

ML4LM Seminar



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1870

Leveraging In Situ and Remote Sensing Observations to Support ML Modeling of Land Surface Processes

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<https://web.stevens.edu/ismart/>



Flooding during Hurricane Sandy in NYC on October 29-30, 2012



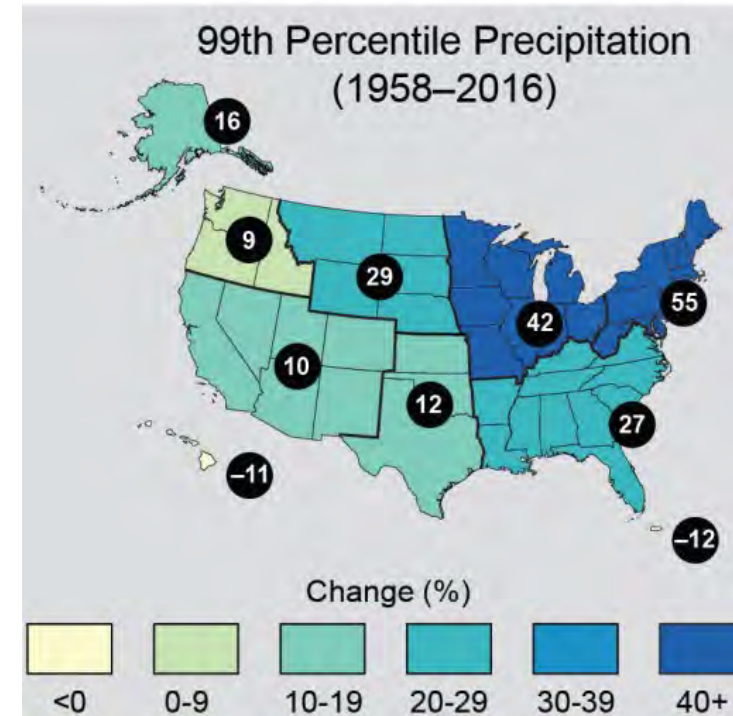
- Hurricane Sandy caused an estimated \$19 billion in damage in New York City alone.
- The storm surge in New York Harbor reached a record high of 13.88 feet.
- Subway tunnels and the World Trade Center site were flooded with up to 7 million gallons of water.
- The flooding caused major damage to hospitals, schools, and other critical infrastructure.
- The flooding led to widespread power outages and communication failures.



Increasing threat of multi flood hazards in the northeastern United States

- Heavy precipitation events in most parts of the United States have increased in both intensity and frequency since 1901 (*high confidence*). There are important regional differences in trends, with the largest increases occurring in the northeastern United States (*high confidence*)*
- 40% of the US population lives in counties near coastal and tidal areas
- Devastating economic consequences and significant loss of lives due to coastal flooding (e.g. Super storm Sandy, in 2012, caused an estimated loss of \$50 billion in infrastructure damages (NOAA, 2013). Hurricane Maria (2017), Florence (2018) and Dorian (2019) are more recent examples.)
- Several flood alert systems are currently operational around the world, focusing on global, regional and local scales (example: SFAS).
- Forecasting coastal and inland flooding in estuaries is particularly challenging and requires the integration of complex coastal and riverine processes

Observed Change in Heavy Precipitation



The map shows percent increases in the amount of precipitation falling in daily events that exceed the 99th percentile of all non-zero precipitation days (top 1 percent of all daily precipitation events) from 1958 to 2016 for each region of the United States. The number in each black circle is the percent change over the entire period (1958–2016).

* Source: Climate Science Special Report: Fourth National Climate Assessment, Volume I

<https://science2017.globalchange.gov/chapter/executive-summary/#fig-6>

Abundance of observations to model weather hazards



Making use of all available data is a challenge



More observation does not necessarily mean better information

- GOS Trends:

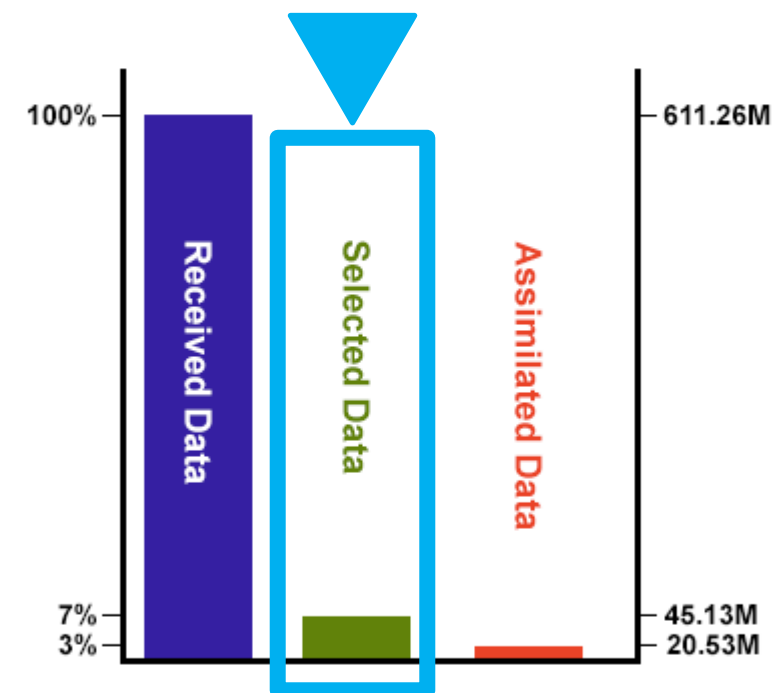
- New Players in Global Observing System
- New Sensors (higher resolutions, new features)
- New technologies (small sats, reflectometry, etc)
- Emergence of New GOS (IoT, etc)
- Emergence of potential new Payload hosting platforms (Gliders, UxS, Near-Space platforms, rideshare, etc)
- Increase in volume and diversity of data
- Commercialization of satellite data and new business models



Trends in Global Earth Observation Systems



Daily Percentage of Data
Ingested Into NWP Models
(ECMWF, 2016)



Received: All observations received operationally from providers

Selected: Observations selected as suitable for use

Assimilated: Observations actually used by NWP models

©The COMET Program

• GOS Trends:

- New Sensors (higher resolutions, etc)
- New technologies (small sats, etc)
- Emergence of New GOS (IoT, etc)
- New Players in GOS (international, commercial, etc)
- **Significant Increase in volume and diversity of data**

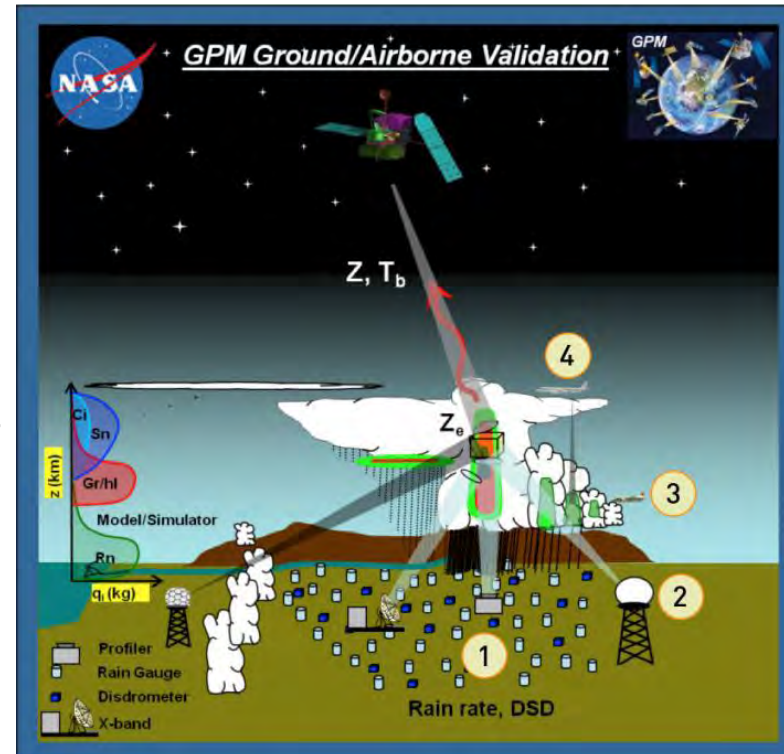
• Parallel Trends

- Budget, HPC Constraints
- Higher societal impact
- Higher user's expectations of enhanced model resolutions, accuracy

Courtesy of Sid Boukabara

Overarching questions:

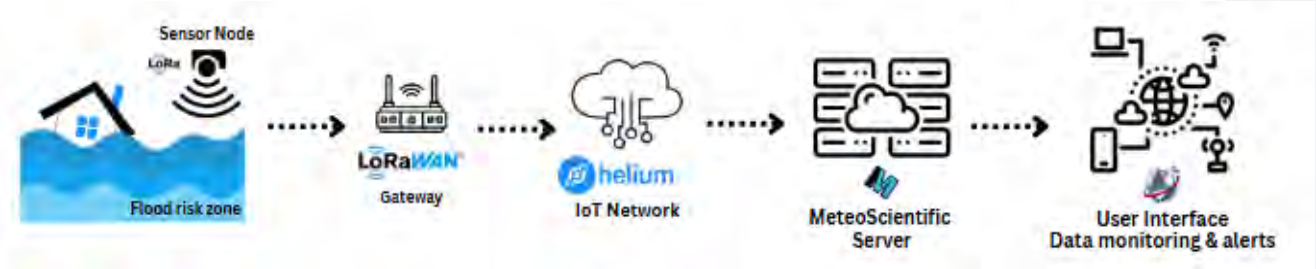
- How could we use observations to their full potential to enhance our understanding of extreme events?
- How can we deal with the increasing amount of data that we are receiving from different observation platforms? More observation does not necessarily mean better information (for example: precipitations)
- How can we compromise between the abundance of information from different observation sources and the added complexity to our models?
- How can we integrate observations across different scales, local (in situ), regional, and global?



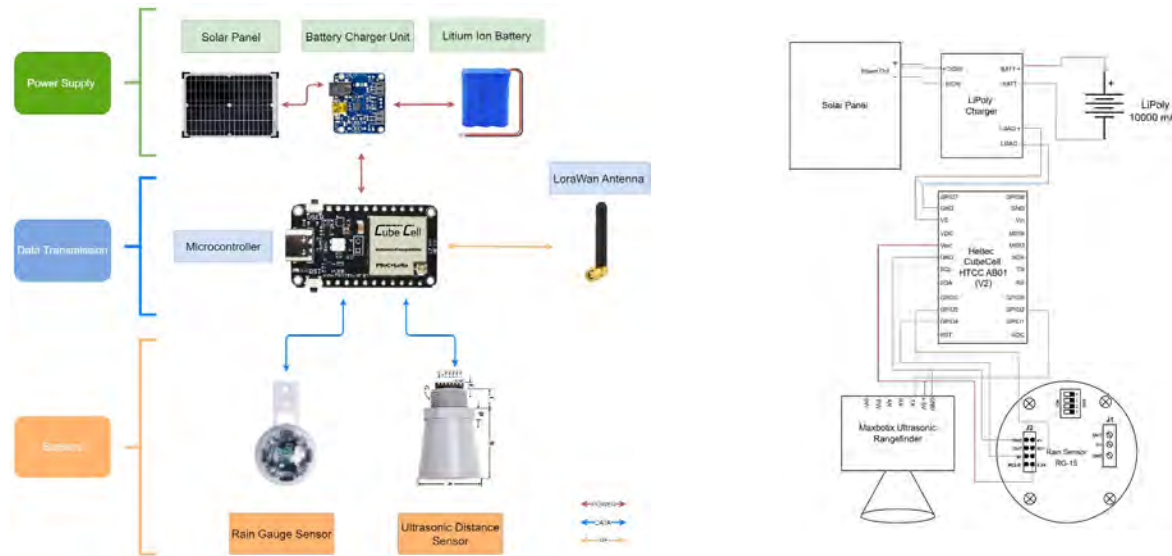
Different sensors=different observations

Stevens i-SMART LAB Flood and Rainfall Sensing

- Low-cost
- Low Power
- Low Maintenance (once per 6 months)
- Ready to use (no installation steps)
- Real-Time **Water Level above ground & Precipitation** measurements



Network Configuration



Sensors Hardware Diagram



Current Configuration of Sensors
Example of Pre-deployment Tests @ Stevens

Network Configuration

- Westwood, NJ and Hoboken, NJ (**11** active sensors)
 - Differentiate between rainfall-induced and no-rain floods

- Real-Time Data Monitoring Dashboard

https://web.stevens.edu/ismart/land_products/NJFloodNet.html

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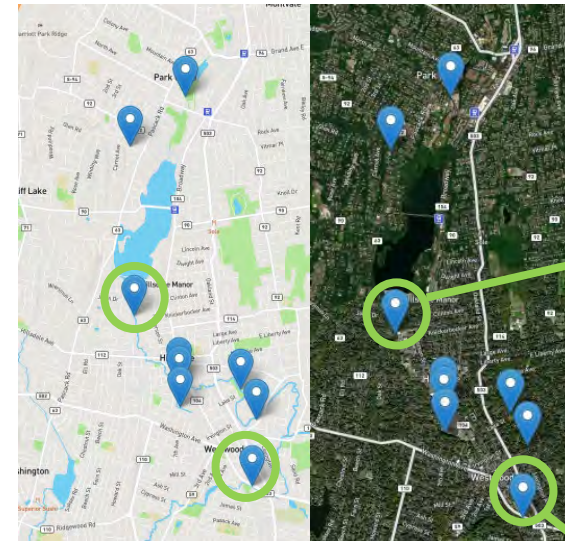
IEEE INTERNET OF THINGS JOURNAL, VOL. 13, NO. 4, 15 FEBRUARY 2026

Dual-Purpose and Low-Cost IoT-Based Sensor Network for Real-Time Rainfall and Urban Flood Monitoring

Ismail Gul¹, Mohamed Abdelkader², Kyle Mackelburg³, and Marouane Temimi¹

Abstract—This work aims to develop an integrated framework based on measurements from a dual-function, low-cost Internet of Things (IoT)-based sensor network capable of measuring rainfall and surface water level simultaneously to enable real-time data for actionable decision-making during extreme events and address observational gaps in flood-prone urban areas. This study presents a novel urban flood monitoring network using observations from co-located water level and rainfall sensors. The high-density IoT sensor network measures rainfall using a Hydreon RG-15 Optical sensor and water level using a Maxbotix MB7389 ultrasonic distance sensor at 1-min intervals. This sensor network allows for real-time monitoring of local flood and rainfall events, which is an improvement over the traditional high-water mark observations. The proposed network is operational in two cities in New Jersey, USA, and constitutes the first step

well-established networks to measure water levels in cities' streets. In urban areas, the response time of watersheds is usually very short due to the high imperviousness percentage, which implies that flood inundations can evolve very rapidly. Coastal cities face additional complexities due to potential ocean surges that compound with runoff from intense rainfall, which can exacerbate flooding and rapidly exceed the retention capacity of drainage systems [7]. Conventional flood depth measurement in urban settings, which heavily rely on high water marks (HWMs), only record peak inundation depths and fail to provide a continuous timeline of flood development [8], [9], [10], [11]. In the United States, the United States Geological Survey (USGS) collects and reports HWM in urban



<https://ieeexplore.ieee.org/abstract/document/11265741>



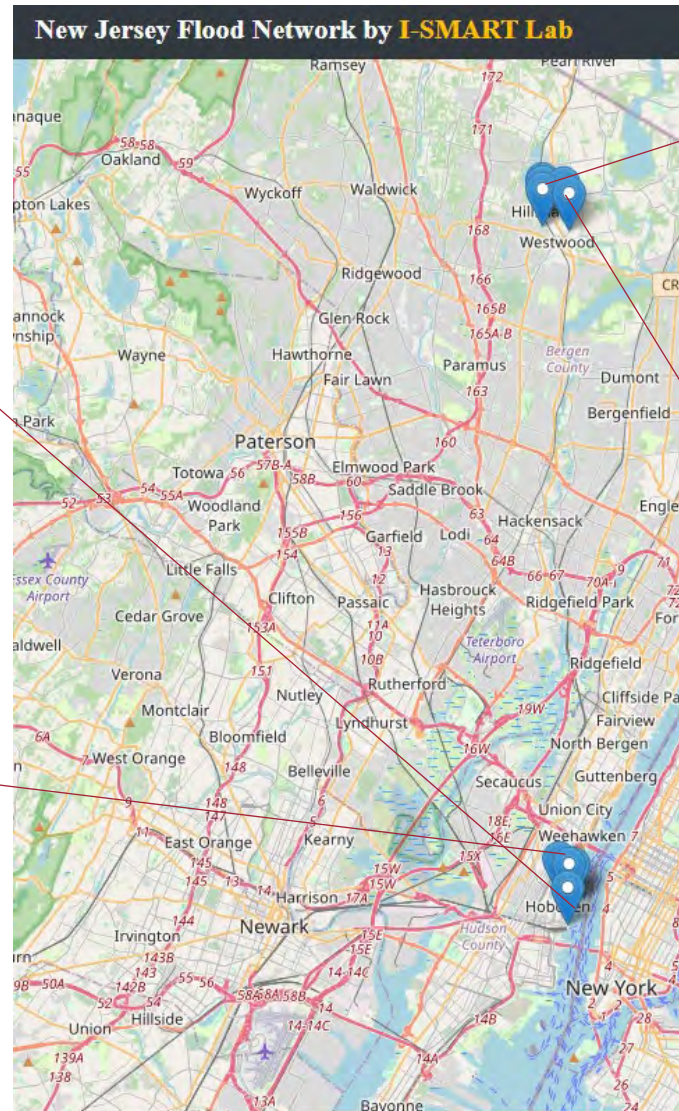
Advancing Flood Inundation Monitoring in NJ through Sensor Deployment



Hoboken / NJ Transit Terminal



Deployment



Overbrook Park
Westwood, NJ



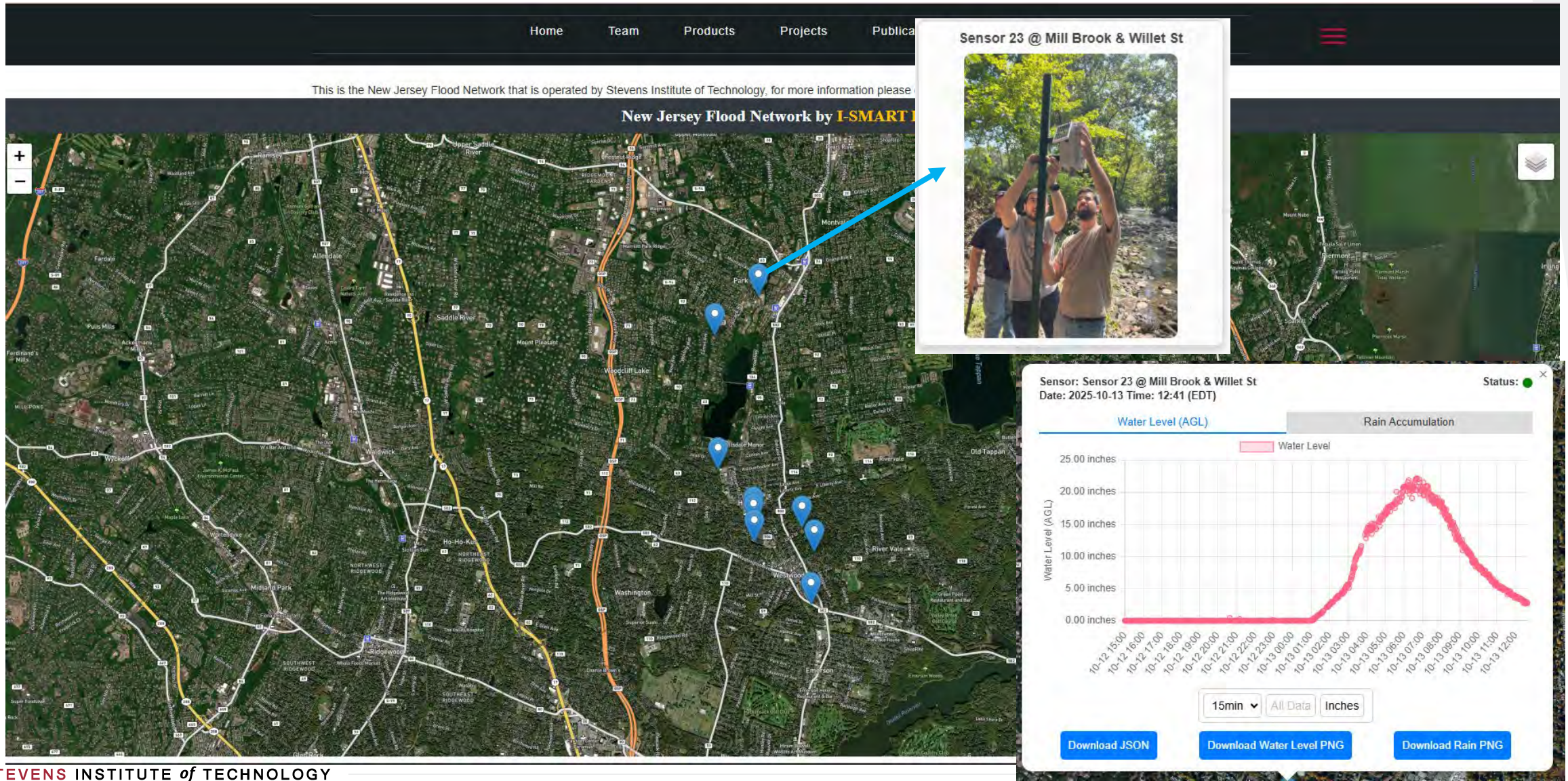
Willow Ave
Hoboken



Lake St, Westwood, NJ

OEMs access to real-time observations of flood events

https://web.stevens.edu/ismart/land_products/NJFloodNet.html



DPW Sensor

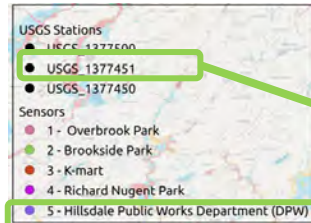
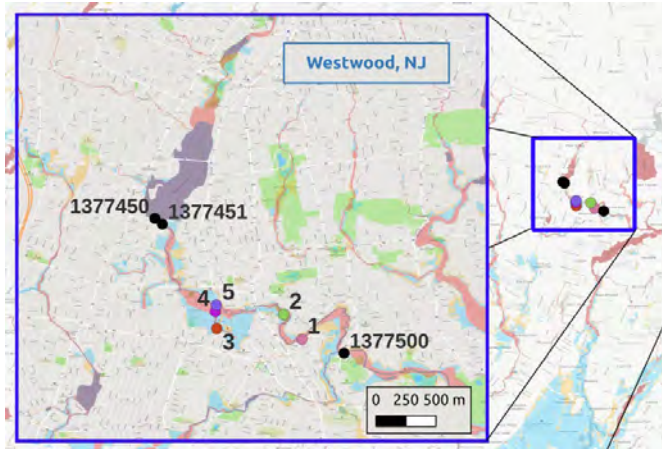
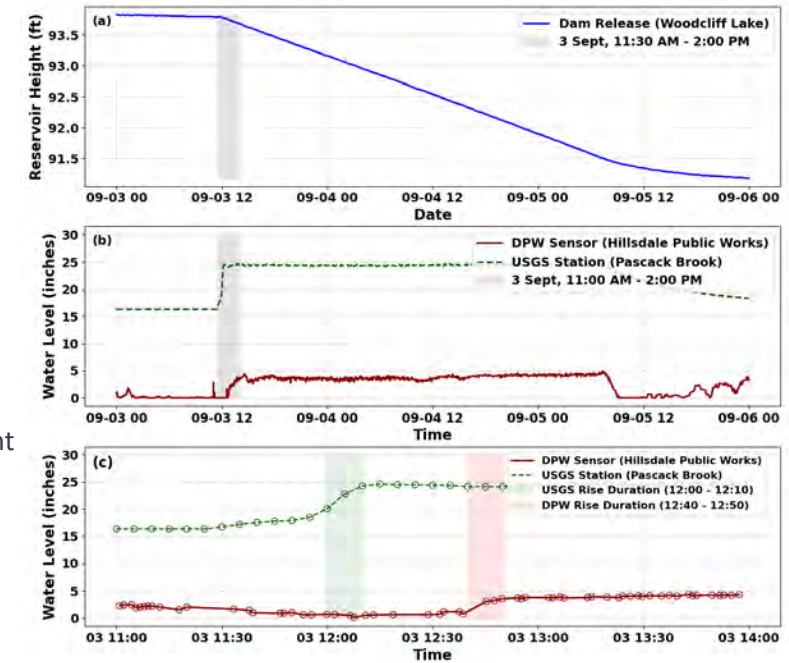
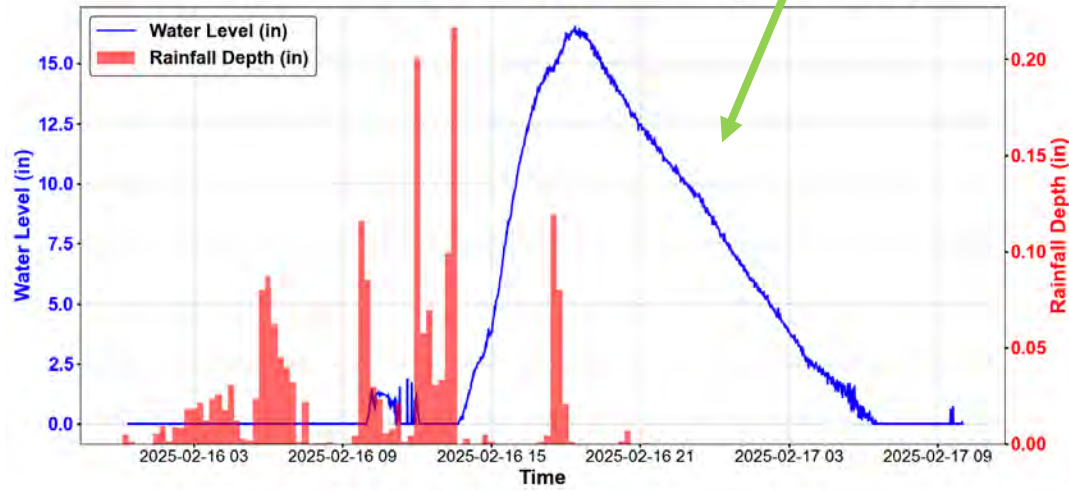


