Disaster Damage Detection

Disaster Damage Detection

UNIVERSITY of WASHINGTON
eScience Institute
DATA SCIENCE FOR SOCIAL GOOD

Sean Chen

Andrew Escay

Chris Haberland

Tessa Schneider

An Yan

DSSG Fellows

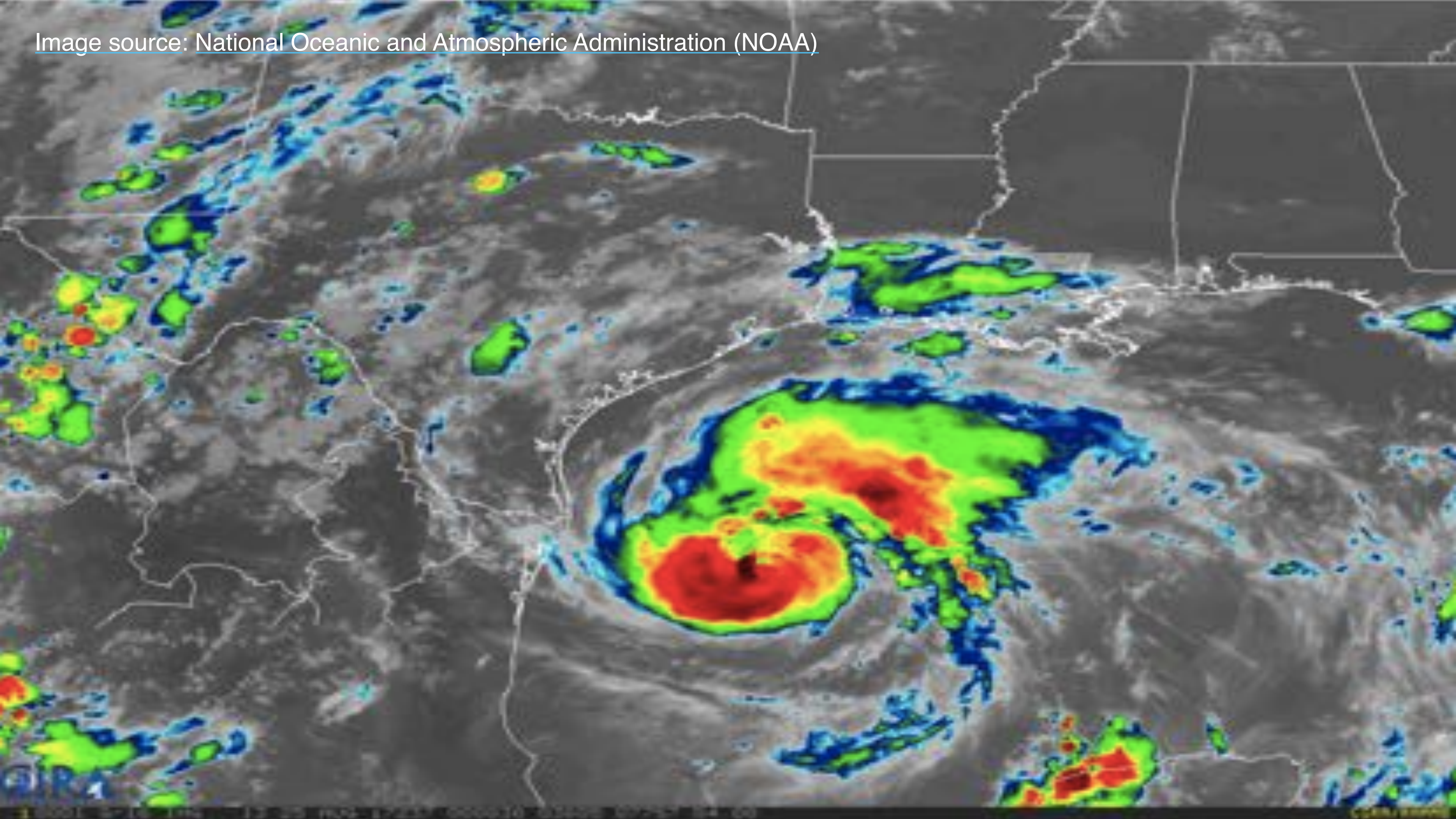
Valentina Staneva

Data Scientist

Youngjun Choe

Project Lead

Image source: National Oceanic and Atmospheric Administration (NOAA)



