CAMPUS FLOOD ASSESSMENT THROUGH A WEB-INTERFASE POWERED BY AI: UNDERSTANDING STUDENT PERCEPTION OF RISK DURING FLOODING EVENTS

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ABSTRACT

In recent years, the global community has seen a significant increase in flood disasters due to climate change and urbanization, with educational institutions needing to be more immune to these challenges. Specifically, Florida and Georgia have experienced four major hurricanes over the past decade, resulting in damages exceeding $120 billion. Additionally, there has been a noticeable increase in frequent, small-magnitude flooding events, particularly in coastal regions with rising sea levels. Despite these risks, most higher education research focuses on campus sustainability or reducing carbon footprints. University students are particularly vulnerable to flooding due to limited financial resources and the need for more awareness about local risks and disaster preparedness. This project aimed to understand the human perception of flood risks at the street level. To undertake this project, we collected data in two primary categories: aerial imagery (including satellite images, flood, density maps, and digital elevation models) and human-scale data (street view images). Subsequently, we created a Web interface curated to display specific information on campus infrastructure to capture student perceptions of the risk of flooding. During a two-day session in Spring 2024, we conducted a workshop with males and females aged 19 to 40 to collect an initial dataset to understand student perception of risk and the objects or built environment factors contributing to such perception. In conclusion, the most frequently mentioned concerns included risks associated with trees falling due to wind and flood damage onto houses and cars, highlighting the need for targeted interventions to mitigate these risks. Additionally, students often felt unsafe on campus, considering the street-level image, emphasizing the importance of enhancing campus infrastructure and safety measures to improve overall security and preparedness.

METHODOLOGY

The project was executed in three stages:

1. Data Collection:
   - Aerial Imagery: Satellite images, flood maps, density maps, and DEMs.
   - Street View Images
2. Web Interface Development:
   - Integrate aerial and street-level data.
   - Display this data, allowing users to view critical infrastructure and potential flood zones and fill out survey.
3. Workshop & Data Analysis
   - Two-day workshop with participants (ages 19 to 40) from diverse backgrounds.
   - Collected feedback on flood risk perception via: Surveys and focus group discussions.
   - Analyzed responses to identify:
     - Key themes in flood risk perception.
     - Factors influencing participants' feelings of security or insecurity.

