# White Paper Analysis: Satellite Intelligence for Catastrophic Natural Disaster Recovery

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## Abstract

Catastrophic natural disasters, such as earthquakes, hurricanes, tornadoes, and wildfires, often strike without any warning. Especially for individuals or communities that are unprepared, these events lead to widespread devastation and impose complex recovery challenges for emergency medical services and other first responders to respond to the situation. Despite the multitude of significant technological advancements of the 21st century, the ability to effectively and accurately assess damage for a successful response remains quite difficult. This is predominantly due to outdated and disrupted ground-based assessment methods that severely tax manpower and limit capability to provide humanitarian aid, assistance, and disaster relief. This initiative leveraged multiple advanced machine learning techniques and high-resolution satellite imagery to automate natural disaster damage assessments. Ultimately, enabling efficient resource allocation and improving situational awareness for emergency medical services and first responders alike. Additionally, this initiative seeks to integrate remote sensing and geospatial imagery with machine learning, thus strategically enhancing disaster response operations overall.

Similar to how emergency room physicians and medical personnel triage patients according to severity and try to maximize lives saved, this technology will assist in area triage to detect and ultimately accelerate recovery and save lives of those affected by natural disasters. Among the multiple models evaluated, U-Net emerged as the top performer for building localization, while MobileNet excelled in damage classification. Furthermore, with its computational efficiency and high accuracy ensures timely and reliable damage assessments giving it a distinct advantage over more complex models like ResNet50 for quick large-scale disaster initiatives. MobileNet outperforms SimpleCNN and ResNet50 across most metrics, displaying the highest precision (0.7041), recall (0.7034), and F1-score (0.7029), along with a greater IoU (0.5461) and pixel accuracy (0.7034). The results presented U-Net outperformed FCN due to its higher recall (0.956) and F1-Score (0.9336), making it more effective in accurately capturing building boundaries and minimizing false negatives. U-Net's overall segmentation accuracy is more robust.

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## 1. Introduction

Natural disasters can occur in a variety of environments and communities and can strike unpredictably. This fact is true of hurricanes, wildfires, and earthquakes which can significantly disrupt communities on a large scale likely without warning. Traditional aerial-based and ground-based damage assessment methods currently used in today's society, while effective, are frequently hindered by damaged roadways, poor weather, and hazardous conditions. This application can be used across various natural disasters—such as wildfires, tsunamis, and earthquakes—to analyze pre- and post-disaster imagery for efficient triage and response. However, this analysis will primarily focus on hurricanes, specifically in response to the recent devastation caused by Hurricane Helene, which impacted millions in the southeastern United States. To overcome these limitations, this project proposes the use of machine learning (ML) models integrated into geospatial analysis of satellite and remote sensing imagery to automate damage assessments and improve their efficacy during dire situations. This approach aims to speed up first responder support and optimize resource allocation for recovery efforts.

## 2. Business Background

Traditional damage assessment techniques demand significant personnel, time, and resources, which can hinder response efficiency. Historical examples, such as Hurricane Katrina in 2005, Hurricane Michael in 2018, and most recently Hurricane Helene in 2024, underscore the ongoing challenges of disaster recovery. Often these events are earmarked by significantly delayed response times, limited resource allocation and distribution, and multiple casualties or fatalities throughout affected areas. Most critically, the safety of first responders in damaged or uncertain zones is paramount. Integrating ML capabilities with satellite imagery presents a transformative approach to overcoming these limitations in disaster management.

## 3. Problem Statement

Natural disasters can occur without warning and even with the advancement in technology it is still nearly impossible to prevent. These occurrences leave widespread devastation throughout any communities it touches. In order for key partners and government agencies to effectively implement a humanitarian response in regards to the aftermath of natural disasters, they would require accurate damage assessments. Traditional ground-based damage assessment methods, while effective, are often disrupted by destroyed roadways and any other inherent dangers associated with disaster zones. This project seeks to leverage the application of advanced machine learning techniques in order to utilize high-resolution satellite images in order to identify proper impact reports. Automating the analysis of satellite data, one aims to enhance and provide situational awareness for first responders. This definitely allows for proper resource allocation to the areas most impacted. Integration of these techniques with satellite imagery can optimize disaster response operations, ultimately accelerating recovery efforts and saving lives.

