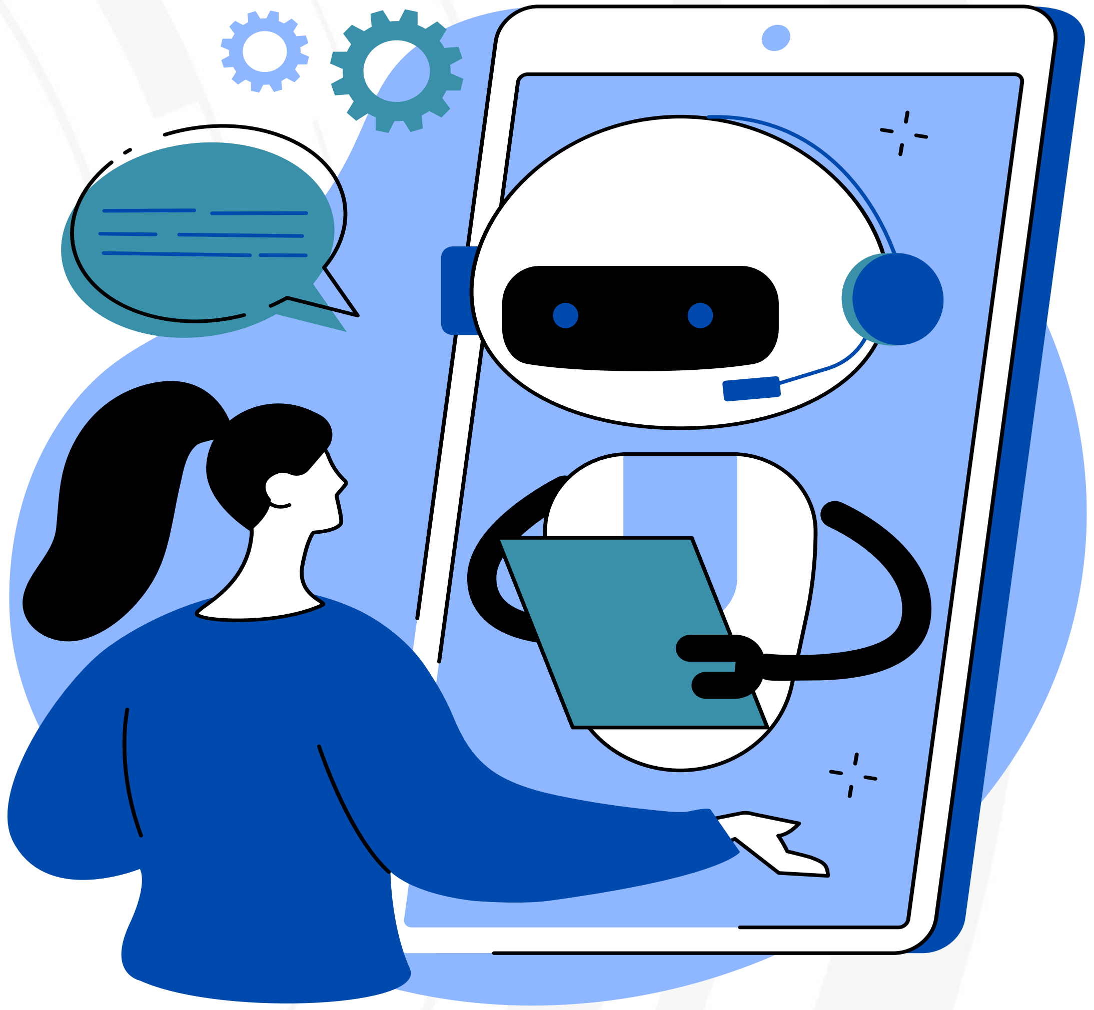
# Automating the Future

## AI/ML in Compound Flooding and H&H Modeling



NUECES BASIN Summit

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OPEN *the* APERTURE

# Outline

- Why does AI matter?
- AI-driven High Water Mark Estimation
- ML to Map the Unmapped
- Transferability of AI Flood Models

**Maryam Pakdehi, PhD**

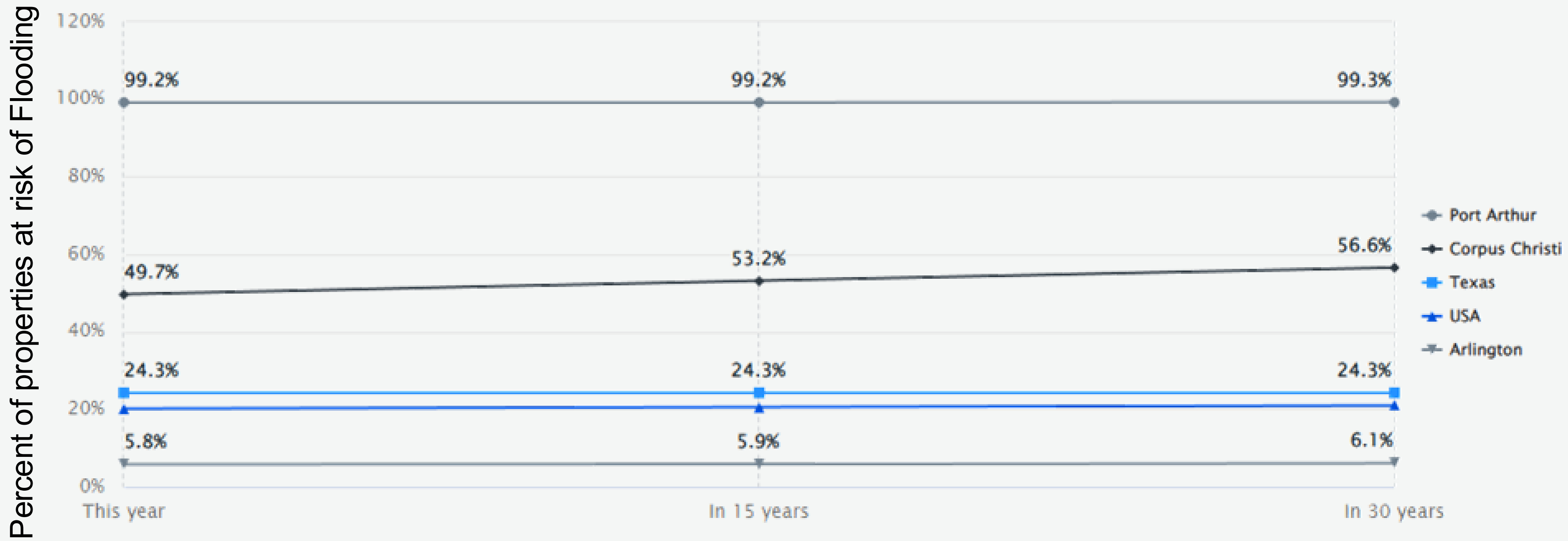
Civil Associate – Water Resources

**Shubham Jain, PhD, EIT**

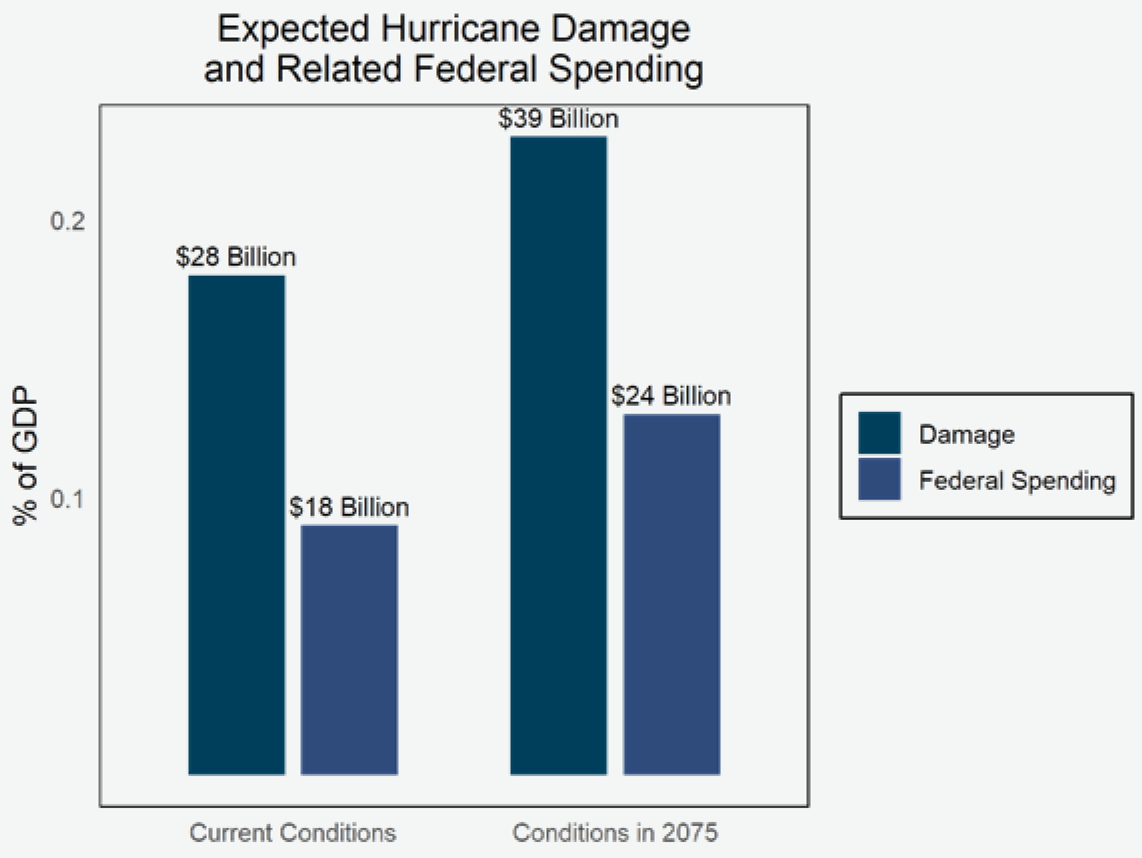
Civil Associate – Water Resources

# Why does AI matter?

# Flood Risk Is Rising




*Source – FirstStreet*




*Source - ASFPM*

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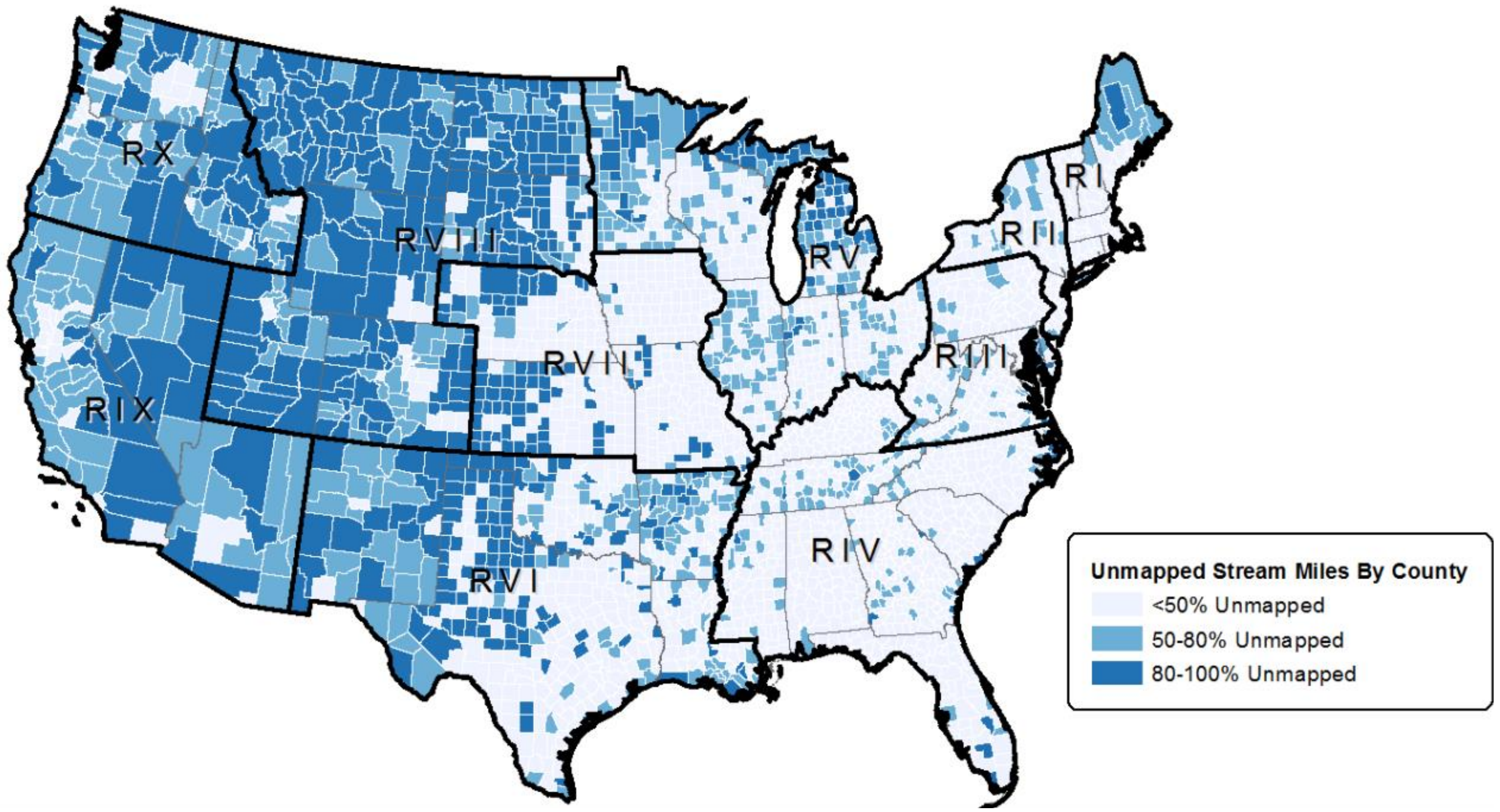
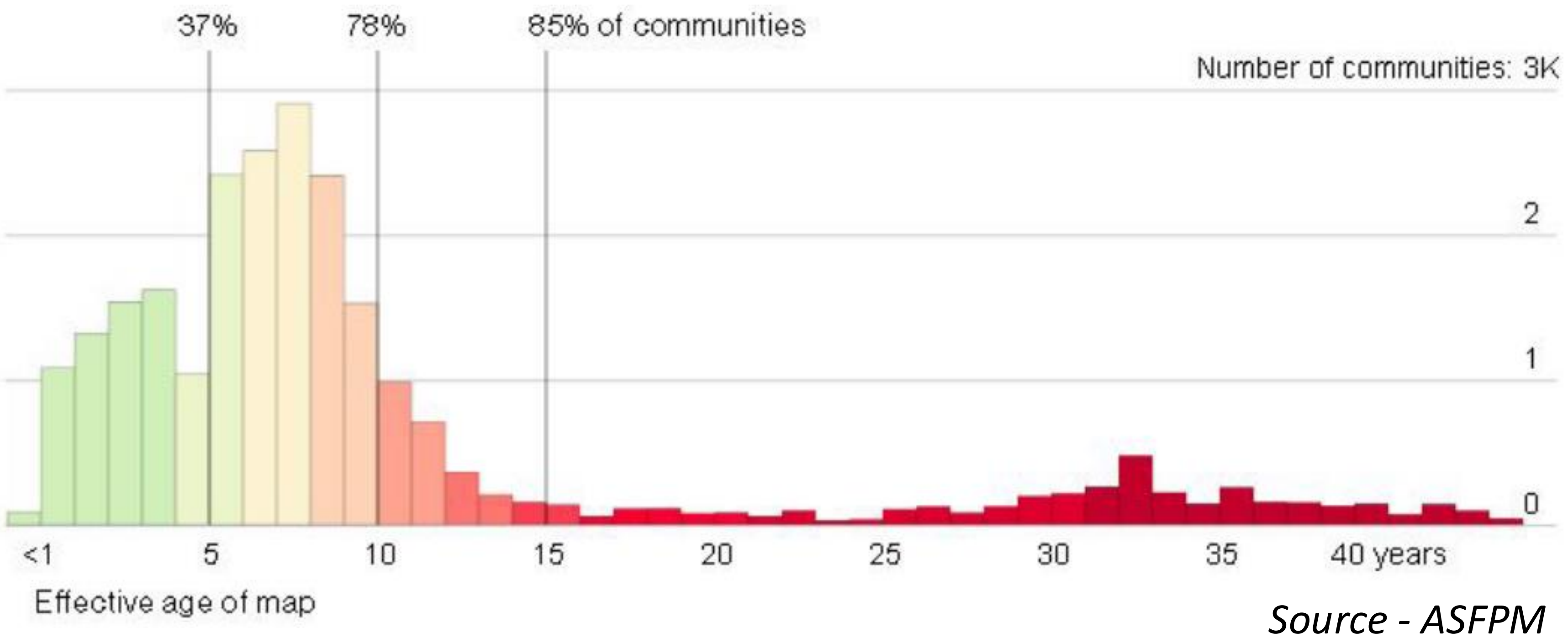
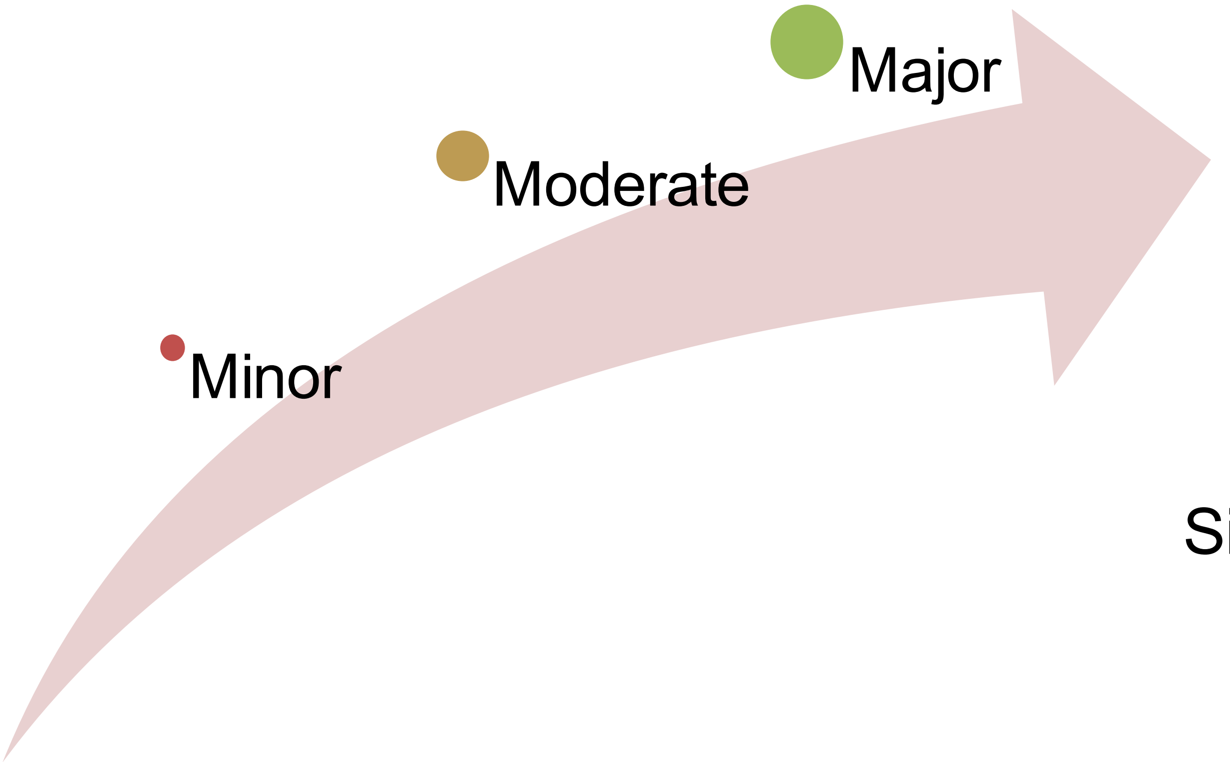
# Are Our Models Keeping Up?




