Regional & Global Model Analysis

Novel Approaches with AI/ML in Flood Modeling

Coastal and Urban Flooding: Integrated Data-Driven Modeling with AI/ML to Address the Grand Challenge

Shuyi S. Chen and Brandon Kerns
Department of Atmospheric Sciences
University of Washington

Brandon Kerns

Alton Daley

Chad Small

Flooding – A Grand Challenge Requires Integrated Interdisciplinary Research

Warming Climate
Sea Level Rise

Heavy Rainfall (Atmosphere)

Storm Surge (Ocean)

Flooding

River-Streamflow (Hydrology)

Built Environment (Engineering)

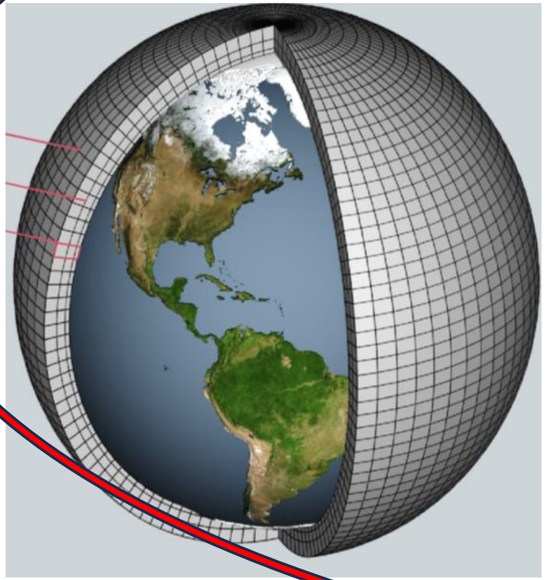
Challenges: High-resolution full physics models are computational expensive, data volume, etc.

Ways forward: New ways of downscaling: Global Earth system models -->AI/ML --> Regional coupled atmosphere-wave-ocean-land models --> AI/ML --> Flooding

Phase II – large-scale drivers of extremes (Mosaic4E)

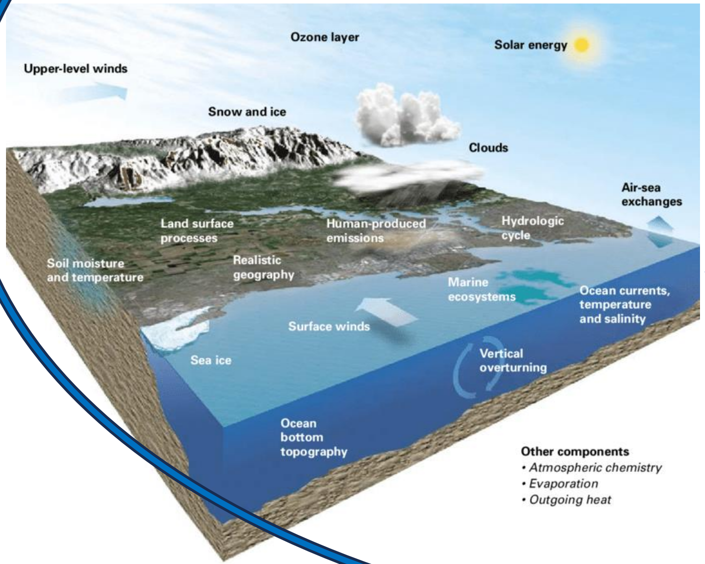
Phase I

Global large-scale circulation features that are most relevant: MJO, ITCZ, Jetstream, ARs, etc.



AI/ML

Regional, coastal high-res coupled atmos-wave-ocean model (UWIN-CM) and obs



AI/ML

Coastal-urban flooding, ultra-high-res hydro- and storm surge models

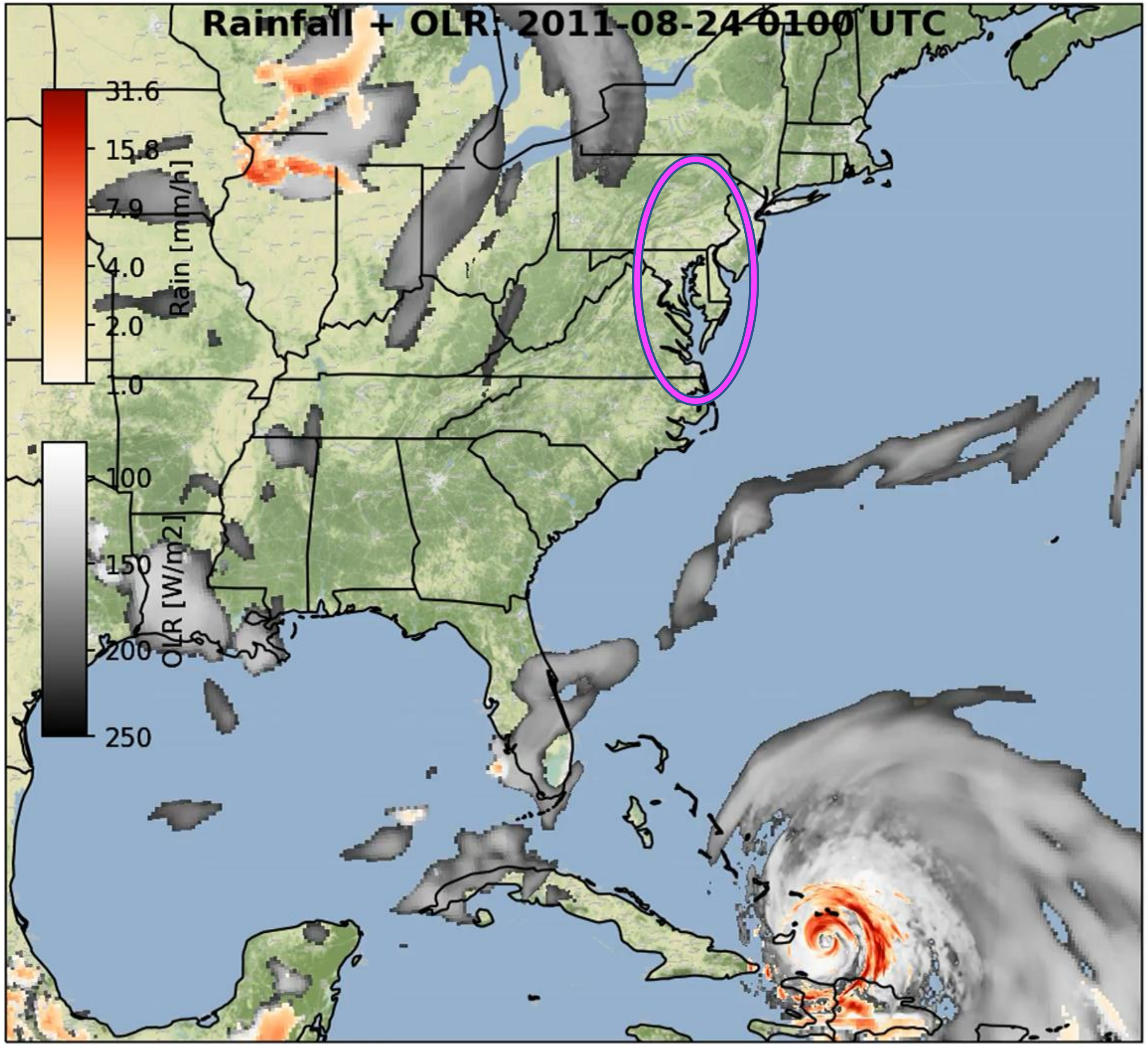
Major Flooding: Aug 24-Sep 12, 2011

Three TCs:

