Visualizing and Assessing Disaster Damage Using 360 and Aerial Imagery

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ABSTRACT

This poster summarizes research and development conducted by the Pacific Urban Resilience Lab and the National Disaster Preparedness Training Center (ndptc.hawaii.edu) on the visualization and assessment of damage from wildfires, storms, and other hazards. In addition to comparing different equipment, software, and platforms, the integration of 360 imagery with drone, aerial, and satellite imagery for the purposes of situational awareness, damage assessment, response and recovery functions are described and evaluated. Several examples from recent disasters are included as well as a discussion of field capture, data management, and working with communities. The poster focuses on the intersecting requirements and perspectives of researchers, emergency managers, responders, recovery support professionals, and impacted communities. Issues regarding sensitive, confidential, and proprietary data and the use and sharing of information on disaster impacts are discussed. In addition to technologists, the poster intends to inform hazards and social science researchers, planners working on recovery and those interested in mitigation, and adaptation of environments and communities damaged by diverse hazards and threats.

DATA

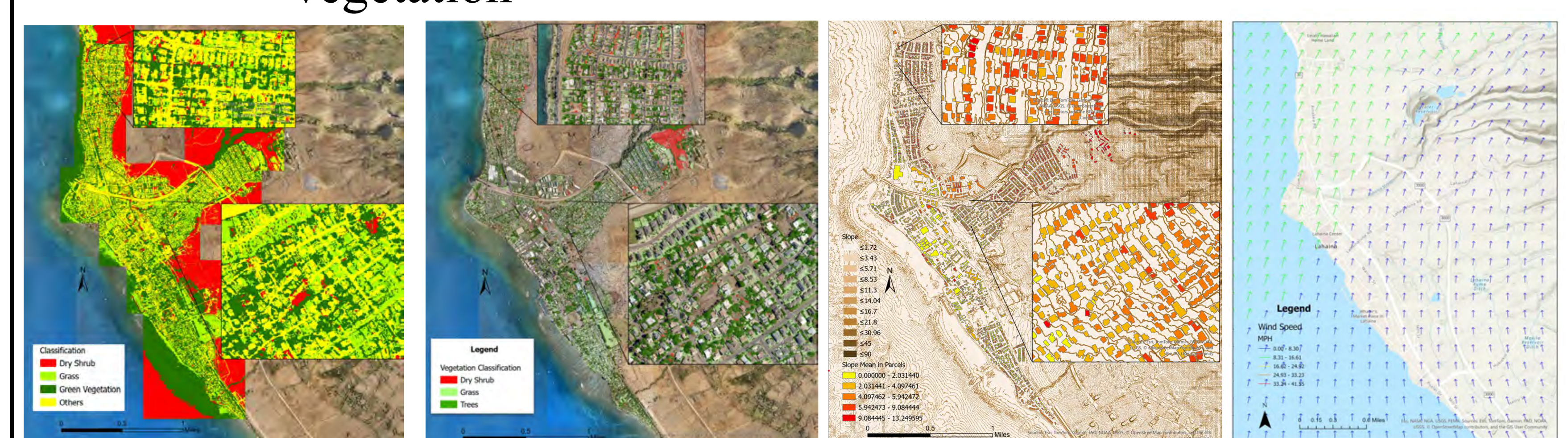
Panoramic Imagery—Post-disaster capture/Google Street View comparison

