



# Space Level AI for Monitoring Infrastructure Networks

How AI and Computer  
Vision come together to  
decode satellite images

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BEL– 20 Sep, 2022

# About Me

## Energy Networks

## Data Sci for Smart Grid

## Data Sci for Smart Grid & City

2005



BS, EE

2008



MS, ME

2013



MS, IE  
PhD, EE

2015



Postdoc, EECS

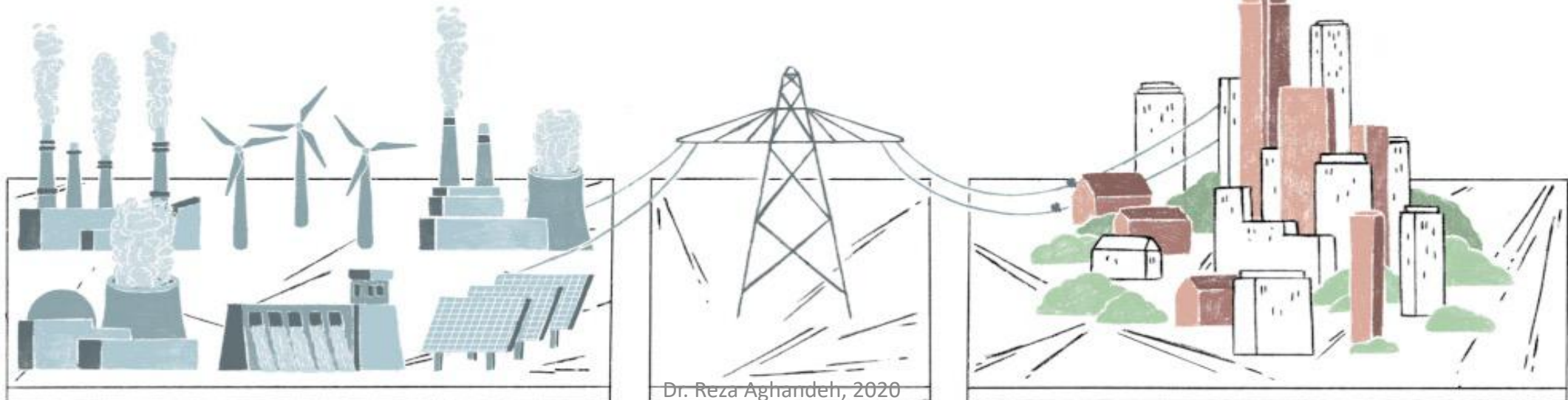
2018



Assistant Prof,  
ECE



Full Prof,  
EECS





# Acknowledgments



**Michele Gazzea**  
**PhD Candidate @Ci2Lab**  
**Western Norway University**

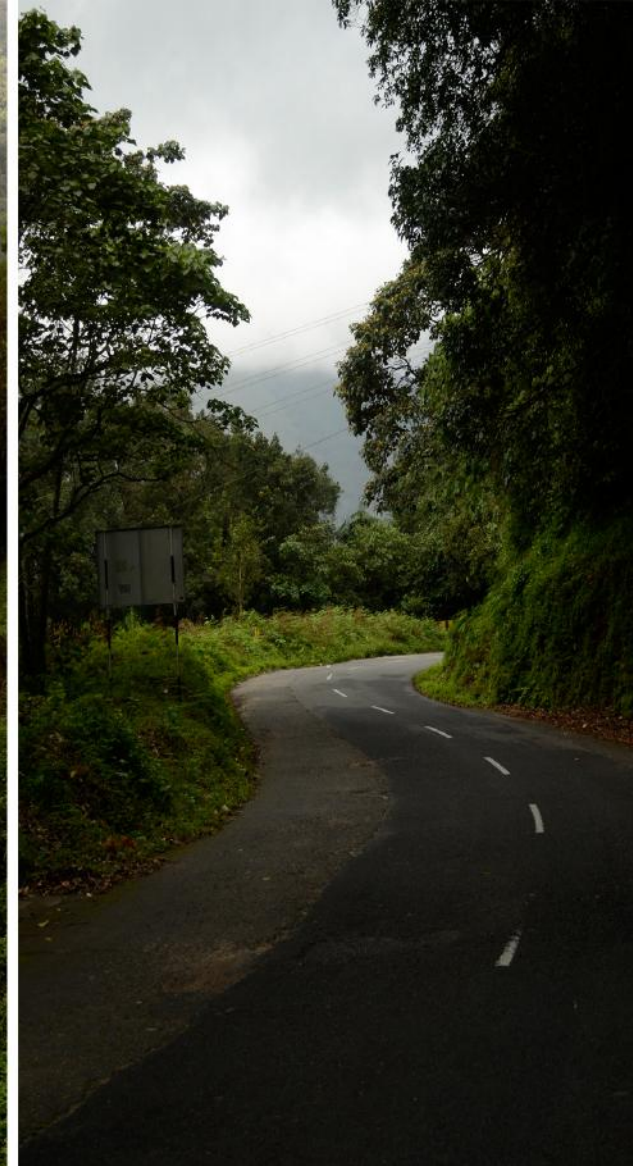
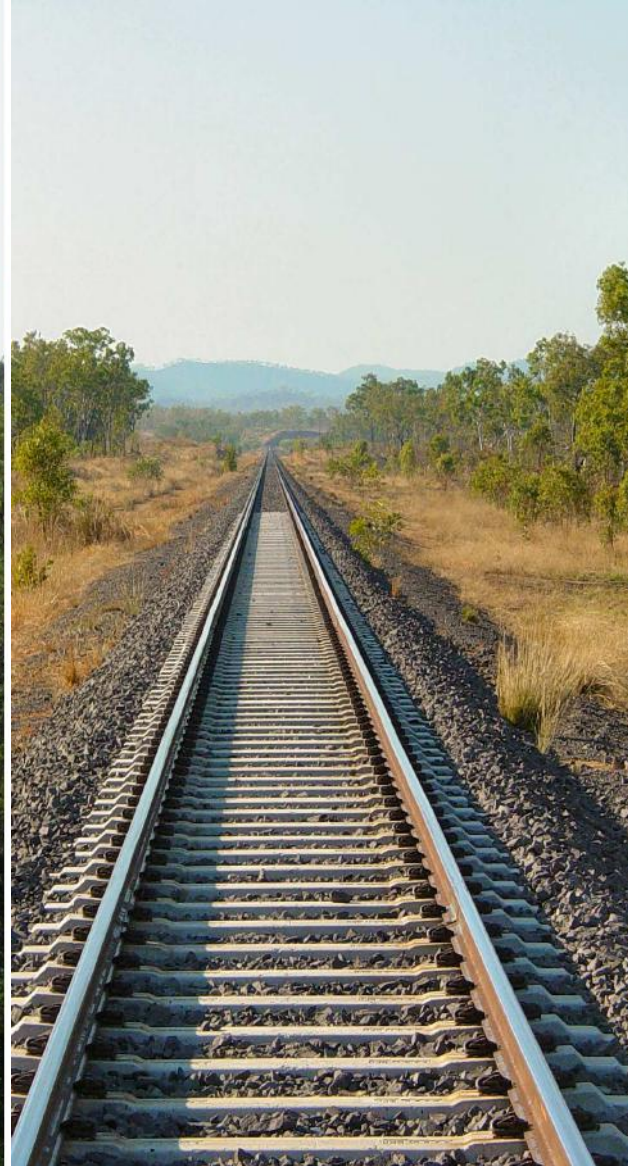


**Eren E Ozguven**  
**Associate Prof. @CEE**  
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**PhD Candidate @CEE**  
**Florida State University**





**Infrastructures are exposed to climate and environment...**



Landslide, Alta, Norway 2020



# But **Climate Change** is brutal to them...

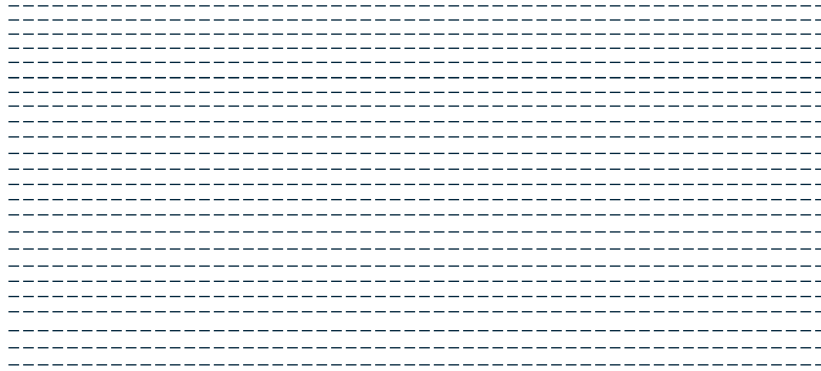
e.g., hurricane damages in the only USA is \$1.75 Trillion 1980-2019.

Bad Neuenahr-Ahrweiler, Germany 2020



Hurricane Michael, Tallahassee, USA, 2018





384 400 km



Total length of roads : 64,285,009 km\* Wikipedia

# Its hard to keep eyes on infrastructures!

- EU Power Lines 25 x to the moon!
- Roadways go around the globe 1604 times!

# Situational Awareness

## Conventional

using people on the ground ,  
helicopters, or drones.

