

Tracking the Storm: Visualizing Trends in U.S. Hurricanes and Climate Impact

Adithya Singupati, Mohit Sai Tatineni, Rasaghna Kuturu, and Ruth Balaji

1. Abstract

Hurricanes are among the most impactful natural disasters, causing significant economic, environmental, and societal damage. With their frequency and intensity escalating due to climate change, understanding hurricane dynamics is crucial for improving preparedness and resilience. This study leverages decades of U.S. hurricane data to analyze key variables such as wind speed, pressure, spatial trajectories, and temporal patterns. Using advanced visualization techniques, including multivariate scatterplots, temporal gradients, and geospatial overlays, the research uncovers critical insights into storm behavior, such as wind asymmetries, pressure-intensity relationships, and spatial-temporal evolution. These findings contribute to a deeper understanding of hurricane dynamics, offering actionable insights for climate research, disaster management, and policy development.

2. Introduction

2.1. Motivation

Hurricanes are among the most destructive natural disasters, causing extensive damage through powerful winds, heavy rainfall, and storm surges. In the United States alone, hurricanes have resulted in over \$1 trillion in damages since 1980, displacing millions of people and overwhelming critical infrastructure (NOAA, 2022) [3]. Climate change has intensified these storms, with

Category 4 and 5 hurricanes—the most catastrophic—becoming 30% more frequent over the past 40 years (Kossin et al., 2020) [8].

Recent events exemplify the growing risks. In September 2024, Hurricane Helene, a Category 4 storm, devastated Florida's Big Bend region, causing catastrophic flooding that extended into western North Carolina. This event claimed 234 lives and caused damages exceeding \$89 billion. Shortly thereafter, Hurricane Milton struck Florida's west coast as a Category 5 storm, resulting in 35 fatalities and over \$85 billion in damages. These back-to-back disasters underscore the escalating threat and highlight the urgent need for a deeper understanding of hurricane dynamics.

As hurricanes grow in intensity and frequency, it is imperative to enhance our ability to analyze and communicate their impacts. Effective data analysis and clear visualizations are essential tools for protecting vulnerable communities, informing policymakers, and improving disaster preparedness strategies. This study leverages decades of hurricane data to explore trends in frequency, intensity, and geographic distribution, providing critical insights into hurricane behavior in an era of rapidly changing climate conditions.

2.2. Background

The coastal regions of the United States, particularly along the Gulf and Atlantic coasts, have long been vulnerable to hurricanes. With the growing influence of climate change, these storms are becoming more frequent and intense, posing significant challenges for researchers, policymakers, and disaster response teams. Recent studies (Knutson et al., 2019 [1]; Gray, 2005 [2]) highlight the role of human-induced climate change in intensifying tropical cyclones, with rising global temperatures contributing to the development of larger, more destructive hurricanes.

This project aims to analyze and map historical U.S. hurricane landfalls to identify patterns in frequency, intensity, and high-risk areas, particularly in the context of climate change. By examining a dataset containing details such as landfall dates, locations, wind speeds, and meteorological variables, the study seeks to uncover trends that are critical for disaster preparedness and risk mitigation. Understanding these patterns will provide vulnerable regions with actionable insights to enhance their capacity to respond to future storms.

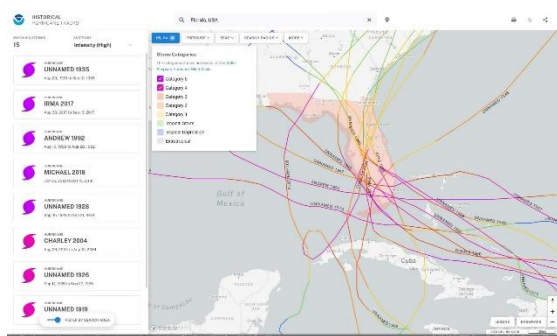


Figure 1: NOAA's *Historical Hurricane Tracks* map, offers an extensive dataset but is overwhelming due to the large volume of information present [3].

The motivation for this project stems from the increasing need to adapt disaster response strategies as hurricanes become more unpredictable. The project will explore how hurricane activity has changed in recent decades and how this information can be used to inform policymakers, disaster response teams, and affected communities. The insights gained from this analysis will be instrumental in shaping future disaster preparedness strategies. Existing visualizations, such as NOAA's Historical Hurricane Tracks map (Figure 1), provide comprehensive data but are often cluttered and difficult to interpret due to the sheer volume of information.



Figure 2: The Washington Post's Mapping Every U.S. Hurricane, which simplifies hurricane path data, but lacks interactivity and depth for more detailed exploration of trends [4].

A more refined approach, like The Washington Post's Mapping Every U.S. Hurricane (Figure 2), presents a simplified overview of storm paths but lacks interactivity and depth. Similarly, FiveThirtyEight's The Rising Costs of Hurricanes focuses on the financial toll of storms but doesn't address meteorological trends.

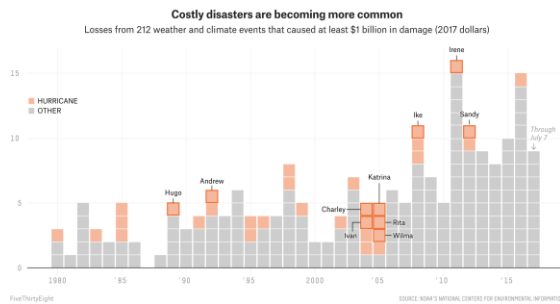


Figure 3: FiveThirtyEight's The Rising Costs of Hurricanes graph, which highlights economic impacts but doesn't offer a deeper analysis of storm characteristics or climate change implications [5].

2.3. Objective

This project aims to provide a comprehensive analysis of hurricane dynamics by leveraging advanced visualization techniques to uncover patterns in frequency, intensity, geographic distribution, and storm lifespans. By integrating time-series analyses, geospatial distributions, and multivariate relationships, the study offers a multidimensional exploration of hurricane behavior under changing climatic conditions.

The visualizations developed in this project, including correlations between wind speed and minimum pressure, seasonal activity trends, and geospatial landfall patterns, reveal nuanced insights into hurricane dynamics. Time-series decomposition highlights long-term trends alongside seasonal variations, while cluster analyses uncover relationships between storm paths and lifespans, addressing gaps overlooked by simpler analyses.

The findings have practical implications for climate research and disaster preparedness, offering actionable insights for identifying high-risk areas and understanding the increasing intensity of hurricanes. By synthesizing complex datasets into clear,

interactive visualizations, this project bridges gaps in existing tools and contributes to a deeper understanding of hurricane behavior and its connection to climate change.

3. Dataset and Analysis

3.1. Analysis of Data

The dataset used in this project is a comprehensive tabular resource, spanning the years 1851 to 2015, with 49,105 entries across 22 columns [7]. It contains both numerical and categorical data related to historical hurricanes in the United States, making it ideal for analyzing long-term trends and patterns in hurricane activity. Key features of the dataset include:

- Unique Identifiers:**
Each hurricane is represented by a unique ID for tracking.
- Temporal Data:**
Detailed event dates and times for accurate chronological analysis.
- Geospatial Coordinates:**
Latitude and longitude data to map hurricane trajectories and landfalls.
- Meteorological Variables:**
Maximum wind speed, Minimum pressure and Wind measurements at varying intensities (low, moderate, and high) across different quadrants (northeast, southeast, southwest, northwest).

The dataset's detailed structure allows for a thorough analysis of hurricane frequency, intensity, geographic distribution, and lifespans. Its richness supports the project's

objectives of uncovering long-term trends and providing actionable insights for disaster preparedness and climate research.

