AI Application in Water Resources Management

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Photo: DeLuca Preserve, September 3, 202

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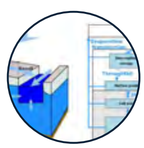
Hydrology & Water Quality Program, RCREC Ona

Data Collection
Field Survey



Hydrologic models
(Numerical/physical/
mathematical models)

Remote Sensing
AI/ML models

Practical Implementation
Strategies

Phase 1: instrumentation

Phase 2: Long –term evaluation

Phase 3: implementation

- Phase 1: Establishing a robust **monitoring and instrumentation** network
- Phase 2: **Existing condition evaluation**
- Phase 3: **Implementation:** Translating our findings into practical implementation strategies.

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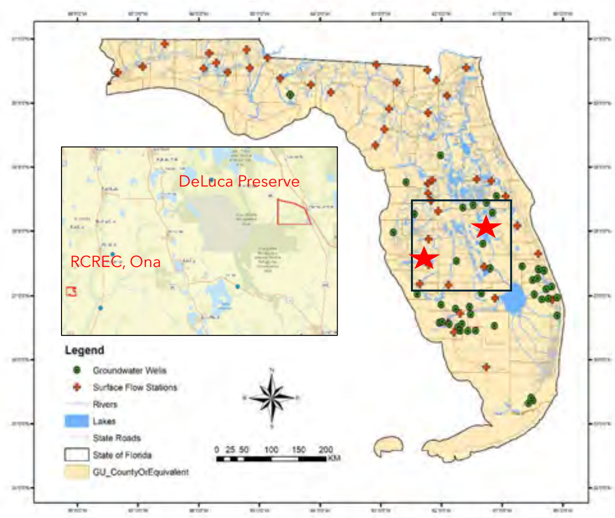
Instrumentation and Data Monitoring Sites



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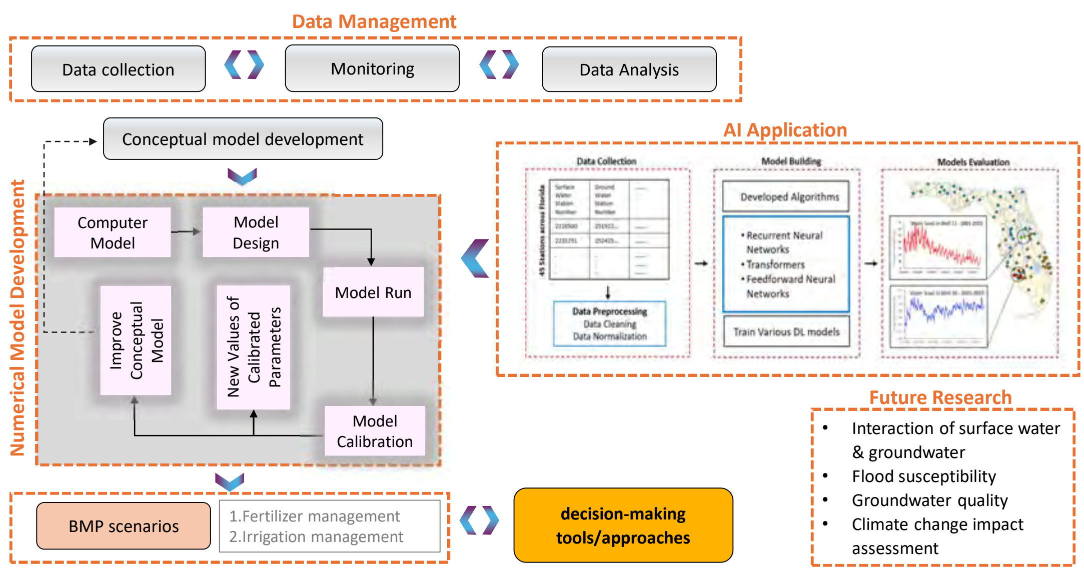
Phase 2: Long-term evaluation