The Problem

The Problem

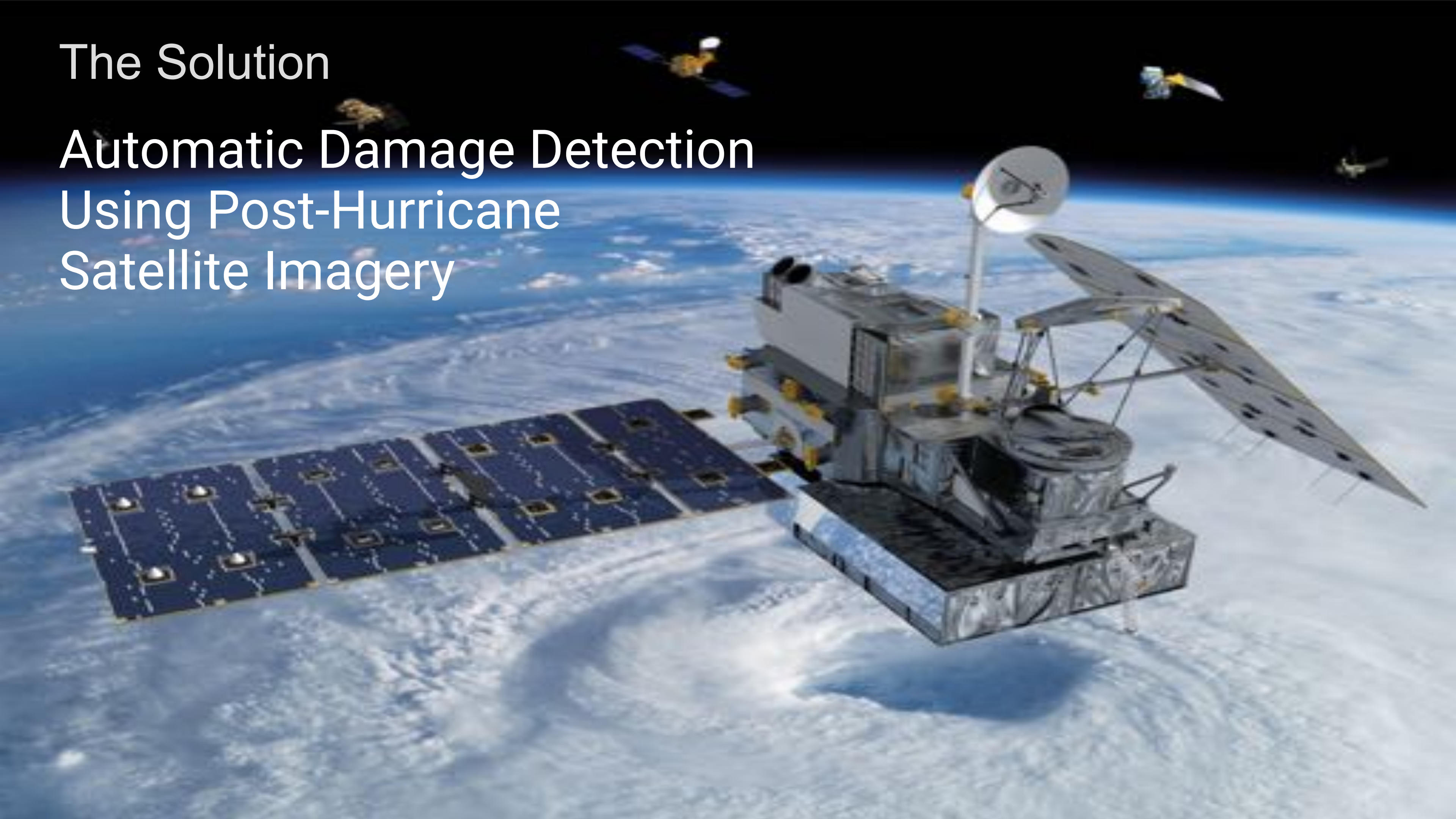


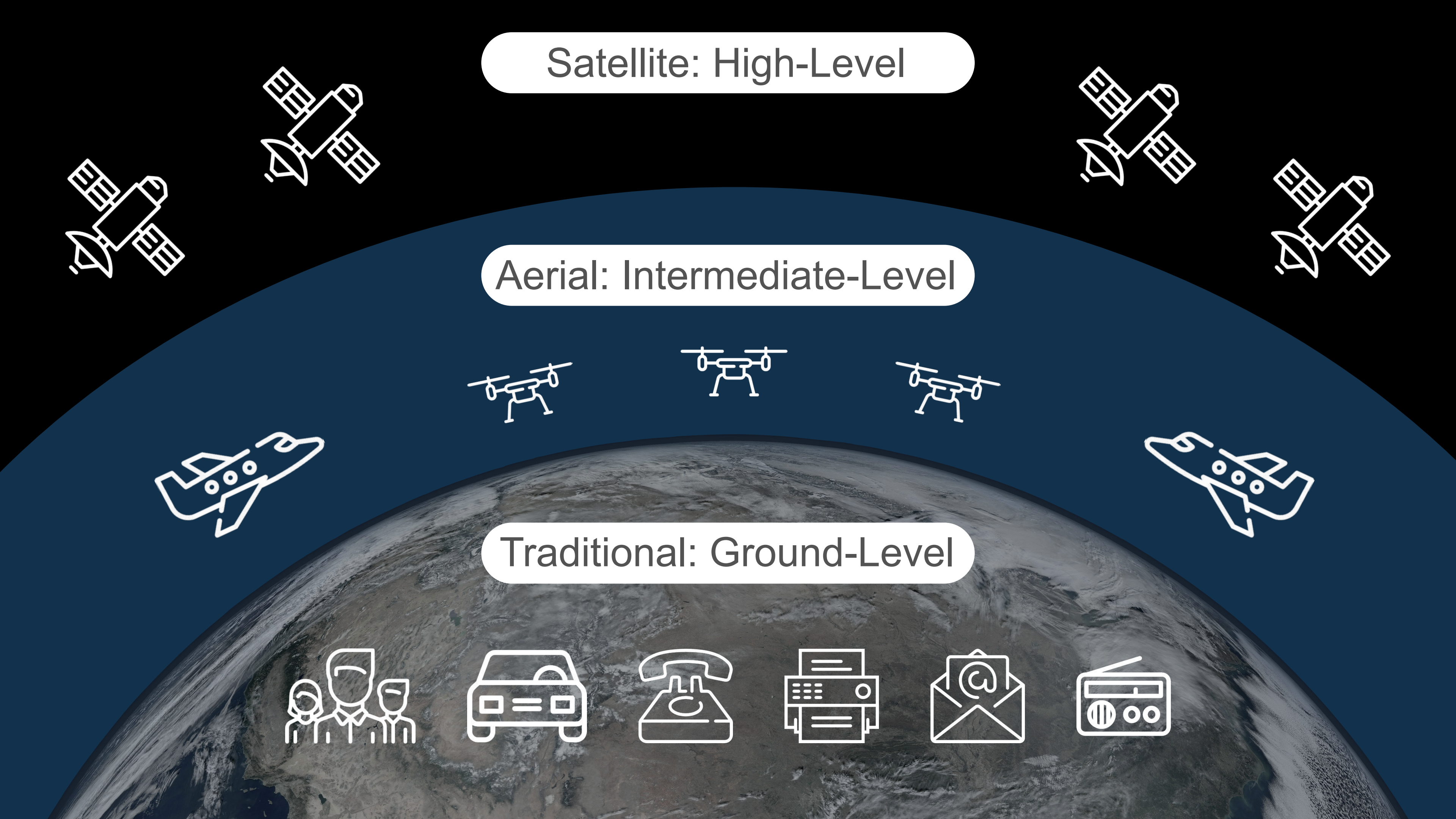




The Solution

Automatic Damage Detection Using Post-Hurricane Satellite Imagery




Satellite: High-Level
Aerial: Intermediate-Level
Traditional: Ground-Level

Creating Training Data

Model Selection

Model Implementation

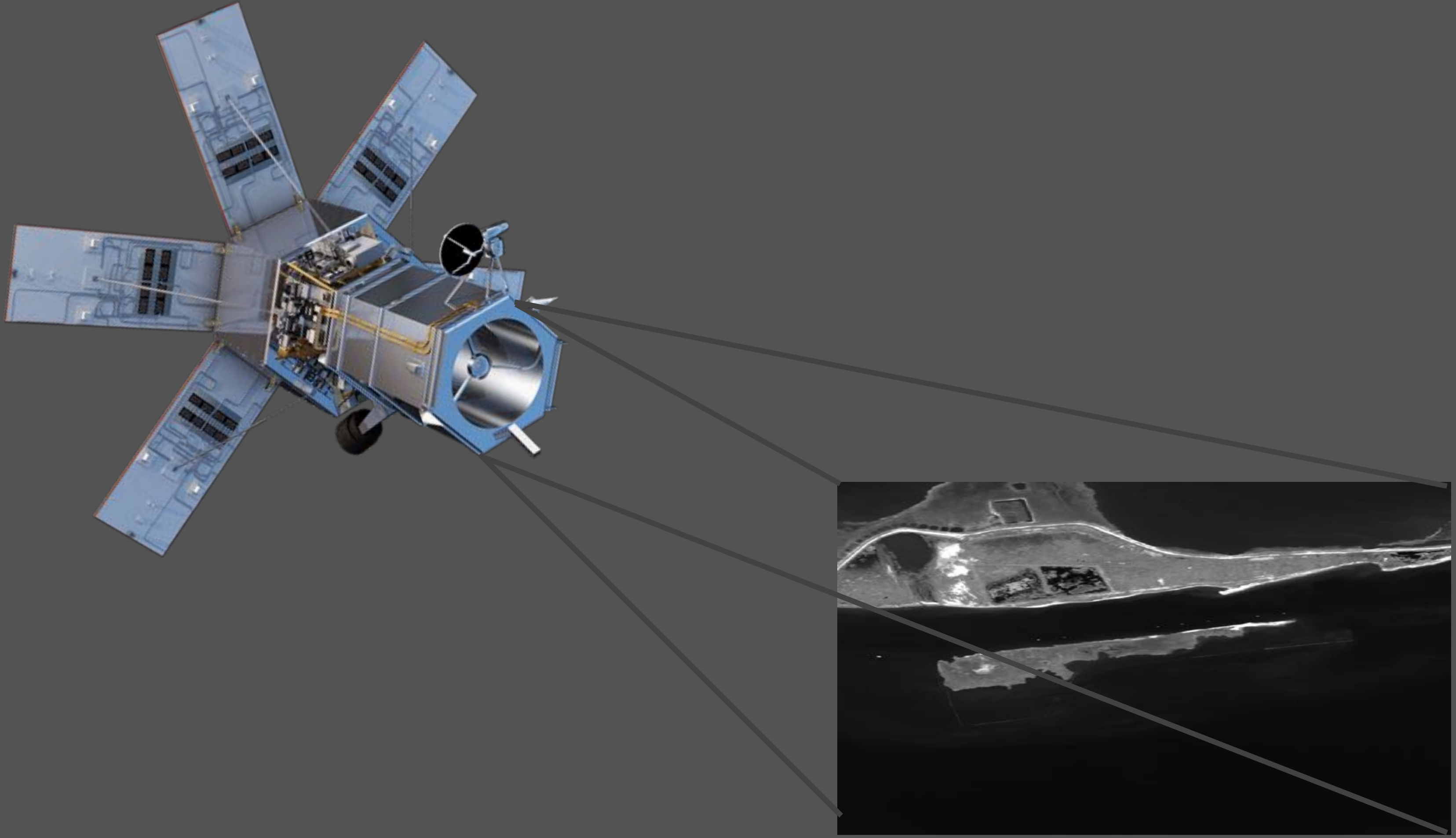
Model Results

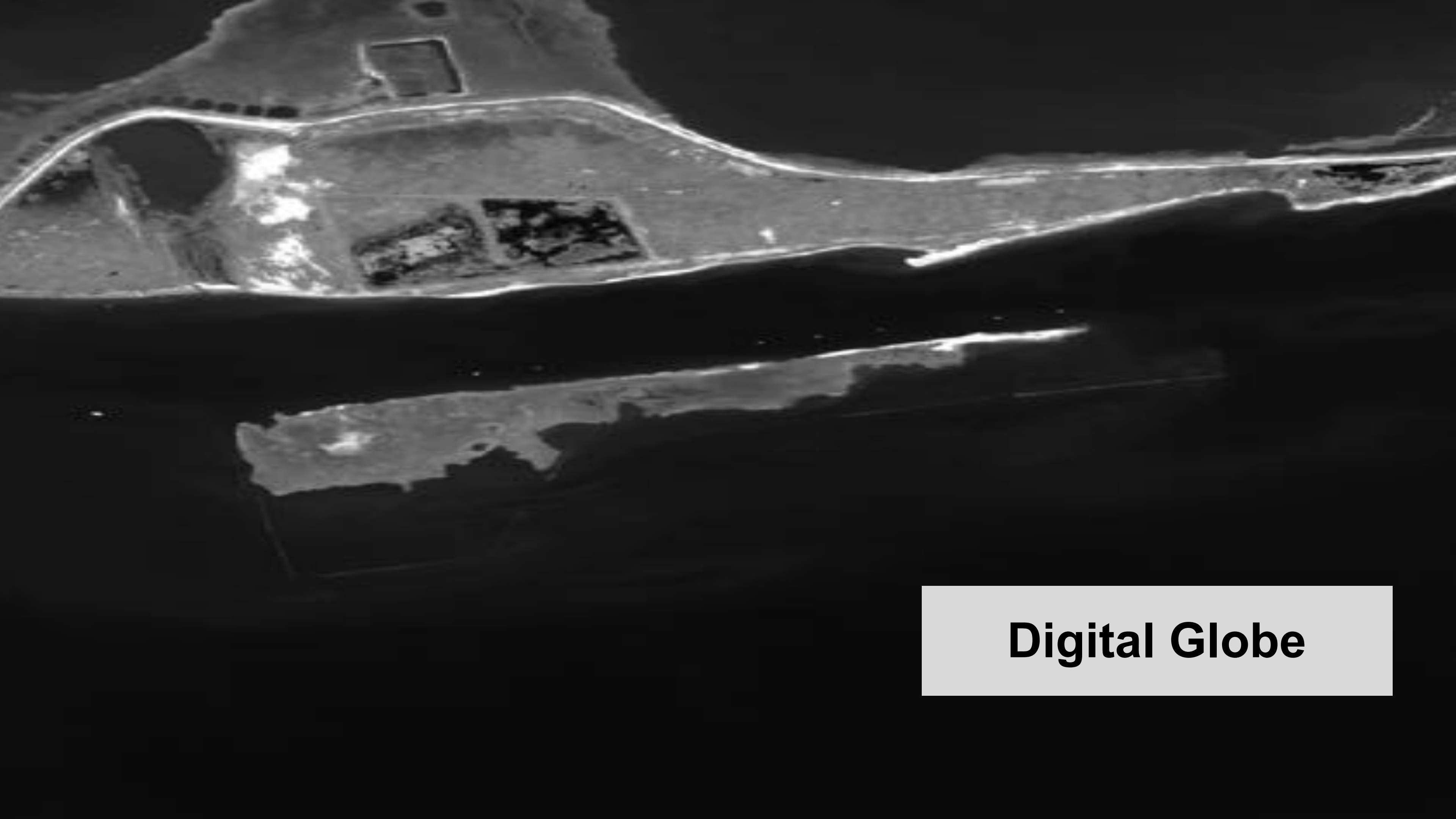
Creating Training Data

Model Selection

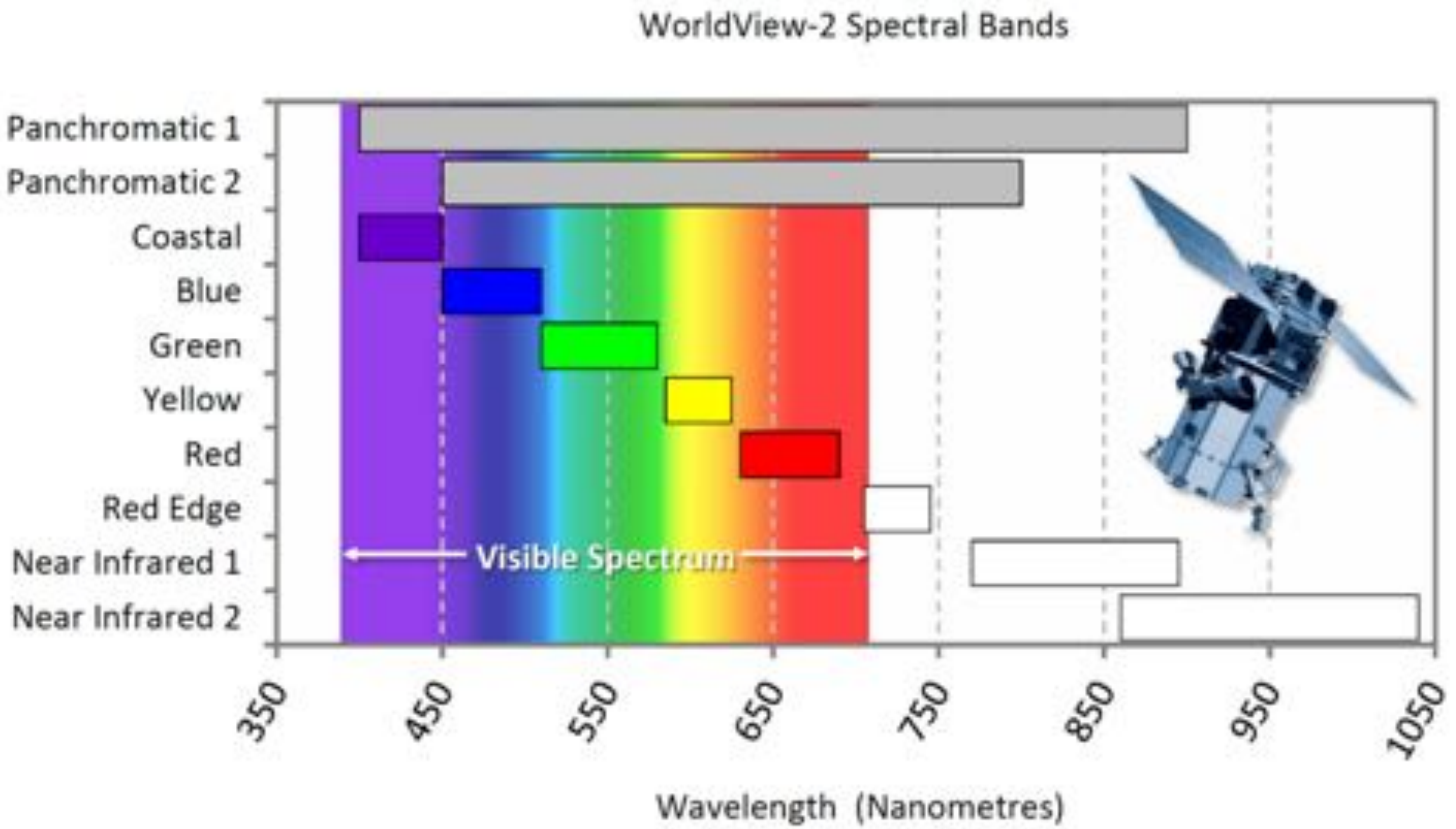
Model Implementation

Model Results



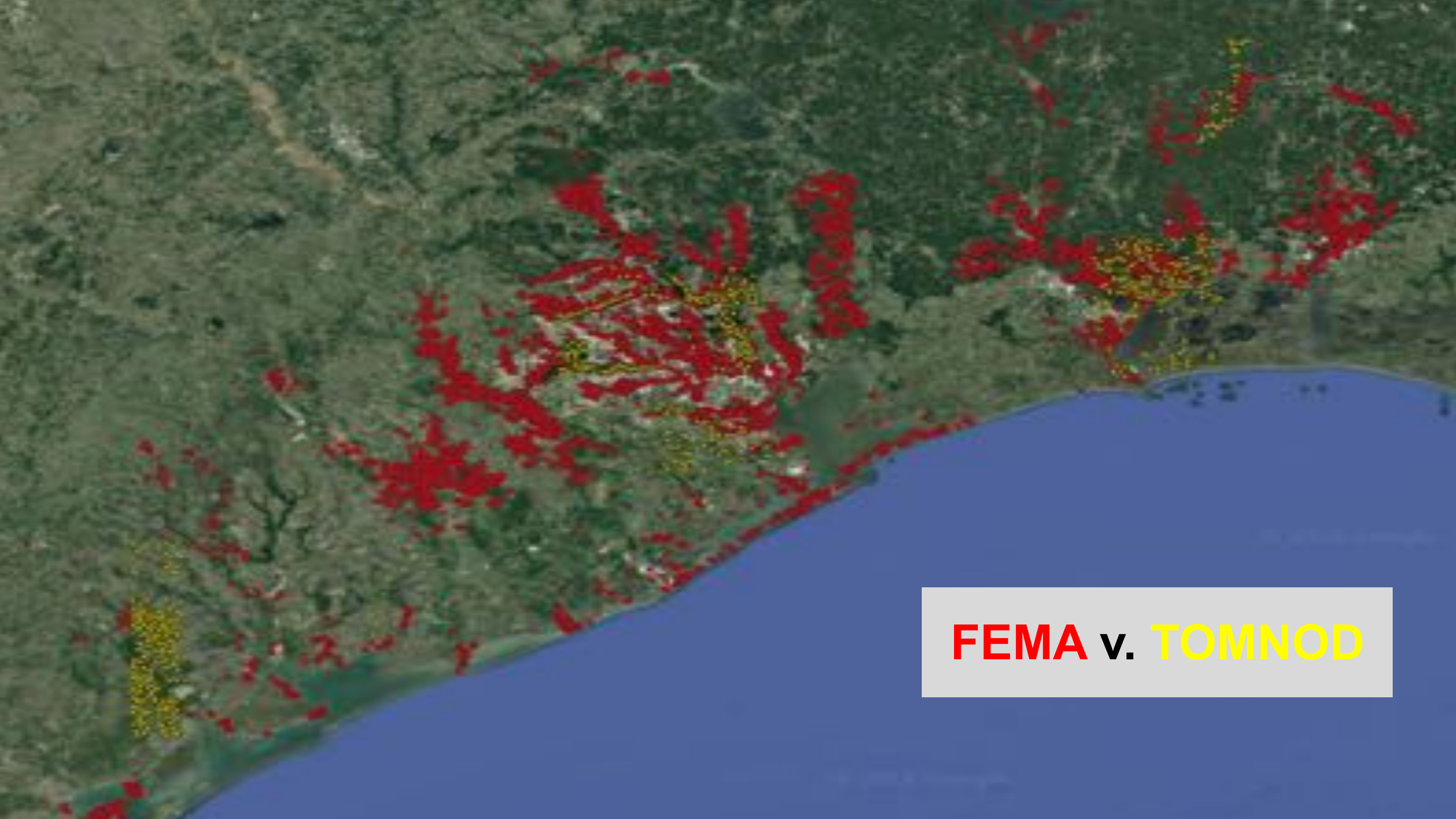

Digital Globe

NOAA


WorldView-2 Spectral Bands
Panchromatic 1
Panchromatic 2
Coastal
Blue
Green
Yellow
Red
Red Edge
Near Infrared 1
Near Infrared 2
Visible Spectrum
350
450
550
650
750
850
950
1050
Wavelength (Nanometres)


tomnod
Hurricane Maria
Sign In
Trash Heap
Flooded / Blocked Road
Blocked Bridge
Flooded / Damaged Building

TOMNOD


FEMA v. TOMNOD


Oak Ridge National Labs


Microsoft

Creating Training Data

Model Selection

Model Implementation

Model Results

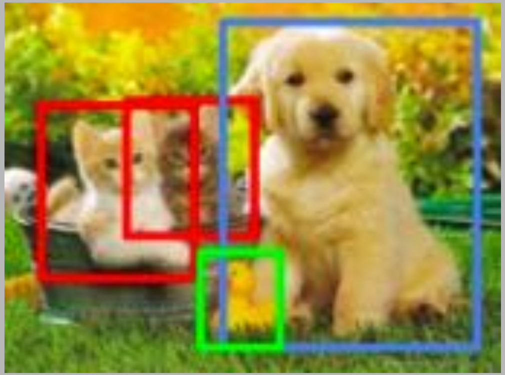
Computer Vision Tasks