ID	Year	Month	Day	Lat	Long	Pressure	Wind	Temp	Humidity	Clouds	Rain	Storm	Intensity	Category	Damage	Deaths	Injuries	Evacuated	Sheltered	Relief	Recovery	Notes
1	1950	1	1	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
2	1950	1	2	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
3	1950	1	3	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
4	1950	1	4	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
5	1950	1	5	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
6	1950	1	6	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
7	1950	1	7	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
8	1950	1	8	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
9	1950	1	9	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
10	1950	1	10	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
11	1950	1	11	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
12	1950	1	12	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
13	1950	2	1	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
14	1950	2	2	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
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16	1950	2	4	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
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18	1950	2	6	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
19	1950	2	7	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
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29	1950	3	5	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
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31	1950	3	7	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
32	1950	3	8	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
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34	1950	3	10	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
35	1950	3	11	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
36	1950	3	12	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
37	1950	4	1	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
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75	1950	7	3	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
76	1950	7	4	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
77	1950	7	5	28.5	-80.5	1013	15	25.0	75	50	0.0	0	1	1	0	0	0	0	0	0	0	
78	1950	7	6	28.5	-80.5	1013																

Since 1950 Atlantic hurricanes making landfall in the US have been increasing

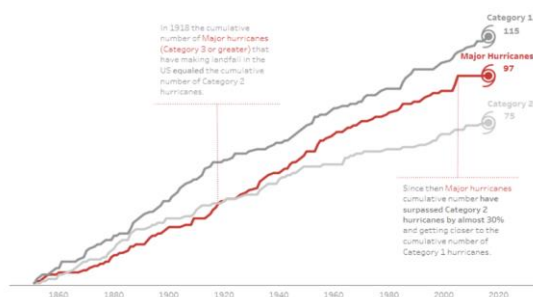


Figure 5: Time-Series Plot.

2. Geospatial Visualizations

Geospatial techniques, such as heatmaps and trajectory maps, were used to map hurricane paths, density, and regional hotspots. Heatmaps effectively highlighted areas of frequent hurricane activity, while trajectory maps illustrated storm paths. However, static visuals were found to lack interactivity and clarity in dense regions. To overcome these challenges, interactive heatmaps with temporal sliders were chosen, offering dynamic exploration of spatial data while maintaining visual clarity.

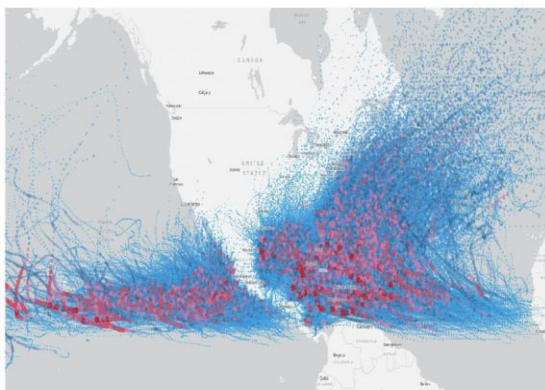


Figure 6: Geospatial Visualization [13].

3. Scatterplots and Pairplots

Scatterplots and pairplots were used to investigate relationships between variables like wind speed, pressure, and storm categories. Scatterplots, enhanced with transparency and color-coded variables, effectively captured key correlations and

multivariate interactions. Pairplots, though useful for smaller datasets, suffered from overplotting and clutter when applied to dense data. Consequently, they were selectively applied to smaller subsets to ensure interpretability.

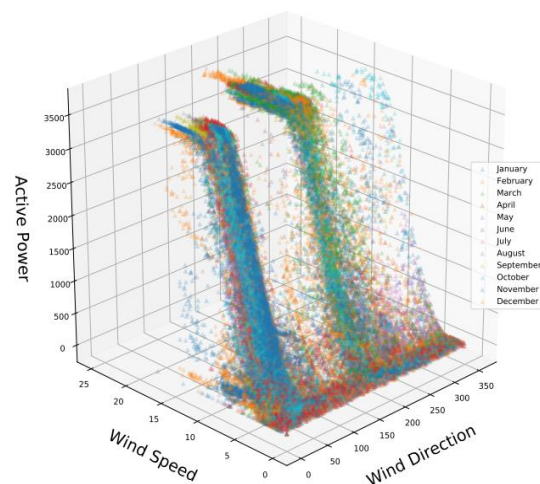


Figure 7: Scatter Plot

4. Boxplots and KDE Plots

Boxplots and KDE plots were used to visualize seasonal variations and intensity distributions. Boxplots highlighted monthly patterns of hurricane activity, particularly during peak months, while KDE plots showcased the rarity of extreme storms through smoothed probability distributions. Though less effective for long-term trends, these plots provided valuable insights into seasonal and distributional characteristics of hurricanes.

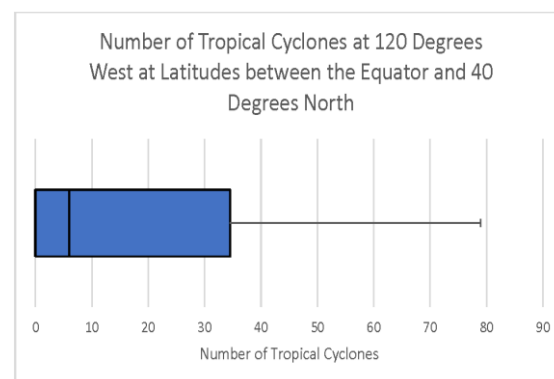


Figure 8: Box Plot [11].

5. Cluster Analysis

Cluster analysis was applied to group hurricanes based on their paths and behaviors. Using cluster graphs with labeled groupings, distinct spatial clusters were identified, revealing patterns in storm origins and trajectories. Despite challenges in interpreting cluster boundaries without geographic overlays, this method effectively highlighted high-risk regions and unique storm behaviors, offering actionable insights for spatial analysis.

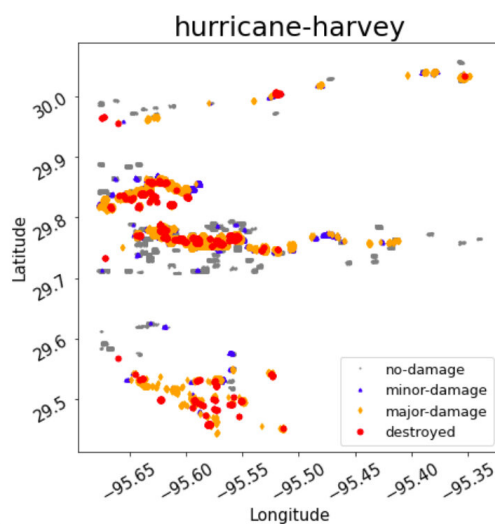


Figure 9: Cluster Analysis [12].

3.3. Failed Experiments

Several visualization experiments did not yield meaningful results or presented challenges that required iterative refinements:

1. 3D Visualizations

3D scatterplots were initially tested to represent spatial hurricane data, aiming to add depth to the analysis. However, overlapping points and limited interactivity rendered these visualizations difficult to interpret. The complexity of 3D representations often obscured insights rather than enhancing clarity. As a result, the focus shifted toward 2D geospatial

visualizations, which offered better interactivity and readability while preserving the spatial detail needed for analysis.

2. Overloaded Pairplots

Pairplots were utilized to explore multivariate relationships, including wind speed, pressure, and storm categories. However, early attempts included too many variables simultaneously, resulting in visually overwhelming and cluttered plots. This lack of clarity hindered effective pattern recognition. To address this, the approach was refined by selectively focusing on key variables and applying pairplots to smaller, targeted subsets of the data, improving their interpretability and analytical value.

