Port Arthur (TX, USA) after Hurricane Harvey (Source: Air National Guard 2017)

Compound hazards in coastal urban systems: Interactions, impacts, and adaptation

Paola Passalacqua

ETH Zürich & Eawag

U.S. DEPARTMENT OF ENERGY

TEXAS The University of Texas at Austin

eawag aquatic research

ETH zürich

Dedication

This lecture is dedicated to the memory of

Tobias Houghton

PhD student (2024-2025)

who started his PhD on this research with curiosity, generosity, and promise.

Research contributions and collaborations

Key contributors (featured in this lecture):

Rishika Ananthula (PhD student)

Mark Wang (PhD student)

Dr. Matthew Preisser (Post-doc)

With contributions from:

The SETx-UIFL research team, including faculty, students, and collaborators from partner institutions, local governments, industry, and community organizations.

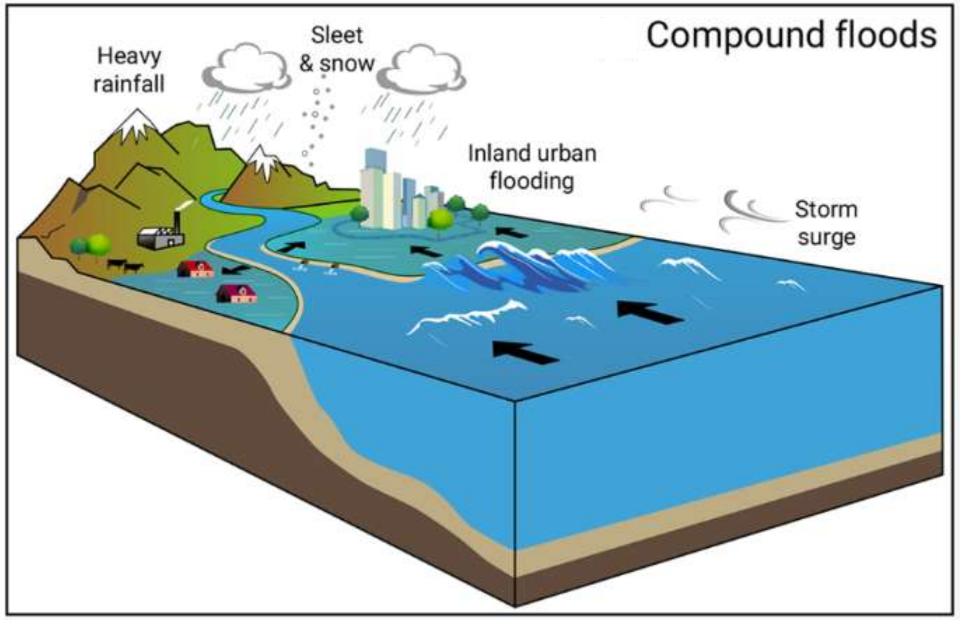
Coastal communities face a growing convergence of acute and chronic stressors

Beaumont after Hurricane Harvey (Source: Air National Guard 2017)

Cooling center in Texas (Source: ktsm.com/news)

Chronic: persistent, over many decades or centuries (e.g., extreme heat, air pollution, sea-level rise, subsidence, socio-economic-vulnerability)

Acute: during a flood event or few seasons (e.g., storms, air pollution incidents)



Green et al., Natural Hazards and Earth System Sciences, 2025

Beaumont after Hurricane Harvey (Source: Air National Guard 2017)