- Hurricane **Irene** (2011, 08/24-29)
- Hurricane **Katia** (2011, 8/29-9/10)
- Tropical Storm **Lee** (2011, 09/2-12)

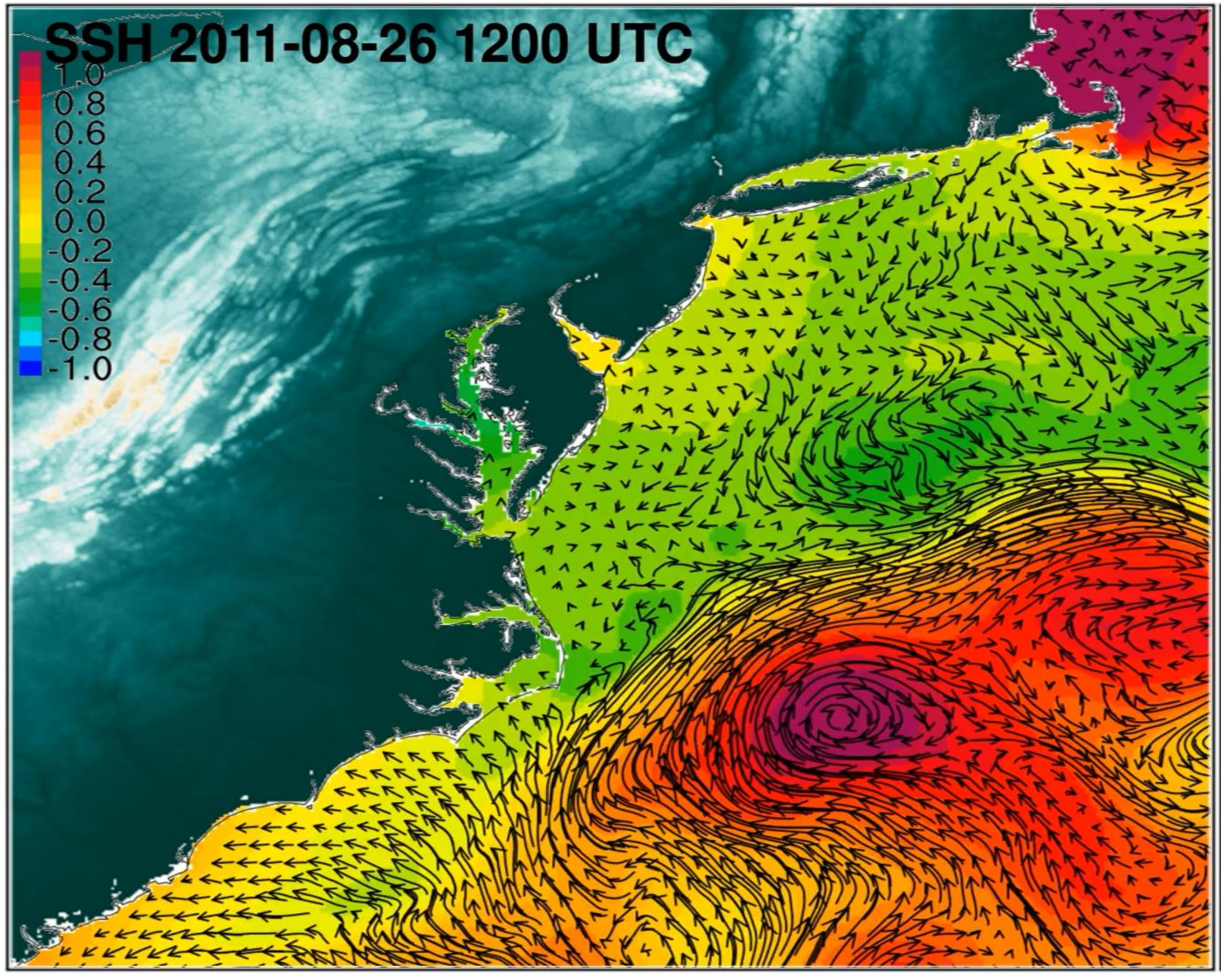
UWIN-CM –coupled atmos-wave-ocean model (Chen et al. 2013, Chen & Curcic 2016)

- Weather Research and Forecasting (WRF):
  1.3/4/12 km horizontal resolution 45 vertical levels,
- University of Miami Wave Model (UMWM):
  4 km horizontal resolution, 36 directional bins and 37 frequency bins from 0.0313 – 2.0 Hz
- HYbrid Coordinate Ocean Model (HYCOM):
  1/25 deg (~4 km) horizontal resolution, 41 vertical levels;

