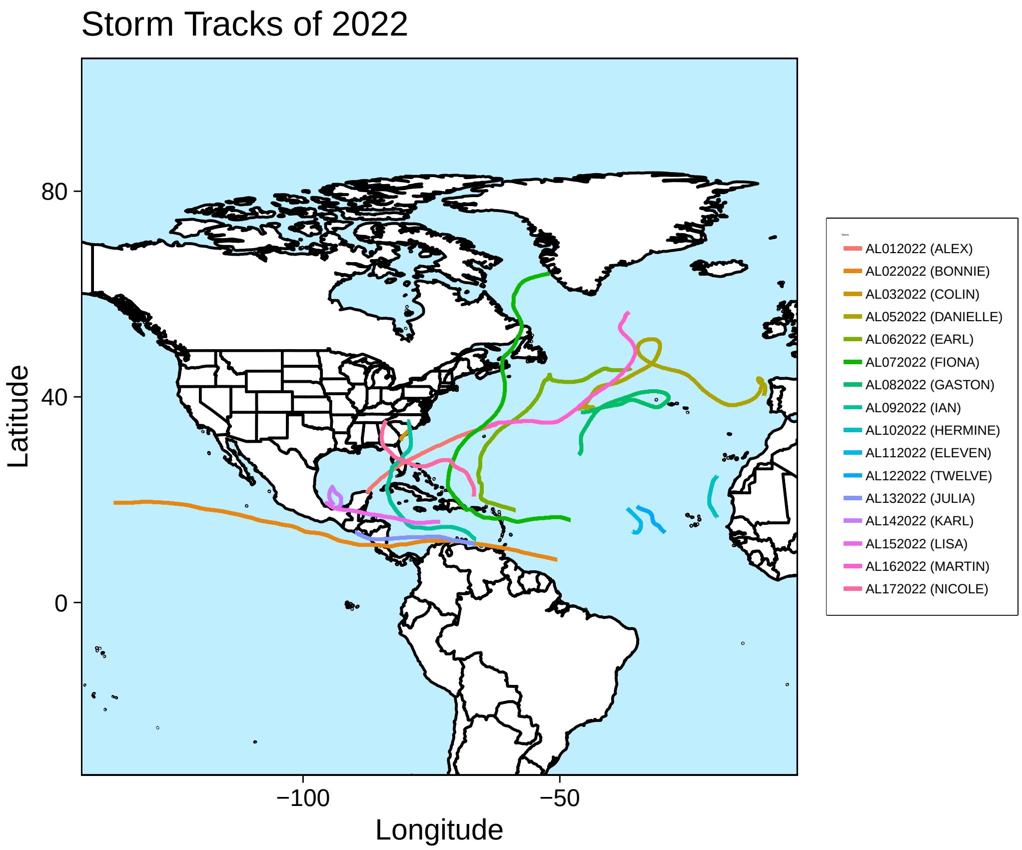
```
# track of 2020 storms
dat.2020 <- hurdat[grepl(2020, hurdat$date.time),]
storm_name <- unique(dat.2020$name)
year <- rep(2020, times=length(storm_name))
map.2020 <- track_map(storm_name, year, hurdat) +
            theme(legend.text = element_text(size=5),
            legend.key.size = unit(0.3, "cm"),
            legend.title = element_text(size=1)) +
  labs(title="Storm Tracks of 2020")

print(map.2020)
```


Storm Tracks of 2020
Latitude
Longitude
60
30
0
−100
−75
−50
−25
0
AL012020 (ARTHUR)
AL022020 (BERTHA)
AL032020 (CRISTOBAL)
AL042020 (DOLLY)
AL052020 (EDOUARD)
AL062020 (FAY)
AL072020 (GONZALO)
AL082020 (HANNA)
AL092020 (ISAIAS)
AL102020 (TEN)
AL112020 (JOSEPHINE)
AL122020 (KYLE)
AL132020 (LAURA)
AL142020 (MARCO)
AL152020 (OMAR)
AL162020 (NANA)
AL172020 (PAULETTE)
AL182020 (RENE)
AL192020 (SALLY)
AL202020 (TEDDY)
AL212020 (VICKY)
AL222020 (BETA)
AL232020 (WILFRED)
AL242020 (ALPHA)
AL252020 (GAMMA)
AL262020 (DELTA)
AL272020 (EPSILON)
AL282020 (ZETA)
AL292020 (ETA)
AL302020 (THETA)
AL312020 (IOTA)

```
# track of 2021 storms
dat.2021 <- hurdat[grepl(2021, hurdat$date.time),]
storm_name <- unique(dat.2021$name)
year <- rep(2021, times=length(storm_name))
map.2021 <- track_map(storm_name, year, hurdat) +
            theme(legend.text = element_text(size=5),
            legend.key.size = unit(0.3, "cm"),
            legend.title = element_text(size=1)) +
  labs(title="Storm Tracks of 2021")
print(map.2021)
```



