Nearmap AI Model Release Report: Hurricane Vulnerability Score B.0

Contents

Executive Summary 2
Introduction 2
About the Hurricane Vulnerability Score 2
Integration into Nearmap Features API 3
Validation 4
Implementation Guidance 11
Conclusion 11
Appendix 12

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Executive Summary

The Hurricane Vulnerability Score is a 1-5 rating (1=most vulnerable, 5=most resilient) that differentiates buildings' susceptibility to tropical cyclone wind damage based on roof characteristics and surrounding conditions. This release report validates version B.0, which deploys the original Betterview-trained model on Gen 6 Nearmap AI features.

Validation Dataset: 141,889 buildings across 7 U.S. tropical cyclones (2019-2024), spanning tropical storm through Category 4 conditions, with 17,885 damaged buildings identified via post-event imagery.

Performance Metrics: - Overall discrimination: AUC 0.619 (Gini 0.238) - Performance improves with wind intensity: AUC ranges from 0.579 at Cat1 to 0.711 at Cat4 - Consistent across geographies: AUC 0.608-0.651 across validated states - Stable across events: AUC 0.590-0.622 across individual storms

Key Value Proposition: The score provides meaningful risk segmentation beyond geographic exposure alone. Buildings with vulnerability scores of 4-5 show 2-3x lower damage rates compared to scores of 1-2 within the same wind exposure zones, enabling more refined pricing, underwriting, and risk selection.

Applicability: Wind damage only (not flood). Validated for U.S. tropical cyclone exposure. Approved for direct use in rating in 9 states/districts including Florida, Louisiana, and Texas.

Implementation: Available via Nearmap Features API with simple parameter flag (`include=hurricaneScore`).

Introduction

This document is the technical release report for the Nearmap Hurricane Vulnerability Score. The intended audience is technical in nature, both within Nearmap, and technical users (such as data scientists, actuaries and software developers) of Nearmap AI products in customer organizations.

It acts as more detailed source material to supplement the public product documentation available on the Nearmap Help Center. The original Hurricane Vulnerability Score whitepaper provides additional information on how the model was originally developed.

Release Scope

The scope of this release is the "B.x" series of the Hurricane Vulnerability Score, which is the first major version released on Gen 6 Nearmap data after the Betterview acquisition.

About the Hurricane Vulnerability Score

The Hurricane Vulnerability Score is a score from 1-5 that differentiates between buildings based on their relative susceptibility to sustaining wind damage if exposed to tropical storm or hurricane force winds during a tropical cyclone event. A score of 1 represents the most vulnerable to tropical cyclone wind damage, and a score of 5 represents the most resilient.

The model was trained in 2022 at Betterview, which was acquired by Nearmap in 2023. Approximately 60,000 buildings in Lake Charles, Louisiana that were exposed to Hurricane Laura in August 2020 formed the basis of the initial modeling dataset, and subsequent validation has been done on numerous storms including 4 prior to initial release, and 7 presented in this release report.

The following features showed statistically significant correlation with post-storm damage outcomes as derived from post-cat imagery, and were therefore included in the final model:

- Roof Material
- Roof Shape
- Staining
- Missing Shingles
- Tree Overhang
- Worn Shingles
- Patching
- Rusting
- Defensible Space

The Hurricane Vulnerability Score can be used to differentiate between buildings/properties that are in similar geographical areas (and thus exposed to similar tropical cyclone hazard levels) but have different overall risk levels based on the buildings' characteristics and surroundings.

Based on these features, a building is assigned a vulnerability probability from the raw machine learning model output. This probability approximately represents the likelihood the building can withstand hurricane-force winds if exposed (note that it is not a proper calibrated-probability but rather an ordinal indication of survivability). A higher vulnerability probability indicates higher resilience; lower vulnerability probability indicates higher susceptibility to damage.

The vulnerability probability is binned into 5 categories, which produces the final Hurricane Vulnerability Score.

Geographic Applicability

The Hurricane Vulnerability Score is theoretically applicable to any building exposed to risk of wind damage from a tropical cyclone event. However, if roof types in another geography are substantially different than those the model was trained on (e.g., if roof material patterns are different), reduced performance is expected.

Validation is presented herein using buildings exposed to 7 United States tropical cyclone events.

Validation on tropical cyclones from other geographies is forthcoming pending sufficient data availability.

Peril Applicability

The Hurricane Vulnerability Score correlates with damage caused by hurricane-force winds.

It does not apply to flood-induced damage in a tropical cyclone event and is not expected / designed to perform well on flood damage/claims.

Note on Validation Methodology: This validation uses post-cyclone damage detected via imagery analysis. While the Damage Classifications AI is designed to identify wind-induced structural damage, the model's use of pre-event roof condition features means some correlation may reflect buildings' general vulnerability rather than purely cyclone-specific risk. The moderate AUC values (0.61-0.62) and performance scaling with wind intensity suggest this effect is limited. Future validation using insurance claims data will further isolate hurricane-specific predictive power.

Regulatory Approvals

The Nearmap Hurricane Vulnerability Score is approved for use directly in rating in the following states / districts:

- Alabama
- Delaware
- Georgia
- Louisiana
- Maryland
- Massachusetts
- Mississippi
- Texas
- Washington D.C.

For more information on rating with the Hurricane Vulnerability Score and detailed list of SERFF numbers, reach out to your Nearmap account representative.

Integration into Nearmap Features API

Upon acquisition of Betterview, Nearmap integrated the Hurricane Vulnerability Score into the Features API. The score model remains unchanged from the original Betterview release, but is now powered by highly accurate Gen 6 features.

The model uses 9 roof characteristics as input features: roof material (shingle), roof shape (flat/hip), staining, missing shingles, tree overhang, worn shingles, patching, and rusting. Additionally, defensible space is calculated in three zones around the building periphery (0-5 feet, 5-30 feet, and 30-100 feet) based on nearby buildings, vegetation, and yard debris.

The first version of the Hurricane Vulnerability Score deployed on the Nearmap Features API is called version `B.0` to acknowledge the update associated with powering the score with Gen 6 features. The score model itself remains unchanged relative to the originally-trained model from 2022.

Detailed Gen 6 feature class mappings are provided in the Appendix.

Validation

To validate the performance of the Hurricane Vulnerability Score B.0, a dataset of 141,889 buildings was created representing buildings exposed to 7 U.S. tropical cyclone events (6 hurricanes + 1 tropical storm).

Dataset Generation

The validation dataset used in this report is derived from imagery captured before and immediately after 7 U.S. tropical cyclone events: Hurricane Beryl, Hurricane Dorian, Tropical Storm Henri, Hurricane Ian, Hurricane Ida, Hurricane Idalia, and Hurricane Laura. To create the dataset, 6M+ building lifecycle geometries were extracted via Nearmap Features API from post-event imagery captured as part of Nearmap's Impact Response program. Damage statuses were pulled for each building using the Nearmap Damage Classifications AI.

Expected wind speed was assigned to each building according to the forecasted wind speeds at landfall according to the National Hurricane Center forecast archive for each event (source). The building distribution and damage rate by wind speed are shown in the following figure, where probability of damage is percent of buildings with damage status of "Minor" or worse.

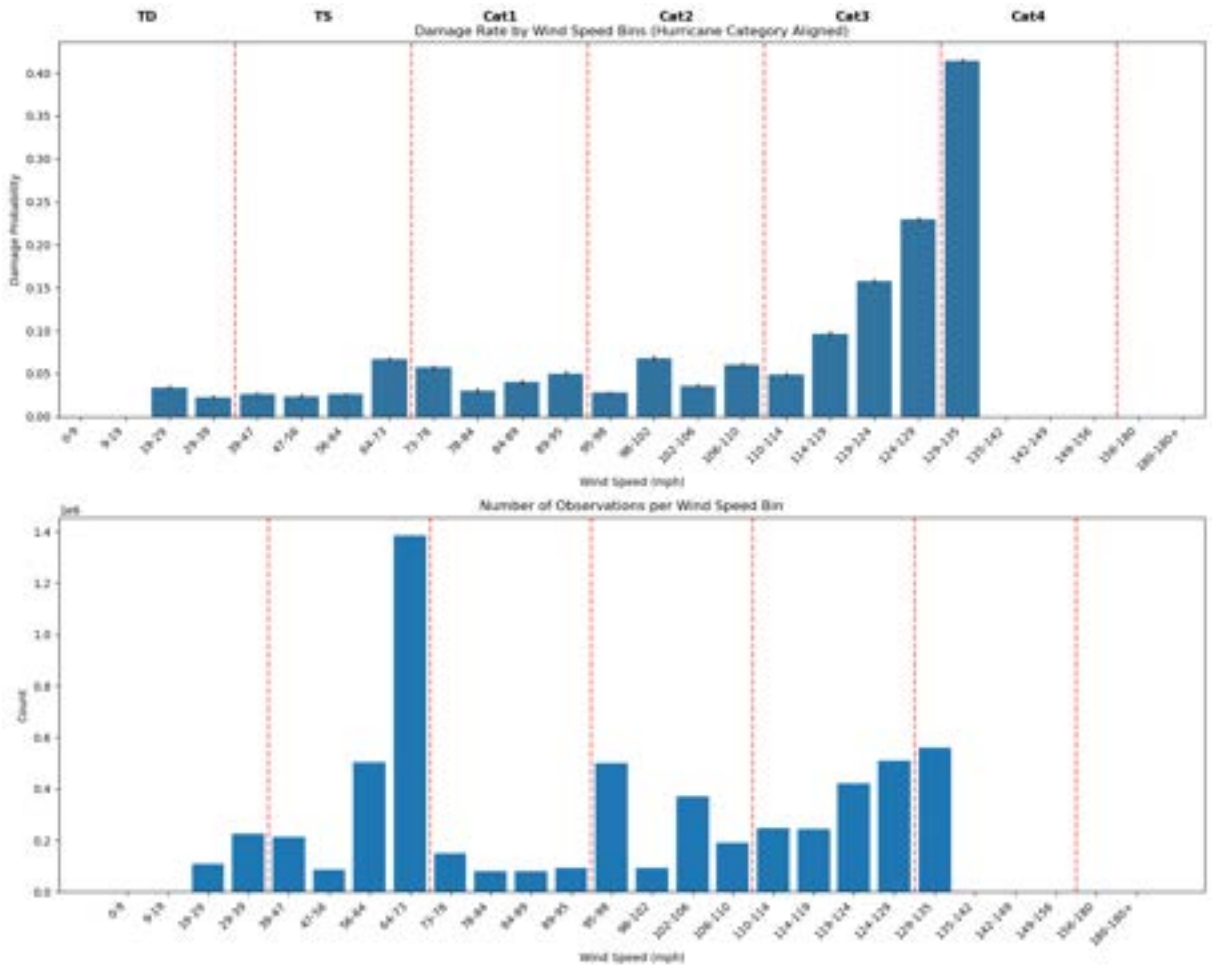

Figure 1: Distribution of roofs and damage probability by wind speed for full 6M+ dataset

These 6M+ buildings were downsampled to 150K, with sample weights favoring wind speeds where damage probability changed most rapidly (Categories 2 and 3). For each sampled geometry, its corresponding pre-event roof footprint and Hurricane Vulnerability Score were retrieved from the Features API using the most recent Nearmap image of the building prior to the storm. The final dataset contains ~142k buildings with complete pre- and post-event data.

Dataset Distribution

The final validation dataset includes 141,889 buildings exposed to 7 tropical cyclone events across diverse wind conditions:

Event Name	US Landfall Date	Saffir-Simpson Category	Buildings	Damaged Buildings	Damage Rate
Hurricane Beryl	July 8, 2024	Category 1	14,286	930	6.5%
Hurricane Dorian	September 6, 2019	Category 2	3,777	104	2.8%
Tropical Storm Henri	August 22, 2021	Tropical Storm	968	15	1.5%
Hurricane Ian	September 28, 2022	Category 4	88,491	8,308	9.4%
Hurricane Ida	August 29, 2021	Category 4	24,016	5,891	24.5%

Event Name	US Landfall Date	Saffir-Simpson Category	Buildings	Damaged Buildings	Damage Rate
Hurricane Idalia	August 29, 2023	Category 3	3,061	196	6.4%
Hurricane Laura	August 27, 2020	Category 4	7,290	2,441	33.5%
Total			**141,889**	**17,885**	**12.6%**

The dataset includes substantial representation across wind speed categories, with expected wind speed assigned to each building based on National Hurricane Center forecasts:

Wind Category	Buildings	Damaged Buildings	Damage Rate	Mean Wind Speed (mph)
TD (Tropical Depression)	7,356	190	2.6%	31.6
TS (Tropical Storm)	13,840	713	5.2%	64.8
Cat1	20,900	878	4.2%	83.0
Cat2	35,878	1,199	3.3%	101.1
Cat3	42,855	6,307	14.7%	121.4
Cat4	21,060	8,598	40.8%	133.1

The distribution of buildings by event and wind category is provided in the Appendix.

