Exploratory Advanced Research Program

Innovative Methods to Detect and Measure Flooded Roadways

Workshop Summary Report

EXPLORATORY ADVANCED RESEARCH

U.S. Department of Transportation
Federal Highway Administration

Turner-Fairbank
Highway Research Center

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Technical Report Documentation Page

<table>
<tr><td>1. Report No.
FHWA-HRT-24-006</td><td colspan="3">2. Government Accession No.</td><td colspan="2">3. Recipient’s Catalog No.</td></tr>
<tr><td colspan="4" rowspan="2">4. Title and Subtitle
Innovative Methods to Detect and Measure Flooded Roadways</td><td colspan="2">5. Report Date
April 2024</td></tr>
<tr><td colspan="2">6. Performing Organization Code</td></tr>
<tr><td colspan="4">7. Author(s)
Douglas Leung and Mark Mockett</td><td colspan="2">8. Performing Organization Report No.</td></tr>
<tr><td colspan="4" rowspan="2">9. Performing Organization Name and Address
Volpe National Transportation Systems Center
55 Broadway, Kendall Square
Cambridge, MA 02142

Schatz Publishing Group
11950 W. Highland Ave.
Blackwell, OK 74631</td><td colspan="2">10. Work Unit No.</td></tr>
<tr><td colspan="2">11. Contract or Grant No.
693JJ319N300057</td></tr>
<tr><td colspan="4" rowspan="2">12. Sponsoring Agency Name and Address
Federal Highway Administration
6300 Georgetown Pike
McLean, VA 22101-2296</td><td colspan="2">13. Type of Report and Period Covered
Workshop Summary Report
May 30 and 31, 2023</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code
HRTM-30</td></tr>
<tr><td colspan="6">15. Supplementary Notes</td></tr>
<tr><td colspan="6">16. Abstract
On May 30 and 31, 2023, the Federal Highway Administration’s Exploratory Advanced Research Program held a workshop showcasing groundbreaking methods to detect, predict, and model roadway flooding, focusing on implementing machine-learning and artificial intelligence technologies. The purpose of the workshop was to identify the maturity, piloting techniques, and lessons from deployments of novel data collection and modeling methods in managing roadway flood hazards. Organizers wanted participants to learn how to leverage engineering, computer and climate science, and social science expertise for roadway flooding methodologies. The presentations and subsequent discussions identified critical gaps in data availability and areas for collaboration between public institutions, private firms, and researchers.</td></tr>
<tr><td colspan="3">17. Key Words
Roadway flooding, artificial intelligence, machine learning</td><td colspan="3">18. Distribution Statement
No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22161.
https://www.ntis.gov</td></tr>
<tr><td colspan="2">19. Security Classif. (of this report)
Unclassified</td><td colspan="2">20. Security Classif.
(of this page)
Unclassified</td><td>21. No. of Pages
24</td><td>22. Price
N/A</td></tr>
</table>

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized.

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.755	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or “metric ton”)	Mg (or “t”)
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or “t”)	megagrams (or “metric ton”)	1.103	short tons (2,000 lbs)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbfin^2

*SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (revised March 2003)

Contents

LIST OF FIGURES

WORKSHOP BACKGROUND

On May 30 and 31, 2023, the Federal Highway Administration's (FHWA) Exploratory Advanced Research (EAR) Program held an event, Innovative Methods in Roadway Flooding Workshop, that showcased groundbreaking methods to detect, predict, and model roadway flooding using machine-learning (ML) and artificial intelligence (AI) technologies. The workshop aimed to identify the maturity, piloting techniques, and lessons from deployments of novel data collection and modeling methods in managing roadway flooding hazards. The workshop organizers wanted participants to learn how to leverage engineering, computer and climate science, and social science expertise for roadway flooding methodologies. These presentations showcased early-stage research. The presentations and subsequent discussions identified critical gaps in data availability and areas for collaboration between public institutions, private firms, and researchers (FHWA 2023).

The workshop featured the following presentations (FHWA 2023):

1. Presentation 1. Ahmed Mustafa and Pablo Herreros-Cantis, New School—AI-Powered Flood Simulations: Overcoming Traditional Hydraulic Model Limitations.
2. Presentation 2. Brett Sanders, University of California Irvine—Fine Resolution Inundation Modeling in Southern California.
3. Presentation 3. Mikhail Chester, Arizona State University—Community-Based Automated Flood Detection and Warning Systems.
4. Presentation 4. Mecit Cetin and Khan Iftekharuddin, Old Dominion University—Recurrent Roadway Flooding: Image-Based Detection, Driver Behavior, and Impacts on Traffic Flow.
5. Presentation 5. Andrea Silverman, New York University—FloodNet: Real-Time, Hyperlocal Flood Monitoring in New York City.
6. Presentation 6. Mayank Ojha and Miho Mazereeuw, Massachusetts Institute of Technology (MIT)—Crowdsourcing and AI for Roadway Flood Management.
7. Presentation 7. Valeriy Ivanov, University of Michigan—Flood Ensemble Predictions: From Pushed-Forward Parametric Uncertainty to Probabilistic Error Estimation.

