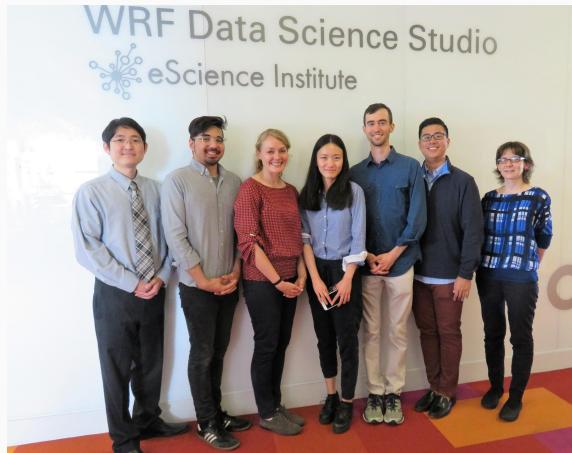


# From Open Satellite Data To Emergency Response

Valentina Staneva, eScience Institute, UW



## Building Damage Detection in Post-Hurricane Images

(summer Data Science for Social Good project 2018)

Sean Chen, New York University

Andrew Escay, University of the Philippines

Christopher Haberland, University of Washington

Tessa Schneider, Hertie School of Governance

An Yan, University of Washington

Youngjun Choe, University of Washington



# The Problem



<http://blog.digitalglobe.com/news/team-rubicon-uses-digitalglobe-technology-to-aid-houston-residents-after-hurricane-harvey/>



Flooding on the outskirts of Houston, Texas, August 31, 2017 (Photo credit: South Carolina National Guard)  
<https://www.planet.com/insights/anatomy-of-a-catastrophe/>



Satellite: High-Level



Aerial: Intermediate-Level



Traditional: Ground-Level

# Digital Globe Open Data



Active Event

All Events

## All Events

California Wildfires | 11.01.18

[More info >](#)

Super Typhoon Yutu | 10.24.18

[More info >](#)

Hurricane Willa | 10.23.18

[More info >](#)

Hurricane Michael | 10.10.18

[More info >](#)

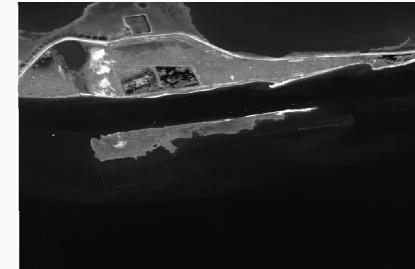
## Hurricane Harvey

09.03.17

1020010065114800 ▾

### Preview

File Size	File Name	All Links
732 MB	3002123.tif	
250 MB	3002123.tif.ovr	
732 MB	3002132.tif	
250 MB	3002132.tif.ovr	
732 MB	3002133.tif	
250 MB	3002133.tif.ovr	
732 MB	3002301.tif	
250 MB	3002301.tif.ovr	
732 MB	3002303.tif	
250 MB	3002303.tif.ovr	
732 MB	3002310.tif	
250 MB	3002310.tif.ovr	
732 MB	3002311.tif	
250 MB	3002311.tif.ovr	
732 MB	3002312.tif	
250 MB	3002312.tif.ovr	
732 MB	3002313.tif	



- 3 TB of image data
- Missing data, missing bands
- Clouds
- Crowdsourced manual annotations in JSON (Tomnod)

# NOAA Public Data

 NOAA  
National Geodetic Survey

## Emergency Response Imagery

National Geodetic Survey

NGS Home | About NGS | Data & Imagery | Tools | Surveys | Science & Education | Search

The imagery posted on this site was acquired by the [NOAA Remote Sensing Division](#) to support NOAA homeland security and emergency response requirements. In addition, it will be used for ongoing research efforts for testing and developing standards for airborne digital imagery.

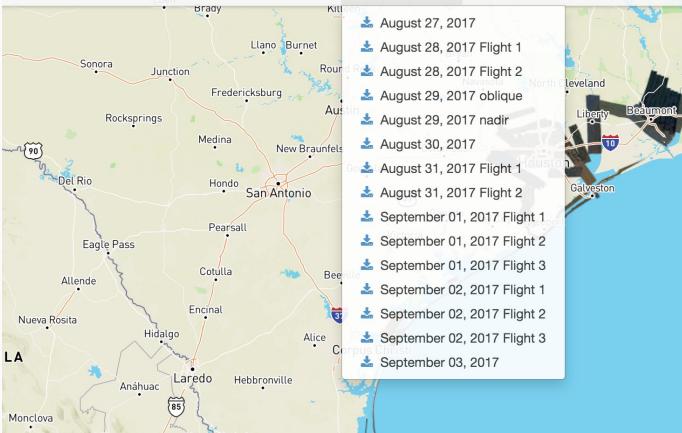
Tips for navigating the Emergency Response Imagery Viewer.

**Emergency Response Imagery:**

- Hurricane Barry (2019)
- Hurricane Michael (2018)
- Hurricane Florence (2018)
- Tropical Storm Gordon (2018)
- Hurricane Nate (2017)
- Hurricane Maria (2017)
- Hurricane Irma (2017)
- Hurricane Harvey (2017)
- Hurricane Matthew (2016)
- Louisiana Flooding (2016)
- Midwest U.S. Flooding (2015)
- Illinois Tornadoes (2015)
- Hurricane Arthur (2014)
- Hurricane Sandy (2012)
- Hurricane Isaac (2012)
- Hurricane Irene (2011)
- Joplin, MO Tornado (2011)
- Tuscaloosa, AL Tornado (2011)
- North Dakota Flooding (2011)