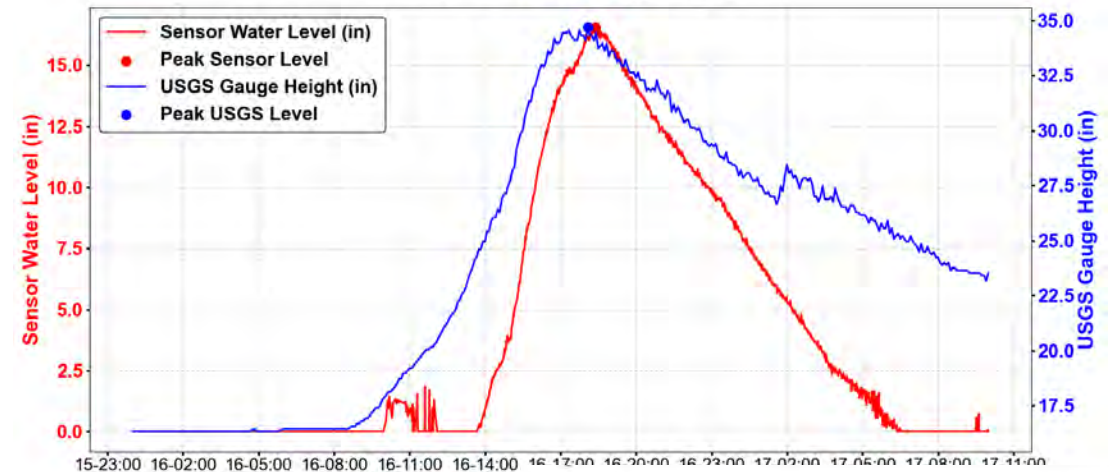
Photo taken during Sensor Placement assessment
Visit on 08/03/2024 @ DPW



Water Level and 15-min Rainfall Depth Over Time (16-17 Feb 2025)



Sensor vs USGS Gage Height



➤ 20 to 40 minutes lag time from the Reservoir outlet to DPW

Measurement	Value (inches)	Timestamp (EDT)
Peak Sensor Water Level	16.54	2025-02-16 18:22:42
Peak USGS Gage Height	34.68	2025-02-16 18:05:00



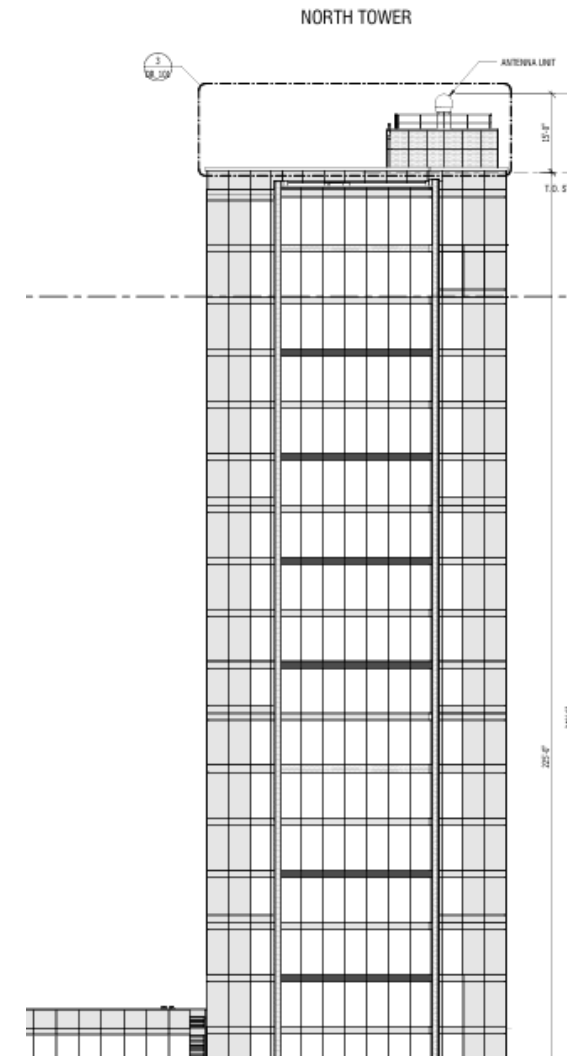
SHARP: Stevens High-resolution Atmospheric Radar Project

Compact X-band Dual Polarimetric
Doppler Weather Radar



WR2120

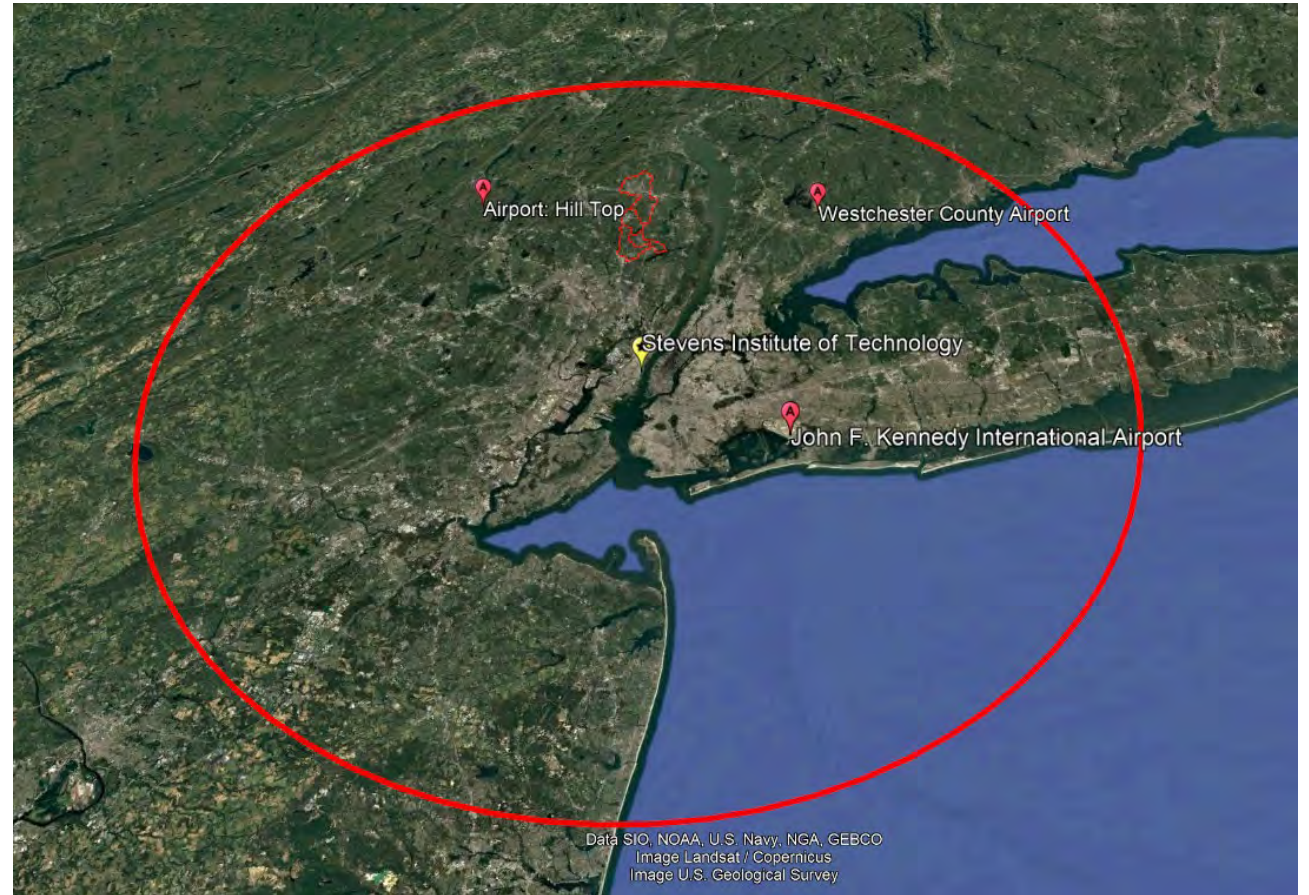
*Dual polarimetry for
High performance!*



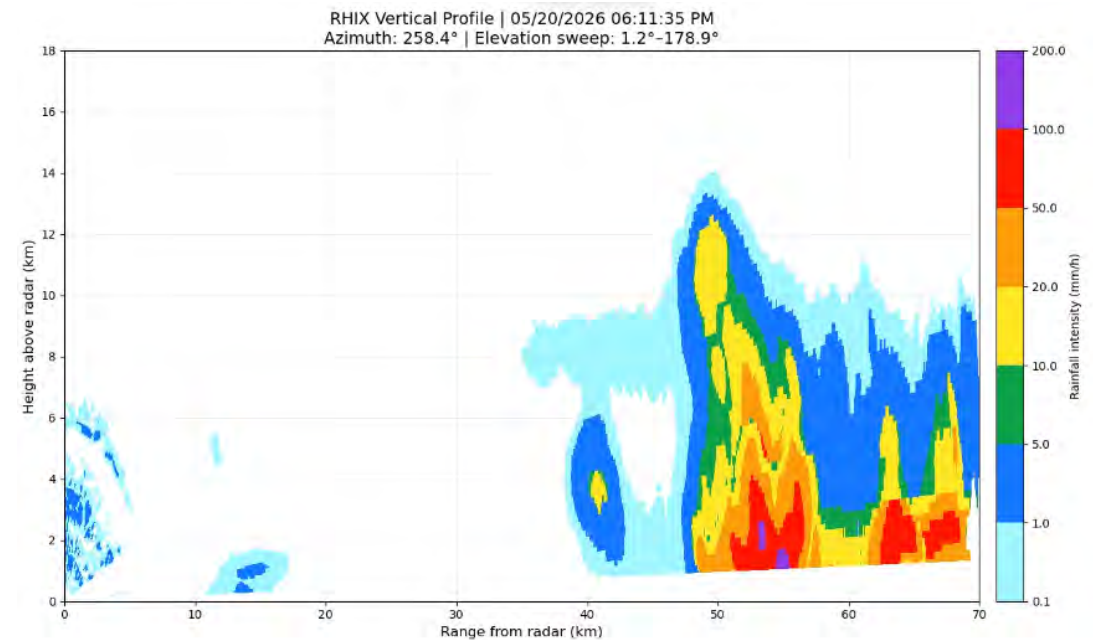
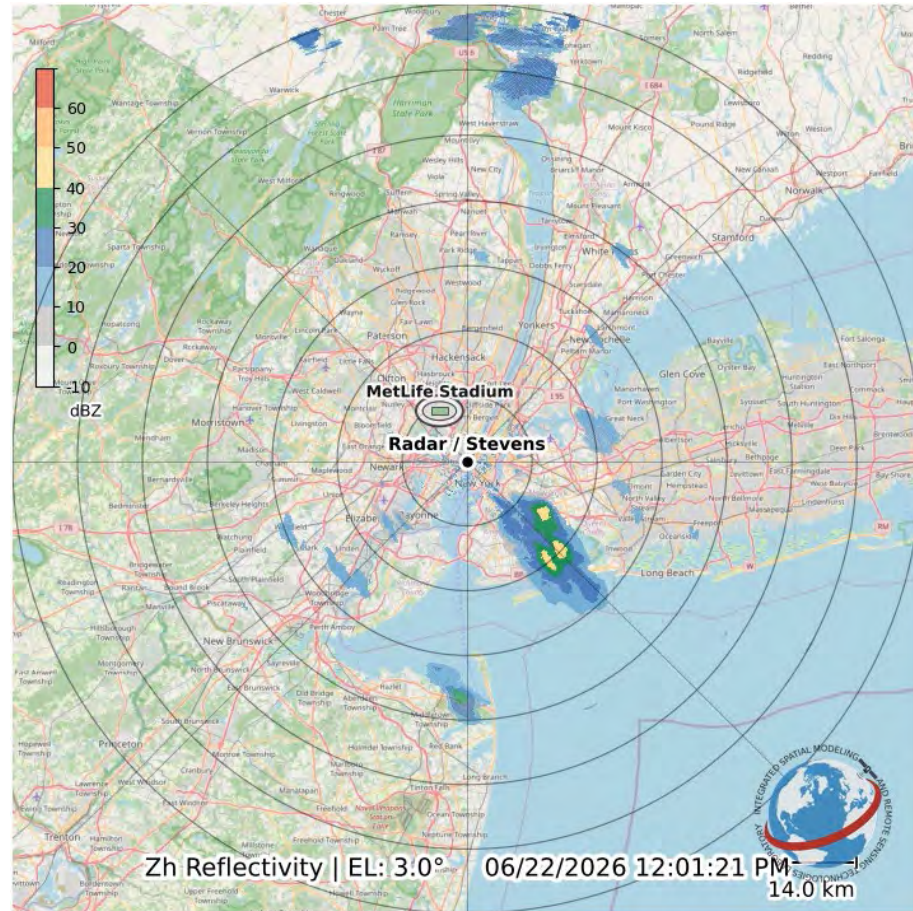
Coverage

<https://www.stevens.edu/news/stevens-institute-of-technology-installs-advanced-x-band-weather-radar-to>

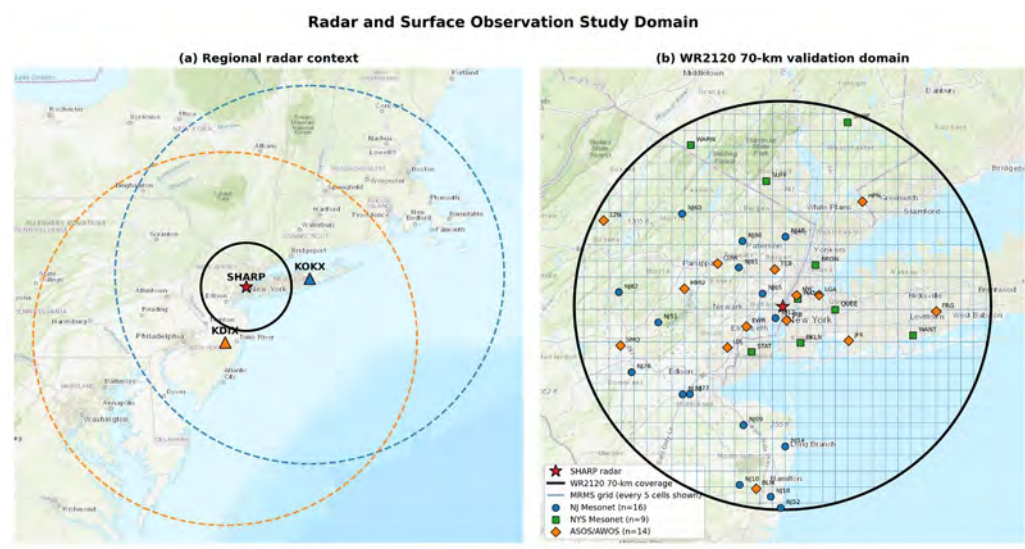
- > 40 miles range



World Cup Game at MetLife Stadium

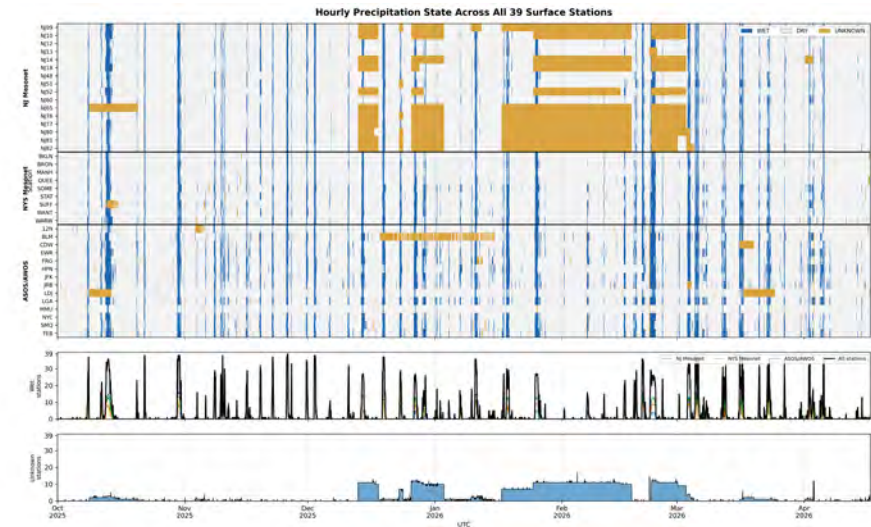


Blending S- and X-Band radar data: in progress

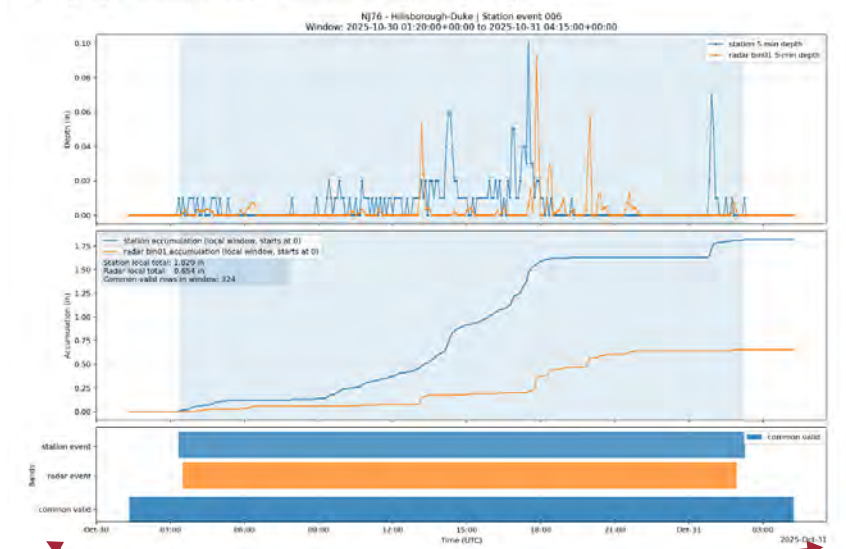


Left: KOKX and KDIX shown to 300-km range with the WR2120 validation domain. Right: WR2120 70-km domain with MRMS grid and surface observing networks. MRMS grid near WR2120: 0.84 km x 1.11 km; 16,404 grid centers within the 70-km radius.

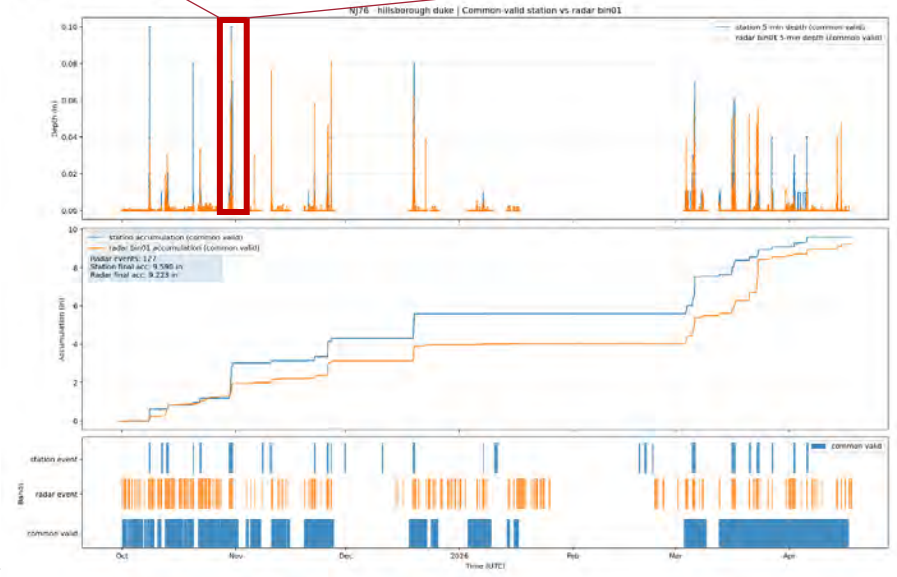
- SHARP
- KOKX level II
- KDIX level II
- Level III
- MRMS
- NJ Mesonet
- NY Mesonet
- ASOS/AWOS



event_006_20251030T032000Z_20251031T021500Z_station_radar_bin01



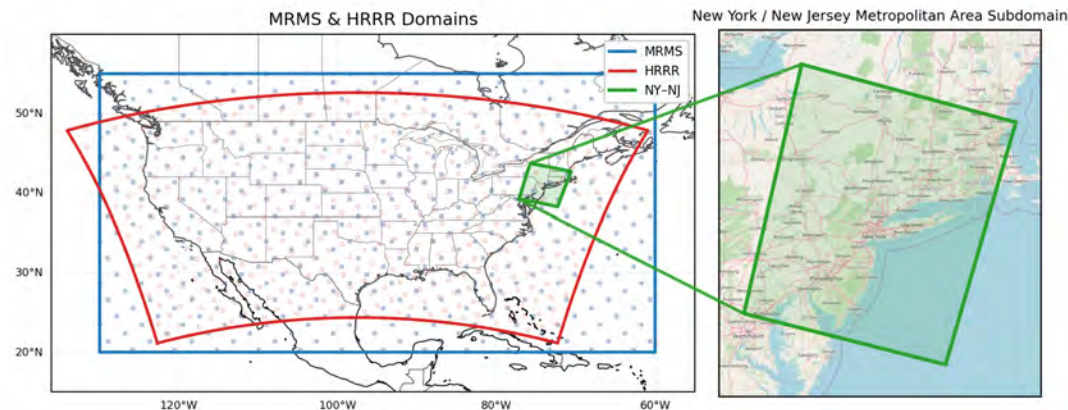
NJ76



Blending Nowcasting

Enhancing Precipitation Nowcasting Guided by Physics-Based Predictions

- MRMS and HRRR



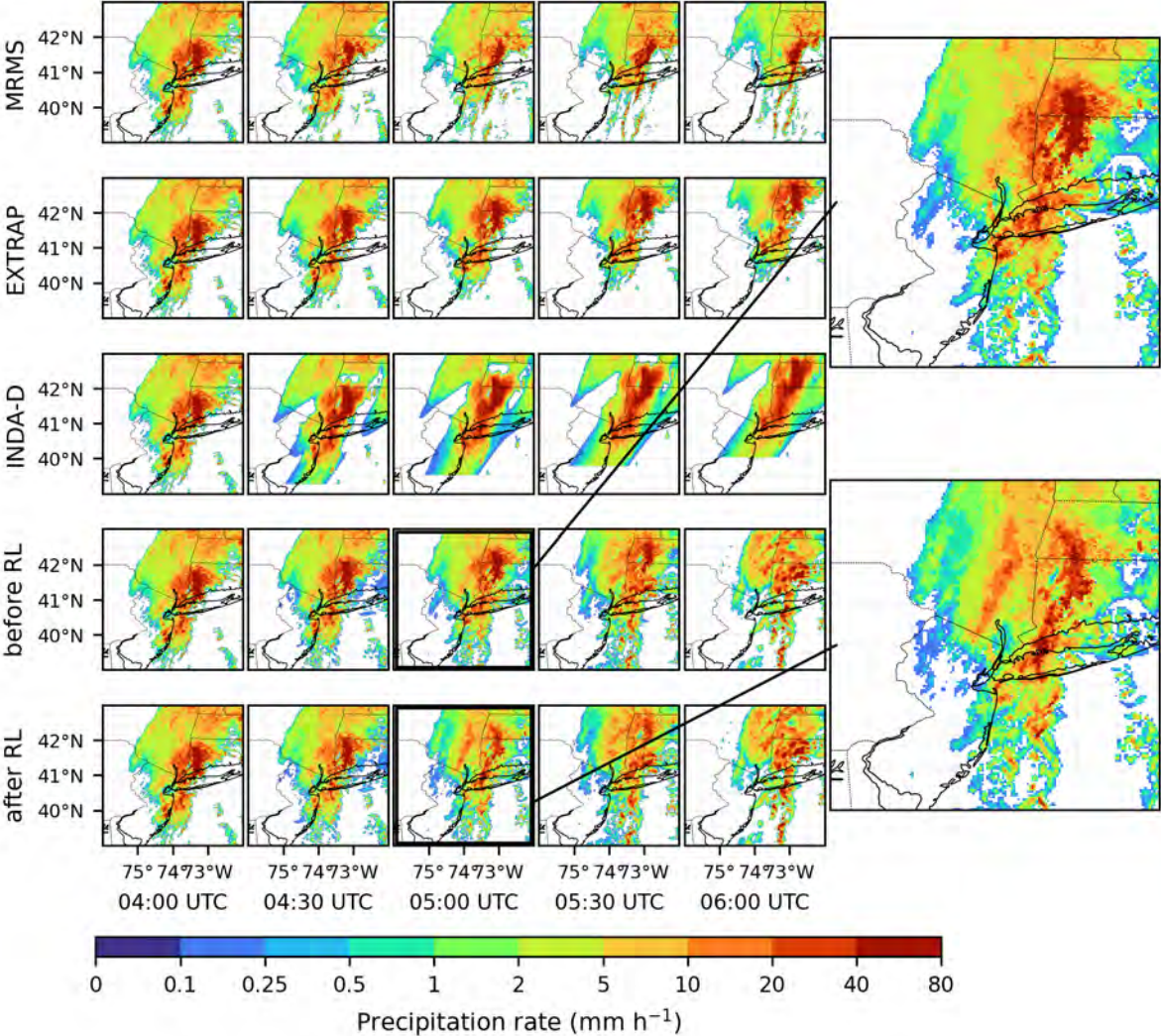
Enhancing Precipitation Nowcasting Guided by Physics-Based Predictions

Ismail Gul, Marouane Temimi, V. Chandrasekar

Abstract—This work aims to develop an integrated precipitation nowcasting framework based on blending high-temporal-resolution radar estimates and hourly physics-based numerical weather predictions. The proposed framework includes linear temporal blending of the National Oceanic and Atmospheric Administration's (NOAA) open available Multi-Radar Multi-Sensor (MRMS) radar estimates and High-Resolution Rapid Refresh (HRRRR) model data. The novelty of this work consists of performing amplitude correction based on hourly cumulative rainfall accumulation and obtaining reconstructed instantaneous rain rate fields that are consistent with the hourly total estimates by treating the hourly accumulation fields as motion-blurred images. Regional analysis, verification, and validation of the proposed methodology are conducted for the New York-New Jersey metropolitan area using five major events that have occurred in recent years. Key findings include (i) the proposed amplitude correction algorithm increases the Pearson correlation coefficient by around 0.15 over conventional linear blending methodology when hourly cumulative estimations are near perfect, (ii) blending methodologies' lead time is directly correlated to the prediction success of the numerical weather products, (iii) blending weights' adjustment based on the previous prediction success is effective to reduce the drawbacks of the blending methodologies for operational context when NWP products give degraded results.