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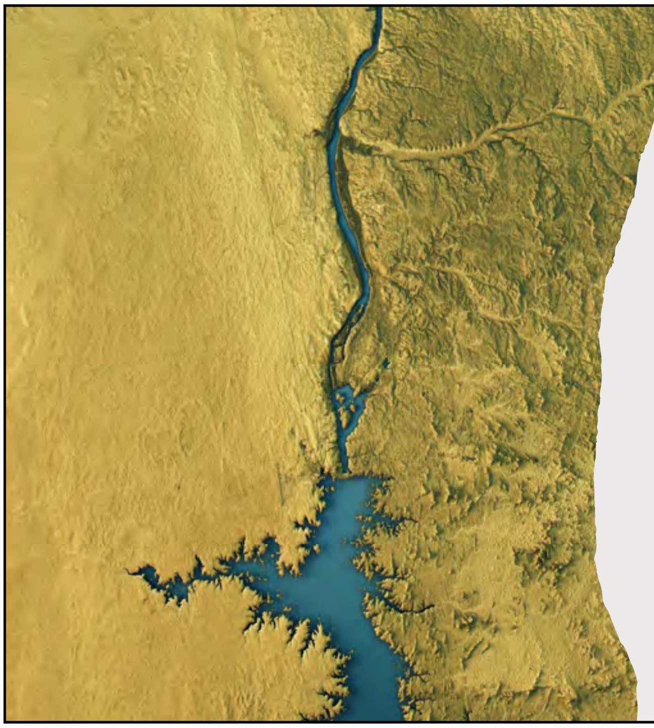

Modeling & AI Studies

Goals and Plans

- **To provide a tool for simulating water systems; evaluating the effectiveness of existing and alternate practices in improving the water quantity and quality in Florida's cattle ranches and underlying surficial aquifer.**

- Hydrologic and numerical modeling to be able to simulate the water system and predict how the system can be affected by changes in stresses
  - Propose alternative BMP scenarios
  - Prioritizing BMPs to enhance water quality
- AI modeling techniques to forecast/simulate groundwater parameters

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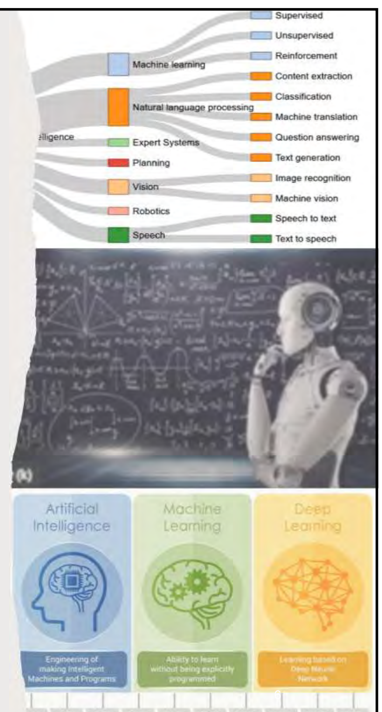
AI Research at RCREC

- Our work focuses on three main areas:
- 1. AI as a **forecasting tool** – to simulate and predict water quality, hydrology, and environmental conditions
- 2. AI for **risk assessment and vulnerability analysis** – geospatial maps of Florida
- 3. **AI as a service** (**ongoing**): A tool for Landowners; AI-powered decision-support platforms – delivering insights directly to farmers, ranchers, and land managers so they can make informed choices



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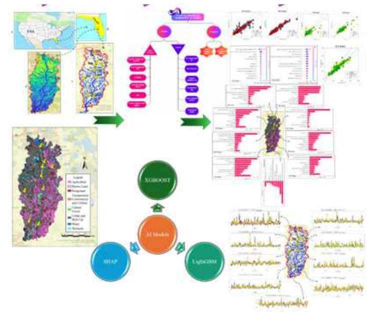
1. AI as a forecasting tool

- Soil moisture, and temperature
- **Surface water discharges in the river systems of Florida**
- **Groundwater elevations in the Surficial Aquifer of Florida**
- Water quality (N) in surface water systems in the Peace River basin
- Turbidity



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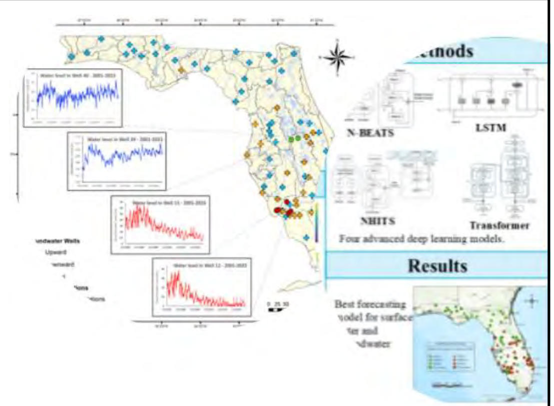
Golmohammadi, G., Biazar, S. M., Nedhunuri, R. R., and N. Tziolas. 2025. Applications of Artificial Intelligence (AI) in Water Resources Forecasting. EDIS (accepted)

Forecasting Groundwater level and Surface Flow Discharge in Florida

Using Advanced Machine Learning Models



Groundwater Level and Surface Flow Discharge

Why Using AI for this project?

