# Application of Emerging Technologies for Levee Monitoring

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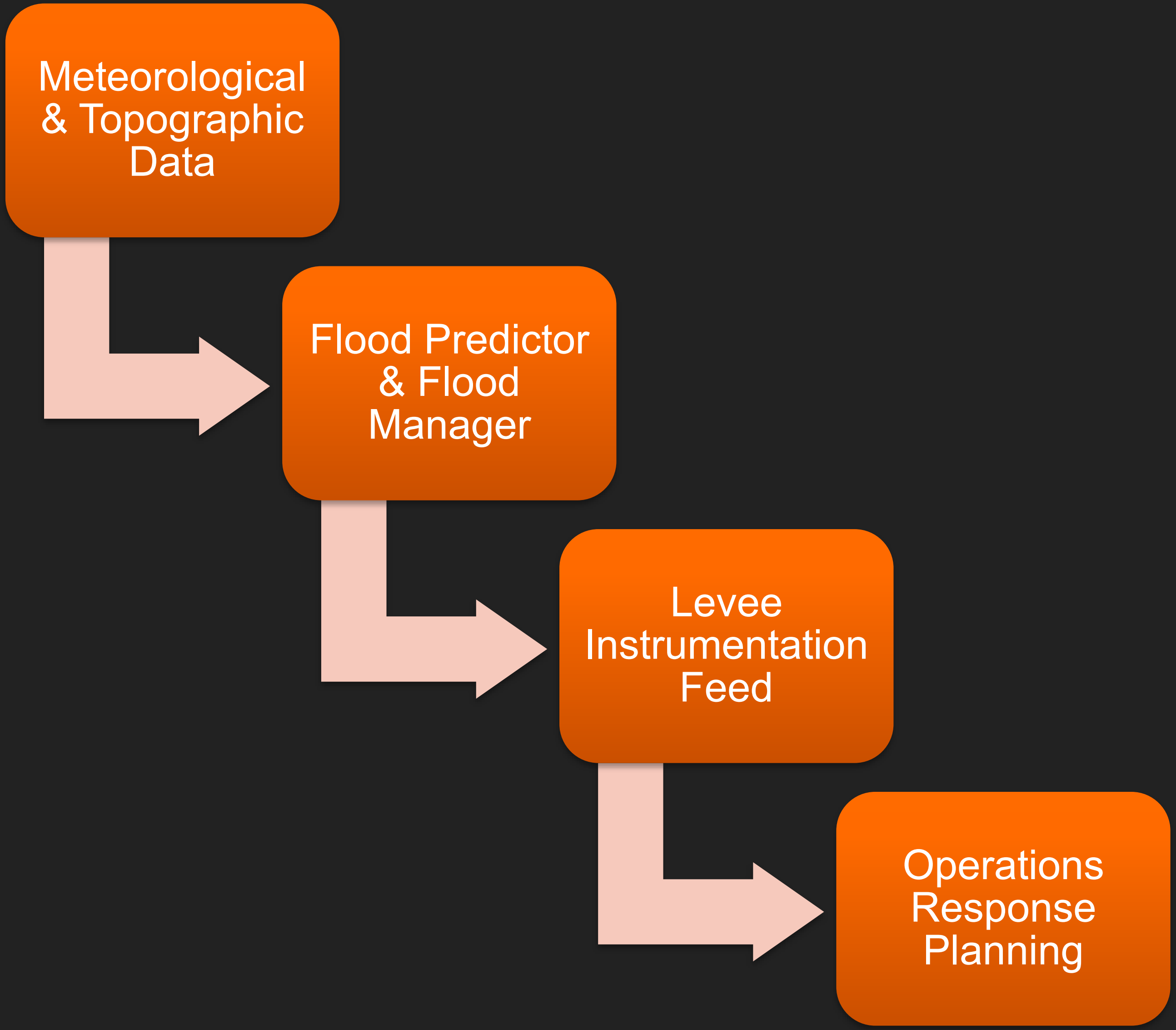
SFSLD Conference 2023

# Systematic Levee Monitoring Model




- EAP
- Communication
- Structural Responses
- Flood Operations Planning


STANTEC CAN
PREDICT THIS.
Flood Predictor
Stantec.io
SPEED LIMIT 20
DEAD END
HIGH WATER
NO OUTLET

# Why is this important?

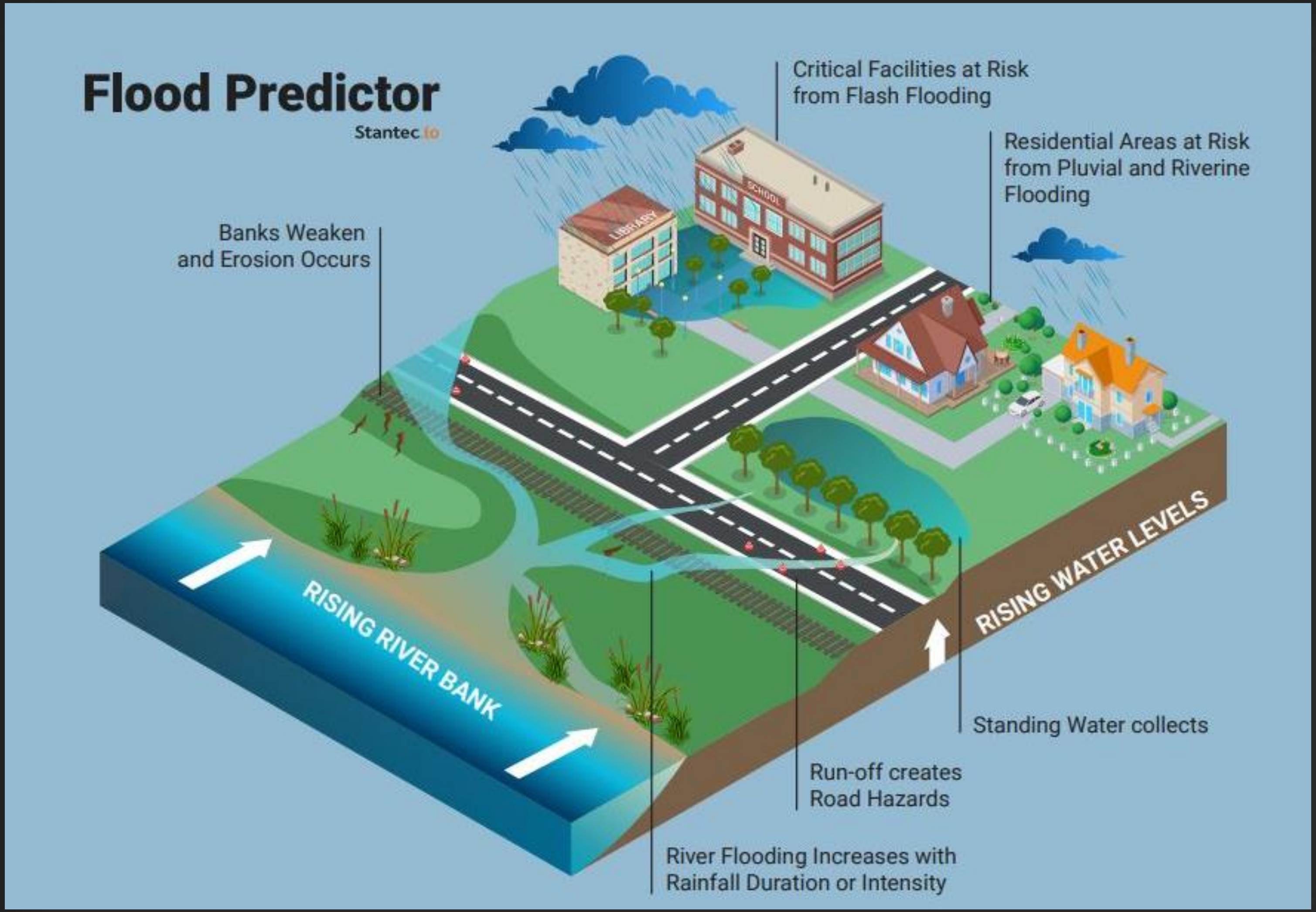
Traditional modeling methodology complexity hinders the rapid production of assessments on impending flood events at a time scale amenable for effective decision support.

