An Analysis of Historical Storm Data

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Project Goals/Summary

- Core Hypothesis: Hurricanes and Tropical Storms have gotten stronger and more numerous in the last few decades.
- Utilize Atlantic Hurricane Database Data from the National Hurricane Center to study storm characteristics
  - https://www.nhc.noaa.gov/data/#hurdat
- Analysis Questions:
  - Have Hurricanes and Tropical Storms gotten stronger in the last 35 years? -Results mixed.
  - Have they gotten more numerous? -Results trend towards yes.
  - Do storms of greater strength last longer? -Results indicate yes.
  - What cities have the highest frequency of storms making landfall? -Havenlock, NC and Tallahasee, FL
  - Of those cities, which ones are near the largest storms? -Wilmington, NC
  - What part of hurricane season has the most storms? -Late August - September

Background Data Information

- Primary Characteristics of a Hurricane (measured every 6 hours):
  - Start/End Date - For storm duration and whether it occurred during Hurricane Season.
    - June-November
  - Maximum Sustained Wind Speed (knots-mph) - measured inside the eyewall, represents average over one minute. Used to determine storm category with Saffir-Simpson Scale.
    - Tropical Storm - 39-73 mph
    - Category 1 - 74-95 mph
    - Category 5 - >156 mph
  - Barometric Pressure (mbars) - measures atmospheric pressure inside the storm. The lower the pressure, the stronger the storm. Standard atmospheric pressure is 1013.25 mbars.
    - Category 1 - >980 mbars
    - Category 5 - <920 mbars
  - Location (Latitude/Longitude in degrees) - location of the center (eye) of the storm.
  - Landfall - indicates when the storm hit land. Use landfall location with CitiPy to get nearest city.

Data Acquisition Challenges

- Pulling data into a readable dataframe
  - Solved by manipulating it into a CSV file using VBS and adding column headers.
- CitiPy doesn’t accept latitude and longitude coordinates that include cardinal direction.
  - Solved by removing cardinal directions from data and using negative numbers to indicate W and S.

Data Cleanup & Exploration Challenges

- Data was organized with the storm ID and name as a header row before each storm's data. Solved by creating a loop that looked for header row as a variable and appended to a list with the rest of the storm's data.

```
AL092011,            IRENE,     39,
20110821, 0000,  , TS, 15.0N,  59.0W,  45, 1006,  105,    0,    0,   45,    0,    0,    0,    0,    0,    0,    0,    0,
20110821, 0600,  , TS, 16.0N,  60.6W,  45, 1006,  130,    0,    0,   80,    0,    0,    0,    0,    0,    0,    0,    0,
20110821, 1200,  , TS, 16.8N,  62.2W,  45, 1005,  130,    0,    0,   70,    0,    0,    0,    0,    0,    0,    0,    0,
20110821, 1800,  , TS, 17.5N,  63.7W,  50,  999,  130,   20,    0,   70,   30,    0,    0,    0,    0,    0,    0,    0,
20110822, 0000,  , TS, 17.9N,  65.0W,  60,  993,  130,   30,   30,   90,   30,    0,    0,   30,    0,    0,    0,    0,
20110822, 0600,  , HU, 18.2N,  65.9W,  65,  990,  130,   60,   60,   90,   40,   25,   20,   35,   25,    0,    0,    0,
20110822, 1200,  , HU, 18.9N,  67.0W,  70,  989,  160,   60,   60,   90,   40,   25,   20,   35,   25,    0,    0,    0,
20110822, 1800,  , HU, 19.3N,  68.0W,  75,  988,  160,   60,   40,   90,   40,   30,   20,   35,   25,    0,    0,    0,
20110823, 0000,  , HU, 19.7N,  68.8W,  80,  981,  160,   70,   50,  100,   70,   30,   30,   70,   25,    0,    0,   35,
20110823, 0600,  , HU, 20.1N,  69.7W,  80,  978,  180,  120,   90,  130,   90,   60,   40,   70,   45,   30,   20,   35,
20110823, 1200,  , HU, 20.4N,  70.6W,  80,  978,  180,  120,   90,  130,   90,   60,   40,   70,   40,   30,   20,   35,
```