DATA COLLECTION

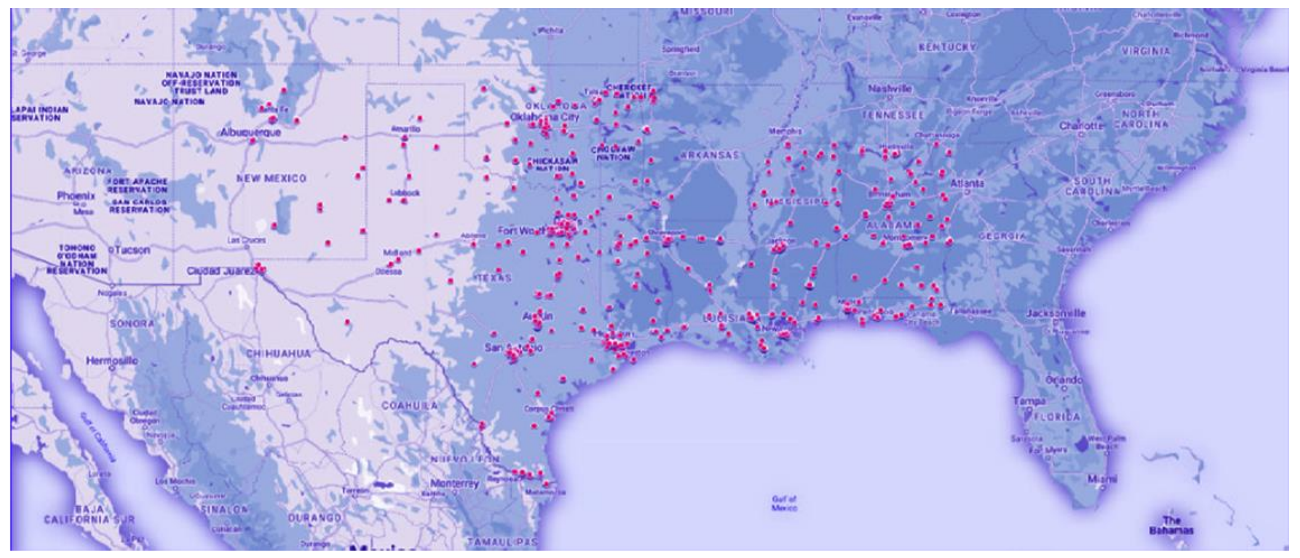

Figure 1 List of Universities Along the Gulf of Mexico

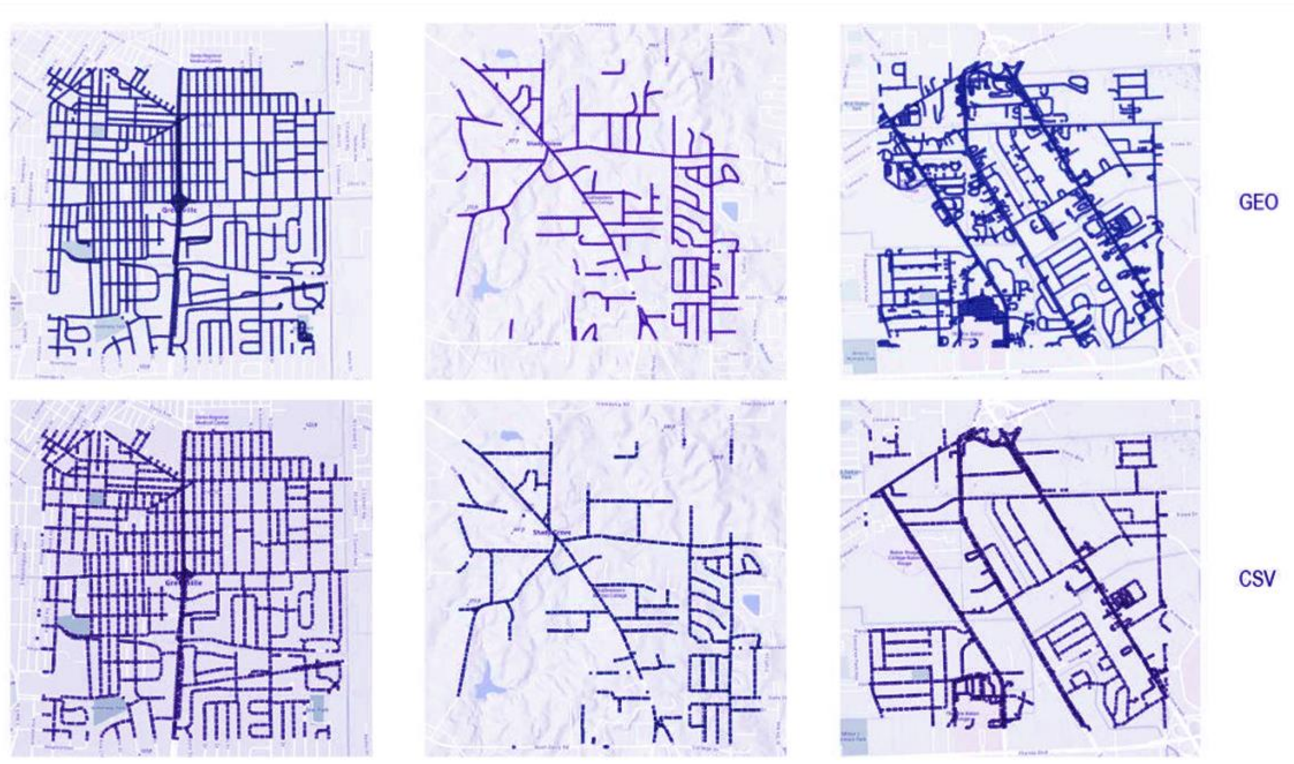

Figure 2 Showcase of the filtering decision to filter out campuses that didn't have more than 80% street view data

DATA SOURCES:

- Google Street View (GSV), flood maps, density maps, and Digital Elevation Models (DEM)
- Tools Used:
  - Google API and ArcGIS for street views and aerial imagery.
  - Open Street Map (OSM) API to extract the road network within a 5 km radius.
- Grid Setup:
  - A 12.5-meter grid was used to map geo-coordinates along road axes.
  - Selected campuses with 80%+ street view image coverage for completeness.

