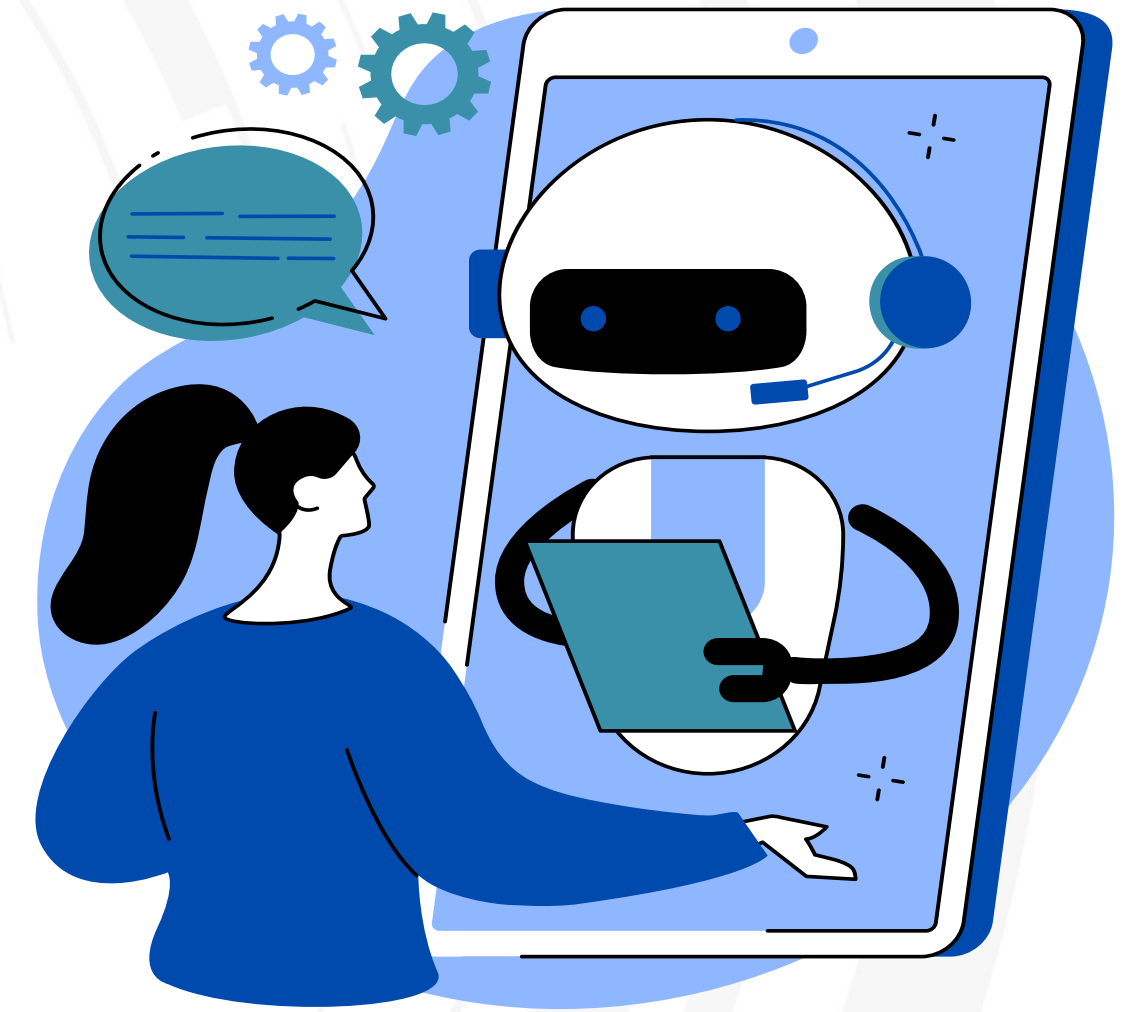


Automating the Future

AI/ML in Compound Flooding and H&H
Modeling



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



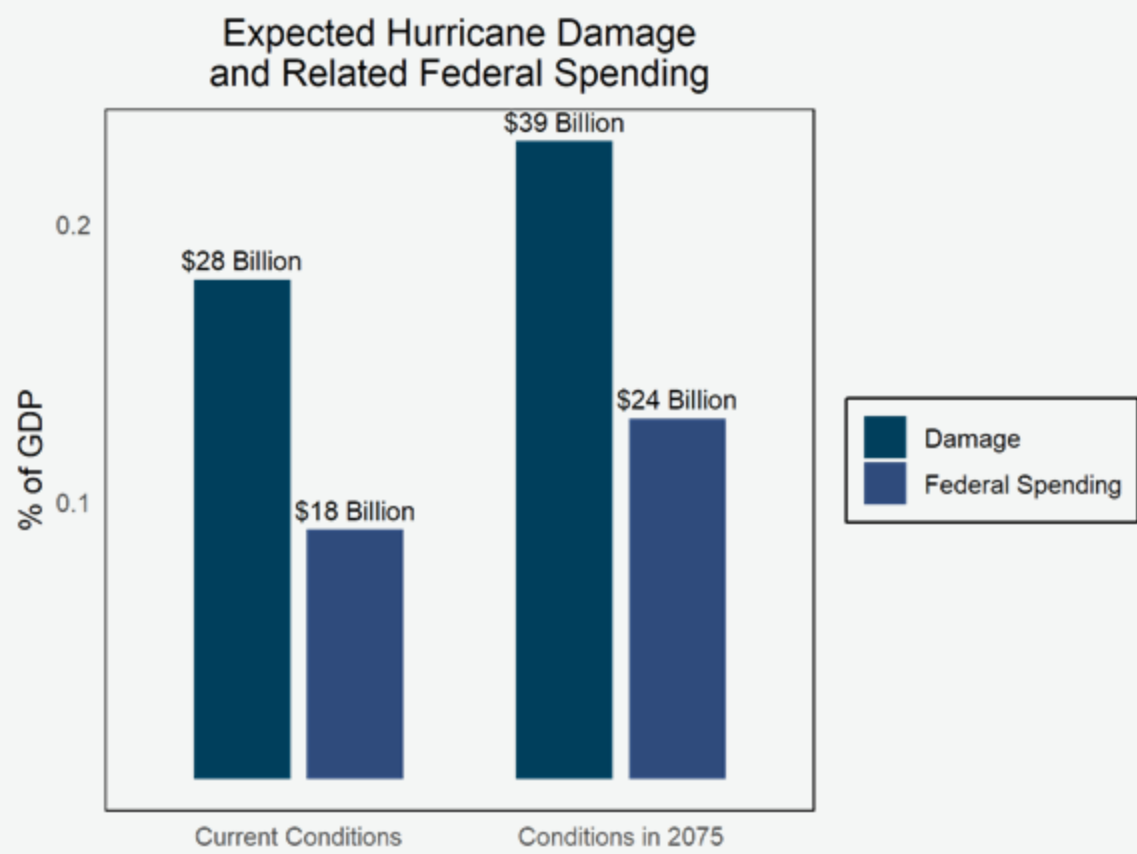
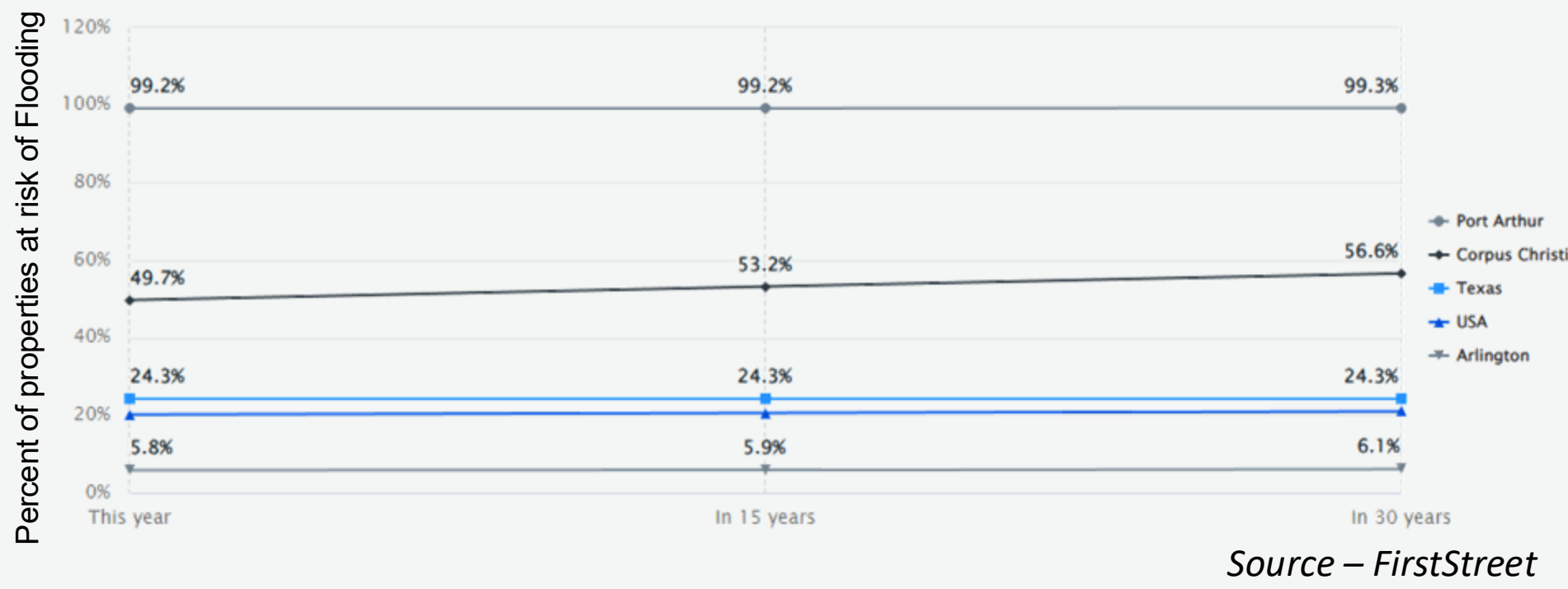
Shubham Jain, PhD, EIT

Civil Associate – Water Resources

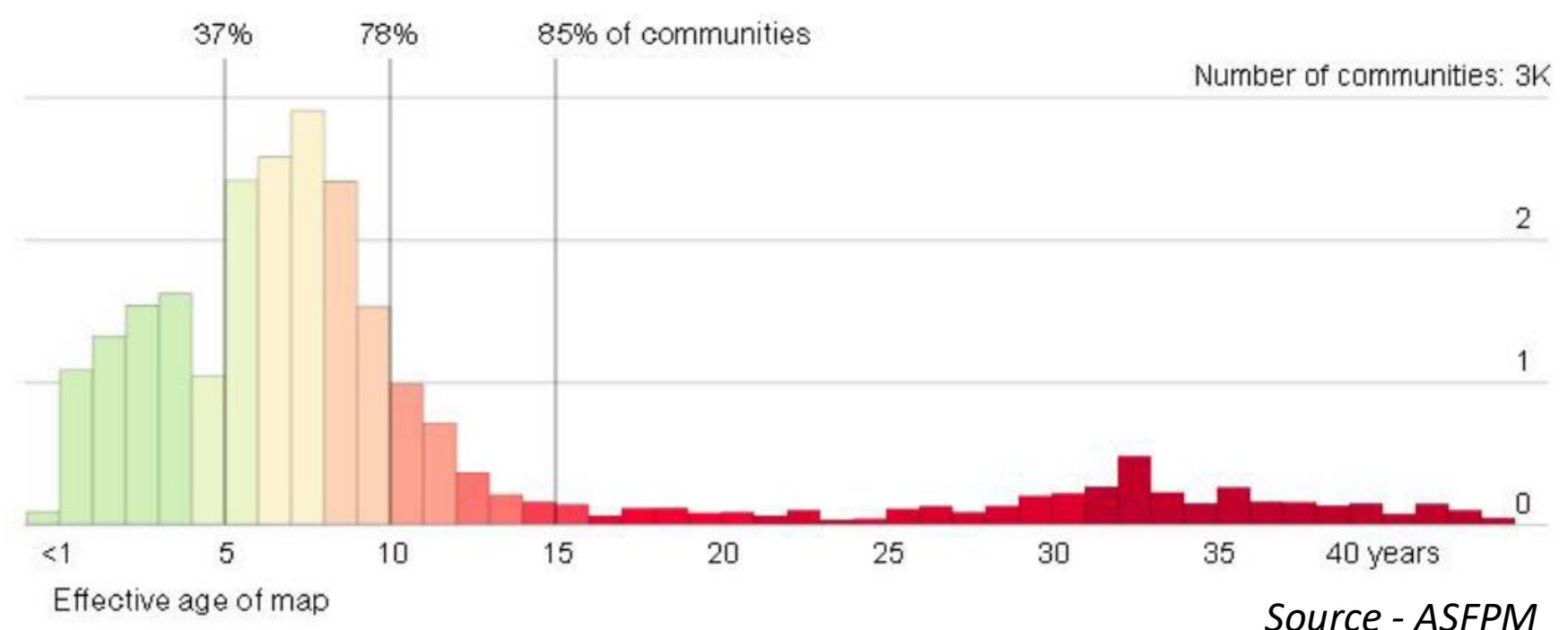
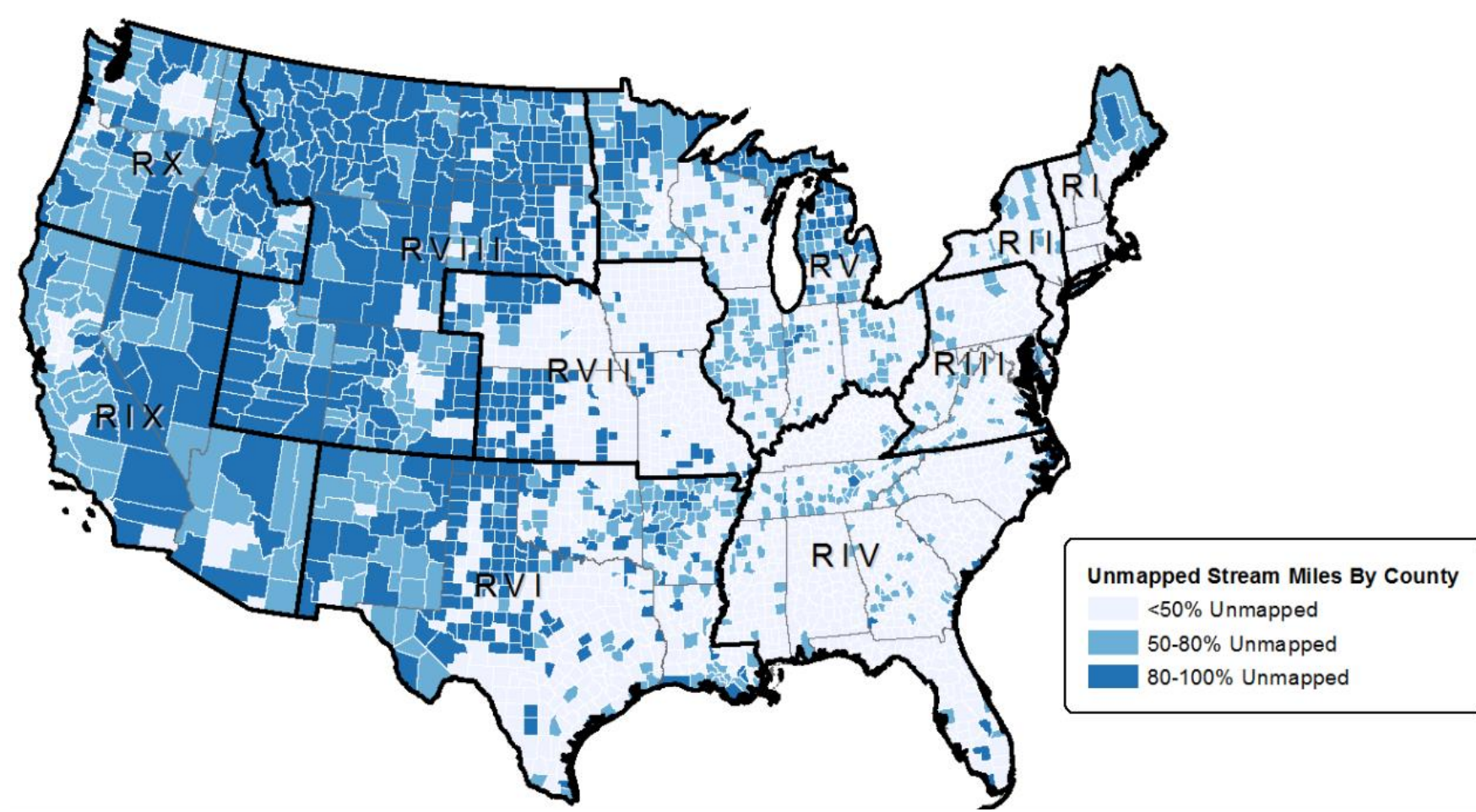
Why does AI matter?