Satellite Imagery/Aerial Imagery/ Drone Imagery

Before | After

Data Extraction and Classification

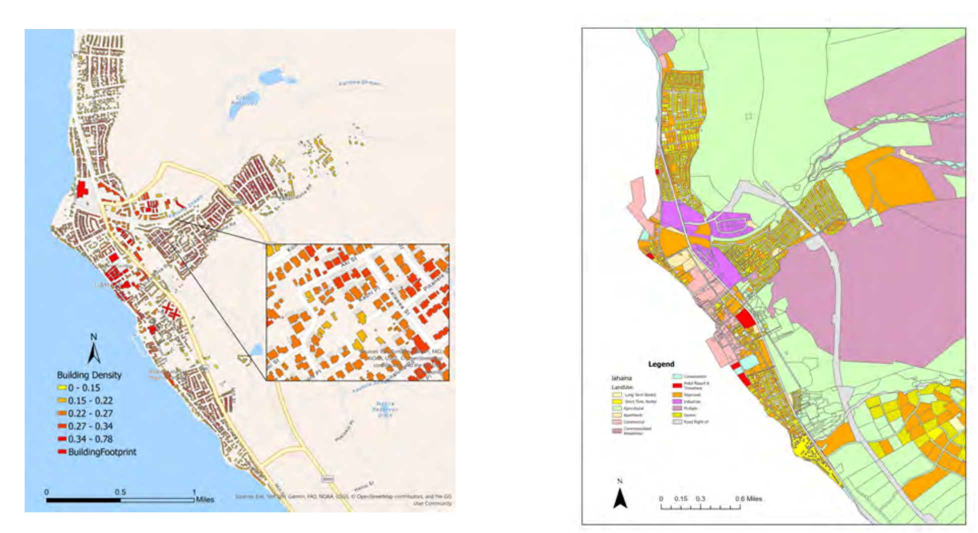
Vegetation | Slope | Wind



Building Characteristics/Parcel Information

Construction Type | Exterior Wall Material | Roof Material | Year Built

Building Density | Land Use



METHODOLOGY

Dasymetric Modeling/Data Processing Framework

Parcel-Level Wildfire Risk Index:

$$R_p = \sum_{i=1}^{n} w_i \cdot V_{ip} \qquad V_{ip} = \frac{\sum_j A_{pj} \cdot v_{ij}}{\sum_j A_{pj}}$$

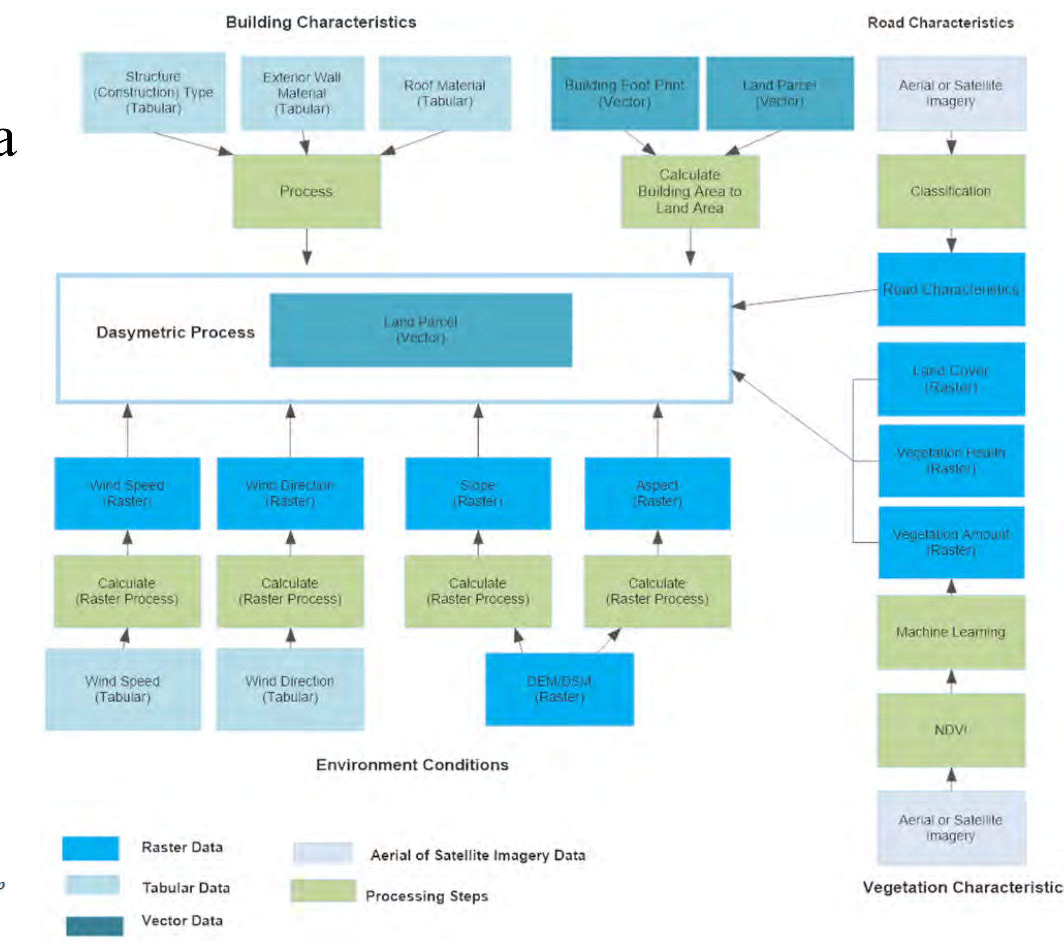
R_p is the wildfire risk score for parcel *p*

