

A Multi-Faceted Look at Storms:

**Trends, Impacts, and Public
Sentiments**

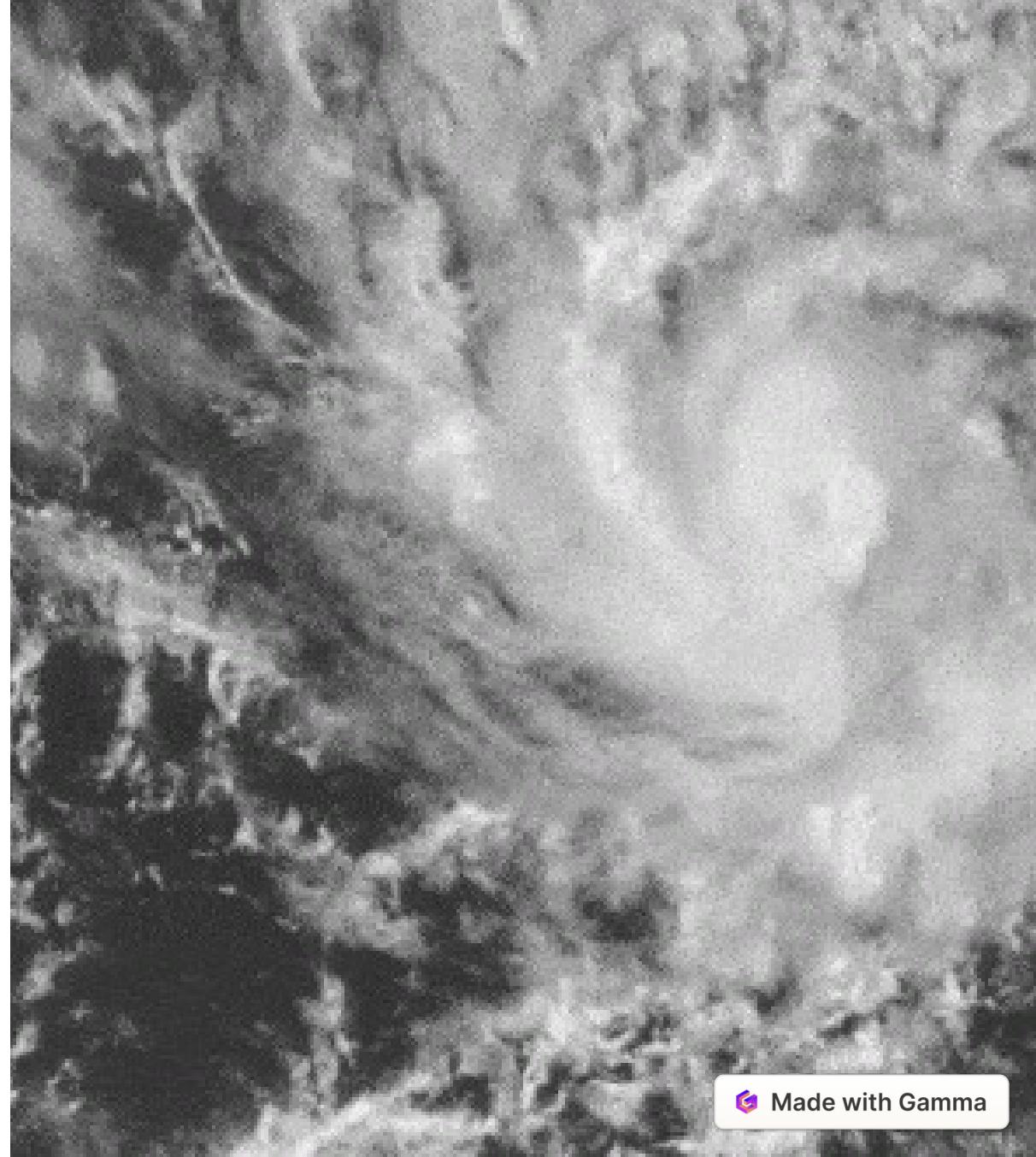
Aleksandra Kutz

Daniel Allen

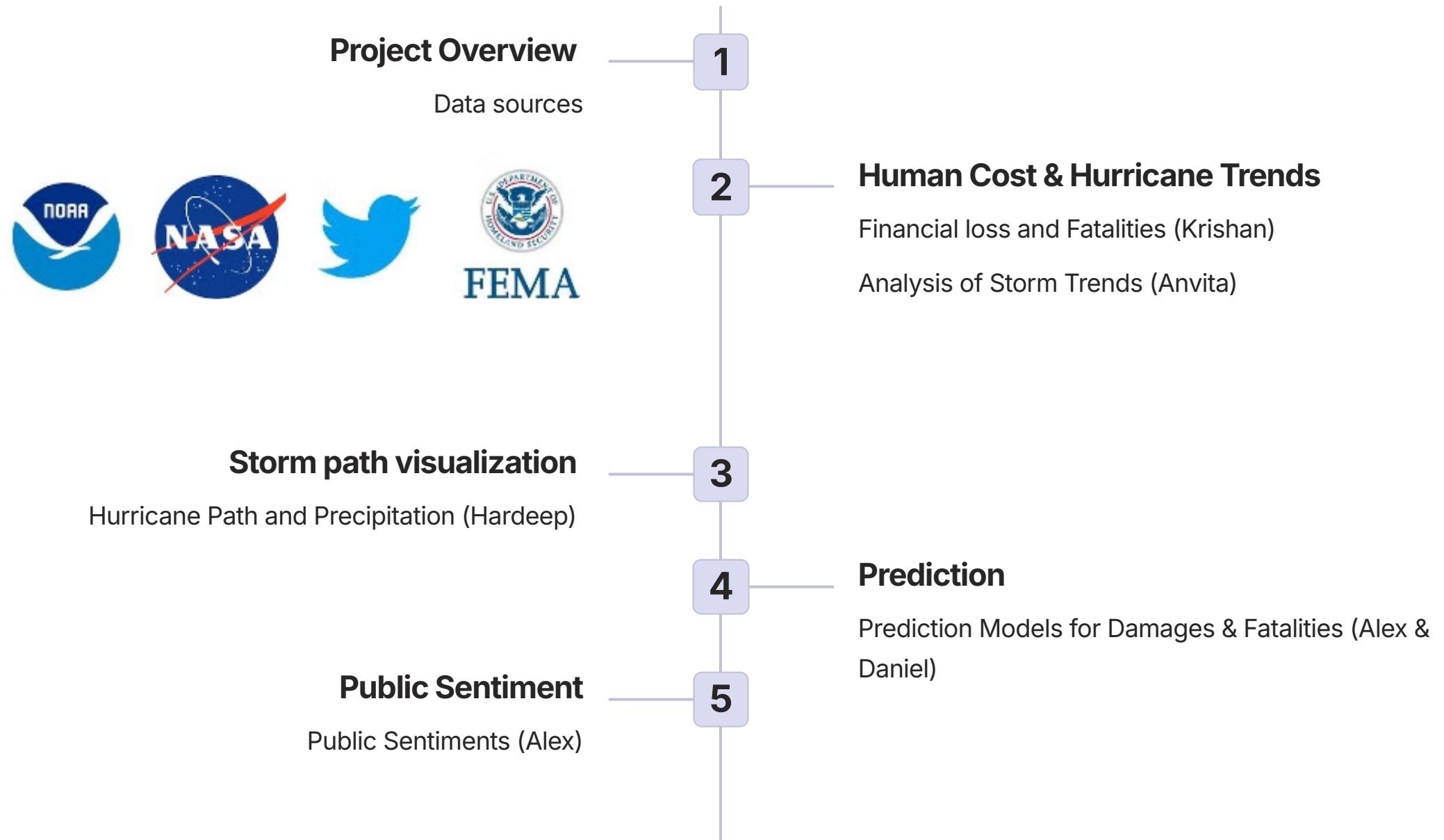
Anvita Iyer

Krishan Pandey

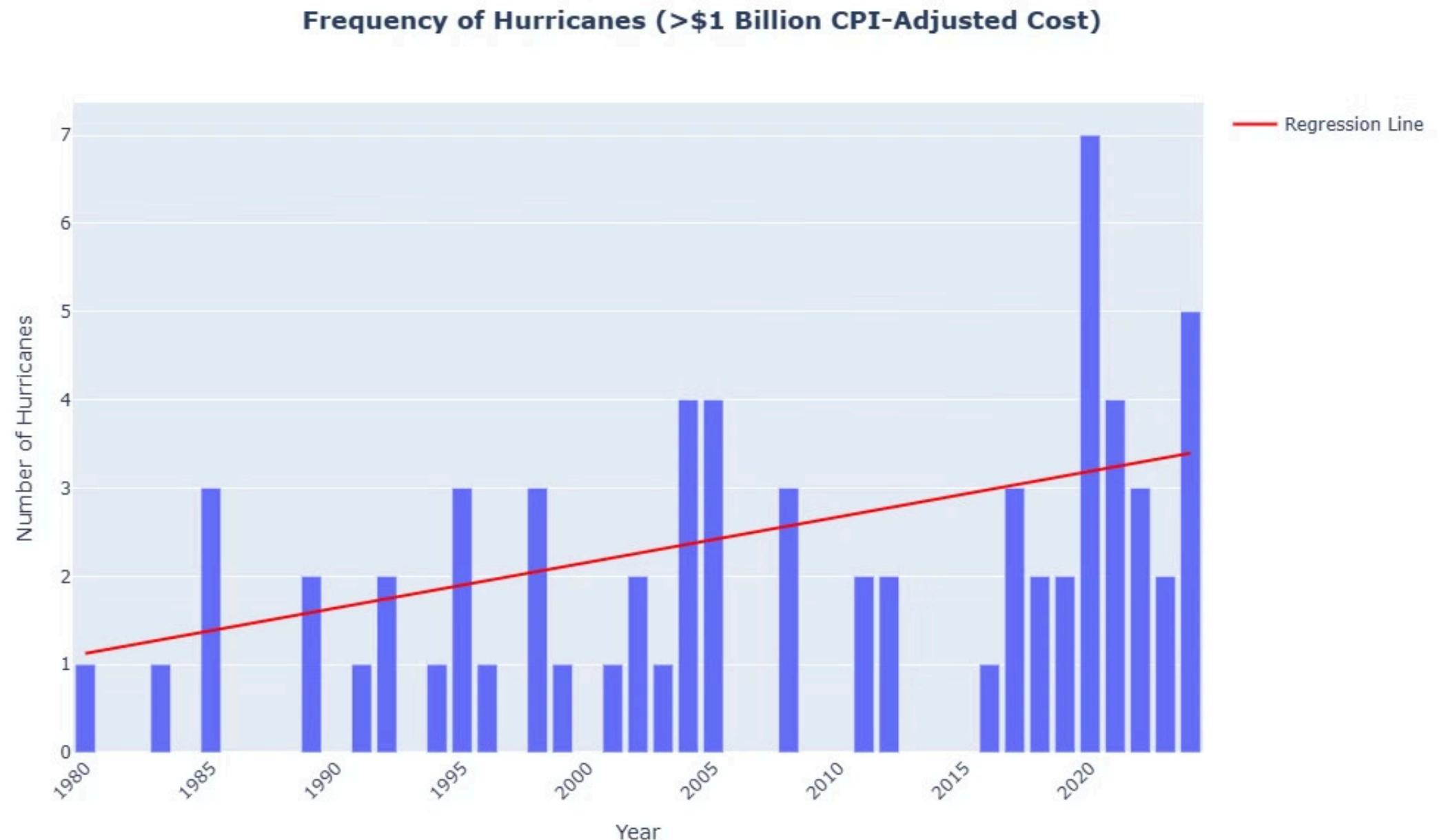
Hardeep Gumber



Key Topics: Hurricane Analysis and Impact

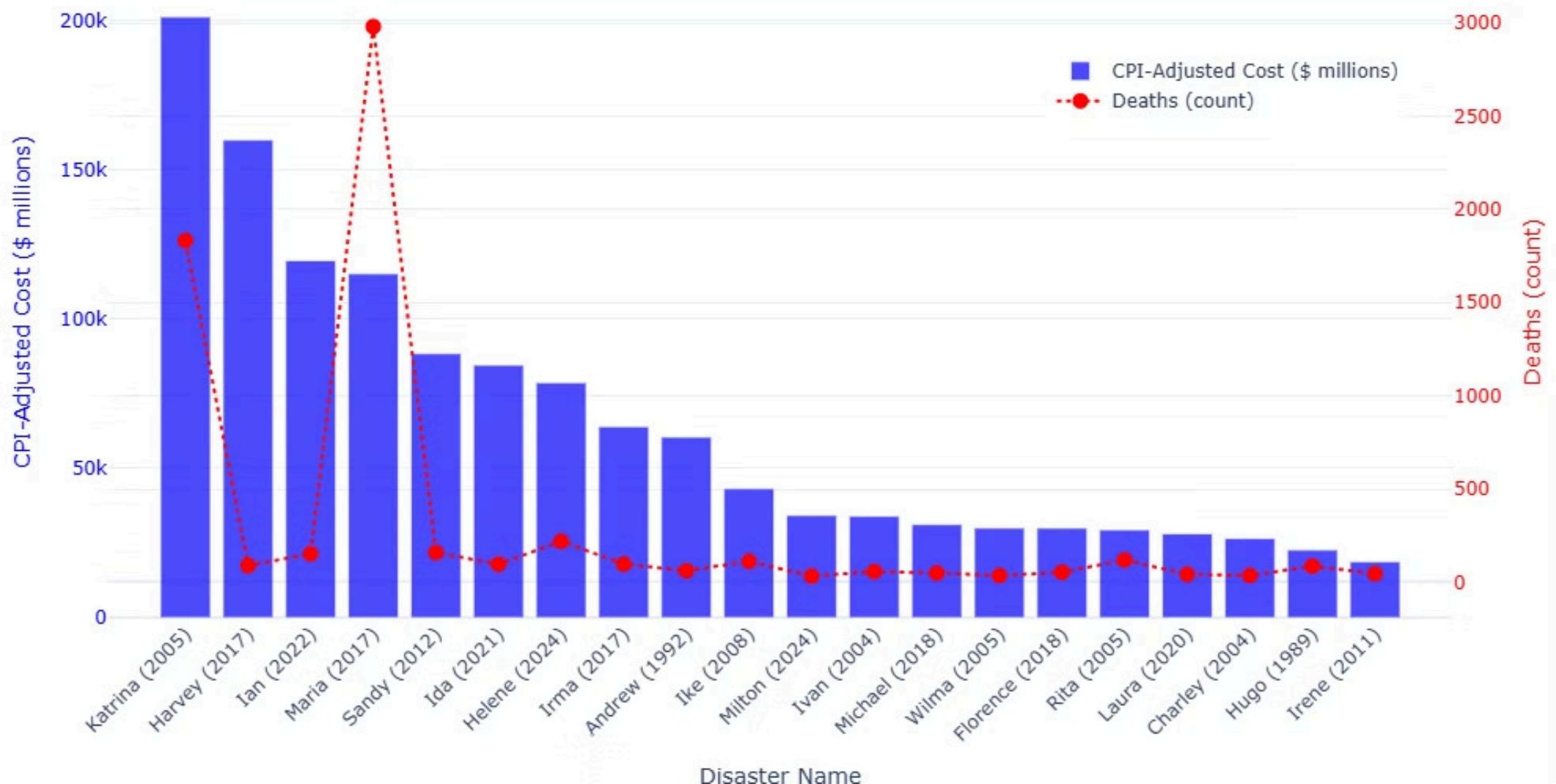


Frequency of Hurricanes (>\$1 billion cost; 1980-2024)



Correlation of Top 20 >\$1 Billion Dollar Hurricanes with Deaths (1980-2024)

Top 20 Hurricanes by CPI-Adjusted Cost (>\$ 1 billion) and Deaths; 1980-2024)



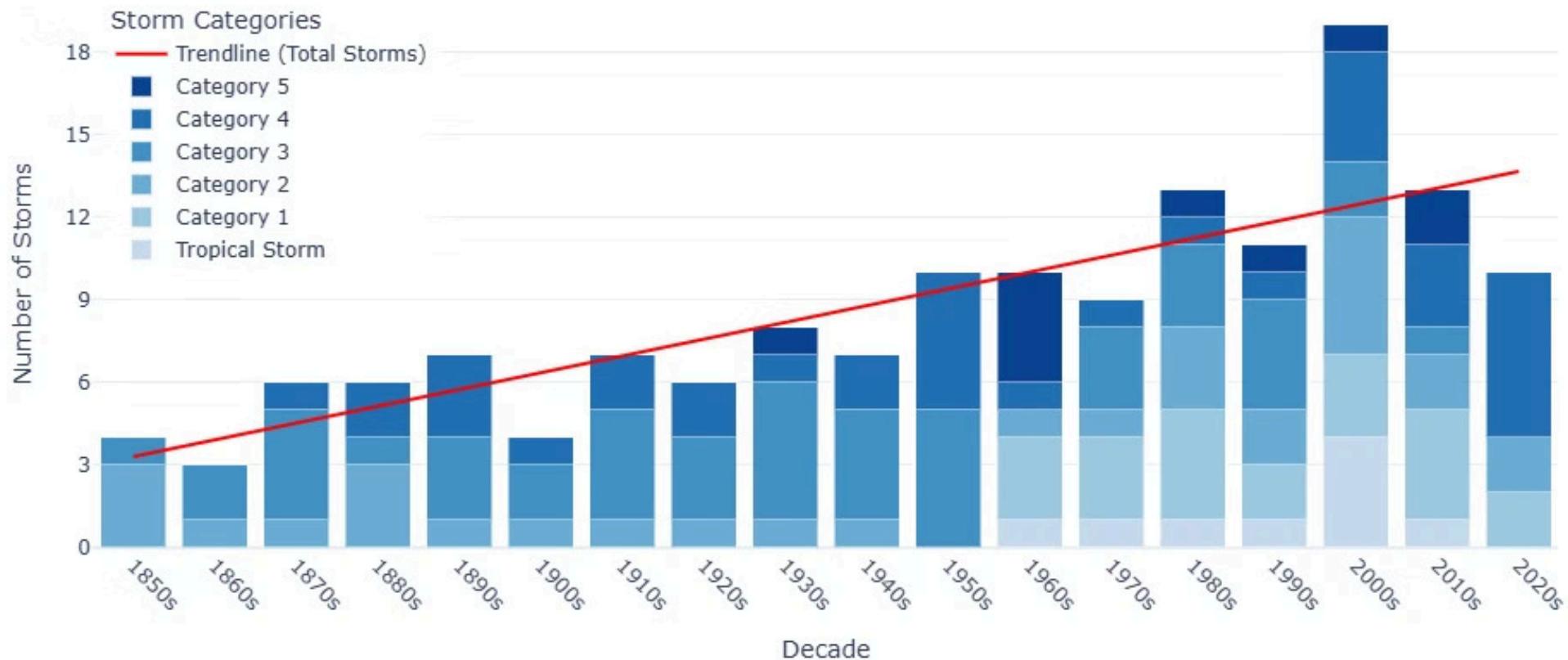