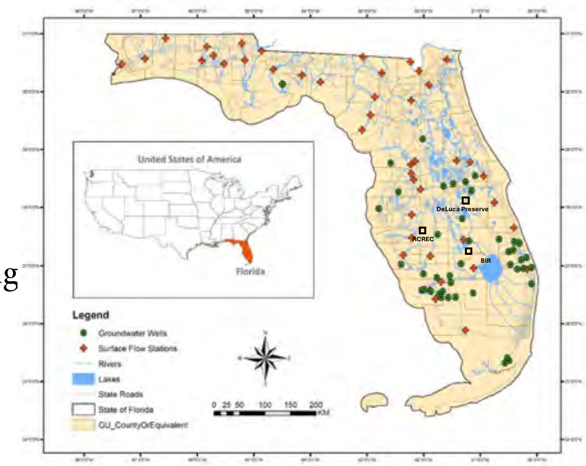
- Numerical models (MODFLOW, WAM and MIKE+ models)
- **Solid understanding of the fundamental hydrogeological concepts and mechanistic principles!**

Challenges:

- Lack of data, expensive, and time-consuming
- Calibration was almost impossible in some cases!

Using AI could help in:

- Lack of data
- Timing



AI models are particularly well-suited for **large-scale** applications and offer significant advantages over traditional models in terms of speed, scalability, and ease of deployment.

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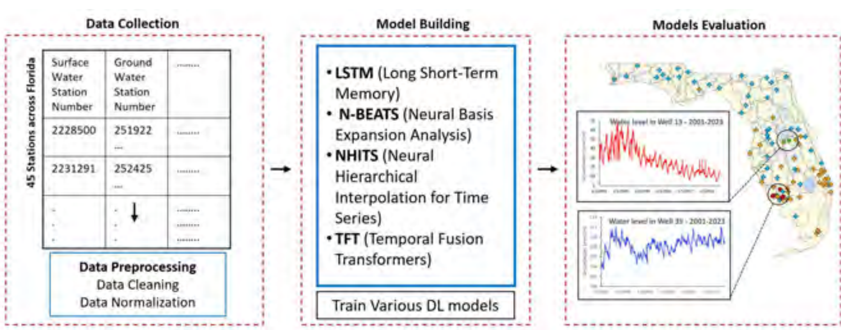
Deep Learning Algorithms

- Long Short-Term Memory (LSTM),
- Neural Hierarchical Interpolation for Time Series (N-HiTS), and
- Neural Basis Expansion Analysis for Interpretable Time Series Forecasting (N-BEATS),
- Transformer



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Deep Learning Algorithms

LSTM (Long Short-Term Memory)
- Captures long-term dependencies in sequential data
- Well-suited for hydrological systems influenced by past precipitation and seasonal trends

N-BEATS (Neural Basis Expansion Analysis for Time Series)
- Designed specifically for time series forecasting
- High accuracy without domain-specific assumptions
- Offers interpretability, valuable for environmental decision-making

N-HiTS (Neural Hierarchical Interpolation for Time Series)
- Extends N-BEATS with hierarchical structure
- Effective for long-horizon and multiscale temporal patterns

Transformer
- Utilizes attention mechanisms to model global dependencies
- Excels in capturing complex and non-linear relationships
- Gaining traction in hydrological forecasting for its scalability and performance

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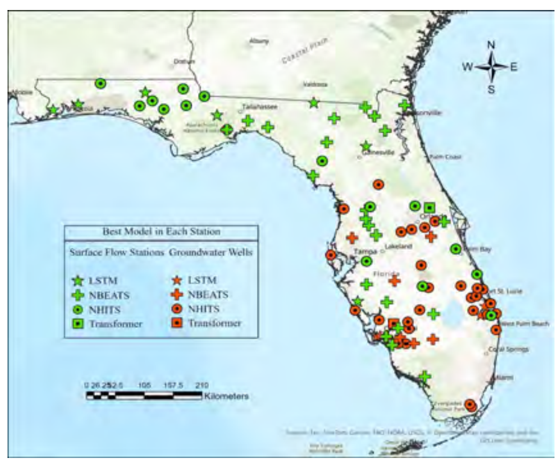
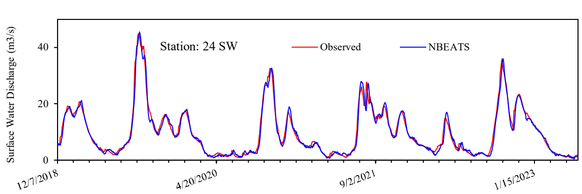
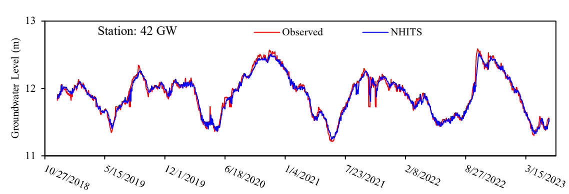
Model Performance