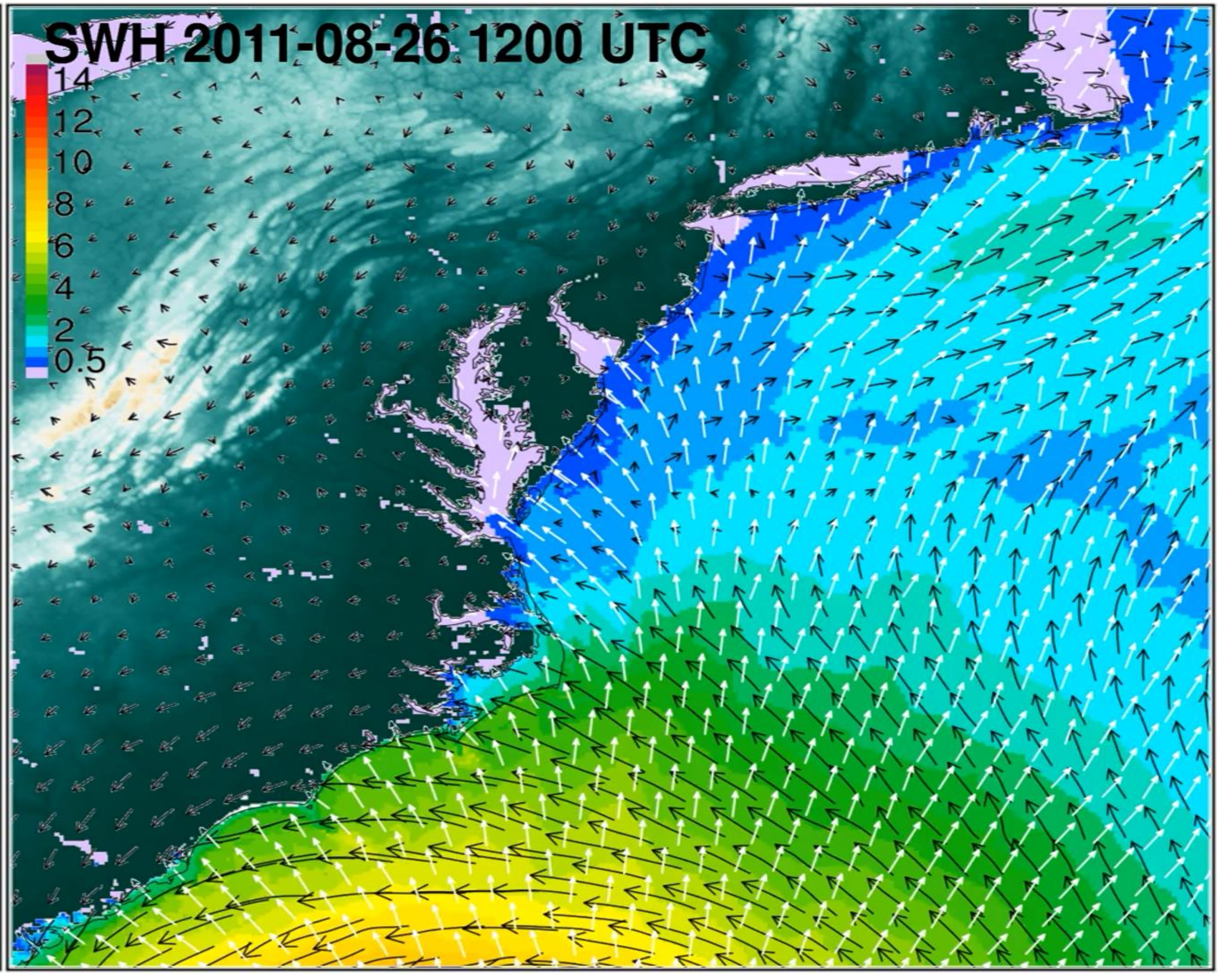


UWIN-CM Simulations of Hurricane Irene

Sea Surface Height Anomaly



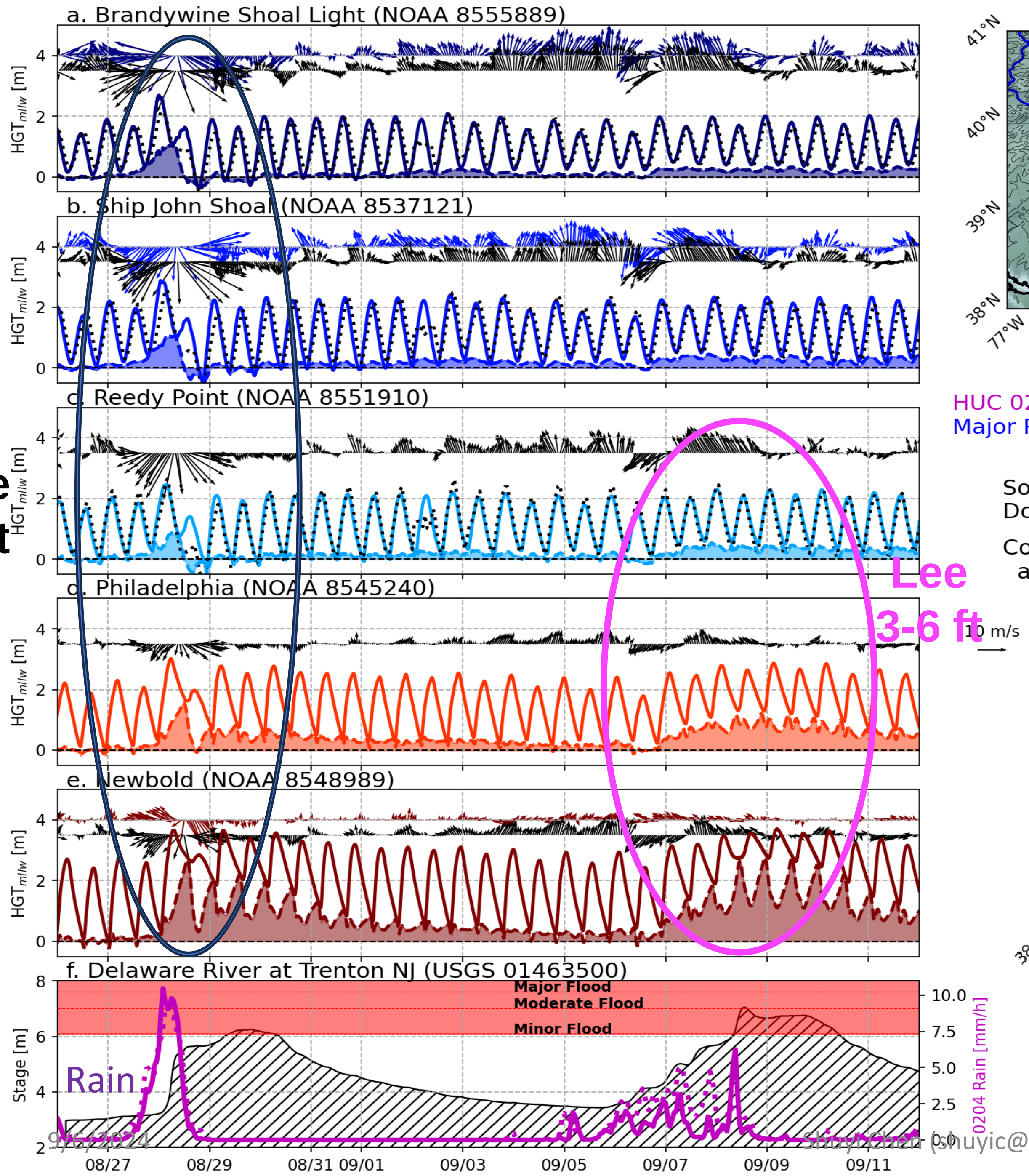
Significant Wave Height and Wind

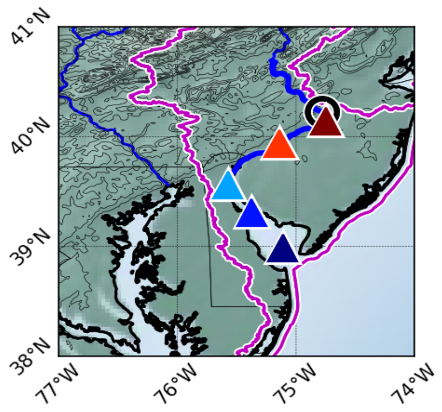


Kerns and Chen (2023a *Natural Hazards*)

- UWIN-CM simulated and observed wind, rain, water level (tides and flood stage data)