- Even though Katrina (2005) has been the most expensive hurricane event, the most fatalities happened during hurricane Maria (2017) in Puerto Rico.
- It highlights that damages and fatalities are dependent on multiple factors, not just the hurricane severity.

Hurricane Categories - Saffir-Simpson Hurricane Wind Scale

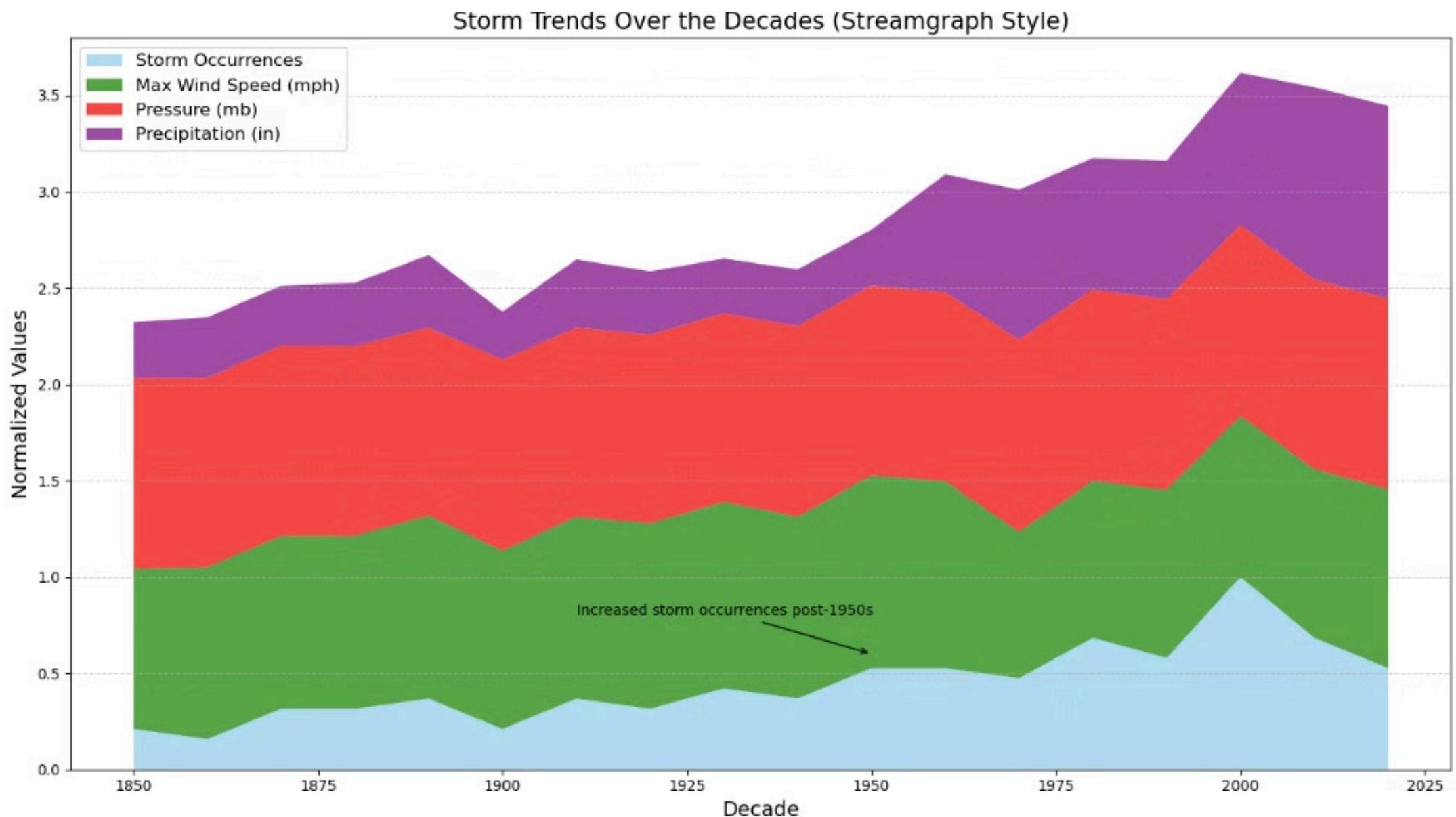
Category	Max sustained wind	Examples
1	74-95 mph (64-82 knots)	Humberto (2007)
2	96-110 mph (83-95 knots)	Zeta, Sally (2020)
3	111-129 mph (96-112 knots)	Ian (2022)
4	130-156 mph (113-136 knots)	Harvey, Maria (2017)
5	>= 157 mph (>= 137 knots)	Katrina (2005), Andrew (1992)