*Source - ASFPM*

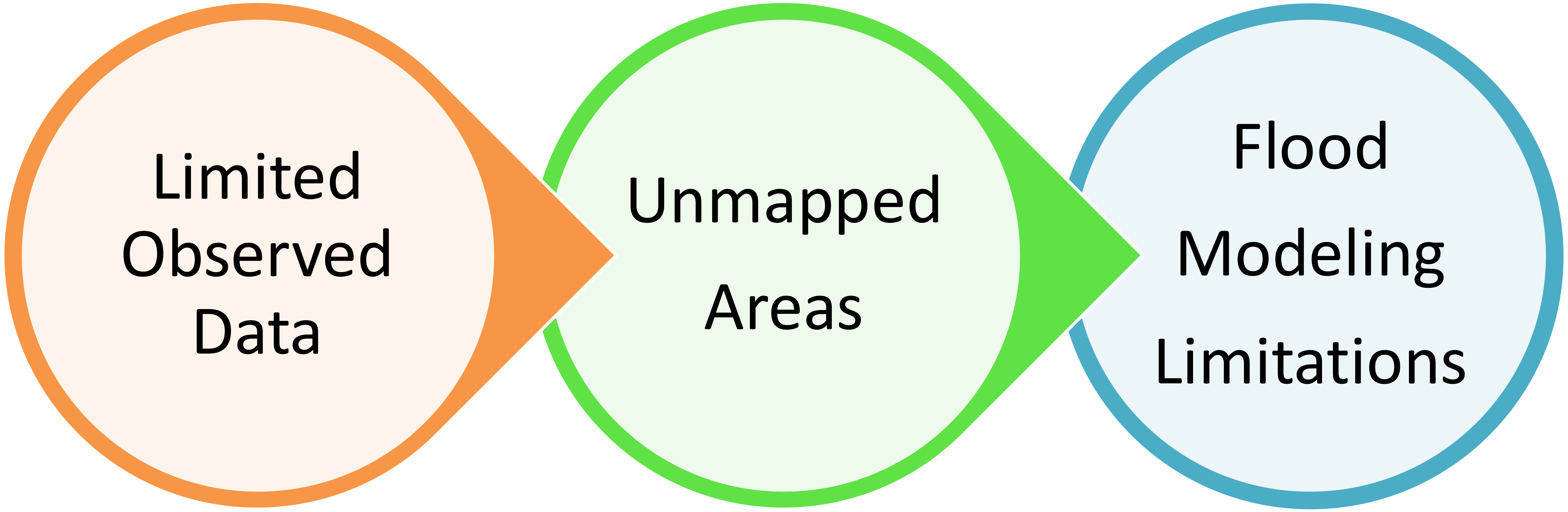
# Flood Damages




| | Globe | US |
|---|---|---|
| Since 1980: | + $1 trillion | $ 36.2 billion |
| | 220,000 fatalities | 26.4% by 2050 |