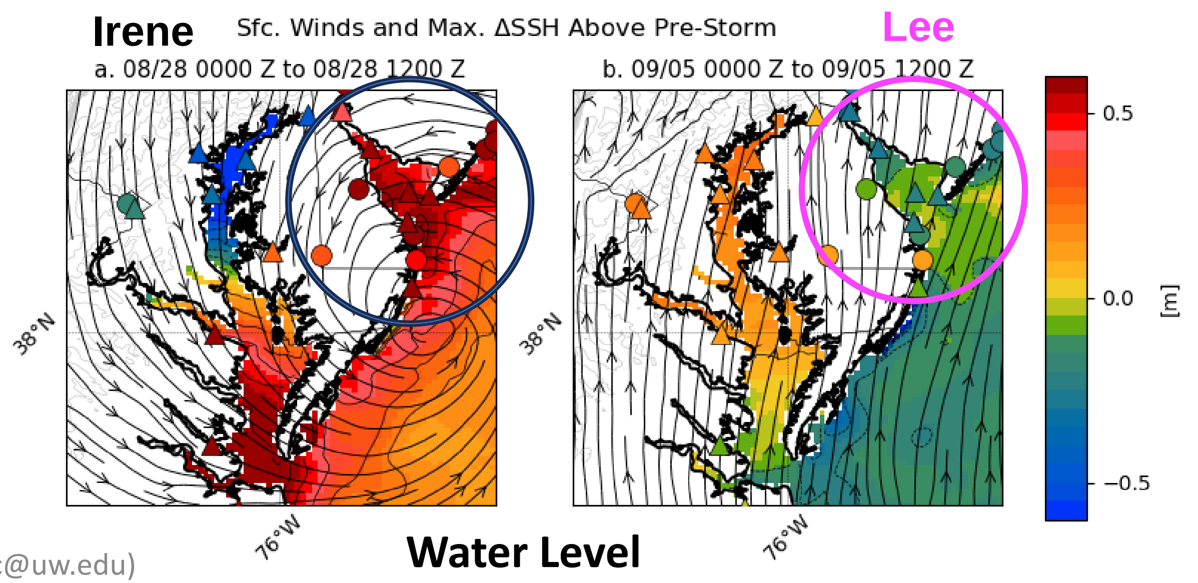
Irene
3-6 ft

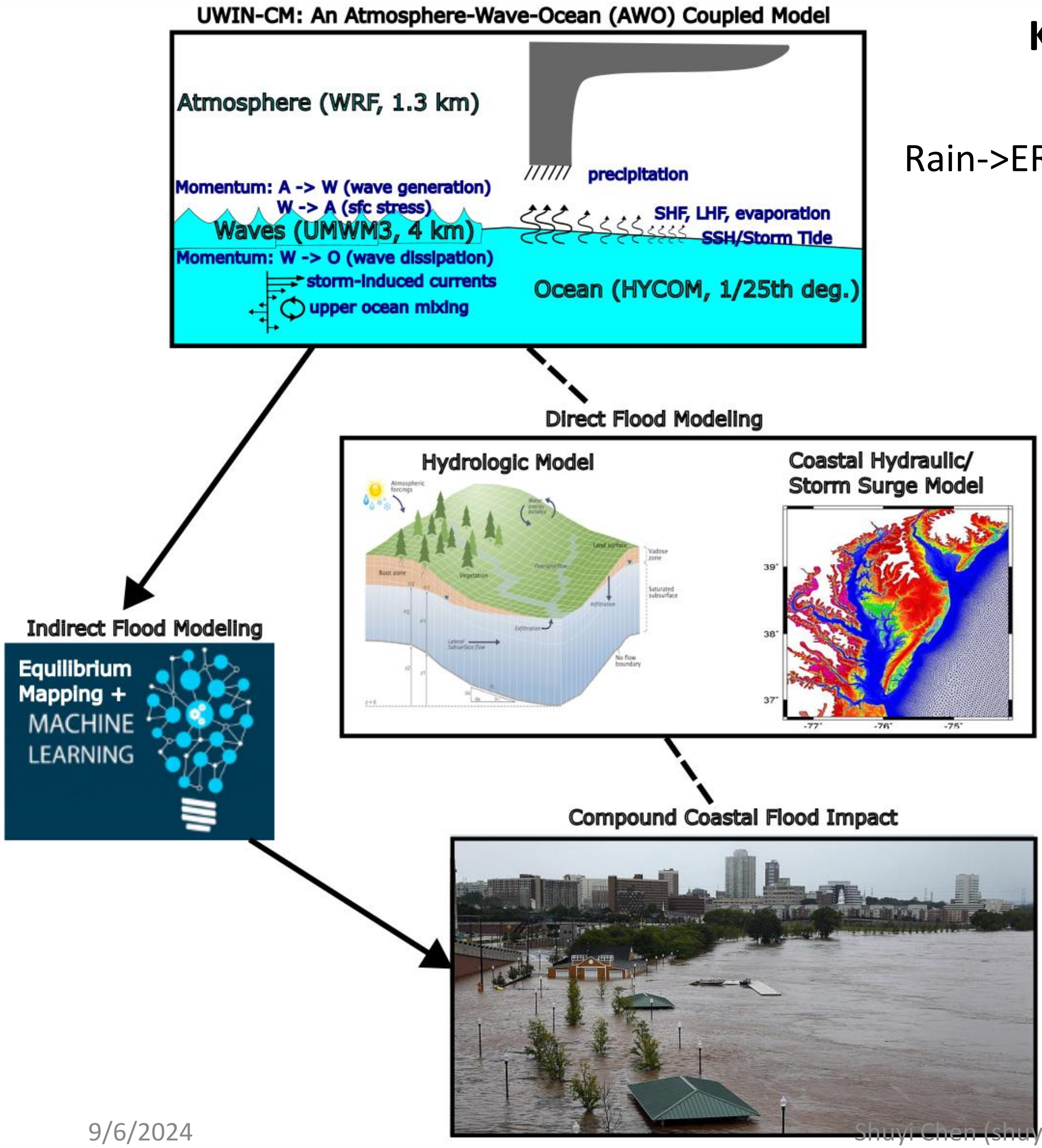




Solid, colored = Obs.
Dotted, black = UWIN-CM

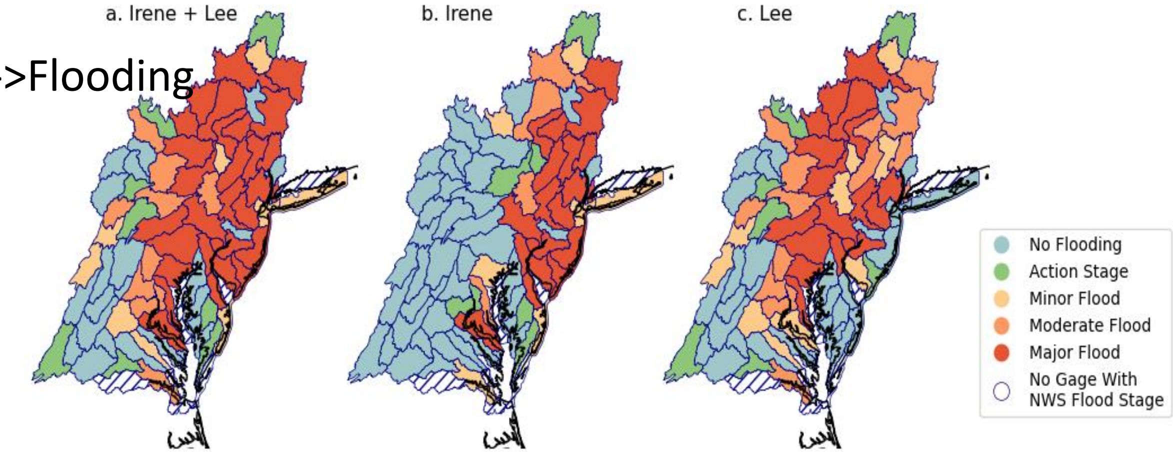
Color shading = Obs. HGT above/below astronomical.