## Hurricane HARVEY Imagery

About | Download | Contact



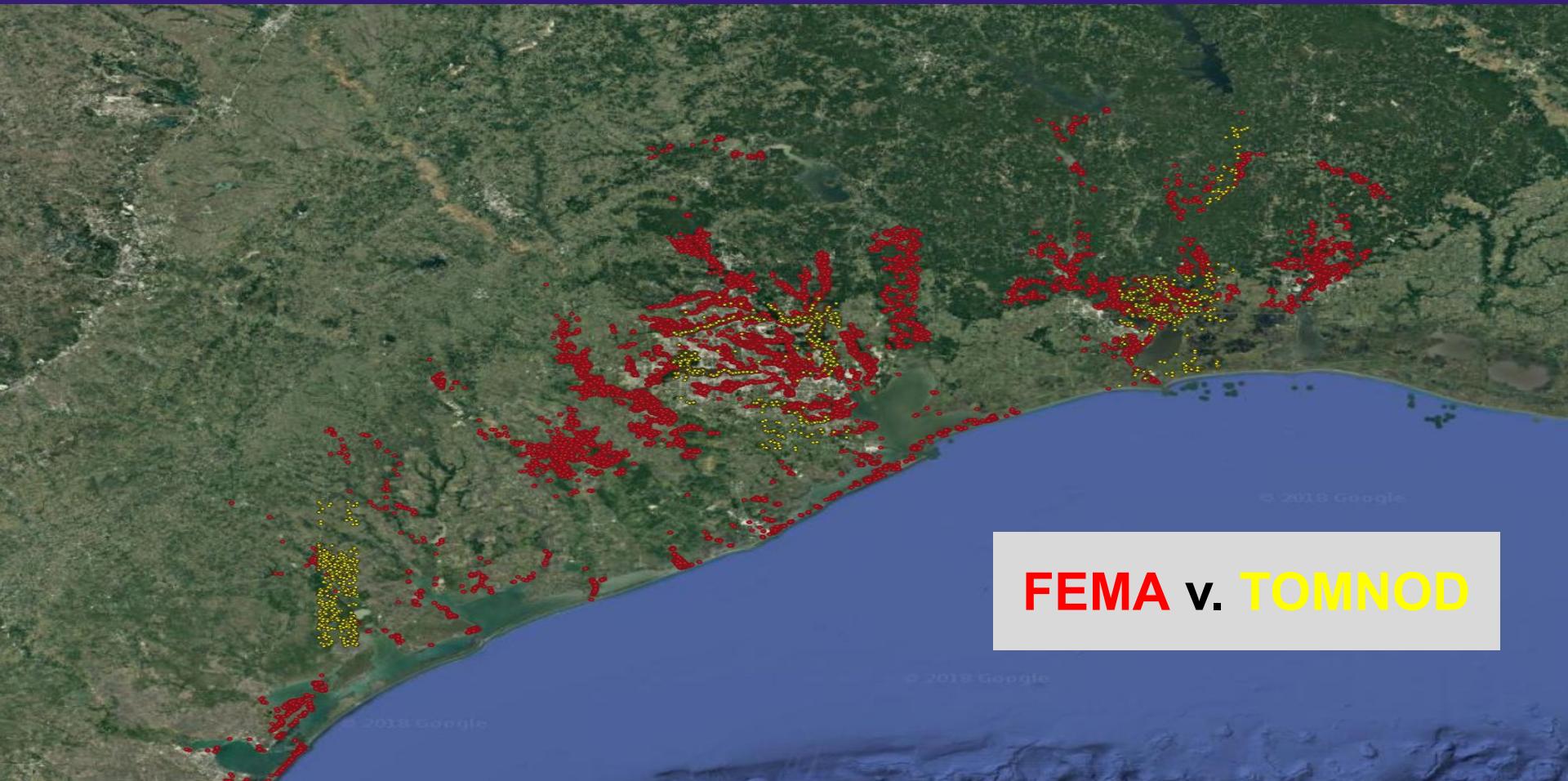
A map of the southern United States, focusing on Texas and parts of Louisiana, Oklahoma, and New Mexico. Major cities labeled include Brady, Llano, Burnet, Round Rock, Fredericksburg, Killeen, Austin, San Antonio, Pearsall, Eagle Pass, Cotulla, Alice, Laredo, and Hebbronville. State boundaries for Texas, New Mexico, and Oklahoma are shown. A legend indicates flight paths: orange lines for nadir flights, blue lines for oblique flights, and green lines for flight 1 and flight 2. A callout box on the right lists the dates of the flights:

- August 27, 2017
- August 28, 2017 Flight 1
- August 28, 2017 Flight 2
- August 29, 2017 oblique
- August 29, 2017 nadir
- August 30, 2017
- August 31, 2017 Flight 1
- August 31, 2017 Flight 2
- September 01, 2017 Flight 1
- September 01, 2017 Flight 2
- September 01, 2017 Flight 3
- September 02, 2017 Flight 1
- September 02, 2017 Flight 2
- September 02, 2017 Flight 3
- September 03, 2017