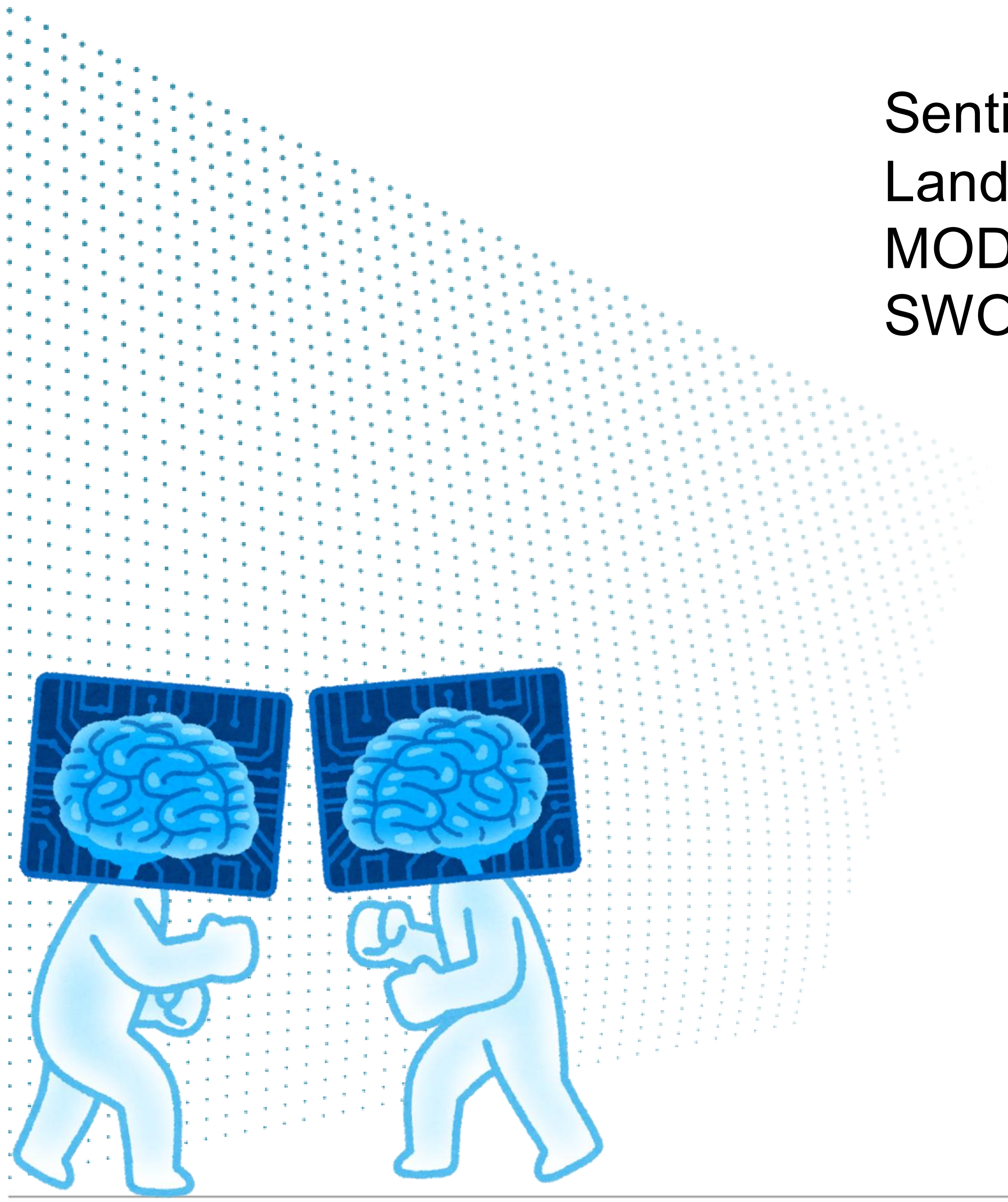
→ Mitigation Plans

# Challenges


Limited Observed Data
Unmapped Areas
Flood Modeling Limitations

# Challenges

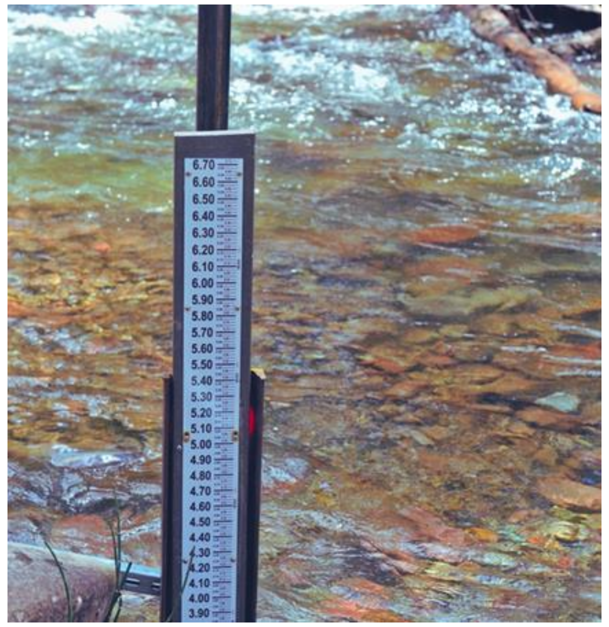
Limited Observed Data



Sentinel
Landsat
MODIS
SWOT

11,340

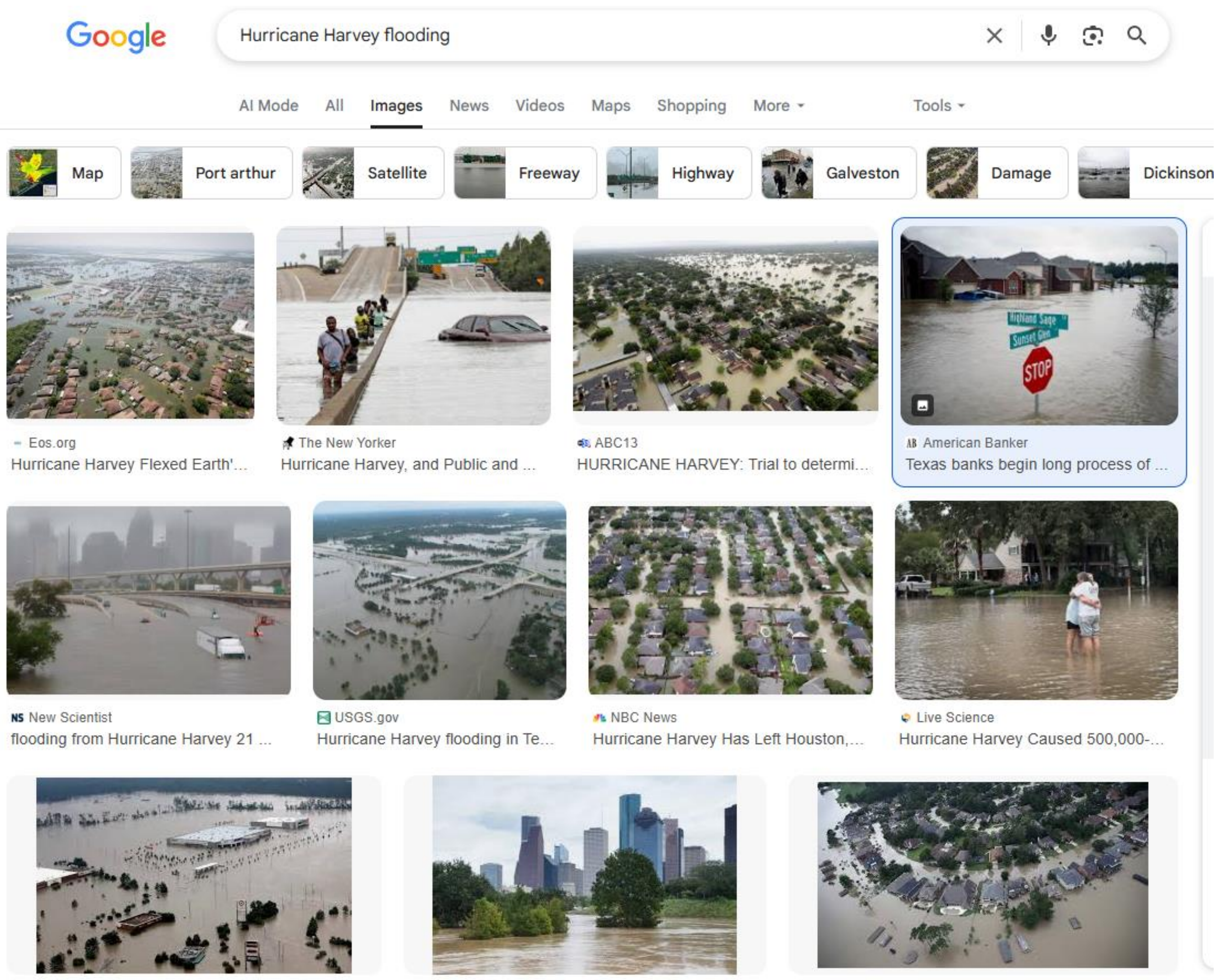
+160,000

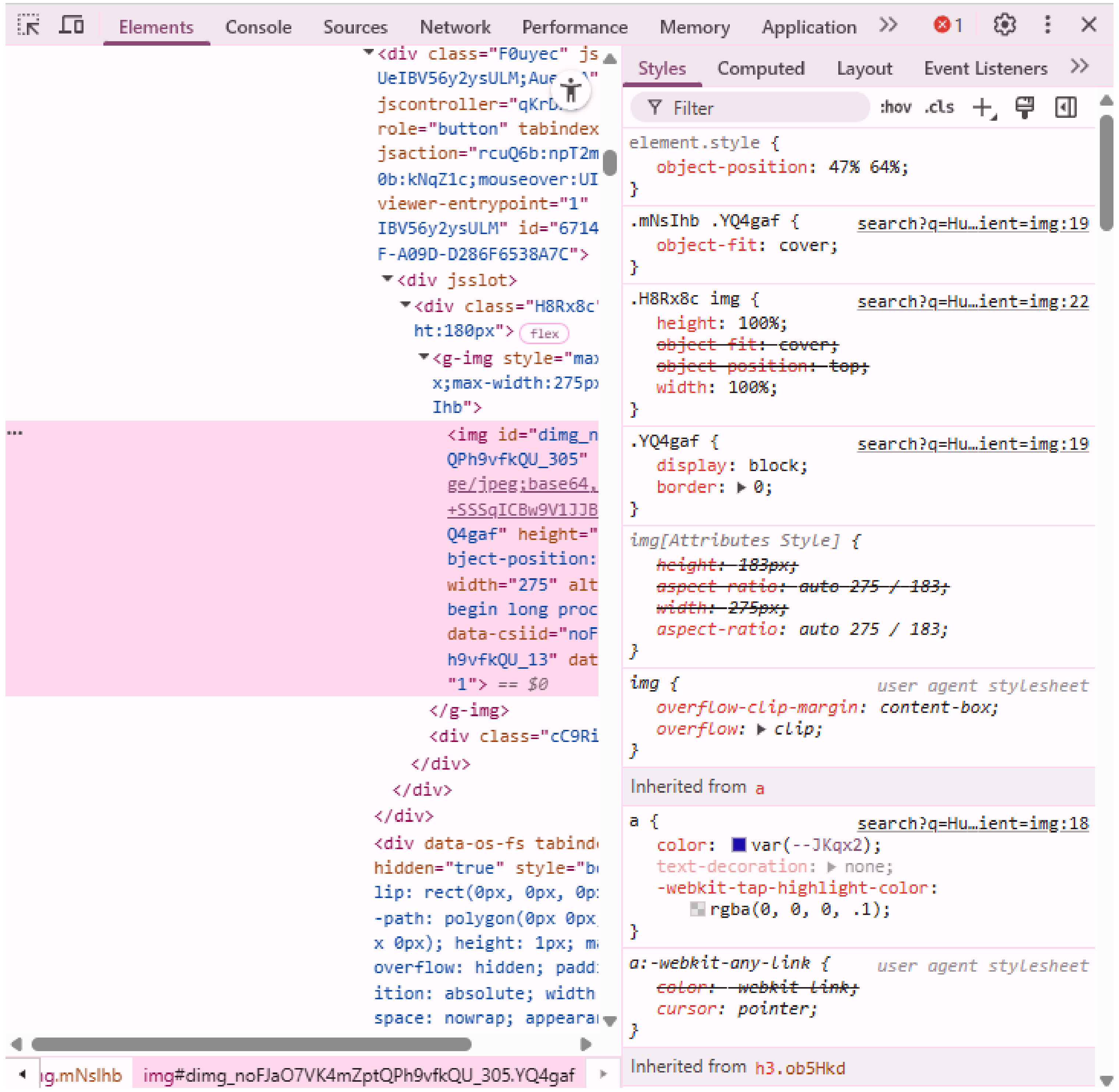


# AI-Driven High Water Mark Estimation

# Community-sourced Flood Images

Limited Observed Data



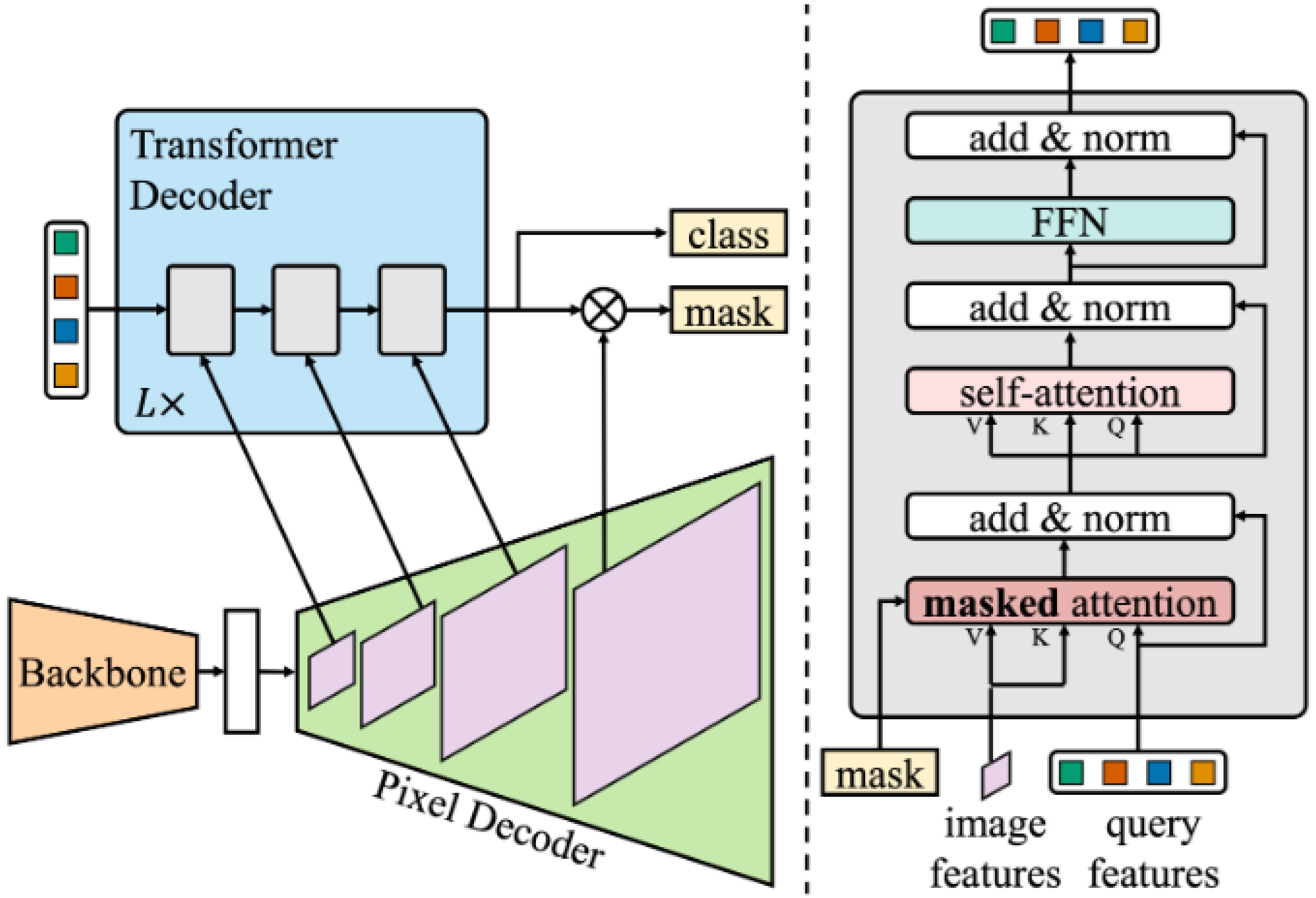
# AI-based Image Segmentation

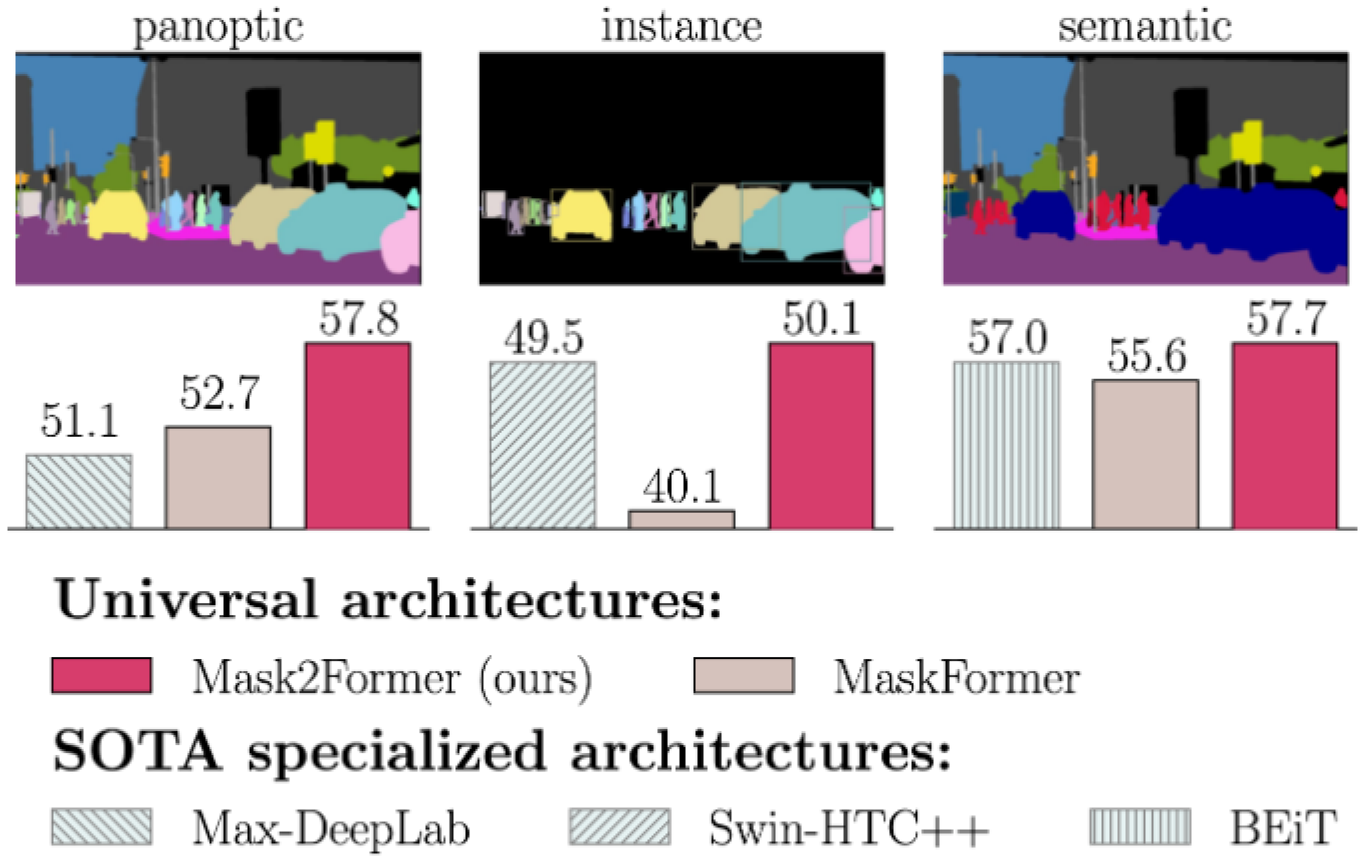
Limited
Observed
Data

**Masked-attention Mask Transformer for Universal Image Segmentation**

Bowen Cheng[1,2*] Ishan Misra[1] Alexander G. Schwing[2] Alexander Kirillov[1] Rohit Girdhar[1]
[1]Facebook AI Research (FAIR) [2]University of Illinois at Urbana-Champaign (UIUC)
https://bowenc0221.github.io/mask2former

## Mask2Former



# AI-based Image Segmentation

Limited Observed Data

# Flood Depth Estimation using GPT 4o Model

Limited Observed Data

Akinboyewa *et al. Computational Urban Science* (2024) 4:12
https://doi.org/10.1007/s43762-024-00123-3

Computational Urban Science

**ORIGINAL PAPER** **Open Access**

Check for updates

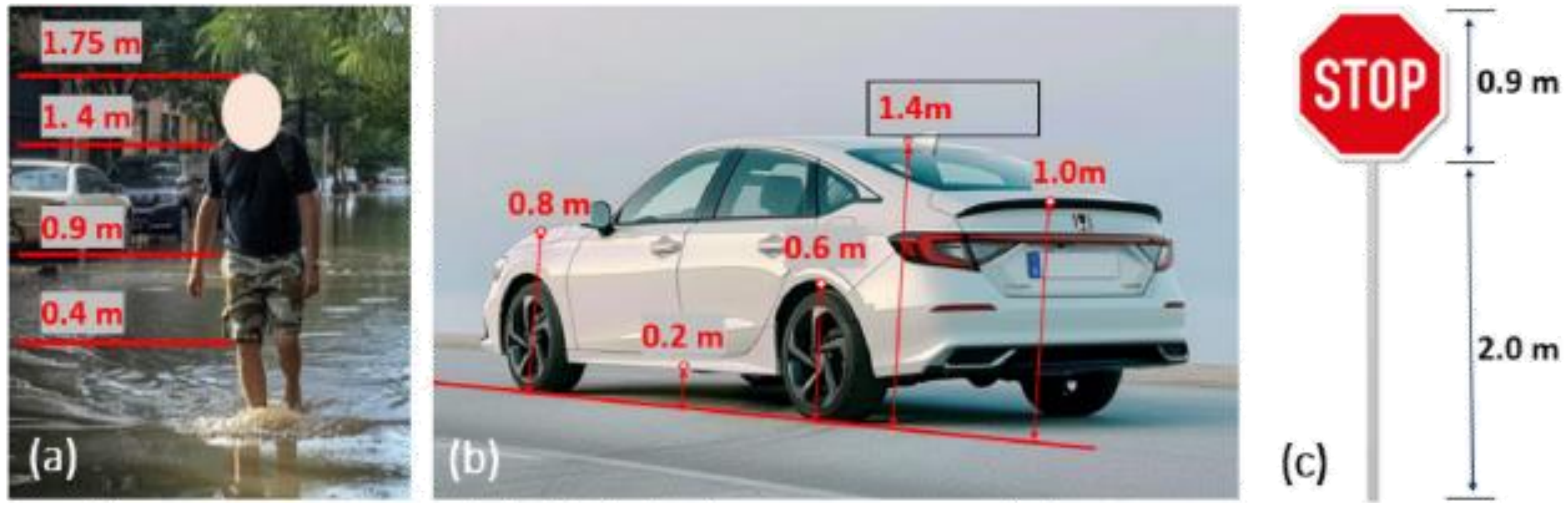
## Automated floodwater depth estimation using large multimodal model for rapid flood mapping

Temitope Akinboyewa[1], Huan Ning[1], M. Naser Lessani[1] and Zhenlong Li[1*]

**Abstract**

Information on the depth of floodwater is crucial for rapid mapping of areas affected by floods. However, previous approaches for estimating floodwater depth, including field surveys, remote sensing, and machine learning techniques, can be time-consuming and resource-intensive. This paper presents an automated and rapid approach for estimating floodwater depth from on-site flood photos. A pre-trained large multimodal model, Generative pre-trained transformers (GPT-4) Vision, was used specifically for estimating floodwater. The input data were flood photos that contained referenced objects, such as street signs, cars, people, and buildings. Using the heights of the common objects as references, the model returned the floodwater depth as the output. Results show that the proposed approach can rapidly provide a consistent and reliable estimation of floodwater depth from flood photos. Such rapid estimation is transformative in flood inundation mapping and assessing the severity of the flood in near-real time, which is essential for effective flood response strategies.

**Keywords** Flood mapping, Large multimodal model, Large language model, ChatGPT, GeoAI, Disaster management

# Automated Depth Estimation Using AI

Limited
Observed
Data


# Flooding Extent Estimation

Limited Observed Data

# Automating Geolocation of Images

Limited
Observed
Data


# Gaps in Flood Risk Mapping

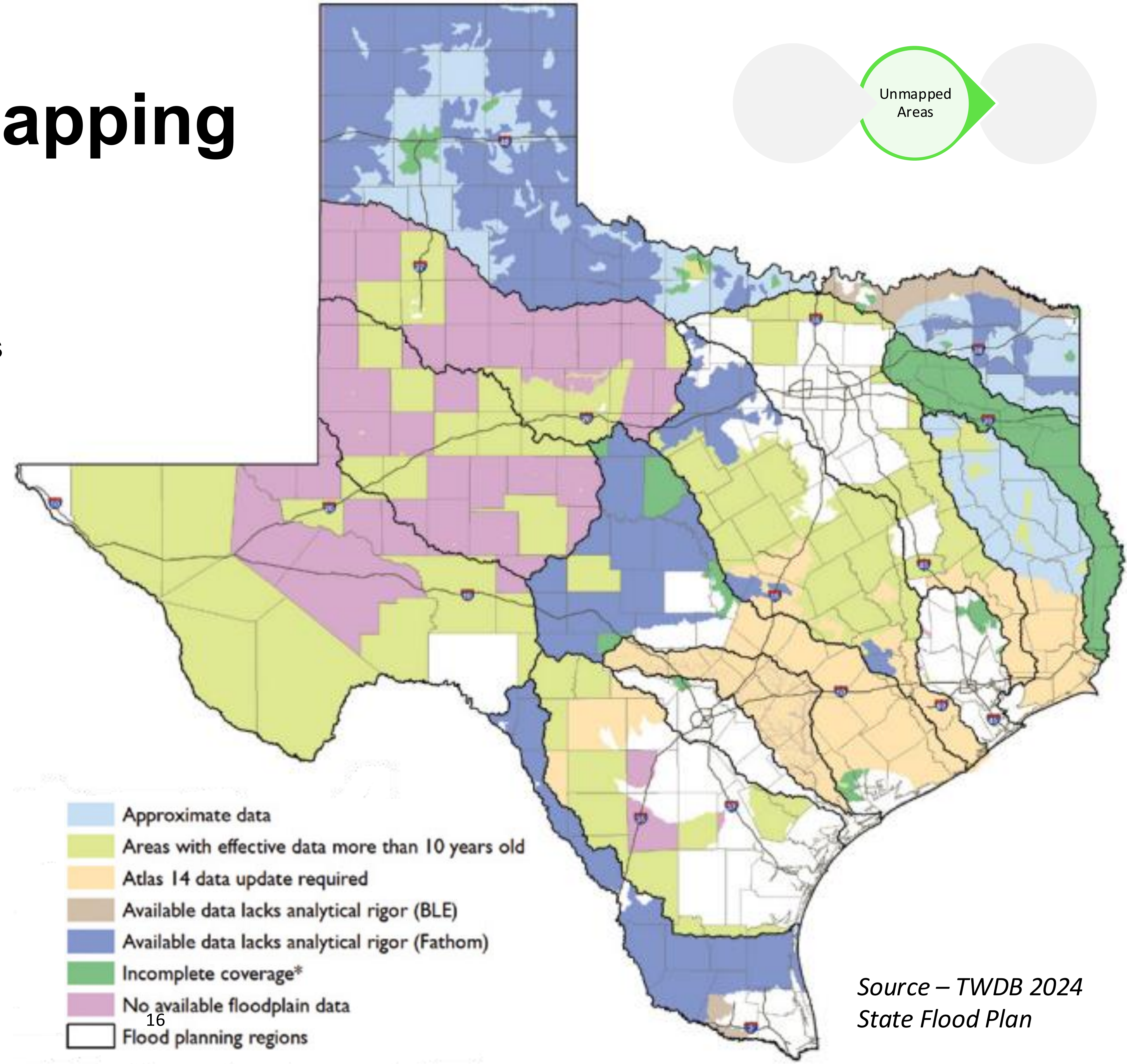
Unmapped Areas

**121** Counties in Texas do not have effective Flood Insurance Rate Maps

**4** Counties are partially mapped

**>600** Square miles of flood prone area with unknown annual chance floodplain

**>600k** Population in flood prone area with unknown annual chance floodplain




*Source – TWDB 2024 State Flood Plan*

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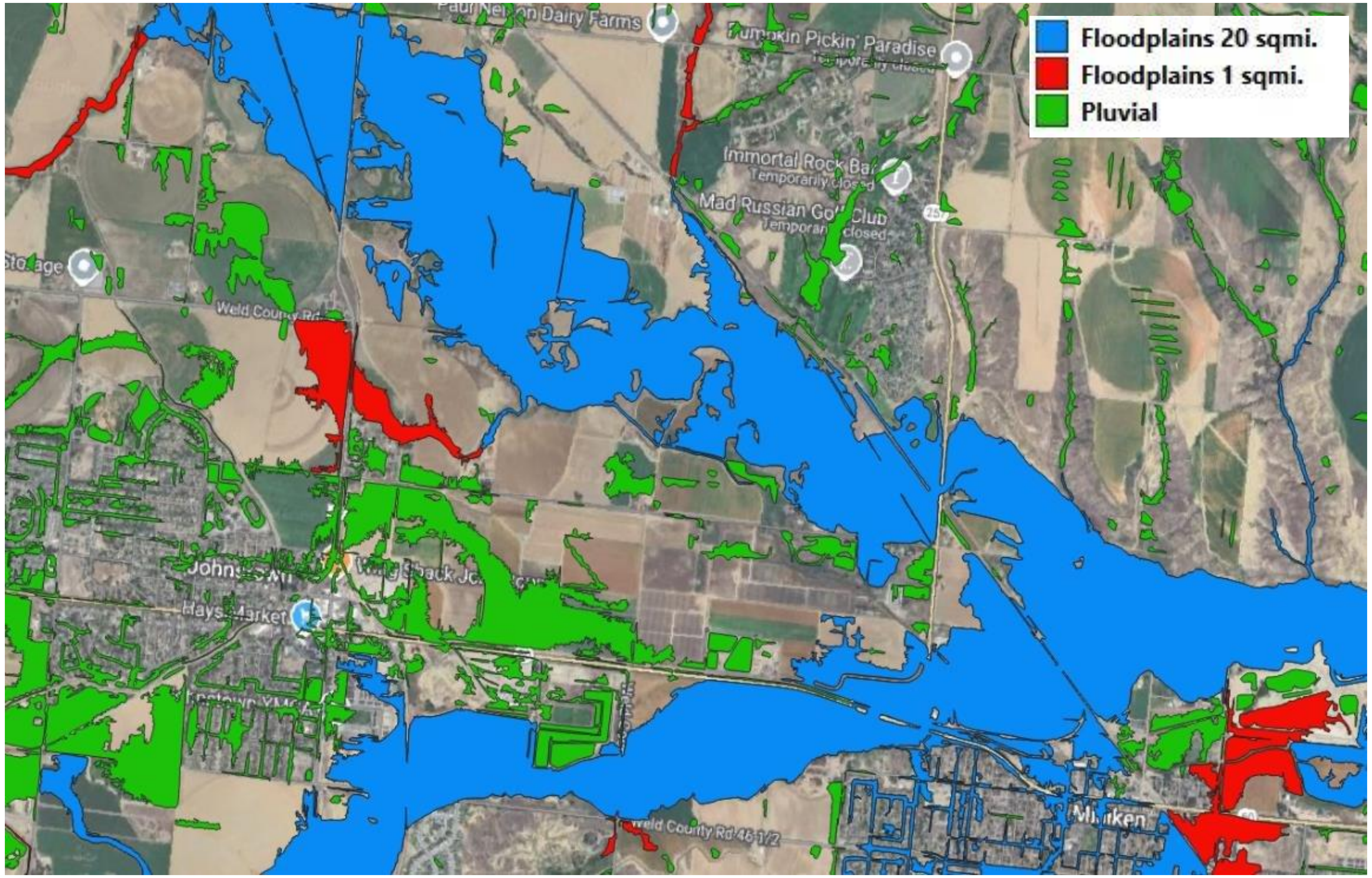
# Machine Learning to *Map the Unmapped*