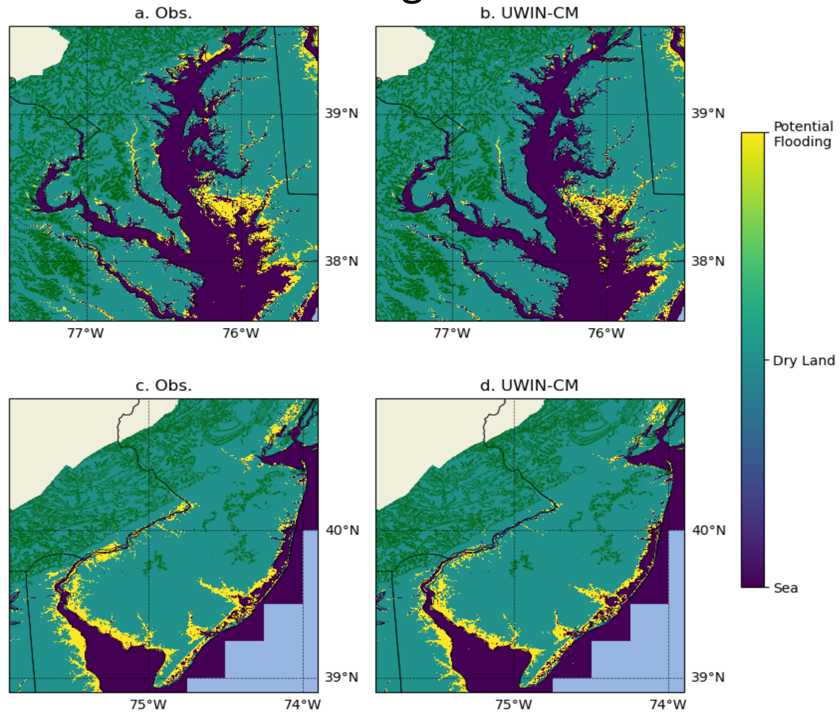


Kerns and Chen (2023a, *Natural Hazards*; 2023b, *WAF*)

Rain->ERM->Flooding



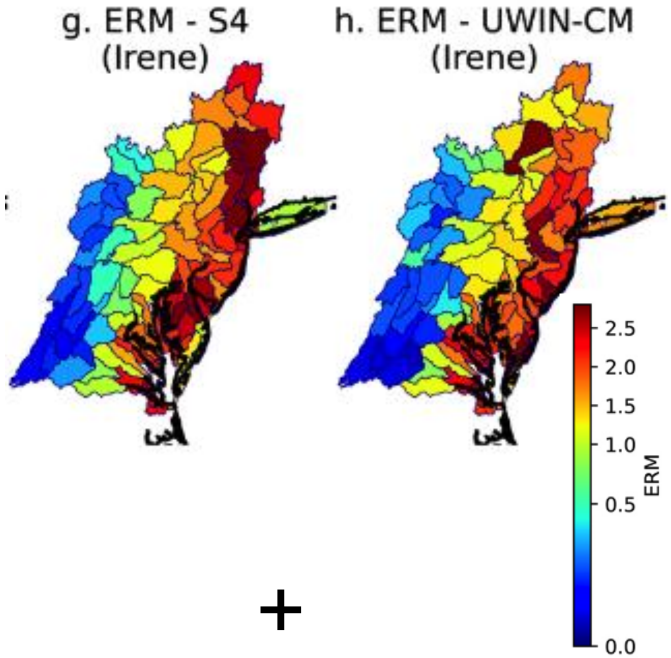
Rain + SSH -> local flooding



Input Layer

Extreme Rain Multiplier (ERM)

Precip Input from:
- Observations (Stage IV)
- Model (UWIN-CM)



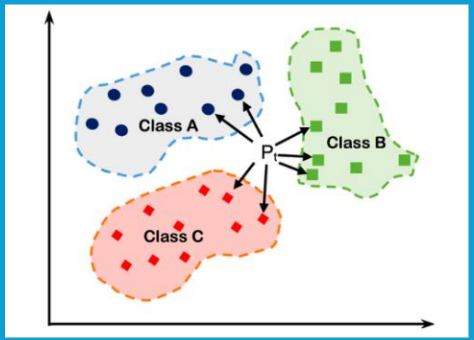
+

- (Day –1) Flood Stage Data
- (Day–1) ERM

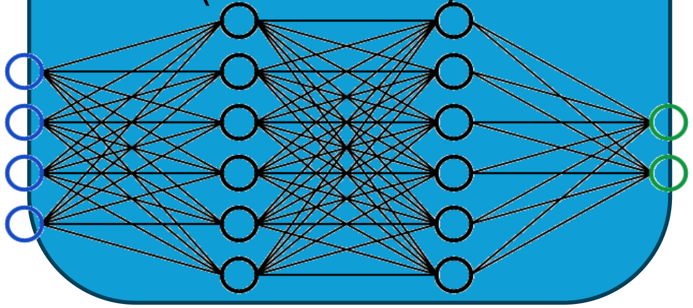
Machine Learning Models

Preprocess

K Nearest Neighbors
(Kerns and Chen (2023, WAF)



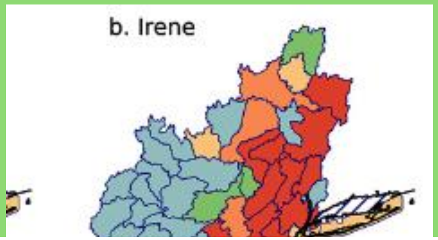
Neural Network
(future work)