4. Results and Insights

4.1. Visualizations & Insights

1. Temporal Trends in Hurricane Activity

1.1. Bar Chart of Hurricane Frequency by Year

The bar chart illustrates the frequency of hurricanes over time, covering the period from 1851 to 2015. In the early years of the dataset, hurricane occurrences were relatively low, reflecting either fewer storms or limitations in observation and reporting methods during that era.

As the timeline progresses into the latter half of the 19th century, hurricane activity shows a steady increase. This upward trend likely reflects improvements in storm detection and documentation alongside changes in climatic conditions.

The data reveals noticeable fluctuations, with periodic spikes in hurricane activity during certain years. These variations suggest the influence of natural climatic cycles or anomalies, such as El Niño and La Niña events, which can affect the frequency and intensity of storms.

Over the entire observed period, the frequency of hurricanes demonstrates a general upward trend, culminating in a peak in recent decades. This pattern may be attributed to a combination of factors, including global warming, improved detection technology, and heightened monitoring efforts in the modern era. These findings underscore the evolving nature of hurricane activity and highlight the importance of continuous monitoring and research to better understand long-term trends.

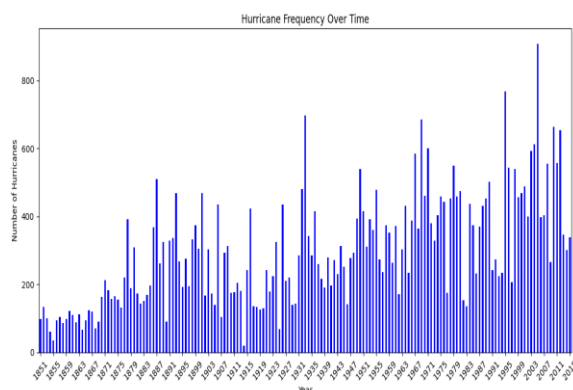


Figure 10: Bar Chart of Hurricane Frequency by Year.

1.2. Line Plot of Maximum Wind Speeds Over Time

The line plot depicts trends in maximum wind speeds from 1850 to the early 2000s, showcasing the variability and evolution of hurricane intensity over time. In the earlier years, wind speeds display considerable fluctuations without a clear or consistent pattern, reflecting the natural variability of

storms and potential limitations in historical data collection.

As the timeline progresses, particularly from the mid-20th century onwards, there is a noticeable upward trend in maximum wind speeds. This gradual increase may be indicative of stronger hurricanes forming over time, possibly driven by factors such as warming ocean temperatures and changing atmospheric conditions. Alternatively, it may reflect advancements in measurement techniques and improved accuracy in recording wind speeds.

Peaks in wind speed become more pronounced in recent decades, highlighting the emergence of more intense storms. This trend could signify a shift toward higher-intensity hurricanes, consistent with the growing impact of global climate change on extreme weather events.

Despite the overall upward trend, the data remains highly variable, with both exceptionally high and low wind speeds occurring unpredictably throughout the period. This variability underscores the complex interplay of factors influencing hurricane intensity and highlights the need for continued research into the drivers of these changes.

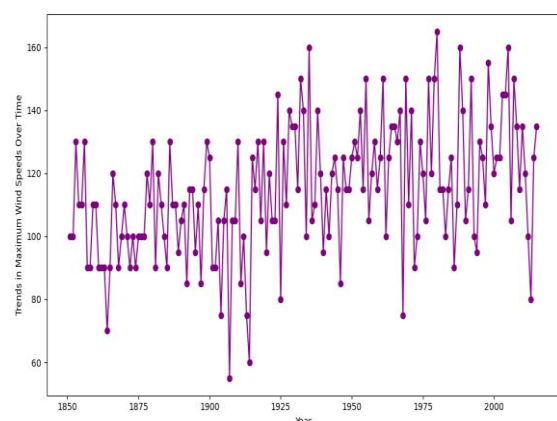


Figure 11: Line Plot of Maximum Wind Speeds Over Time.

1.3. Bar Chart of Analyzing the distribution of wind speed for 2005

The hurricane data from 2005 (the year with highest occurrence of hurricanes) reveals that the majority of storms during the year exhibited wind speeds in the 20-40 knot range, indicating that most hurricanes were of relatively low intensity. This suggests that weaker hurricanes were more common than stronger ones in this period.

The distribution of hurricane wind speeds is notably right-skewed, with fewer occurrences at higher wind speeds. This pattern highlights the relative rarity of strong hurricanes, emphasizing that extreme weather events with high wind speeds were infrequent compared to their less intense counterparts.

Notably, the 20-40 knot range accounted for the highest frequency of hurricanes, with over 250 storms falling into this category. This underscores the dominance of low-intensity hurricanes during 2005. However, a small subset of hurricanes registered wind speeds exceeding 100 knots. These storms, though fewer in number, represent the most powerful and potentially devastating events of the year, posing significant risks to affected regions.

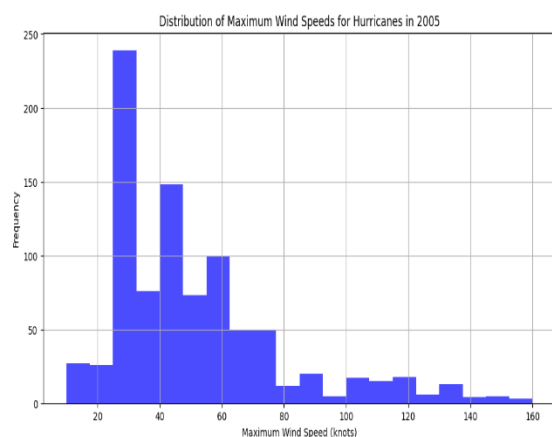


Figure 12: Bar chart of analyzing the distribution of wind speed for 2005.

1.4. Bar Chart of Hurricane Frequency by Decade

The bar chart illustrates the frequency of hurricanes by decade, revealing a distinct upward trend in hurricane activity from the mid-19th century through the mid-20th century. This steady increase reflects the growth in recorded storm events, likely influenced by improvements in storm detection and reporting technologies during this period.

The frequency of hurricanes continues to rise, peaking in the 2000s, which represents the decade with the highest recorded activity. This peak underscores a period of heightened hurricane occurrence, possibly driven by favorable climate patterns or improved monitoring capabilities.

Following this peak, there is a gradual decline in hurricane frequency in subsequent decades. The noticeable decrease may be attributed to a combination of factors, such as shifts in climate dynamics, enhanced early warning systems that detect and track hurricanes earlier, and potential changes in data collection and reporting methodologies.

The overall trend highlights a significant increase in hurricane activity through the 20th century, culminating in a peak in the 2000s, followed by a slight decline in more recent decades. This pattern emphasizes the evolving nature of hurricane activity and the role of technological and environmental factors in shaping our understanding of storm trends over time.

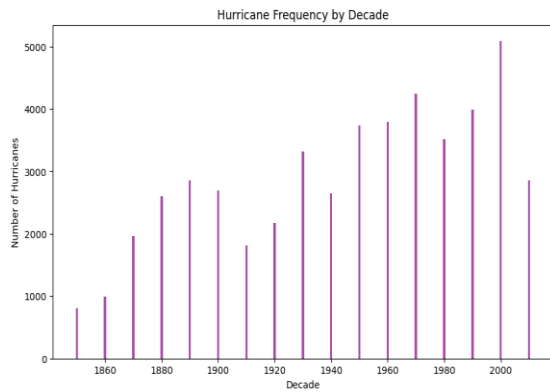


Figure 13: Bar Chart of Hurricane Frequency by Decade.

1.5. Line Plot of Relationship Between Minimum Pressure and Number of Hurricanes

The line plot illustrates the relationship between minimum pressure (in hPa) and the number of hurricanes, revealing key insights into the distribution and intensity of storms. The plot shows that hurricanes are most frequent at pressures around 1000 hPa, with the count peaking sharply near this value. This suggests that moderate-intensity storms are the most common.