Overall Lift Analysis

For the lift analysis, a building is classified as damaged if it sustained any visible damage (damage class at least 1 - Affected). The Hurricane Vulnerability Score demonstrates strong predictive power in differentiating between buildings that sustained damage versus those that did not.

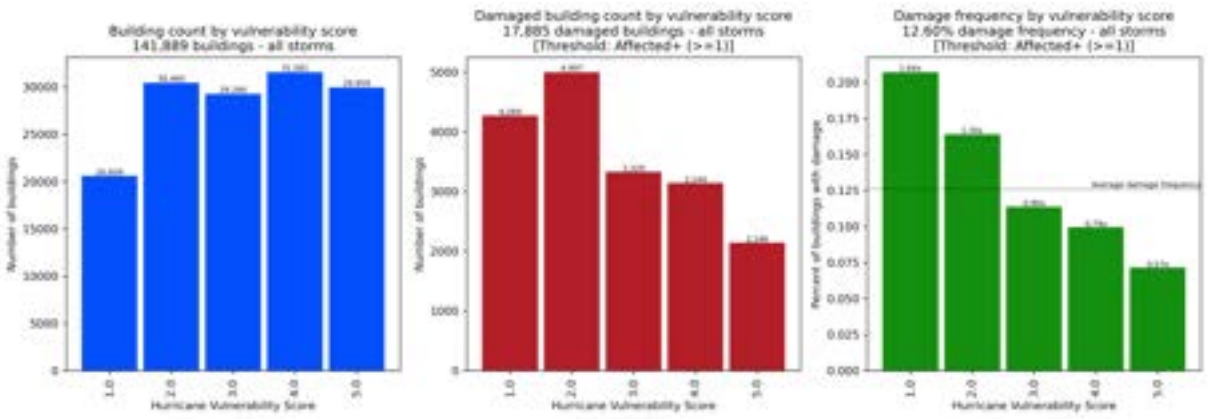

Figure 2: Overall Lift Analysis

The overall lift chart demonstrates:

- **Left panel**: Distribution of exposures across vulnerability scores, showing good representation across all score categories
- **Middle panel**: Damage counts increase substantially with higher vulnerability scores
- **Right panel**: Damage frequency shows strong monotonic relationship with vulnerability score, with higher scores showing multiples (e.g., 2-3x) of the baseline claim frequency

Key findings across all 141,889 buildings

- The score shows clear lift across all vulnerability categories

- Higher vulnerability scores (4-5) show significantly reduced damage rates compared to lower scores (1-2)
- The model maintains predictive power across diverse tropical cyclone wind conditions

Lift Summary

This section presents discrimination metrics (AUC and Gini Index) that quantify the Hurricane Vulnerability Score's predictive performance across various sub-groups.

Understanding the Metrics:

- **AUC (Area Under the ROC Curve)**: Measures the model's ability to correctly rank-order buildings by damage likelihood. Values range from 0.5 (no predictive power, random guessing) to 1.0 (perfect discrimination). Higher AUC indicates better ability to assign lower vulnerability scores to buildings that will sustain damage.
- **Gini Index**: Derived from AUC using the formula Gini = 2×AUC - 1, ranging from 0 to 1. Commonly used in insurance and actuarial contexts as an alternative presentation of model discrimination, with the same interpretation: higher values indicate stronger differentiation between damaged and undamaged buildings.

Performance Summary:

Metric Type	Overall	Wind Speed Range	Event Range	State Range
Vulnerability Probability				
AUC	0.619	0.579 - 0.711	0.590 - 0.622	0.608 - 0.651
Gini	0.238	0.158 - 0.422	0.180 - 0.244	0.216 - 0.302
Vulnerability Score (1-5)				
AUC	0.614	0.579 - 0.704	0.588 - 0.616	0.601 - 0.641
Gini	0.228	0.158 - 0.408	0.176 - 0.232	0.202 - 0.282

The following subgroups were analyzed:

- **Wind speed category**: Based on location-level expected wind speed binned into Saffir Simpson categories (TD, TS, Cat1-4)
- **Event**: Individual storms with at least 150 damaged properties in the dataset
- **State**: Geographic regions with at least 150 damaged properties in the dataset

Continuous Vulnerability Probability:

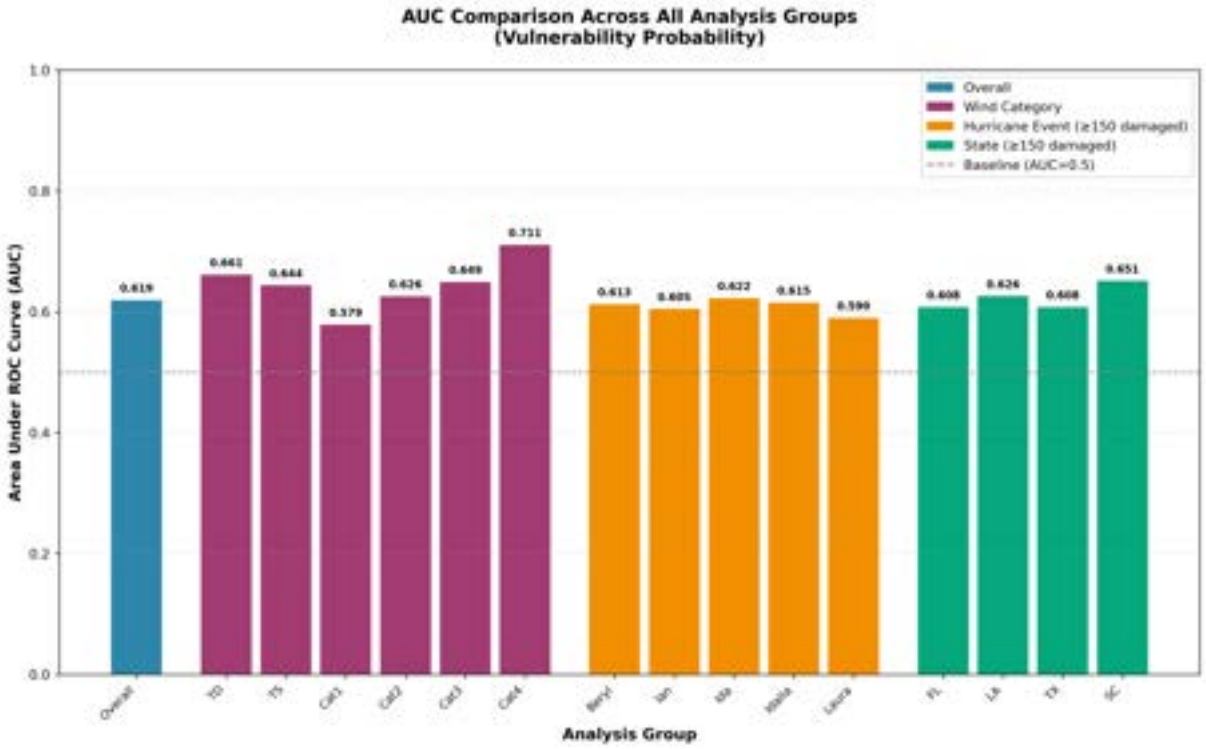

Figure 3: AUC Comparison - Vulnerability Probability

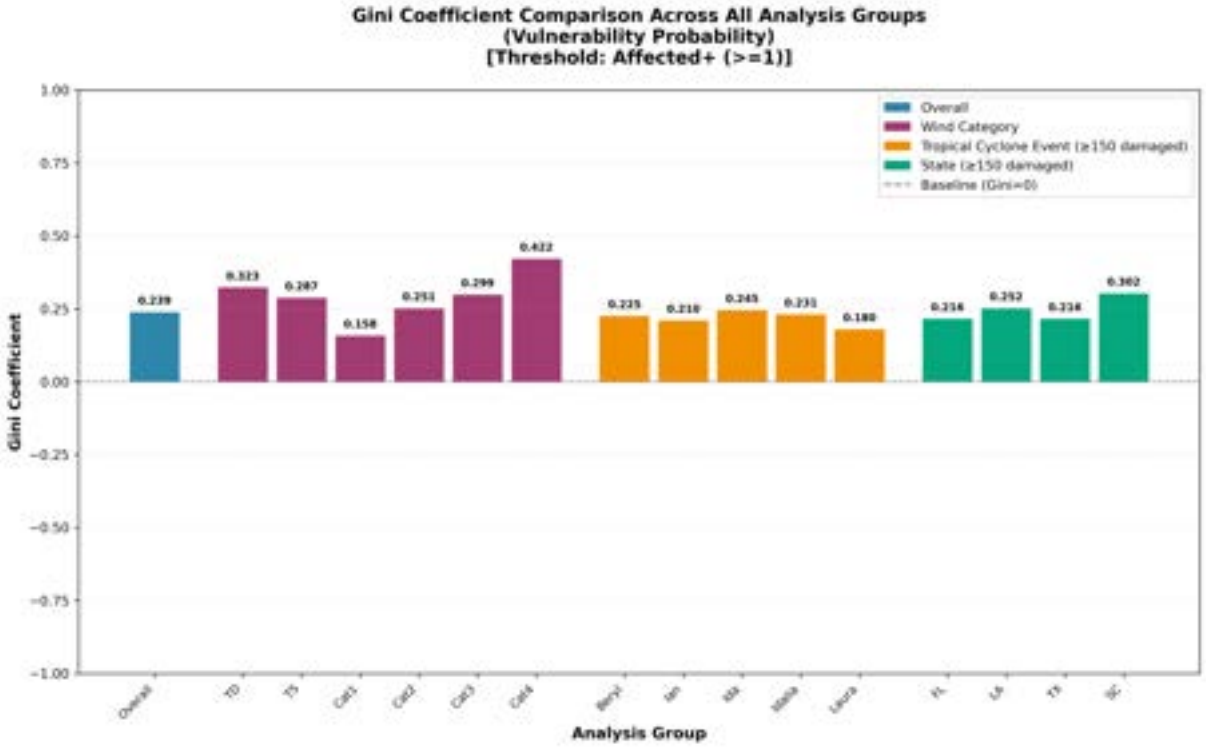

Figure 4: Gini Comparison - Vulnerability Probability

The vulnerability probability represents the continuous output from the underlying machine learning model before binning into discrete categories.