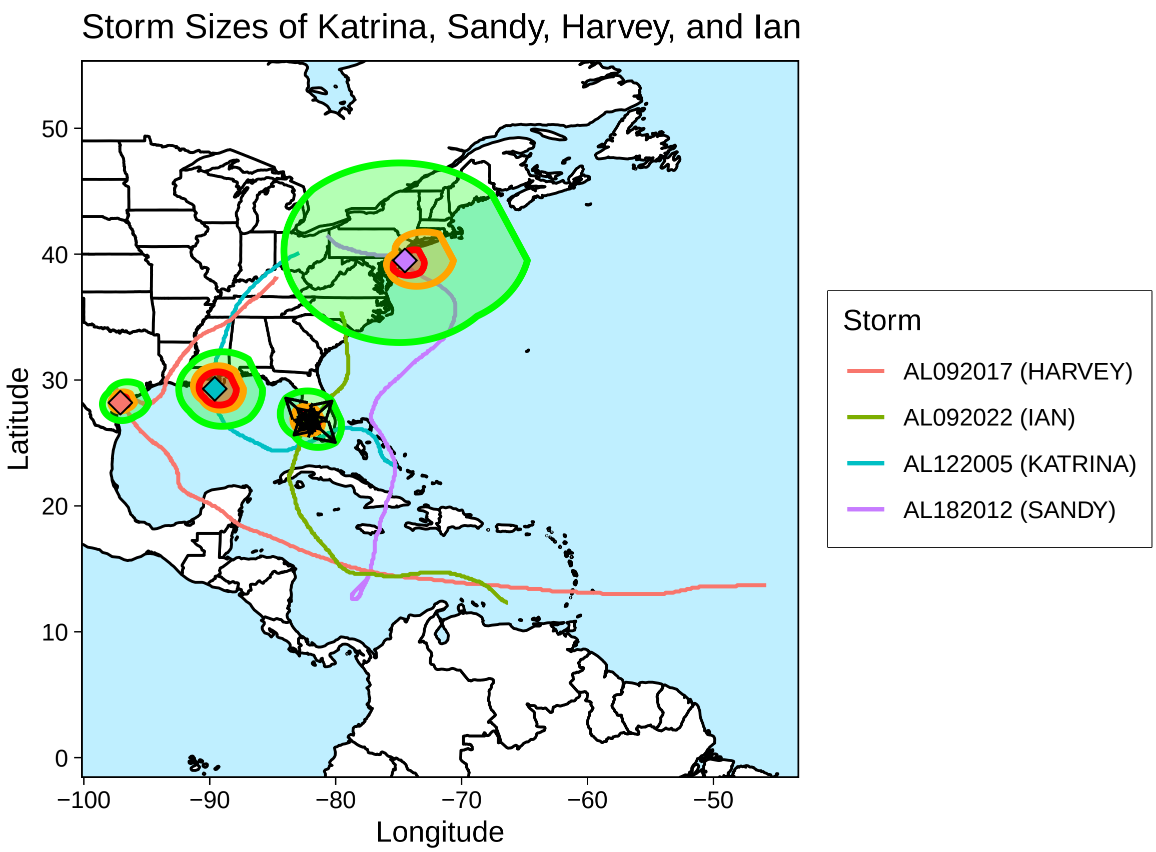
```
# track of 2022 storms
dat.2022 <- hurdat[grepl(2022, hurdat$date.time),]
storm_name <- unique(dat.2022$name)
year <- rep(2022, times=length(storm_name))
map.2022 <- track_map(storm_name, year, hurdat) +
            theme(legend.text = element_text(size=5),
            legend.key.size = unit(0.3, "cm"),
            legend.title = element_text(size=1)) +
  labs(title="Storm Tracks of 2022")
print(map.2022)
```



Hurricanes Katrina, Sandy, Harvey, and Ian

Positions and sizes of hurricane Katrina (2005), Sandy (2012), Harvey (2017), and Ian (2022) where they made their strongest landfall.

```
katrina <- landfall("KATRINA", 2005, hurdat, method="landfall.strongest")
sandy <- landfall("SANDY", 2012, hurdat, method="landfall.strongest")
harvey <- landfall("HARVEY", 2017, hurdat, method="landfall.strongest")
ian <- landfall("IAN", 2022, hurdat, method="landfall.strongest")

storm_size( c("KATRINA", "SANDY", "HARVEY", "IAN"),
        c(2005, 2012, 2017, 2022), hurdat,
        c(katrina$date.time, sandy$date.time, harvey$date.time, ian$date.time),
        path = TRUE ) +
  labs(title="Storm Sizes of Katrina, Sandy, Harvey, and Ian")
```



Individual storm information

Data frame containing information for each individual storm (1851-2022)

```
storm.id = unique(hurdat$id)
storm.name <- c()
storm.max.wind <- c()
storm.min.pressure <- c()
landfall.check <- c()
ACE <- c()

for( i in seq_along(storm.id) ){
  tmp.dat <- hurdat[ which( hurdat$id == storm.id[i] ),]
  storm.name[i] <- tmp.dat$name[1]
  storm.max.wind[i] <- max( tmp.dat$max.wind )
  storm.min.pressure[i] <- min(tmp.dat$min.pressure )
  tmp.year <- substr( storm.id[i], 5, 8)
  landfall.check[i] <- landfall( storm.id[i], tmp.year, hurdat, method="landfall.check")
  ACE[i] <- cyclone_energy( storm.id[i], tmp.year, hurdat)
}

storm.info <- data.frame(
  id = storm.id,
  name = storm.name,
  max.wind = storm.max.wind,
  min.pressure = storm.min.pressure,
  landfall = landfall.check,
  ace = ACE )

head(storm.info)
```

```
##          id    name max.wind min.pressure landfall   ace
## 1 AL011851 UNNAMED       80           NA     TRUE  4.91
## 2 AL021851 UNNAMED       80           NA    FALSE  0.64
## 3 AL031851 UNNAMED       50           NA    FALSE  0.25
## 4 AL041851 UNNAMED      100           NA     TRUE 21.83
## 5 AL051851 UNNAMED       50           NA    FALSE  4.00
## 6 AL061851 UNNAMED       60           NA     TRUE  4.61
```

Analysis of interest

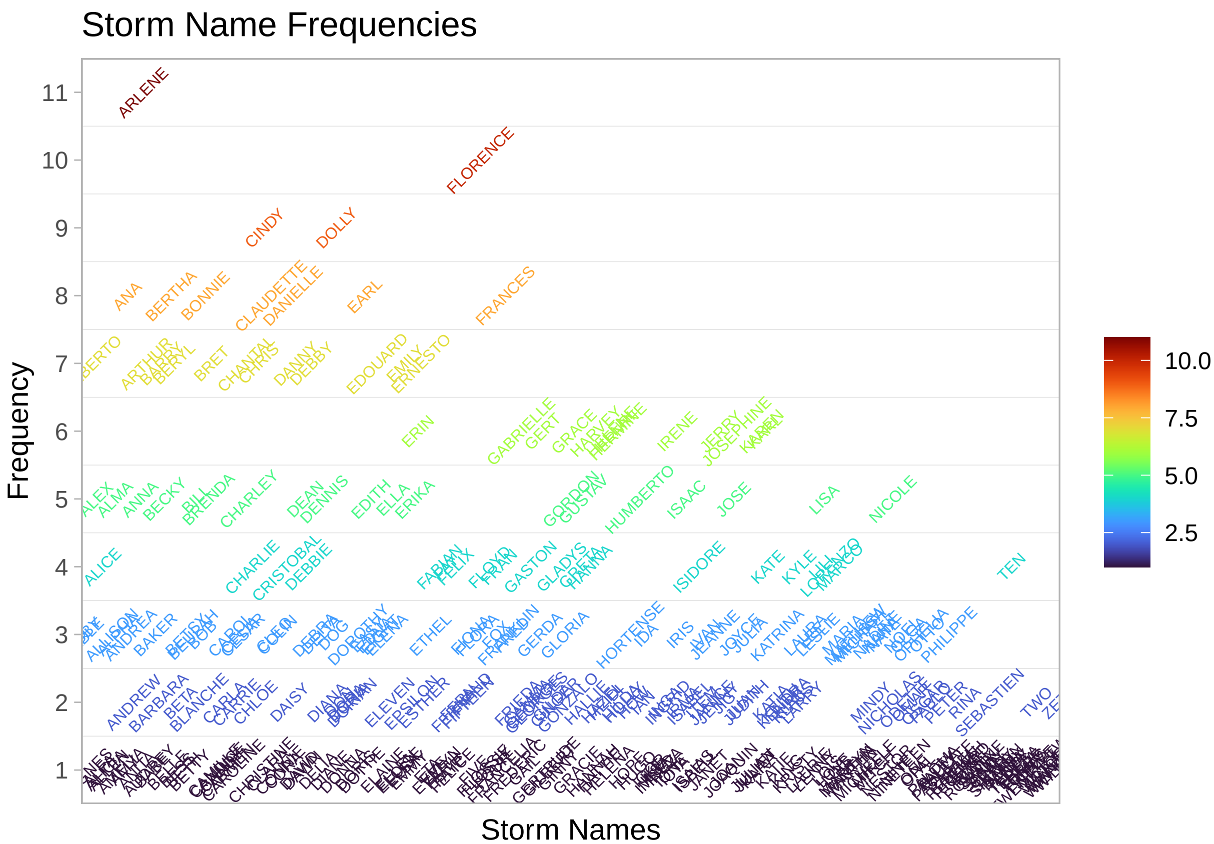
Examining name frequency.