KEY INSIGHTS FOR TRANSPORTATION

The workshop had the following takeaways (FHWA 2023):

- Integrating AI into hydraulic and hydrologic (H&H) models may enable rapid production of large-scale, detailed city flood simulations. AI-trained surrogate models, which mathematically approximate flooding dynamics, may run simulations more rapidly than traditional H&H models and provide uncertainty ranges of flood model predictions. (See presentations 1 and 7.) New methods potentially overcome computational bottlenecks to reduce the time and processing power required to generate high-resolution models compared to traditional approaches.

- Obtaining precise and validated infrastructure data is essential for high-quality models, but a critical gap exists in calibration and validation data availability, especially for subsurface infrastructure. To use AI-assisted modeling tools, practitioners need access to high-quality water and stormwater infrastructure data.

- Integrating and analyzing diverse information sources, such as sensors, meteorological data, and crowdsourced observations, is a significant challenge to providing real-time flood detection. (See presentations 2, 3, and 5.) A key research opportunity is acquiring mobile device location data from service providers and application metadata. (See the workshop wrap-up discussion section and presentations 1 and 2.)

- Deploying a dedicated network of flooding sensors for more detailed flooding awareness provides higher quality data but requires key prioritization to manage limited resources. Researchers in Arizona and New York City, NY, have piloted real-time flood detection solutions to integrate citywide (e.g., social media, gauges, mobile hydrology) and local data (e.g., sensor/floodcam) sources. (See presentations 3 and 5.) The placement of sensors is prioritized based on stakeholder needs. (See the workshop wrap-up discussion and presentations 5 and 6.)

- Implementing new data sources (such as crowdsourced imagery) will help researchers determine valuable insights for emergency managers, including impacts on vehicle flow. (See presentations 4 and 6.) Computer vision approaches to coastal city flooding demonstrate that ML algorithms can extract information from images and video to estimate floodwater depth and extent accurately. (See presentation 4.) Cities that collect data on vehicles per roadway per hour (traffic flow) can use AI to estimate flooding impacts on roadway traffic flow. (See presentation 4.) MIT's RiskMap tool deploys crowdsourced social media information and ML to distill useful analysis from the high volume of imagery data during flood events (MIT 2016). (See presentation 6.)

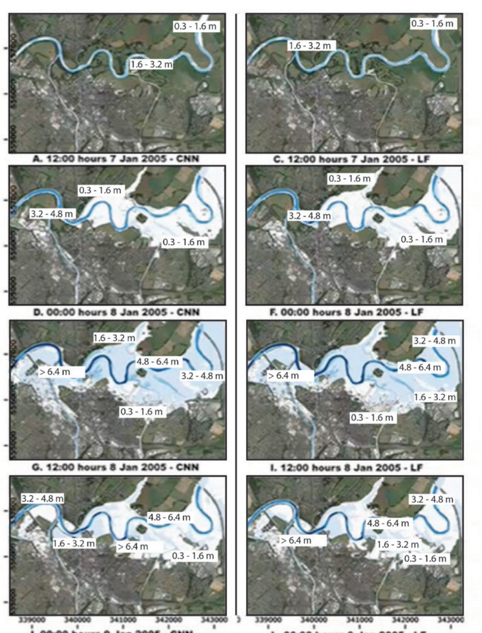
PRESENTATION 1. AHMED MUSTAFA AND PABLO HERREROS-CANTIS, NEW SCHOOL—AI-POWERED FLOOD SIMULATIONS—OVERCOMING TRADITIONAL HYDRAULIC MODEL LIMITATIONS

Mustafa and Herreros-Cantis presented research on high-resolution simulations of urban flooding in U.S. cities (FHWA 2023). They discussed how AI may help overcome the limitations of traditional hydraulic models, such as computation time and resource constraints.

The presentation had the following significant points (FHWA 2023):

- Technology—CityCAT, the flood model used in the project, has relatively low data requirements and can compute the infiltration of surface runoff on impervious surfaces (Engineering and Physical Sciences Research Council n.d.).

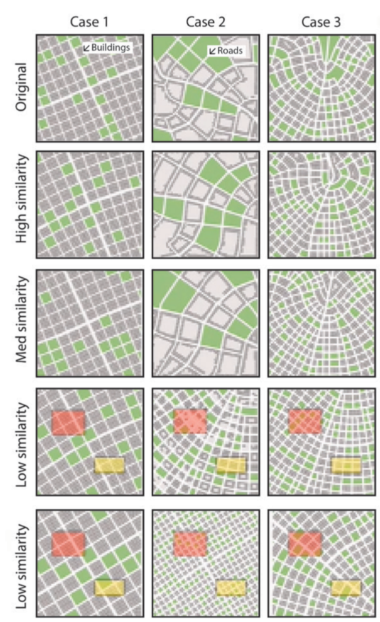
- Method—The project assessed flood simulation of models before and after AI assistance, comparing the cost, required computing power, and time. Before implementing generative AI, the project used cloud computing services to overcome computational limitations, as CityCAT and similar tools are resource intensive.



© 2020 Kabir et al.
LF = LISFLOOD-FP.
Figure 1. Flood inundation predictions, with CNN on the left and LF on the right (Kabir et al. 2020).