Simply put, you don't get the information you need quickly enough.

# What is Flood Predictor?

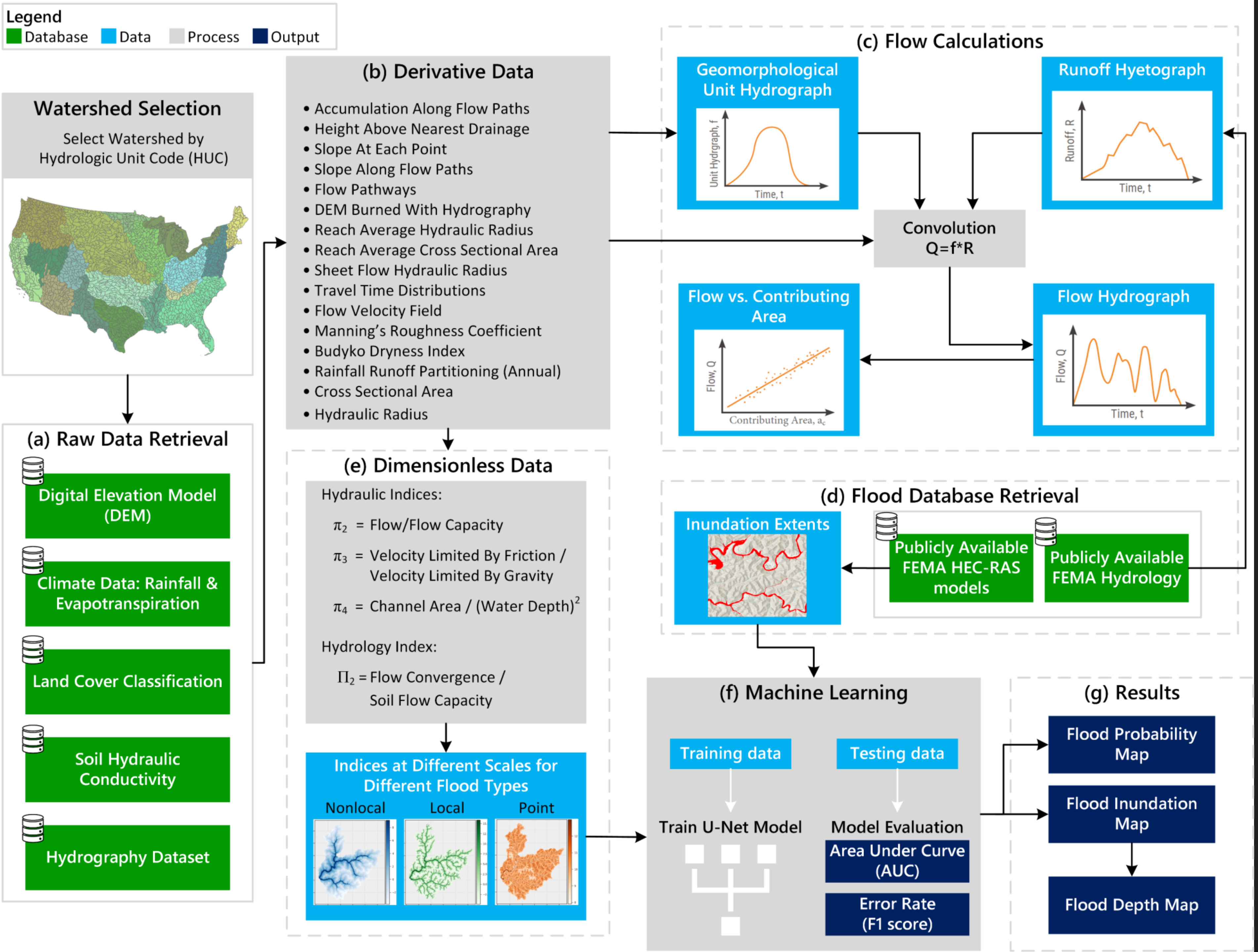
A flood inundation mapping product that applies **machine learning** for prediction and probability.

It provides reliable, data-driven **flood risk results in near real-time**.



# Flood Predictor Benefits

- ✓ Speed - predictions made in minutes
- ✓ Quality - high resolution, latest inputs, best-in-class
- ✓ Validity - leverages and aligns to most recent FEMA data
- ✓ Scalability - flood risk anywhere, even unmapped areas
- ✓ Versatility – base level, user defined, historic, forecast, & future conditions



Legend
Database
Data
Process
Output
Watershed Selection
Select Watershed by
Hydrologic Unit Code (HUC)
(a) Raw Data Retrieval
Digital Elevation Model (DEM)
Climate Data: Rainfall & Evapotranspiration
Land Cover Classification
Soil Hydraulic Conductivity
Hydrography Dataset
(b) Derivative Data
• Accumulation Along Flow Paths
• Height Above Nearest Drainage
• Slope At Each Point
• Slope Along Flow Paths
• Flow Pathways
• DEM Burned With Hydrography
• Reach Average Hydraulic Radius
• Reach Average Cross Sectional Area
• Sheet Flow Hydraulic Radius
• Travel Time Distributions
• Flow Velocity Field
• Manning's Roughness Coefficient
• Budyko Dryness Index
• Rainfall Runoff Partitioning (Annual)
• Cross Sectional Area
• Hydraulic Radius
(e) Dimensionless Data
Hydraulic Indices:
$\pi_2$ = Flow/Flow Capacity
$\pi_3$ = Velocity Limited By Friction / Velocity Limited By Gravity
$\pi_4$ = Channel Area / (Water Depth)$^2$
Hydrology Index:
$\Pi_2$ = Flow Convergence / Soil Flow Capacity
Indices at Different Scales for Different Flood Types
Nonlocal
Local
Point
(c) Flow Calculations
Geomorphological Unit Hydrograph
Unit Hydrograph, f
Time, t
Runoff Hyetograph
Runoff, R
Time, t
Convolution
Q=f*R
Flow vs. Contributing Area
Flow, Q
Contributing Area, $a_c$
Flow Hydrograph
Flow, Q
Time, t
(d) Flood Database Retrieval
Inundation Extents
Publicly Available FEMA HEC-RAS models
Publicly Available FEMA Hydrology
(f) Machine Learning
Training data
Testing data
Train U-Net Model
Model Evaluation
Area Under Curve (AUC)
Error Rate (F1 score)
(g) Results
Flood Probability Map
Flood Inundation Map
Flood Depth Map

# Flood Predictor White Paper

## Peer Reviewed White Paper:

https://arxiv.org/pdf/2211.00636.pdf



### Pi theorem formulation of flood mapping

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(Dated: November 17, 2022)

While physical phenomena are stated in terms of physical laws that are homogeneous in all dimensions, the mechanisms and patterns of the physical phenomena are independent of the form of the units describing the physical process. Accordingly, across different conditions, the similarity of a process may be captured through a dimensionless reformulation of the physical problem with Buckingham Π theorem. Here, we apply Buckingham Π theorem for creating dimensionless indices for capturing the similarity of the flood process, and in turn, these indices allow machine learning to map the likelihood of pluvial (flash) flooding over a landscape. In particular, we use these dimensionless predictors with a logistic regression machine learning (ML) model for a probabilistic determination of flood risk. The logistic regression derived flood maps compare well to 2D hydraulic model results that are the basis of the Federal Emergency Management Agency (FEMA) maps. As a result, the indices and logistic regression also provide the potential to expand existing FEMA maps to new (unmapped) areas and a wider spectrum of flood flows and precipitation events. Our results demonstrate that the new dimensionless indices capture the similarity of the flood process across different topographies and climate regions. Consequently, these dimensionless indices may expand observations of flooding (e.g., satellite) to the risk of flooding in new areas, as well as provide a basis for the rapid, real-time estimation of flood risk on a worldwide scale.