Storm Occurrences over the Decades

Total Storm Occurrences Grouped by Decades (1851 and onwards) with Categories

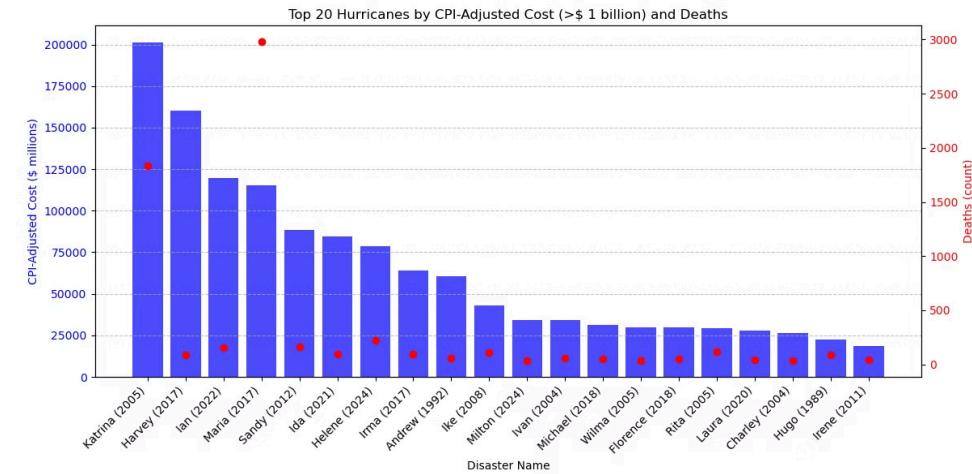
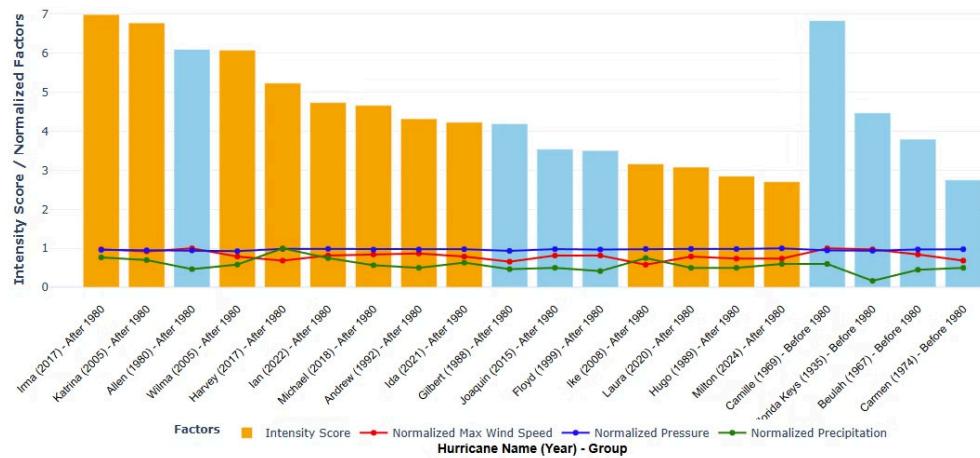


Storm Characteristics over the Decades



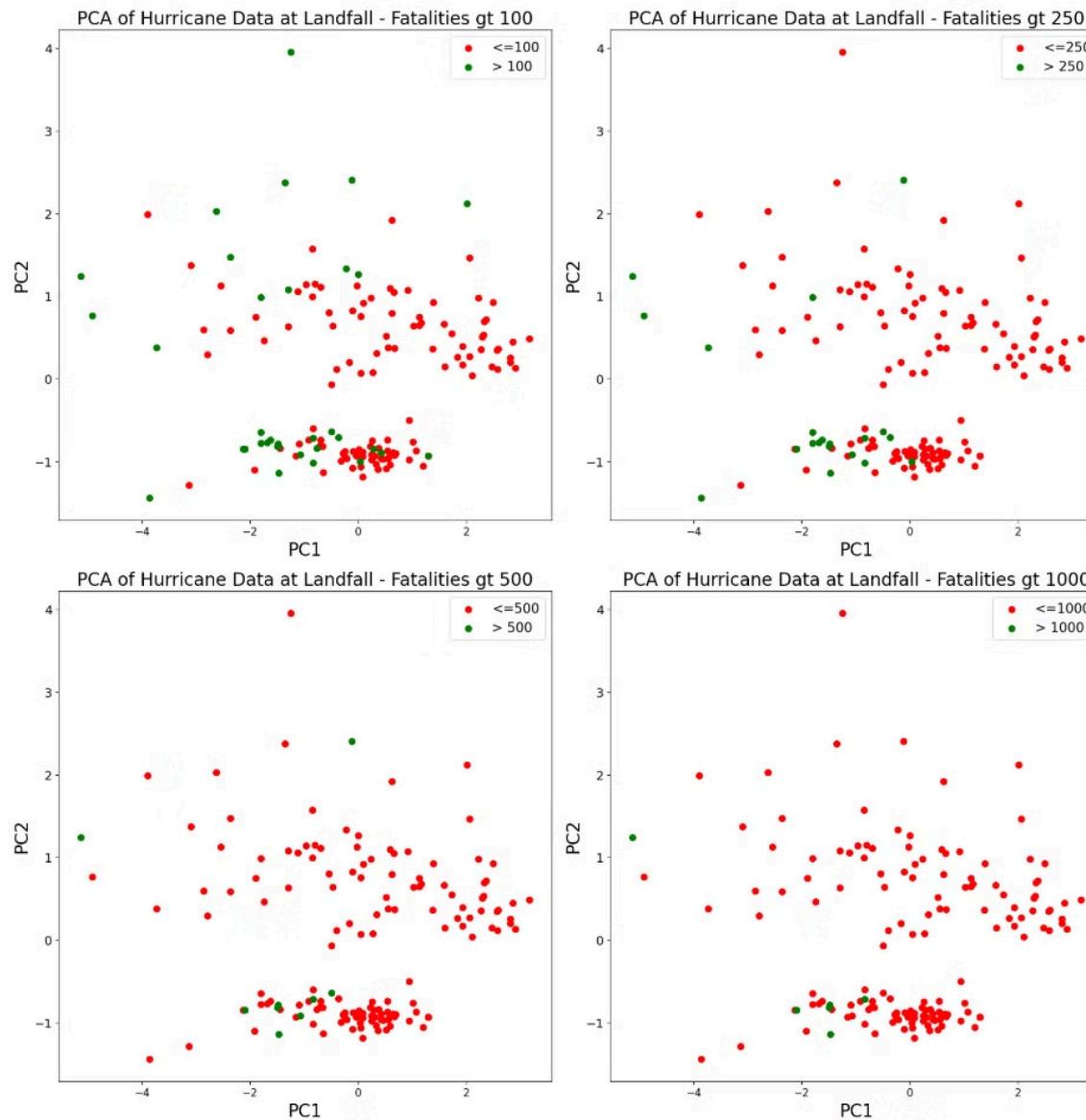
Top 20 Most Intense Storms

Top 20 Storms Grouped by Before and After 1980 Based on Intensity Score



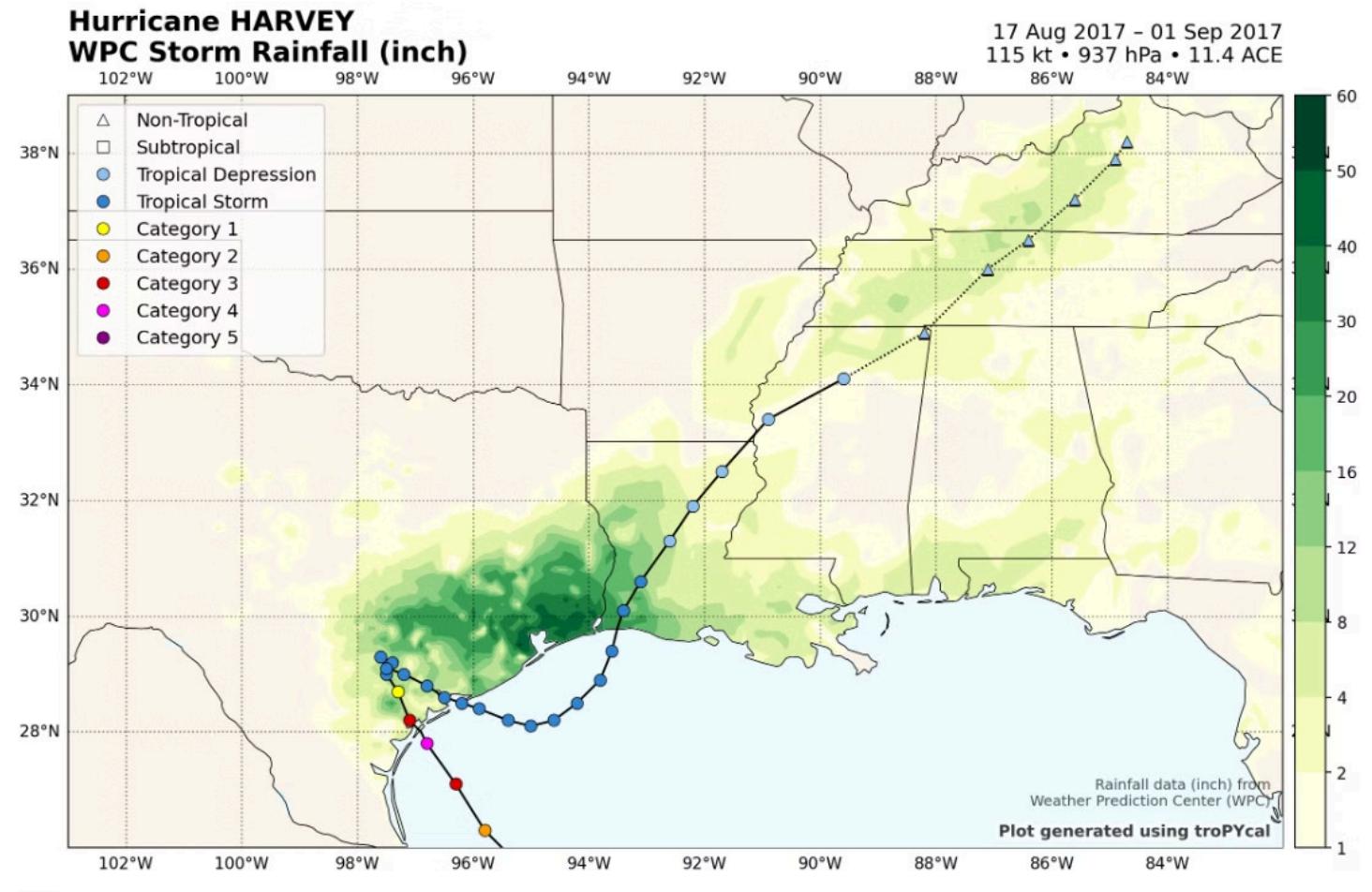
PCA: Fatalities from Hurricane Parameters

Max wind speed, pressure, storm surge and precipitation

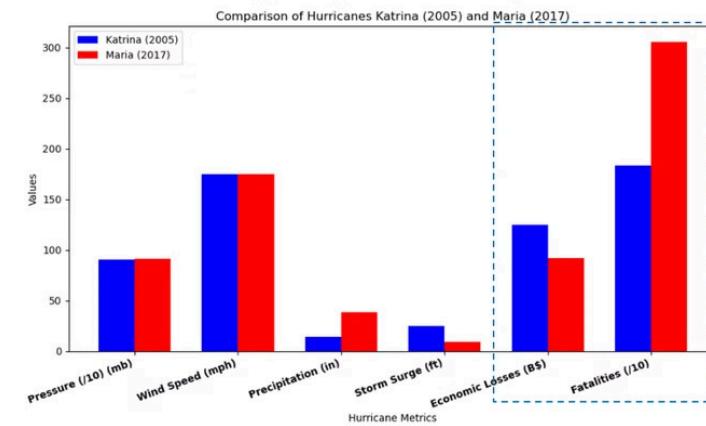
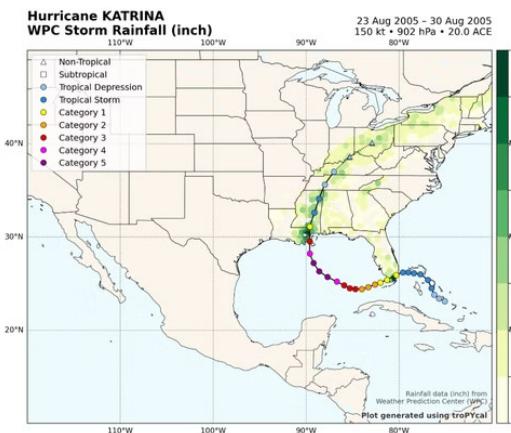
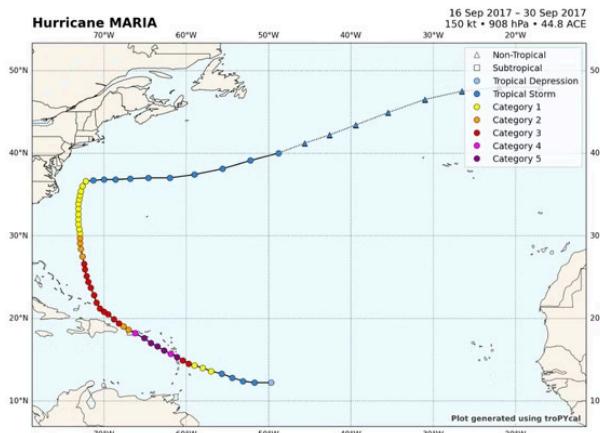


Hurricane Harvey's Path and Precipitation

- **Landfall:** Rockport, Texas
- **Category:** 4
- **Rainfall:** up to 60 inches
- **Storm surge:** 9 feet
- **Fatalities:** 175
- **Economic damage:** \$125 billion
- **Infrastructure:** Over 300,000 buildings



Island (Maria-4) vs. Mainland (Katrina -5) Hurricane Analysis



The number of fatalities is influenced by the landfall location and the effectiveness of resource management.