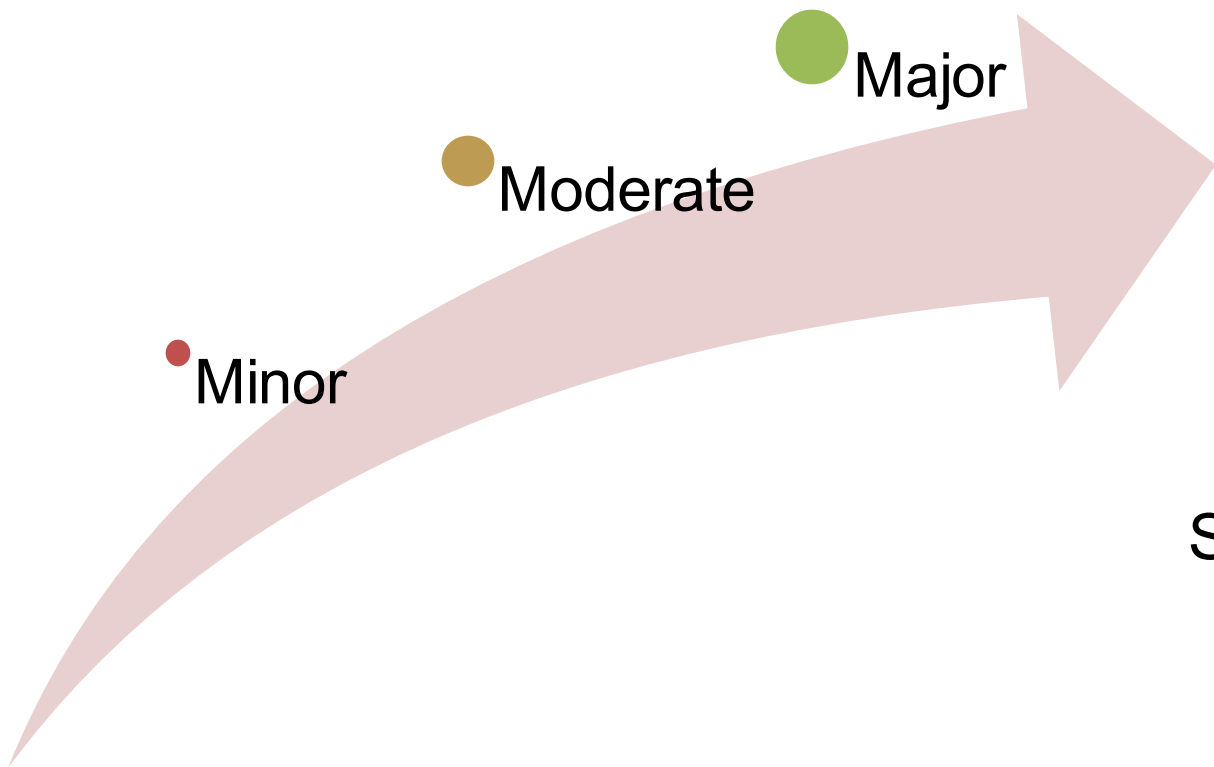
Flood Risk Is Rising



Are Our Models Keeping Up?



Flood Damages



Since 1980:

Globe

+ \$1 trillion

220,000 fatalities



US

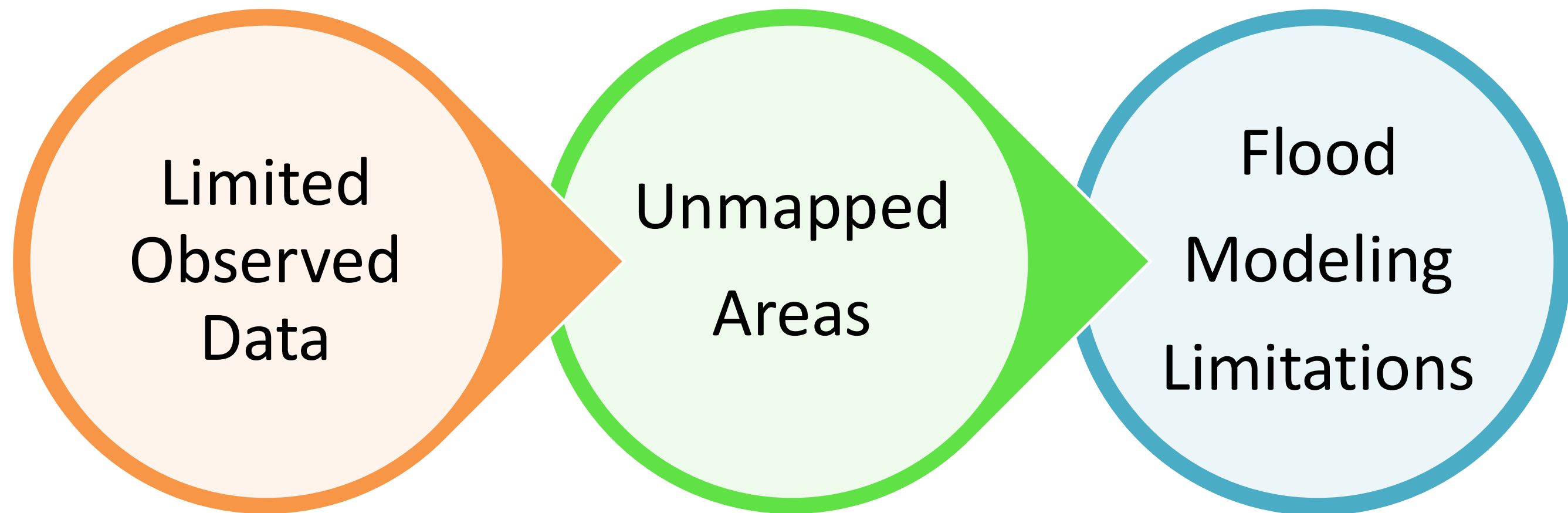
\$ 36.2 billion

26.4% by 2050



 Mitigation Plans

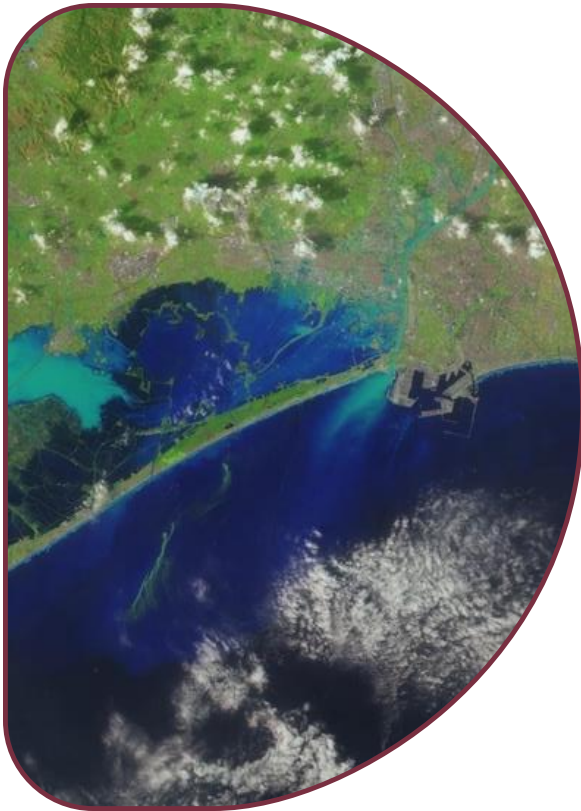
Challenges



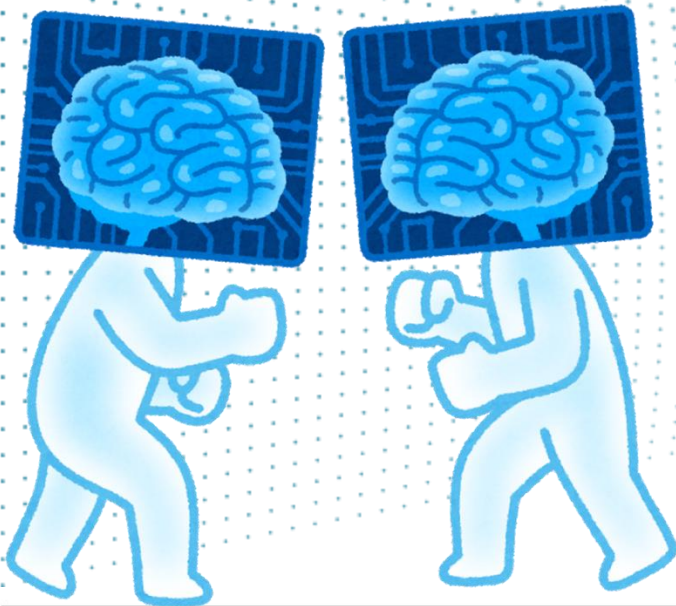
Challenges

Limited
Observed
Data

Sentinel
Landsat
MODIS
SWOT

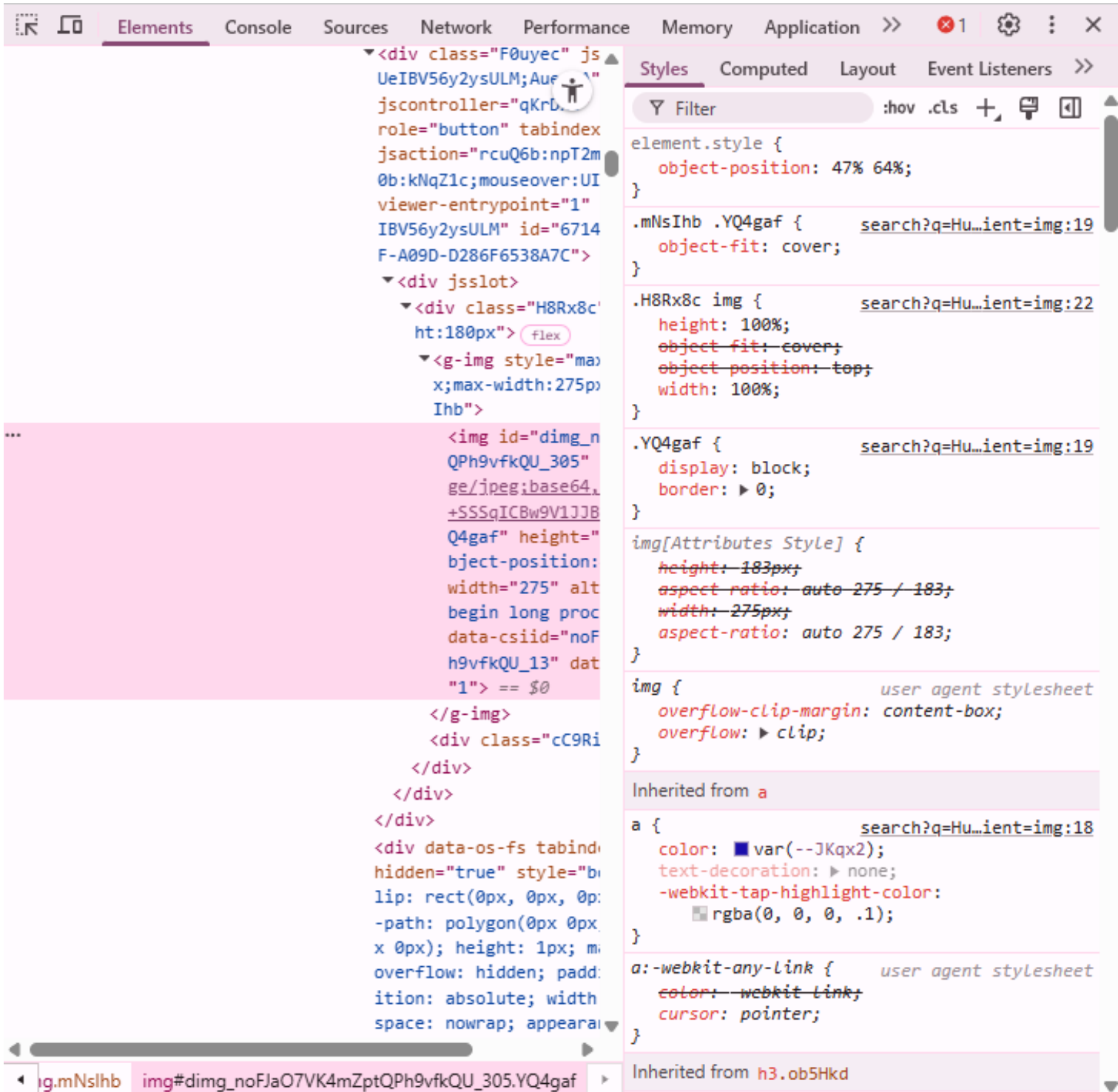
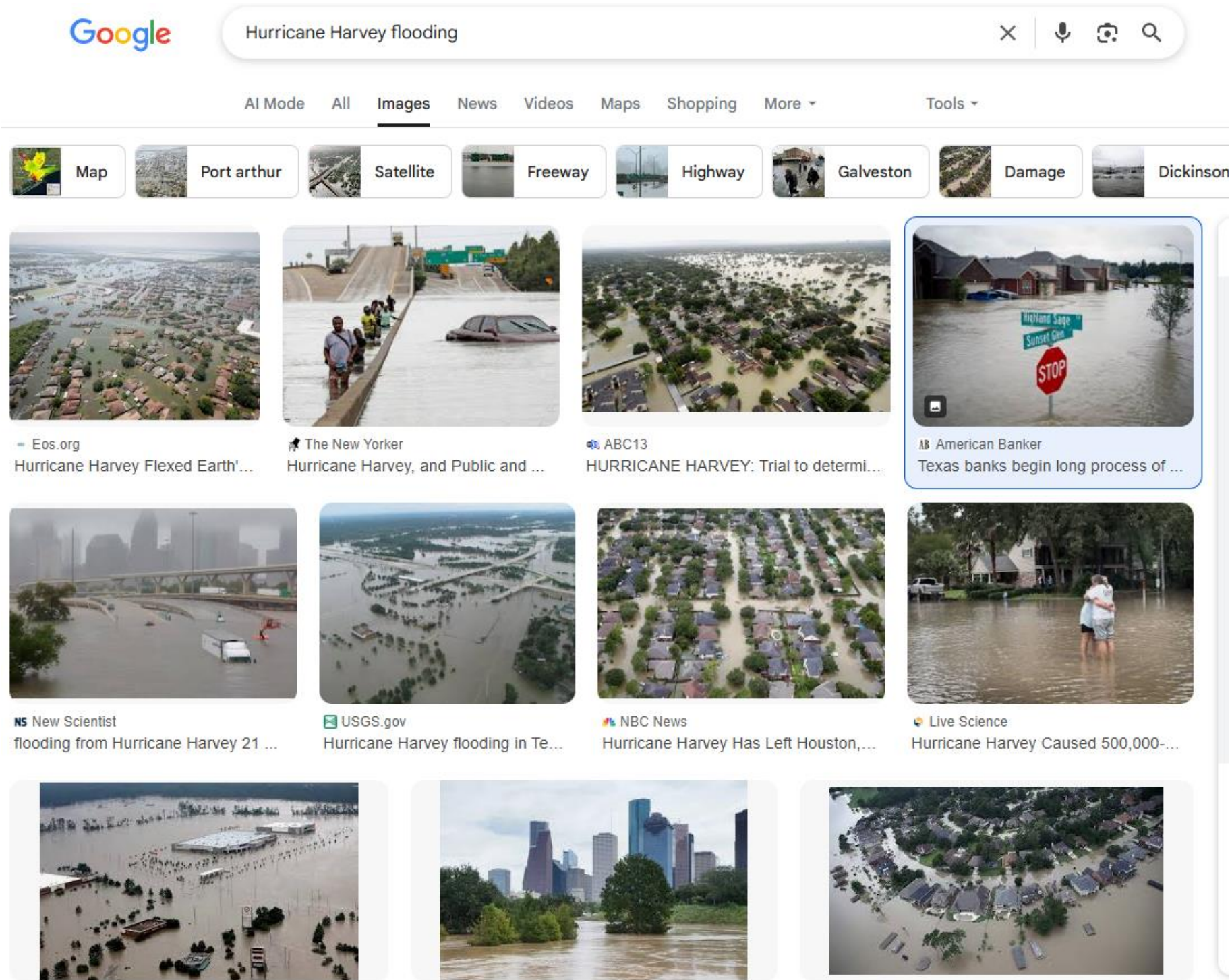
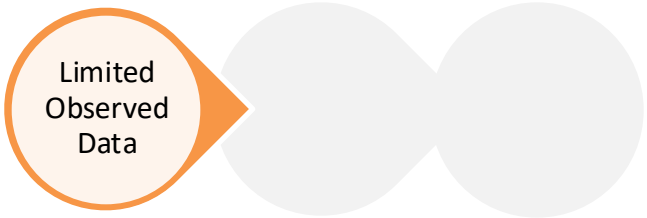