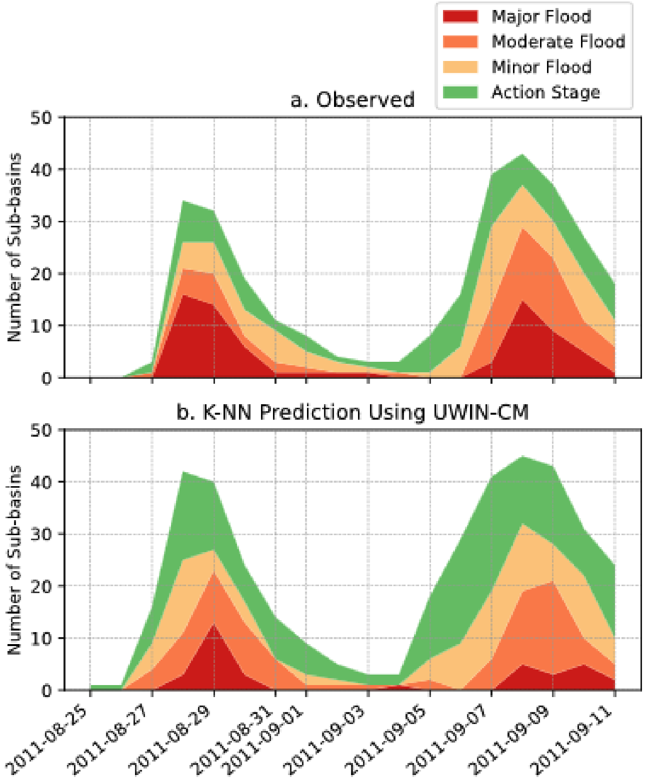


Train and Predict

Output Layer

Prediction:
- Today's flooding
  - NWS Flood Stage
  - Global Database





ICoM Phase I Research and Transition to Phase II

Phase I. High-resolution coupled atmosphere-wave-ocean modeling and observational data analysis for coastal-inland flooding from TCs

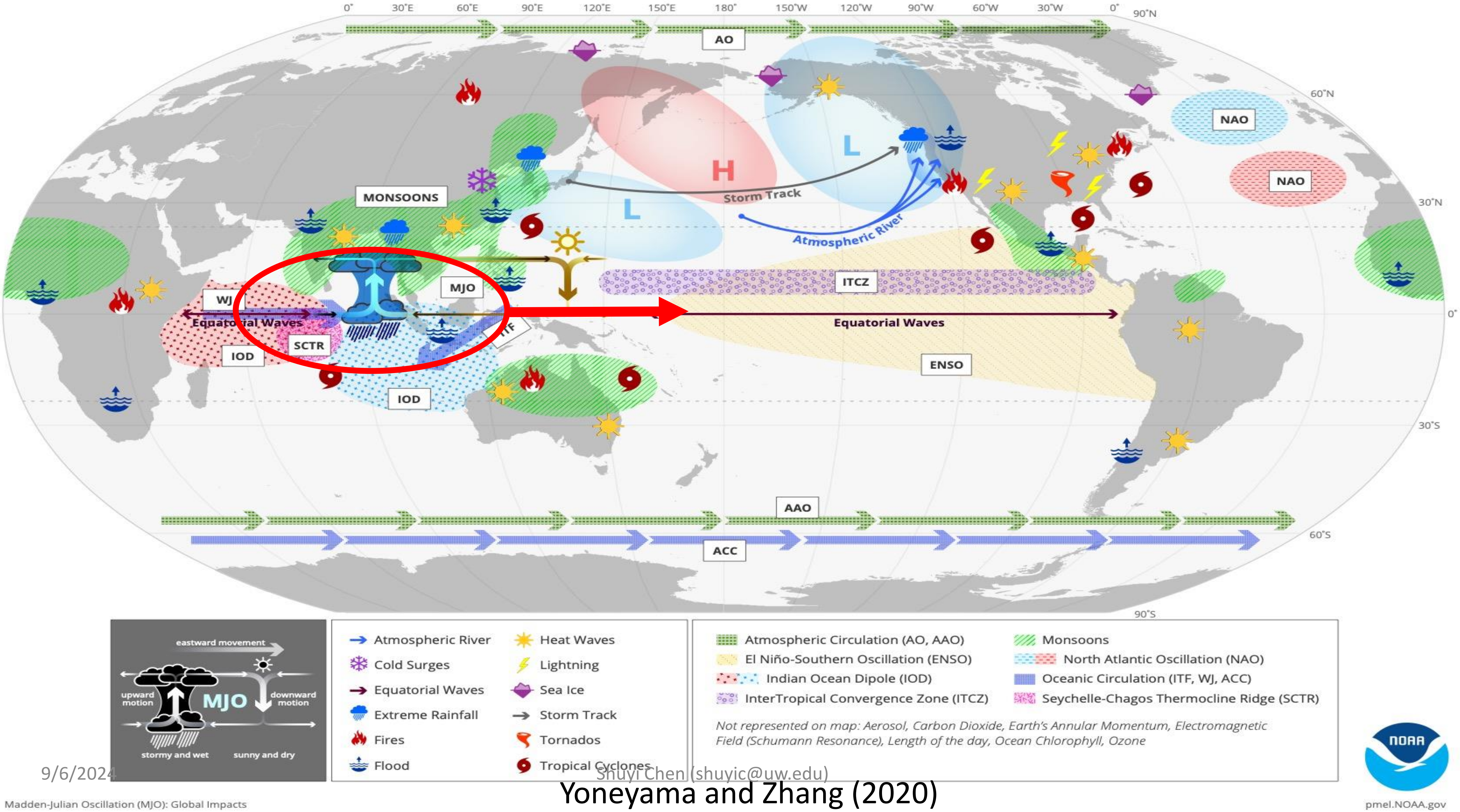
- Kerns and Chen (2022, *Natural Hazards*)
- Kerns and Chen (2023, *WAF*)
- Mazza and Chen (2023a, *JGR*)
- Mazza and Chen (2023b, *J. Hydrometeor.*)

Phase II. Multiscale Objects-Tracking and AI Climate Modeling for Extremes (Mosaic4E)

- **Extreme events often occur at the interface of multiscale phenomena over a wide range of spatial and time scales (minutes to decades, meters to global)**
- **How best define extreme rainfall and flooding risk (and other extremes)**
- **Using AI/ML to better understand and predict extremes – bridging/filling gaps**

Shuyi Chen (shuyic@uw.edu)

MADDEN-JULIAN OSCILLATION (MJO): GLOBAL IMPACTS

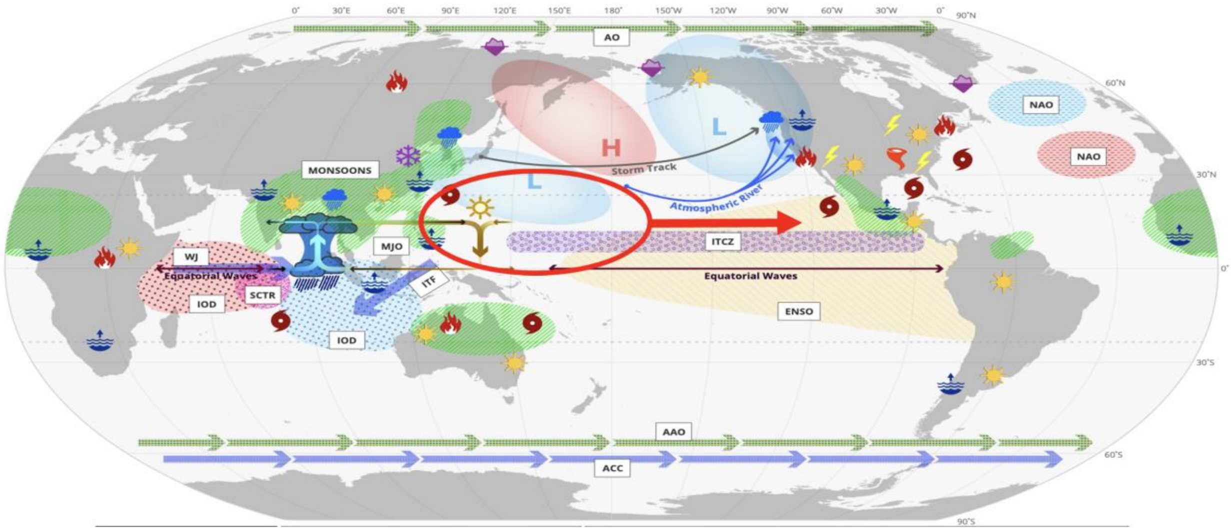


Yoneyama and Zhang (2020)