Key findings:

- **Overall performance**: AUC 0.619 (Gini 0.238) across all 141,889 buildings
- **Wind speed pattern**: Performance improves significantly with wind intensity
  - Cat1: AUC 0.579 (Gini 0.158)
  - Cat4: AUC 0.711 (Gini 0.422)
  - This indicates building characteristics become more determinative at higher wind speeds
- **Event consistency**: AUC ranges from 0.590 (Laura) to 0.622 (Ida), demonstrating stable performance across different storms
- **Geographic consistency**: AUC ranges from 0.608 (Florida, Texas) to 0.651 (South Carolina), showing reliable performance across states

Discrete Vulnerability Score (1-5):

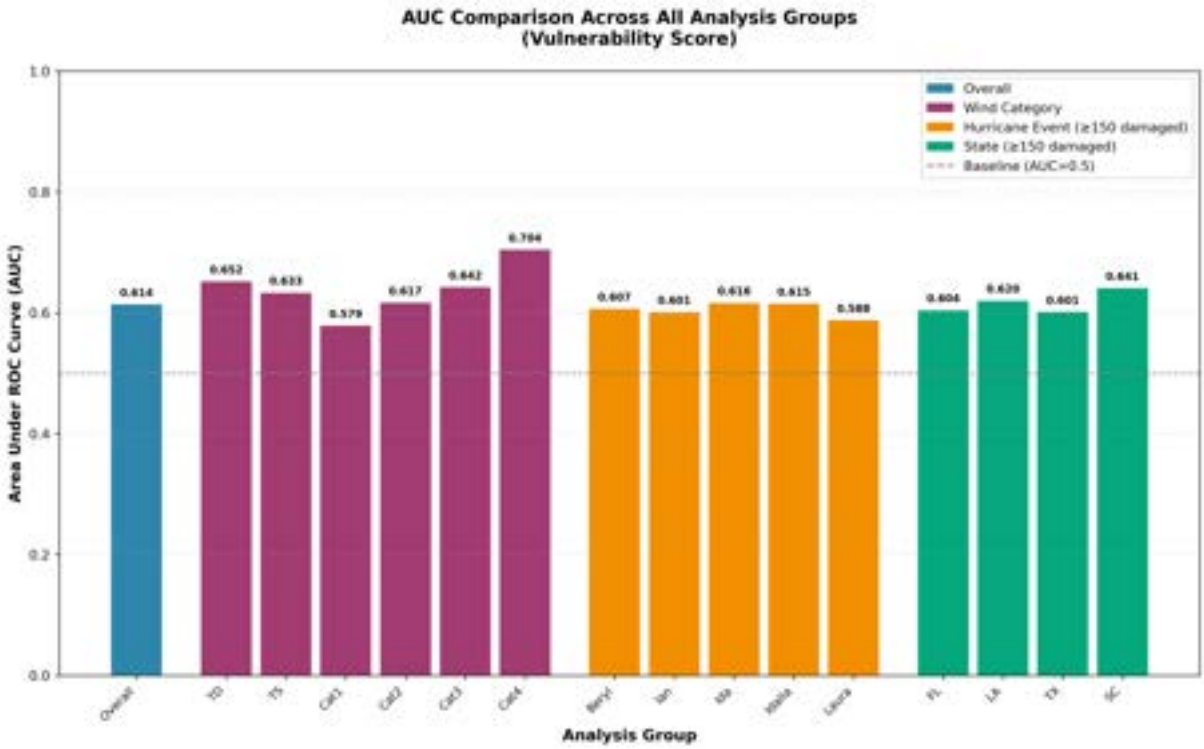

Figure 5: AUC Comparison - Vulnerability Score

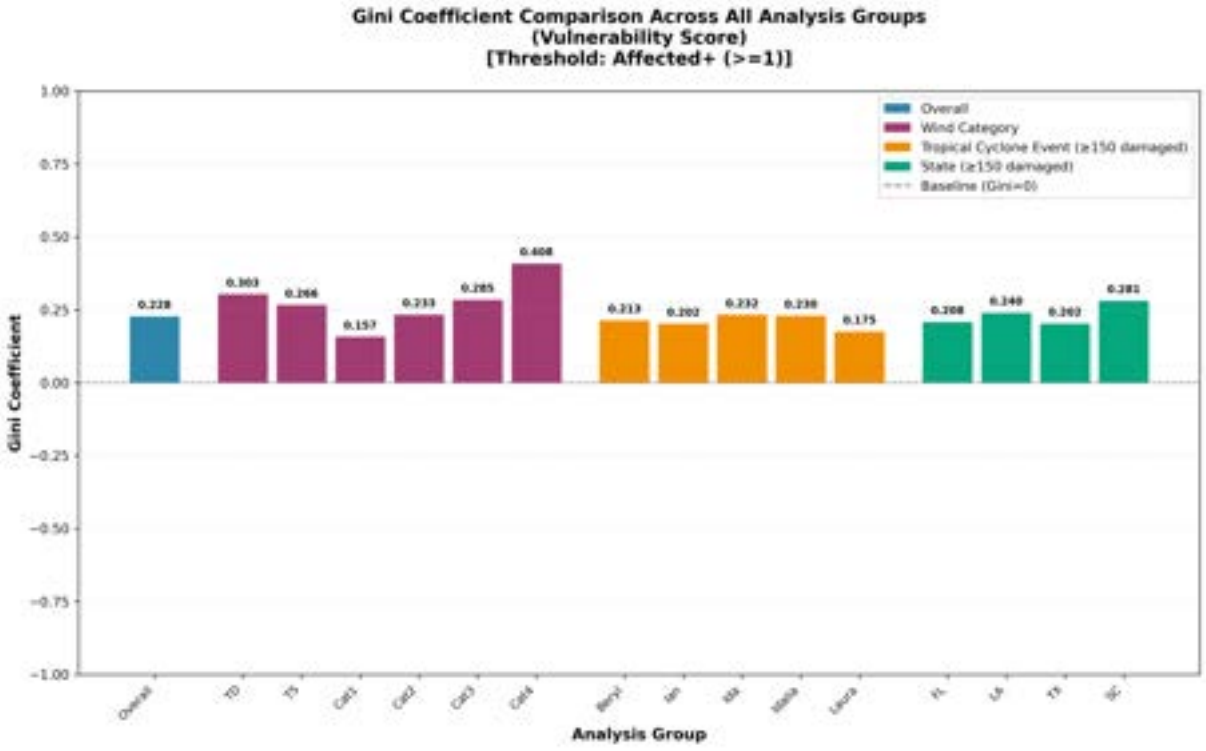

Figure 6: Gini Comparison - Vulnerability Score

The vulnerability score represents the discrete 1-5 binned score delivered via the Features API—the practical implementation that customers use.

Key findings:

- **Overall performance**: AUC 0.614 (Gini 0.228)
- **Minimal information loss**: Only 0.005 AUC decrease from continuous probability to discrete score, validating that the 1-5 binning preserves discriminatory power
- **Consistent across conditions**:
  - Wind categories: AUC 0.579-0.704
  - Tropical cyclone events: AUC 0.588-0.616
  - States: AUC 0.601-0.641

Practical Interpretation for Insurance Applications:

These discrimination metrics demonstrate strong risk segmentation capabilities for pricing, underwriting, and claims management:

- **Risk differentiation**: An AUC of 0.61-0.62 indicates the score effectively stratifies tropical cyclone wind risk beyond what geographic exposure alone provides. The score can meaningfully separate higher-risk from lower-risk buildings within the same wind zone.
- **Operational efficiency**: The discrete 1-5 score format retains nearly all predictive information (0.614 vs 0.619 AUC) while being significantly easier to interpret, implement in rating plans, and communicate to stakeholders.
- **Performance scaling**: The increasing AUC at higher wind speeds (particularly Cat3-4, reaching 0.70+) demonstrates the score is most valuable precisely where it matters most—in severe tropical cyclone conditions where building characteristics most influence damage outcomes and where accurate risk differentiation has the greatest financial impact.

Full lift graphs for all sub-groups can be found in the Appendix.

Implementation Guidance

The Hurricane Vulnerability Score can be obtained via the Nearmap Features API by calling the roof and building lifecycle feature classes with the `hurricaneScore` include parameter.

To retrieve the score for a location:

1. Make a Features API request for the target location
2. Include roof (`c08255a4-ba9f-562b-932c-ff76f2faeeeb`) and building lifecycle (`91987430-6739-5e16-b92f-b830d`) feature classes in the request
3. Add `include=hurricaneScore` to the query parameters

It is additionally recommended to set `parcelMode=True` when obtaining the Hurricane Vulnerability Score in order to ensure the scored roof is only the portion associated with the target address / parcel.

Roofs and buildings lifecycles with a score returned are determined to be the building footprints; features without a hurricane score can be dropped from subsequent analysis.

For detailed implementation instructions, API endpoints, request/response formats, and code examples, please refer to the Nearmap API Documentation.

Conclusion

The validation presented herein demonstrates that the Hurricane Vulnerability Score B.0, originally trained at Betterview and now newly powered by Gen 6 Nearmap AI features, maintains strong predictive performance across diverse hurricane events, wind speed categories, and geographic regions. The score effectively differentiates between buildings with different damage susceptibilities, providing valuable risk stratification for insurance and risk management applications across quoting, underwriting, claims and renewals.

These results validate that the integration of the Hurricane Vulnerability Score model with Gen 6 AI features successfully preserves the model's predictive capabilities while leveraging Nearmap's highly accurate feature detection.

Appendix

Gen 6 Feature Class Mappings

The following mappings are used to create model input features using Gen 6 AI data:

Original Feature Name	Gen 6 Feature Class ID	Gen 6 Official Name	Gen 6 Vector ID
Roof Material	4bbf8dbd-cc81-5773-961f-0121101422be	Shingle	28
Roof Shape	1ab60ef7-e770-5ab6-995e-124676b2be11	Flat	composite class
Roof Shape	ac0a5f75-d8aa-554c-8a43-cee9684ef9e9	Hip	30
Staining	319f552f-f4b7-520d-9b16-c8abb394b043	Roof Staining	259
Missing Shingles	dec855e2-ae6f-56b5-9cbb-f9967ff8ca12	Missing Roof Tile or Shingle	126
Tree Overhang	8e9448bd-4669-5f46-b8f0-840fee25c34c	Tree Overhang	composite class
Worn Shingles	97a6f930-82ae-55f2-b856-635e2250af29	Worn Shingles	277
Patching	8b30838b-af41-5d1d-bdbd-29e682fe3b00	Roof Patching	214
Rust	526496bf-7344-5024-82d7-77ceb671feb4	Roof Rusting	84

Defensible space is calculated in three zones around the periphery of the scored building: 0-5 feet, 5-30 feet, and 30-100 feet and utilizes the following Gen 6 feature classes:

Original Feature Name	Gen 6 Feature Class ID	Gen 6 Official Name	Gen 6 Vector ID
Other Buildings	c08255a4-ba9f-562b-932c-ff76f2faeeeb	Roof	2
Vegetation	30fc0c55-2b61-569f-b424-44082987ecb9	Medium and High Vegetation with Woody Vegetation	composite class
Yard Debris	405efaad-4b79-585d-88d8-43ae5fbb6f05	Yard Debris	200

Dataset Distribution by Event and Wind Category

Distribution of buildings by event and wind category:

Event Name	TD	TS	Cat1	Cat2	Cat3	Cat4
Hurricane Beryl	0	10,506	3,780	0	0	0
Hurricane Dorian	2,785	992	0	0	0	0
Tropical Storm Henri	0	968	0	0	0	0
Hurricane Ian	4,571	1,216	14,100	31,102	22,283	15,219
Hurricane Ida	0	0	574	3,284	17,439	2,719
Hurricane Idalia	0	158	2,446	345	112	0
Hurricane Laura	0	0	0	1,147	3,021	3,122

Lift by Wind Category

The Hurricane Vulnerability Score maintains strong predictive performance across different wind speed categories, showing it is applicable even in minor wind conditions. This consistent performance across

wind categories validates that the score captures building-specific vulnerability independent of wind hazard intensity.