Type	Model	RMSE	NRMSE	NSE
Groundwater	LSTM	0.196	0.073	0.845
	NBEATS	0.158	0.063	0.866
	NHITS	**0.183**	**0.064**	**0.872**
	Transformer	0.225	0.083	0.797
Surface Water	LSTM	19.322	0.059	0.582
	NBEATS	**17.738**	**0.052**	**0.606**
	NHITS	16.569	0.061	0.533
	Transformer	23.247	0.071	0.460







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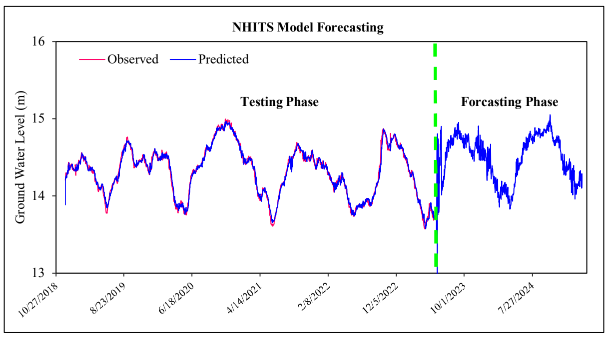
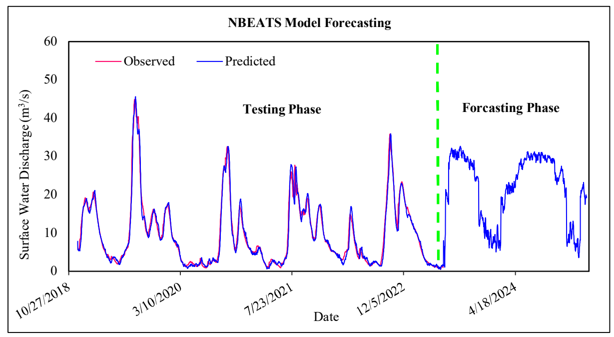
Forecasting

- Period: 21 months (from **June 1, 2023,** and **March 3, 2025**)
- N-HITS for groundwater
- NBEATS for surface water





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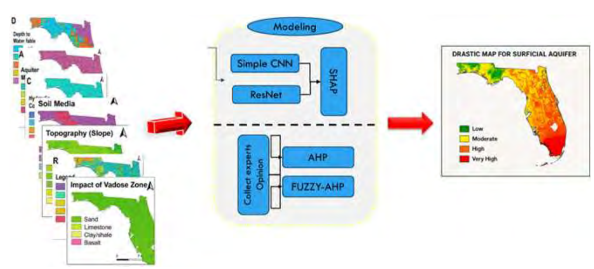
2. AI as a risk assessment/susceptibility assessment tool

- Flood susceptibility
- Groundwater vulnerability
- Drought susceptibility (ongoing)
- Sinkhole susceptibility (ongoing)



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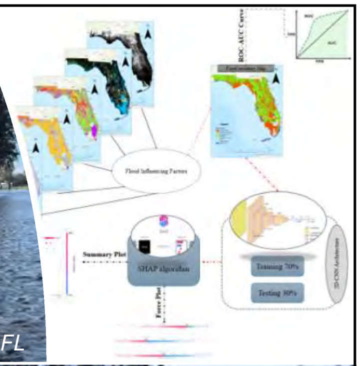
Flood Susceptibility Mapping in Florida

Using Explainable Artificial Intelligence (XAI) Models



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Flood Susceptibility Mapping (FSM) in Florida

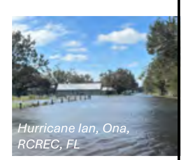
Flood Risk in Florida

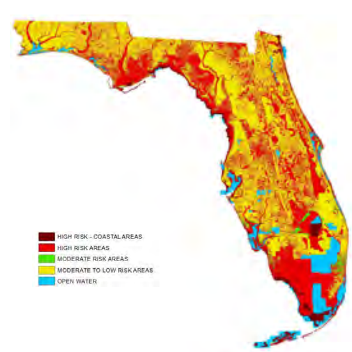
- Florida is highly susceptible to floods due to its low-lying topography, heavy rainfall, hurricanes, and storm surges.
- Frequent flood events result in significant economic losses and impact communities.