11,340
+160,000

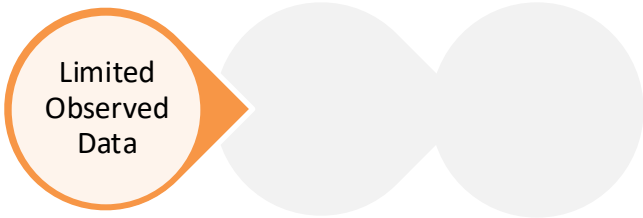


AI-Driven High Water Mark Estimation

Community-sourced Flood Images



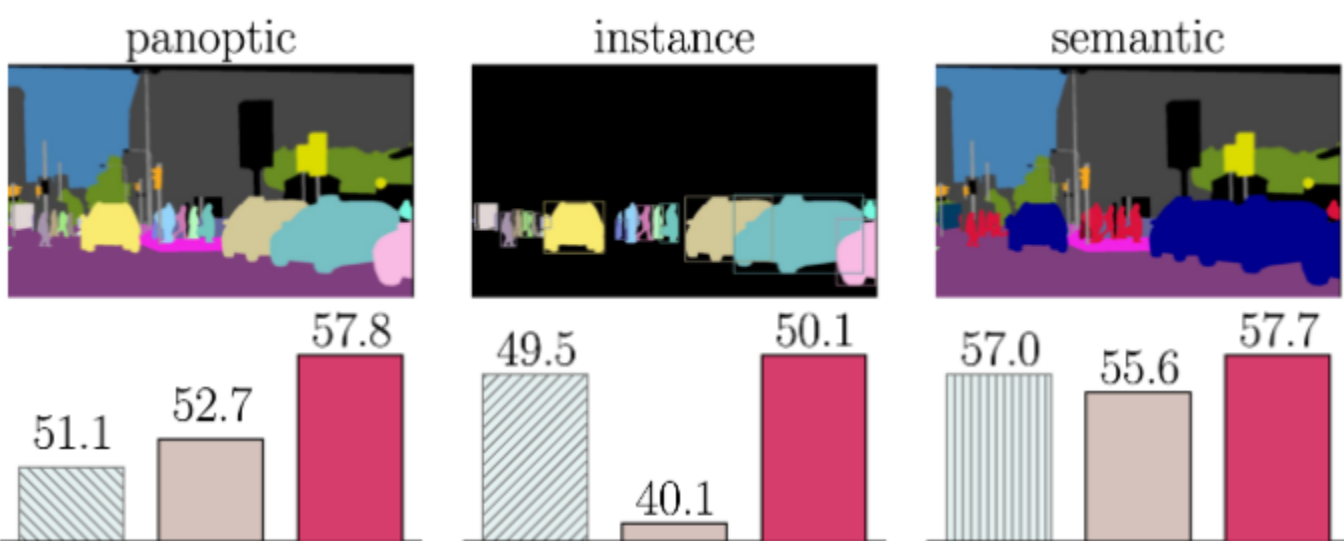
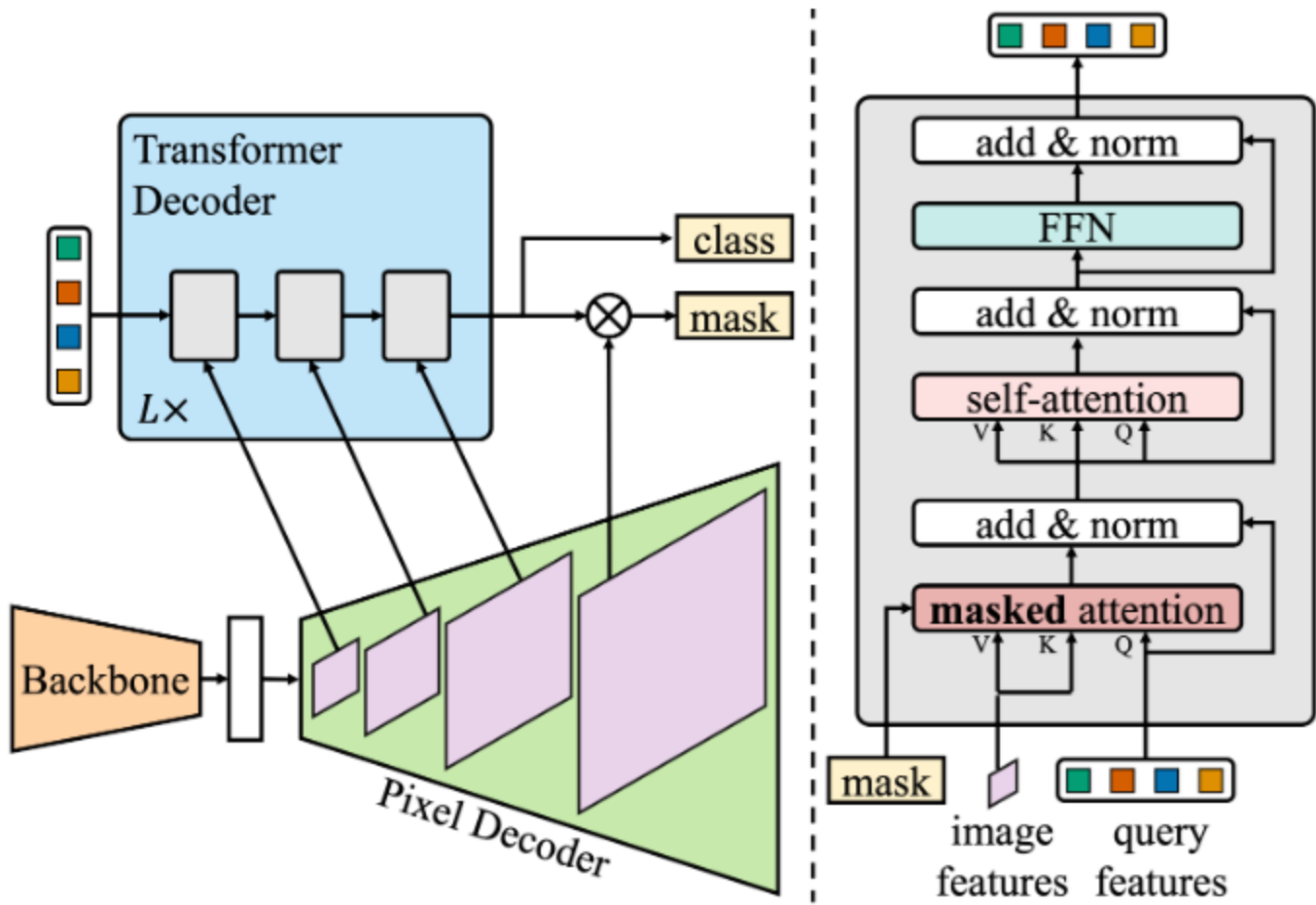
AI-based Image Segmentation



Masked-attention Mask Transformer for Universal Image Segmentation

Bowen Cheng^{1,2*} Ishan Misra¹ Alexander G. Schwing² Alexander Kirillov¹ Rohit Girdhar¹
¹Facebook AI Research (FAIR) ²University of Illinois at Urbana-Champaign (UIUC)
<https://bowenc0221.github.io/mask2former>

Mask2Former



Universal architectures:
Mask2Former (ours) MaskFormer

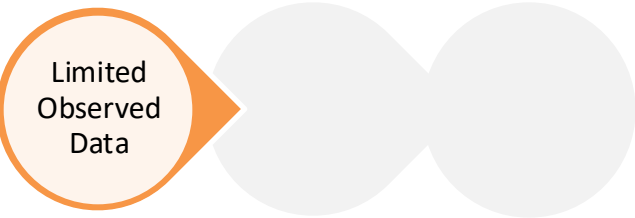
SOTA specialized architectures:
Max-DeepLab Swin-HTC++ BEiT

AI-based Image Segmentation

Limited
Observed
Data



Flood Depth Estimation using GPT 4o Model



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

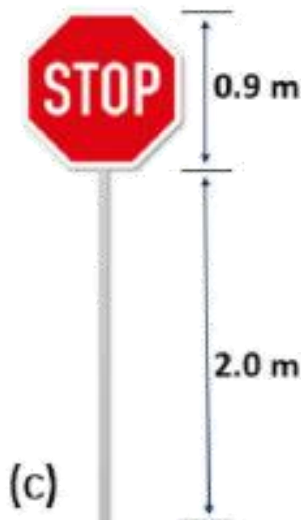
Automated floodwater depth estimation using large multimodal model for rapid flood mapping

Temitope Akinboyewa¹, Huan Ning¹, M. Naser Lessani¹ 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



Flooding Extent Estimation

Limited
Observed
Data

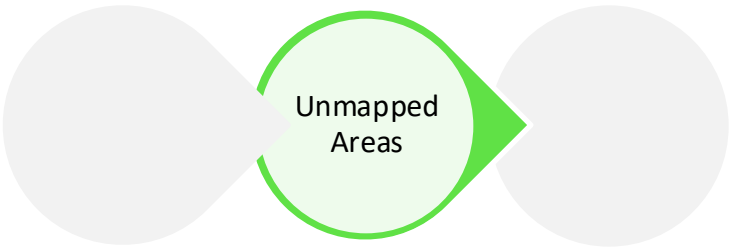


Automating Geolocation of Images

Limited
Observed
Data



Gaps in Flood Risk Mapping

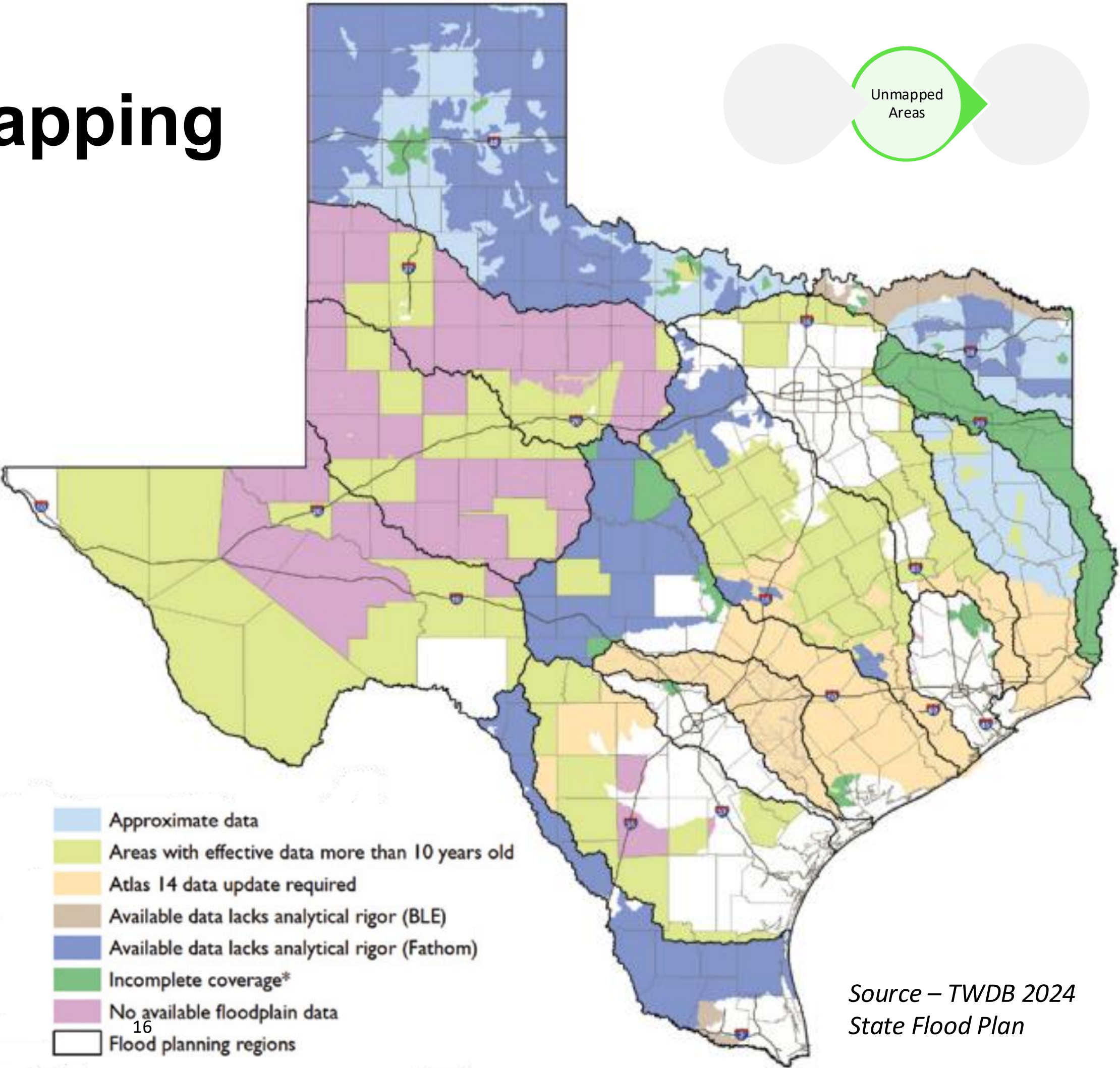


121 Counties in Texas do not have effective Flood Insurance Rate Maps

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



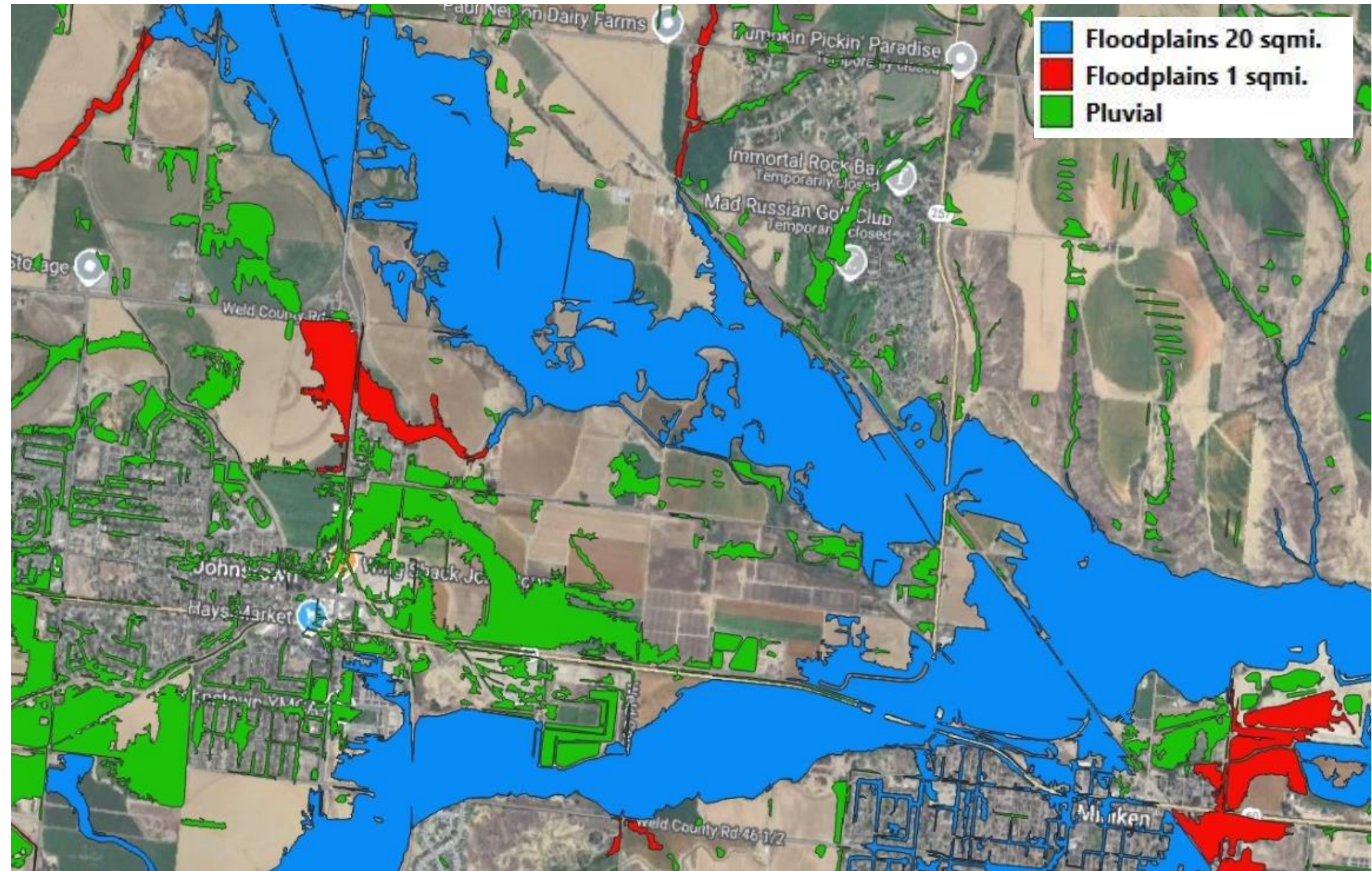
- Approximate data
- Areas with effective data more than 10 years old
- Atlas 14 data update required
- Available data lacks analytical rigor (BLE)
- Available data lacks analytical rigor (Fathom)
- Incomplete coverage*
- No available floodplain data
- Flood planning regions