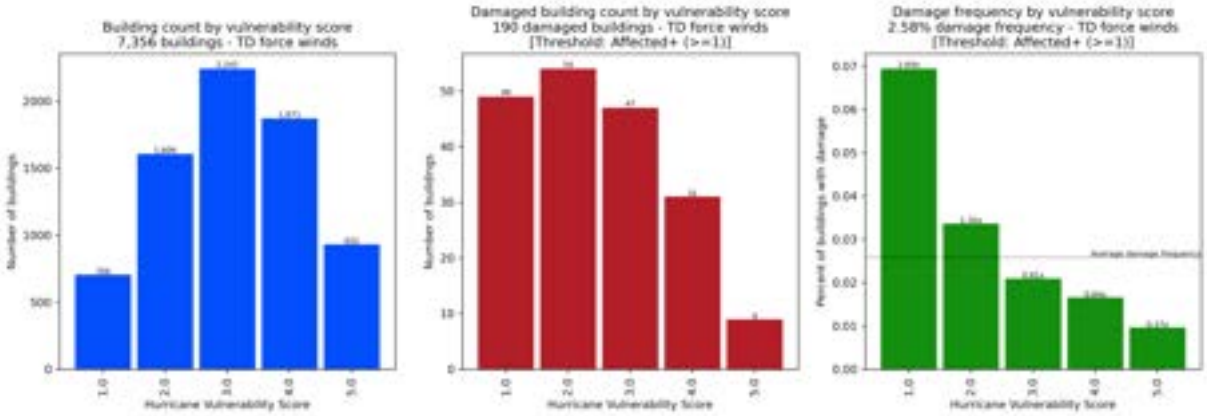

Figure 7: Lift - Tropical Depression

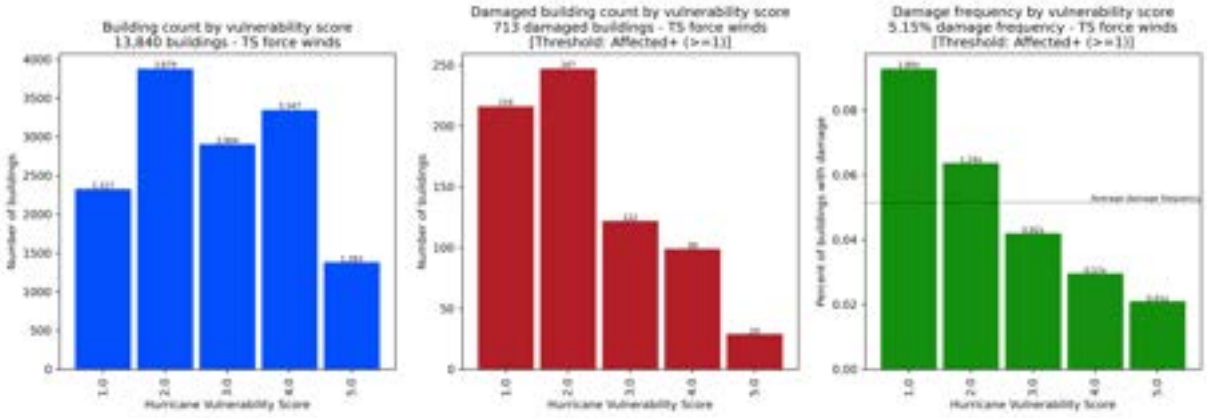

Figure 8: Lift - Tropical Storm

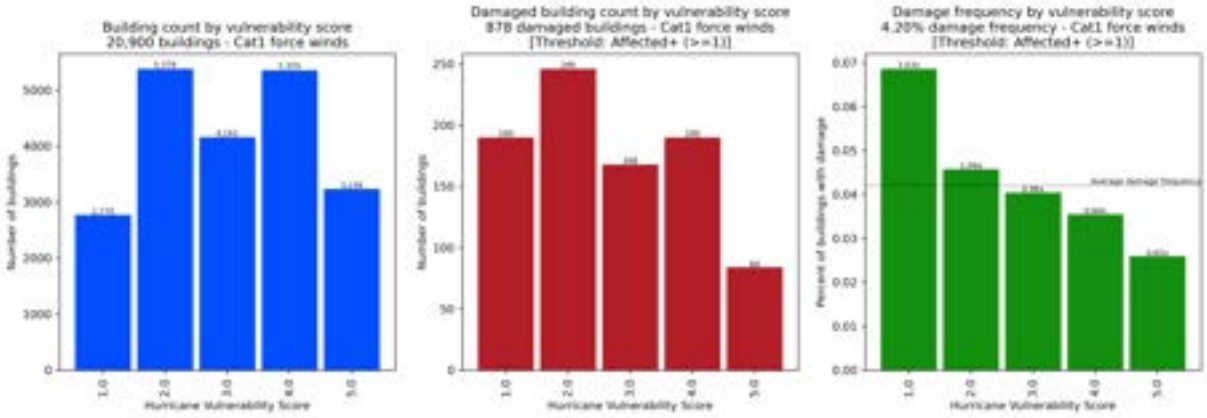

Figure 9: Lift - Category 1

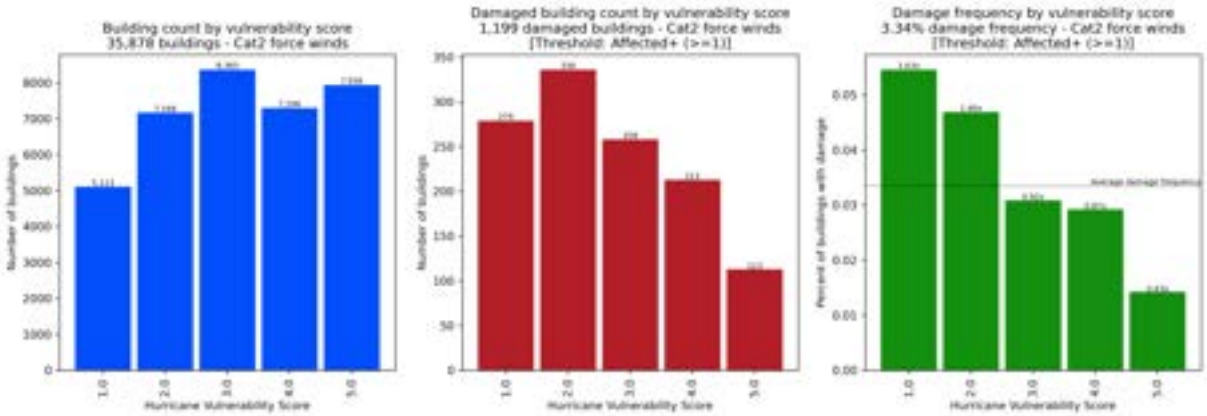

Figure 10: Lift - Category 2

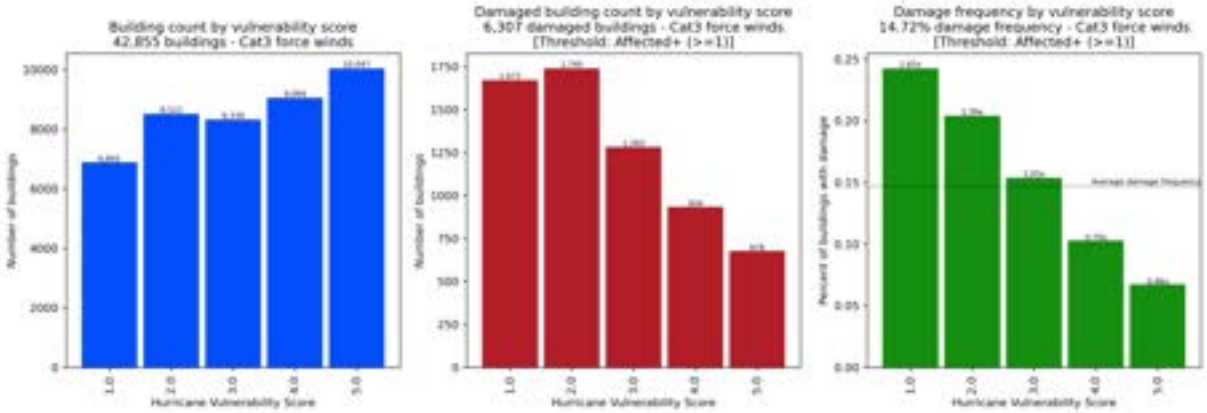

Figure 11: Lift - Category 3

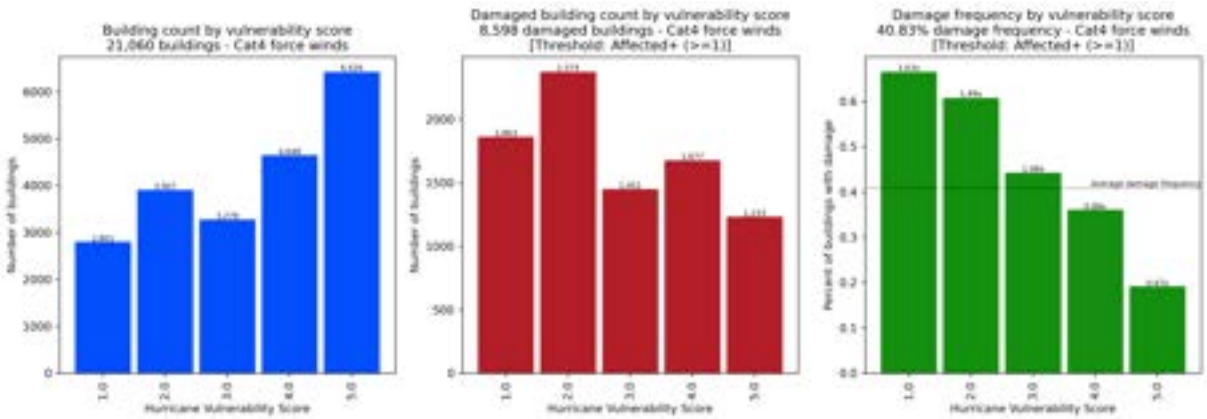

Figure 12: Lift - Category 4

Lift by Event

Lift graphs are also presented by storm; storms for which there were less than 150 damaged buildings in the dataset are excluded to ensure sufficient sample size.

The score consistently shows ability to segment roofs by their damage likelihood, with a few minor reversals found in Hurricane Ian (score 3 has 0.05 lower damage rate than score 4) and Hurricane Idalia (score 2 has 0.24 lower damage rate than score 3).

