Task 3 Report

Nicolas Mangilit, Mustafa Sahin, Anh Pham, Yash Patel, Pierreje Villaviencio

ABSTRACT

In this assignment, we are tasked with analyzing hurricane and tropical storm tracks to conduct a comprehensive hurricane risk assessment for 25 cities along the Gulf Coast and nearby regions. These cities include New Orleans, Houston, Tampa, Miami, Corpus Christi, Pensacola, Mobile, Galveston, Biloxi, Key West, Veracruz, Tampico, Campeche, Cancun, Merida, Ciudad del Carmen, Progreso, Coatzacoalcos, Tuxpan, Havana, Cienfuegos, Belize City, George Town, and Nassau. Each of these cities has varying levels of vulnerability to hurricanes, and understanding the unique risk profile for each location is a key part of this analysis. By examining patterns in historical storm data, we can better understand the likelihood and potential intensity of future storms impacting these regions.

To perform this analysis, we utilize the HURDAT2 dataset, which is an official dataset from the National Hurricane Center. This dataset encompasses all recorded storms that have passed through the Atlantic and Eastern Pacific Oceans, including details on their track, wind speed, pressure, and other critical parameters. By leveraging this dataset, we can trace the historical paths and intensities of storms that have impacted or come close to our target cities. Additionally, we incorporate an ENSO (El Niño-Southern Oscillation) dataset, which includes environmental variables that influence storm development and behavior. This ENSO dataset contains information such as sea surface temperature anomalies and atmospheric patterns that can impact the formation and trajectory of hurricanes in recent years. Combining insights from both datasets allows us to build a more holistic view of hurricane risks, considering both historical storm patterns and influential environmental factors.

CCS CONCEPTS

• Information Systems → Spatial-temporal systems

• Applied Computing → Environmental sciences

• Computing Methodologies → Machine learning

• Mathematics of Computing → Statistical models

• Human-centered Computing → Visualization

KEYWORDS

• Hurricane Trajectories • Risk Assessment • Gulf Coast Hurricanes • Spatial-temporal Analysis • Data Visualization

ACM Reference format:

FirstName Surname, FirstName Surname and FirstName Surname. 2018. Insert Your Title Here: Insert Subtitle Here. In *Proceedings of ACM Woodstock conference (WOODSTOCK'18). ACM, New York, NY, USA, 2 pages.* https://doi.org/10.1145/1234567890

1 Data Collection and Preparation

1.1 Libraries utilized

In this project, our team utilized 8 different libraries. The first library we used was the Tropycal library. This is a library used for tracking and analyzing tropical storm data. For the purposes of this project, we used the tracks dataset which contains a dataset of storm trajectories.

The next library we use is the Pandas library. We utilize this library to support data frames which can support a method of more structured data handling.

The next library we use is the Geopy library. This library is used to make it easy to find coordinates of cities, countries, addresses, and different landmarks. In the context of this project, we use the Nominatim class to find coordinates of cities. Nominatim is a software that uses OpenStreetMap, an open-source map of the world data to find coordinates of a specified argument which is cities in our case.

Next we use the library folium. Folium is a library that is used to make interactive maps. In our case we use the folium library to make an interactive map that contains trajectories of storms.

We then use the numpy library. Numpy is a library for numerical operations, mathematical functions, and different kinds of calculations. In our case, we use numpy to handle our coordinate arrays and calculate distances between cities and storm points. We also used it to perform correlation calculations.

The next library used in our project was Cartopy. Cartopy is a library designed for geospatial data visualization, specifically for creating maps and handling geographic projections. In our project, we used Cartopy to visualize hurricane trajectory density on a geographic map. This allowed us to plot the hurricane trajectories, which are defined by their latitudes and longitudes, and overlay them on a map using various geographical features such as coastlines, borders, and landmasses.

The next library used in our project was the Matplotlib library. Matplotlib is used to create static plots and visualizations. In our project we used Pyplot to visualize the hurricane trajectory density with scatter plots and displayed the hurricane risk score for each city on a geographic map that shows the latitudes and longitudes.