Machine Learning to *Map the Unmapped*

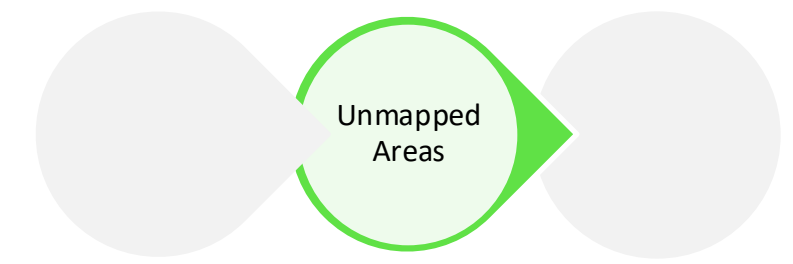
Data-driven Flood Extent Estimation

Unmapped
Areas

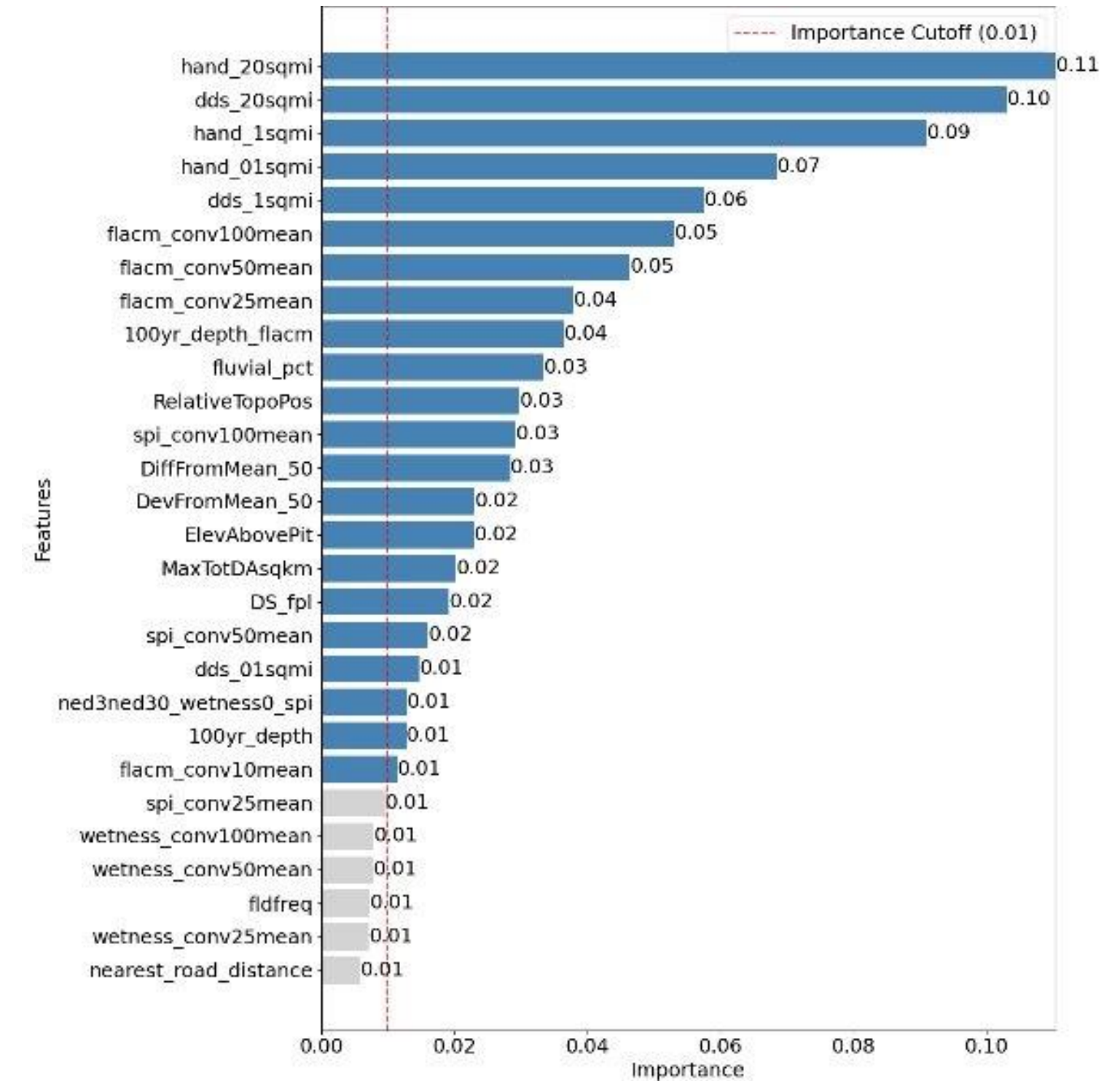
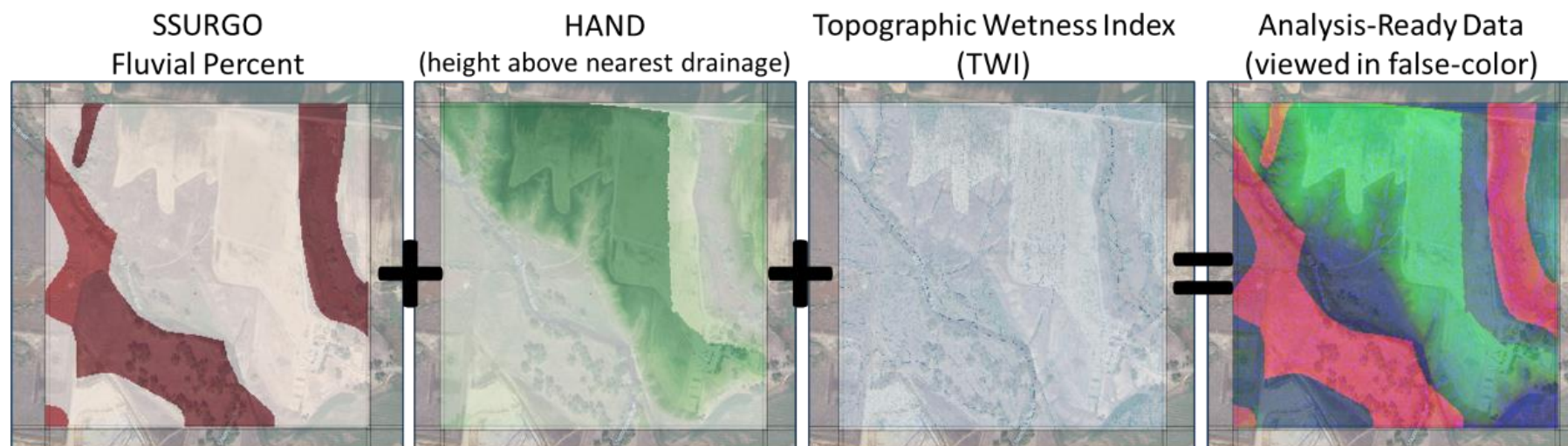
- **Dry**
- **Pluvial**
- **1 square-mile floodplains**
- **20 square-mile floodplains**



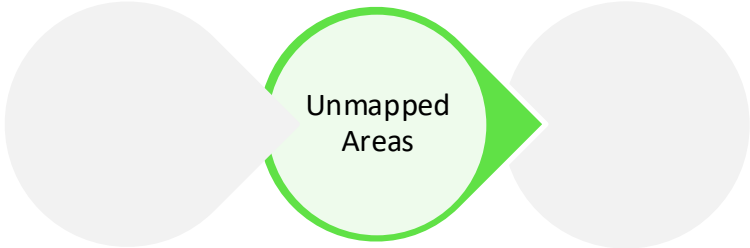
Feature Importance



- 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.



Prediction Probability

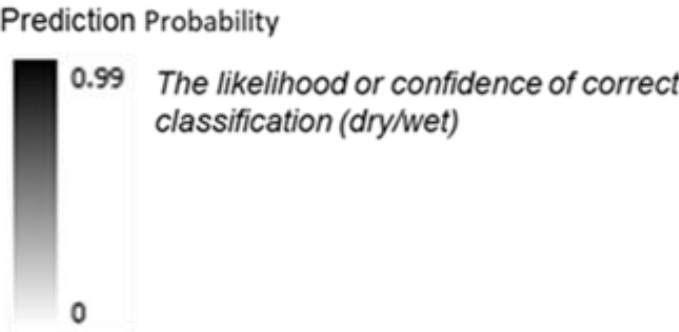
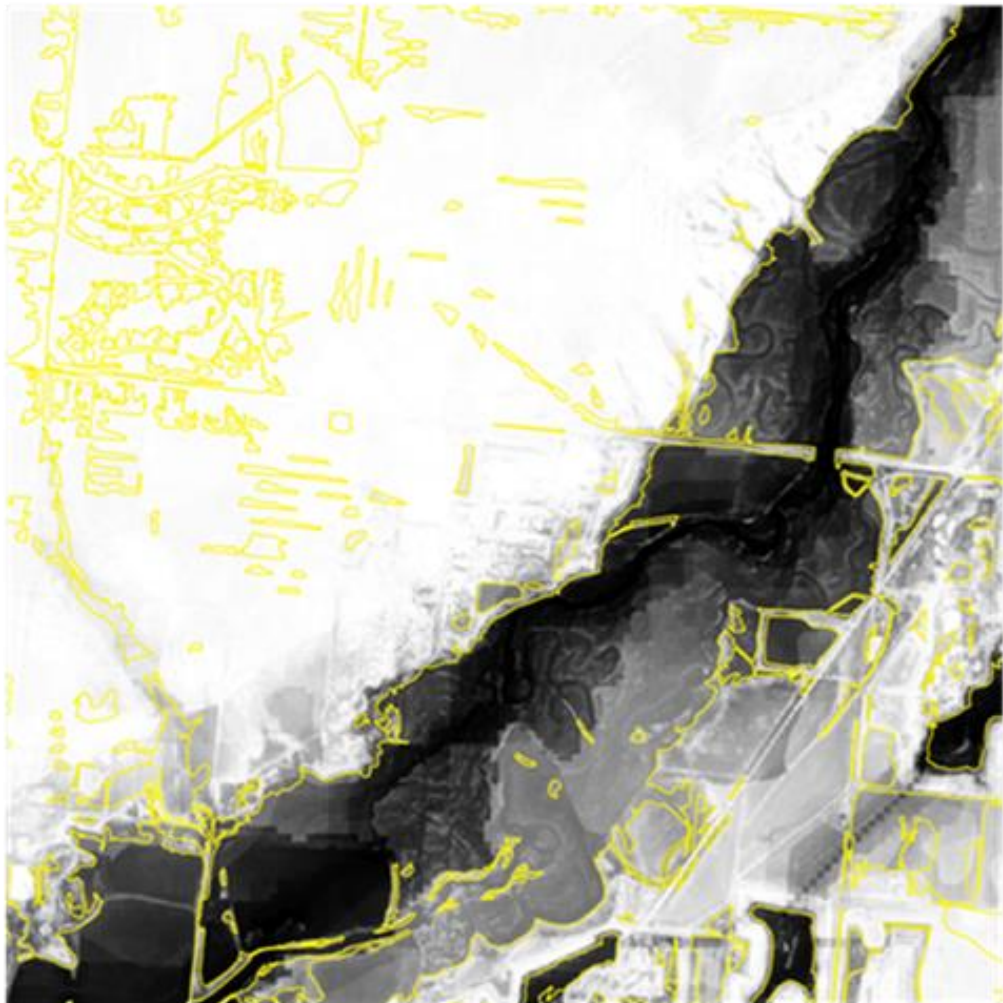


100-year, Fluvial + Pluvial Flooding



Fluvial and Pluvial Flooding (100-yr)

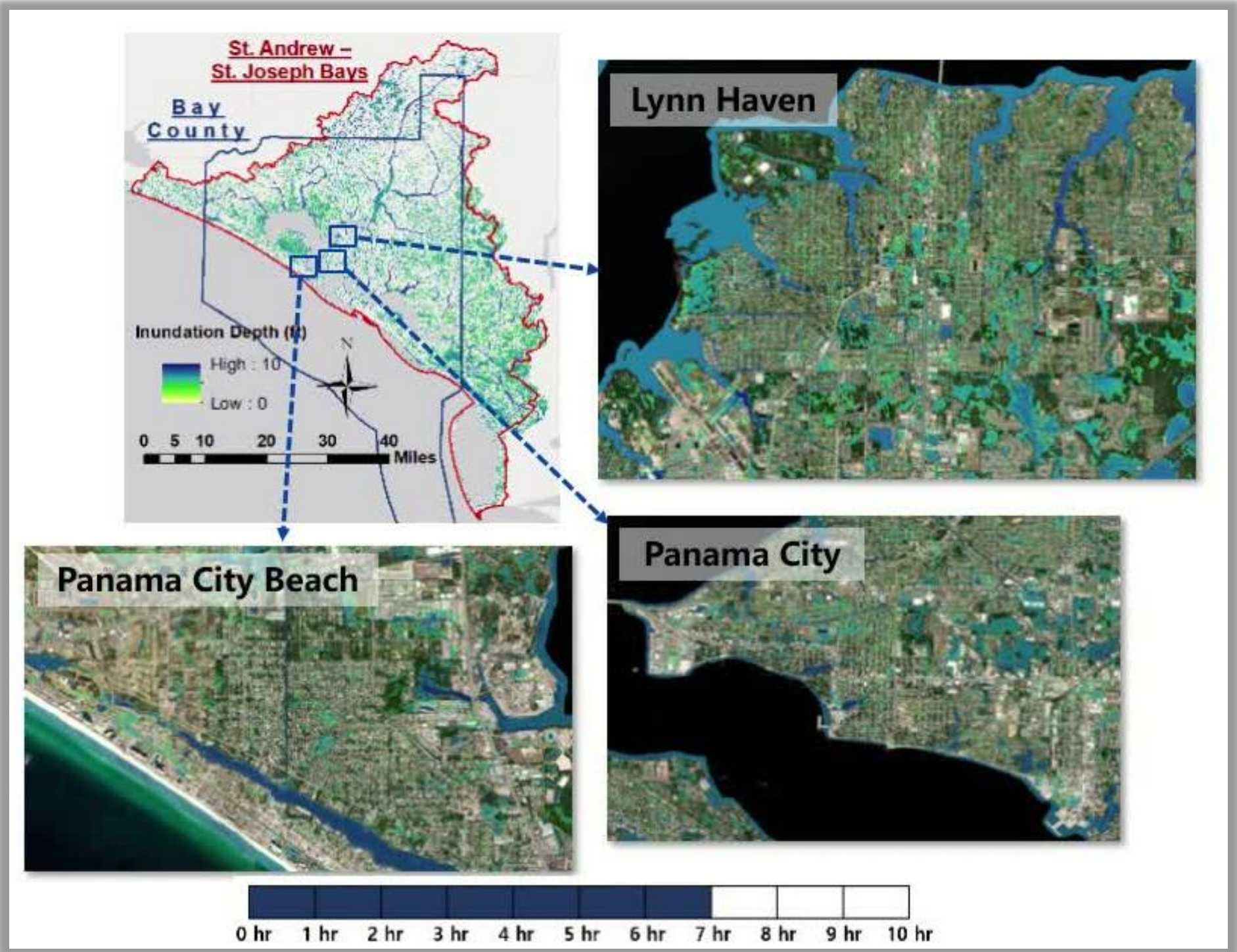
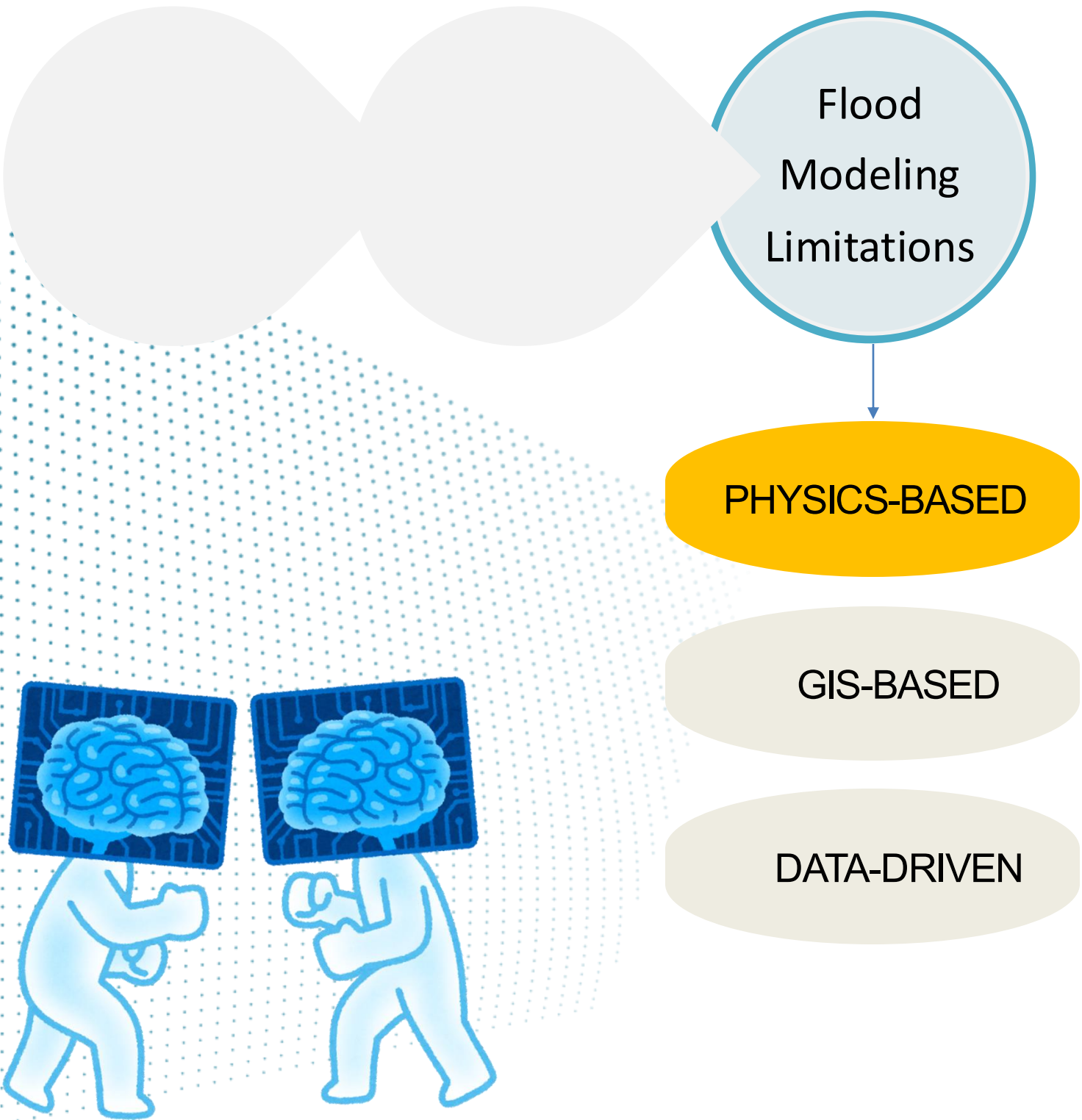
20-sq.mi. drainage (minimum) floodplain probability



