# Enhancing Climate-Resilient Urban Flood Early Warning through Image-Based Monitoring and Hydrodynamic Model Updating for Disaster Risk Reduction

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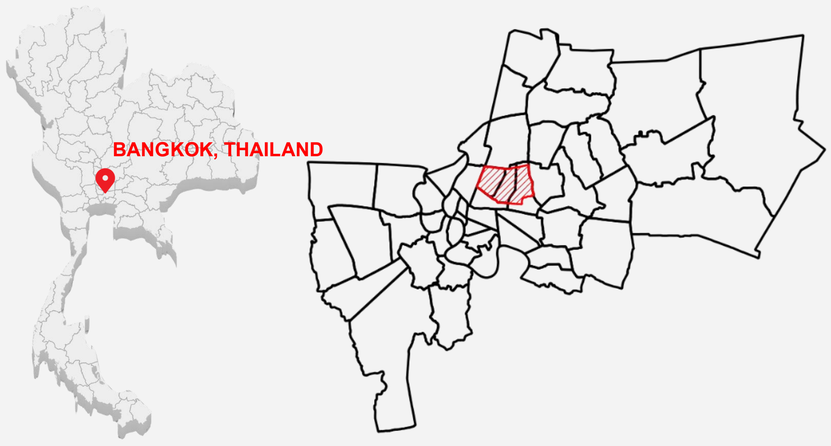
## Introduction

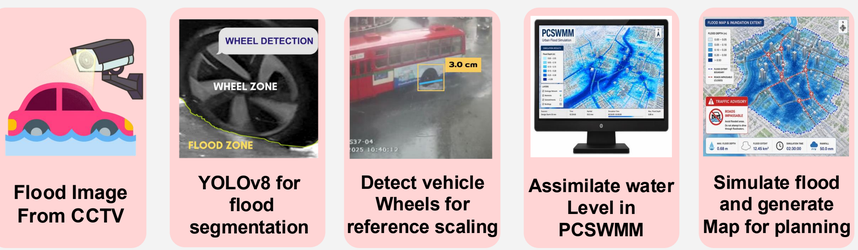
- **Urban flood risk is intensifying due to climate change and high-intensity rainfall, especially in cities with limited drainage capacity.**
- **Accurate and time-resolved flood-depth information is critical for early warning, emergency response, and disaster risk reduction.**
- **This study proposes a near real-time flood monitoring framework that integrates image-based flood detection using YOLOv8-seg with a two-dimensional hydrodynamic model (PCSWMM) to improve inundation mapping accuracy and warning reliability.**



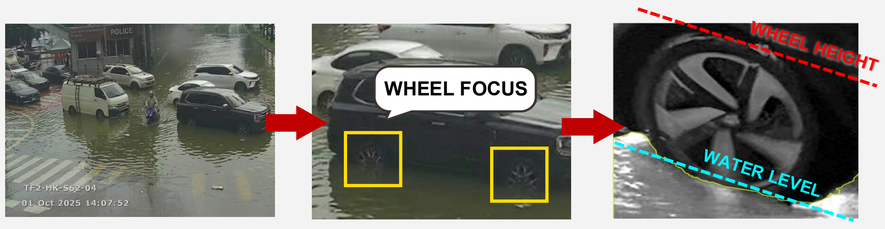

## Methodology

### 1. INTEGRATED FRAMEWORK OVERVIEW

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| **Image Acquisition** | **Image Processing** | **Depth Estimation** | **Model Updating** | **Flood Map Prediction** |
| Flood Image From CCTV | YOLOv8 for flood segmentation | Detect vehicle Wheels for reference scaling | Assimilate water Level in PCSWMM | Simulate flood and generate Map for planning |




### 2. Image-Based Flood Depth Detection



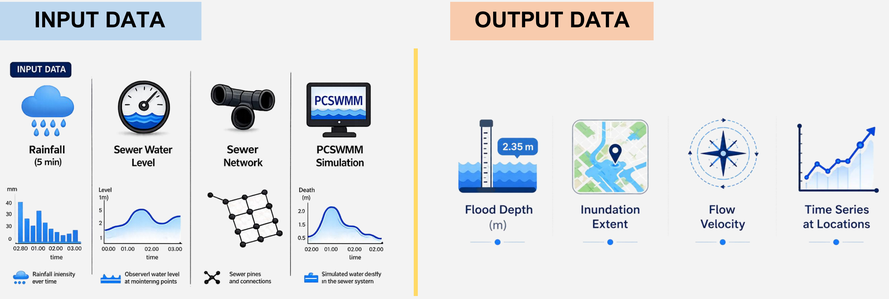

Flood event images from CCTV systems | Detect flood zones and wheel positions | Estimate water level using wheel as reference

$$Scale = \frac{H_{real}}{H_{pixel}} \qquad D_{real} = D_{pixel} \times Scale$$

$H_{real}$ = Real wheel diameter (cm.) $D_{real}$ = Real Water Level (cm.)