Classification

Single object

Segmentation

Object Detection



Multiple objects

https://medium.com/comet-app/review-of-deep-learning-algorithms-for-object-detection-c1f3d437b852

Computer Vision with Satellite Imagery

Classification

Building y/n

DigitalGlobe Hurricane Harvey satellite imagery

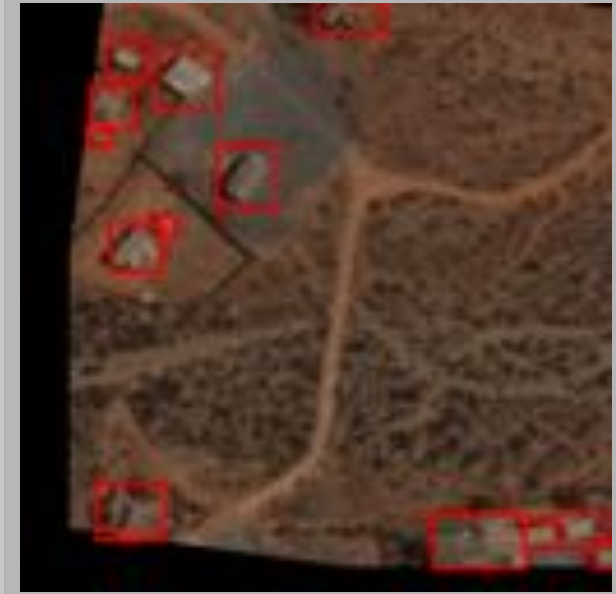
Segmentation

Flooded Roads vs. Background

https://devblogs.nvidia.com/solving-spacenet-road-detection-challenge-deep-learning/

Object Detection

Buildings with Bounding Boxes



https://medium.com/@dariusl/object-detection-baselines-in-overhead-imagery-with-diux-xview-c39b1852f24f

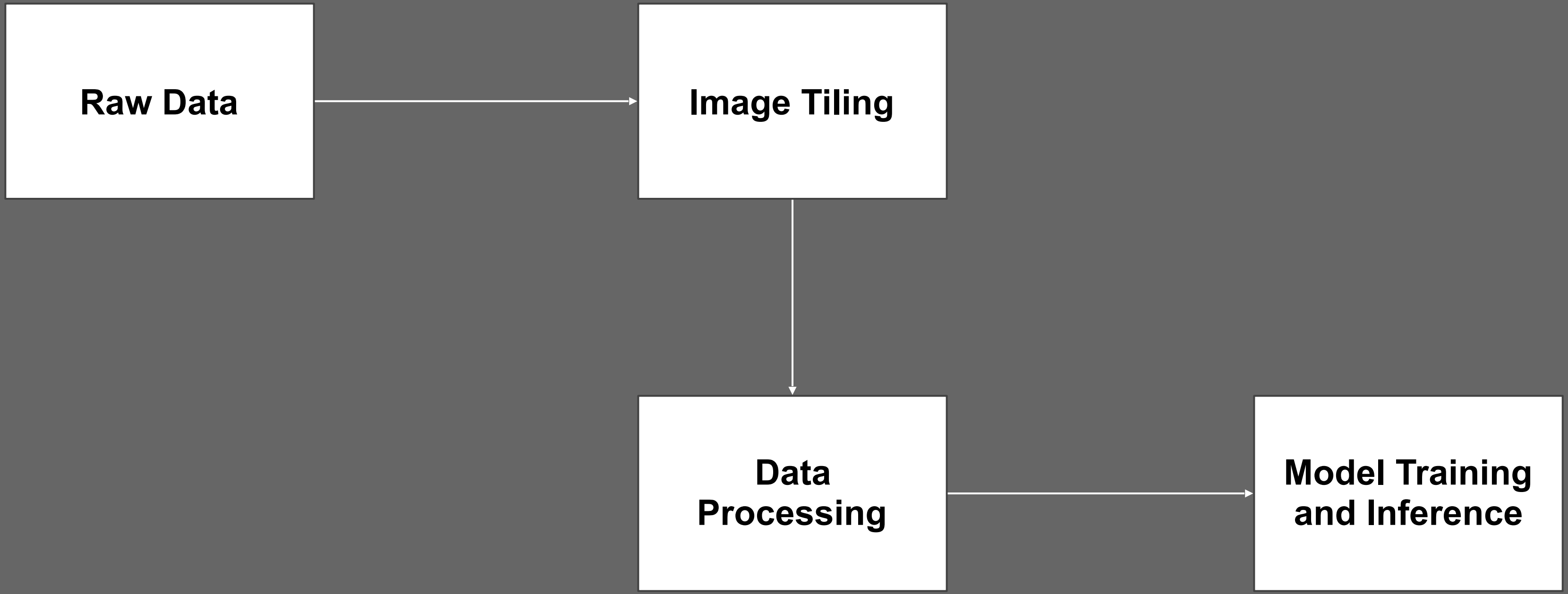
Object Detection

- 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

Pipeline


Raw Data
Image Tiling
Data Processing
Model Training and Inference

Creating Training Data

Model Selection

Model Implementation

Model Results

Experiment Setup

Data

- Satellite Imagery / Aerial Imagery
- Bounding boxes with labels
- Input size: 200 x 200

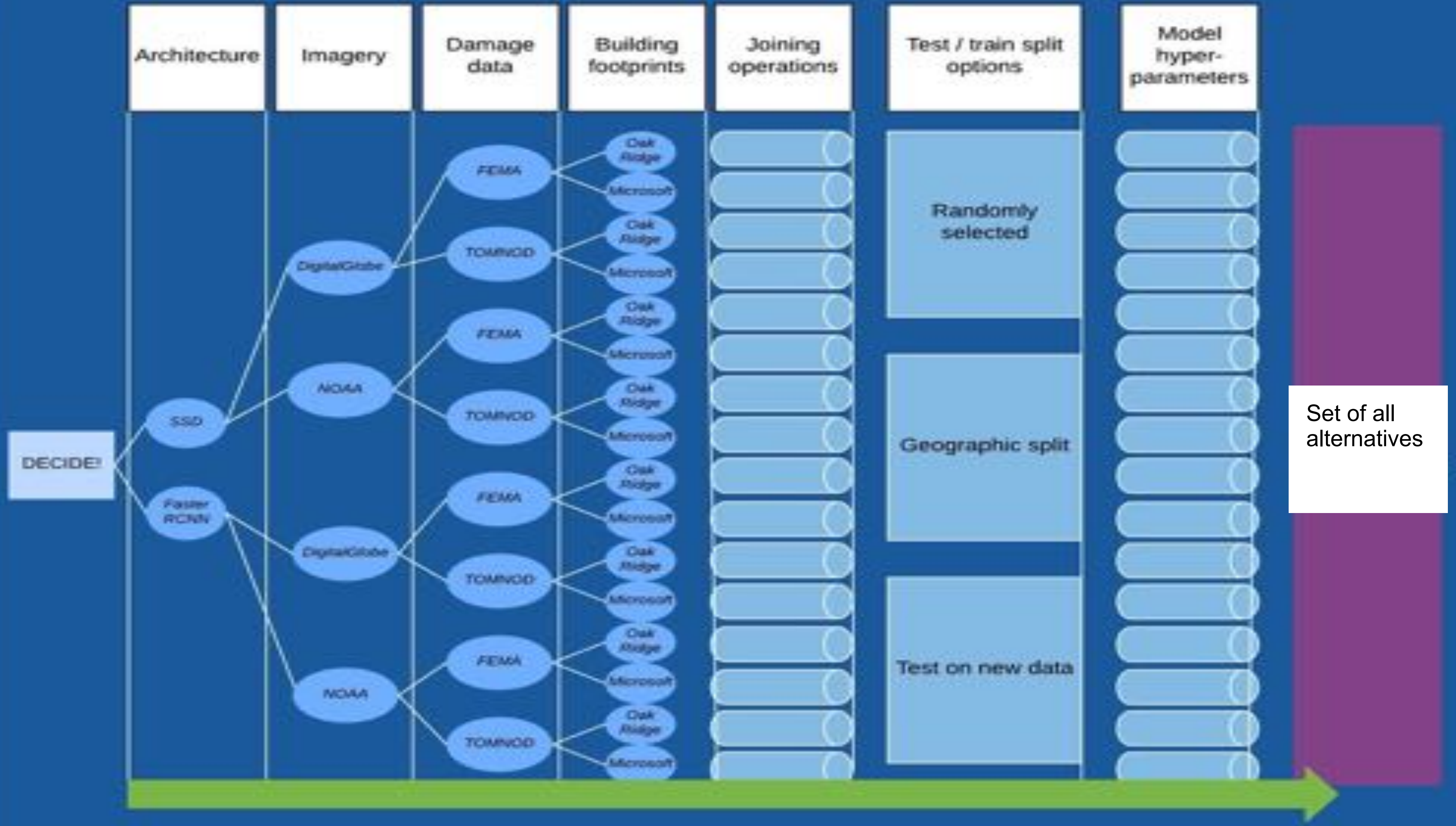
Data Augmentation

- Translation
- Rotation
- Blur
- Zoom In
- Zoom Out
- Flip
- ...

