Near Real-Time Flood Mapping Using Satellite Images and Deep Learning
Case Study: Miami-Dade County, FL

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Overview

- Urban floods occurred about every 2-3 days over the past 25 years (NOAA).
- Urban flooding is not easily trackable because of:
  - Dynamic urban environments
  - Impacts of climate change
  - Insufficient flood event data
  - Lack of real-time monitoring systems

Problem Statement: Urban Flood Mapping Methods

Urban Flood Mapping Methods

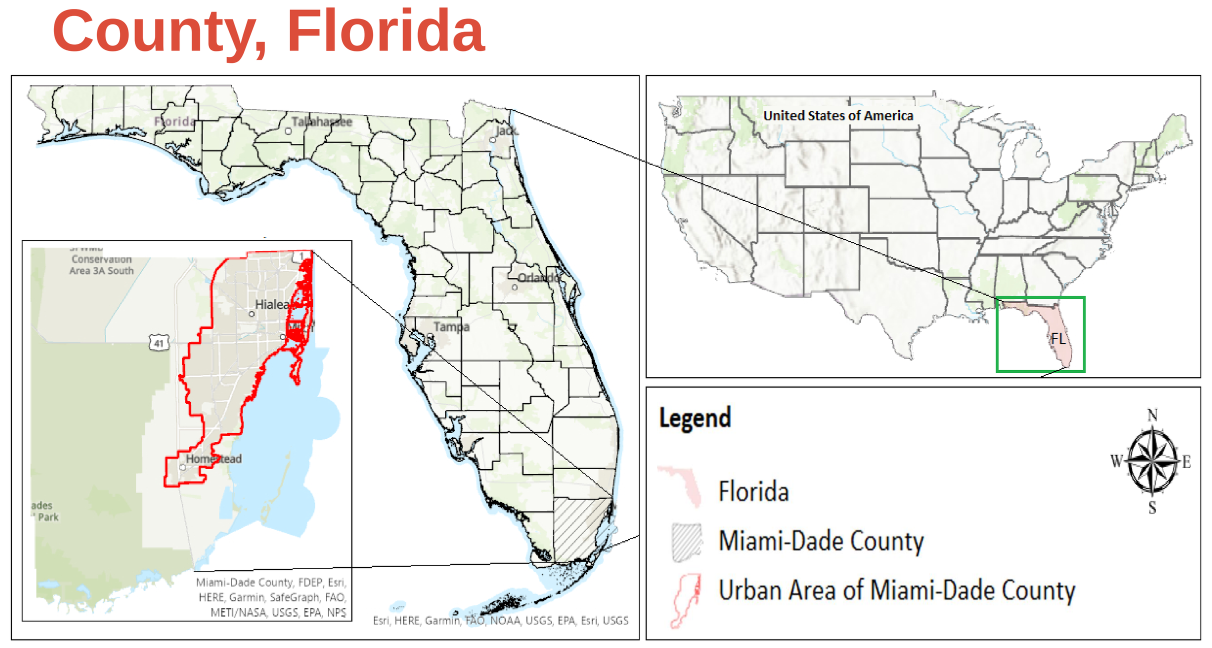
Physics-based | Remote Sensing | Geographic Information Systems | Deep Learning

- Insufficient integration of critical flood-influencing data, such as rainfall patterns and terrain-related spatial information.
- Limited event scope and focused exclusively on specific major events (e.g., major storms).