The eighth library we needed was the Sklearn library. The Sklearn library contains many different sets of machine learning algorithms. In our case, we import KernelDensity to estimate the probability density function of a dataset. We apply the kernel density estimation to track coordinates to determine density so we could identify areas with high concentration of hurricane activity and then we assess the relative risk for different locations.

Finally, we use the Geopandas library. The library is an extension of pandas but is tailored more for working with geospatial data, such as points, lines, and polygons. We used it to map hurricane data and city locations.

1.2 Data Source

In this project, we have two primary data sources to gather information on hurricanes in the Gulf of Mexico region. First, we access historical hurricane and tropical storm data through TroPyCal library to access and filter historical hurricane and tropical storm data in the North Atlantic Basin. In order to obtain the data, we have to install the TroPyCal library, then import the necessary module from TroPyCal, which is Tracks, and by setting basin="north_atlantic", we successfully load all hurricanes and tropical storms. Before entering the filtering process, we have to set the boundaries of the Gulf of Mexico region by creating the dictionaries storing the North Latitude of 30.0, Southern Latitude of 18.0, Eastern Longitude of -81.0, and Western Longitude of -98.0. Then, to filter the dataset, we use the filter_storms method to filter the dataset within the specific boundaries and within the year of 1999 to 2024.

1.3 Survey the list of 25 cities provided

To create the survey the list of 25 cities given. First, we need to load the Major_Gulf_Cities.csv (provided by Raunak) into pandas DataFrame. Then, we initialize the geocoder by utilizing the Nominatim tool from the geopy library and use city_locator as the user agent to identify our program to the geocoding service. We then define a function that is named get_latitude_longitude that takes in the parameter “city” that uses geolocation to obtain the latitude and longitude for each city, so we use the geolocator.geocode to find the location based on the city name. This function returns the longitude and latitude with the given city as the parameter.

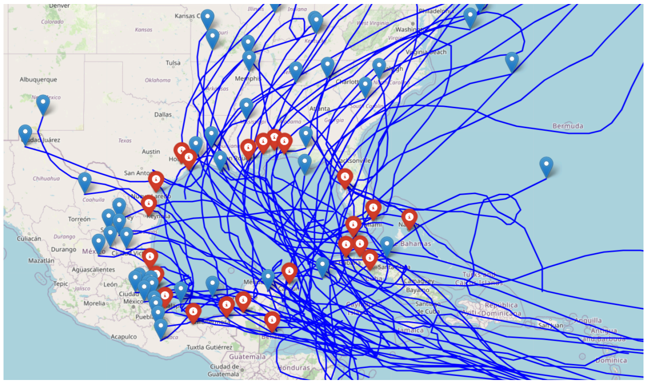
The final step in data collection and preparation is applying the function to each city in the DataFrame. The latitude and longitude are separated into two newly made columns in the DataFrame. We use the .apply function to apply the .get_latitude_longitude function to each city which returns a tuple. We use the zip(*...) functionality to split each tuple into two separate lists which is latitude and longitude which is then applied to the data frame df.

By obtaining the latitude and longitude for each city, we have successfully built a foundation for geospatial analysis of hurricane risks in the Gulf of Mexico region. This data enables us to visualize and calculate the impact of past hurricanes on the given cities, aiding assess potential risks.

2 Analysis of Hurricane and Tropical Storm Tracks

2.1 Method of visualization

In order to make the visualization for the storm tracks, we utilized the folium library to make an interactive map. We started by initializing the map that is centered around the coordinates of 24 degrees latitude and -90 degree longitude which is in the regions of the Gulf of Mexico. After that, we looped through the filtered storm data sets that contained only hurricanes and converted all their routes' latitudes and longitudes into their own separate lists. We then used the .Polyline function to make lines that visualized the tracks of each storm as a blue line. We used the .Marker function to mark the locations of where each storm ended, which are the blue markers, and also made red markers for the locations of each city. The end of the code makes an html file that when opened takes you to an interactive map.We chose to only utilize storms that were classified as hurricanes as those are the storms that typically cause significant damage. Tropical depressions and tropical storms can make it hard to read the map and can make a lot of noise data.