Sentiment - What is that and Why does it matter?

Sentiment is the feeling or mood shown in a piece of text.

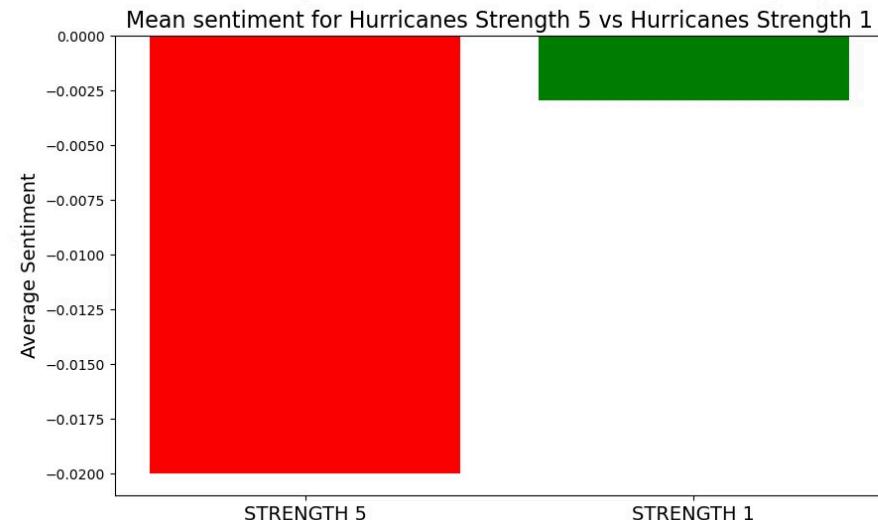
It can be positive, neutral or negative.

Sentiment analysis helps us see how people react to an event.

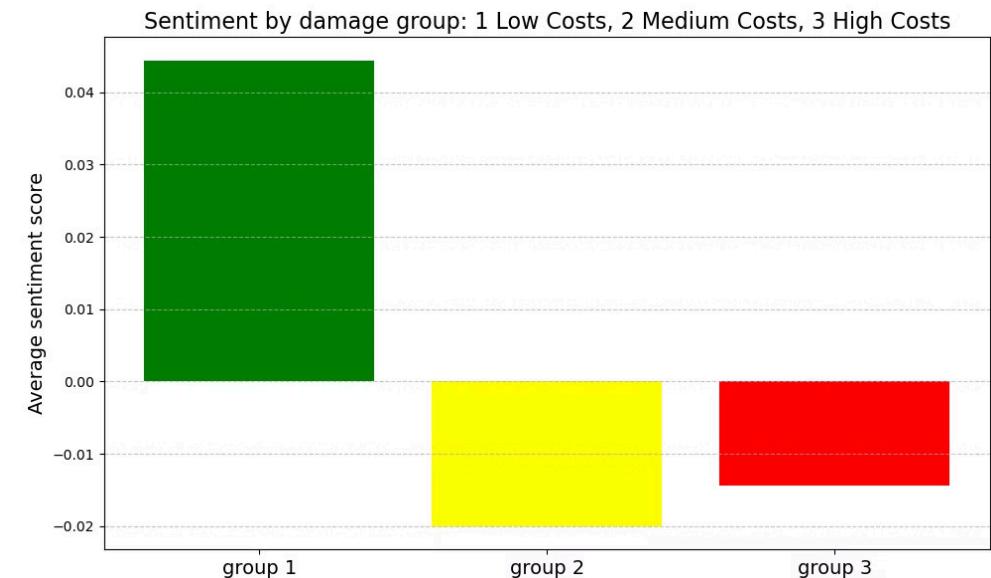
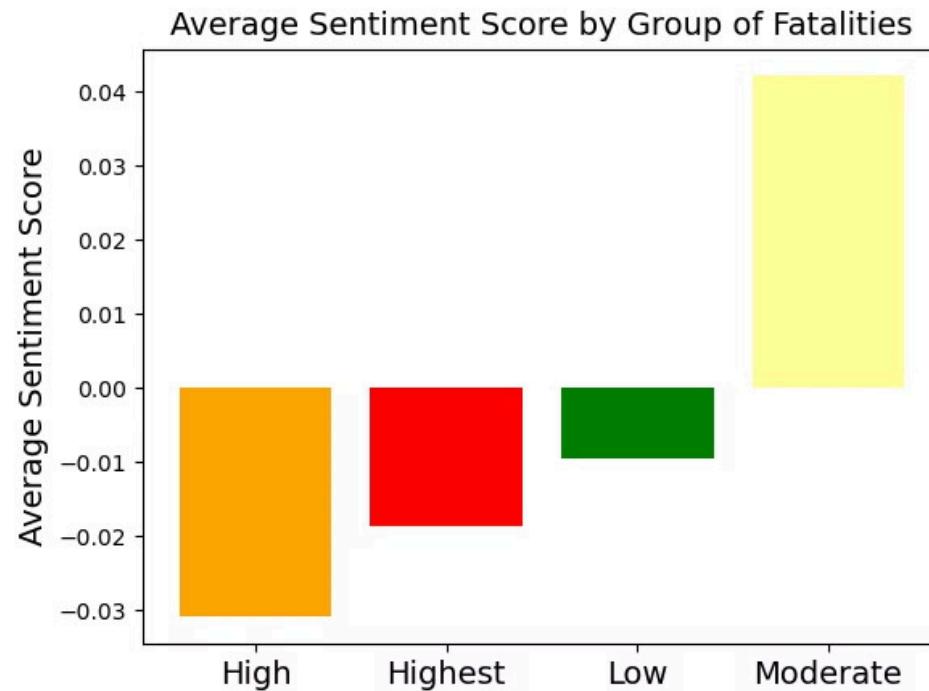
It can show whether the public had a positive or negative reaction.

NLTK (Natural Language Toolkit), Word Clouds,

VADER (Valence Aware Dictionary and sEntiment Reasoner)

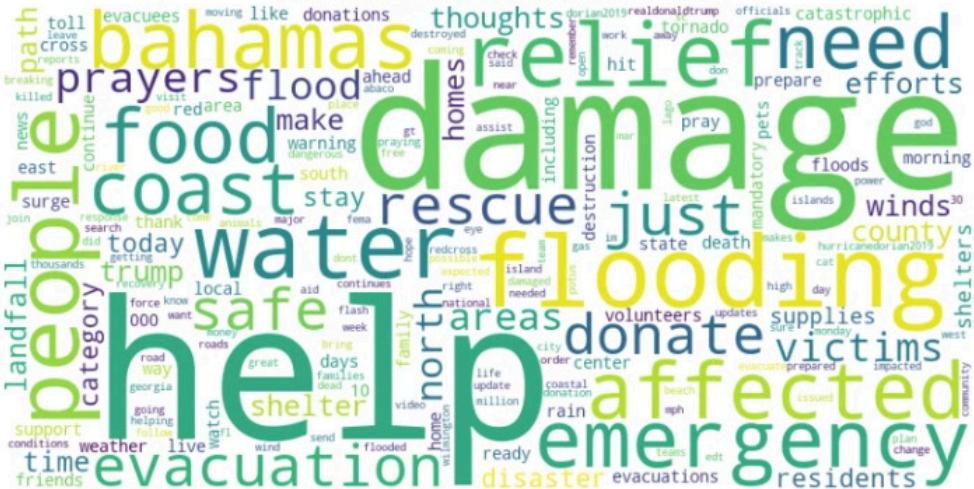


Average Sentiment Distribution Across Hurricanes Grouped by Fatalities and Cost of Damage

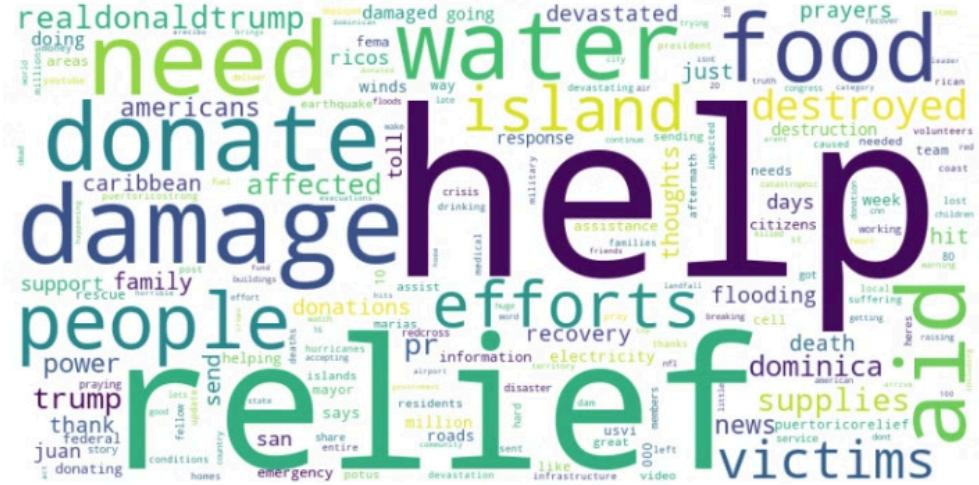


Average Sentiment Distribution Across Hurricanes Grouped by Fatalities

Word Cloud for g.1 (Lowest Fatality Group)



Word Cloud for g.3 (Highest Fatality Group)