<u>Takeaway Points</u>:

- **High-resolution fully coupled atmosphere-wave-ocean-land model with ML can be used effectively for flood risk forecast**
- **Multiscale drivers are important for extreme events, not only local/regional players but also teleconnections of global systems from subseasonal (e.g., MJO), seasonal (e.g., ITCZ, monsoon), to longer time scales (e.g., ENSO, NAO, PDO)**
- **Mosaic4E will be further developed with AI/ML to provide a new capability for better understanding and predict extreme events (e.g., floods, heatwaves, drought, etc.)**

MADDEN-JULIAN OSCILLATION (MJO): GLOBAL IMPACTS



Shuyi Chen (shuyic@uw.edu)

Extra slide

ERM (Extreme Rainfall Multiplier) - A linear multiplier of a location dependent typical heavy rainfall threshold (i.e. the median of the maximum daily rainfall each year.) A "typical" heavy rain event is considered to be the environment that is relatively well adapted to (**Bosma et al. 2020, BAMS**)

$$\mathrm{ERM}_{s,x,t} = \frac{R_{s,x,t}}{R_{x,t}^{T\text{-yr}}}.$$

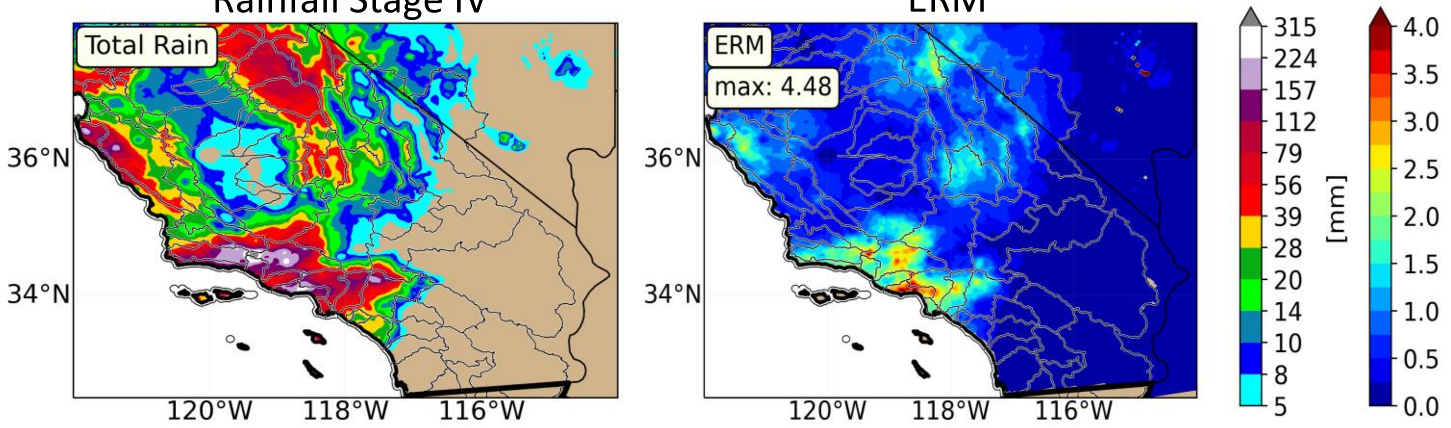
(Median Annual Daily Max)

ERM and flood potential (Bosma et al. 2020, Kerns and Chen 2022, Mazza and Chen 2023):

- **ERM > 1.5: Flooding**
- **ERM > 3.0: Significant flooding**
- **ERM > 5.0: Extreme flooding, e.g. Hurricane Harvey (2017), Florence (2018)**

1,000 Year Flood LA County, CA (Feb 5, 2024)