Pluvial flooding probability



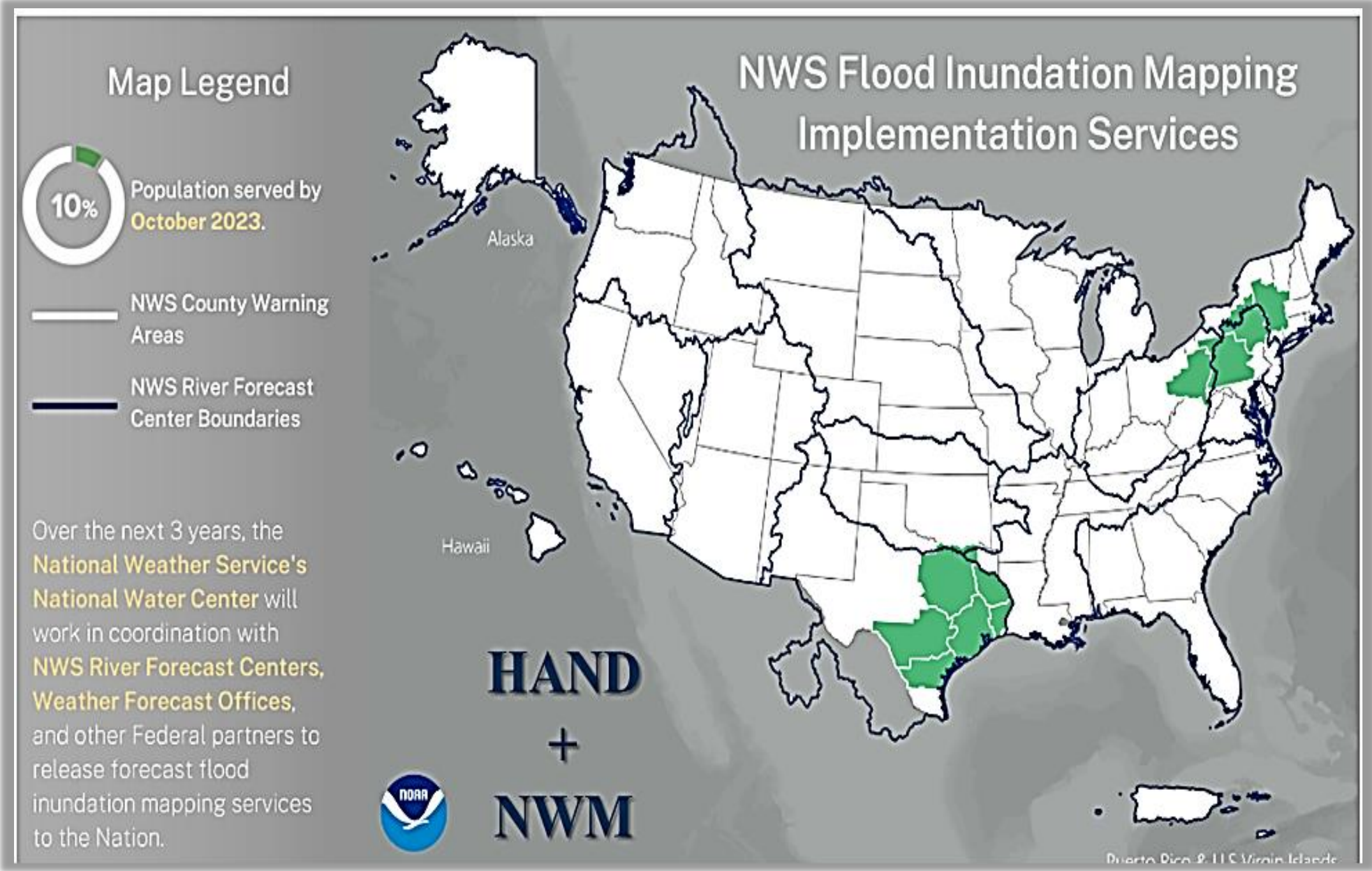
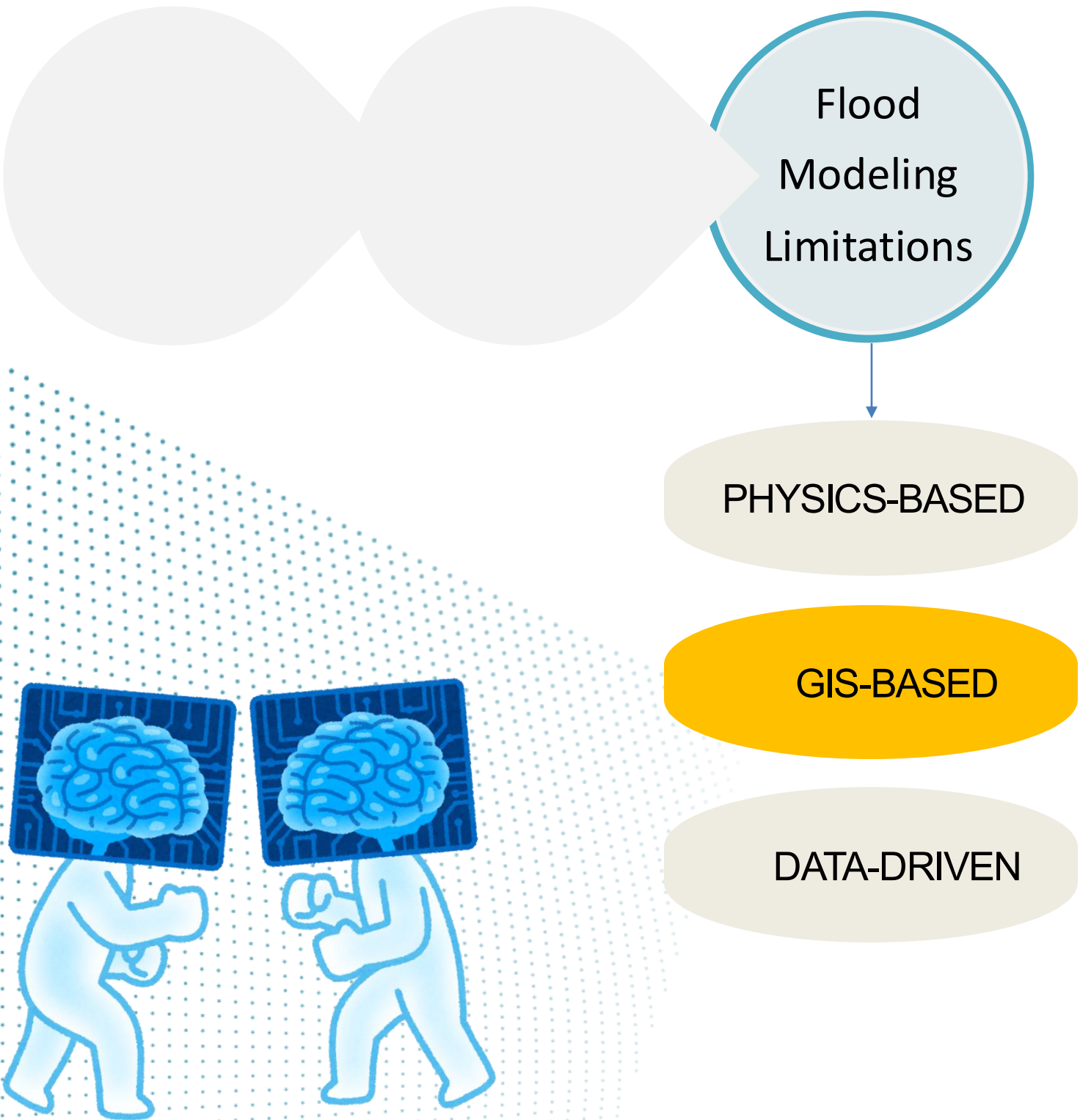
Challenges



HEC-RAS, RASPLOT, Delft3D-Flow

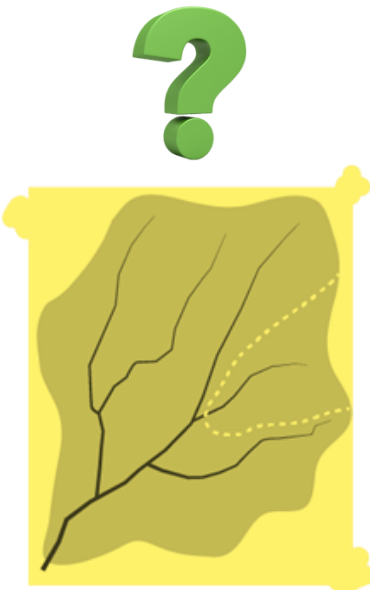
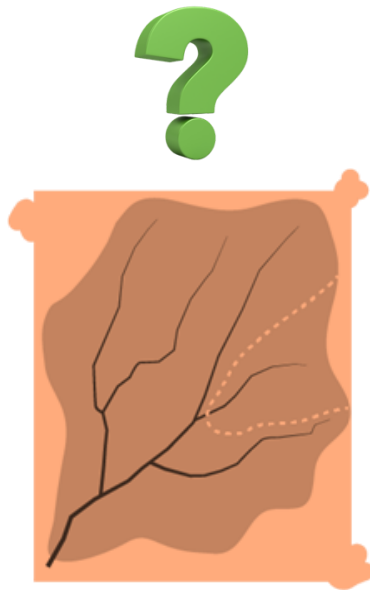
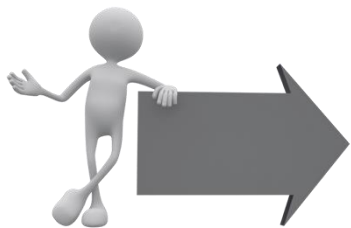
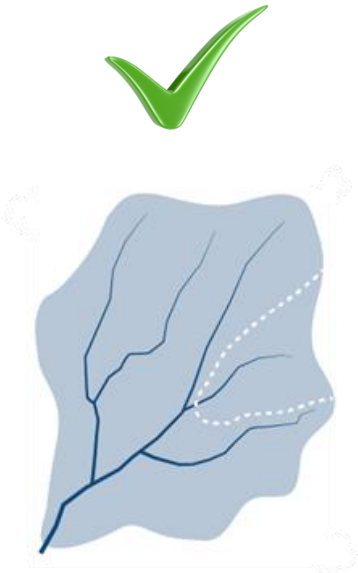
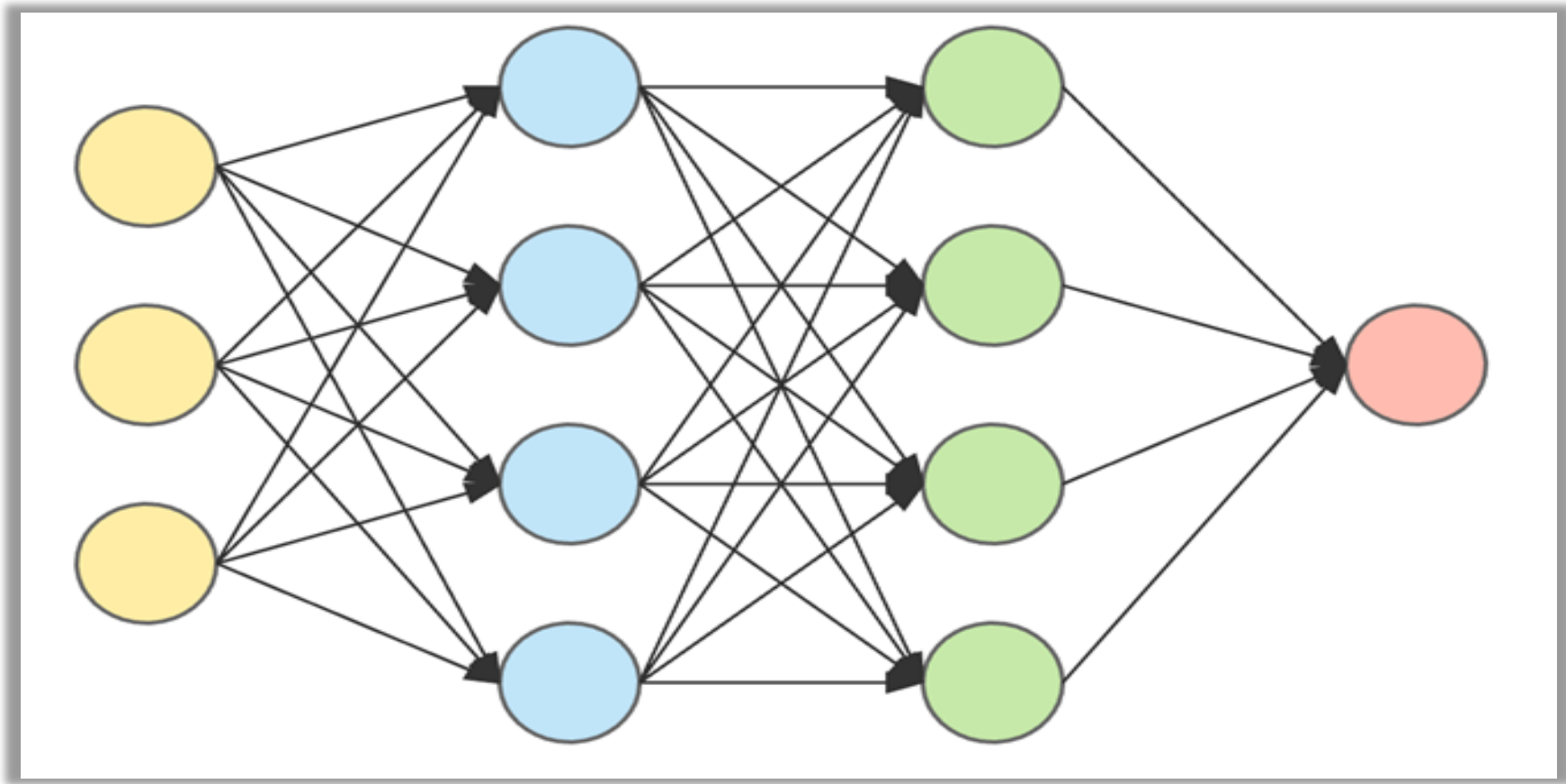
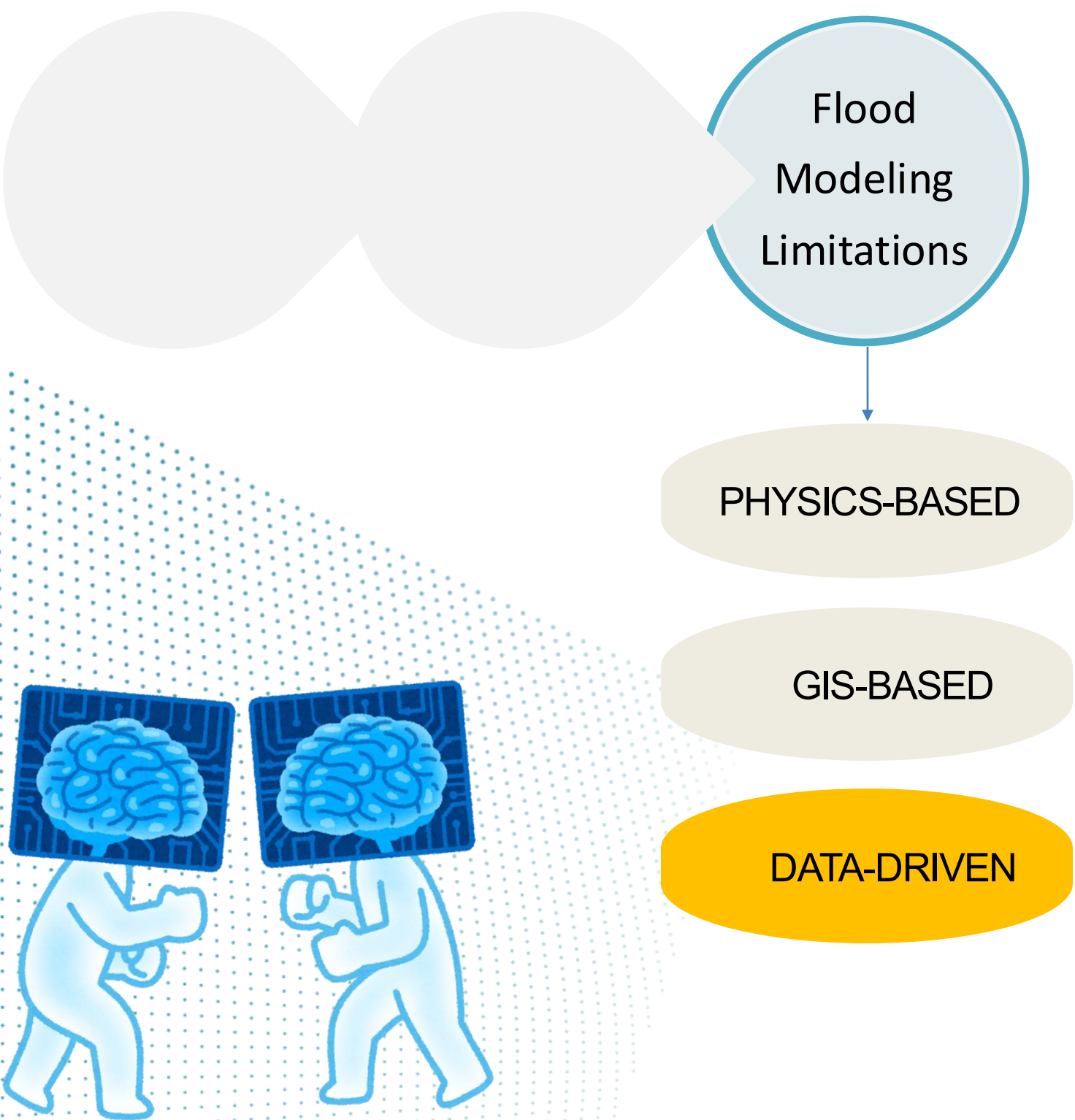