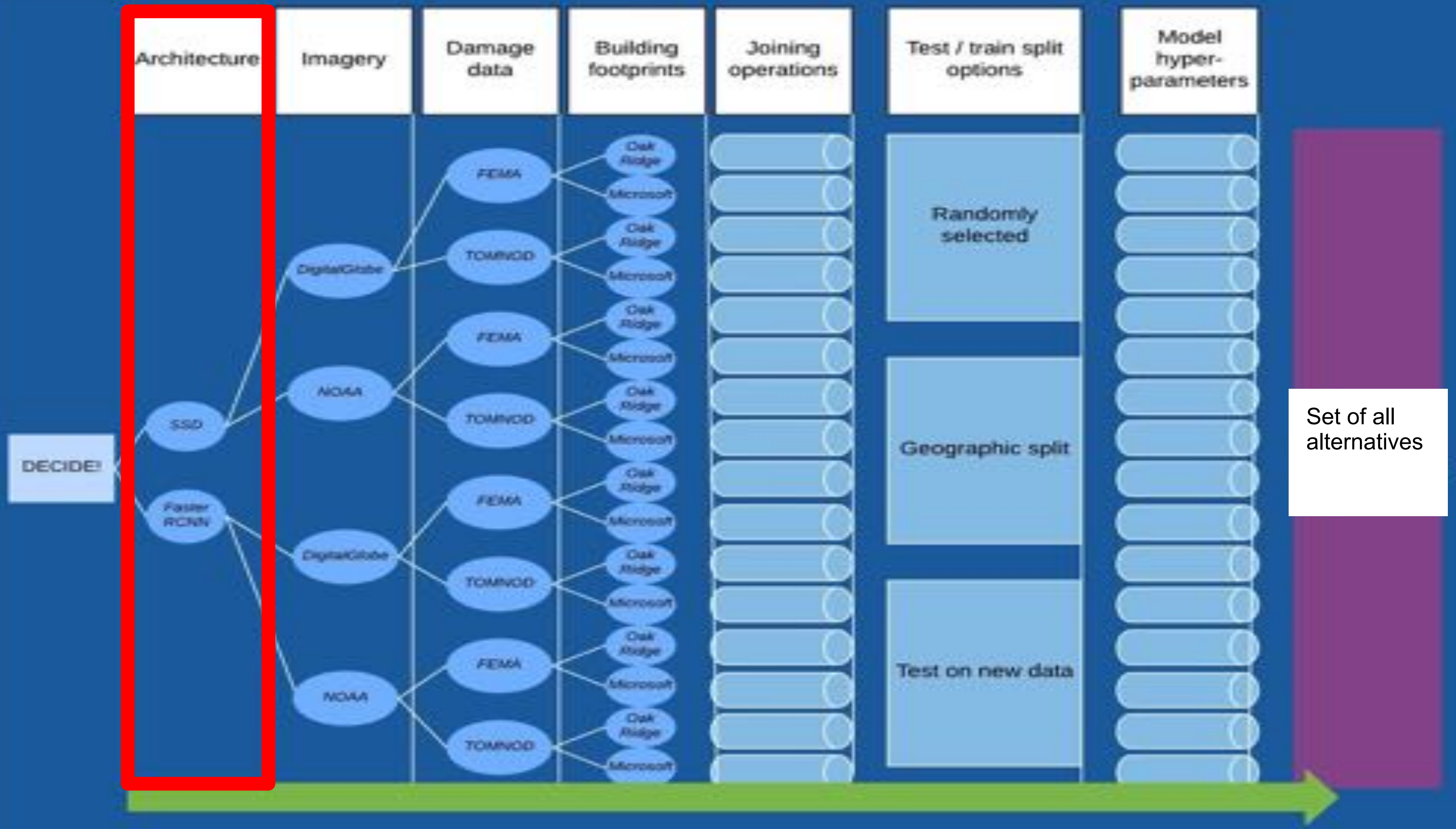
Platform

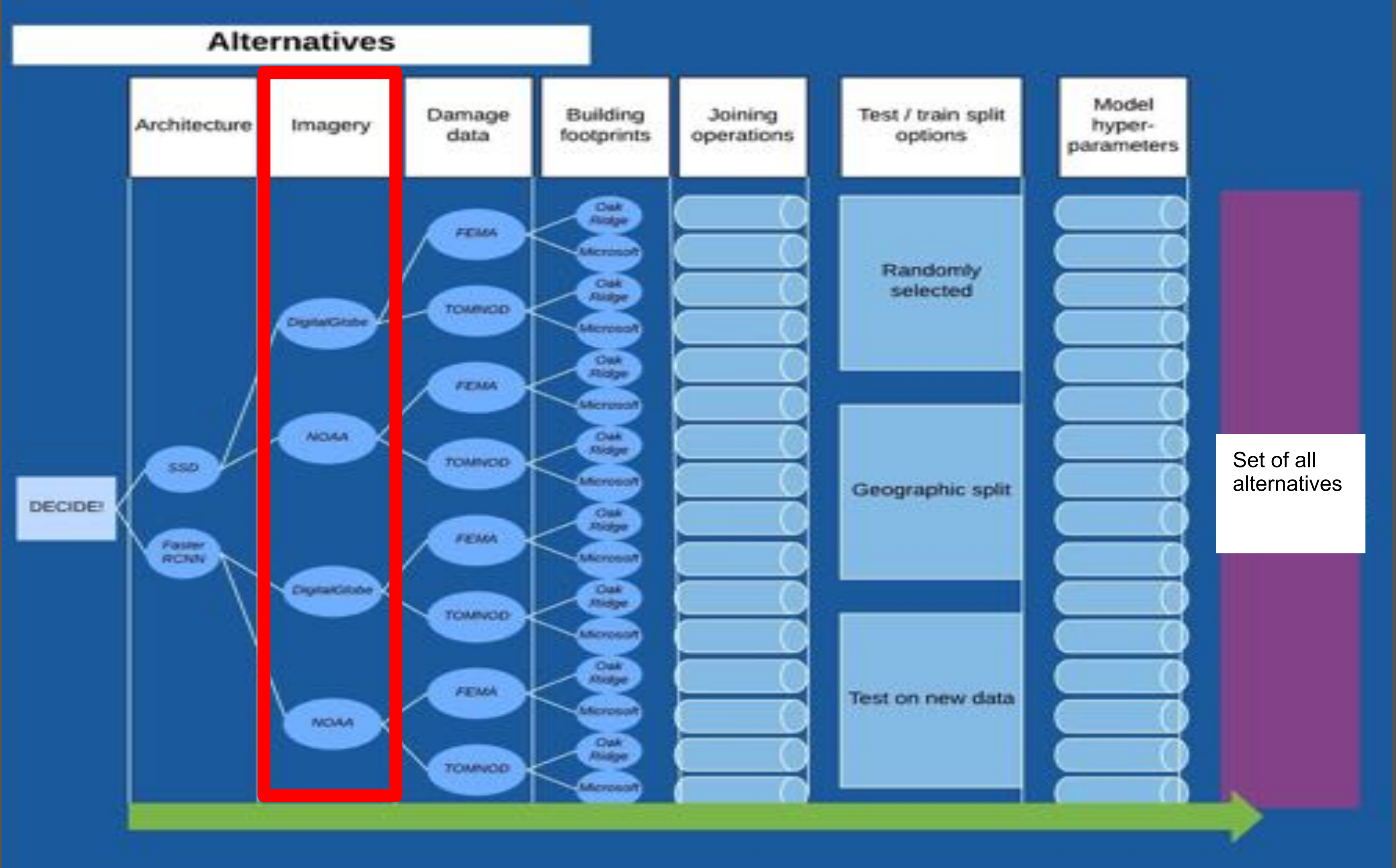
- GPU: Tesla K80 on AWS
- Implementation: Tensorflow