Rainfall Stage IV ERM

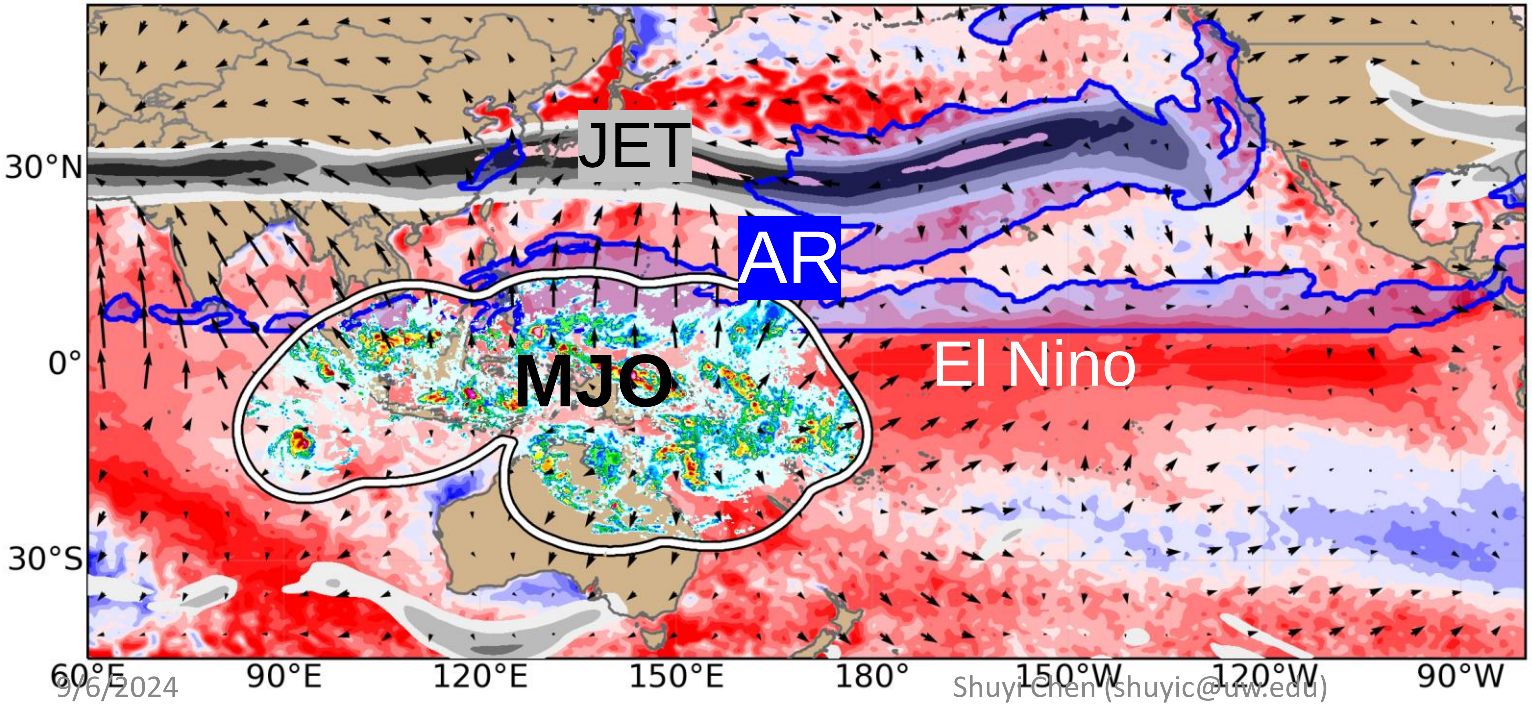


Flooding

Kyle Grillot / The Washington Post

Marcio Jose Sanchez / Associated Press

Key Players: El Nino, MJO, Jet, and Atmospheric River 1/20/24

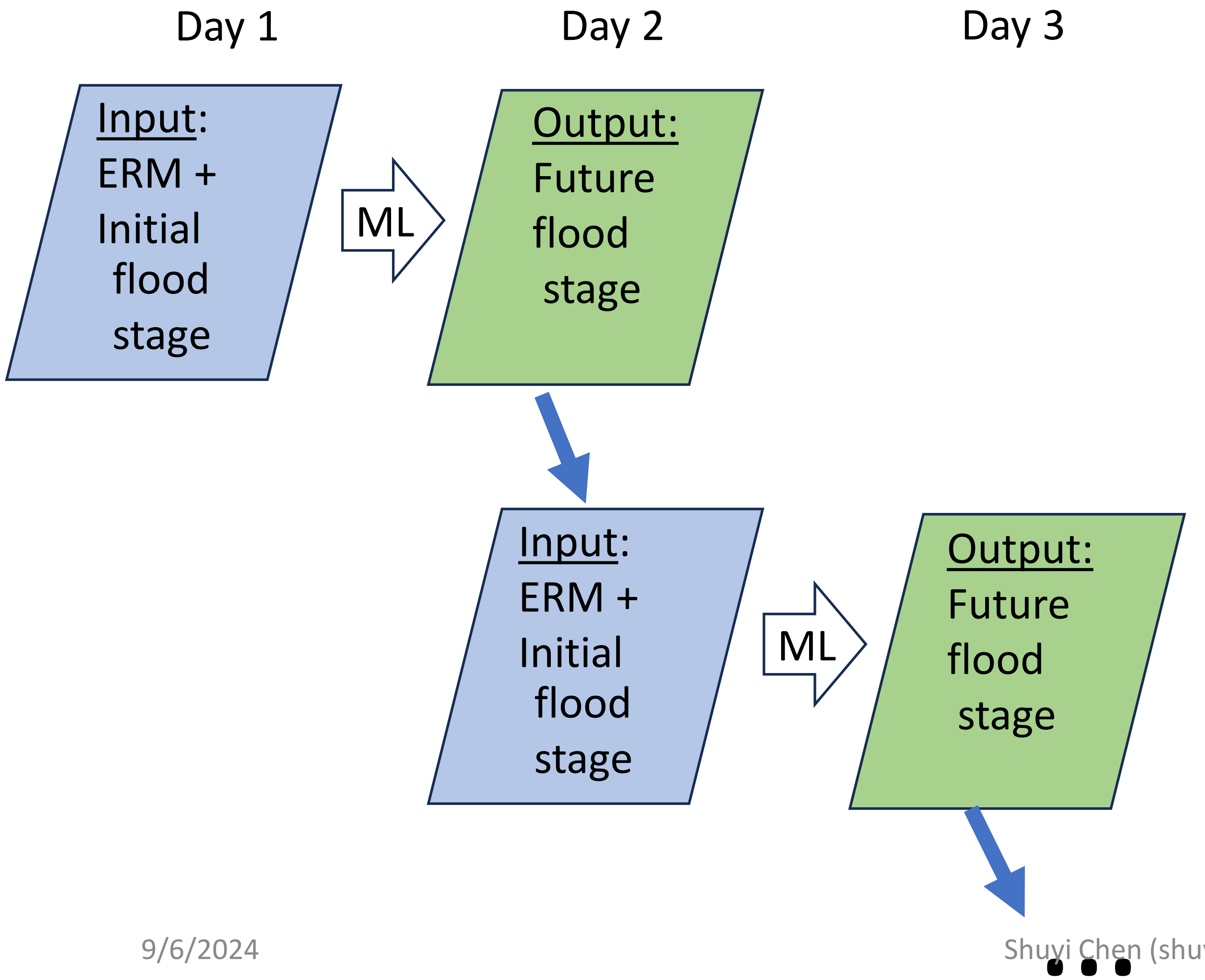


Mazza, Chen, Kerns (2024)

Deployment Schemes for ERM – Flooding ML Models

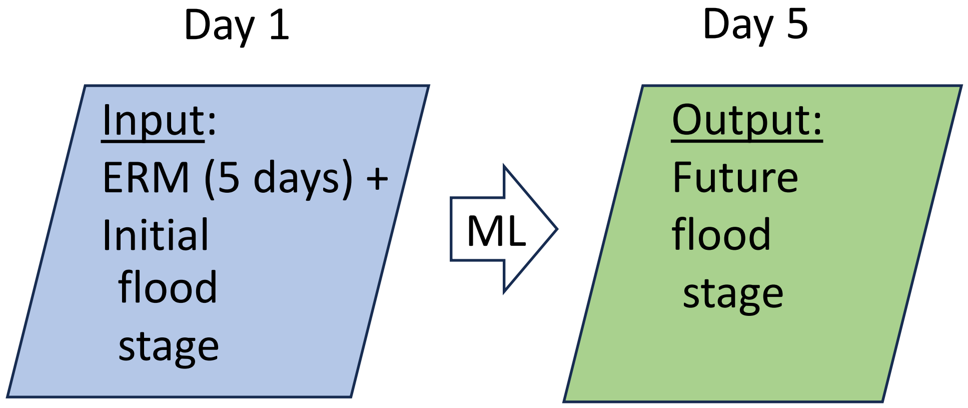
Sequentially day by day:

- Train ML model for 1 day lead time
- The output of one day is the input for the next day



Train ML model specific to the lead time

- A separate ML model trained for each lead time
- Can ingest a time series of ERM
- Potentially can predict a time series of flooding



Shuyi Chen (shuyic@uw.edu)