- Insight—AI enhances the capabilities of hydraulic models; however, higher resolution data are exponentially more expensive, and certain data types, such as buildings versus land cover, have limitations. AI models may incorporate more variables than traditional hydraulic models, such as transportation and water infrastructure. The presentation showcased the potential of training deep-learning models, particularly convolutional neural networks (CNN), to generate flood simulations; figure 1 shows how similarly CNN can match existing models. CNNs can process images and text as layers and output probability distributions, making them useful for image classification with minimal processing. AI may improve the flood modeling process by synthesizing missing data, quantifying and analyzing uncertainties.

- Insight—The results showed that modeling options for flood risk reduction and water depth reduction in important areas can be achieved in seconds using the AI-powered optimization engine. (See figure 2.) AI can be trained on the output of



© 2020 Mustafa et al.
Med. = median.
Figure 2. Image. Examples of flood predictions for different street networks and land uses. Users can generate optimal urban layouts to reduce flood risk, including priority areas marked by boxes (Mustafa et al. 2020).

hydraulic models, allowing for the rapid generation of flood simulations and the development of more advanced and sophisticated models. The use of the CNN and Markov chain Monte Carlo optimization engine (i.e., a system that explores different possibilities step by step to compute the best solution to a problem) in urban layout design provides a new strategy to mitigate flooding. Users can direct the AI to develop different design permutations for a given urban area by designating high-priority areas and choosing various flood depth exposure levels. The training mode for the optimization engine involved 7,000 offline simulations with the WOLF two-dimensional (2D) hydraulic model for more than 1 mo, using 10 workstations; figure 3 shows the predictions of the CNN model compared with the WOLF 2D model (University of Liege 2023). The presentation referenced previous studies that trained CNNs on 2D models and used Bayesian statistical methods (i.e., updating prior knowledge based on new data and information) for rapid computation and simulation of historical events (Kabir et al. 2020; Mustafa et al. 2020).

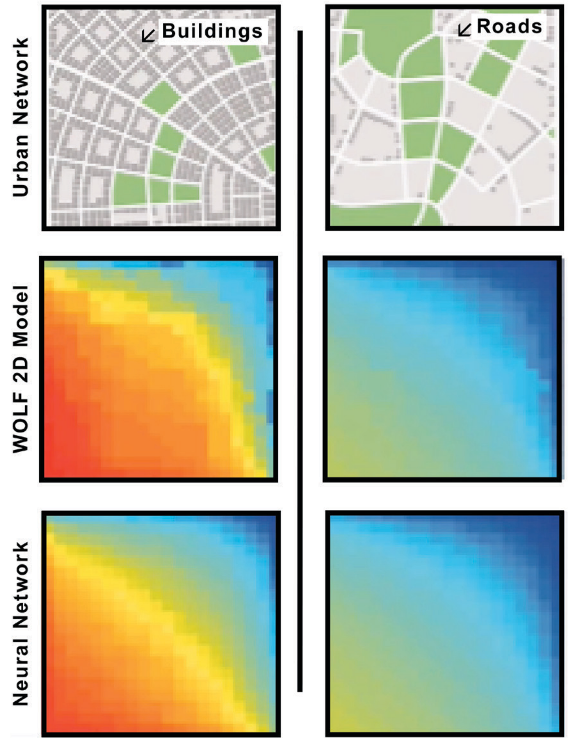


Figure 3. Image. Comparison of flood depths as predicted by traditional (middle row) and AI (bottom row) flood models for urban (left) and suburban (right) layouts (Mustafa et al. 2020).

Question for presenters (FHWA 2023)

How significant are the issues with lack of data on subsurface conditions?

- **Mustafa:** Lack of subsurface data are less significant in urban areas because of the high number of impervious surfaces, which changes stormwater and fluvial runoff.

- **Herrero:** Currently, there are issues with inaccurate representation of sea-level rise and modeling of sewer backup.

PRESENTATION 2. BRETT SANDERS, UNIVERSITY OF CALIFORNIA IRVINE —FINE RESOLUTION INUNDATION MODELING IN SOUTHERN CALIFORNIA

Sanders presented research on fine-resolution inundation modeling in southern California and the interaction between flooding dynamics and transportation infrastructure performance. Flooding significantly disrupts transportation networks during storm events, and transportation infrastructure plays a role in the distribution of flood inundation. New computational methods provide opportunities to rapidly develop city-scale, detailed flood models (FHWA 2023).

Sanders' presentation had the following significant points (FHWA 2023):

- Technology—Sanders introduced the Parallel Raster Inundation Model (PRIMo) and data processing methods to support detailed modeling and analysis of urban flooding, including estimating flood depth along land parcels and roadways (Sanders and Schubert 2019). PRIMo uses the subgrid modeling method, incorporating fine-grid, higher resolution information to update coarse-grid, lower resolution data and improve accuracy.

- Method—The project incorporates built infrastructure into the digital elevation model (DEM), improving model outcomes. Sanders addressed how transportation infrastructure, such as elevated roadways, affects flood extents. In addition, many flood simulations ignore how small pipes, inlets, and culverts impact drainage. The researchers developed a coupled one-dimensional (1D) model in which linear data, such as pipes, are "burned in" to the DEM.

- Insight—PRIMo overcomes the computational bottleneck to high-resolution flood modeling. Researchers tested PRIMo as an alternative solution to overcome bottlenecks that have hindered fine-resolution urban flood modeling. PRIMo uses parallel scaling (i.e., a strategy in computing to add more processors or servers to handle more work simultaneously) and rasterization (i.e., the technique of converting data associated with lines or shapes to be associated with a grid), enabling practical, city-scale flood simulations. The hydro-conditioning method, as demonstrated in a study by Kahl et al. (2022), was mentioned as an effective approach to simulate flooding over large spatial extents with high-resolution data, utilizing dual grid modeling to expedite processing.