## 4. Summary of EDA Findings

The Exploratory Data Analysis (EDA) began with the integration of satellite imagery into hurricane_pre_df and hurricane_post_df into a single dataset, comprising of 2,438 entries. These images were stored in an Amazon S3 bucket, which served as a centralized repository for efficient data storage and retrieval. The integration process ensured seamless access to the imagery data and facilitated robust analysis. Utilizing a combination of statistical and graphical techniques employed the uncovering of key insights into the data's structure, patterns, and relationships. Univariate analysis explored individual variables, while multivariate analysis examined interactions between them. Tools such as plots and heatmaps were utilized to visualize data distributions, variable relationships, and correlations. These visualizations facilitated the identification of trends, patterns, and potential issues, including multicollinearity, outliers, and missing data—factors that were pivotal for informing subsequent preprocessing steps.

The two correlation matrices provided insights into relationships between satellite observation features related to disaster types and statuses. The color gradient, with red indicating strong positive correlations and blue indicating strong negative ones, highlights key trends. Features like off_nadir_angle and pan_resolution are highly correlated, suggesting that as the satellite's angle from nadir increases, the spatial resolution changes, while gsd (Ground Sample Distance) positively correlates with off_nadir_angle and negatively with pan_resolution, indicating higher resolution with smaller GSD values. By disaster type (flooding or wind), weaker correlations are observed, with disaster type showing minor negative correlations with satellite angles and resolutions, suggesting slightly better resolution for wind-related imagery. By disaster status (pre- or post-disaster), stronger patterns emerge: off_nadir_angle and pan_resolution positively correlate with post-disaster observations, while sun_azimuth and sun_elevation show slight declines. Notably, target_azimuth decreases significantly post-disaster, and gsd shows an increasing trend. Strong correlations highlight the need for feature selection or dimensionality reduction to manage multicollinearity in modeling.

Figure 1

*Damage Classification by Disaster Type*

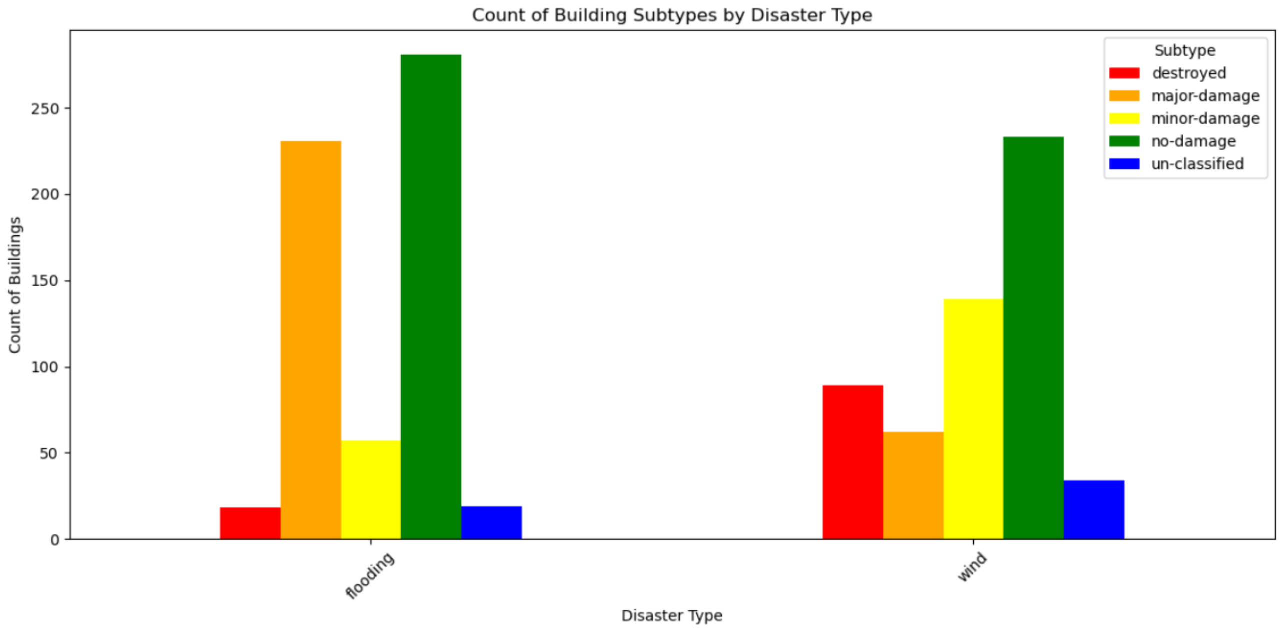
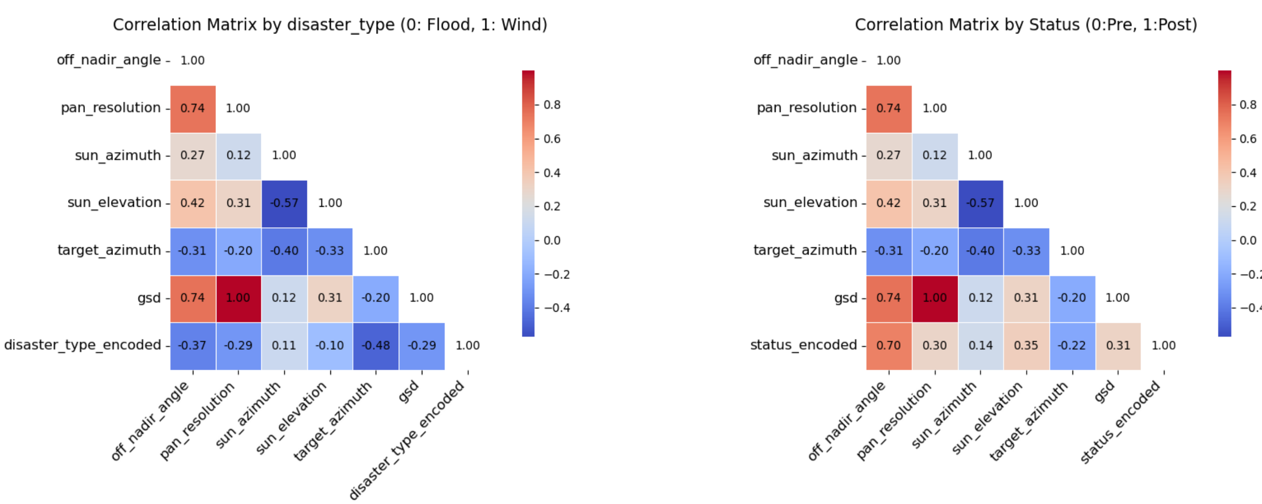