Context: The Southeast Texas Urban Integrated Field Laboratory

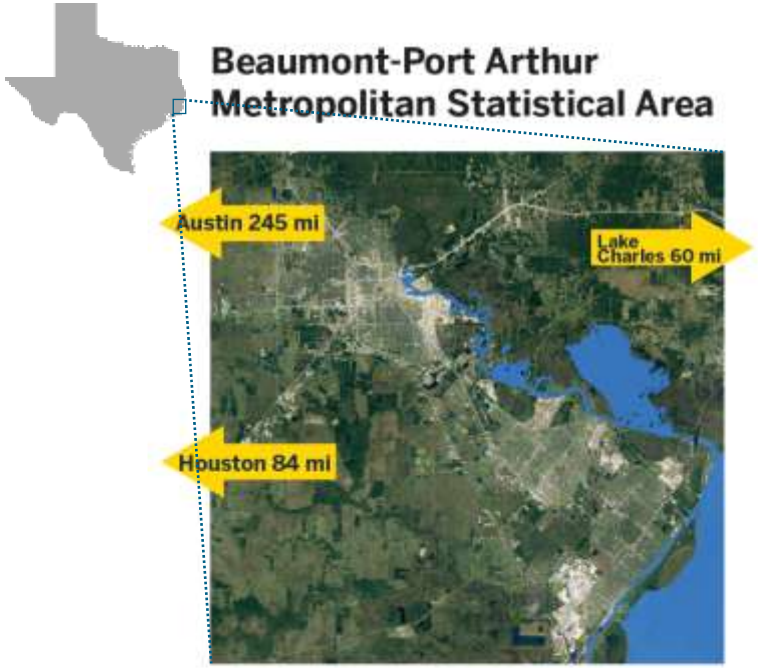
- Which processes and variables need to be captured in regional scale hydrological and atmospheric models so that they are representative of the conditions experienced by local communities and help inform adaptation strategies?
- How can we understand the linkages between and within natural, built, and social systems in urbanized regions to better support natural and human resilience?

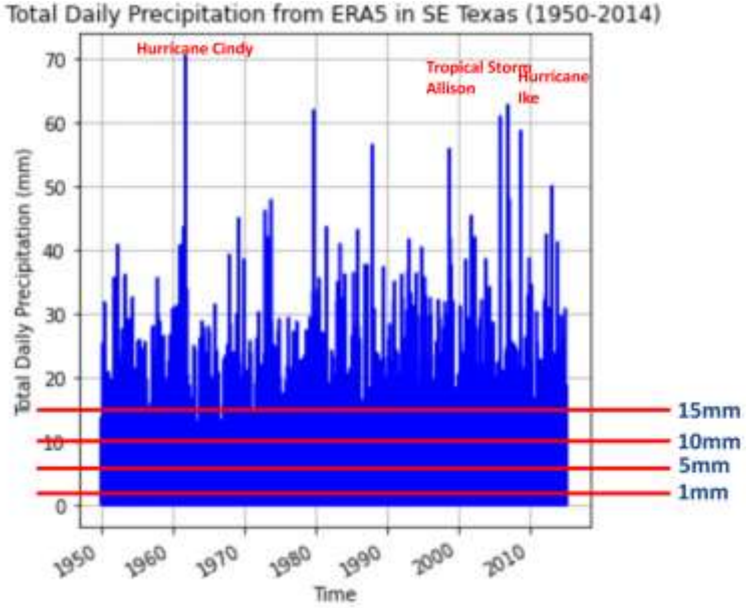
SETx: acute-on-chronic hazards impacting vulnerable communities