Keywords: Pluvial flooding, Buckingham Π theorem, Machine learning, Flood mapping

#### I. INTRODUCTION

Flash flooding is a deadly form of flooding, and a lack of real-time flash flood forecasting has resulted in nearly a hundred annual deaths in the United States alone [1, 2]. While we have sophisticated forecasts of weather, e.g., the High-Resolution Rapid Refresh (HRRR) model [3], we lack real time flood predictions—in part because existing flood forecasting primarily focuses on the large rivers and streams, while neglecting the small streams and flow paths of flash flooding [1]. Modeling all the flow paths at scale is financially and computationally expensive because existing methods typically center around spatially explicit hydraulic models. Hydraulic models (such as HEC-RAS) may be used at the continental scale for detailed risk assessments of flooding [4, 5]; however, most forecasting efforts with hydraulic models focus on the main river reaches [6] and do not provide an economical prediction for flood warnings that are rapid and worldwide in coverage. Furthermore, most hydraulic and flood hydrology models originated in a data-limited era with a focus on more detailed process descriptions that are spatially explicit [7]; however, such an approach often is over-parameterized [8]—potentially leading to the issue of equifinality [9, 10]. Thus, a hydraulic or hydrology model, once calibrated to one area, is not readily transferred to a new area. Differently, the growth of remote sensing data on a global basis provides the potential of rapid, more accurate, and data-driven flood prediction and mapping based on machine learning (ML) [11]. ML provides this potential by elucidating patterns in data that may be more difficult to find with a more traditional modeling approach.

In hydraulic modeling, Manning's equation commonly is used for the rapid delineation of flood extents by calculating flood stages based on both a given flow forecast (e.g., the National Water model) and the reach average values for the cross section area, wetted perimeter, and surface area of flow [12]. Based on these average values, a rating curve is calculated, and in turn, the rating curve is used to calculate a water surface elevation for a given flow rate [12]. Flooding then is mapped as areas where this water surface elevation exceeds the height above nearest drainage

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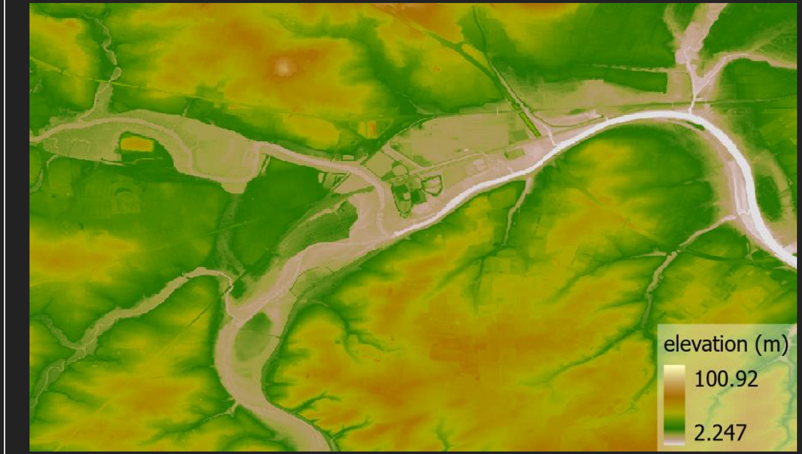
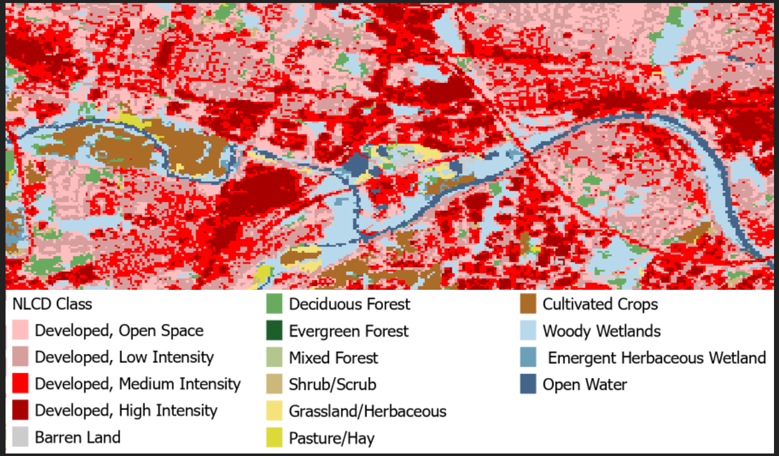
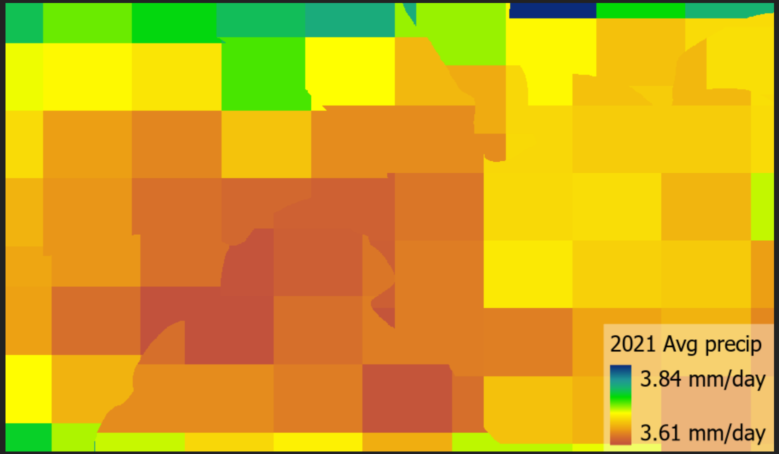
# Engineering Features: Data Harvesting