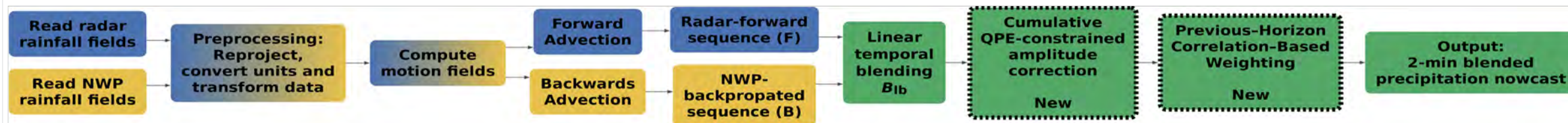
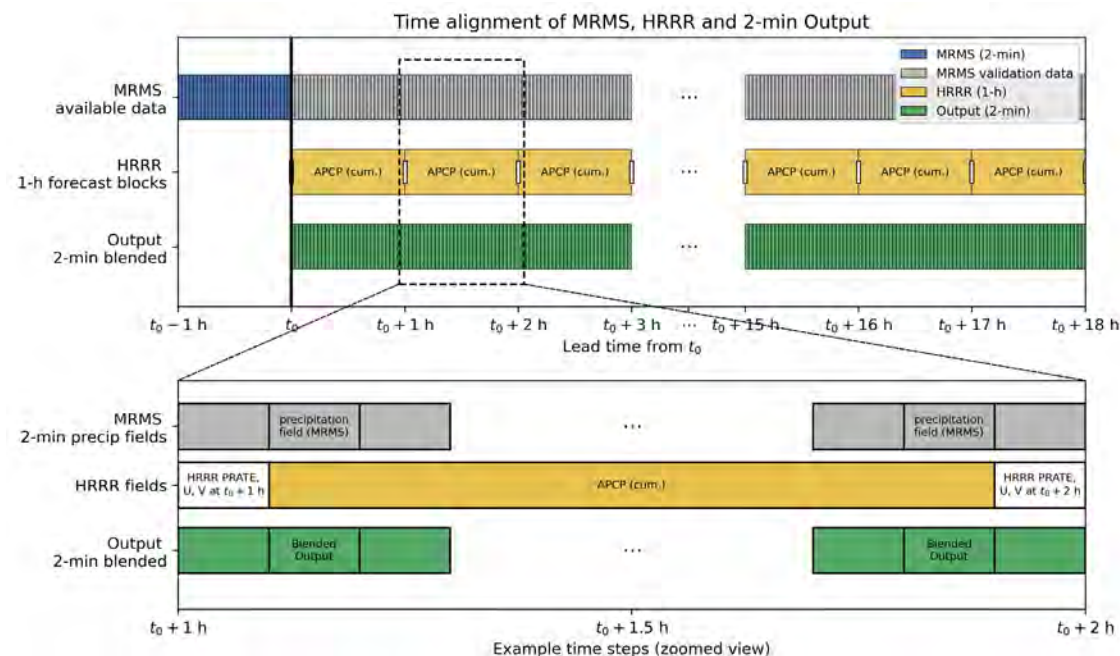
Index Terms—Weather nowcasting, Precipitation nowcasting, Radar-based rainfall estimation, Numerical weather prediction, Data fusion

spatial detail, and minute-scale updates demanded by urban hydrometeorological applications [9]. In line with this, a broad literature has emerged to address this problem. Radar-based nowcasting methods include deterministic schemes [10]–[12] and probabilistic approaches that represent uncertainty through stochastic perturbations [13]–[16] and multi-scale frameworks, [17], [18]. Field-based methods start by estimating how the rainfall field is moving, using the gridded observations to compute an advection field. In order to improve forecast accuracy, stochastic processes may be incorporated into these models to account for uncertainty and the evolving characteristics, such as shape and intensity of precipitation as it develops [19]. Most probabilistic solutions are generated by perturbing the main output with a certain amount of noise [20], which, while sometimes improving skill scores, does not always yield realistic forecasts. Object-oriented approaches first isolate individual storm cells and then track them explicitly [21], [22]. Analogue-based techniques take a different route: they scan historical archives for past cases that are similar to the current state [23], [24]. Furthermore, work has been done to make these algorithms open-source and publicly available, with Pysteps serving as a key example [25]. This framework has grown rapidly and expanded to incorporate many nowcasting approaches, including those



Methodology

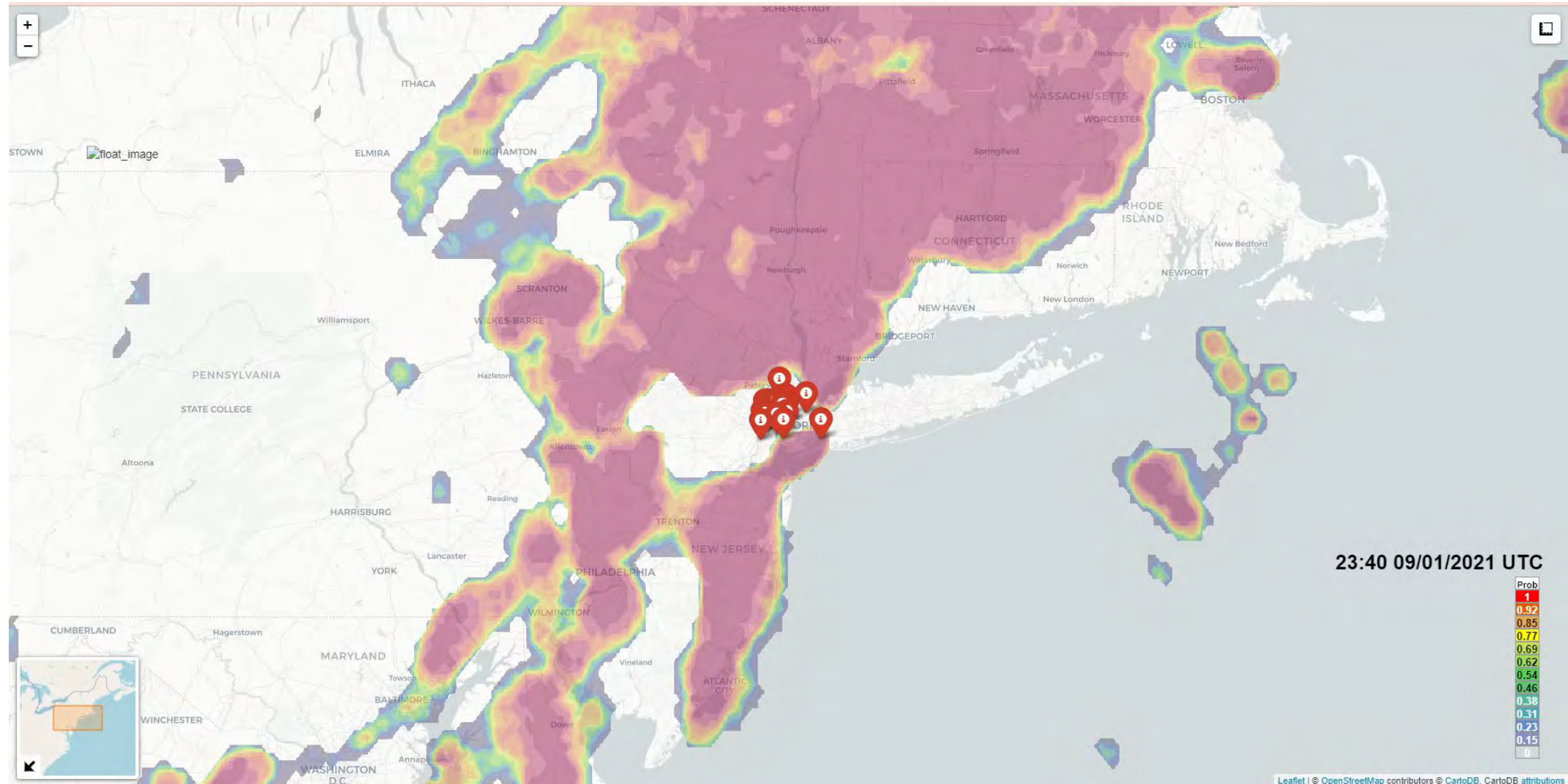
- **Novelty:** Cumulative QPE-constrained Amplitude correction
 - Hourly accumulated precipitation treated as a motion-blurred image
 - Deconvolution-based amplitude correction applied to reconstructed 2-min rain-rate fields
 - Amplitude correction constrained by forecasted cumulative QPE
 - Adaptive correlation-based weighting applied for robustness under degraded NWP forecast conditions



Data-driven techniques for Precipitation NOWCASTING

EXAMPLE: Super Storm Ida in September 2021

https://web.stevens.edu/ismart/atmosphere_products/ida_nowcasting.html



The simulation of streamflow with the LSTM model across the continental United States

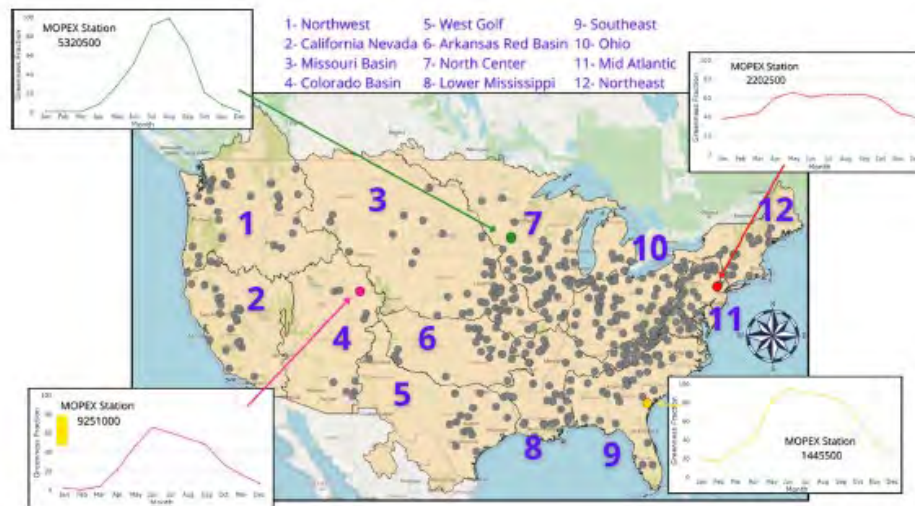


Fig. 1 Geographical distribution of MOPEX basins over the contiguous US

LSTM model

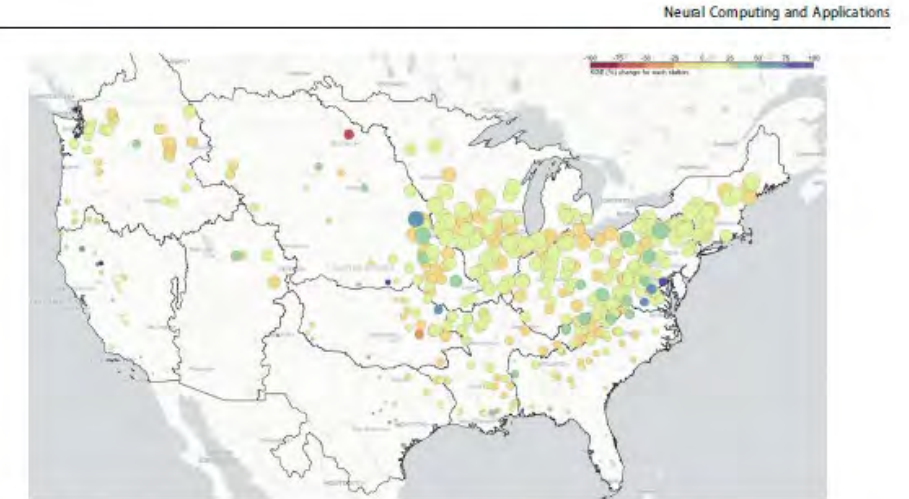


Fig. 7 Spatial distribution of the change in KGE values after adding the greenness fraction to the LSTM models

There is no free lunch! A large number of observations (over several decades) was used to train and validate the LSTM model

Tounsi, A., Abdelkader, M. & Temimi, M. Assessing the simulation of streamflow with the LSTM model across the continental United States using the MOPEX dataset. *Neural Comput & Applic* 35, 22469–22486 (2023). <https://doi.org/10.1007/s00521-023->



Machine Learning-based method to infer reservoir operation rules

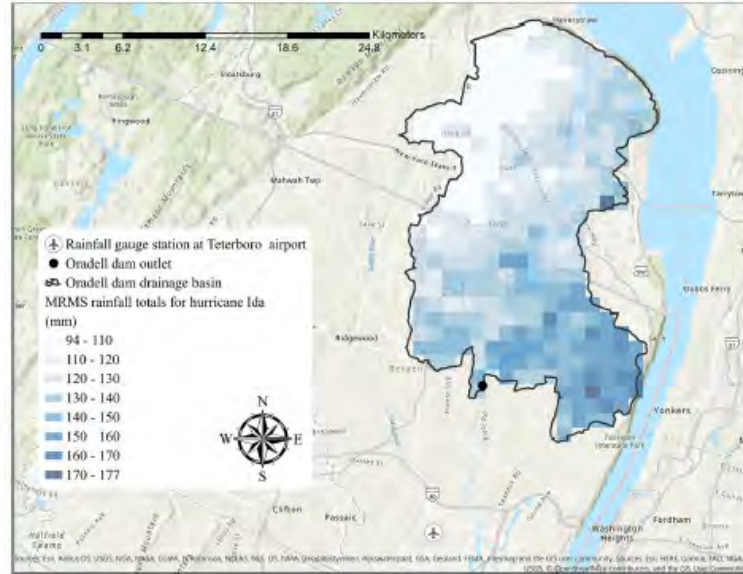


Fig. 7 Spatial distribution of MRMS precipitation during Hurricane Ida in the Hackensack Watershed

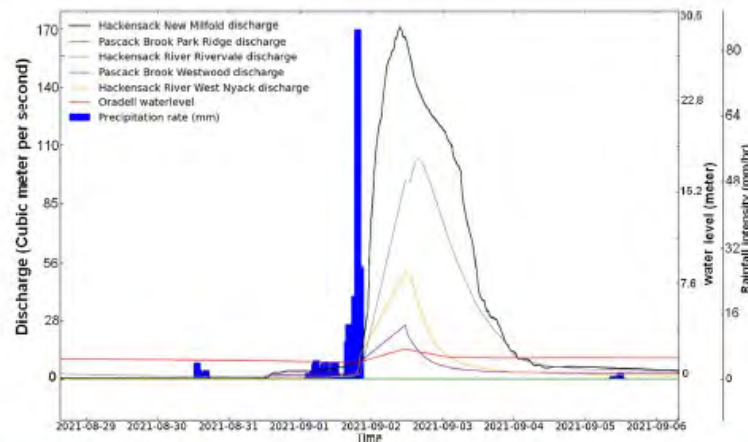


Fig. 8 Plot of upstream and downstream discharge and precipitation time series (MRMS), the water level in Oradell (before and after the rain), and predicted rain for Hurricane Ida

Neural Computing and Applications
<https://doi.org/10.1007/s00521-022-07500-1>

ORIGINAL ARTICLE

On the use of machine learning to account for reservoir management rules and predict streamflow

Achraf Tounsi¹ · Marouane Temimi¹ · Jonathan J. Gourley²

Received: 5 February 2022 / Accepted: 1 June 2022
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Abstract

This study aims to develop a Machine Learning (ML)-based technique to infer reservoir management rules and predict downstream discharge values. The case study is the Hackensack River Watershed in New Jersey, USA. A Long Short-Term Memory (LSTM) model was used to predict streamflow values at the USGS station at New Milford, right downstream of Oradell reservoir. A good agreement between observed and simulated streamflow values was obtained during the 2020–2021 testing period. An NSE value of 0.93 was determined with the 48-h precipitation lead time, suggesting that the 48-h precipitation forecast mostly drives releases Oradell reservoir. The developed model was tested during Hurricane Ida. The analysis revealed that a similar NSE of 0.95 was obtained with a 48-h precipitation lead time followed by the 12-h lead time model, which was based on the watershed response time. In addition, the conducted feature analysis revealed that only four out of the seven upstream USGS stations in the watershed have a significant impact on the model's performance. This work implies that ML can capture reservoir management rules and predict reservoir releases using precipitation and upstream flow data as input variables. This study lays the groundwork for a generalization of the method over the CONUS to infer reservoirs' operation rules for streamflow simulation.

Keywords Machine learning · LSTM · Streamflow · MRMS · Precipitation · Water reservoir

1 Introduction

Flooding is a natural disaster with consequences that are particularly severe in urban areas where significant damages to infrastructure are often reported [1]. Predicting hydrological processes in urban areas is challenging, especially in the presence of reservoirs that are commonly used for flood control and impact mitigation. The presence of water reservoirs along streams, which is common in or

around urban areas, and their releases depending on specific management rules dictated by their managers is an example that illustrates the complexity of modeling hydrological processes in urban areas. To accurately predict urban flooding and its risk, it is vital to account for anthropogenic factors, especially those introduced by streamflow regulation that alters natural streamflow regimes through reservoir management [2, 3].

Several hydrological models have been developed to study watershed hydrology with applications in rural and urban areas [4, 5]. Models like SWMM, HEC-RAS [6], TUFLOW [7], CSIRO TVD, and AutoRAPID [8] are often used to simulate urban hydrological processes while accounting for the combination of riverine and urban flooding. The models are usually developed in 1D, 2D, or a combination of 1D-2D configurations. The 1D modeling component usually covers the streams, the subsurface drainage network, and major drainage center lines in a watershed. The 2D modeling component simulates the lateral expansion of flood inundation. The 1D and 2D components have usually coupled both ways. Introducing

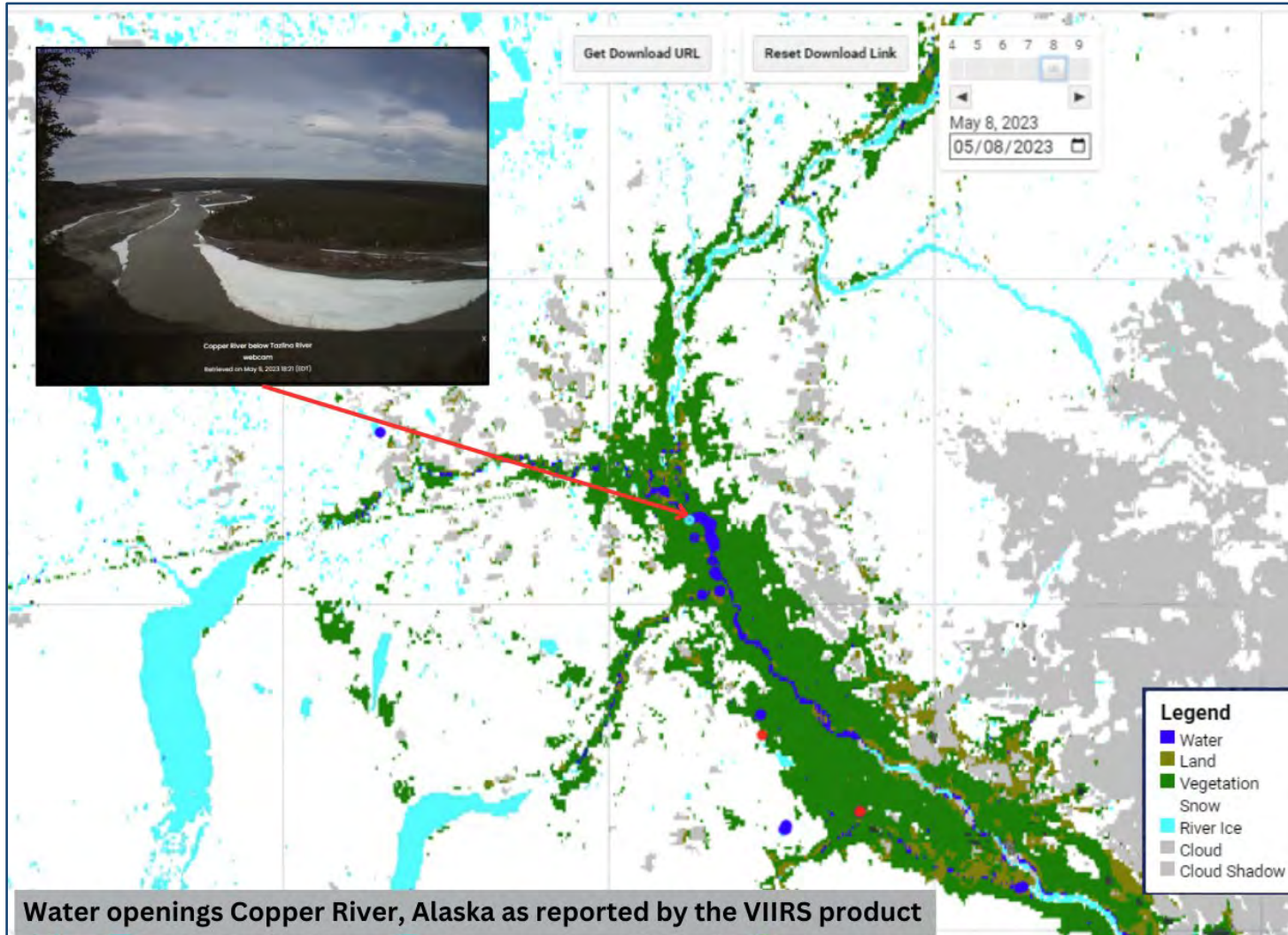
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¹ Department of Civil, Environmental, and Ocean Engineering, Stevens Institute of Technology, 1 Castle Point Terrace, Hoboken, NJ 07030, USA

² National Oceanic and Atmospheric Administration (NOAA), National Severe Storms Laboratory, Norman, OK, USA

Use of deep learning to segment satellite images in support of NOAA NWS river ice monitoring

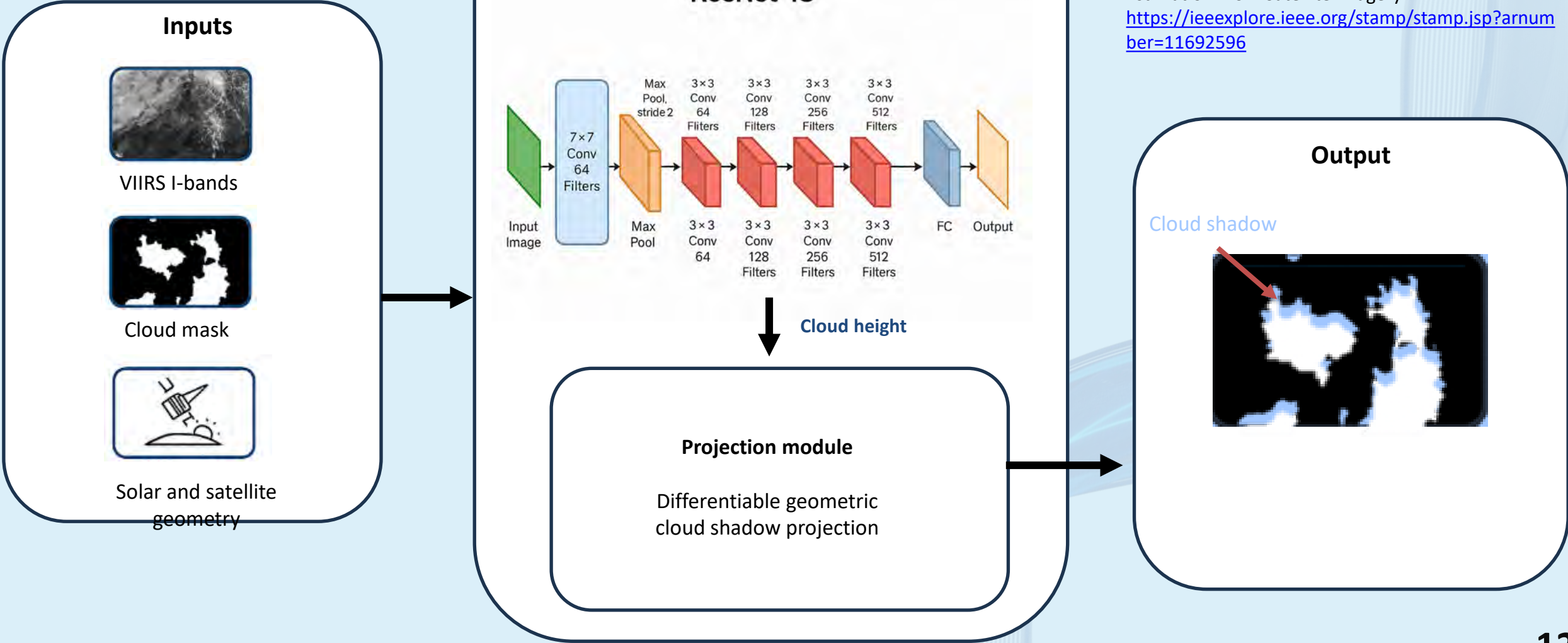
https://web.stevens.edu/ismart/land_products/rivericemapping.html



- Developed an automated, multi-source remote sensing system that offers near real-time, accurate insights into river ice and surface conditions, enhancing responsiveness to ice dynamics and related hazards.
- Inclusion of citizen science data provides essential ground-truth observations that significantly enhance satellite data analysis.