# Data-driven Flood Extent Estimation

- Dry
- Pluvial
- 1 square-mile floodplains
- 20 square-mile floodplains

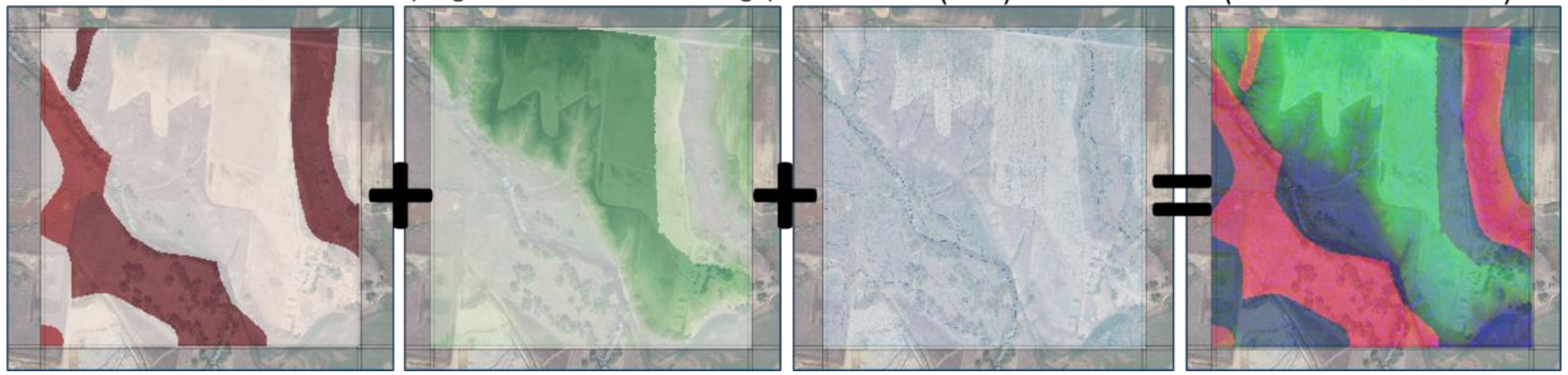


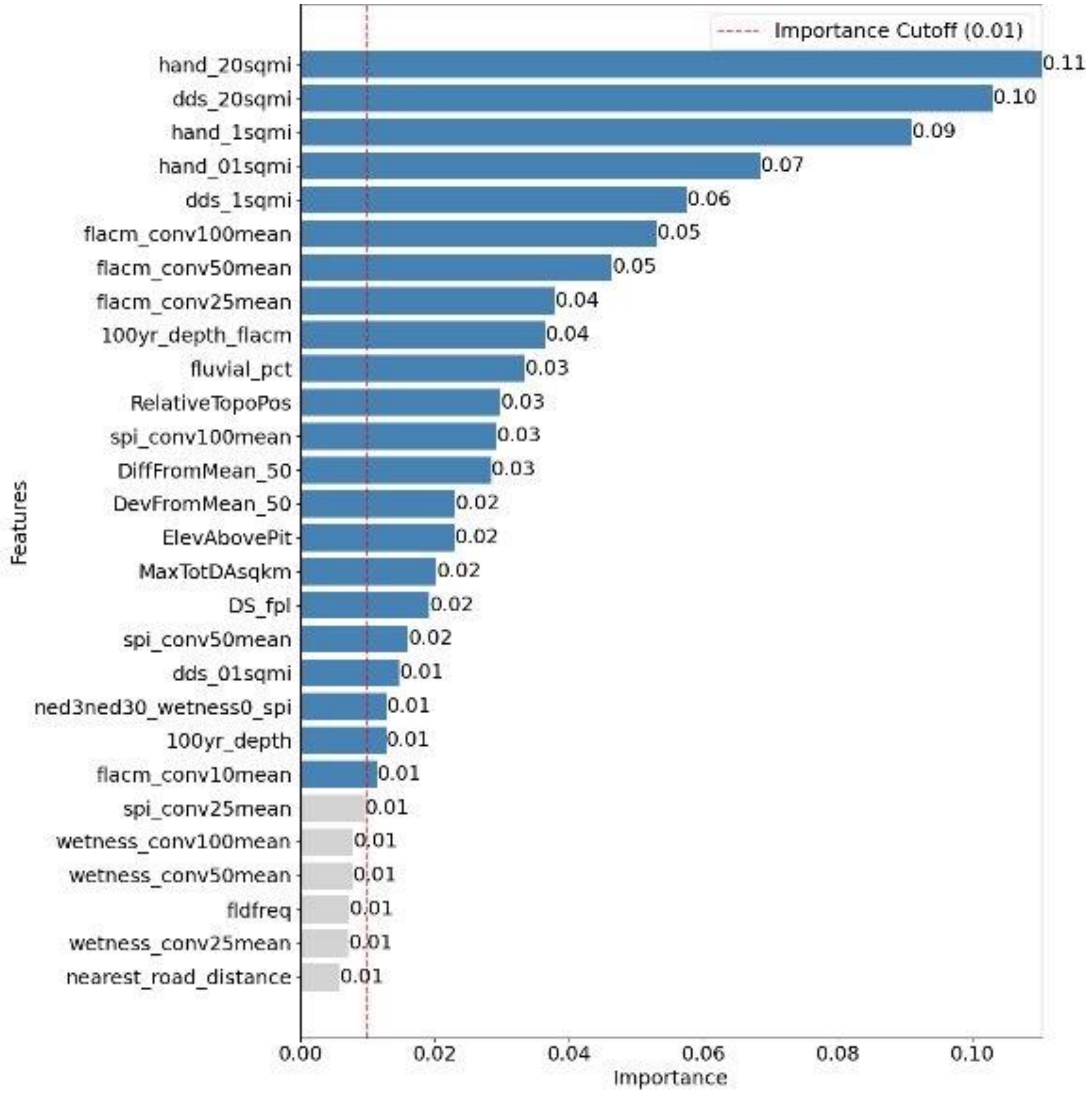
# Feature Importance

Unmapped Areas

- Height Above Nearest Drainage (HAND) and Downslope Distance to Stream (dds) are the most impactful features.
- Convolution-based hydrological features have more impact than their absolute versions.
- Landcover and soil-based features have the least impact.

SSURGO Fluvial Percent | HAND (height above nearest drainage) | Topographic Wetness Index (TWI) | Analysis-Ready Data (viewed in false-color)



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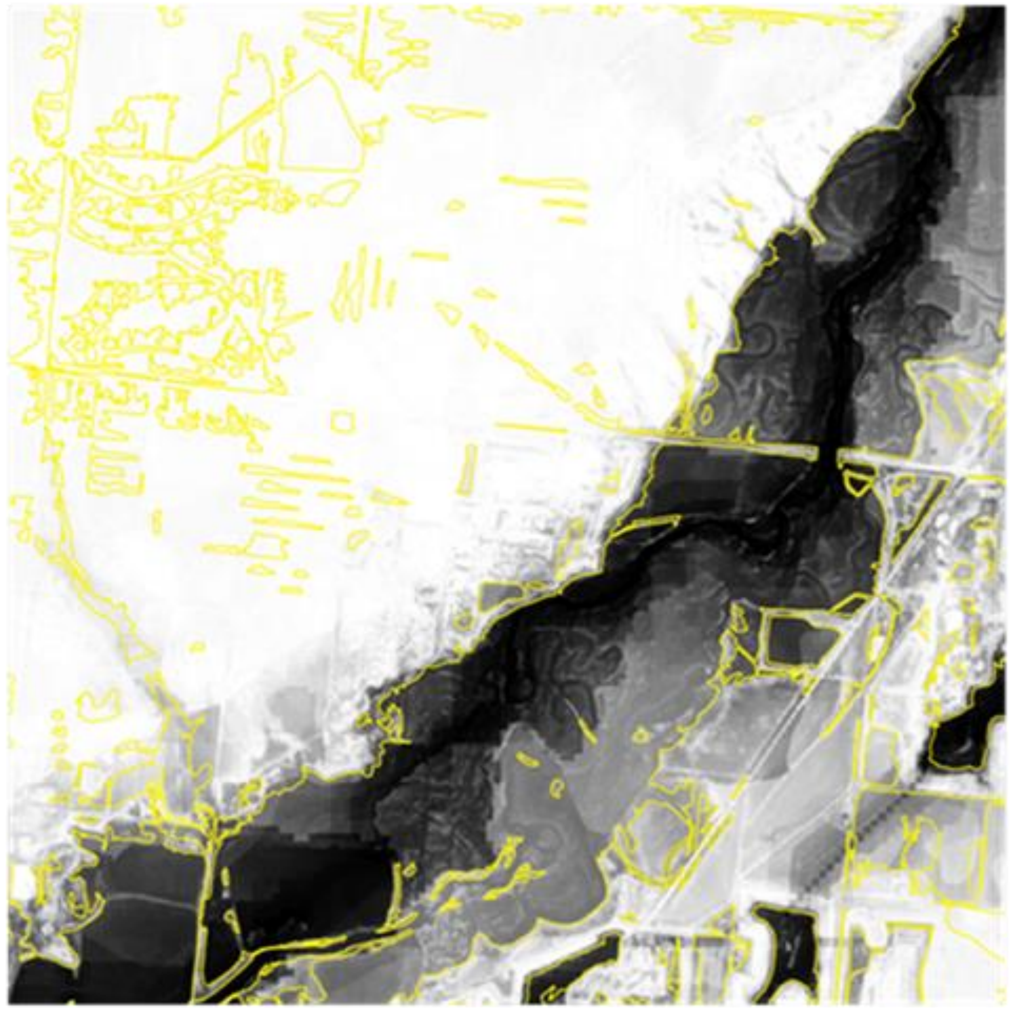
# Prediction Probability

100-year, Fluvial + Pluvial Flooding

Fluvial and Pluvial Flooding (100-yr)