As minimum pressure decreases below 1000 hPa, the number of hurricanes gradually declines. This reflects the relative rarity of storms with extremely low pressures, which are typically the most intense hurricanes. These low-pressure systems are less frequent but often associated with greater destructive potential.

Similarly, as pressure increases above 1000 hPa, the frequency of hurricanes also diminishes. This trend highlights the scarcity of weaker storms or tropical depressions within the dataset, suggesting that storms with higher minimum pressures are less likely to develop or be recorded as hurricanes.

Overall, the pattern emphasizes a strong correlation between lower pressure and

storm intensity, with most hurricanes clustering around moderate pressure levels. This distribution provides valuable insights into the typical pressure ranges associated with hurricanes and underscores the critical role of pressure in defining storm strength and frequency.

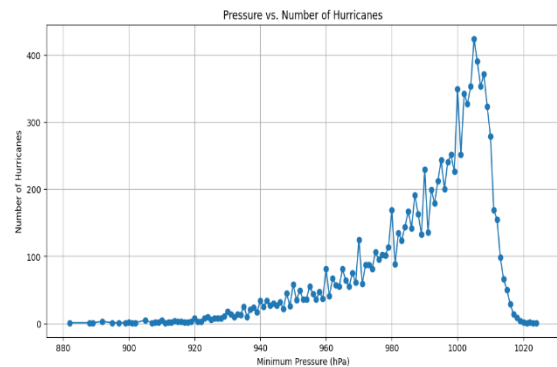


Figure 14: Line Plot of Relationship Between Minimum Pressure and Number of Hurricanes.

2. Seasonal Patterns

2.1. Bar Chart of Hurricane Frequency by Month

The bar chart illustrating hurricane frequency by month highlights a well-defined seasonal pattern in storm activity. From January through May, hurricane occurrences are minimal, reflecting the off-season for Atlantic hurricanes when atmospheric and oceanic conditions are less favorable for storm development.

Hurricane activity begins to rise gradually in June, signalling the onset of the official hurricane season. This increase accelerates during the summer months, peaking sharply in August and September. These two months stand out as the most active period for hurricanes, driven by optimal conditions such as warm sea surface temperatures and conducive atmospheric dynamics that fuel storm formation and intensification.

Following this peak, hurricane activity declines in October as seasonal conditions

become less supportive of storm development. By November and December, the frequency of hurricanes tapers off significantly, marking the transition into the off-season.

This observed pattern aligns closely with the typical Atlantic hurricane season, characterized by the highest storm activity in late summer and early fall. The data underscores the influence of seasonal environmental factors on hurricane formation and highlights the critical need for preparedness during the peak months of August and September.

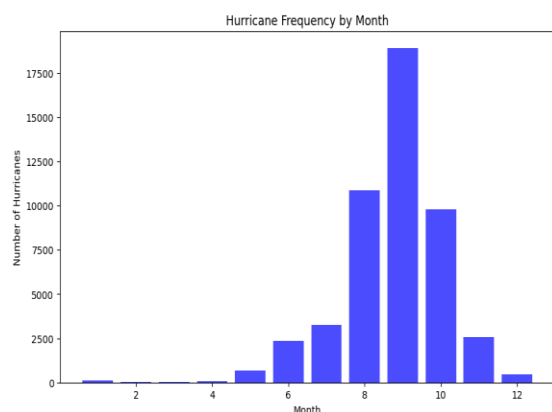


Figure 15: Bar Chart of Hurricane Frequency by Month.

2.2. Bar Chart of Wind Speed Distribution for Hurricanes in September

The analysis of hurricane activity in September reveals that the majority of storms during this month had maximum wind speeds between 20-60 knots. This indicates that most hurricanes were weaker tropical storms or low-intensity hurricanes, contributing to a larger proportion of less severe weather events during the peak of hurricane season.

A significant number of hurricanes were observed with wind speeds in the 60-100 knot range. These storms represent more

intense hurricanes, indicating an increased likelihood of stronger weather systems occurring alongside the majority of weaker storms.

Additionally, a small subset of hurricanes in September recorded wind speeds exceeding 100 knots. These storms were the most powerful and potentially destructive, highlighting the risk of extreme weather events even within the context of a month dominated by less severe storms.

The overall distribution of wind speeds is right-skewed, with the majority of hurricanes at lower intensity levels and a smaller number achieving significantly higher wind speeds. This pattern underscores the variability in hurricane intensity, emphasizing that while most storms are less severe, the potential for highly destructive hurricanes remains a critical concern during September, the most active month of the hurricane season.

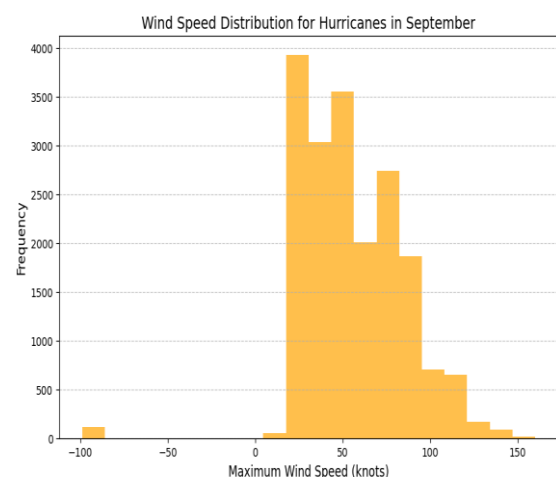


Figure 16: Bar Chart of Wind Speed Distribution for Hurricanes in September.

2.3. Box Plot of Maximum Wind Speeds by Month

The box plot illustrates the distribution of maximum wind speeds for hurricanes across different months, highlighting seasonal variations in storm intensity. From

January to May, median wind speeds remain relatively consistent, with moderate ranges and fewer extreme values. This suggests a quieter period with less intense storms, reflecting the typical off-season for hurricanes.

Starting in June, the variability in wind speeds begins to increase, as indicated by the wider interquartile ranges and the emergence of more outliers. This marks the onset of the hurricane season, with conditions becoming increasingly favorable for storm development and intensification.

The months of August, September, and October show the peak in both maximum wind speeds and variability. During this period, median wind speeds rise significantly, and the distributions broaden, with a notable increase in the number of extreme outliers. This pattern aligns with the peak of the hurricane season, when powerful storms are more likely to occur due to optimal atmospheric and oceanic conditions.

After October, wind speeds and their variability gradually decrease, returning to lower levels by December. This decline corresponds to the transition out of the hurricane season, as environmental factors become less conducive to storm formation. This seasonal analysis underscores the heightened risk during late summer and early fall and the relative stability of wind speeds outside this active period.

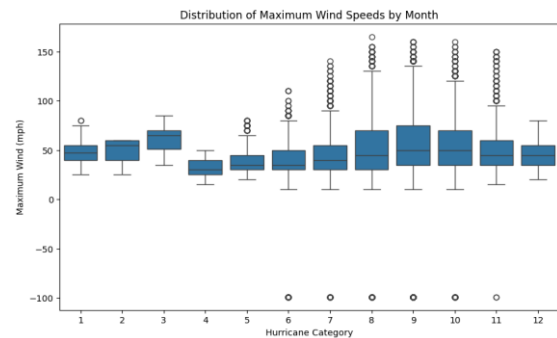


Figure 17: Box Plot of Maximum Wind Speeds by Month.

3. Hurricane Intensity Trends

3.1. Plot of Maximum Wind Over Time

The analysis of hurricane intensity categories over time reveals distinct trends in their frequency and variability. Category 1 hurricanes exhibit a moderately high and stable range throughout the timeline, with no sharp declines or anomalies. This indicates a consistent frequency of occurrence, reflecting the stability of this category over time.