High-Level Methods & Approach Summary



Cherif et al. 2026. DiffShadow-AI: A Novel Differentiable Geometry-Aware Framework for Joint Cloud Shadow Detection and Cloud Height Estimation From Satellite Imagery
<https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=11692596>



IMPROVING WEATHER FORECAST ACCURACY OVER NEW YORK CITY

PhD Candidate

Jorge Humberto Bravo Méndez

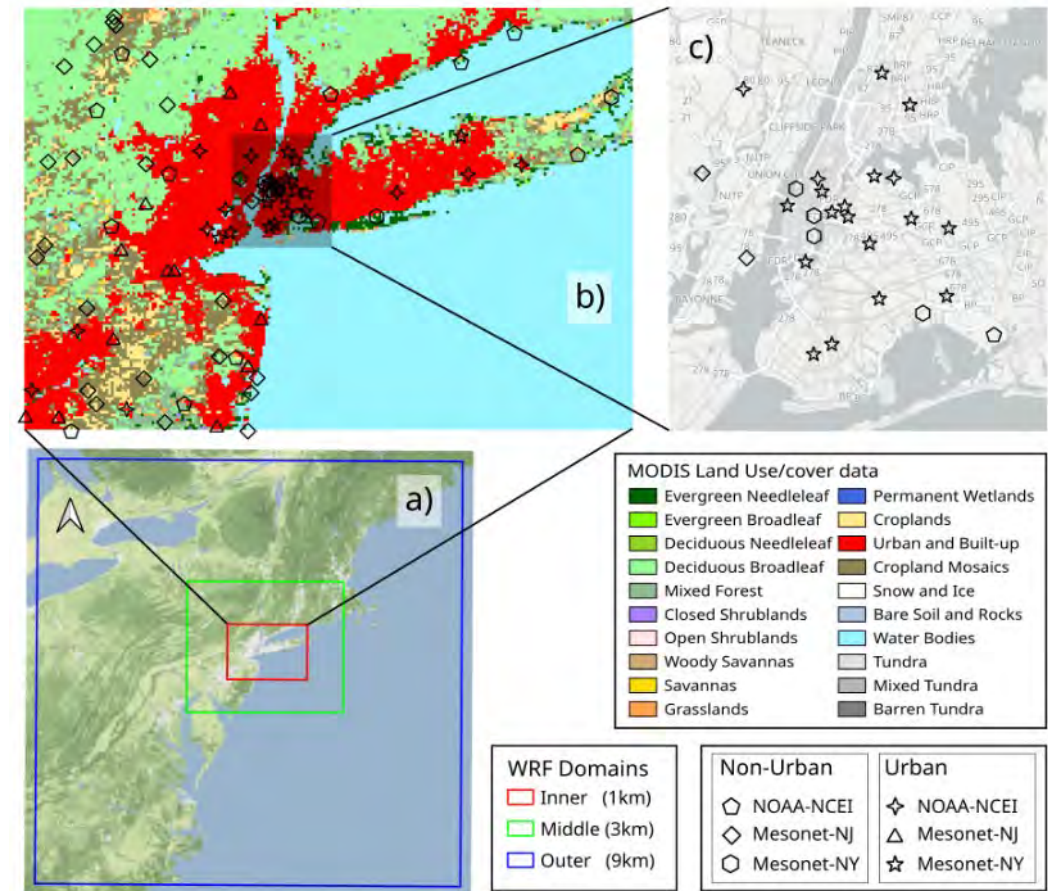
WRF as baseline

Evaluation of WRF high-resolution
simulation of extreme precipitation over
New York City Metropolitan Area

Traditional downscaling

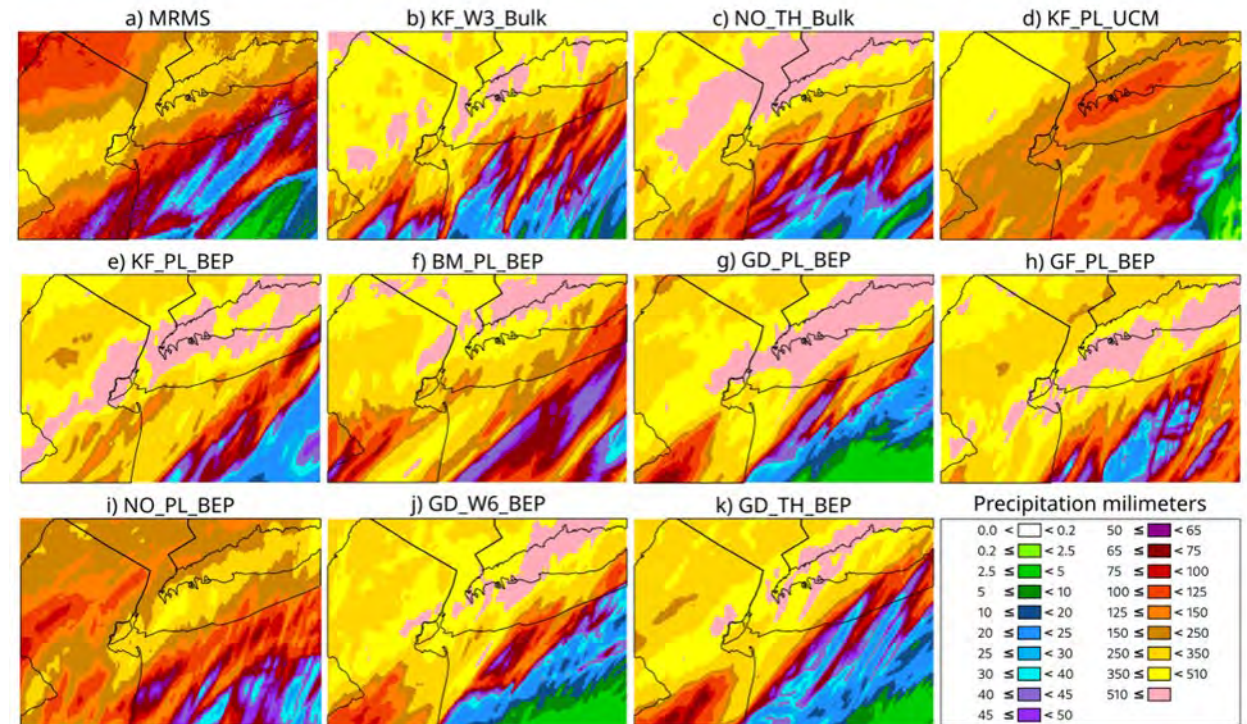
Objective & Motivation

- Evaluate WRF performance for **extreme precipitation in NYCMA**
- Focus on urban impacts during **Hurricane Ida (Sep 2021)**
- Use WRF for high-resolution downscaling
Assess sensitivity to **physics parameterizations (urban, microphysics, convection)**
- Goal: identify **optimal configuration for accurate precipitation modeling**



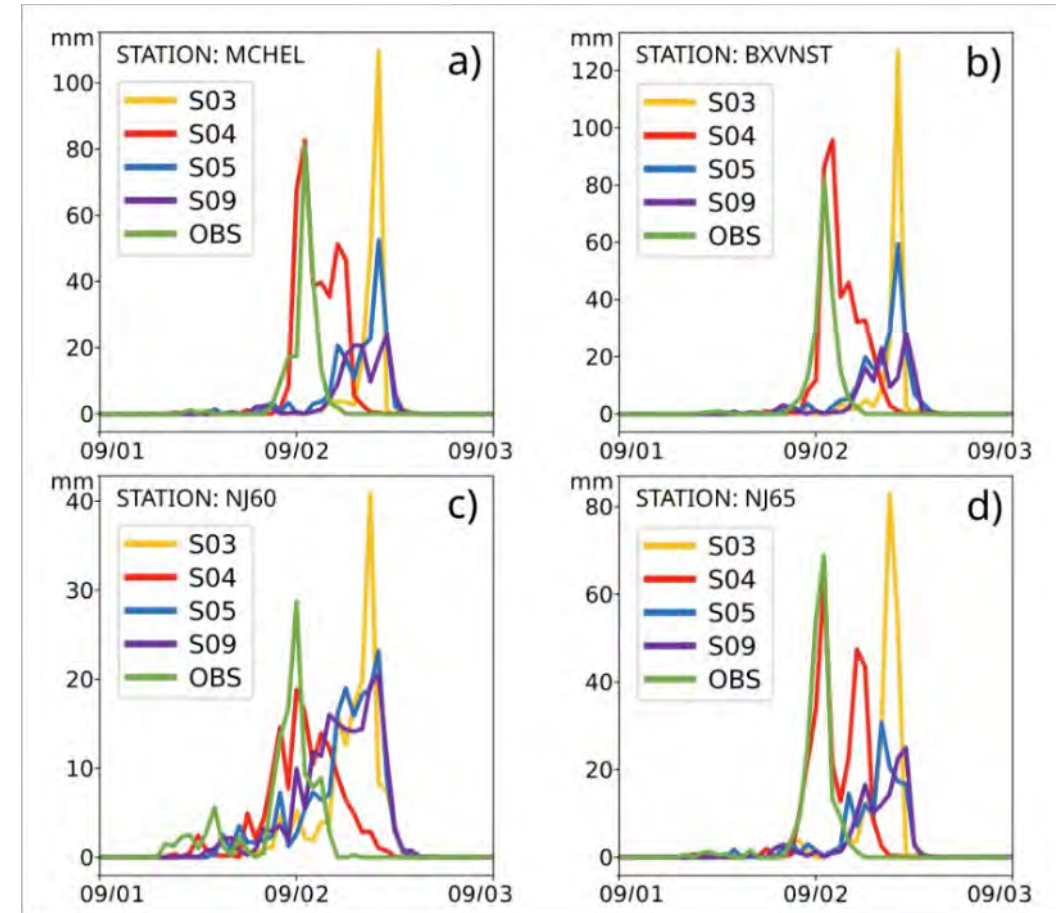
Methodology & Results

- **WRF v4.2.2** with nested domains (9–3–1 km over NYCMA)
- **ERA5** data for **sensitivity experiments**; **GFS** data to evaluate the **optimal configuration**.
- Multiple configurations: **microphysics, cumulus, and urban schemes (Bulk, UCM, BEP)**
- Validation using **Mesonet (NY/NJ), NOAA, and MRMS datasets**
- Performance evaluated with **PTD, PD, SSIM metrics**
- **Key Results:**
 - Strong sensitivity to parameterization choices
 - Best performance: **BEP + Lin + Betts–Miller configuration**
 - Accurately captures **timing and spatial patterns of extreme rainfall**
 - High agreement with **observations and MRMS data**



Contribution

- Establishes **baseline performance of WRF** for urban precipitation
- Highlights importance of **urban parameterization**
- Demonstrates sensitivity to **grid structure and physics schemes**
- The **structured-grid nested domain** arrangement serves as a basis for future comparison.
- **Impact:**
 - Motivates transition to **next-generation models (MPAS)**
 - Provides **validation framework (observations + MRMS)**
 - Serves as reference for all subsequent studies



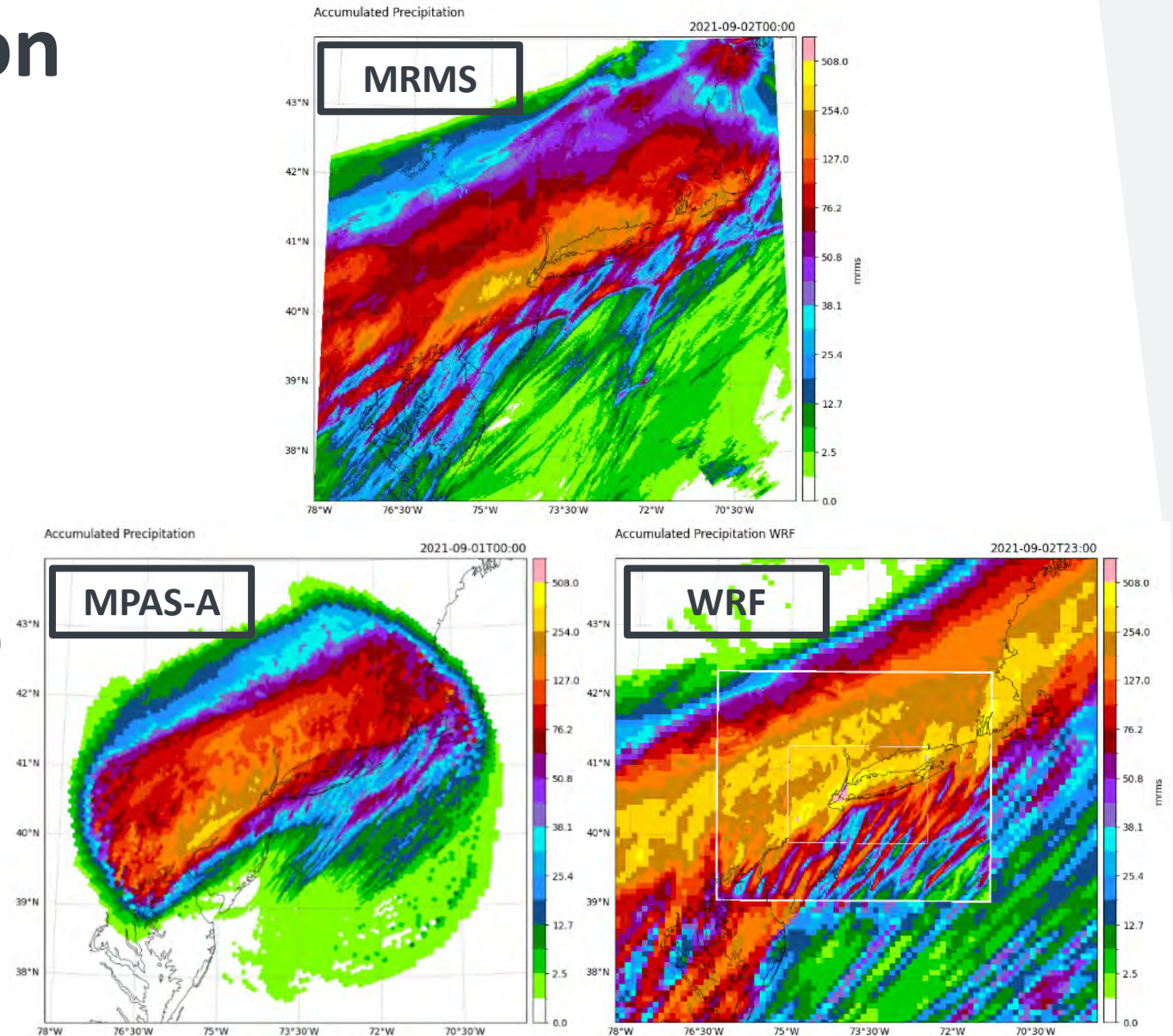
WRF to MPAS-A

Comparing WRF and MPAS-A Simulations
of Extreme Rainfall from Superstorm Ida
in the New York City Metropolitan Area

WRF and MPAS-A Comparison

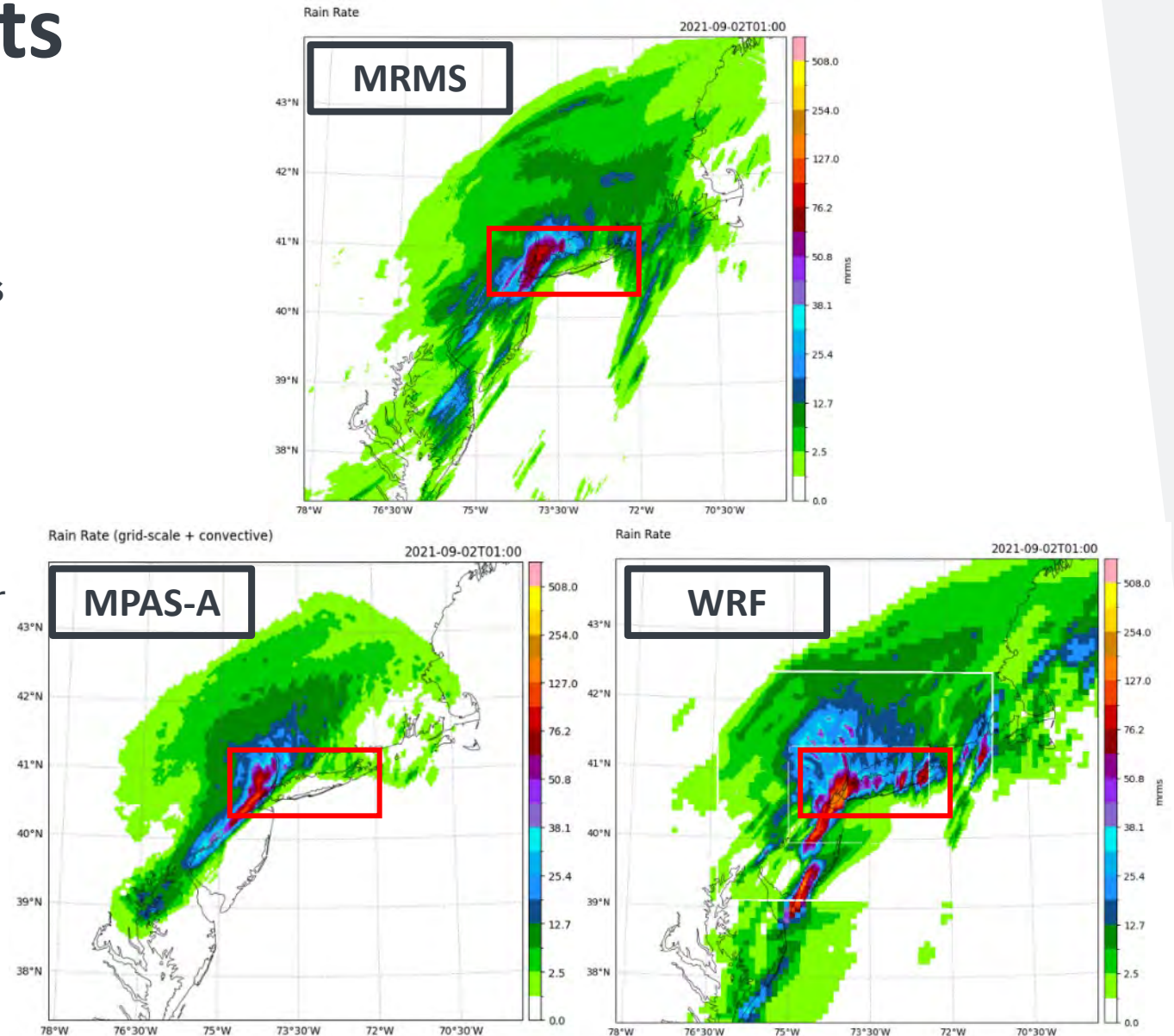
Objective & Motivation

- Compare **WRF (nested grids)** vs **MPAS-A (unstructured mesh)**
- Improve prediction of **extreme precipitation over NYCMA**
- **Key Idea:**
 - MPAS enables **seamless multiscale representation** (no nested domains)
- **Approach:**
 - Same case study: **Hurricane Ida (2021)**
 - Use **consistent high-resolution configurations (~1 km)**
 - Evaluate differences in **storm structure, timing, and spatial distribution**



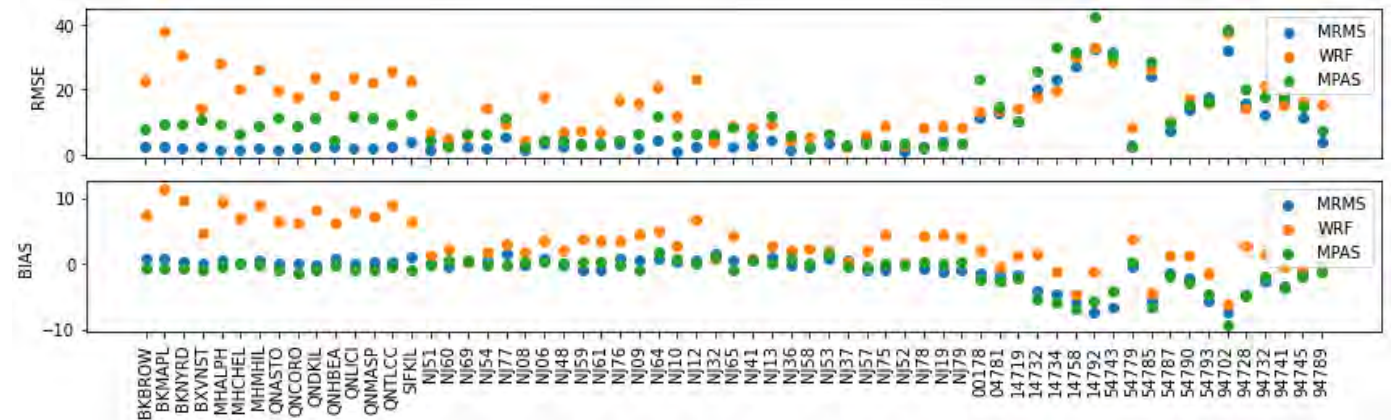
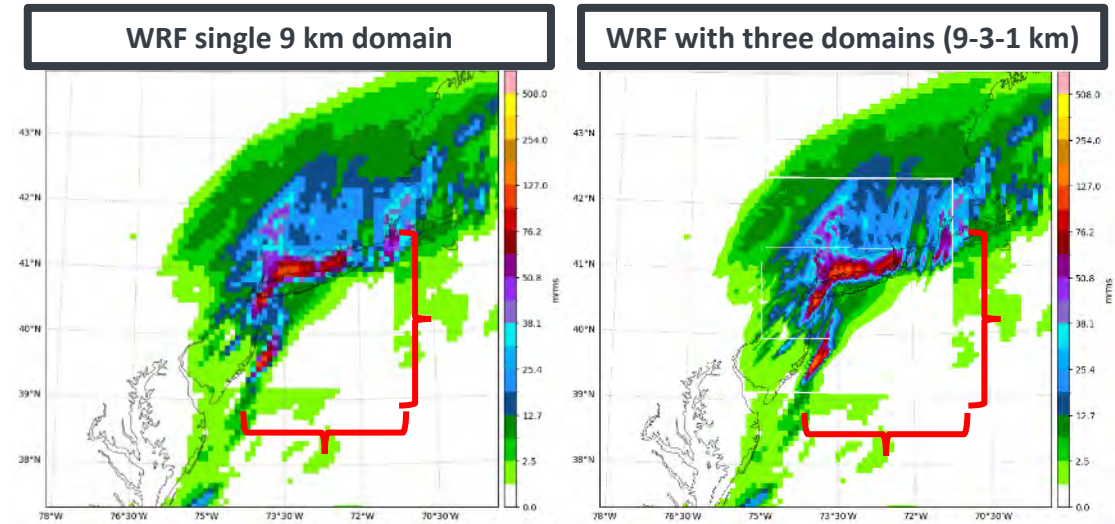
Methodology & Results