- Costly
- Time consuming
- highly prone to weather and ground conditions

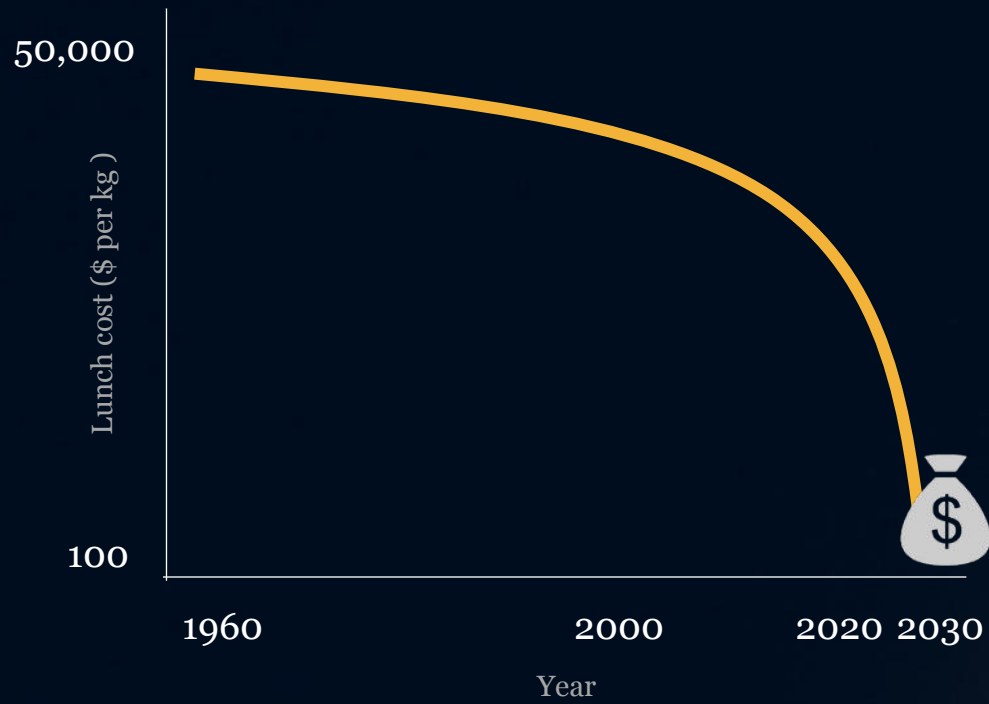


## Satellites

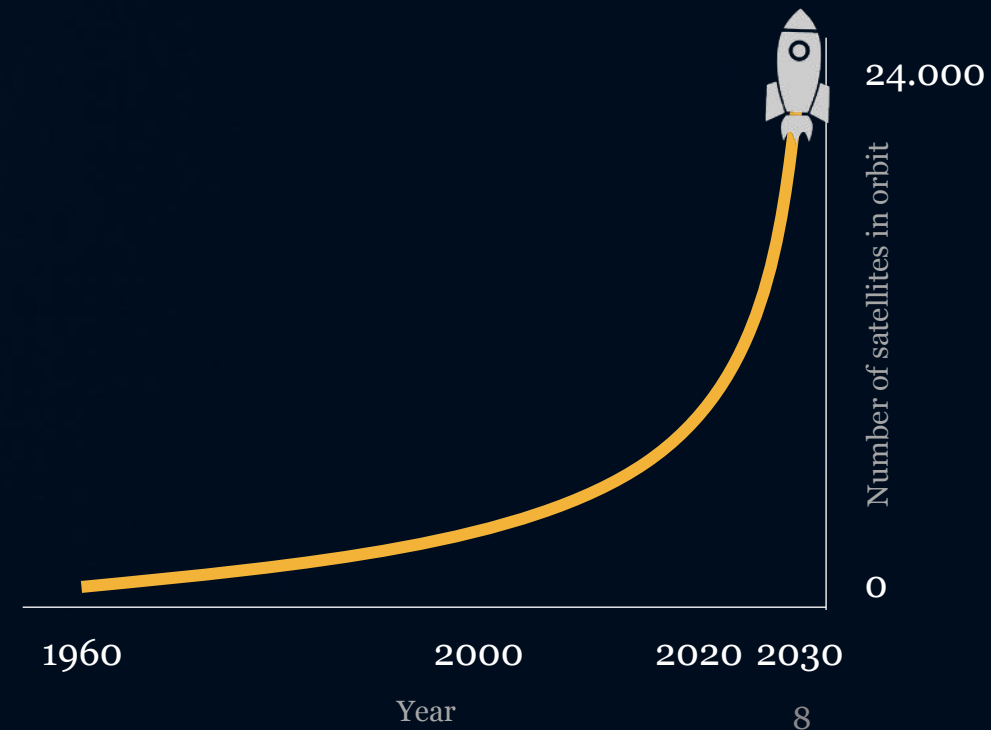
using satellite images and machine  
learning methods can:

- lower the cost
- reduce inspection time
- less prone to weather and ground condition
- high frequency observations



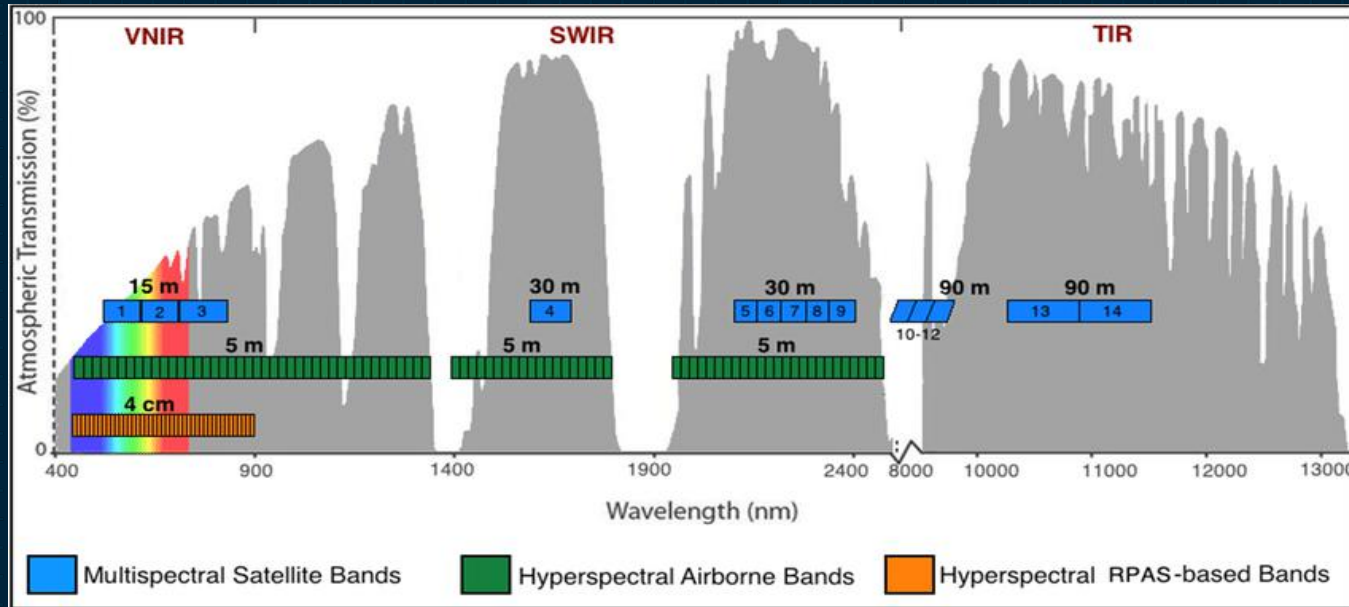


# The space revolution is taking off

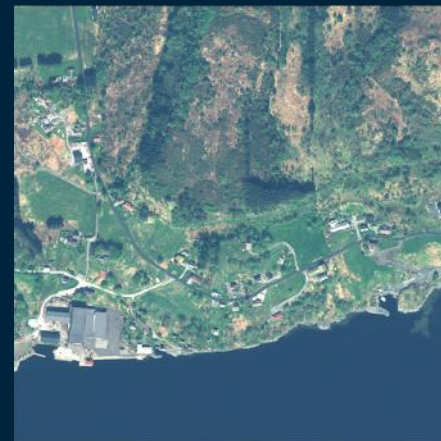
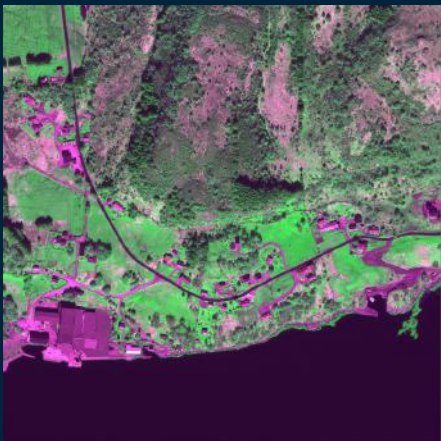




# Multispectral Satellites Perception



Compared  
to a human,  
**AI** can see more in  
each image



What  
higher  
resolution at  
lower cost  
means

A substation as seen in different satellite image resolution



0.5 m/px



3 m/px



10 m/px

A section of railway as seen in different satellite image resolution



0.5 m/px

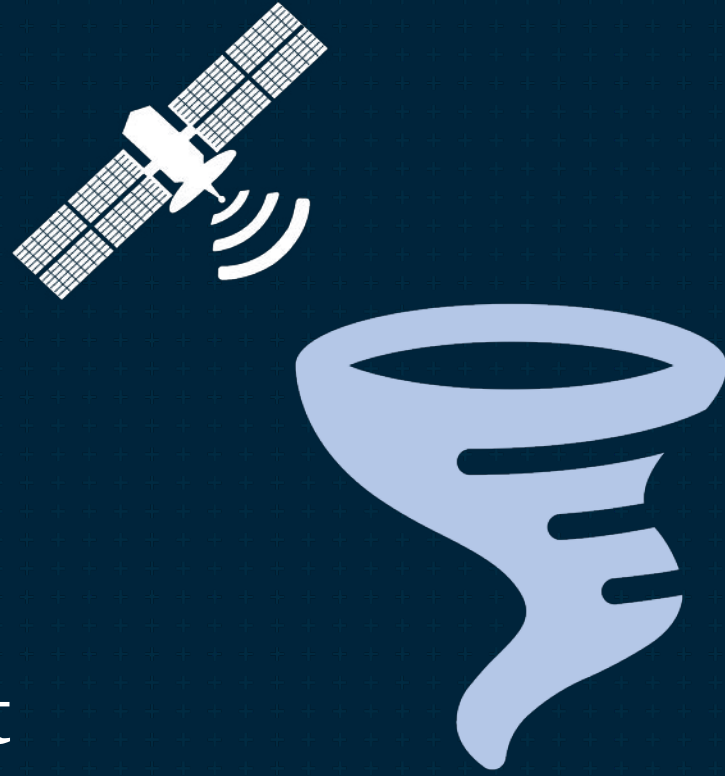


3 m/px



10 m/px





## Pre-Storm Assessment

- Vulnerability analysis
- Prevention and resilience

## Post-Storm Assessment

- Damage assessment
- Recovery optimization



# Post-Storm Assessment (Recovery)



**Hurricane Michael,  
Tallahassee, FL, Oct**



# Use Case

Hurricane Michael, Tallahassee, FL, Oct  
2018



September  
2018

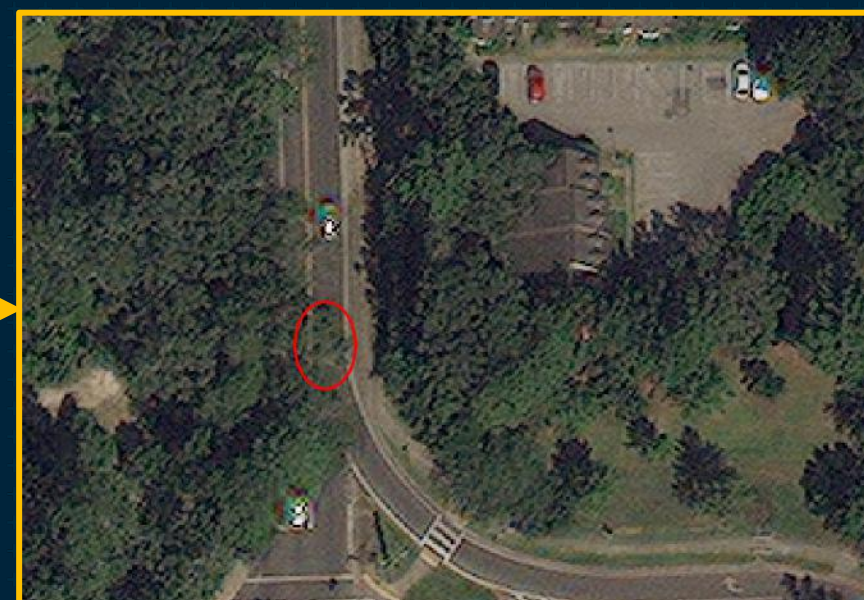
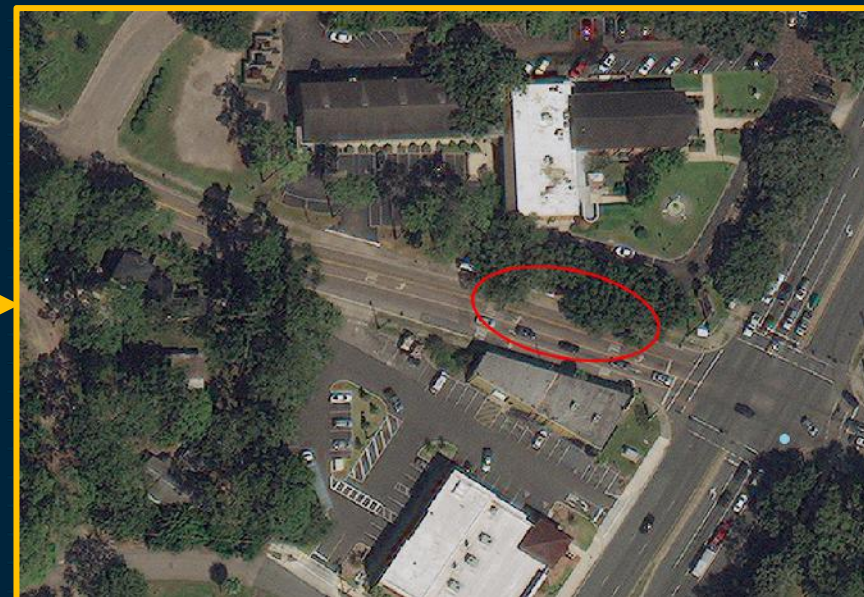