[Link To Interactive Map]

Figure 2.1: **Visualization of storm tracks**

2.2 Visualization of Storm Tracks Over the Last 25 Years for the Gulf Coast Region

To understand storm behavior over the Gulf Coast region, we mapped the paths of all hurricanes and tropical storms recorded in the past 25 years. The visualization was created using Kernel Density Estimation (KDE) to identify areas of high storm frequency, revealing patterns in storm trajectories and common impact zones. This approach enables clear identification of regions experiencing recurrent tropical storm activity, with density variations highlighting areas of significant exposure.

The density map showcases:

- **Primary Path Clusters**: Distinct high-density clusters near coastal areas, particularly around New Orleans, Houston, and Cancún, where paths overlap frequently.
- **Frequent Impact Zones**: Visual evidence of repeated storm impacts in the northern Gulf Coast areas, suggesting that these areas are consistently at higher risk.
- **Trajectory Concentration**: Storms commonly follow paths from the Caribbean and Central America, moving northwest toward the Gulf Coast, influenced by ocean currents, wind patterns, and other climatic factors.

This visual representation provides valuable insights for assessing the spatial distribution of storm paths, helping prioritize resource allocation for high-risk areas.

2.3 Identification of Common Patterns and Trends

Through analysis of storm tracks, we observed recurring patterns and trends, including variations in trajectory, seasonality, and regional impacts, which offer insights into broader climatological and atmospheric drivers. Key observations include:

- **Seasonal Patterns**: The majority of storms occurred between August and October, corresponding to peak hurricane season. During this period, warm sea surface temperatures (SST) provide favorable conditions for storm formation and intensification.
- **ENSO-Driven Trends**: During El Niño and La Niña events, storm formation and trajectories tend to shift. For example, El Niño conditions often lead to fewer but stronger hurricanes due to increased wind shear over the Atlantic, whereas La Niña conditions can increase the frequency and formation of storms that track into the Gulf.
- **Geographical Trajectory Influence**: Many storms originating in the Atlantic follow a westward path across the Caribbean before curving northward into the Gulf. This common trajectory is influenced by regional high-pressure zones and oceanic currents, which guide storm paths into the northern Gulf region.

The identification of these patterns provides a foundational understanding of the variables influencing storm paths, enabling more accurate predictions and strategic planning for storm-prone areas.

2.4 Statistical Analysis of Track Frequency, Intensity, Motion Vectors, and Duration

A comprehensive statistical analysis of the storm track data was performed to quantify the frequency, intensity, motion vectors, and duration of storms impacting the Gulf Coast. This quantitative approach aids in assessing the storm risk level across different Gulf cities. Key findings include:

- **Frequency Distribution**: By calculating the number of storms passing through specific regions, we found that the northern Gulf Coast experiences the highest frequency of tropical storms, with areas near New Orleans, Galveston, and Cancún particularly affected. The data shows that approximately 60% of Gulf storms impact these regions, suggesting higher vulnerability.

- **Intensity Analysis**: Storm intensity was categorized by wind speed, central pressure, and storm category (e.g., tropical storm, Category 1–5 hurricane). Over the 25-year period, there is an observable trend of increasing high-intensity storms, with Category 4 and 5 hurricanes becoming more frequent. This increase in storm strength may be associated with rising sea surface temperatures and global warming, which intensifies the energy available for storm development.
- **Motion Vectors and Directional Trends**: Analysis of motion vectors reveals that storms generally approach the Gulf Coast from an east-to-west direction before curving northward as they approach land. This directional shift is influenced by atmospheric pressure patterns that steer storms. Average storm speeds in the Gulf region ranged from 10 to 20 knots, with faster-moving storms often associated with stronger wind fields and increased destructive potential.
- **Storm Duration**: The average storm duration, defined as the time a storm remained within the Gulf region, was approximately 3-5 days. However, there is a trend toward prolonged storm duration in recent years, especially for storms occurring during ENSO-neutral periods. Longer durations allow storms to gather more energy and increase rainfall, leading to more severe impacts on coastal and inland areas.