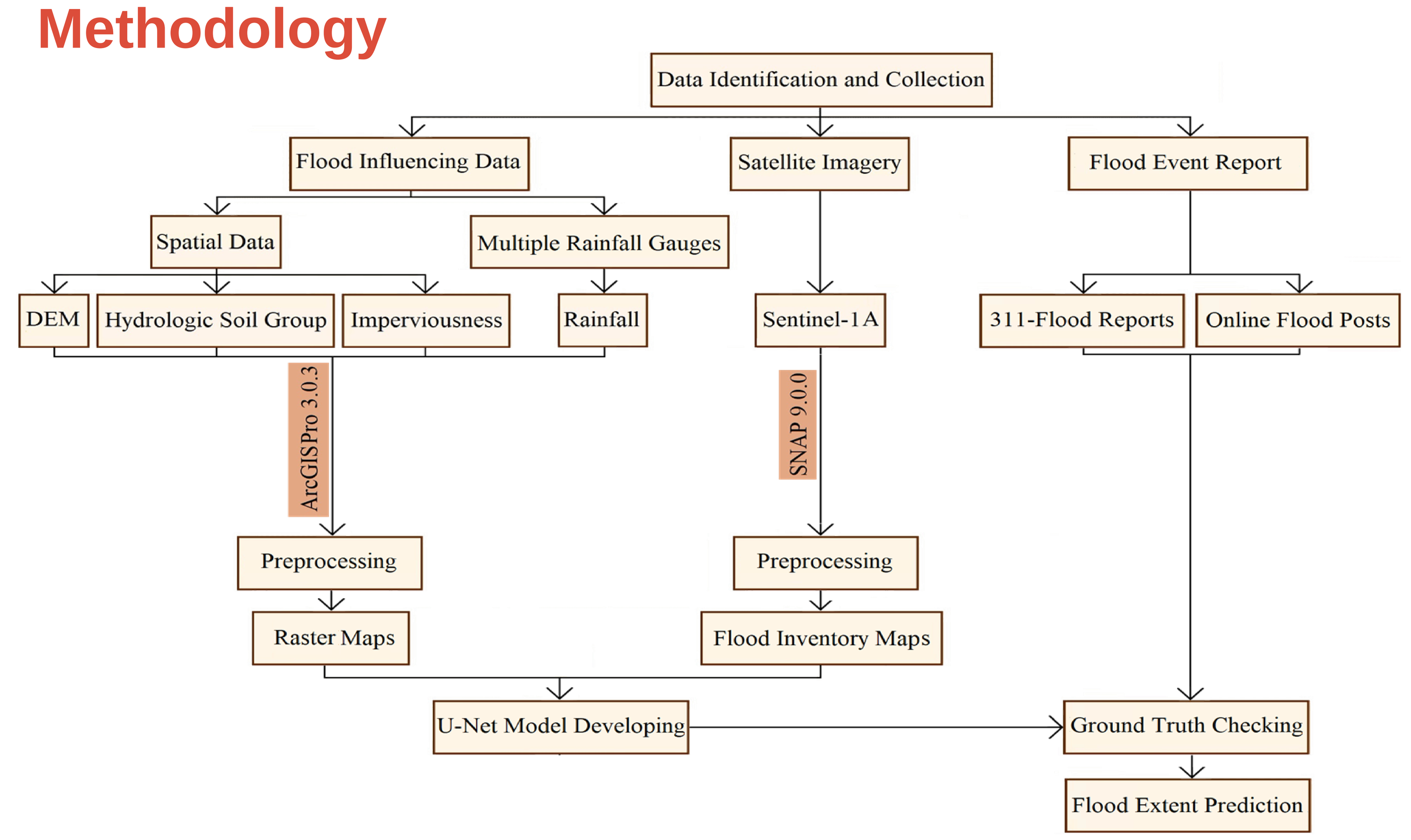
Objectives

- Developing a deep learning model for predicting near-real time urban flood extents resulting from rainfall (pluvial flood) using a CNN network (U-Net).
- Addressing the limitations of spatial-temporal resolution found in previous studies by:
  - Providing a more accurate and comprehensive urban flood mapping over an extended period (2014-2023).
  - Incorporating terrain-related spatial data.
  - Utilizing daily rainfall and Sentinel-1