In contrast, Category 2 hurricanes show greater variability, with noticeable spikes that suggest occasional increases in activity. This category's timeline features both high and low extremes, emphasizing a more dynamic pattern compared to Category 1.

Category 3 hurricanes follow a trend similar to Category 1 but display slightly more pronounced fluctuations. Peaks and troughs are evident, indicating periods of increased activity interspersed with quieter phases. While these fluctuations are more apparent, the overall trend remains relatively stable compared to higher categories.

The most variability is observed in Category 4 hurricanes, characterized by significant peaks and declines. These fluctuations suggest sporadic occurrences,

making this category less consistent over time than the lower-intensity categories. This variability could be influenced by external factors such as climate anomalies or variations in reporting practices.

Overall, Categories 1 and 3 demonstrate relative stability in their frequency, whereas Categories 2 and 4 exhibit marked variability. This analysis highlights how hurricane intensity varies by category, with higher-intensity hurricanes (e.g., Category 4) showing less stability and more dynamic patterns than lower categories. These findings offer insights into the behavior of hurricanes across different intensity levels and underline the influence of external factors on their occurrence.

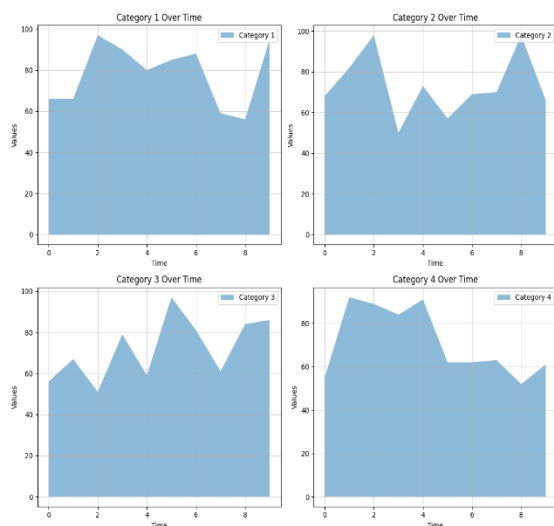


Figure 18: Plot of Maximum Wind Over Time.

4. Geographic Distribution

4.1. Heatmap of Hurricane Density

The heatmap visualization effectively demonstrates the density or intensity of data points within a specific region. Areas represented by brighter colors, transitioning from green to yellow and red, indicate regions of higher density or frequency of activity. These regions stand out as focal

points where values or occurrences are significantly concentrated.

In contrast, darker blue regions reflect areas with lower density, where activity is sparse or less frequent. Black areas on the heatmap signify the absence of activity, marking regions with no recorded data points or events.

The clustering of brighter colors in specific sections highlights hotspots or zones of heightened activity. These focal areas suggest trends or patterns within the dataset, providing valuable insights into regions of interest or concern when compared to the surrounding areas with lower intensity. This visualization helps identify and analyse spatial or categorical distribution patterns effectively.

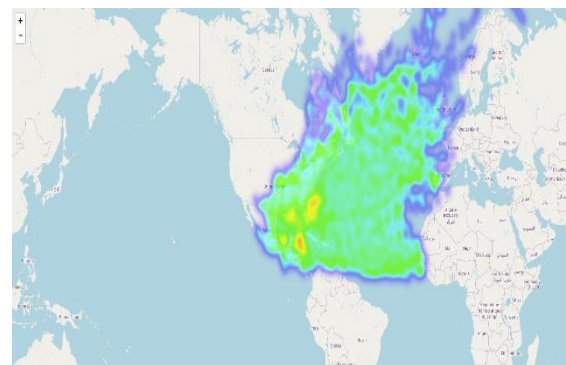


Figure 19: Heatmap of Hurricane Density.

4.2. Cluster Analysis of Hurricane Paths

The scatter plot provides a visualization of hurricane paths, clustered by region, with each cluster distinguished by a unique color. The x-axis represents longitude, while the y-axis represents latitude, allowing for a clear geographic grouping of hurricanes based on their trajectories.

One notable cluster is concentrated in the southern latitudes and spans a relatively narrow longitudinal range, likely corresponding to hurricanes that form and remain within tropical regions. These

storms are typically influenced by warm ocean temperatures and stable atmospheric conditions prevalent in these areas.

Other clusters extend into higher latitudes, representing hurricanes that move further north. These storms often undergo transitions into extratropical systems as they encounter cooler waters and different atmospheric dynamics. The dispersion of these clusters illustrates the variability in hurricane paths and behaviors.

The separation between clusters reflects variations in hurricane activity influenced by geographic and environmental factors, such as ocean temperatures, atmospheric conditions, and prevailing wind patterns. These distinctions help identify regions with specific storm characteristics and behaviors.

Additionally, one cluster appears out of place at a far-right longitude, potentially signalling anomalous data or unique storm behavior. This anomaly warrants further investigation to determine whether it reflects an error or an unusual hurricane trajectory. Overall, this visualization effectively highlights the geographic patterns and differences in hurricane paths, offering valuable insights into storm behavior and regional activity.

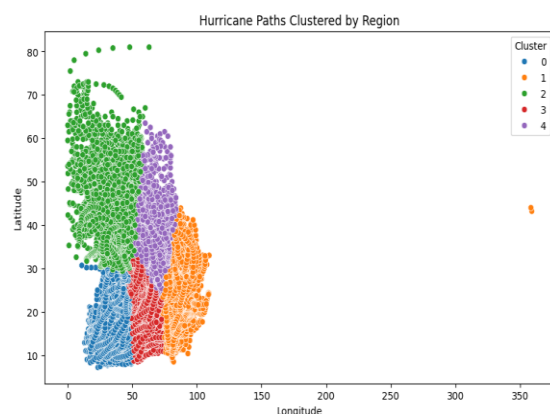


Figure 20: Cluster Analysis of Hurricane Paths.

5. Statistical Relationships

5.1. Correlation Matrix

The correlation matrix provides an overview of the relationships between three key variables: Maximum Wind, Minimum Pressure, and Year. The diagonal values, all equal to 1.00, confirm that each variable is perfectly correlated with itself, serving as a baseline for interpretation.

The correlation between Maximum Wind and Minimum Pressure is near zero (0.01), indicating no significant linear relationship between these variables. This suggests that variations in one do not predict changes in the other within the dataset.

The relationship between Minimum Pressure and Year shows a strong positive correlation (0.72). This indicates a trend toward lower minimum pressures as time progresses, which could reflect an increase in the intensity of storms in recent years. Lower minimum pressures are often associated with more powerful hurricanes, making this trend noteworthy for understanding changes in storm dynamics over time.

In contrast, the correlation between Maximum Wind and Year is weakly negative (-0.22). This suggests a slight decrease in maximum wind speeds over the observed period. However, the weak nature of this correlation indicates that this trend is not very pronounced and may be influenced by other factors or variability in the data.

Overall, the correlation matrix highlights key insights into the interrelationships among these variables. The strong connection between Year and Minimum Pressure stands out as a significant finding, while the weaker correlations suggest more

nuanced dynamics that may require additional investigation.

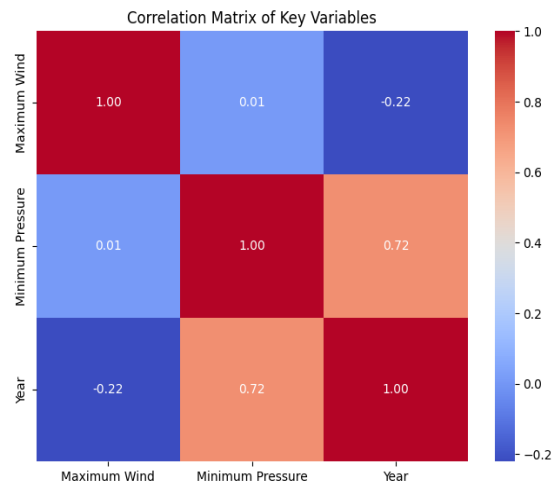


Figure 21: Correlation Matrix.