20-sq.mi. drainage (minimum) floodplain probability



Prediction Probability

0.99 *The likelihood or confidence of correct classification (dry/wet)*

0

Pluvial flooding probability

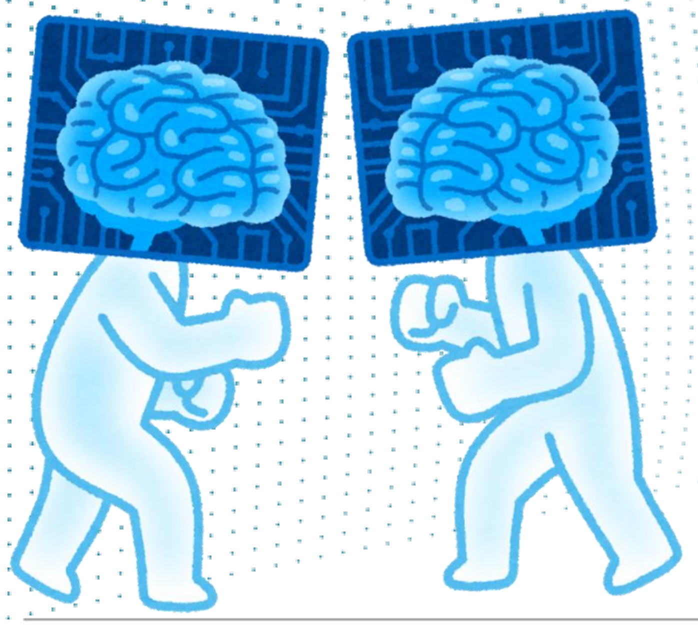
# Challenges

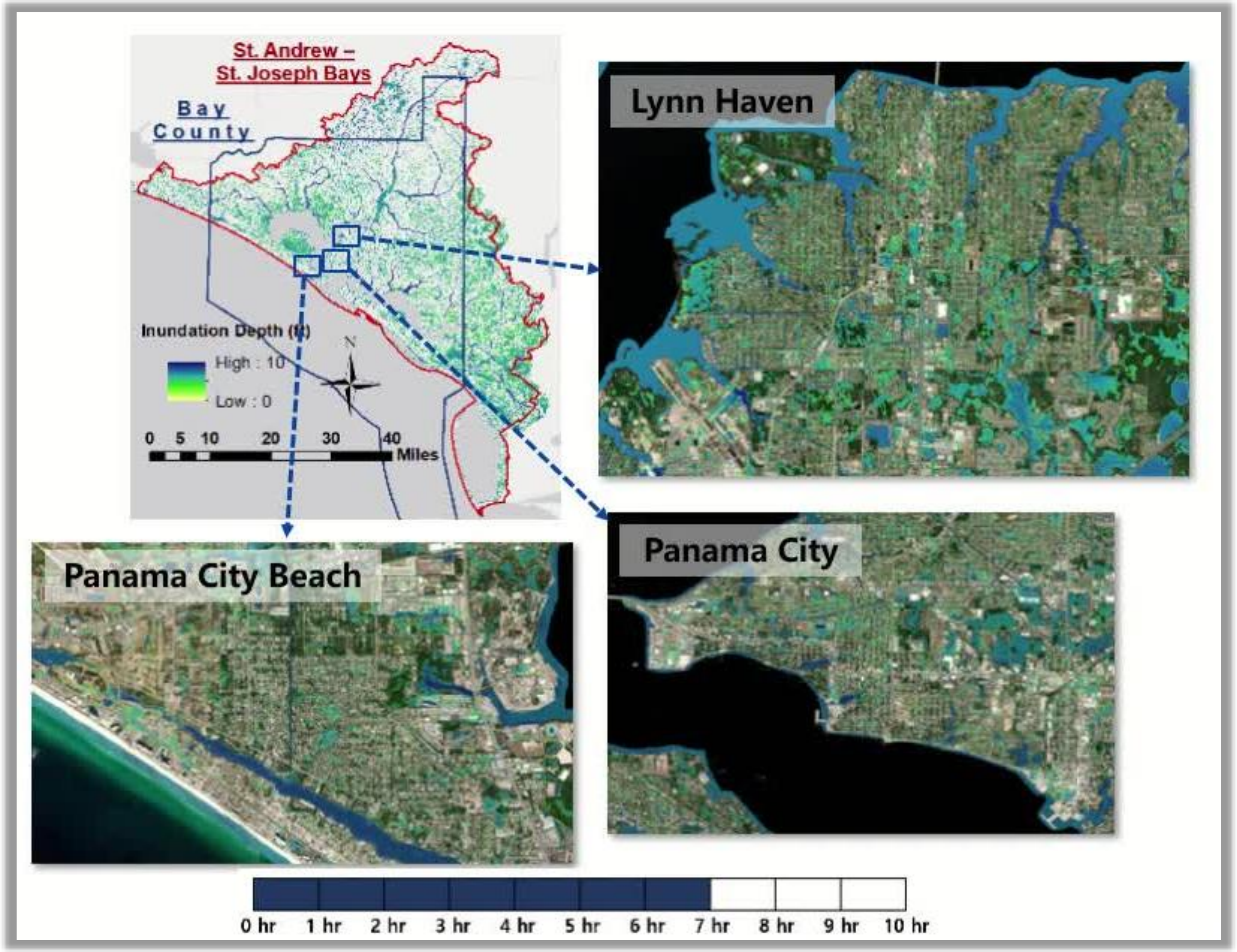
Flood Modeling Limitations

PHYSICS-BASED

GIS-BASED

DATA-DRIVEN






HEC-RAS, RASPLOT, Delft3D-Flow

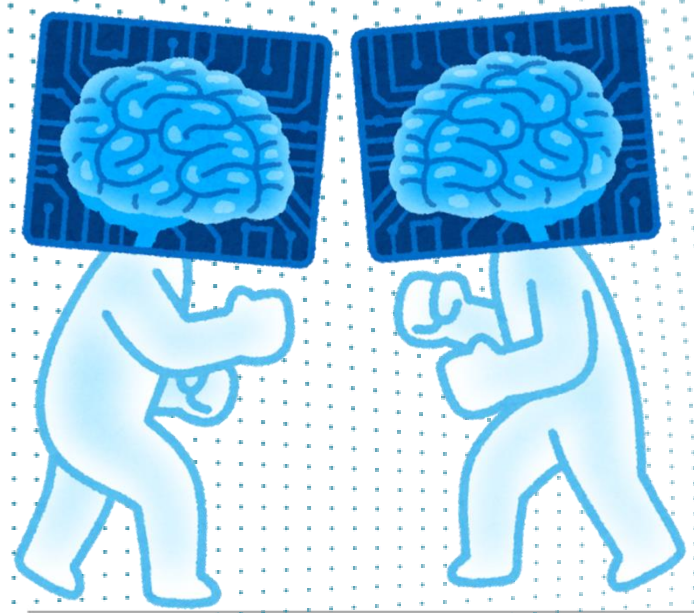
# Challenges

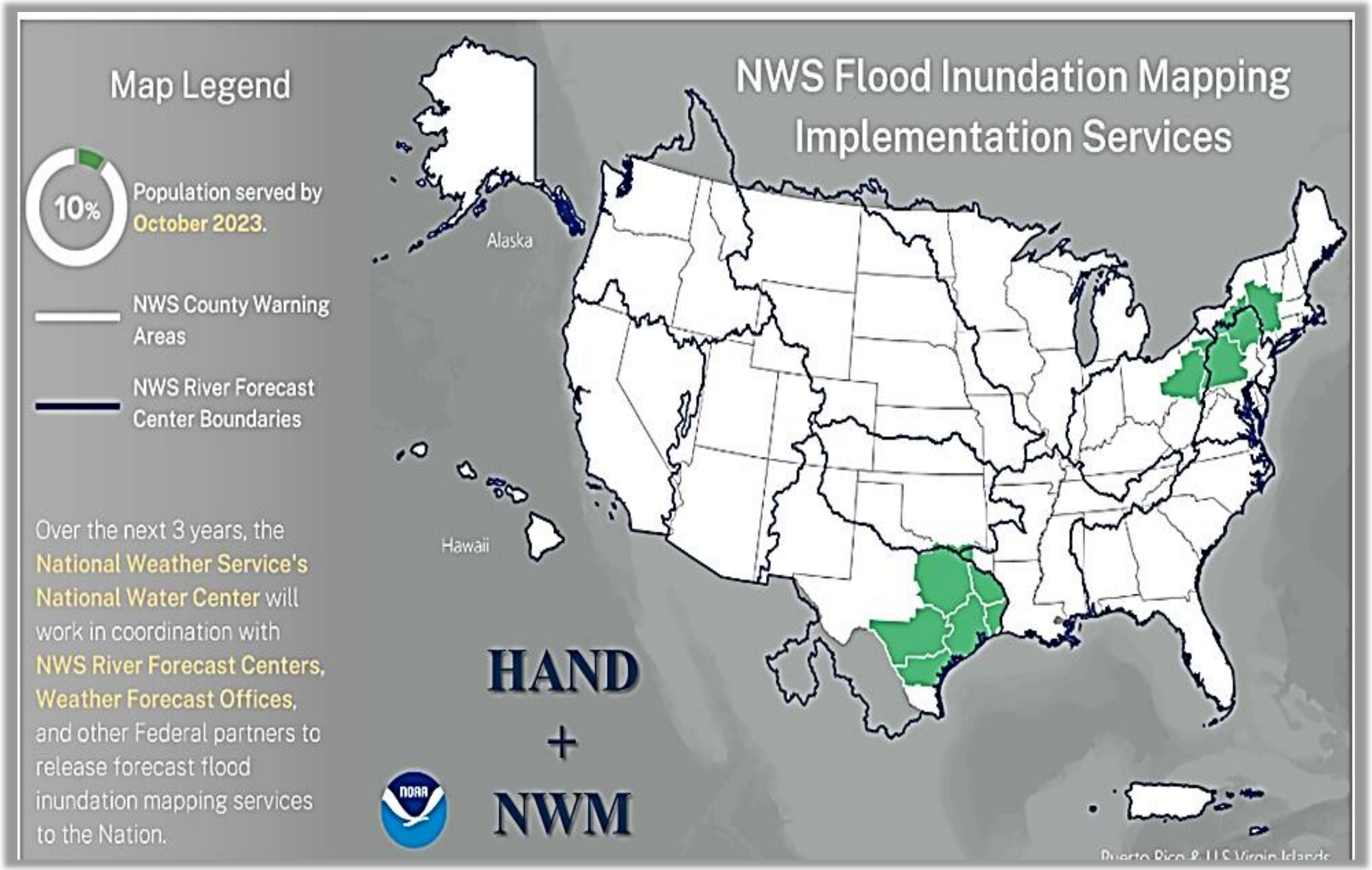
Flood Modeling Limitations

PHYSICS-BASED

GIS-BASED

DATA-DRIVEN






Bathtub, HAND

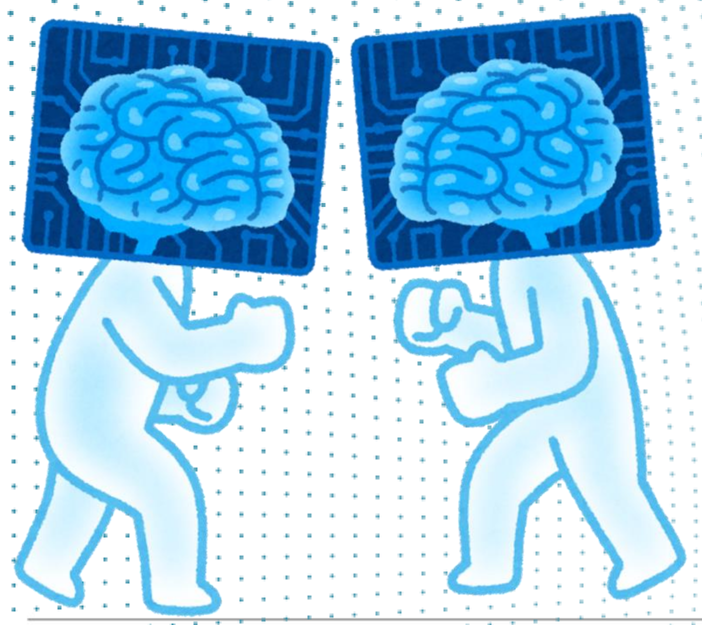
# Challenges

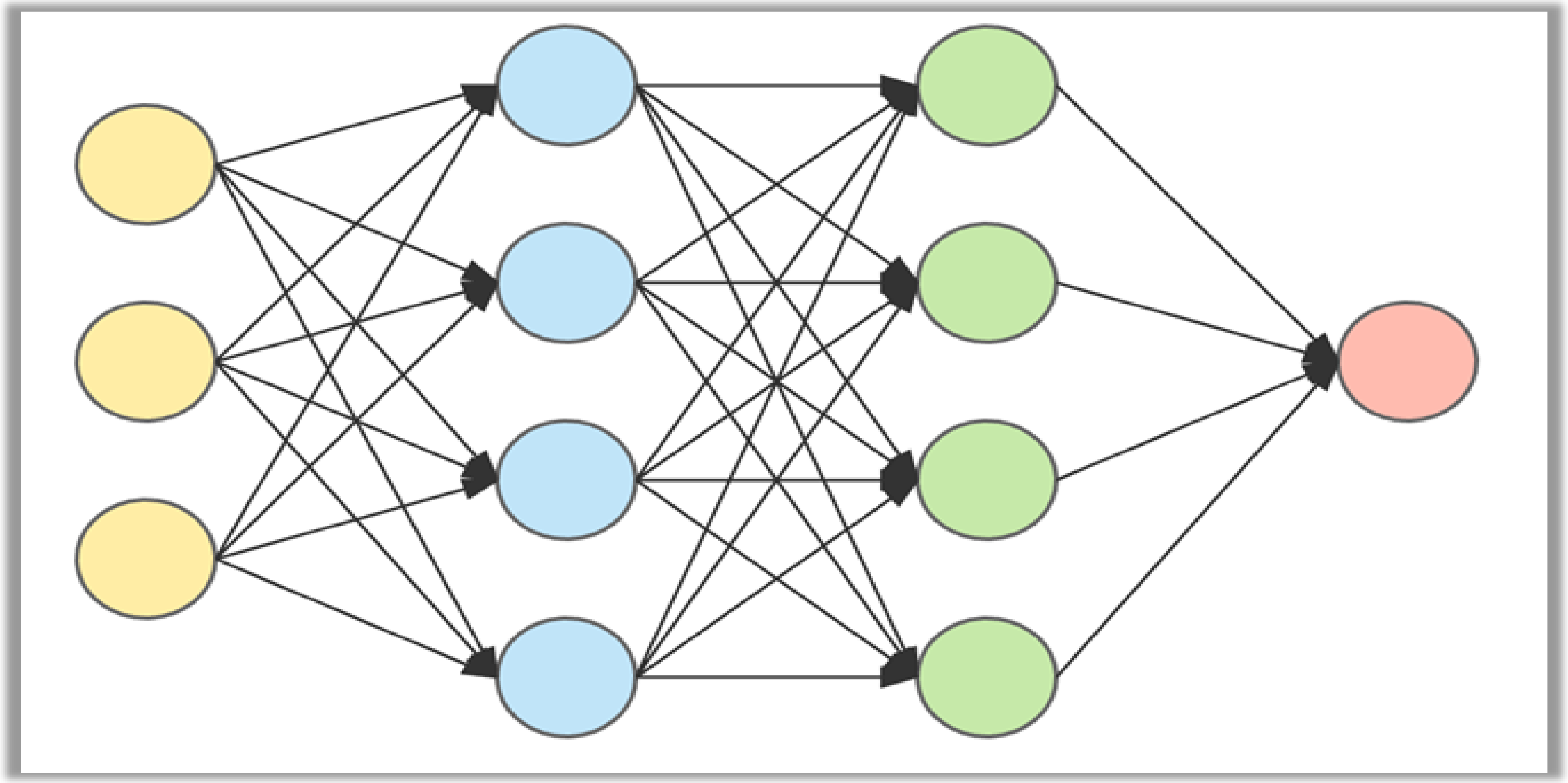
Flood Modeling Limitations

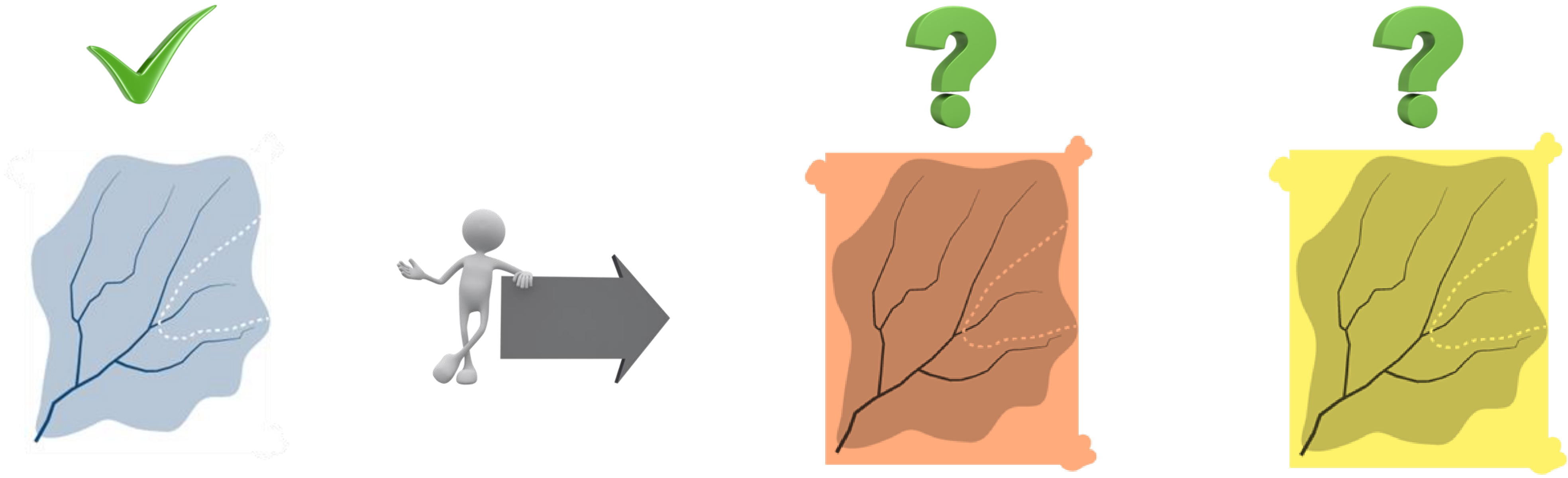
PHYSICS-BASED

GIS-BASED

DATA-DRIVEN







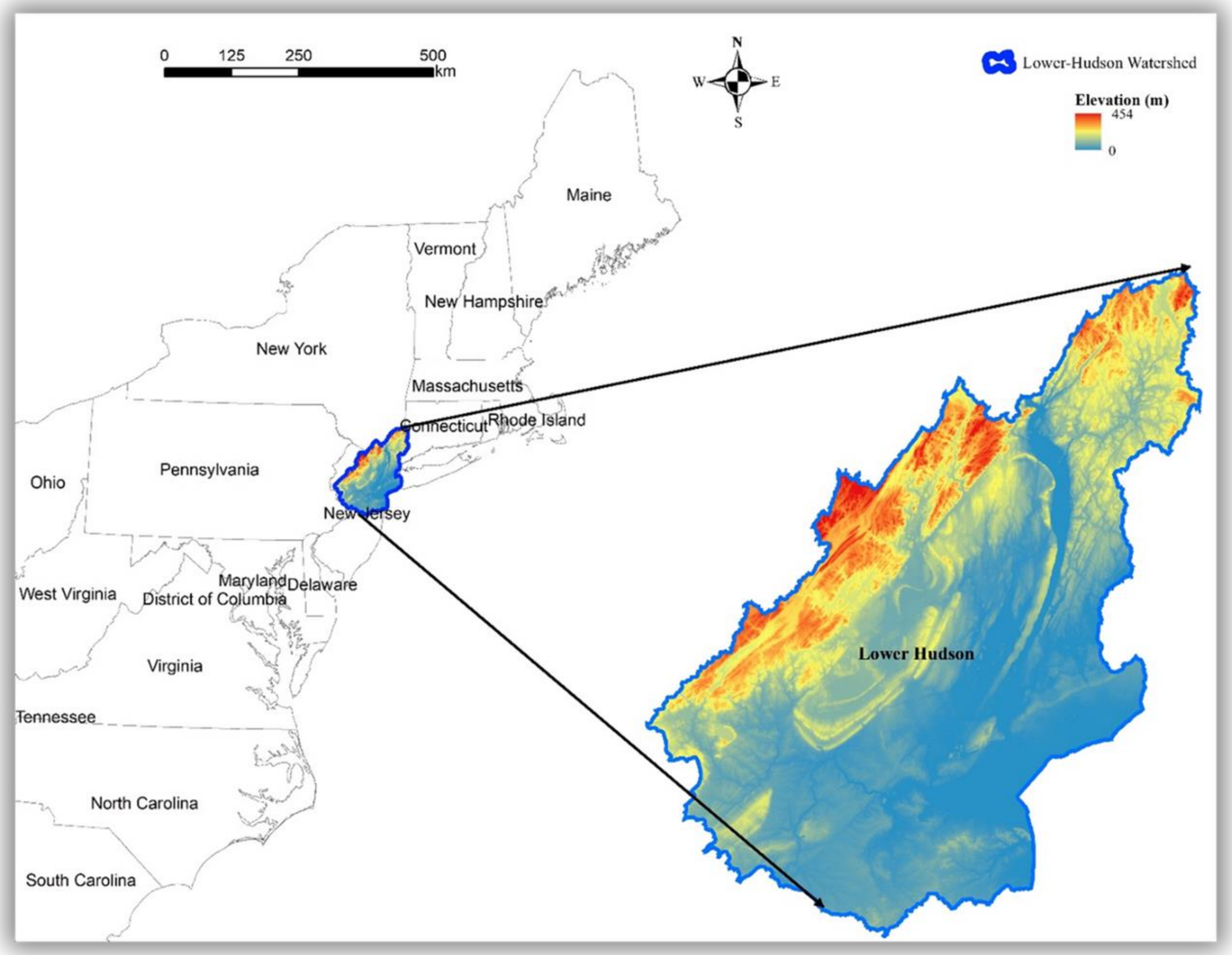
# Transferability of ML Flood Models

# Overarching Goal

Evaluate the **ML model** performance for **hindcasting** flood **depths** and test its **transferability** across **different flood events** in a **coastal** watershed.

# Hurricane Ida (2021)


# Study Area


0 125 250 500
km
N
W E
S
Lower-Hudson Watershed
Elevation (m)
454
0
Maine
Vermont
New Hampshire
New York
Massachusetts
Connecticut
Rhode Island
Ohio
Pennsylvania
New Jersey
West Virginia
Maryland
Delaware
District of Columbia
Virginia
Tennessee
North Carolina
South Carolina
Lower Hudson