October 2018

Data SIO, NOAA, U.S. Navy, NGA, GEBCO  
Image Landsat / Copernicus  
Image IBCAO

Google Earth

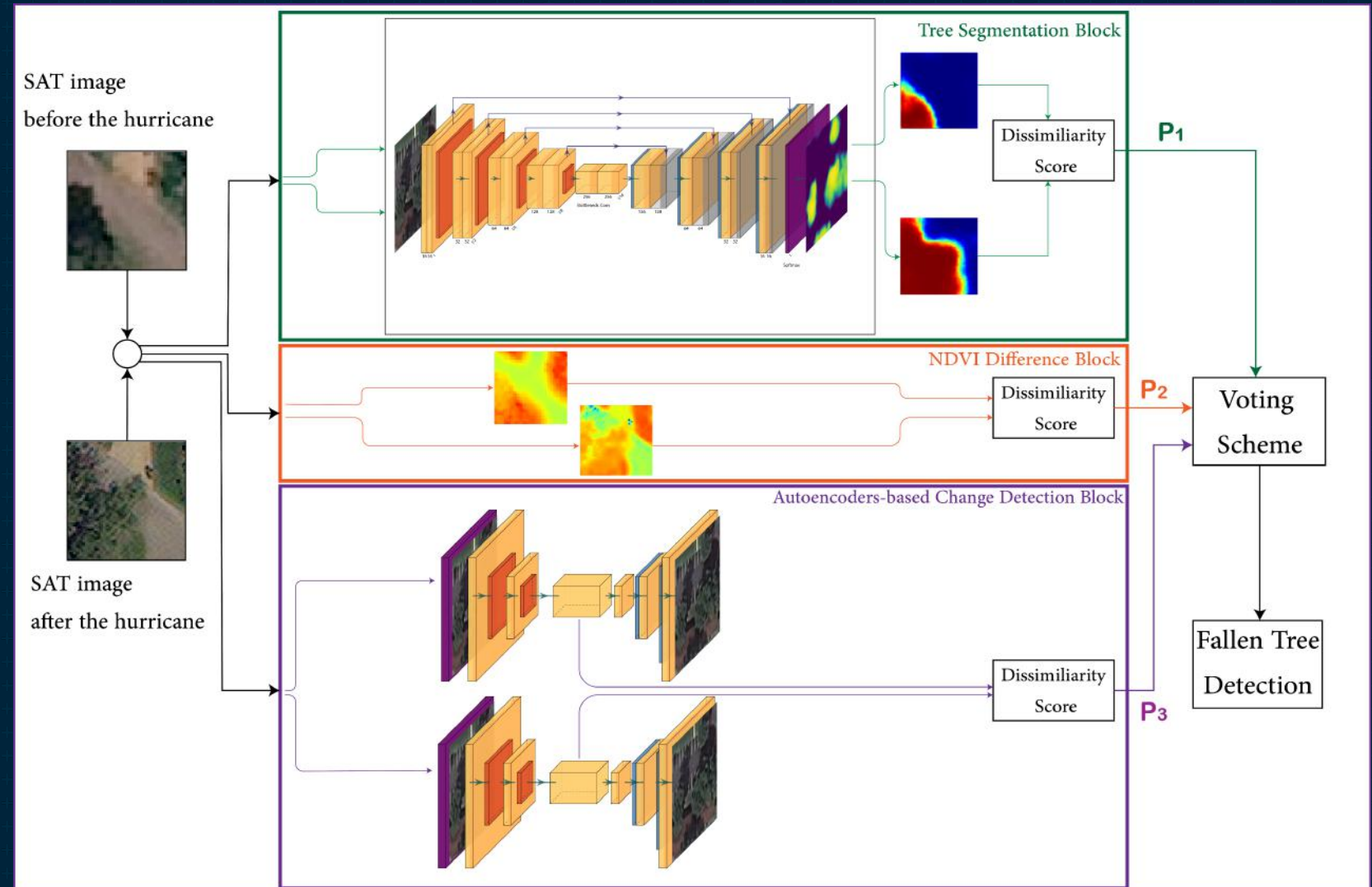




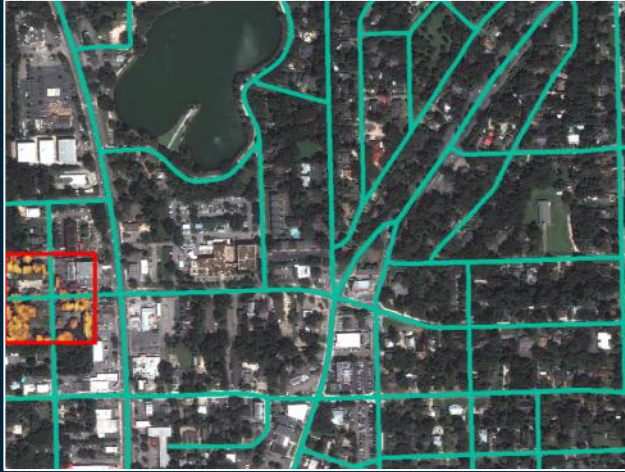


# Our Method

An unsupervised anomaly detection approach without labeled data for fallen trees.



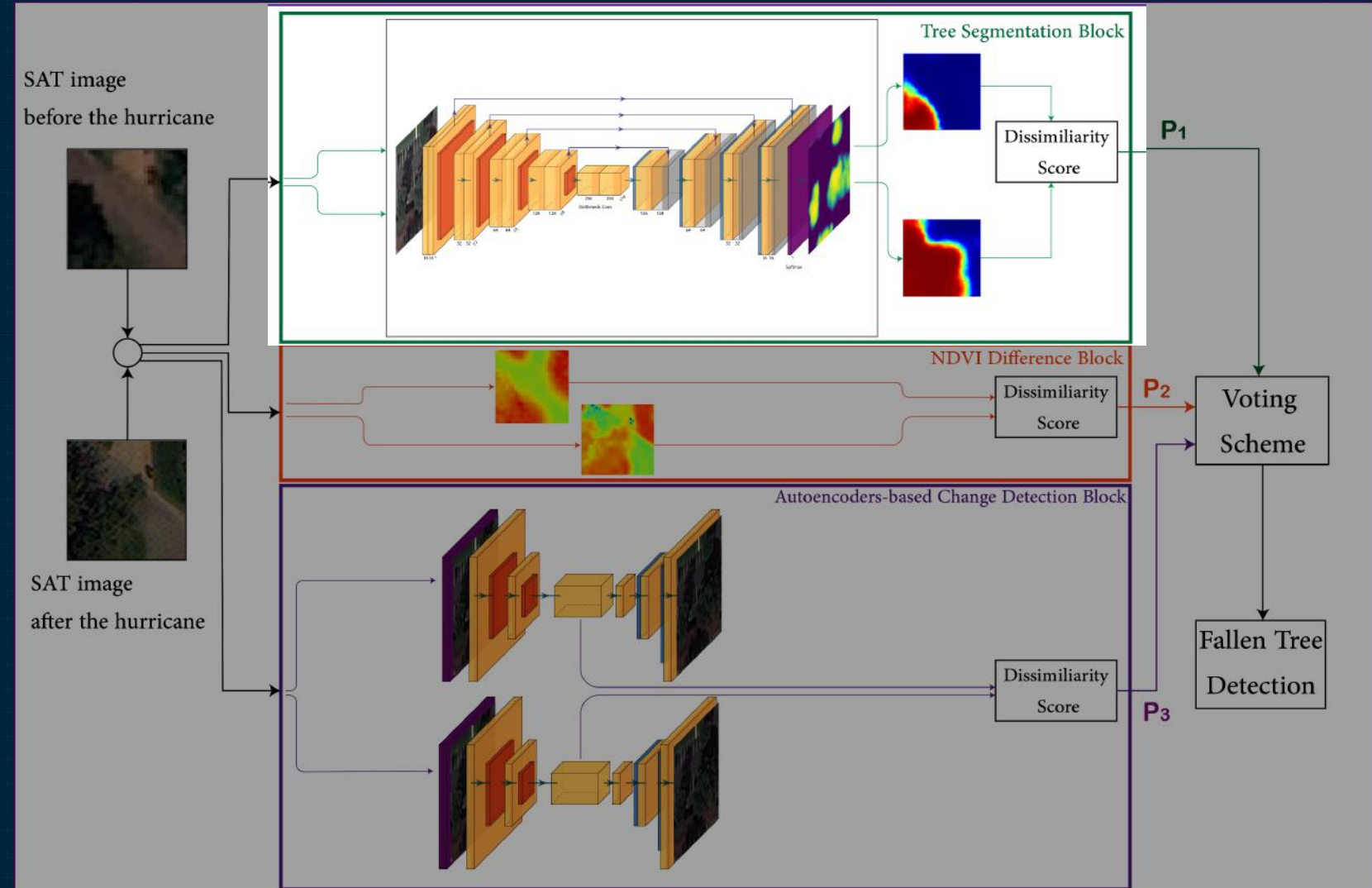
# Tree Segmentation Block



The model is based on the *Unet* architecture trained to recognize trees in images.