Figure 2

*Correlation Matrix by Disaster Type/Status*



# 5. Business Questions

1. How accurate can the models be from the utilization of high-resolution imagery when assessing natural disasters damage?
2. How can the information from satellite imagery damage assessments aide in prioritization of proper resource allocation needs?
3. How can first responders strategies improve from situational awareness provided from these damage assessments?
4. What is the difference between an automated satellite image damage assessment and the traditional manpower-based approach in terms of speed and accuracy?
5. What are the potential limitations of solely using Machine Learning for disaster impact initiatives?

# 6. Scope of Analysis

This analysis focuses on high-resolution satellite imagery of hurricanes affecting the United States, covering both pre- and post-disaster scenarios. These images are stored in an Amazon S3 bucket, the dataset includes various hurricane events, enabling assessments of flooding and wind damage to infrastructure, vegetation, and urban areas. Machine learning techniques were applied to automate the damage classification assessment, providing faster and more accurate insights. The study emphasizes identifying critical damage patterns to synthesize proper resource allocation with enhanced first responder situational awareness, ultimately optimizing disaster response and recovery efforts.

# 7. Approach

The desired approach for this project was to focus on two core tasks: building localization and damage classification, both utilizing high-resolution satellite imagery. For building localization, pre-disaster satellite images are used to train a semantic segmentation model that identifies building footprints. The model produces binary masks highlighting regions of interest for further analysis. In regards to damage classification, the second task, it involves training a multiclass segmentation model on paired pre- and post-disaster images. This model predicts pixel-wise damage levels within the identified urban regions, categorizing them as un-classified, no-damage, minor damage, major damage, or destroyed.

Preprocessing includes preparing paired pre- and post-disaster images, ensuring alignment and consistency for model training. Evaluation metrics such as Intersection-over-Union (IoU) and pixel accuracy are employed to measure the performance of both models. These metrics ensure the reliability of building localization and damage classification for disaster damage assessments.