One interesting thing about the dataset can be seen when looking at the names of the hurricanes. The naming of North Atlantic tropical cyclones is currently under the oversight of the Hurricane Committee of the World Meteorological Organization (WMO). This group maintains six alphabetic lists of twenty-one names, with one list used each year. The names on each list are used in alphabetical order for tropical storms and hurricanes. This usually results in each name being reused every six years. However, in the case when a storm is particularly deadly or damaging, that storm's name is retired, and a replacement starting with the same letter is selected to take its place. The decision whether to remove a name in a given season is made at the annual session of the WMO Hurricane Committee in the spring of the following year.

Since the formal start of naming during the 1947 Atlantic hurricane season, an average of one Atlantic storm name has been retired each year, though many seasons (most recently 2014) did not have any names retired.

The frequency of hurricane names can be seen below with Arlene, Florence, Cindy, and Dolly being the most commonly used name. Thanks Arlene, Florence, Cindy, and Dolly for not being so dangerous!

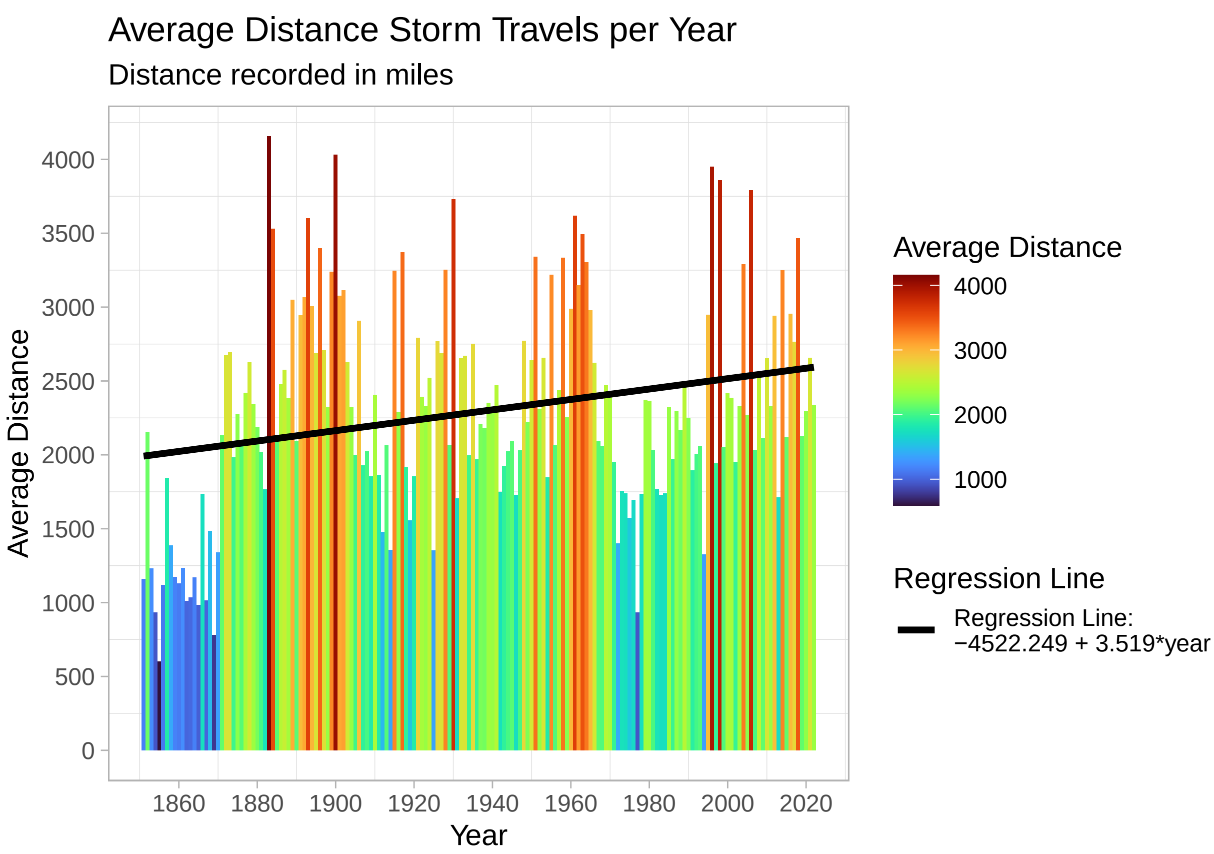
```
storm.name.dat <- data.frame( name = storm.info$name )%>%
    filter( name != "UNNAMED" ) %>%
    count( name )

ggplot( data = storm.name.dat, aes(x=name, y=n, label=name, color=n) ) +
    geom_text(size=2, angle=45) +
  theme_light() + scale_y_continuous(n.breaks=12) +
  labs(y="Frequency", x="Storm Names", title="Storm Name Frequencies",
       color="") +
  theme(panel.grid.major = element_blank(),
        axis.text.x = element_blank(),
        axis.ticks.x = element_blank() ) +
  viridis::scale_color_viridis(option="turbo")
```