Alternatives

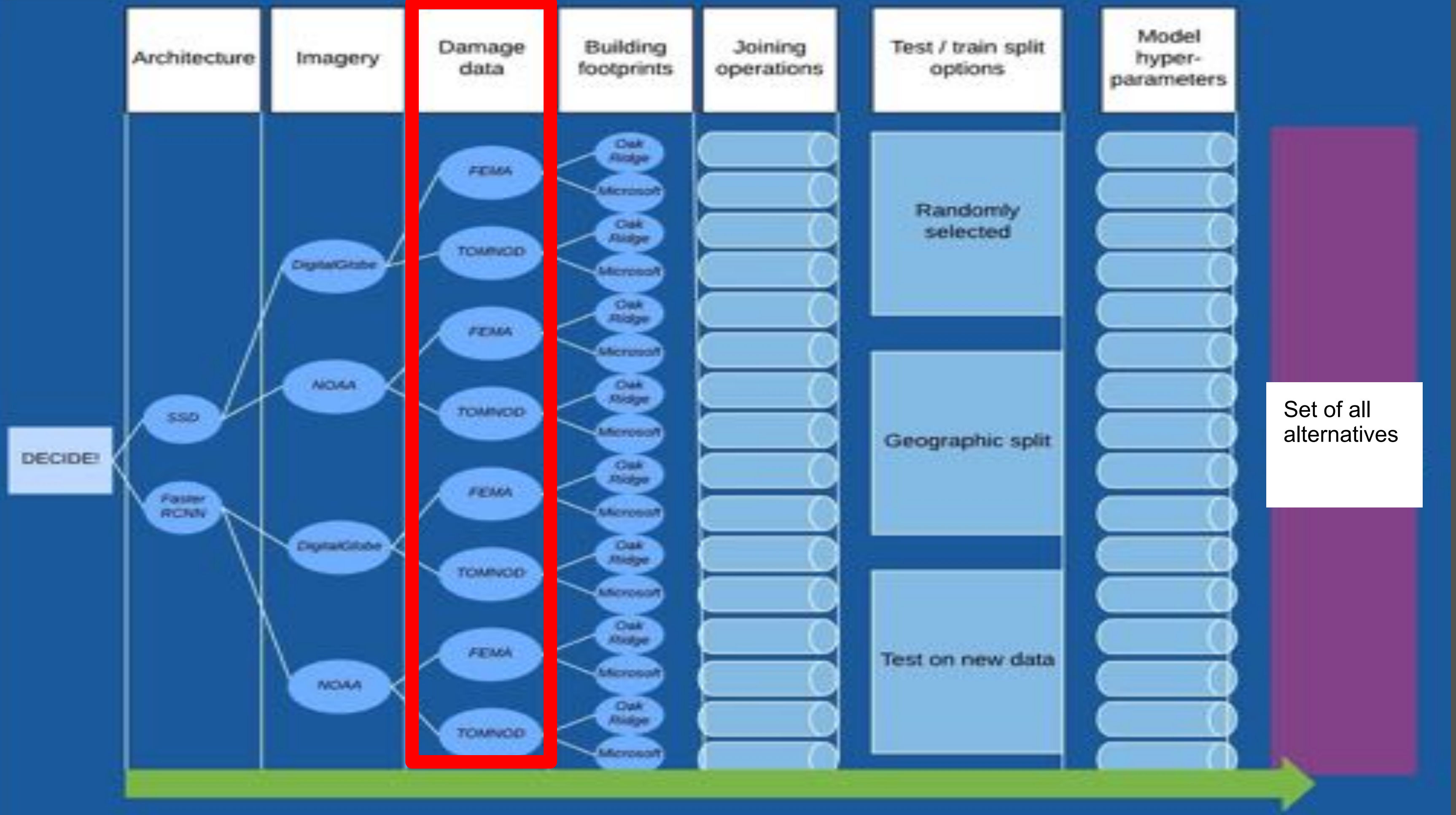


Alternatives



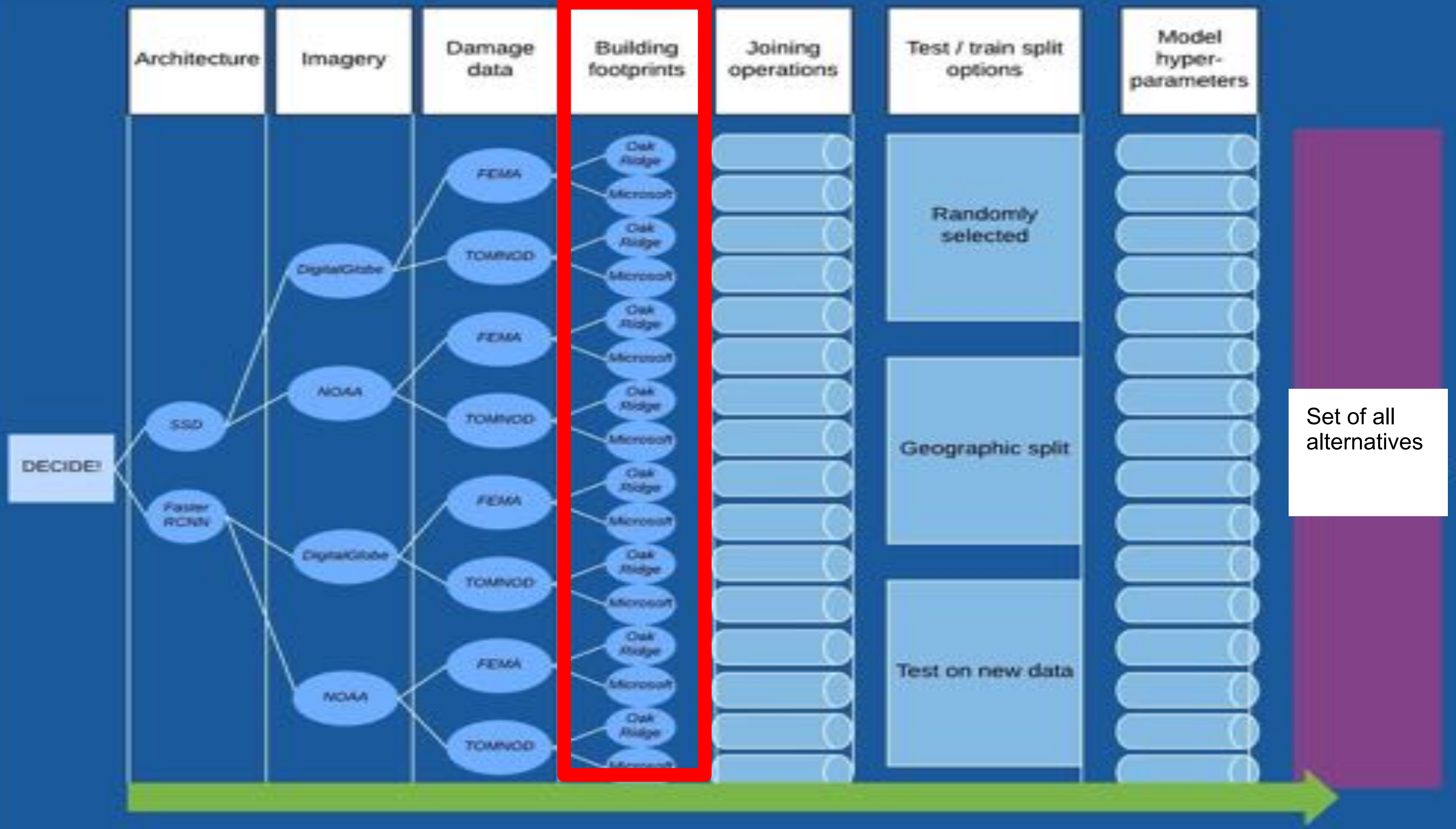

Alternatives
Architecture
Imagery
Damage data
Building footprints
Joining operations
Test / train split options
Model hyper-parameters
DECIDE!
SSD
Faster RCNN
DigitalGlobe
NOAA
DigitalGlobe
NOAA
FEMA
TOMNOD
FEMA
TOMNOD
FEMA
TOMNOD
FEMA
TOMNOD
Oak Ridge
Microsoft
Randomly selected
Geographic split
Test on new data
Set of all alternatives