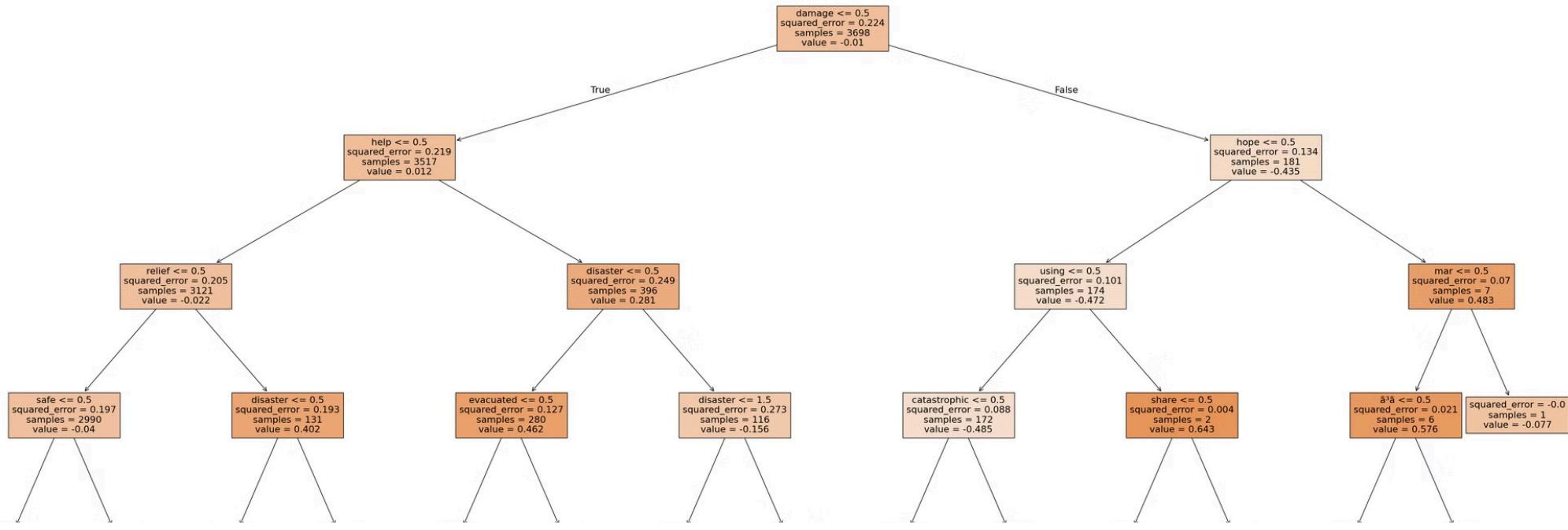


Word Cloud for Hurricanes Grouped by Damage Costs

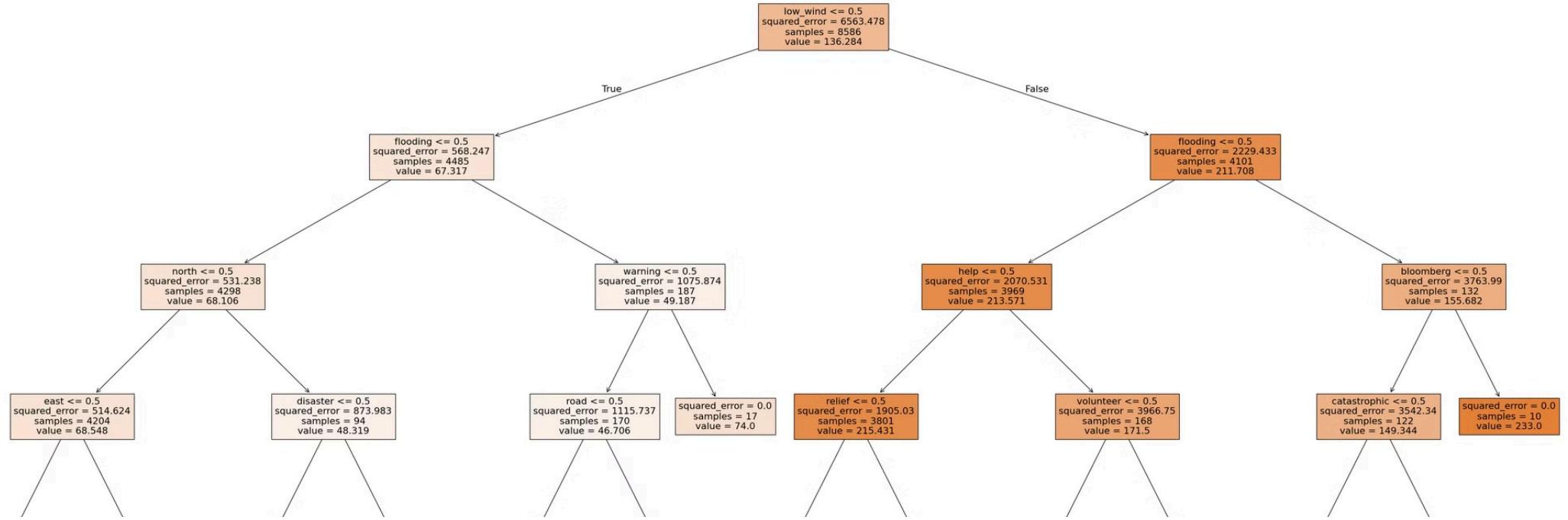
Low costs

Medium costs

High costs



Regression Tree Based on Hurricane-Related Tweets Predicting Sentiment Value



How do Wind Parameters influence the Regression Tree's Prediction of Fatalities?

Our Models to Predict Hurricanes

Cost of Damage:

82% Accuracy to predict 1 from 3 classes.

We used RandomForestClassifier as a base model, and improved it by using XGBClassifier with RandomizedSearchCV.

["CPI-Adjusted Cost_class"]

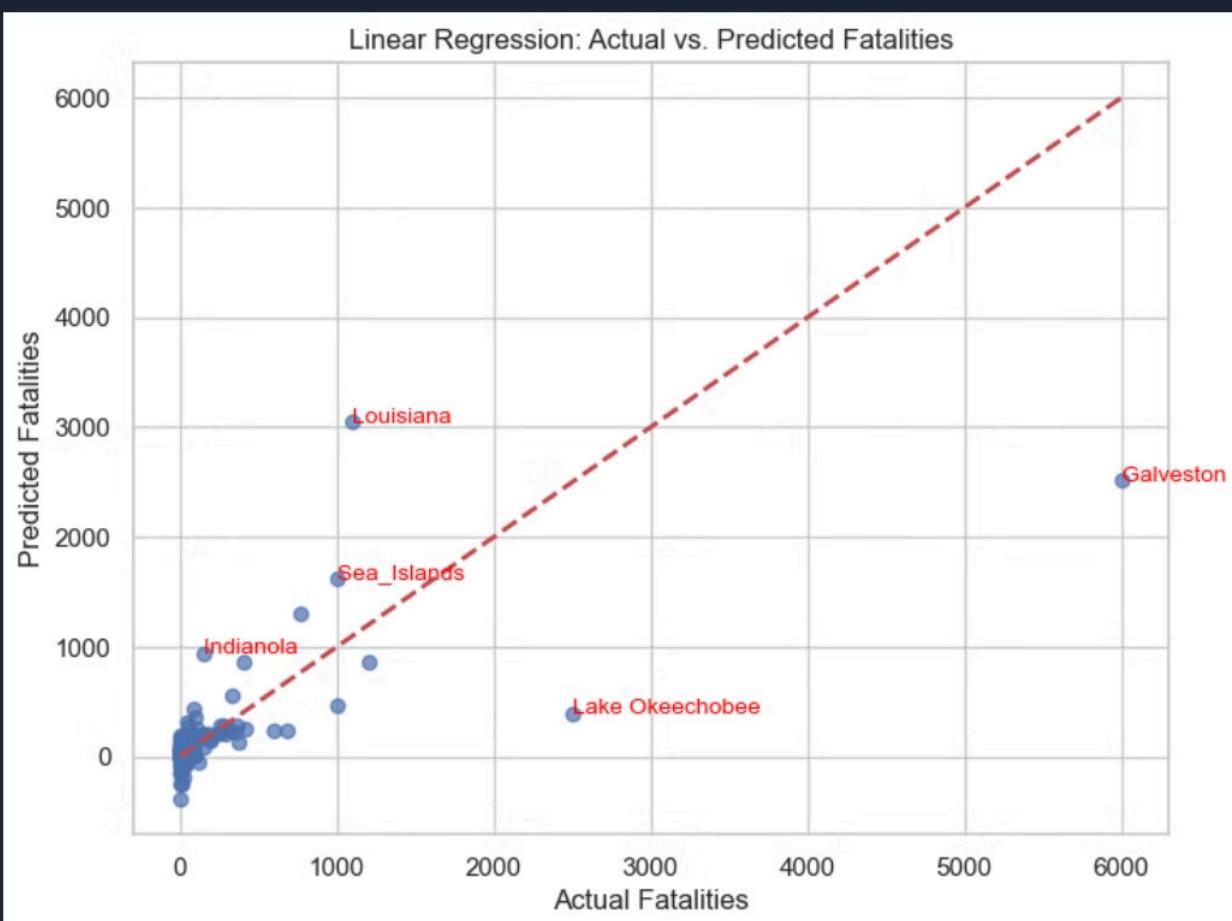
Number of Fatalities:

63% Accuracy to predict 1 from 4 classes.

(96% Accuracy if it's a binary class)

We used RandomForestClassifier as a base model and improved it with XGBClassifier.

["Fatal_class"]



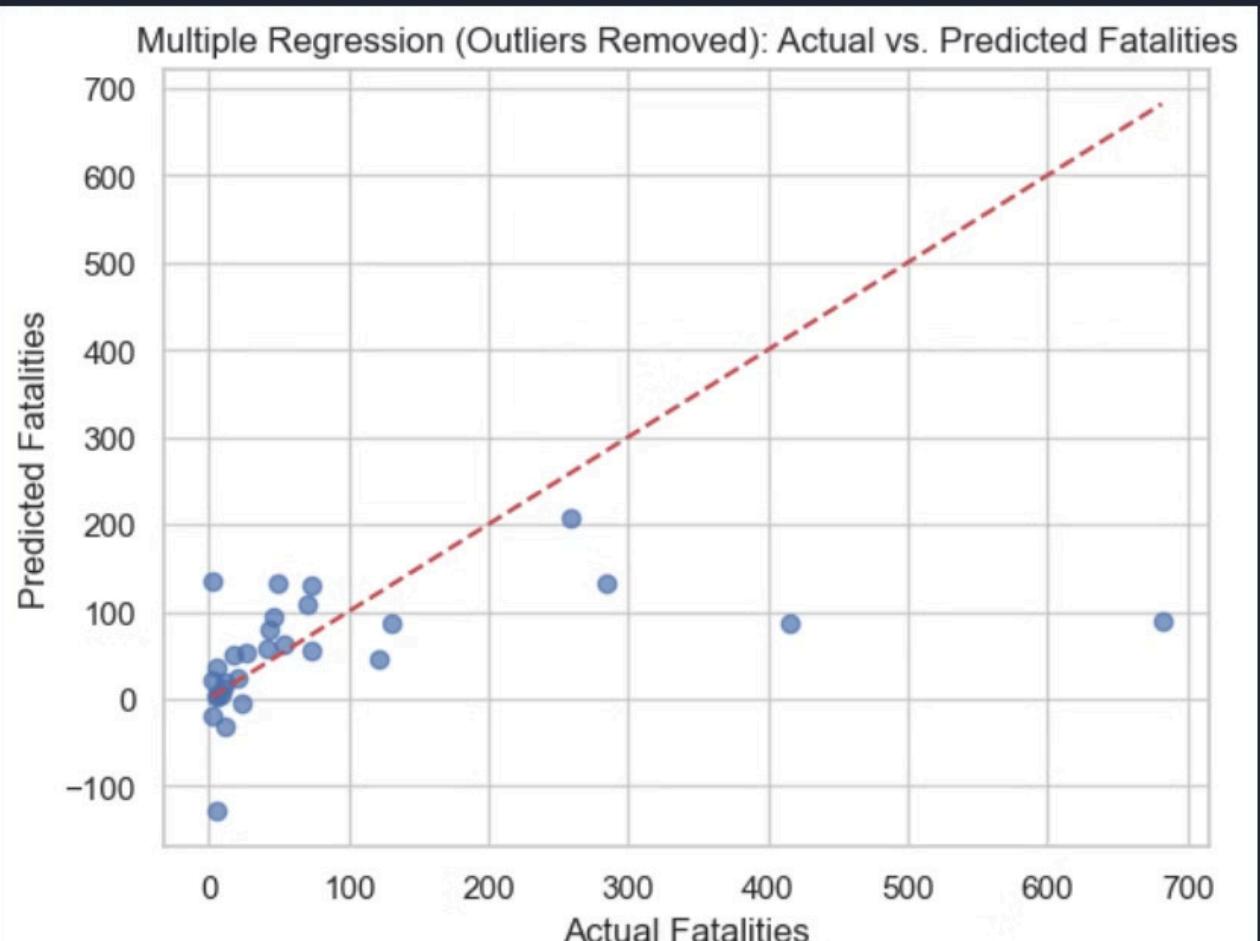
Identified Outliers:

	Hurricanes	Fatalities
124	Galveston	6000
110	Lake Okeechobee	2500
131	Louisiana	1100
133	Indianola	150
130	Sea_Islands	1000

- **Outliers Identified:** Major hurricane events such as **Galveston (6000 fatalities)**, **Lake Okeechobee (2500 fatalities)**, and **Louisiana (1100 fatalities)** deviate significantly from the model's predictions.
- **Prediction vs. Actual Trends:** The majority of points cluster near the **regression line**, indicating reasonable predictive performance, but extreme fatality events are **underestimated** by the model.
- **Systematic Underprediction:** The model struggles with high-fatality hurricanes, suggesting **nonlinear relationships or missing key predictive features** in the dataset.