The dissimilarity score  $D_{tree}$ :

$$D_{tree} = \iint_{Patch} (M_{aft}^{tree} - M_{bfr}^{tree}) \times K$$





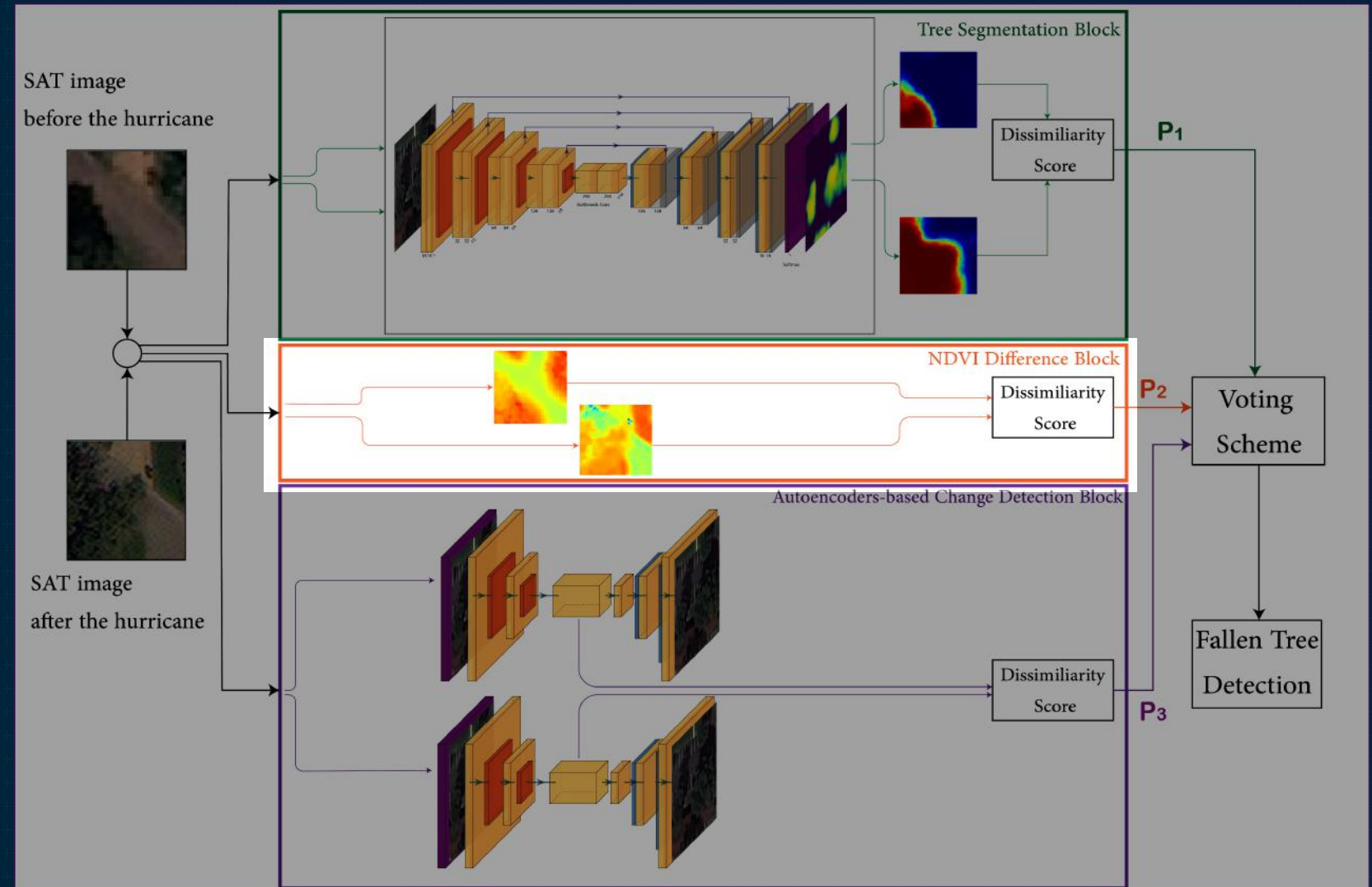
# Normalized Difference Vegetation Index (NDVI) Block

NDVI is computed as:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$$

The dissimilarity score  $D_{NDVI}$ :

$$D_{NDVI} = \iint_{Patch} (NDVI_{aft} - NDVI_{bfr}) \times K$$

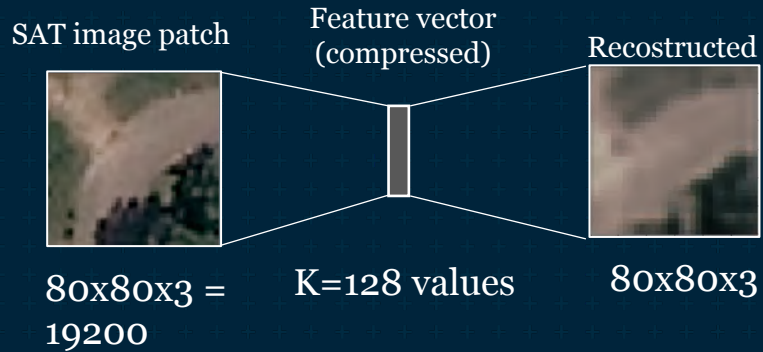


# Variational Auto-Encoder Block

$$Loss = MSE(x, \tilde{x}) + KL(p_{\theta}(x|z) || p(z))$$

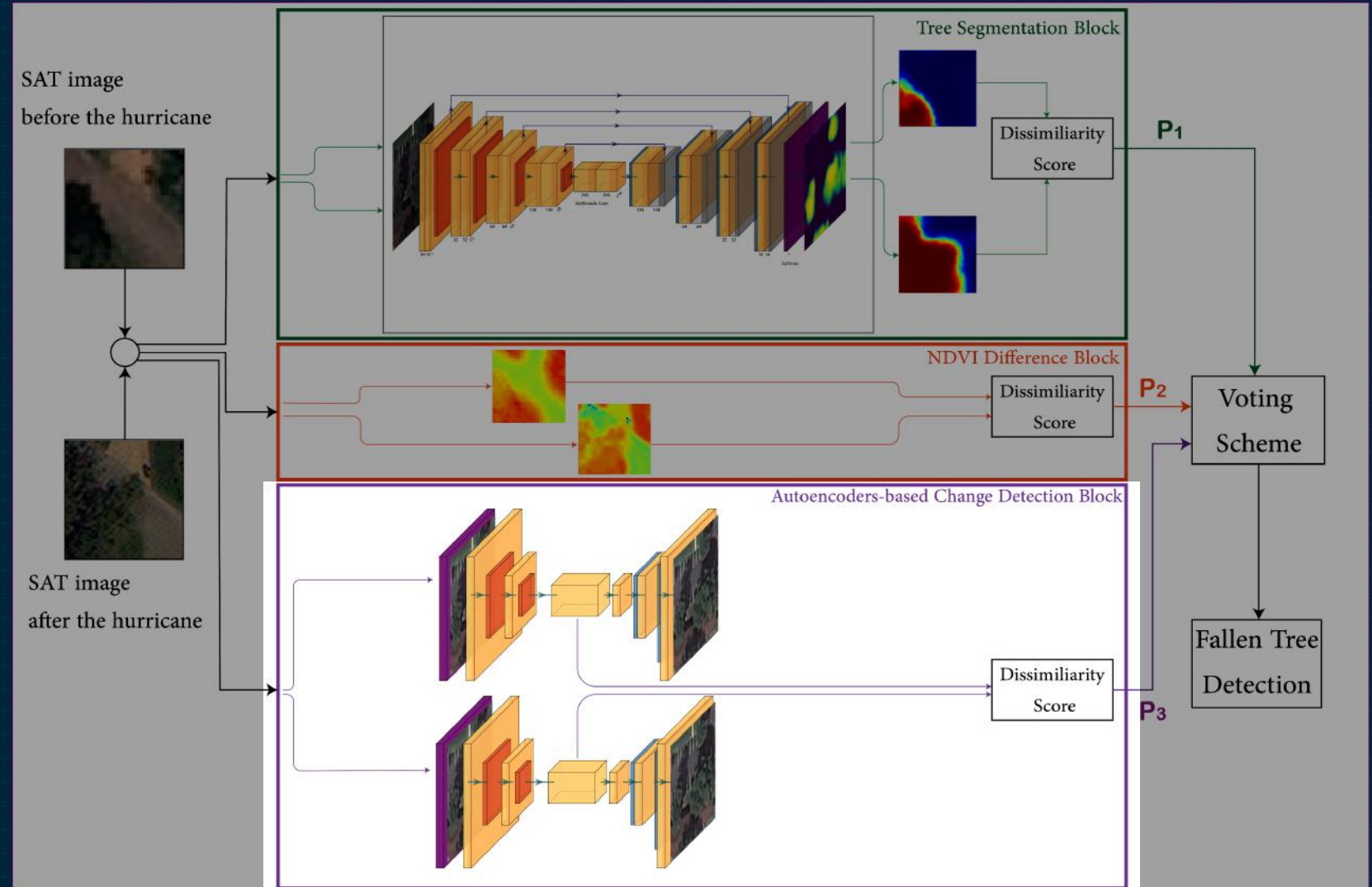
Reconstruction loss term

Regularization term



The dissimilarity score  $D_{VAE}$ :