DATA COLLECTED:

- Total Images: 675,486 across 30 universities, including:
  - 96,498 satellite images.
  - 192,996 street view images.
  - 96,498 flood maps.
  - 96,498 density maps.
  - 96,498 DEM maps.

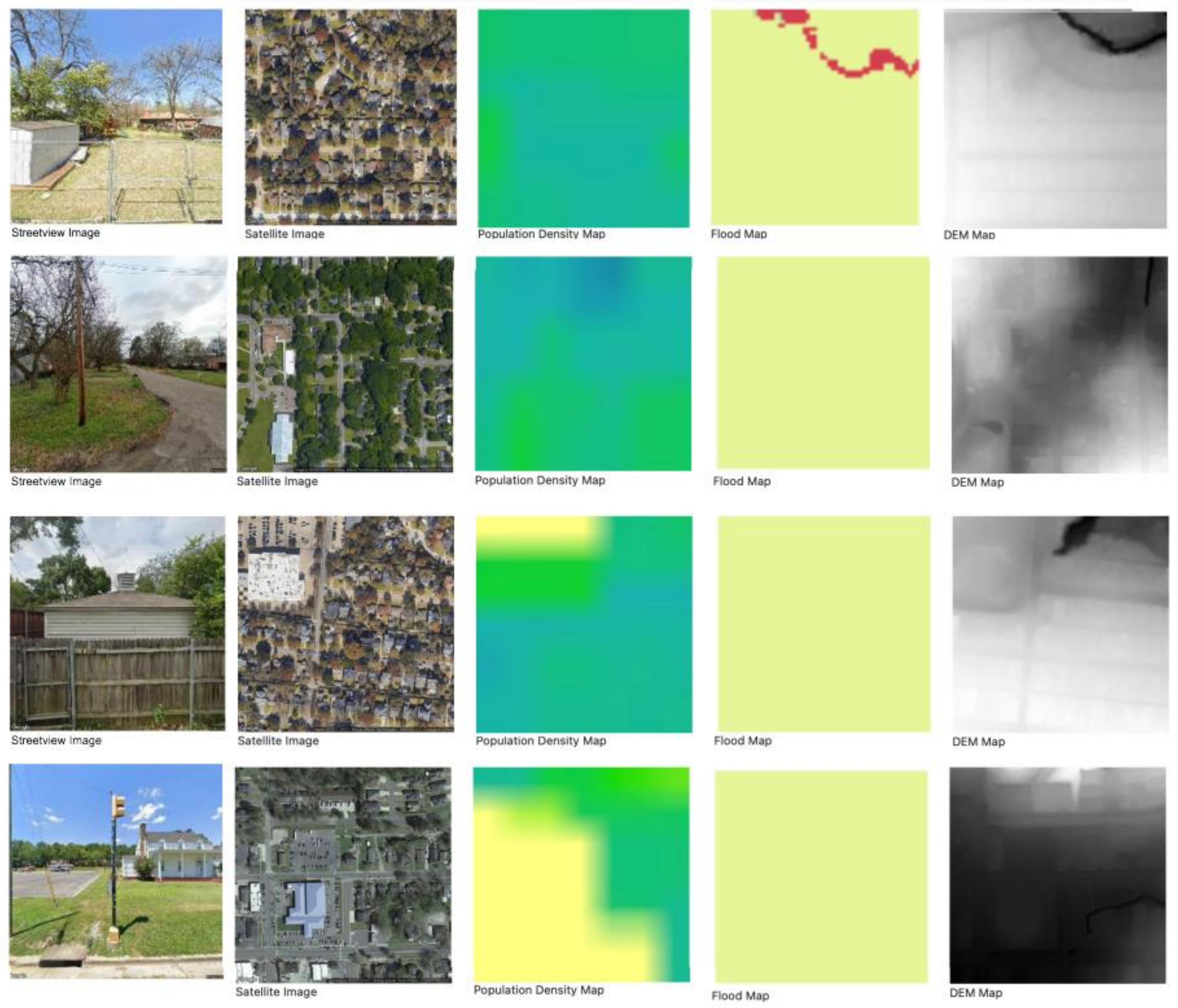

Figure 3 Coordinates of Locations Selected

WEB INTERFACE

1. Feature Extraction using Pre-trained CNN Models from street view images :
   - Models used: InceptionV3, DenseNet169, EfficientNetB5/B7, VGG16/VGG19, and ResNet50.
   - These models extract meaningful, high-dimensional features from street view images.
2. Data Clustering with Self-Organizing Map (SOM):
   - These feature vectors are then fed into the SOM, which organizes the images into clusters based on their similarity
3. Object detection algorithm:
   - using Inception-ResNet-v2 to identify objects like buildings, roads, and electricity poles.