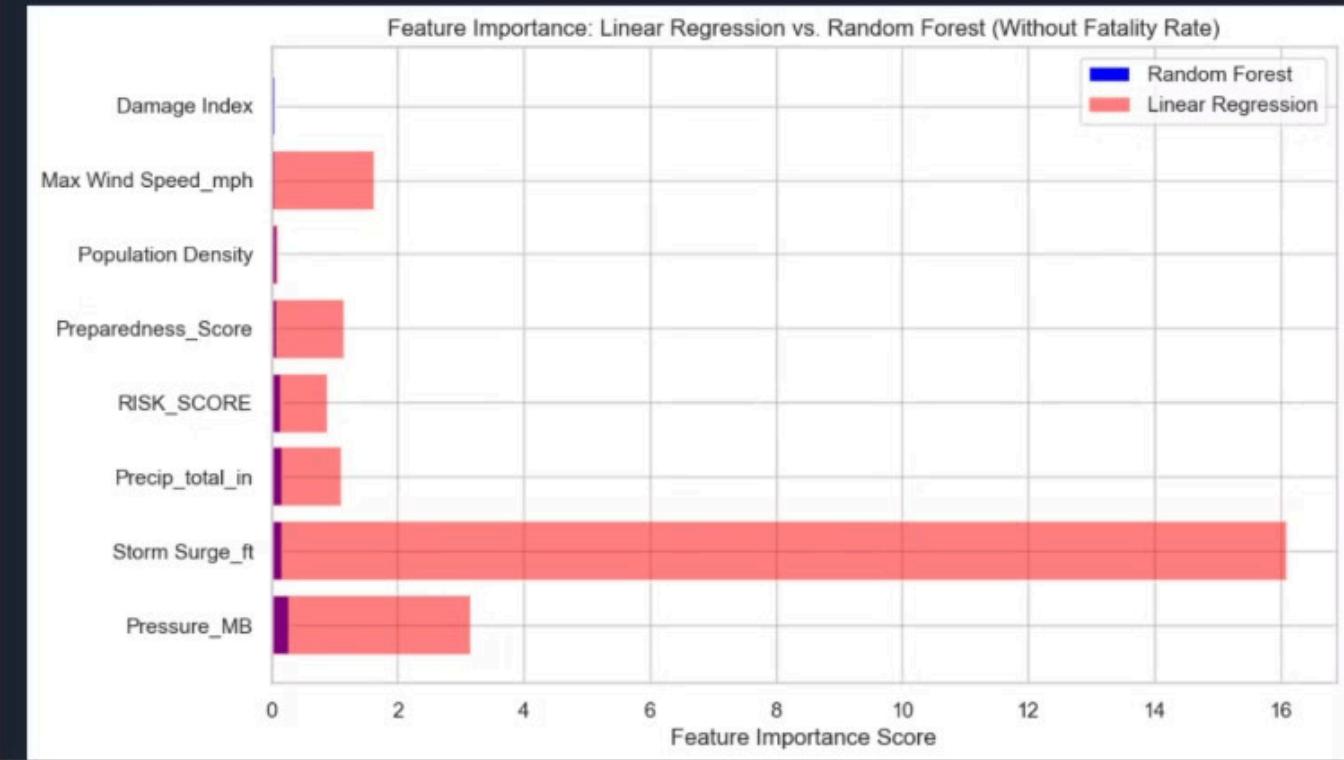
Mean Squared Error: 18970.57988204361

R²: 0.1281518636778829



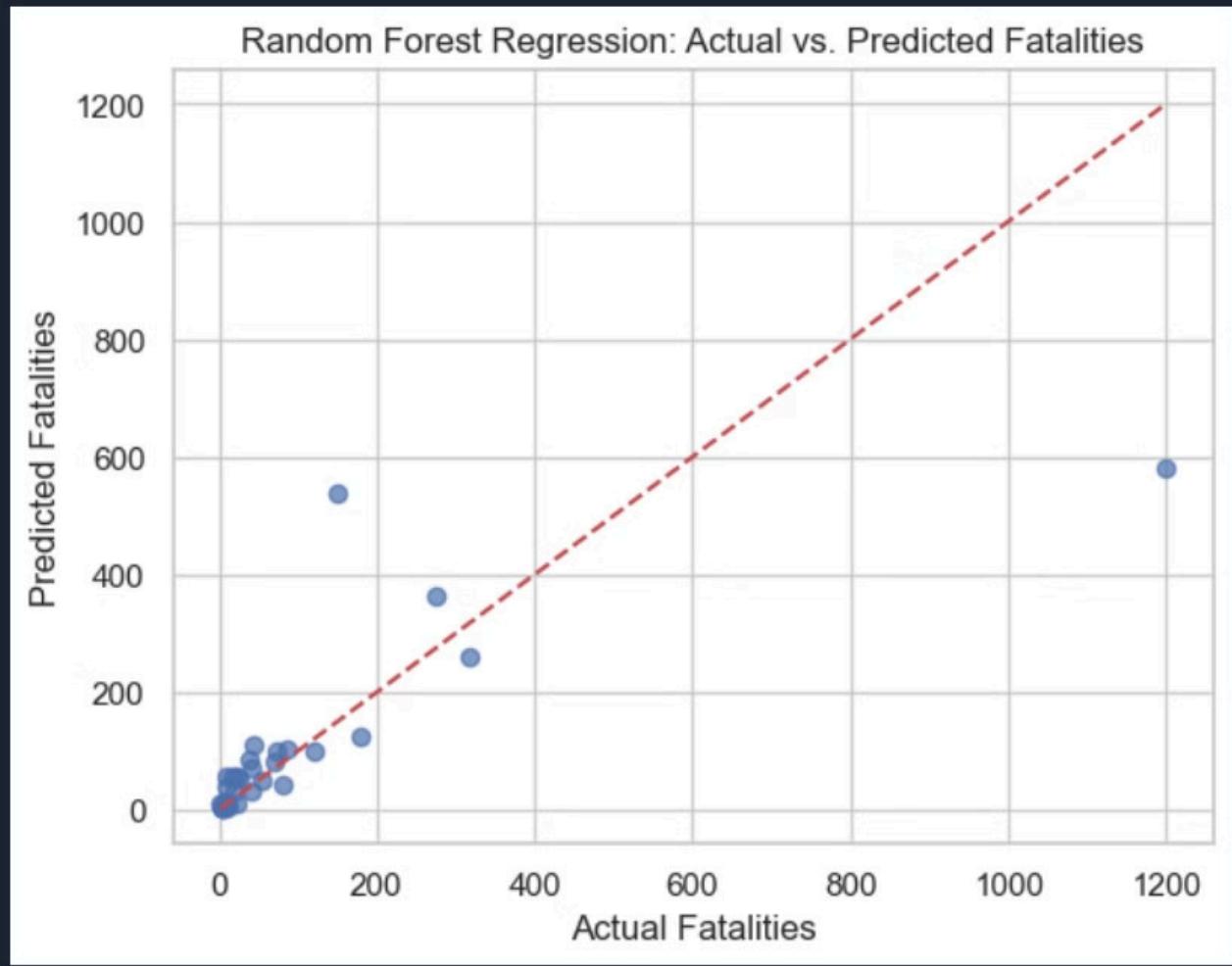
- **The model struggles to predict fatalities accurately.** The R² score is only 0.13, meaning it explains just 13% of the changes in fatalities—which is very low.
- **Most predictions are close to zero.** The model often **underestimates fatalities**, especially for larger storms, and even predicts **negative fatalities**, which is not realistic.
- **Removing outliers didn't fix the problem.** Even after **removing extreme storms**, the model still doesn't follow the trend well, suggesting **it may be missing key hurricane impact factors**.

Feature Importance Comparison (Without Fatality Rate):			
	Feature	Linear Regression	Random Forest
1	Pressure_MB	3.144191e+00	0.266418
2	Storm Surge_ft	1.608365e+01	0.171550
3	Precip_total_in	1.100919e+00	0.151907
4	RISK_SCORE	8.866127e-01	0.140400
7	Preparedness_Score	1.141094e+00	0.079736
5	Population Density	8.855626e-02	0.067983
0	Max Wind Speed_mph	1.621071e+00	0.061143
6	Damage Index	7.487204e-07	0.060863



- **Linear Regression puts too much focus on individual weather factors.** It thinks **Storm Surge and Pressure** are the most important, but this might be **over-exaggerated** because the model assumes straight-line relationships.
- **Random Forest spreads out the importance more evenly.** It balances storm-related features like wind speed and **doesn't let one factor dominate**, which helps it better understand complex storms.
- **Different models see hurricane impacts in different ways.** Linear models **focus on a few strong factors**, while Random Forest considers how multiple factors work together, making it **better at predicting real-world hurricane deaths**.

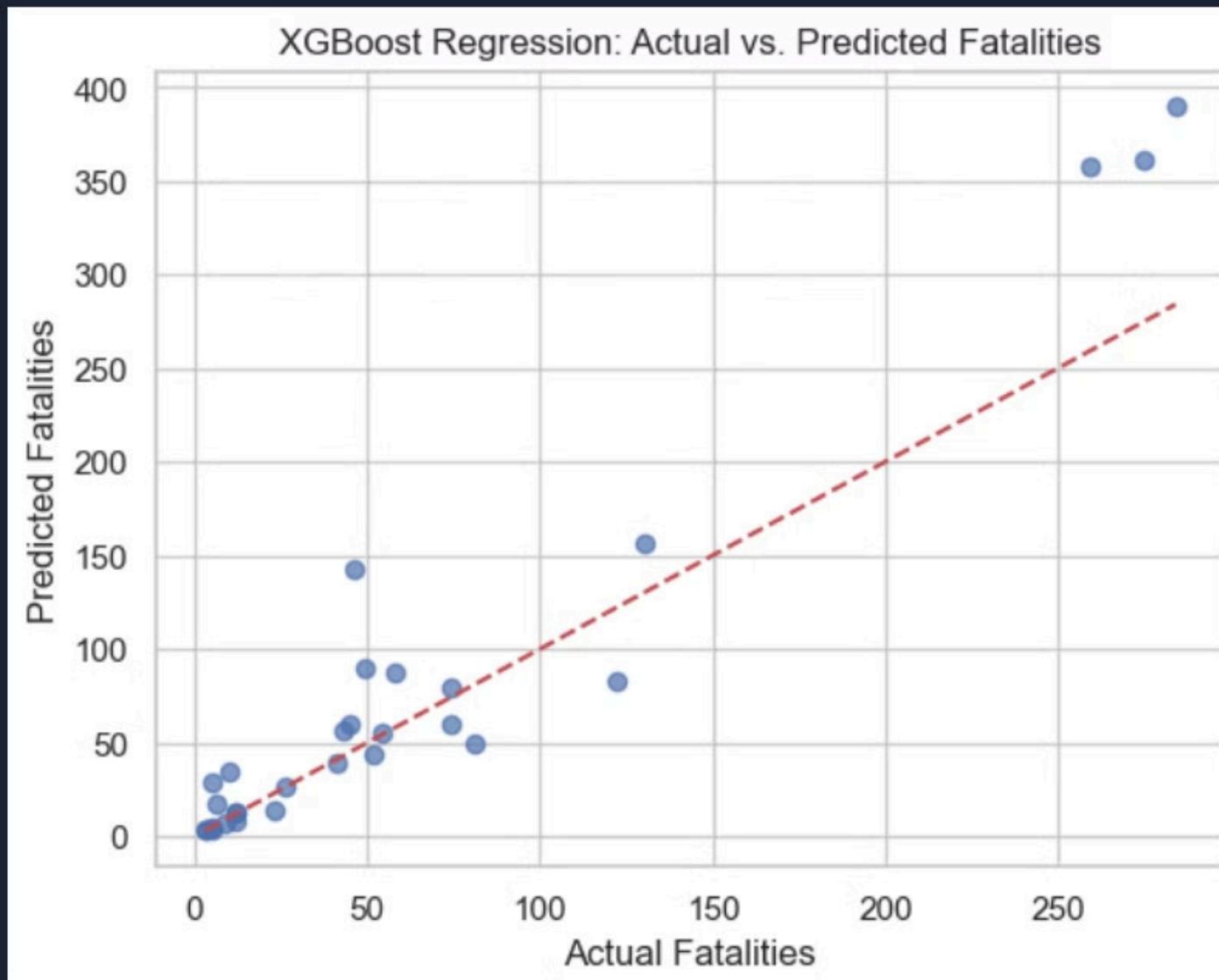
Mean Squared Error: 18813.750976666666
 R^2 : 0.6064191518576794



- It is unrealistic to use fatality rate to predict fatality rate. It maybe good for historical measures but not predators .
- Exposure Factors May Have Influenced the Results Too Much. If features like population density or preparedness score were based on data collected after the storm, then the model isn't truly predicting fatalities—it's just repeating patterns it already saw.
- Test Data May Have Been Too Similar to Training Data. If some of the same hurricanes were in both training and testing datasets, the model wasn't really predicting new hurricanes—it was memorizing old ones, leading to higher R^2 than expected