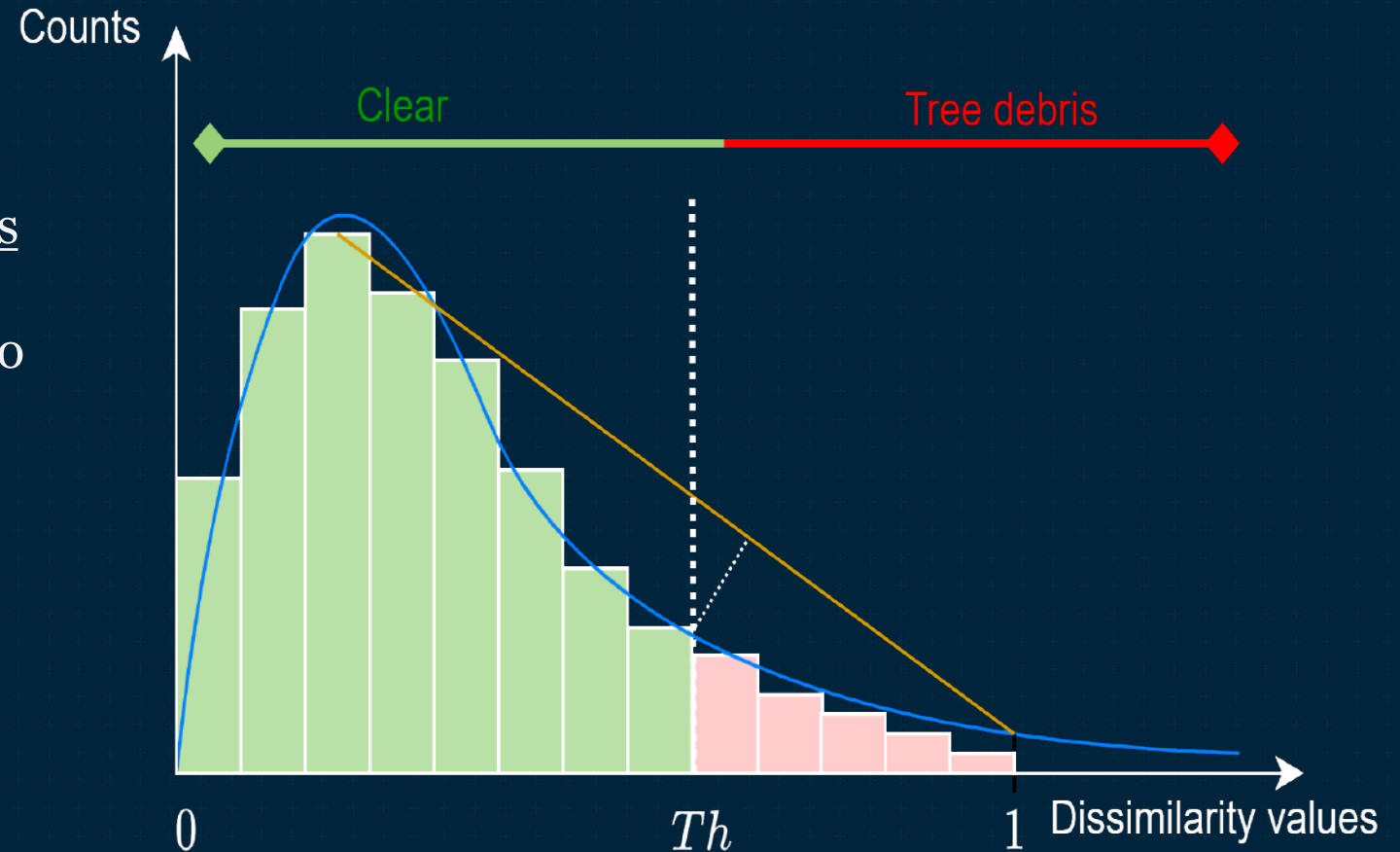
$$D_{VAE} = |F_{aft} - F_{bfr}|_2$$



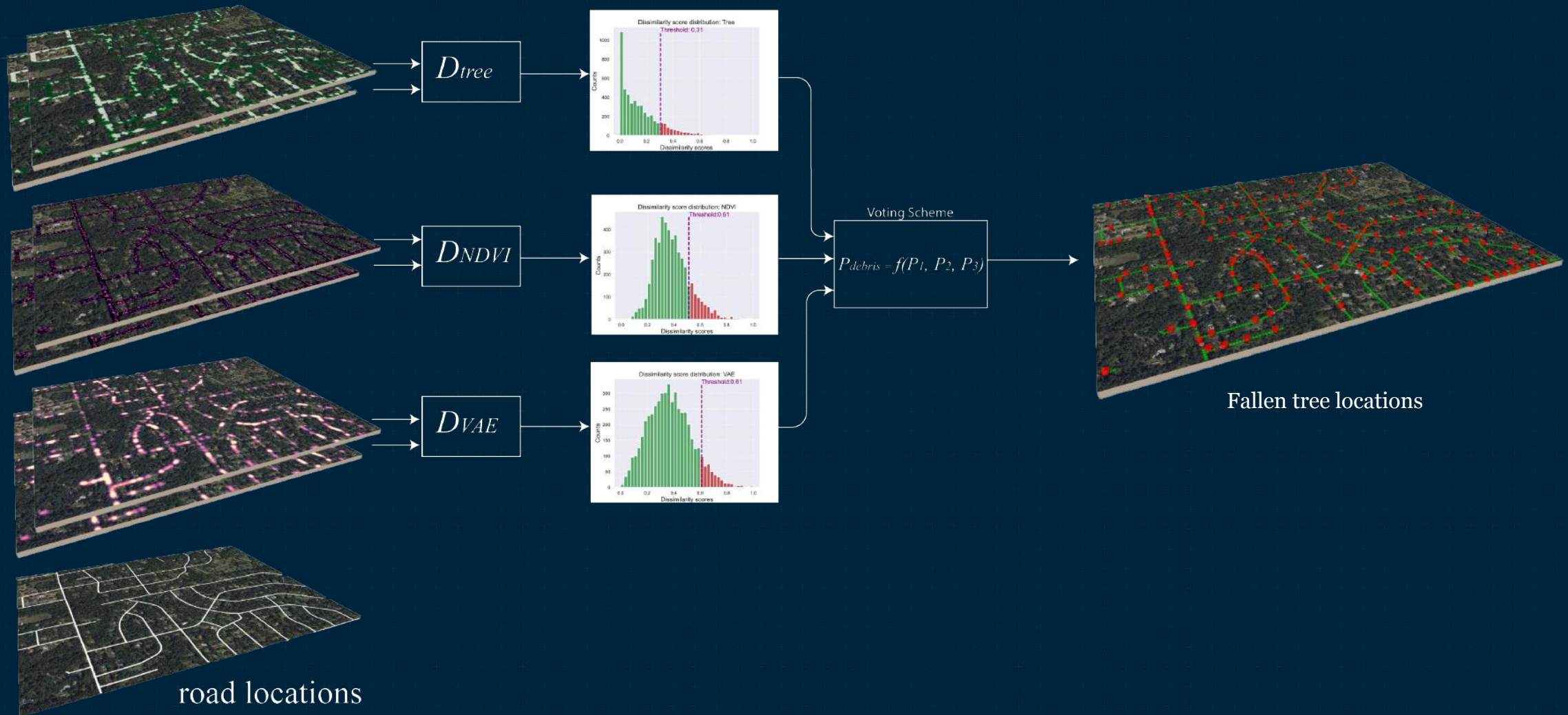


# Fallen Tree Detection Block

- Dissimilarity score histograms ( $D_{tree}$ ,  $D_{NDVI}$ ,  $D_{VAE}$ ) are unimodal distributions where one group (no-fallen tree) dominates the histogram with respect to the secondary group (fallen tree).
- We used the maximum deviation method to compute a threshold and divide the histogram in two parts.

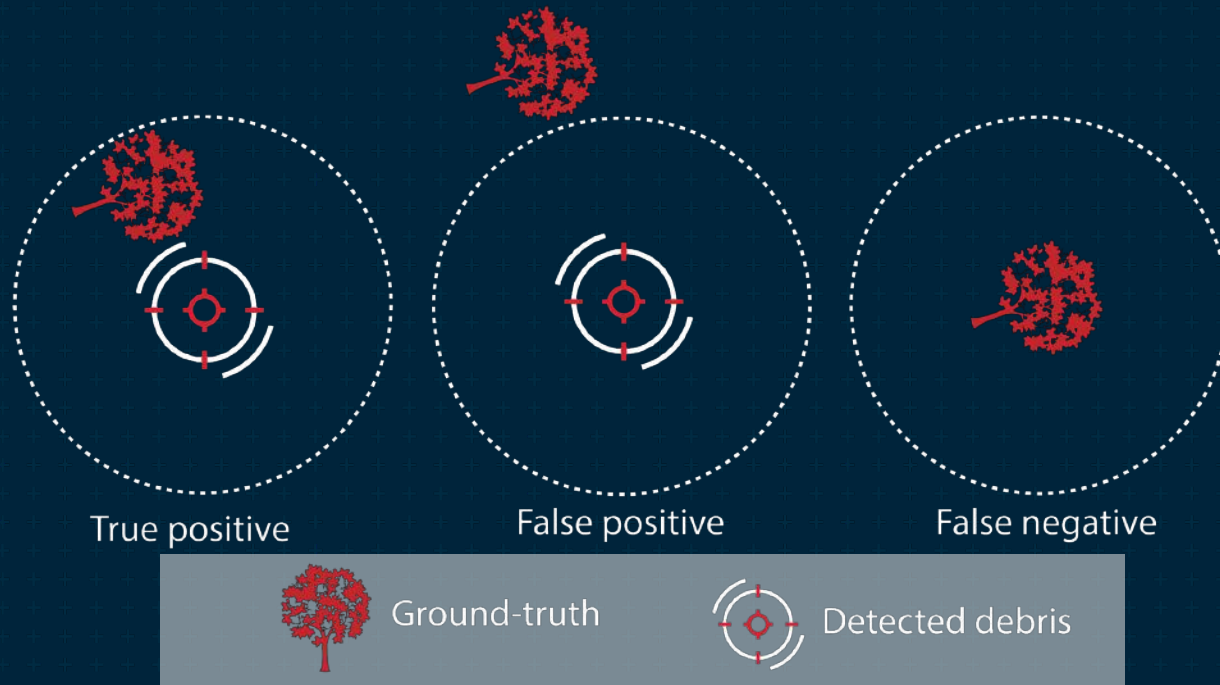


# Results





# Results



Algorithm	F1-score
Our approach	<b>0.859</b>
Sparse AEs <a href="#">[1]</a>	0.642
Joint AEs <a href="#">[2]</a>	0.744
CNN <a href="#">[3]</a>	0.821
GLCM+SVM <a href="#">[4]</a>	0.748
LBP+SVM <a href="#">[5]</a>	0.757

$$F1score = \frac{2(Recall + Precision)}{(Recall \cdot Precision)}$$



# Pre-Storm Assessment (Preparedness)





# Vulnerability Formulation

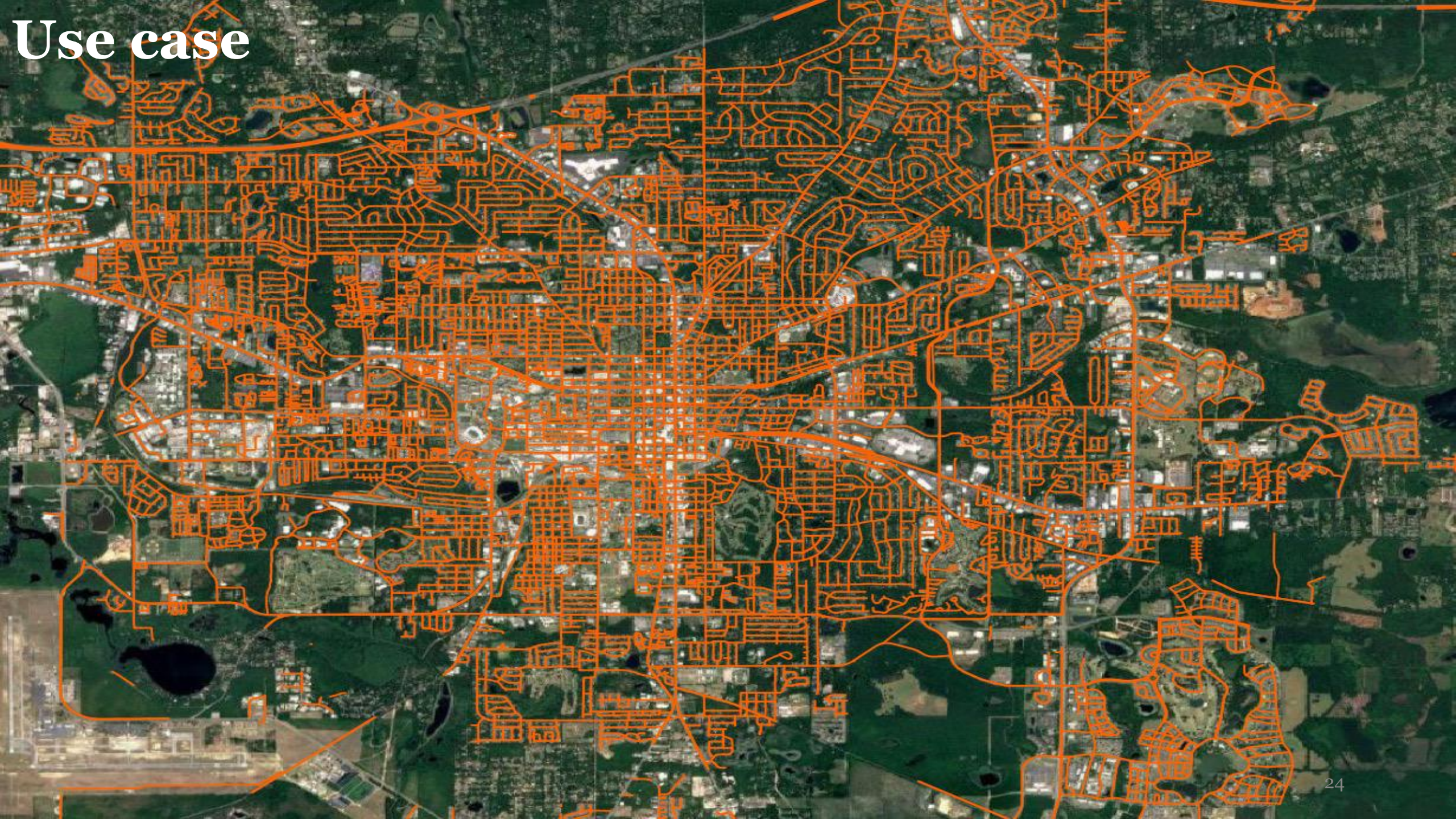
The infrastructure vulnerability is calculated as a combination of vegetation exposure to roadway  $E$  and the impact ( $I$ ) of a roadway closure

$$\begin{aligned} &Vulnerability(V) \\ &= Impact(I) \times Vegetation Exposure (E) \end{aligned}$$