Importance of Flood Susceptibility Mapping:

- Identifies areas at high risk of flooding.
- Aids in effective disaster management, urban planning, and mitigation strategies.

https://waterwatch.usgs.gov/index.php?id=flood&sid=w__map&r=fl





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Flood Susceptibility Mapping (FSM):

Flood Susceptibility Mapping Methods:

- **Traditional Models:** Hydrological, hydrodynamic, statistical, and Multi-Criteria Decision Analysis (MCDA).
- **Machine Learning Models:**
  - hybrid machine learning and deep learning models offer higher accuracy than traditional models
  - However, these models are often "black boxes," limiting their practical utility.

Explainable AI (XAI) in Geospatial Applications:

- XAI techniques like SHAP provide transparency and interpretability.
- Enhances stakeholder trust and facilitates informed decision-making.

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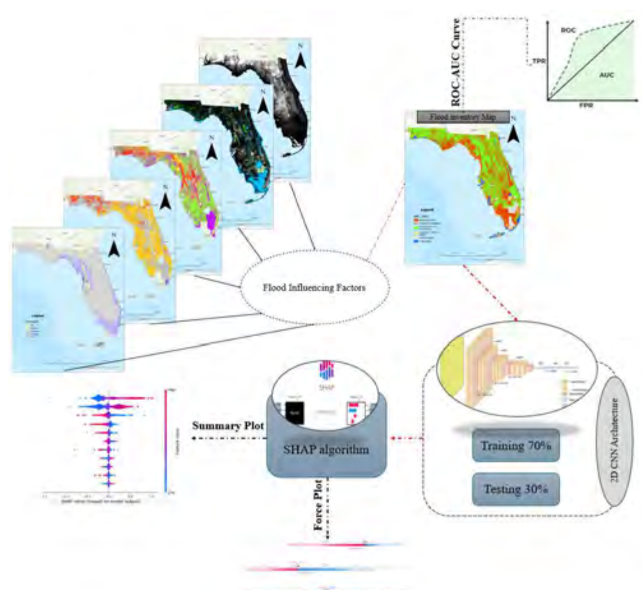
Study Objective:

Primary Goal:

- Develop an accurate and interpretable flood susceptibility map for the state of Florida.

Specific Objectives:

- Develop FSM using traditional methods
- Utilize a 2D Convolutional Neural Network (CNN) and Residual Network (ResNet) to predict flood-prone areas.
- Incorporate Shapley Additive Explanations (SHAP) to interpret the CNN model's predictions.
- Identify and analyze key factors influencing flood susceptibility.



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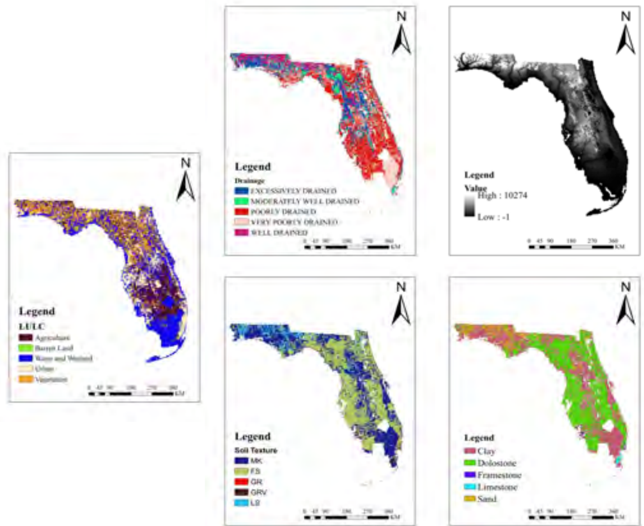
Flood Susceptibility Mapping Using AHP model (Traditional)

- 13 flood-triggering factors encompassing geographical, soil, and forest attributes.
- **Geographical Factors:**
  - **Landcover**, forest type, forest density, pasture, wetland and drainage
  - **Topography**, slope
  - **Lithology**
- **Soil Attributes:**
  - **Soil Texture**
  - **Soil Drain**