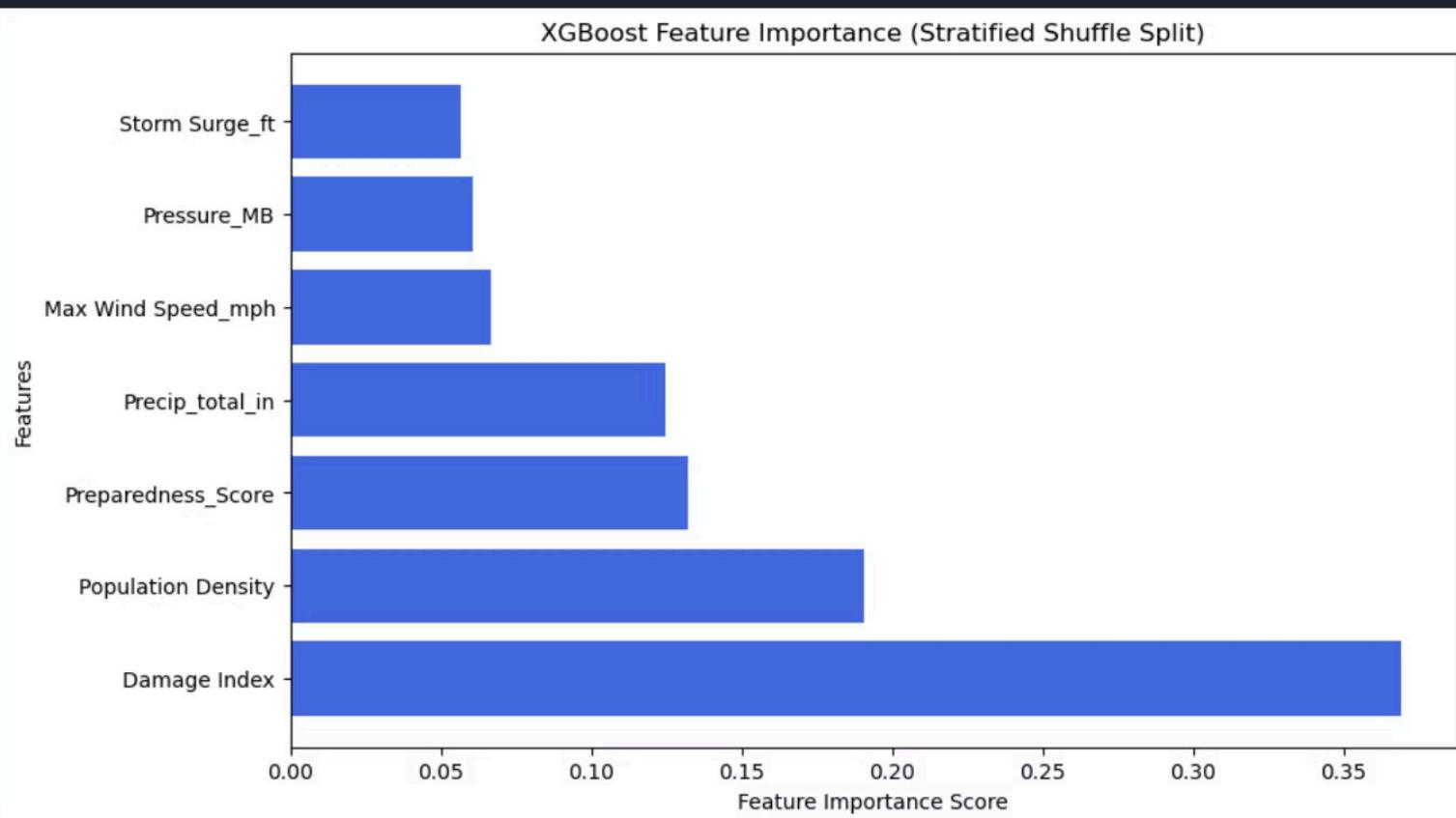
XGBoost Mean Squared Error: 1566.420654296875

XGBoost R²: 0.7472000122070312



- **Model might be using future data.** If it learned from **post-storm information**, it would **predict fatalities too well**, making it look more accurate than it really is.
- **Predictions are too close to actual values.** The **high R² (0.75)** suggests the model may have **seen similar data during training**, meaning it's **memorizing instead of truly predicting**.
- **It underestimates extreme events.** The model **struggles with higher fatality storms**, meaning it **might be missing key disaster impact factors**.

```
Feature Importance Analysis:
      Feature  Importance
5     Damage Index  0.368847
4   Population Density  0.190847
6  Preparedness_Score  0.132103
3   Precip_total_in  0.124479
0  Max Wind Speed_mph  0.066500
1    Pressure_MB  0.060499
2   Storm Surge_ft  0.056726
```



- **Damage Index and Population Density dominate**, meaning the model focuses more on exposure than storm severity.
- **Wind Speed, Pressure, and Storm Surge are weak**, suggesting the model isn't prioritizing meteorological factors.
- **Possible data leakage if Damage Index includes post-storm data**, making predictions misleading.



```
TEST 2 - Interaction Features (Without Damage Index)
```

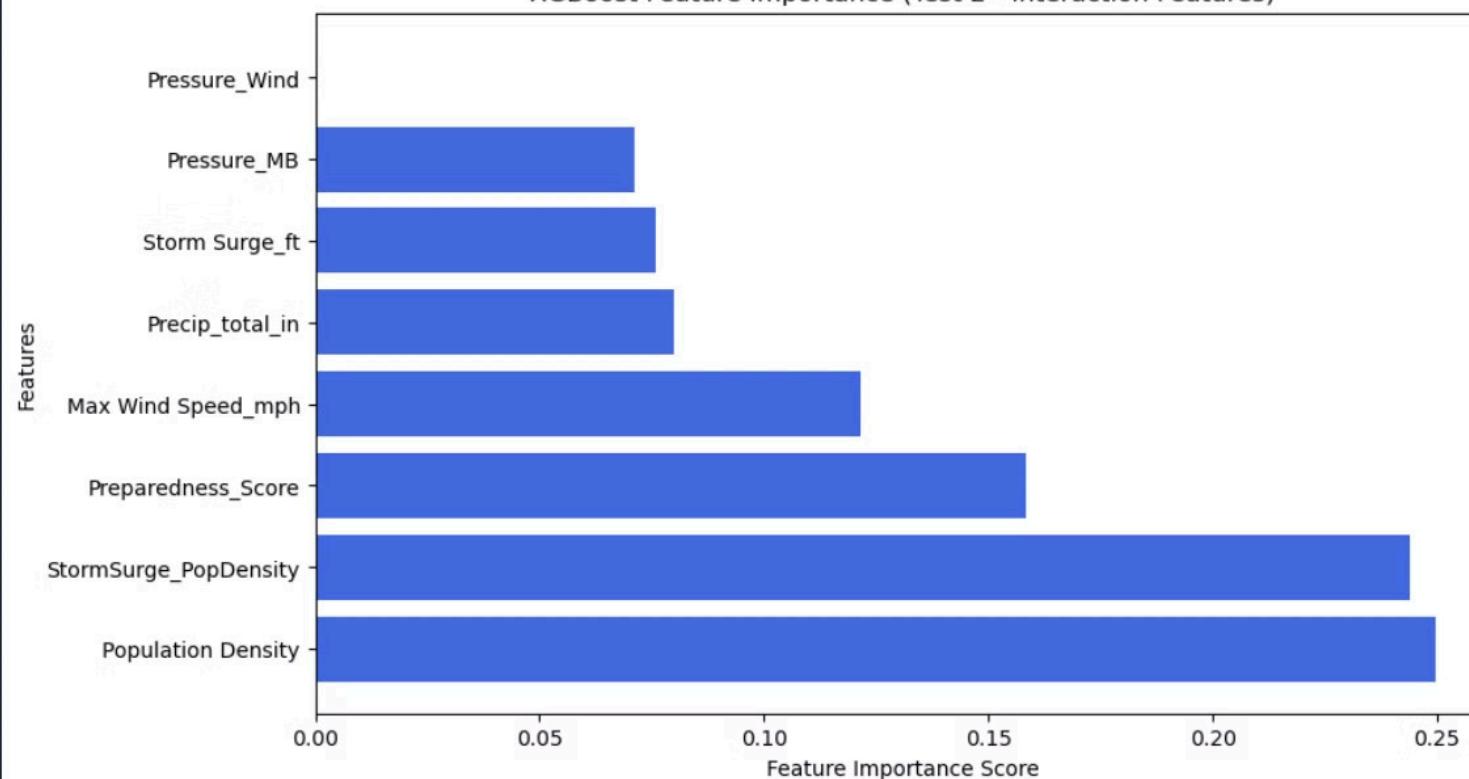
```
Mean Squared Error: 5.3099
```

```
R2 Score: 0.7422
```

```
Feature Importance Analysis (Test 2):
```

	Feature	Importance
4	Population Density	0.249506
6	StormSurge_PopDensity	0.243775
5	Preparedness_Score	0.158501
0	Max Wind Speed_mph	0.121563
3	Precip_total_in	0.079852
2	Storm Surge_ft	0.075789
1	Pressure_MB	0.071014
7	Pressure_Wind	0.000000

XGBoost Feature Importance (Test 2 - Interaction Features)



- Removing Damage Index shifted importance to Population Density and Storm Surge interactions, but exposure still dominates.

- Meteorological factors like Wind Speed and Pressure improved slightly, but not enough to drive predictions.

- Pressure_Wind had no impact, showing some interaction features didn't help the model.



TEST 5 – Feature Scaling & Regularization

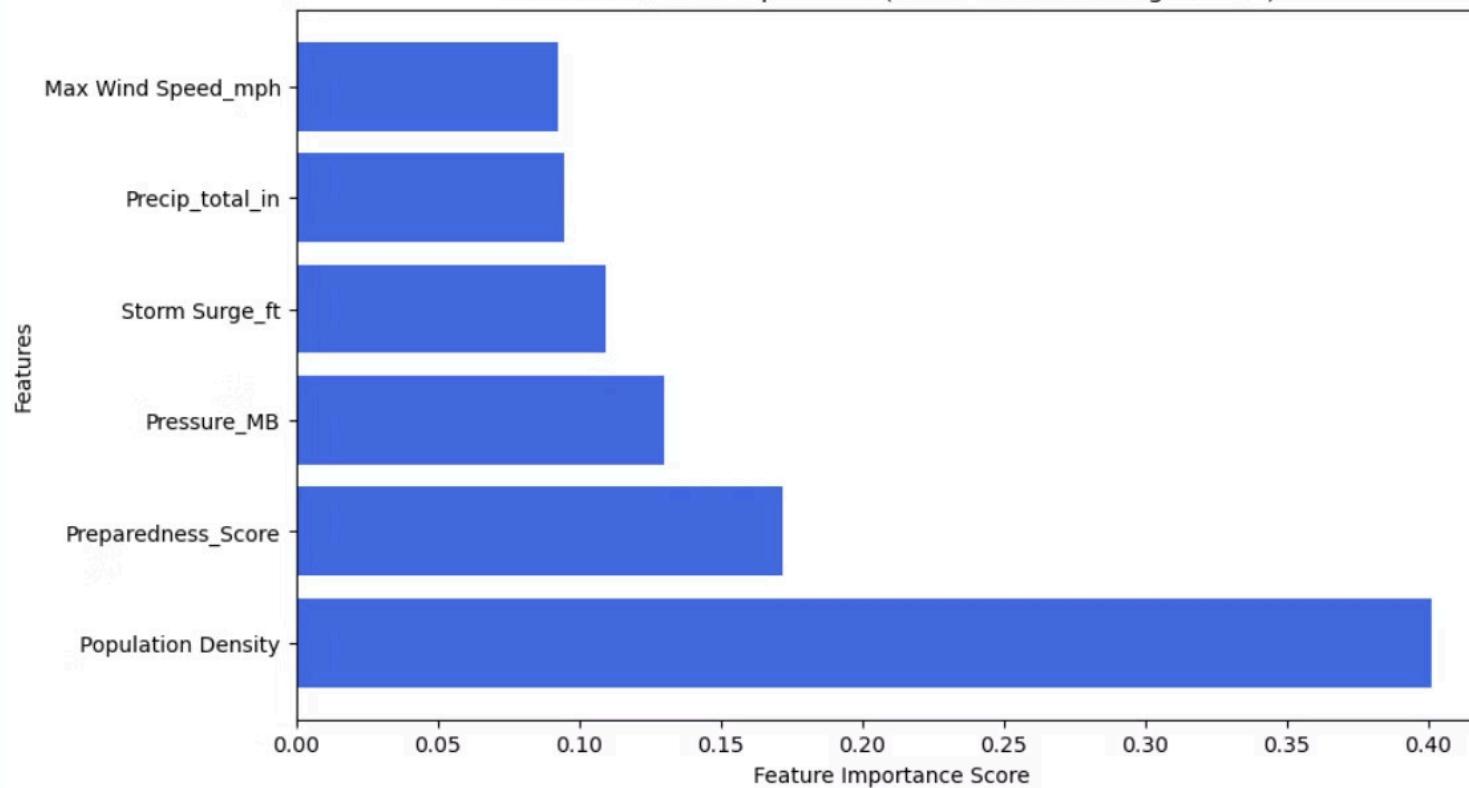
Mean Squared Error: 6.6361

R² Score: 0.6778

Feature Importance Analysis (Test 5):

	Feature	Importance
4	Population Density	0.401053
5	Preparedness_Score	0.171887
1	Pressure_MB	0.130088
2	Storm Surge_ft	0.109360
3	Precip_total_in	0.094717
0	Max Wind Speed_mph	0.092896

XGBoost Feature Importance (Test 5 - Scaled & Regularized)