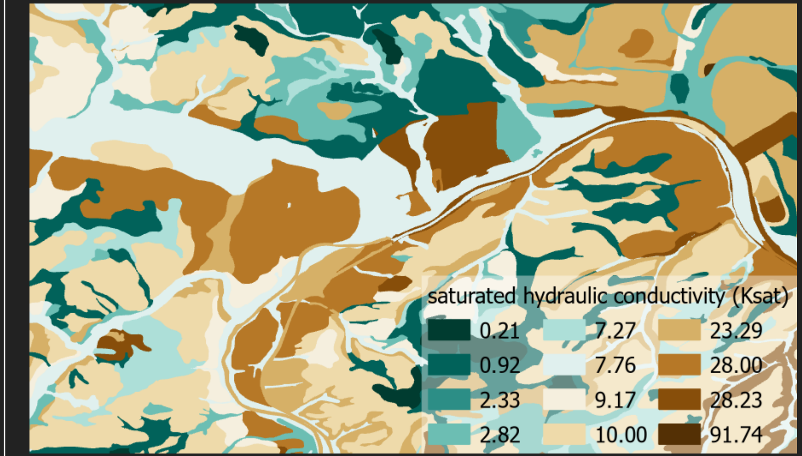
USGS: Digital Elevation Model



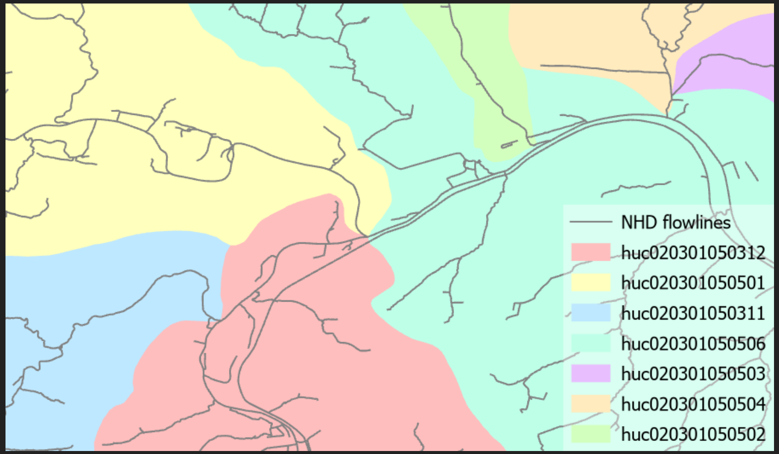
MRLC: Land Cover Classification



Daymet: Precipitation and PET

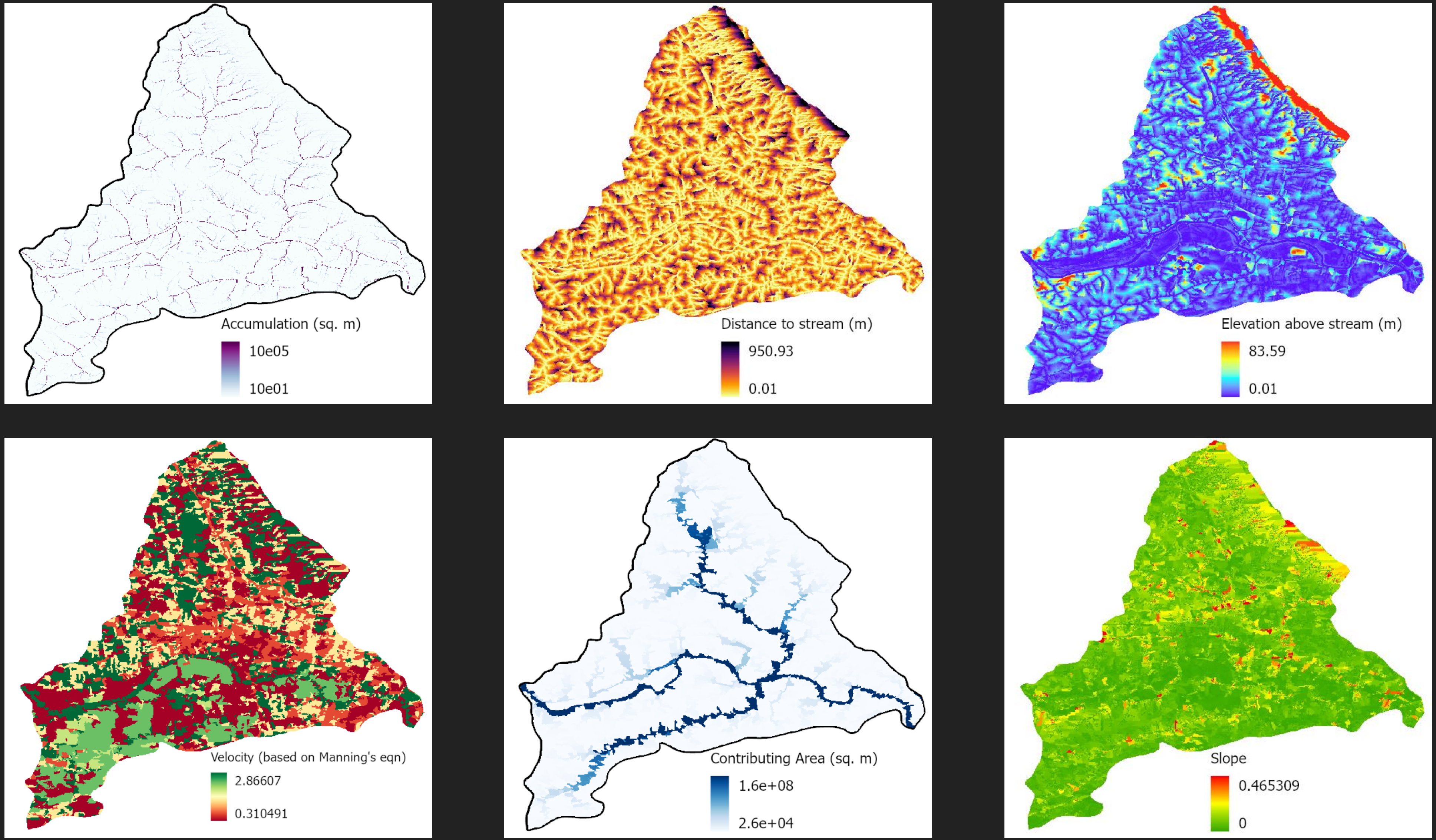


SSURGO: Saturated Hydraulic Conductivity



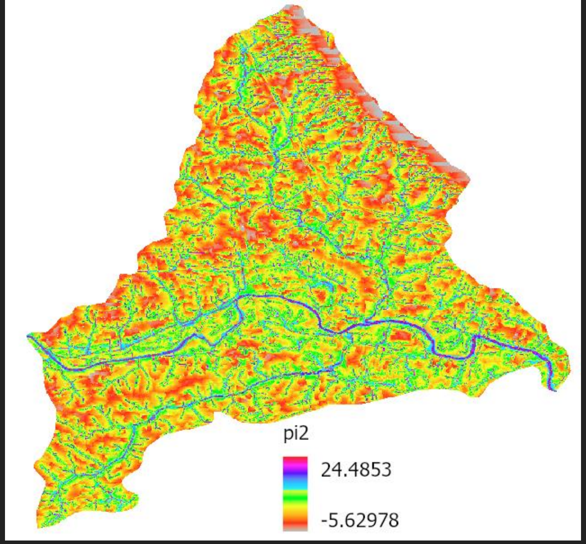
NHD: HUC12 boundaries & flowlines

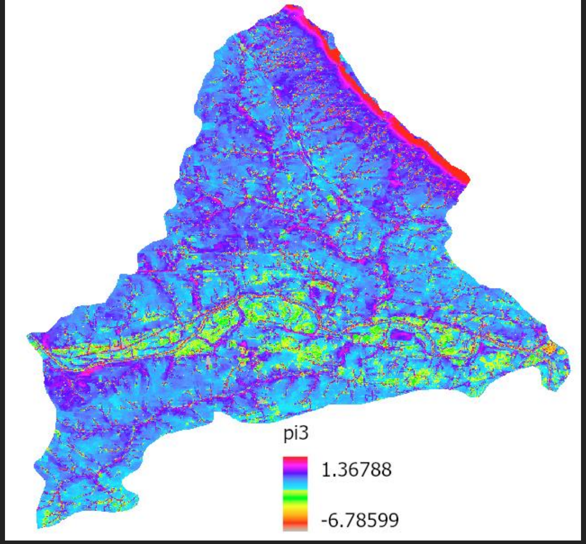
# Engineering Features: Data Derivatives