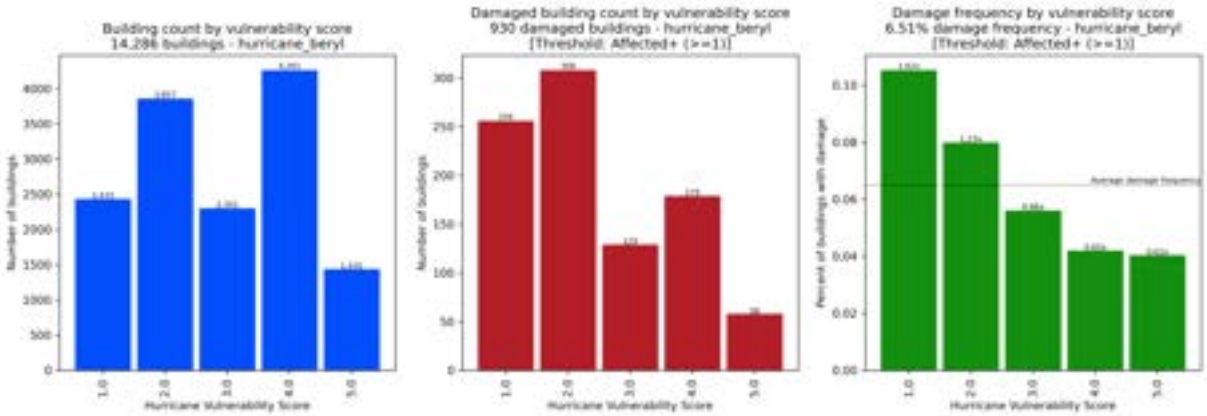

Figure 13: Lift - Hurricane Beryl

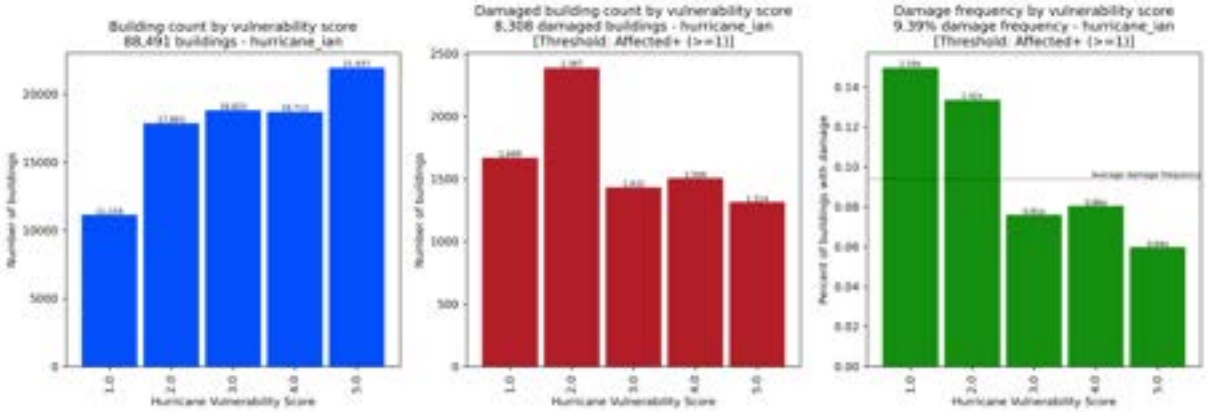

Figure 14: Lift - Hurricane Ian

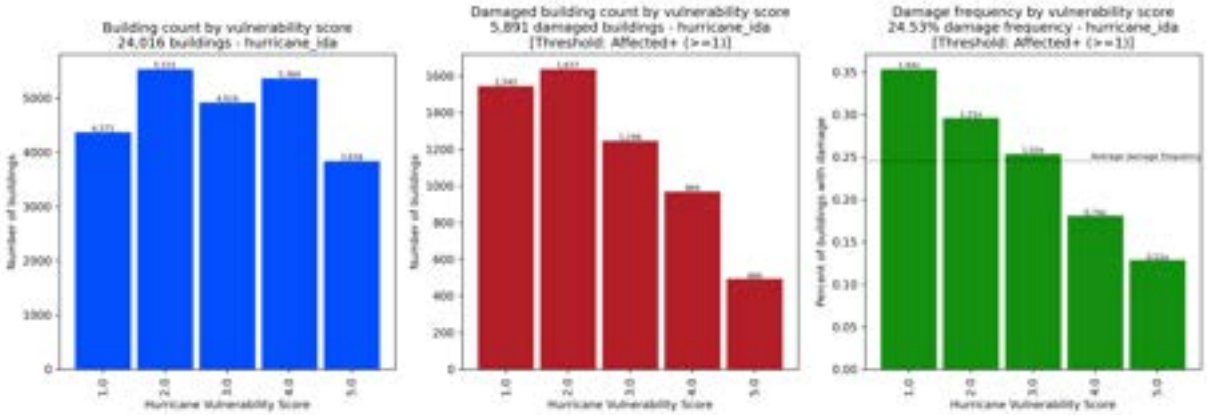

Figure 15: Lift - Hurricane Ida

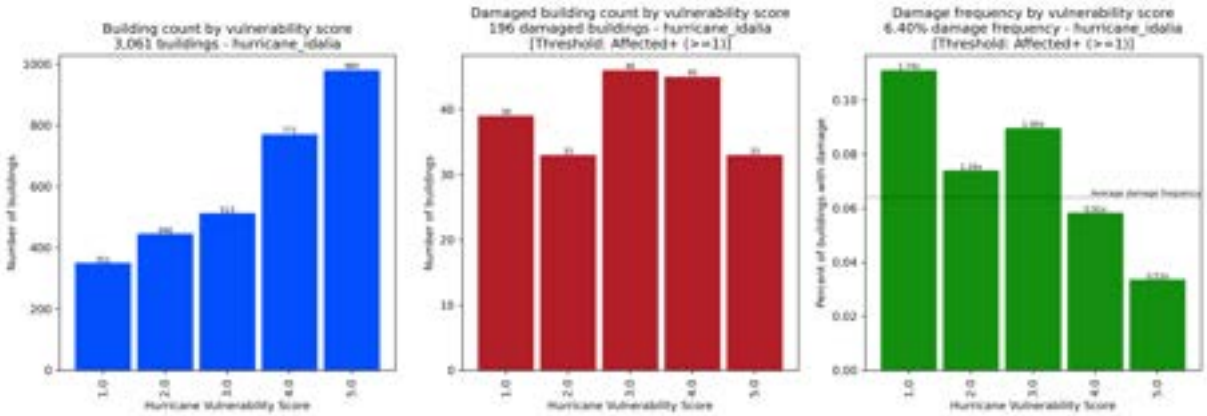

Figure 16: Lift - Hurricane Idalia

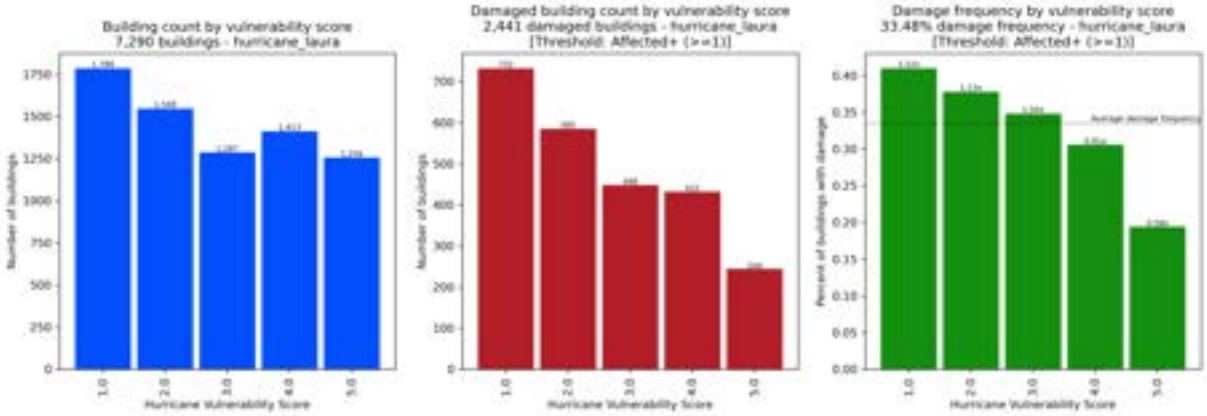

Figure 17: Lift - Hurricane Laura

Lift by State

Lift graphs are lastly presented by state; states for which there were less than 150 damaged buildings in the dataset are excluded to ensure sufficient sample size.

The score consistently shows ability to segment roofs by their damage likelihood across geographies, with a one minor reversal in the Florida exhibit (score 3 has 0.02 lower damage rate than score 4).

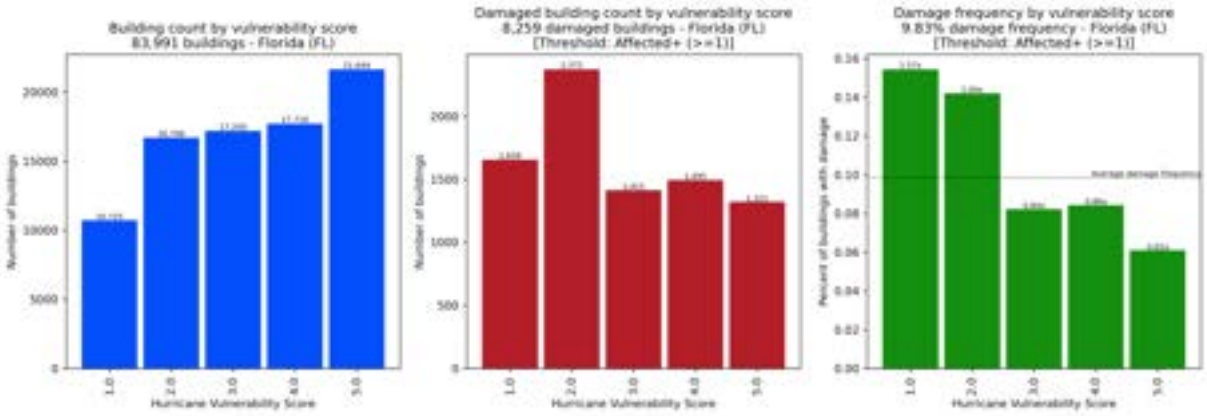

Figure 18: Lift - Florida

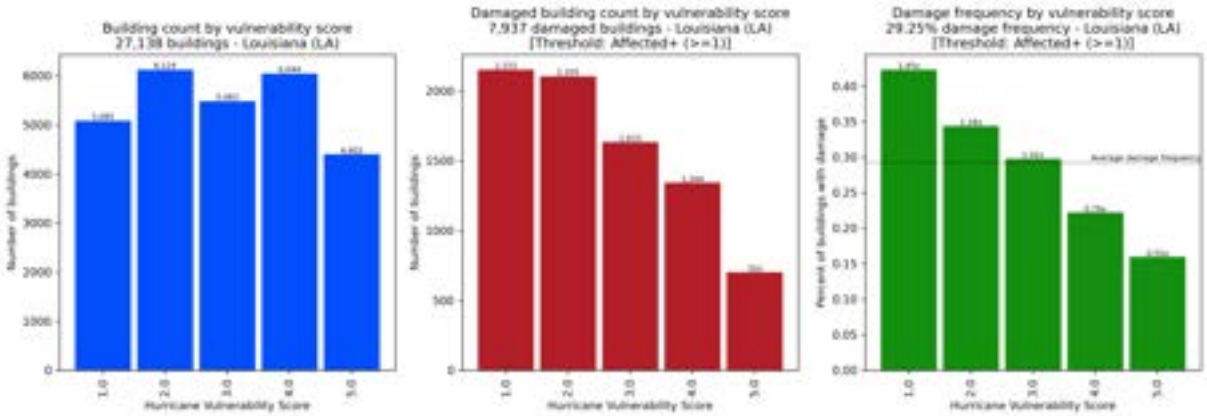

Figure 19: Lift - Louisiana

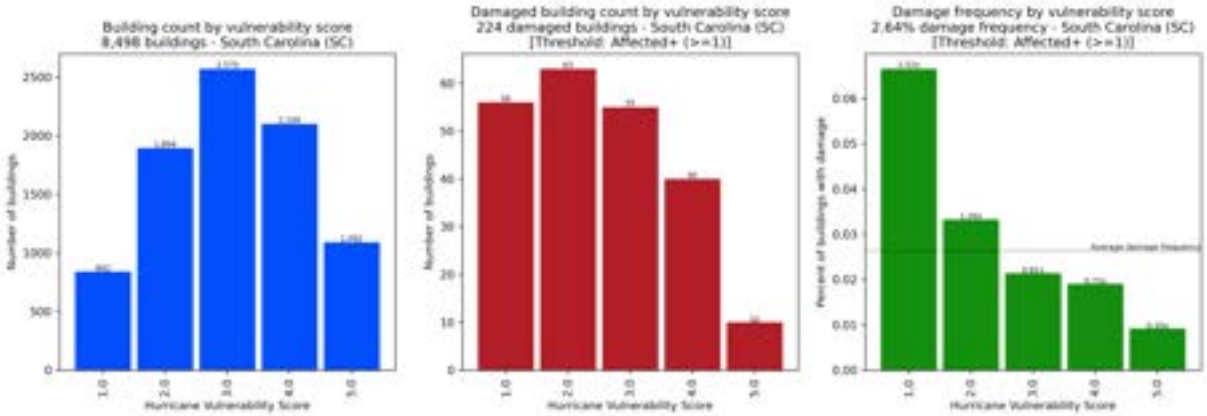

Figure 20: Lift - South Carolina

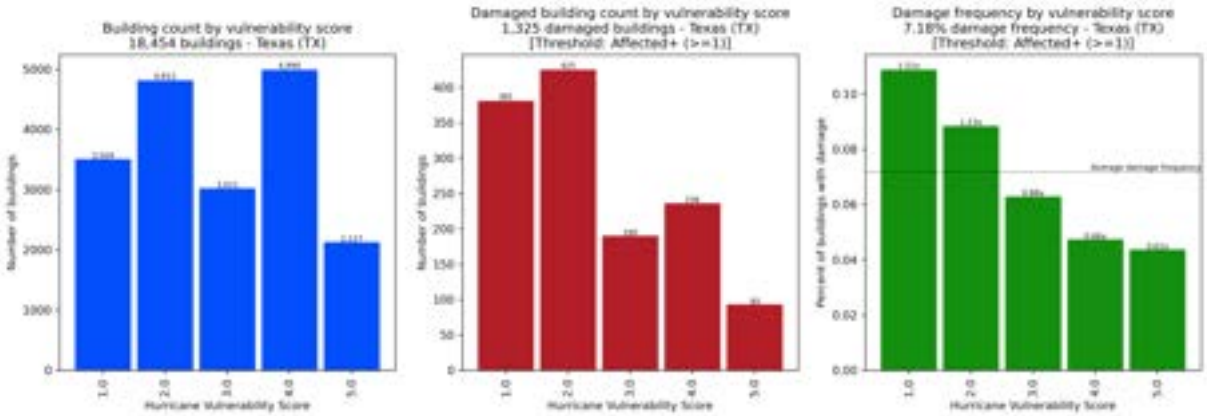

Figure 21: Lift - Texas

Validation Maps

The following maps visualize the geographic distribution of buildings in the validation dataset. Each figure shows three views: expected wind speed (left), hurricane vulnerability score (center), and damage class (right).