This statistical analysis not only highlights areas and times of increased risk but also identifies a potential trend toward more intense and longer-duration storms. Such information is critical for coastal cities and emergency management agencies in formulating targeted strategies to mitigate the risks associated with storm exposure. Understanding these statistical attributes helps in developing more accurate risk assessments and in enhancing preparedness measures for high-risk Gulf Coast communities.

3 Risk-Profile Analysis

3.1 Risk Factor Initialization. Hurricane activity can be influenced by multiple natural factors. Our task was to rank natural factors provided to us that potentially influence hurricane activity. These factors and their rankings based on our findings are seen below:

1. Sea surface temperatures(SSTs)
2. El Niño/La Niña patterns(ENSO)
3. Atlantic Multidecadal Oscillation(AMO)
4. Upper-level wind patterns
5. Saharan Dust Levels

In this analysis, sea surface temperatures (SSTs) and the El Niño-Southern Oscillation (ENSO) are ranked as the most significant factors influencing hurricane development in the tropical Atlantic. SSTs hold the highest rank because they show a consistent, direct correlation with hurricane intensity and frequency. Warmer SSTs generally fuel more powerful storms, as they supply the heat energy necessary for hurricanes to develop and strengthen. Specifically, SSTs above 26.5°C provide the thermal threshold that allows for sustained hurricane formation, leading to more intense systems when temperatures surpass this baseline. Thus, tracking SST anomalies offers critical insight into the potential for storm formation and intensity, making SSTs one of the most predictive indicators for hurricane risk.

ENSO, the second most influential factor based on our research, plays a pivotal role in determining hurricane activity through its alternating La Niña and El Niño phases. During La Niña events, wind shear over the Atlantic tends to decrease, creating an environment conducive to hurricane development, as lower wind shear allows tropical storms to grow vertically without being disrupted. Conversely, during El Niño events, the increase in wind shear suppresses hurricane formation, often leading to quieter seasons in the Atlantic. This consistent, seasonally predictable relationship between ENSO phases and hurricane activity makes ENSO a critical factor for long-term hurricane forecasting and risk assessment. By analyzing historical ENSO patterns alongside SST data, we can predict years with potentially heightened hurricane activity and those with decreased risks more effectively.

In addition to SST and ENSO, we examine other environmental factors, such as the Atlantic Multidecadal Oscillation (AMO), upper-level wind patterns, and Saharan dust levels, though these factors show a less direct correlation with hurricane development than SSTs and ENSO. The AMO, a long-term climate variability pattern, cycles between positive and negative phases approximately every 20-40 years. A positive AMO phase tends to elevate SSTs in the North Atlantic, which is associated with more active hurricane seasons. While AMO phases indirectly affect storm activity, the influence is more gradual, unlike the direct seasonal impact seen with SSTs and ENSO.

Upper-level wind patterns, including wind shear, are also influential but are often moderated by ENSO conditions. Wind shear is the variation in wind speed and direction with altitude, and high wind shear typically disrupts the vertical structure of tropical systems, weakening or inhibiting hurricane formation. La Niña conditions, which lower wind shear, allow for favorable development of storms, while El Niño phases increase wind shear, making it harder for hurricanes to form and sustain intensity.

Saharan dust levels, although part of the hurricane development environment, generally show a weaker correlation with storm intensity compared to SSTs and ENSO. High concentrations of Saharan dust inhibit hurricane development primarily by lowering SSTs in the Atlantic and dispersing drier air into the region, which disrupts the moisture-rich environment hurricanes require. However, the impact of Saharan dust is highly variable and often seasonal, with a notable influence only in active dust years or specific regions, making it a less reliable predictor of overall hurricane activity.