- 400GB of image data
- No clouds

# Damage Annotations

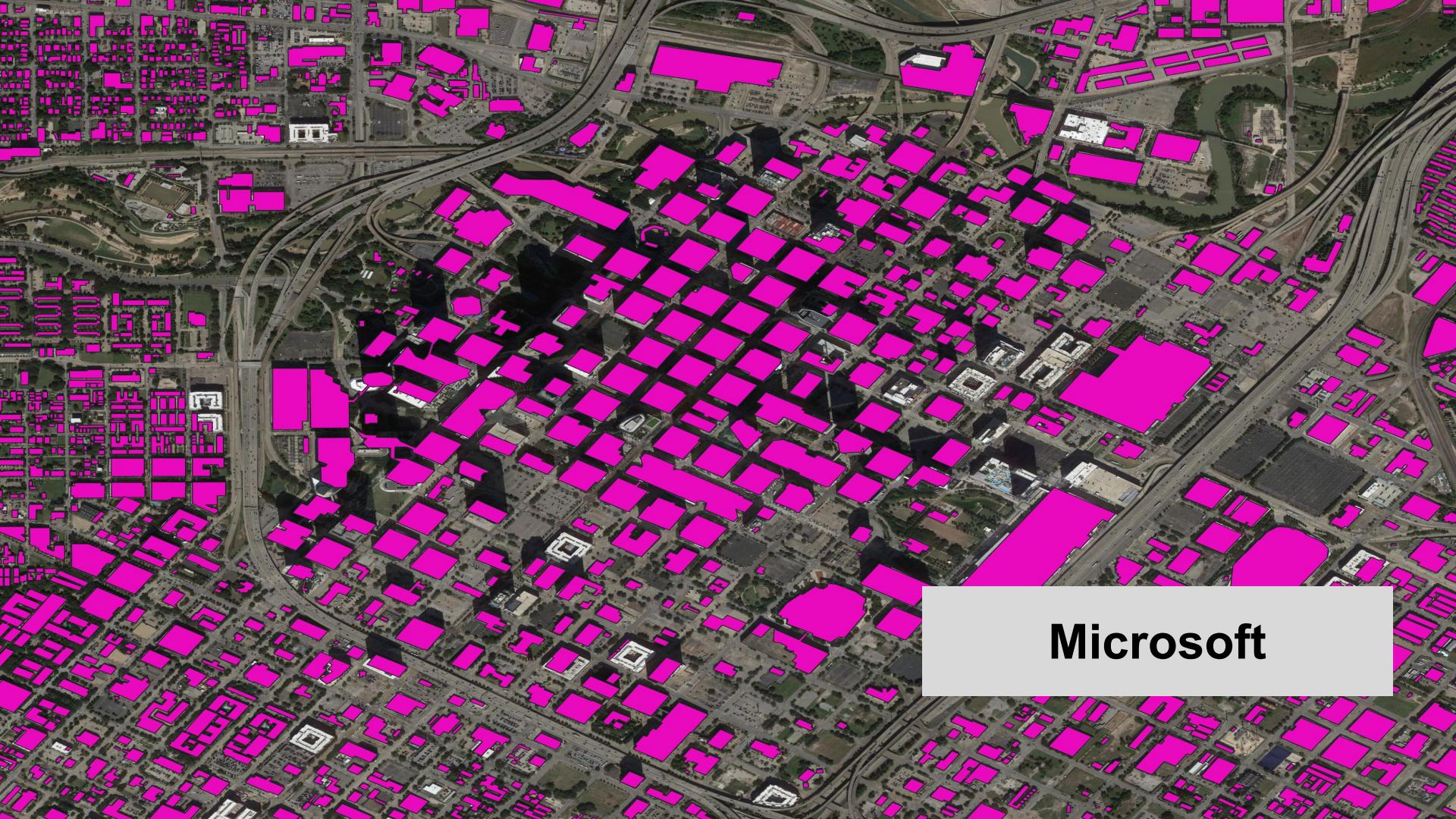


FEMA v. TOMNOD

# Building Footprints



Oak Ridge National Labs



Aerial map showing a large urban area with numerous buildings highlighted in pink. The pink areas are concentrated in several distinct clusters, primarily in the center and upper right of the frame, representing Microsoft's presence in the region. The map includes a complex network of roads, highways, and green spaces.

**Microsoft**

# Object Detection (A Deep Learning Approach)

- Faster R-CNN (Ren et al., 2015)
- Single Shot MultiBox Detector (SSD)  
(Liu et al., 2016)