# Engineering Features: Dimensionless Features

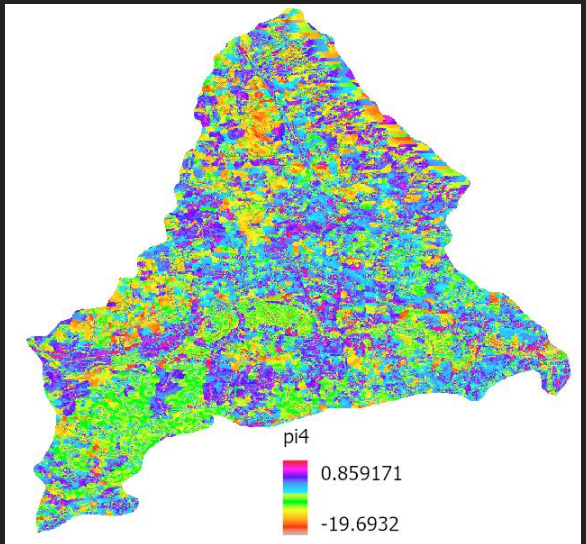
$$\frac{Flow}{Flow\ Capacity}$$

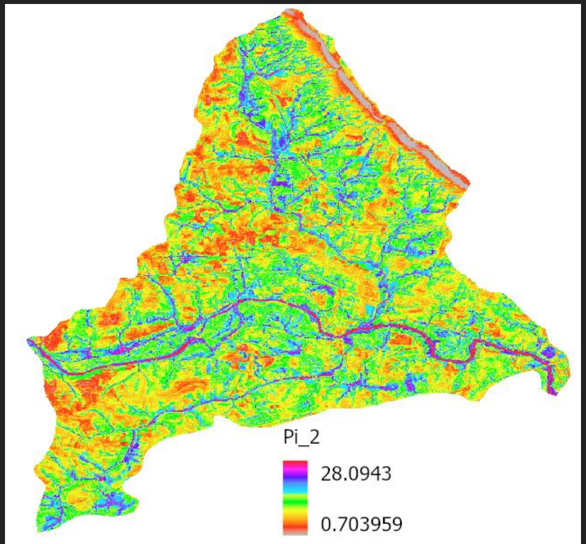



$$\frac{Friction\ Force}{Gravitational\ Force}$$

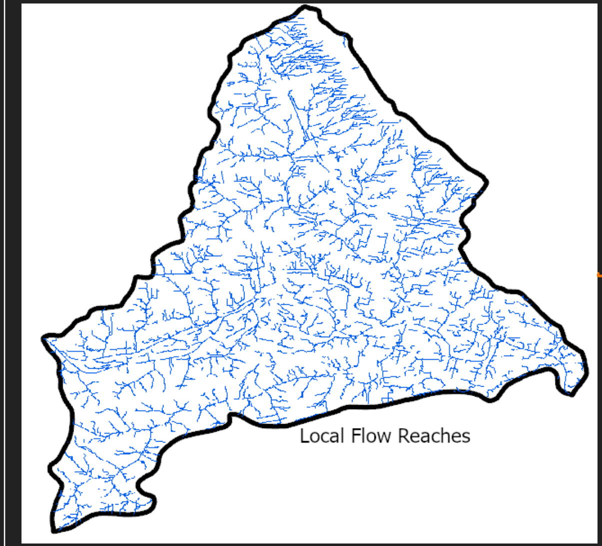
$$\frac{Channel\ Area}{Water\ Depth^2}$$