$H_{pixel}$ = wheel diameter in image (pixel) $D_{pixel}$ = Pixel Distance to waterline (pixel)

### 3. Hydrodynamic Model Input and Output




### 4. DECISION SUPPORT


## Results

### 1. Image-Based Depth Estimation Performance

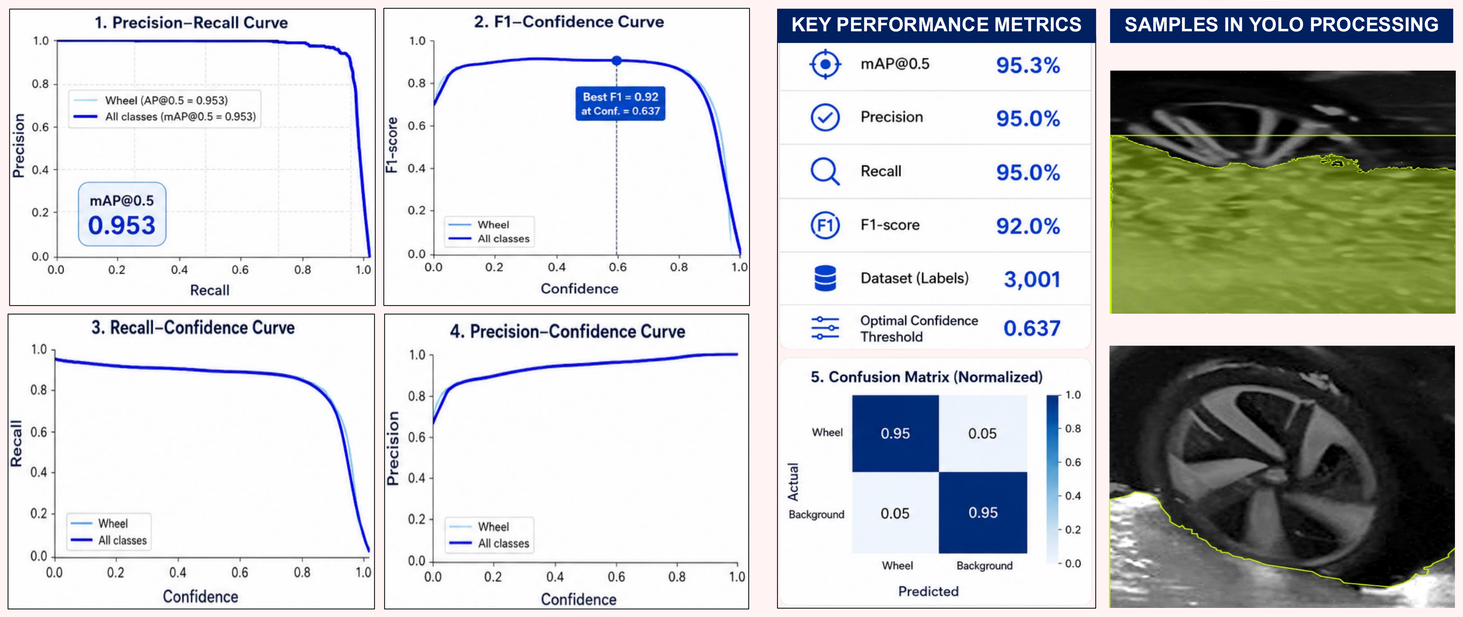



*Figure 1. Performance Evaluation of the YOLOv8-Based Wheel Detection Model for Flood Depth Estimation*

### 2. Hydrodynamic Model Performance (PCSWMM)

**Calibration - 10 October 2025** | **Validation - 9 May 2025**

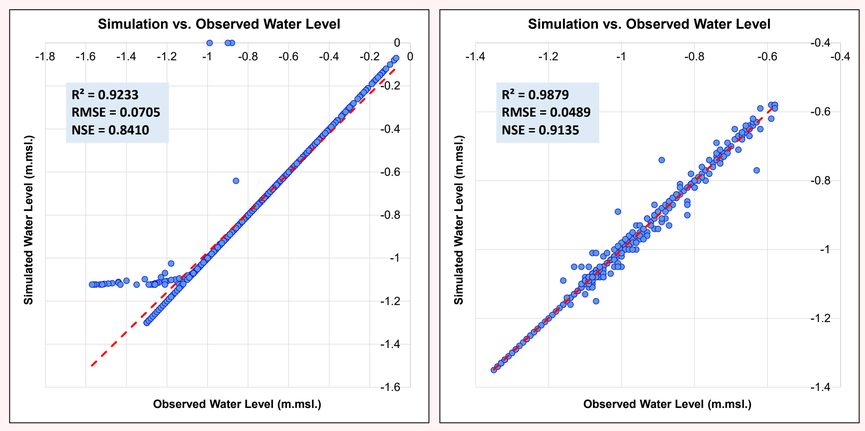



*Figure 2. Calibration & Validation Results of the PCSWMM Model: Simulated versus Observed Water Levels*