# Observed Flood Data

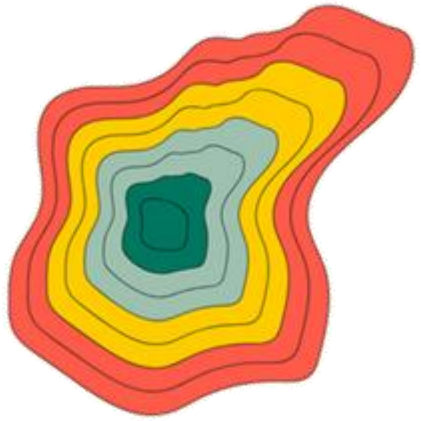
# Features

GEOGRAPHIC LOCATION

HYDROLOGIC

METEOROLOGIC

TOPOGRAPHIC

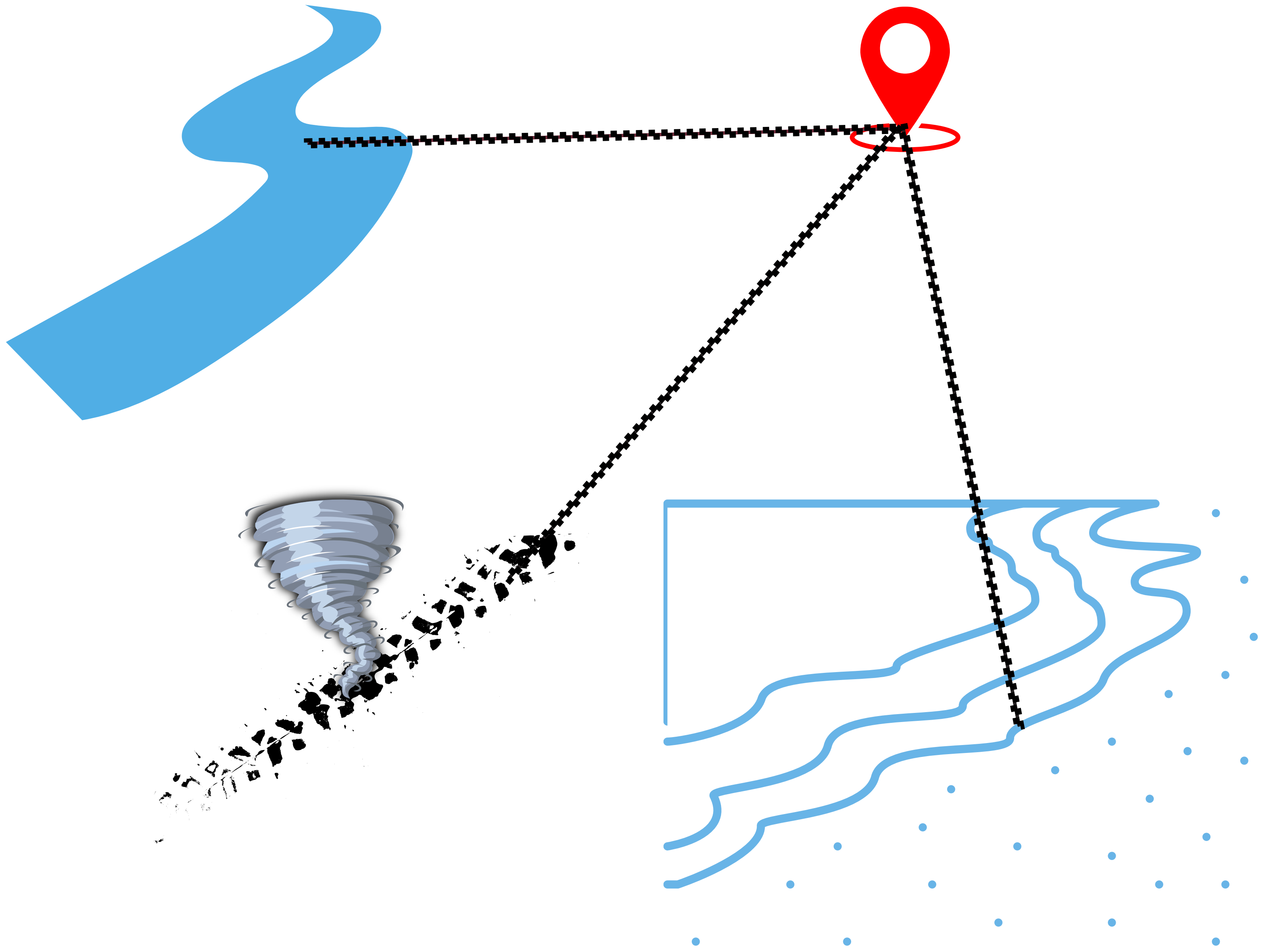


LAND SURFACE

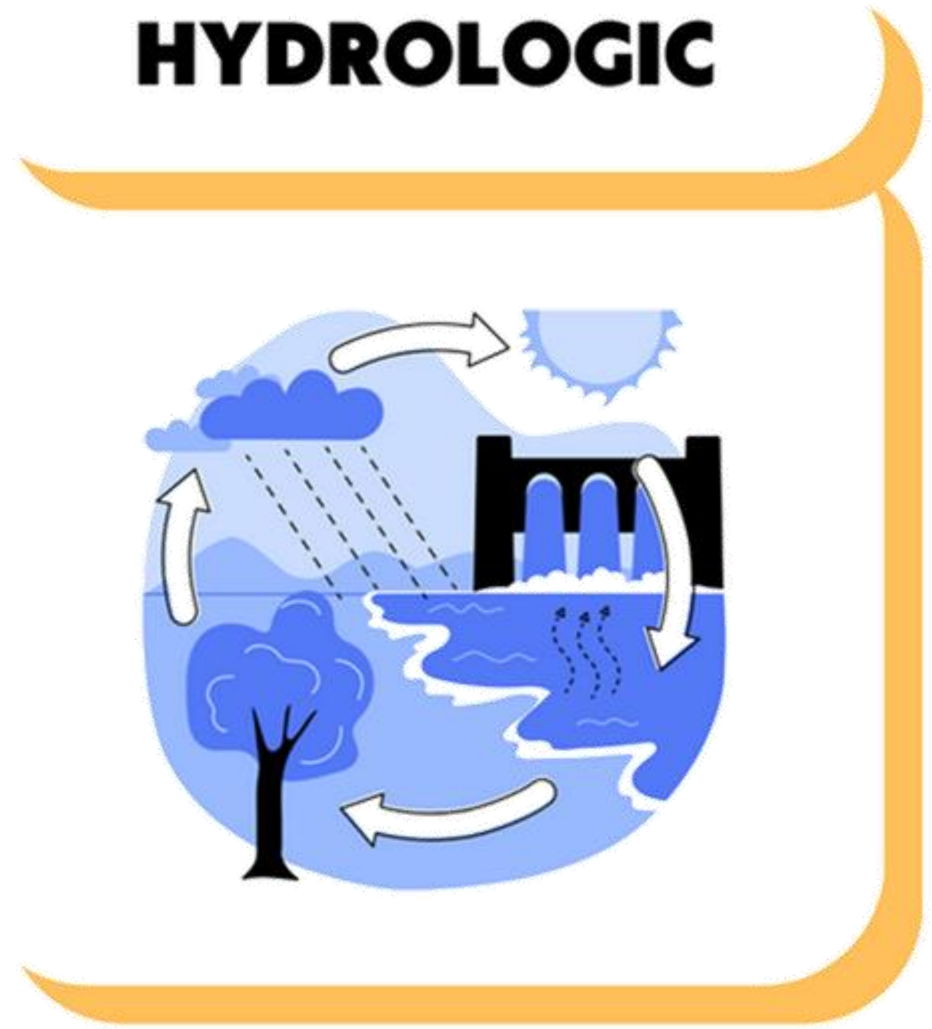
SOIL

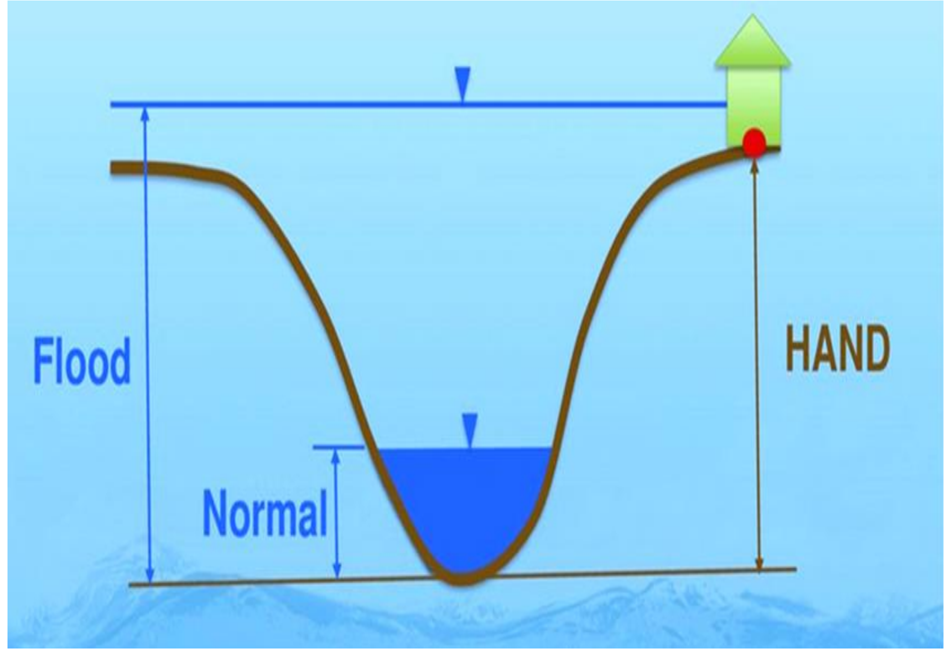
HYDRODYNAMIC

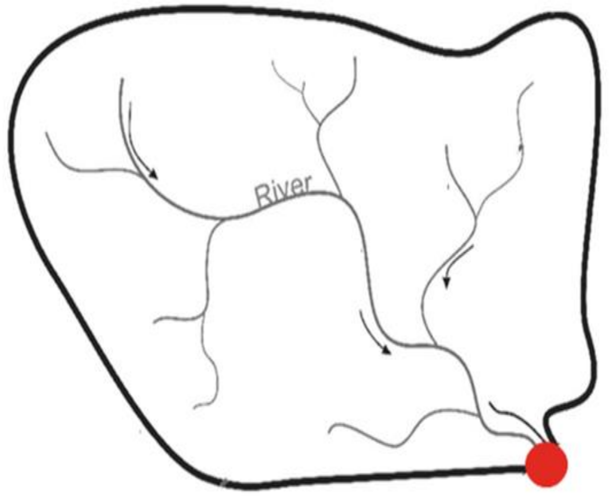
# Features

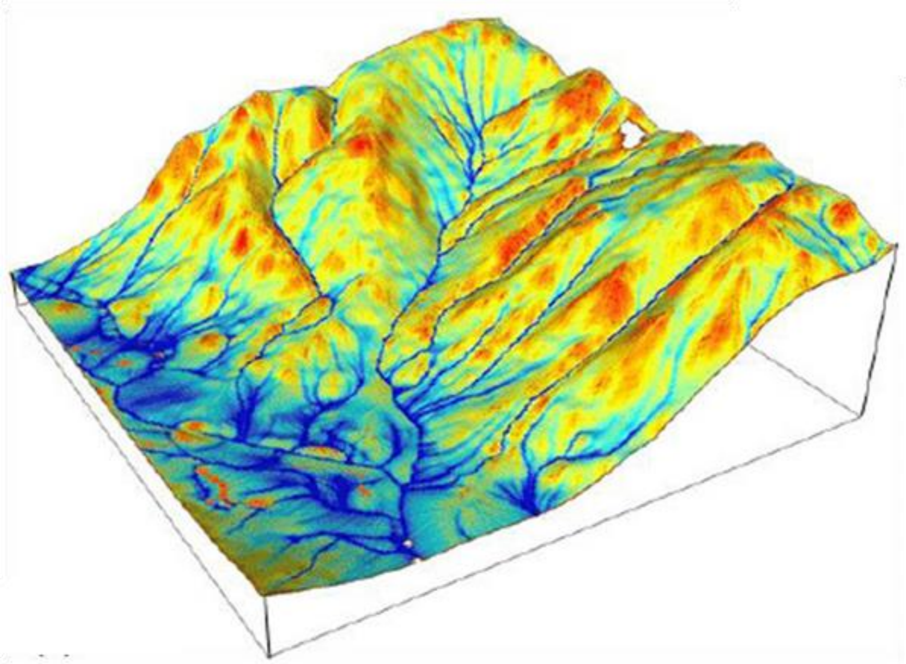



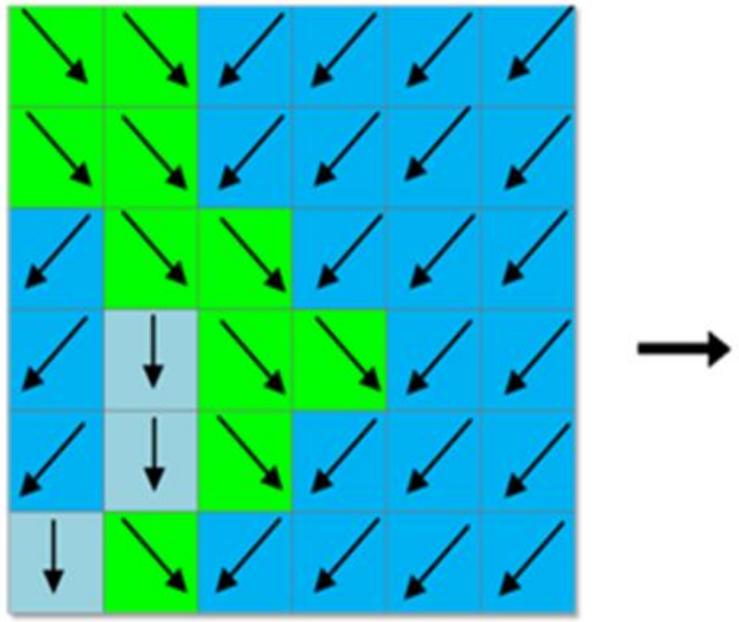
# Features



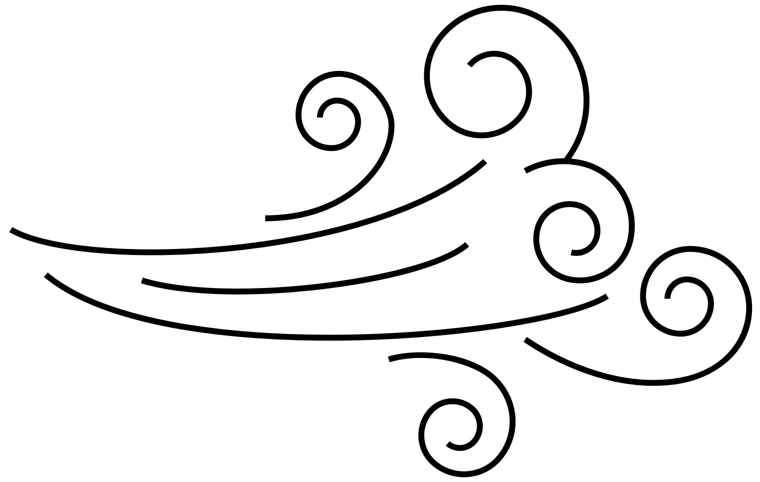


Flow Direction

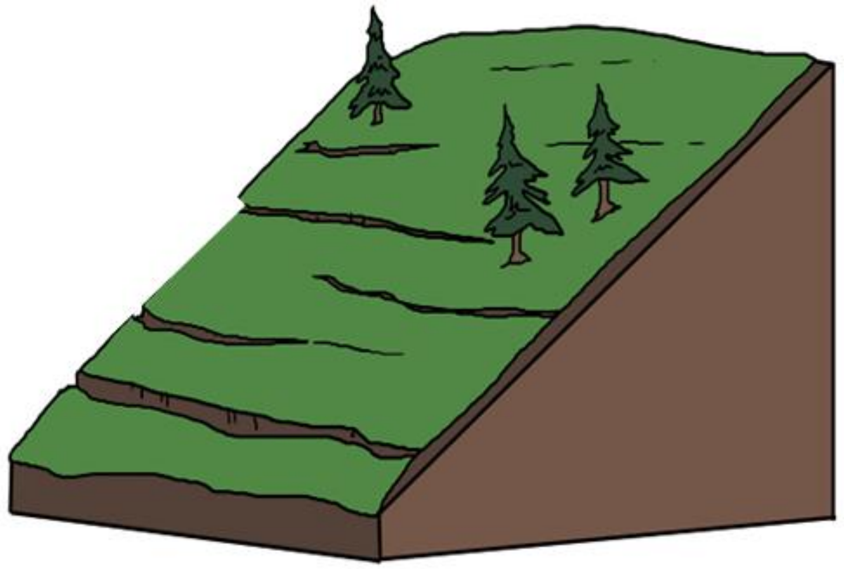
| | | | | | |
|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 2 | 2 | 1 | 1 | 0 |
| 0 | 4 | 5 | 2 | 1 | 0 |
| 0 | 0 | 8 | 8 | 1 | 0 |
| 0 | 1 | 0 | 11 | 10 | 0 |
| 0 | 2 | 12 | 12 | 1 | 0 |