Storm Name Frequencies
Frequency
Storm Names
11
10
9
8
7
6
5
4
3
2
1
10.0
7.5
5.0
2.5
ARLENE
FLORENCE
CINDY
DOLLY
ANA
BERTHA
BONNIE
CLAUDETTE
DANIELLE
EARL
FRANCES
ARTHUR
BRET
EDOUARD
ERNESTO
ERIN
GABRIELLE
GERT
GRACE
IRENE
ALEX
ALMA
ANNA
BECKY
BRENDA
CHARLEY
DEAN
DENNIS
EDITH
ELLA
ERIKA
GORDON
GUSTAV
HUMBERTO
ISAAC
JOSE
LISA
NICOLE
ALICE
CHARLIE
CRISTOBAL
DEBBIE
GASTON
ISIDORE
KATE
KYLE
TEN
BAKER
ETHEL
GERDA
GLORIA
HORTENSE
IRIS
KATRINA
PHILIPPE
ANDREW
BARBARA
DAISY
ELEVEN
SEBASTIEN
TWO

Examining average storm distance per year

The distances traveled in miles by each storm per year was also looked at. The distance was computed by taking the storm center's interpolated longitude and latitudes and summing the distance between each point. The distances were averaged between each storm, and, as shown below, revealed that the average distances are increasing with time. Linear regression was used to look at the relationship presenting the model: $Y_i = -4522.249 + 3.519 * year$.

```
storm.dat.dis <- data.frame( id = unique(hurdat$id ) )

for( i in seq_along(storm.dat.dis$id) ){
    tmp.dat <- hurdat %>% filter( id == storm.dat.dis$id[i] )
    tmp.year <- substr( tmp.dat$id[1], 5, 8)
    storm <- interp_track( tmp.dat$id[1], tmp.year, hurdat ) %>%
        select( longitude, latitude )
    dis <- fields::rdist.earth.vec(
    storm[1:(nrow(storm)-1),], storm[2:nrow(storm),], miles=TRUE )
    storm.dat.dis$distance[i] <- sum(dis)
}
storm.dat.dis$distance <- ifelse(is.na(storm.dat.dis$distance), 0,
                                 storm.dat.dis$distance)
storm.dat.dis$year <- substr(storm.dat.dis$id, 5, 8)

distance.df <- data.frame(year = as.numeric( unique(storm.dat.dis$year)) )
for( i in seq_along(unique(distance.df$year)) ){
    tmp.df <- storm.dat.dis %>% filter(year==unique(storm.dat.dis$year)[i])
    distance.df$avg.distance[i] <- mean(tmp.df$distance)
}

#summary( lm( avg.distance~year, data=distance.df ) )

ggplot(data=distance.df) +
  geom_col(aes(x=year, y=avg.distance, fill=avg.distance)) +
  stat_function(fun=function(year) -4522.249 + 3.519*year,
                aes(color="Regression Line:\n-4522.249 + 3.519*year"), lwd=1.2) +
  scale_color_manual(values = "black", guide = guide_legend(title = "Regression Line")) +
  theme_light() +
  labs(x="Year", y="Average Distance",
       title="Average Distance Storm Travels per Year", color="",
       fill="Average Distance", subtitle="Distance recorded in miles") +
  scale_y_continuous(n.breaks=10) +
  scale_x_continuous(n.breaks=10) +
  theme(panel.grid.major=element_blank()) +
  viridis::scale_fill_viridis(option="turbo")
```


Average Distance Storm Travels per Year
Distance recorded in miles
Average Distance
Year
0
500
1000
1500
2000
2500
3000
3500
4000
1860
1880
1900
1920
1940
1960
1980
2000
2020
Average Distance
4000
3000
2000
1000
Regression Line
Regression Line:
−4522.249 + 3.519*year

Landfalling hurricanes

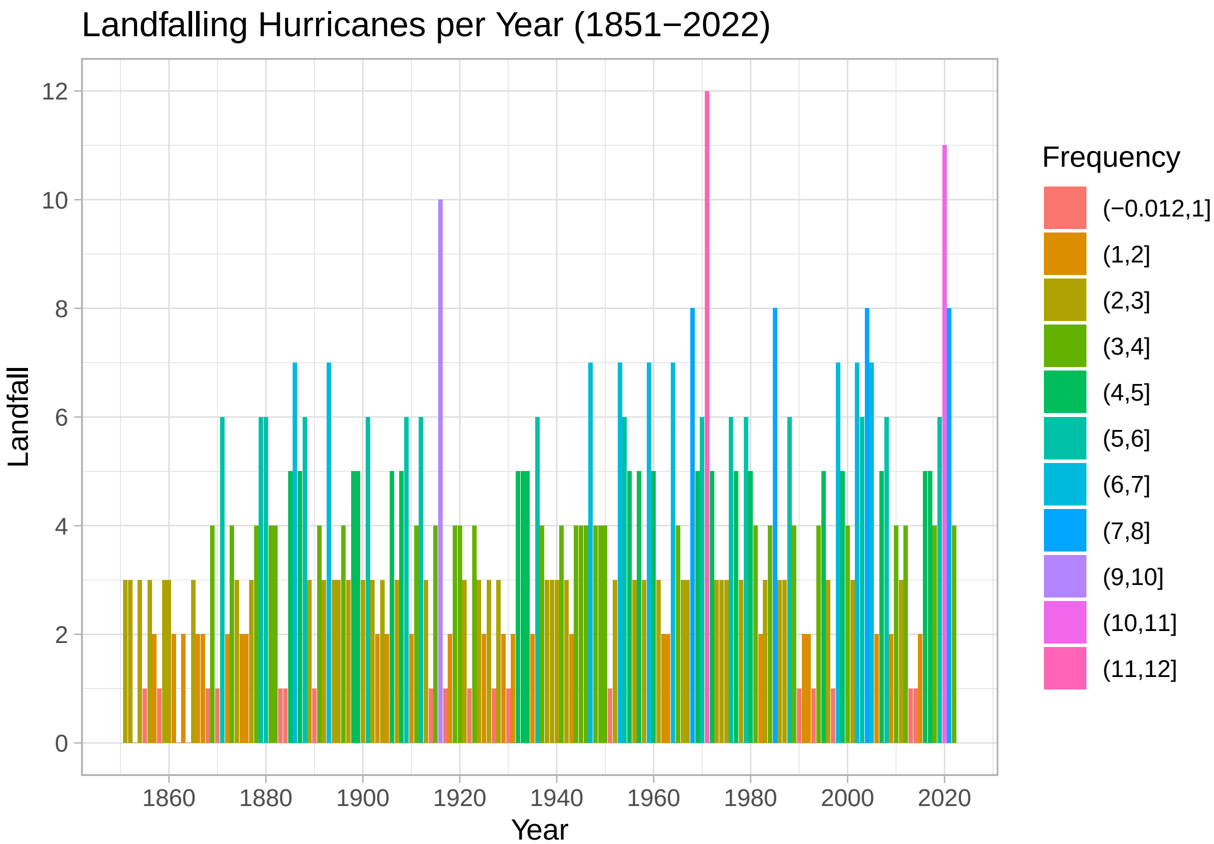
landfalling hurricane frequency over the years