- Insight—Increased resolution enables faster, more accurate assessment of flood risk at the city scale. The presentation also referred to a study by Sanders et al. (2023) that focused on improving Federal Emergency Management Agency (FEMA) maps with increased resolution and providing a more realistic understanding of channel capacity under 100-yr flood conditions, significantly impacting the population of Los Angeles, CA. Fine resolution inundation modeling can be fast and reasonably accurate,

Figure 4. Image. Adding channels (left) and underpasses (right) to DEM (Kahl et al. 2022; Sanders et al. 2023).

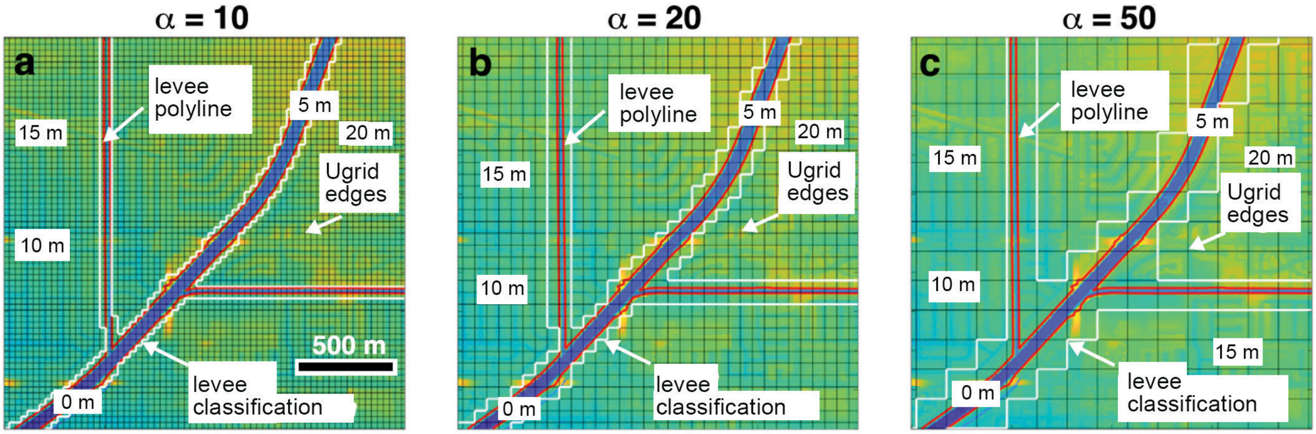


Figure 5. Image. Comparison of grid edge classification as levees at different grid sizes α (Kahl et al. 2022).

with 3-m resolution in megacities being 20 times faster than real-time run on a computer with urban textures influencing flooding distribution.

Questions for Sanders (FHWA 2023)

How did you resolve the issue of "false blockages," in which models interpreting 1D imagery believe that infrastructure, such as elevated highways, prevents inundation?

Sanders: We gained access to culvert shapefiles/datasets from public works and overlaid these with the DEMs. This action enabled more accurate drainage modeling.

Following up on the previous question, is the process for finding data to burn into the DEM automated?

Collaborator Jo Schubert: The process was somewhat automated; we were able to automate finding the centerline of channels, extracting points, and looking for abrupt changes like high points. For elevated roadways, models looked for places like bridges. Although this process was mostly automated, we sometimes edited the output based on site parameters. We need channel widths to approximate drainage, but sometimes this parameter is not in the data (for example, in storm drain data). Sometimes we made estimated guesses, which produced procedural uncertainty.

What are your thoughts on how to incorporate stormwater infrastructure (e.g., pipes, sewers, detention ponds) in the models? Do you use it? When is it vital, and when is it safe to neglect?

Sanders: It's tough to answer that question. I haven't done a deep dive into differences in skill versus infrastructure representation. But I like to think about three levels of infrastructure: main channels, secondary channels and pipes, and curb inlets and small subsurface pipes to the next big drain. We try to resolve levels one and two in our models. Larger events are easier to simulate; smaller events are more difficult. For example, clogged pipes create uncertainty.

PRESENTATION 3. MIKHAIL CHESTER, ARIZONA STATE UNIVERSITY —COMMUNITY-BASED AUTOMATED FLOOD DETECTION AND WARNING SYSTEMS

In his presentation, Chester discussed the FloodAware project, which aims to create a "smart city" vision of urban flood management by using networked technologies and hydrological modeling for real-time flood detection and warning systems (FloodAware 2022). The project's goal is to provide both authorities and citizens with up-to-date information about current and expected flooding risks (FHWA 2023).

Chester's presentation had the following significant points (FHWA 2023):

- Technology—FloodAware consists of sensors, citizen engagement, desktop and mobile interfaces, and the centralized FloodAware server. Chester introduced the communication aspect of the FloodAware system, featuring the Integrated Flood Stage Observation Network, a cloud-based platform with a Web application, real-time server, and Structured Query Language database that provides public availability of flood information. Chester highlighted the challenges of existing camera sensors, including factors such as camera age, identifying suitable angles and camera resolution to capture flooding, inability to connect to existing power supplies, and the need for built-in modems to control camera activation.
- Method—Communities need low-cost ways to determine where flooding is and how to respond at any given time. The presentation highlighted the gap in publicly available flood detection applications, questioning why vehicle routing applications used by drivers do not provide real-time flood information and emphasizing the need to empower communities and provide alternatives to centralized solutions.