Table 2

*Localization Performance Metrics*

| Model | FCN | U-Net |
|---|---|---|
| Precision | 0.9417 | 0.9122 |
| Recall | 0.8862 | 0.9561 |
| F1-Score | 0.9131 | 0.9336 |
| IoU | 0.8401 | 0.8755 |
| Pixel Accuracy | 0.9846 | 0.9876 |
| MSE | 0.0102 | 0.0094 |
| True Positives | 1296976 | 1399334 |
| False Positives | 80336 | 134716 |
| False Negatives | 166557 | 64199 |
| True Negatives | 14446915 | 14392535 |
| Robustness Loss | 0.7864 | 0.733 |
| Robustness Accuracy | 0.8794 | 0.8753 |

Table 3

*Damage Classification Performance Metrics*

| Model | SimpleCNN | MobileNet | ResNet50 |
|---|---|---|---|
| Precision | 0.5522 | 0.7041 | 0.6738 |
| Recall | 0.5814 | 0.7034 | 0.6674 |
| F1-Score | 0.5521 | 0.7029 | 0.6694 |
| IoU | 0.4001 | 0.5461 | 0.5066 |
| Pixel Accuracy | 0.5814 | 0.7034 | 0.6674 |
| MSE | 0.6954 | 0.5325 | 0.6497 |

| | | | |
|---|---|---|---|
| **True Positives** | 4207 | 5090 | 4829 |
| **False Positives** | 3029 | 2146 | 2407 |
| **False Negatives** | 3029 | 2146 | 2407 |
| **True Negatives** | 18679 | 19562 | 19301 |
| **Robustness Loss** | 0.3011 | 0.1944 | 0.2266 |
| **Robustness Accuracy** | 0.2282 | 0.5513 | 0.4502 |

## 8. Limitations

The proposed methodology, while innovative, faces several limiting factors. One significant challenge lies in the computational resource demand required to process a large quantity of high-resolution satellite imagery and then train advanced machine learning models. These tasks demand substantial processing power, memory, and storage, which may not always be readily available, especially for large-scale natural disasters. Furthermore, the scalability of the approach is another critical concern, as adapting the models to handle various types of natural disasters—such as hurricanes, earthquakes, and wildfires which would requires extensive retraining and fine-tuning, further straining any available computational resources. This limitation highlights the need for optimized algorithms, cloud-based solutions, or access to high-performance computing infrastructures to ensure consistent and efficient performance across diverse disaster scenarios.

## 9. Solution Details

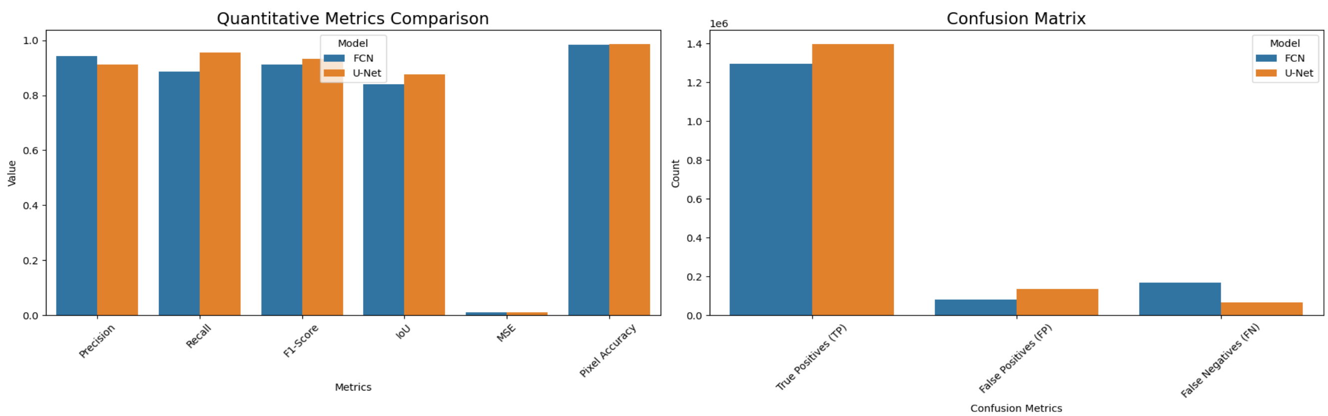
The solution is centered on a two-stage modeling approach which is first building localization and secondly damage classification then evaluated through comprehensive performance metrics.

For building localization, two models were tested: Fully Convolutional Network (FCN) and U-Net. U-Net outperformed FCN in key metrics, demonstrating higher IoU (0.8755), F1-score (0.9336), and pixel accuracy (0.9876), demonstrating its superior ability to accurately segment building footprints. U-Net also achieved lower Mean Squared Error (MSE) and robustness loss, highlighting its efficiency and stability. Although U-Net produced more false positives of 134,716 as opposed to 80,336, it largely has fewer false negatives 64,199 versus 166,557 which suggests it minimizes missed detections, making it a more reliable choice for identifying regions of interest.