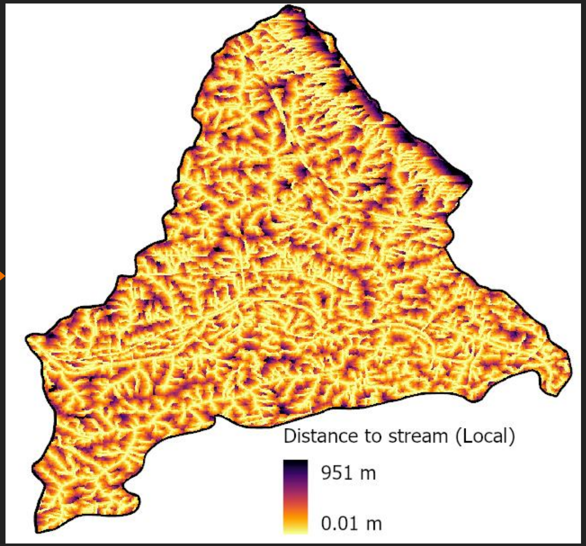



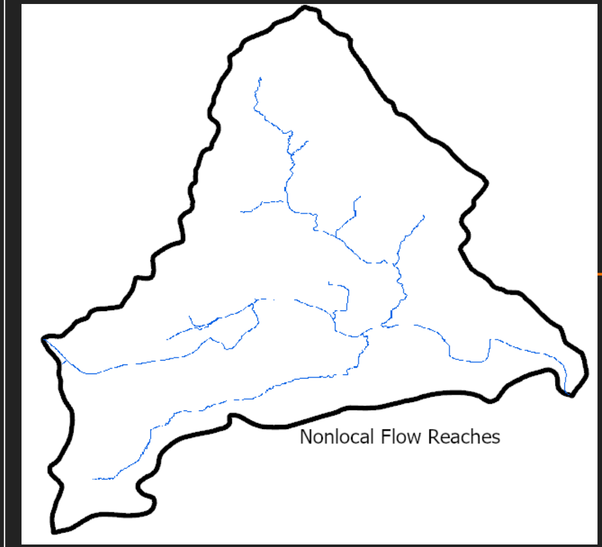

$$\frac{Recharge}{Soil\ Flow\ Capacity}$$

# Engineering Features: At Different Scales

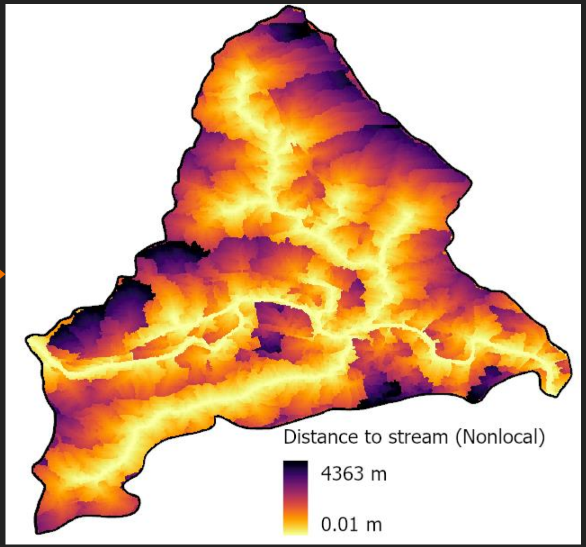



*data derivatives*



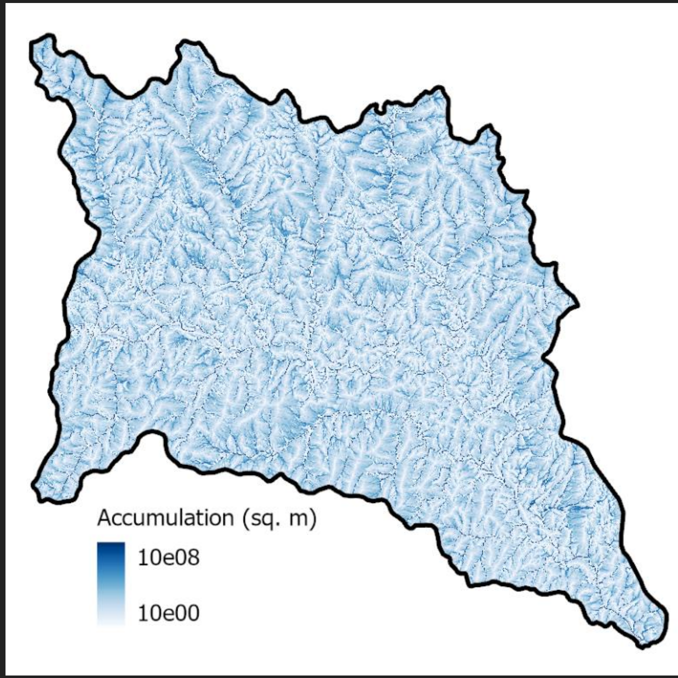

*data derivatives*




- Large drainages/waterways will differentially impact flood dynamics.
- Flow accumulation defines scales for flash flooding
- Stream orders defines scales for riverine flooding

# Engineering Features: Flood Type

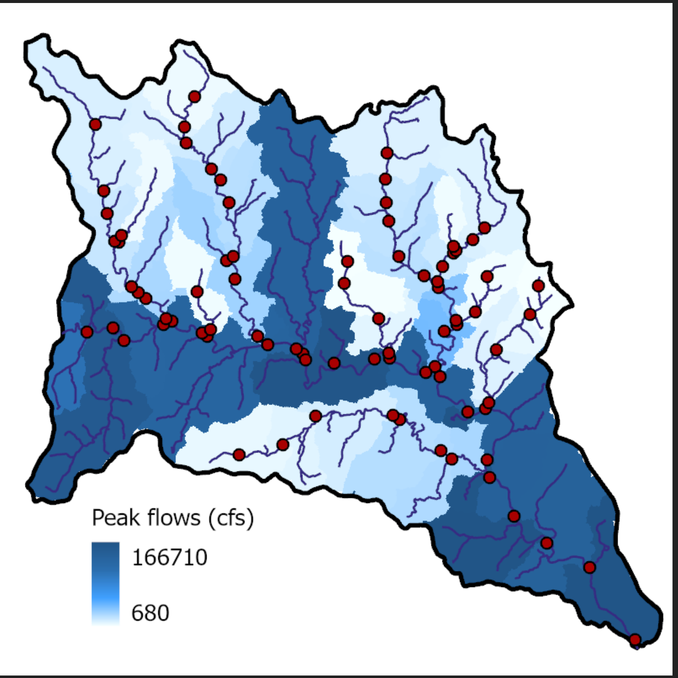
Flash Flooding




Flow: contributing area & runoff

$$\frac{Flow}{Flow\ Capacity}$$

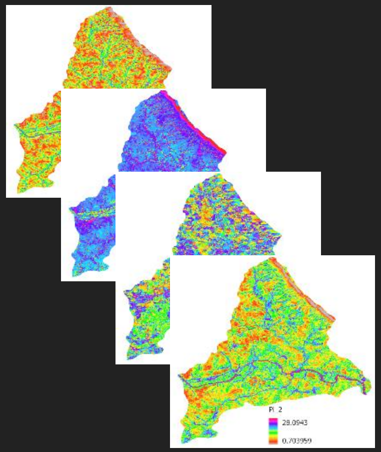
Riverine Flooding




Flow = measured peak flow rate

# Model Training

**Dimensionless Engineering Features**



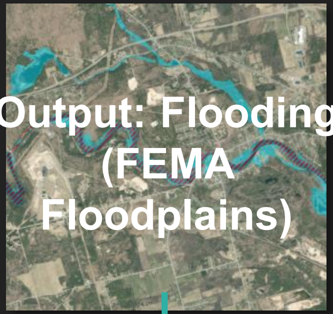
Hydraulics Index 1

Hydraulics Index 2

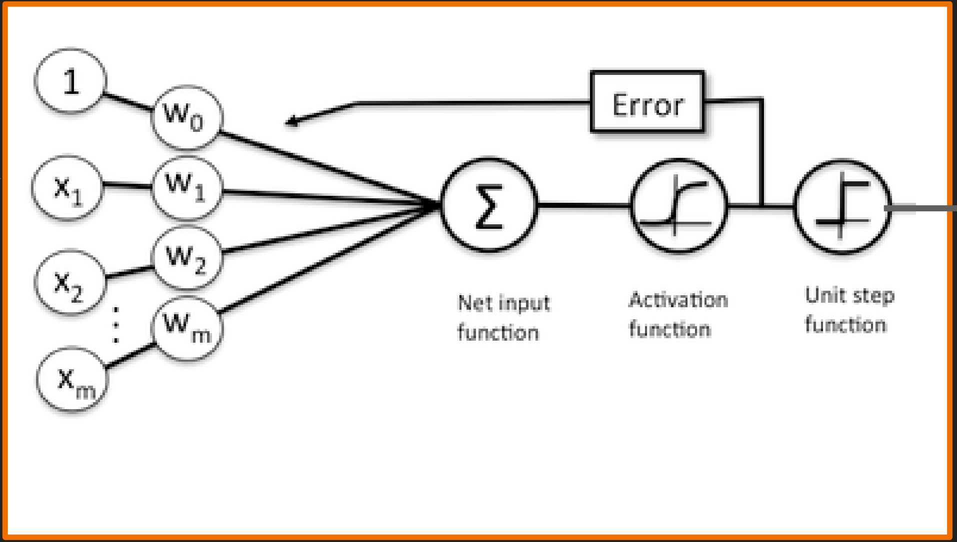
Hydraulics Index 3

Hydrology Index

**Input: Storm Conditions & Flows**



**Output: Flooding (FEMA Floodplains)**



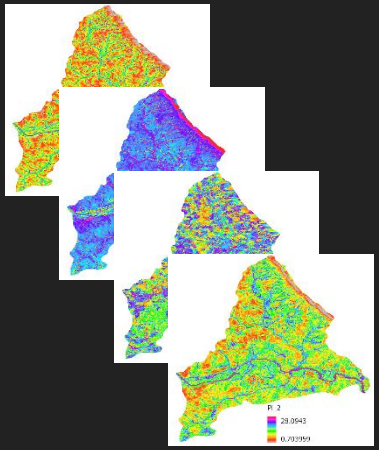

**Flood Predictor Engine**

Maintained and updated regularly

# Model Predictions

User Defined Hydrologic Condition (e.g. 10%, 1%, 0.2%)

**Dimensionless Engineering Features (Prediction Site)**



- Hydraulics Index 1 →
- Hydraulics Index 2 →
- Hydraulics Index 3 →
- Hydrology Index →

**Flood Predictor Engine**

**Flood Prediction**

**Flood Probability**

**Processing Time**

| 0-3 Hours | 0-20 Minutes |
|---|---|

# 85-95%

With Flood Predictor, we can predict flood risk in real-time that is 85-95% correlated to physics-based model results – **in a matter of seconds.**

It has shown good accuracy when compared against actual flooding events – perfect for early warning and situational awareness.