- High-resolution simulations using **WRF** (nested: 9–3–1 km) and **MPAS-A** (variable mesh ~9–1 km)
- Both models initialized with **ERA5 reanalysis data**
- Consistent setup: aligned **physics schemes and convection-permitting configurations**
- Validation using **Mesonet (NY/NJ)** and **NOAA observations**
- **Key Results:**
 - MPAS-A generally outperforms WRF under CP settings
 - Better agreement with observed precipitation
 - Improved representation across station networks
- **Key Insight:**
 - Unstructured mesh improves **multiscale representation of precipitation processes**



Contribution

- Transition from **traditional (WRF)** to **next-generation modeling (MPAS)**
- Demonstrates added value of **multiscale (MPAS) representation over NYCMA**
- **Impact:**
 - Bridges evaluation → innovation → validation
 - Key step toward **advanced urban precipitation modeling**





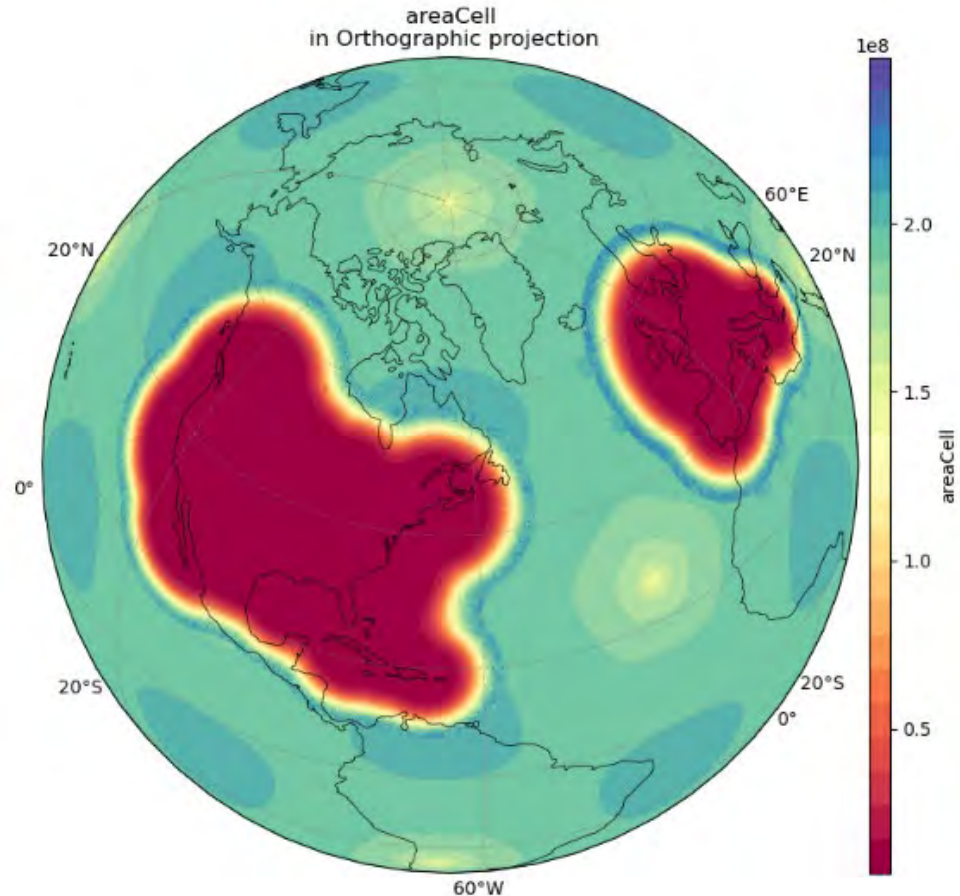
MPAS-viewer

A Python package for an efficient
visualization of the MPAS-atmosphere
unstructured mesh

Visualization Tool Development

Objective & Motivation

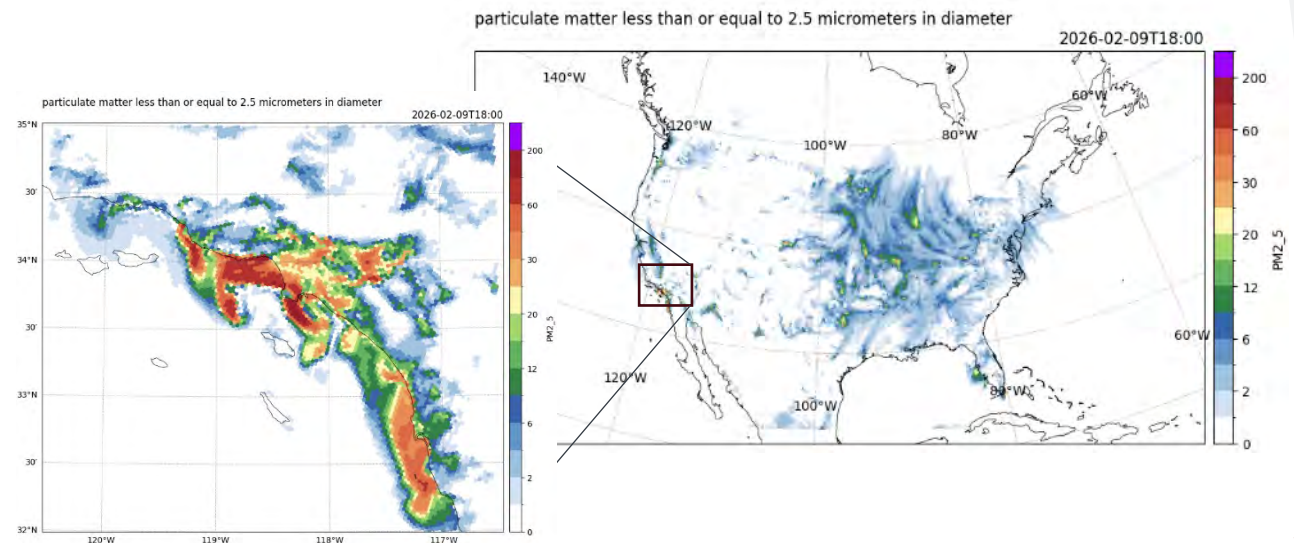
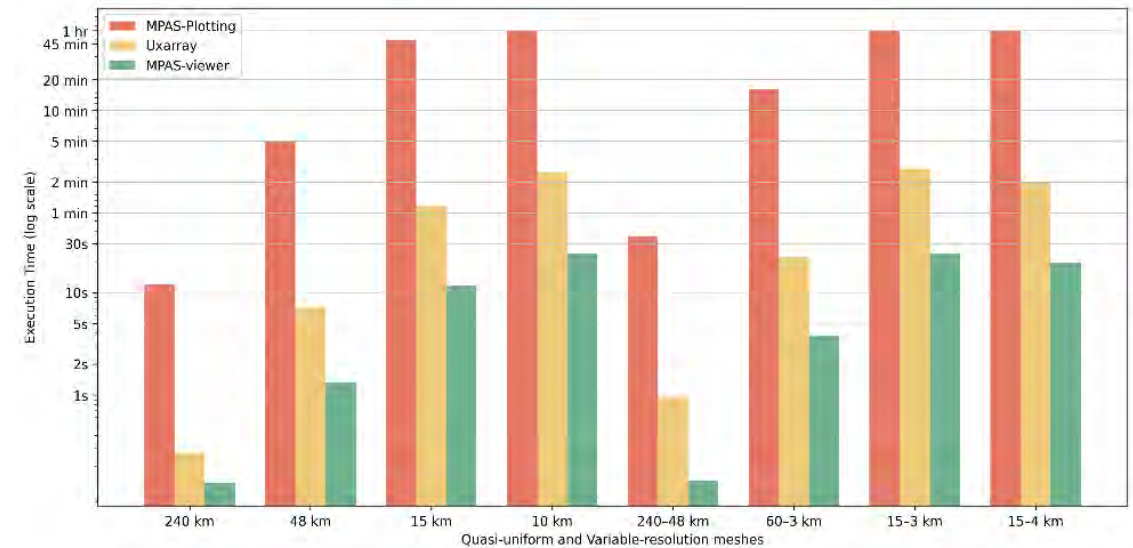
- MPAS uses **unstructured Voronoi mesh**
- Advantage: better **multiscale atmospheric representation**
- Challenge: **difficult data processing and visualization**
- Develop a tool for **efficient visualization of MPAS-A outputs**
- **Limitations of existing tools:**
 - Require **remeshing/interpolation**
 - High computational cost
 - Potential loss of spatial accuracy
- **Proposed Solution:**
 - **MPAS-viewer** → direct visualization on native mesh
 - Improves **efficiency, accessibility, and analysis**



Global High-Resolution Atmospheric Forecasting (GRAF)
model global variable-resolution mesh (15 – 4 km)

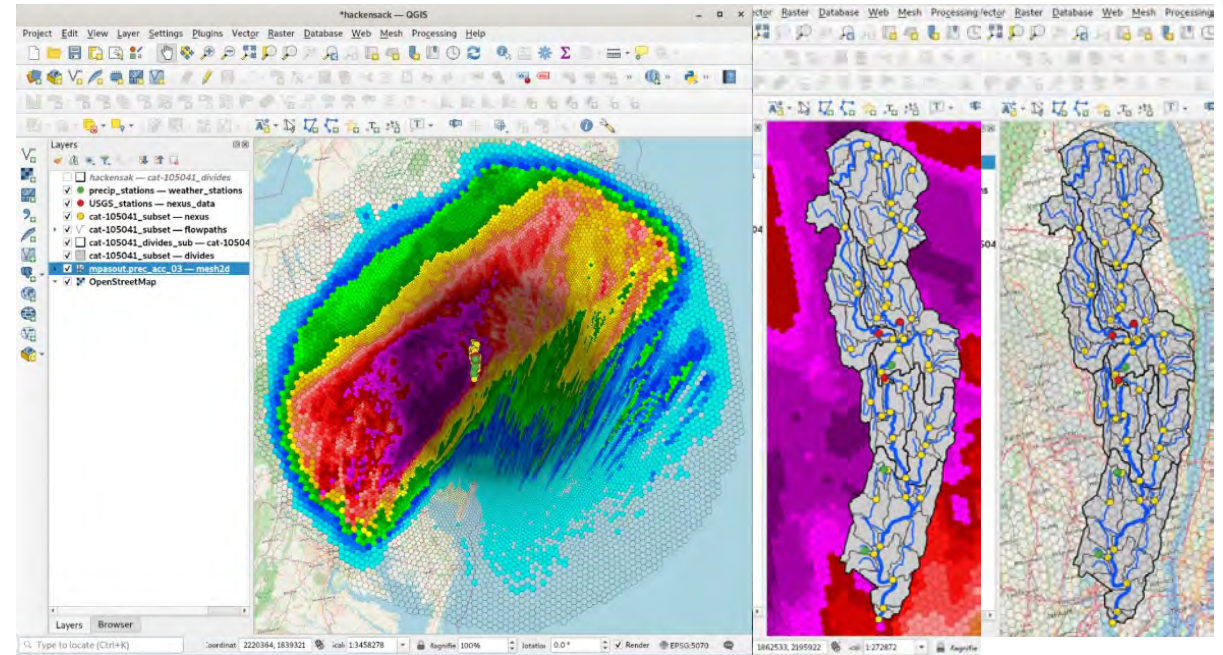
Methodology & Results

- Developed **MPAS-viewer**: Python-based post-processing tool
- Built with **Basic Python libraries**
- Operates directly on **MPAS NetCDF (UGRID format)**
- No remeshing or interpolation required
- **Innovation:**
 - Direct rendering on **native unstructured mesh (SCVT)**
 - Uses **optimized array operations** → **faster performance**
- Preserves spatial accuracy of unstructured grids
- **Key Results:**
 - Significant speed improvement over existing tools
 - Handles **millions of cells in seconds**
 - Supports **maps, time series, and vertical analysis**

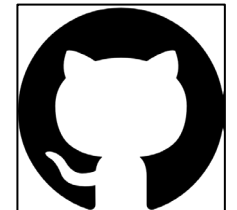


Contribution

- Serves as **support** for MPAS analysis
- Solves challenges of **unstructured-grid data visualization and processing**
- Enables effective use of **MPAS simulations for evaluation and comparison**
- **Innovation:**
 - Facilitates transition plotting from **WRF (structured) → MPAS (unstructured)**
 - Enhances **workflow efficiency and data interpretation**



Workshop Title: MPAS-Viewer: Python-Based Exploration of MPAS Unstructured Mesh data with UGRID export for QGIS visualization
Final Workshop Number: SCIWS26
Date and Time: Sunday, 6 December 2026, 13:00 - 16:30 PST



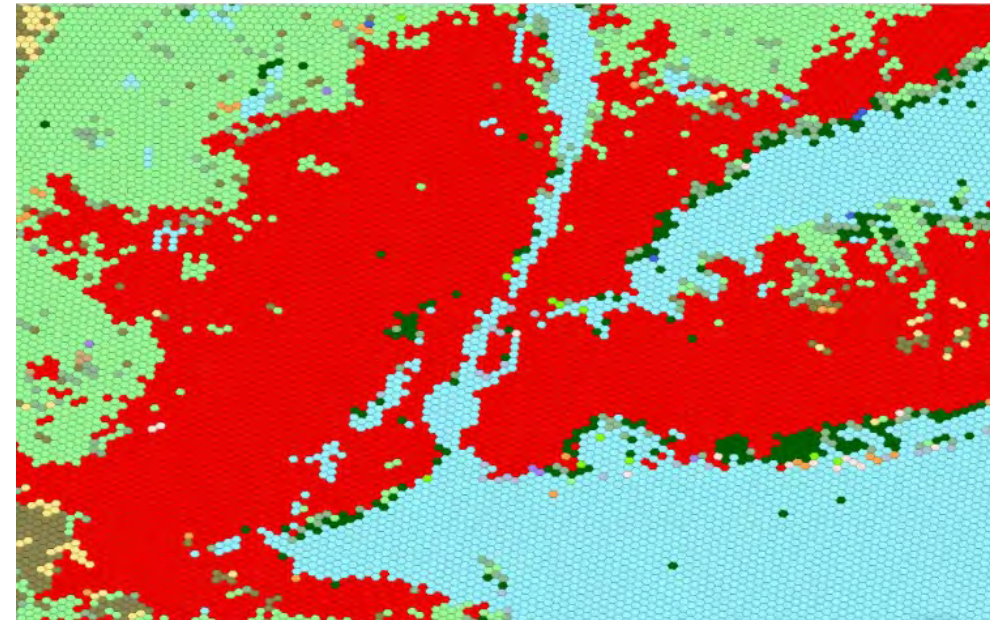
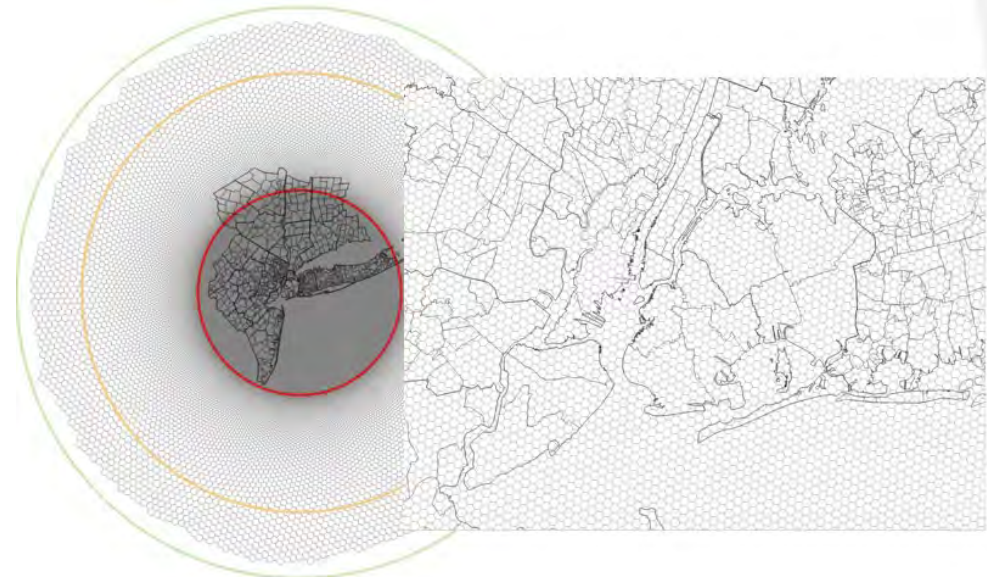
The LULC

Sensitivity of MPAS-A Simulated Urban
Precipitation to Surface Roughness
Length

Surface Parameter Sensitivity

Objective & Motivation

- Improve **MPAS-A** performance for urban **precipitation** in NYCMA
- Move from **model comparison** → **model refinement**
- Address lack of **urban parameterizations** in **MPAS-A**
- **Approach:**
 - Implement **Noah-MP** land surface model
 - Incorporate **Local Climate Zones (LCZs)**
 - Focus on Refine **Surface Roughness representation**
- **Goal:**
 - Enhance representation of **land-atmosphere interactions**
 - Improve simulation of **extreme urban precipitation**



Working hypothesis

- **Surface Roughness and Atmospheric Processes**
- **Surface roughness (z_0)** controls exchange of: Momentum, Heat, and Moisture (*Weston et al., 2018*)
- **Impact on Atmosphere** (*Reddy et al., 2020*) :
- **Wind Speed:**
 - Higher roughness: $\uparrow$ drag $\rightarrow$ $\downarrow$ near-surface wind
 - Lower roughness: $\uparrow$ wind speed
- **Surface Temperature:**
 - Roughness affects **heat exchange coefficient** C_h
 - Lower C_h : $\downarrow$ sensible heat flux $\rightarrow$ $\uparrow$ surface temperature
- **Key Mechanism:**
 - Urban roughness alters **wind flow and storm dynamics**
 - Can increase **storm residence time and rainfall accumulation** (*Moraglia et al., 2026*)

- The near-surface horizontal wind speed $U(z)$ is approximated by:
 - $$U(z) = \frac{u_*}{\kappa} \left[\ln \left(\frac{z}{z_{0m}} \right) - \psi_m \left(\frac{z}{L} \right) \right]$$
- Where:
 - u^* : friction velocity
 - κ : von Kármán constant (~ 0.4)
 - z : measurement height
 - L : Monin–Obukhov length
 - ψ_m : stability correction function for momentum
- The coefficient C_h is given by:
 - $$C_h = \frac{\kappa^2}{\left[\ln \left(\frac{z}{z_{0m}} \right) - \psi_m \left(\frac{z}{L} \right) \right] \cdot \left[\ln \left(\frac{z}{z_{0h}} \right) - \psi_h \left(\frac{z}{L} \right) \right]}$$
- Where:
 - z_{0m} : roughness length for momentum
 - z_{0h} : roughness length for heat
 - ψ_h : stability correction for heat

Contribution

- Final stage: **from evaluation → physical model improvement**
- Enhances **MPAS-A** realism in urban environments
- Investigates role of **surface roughness in precipitation processes**
- **Scientific Contribution:**
 - Quantifies impact on **storm dynamics, intensity, and spatial distribution**
 - Links **urban morphology ↔ precipitation behavior**
 - Addresses lack of **urban parameterization in MPAS-A**
- **Integration with Dissertation:**
 - Builds on **MPAS (Study 2)**
 - Uses tools from **Study 3**
 - Validated with framework from **Study 4**
- **Impact:**
 - Improves **urban precipitation modeling and forecasting**
 - Supports **flood prediction and urban resilience**

Image taken from; Chao Yuan, et al (2014)

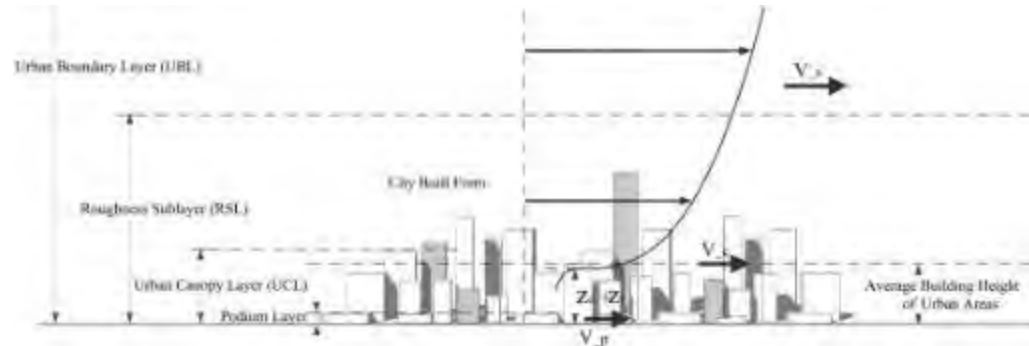
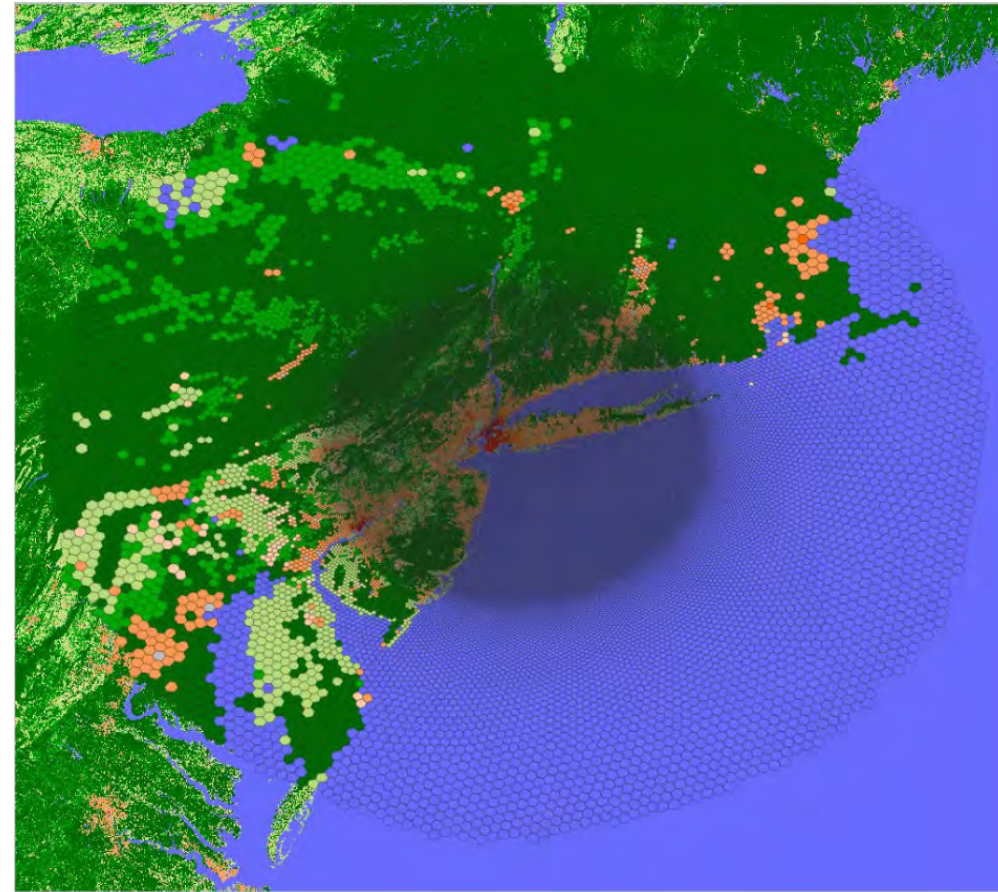
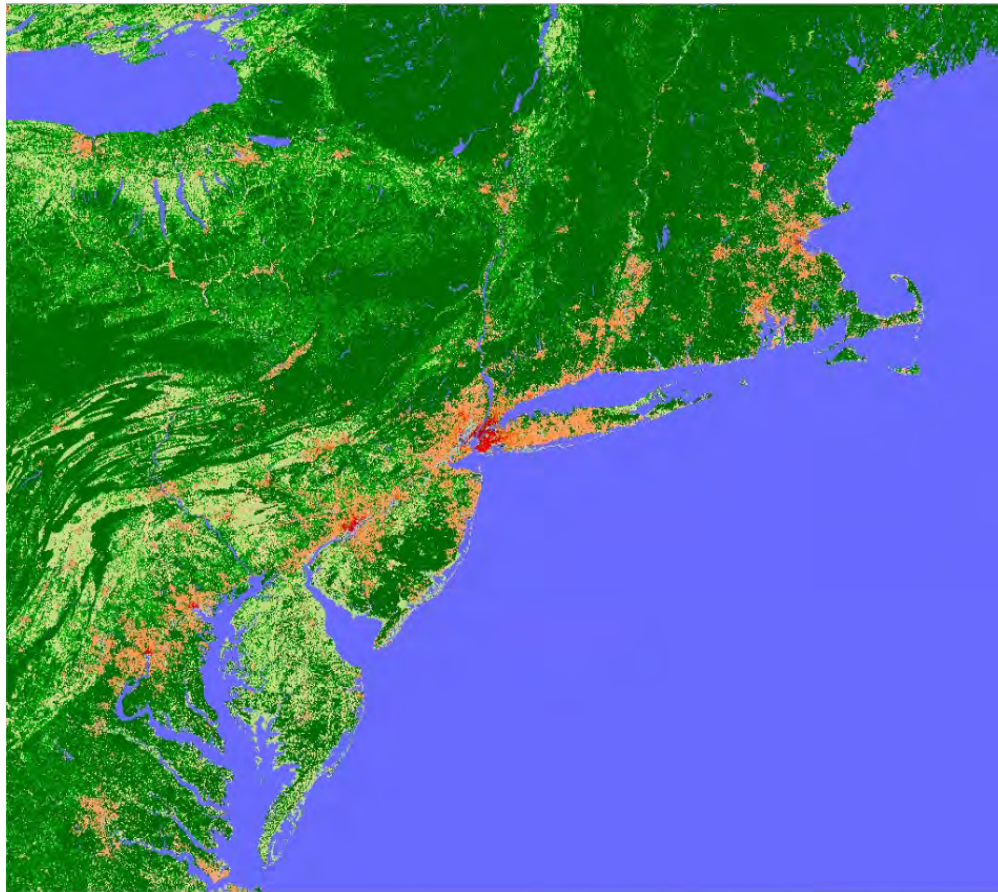