For damage classification, SimpleCNN, MobileNet, and ResNet50 models were assessed. Ultimately, MobileNet delivered the best overall performance, achieving the highest precision (0.7041), recall (0.7034), and IoU (0.5461), as well as the lowest MSE (0.5325) among the three. Its balance of high true positives (5,090) and low false positives (2,146) underscores its accuracy in categorizing damage levels across the four defined categories. While ResNet50 also performed well, MobileNet's robustness and computational efficiency made it the preferred model for this handling this computational heavy task.

Figure 6

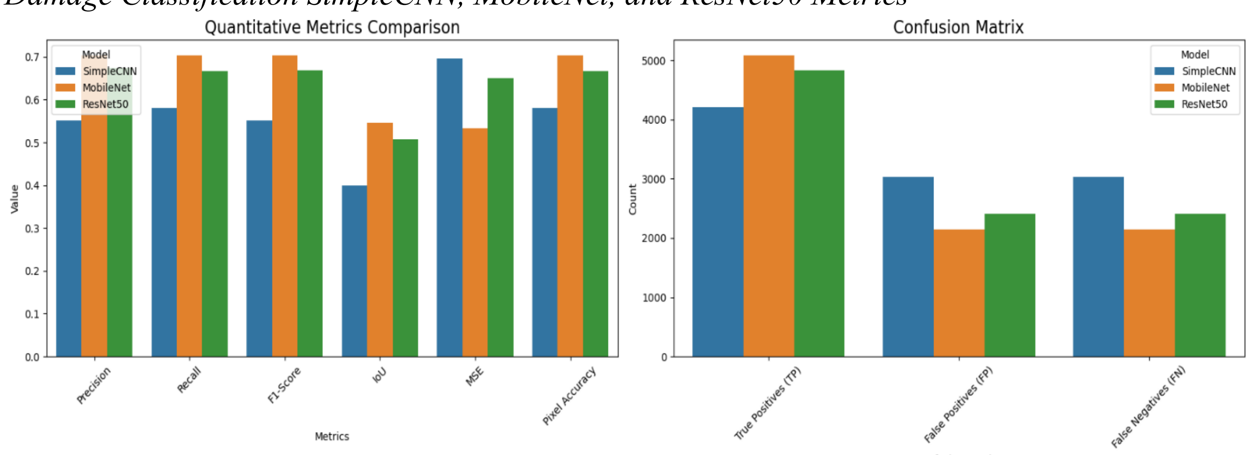
*Building Localization – FCN and U-Net Metrics*




The combined results illustrate the potential of using U-Net for localization and MobileNet for damage classification in disaster scenarios. These models optimize segmentation accuracy and damage prediction, addressing the critical need for timely and precise disaster damage assessments to aid first responders in developing data driven strategies. However, integrating these solutions requires sufficient computational resources and scalability enhancements to handle the diverse data complexities that are imposed from varying disaster types.

Figure 7

*Damage Classification SimpleCNN, MobileNet, and ResNet50 Metrics*



## 10. Concluding Summary

This project has successfully demonstrated the value of automation in post-disaster damage assessments, highlighting its potential to enhance the efficiency and precision of recovery efforts. Leveraging machine learning models like U-Net and MobileNet achieves robust performance metrics. U-Net excelled in building localization with an IoU of 0.8755, an F1-score of 0.9336, and a pixel accuracy of 0.9876, ensuring accurate identification of affected regions. MobileNet proved to be the most effective in damage classification with achieving an IoU of 0.5461, an F1-score of 0.7029, and a pixel accuracy of 0.7034, strategically detailing the categorization of damage levels. These models provided timely, accurate impact reports that have the potential to aid first responders in prioritizing interventions and allocating resources more effectively. Additionally, the study underscores the scalability of this approach, making it adaptable to various disaster types, thereby enhancing disaster management strategies at the global level. Regions around the world face diverse and severe natural disasters and with the integration of machine learning with satellite imagery it offers a transformative solution for accelerating recovery and ensuring more efficient responses. This innovation marks a significant step toward a more resilient and prepared future.

## 11. Call to Action

To enhance disaster response, it is recommended to expand the utilization of the xView2 geospatial imagery, which provides thousands of valuable pre- and post-disaster images. Having a limited file storage capacity, it’s also essential to optimize cloud storage and processing capabilities for quick access to imagery and model outputs. Real-world testing of the models in live disaster scenarios is crucial for fine-tuning and validating their effectiveness. Finally, developing intuitive dashboards from the developed model will enable first responders and decision-makers to easily access actionable insights in a digestible way to the users, and other stakeholders.

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