*Stantec's Flood Predictor has an accuracy of prediction rate of 98% using the area under curve (AUC) method for accuracy assessment. When measured as an F1 Score Flood Predictor achieves 87%.*

# Waverly, Tennessee August 2021 Flash Flood

(Flash Flood Prediction Site)

*August '21 Flash Flood Event*

Flood Predictor Output, Probability of Flooding

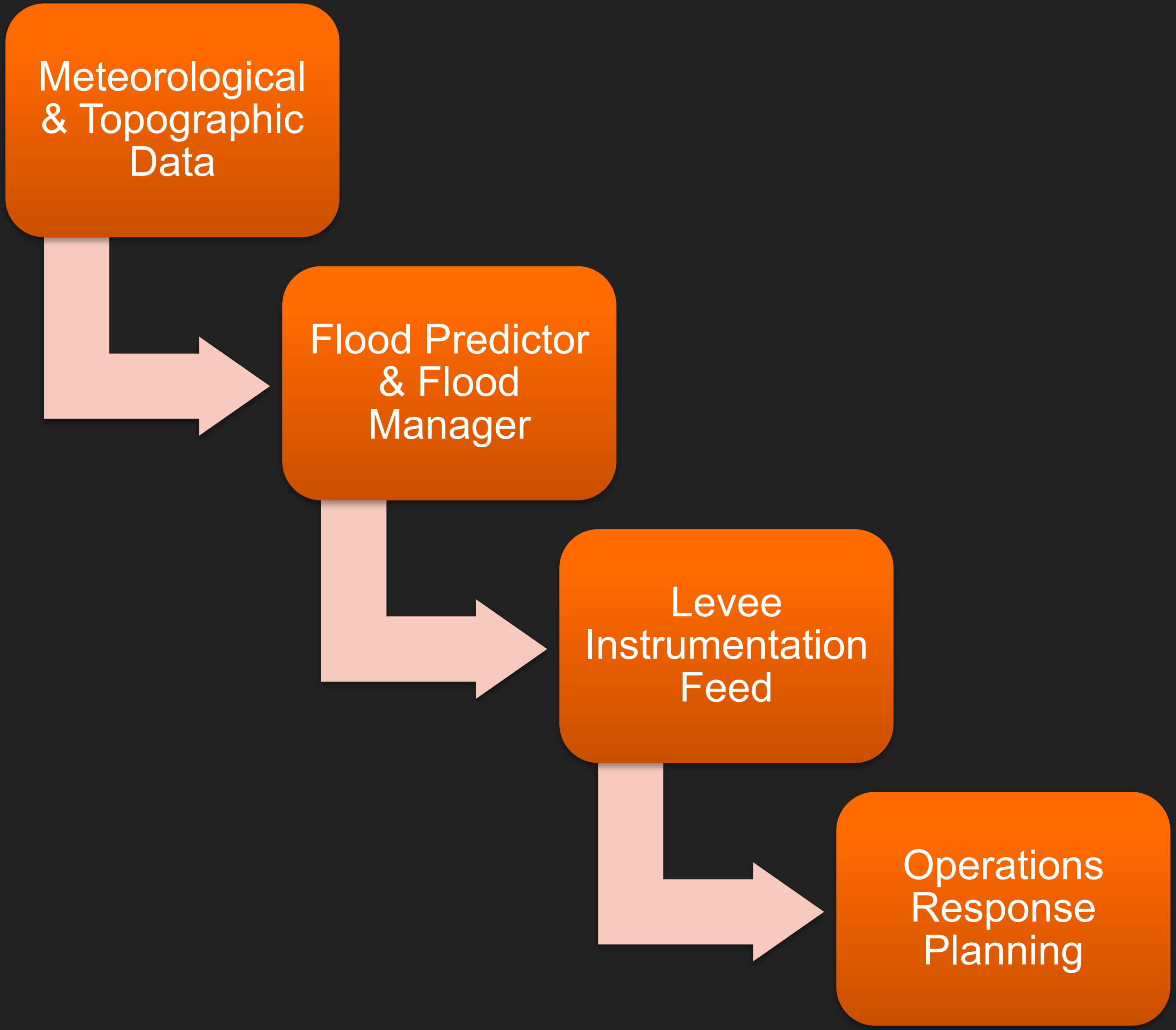
# North Fork Kentucky Watershed, Kentucky
(Riverine Prediction Site)

2022 Preliminary FEMA
1% Annual Chance Floodplain

Flood Predictor Output,
1% Annual Chance Floodplain

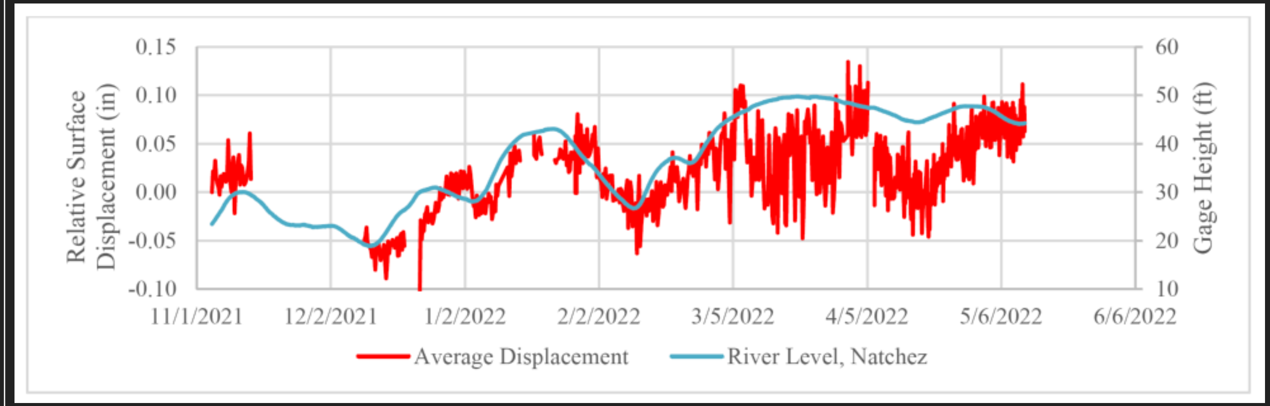
Flood Predictor Output,
Probability of Flooding