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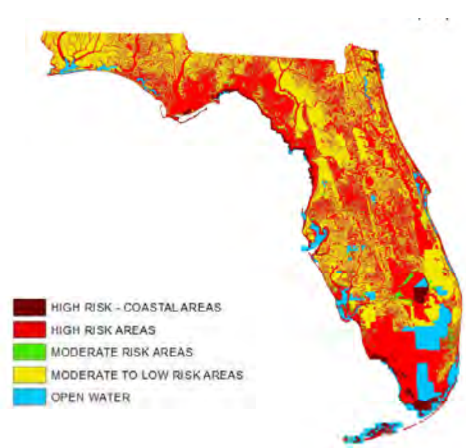
Flood Susceptibility Mapping Using AHP model (Traditional)

- **Data Processing:** GIS techniques were used to derive key parameters, process maps and reclassifying
- **Analytical Hierarchy Process (AHP):** weighting factors
- **Flood Susceptibility Mapping:** using The weighted linear combination method to combine the weighted factors:
- $FS = \sum_{i=1}^{n} w_i . x_i$
- where FS is the flood susceptibility index, w_i is the weight of factor i, and x_i is the factor class.



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Flood Susceptibility Mapping
Using Explainable Artificial Intelligence (XAI) Models

13 flood-triggering factors encompassing geographical, soil, and forest attributes.

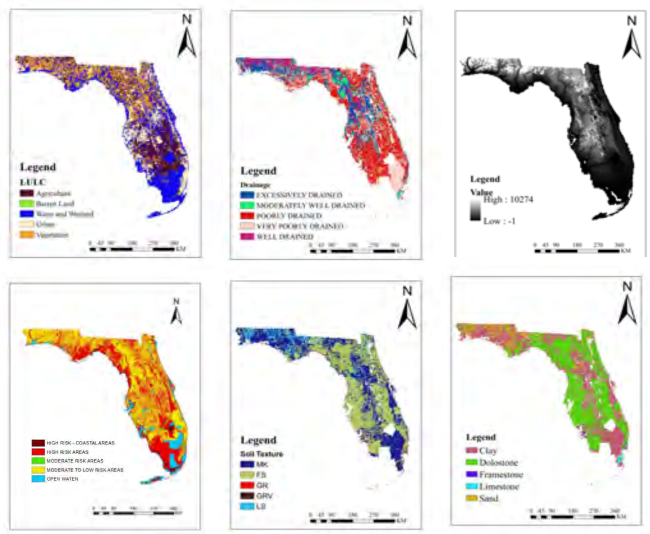
Geographical Factors:

1. Landcover, Forest type, Forest Density, Pasture, wetland
2. Topography, slope
3. Lithology

Soil Attributes:

4. Soil Texture
5. Soil Drain

Flood Inventory Map: provides key information about historical flood event characteristics



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Data Preprocessing:

- **Data Collection & Format Standardization**
  - Collected 13 geospatial input parameters (e.g., TWI, slope, soil type) and 1 flood inventory map, all in GeoTIFF format for consistency in spatial analysis.
  - Ensured uniform spatial resolution (10m × 10m), coordinate reference system, and file format across all datasets.
- **Spatial Alignment & Cropping**
  - Cropped all raster layers to a fixed spatial boundary to ensure consistent Pixel Count and Alignment
- **Handling Missing Data**
  - Applied linear interpolation to fill gaps in continuous-valued raster datasets, and sinking and filling and removing no-data values from images.
- **Data Normalization**
  - Applied normalization to rescale pixel values between 0 and 1. Handled datasets with varying value ranges (binary vs. continuous) appropriately.
- **Raster Tiling**
  - Split each raster layer into 128 × 128 pixel tiles for scalable processing.
  - Generated 316,274 tiles per parameter.