Data Cleanup & Exploration Challenges

- Getting start and end date for entire storm while at least at Tropical Storm strength. Solved by creating dataframe with min date, max date, and duration. Merge new columns to original file.
- Get nearest city for storms that made landfall. Solved by creating dataframe to get only storms that reached landfall and used CitiPy API to get nearest city with new columns: Landfall lat, long, max wind speed, and nearest city. Merged to original dataframe.

```python
# Get min date (when storm became Tropical Storm) and Max Date (When storm is no longer a tropical storm)
# Calculate the duration

storm_gb = hurricane_df_clean.groupby('Storm_Id')
storm_sgb = storm_gb['Date']
start_date = storm_sgb.min()
end_date = storm_sgb.max()
duration = end_date - start_date
```

```python
#Merge Start Date, End Date, and Duration to original dataframe.
start_end_df = pd.DataFrame({"Start Date": start_date
                             ,"End Date": end_date
                             ,"Duration" : duration
                            }).reset_index()

merge_df = pd.merge(hurricane_df_clean, start_end_df, how="outer", on="Storm_Id")

merge_df.head(100)
```

Data Cleanup & Exploration Challenges

- Get all values from row with max wind speed for each storm. Solved by googling and finding idxmax() function to allow for this.

```
# Find row with max windspeed and return all columns in that row.
clean_storm_df =
storm_added_fields_df.iloc[storm_added_fields_df.reset_index().groupby(['Storm ID'])["Max Windspeed"].idxmax()]
clean_storm_df.head()
```

https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.idxmax.html

Data Visualization Challenges

- Original dataset was intended to only cover 15 years, but plots of storm variables showed no clear trends over that time period.
    - Solved by increasing it to 35 to make the trends clearer.
- When filtering the storms for category 3 or stronger, some years didn't have any of that strength. This caused them to disappear from the dataset.
    - Solved by first creating a data frame with counts grouped in years. Then adding a new column to said dataframe with the count of storms category 3 or stronger, using a .fillna(0) command on a dataframe containing all the years.

```
# Create df with counts to ensure no year is left behind
count_df = grouped.count()
# Count storms category 3 or stronger
over3_count = clean_storm_df[clean_storm_df['Category Value'] >= 3].groupby(['Year']).size()
# Add count over 3 to count data frame
count_df['Over 3'] = over3_count
# Replace NaN values with zeros
count_df = count_df.fillna(0)
```

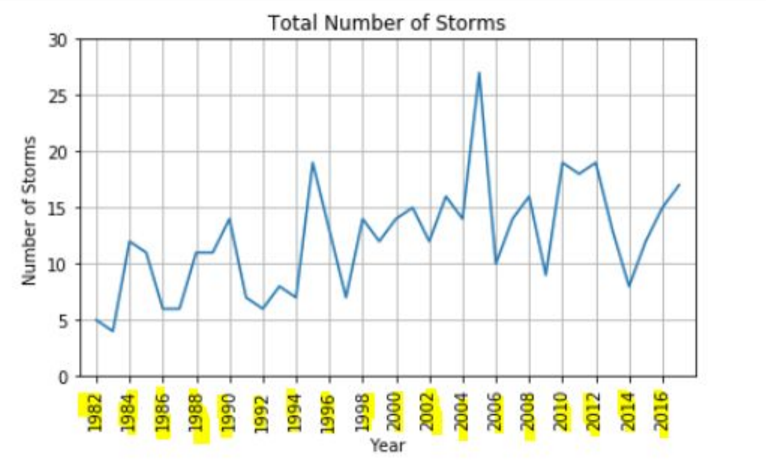
Data Visualization Challenges

- Couldn't filter storms by category using a >= conditional, since they were initially named with a string format
  - Solved by adding a new column to the data frame indicating category with an integer. This was achieved by binning.