In our study we are interested in estimating the roadway vulnerabilities against storms

- $E \propto$  tree density, tree height, tree health, ...
- $I \propto$  network topology, traffic amount, number of citizens affected,...

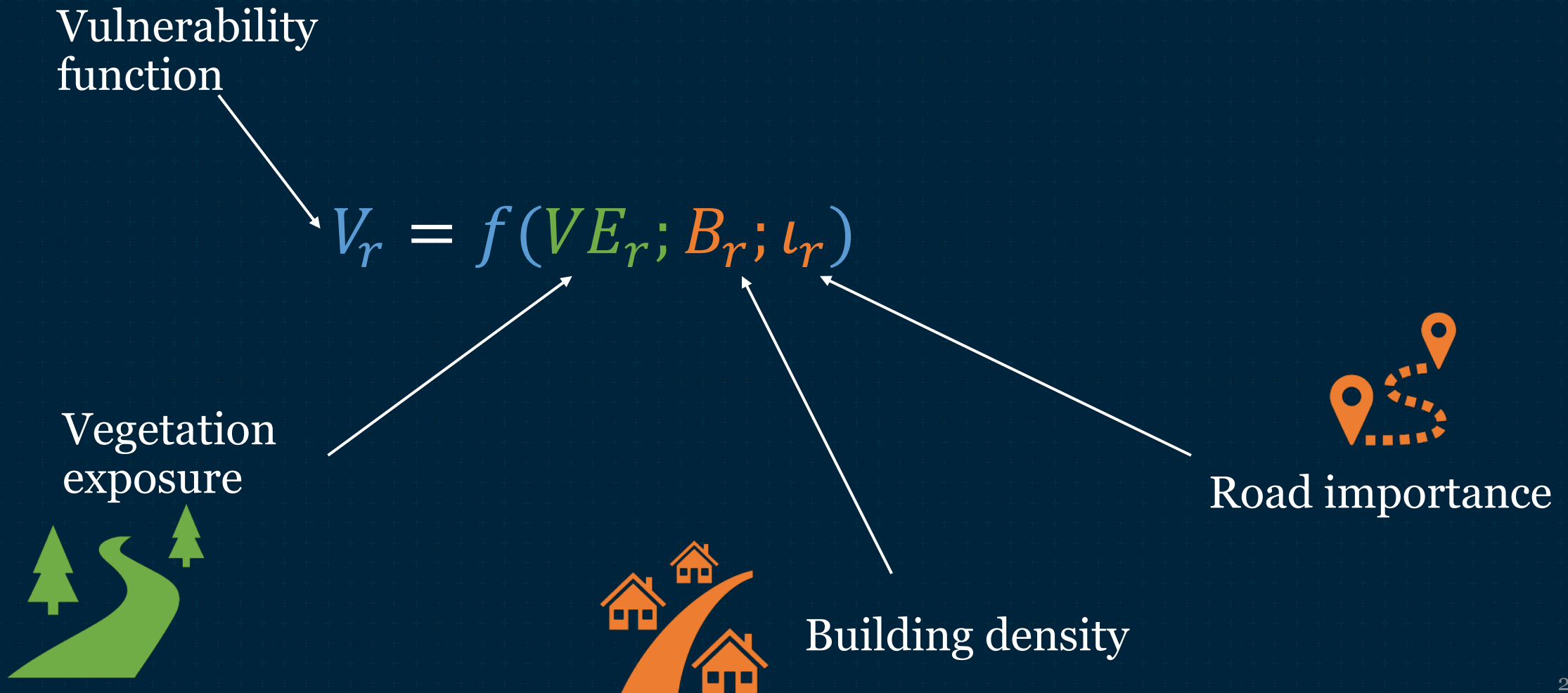




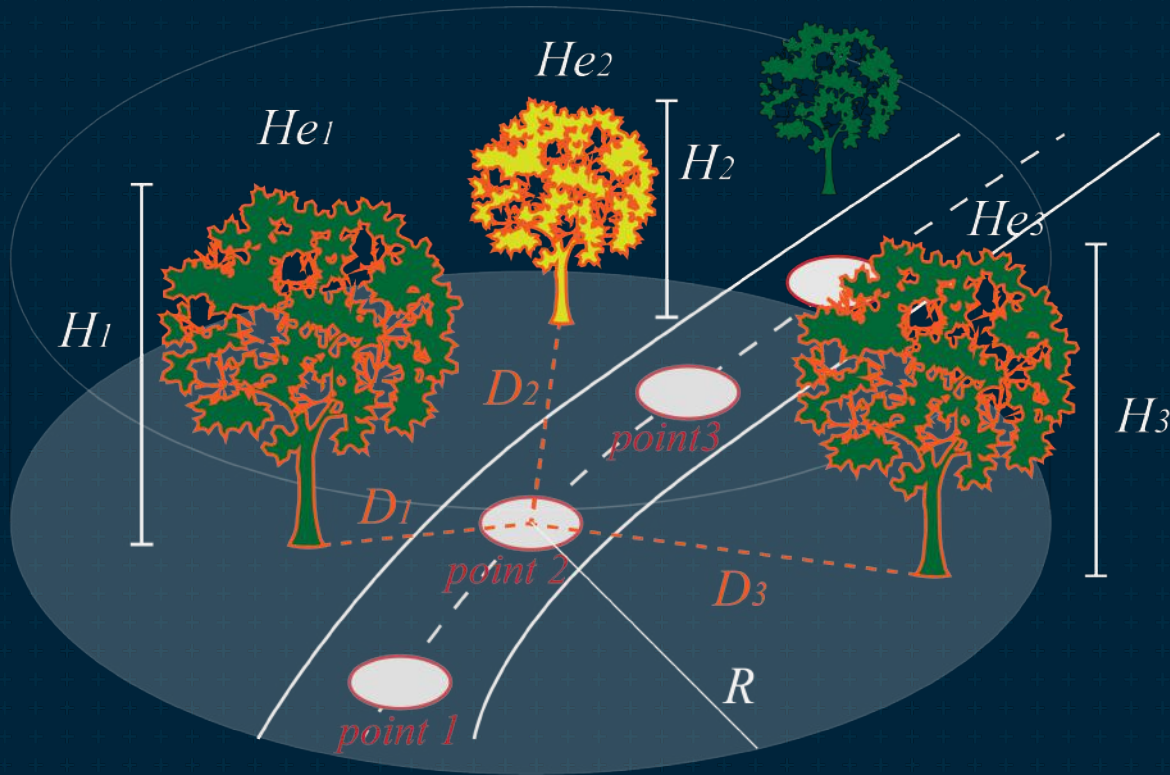
# Use case



# Vulnerability Model for Each Road $r$

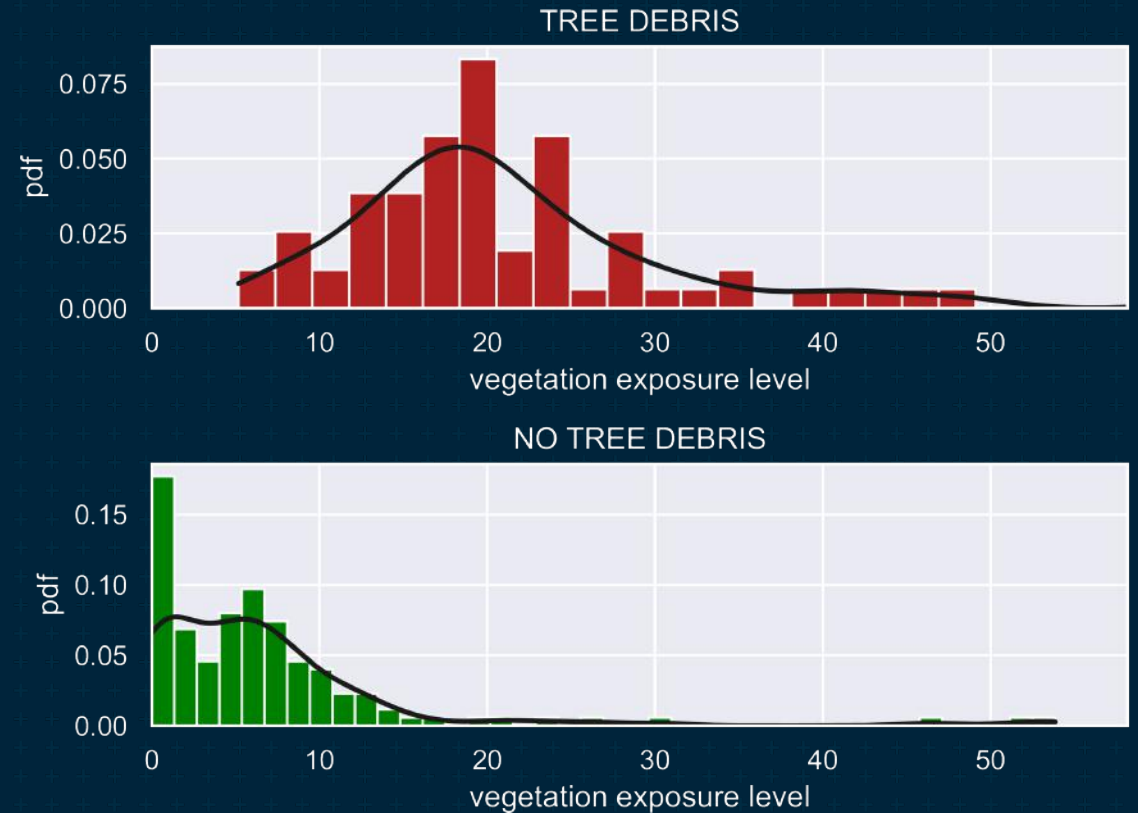


# Vegetation Exposure



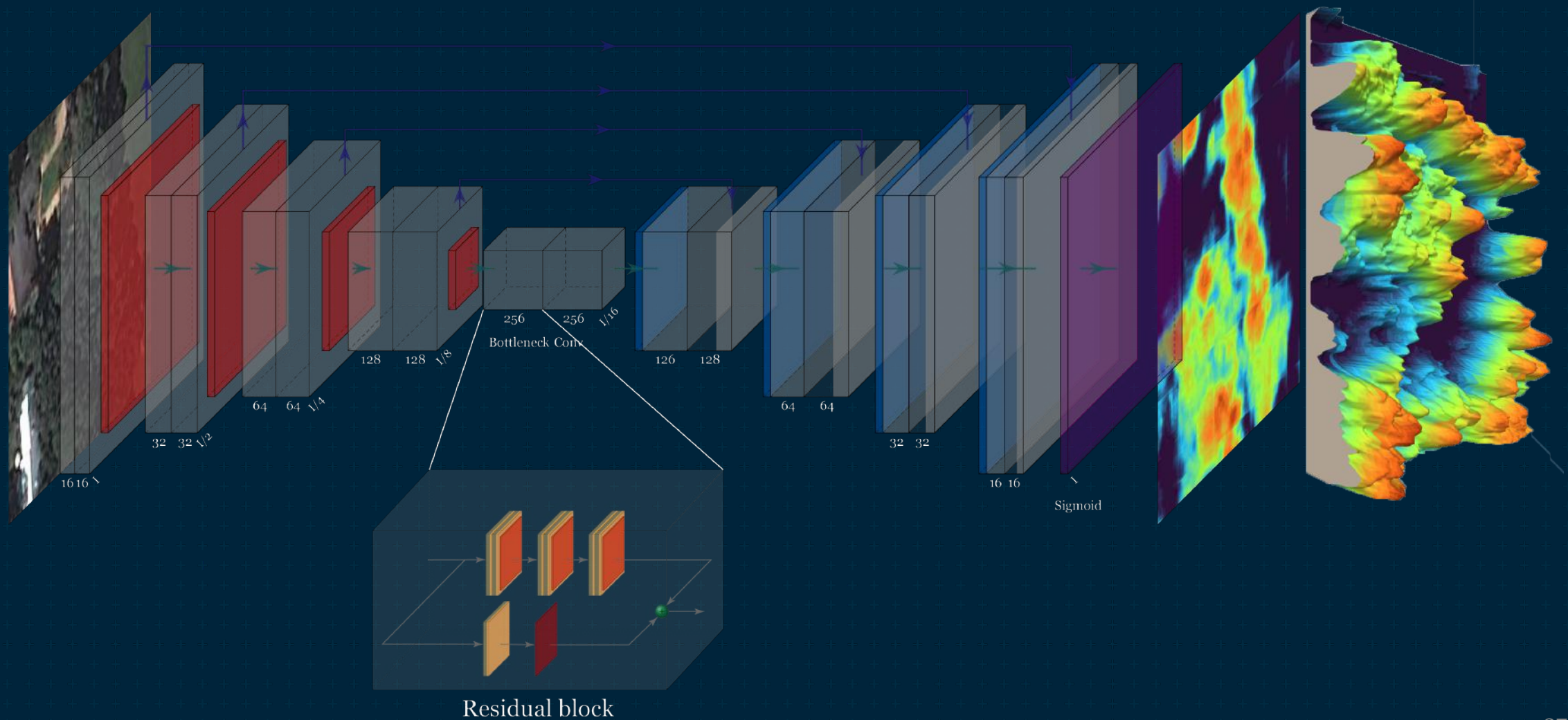
$$VE_{road} = \max(VE_{point}) \quad \forall point \in road$$

$$VE_{point} = f(tree\_param)$$