With the intent of determining if the number of landfalling hurricanes is increasing over time, the landfall function is quite valuable. To begin, we use the landfall function to determine the number of landfalling hurricanes each year using the storm.info data frame previously built.

```
# gather range of years available in hurdat dataset
storm.year.range <- range(hurdat$date.time)
storm.years <- seq( 1851, 2022, by=1)

# construct data frame for landfall data
landfall.dat <- data.frame( year = storm.years )
for( i in 1:nrow(landfall.dat ) ){
  tmp.dat <- storm.info[ grepl( landfall.dat$year[i], storm.info$id), ]
  landfall.dat$freq[i] <- sum( tmp.dat$landfall )
  landfall.dat$total.storms[i] <- nrow( tmp.dat )
  landfall.dat$rate[i] <- landfall.dat$freq[i] / landfall.dat$total.storms[i]
}
```

With the landfall data at our disposal, we use a histogram to observe the number of landfalling hurricanes per year. The plot presents the frequency of hurricane landfalls from 1851 to 2022, with a range of zero to twelve occurrences. This histogram displays a higher frequency of landfalls concentrated in the later years indicating a reasonable argument that the number of landfalls per year is increasing.

```
landfall.hist <- ggplot(data=landfall.dat ) +
  geom_col(aes(x=year, y=freq, fill=cut(freq, 12))) +
  labs(x="Year", y="Landfall",
       title="Landfalling Hurricanes per Year (1851-2022)", fill="Frequency") +
  theme_light() +
  scale_y_continuous(n.breaks=7) + scale_x_continuous(n.breaks = 10)
landfall.hist
```



To further investigate if the number of landfalling hurricanes is increasing over time, poisson regression is used to model landfall frequency on year. The following summary reveals an intercept estimate of -4.9510224 and a year estimate of 0.0032334 along with a significance level of 0.00143 and 5.14e-05, respectively. This gives us the model: $\ln(\mu) = -4.9510224 + 0.0032334 * year$ where μ is the expected number of landfalls.

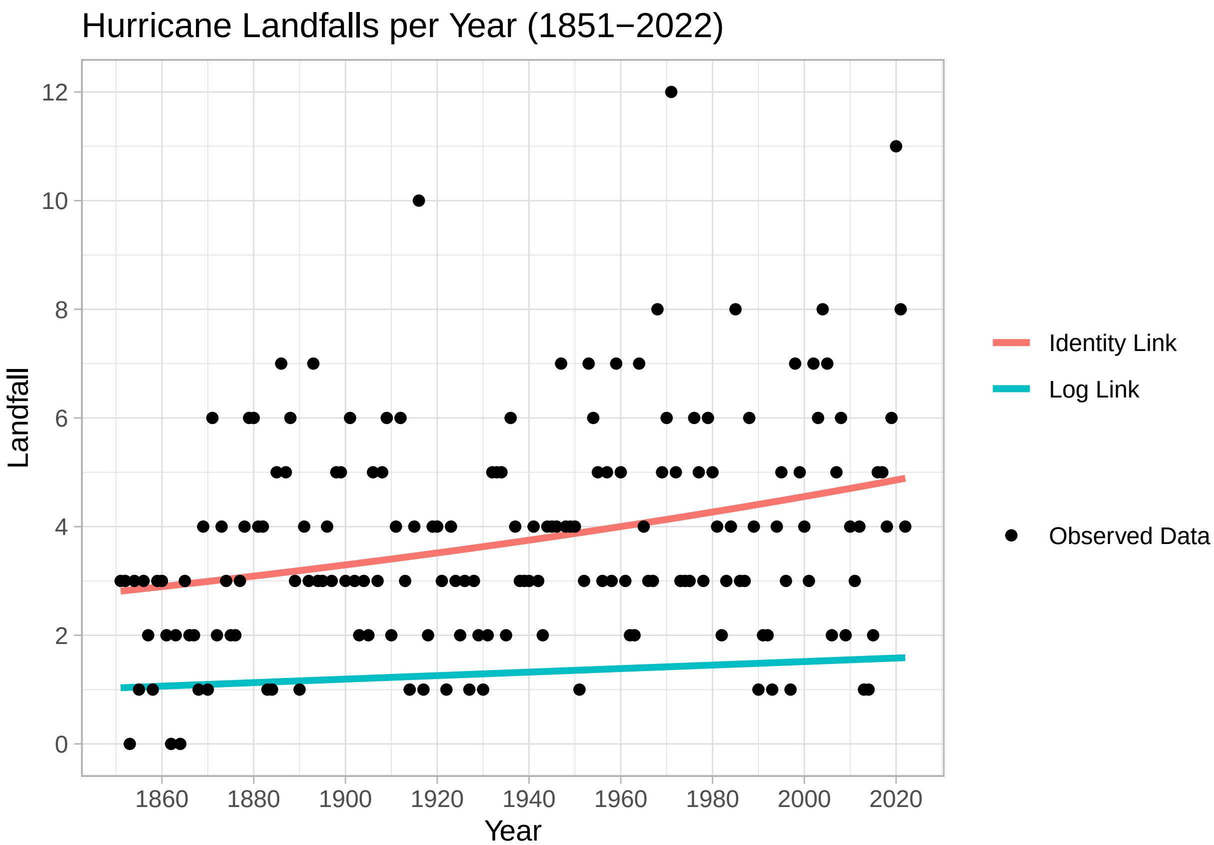
```
landfall.mod <- glm( freq ~ year, data=landfall.dat, family=poisson)
summary(landfall.mod)
```

```
##
## Call:
## glm(formula = freq ~ year, family = poisson, data = landfall.dat)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4220  -0.6724  -0.1334   0.5093   3.1306
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -4.9510224  1.5531736  -3.188  0.00143 **
## year         0.0032334  0.0007985   4.049 5.14e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 194.47  on 171  degrees of freedom
## Residual deviance: 177.95  on 170  degrees of freedom
## AIC: 704.29
```

```
##
## Number of Fisher Scoring iterations: 4
```