Alternatives

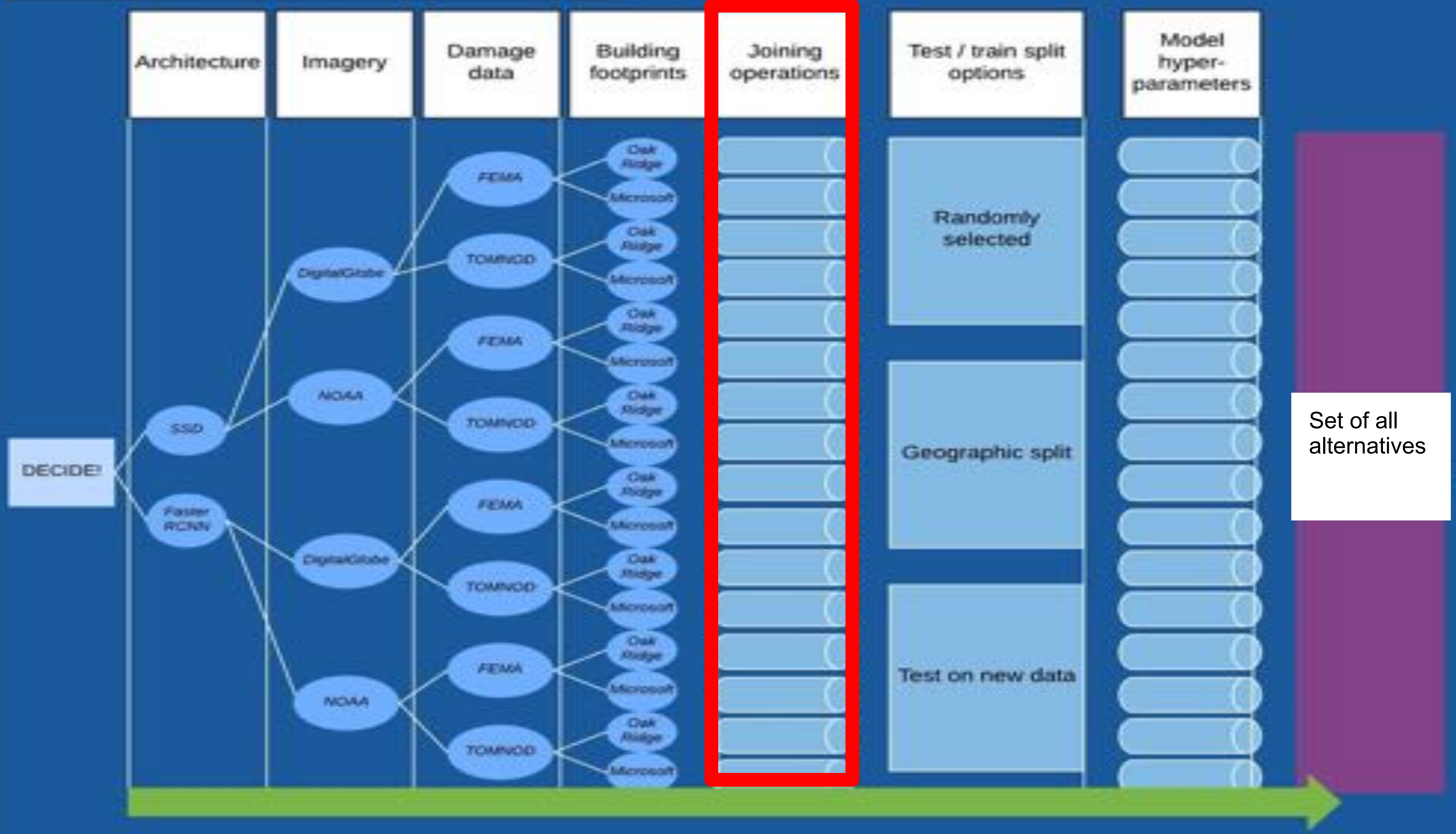


Set of all alternatives

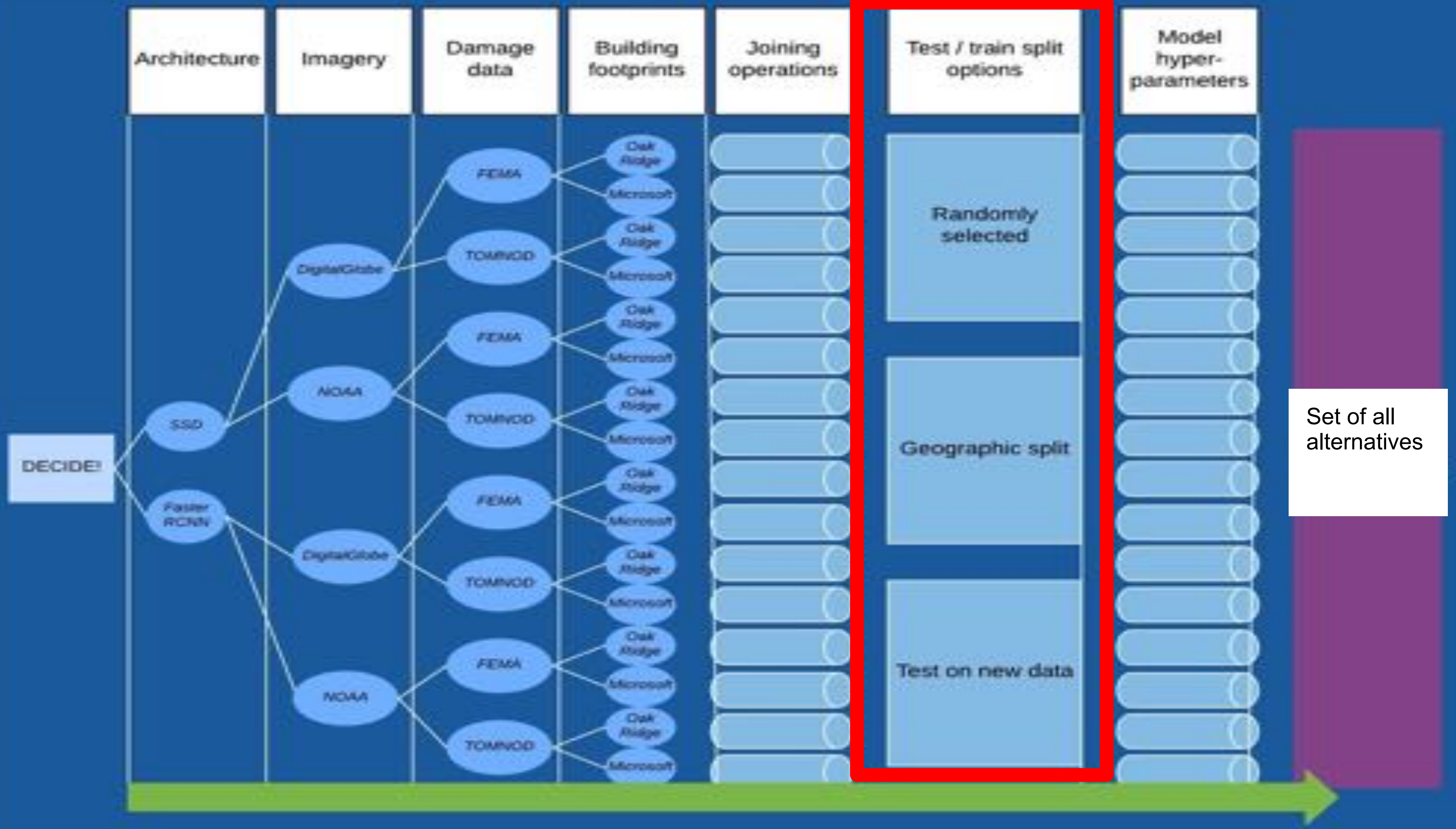
Alternatives

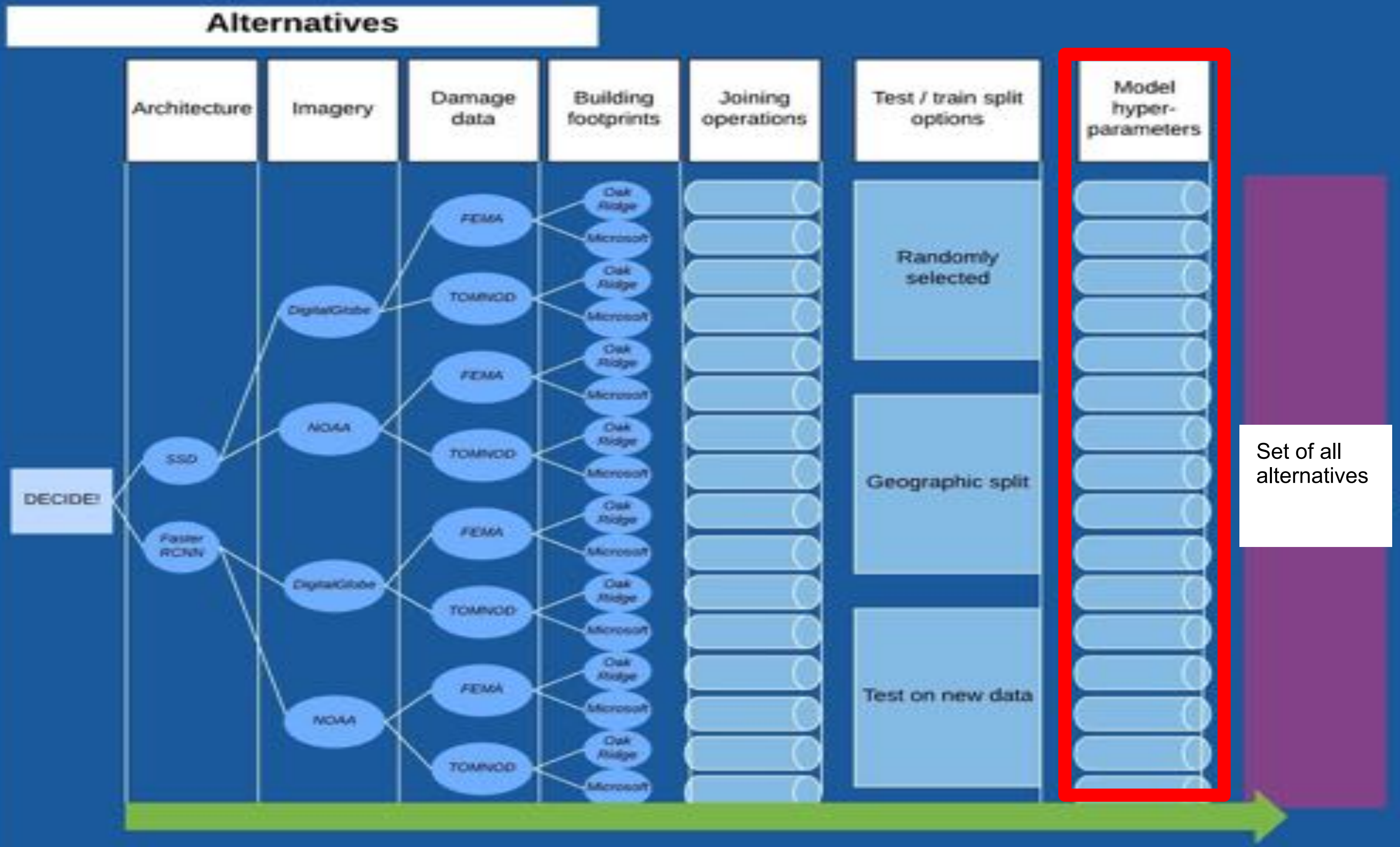


Alternatives



Alternatives




Alternatives
Architecture
Imagery
Damage data
Building footprints
Joining operations
Test / train split options
Model hyper-parameters
DECIDE!
SSD
Faster RCNN
DigitalGlobe
NOAA
FEMA
TOMNOD
Oak Ridge
Microsoft
Randomly selected
Geographic split
Test on new data
Set of all alternatives

Run Alternatives

	Detection Algorithm	Imagery data	Damage data	Building footprints	Train/Test Split
1	SSD	Satellite (DigitalGlobe)	Annotated points (TOMNOD)	Joined dataset (Microsoft, Oak Ridge)	Random selection within same geographic area
2	SSD	Aerial (NOAA)	Parcel-based assessment (FEMA)	Microsoft building footprints	Random selection within same geographic area
3	Faster R-CNN	Satellite (DigitalGlobe)	Annotated points (TOMNOD)	Joined dataset (Microsoft, Oak Ridge)	Random selection within same geographic area

Creating Training Data

Model Selection

Model Implementation

Model Results

Evaluation: IoU (Intersection over Union)