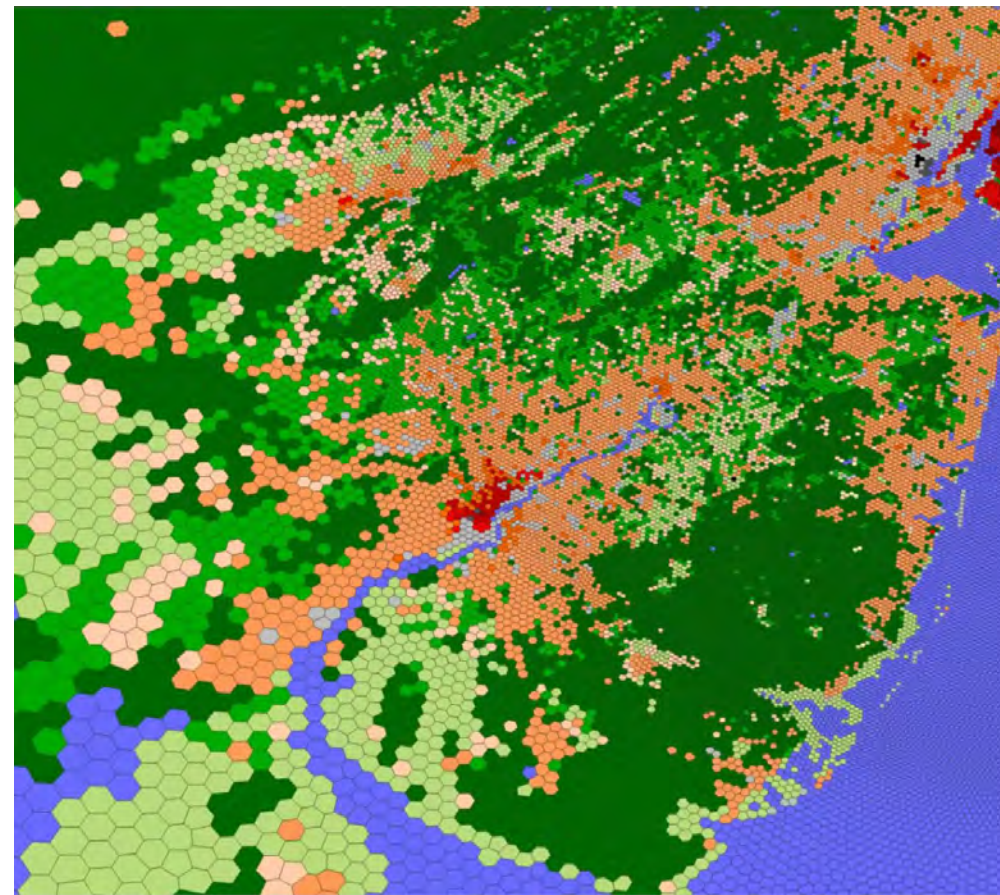
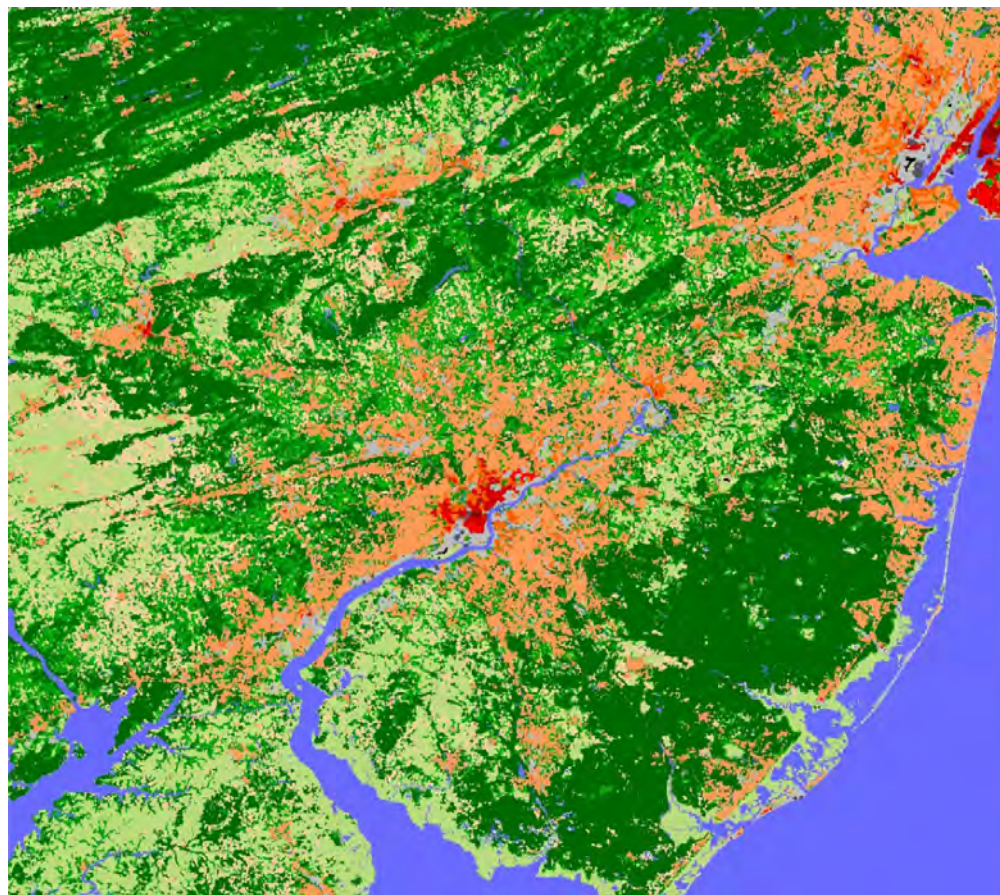
Image taken from reddit





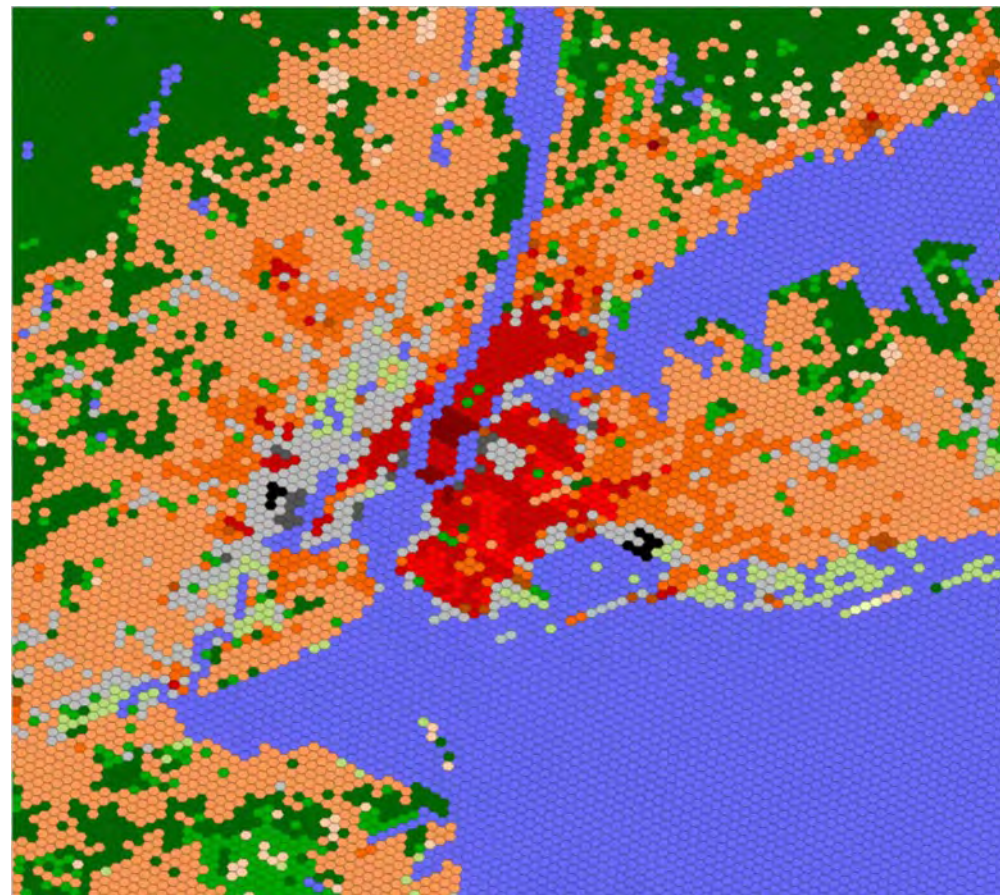
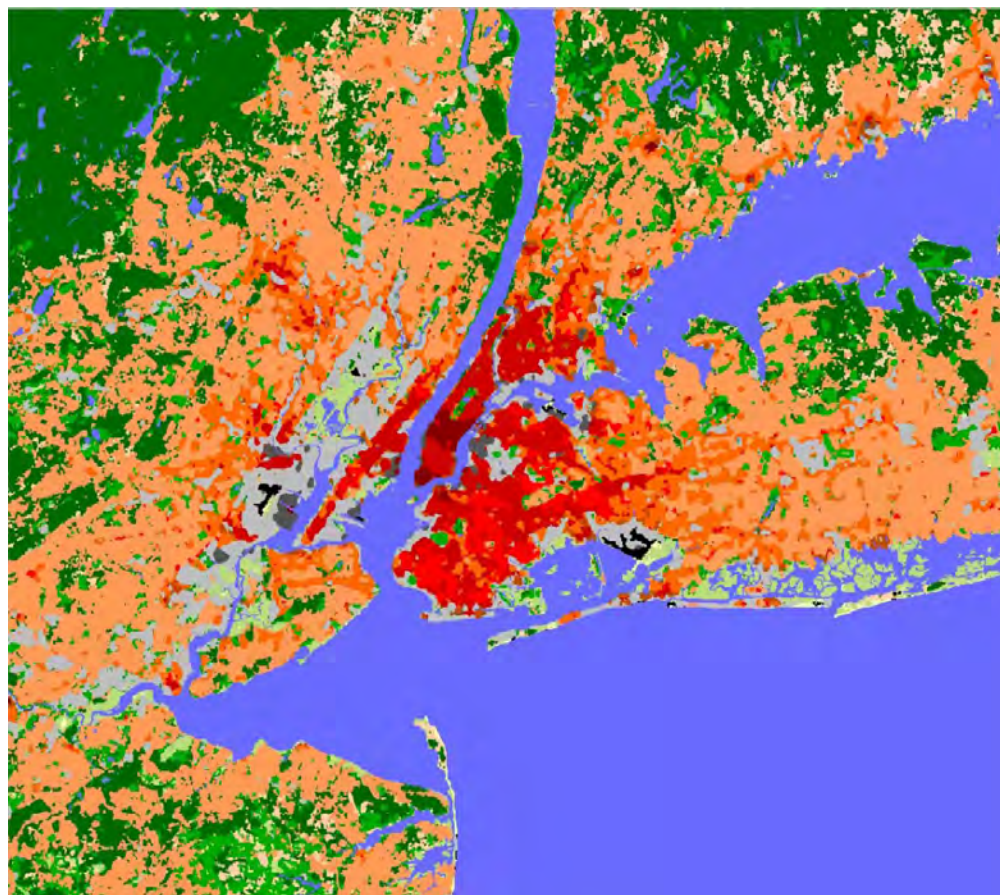
- LCZ Classes**
- Compact High-rise
 - Compact Mid-rise
 - Compact Low-rise
 - Open High-rise
 - Open Mid-rise
 - Open Low-rise
 - Lightweight Low-rise
 - Large Low-rise
 - Sparsely Built
 - Heavy Industry
 - Dense Trees
 - Scattered Trees
 - Bush/Scrub
 - Low Plants
 - Bare Rock/Paved
 - Bare Soil/Sand
 - Water





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Expected Scientific Contributions

The aim of this dissertation is not only to improve urban precipitation modeling, but also to advance scientific understanding of atmospheric processes in complex urban environments.

- Establishes **baseline performance of WRF** for urban extreme precipitation
- Evaluates **MPAS-A vs WRF**, advancing next-generation modeling
- **Validation & Data:**
 - Provides robust framework for **MRMS & Stage IV evaluation**
 - Reduces uncertainty in **precipitation datasets**
- **Model Improvement:**
 - Enhances urban modeling using **roughness, LCZs, and Noah-MP**
 - Improves representation of **land-atmosphere interactions**
- **Key Contributions:**
 - Continue the development of **MPAS-viewer**, which will facilitate the **transition from WRF to MPAS-A**
 - Improves **precipitation simulation and understanding**
 - Reduces **uncertainty in data and models**
 - Enhances representation of **urban processes**
- **Impact:**
 - Supports **accurate forecasting in urban areas (NYCMA)**
 - Contributes to **risk mitigation, preparedness, and resilience**



Stevens Flood Advisory System (SAFAS)

Mahmoud Ayyad

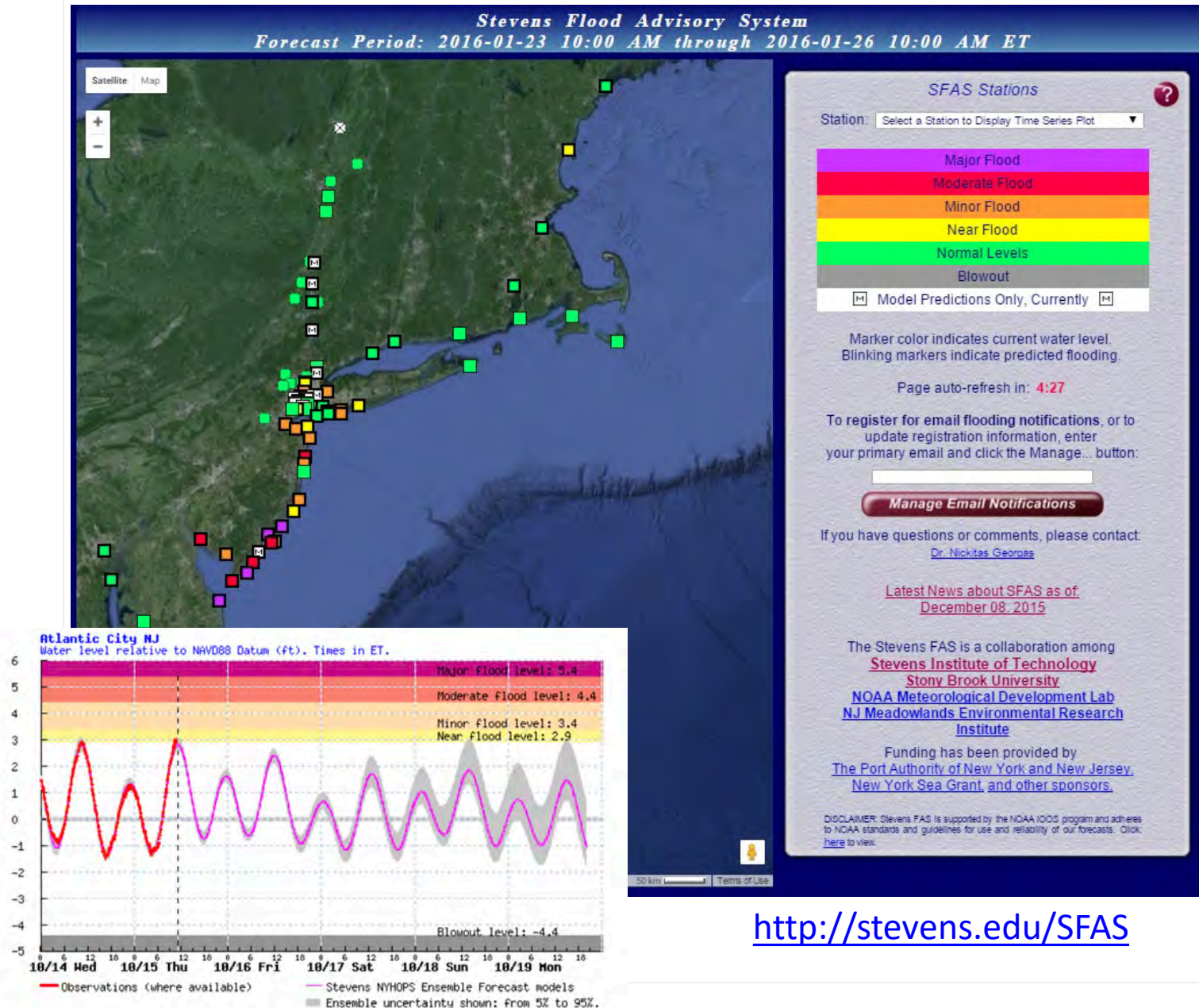
Research Assistant Professor

Email: mayyad@stevens.edu

Physics-based model: Stevens Flood Advisory System

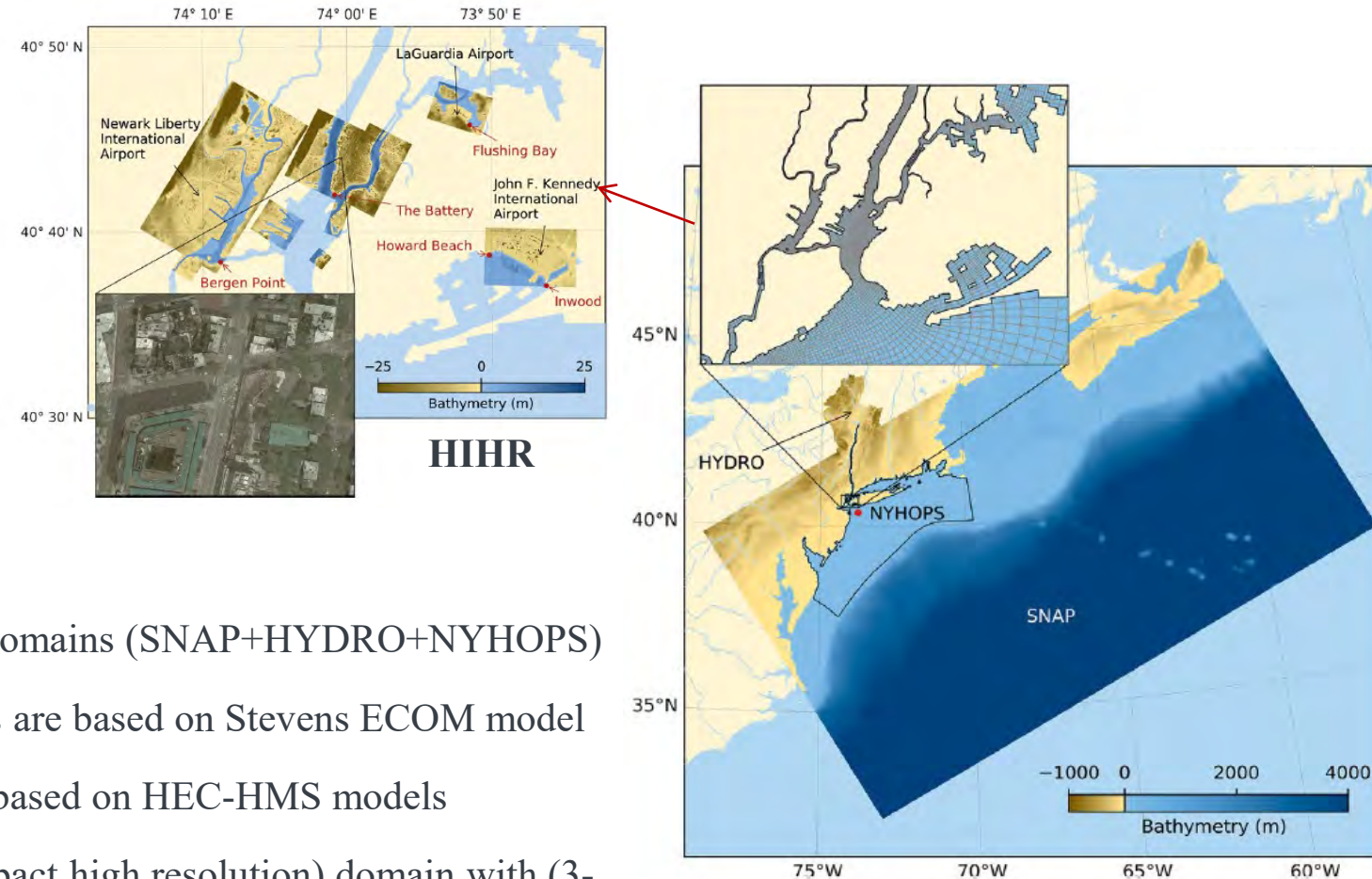
Key Features

- SFAS is an operational ensemble prediction system which provides 24/7 four-day prediction of water levels along the shores of NJ and NY since 2015
- Water levels forecasts and an uncertainty range
- Includes river effects on coastal flooding
- Simulations supported by real-time data from over 120 observation stations along NY and NJ.
- Data is provided to agencies / localities / industry partners (NOAA, PA, NYDEP, NJ Transit, PSEG, ...)
- Sends emails for flood watches and advisories



Physics-based model: Stevens Flood Advisory System

Stevens presently runs a state-of-the-art probabilistic coastal-hydrologic forecast system



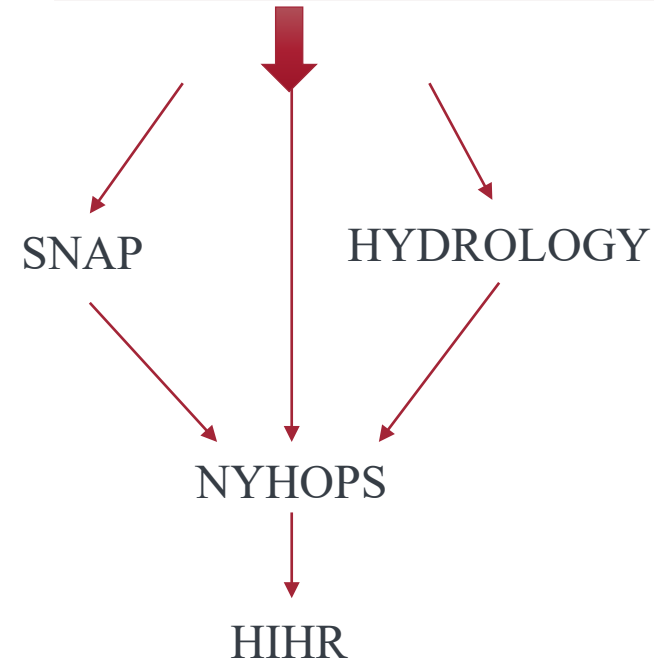
- Nested model domains (SNAP+HYDRO+NYHOPS)
- Hydrodynamics are based on Stevens ECOM model
- Hydrology are based on HEC-HMS models
- HIHR (high impact high resolution) domain with (3-10 m) resolution for Port Authority sites

Jordi et al. (2019) "A next generation coastal ocean operational system"

Stevens Flood Advisory System

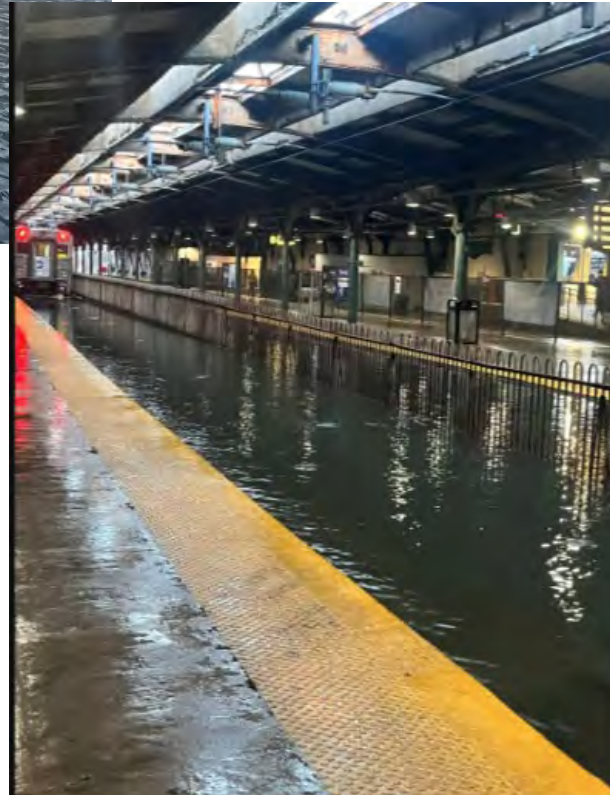
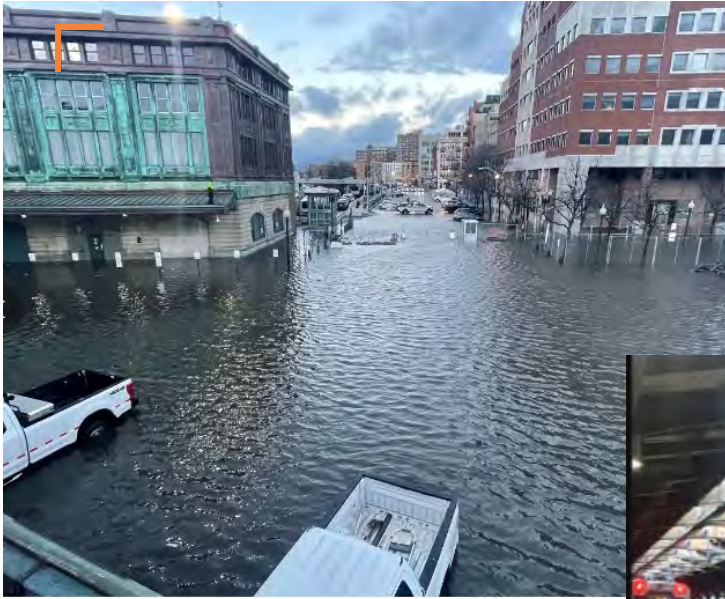
- Ensemble of 96 weather forecast models is used for water level forecasting,
- Ensemble weighted average based on recent RMSE and bias,
- 90% confidence “spread” based on ensemble empirical distribution