V_{ip} is the value of the ancillary variable *i* disaggregated to parcel *p*

w_i is the weight or importance of variable i in contributing to fire risk (this can be gathered through expert knowledge, literature review, or through training and machine learning technology)

n is the number of variables considered (e.g., vegetation type, wind speed, slope, …)

$$R_p = w_1 \cdot \bar{v}_{veg,p} + w_2 \cdot \bar{v}_{wind,p} + w_3 \cdot mat_p + w_4 \cdot slope_p + w_5 \cdot ignition_p$$



Integration with Graph Theoretic Fire Spread Modeling

The graph for the fire spread can be defined as $G = (V, E)$

Where: Each node $p \in V$: which is a parcel. Each edge $(p,q) \in E$: an adjacency or proximity link between parcels *p* and *q*. Each edge has a spread probability P_{pq}: which is the probability that the fire spreads from *p* to *q*

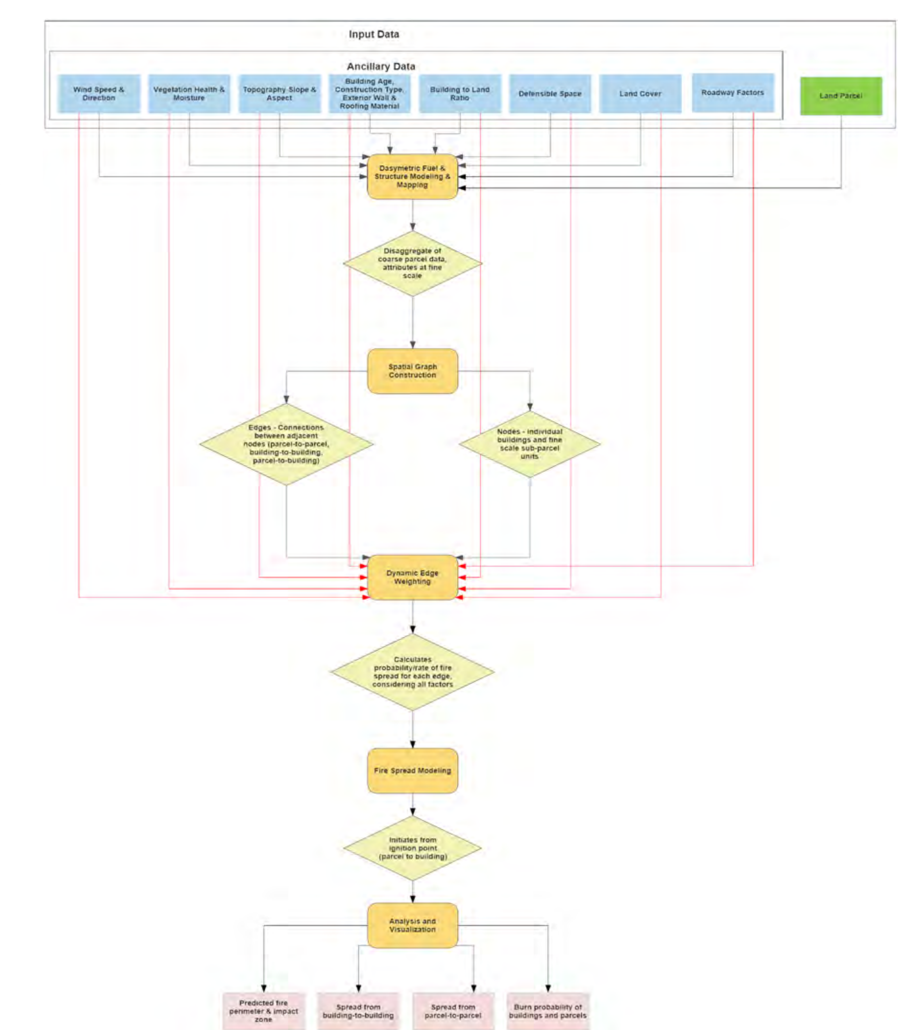
$$P_{pq} = \sigma(\alpha R_p + \beta R_q + \gamma W_{pq} - \delta D_{pq} + \epsilon F_{pq})$$

R_p, R_q : are the risk scores from the dasymetric step

W_{pq} : is the wind alignment between ppp and qqq (positive if wind favors spread)

D_{pq} : is the edge length or separation distance

F_{pq} : is the fuel continuity factor (e.g., percent vegetation continuity)



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