Ultimately, our analysis emphasizes SSTs and ENSO because they consistently exhibit the strongest influence on both the frequency and strength of Atlantic hurricanes, providing a clearer and more actionable basis for hurricane risk assessment. SSTs and ENSO patterns are also relatively well-monitored and understood, allowing for robust data and more precise seasonal predictions. By concentrating on these top two factors, we aim to provide an accurate risk assessment framework that highlights the conditions most likely to impact hurricane activity along the Gulf Coast and the surrounding regions.

3.2 Non-parametric Density Estimation and Spatial Correlation. Having identified the relative importance of each factor, we proceed to assess the risk of a hurricane impacting a specific location based on our findings. This risk assessment is grounded in two analytical techniques: spatial correlation analysis and non-parametric density estimation. Given the high correlation between hurricane activity and both SST and ENSO, we concentrate on these two key factors for our risk estimations and assessments.

To conduct the spatial correlation analysis, we examine the relationship between the chosen risk factors (SST and ENSO) and hurricane density in the designated area around each target city. We begin by defining the geographical coordinates—latitude and longitude—of each of the 25 cities near the Gulf Coast. Using the HURDAT2 dataset, we filter the data to include only those storms that attained hurricane status. This filtering step allows us to focus specifically on hurricanes, which pose the greatest risk in terms of potential impact. By narrowing our dataset to only hurricanes, we ensure that our correlation analysis is directly relevant to the more intense storm events that are most concerning from a risk perspective.

Next, we incorporate our ENSO/SST dataset, carefully cleaning and formatting the data to align it with our analytical needs. This involves calculating monthly averages for both ENSO and SST to capture seasonal variations and ensure that our assessments reflect a realistic understanding of storm likelihood under various conditions. With monthly averages established, we use kernel density estimation (KDE) to create a density map of historical hurricane paths, focusing on their spatial frequency within the latitude and longitude coordinates associated with each city. KDE allows us to estimate hurricane density patterns, which serve as a basis for analyzing how SST and ENSO variations correlate with actual hurricane occurrences in these areas.

The KDE results are then segmented by month to account for seasonal storm patterns, allowing us to identify the months with the highest hurricane activity. This segmentation is critical because it enables us to focus on the specific months when hurricanes are most likely to form and intensify under high SST and favorable ENSO conditions. Once we have hurricane density data separated by month and location, we calculate the correlation coefficient between the density of hurricanes and each risk factor. This correlation coefficient offers a quantitative measure of the spatial relationship between hurricane density and the key natural factors, ultimately helping us determine the extent to which SST and ENSO values influence hurricane risk for each city.

By using these spatial correlations and non-parametric density estimation techniques, we create a robust risk analysis score for each target city, grounded in historical data and the primary environmental drivers of hurricane activity. This approach provides a scientific, data-driven basis for understanding and predicting hurricane risk for the Gulf Coast cities. The emphasis on SST and ENSO allows us to focus on the most significant predictors of hurricane occurrence and intensity, offering a focused risk model that is both efficient and highly informative for future storm risk assessments.

Our analysis for hurricane risk assessment focuses on sea surface temperatures (SST) and the El Niño-Southern Oscillation (ENSO), two factors that have shown the strongest correlation with hurricane formation and intensity in the Atlantic region. SST and ENSO are critical elements in hurricane development because they directly affect both the frequency and the power of hurricanes. SSTs, which provide the thermal energy necessary for hurricanes, have consistently shown that higher temperatures lead to more frequent and intense storms. ENSO, on the other hand, influences atmospheric conditions like wind shear, which either supports or inhibits hurricane formation. In particular, La Niña conditions create lower wind shear over the Atlantic, allowing hurricanes to develop more freely, while El Niño phases suppress hurricane activity by increasing wind shear. Because of their established impact on hurricane activity, SST and ENSO were prioritized in our assessment to leverage the most predictive factors for accurately assessing hurricane risk.