POOR

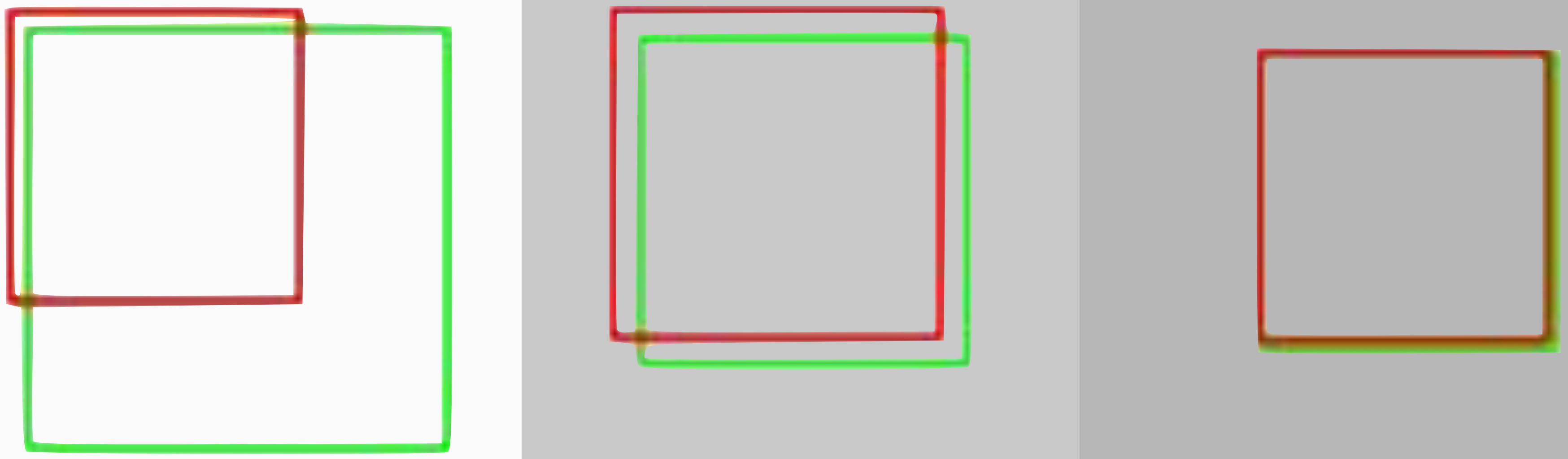
IoU: 0.4034

GOOD

IoU: 0.7330

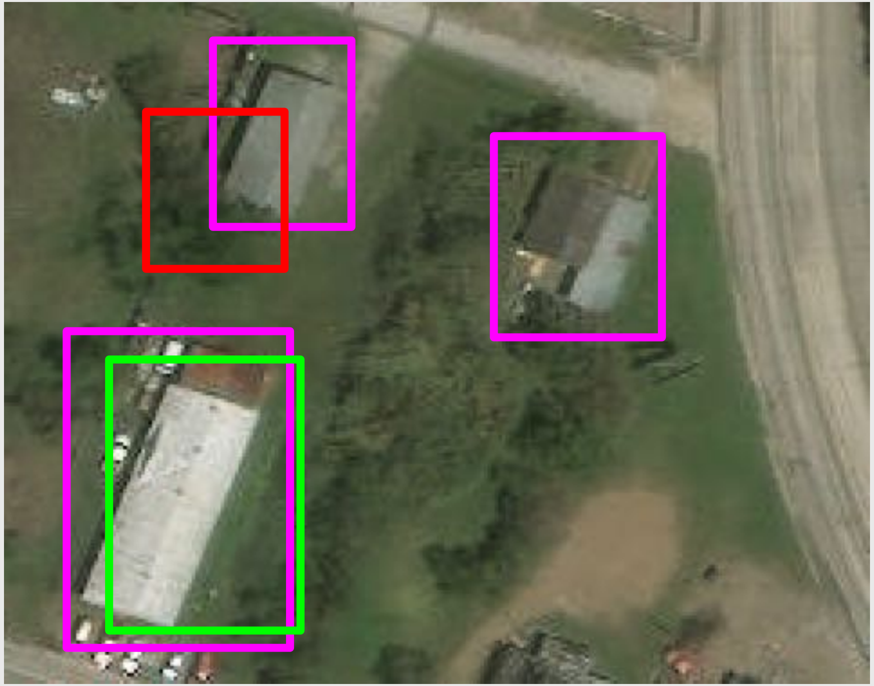
EXCELLENT

IoU: 0.9264



Evaluation

IoU (Intersection over Union) at .5

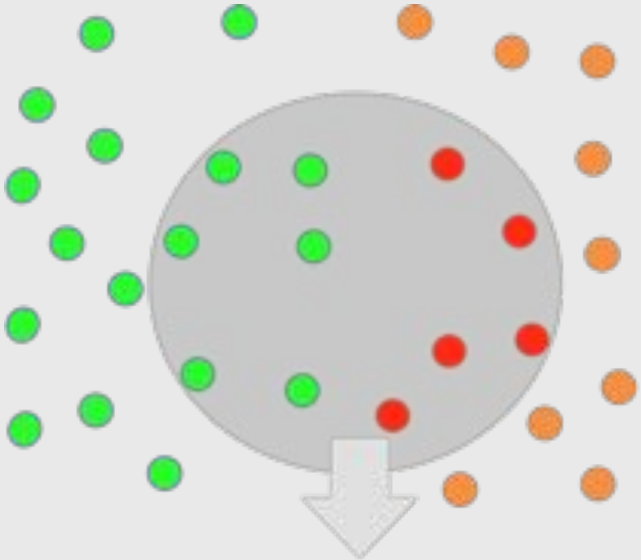


— Human-labeled box

— Model “yes”, TRUE

— Model “yes”, FALSE

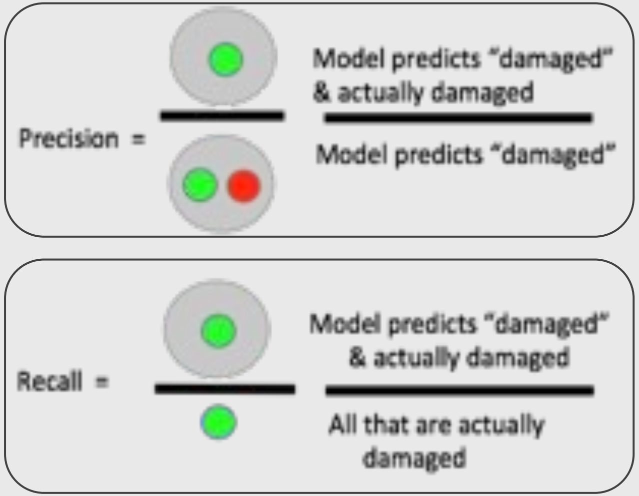
Evaluation: Scoring



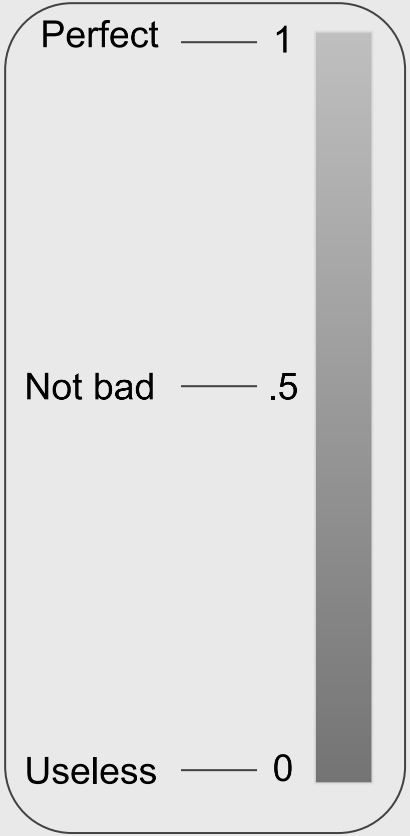
Damaged

Not Damaged

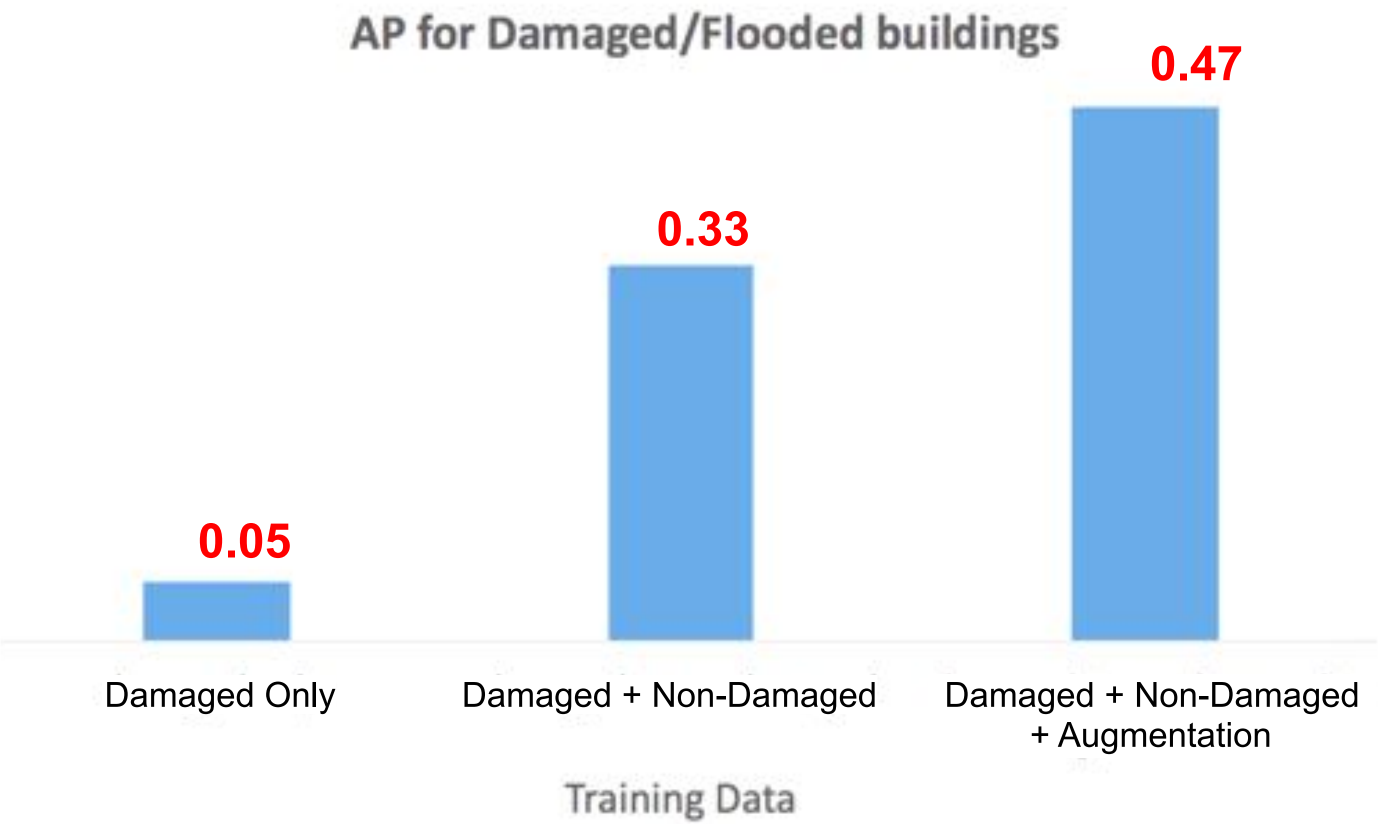
Model Predicts:
“Damaged”



Score (mean Average Precision)



Results


AP for Damaged/Flooded buildings
0.05
0.33
0.47
Damaged Only
Damaged + Non-Damaged
Damaged + Non-Damaged + Augmentation
Training Data

Results

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

Evaluation

Human-labeled data

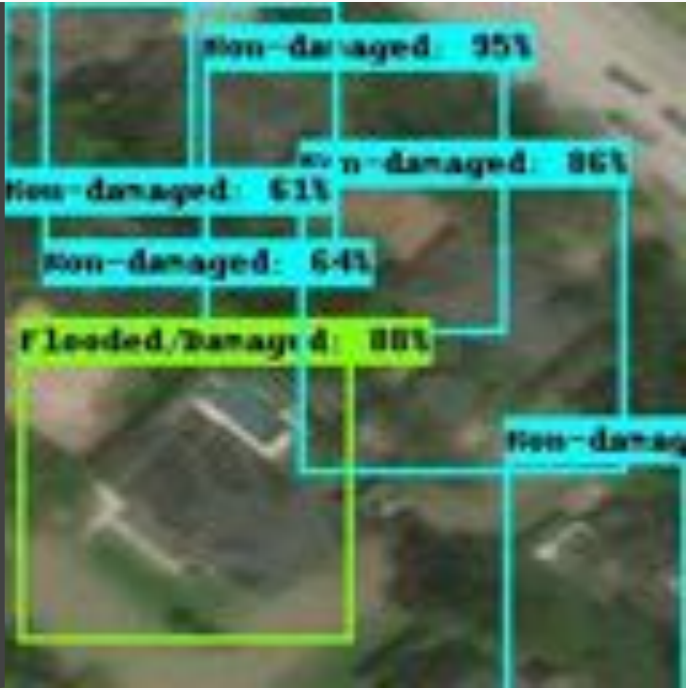
Predicted output

Identify Flooded Buildings

Evaluation

Human-labeled data

Predicted output



Identify Flooded Buildings

Evaluation

Human-labeled data

Predicted output

Identify Damaged Buildings (Blue Tarp)

Human-labeled data | Predicted output

Identify Damaged Buildings

Creating Training Data

Model Selection

Model Implementation

Model Results

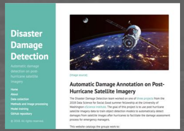
Creating Training Data

Model Selection

Model Implementation

Model Results

GeoServer



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


Disaster
Damage
Detection

GORDON AND BETTY MOORE FOUNDATION

Washington Research FOUNDATION

Microsoft

ALFRED P. SLOAN FOUNDATION 1934

UNIVERSITY of WASHINGTON eScience Institute

Urban@UW

CASCADIA URBAN ANALYTICS COOPERATIVE

Questions

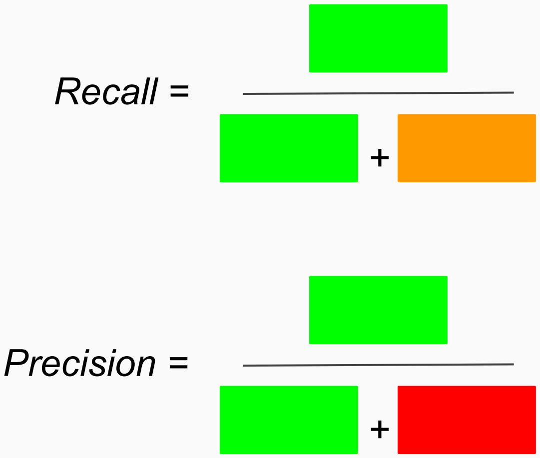
Evaluation

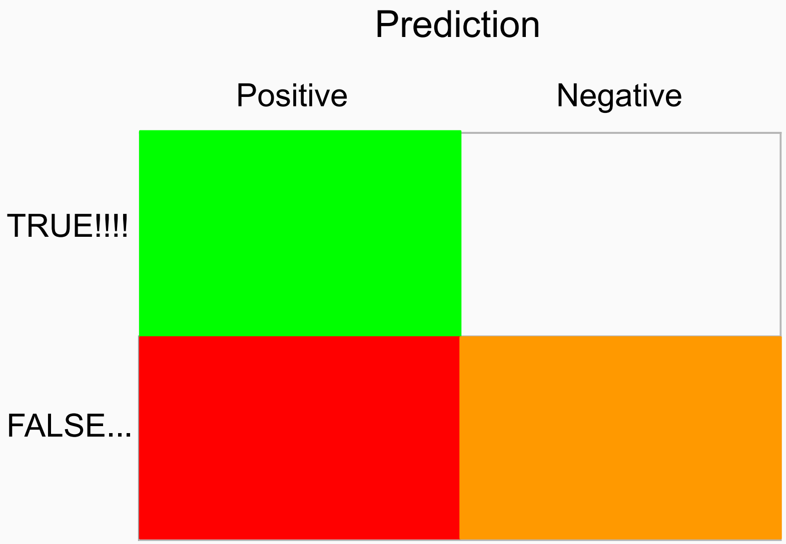
- Human-labeled box
- Model prediction
- True positive count
- False positive count
- False negative count

		Model prediction	
		Positive	Negative
Actual	TRUE!!!!		
	FALSE...		