U.S. DEPARTMENT OF ENERGY

SETx URBAN IFL

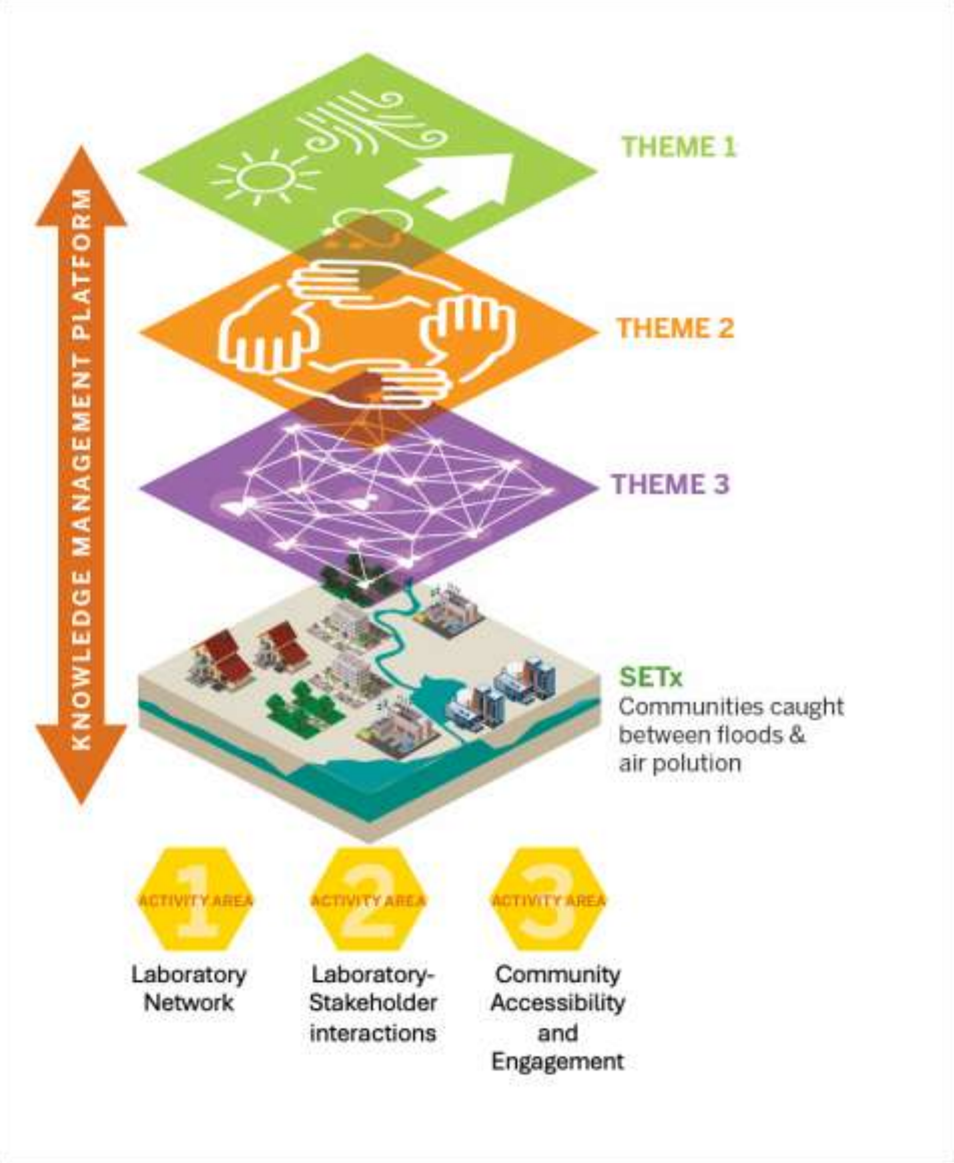
Southeast Texas: acute on chronic hazards impacting communities





- Frequent acute (e.g. compound flooding) on chronic (e.g. toxic air pollution) hazards, expected to worsen with climate change, aging infrastructure, etc.
- Continuous urban expansion and increased impervious cover over past several decades
- Home to one of the largest petrochemical industrial complexes
- Ranks in the top 10% of most polluted US communities
- Represents urban conditions along the Gulf Coast – experiencing population and industrial transitions but with less resources available than larger cities
- A quarter of families and 40% of children in poverty
- SETx-UIFL builds on existing work, including major expansion of the flood sensing and air sensing networks

Providing better data, modeling, & planning to support climate adaptation in SETx and the Gulf Region



Goal: Co-develop data and decision-making frameworks with stakeholders to aid community-led development of adaptation strategies

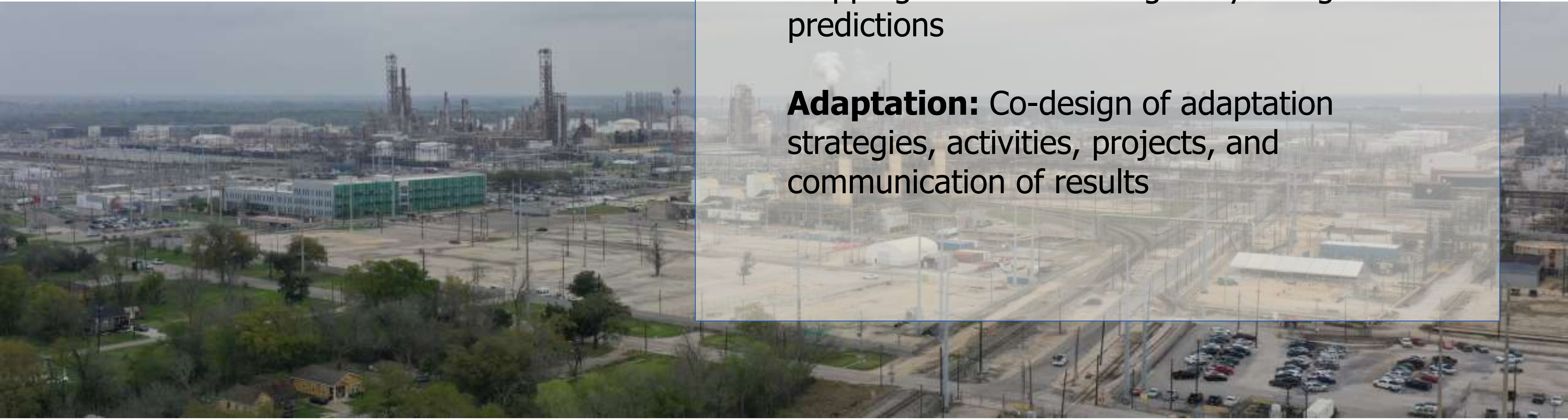
Approach to engagement: engage in two-way relationships between decision makers/residents and researchers to ensure stakeholder knowledge is incorporated into modeling and scenarios development and that data from SETx-UIFL research are useful for and incorporated into community-led climate adaptation decision-making