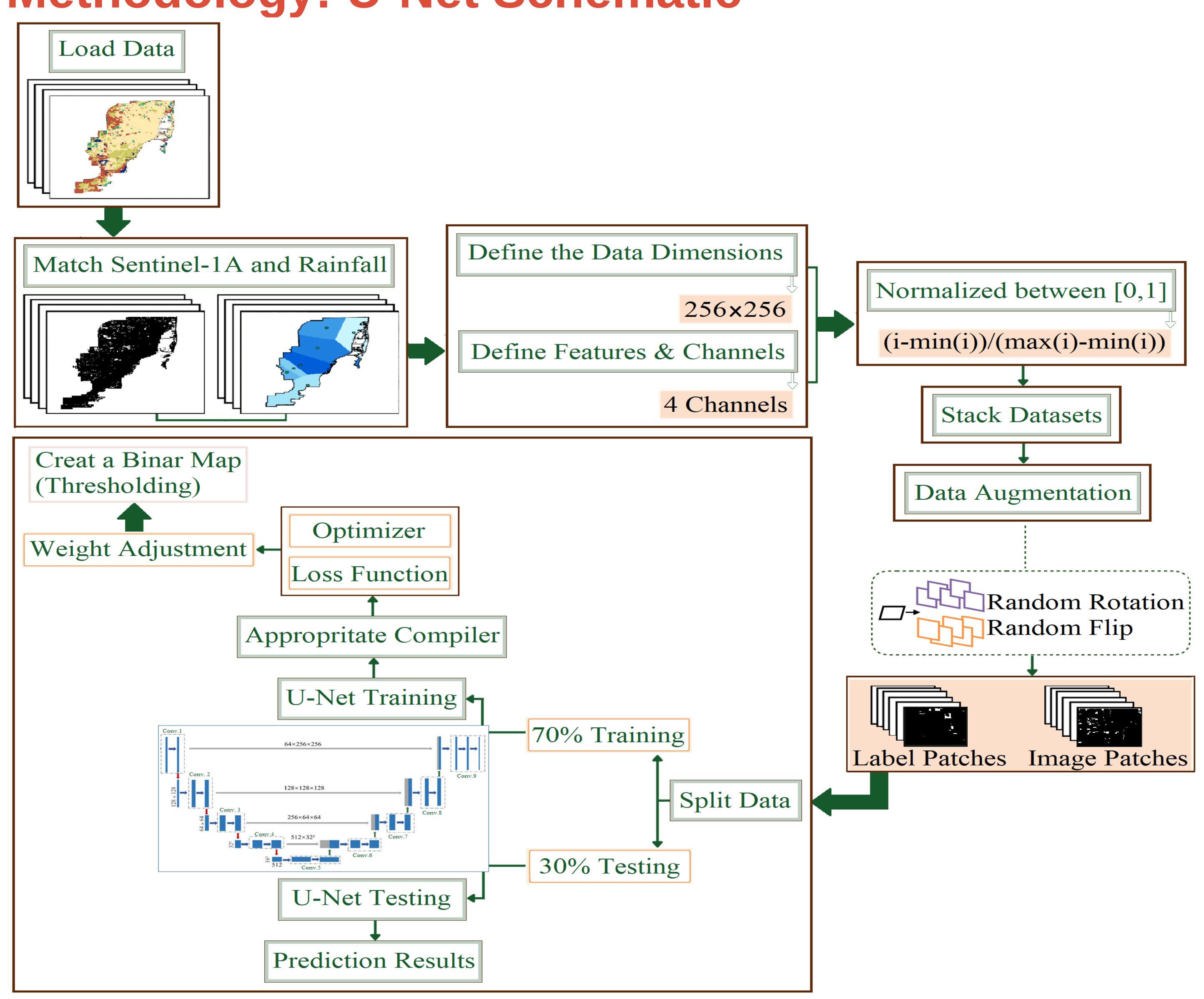
Study Area: Urban Areas of Miami-Dade County, Florida