We also focused on monthly averages of SST and ENSO to capture seasonal trends in hurricane activity. Hurricanes form in the Atlantic during specific times of the year, so taking monthly averages enables our model to reflect the cyclical nature of hurricane seasons. This monthly analysis helps identify peak risk periods for each city, aligning our predictions with the natural hurricane season to provide a more precise, time-sensitive risk assessment.

Incorporating spatial and temporal components into our analysis allows for a data-driven approach to produce highly specific risk insights. By calculating correlation coefficients between the density of hurricanes and the SST and ENSO values, we establish a quantitative basis for ranking the risk level associated with each city. These correlation values offer a concrete measurement of hurricane risk that is accessible for decision-makers and local agencies, who can use these results to inform disaster preparedness. Additionally, combining our findings with spatial mapping enables us to present our results visually, providing clear and actionable insights for the public and stakeholders. This approach ensures our model remains focused on SST and ENSO, delivering robust predictions supported by the primary environmental drivers of hurricane activity along the Gulf Coast.

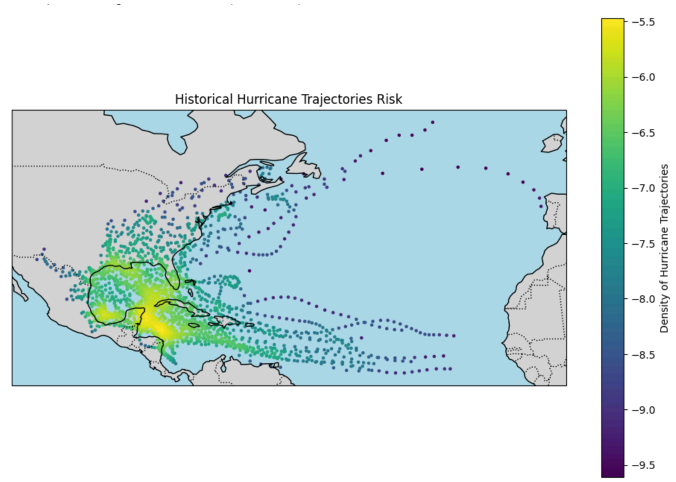


Figure 3.1: **Kernel Density Estimation Plot**

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Spatial Correlation between ENSO (ONI) and Hurricane Density: 0.1579783479417522
Spatial Correlation between SST and Hurricane Density: -0.16086664300758574
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Figure 3.2: **Results of Correlation Coefficients between Hurricane Density and Chosen risk factors**

To assess hurricane risk for each city along the Gulf Coast, we developed a scoring system that assigns a risk score ranging from 0 to 100, where 0 indicates a minimal or nonexistent risk of hurricane activity, and 100 represents a very high risk of hurricane occurrence. This scoring approach allows us to standardize risk assessment across multiple locations by distilling complex environmental and spatial data into a single, comprehensible metric.

We begin by using the longitude and latitude coordinates previously identified for each target city, ensuring that our calculations are geographically precise. Each city's location serves as an anchor point for assessing the proximity of historical hurricane paths recorded in the HURDAT2 dataset. By identifying the closest historical hurricane data point relative to each city's coordinates, we establish a foundation for estimating that city's risk based on past hurricane activity patterns. This process involves calculating the distance between each city's location and recorded hurricane tracks, prioritizing points where hurricanes have reached their peak intensities, as these events represent the greatest potential hazard.

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Given that hurricanes are most active in the Atlantic basin during the summer and early fall, we chose July as a representative month for our calculations. By focusing on a peak month of hurricane season, we can capture a more accurate seasonal risk profile that aligns with historical hurricane frequency and intensity. We then draw from our ENSO dataset to extract the Oceanic Niño Index (ONI) and SST values for July, as these variables are fundamental in predicting hurricane likelihood and intensity. The ONI value is particularly crucial in this assessment because it captures the current state of the ENSO cycle—either El Niño, La Niña, or neutral—which has a direct impact on atmospheric conditions favorable or unfavorable to hurricane formation.