- SETx-FCS (Flood Coordination Study): led by Liv Haselbach (Lamar University PI) includes SETx counties, cities, river authorities, drainage districts, industries, federal agencies
- Resident groups working with Texas Target Communities and community-level stakeholders and community leaders experienced in the challenges faced by local populations

Interactions: Precipitation-discharge patterns, heat-flooding events, and future projections

Impacts: Compound flood inundation mapping and downscaling of hydrological predictions

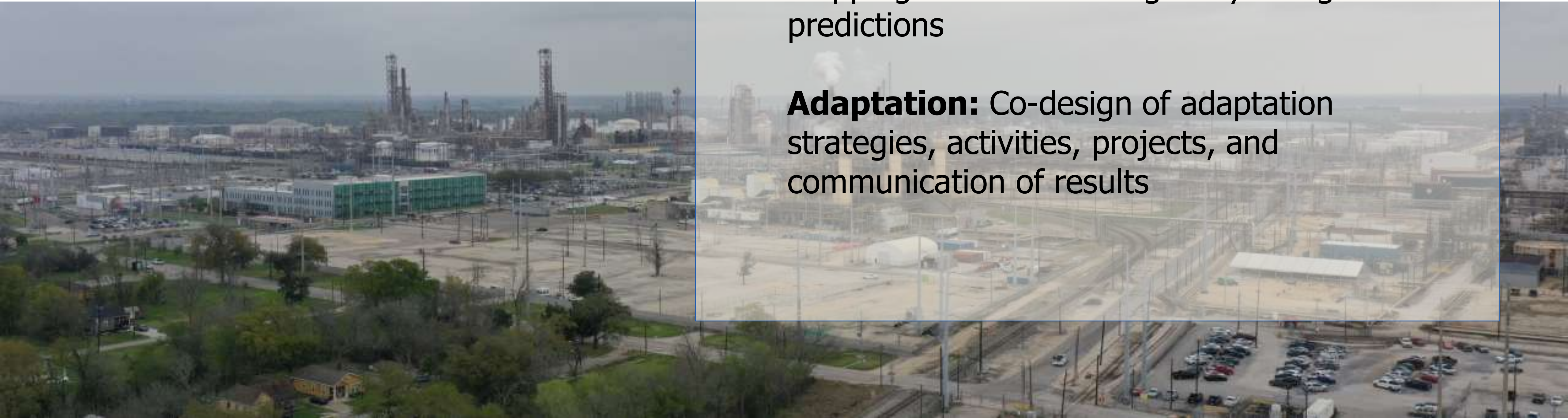
Adaptation: Co-design of adaptation strategies, activities, projects, and communication of results



Interactions: Precipitation-discharge patterns, heat-flooding events, and future projections

Impacts: Compound flood inundation mapping and downscaling of hydrological predictions