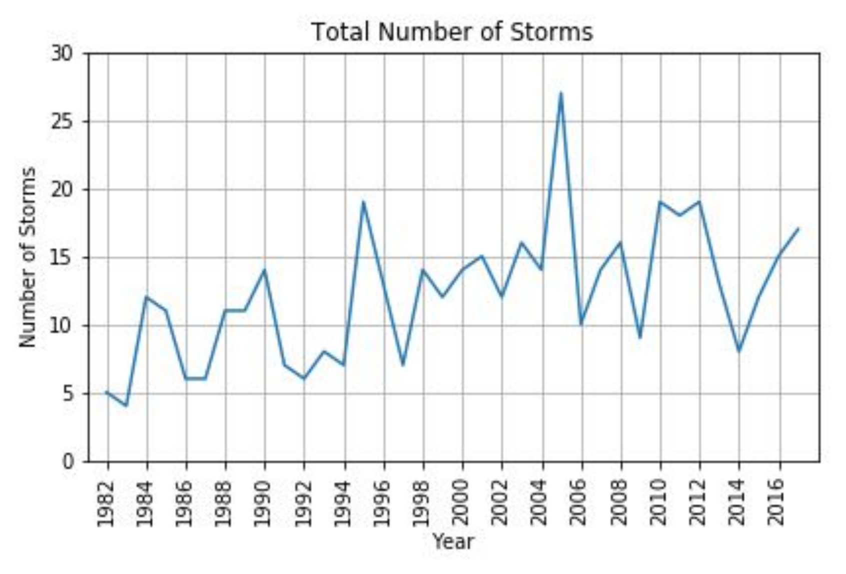
```
# Create Bins for each storm category according to https://en.wikipedia.org/wiki/Maximum_sustained_wind
min_wind = clean_storm_df["Max Windspeed"].min()
print(min_wind)
bins = [33, 63, 82, 95, 112, 136, 170]

# Create the names for the four bins
category_names = ['Tropical Storm', 'Category One', 'Category Two', 'Category Three', 'Category Four', 'Category Five']
category_values = [0,1, 2, 3, 4, 5]

# Create new category column
storm_category = pd.cut(clean_storm_df["Max Windspeed"], bins, labels=category_names)
category_value = pd.cut(clean_storm_df["Max Windspeed"], bins, labels=category_values)
```

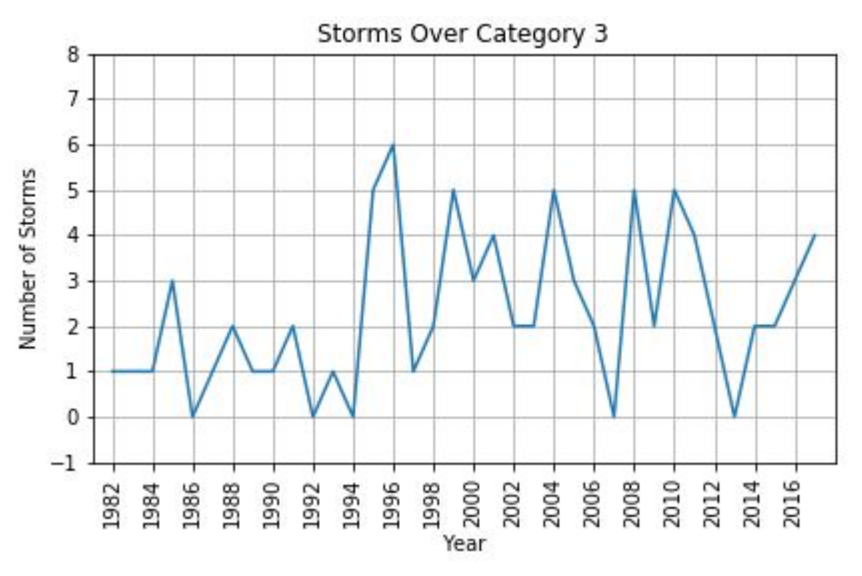
Data Visualization Challenges

- The graph tick labels for years were too crowded and hard to read.
  - Solved by: Setting up the tick labels to only show every two years and making them vertical using the .xticks() command and lengthening the graph by using the .tight_layout() command.