- **Scaling and regularization didn't fix exposure bias.**

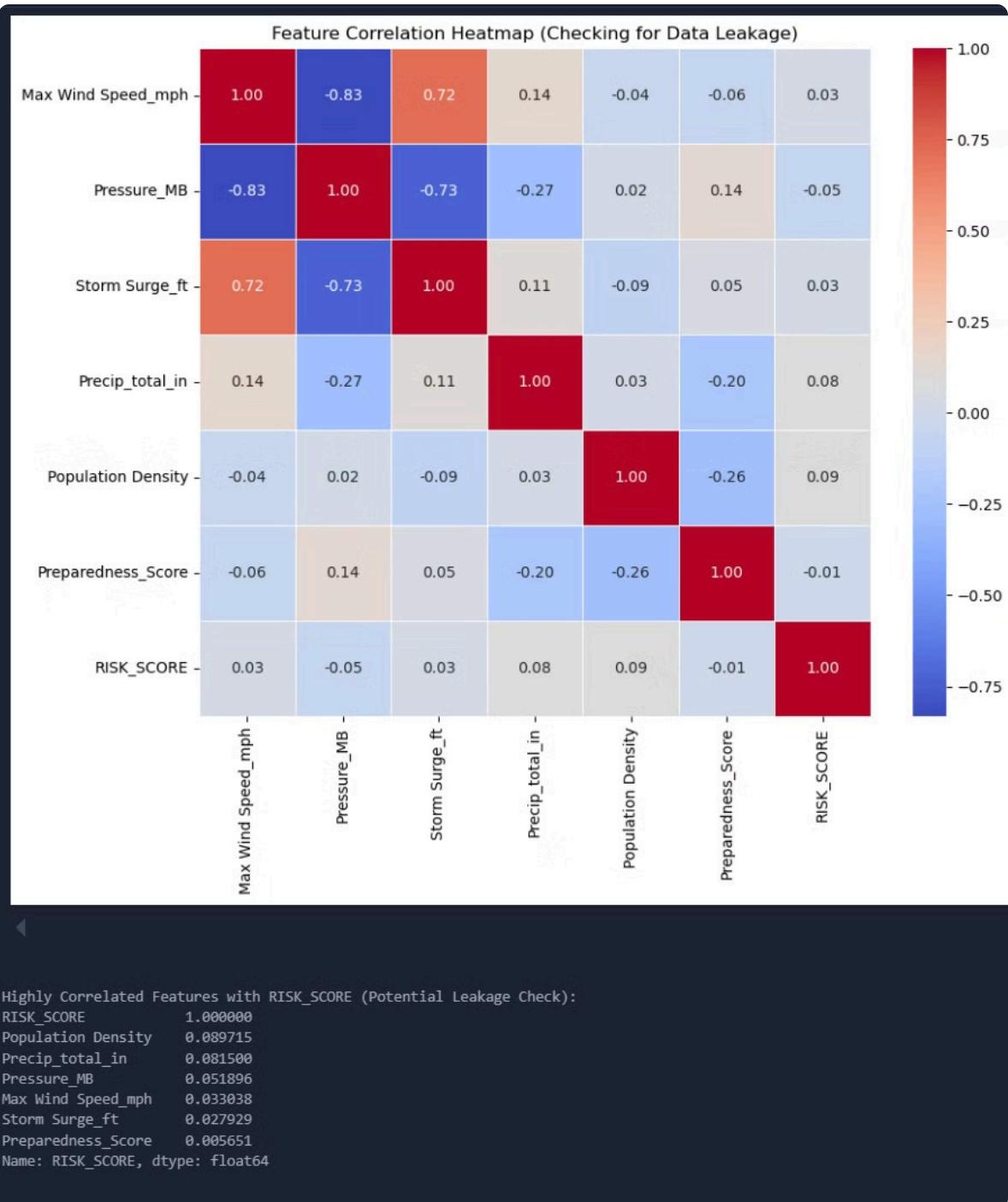
Population Density still dominates.

- **Storm Surge, Pressure, and Wind Speed gained importance**, but they're still weaker than exposure factors.

- **The model is slightly more balanced**, but more adjustments are needed to focus on storm severity.



Made with Gamma



- **No extreme data leakage found.** Population Density has a weak correlation (0.09) with Risk Score.
- **Meteorological features (Wind Speed, Storm Surge, Pressure) are weakly linked** to Risk Score, meaning storm severity isn't driving predictions.
- **The model still relies on exposure features**, but there's no direct sign of it using post-storm data incorrectly.

RANDOM FOREST MODEL - Quick Test

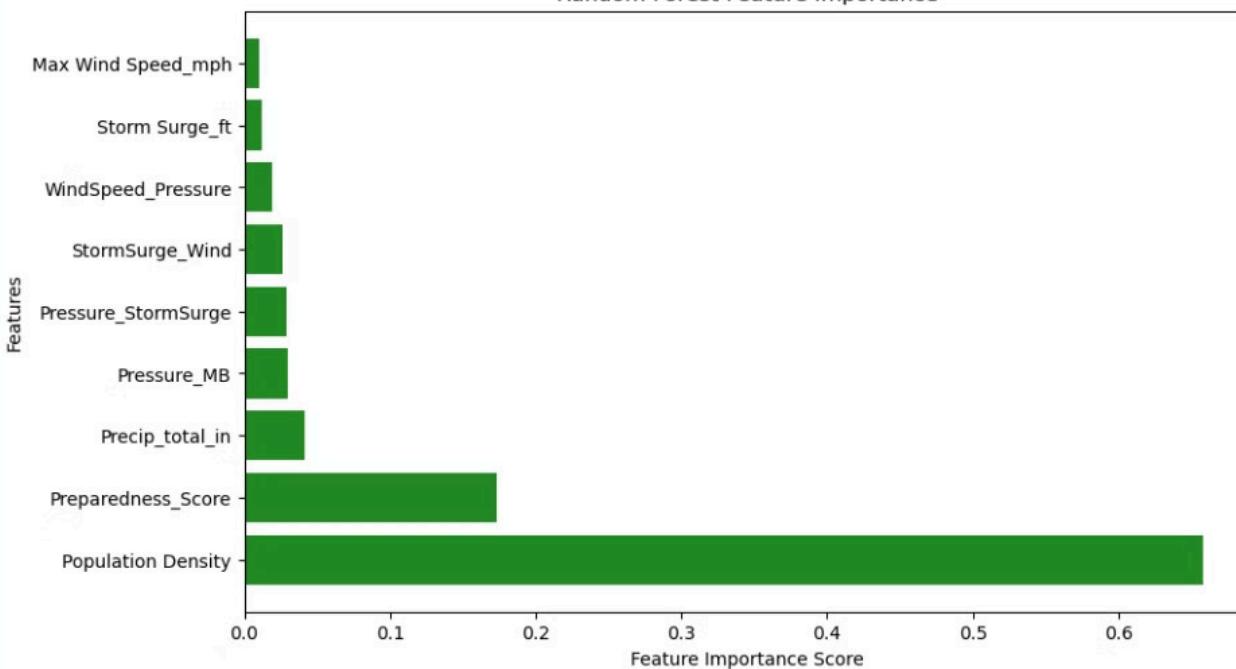
Mean Squared Error: 5.5260

R² Score: 0.7317

Feature Importance Analysis (Random Forest):

	Feature	Importance
4	Population Density	0.657638
5	Preparedness_Score	0.173675
3	Precip_total_in	0.041480
1	Pressure_MB	0.030176
8	Pressure_StormSurge	0.029188
7	StormSurge_Wind	0.026176
6	WindSpeed_Pressure	0.019529
2	Storm Surge_ft	0.011907
0	Max Wind Speed_mph	0.010232

Random Forest Feature Importance



- **Population Density dominates predictions**, meaning the model relies more on where people live than storm severity.
- **Meteorological features (Wind Speed, Storm Surge, Pressure) have low importance**, showing the model isn't prioritizing storm strength.
- **Preparedness Score is the second most important**, suggesting the model factors in how well communities are ready but still undervalues storm intensity.



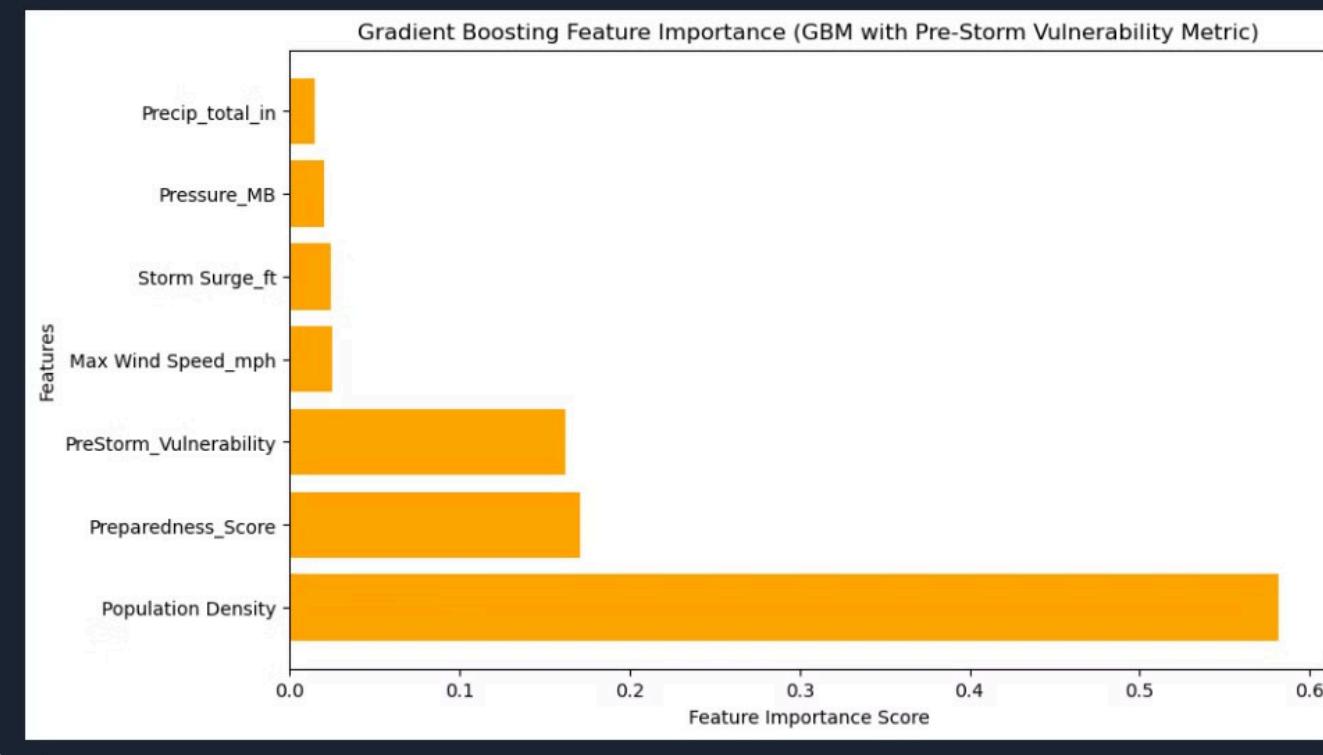
TEST 14 – GBM with Engineered Pre-Storm Vulnerability Metric

Mean Squared Error: 3.4377

R² Score: 0.8331

Feature Importance Analysis (GBM with Pre-Storm Metric):

	Feature	Importance
4	Population Density	0.581991
6	Preparedness_Score	0.170967
5	PreStorm_Vulnerability	0.162209
0	Max Wind Speed_mph	0.025286
2	Storm Surge_ft	0.024336
1	Pressure_MB	0.020339
3	Precip_total_in	0.014872



- **Population Density is still the most important**, meaning exposure remains the biggest factor in predicting fatalities.
- **Pre-Storm Vulnerability helped but didn't shift focus to storm severity**, showing the model still favors meteorological factors.
- **Meteorological factors (Wind Speed, Storm Surge, Pressure) remain weak**, meaning storm intensity isn't driving predictions enough.

- The model failed badly, with an R² of -1.33, meaning it made worse predictions than just guessing.
- Loss decreased over time, showing the model learned patterns, but they weren't useful for predicting fatalities.
- Neural networks did not work well for this dataset, confirming that simpler models like GBM were the better choice.

Key Takeaways

Hurricane Trends

Hurricane occurrence and intensity have increased in recent decades.

Feature Engineering

Ratio-based features (e.g., wind/pressure) were introduced to enhance model accuracy.

Data Handling

Handling missing data (dropping vs. median fill) significantly affects prediction outcomes.

Financial Loss Correlation

Financial losses are closely linked to deaths, storm surge, precipitation, and pressure.

Fatality Correlation

Fatalities are most strongly correlated with storm surge, wind speed, and pressure.



Made with Gamma

Thank you Professor, Andrew and the instructional team!



Your guidance has been our **calm before the storm**, helping us **weather challenges** with confidence. We appreciate your **steady leadership** throughout this journey!