Challenges



Bathtub, HAND

Challenges



Transferability of ML Flood Models

Overarching Goal

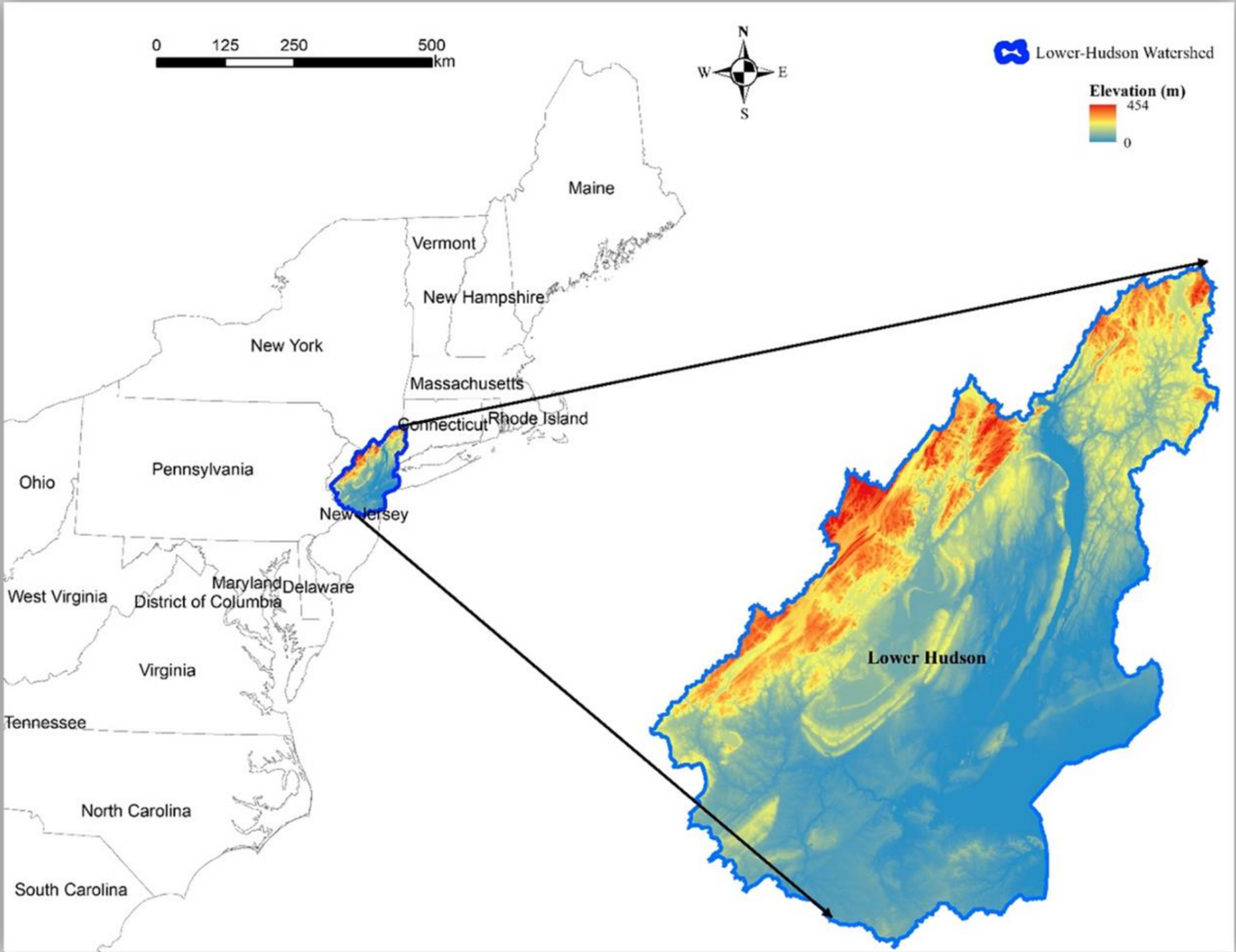
Evaluate the **ML model** performance for **hindcasting flood depths** and test its **transferability** across **different flood events** in a **coastal watershed**.



Hurricane Ida (2021)



Study Area



Observed Flood Data



Features

GEOGRAPHIC LOCATION



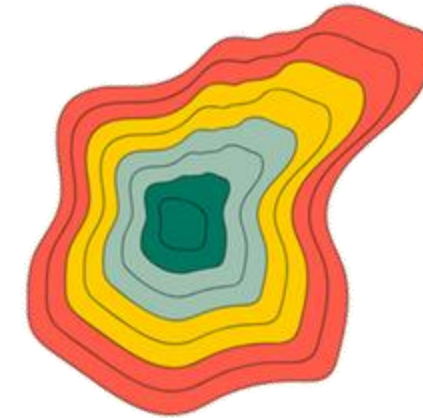
HYDROLOGIC



METEOROLOGIC



TOPOGRAPHIC



LAND SURFACE



SOIL

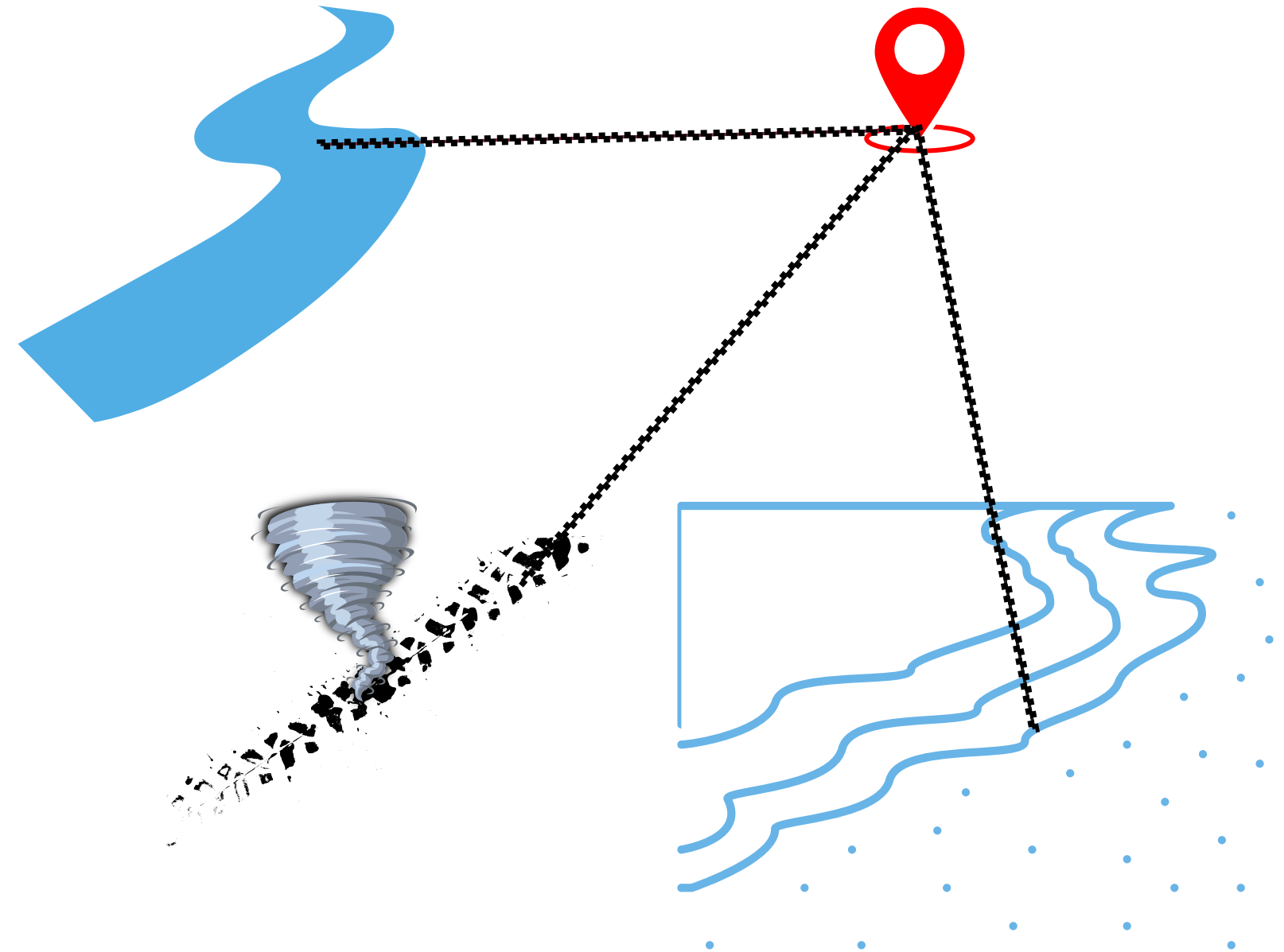


HYDRODYNAMIC



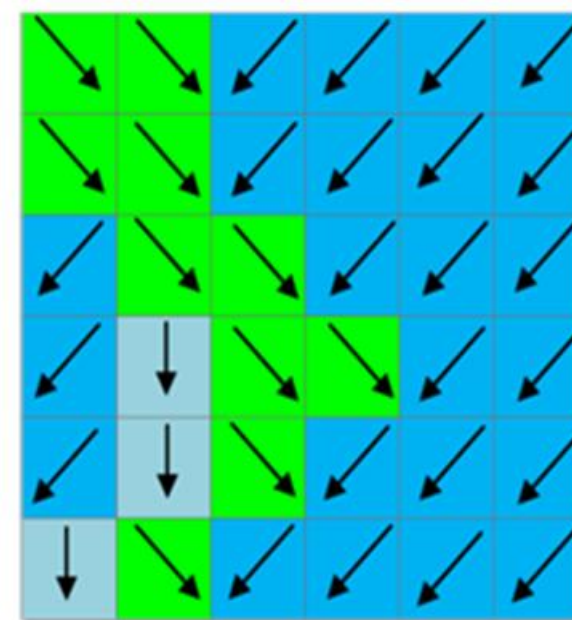
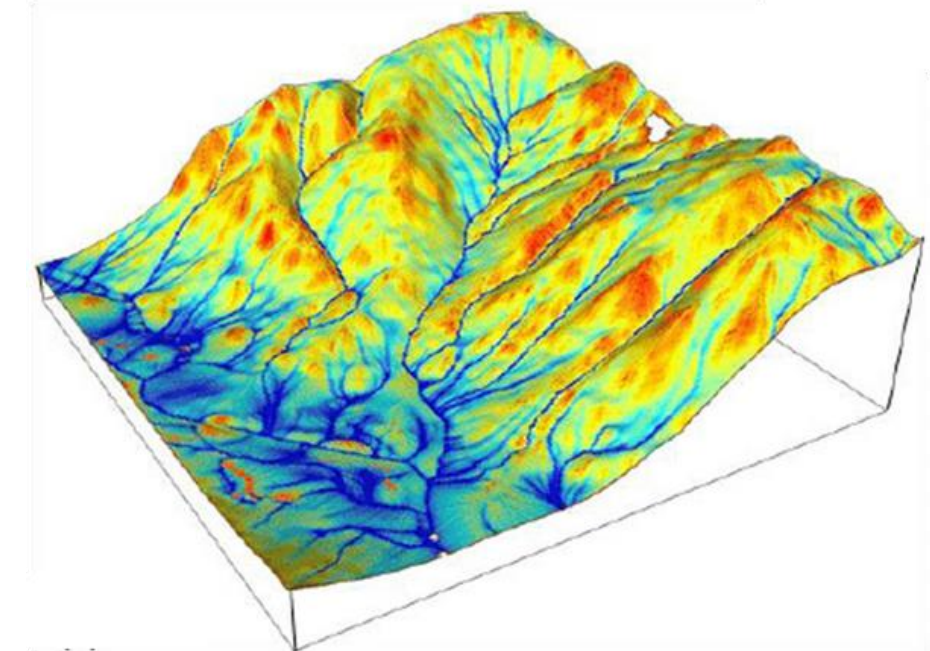
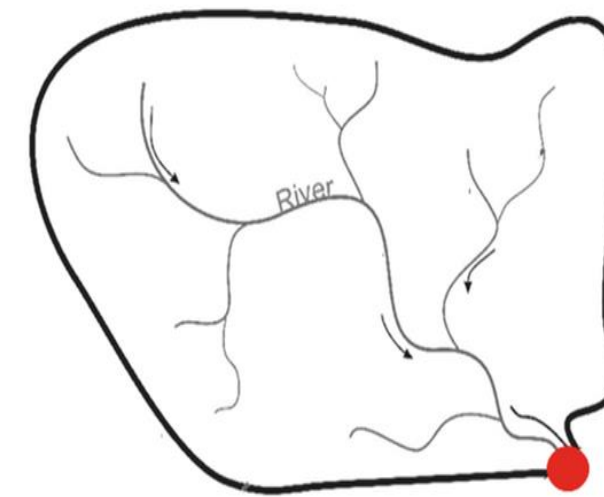
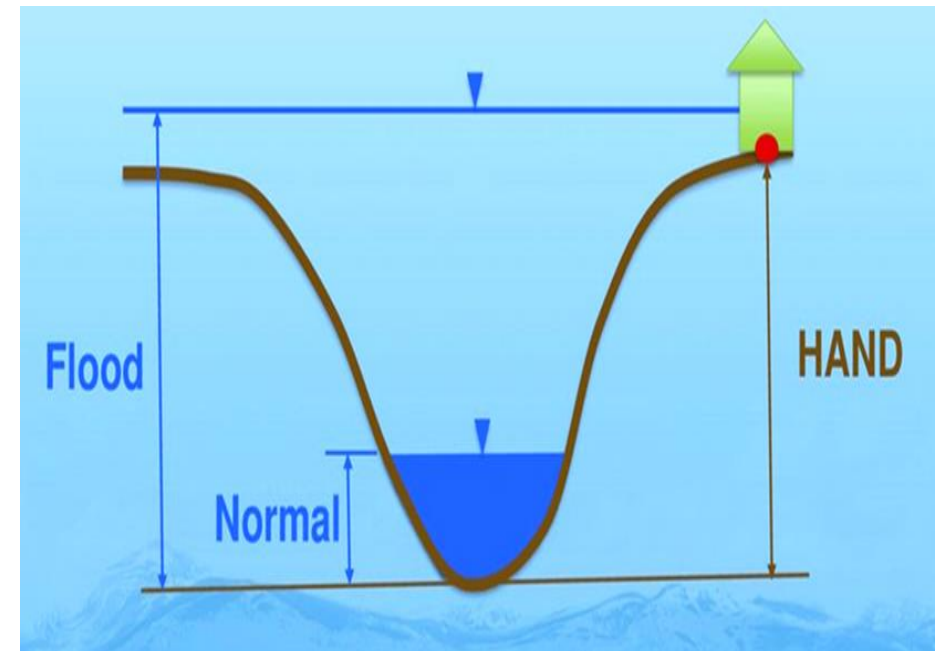
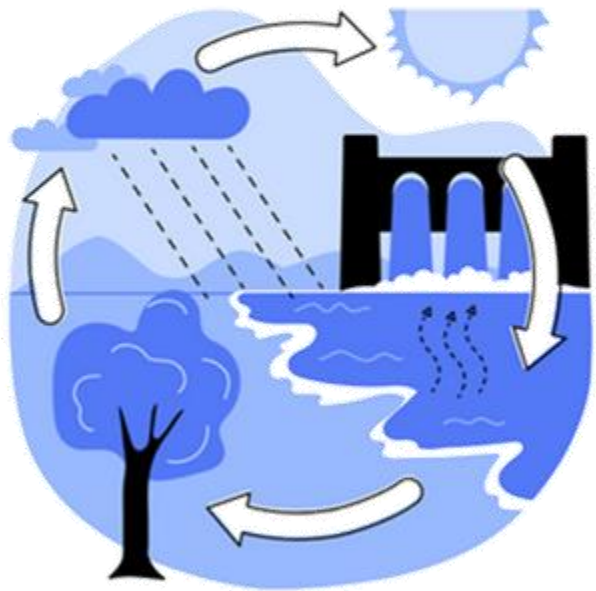
Features