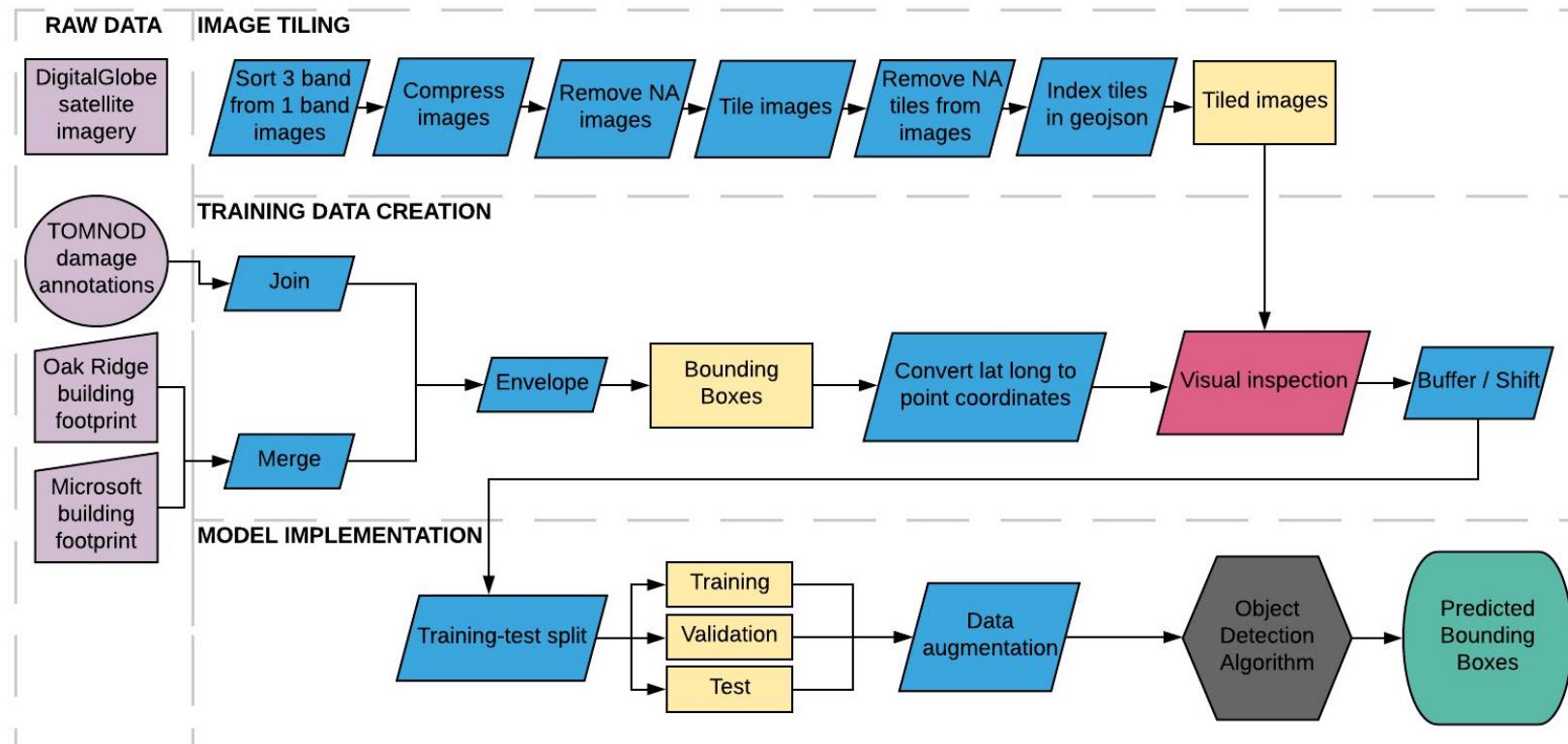


TOMNOD damage predictions with SSD

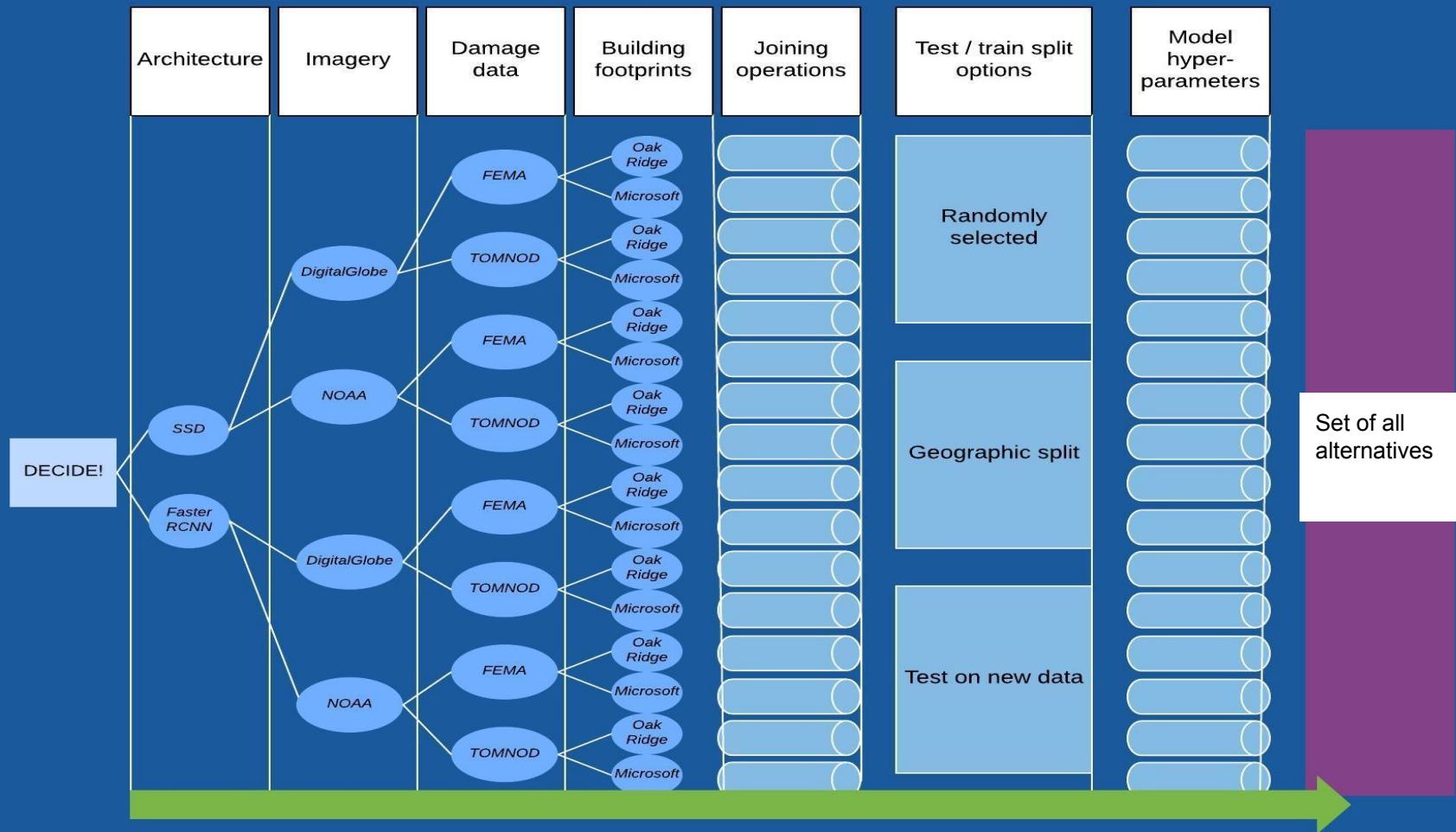


NOAA damage predictions with SSD

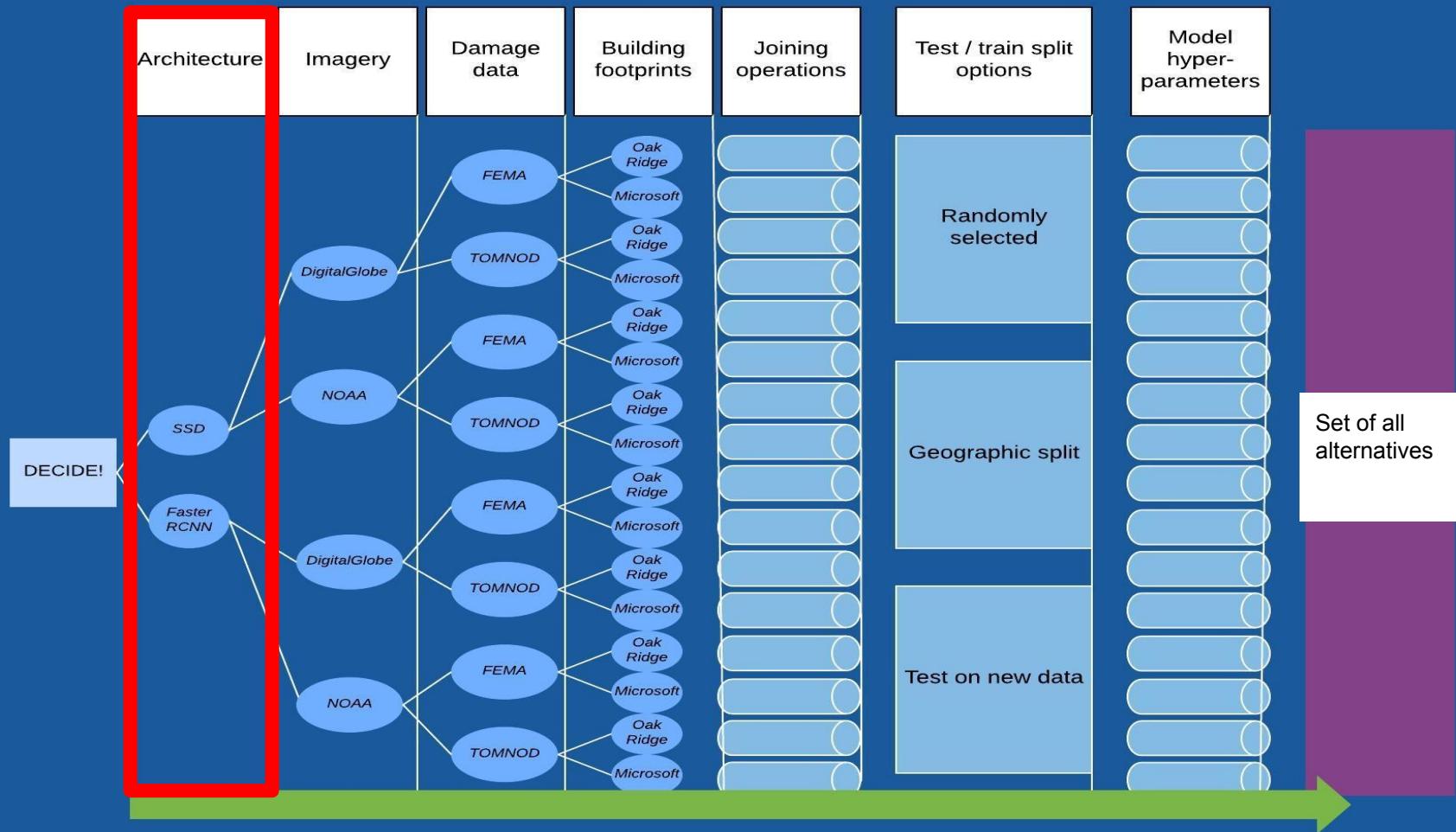
# Data Processing Pipeline



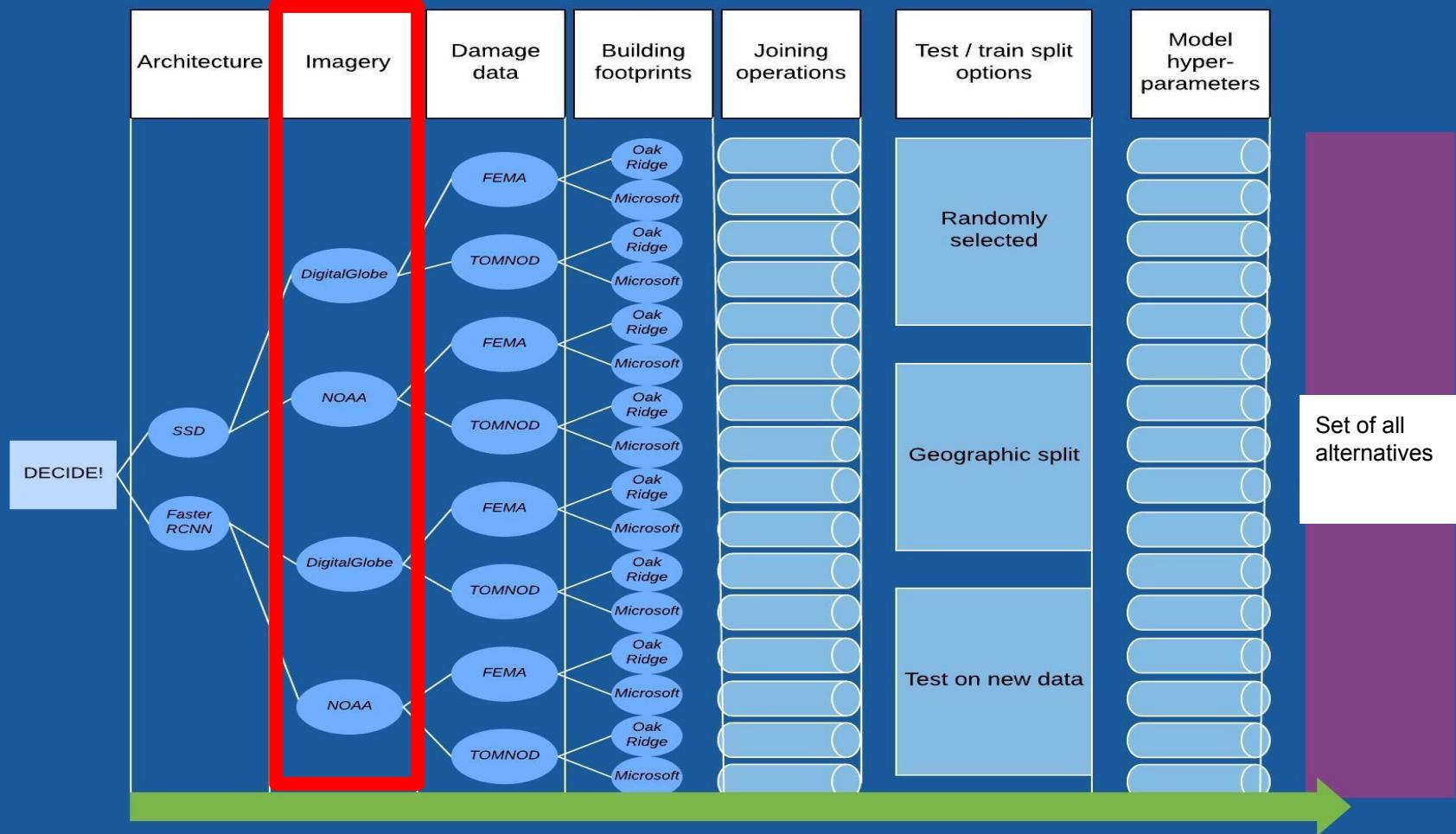
# Alternatives



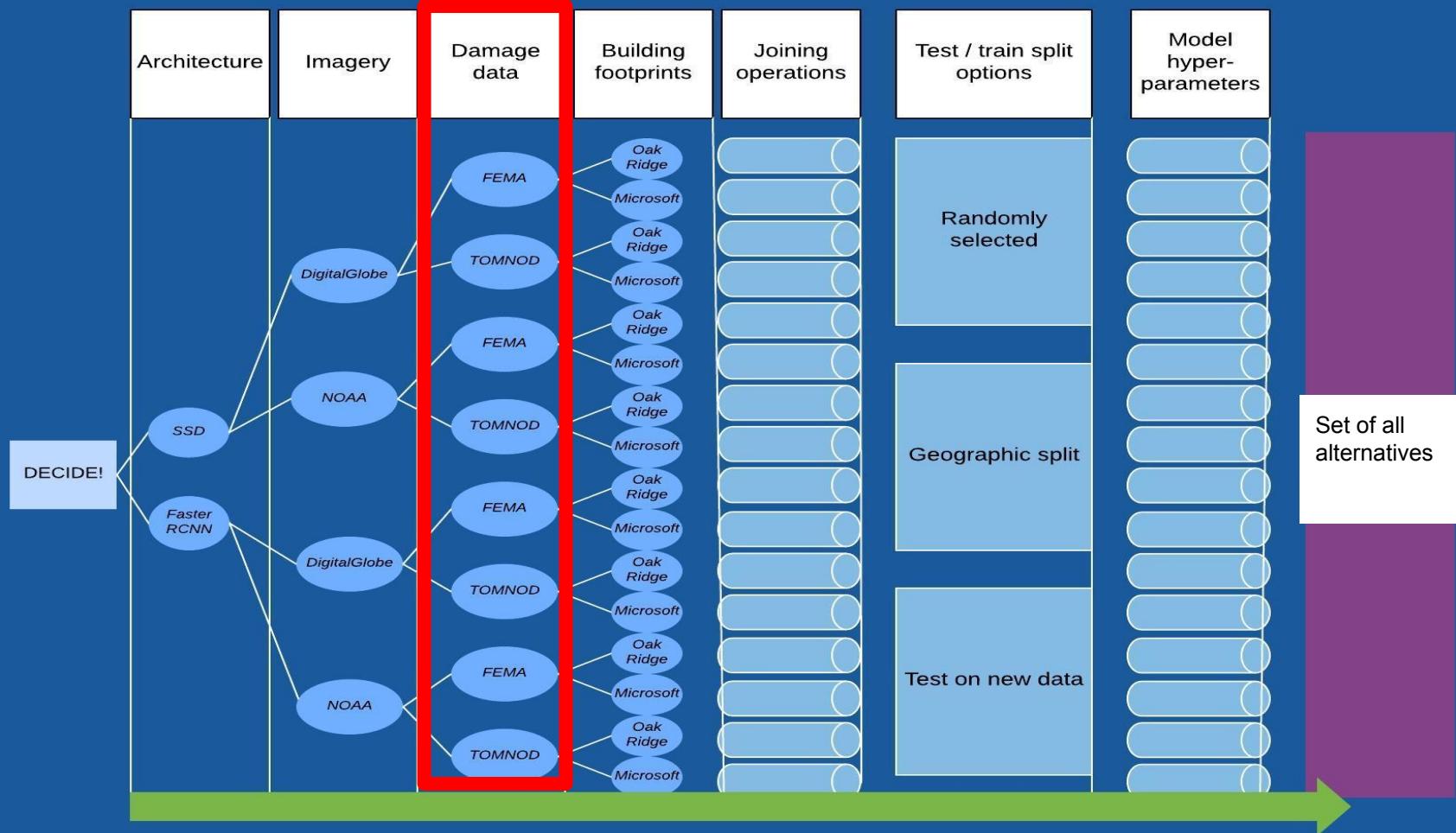
## Alternatives



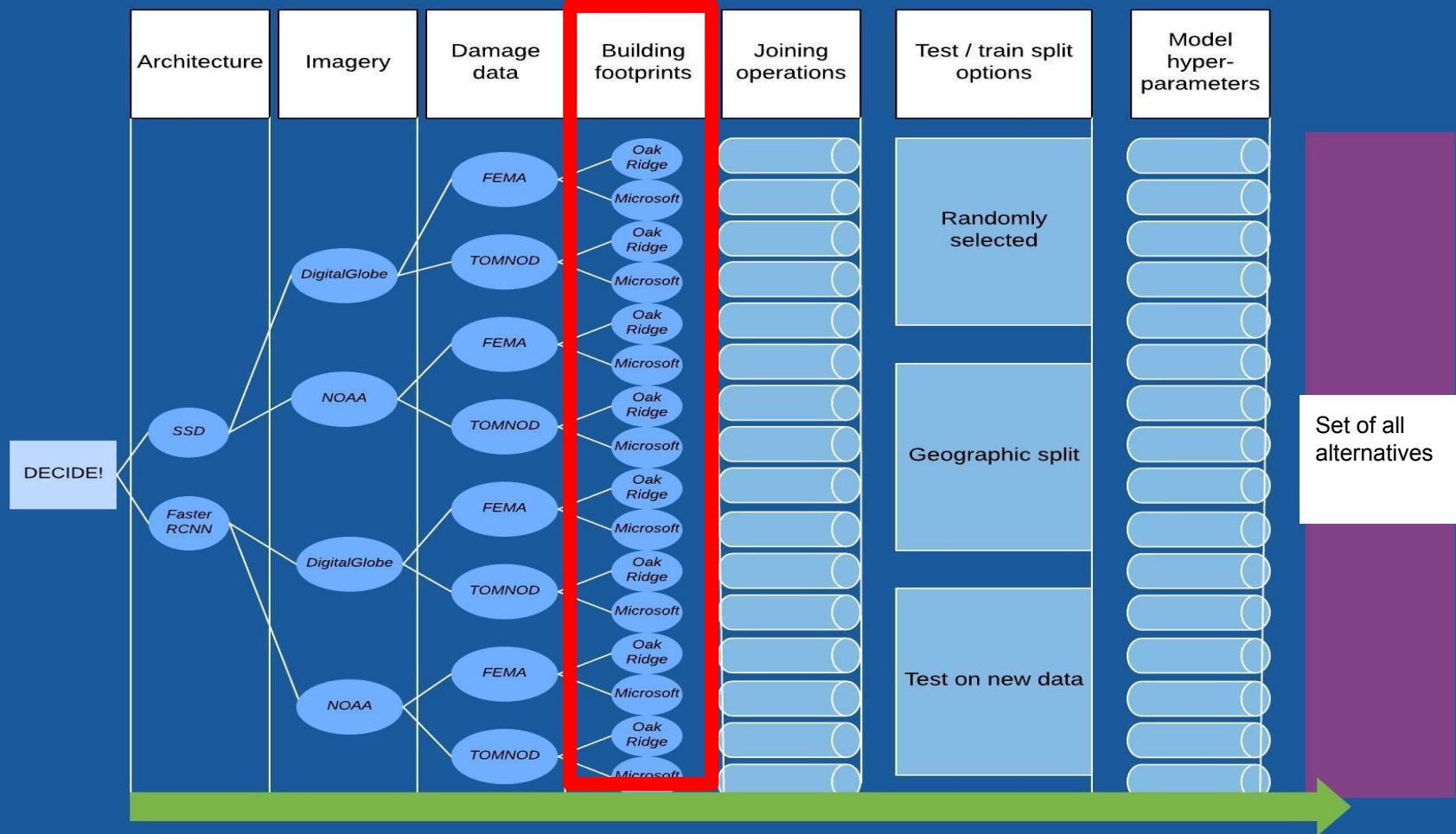
# Alternatives



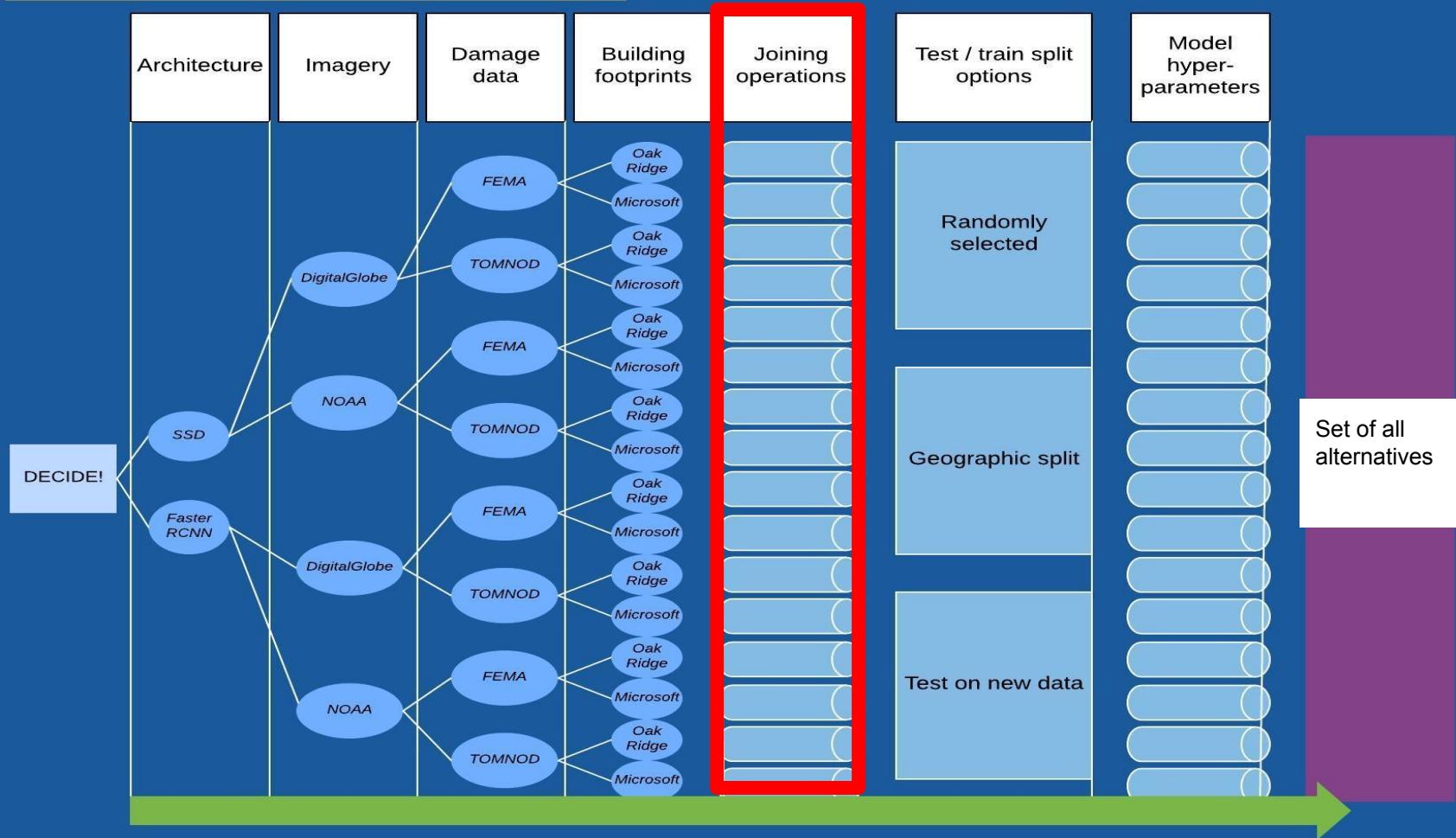
## Alternatives



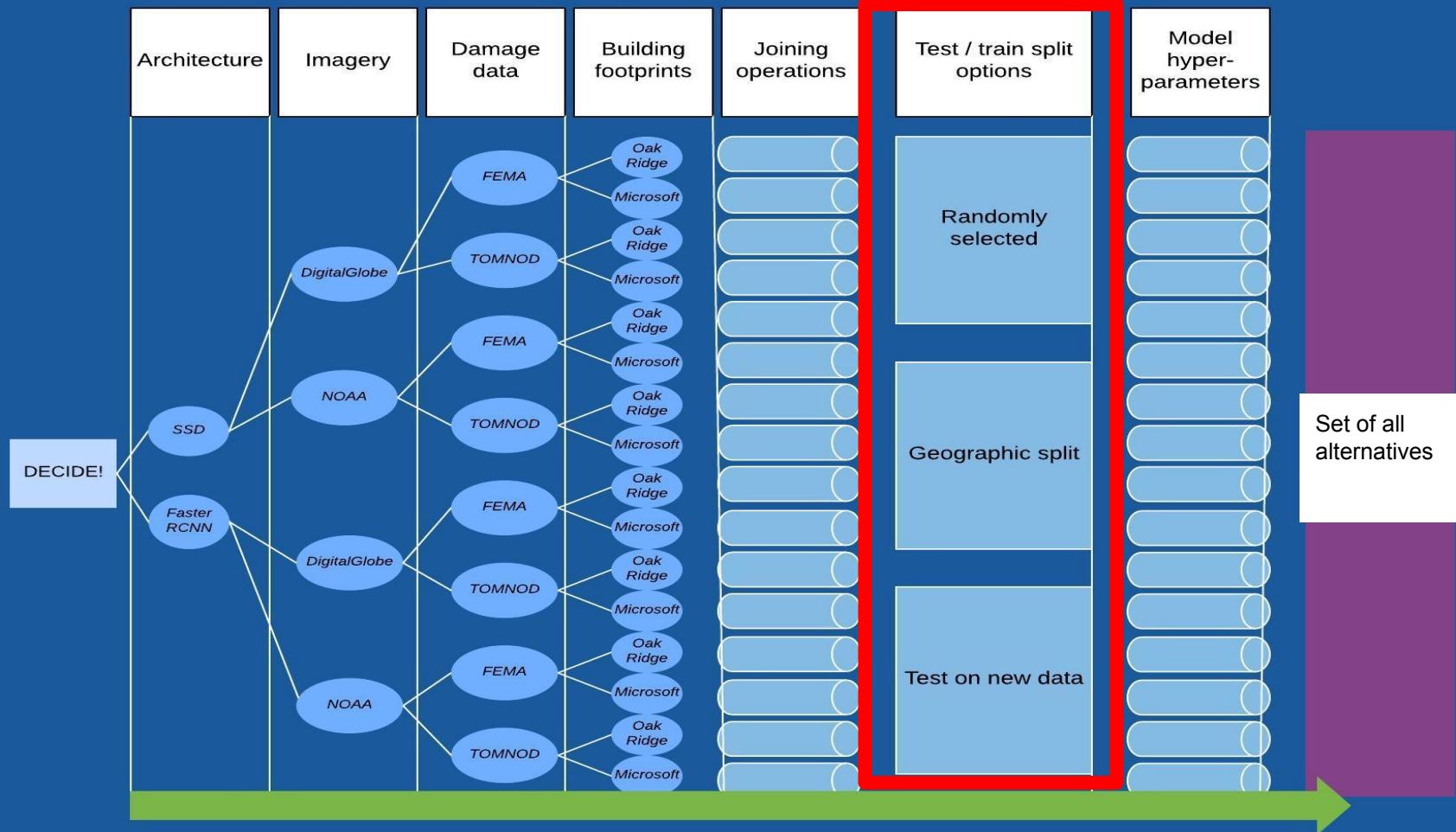
## Alternatives



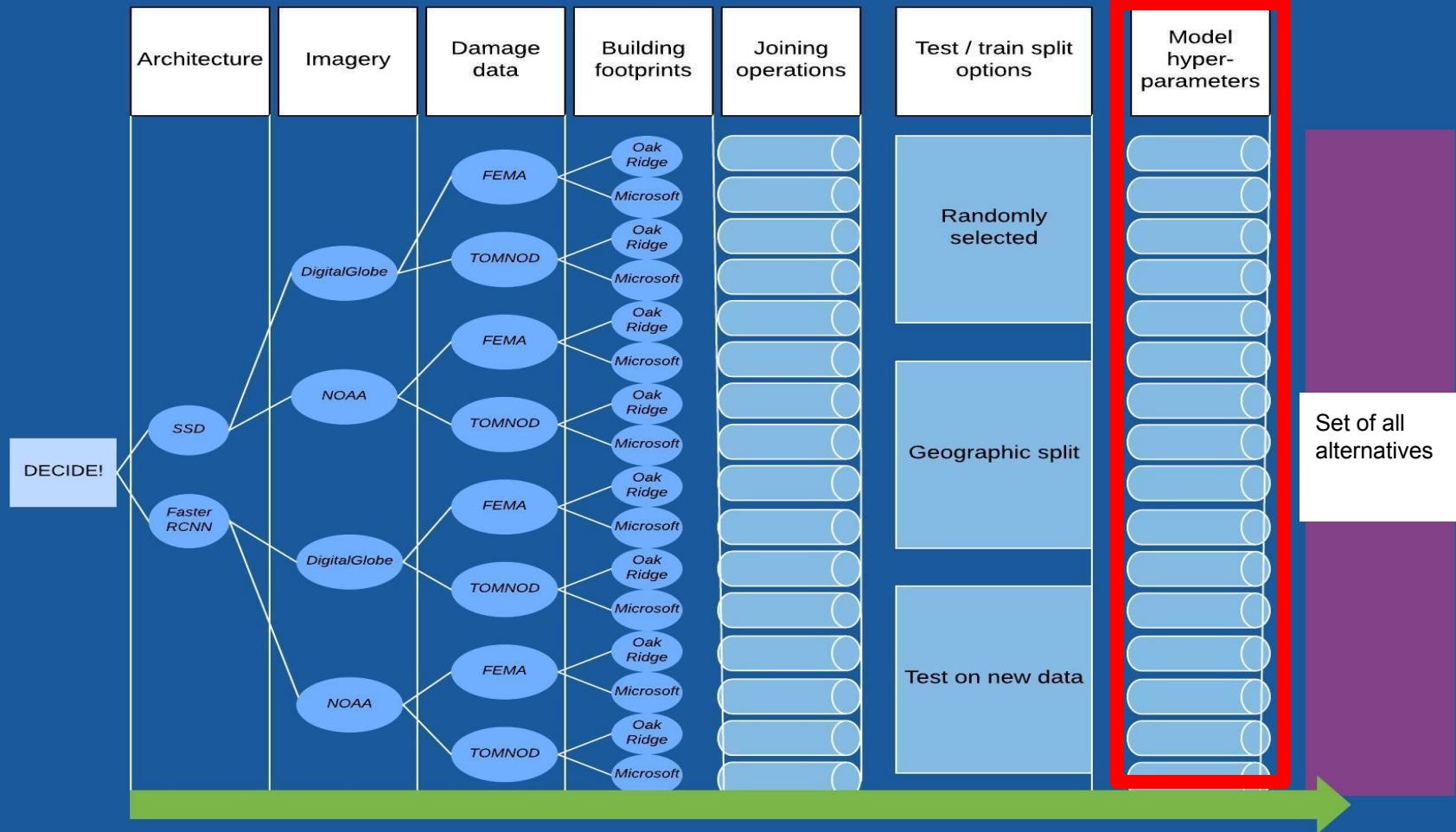
## Alternatives



## Alternatives



# Alternatives



## Results (Average Precision)

Alternative	Flooded/Damaged	Non-damaged	Evaluation Score (mAP)