Evaluation

Precision and Recall



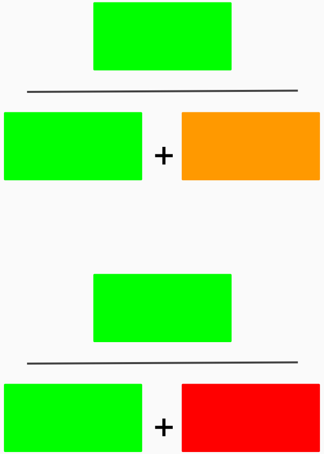


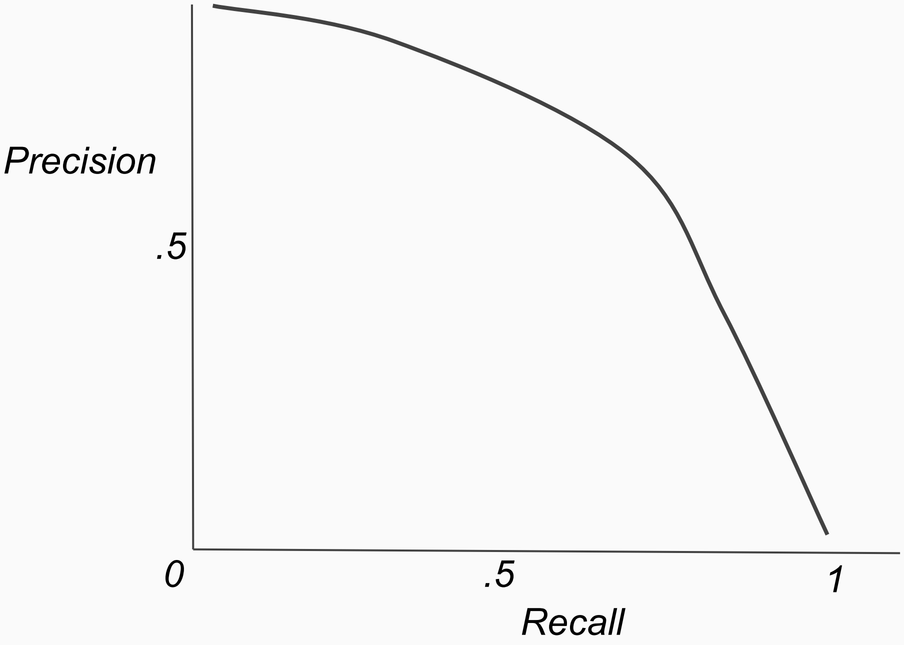
Evaluation

Precision and Recall

Recall =

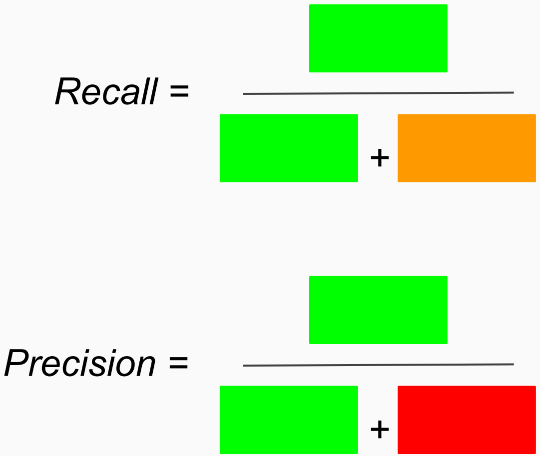
Precision =

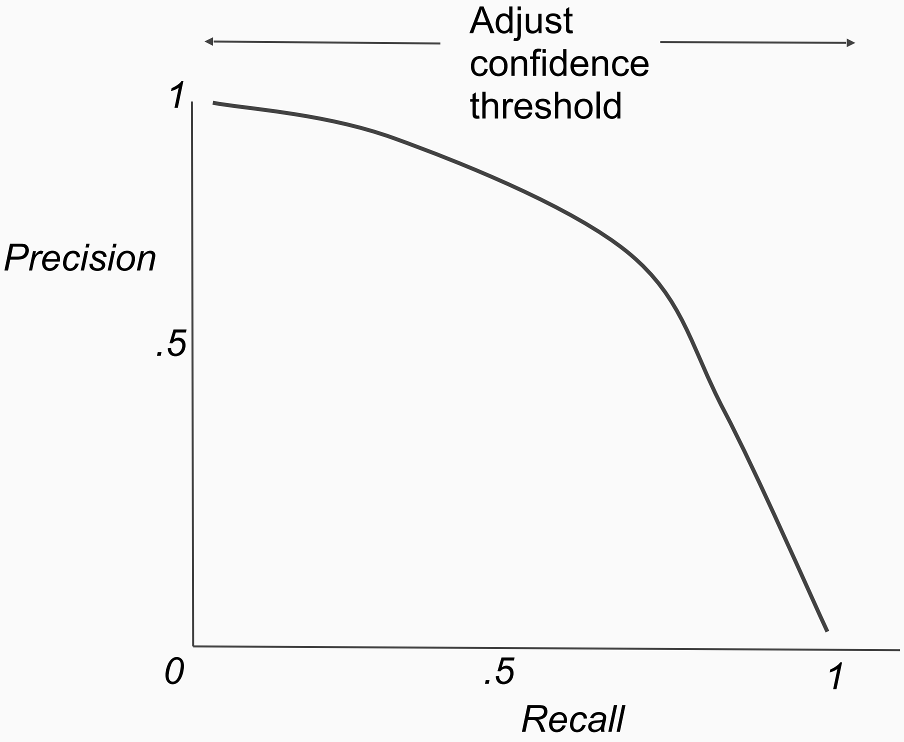




Evaluation

Precision and Recall

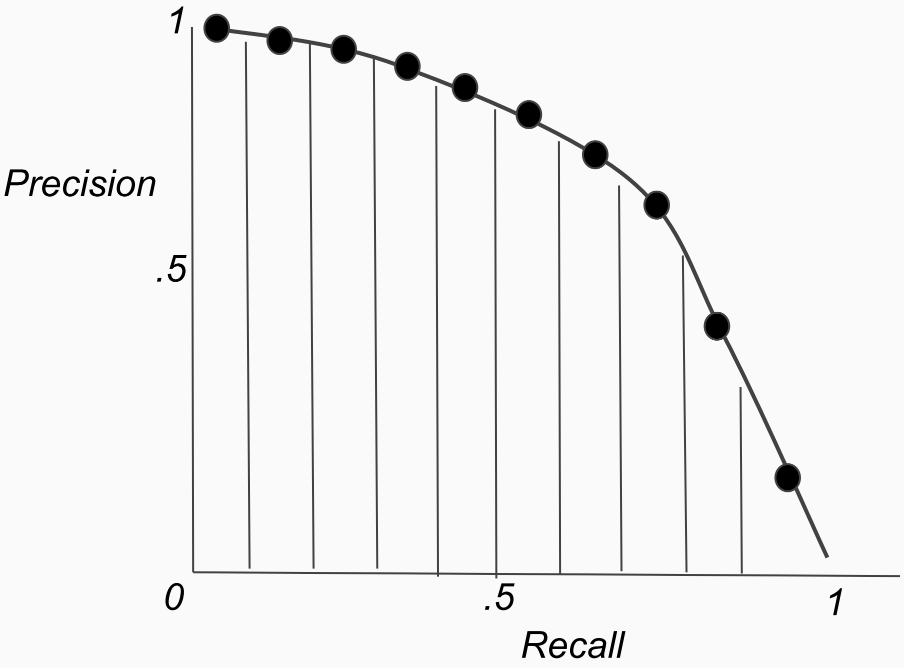




Evaluation

Precision and Recall

Average Precision (AP) = Average precision across evenly divided points on the curve



Evaluation

Mean Average Precision

Mean Average Precision (mAP) = mean of AP for each class (damaged and non-damaged)

$$\frac{AP_{damage} + AP_{non\text{-}damaged}}{2}$$

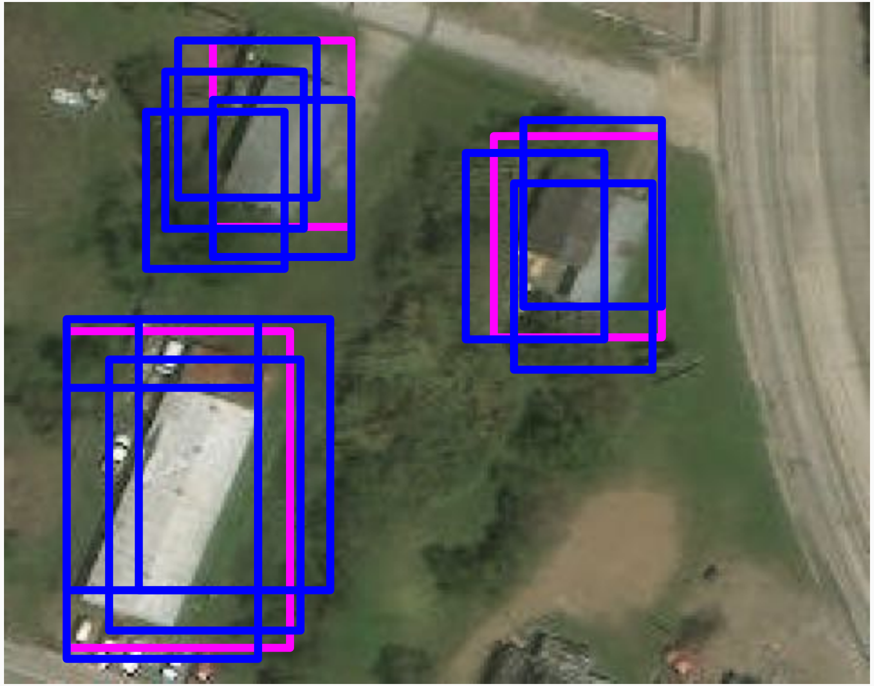
d

Evaluation

Human-labeled box

Evaluation

Non-max suppression at IoU at .5

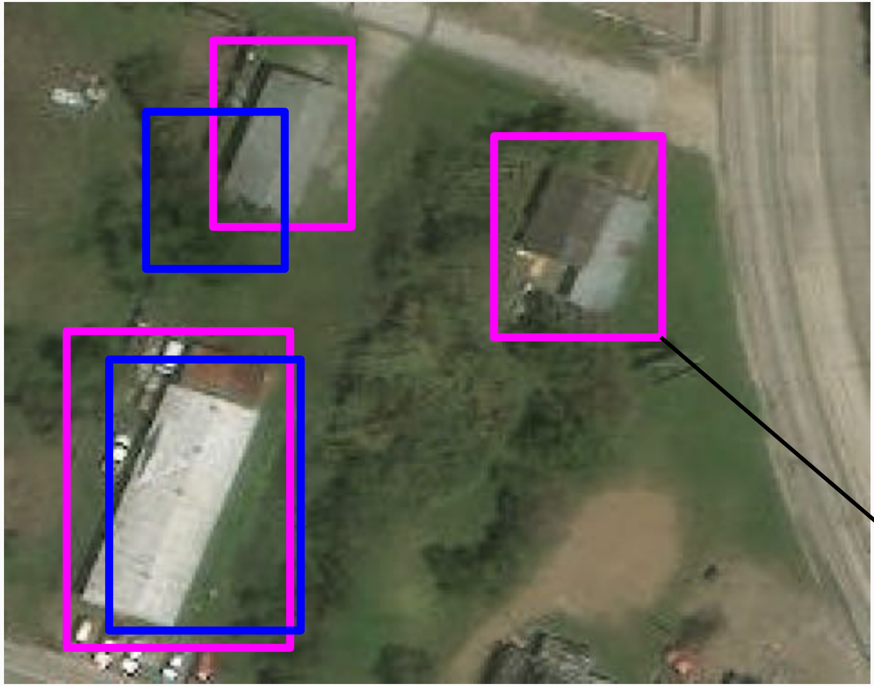


Human-labeled box

Model prediction

Evaluation

Non-max suppression at IoU at .5



— Human-labeled box

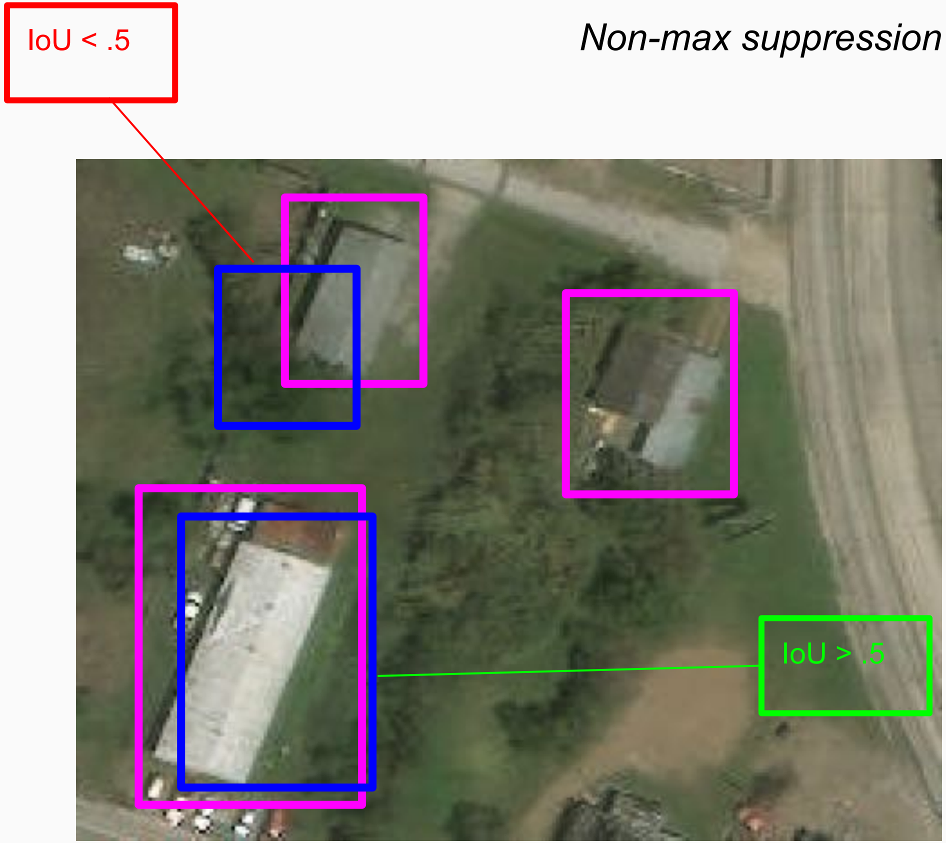
— Model prediction

Highest-confidence box out of overlapping boxes remains

No predicted box with high confidence here

Evaluation

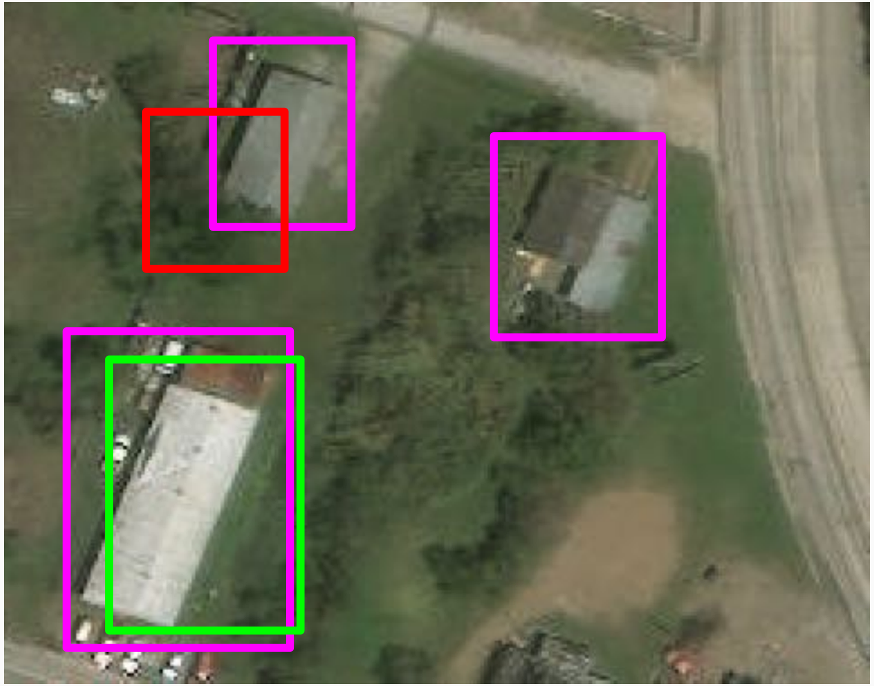
Non-max suppression at IoU at .5



- Human-labeled box
- Model prediction
- Model “yes”, TRUE
- Model “yes”, FALSE

Evaluation

IoU (Intersection over Union) at .5



- Human-labeled box
- Model prediction
- Model “yes”, TRUE
- Model “yes”, FALSE

Evaluation

Scoring

— Human-labeled box

— Model prediction

— Model “yes”, TRUE

— Model “yes”, FALSE

— Model “no”, FALSE

Counts as “correctly” predicted