- Method—FloodAware compiled diverse data sources in two Arizona cities to produce real-time flood risk assessments. The focus of FloodAware is to leverage existing cameras and sensors to create a simple and low-cost threshold for participation by municipalities, enabling them to sense, predict, and inform citizens and city managers about flooding events. The researchers conducted an inventory of candidate information streams for flood detection, including sensors, such as floodcams, gauges, mobile hydrology, crowd hydrology, and social media mining. The crowd hydrology approach seeks to obtain more flood monitoring data by enlisting the assistance of citizen scientists; individuals can follow the QR code or text a phone number that is printed on a flood gauge to report the height of flooding during a given event. (See figure 6 for a demonstration.) The project tested FloodAware during the Arizona monsoon season, deploying stream gauges and floodcams in Flagstaff, AZ, and Phoenix, AZ; gathering flood images and videos from existing cameras for image recognition; and collecting social media data.

- Insights—Beyond the challenge of compiling data, each data source has individual considerations to produce information useful for communities and government. The presentation addressed challenges for social media mining, mobile interfaces, and crowd hydrology, including the time lag between the start of an event and social media postings, image processing challenges for flood gauge measurements, and the usefulness of crowd hydrology in high-traffic areas.

- Insights—Data streams can assist in hydrologic and hydraulic modeling. More data mean better calibration, validation, and assimilation to estimate floodwater level, volume, and extent.

Question for Mikhail Chester (FHWA 2023)

Have you collaborated with companies providing vehicle-routing applications for smartphones?

No, but Waze™, a vehicle-routing application, is integrating flooding impacts into its navigational algorithm. Our project is currently exploring expanded partnerships with public agencies (Waze 2023).

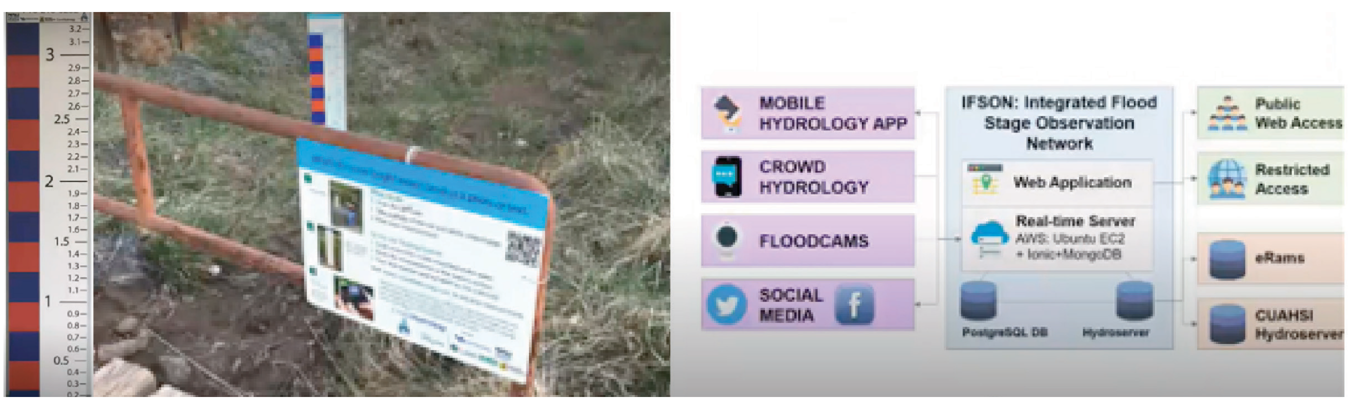


Figure 6. Image. A flood gauge placed in a park for visitors to report water levels via text message and how its data are processed.

PRESENTATION 4. MECIT CETIN AND KHAN IFTEKHARUDDIN, OLD DOMINION UNIVERSITY—RECURRENT ROADWAY FLOODING: IMAGE-BASED DETECTION, DRIVER BEHAVIOR, AND IMPACTS ON TRAFFIC FLOW

Mecit Cetin discussed his team's recent work on recurrent roadway flooding in Norfolk, VA; its impacts on traffic flow and driver behavior; and the use of computer vision-based approaches to detect floodwater on roadways. His presentation also featured findings on AI-aided analysis of flooding impacts on traffic flow.

The presentation had the following major points (FHWA 2023):

- Method—The project tests the functionality of computer vision tools in detecting floods on roadways using image segmentation. Computer vision techniques allow for extracting useful information from image and video data to detect and analyze floodwater on roadways. The presentation highlighted the challenges and approaches in image segmentation—separating floodwater extent from the rest of the image. The team used two methods: superpixel semantic segmentation (i.e., a technique of breaking down an image into segments to analyze them) and the deep-learning architecture full convolutional network (FCN).