SSD on Satellite Imagery	<b>0.47</b>	0.62	0.55
SSD on Aerial Imagery	<b>0.32</b>	0.65	0.48
Faster R-CNN Satellite Imagery	<b>0.31</b>	0.61	0.46

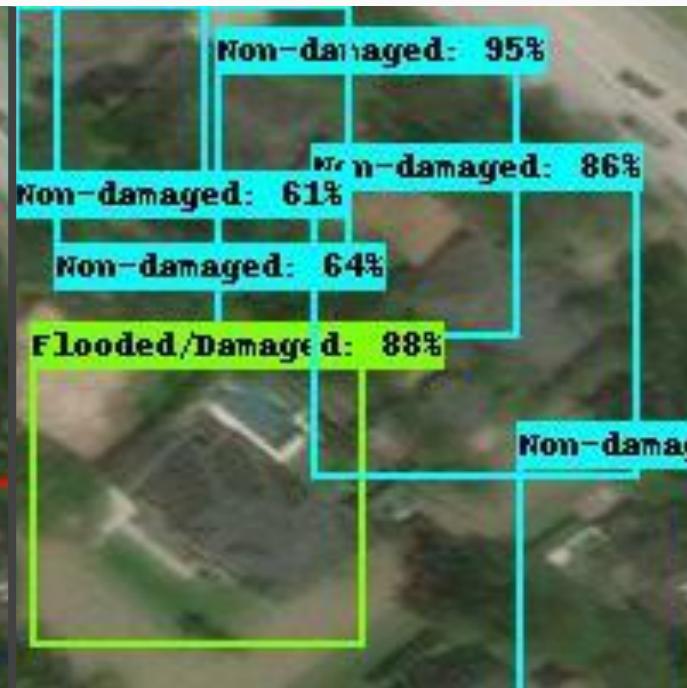
How can we represent the uncertainty to emergency responders?

# Evaluation

Human-labeled data



Predicted output



Identify Flooded Buildings

## Evaluation

Human-labeled data



Predicted output



Identify Damaged Buildings (Blue Tarp)

# Evaluation

Human-labeled data



Predicted output



Identify Damaged Buildings

# Computational Infrastructure

## Hyak University Cluster: Downloading, Compressing and Tiling

### Pros:

- easy to experiment as not charged for every action

### Cons:

- no root access:
  - best to install Python packages through conda
  - Some geospatial libraries conda distributions don't have full functionality
  - no docker support

## Amazon Web Services: Deep Learning

### Pros:

- can use pre-built images: great for deep learning
- can save snapshots of all the work
- can use GPUs without dealing with hardware and drivers
- can use managed databases

### Cons:

- everybody needs to learn about security management
- uploading data is free, but exporting and GPU computations are expensive

## Local QGIS server: Joins and Manual Inspection

### Pros:

- easy to see

### Cons:

- not reproducible

# Sharing Data

## Datasets:

- Compressed and tiled dataset
- Training Dataset
- PostGIS SQL database with geospatial data
- Pickled trained models

## Cloud Backup:

- AWS S3 bucket
- Snapshots for instances + database

## Code on GitHub:

<https://github.com/DDS-Lab/>

## Website:

<https://dds-lab.github.io/disaster-damage-detection/>



Menu ▾



### ⑧ BENCHMARK DATASET FOR AUTOMATIC DAMAGED BUILDING DETECTION FROM POST-HURRICANE REMOTELY SENSED IMAGERY

Citation Author(s): Youngjun Choe (*University of Washington*)  
Valentina Staneva (*University of Washington*)  
Tessa Schneider (*Hertie School of Governance*)  
Andrew Escay (*University of the Philippines*)  
Christopher Haberland (*University of Washington*)  
Sean Chen (*New York University*)

Submitted by: Sean Chen

#### CATEGORIES

- > Remote Sensing
- > Computational Intelligence
- > Environmental

# Satellite Image Analysis

Special Interest Group at UW eScience Institute

## Objectives:

- Build an interdisciplinary community of users of satellite/aerial imagery
- Apply state-of-the-art approaches for large scale data processing and computer vision
- Develop software tools and advance the methodology in the remote sensing field



## Activities:

- Computational Workflow Demos, Tutorials, Hackatons, Networking



Join us [remote\\_sensing@uw.edu!](mailto:remote_sensing@uw.edu)

<https://uwescience.github.io/sat-image-analysis/>

Valentina Staneva: [vms16@uw.edu](mailto:vms16@uw.edu) and Amanda Tan: [amandach@uw.edu](mailto:amandach@uw.edu)