GEOGRAPHIC LOCATION



Features

HYDROLOGIC



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

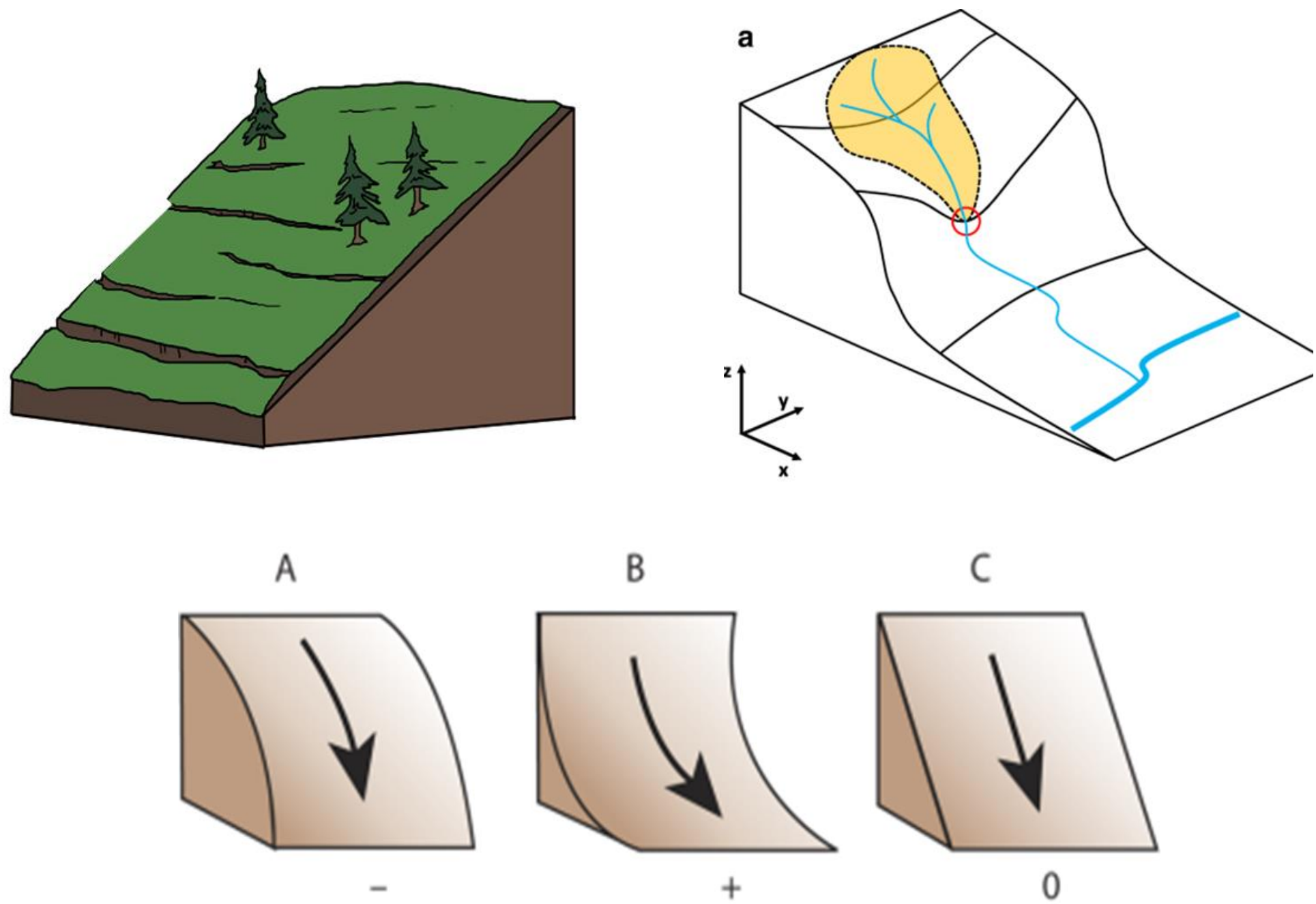


Features

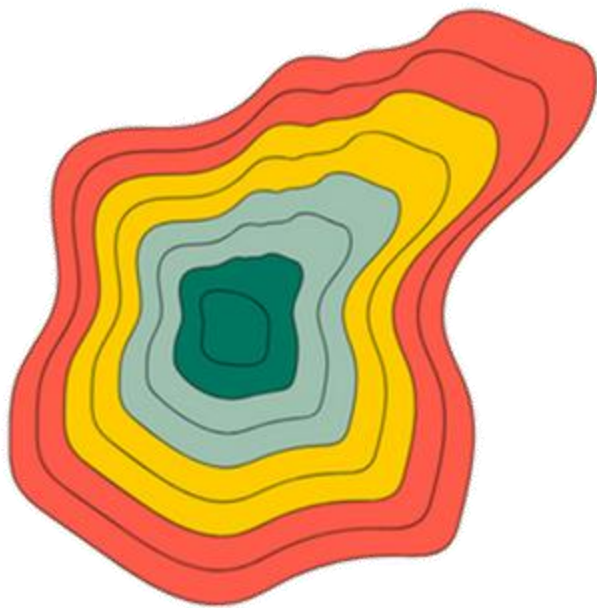


METEOROLOGIC



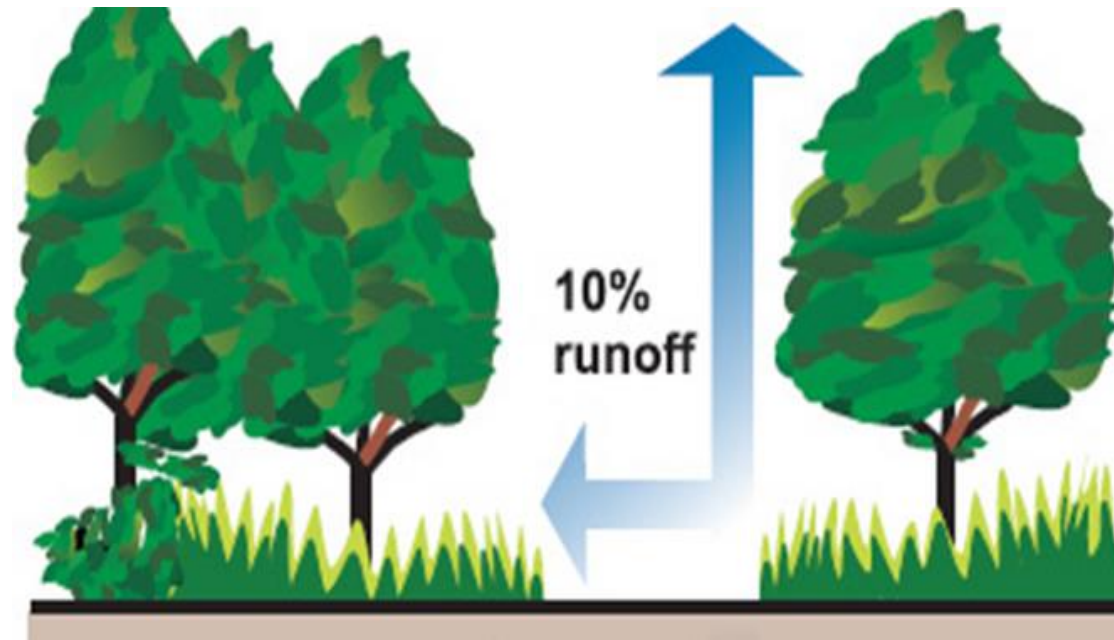


TOPOGRAPHIC



Features

LAND SURFACE



Features



Features

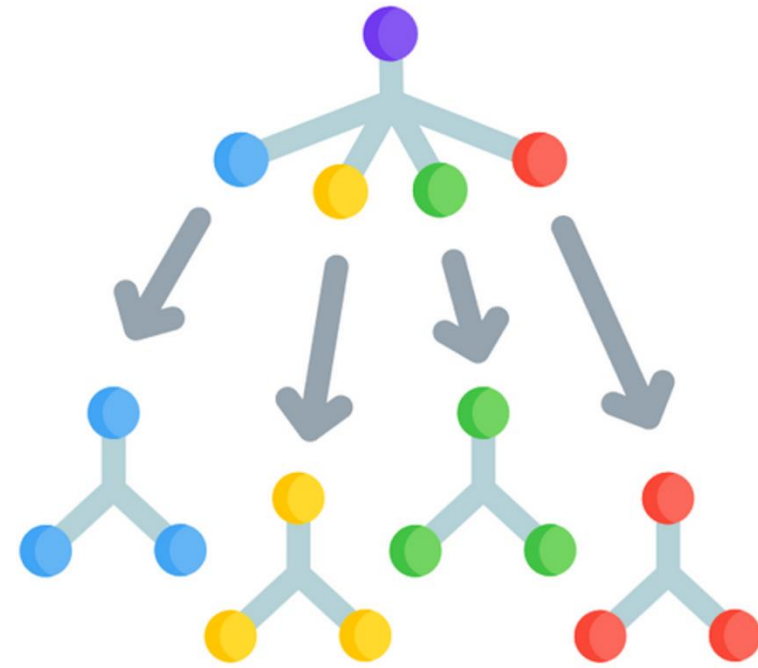
Flood
Modeling
Limitations



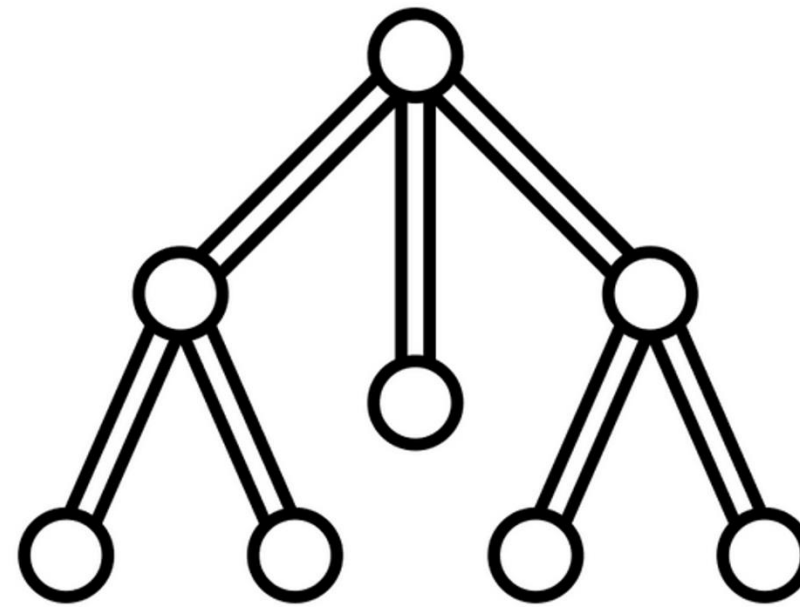
HYDRODYNAMIC



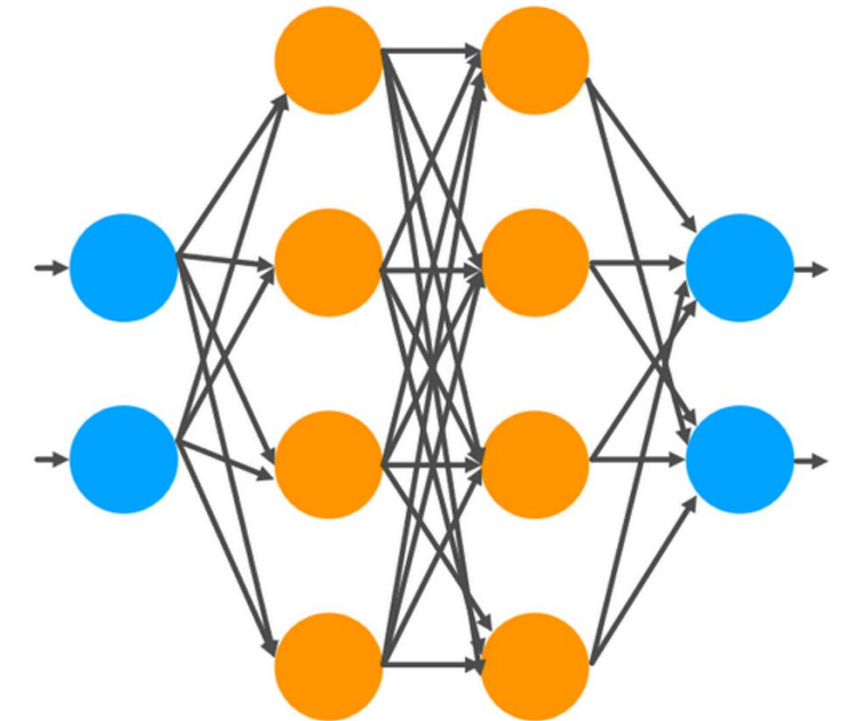
ML Models



RANDOM FOREST



XGBOOST



NEURAL NETWORK

Customized Loss Function



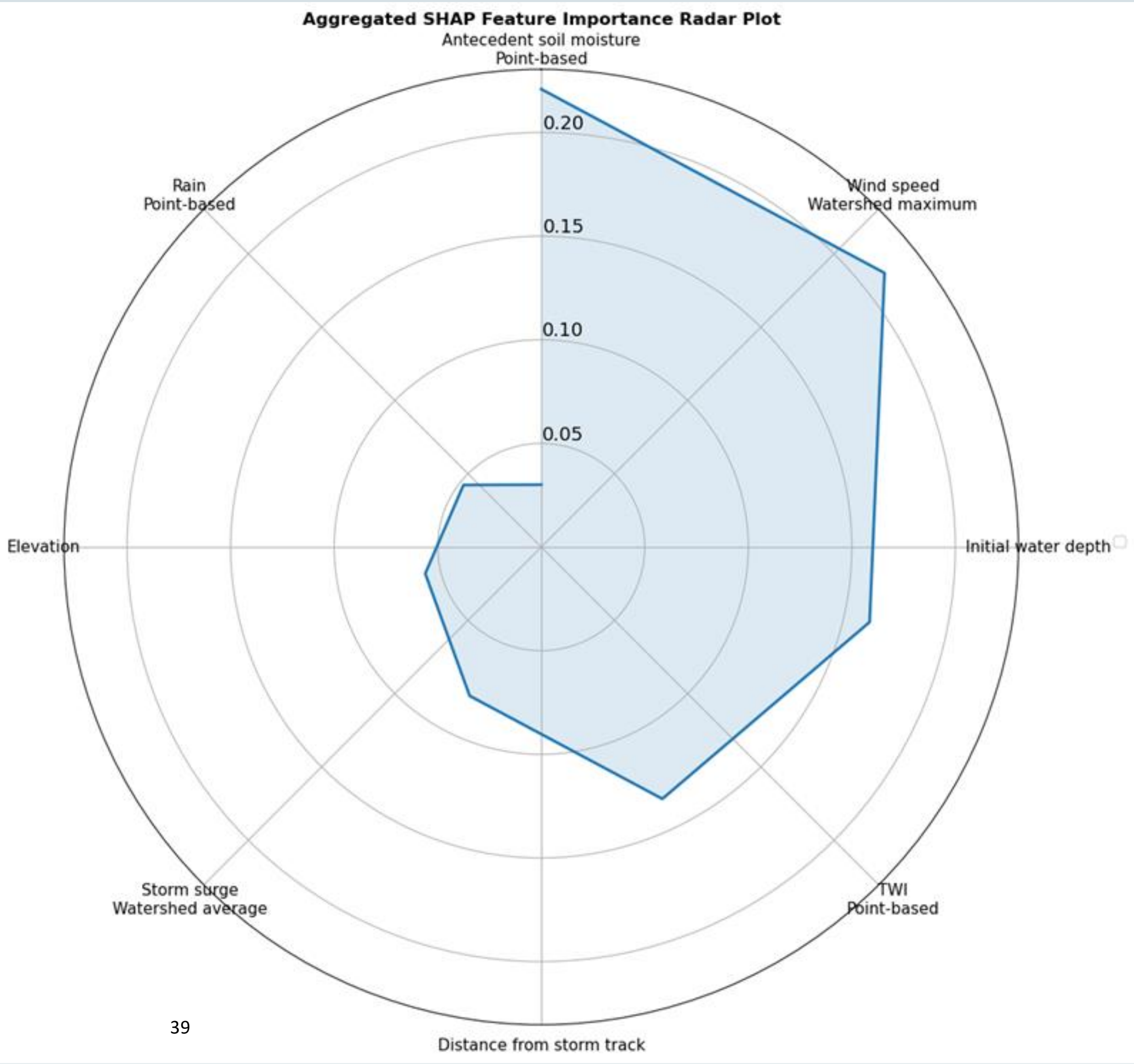
Amount of vertical uncertainty	Uncertainty
Within ± 0.05 foot.	Excellent (E)
Within ± 0.10 foot.	Good (G)
Within ± 0.20 foot.	Fair (F)
Within ± 0.40 foot.	Poor (P)
More than ± 0.40 foot.	Very poor (V)

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

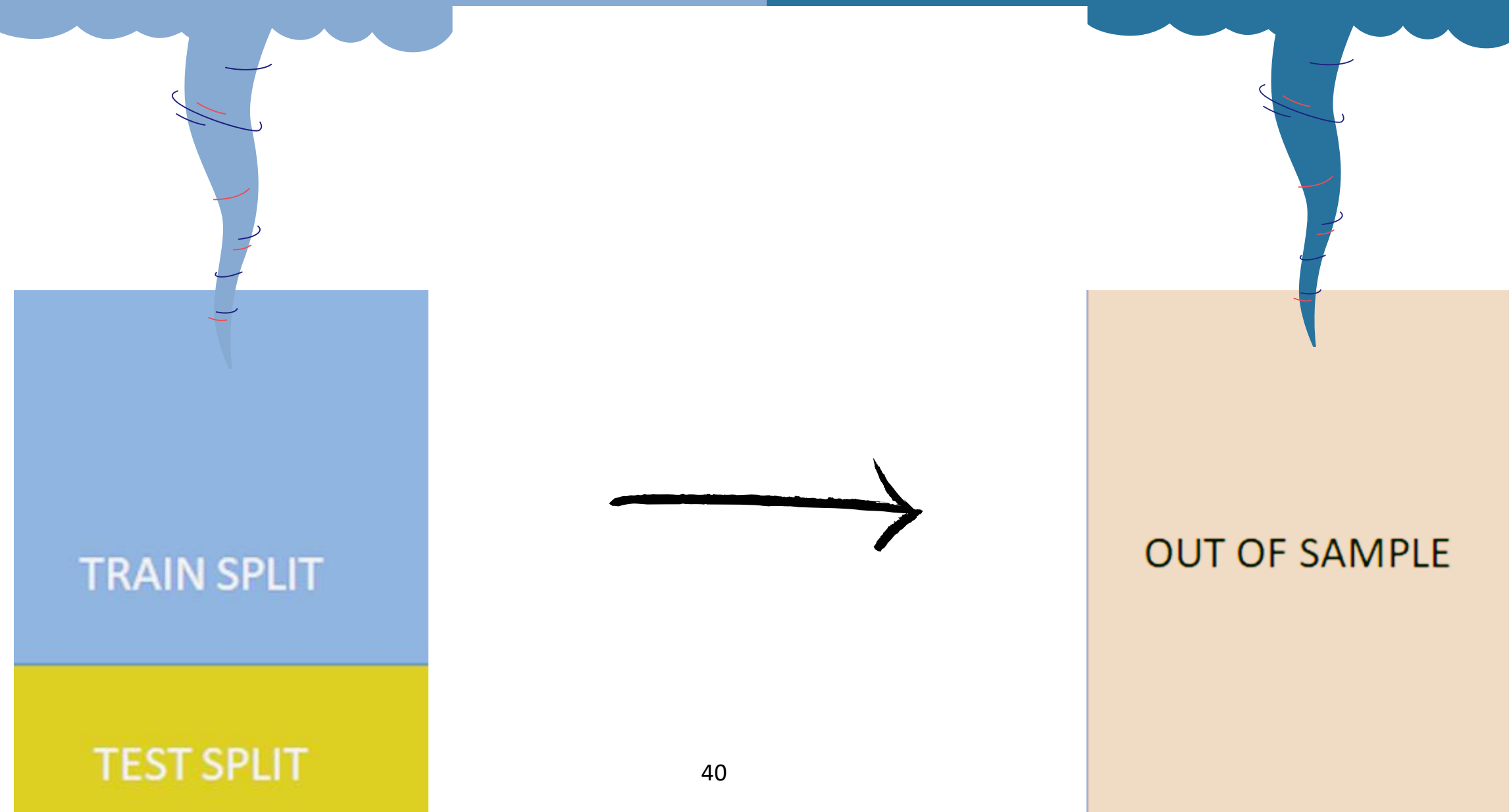
ANN MLP



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)