5.2. Pairplot

The pair plot offers a comprehensive visualization of the relationships between Maximum Wind, Minimum Pressure, and Year, while also illustrating the distribution of each variable.

The diagonal plots show the distributions for each variable. Maximum Wind displays a right-skewed distribution, indicating that lower wind speeds are more common, with fewer instances of extreme high speeds. Minimum Pressure has a bimodal distribution, suggesting the presence of two distinct groups, likely reflecting differences in storm intensity. The distribution for Year reveals an increasing concentration of data points in recent decades, which can be attributed to improved measurement techniques and more consistent record-keeping.

The scatter plots in the off-diagonal grids provide insights into pairwise relationships. The relationship between Maximum Wind and Minimum Pressure is inversely proportional, with higher wind speeds

generally corresponding to lower pressures. This aligns with established hurricane dynamics, where stronger storms are associated with lower central pressures.

The scatter plots involving Year demonstrate an increasing density of data points in more recent years for both Maximum Wind and Minimum Pressure. This trend reflects advancements in storm monitoring and the expansion of historical storm records, resulting in a more comprehensive dataset over time.

Additionally, the data points are color-coded based on storm status (e.g., HU for hurricanes, TS for tropical storms, EX for extratropical systems). This color coding reveals distinct clusters that correspond to differences in storm intensity and characteristics, further enriching the analysis of the relationships between the variables.

Overall, the pair plot provides valuable insights into the trends and relationships among these variables, emphasizing how storm data has evolved over time and how storm characteristics differ by intensity.

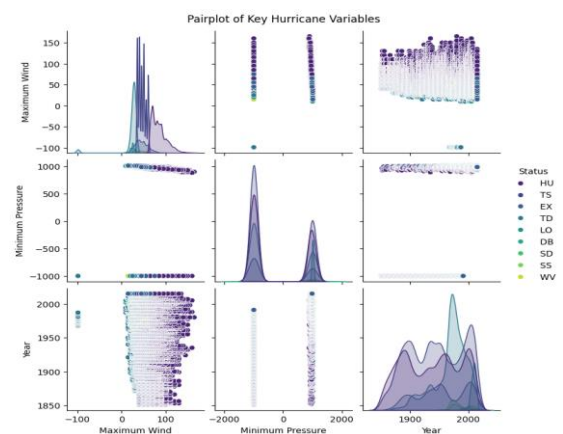


Figure 22: Pairplot.

6. Hurricane Lifespans

6.1. Histogram of Hurricane Lifespans

The histogram illustrates the distribution of hurricane lifespans measured in days, shedding light on the typical duration of these storms. The majority of hurricanes have lifespans between 1 to 5 days, with this range exhibiting the highest frequency. This finding underscores that most hurricanes are relatively short-lived events.

Beyond the 5-day mark, the frequency of hurricanes decreases steadily. This trend indicates that as storms persist for longer durations, their occurrence becomes increasingly rare. Lifespans exceeding 15 days are uncommon, and hurricanes lasting over 20 days are exceptionally rare, representing outliers in the dataset.

This distribution emphasizes that most hurricanes rely on favorable environmental conditions, such as warm ocean waters and conducive atmospheric dynamics, to sustain their intensity and longevity. These conditions often dissipate quickly, leading to the short-lived nature of the majority of storms. The histogram provides a clear depiction of the typical lifespan of hurricanes, with a sharp decline in frequency as durations extend beyond a few days.

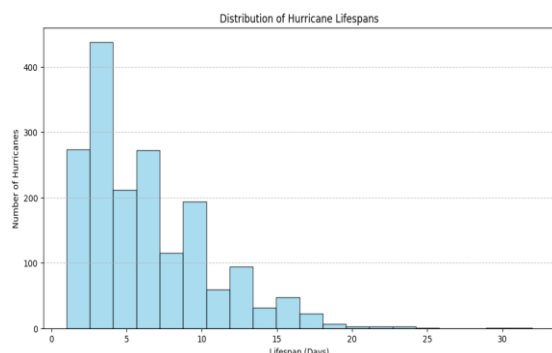


Figure 23: Histogram of Hurricane Lifespans.

7. Cumulative Impact

7.1. Line Plot of Cumulative Hurricane Landfalls

The line plot illustrates the cumulative number of hurricane landfalls over time, spanning from the mid-19th century to the early 21st century. The consistent upward trend indicates a steady increase in the recorded number of landfalls. This pattern could reflect either an actual rise in hurricane landfall occurrences or improvements in detection and record-keeping practices over the years.

The slope of the curve remains relatively uniform, suggesting that the overall rate of landfalls has not undergone significant changes over time. While minor fluctuations are visible, they do not appear to represent substantial shifts in the underlying trend, pointing to a relatively stable long-term pattern.

This visualization highlights the cumulative nature of hurricane activity, capturing the growing total of recorded landfalls over the observed period. It also underscores the influence of historical advancements in tracking and reporting, which likely contributed to the consistent increase in recorded events. The plot provides a clear depiction of how the cumulative total of landfalls has evolved, offering insights into both natural and technological factors shaping the data.

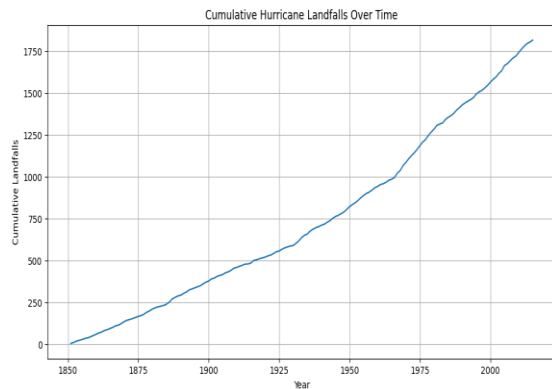


Figure 24: Line Plot of Cumulative Hurricane Landfalls.

8. Directional Patterns

8.1. Polar Plot of Hurricane Directions

The polar chart provides a clear visualization of the distribution of hurricane directions, illustrating the frequency of storms moving in specific compass directions. The data reveals that the most prominent activity is concentrated in the northeast (NE) quadrant, indicating that hurricanes predominantly travel in this direction. This trend is likely driven by atmospheric pressure systems and prevailing wind patterns that steer storms toward the northeast.

Moderate activity is also observed in the northwest (NW) and east (E) directions, reflecting additional common pathways for hurricane movement. In contrast, the southern quadrants (SW and SE) show minimal hurricane frequency, suggesting that storms rarely travel in these directions, likely due to the geographic and atmospheric constraints in hurricane-prone regions.

The radial values of the chart quantify the number of hurricanes for each direction, emphasizing the dominance of the NE quadrant while showcasing the relative

frequencies of other directions. This visualization effectively highlights the primary directional patterns of hurricanes, providing insights into their typical trajectories and the environmental factors influencing their movement.