  The former method divides the image into discrete units (superpixels), and the ML model evaluates whether each piece is flooded, reducing complexity and computational time by analyzing the image at scales larger than a single pixel. (See figure 7.) Unlike traditional networks used for image classification, an FCN retains spatial information throughout its layers, enabling it to efficiently analyze an image and classify each pixel into specific categories. The result is an outline of different objects or regions within the image. An FCN is a sophisticated tool for automated image understanding and segmentation, aiding in identifying and delineating distinct elements in a visual scene.

- Insight—Image segmentation models accurately labeled media as flooded/nonflooded with 90–95 percent accuracy. The performance of the models was evaluated using accuracy metrics, such as precision, recall, and F1 score. Cetin discussed the limitations of the deep-learning/FCN approach, particularly in distinguishing wet surfaces from water during flooding. He proposed alternative methods, such as edge detection (i.e., finding the outlines of objects in an image) and lane segmentation, for more accurate flood extent estimation.

Figure 7. Image. Example of image segmentation.

- Insight—AI approaches enable rapid estimation of floodwater depth using images and reference heights for vehicle components. The presentation addressed the use of computer vision to estimate floodwater depth, using synthetic data and 3D models to train CNN and object detection models, allowing for depth comparisons using reference dimensions of tires.

- Insight—Based on an analysis of an arterial roadway, the project demonstrated that municipalities with video data of past flooding can assess flood impacts on traffic flow and capacity. Expanded roadway data collection could enable better real-time routing and decisionmaking during future floods by providing benchmarks for driver behavior at various flood levels. The researchers studied Hurricane Ian's flooding impacts in 2022 on traffic flow and roadway capacity using sensor data on Hampton Boulevard in Norfolk, VA. The cumulative plots of flow-rate impacts on the road demonstrate the disruptions caused by flooding on traffic flow, showing the contrast between a typical peak flow rate versus the flow rate during a flood event.

Question for Mecit Cetin (FHWA 2023)

Is the reduction in capacity causing changes in route choice or fewer trips during the flood event?

Waze and other navigation applications enable people to choose alternative routes, not necessarily fewer trips (Waze 2023).

Question for both Mikhail Chester and Mecit Cetin (FHWA 2023)

How far are these approaches from producing high-confidence 2D inundation maps (realtime or postevent)? What are the major challenges? Where would you invest most resources?

- **Chester:** A major limitation is the high cost of premium sensors, like cameras. Also, there are limitations on where you can place a camera. The ubiquity of mobile phones can supplement getting real-time location data.

- **Cetin:** A dedicated camera-to-server pipeline is poorly scalable (as it is expensive), so crowdsourced data processing is ideal.

PRESENTATION 5. ANDREA SILVERMAN, NEW YORK UNIVERSITY—FLOODNET: REAL-TIME, HYPERLOCAL FLOOD MONITORING IN NEW YORK CITY

Andrea Silverman presented on FloodNet, a project to collect real-time, hyperlocal flood data in New York City, NY, using low-cost ultrasonic sensors. FloodNet, a partnership between academic researchers, New York City municipal agencies, and community organizations, aims to provide data to support multiple stakeholders with different flood data needs (FloodNet 2021; FHWA 2023).

Their presentation had the following major points (FHWA 2023):

- Technology—The project uses ultrasonic sensors that accurately measure water depth by calculating the time it takes for the pulse to return to the sensor. These measurements are taken every minute, and the data is made available in realtime on an interactive data dashboard.

- Method—FloodNet seeks to collect and analyze quantitative data on urban floods at the city scale. Flooding significantly impacts infrastructure, mobility, public health, and safety, yet there is a lack of quantitative data on urban floods. FloodNet aims to address this gap by systematically collecting data on the presence, depth, and duration of street-level floods.

- Insight—The sensors in two case studies provided detailed information about flood events, including the rate of onset, presence of multiple flooding events, and peak depth. Silverman presented two case studies: the first focused on high-intensity precipitation events (Hurricanes Henri and Ida) in Brooklyn, NY, and the other on coastal community high-tide flooding in Far Rockaway, Queens, NY. Data from the sensors detected flooding before recorded emergency calls.

- Insight—Sensor placement remains a resource allocation challenge. Future steps for FloodNet include securing additional funding to expand the sensor network, improving sensor capabilities, addressing challenges related to connectivity and uptime, and developing data processing techniques to identify and clean anomalies in the sensor data. The project aims to install 500 sensors over the next 5 yr, focusing on placing sensors in areas identified through flood risk analysis and addressing the needs of both communities and government agencies.

- Insight—ML can assist in sensor data analysis. Initial work demonstrates that ML can help researchers clean sensor data by identifying nonflood anomalies, such as when a person walks under the sensor or places a garbage can under the sensor, based on the shape of the sensor's data time series.

Questions for Andrea Silverman

How was sensor accuracy measured?

We used a combination of the ultrasonic sensor manufacturer's quoted specifications of 1-percent accuracy and both field and lab-based testing. The lab-based and field testing involved multiple distance measurements versus ground truth (ruler and laser measures) under different temperature/humidity conditions. We also conducted field and lab-based testing by measuring distances with a National Institute of Standards and Technology-certified ruler to confirm that sensors meet requirements. In the field, we ensured we could see dynamic changes by comparing sensors with National Oceanic and Atmospheric Administration (NOAA) and U.S. Geological Survey tidal gauges. We have also compared sensor readings to certified rulers during flooding events.

Did you use a data reporting standard?