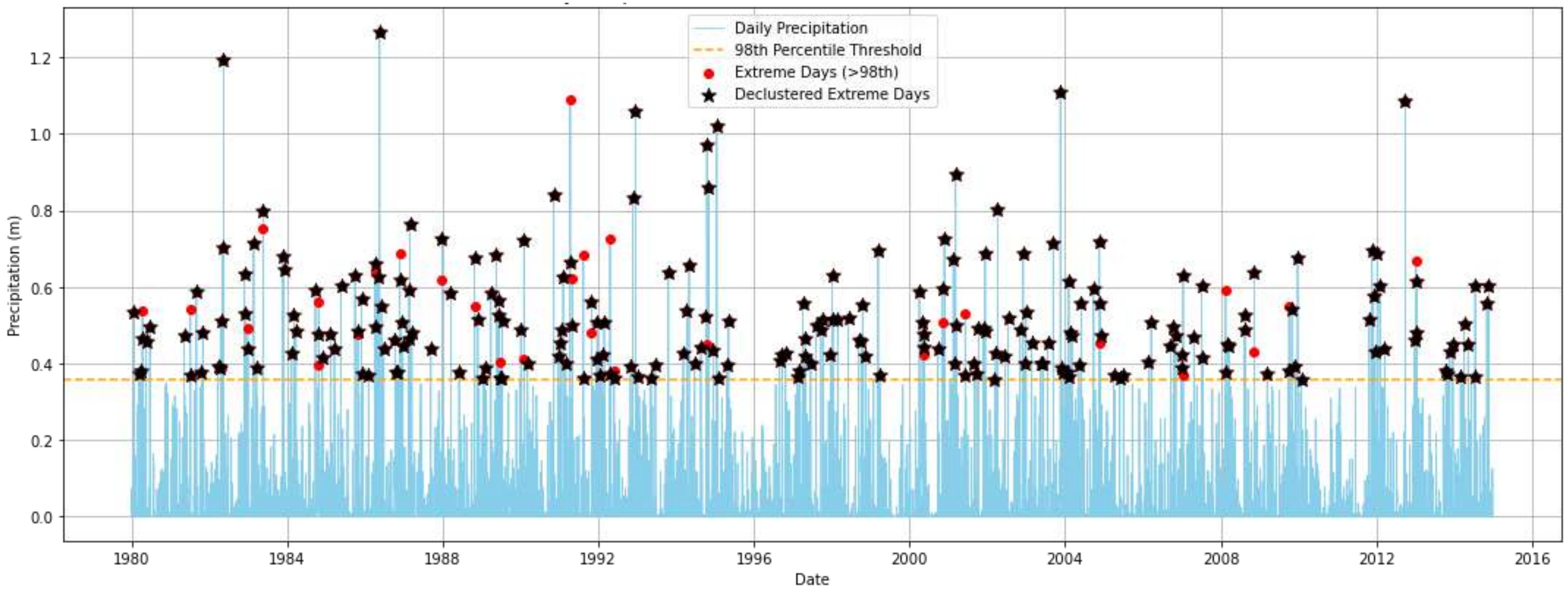
Adaptation: Co-design of adaptation strategies, activities, projects, and communication of results



Temporal Clustering of Extreme Precipitation Events and Hydrologic Response in Southeast Texas

Clustering beyond seasonality: Do extreme precipitation events exhibit significant sub-seasonal temporal clustering beyond what would be expected from seasonal variability alone?