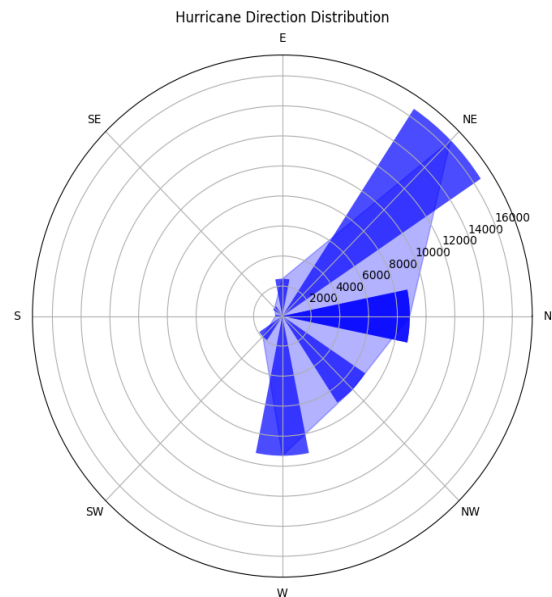


Figure 25: Polar Plot of Hurricane Directions.

8.2. Bar Chart of Average Wind Speeds by Directions

The analysis of hurricane wind speeds by direction reveals significant trends in storm intensity across compass directions. Hurricanes moving in the northeast (NE) direction exhibit the highest average wind speeds across all categories—Low, Moderate, and High. This confirms that hurricanes tend to intensify as they move northeast, likely influenced by favorable atmospheric conditions and prevailing wind patterns.

In the southeast (SE) and northwest (NW) directions, average wind speeds are comparable but slightly lower than those in the NE direction. This indicates that hurricanes maintain moderate intensity while moving in these directions,

suggesting a balance between conducive conditions and limiting factors.

In contrast, the southwest (SW) direction records the lowest average wind speeds. This trend suggests that hurricanes rarely sustain high winds when moving SW, possibly due to interactions with landmasses or cooler water temperatures that inhibit storm intensity.

Interestingly, across all directions, the Low Wind category has the highest average speeds compared to the Moderate and High Wind categories. This indicates that hurricanes with broader wind fields at lower intensities are more common, reflecting the typical structure and behavior of many storms.

Overall, this directional analysis highlights the tendency of hurricanes to intensify in the NE direction, maintain moderate strength in SE and NW directions, and weaken in the SW direction, while also emphasizing the prevalence of broader, low-intensity wind fields in storms.

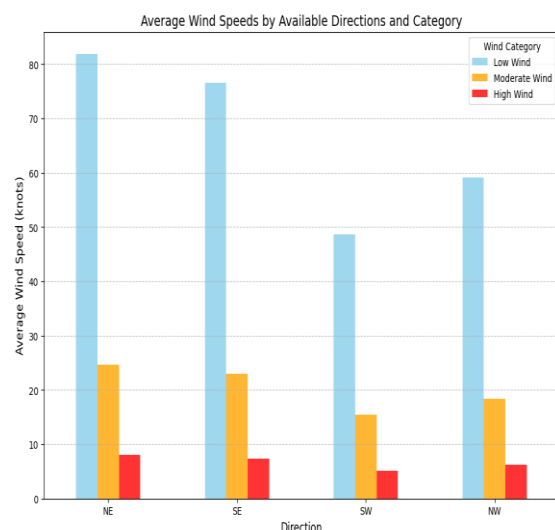


Figure 26: Bar Chart of Average Wind Speeds by Directions.

9. Pressure-Wind Relationships Over Time

9.1. Line chart of trends in Average Minimum Pressure and Wind Speed by Decade

The chart illustrates the trends in two key metrics, Average Minimum Pressure (hPa) and Average Maximum Wind Speed (mph), over time, highlighting notable differences in their behavior and variability.

The blue line, representing Average Minimum Pressure, shows a dramatic shift beginning around the mid-20th century, particularly post-1940. Before this period, values were in the negative range, likely due to early measurement inaccuracies or data inconsistencies. However, after the 1940s, there is a steep positive trend, indicating significant changes in pressure trends. This shift could reflect improvements in measurement techniques, changes in data reporting practices, or environmental factors such as shifts in atmospheric or oceanic conditions during that era.

In contrast, the orange line, representing Average Maximum Wind Speed, remains relatively flat across all decades, indicating stability in wind speeds over time. The consistent scale for wind speed, closer to zero with much less variability, suggests that wind speed has not experienced the same dramatic changes as pressure during the observed period.

The notable increase in Average Minimum Pressure after the 1940s, compared to the flat trend in wind speed, suggests a lack of direct correlation between these two metrics in this dataset. This divergence

emphasizes that changes in one metric do not necessarily reflect similar patterns in the other, potentially due to differences in the underlying factors influencing pressure and wind speed.

Overall, the sharp rise in pressure trends after 1940 highlights the impact of historical advancements in meteorological measurements or significant environmental changes, while the stability in wind speed underscores the need to explore other contributing factors to hurricane dynamics.

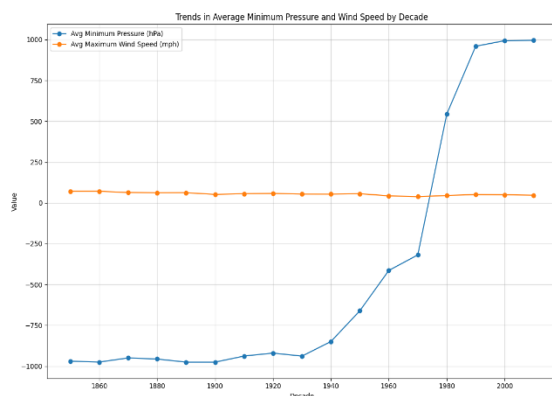


Figure 27: Line chart of trends in Average Minimum Pressure and Wind Speed by Decade.

10. KDE Plot of Wind Speeds

10.1. Kernel Density Estimation (KDE) Plot

The KDE plot provides a detailed visualization of the distribution of maximum wind speeds, highlighting key patterns in storm intensity. The density curve peaks around moderate wind speeds, suggesting that the majority of recorded storms fall within this range and are not extreme in nature. This peak represents the typical intensity of most storms.

As wind speed increases, the density gradually declines, indicating that fewer storms achieve high wind speeds. This trend reflects the relative rarity of extreme

hurricanes, with only a small proportion of storms reaching exceptional intensity.

An isolated density peak is observed at negative wind speeds. This anomaly is likely due to data irregularities, such as measurement errors, data entry mistakes, or cases involving reversed directionality in storm reporting. This warrants further investigation to clarify its origin.

Overall, the plot reveals a skewed distribution, with a concentration of storms at moderate to high wind speeds. This pattern aligns with the characteristics of hurricanes and strong storms, emphasizing that while extreme wind speeds are uncommon, they remain a critical feature of the dataset.

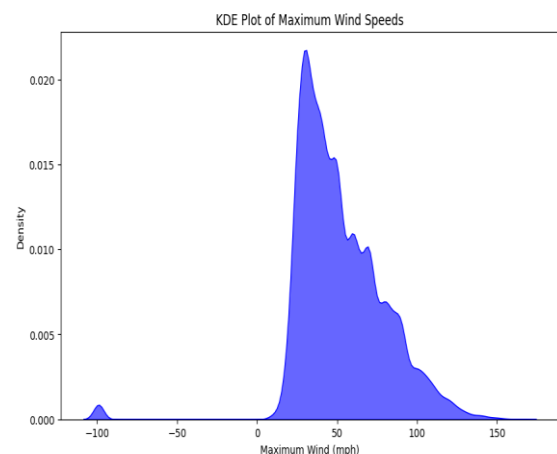


Figure 28: Kernel Density Estimation (KDE) Plot.

11. Time series Analysis

11.1. Time Series Decomposition of Hurricane Counts Over Years

The time series decomposition provides a detailed breakdown of the data into its key components—observed, trend, seasonal, and residual—offering a comprehensive view of the underlying patterns and variations.

The top panel, displaying the observed data, captures the overall fluctuations and variability over time. This provides a high-level view of the data's behavior, setting the stage for a deeper analysis of its components.