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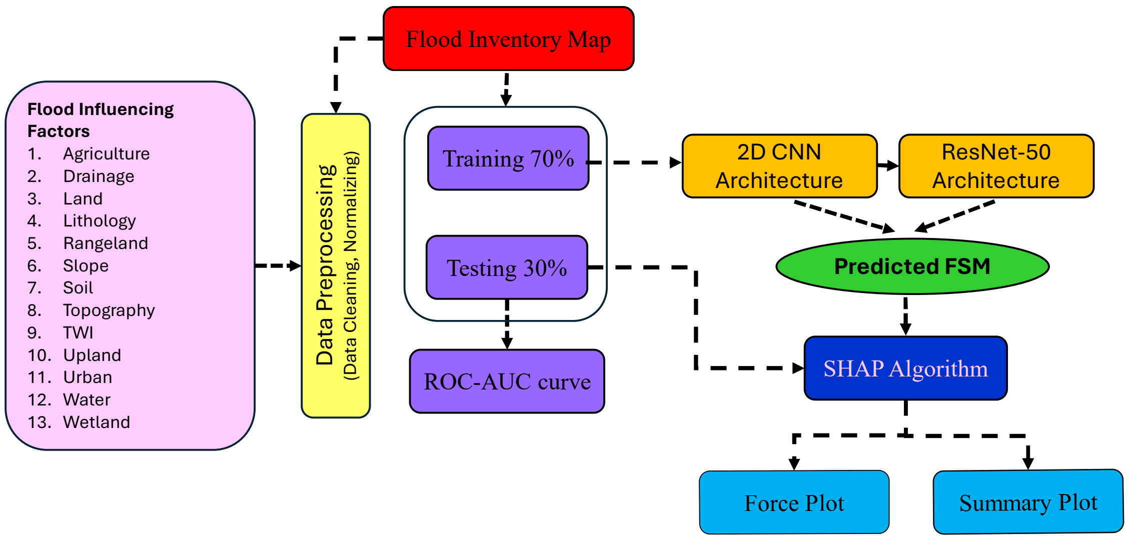

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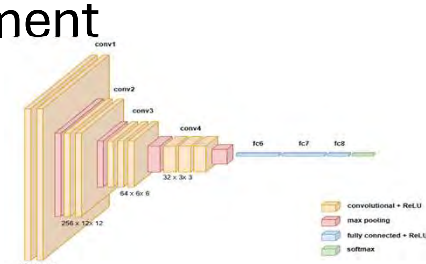
Methodology: Model Development

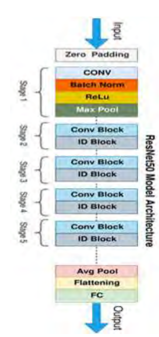
2D Convolutional Neural Network (CNN-2D):

- **Architecture:** Four convolutional layers for feature extraction
- **Pooling layers:** For dimensionality reduction
- **Fully connected dense layer:** For classification



ResNet

- A deep convolutional neural network introduced by Microsoft Research in 2015.
- Solves the vanishing gradient problem using residual (skip) connections.
- Used ResNet-50 model architecture for prediction.
- Modified to accept 13 input bands instead of standard RGB (3 channels).



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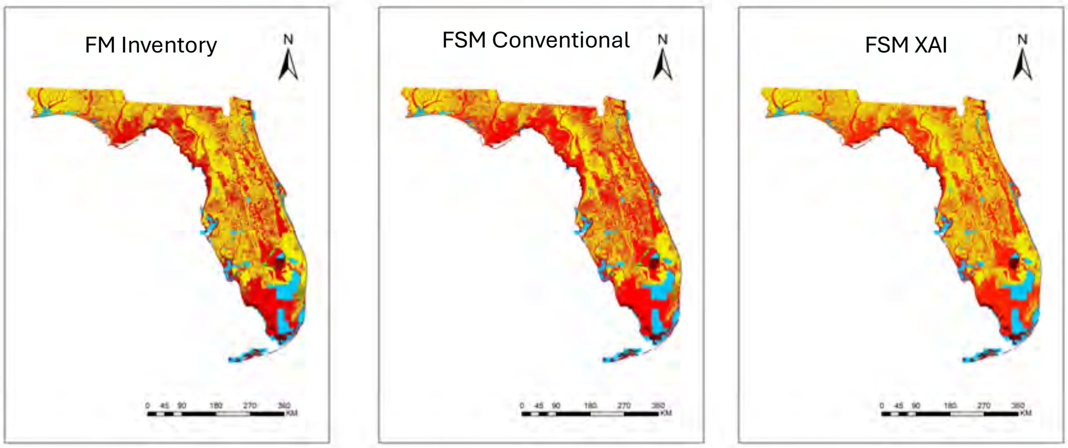
Flood Susceptibility Maps



Performance metric	FSM AI -CNN	FSM AHP
AUC-ROC	0.909	0.630

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XAI model

SHAP (Shapley Additive Explanations):

- A method based on game theory to explain individual predictions of any machine learning model.
- **Transparency:** Breaks down complex model decisions into understandable contributions from each feature.
- **Insight:** Identifies which factors are most influential one.