# Vegetation Height Estimation

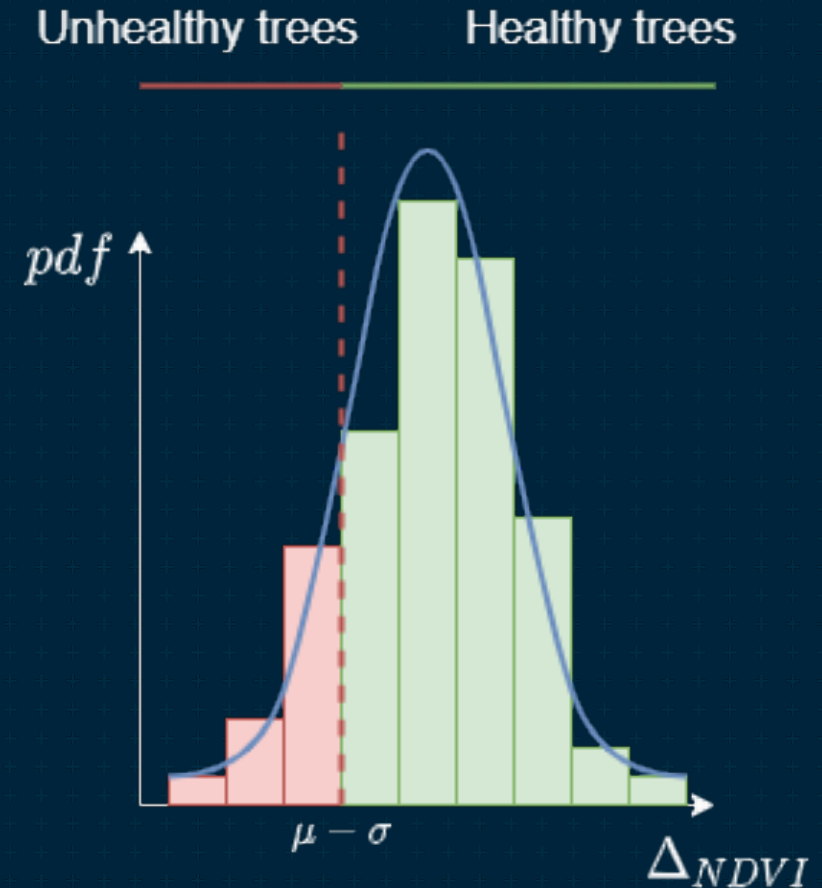


# Vegetation Health Estimation

Normalized Difference Vegetation Index (NDVI) is computed as:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$$

1. Compute NDVI from multi-temporal images
2. Compute the mean value of NDVI over the year
3. Compute  $\Delta NDVI$  between years

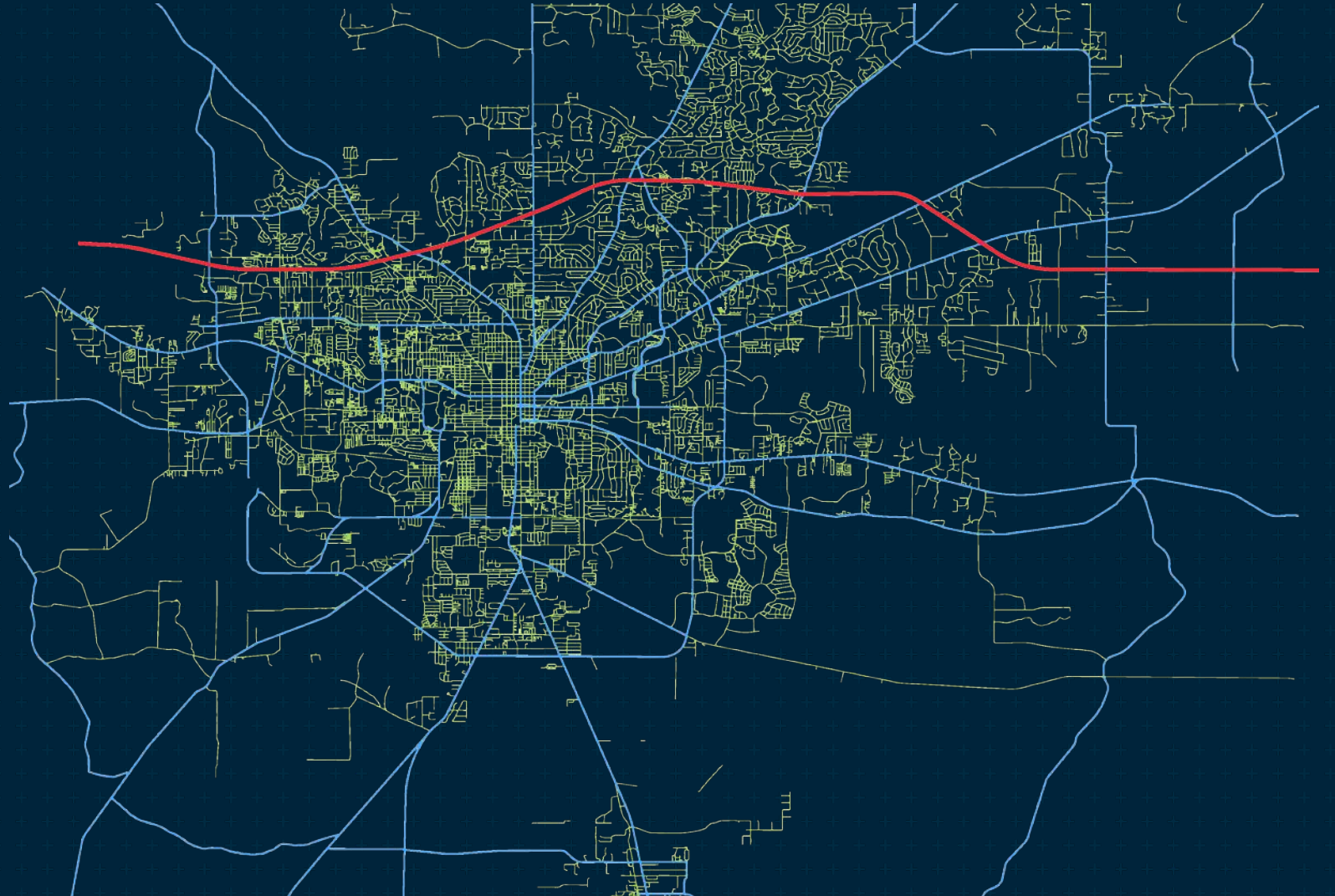




# Roadway Importance

## A) Roadway types:

- National road
- County road
- Normal road



# Roadway Importance

B) Betweenness Centrality over edge, weighted by travel time :