Results



Flood event	R^2	MAE	NRMSE	FQ
		(meters)	(%)	(%)
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

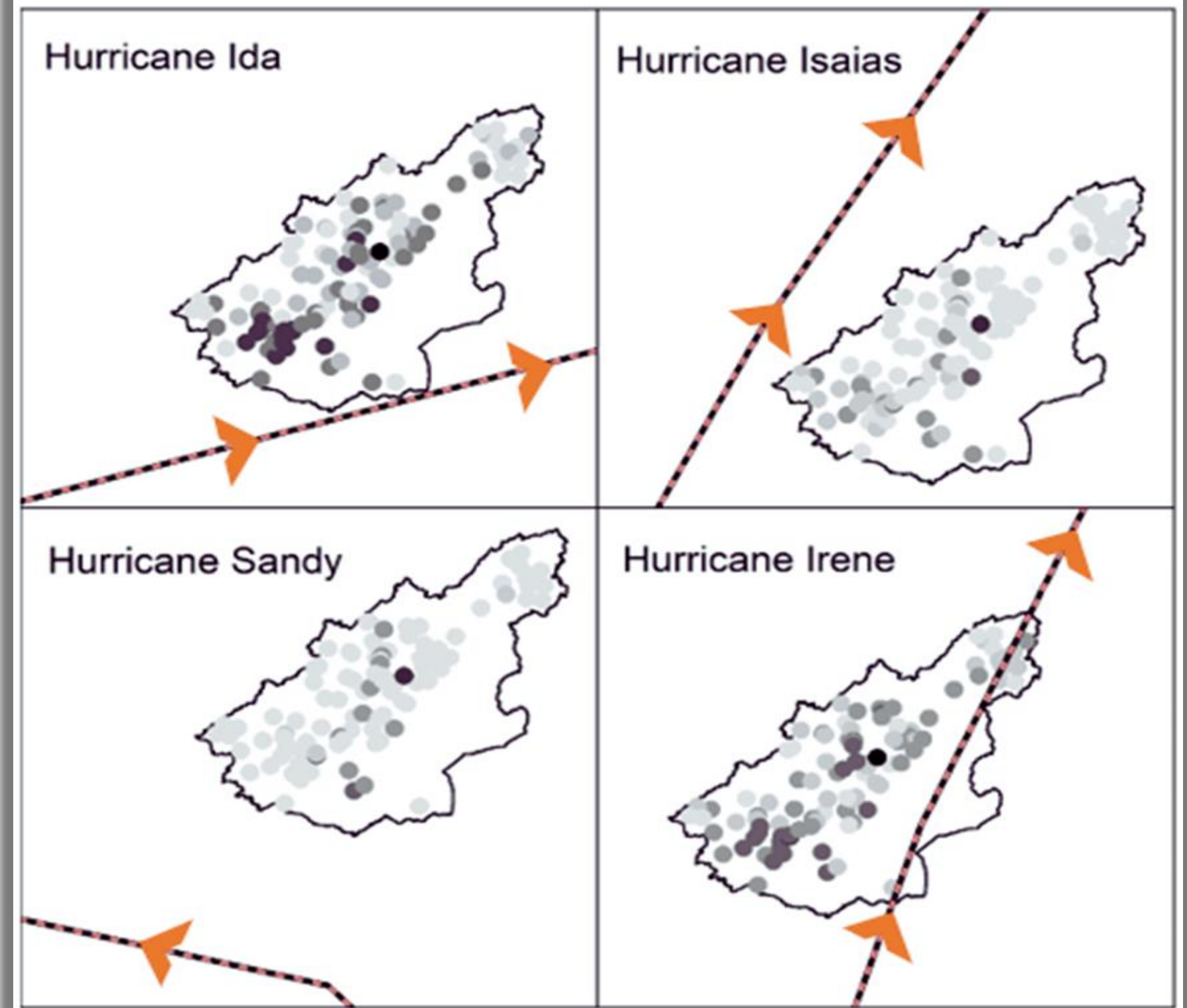
Results



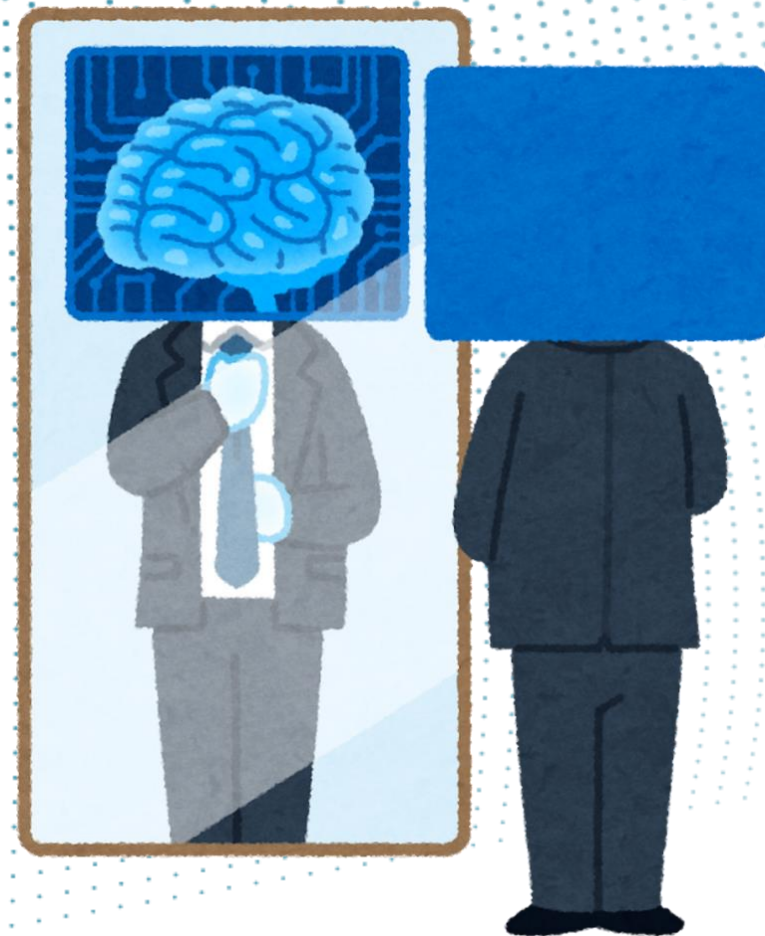
Event	Year	River max water depth (m)	Cumulative rainfall depth (mm)	Antecedent soil moisture (%)	Storm Surge (m)	Max wind speed (m/s)	Distance to storm track (m)
Ida	2021	0.85-36.66	121.92-201.81	21-43%	0.25-0.67	27.64-35.49	0.09-1.1
Isaias	2020	0.22-35.35	17.37-62.22	9-39%	0.20-0.76	48.29-65.33	0.23-1.14
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



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

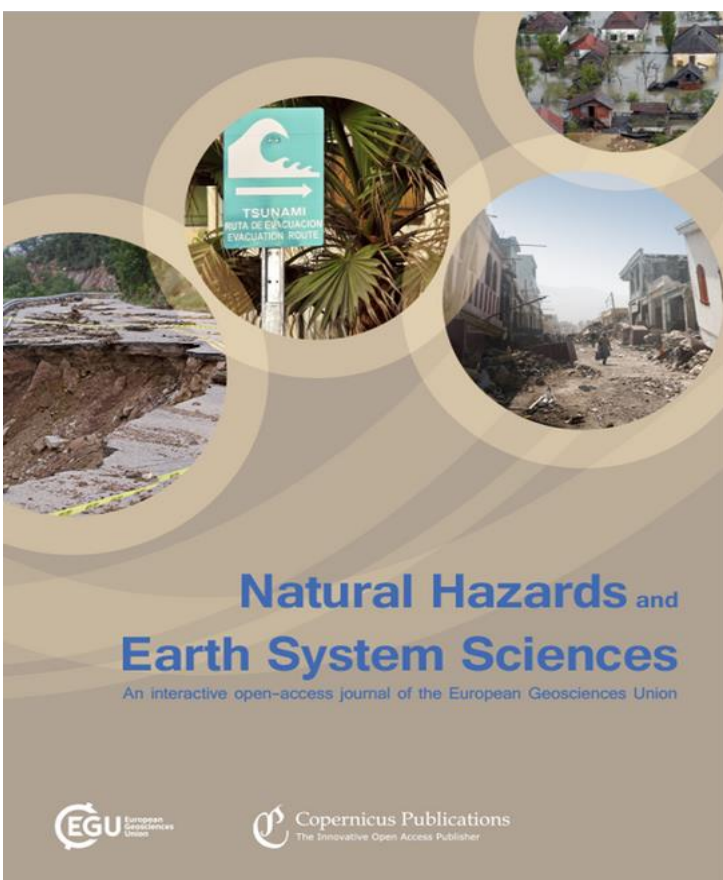


03



Published Papers

Flood
Modeling
Limitations



Natural Hazards and Earth System Sciences
An interactive open-access journal of the European Geosciences Union

EGU European Geosciences Union
Copernicus Publications
The Innovative Open Access Publisher

Nat. Hazards Earth Syst. Sci., 24, 3537–3559, 2024
<https://doi.org/10.5194/nhess-24-3537-2024>
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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}, Behrad Nazari¹, and Eunsom Cho^{1,2}

¹Department of Civil and Environmental Engineering, FAMU-FSU College of Engineering, Tallahassee, FL 32310, USA
²Resilient Infrastructure and Disaster Response Center, FAMU-FSU College of Engineering, Tallahassee, FL 32310, USA
³Department of Civil Engineering, The University of Texas at Arlington, Arlington, TX 76010, USA

Correspondence: Ebrahim Ahmadisharaf (eahmadisharaf@ceng.famu.fsu.edu; easesharif@gmail.com)

Received: 24 August 2023 – Discussion started: 19 September 2023
Revised: 14 June 2024 – Accepted: 2 September 2024 – Published: 17 October 2024

Abstract. Despite applications of machine learning (ML) models for predicting floods, their transferability for out-of-sample data has not been explored. This paper developed an ML-based model for hindcasting maximum river water depths during major events in coastal watersheds and evaluated its transferability across other events (out-of-sample). The model considered the spatial distribution of influential factors that explain the underlying physical processes to hindcast maximum river water depths. Our model evaluations in a six-digit hydrologic unit code (HUC6) watershed in the northeastern USA showed that the model satisfactorily hindcasted maximum water depths at 116 stream gauges during a major flood event, Hurricane Ida (R^2 of 0.94). The pre-trained, validated model was successfully transferred to three other major flood events, hurricanes Isaias, Sandy, and Irene ($R^2 > 0.70$). Our results showed that ML-based models can be transferable for hindcasting maximum river water depths across events when informed by the spatial distribution of pertinent features, their interactions, and underlying physical processes in coastal watersheds.

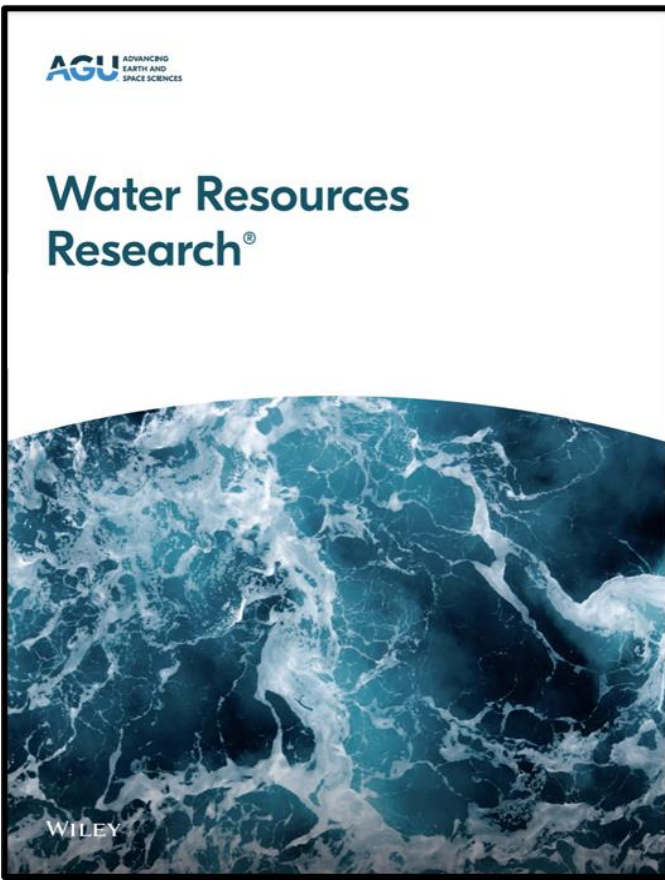
1 Introduction

Floods can damage civil infrastructure, business disruptions, and environmental degradation. Mitigation strategies are planned and implemented to mitigate this damage. To propose effective protection strategies, predictive models are used to evaluate watershed responses under various plausible flood scenarios (Fernández-Pato et al., 2016; Kundzewicz et al., 2019; Viglione et al., 2014). These models are essential tools to inform decision-makers about suitable risk management strategies and actions. Flood models can be broadly categorized as physically based, morphology-based, and data-driven.

Physically based models, widely used for predicting hydrologic events, are considered reliable tools for assessing different flood scenarios (Fernández-Pato et al., 2016). These models solve the shallow-water equations to derive flood characteristics. Developing physically based models requires certain meteorologic, hydrologic, and geomorphologic data. If these data are not available at the desired scale, such models cannot be developed. For instance, global inundation models are available to model flooding across the world, but they may not be efficient for small-scale applications. In such instances, data-driven models can be a flexible alternative as they can adapt to varying levels of data availability by focusing on the features with sufficient data. This flexibility remains one of the advantages of data-driven models over physically based models. Physically based models also need significant computational resources, especially in the case of high-resolution, multidimensional (2D and 3D), or stochastic models that necessitate numerous simulations. To enhance the speed of flood simulations, techniques such as parallel computing, graphics processing units (GPUs), and simplified models have been utilized (Costabile et al., 2017; Kalyanapu et al., 2011; Ming et al., 2020; Sridhar et al., 2021; Zahara et

Published by Copernicus Publications on behalf of the European Geosciences Union.





Water Resources Research
AGU ADVANCING EARTH AND SPACE SCIENCES

Received 23 OCT 2024
Accepted 14 MAR 2025

Water Resources Research
RESEARCH ARTICLE
10.1029/2024WR039244

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

Supporting Information:
Supporting Information may be found in the online version of this article.

Correspondence to:
E. Ahmadisharaf, eahmadisharaf@eng.famu.fsu.edu; easesharif@gmail.com

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Abstract In the absence of adequate observations on the off-channel areas, flood models are typically trained and validated against stream water depths. This approach can be efficient for physics-based models, which incorporate the underlying physical processes, but the efficiency for data-driven models like machine learning (ML) algorithms is unclear. The existing off-channel observations like high-water marks (HWMs) are also subject to uncertainty. This paper addressed three research questions: (a) how useful are ML models, trained with stream gauges, for hindcasting water depths in the off-channel areas? (b) how does incorporating the uncertainty of HWMs improve the model performance? and (c) does the uncertainty incorporation improve the model transferability to other watersheds and events? To answer these questions, we evaluated the performance of ML models across three large coastal watersheds in the US during three hurricanes—Michael, Ida and Ian. The model was developed under three scenarios, which differed in terms of the flood observational data (stream gauges and HWMs) used for their training and validation. A loss function was proposed to incorporate the uncertainty of observations. We found that ML models trained solely by stream gauges performed well only for stream hindcasts. Satisfactory hindcasts on off-channel areas were obtained by incorporating the HWMs' uncertainty via the loss function. This uncertainty incorporation reduced the model bias and resulted in the best transferability to other coastal watersheds and flood events. Our study provides insights about developing transferable ML models for hindcasting water depths on streams and off-channel areas in coastal watersheds during extreme events.

1. Introduction

Flood events impose significant societal and economic burdens that are growingly increased by climate change and sea level rise (Mayou et al., 2024; Taberkhani et al., 2020). Since 1980, floods have caused economic damages surpassing \$1 trillion and resulted in approximately 220,000 fatalities across the globe (Munich Re, 2018). In the US alone, the annual average losses due to flooding and tropical cyclones between 1980 and 2024 are estimated at \$36.2 billion (NOAA NCEI, 2023), with a projected increase in flood risks by 26.4% by 2050 (Wing et al., 2022). To mitigate these losses, management strategies are proposed and implemented. Decisions related to the selection of these strategies are supported by flood models. The efficiency of these models is, thus, linked with the reliability of mitigation strategies and reducing future losses (Ahmadisharaf et al., 2015, 2016; Qi et al., 2021; Tkach & Simonovic, 1997).

Flood models are trained and validated against historical observations. In terms of the location, the observational data can be categorized into streams and off-channel. The former data, which are typically recorded by stream gauges, has a greater number of observations as well as better spatial coverage and temporal resolution. Stream observations also provide more information about the dynamics of multiple flood characteristics such as depth, duration and velocity. Compared to the stream observations, the off-channel data is very limited. Off-channel data can be acquired from satellite imagery (via remote sensing), local reports and high-water marks (HWMs). Satellite-based observations can be limited to locations, the presence of clouds and frequency of observations (Bates, 2023; Neal et al., 2009; Werner et al., 2005). HWMs are not continuous in either time or space. These data are reported only for a limited number of flood events. Studies have leveraged HWMs to validate flood models in off-channel areas (Chen et al., 2021; Diehl et al., 2021; Ferguson et al., 2022; Li et al., 2021; Ortega et al., 2014; Schubert et al., 2022; Zarniello & Bent, 2011; Zarniello et al., 2014; Zheng et al., 2022).





Thank you!

Questions?



Michael Baker
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