Meteorological Forcing	
Ensemble members	
GEFS	(21)
ECMWF	(51)
CMC	(21)
Deterministic members	
NAM, GFS	



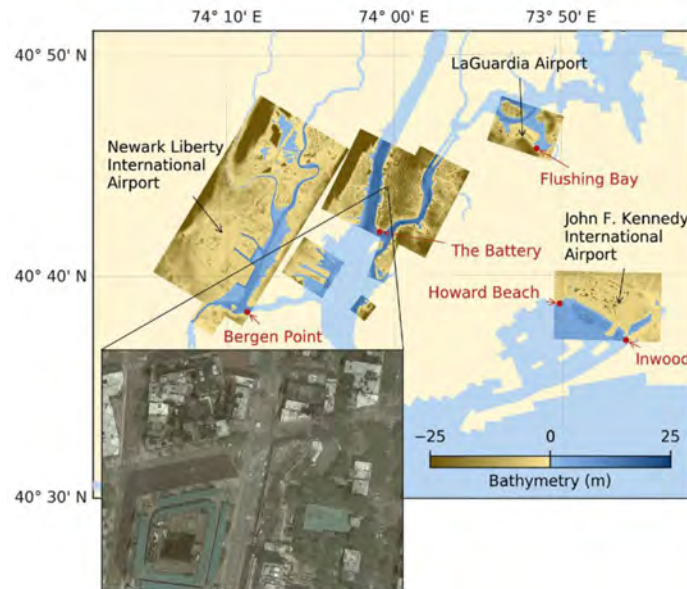
HIHR is run for 3 percentiles (5th, 50th, 95th)
Flood mapping on street-scale level

Street-level storm surge prediction



Resulting Web-Tools: Local Street-Scale Flood Mapping of Useful Flood Metrics

Example: Hurricane Sandy (Jordi et al. 2019)



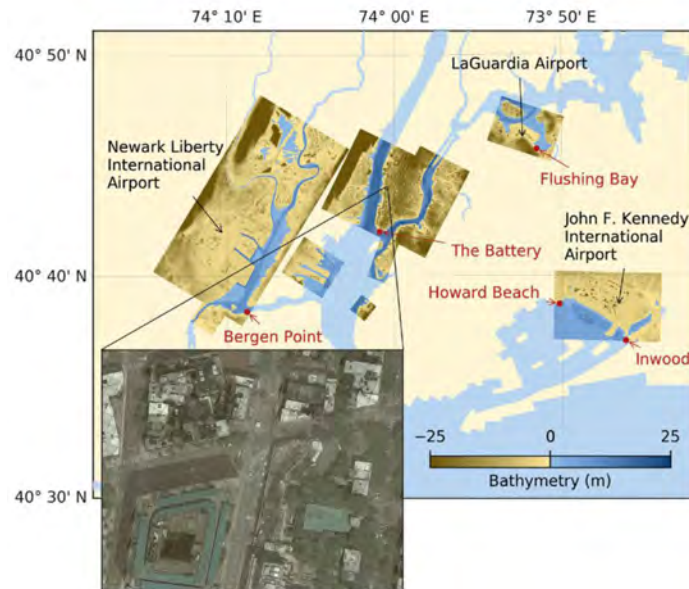
Model resolution from 3 to 10 meters
DEM resolution 1 meter



“Expect at least this much water over ground” (5th percentile)

Resulting Web-Tools: Local Street-Scale Flood Mapping of Useful Flood Metrics

Example: Hurricane Sandy (Jordi et al. 2019)



Model resolution from 3 to 10 meters
DEM resolution 1 meter



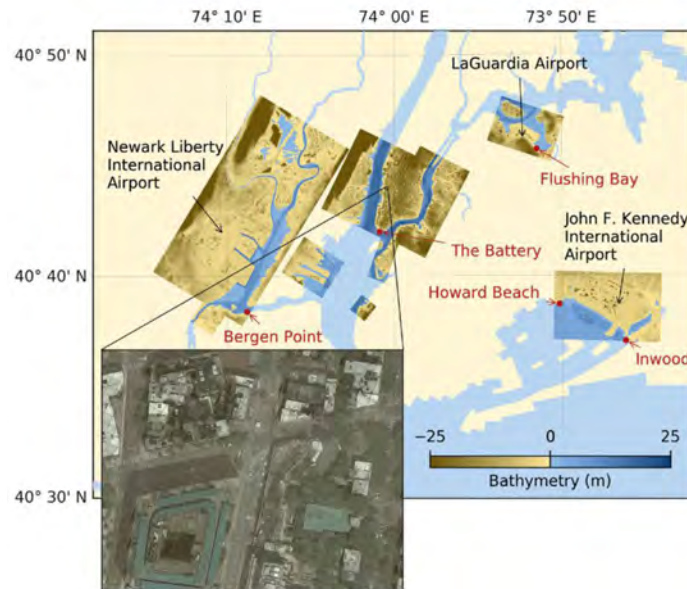
“Most likely flood depth above ground” (50th percentile)

Resulting Web-Tools:

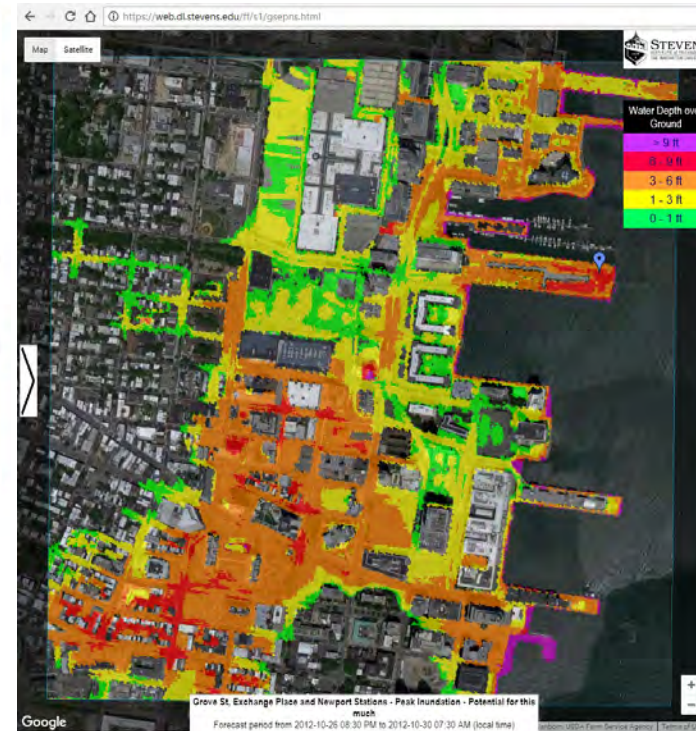
Local Street-Scale Flood Mapping of Useful Flood Metrics

→ e.g. 95th percentile map can be used for evacuation decisions

Example: Hurricane Sandy (Jordi et al. 2019)



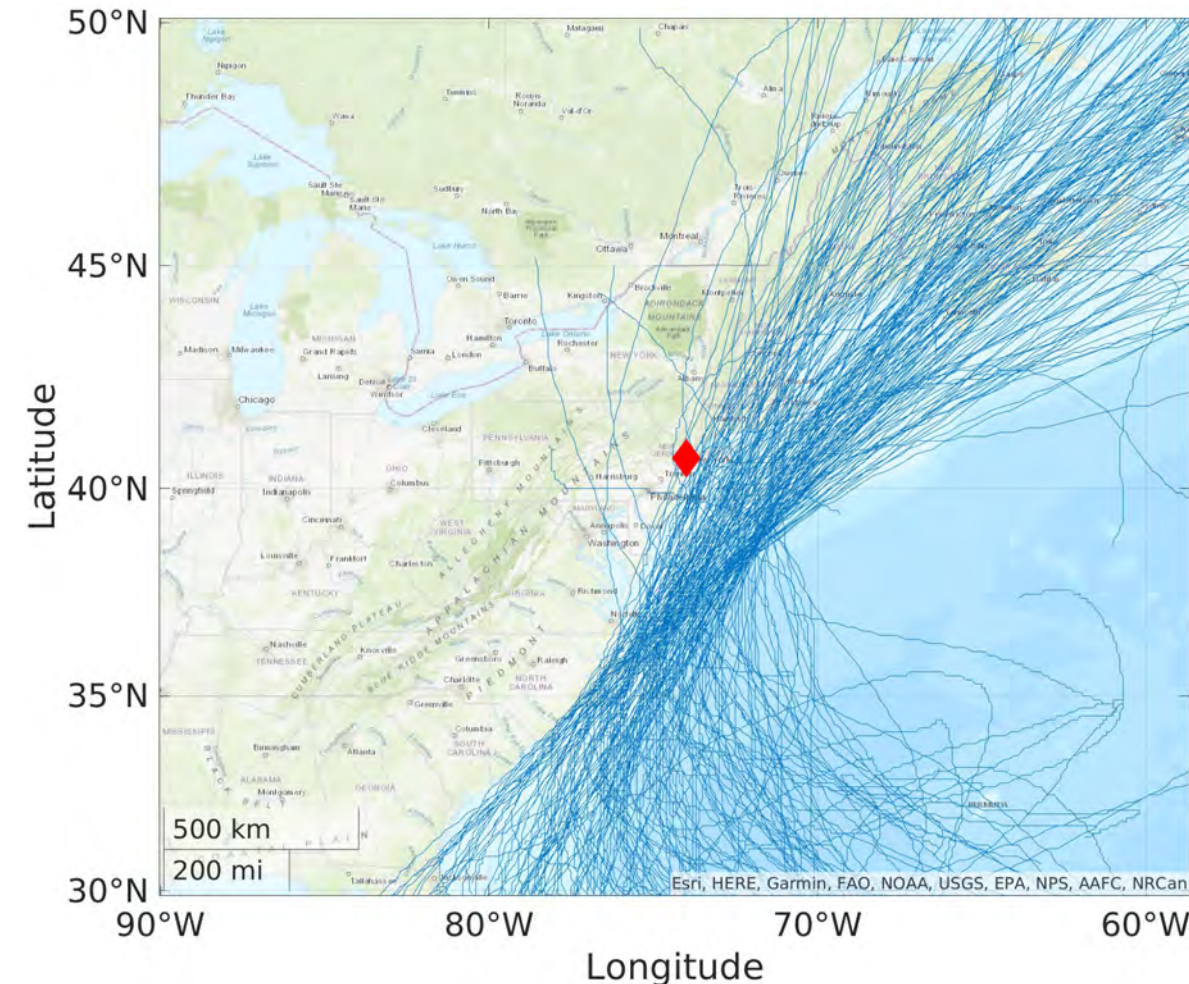
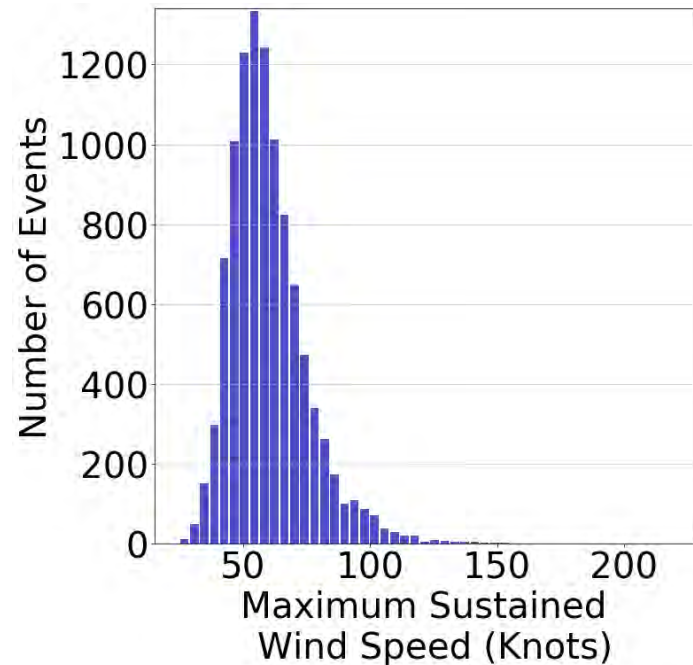
Model resolution from 3 to 10 meters
DEM resolution 1 meter



“Potential for this much water over ground” (95th percentile)

ML4 Storm Surge: Training Data Set Generation

- A total of 10,300 TCs from Marsooli et al. (2020)* are simulated,
- The TCs are normally distributed such that the maximum sustained wind speed has mean value of 60 Knots.

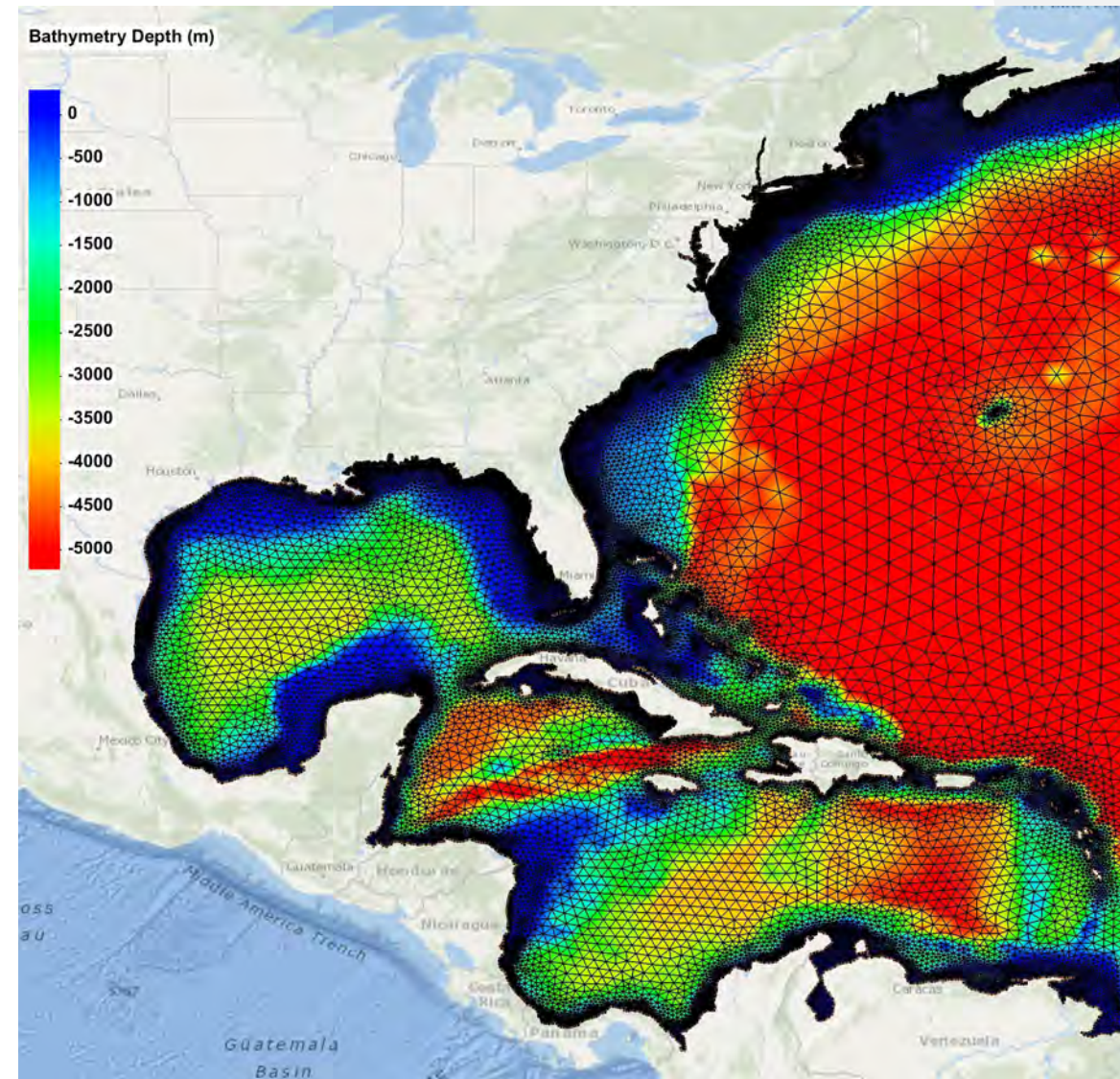


ML4 Storm Surge: Training Data Set Generation

- Hydrodynamic ADCIRC and SWAN coupled models are used to prepare the training data set
- FEMA's validated mesh

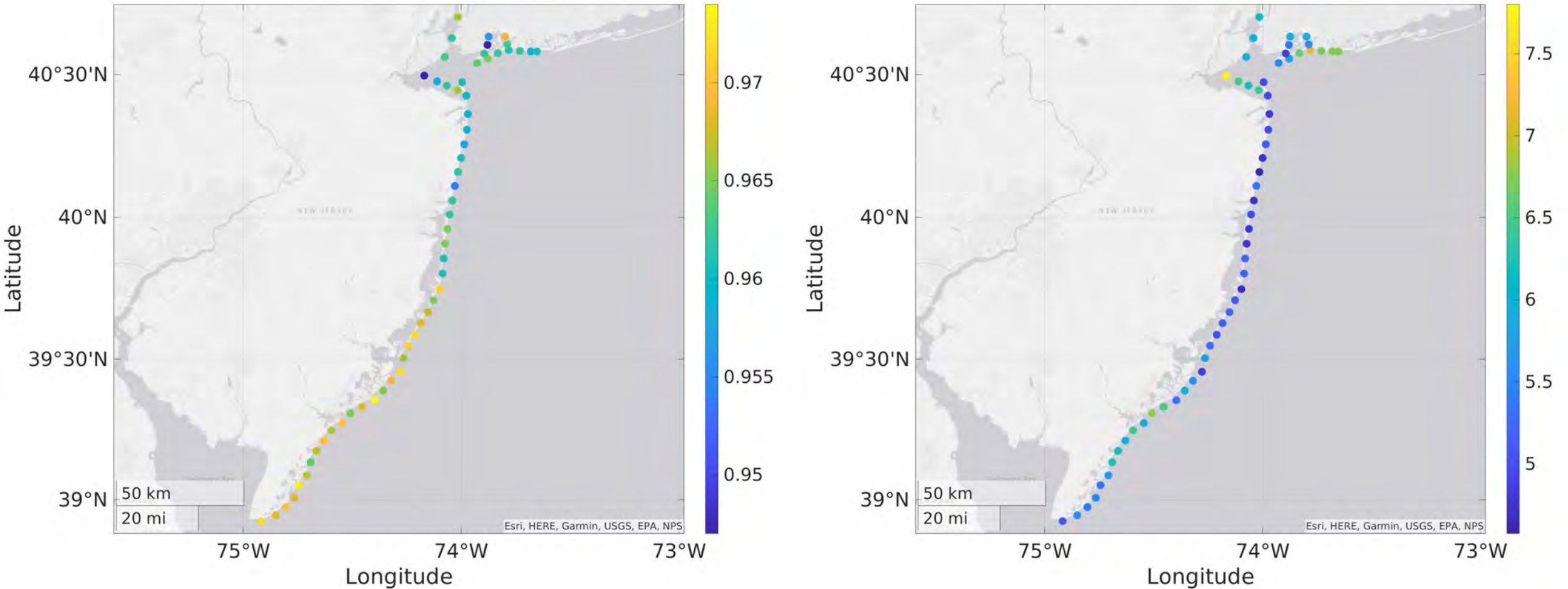
Ayyad M, Hajj MR, Marsooli R. Climate change impact on hurricane storm surge hazards in New York/New Jersey Coastlines using machine-learning. npj Climate and Atmospheric Science. 2023 Jul 14;6(1):88.

Ayyad M, Hajj MR, Marsooli R. Machine learning-based assessment of storm surge in the New York metropolitan area. Scientific Reports. 2022 Nov 10;12(1):19215.



ML4 Storm Surge: Peak Storm Surge Height Validation

Correlation Coefficient (R) RMSE (cm)



Ayyad M, Hajj MR, Marsooli R. Climate change impact on hurricane storm surge hazards in New York/New Jersey Coastlines using machine-learning. npj Climate and Atmospheric Science. 2023 Jul 14;6(1):88.

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ML for River Monitoring

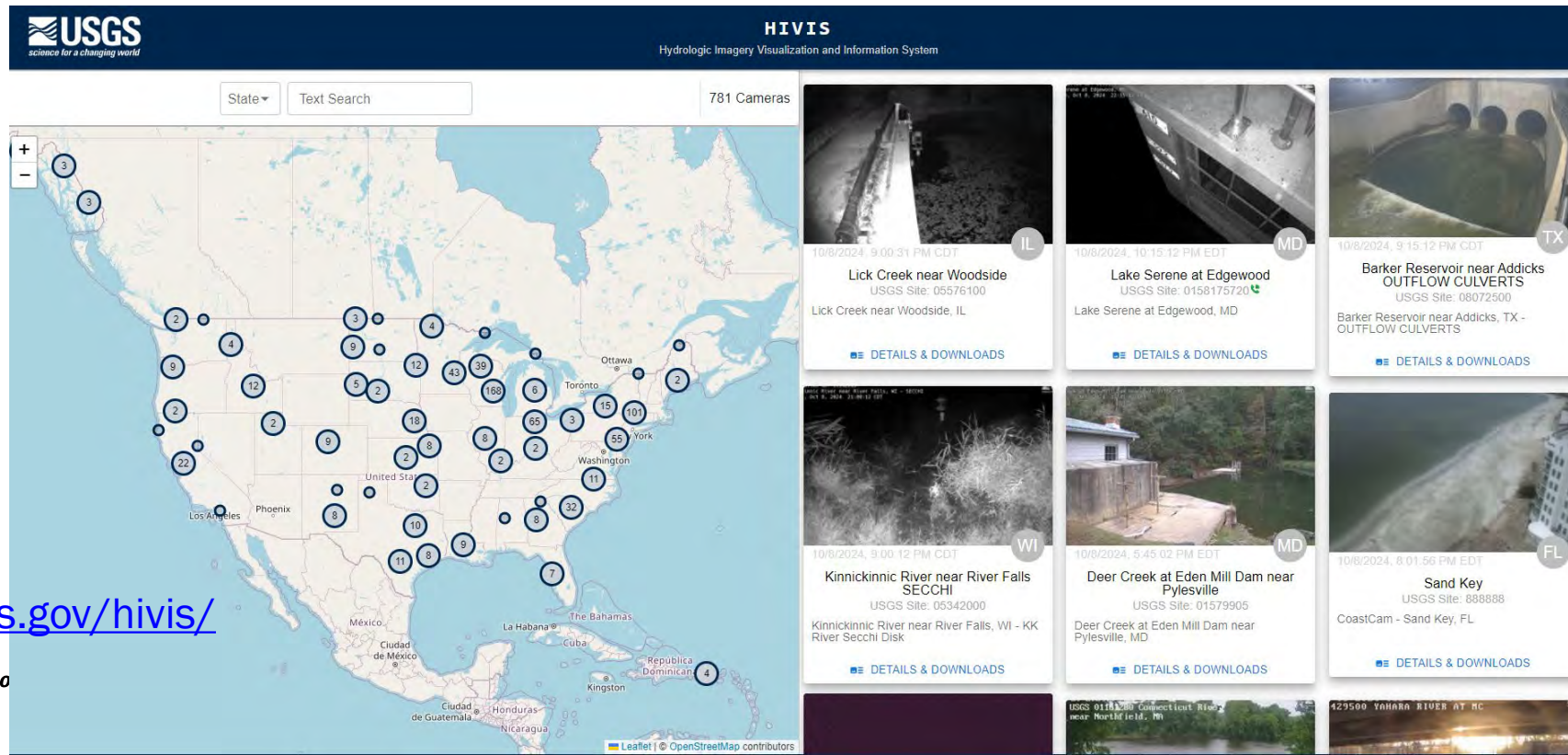
Mahmoud Ayyad

Research Assistant Professor

Email: mayyad@stevens.edu

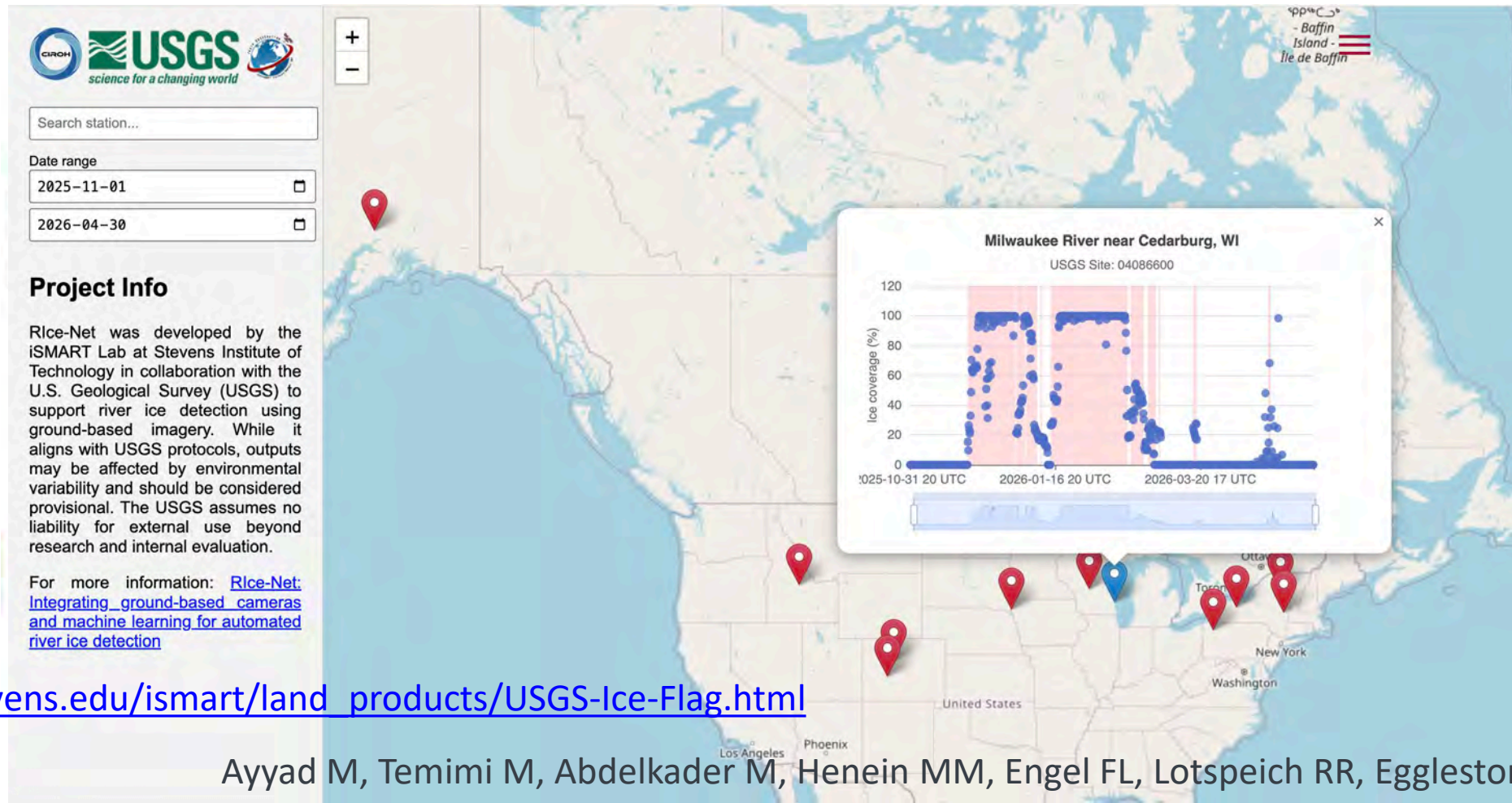
ML4 river monitoring: AI and computer vision to leverage ground-based cameras

- Develop a computer vision-based system to automatically measure streamflow and water level and determine river flow conditions by leveraging the USGS National Imagery Management System (NIMS) and served through the Hydrologic Imagery Visualization and Information System (HIVIS).