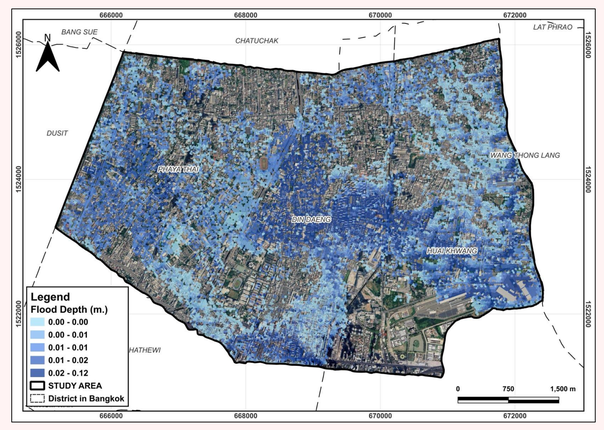
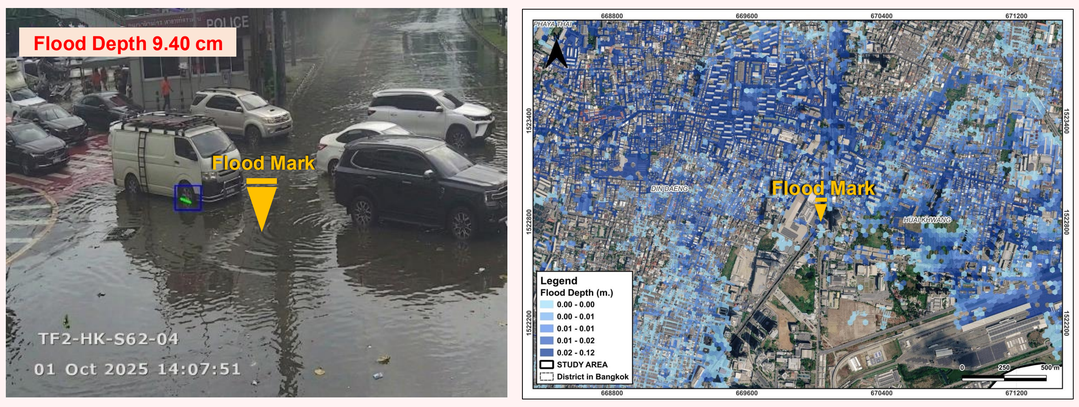



*Figure 3. Spatial Distribution of Flood Depth Generated from the Calibrated PCSWMM Model*

### 3. Integration of CCTV-Based Flood Monitoring and Hydraulic Modeling

CCTV Images → YOLO Processing → Flood Depth Estimated in Flood Mark → Matching with Flood Boundary from PCSWMM → Alert for planning




| Parameter | Value |
|---|---|
| Simulated water depth | 8.0 cm |
| YOLOv8-seg estimated depth | 9.4 cm |
| Difference | 1.4 cm |
| Accuracy (%) | 85.11 |
| Flood pattern agreement | Good |

*Figure 4. Integration of CCTV-Derived Flood Depth and Hydraulic Model Simulation for Flood Assessment*

## Conclusion

### Key Conclusions

- **The image-based flood monitoring approach achieved a flood depth estimation accuracy of 85.11% compared with observed water levels.**
- **The PCSWMM model demonstrated satisfactory calibration and validation performance ($R^2$ = 0.923, NSE = 0.841, RMSE = 0.0705 m).**
- **The estimated flood depth from CCTV imagery (9.4 cm) closely matched the observed water depth (8.0 cm).**
- **Simulated flood inundation patterns were consistent with CCTV observations, particularly along major roads and low-lying urban areas.**

### Contributions

- **Integrates YOLOv8-seg-based image analysis with hydraulic modeling (PCSWMM) for near real-time urban flood monitoring.**
- **Provides an effective framework for flood depth estimation, model validation, and decision support using CCTV imagery.**
- **Enhances flood warning capability and supports urban flood management through improved situational awareness.**
- **Offers a scalable and cost-effective solution for flood monitoring in urban areas with limited hydrological observations.**

### References / Footnotes

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