How does SHAP work?

SHAP calculates the marginal contribution of a feature by comparing outcomes **with** and **without** that feature across all possible combinations of input features.

Step-by-Step Process:

- Think of the features (e.g., land use, soil type) as players in a game.
- The "game" is the model's prediction (e.g., flood risk score).
- SHAP asks: “If we include this feature, how much does it improve the prediction?”

Mathematical Formulation:
The **Shapley value** $\emptyset_i$ for a feature i is computed as:
S: Subset of features excluding i.
N: Set of all features.
n: Total number of features.
$v(S)$: Model’s prediction using subset S of features.

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!} [v(S \cup \{i\}) - v(S)]$$

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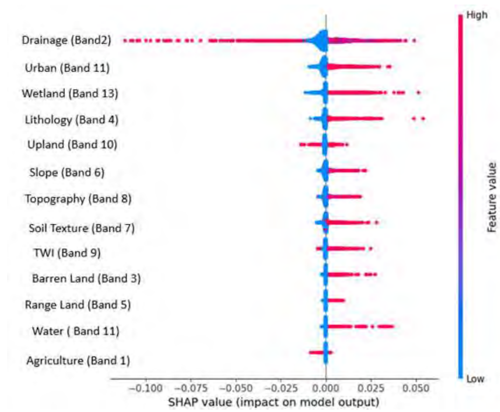
XAI model

Provides Two Main Types of Explanations:
SHAP Summary Plots Global importance: Displays the overall impact of each feature across all predictions.
SHAP Individual Force Plot, Local Explanation: Shows how each feature contributes to the prediction of a single pixel.



Based on the summary plot, we determined that Drainage was the most important variable influencing flood susceptibility, whereas Agriculture was the least important.

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Findings:

- The use of feed forward neural network models, particularly N-HiTS and N-BEATS, offers a promising avenue for enhancing the predictive capabilities of hydrological models.
- The extended forecasting results using deep learning models demonstrated their potential for predicting both surface water discharge and groundwater levels over a nearly two-year horizon
- Flood susceptibility map of Florida was generated by AI, with a higher accuracy compared to traditional methods.
- Using XAI SHAP approach we could identify the importance and influence of parameters
- The approach can be used for other risk/susceptibility assessment such as groundwater vulnerability, drought sinkhole susceptibility maps of Florida

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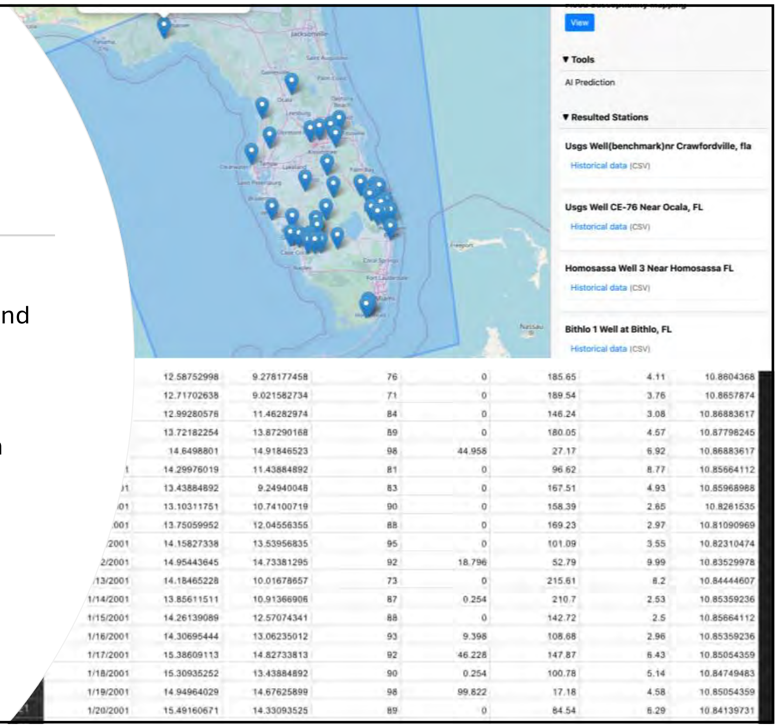
3. AI as a service: Interactive AI platform

- View **AI-generated maps and forecasting results** for water, soil, and climate
- Get **tailored recommendations** for their specific land and region
- Plan around real-time and long-term **environmental conditions**



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