Our calculations then integrate the results from our spatial correlation and KDE density analysis, which we previously computed for each city. The spatial correlation factor, informed by ENSO and SST, provides a location-specific risk profile based on the historical relationship between these natural factors and hurricane density. Meanwhile, KDE adds depth by modeling the historical density of hurricanes across the city's latitude and longitude, offering insights into the likelihood of hurricane landfall in each city's vicinity. This combination of spatial and density data enables a more granular assessment that respects both historical data and environmental conditions tied to hurricane activity.

Once the spatial correlation, KDE density results, and ENSO and SST values are gathered, we calculate a raw risk score for each city. This raw score reflects the likelihood of hurricane occurrence in a particular area given historical and environmental data. However, to make these scores meaningful on a standardized scale, we normalize each score to fall between 0 and 100. This normalization process ensures that the risk scores are comparable across all cities, making it easier to identify which locations are at the highest or lowest risk. Each city's final risk score is thus derived from a blend of historical hurricane density, proximity to past hurricane tracks, and the influence of ENSO and SST during hurricane season.

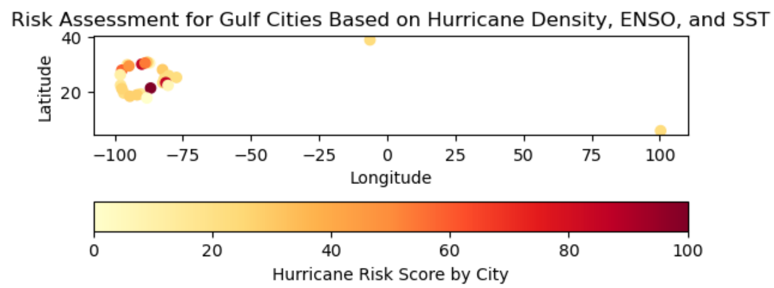

Figure 3.3: **Plot of Risk Assessment for Gulf Cities based on Hurricane Density and Risk Factors**

```
City: New Orleans, Risk Score: 85.26932718912968
City: Houston, Risk Score: 18.195072343862577
City: Tampa, Risk Score: 29.33815772709569
City: Miami, Risk Score: 22.090171716262134
City: Corpus Christi, Risk Score: 58.81242546150012
City: Pensacola, Risk Score: 6.610764968034644
City: Mobile, Risk Score: 29.16406415307445
City: Galveston, Risk Score: 47.338434989875424
City: Biloxi, Risk Score: 53.822501717918854
City: Key West, Risk Score: 21.16691529929075
City: Veracruz, Risk Score: 21.555988398616392
City: Tampico, Risk Score: 16.779508770516188
City: Campeche, Risk Score: 16.779508770516188
City: Cancún, Risk Score: 100.0
City: Mérida, Risk Score: 22.680256492005498
City: Ciudad del Carmen, Risk Score: 27.638372990376453
City: Progreso, Risk Score: 10.958296121335835
City: Coatzacoalcos, Risk Score: 27.638372990376453
City: Tuxpan, Risk Score: 26.270089693244103
City: Havana, Risk Score: 21.16691529929075
City: Varadero, Risk Score: 84.52871384268127
City: Cienfuegos, Risk Score: 6.610764968034644
City: Belize City, Risk Score: 0.0
City: George Town, Risk Score: 22.680256492005498
City: Nassau, Risk Score: 22.090171716262134
```

Figure 3.4: **List of Cities and corresponding Risk Scores**

3.3 Results and Analysis. Regarding the spatial correlation, we can see that the correlation coefficient for ENSO and hurricane activity is ~0.158, which is indicative of a weak positive correlation. A positive correlation indicates that during ENSO periods, there is a slight increase in hurricane density. However, due to the low correlation coefficient, this indicates that this relationship is not strong enough to have a definitive output on hurricane formation. It is worth noting that ENSO's influence is based on whether it is El Niño or La Niña conditions. For example, La Niña conditions (negative ONI values) lead to more favorable conditions for hurricane density, while El Niño conditions are associated with fewer hurricanes due to the increased vertical wind shear. Due to these contrasting conditions, this may have led to a weak positive correlation.