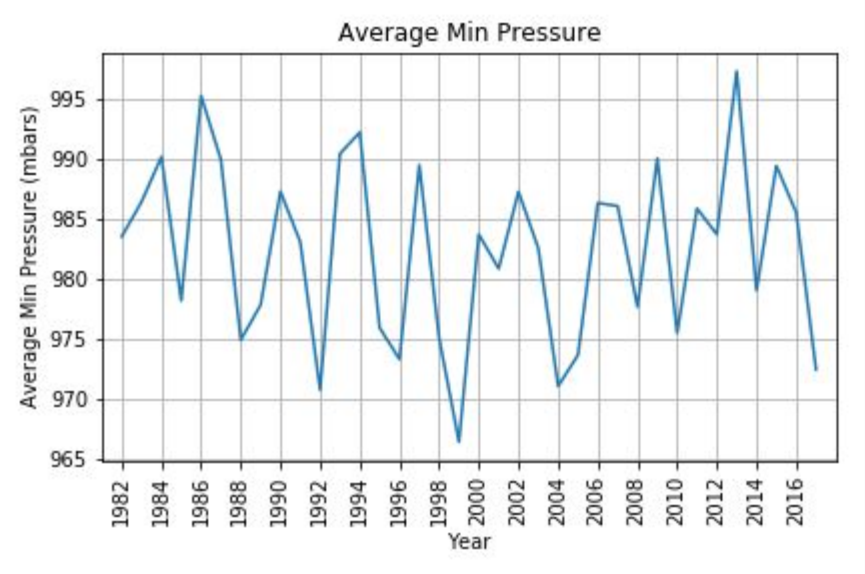


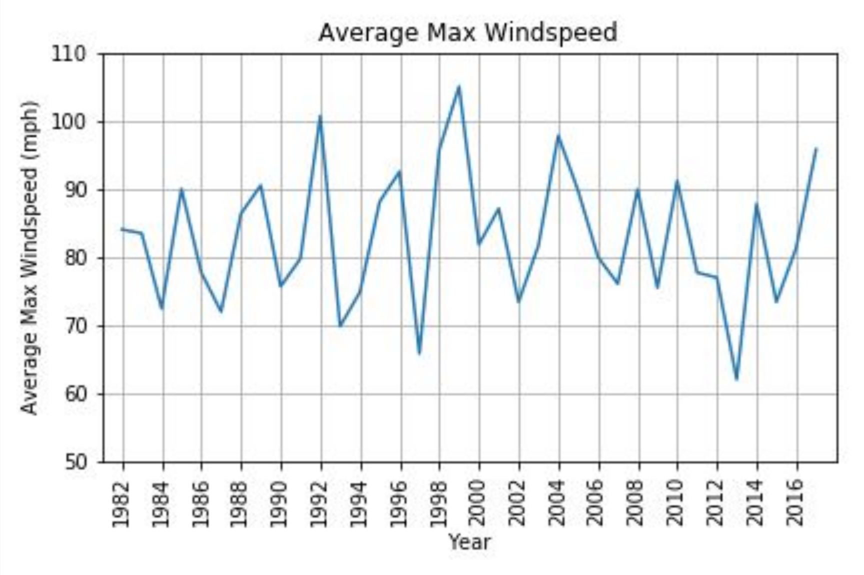
Storm Strength Analysis



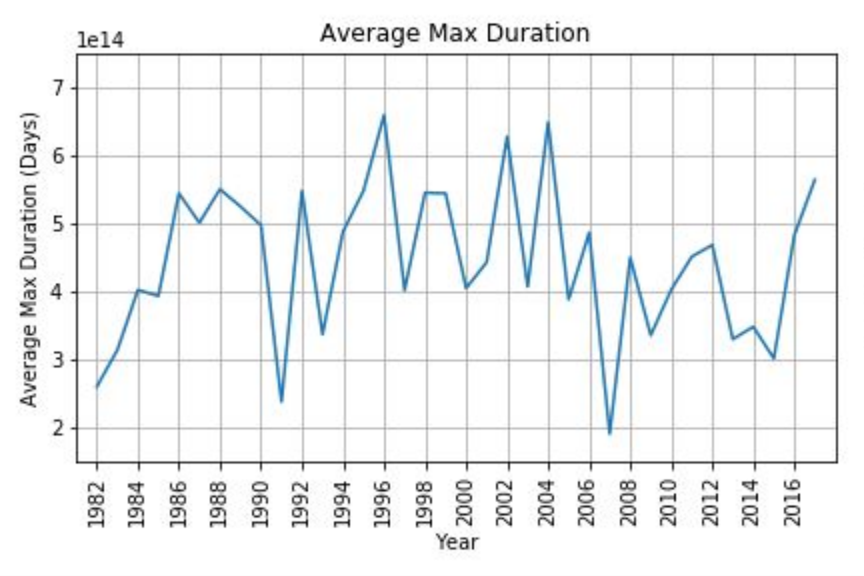


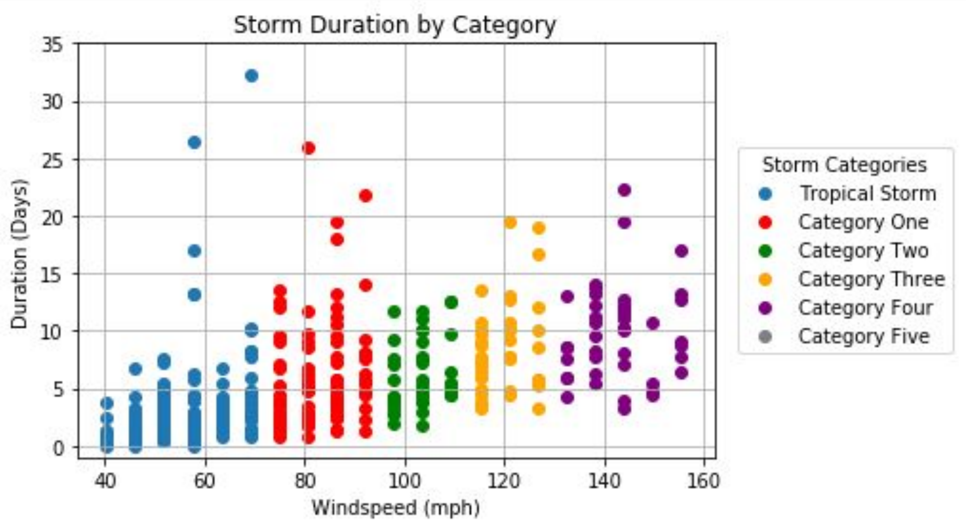
Storm Strength cont.