4. Objects detected are classified into categories based on prior flood risk studies. These categories include:
   - Sill Height: Window
   - Building Typology: Building, Office building, Skyscraper, House, Tower.
   - Street: Road, Sidewalk, Street
   - Structure Attached to Adjacent Building: Porch, Stairs, Door, Window, Door handle.
   - Vehicles and related: Land vehicle, Truck, Bus, Car, Van, Train
   - Electricity pole: Electricity, Electric network, Cable, Power cables, Power grid
   - Fence
   - Outdoor decor
   - Signage: Traffic sign, Stop sign, billboard
   - Streetlight
5. Users answer to some questions in the survey in the second window of the web(figure 4 right).
   - This approach captures insights into which areas are perceived as vulnerable, what objects pose risks during hurricanes, and how safe students feel within certain environments.

Figure 4 left: Self Organizing Maps for the Google Street View Images. Right: Labeling interface, per cell of the SOM

WORKSHOP & DATA ANALYSIS

Throughout the workshop, students shared valuable insights into flood risk perception. This project used a mixed-methods approach, integrating qualitative insights with quantitative data analysis to understand the nuances of flood risk from students' perspectives. Expertise from AI, GIS, and urban planning contributed to this project.

- The text analysis, including word clouds and heatmaps, highlighted key concerns among students.
- Many participants felt unsafe in certain areas, as captured by street-view images, noting that these areas did not resemble typical campus environments.
- Frequently mentioned objects of concern included trees, buildings, vehicles, and power cables. Students also emphasized risks related to "fall," "wind," "damage," and "flood," reflecting concerns about the impact of floods on infrastructure and personal safety.

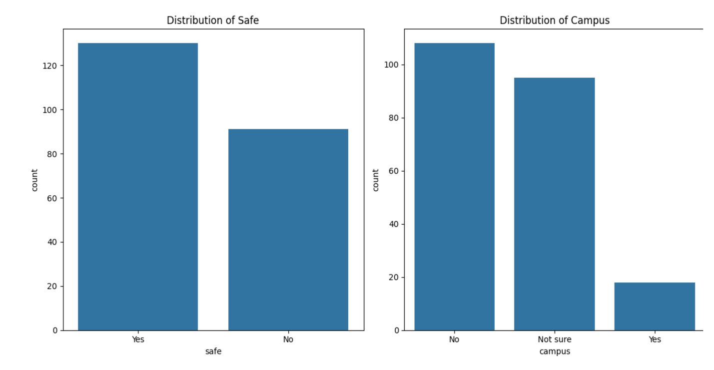

Figure 5 Distribution of the dataset showing students' feelings of safety during a hurricane and their perceptions of whether the street-view image resembles a campus.