Historical extreme precipitation events over SETx from ERA5-Land



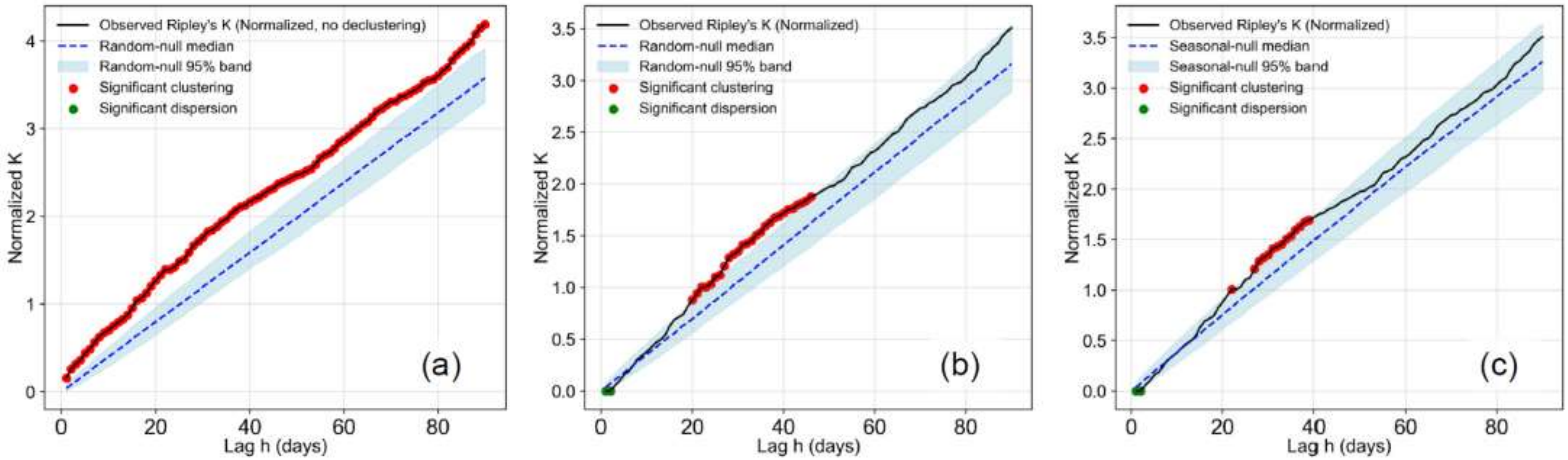
ERA5-Land: global, hourly, ~9 km land-surface reanalysis from 1950 to present, derived from ERA5 atmospheric forcing. Produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) under the Copernicus Climate Change Service (C3S).

Ananthula, Passalacqua, Persad, in preparation.

To quantify clustering, we adapt Ripley’s K to a temporal application

Ripley’s K quantifies whether points in a dataset are clustered, dispersed, or random by comparing the observed spatial distribution to a theoretical random distribution.

Random null (all peaks) | Random null (storm events) | Seasonally structured null (storm events)