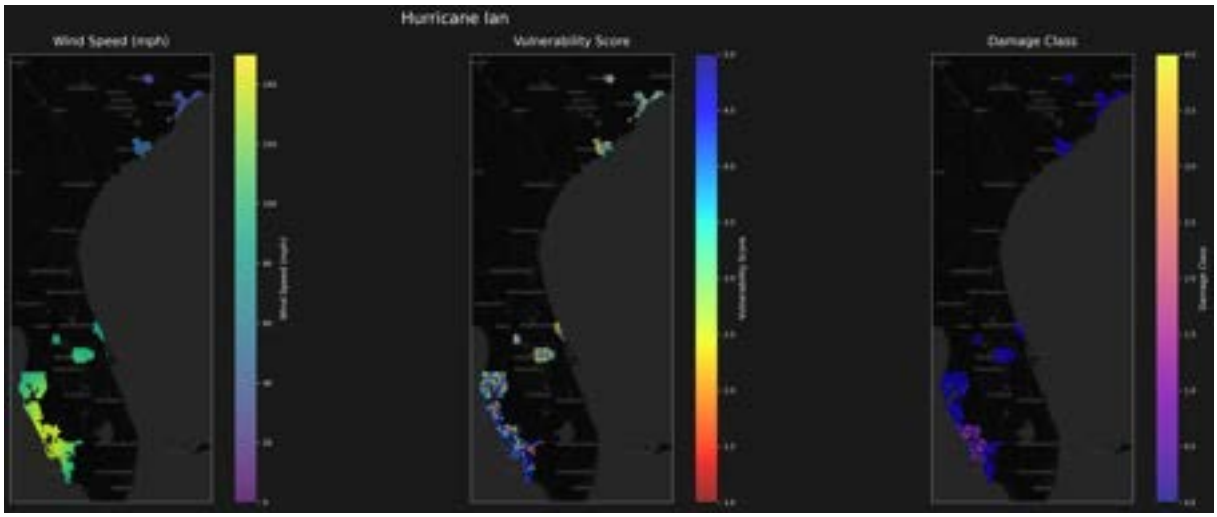

Figure 22: Hurricane Ian - Wind Speed, Vulnerability Score, and Damage Class

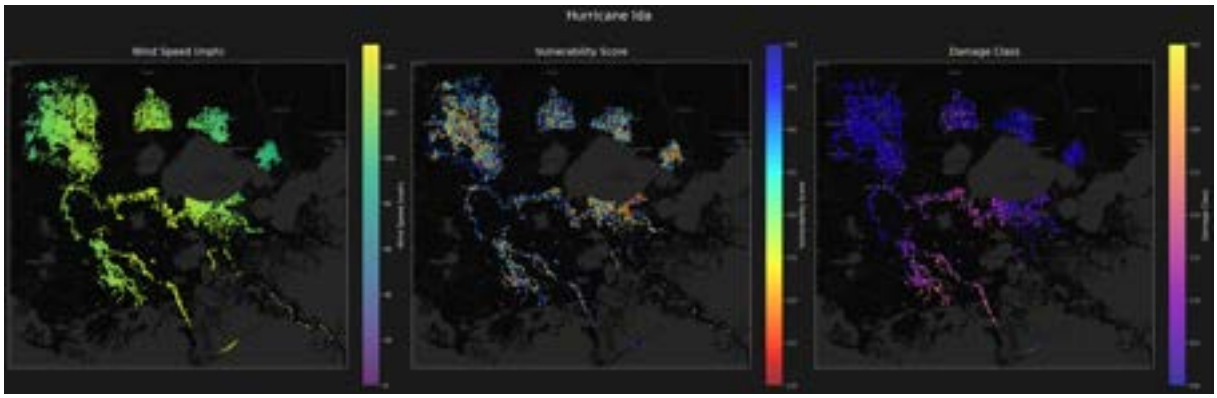

Figure 23: Hurricane Ida - Wind Speed, Vulnerability Score, and Damage Class

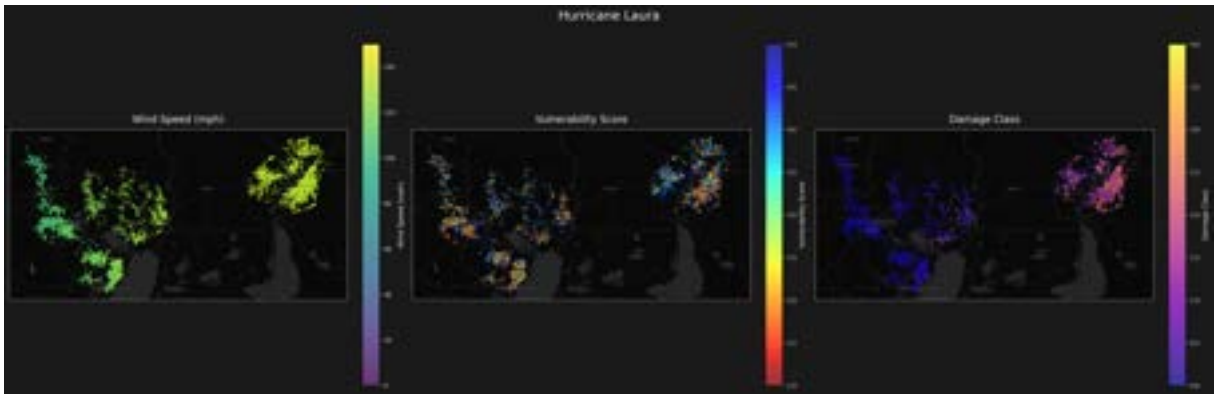

Figure 24: Hurricane Laura - Wind Speed, Vulnerability Score, and Damage Class

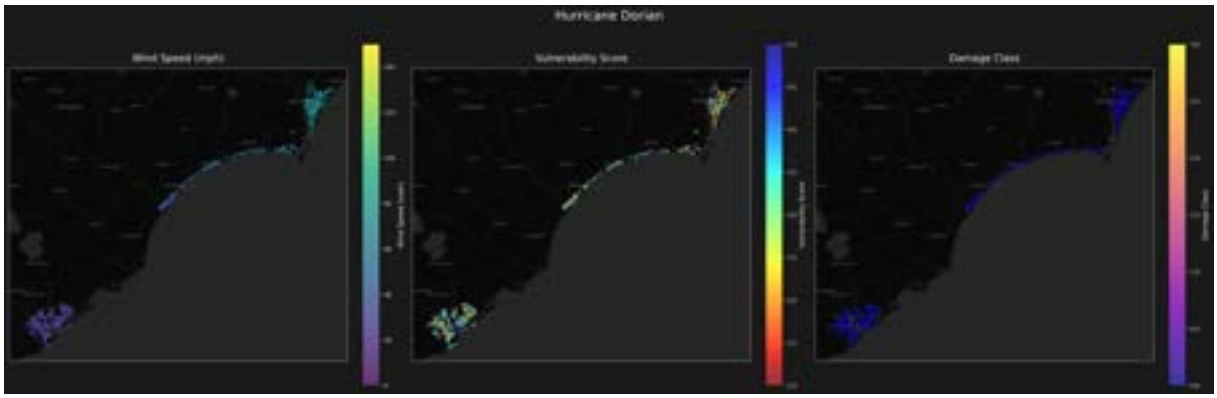

Figure 25: Hurricane Dorian - Wind Speed, Vulnerability Score, and Damage Class

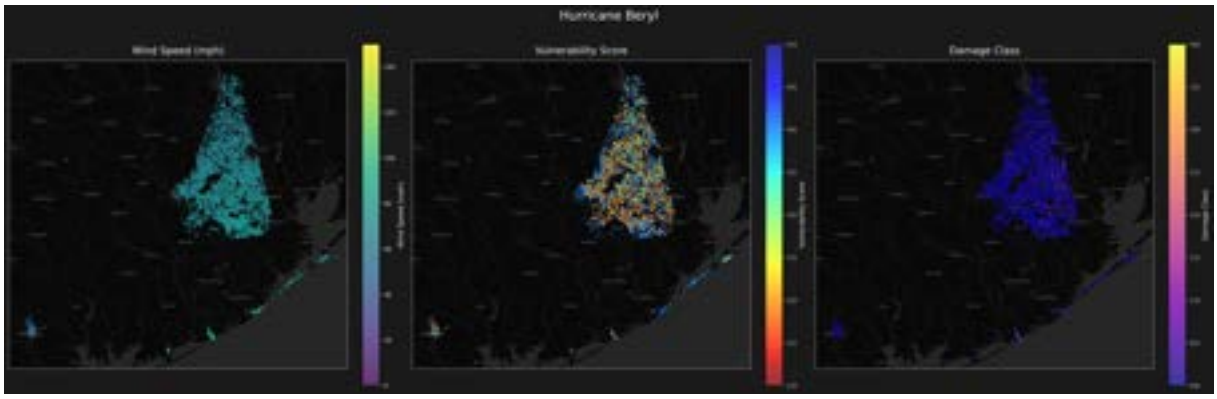

Figure 26: Hurricane Beryl - Wind Speed, Vulnerability Score, and Damage Class

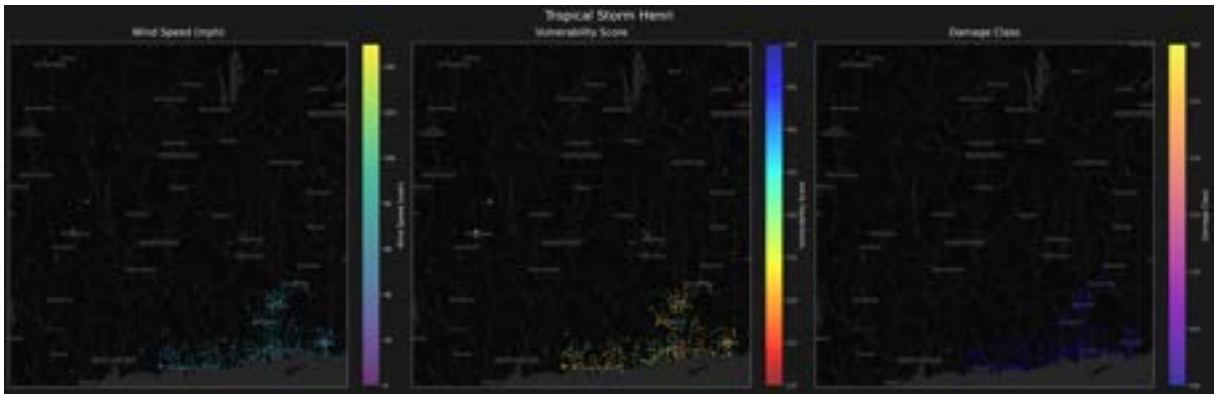

Figure 27: Tropical Storm Henri - Wind Speed, Vulnerability Score, and Damage Class

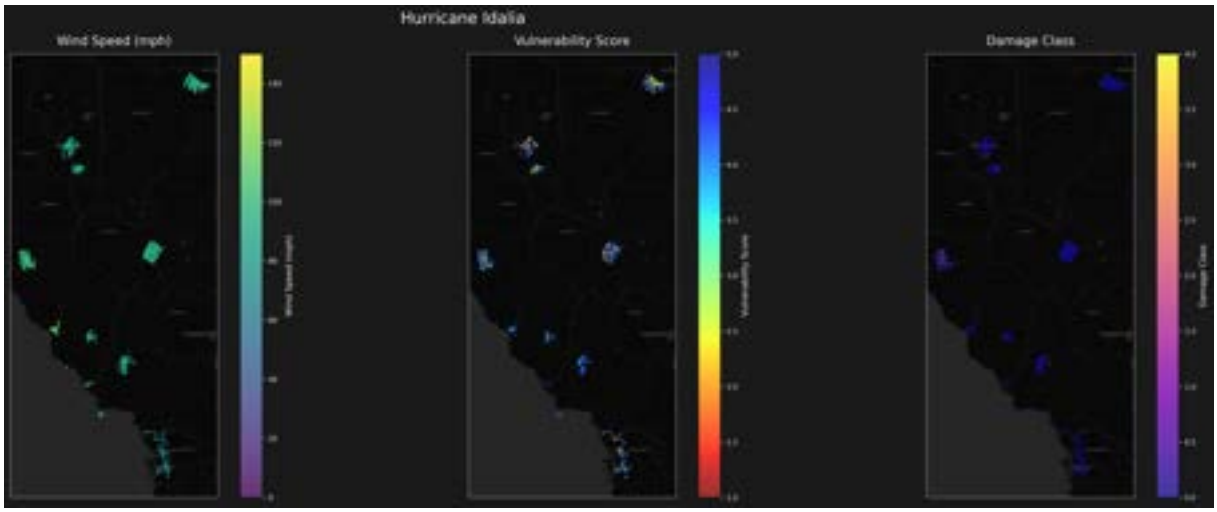

Figure 28: Hurricane Idalia - Wind Speed, Vulnerability Score, and Damage Class

Wind Speed vs Vulnerability Analysis

The following scatter plots show the relationship between wind speed exposure, vulnerability probability, and observed damage outcomes for each hurricane event:

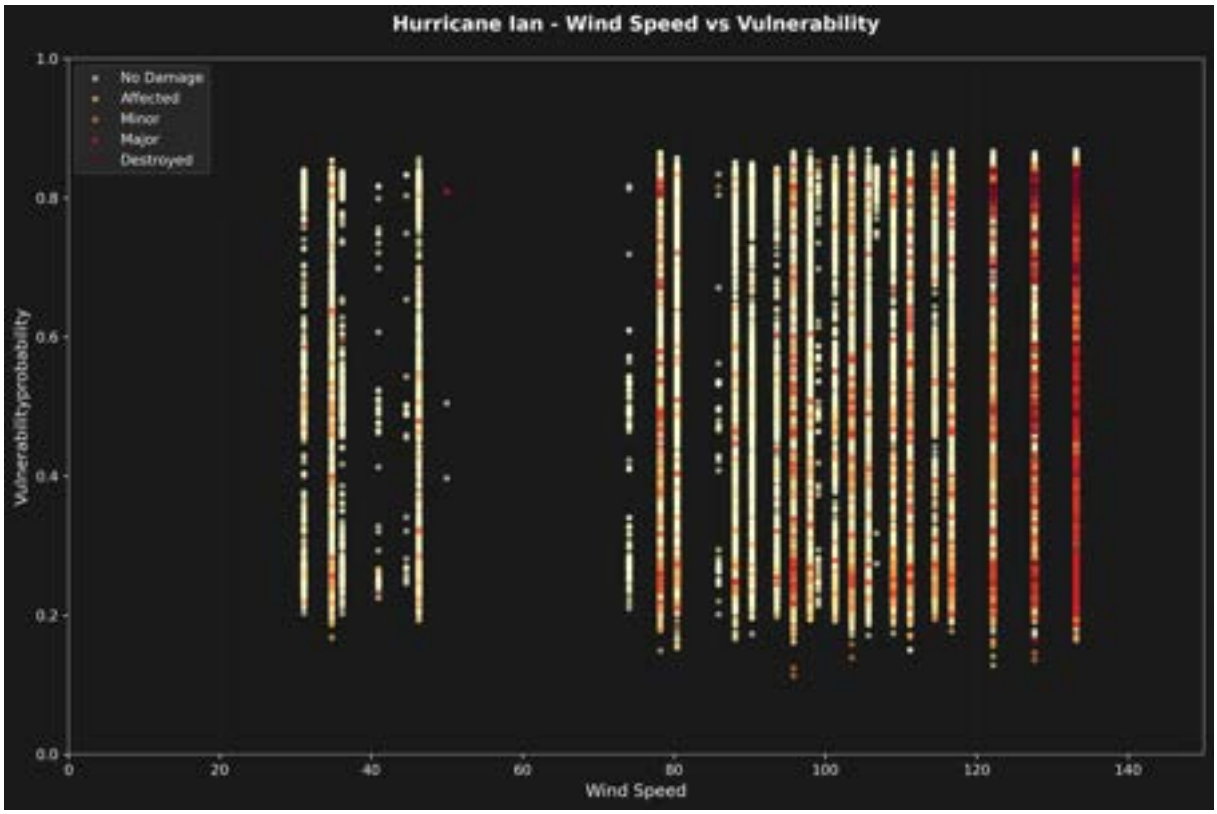

Figure 29: Hurricane Ian - Wind Speed vs Vulnerability

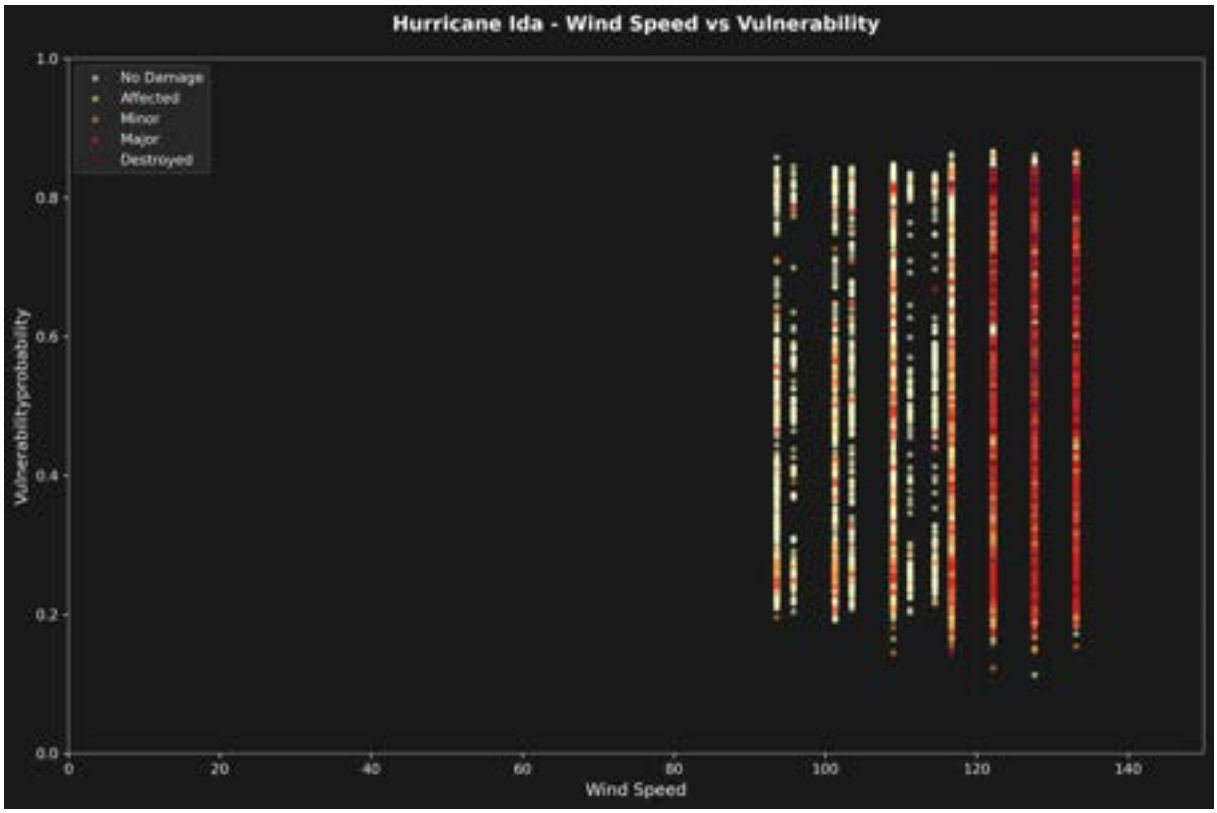

Figure 30: Hurricane Ida - Wind Speed vs Vulnerability

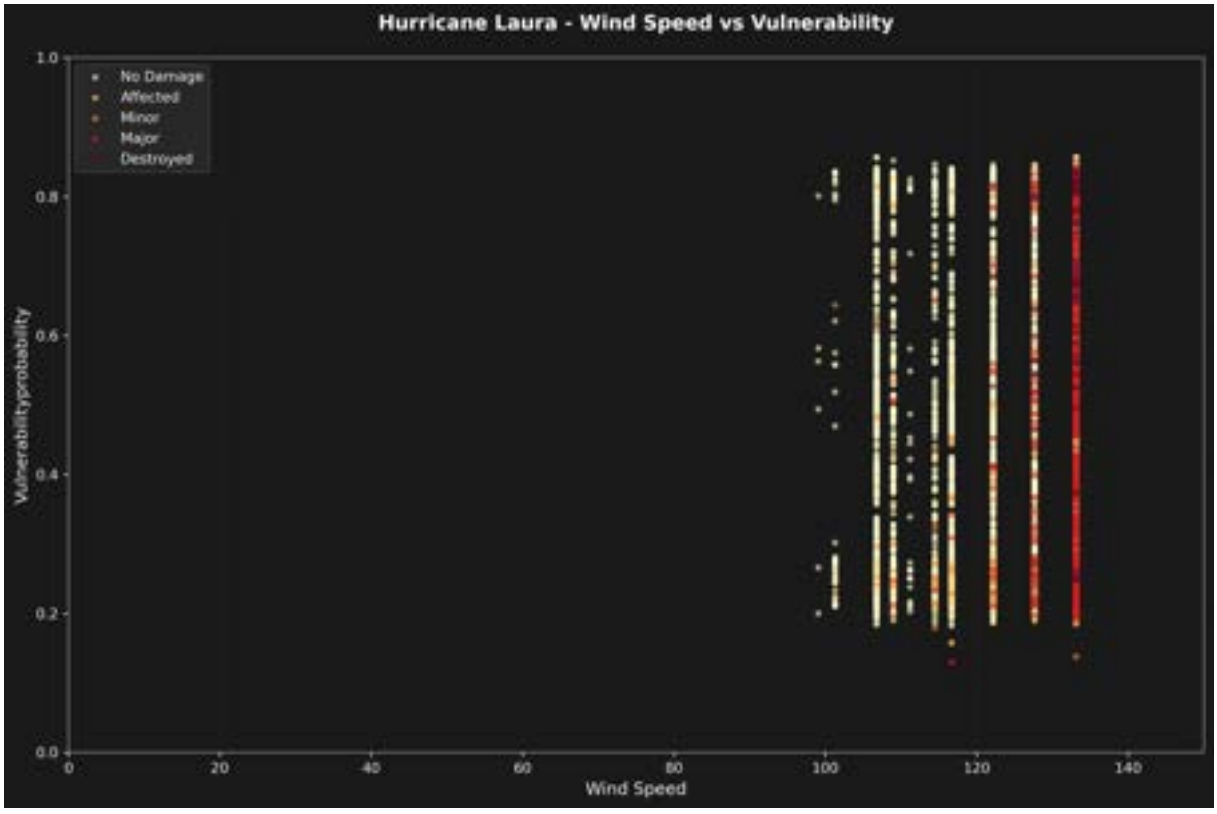

Figure 31: Hurricane Laura - Wind Speed vs Vulnerability

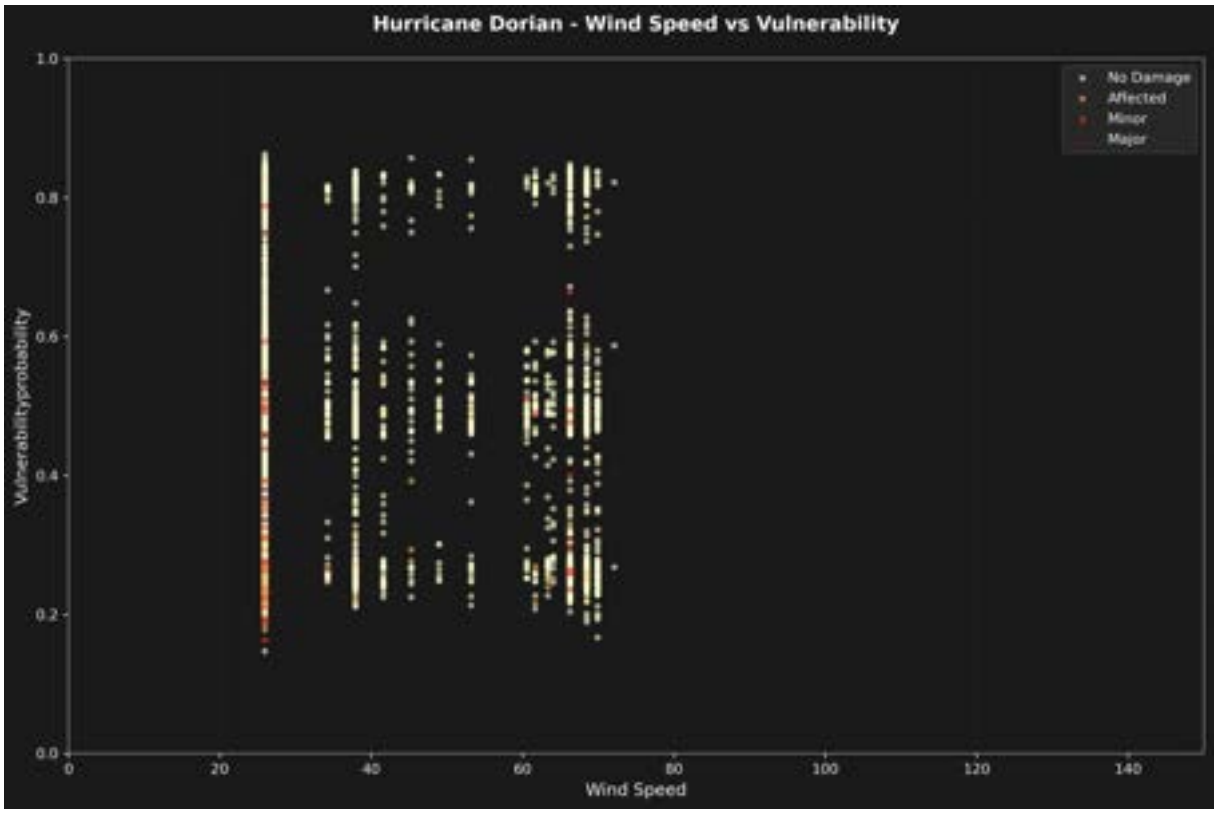