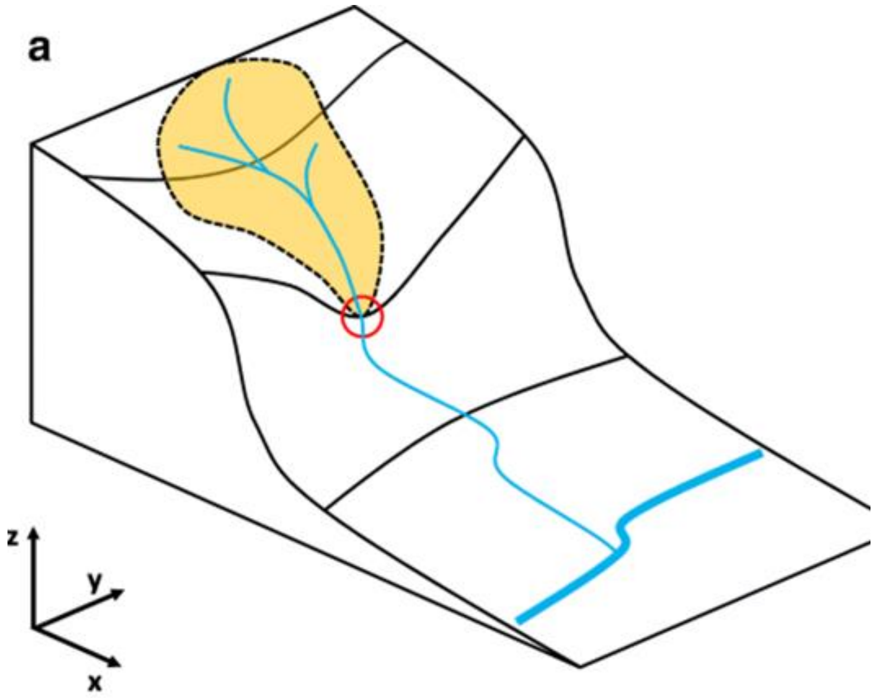
Flow Accumulation

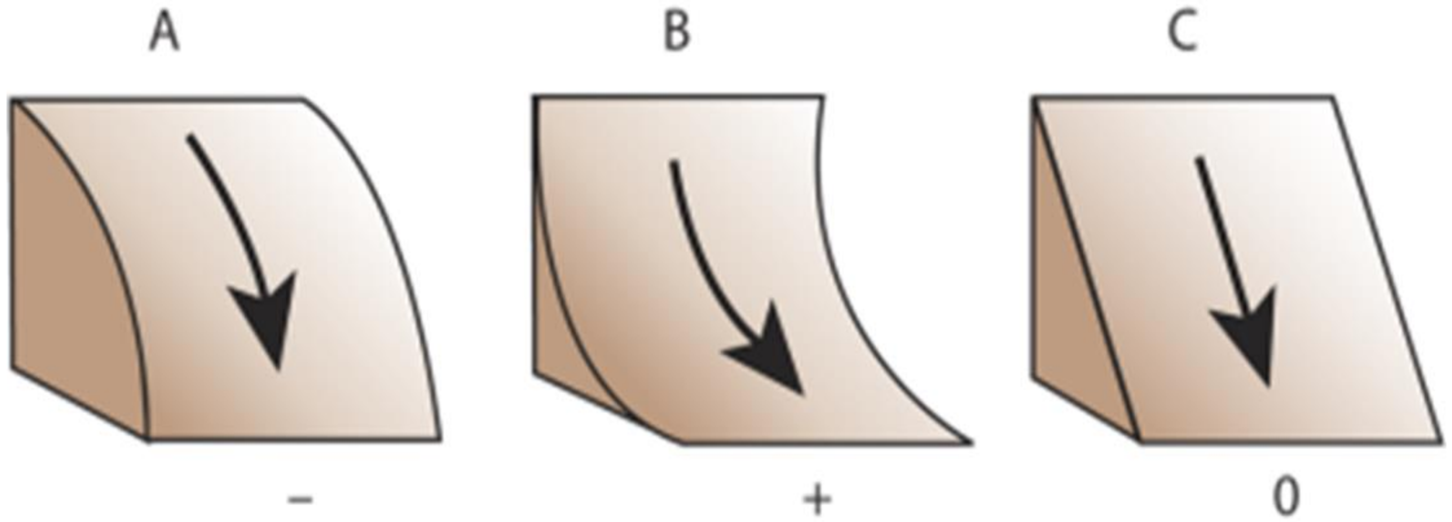
# Features

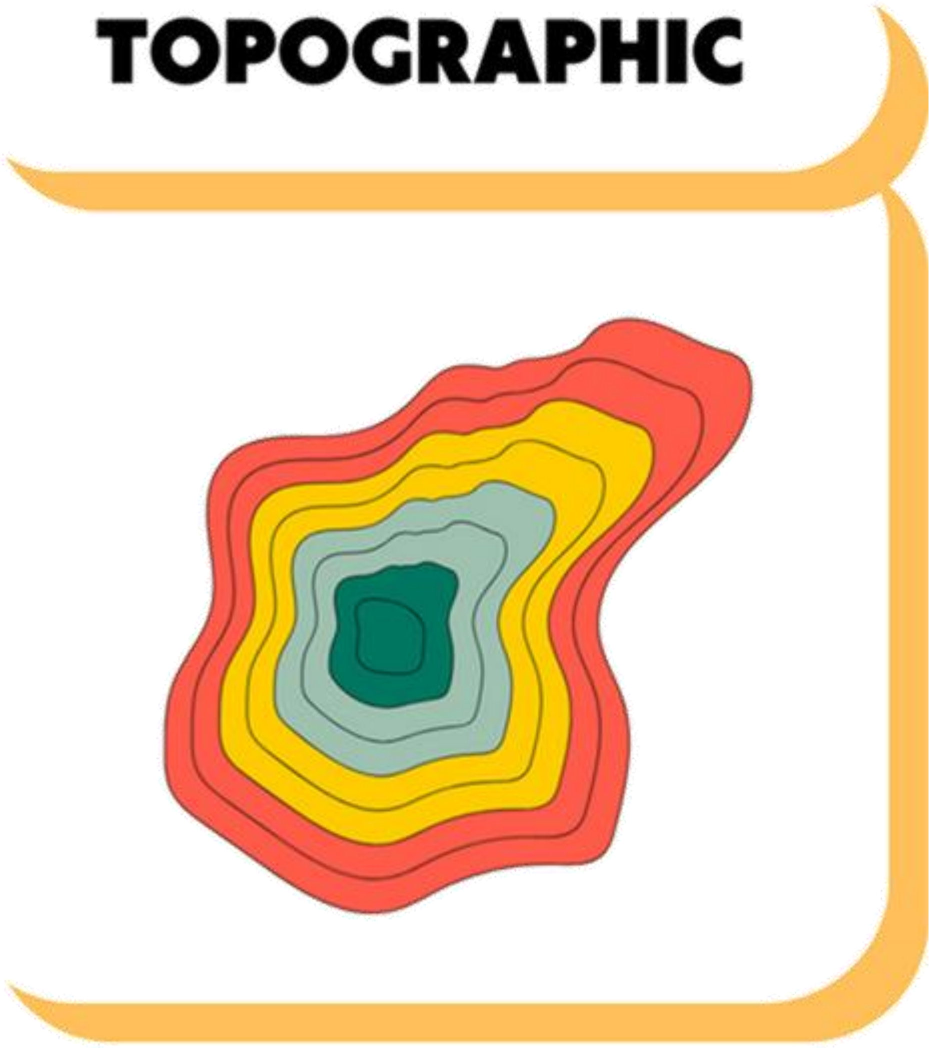


# Features

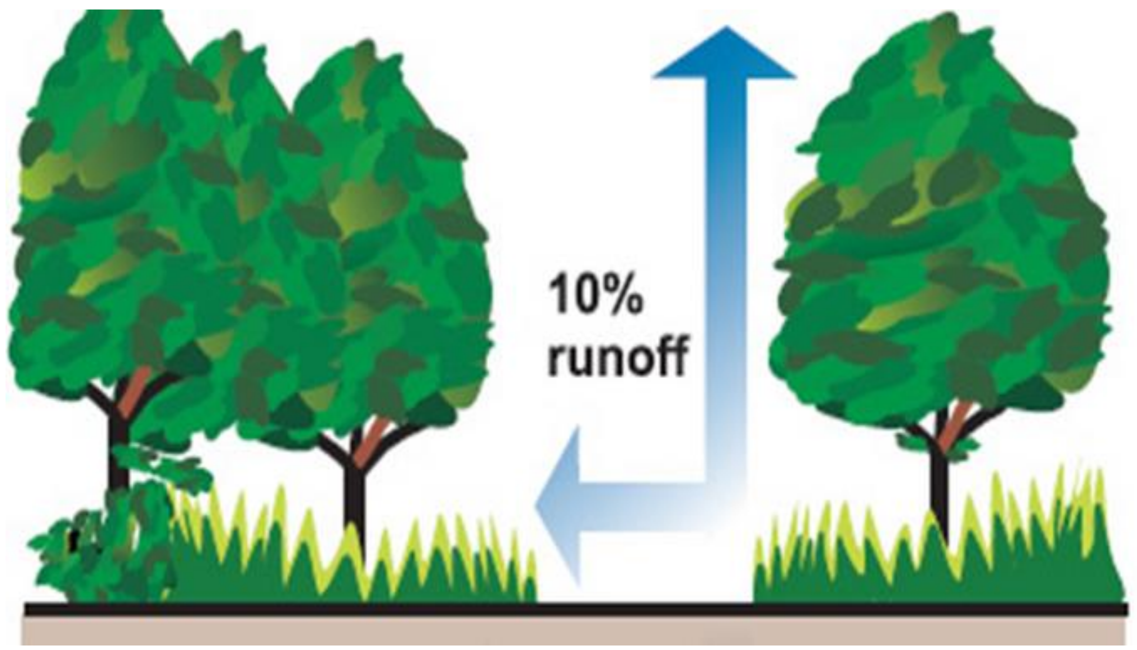




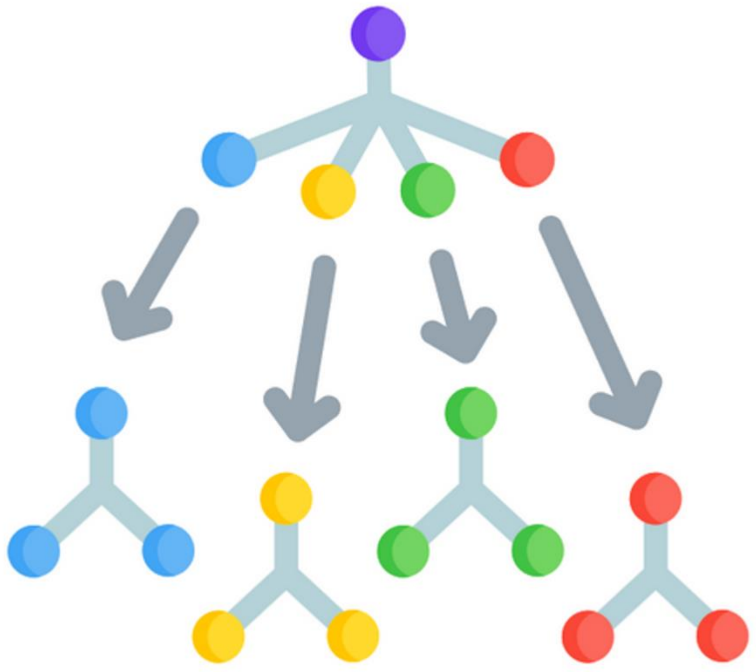
# Features

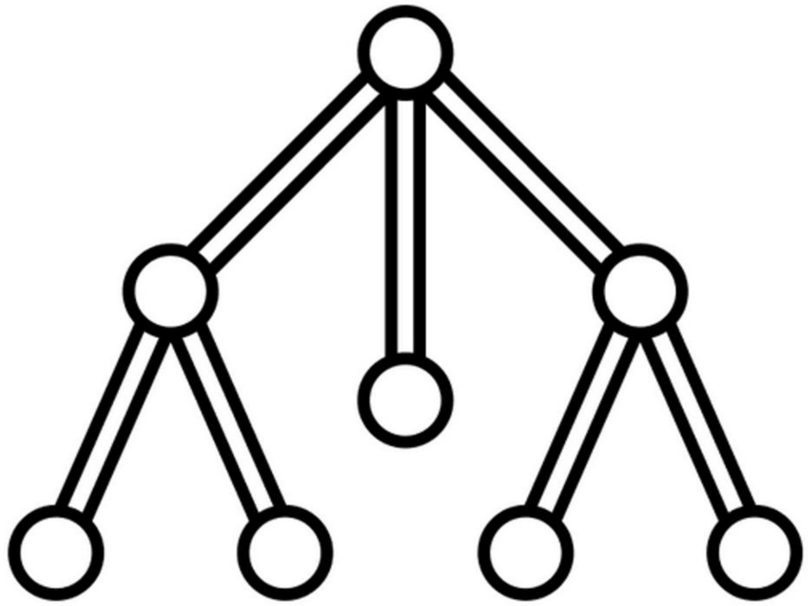

# Features


# Features

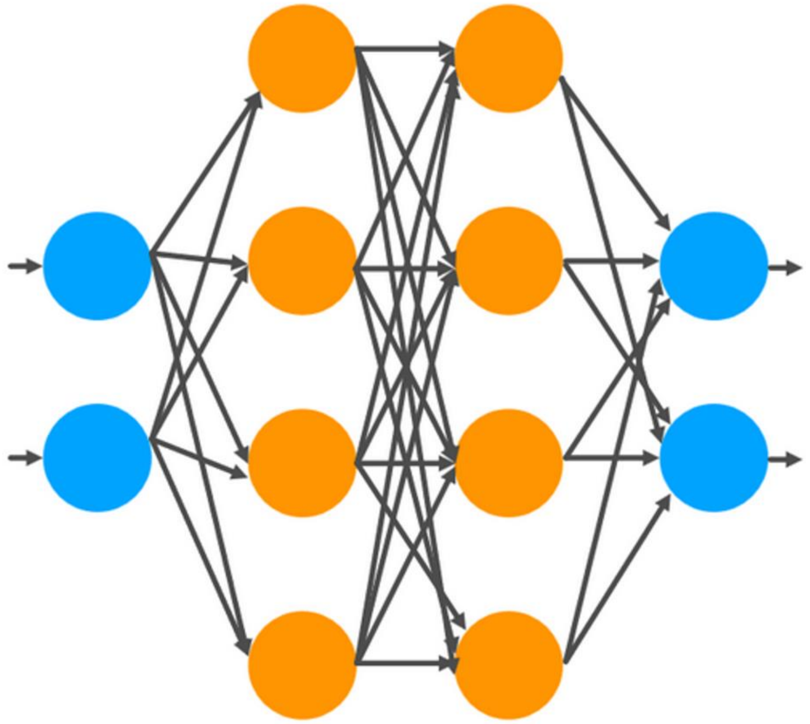
# ML Models



RANDOM FOREST



XGBOOST



NEURAL NETWORK

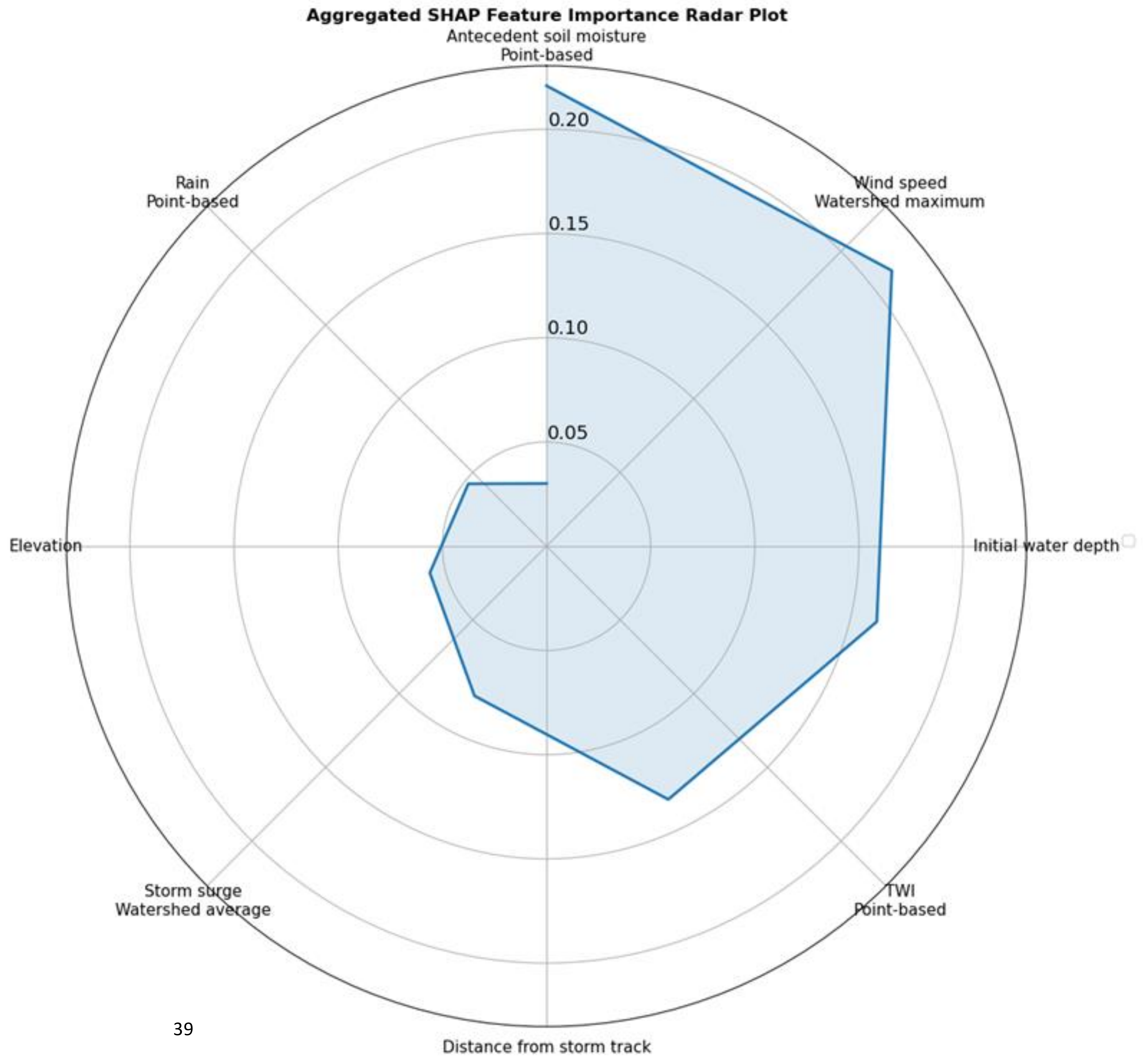
# Customized Loss Function


| Amount of vertical uncertainty | Uncertainty |
|---|---|
| Within ±0.05 foot. | Excellent (E) |
| Within ±0.10 foot. | Good (G) |
| Within ±0.20 foot. | Fair (F) |
| Within ±0.40 foot. | Poor (P) |
| More than ±0.40 foot. | Very poor (V) |

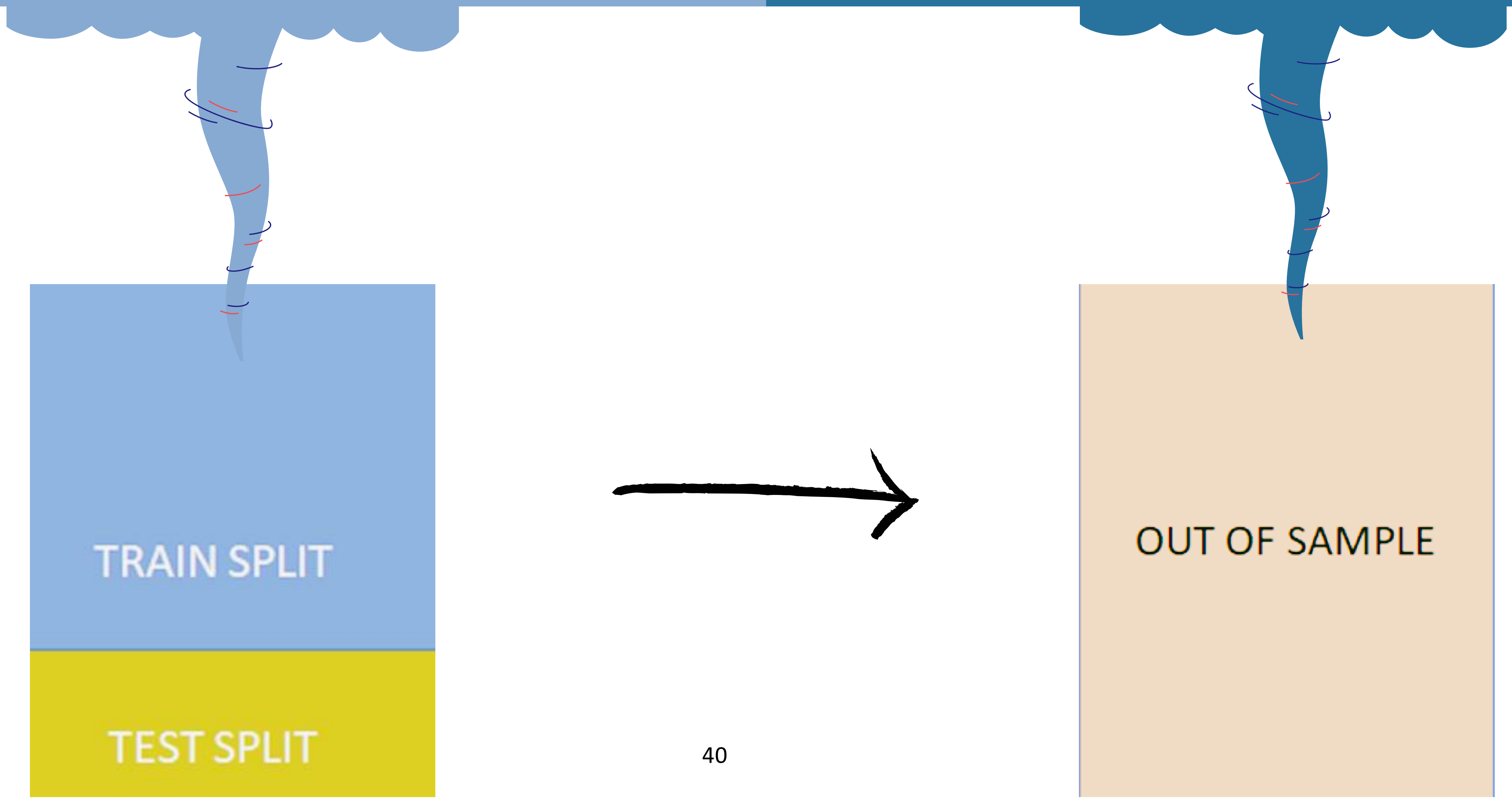
Smith et al. (2021)
Ferguson et al. (2022)
Ortega et al. (2014)

# ANN MLP

| Metrics | Train Data | Test Data |
|---|---|---|
| $R^2$ | 0.94 | 0.91 |
| MAE (m) | 0.64 | 0.77 |
| NRMSE (%) | 24 | 28 |



# Effective?



# Other Flood Events

- Hurricane Isaias (2020)
- Hurricane Sandy (2012)
- Hurricane Irene (2011)