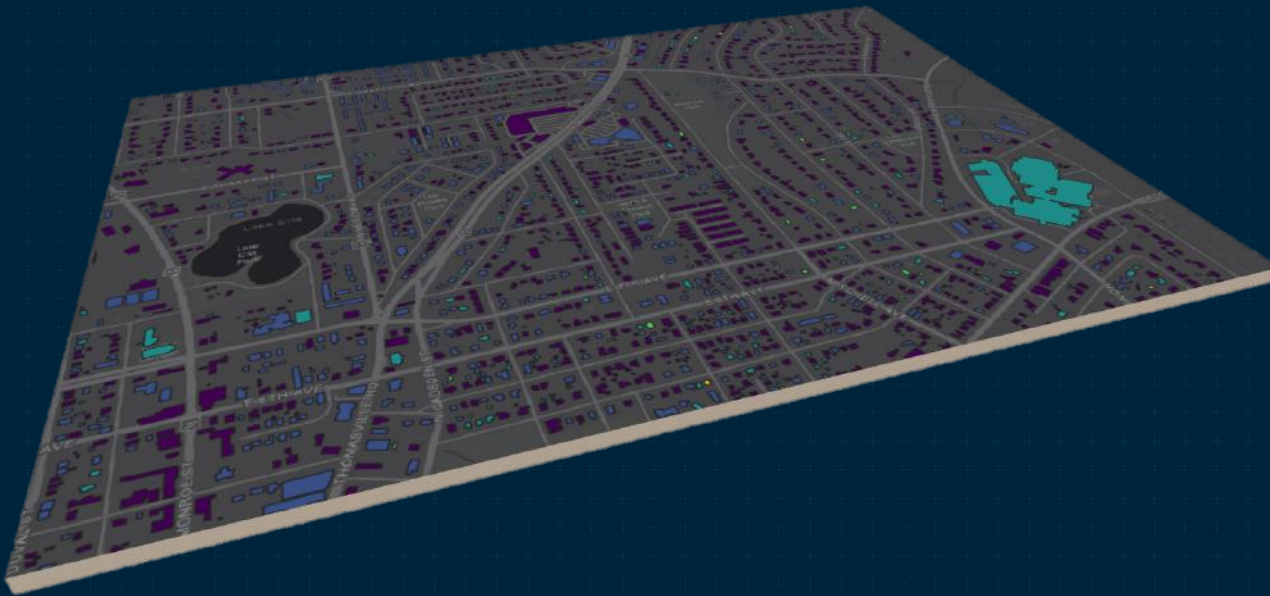
$$c_B(e) = \sum_{s,t \in V} \frac{\sigma(s,t|e)}{\sigma(s,t)}$$

$V$  is the set of nodes,  
 $\sigma(s,t|e)$  is the number of paths  
minimizing the traffic time between  
the two nodes, and  
 $\sigma(s,t)$  is the number of paths  
between the two nodes





# Buildings

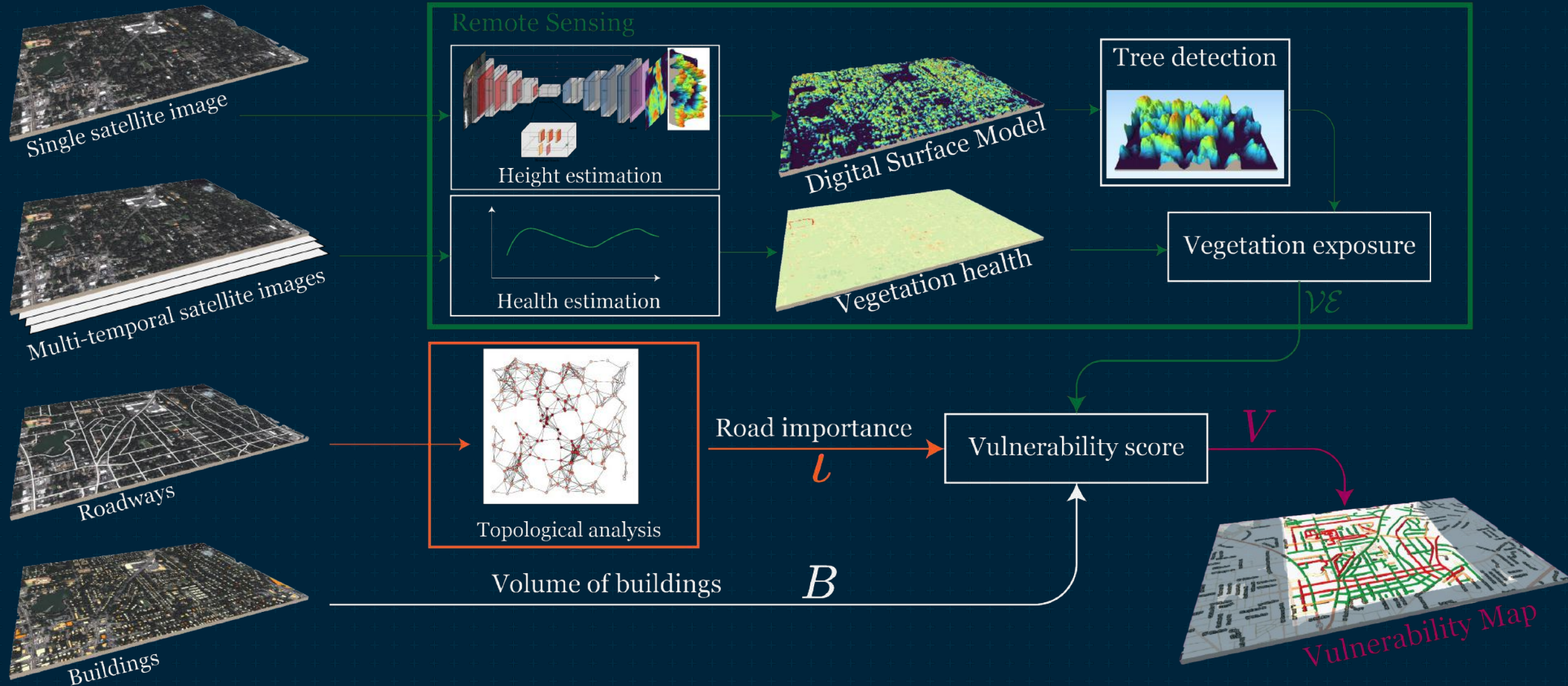


- Buildings footprints from OSM data + height from Lidar
- Critical infrastructures (hospitals, emergency shelters, fire-fighter stations)



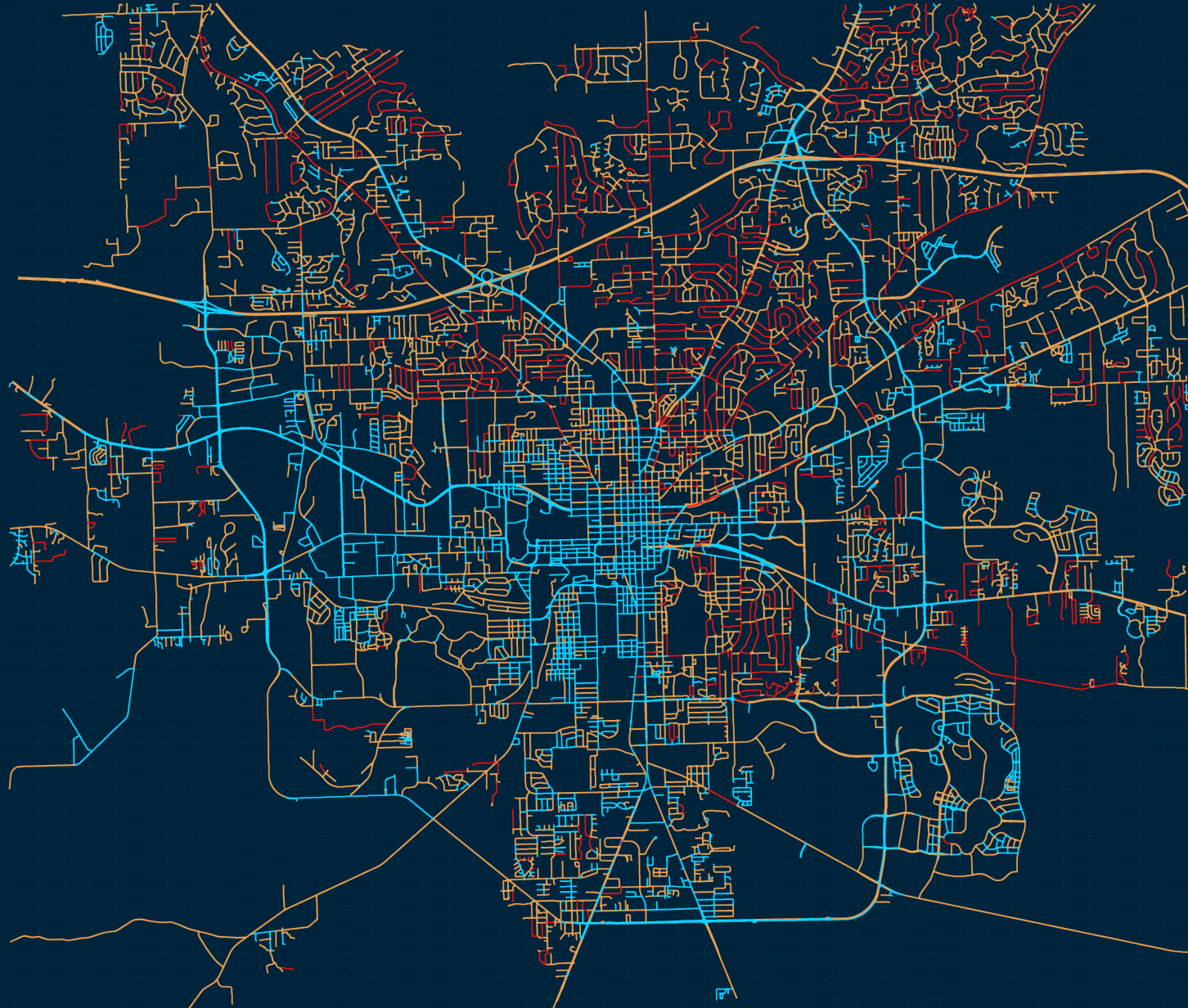
Buildings footprints can also be retrieved directly from satellite images

# Our Method





# Vulnerability Map



# Publications

1. M. Gazzea et al., "Automated Satellite-Based Assessment of Hurricane Impacts on Roadways," in IEEE Transactions on Industrial Informatics, vol. 18, no. 3, pp. 2110-2119, 2022.
2. M. Gazzea et al., "Automated Power Lines Vegetation Monitoring using High-Resolution Satellite Imagery," in IEEE Transactions on Power Delivery, vol. 37, no. 1, pp. 308-316,, 2022.
3. A. Karaer et al., "Remote sensing-based comparative damage assessment of historical storms and hurricanes in Northwestern Florida," in International Journal of Disaster Risk Reduction, vol. 72, pp. 102857, 2022.
4. M. Gazzea et al. Satellite-based Hurricane Risk Assessment for Roadways via Vegetation 3D Modeling and Building Detection. In Transportation Research Board 101th Annual Meeting 2022.
5. A. Karaer et al., "Post-Hurricane Vegetative Debris Assessment Using Spectral Indices Derived from Satellite Imagery," in Transportation Research Record, vol. 2675, pp. 504-523, SAGE, 2021.
6. M. Gazzea et al. Post-hurricanes roadway closure detection using satellite imagery and semi-supervised ensemble learning. In Transportation Research Board 100th Annual Meeting 2021.
7. M. Gazzea et al, "Automated 3D Vegetation Detection Along Power Lines using Monocular Satellite Imagery and Deep Learning," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, 2021, pp. 3721-3724.



# Thank You

Visit us at [www.ci2lab.com](http://www.ci2lab.com)

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