We have plans for the data to meet the standards required for inclusion in the NOAA Hydrometeorological Automated Data System and Meteorological Assimilation Data Ingest System, which include a quality-control protocol for data reporting (NOAA n.d.; NOAA 2022).

How does the density of an urban environment affect placement decisionmaking?

We developed a prioritization of sensor placement based on exposure to previous flood events, then we go down the list, depending on whether there is available infrastructure, especially network access. In some cases, we may have to negotiate with a partner, such as the Metropolitan Transportation Authority, to obtain the rights to place the sensor on a bridge or other element of the built environment.

Due to resource constraints, there is a gap between the availability of sensors and areas at risk. We must contend with data scarcity. One solution is pairing real-time data (measured flood events) with simulation models.

PRESENTATION 6. MAYANK OJHA AND MIHO MAZEREEUW, MIT—CROWDSOURCING AND AI FOR ROADWAY FLOOD MANAGEMENT

The Urban Risk Lab at MIT developed RiskMap, a crowdsourced situational awareness and risk management platform deployed in multiple countries (MIT 2016). The project aimed to integrate crowdsourcing and AI to enhance support for emergency managers and long-term flood risk mitigation solutions. RiskMap addresses the challenge of siloed information sharing during emergencies by providing a consolidated and processed platform for residents to submit observations and data (FHWA 2023).

The presentation had the following major points (FHWA 2023):

- Technology—RiskMap links residents to emergency managers via its interface and dashboard system through a rule-based chatbot on a Web application. On this Web application, residents can progress through a "card deck" to report various observations, including flooding. Real-time maps display the data, which can be filtered by time, and government and emergency management service personnel have access to administrator accounts to communicate with users on supported platforms.

- Method—Integrating crowdsourced data from residents with existing sensor, gauge, and traffic camera information enables the development of a real-time, AI-based triaging system. This system can promptly identify flooding hotspots and support timely decisionmaking processes.

- Method—AI can assist emergency managers by parsing crowdsourced image data. The presentation included use cases of AI triaging crowdsourced images in which the project employed ensemble learning (i.e., combining multiple ML models to improve predictive performance) and multivariate geospatial clustering (i.e., analyzing data clusters on a map based on many variables to find relationships between them). The researchers trained the model using labeled data, including reports from firefighters in Fukuchiyama, Japan, and crowdsourced labeling, along with reliability assessment, was conducted to enhance the model's accuracy.

- Insight—The presentation highlighted the potential to incorporate crowdsourced data from RiskMap into navigation applications. By embedding RiskMap, these applications can help with evacuation and finding shelter during disasters, addressing the issue of directing people toward hazards due to low traffic optimization focus.

- Insight—The project achieved dashboard design improvements by continuously implementing user feedback throughout the lifecycle of the product. The presentation covered user experience research for the React Dashboard, which involves audits and retraining to improve the user experience (Flatlogic n.d.). Implementing human-in-the-loop (i.e., having people double check computing outcomes) and active-learning (i.e., ML algorithm designed to learn from human interaction) paradigms ensures continuous improvement and user engagement.

Question for Mayank Ojha

What is the timing of the label checking? Is it part of an after-action assessment of an event?

We apply Krippendorf's alpha (i.e., a statistic used to measure how many raters agree when evaluating something), then determine whether expert annotations exist (Krippendorff 2013). The threshold for model training is a 70-percent reliability score.

PRESENTATION 7. VALERIY IVANOV, UNIVERSITY OF MICHIGAN—FLOOD ENSEMBLE PREDICTIONS: FROM PUSHED-FORWARD PARAMETRIC UNCERTAINTY TO PROBABILISTIC ERROR ESTIMATION

Valeriy Ivanov's presentation focused on a novel modeling framework for flood forecasting that combines hydrologic-hydrodynamic models, surrogate modeling (i.e., a technique for making a simpler version of a complex computation model), and ML to address computational burden and data-model uncertainties.

The presentation had the following major points (FHWA 2023):

- Method—The project supplements the mature flood modeling technology with novel ML techniques to quantify uncertainty. The proposed methodological framework advocates for the practical utility of high-fidelity models in flood forecasting, with surrogate and ML modeling aiding real-time applications and uncertainty quantification.

- Method—High-resolution rainfall and infrastructure data may improve pluvial (i.e., rainwater) flooding models to perform as well as fluvial (i.e., river) flooding models. The data component of the framework includes high-resolution precipitation forecasts, urban layout information (e.g., buildings, roads, stormwater infrastructure), and calibration and validation data. The availability of urban layout data has significantly improved for cities and municipalities in recent years. Predictive fluvial flooding models have improved significantly since the 1970s and continue to advance.

- Insight—Surrogate models, a proven solution for uncertainty quantification, can replace high-fidelity models for computationally intensive tasks and stack decomposition of model output. Challenges in high-resolution flood prediction include vast computational efforts and the need to rigorously quantify uncertainty in input data, especially precipitation. A case study that used Hurricane Harvey data demonstrated the potential use of surrogate models for routing people away from impacted areas around Houston in 2017 (Ivanov et al. 2021). Polynomial chaos expansion (i.e., measuring how the uncertainty of inputs impact the results of complex computations) models and ML were employed to train and improve the accuracy of the surrogate models.
- Insight—New methods address the challenge of predictive accuracy, including the need to quantify the error between surrogate models and high-fidelity models. The error is decomposed into reducible and irreducible components, with research efforts focused on identifying areas where the surrogate model may not perform well.