This model shows an increasing trend in landfalling hurricanes per year as exhibited by the log-link and identity functions. The log link function is identified as $\ln(\mu) = -4.9510224 + 0.0032334 * year$ and the identity function is identified as $\mu = -4.9510224 + 0.0032334 * year$ where μ is the expected number of landfalling hurricanes.

```
ggplot( data=landfall.dat, aes(x=year, y=freq) ) +
  stat_function( aes(colour="Identity Link"), lwd=1.2,
                 fun=function(year) exp(-4.9510224 + 0.0032334*year ) ) +
  stat_function( aes(colour="Log Link"), lwd=1.2,
                 fun=function(year) -4.9510224 + 0.0032334*year ) +
  geom_point( aes(x=year, y=freq, fill="Observed Data")) +
  scale_y_continuous( n.breaks=8 ) + scale_x_continuous( n.breaks = 10 ) +
  theme_light() + labs( y="Landfall", x="Year",
                        title="Hurricane Landfalls per Year (1851-2022)",
                        color = "", fill="")
```



A confidence interval using the likelihood ratio method is constructed for year for further interpretation. The year estimate is exponentiated for easier interpretation. With an exponentiated confidence interval of (1.0017, 1.0048), a one year increase is associated with an expected increase in landfalls of 0.17% to 0.48%. Furthermore, a 25 year increase is associated with an expected increase in landfalls of 4.3% to 12.8%.

```
CI <- confint( landfall.mod )
```

```
## Waiting for profiling to be done...
```

```
exp( CI[2, ] )
```

```
##    2.5 %   97.5 %
## 1.001673 1.004814
```

```
exp( 25 * CI[2, ] )
```

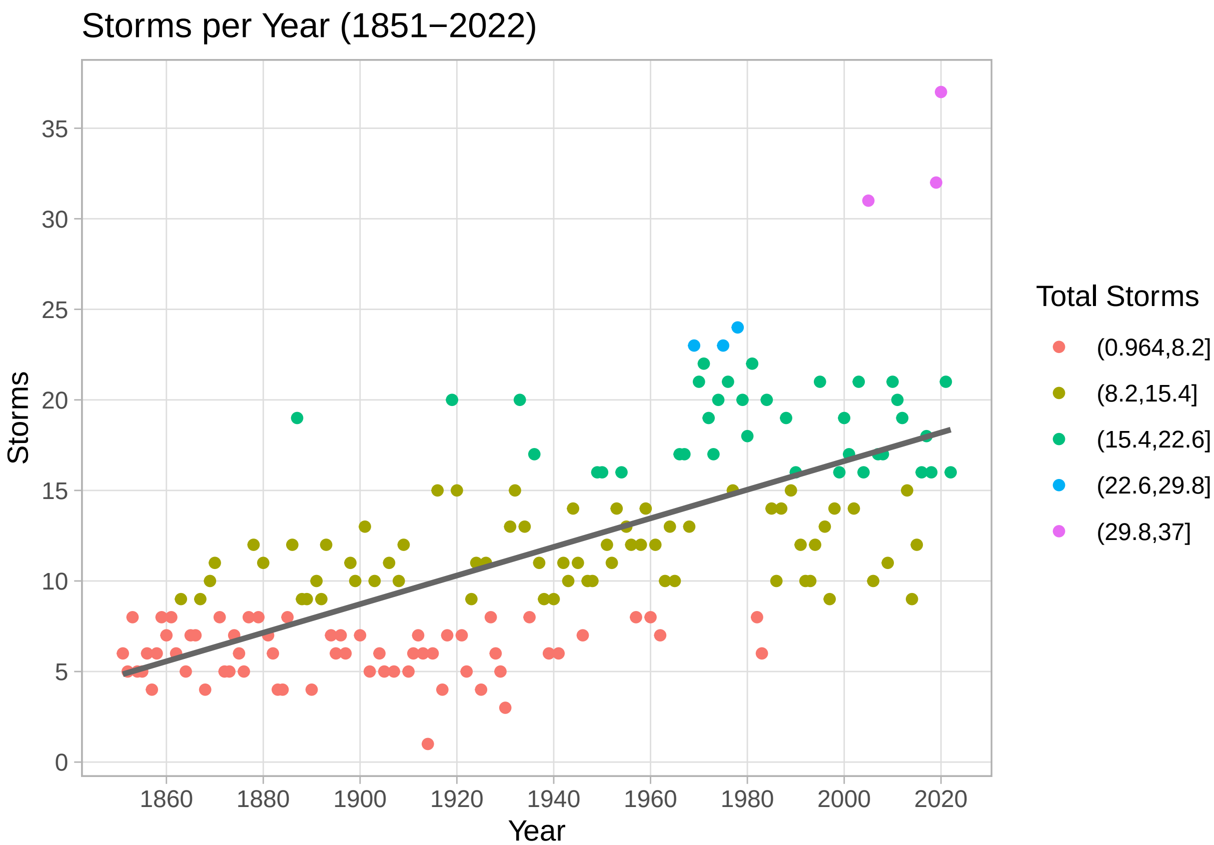
```
##    2.5 %   97.5 %
## 1.042678 1.127577
```

Based off this analysis, we conclude that the number of landfalling hurricanes is increasing per year.