Methodology

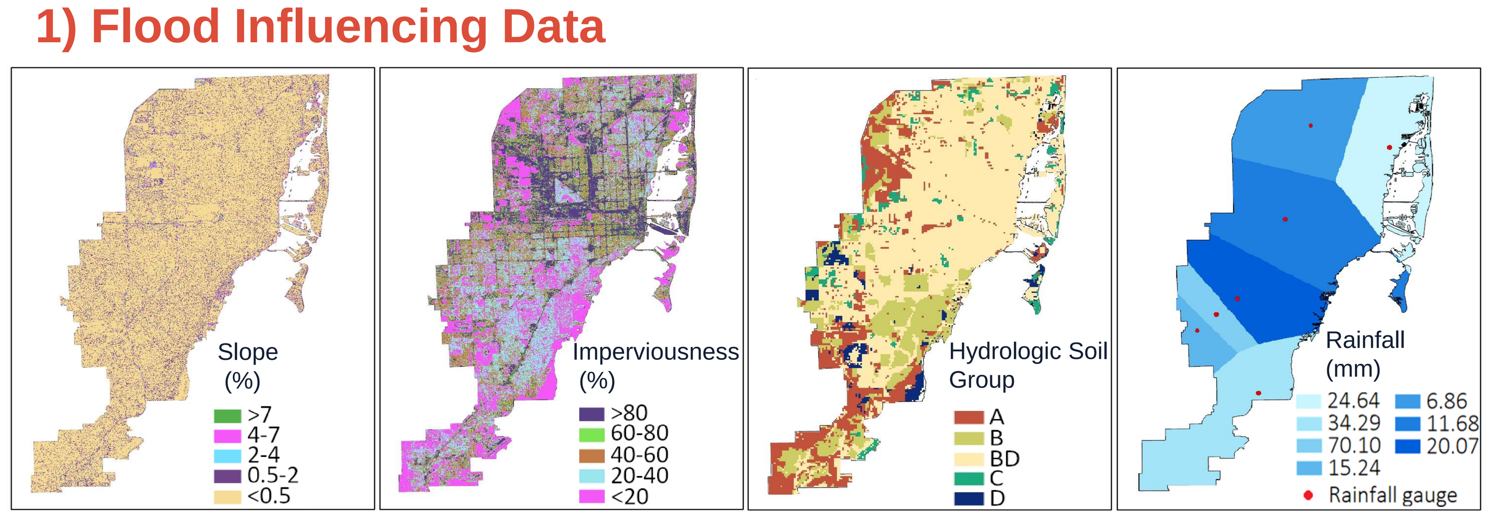


Methodology: U-Net Schematic



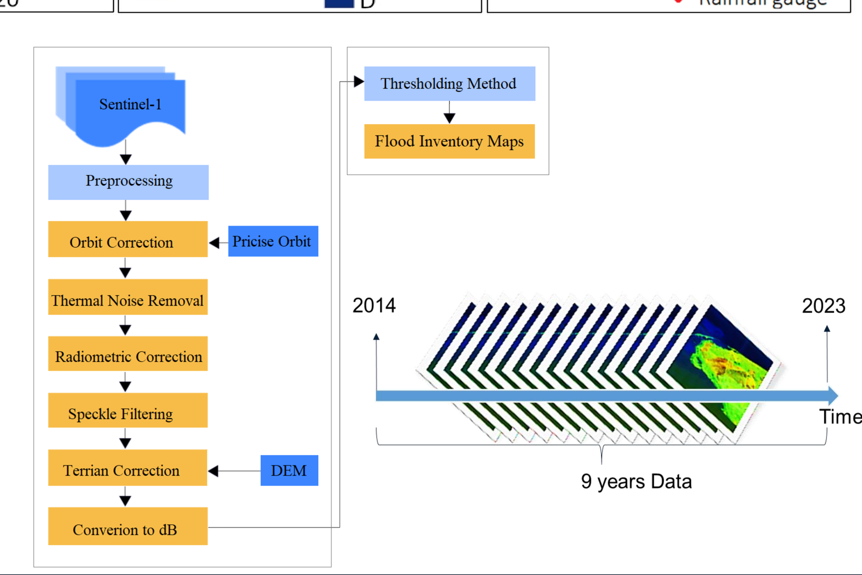
Data

1) Flood Influencing Data



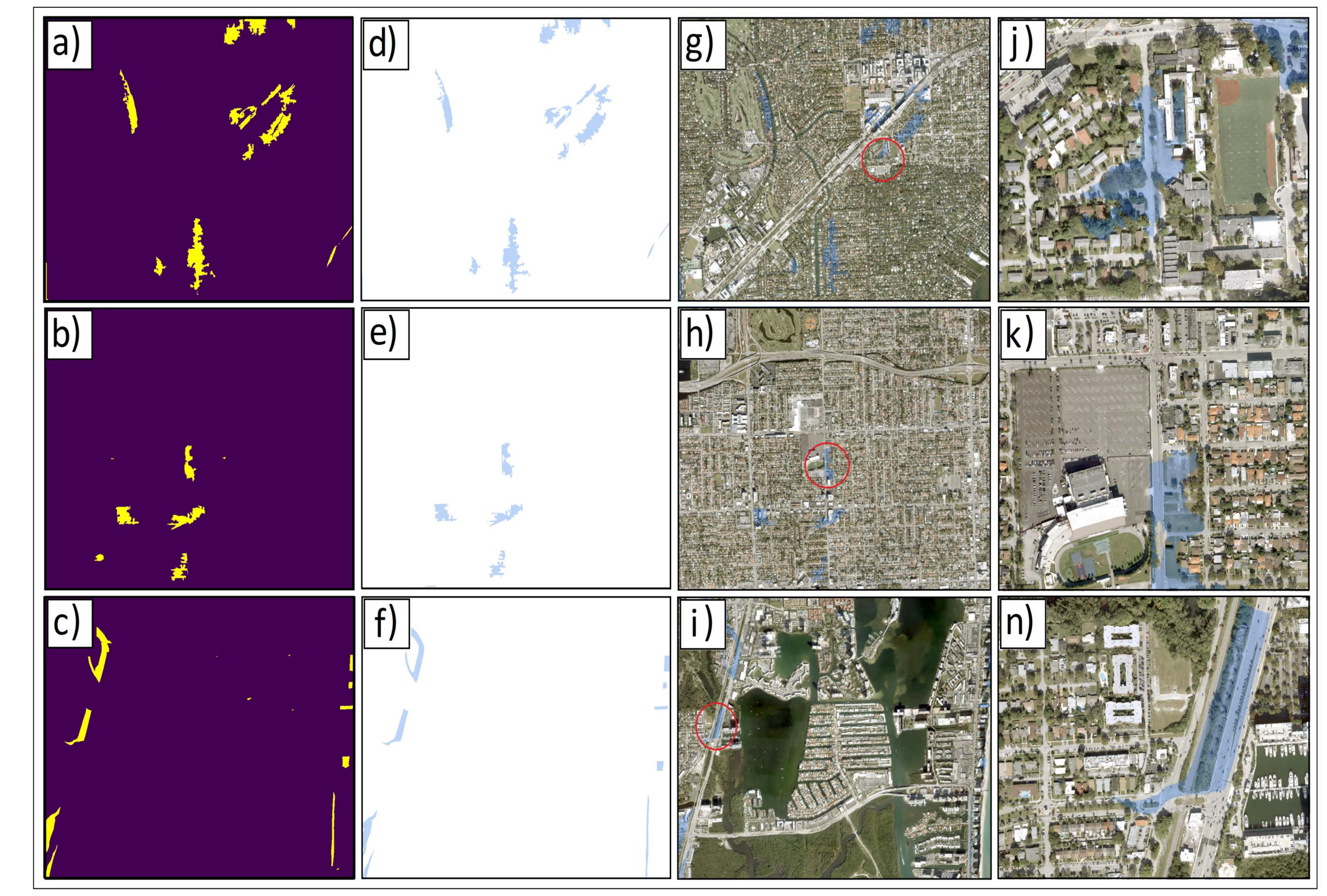
2) Sentinel-1 Images

- Total number of 226 Sentinel-1 images
- Temporal Resolution of 6-12 days



Results

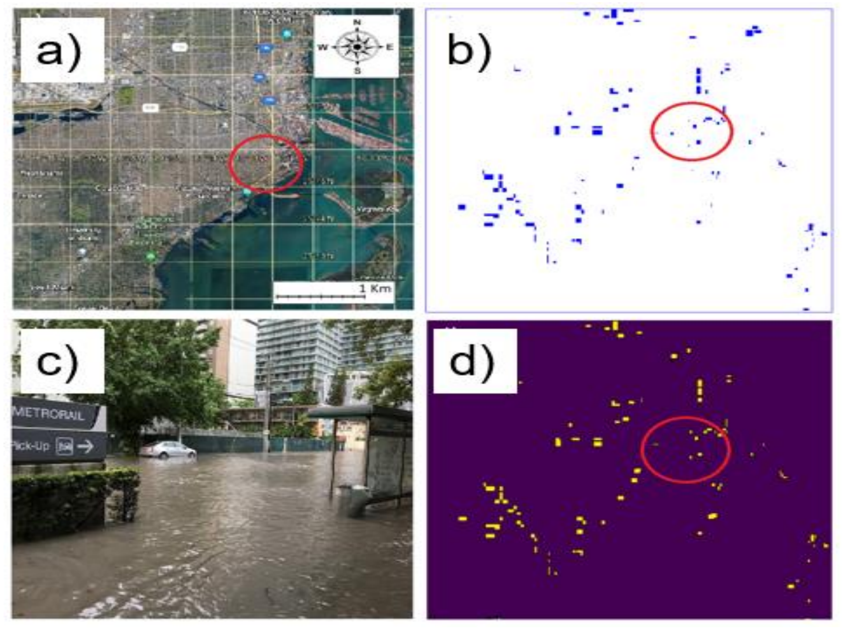
Visualization of flood detection and verification: a, b, and c) flood inventory maps generated by SNAP software for three randomly selected patches, presented flood events with yellow; d, e, and f) the U-Net model's flood prediction; g, h, and i) satellite maps with overlaid ML predictions; j, k, and n) randomly selected zoom-in views from the ground truth imagery.