Figure 32: Hurricane Dorian - Wind Speed vs Vulnerability

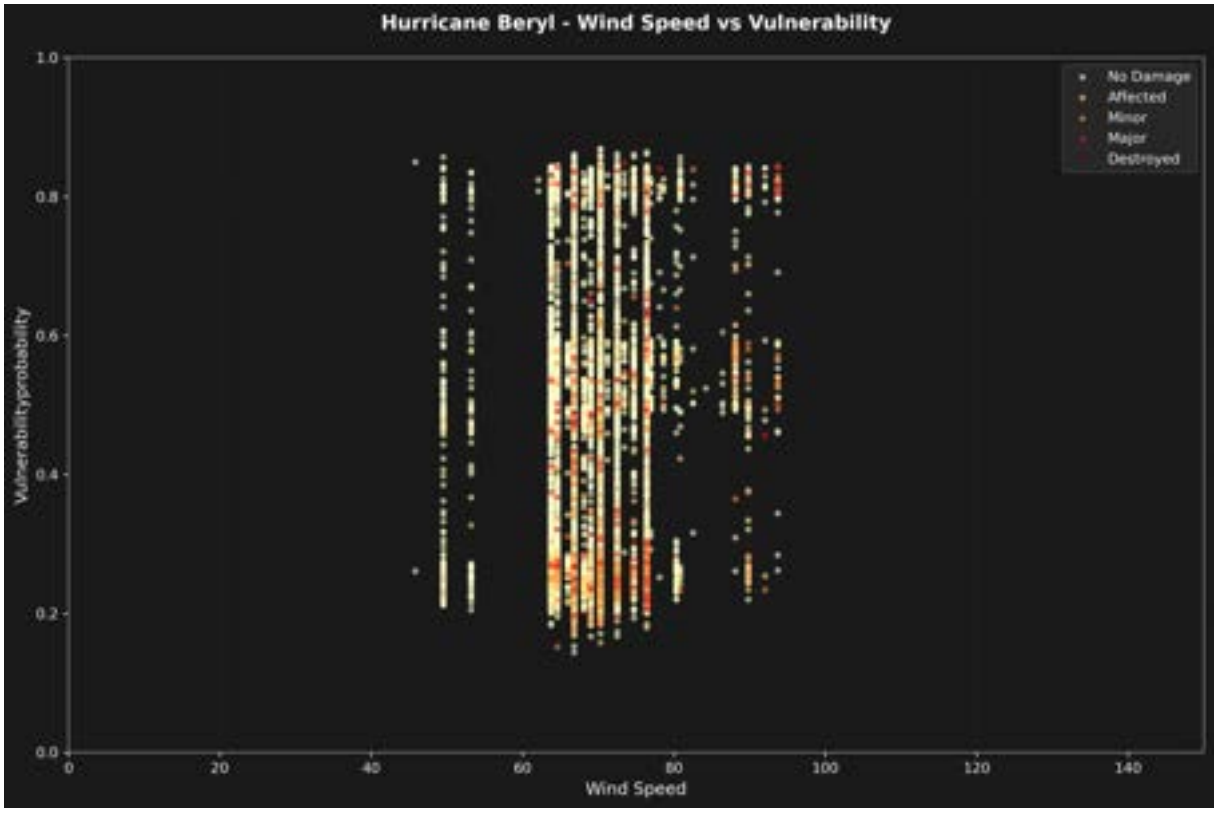

Figure 33: Hurricane Beryl - Wind Speed vs Vulnerability

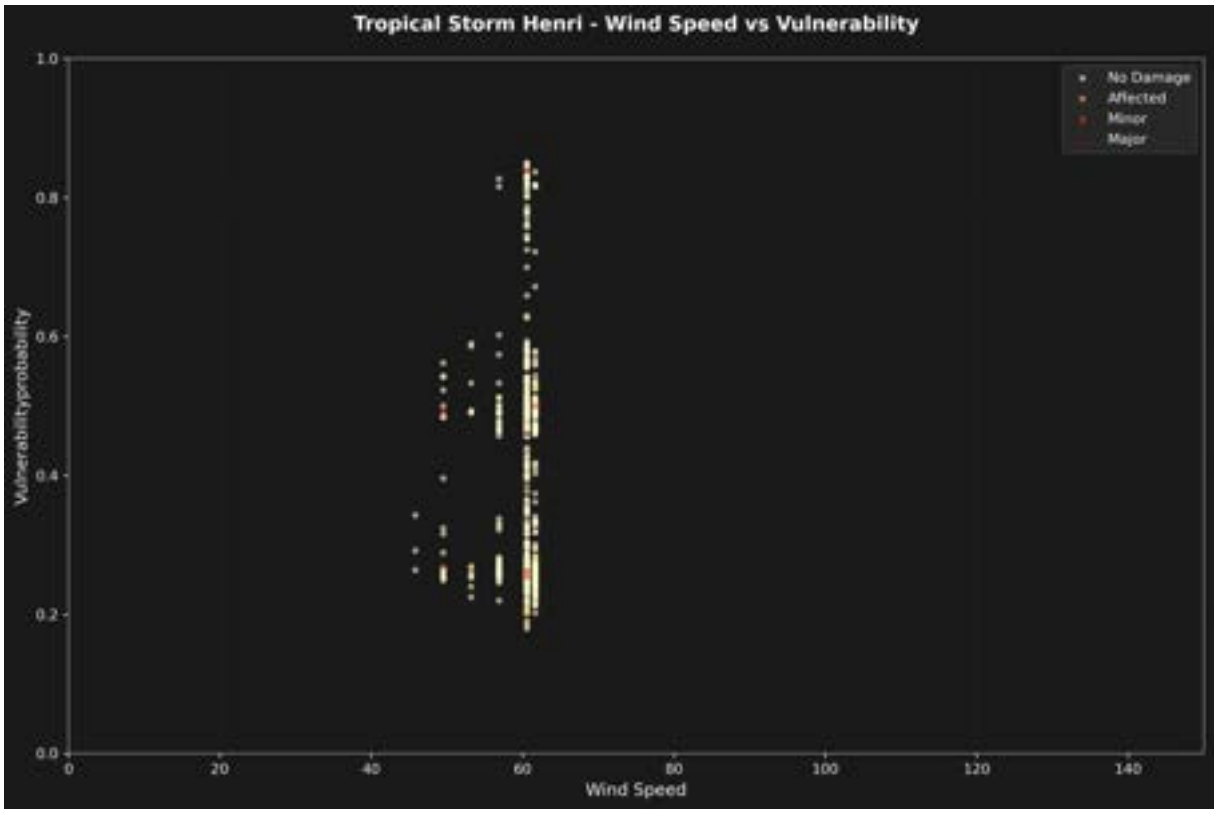

Figure 34: Tropical Storm Henri - Wind Speed vs Vulnerability

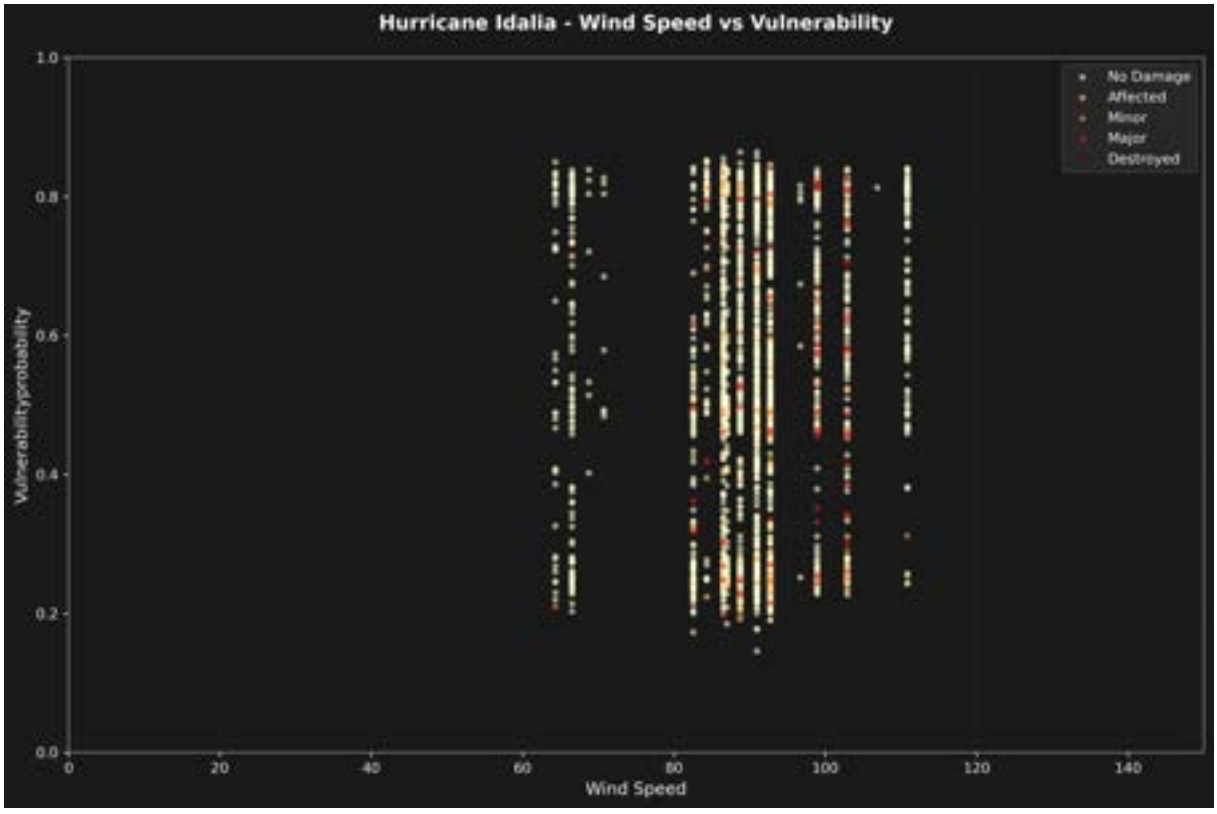

Figure 35: Hurricane Idalia - Wind Speed vs Vulnerability