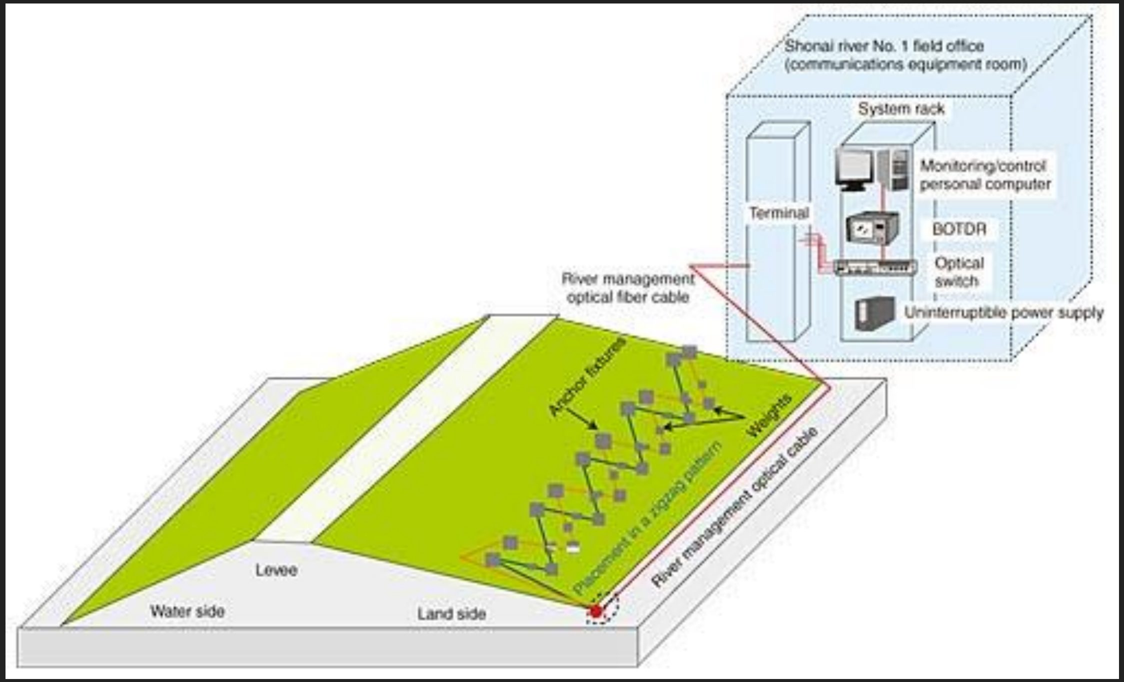
# Systematic Levee Monitoring Model




- EAP
- Communication
- Structural Responses
- Flood Operations Planning

# Section Monitoring – Fiber Optics

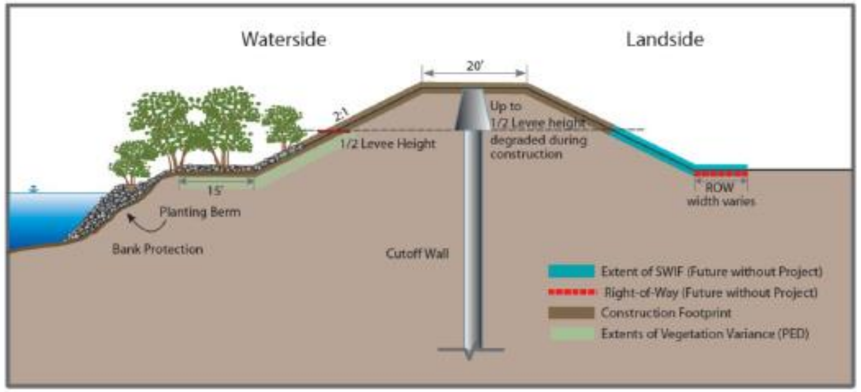


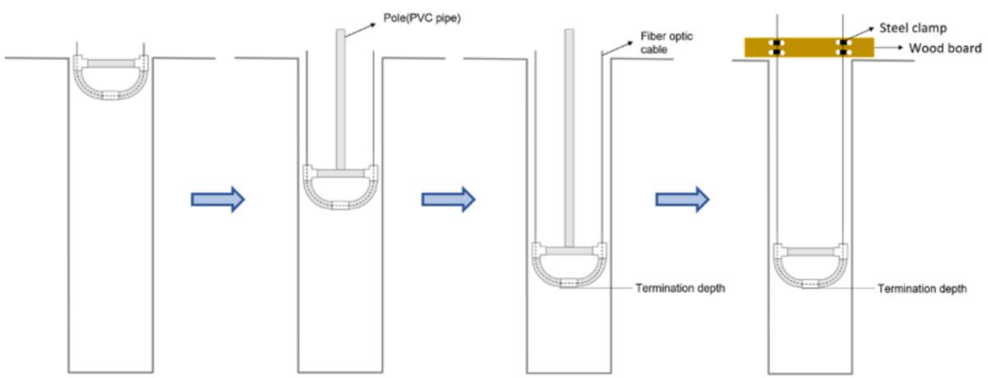

- “The location of the event can be pinpointed with an asset monitoring range of up to 50 km (~31 miles) in each direction – for a span of 100 km (~62 miles).
- As sensors, the fiber optic cables may be affixed to linear assets or buried/embedded in those same structures, depending on the aspects, they are intended to monitor (groundwater pressure, deformation, total stress, temperature, seismic events, leakage, water levels).

# USACE Pilot Levee Instrumentation Project

## American River Levee Upgrade Project




FO Monitoring of cement bentonite cut-off wall, currently upgraded.

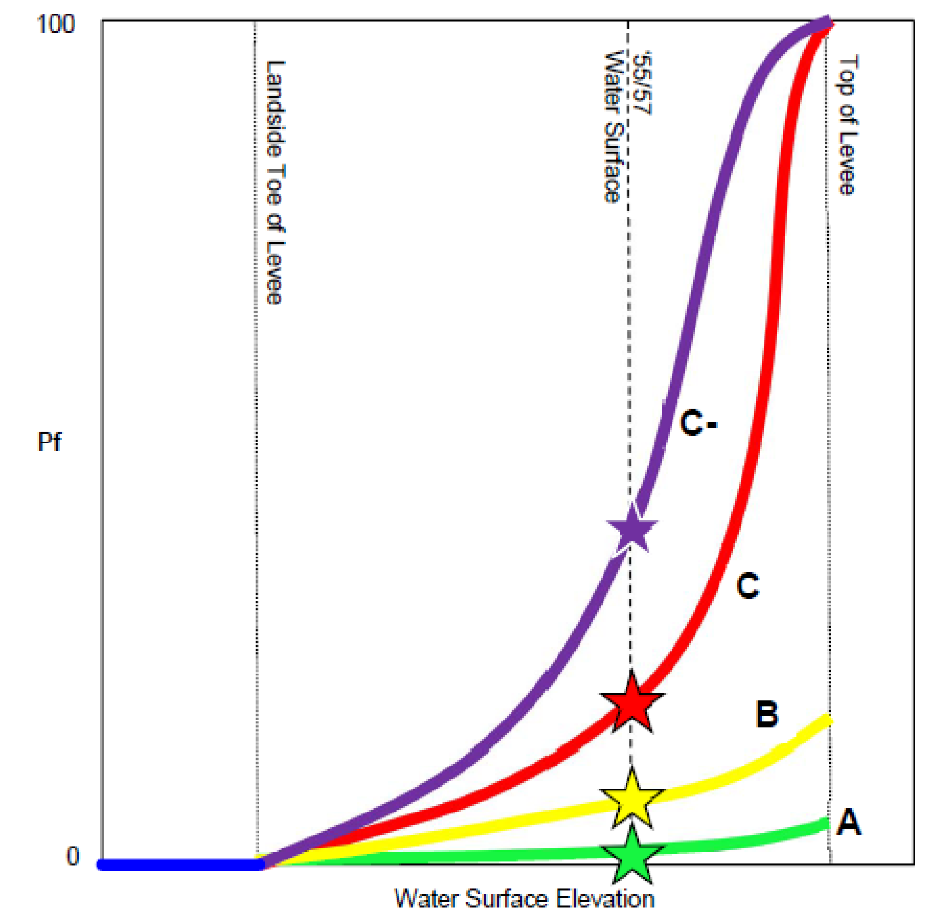




FO cable inside SCCB wall

# Data Requirements

a. Past Performance
b. Recent levee improvements
c. Population at risk
d. Benefits
e. Presence of critical infrastructure
f. Existing CVFPP fragility curves
g. Levee and foundation characteristics
h. Inundation mapping
i. Penetrations
j. Recent penetration rehabilitation efforts
k. Anomalies (animal burrow activity, presence of non-permitted penetrations, etc.)

Fragility Curve



# Flood Predictor Features

- ✓ delivery in minutes
- ✓ fluvial and pluvial flooding
- ✓ base level, historical, forecast, or user defined scenarios
- ✓ depth, water surface elevation, probability, and extent outputs
- ✓ average curve number export
- ✓ streamflow prediction export
- ✓ coastal flooding coming soon!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