Disaster Resilience in OpenStreetMaps

DS 6015

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OpenStreetMap Risk-Targeted Mapping
Project Charter

Project Description:

Support OSM US's disaster relief efforts by providing insight into undermapped areas likely to be impacted by specific natural disasters.

Scope:

Produce county-level data focused on building footprints in OSM and disaster risk from the FEMA National Risk Index (NRI).

Deliverables:

The deliverable will be a Jupyter notebook capable of leveraging FEMA and OSM data and producing visualizations of undermapped, at-risk localities. The derived data used to produce the visualizations will also be included.

Team Members:

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Business Needs:
Identify areas within the US that are undermapped and are at high risk for natural disasters with the goal of developing a tool to prioritize volunteer mapping efforts.

Overview

Problem Statement

OSM data does not capture all the relevant GIS data critical for disaster response support. Gaps in the data are filled in reactively after a disaster.

Project Goal

Provide an interactive tool capable of informing OSM US's proactive data gathering to prioritize at-risk, undermapped areas.

Overview
Data Sources

OpenStreetMap (OSM)
- XML, semi-structured, geospatial data (GIS)

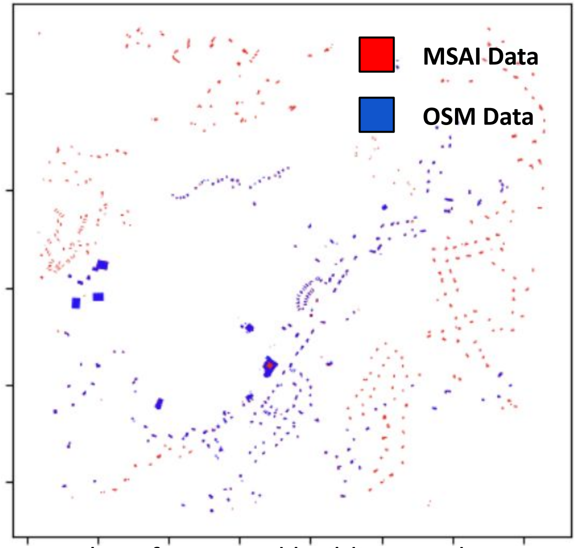
Microsoft Maps Deep Learning Model (MSAI)
- Publicly-available dataset with nearly 130 million computer-generated building footprints

FEMA National Risk Index (NRI)
- Baseline risk assessment tool and interactive dashboard

US Census Boundaries
- Cartographic boundary files

OpenStreetMap USBuildingFootprints FEMA National Risk Index United States Census Bureau

Example of AI-generated building footprints from satellite imagery



Overlay of expected buildings and OSM-mapped buildings

Methods
Derived Undermapped and Priority Statistics

Defining Undermapped

- Focus on buildings and building footprints
- Mapping completion definition:
  - The area covered by structures in OSM vs. in MSAI data (baseline)