The trend component, shown in the second panel, reveals a gradual increase over time, particularly evident in the 20th century. This upward trend likely reflects long-term growth or changes within the data, possibly due to external factors or systemic developments affecting the underlying phenomenon.

The seasonal component, represented in the third panel, exhibits a consistent, repeating pattern over time, highlighting the presence of strong seasonality. This regular cycle underscores the influence of periodic factors that recur at predictable intervals, driving significant portions of the data's variability.

Finally, the residuals, displayed in the bottom panel, appear randomly distributed around zero. This randomness indicates that the decomposition has effectively captured the primary patterns in the data, leaving only noise or unexplained variability in the residuals.

This analysis demonstrates both the long-term growth trend and the strong seasonal cycles present in the dataset, while confirming the effectiveness of the decomposition process in isolating these key components. It provides valuable insights into the structure and drivers of the data, facilitating a clearer understanding of its behavior over time.

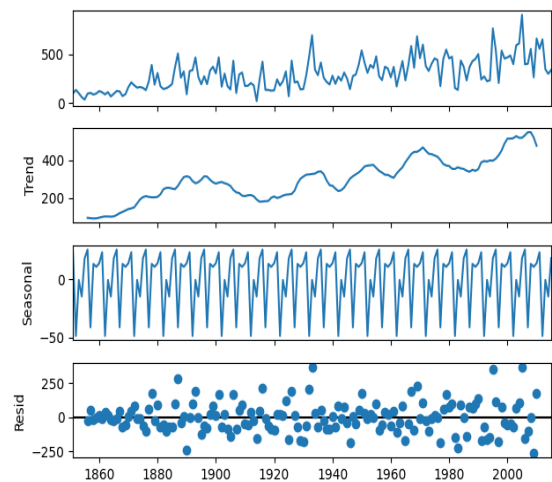


Figure 29: Time Series Decomposition of Hurricane Counts Over Years.

4.2. Challenges and Failed Experiments

1. Outlier Detection and Retention

Identifying and managing outliers was crucial for maintaining the dataset's integrity, especially for variables like maximum wind speed and minimum pressure. However, defining appropriate thresholds posed a challenge since extreme values often represented rare but meaningful hurricane events. Removing too many outliers risked losing critical insights into the most intense storms, necessitating a balanced approach.

2. Complexity of Multivariate Data

Pair plots and scatter plots were initially overwhelmed by overlapping clusters caused by high variability in storm characteristics. This limited the visual clarity and interpretability of the relationships between variables. Filtering the data or categorizing storms by status improved the ability to draw meaningful conclusions.

3. Geospatial Visualizations

Early iterations of heatmaps suffered from clutter due to the high density of hurricane

data, which obscured regional patterns. Refining the heatmaps by filtering based on intensity or clustering by region significantly enhanced their clarity and usability.

4.Temporal Variability and Data Limitations

The relationship between storm characteristics, such as wind speed and pressure, and time was complicated by historical variations in data collection and reporting. For example, underreporting in earlier years likely biased trend analyses, requiring careful consideration when interpreting long-term results.

5. Methodological Adaptations

Time-series decomposition was effective for analyzing long-term and seasonal trends but less suited for capturing short-term anomalies, which required the development of separate anomaly detection methods.

Clustering methods for hurricane paths revealed useful geographic patterns but occasionally produced outliers or misclassified storms due to atypical paths or inconsistent data.

4.3. Insights and Implications

The project utilized a diverse range of visualizations to analyze critical aspects of hurricane activity and their broader implications. Time-series analyses revealed a steady increase in hurricane frequency over the decades, reflecting environmental changes and improved detection technologies. Significant spikes in activity during specific periods were attributed to climatic phenomena such as El Niño and La Niña, underscoring the influence of global weather patterns on storm behavior. A

stacked area chart highlighted a marked rise in severe hurricanes (Categories 3–4), linked to rising sea surface temperatures and shifting atmospheric conditions, indicative of the growing impact of climate change on storm intensity.

Geographic patterns were analyzed using heatmaps, which pinpointed high hurricane activity zones, particularly along warm currents in the Atlantic and Gulf of Mexico, providing clear insights into geographic vulnerabilities. Seasonal trends emerged from monthly frequency analyses, identifying late summer and early fall as peak hurricane periods, emphasizing the predictability of hurricane activity during specific times of the year. Directional trends were visualized using polar charts, which illustrated the predominant northeastward movement of hurricanes, shaped by prevailing wind patterns and atmospheric pressure systems.

Correlation matrices and line charts reinforced fundamental hurricane dynamics, such as the inverse relationship between wind speed and pressure, while clustering methods identified distinct storm trajectories and high-risk regions, providing a more granular understanding of hurricane paths. These visualizations collectively offered a detailed exploration of hurricane behavior, revealing patterns that have significant implications for disaster preparedness and mitigation strategies.

The insights derived from this study are both clear and actionable. Hurricanes are becoming more severe and frequent, reflecting the growing influence of global warming and environmental changes. High-risk regions and specific seasonal

periods emphasize the need for localized disaster preparedness strategies. Directional patterns and clustering insights provide predictive cues for hurricane behavior, aiding in disaster response planning. Additionally, advancements in tracking and detection technologies have significantly enhanced the accuracy and depth of hurricane data, enabling more reliable and actionable analyses.

This analysis successfully captured long-term trends and nuanced patterns in hurricane behavior, offering valuable insights into the evolving nature of these storms. By employing innovative visualization techniques, the project not only deepened the understanding of hurricane dynamics but also provided actionable knowledge to inform climate research, disaster response, and policy development. The study underscores the importance of data-driven strategies in mitigating the increasing impacts of hurricanes in a changing climate.

5. Insights and Future Directions

5.1. Discussion

This study uncovered significant trends in hurricane activity, particularly their increasing frequency and intensity over time. Severe storms, especially those in higher categories (Category 3 and above), have become more common in recent decades. Geographic analysis showed that hurricanes are concentrated in specific hotspots within the Atlantic basin, closely associated with warm ocean currents and atmospheric conditions. Seasonal patterns aligned with expectations, with the majority of hurricanes occurring in late summer and early fall, during the Atlantic hurricane

season. Additionally, directional patterns indicated a predominant northeastward movement of hurricanes, influenced by prevailing winds and atmospheric pressure systems.

However, some limitations must be acknowledged. Incomplete historical records and variations in measurement methods over time may affect the accuracy of long-term trends. The study's focus on the Atlantic basin further limits its generalizability to global hurricane patterns. Addressing these limitations in future work could enhance the robustness and applicability of the findings.

5.2. Conclusion

The findings of this study emphasize that hurricanes are becoming stronger and more frequent, likely as a result of climate change. The analysis also underscored the importance of focusing on specific regions and seasonal patterns to improve preparedness for hurricane activity. By leveraging advanced visualization techniques and comprehensive data analysis, the project provided valuable insights into hurricane behavior and its evolution over time. These results not only enhance our understanding of hurricanes but also offer actionable knowledge for disaster response planning and climate adaptation strategies.

5.3. Future Work

Future research can expand on this study by examining hurricanes on a global scale to compare trends across different regions. Incorporating additional climate data, such as sea surface temperatures, rainfall, and atmospheric pressure variations, could

offer deeper insights into the factors driving hurricane behavior. Machine learning models could further refine predictions of storm intensity and trajectories, enhancing early warning systems.

Lastly, exploring the socioeconomic impacts of hurricanes, including their effects on communities and economies, could help inform more effective disaster planning and recovery efforts. These steps will advance our understanding of hurricanes and support the development of more comprehensive mitigation strategies, ultimately helping communities better prepare for future storms.

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- [13] <https://images.app.goo.gl/UTSurgVtunbsq943A>