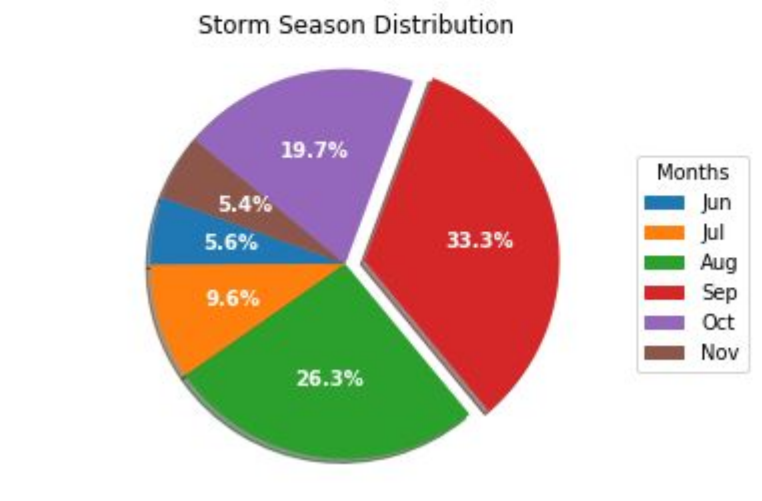


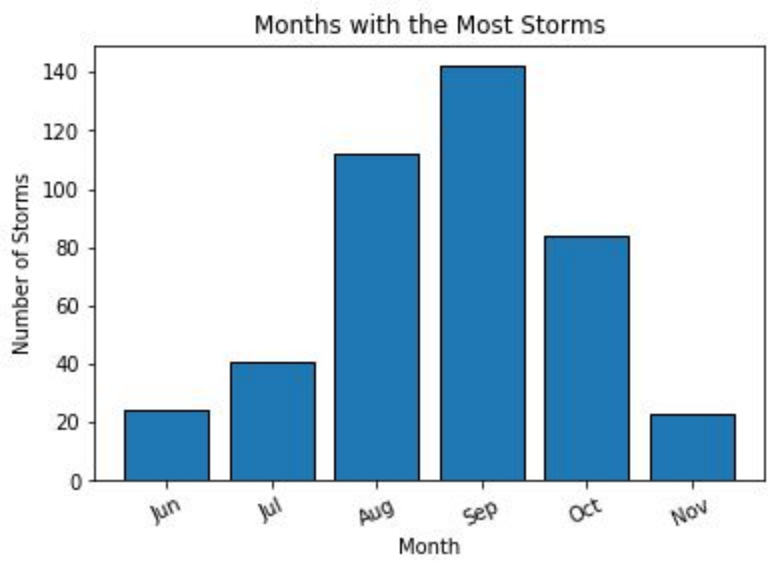
Storm Duration



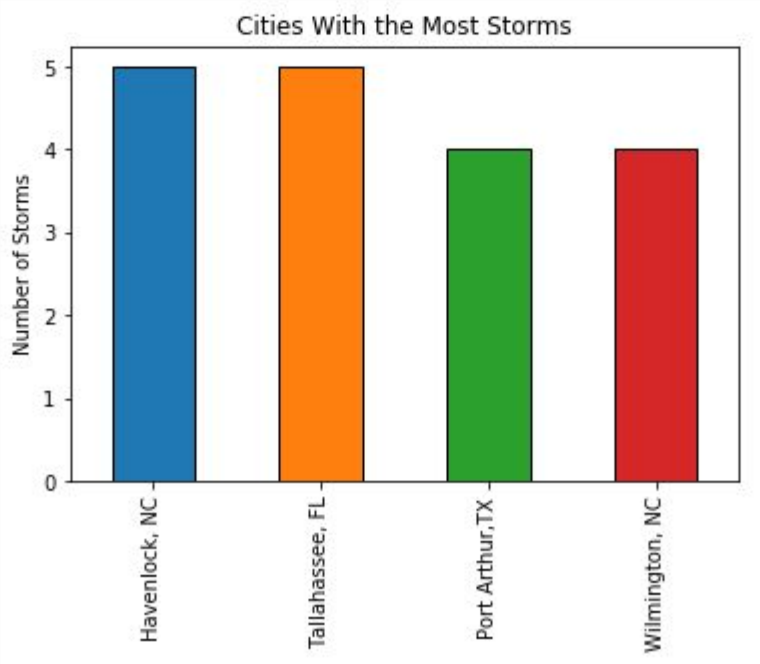


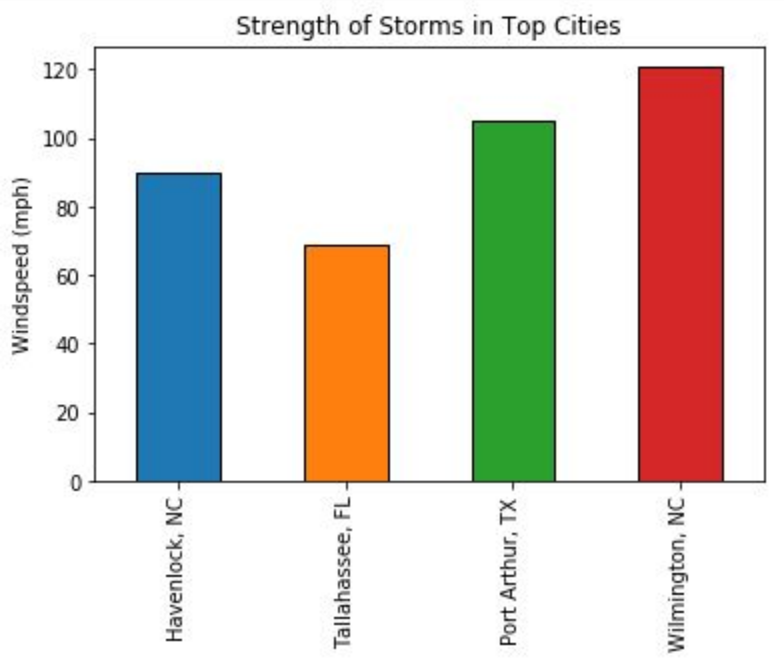
Hurricane Season





Most Storm-Prone Cities





Discussion

1. Storm Strength - number of storms clearly on the rise for all categories, major storms show a positive trend. Trends are not as clear with barometric pressure, though the tendency is for each periodic valley to have a lower minimum value. Max wind speed also has periodic peaks every few years that are increasing in maximum value. Each of the strength-related graphs ends with a trend towards stronger storms in 2017. Expected to see a clearer trend here.
2. Duration - Peak values of year vs. duration graph show increasing trend. Clear increase in minimum storm duration with category. No visible data for category 5.
3. Hurricane Season - September is clearly the most dangerous month with 33% of total storms, but August is a close second with 26.3%. This confirms what we already knew.
4. Hurricane Cities - North Carolina coastal cities (Wilmington, Havenlock) and Tallahassee Florida are the clear winners for number of nearby storms, but Port Arthur Texas is a close second in terms of highest average wind speed.

Post Mortem

- We would be interested to see this dataset over a much longer time period (i.e. 100 years) to get a better idea of the long term trends of storm strength. This would help answer our primary question more clearly.
- Creating a heat map of the most dangerous cities would more efficiently show our results.
- Our current search doesn't include small coastal towns, doing so would likely change our dangerous city results radically.
- Adding population and FEMA data on affected cities would also be useful to get a better idea on storm damage.

Q & A