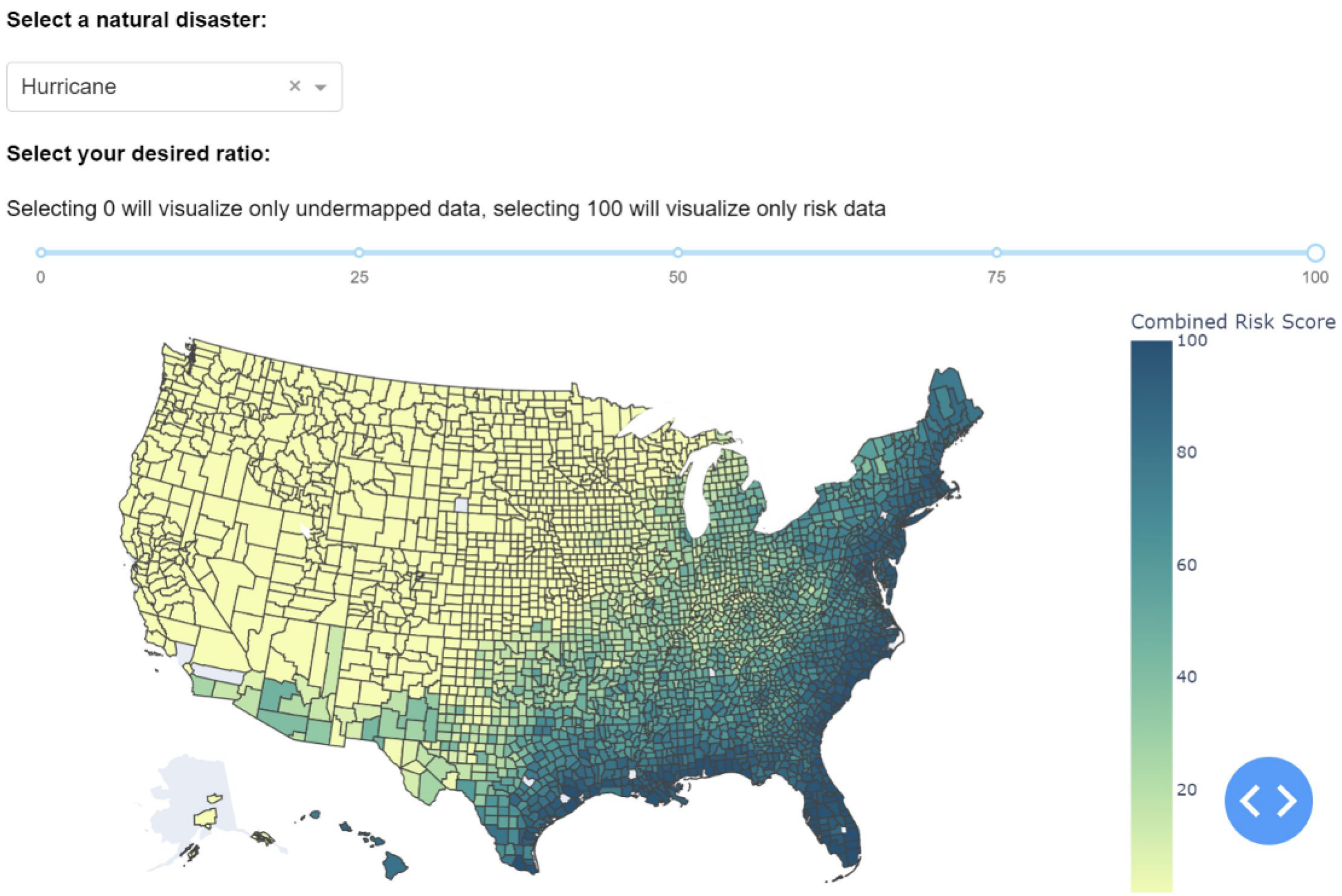
Undermapped Statistic

$$Undermapped\ Statistic\ =\ \left(1-\frac{Area\ of\ OSM\ Building\ Footprints}{Area\ of\ MSAI\ Building\ Footprints}\right)\times\ 100$$

Priority Statistic

$$Priority\ Statistic\ =\ (Risk\ Statistic\ \times Ratio) + (Undermapped\ Statistic \times (1-Ratio)) \times 100$$

Interactive Framework



Interactive Dashboard:

- Created using Dash
- Allows for the dynamic selection:
  - Disaster type of interest
  - Balance between risk and undermapped weighting.

$$(Risk\ Statistic \times Ratio) + (Undermapped\ Statistic \times (1 - Ratio)) \times 100$$