41

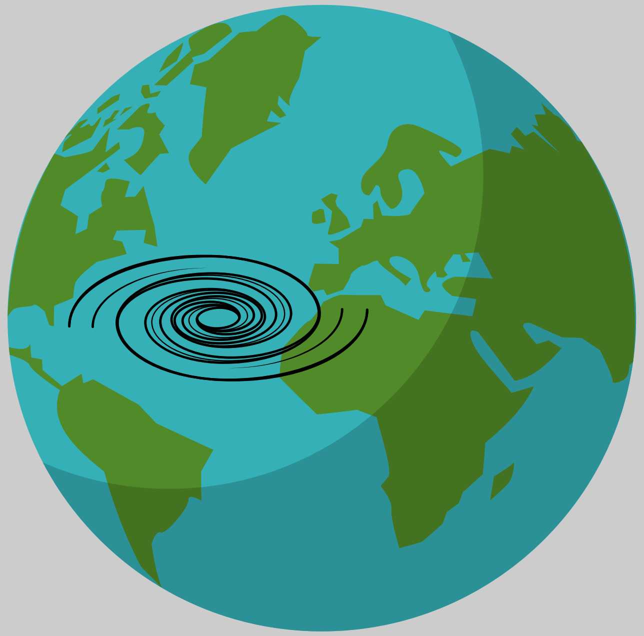
# Results

| Flood event | $R^2$ | MAE (meters) | NRMSE (%) | FQ (%) |
|---|---|---|---|---|
| **Original Model** | | | | |
| Hurricane Ida | 0.94 | 0.64 | 24.1 | 138 |
| **Transferability** | | | | |
| Hurricane Isaias | 0.73 | 1.54 | 86.3 | 326 |
| Hurricane Sandy | 0.70 | 1.71 | 109.2 | 370 |
| Hurricane Irene | 0.85 | 1.12 | 36.7 | 113 |

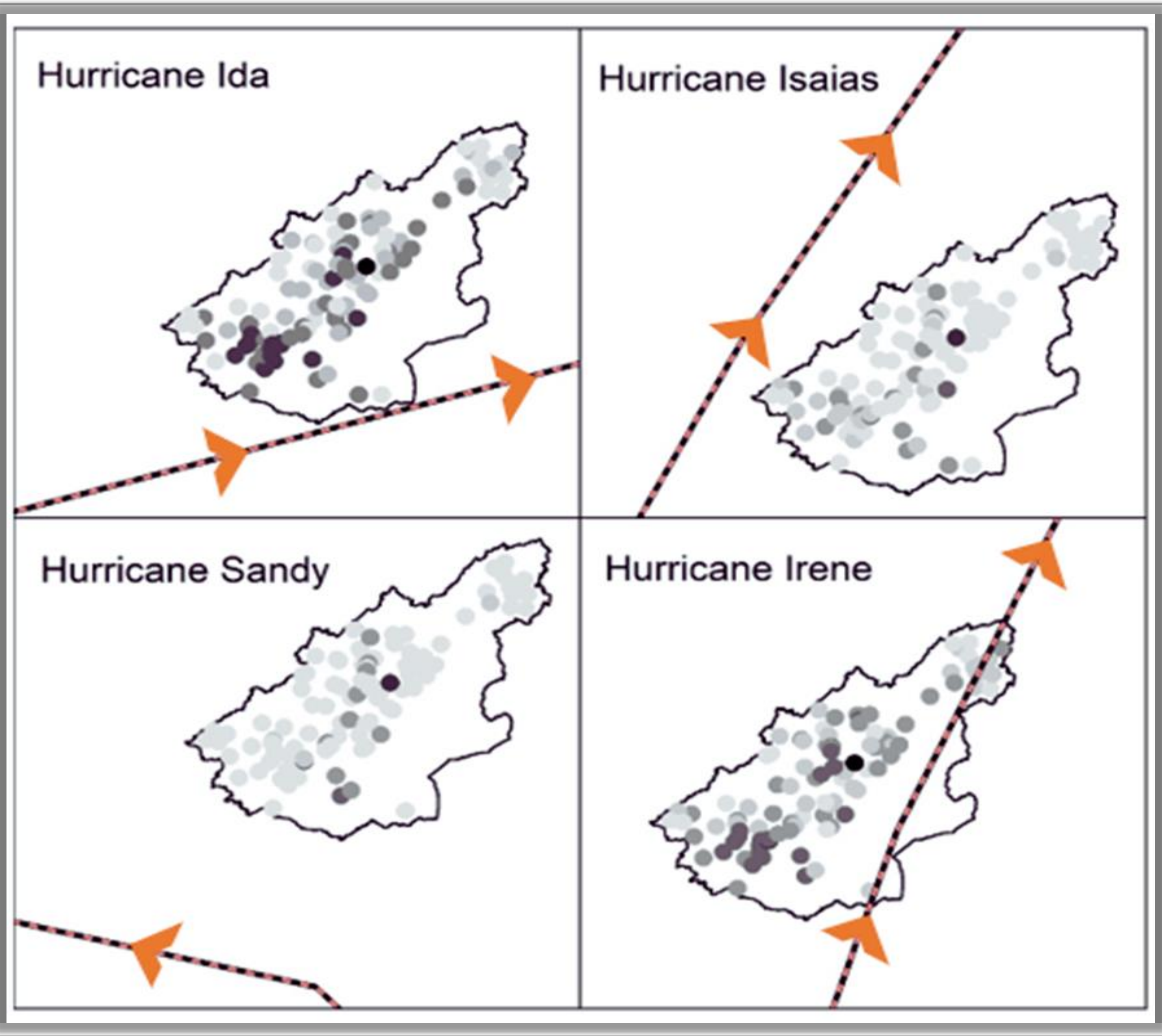
# Results



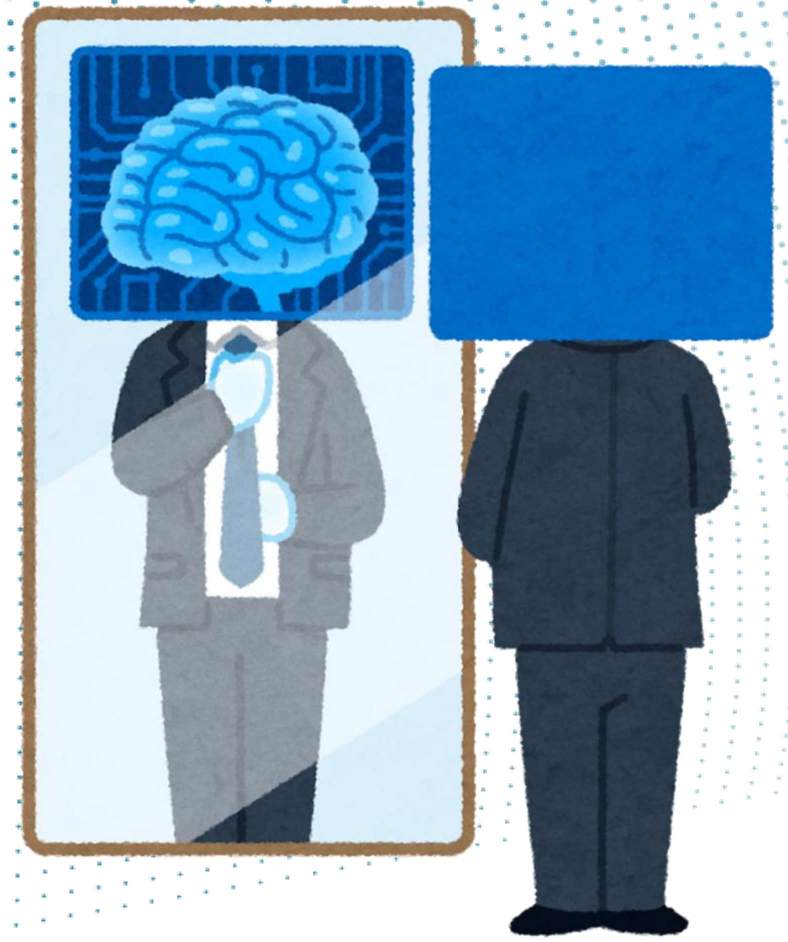
| Event | Year | River max water depth (m) | Cumulative rainfall depth (mm) | Antecedent soil moisture (%) | Storm Surge (m) | Max wind speed (m/s) | Distance to storm track (m) |
|---|---|---|---|---|---|---|---|
| Ida | 2021 | 0.85-36.66 | 121.92-201.81 | 21-43% | 0.25-0.67 | 27.64-35.49 | 0.09-1.1 |
| Isaias | 2020 | 0.22-35.35 | 17.37-62.22 | 9-39% | 0.20-0.76 | 48.29-65.33 | 0.23-1.14 |
| Sandy | 2012 | 0.24-35.98 | 19.83-56.53 | 17-38% | 1.97-2.85 | 63.43-76.97 | 0.77-2.16 |
| Irene | 2011 | 1.03-37.33 | 147.29-217.74 | 19-43% | 1.05-1.37 | 51.05-60.68 | 0.00-0.93 |



# Storm Track


Hurricane Ida
Hurricane Isaias
Hurricane Sandy
Hurricane Irene

# Summary of Flood Modeling



**Performance**

The ML models demonstrated strong performance in hindcasting maximum flood depths for the event they were trained for in coastal watersheds.

**Uncertainty Integration**

Incorporating the uncertainty of flood observations substantially improved the performance and transferability of the hindcast model.

**Application to Unseen data**

Successful transferability across other hurricanes

# Key Takeaways

## *AI in H&H Modeling*

### Data Enrichment

*AI and image recognition can aid in data collection for flood modeling*

01

### Mapping the unmapped

*AI can serve to increase our extent of floodplain mapping to unmonitored areas*

02

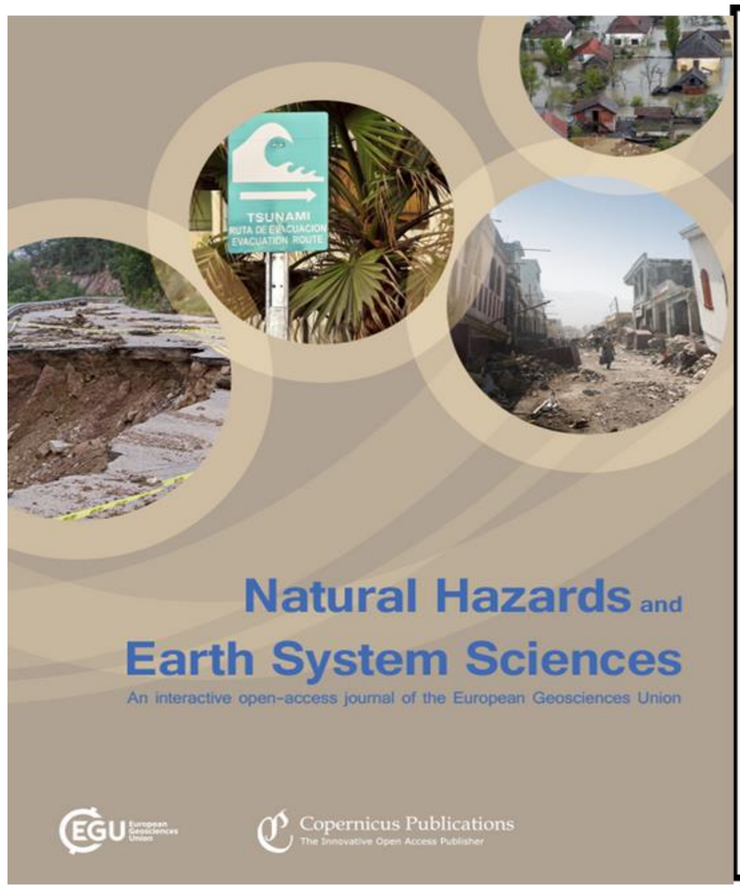
### Enhanced Flood Prediction

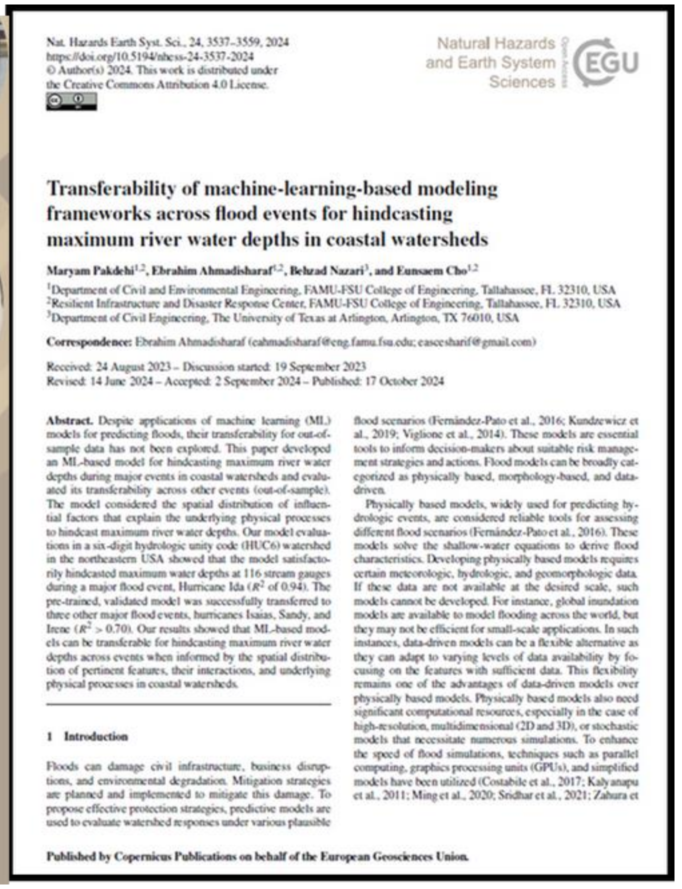
*AI can provide enhanced flood prediction in complex scenarios including **compound flooding***

03

# Published Papers







Nat. Hazards Earth Syst. Sci., 24, 3537–3559, 2024
https://doi.org/10.5194/nhess-24-3537-2024


Natural Hazards and Earth System Sciences

**Transferability of machine-learning-based modeling frameworks across flood events for hindcasting maximum river water depths in coastal watersheds**

Maryam Pakdehi[1,2], Ebrahim Ahmadisharaf[1,2], Behzad Nazari[3], and Eunsaem Cho[1,2]
[1]Department of Civil and Environmental Engineering, FAMU-FSU College of Engineering, Tallahassee, FL 32310, USA
[2]Resilient Infrastructure and Disaster Response Center, FAMU-FSU College of Engineering, Tallahassee, FL 32310, USA
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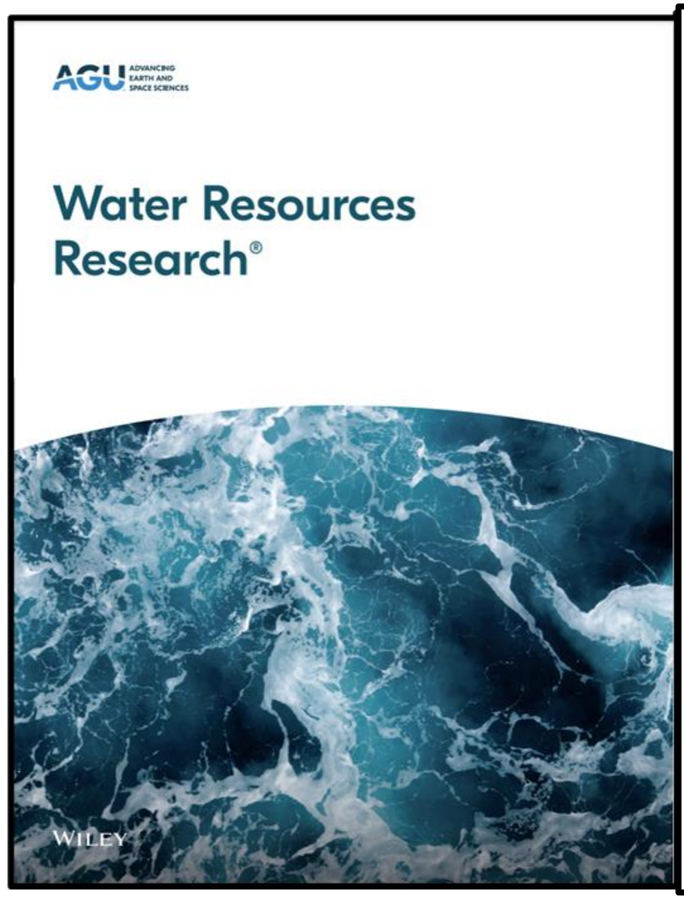


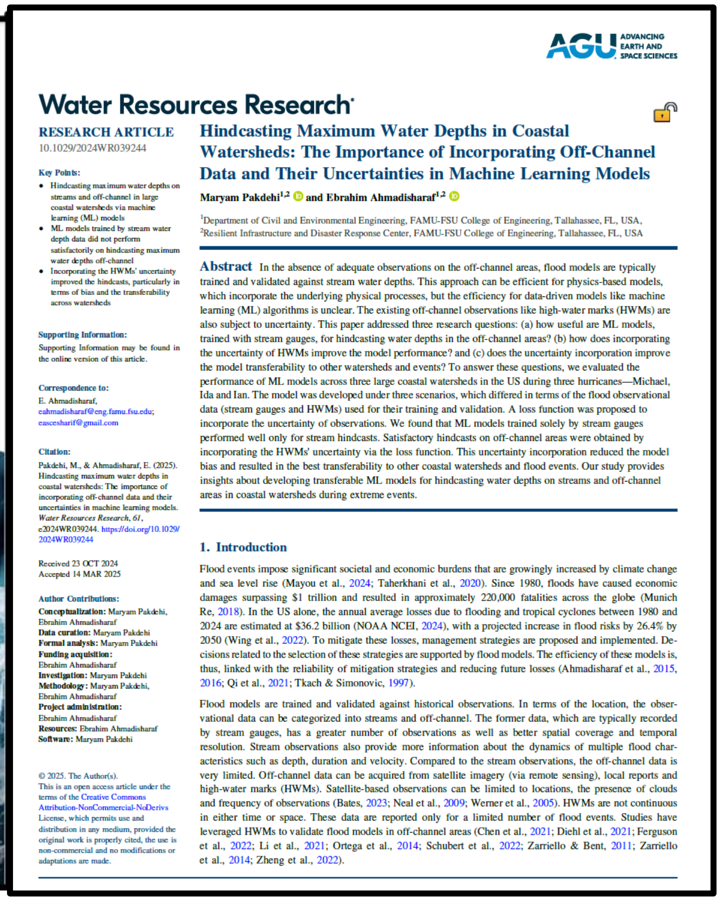
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**Hindcasting Maximum Water Depths in Coastal Watersheds: The Importance of Incorporating Off-Channel Data and Their Uncertainties in Machine Learning Models**

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Key Points:

- Hindcasting maximum water depths on streams and off-channel in large coastal watersheds via machine learning (ML) models
- ML models trained by stream water depth data did not perform satisfactorily on hindcasting maximum water depths off-channel
- Incorporating the HWMs' uncertainty improved the hindcasts, particularly in terms of bias and the transferability across watersheds



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# Thank you!

# Questions?

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