Results: Ground Truthing

Model demonstrates an accurate prediction capability with a Ground Truth Index of 84%.

Figure: Flooding, Miami-Dade County, FL. a) from Google Earth, b) prediction, c) social media posts, d) flood inventory



Results: Sensitivity Analysis

Input Data	Precision	Recall	F1Score	Overall Accuracy
Slope + HSG + Imperviousness + Rainfall	94.07	86.00	89.85	93.73
Slope + Imperviousness + Rainfall	93.47	85.76	89.45	93.35
Slope + HSG + Rainfall	93.22	85.59	89.28	93.18
HSG + Imperviousness + Rainfall	92.85	85.34	88.97	92.90
Imperviousness + Rainfall	92.14	84.97	88.42	92.75
HSG + Rainfall	91.93	84.42	88.05	92.60
Slope + Rainfall	91.67	84.25	87.82	92.45
Rainfall	90.03	83.27	86.52	91.57

Conclusion

- Extended the model's application beyond traditional flood mapping to develop a Near Real-Time flood mapping system.
- Enabled more comprehensive flood mapping across various conditions and areas.
- Achieved high-resolution (10-meter) for detailed flood extent predictions.

Citation

Mohamadiazar, N., Ebrahimian, A., & Hosseiny, H. (2024). Integrating deep learning, satellite image processing, and spatial-temporal analysis for urban flood prediction. Journal of Hydrology, Volume 639, 131508.

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