Challenges

GIS Data

- Deconflicting projection differences

Baseline Metric

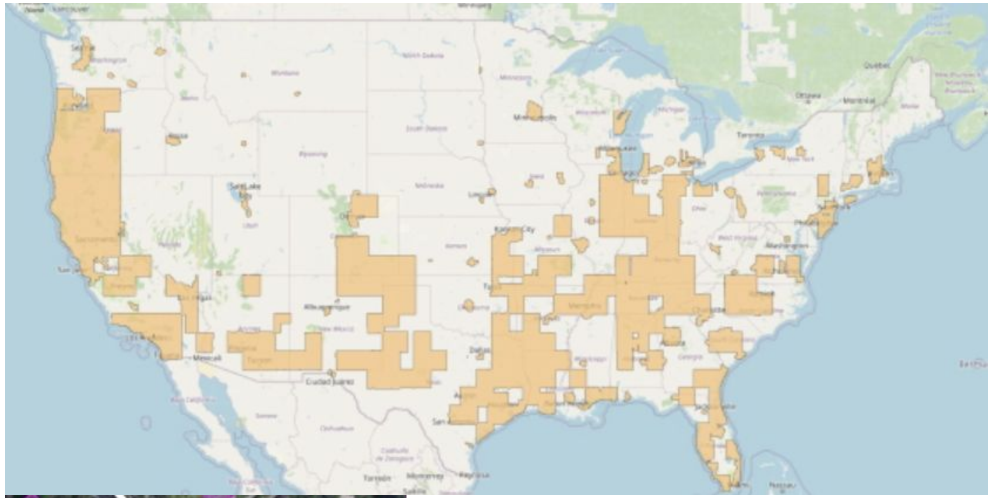
- Defining undermapped & overmapped

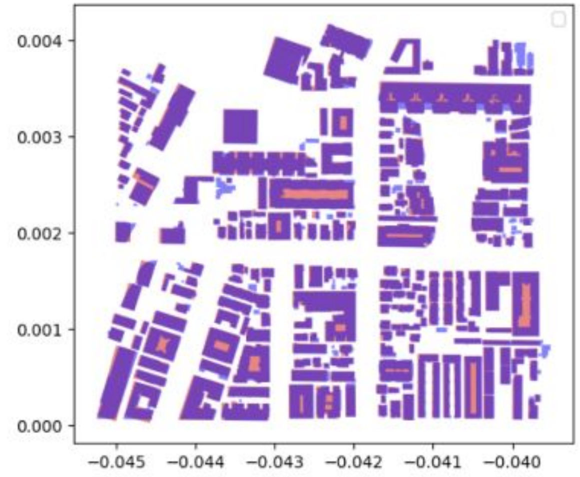
The Approach

- Configuring Third Party APIs
  - Google Places API constraints
  - Lack of comprehensive, low-cost data

MSAI Data

- Overcoming limitations
  - Varying data vintage 2012, 2019-2020
  - Simplified geometric shapes
  - 94.0% building recall





Conclusion

A combination of human-generated building footprints and computer-generated building footprints with a use-case dataset is feasible to generate an intuitive yet effective metric for understanding a region’s combined level of mapping within OSM and level of risk from a given.

References

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Image Sources

- https://www.basecampconnect.com/natural-disasters-and-communication-challenges/
- https://www.cnet.com/home/energy-and-utilities/natural-disaster-guide-how-to-prep-for-wildfires-hurricanes-storms-and-more/
- https://www.voanews.com/a/disaster-challenge-aids-australia-s-response-to-natural-hazards/6789575.html
- https://www.theactuary.com/2021/01/13/insured-losses-natural-disasters-rise-2020
- https://svs.gsfc.nasa.gov/2396

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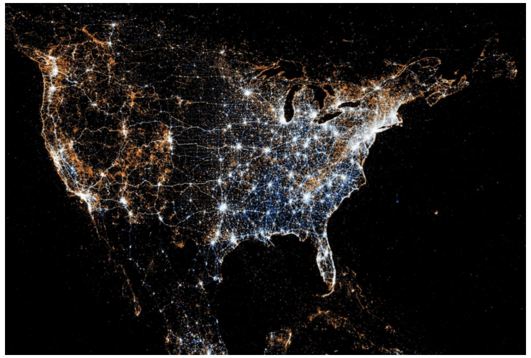
Backup Slides

Future Research

- Address the limitations to greatly improve the accuracy and reduce dependence on external datasets with unclear data vintage
  - Use updated imagery
- Redefine the undermapped statistic using different baseline data
  - i.e. social media activity, nighttime light activity, USPS address data, etc.



Social Media Activity

Nighttime Light Activity