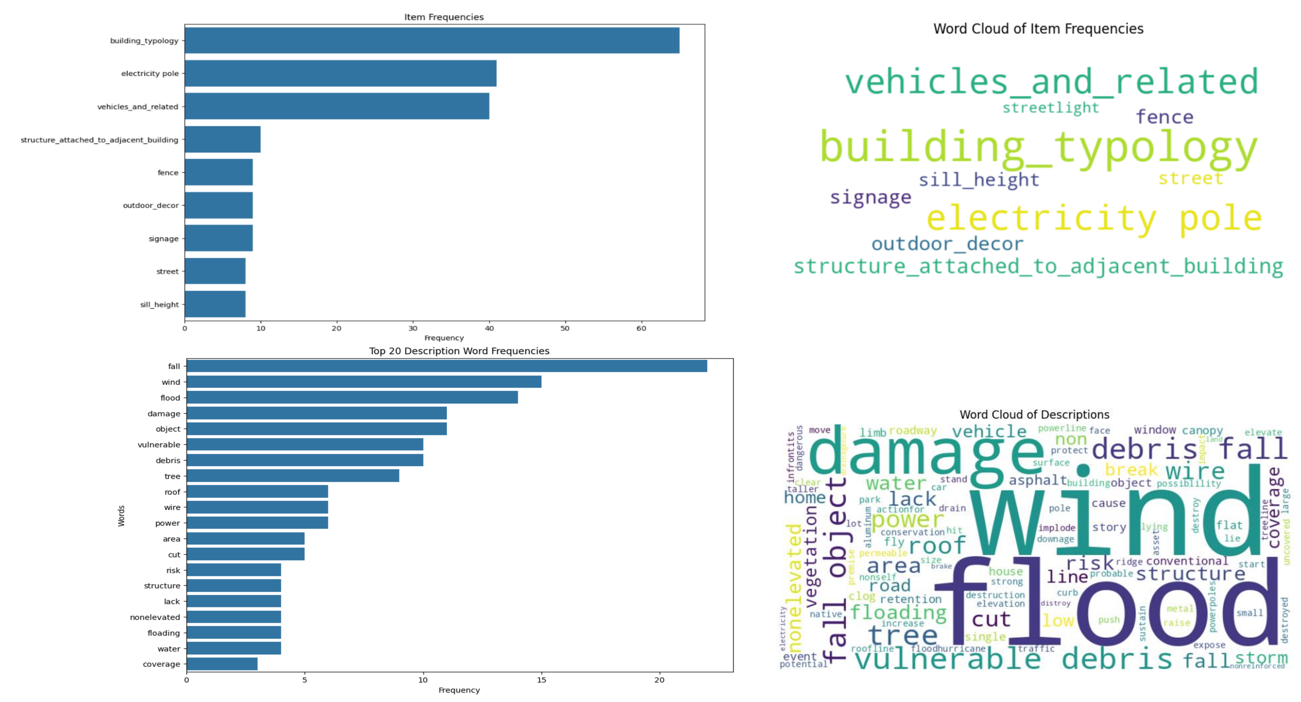

Figure 6 The first row displays the most common items mentioned by students as risk items (left) and their corresponding word cloud (right). The second row shows the most frequent descriptive words associated with these items (left) and their word cloud representation (right).

- The heatmaps further revealed high-frequency clusters linked to specific hazards:
  - Buildings: Associated with "damage" and "flood," raising concerns about structural safety.
  - Vehicles: Linked with "risk" and "damage," reflecting worries about vehicle safety during floods.
  - Electricity Poles: Connected with "fall" and "power," highlighting the risks of power failures during storms.

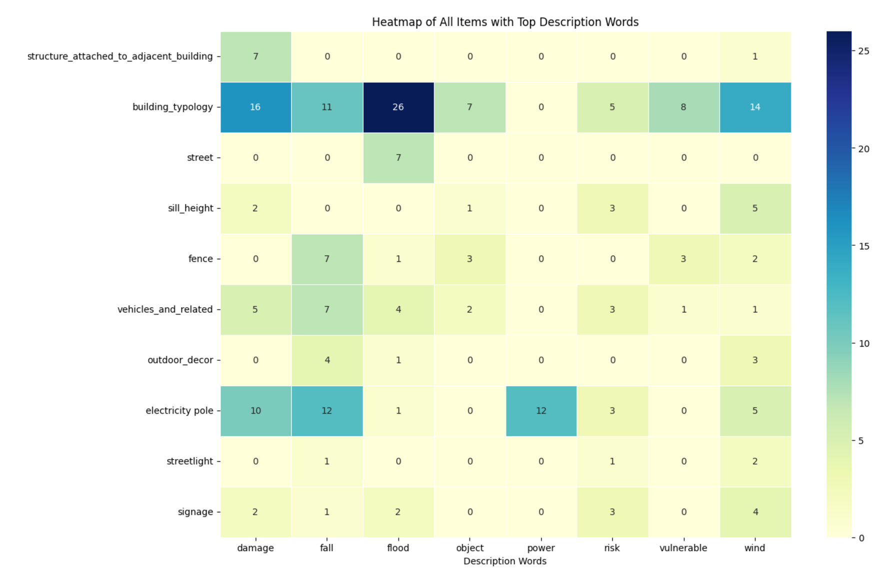

Figure 7 Heatmap of Most Frequent Items and Description Words

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