HOW WERE USE CASES OR GEOGRAPHIC SCALE CONSIDERED WHEN DEVELOPING METHODS FOR DIFFERENT USES, SUCH AS SHORT-TERM OPERATIONS OR LONG-TERM DECISIONS ABOUT ASSET LIFECYCLE?

One challenge that the research team for presentation 4 has encountered in Virginia is getting permissions for placing sensors. The team has had difficulty negotiating with different levels of government (Federal Government, State departments of transportation (DOTs), local agencies) for permission to conduct sensor placement and maintenance on highways, for example.

RESEARCHERS NEED TO OBTAIN PERMISSION FROM A STATE OR LOCAL DOT TO PLACE SENSORS ON ROADS. HOW CAN ISSUES OF INTERAGENCY COOPERATION BE ADDRESSED?

Working with State DOTs may be more difficult than local DOTs, but FHWA division offices can work with States to resolve issues from specific projects. There are some technical issues that come into play as well: local roads might have better access to power sources and may be easier to implement maintenance plans and install sensors and other equipment.

SENSOR PLACEMENT IS IMPORTANT FOR VALIDATION OF MODELS. IF RESEARCHERS HAVE ACCESS TO SENSOR DATA, WHAT IS THE BEST TYPE TO HAVE?

- Placement of sensors is tied to engineering research and modeling. Place the sensors where a local government knows flooding happens historically.

- Flood modeling is not contiguous, and sensor data is not contiguous. Infrastructure is a confounding variable. How do we reconstruct manholes?

- Sensor density and location depend on the use. FHWA is seeking information for highway operations. The sensors and models really need to work across domains for emergency services, agencies, power systems, and housing.

HOW DO RESEARCHERS MAKE THE DATA AND MODELS WORK ACROSS DOMAINS, AND HOW MUCH DO RESEARCHERS NEED TO CUSTOMIZE?

- Researchers should be open to using different types of data. Analysis depends on what stakeholders need. Data collected for the FloodNet project are somewhat universal in that such data cover different types of flooding. The FloodNet project is open access.

- Sensors need to complement models depending on scale and context; researchers can't afford to run large-scale models for every instance of nuisance flooding, but they are essential for planning purposes. Considering fluvial versus nuisance flooding is important when using modeling and sensor data.

WHAT ARE THE CHALLENGES OF FOCUSING ON A SPECIFIC TYPE OF FLOODING VERSUS A MORE GENERALIST APPROACH?

- Valeriy Ivanov's team focused on fluvial flooding and directed students to find data. The team scoured the internet and added images to a database. They noticed patterns and found new data sources, such as urban intersection cameras. A connection needs to be made between those searching for data and those collecting it. FEMA does have good data, including damage to property and locations.

- Cities are getting better at maintaining flood data imagery.

WHAT STRATEGIES FOR WORKING WITH STATE AND LOCAL DOTS TO GET DATA HAVE BEEN SUCCESSFUL? SHOULD RESEARCHERS HAVE PARTNERSHIPS WITH MANY GROUPS OR WORK EXTENSIVELY WITH A FEW GROUPS?

City Government connections/partners and access to their networks enabled the success of Silverman's project.

Conclusions

The workshop participants reached the following conclusions (FHWA 2023):

- AI enables the deployment of crowdsourced social media data to provide real-time, preprocessed information about roadway conditions to aid emergency managers and transportation planners in making decisions and informing the public.
- The sensor-to-server model addressed in presentations 3 and 5—with further development and testing—can address driving/navigational applications' routing problems during emergencies.
- High-fidelity, human-scale flood predictions can answer the question, "Is it possible to route people away from the area of impact?"
- Multiple presentations demonstrated that AI reduces or eliminates computational bottlenecks in high-fidelity flood modeling. Model performance improvements combined with increased infrastructure data availability result in near real-time production of accurate citywide flooding simulations. Beyond an institutional focus on data availability, research is looking at improving uncertainty quantification.

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EAR Program Results

As a proponent of applying ideas across traditional research fields to stimulate new problem-solving approaches, the EAR Program strives to develop partnerships with the public and private sector. The program bridges basic research (e.g., academic work funded by National Science Foundation grants) and applied research (e.g., studies funded by State DOTs). In addition to sponsoring projects that advance the development of highway infrastructure and operations, the EAR Program is committed to promoting cross-fertilization with other technical fields, furthering promising lines of research, and deepening vital research capacity.

Getting Involved with the EAR Program

To take advantage of a broad variety of scientific and engineering discoveries, the EAR Program involves both traditional stakeholders (State department of transportation researchers, University Transportation Center researchers, and Transportation Research Board committee and panel members) and nontraditional stakeholders (investigators from private industry, related disciplines in academia, and research programs in other countries) throughout the research process.

EXPLORATORY ADVANCED RESEARCH

U.S. Department of Transportation
Federal Highway Administration

Recommended citation: Federal Highway Administration,
Innovative Methods to Detect and Measure Flooded Roadways
(Washington, DC: 2024) https://doi.org/10.21949/1521787

FHWA-HRT-24-006
HRTM-30/04-24(WEB)E