Meanwhile, the correlation coefficient for SSTs is -0.160, indicating a weak negative correlation. This indicates that warmer sea surface temperatures negatively affect the hurricane density in the Atlantic. This is counterintuitive to what was previously researched, as warmer waters usually fuel the formation of hurricanes. However, this weak correlation could be the product of other factors, such as ENSO and vertical wind shear, inhibiting hurricane development despite higher SSTs.

These results are surprising, as these two variables were expected to have stronger correlations due to how they were initially ranked from prior research. That being said, it can be attributed to the fact that there are multiple data points in a non-linear fashion, a high variability in data provided, or any of the many stated reasons above.

Regarding the normalized risk scores of each city provided, we can see that Cancún, New Orleans, and Varadero have high-risk scores. This is likely due to the geographic location of each city. For example, Cancún is prone to hurricanes due to its location along the Yucatan Peninsula. New Orleans is mostly below sea level, making it more susceptible to hurricanes. This indicates that geographic location also plays a big factor as a potential risk factor when determining hurricane activity in a specific area, even if most if not all of the cities are along the Gulf of Mexico.

On the contrary, Belize City, Pensacola, and Cienfuegos scored low in terms of risk score. While these countries do have hurricanes, they are likely protected due to their geographic location and elements. For example, Pensacola and Cienfuegos are 102’ and 82’ above sea level respectively, meaning they are less likely to be hit by hurricanes. Belize City, while at sea level, is one of the most southern cities, meaning it could likely be protected by land directly north of it. These low scores could also be a

Overall, both ENSO and SST have weak correlations with hurricane density, suggesting that other factors might be more significant drivers of hurricane activity. The risk scores highlighted significant spatial variability, with cities like Cancún and New Orleans at very high risk, while others like Belize City face minimal risk. Incorporating additional variables, such as the above upper-level wind patterns and Saharan Dust levels, could provide a more comprehensive understanding of hurricane dynamics and improve predictive capabilities.

4 Project contributions

4.1 Anh Pham

Anh Pham took lead in the first part which was the data collection and preparation. She provided the code for the Gulf_Cities data frame and found the latitudes and longitudes for each of the cities. She also filtered the data set to make sure that we were only looking at storms that affected the Gulf of Mexico in the past 25 years.

4.2 Nicolas Mangilit

Nicolas Mangilit collaboratively worked with Mustafa Sahin to take lead in the analysis of hurricane tracks. He also assisted with filtering the data further by making sure that the dataset only worked with storms that were classified as hurricanes, omitting tropical storms and tropical depressions. He worked on the code that created the interactive map that displayed the storm's tracks and the locations of the cities. He also helped Mustafa with the report on statistical analysis of track frequency, intensity, and duration.

4.3 Mustafa Sahin

Mustafa Sahin, as previously stated, took the lead with Nicolas Mangilit on the analysis of hurricane tracks. He assisted with the visualization code that Nicolas worked on and worked on the report on statistical analysis of track frequency, intensity, and duration.

4.4 Yash Patel

Yash Patel, along with Pierreje Villaviencio, took lead on the risk-profile analysis. Yash primarily worked on the code that provided the density map and risk assessment for each city. He also assisted Pierreje Villaviencio with the summarization of the findings.

4.5 Pierreje Villiencio

Pierreje Villaviencio, as previously mentioned, worked with Yash to take lead in the risk-profile analysis. He assisted Yash with the code and primarily worked on the summarization of the findings based on the risk assessment.

4.6 Overall team contributions

Everyone in the team worked together to cultivate the ending report. We all assisted each other when it came to debugging code and fact checking each other to make sure that any data or information given was correct. The team had good chemistry and everyone contributed the same amount of work.

ACKNOWLEDGMENTS

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