A brief investigation was conducted to understand why this is happening, and the total number of storms per year was plotted. The following plot shows a fairly significant increase per year which would make sense of this increasing landfall.

```
ggplot( data=landfall.dat ) +
  geom_point( aes(x=year, y=total.storms, color=cut(total.storms, 5)) ) +
  geom_smooth(aes(x=year, y=total.storms),
            method=lm, se=FALSE, group=1, colour="grey40", alpha=0.1) +
  labs(x="Year", y="Storms",
       title="Storms per Year (1851-2022)", color="Total Storms") +
  scale_y_continuous(n.breaks=7) + scale_x_continuous(n.breaks=10) +
  theme_light() + theme(panel.grid.minor = element_blank())
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



Other factors contributing to this growing amount of landfalling hurricanes could be climate change, improved technology, population growth and urbanization, and natural climate variability. Unfortunately, they can not be analyzed due to the limitations of the information within the hurdat data set.

Intensity of tropical cyclones

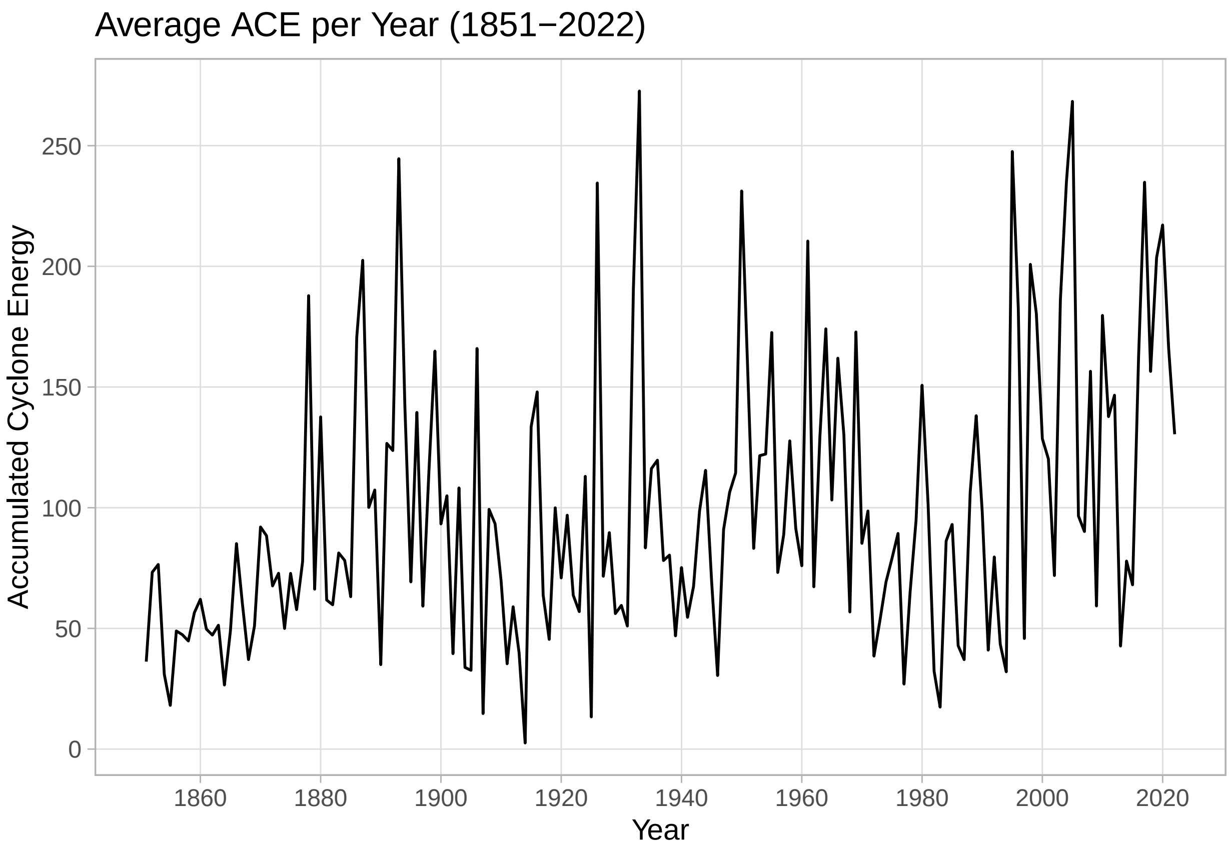
understanding the behavior of tropical cyclones across time

The cyclone_energy function is a valuable tool for determining if the intensity of cyclones is increasing over time. To understand if the intensity is increasing, we look at the total accumulated cyclone energy generated from every storm each year. The storm.info dataframe offers the accumulated cyclone energy for each storm, which can be used to find the total accumulated cyclone energy per year. It is worth noting that the ACE calculated by the cyclone_energy function is based on storm measurements taken every six hours for storms with a maximum wind speed greater than 35.

```
# gather range of years available in hurdat dataset
storm.year.range <- range(hurdat$date.time)
storm.years <- seq( 1851, 2022, by=1)

# construct data frame for ACE data
cyclone.dat <- data.frame( year = storm.years )
for( i in 1:nrow( cyclone.dat ) ){
  tmp.dat <- storm.info[ grepl( cyclone.dat$year[i], storm.info$id), ]
  cyclone.dat$ace[i] <- sum( tmp.dat$ace )
}
```

A line plot is used to visualize the total ACE per year. The total ACE ranges from 2 to 273 between 1851 to 2022 where one unit of ACE is equal to $10^{-4}kn^{-2}$. The data suggest a possible increasing trend.