<https://apps.usgs.gov/hivis/>

ML4 river monitoring: AI and computer vision to leverage ground-based cameras



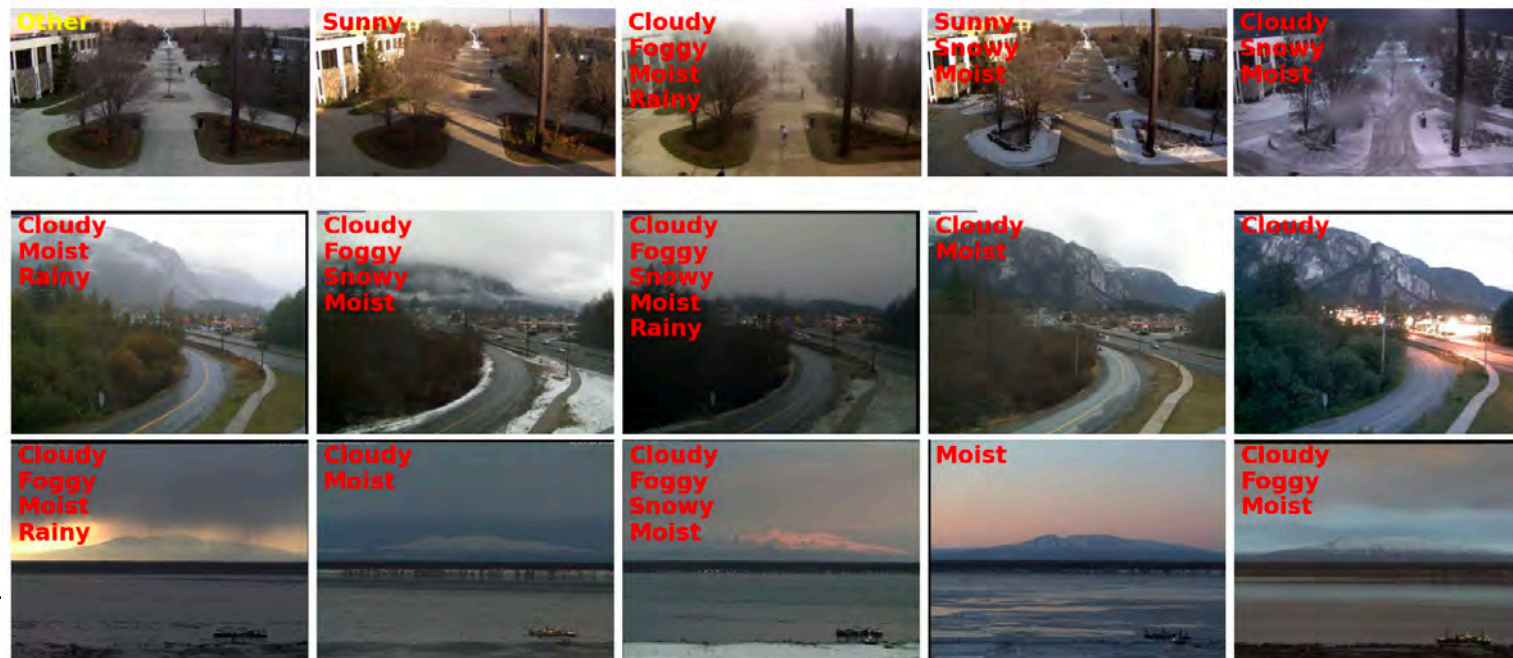
https://web.stevens.edu/ismart/land_products/USGS-Ice-Flag.html

Ayyad M, Temimi M, Abdelkader M, Henein MM, Engel FL, Lotspeich RR, Eggleston JR. Rice-Net: Integrating ground-based cameras and machine learning for automated river ice detection. Environmental Modelling & Software. 2025 May 30;190:106454.



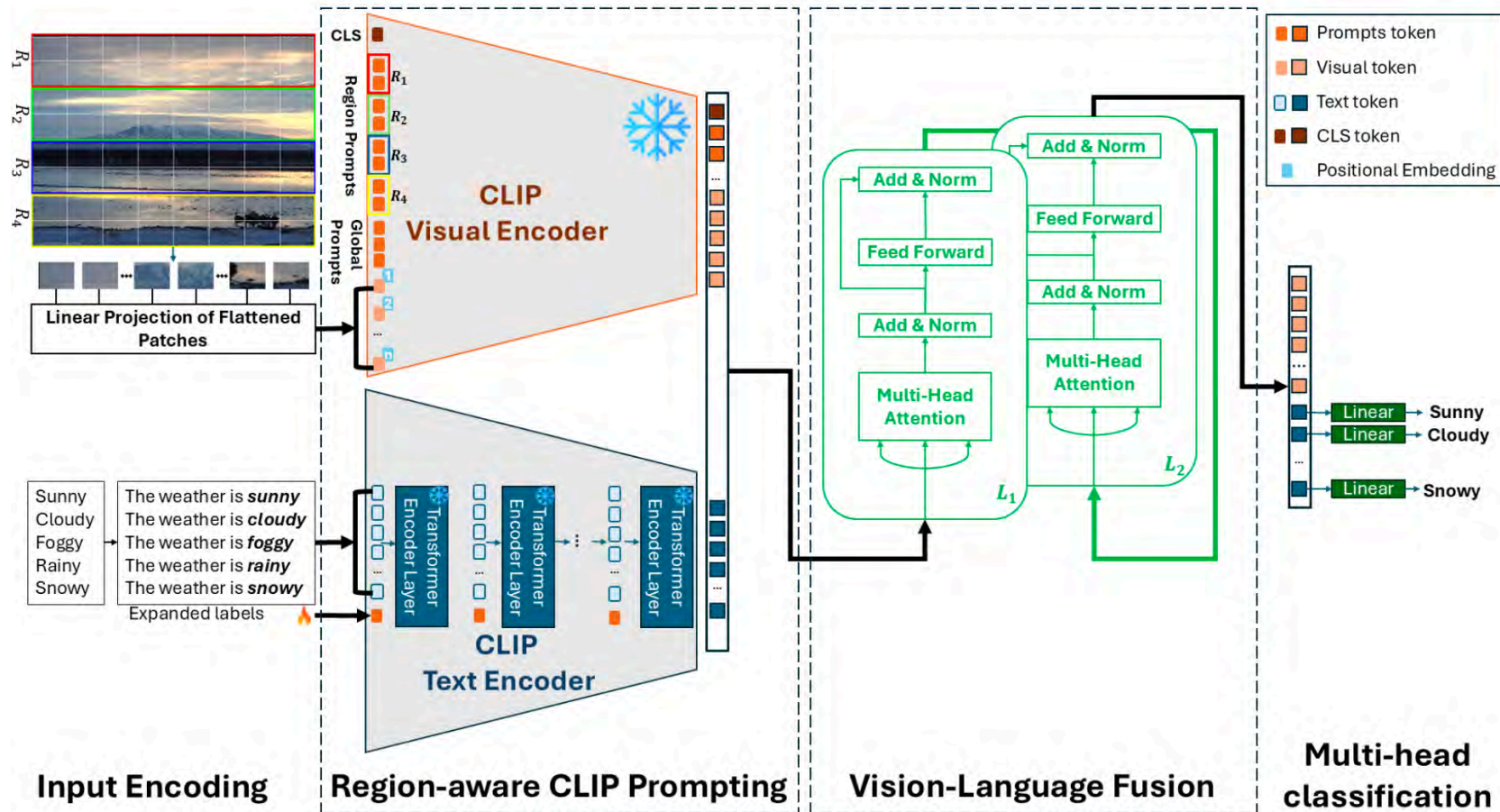
ML4 river monitoring : AI and computer vision to leverage ground-based cameras

- The performance of the Rice-Net is negatively impacted by environmental factors such as haziness, rain drops, sun reflections, and shadows.
- Provide a QA for images captured through NIMS.
- Develop a framework to preprocess HIVIS images and reduce environmental degradation.



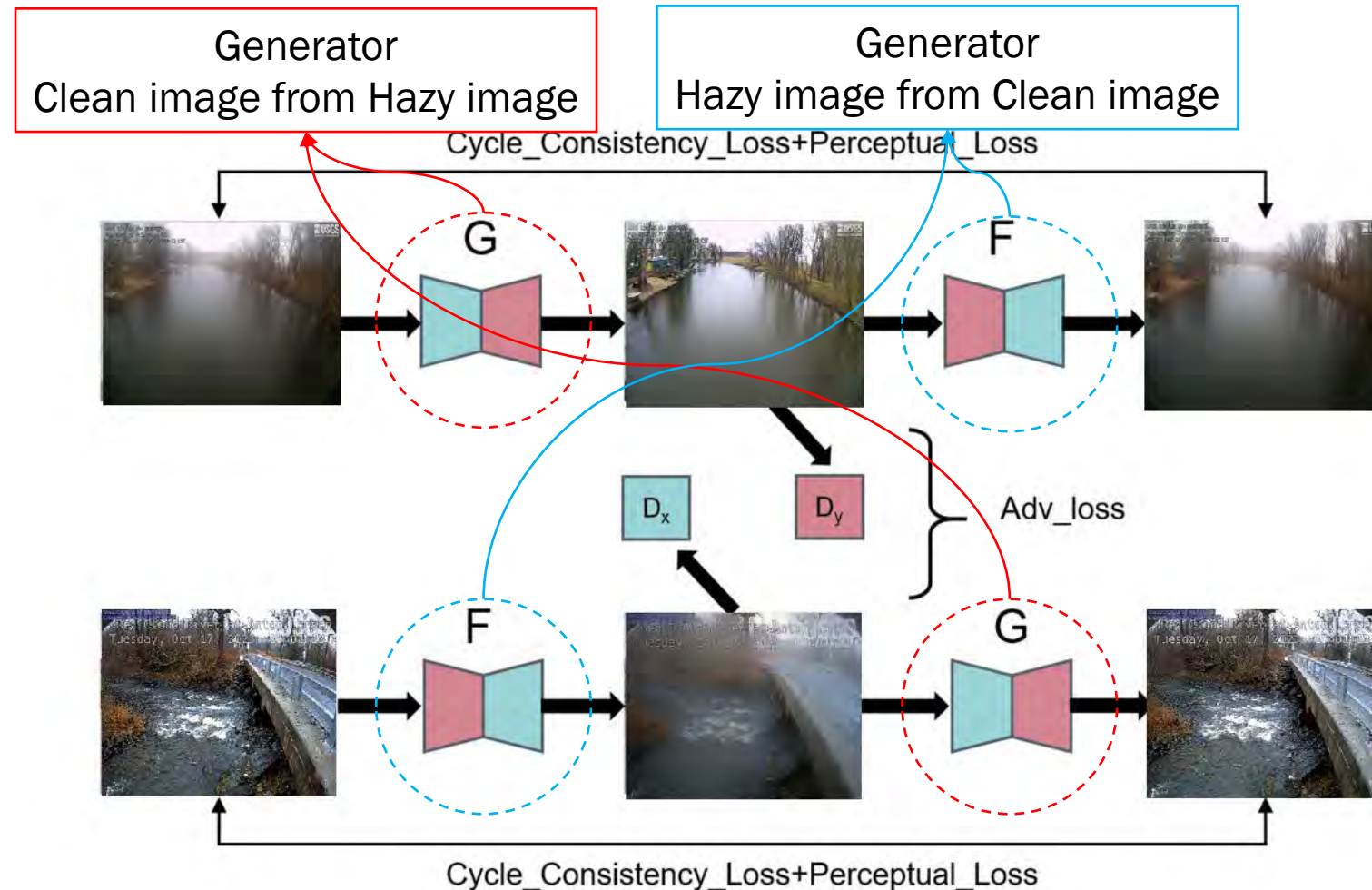
ML4 river monitoring : AI and computer vision to leverage ground-based cameras

CLIMAT: CLIP-based model for multi-label weather recognition

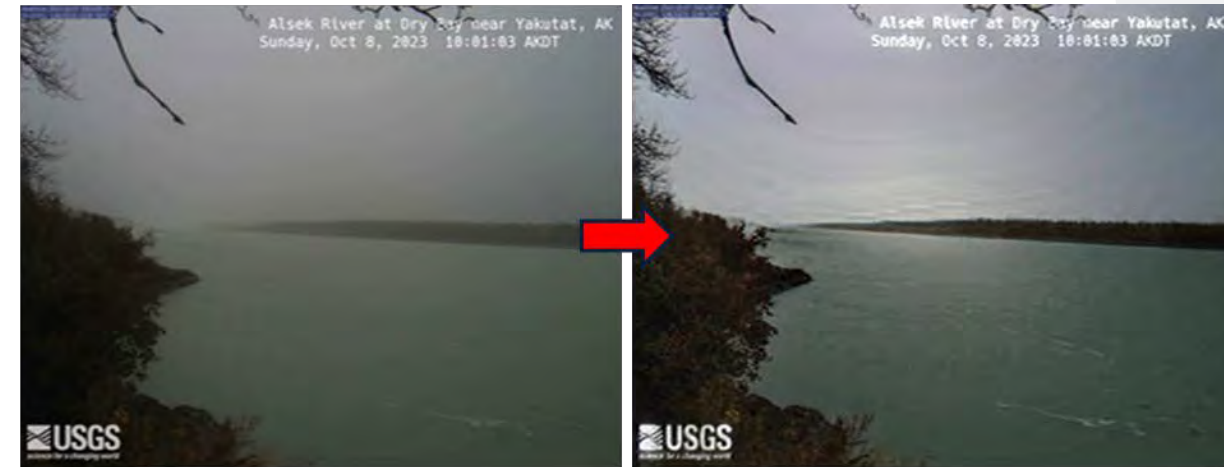


ML4 river monitoring : AI and computer vision to leverage ground-based cameras

Dehazing



ML4 river monitoring: AI and computer vision to leverage ground-based cameras

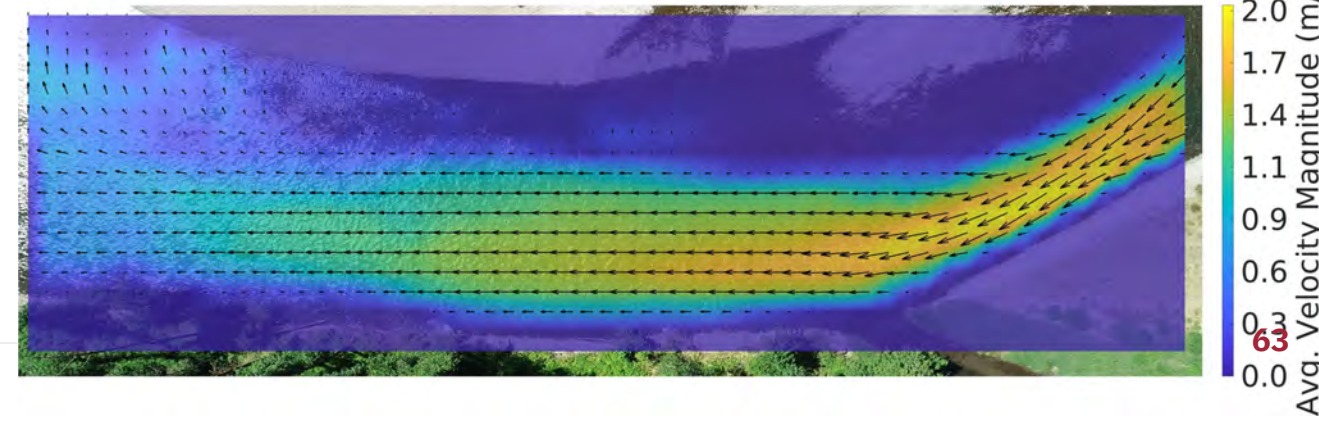
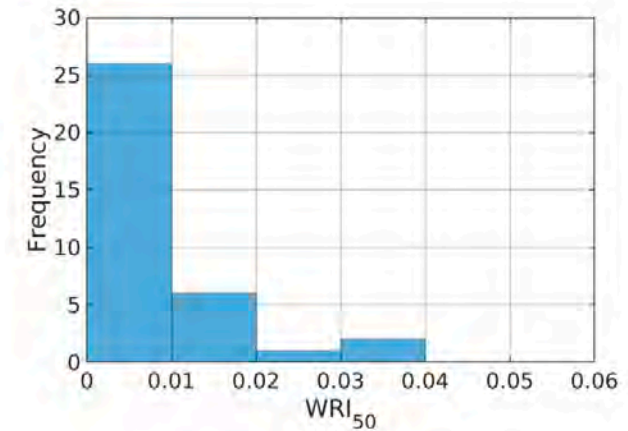
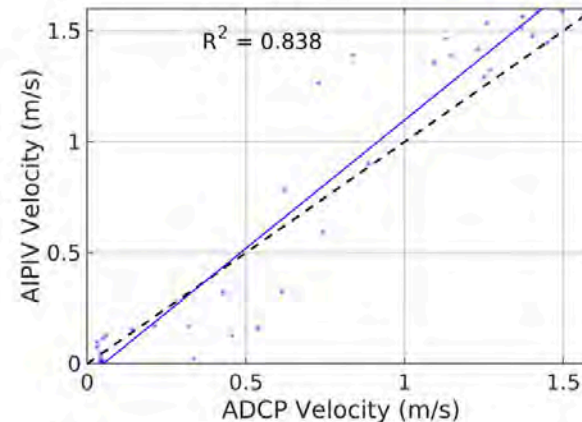
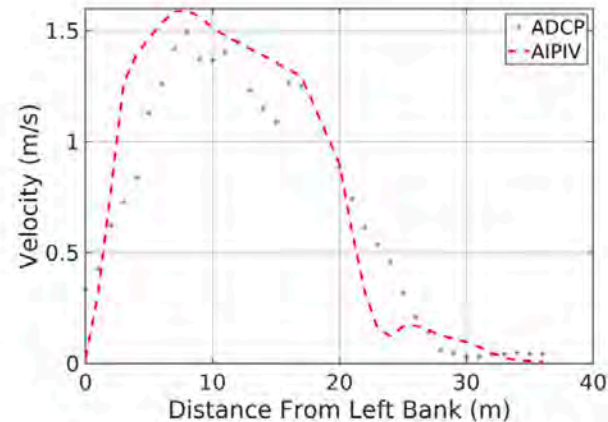


ML4 river monitoring: AI and computer vision to leverage ground-based cameras

- AIPIV: Develop a data-driven-based method to continuously monitoring the surface velocity field using videos

ML4 river monitoring: AI and computer vision to leverage ground-based cameras

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ML4 river monitoring: AI and computer vision to leverage ground-based cameras

- AIPIV: Develop a data-driven-based method to continuously monitoring the surface velocity field using videos

River Name	Algorithm	RMSE (m/s) ↓			MAPE (%) ↓		
Murg	PIV (Tlhomole et al., 2025)	0.14			16.07		
	PTV (Tlhomole et al., 2025)	0.15			16.47		
	HS (Tlhomole et al., 2025)	0.34			41.60		
	UnLiteFlowNet-PIV (Tlhomole et al., 2025)	0.36			44.88		
	RAFT (Tlhomole et al., 2025)	0.27			30.53		
	Physics-Informed (Tlhomole et al., 2025)	0.46			58.29		
	AIPIV (Ours)	0.11			13.11		
		R ² ↑	N-RMSE ↓	N-MB ↓	WRI ₅₀ ↓	WMI ₅₀ ↓	CMRI ₅₀ ↓
Androscoggin	2D-STIV exhaustive (Legleiter et al., 2024)	0.864	0.247	0.289	0.0006	0.1927	0.0981
	2D-STIV optimization (Legleiter et al., 2024)	0.774	0.195	0.290	0.0007	0.1821	0.0927
	Per-frame pair PIV (Legleiter et al., 2024)	0.505	0.150	0.333	0.0011	0.1494	0.0773
	Ensemble PIV (Legleiter et al., 2024)	0.866	0.240	0.275	0.0005	0.1846	0.0933
	AIPIV (Ours)	0.623	0.216	0.0055	0.0058	0.137	0.0728
North Santiam	2D-STIV exhaustive (Legleiter et al., 2024)	0.029	0.842	1.146	0.0089	0.3209	0.1618
	2D-STIV optimization (Legleiter et al., 2024)	0.755	0.516	0.641	0.0345	0.3839	0.2426
	Per-frame pair PIV (Legleiter et al., 2024)	0.730	0.325	0.491	0.0054	0.3472	0.1782
	Ensemble PIV (Legleiter et al., 2024)	0.781	0.491	0.699	0.0041	0.4714	0.2375
	AIPIV (Ours)	0.838	0.309	0.072	0.0015	0.1713	0.0862

Conclusions

- **Big Data Challenge** already here. ML allows us to address this challenge and leverage the huge amount of data available for us.
- **AI/ML approach is an evolution of how to exploit and process data (Fortran -> Python -> TensorFlow->..) to better emulate processes**
- **In some cases, AI is to complement or enhance, not necessarily fully replace (case of combining Physics-modeling and AI-based correction)**
- **Two major drivers will continue to make AI attractive in our field: (1) Significantly increased efficiency (therefore driving down cost) and enhancement of skills (accounting for unknown or difficult to model phenomena, etc present in the data)**
- **AI is a transformative technology for Environmental data processing & exploitation AND in NWP. In particular for Satellite and other high-volume data**





CIROH

Cooperative Institute for Research
to Operations in Hydrology



FEMA



WESTWOOD
NEW JERSEY





THANK YOU

Marouane Temimi

Professor and Associate Dean for Research

Department of Civil, Environmental, and Ocean Engineering (CEOE)

Stevens Institute of Technology

Email: mtemimi@stevens.edu

Web site: <https://web.stevens.edu/ismart/>