```
ggplot(data=cyclone.dat ) +
  geom_path(aes(x=year, y=ace)) +
  labs(x="Year", y="Accumulated Cyclone Energy",
       title="Average ACE per Year (1851-2022)") +
  scale_y_continuous(n.breaks=7) + scale_x_continuous(n.breaks=10) +
  theme_light() + theme(panel.grid.minor = element_blank())
```



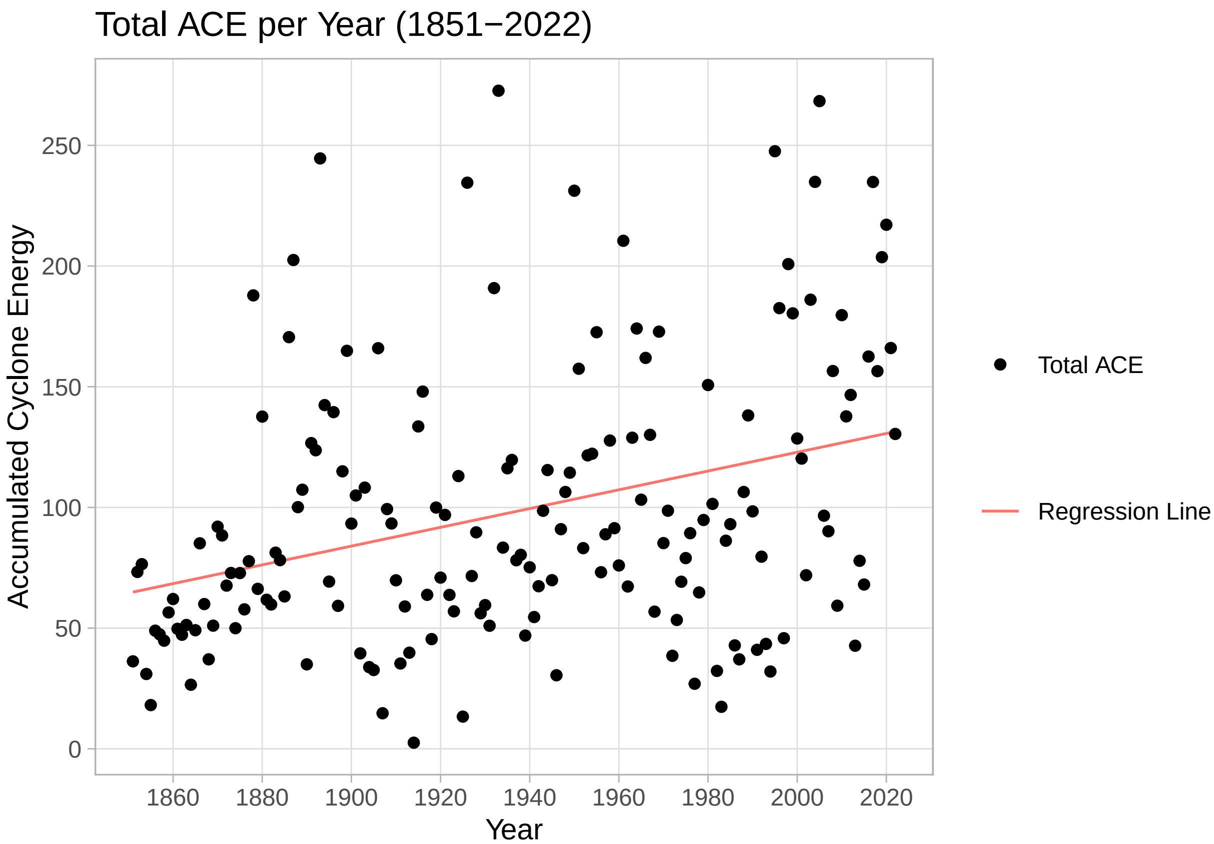
Linear regression is used to model the total ACE on year to further examine this increasing relationship. The following summary displays an intercept estimate of -654.78611 and a year estimate of 0.38882 along with a significance level of 6.73e-05 and 5.32e-06, respectively. This produces the model: $Y_i = -654.78611 + 0.38882 * year$ where Y_i is the average ACE.

```
cyclone.mod <- lm( ace ~ year, data=cyclone.dat )
summary(cyclone.mod)
```

```
##
## Call:
## lm(formula = ace ~ year, data = cyclone.dat)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -98.84 -34.20 -12.27  21.32 175.84
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -654.78611  160.21370  -4.087 6.73e-05 ***
## year           0.38882    0.08271   4.701 5.32e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 53.86 on 170 degrees of freedom
## Multiple R-squared:  0.115,  Adjusted R-squared:  0.1098
## F-statistic:  22.1 on 1 and 170 DF,  p-value: 5.322e-06
```

The linear regression line displays the increasing relationship between the total accumulated cyclone energy and year.

```
ggplot(data=cyclone.dat ) +
  stat_function( fun=function(year) -654.78611 + 0.38882*year,
                 aes(color="Regression Line") ) +
  geom_point(aes(x=year, y=ace, fill="Total ACE")) +
  scale_y_continuous(n.breaks=7) + scale_x_continuous(n.breaks=10) +
  theme_light() + theme(panel.grid.minor = element_blank()) +
  labs(x="Year", y="Accumulated Cyclone Energy",
       title="Total ACE per Year (1851-2022)",
       colour="", fill="")
```



A 95% confidence interval is constructed for year for further interpretation. The confidence interval suggests that every year, the total accumulated cyclone energy increase on average by 0.227 to 0.551. Furthermore, every 25 years, the average accumulated cyclone energy decreases on average by 5.67 to 13.77.

```
( CI <- c(0.38882 - 1.96*0.08271, 0.38882 + 1.96*0.08271) )
```

```
## [1] 0.2267084 0.5509316
```

```
( 25*CI )
```

```
## [1]  5.66771 13.77329
```

Based off this analysis, we conclude that the total accumulated cyclone energy is increasing each year.

Accumulated Cyclone Energy (ACE) is influenced by a variety of factors such as sea surface temperature, wind shear, humidity, and atmospheric instability. These factors can affect the intensity, duration, and frequency of tropical cyclones, all of which contribute to ACE. Additionally, climate change is thought to be contributing to the increase in ACE as warmer sea surface temperatures provide more energy to storms, leading to more intense and frequent tropical cyclones.

The Storm Media

media regarding the relationships between tropical cyclones and climate change

The Center for Climate and Energy Solutions claims that climate change is worsening hurricane impacts in the United States by increasing the intensity and decreasing the speed at which they travel. These trends are resulting in hurricanes being far more costly in terms of both physical damages and deaths. Hurricanes are subject to a number of climate change-related influences such as warmer sea surface temperatures, sea levels rising, changes in the atmosphere, and the warming of mid-latitudes that could be changing the pattern of tropical storms.

ChatGPT builds on this claim stating warmer sea surface temperatures provide more energy for these storms to grow and strengthen, leading to more frequent and intense storms. As sea levels continue to rise due to climate change, tropical cyclones are able to produce higher storm surges that can cause more extensive flooding in coastal areas. There is some evidence to suggest that climate change is affecting the paths that tropical cyclones take. Some studies have found that storms are moving more slowly and stalling in certain areas for longer periods, which can lead to more widespread and prolonged impacts from wind and flooding.

This claim is supported by the data we have analyzed. This can be seen in the plot above that shows Total Accumulated Cyclone Energy per year from 1851-2022 increasing over time. According to NOAA's 2021 Annual Climate Report, the combined land and ocean temperature has increased at an average rate of 0.14 degrees Fahrenheit per decade since 1880, and the average rate of increase since 1981 has been more than twice as fast: 0.32 °F per decade. Consistent with the previously made claim, this increased temperature/worsened climate change and increased ACE over time leads us to suspect correlation between the two.