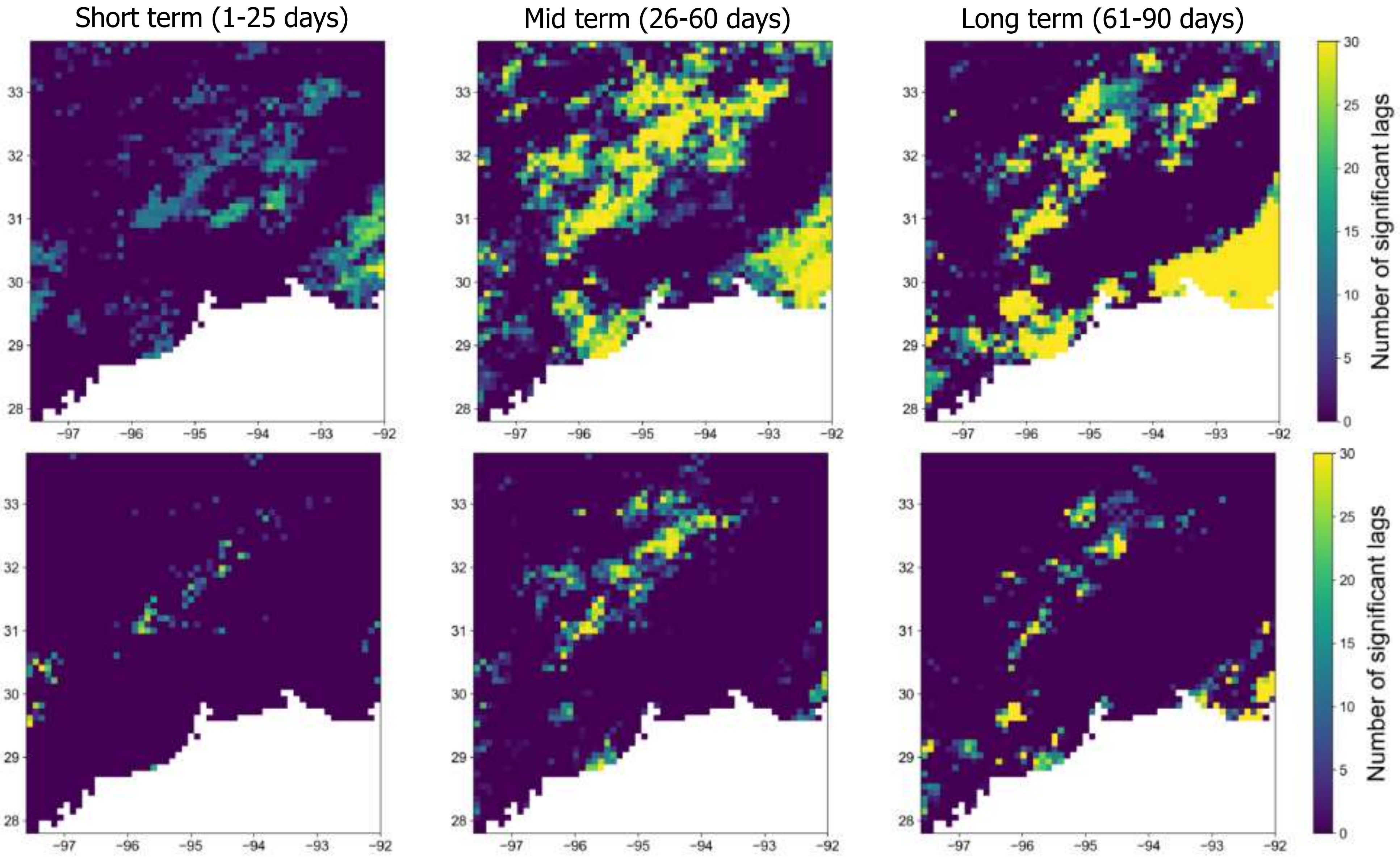


$$K(h) = \frac{T}{n(n-1)} \sum_{i=1}^{n} \sum_{j \neq i}^{n} I\, |t_i - t_j| \leq h$$

Ananthula, Passalacqua, Persad, in preparation

1. Identify extreme precipitation events and de-cluster to ensure event independence.
2. Apply temporal Ripley’s K analysis using two null models with Monte Carlo simulations:
   - Random Poisson (homogenous) null model
   - Seasonally structured (non-homogenous) null model
3. Identify significant temporal clustering

More pronounced clustering occurs in the mid-term lag range



All clustering
Using random null model

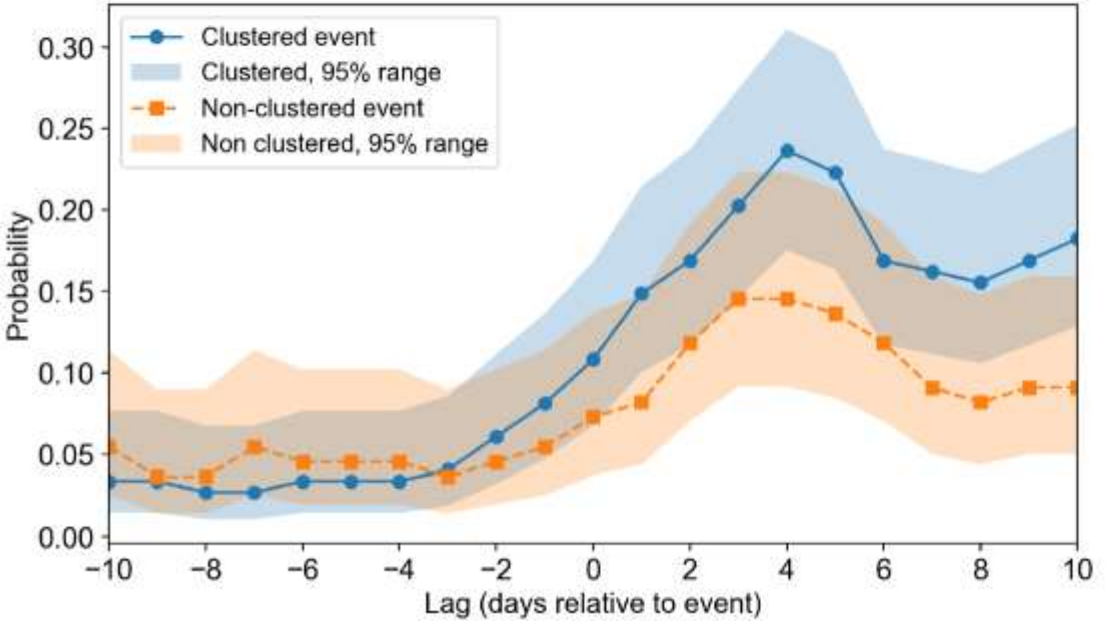
Filtering out patterns driven by seasonality

Using non-homogenous (seasonally structured) null model

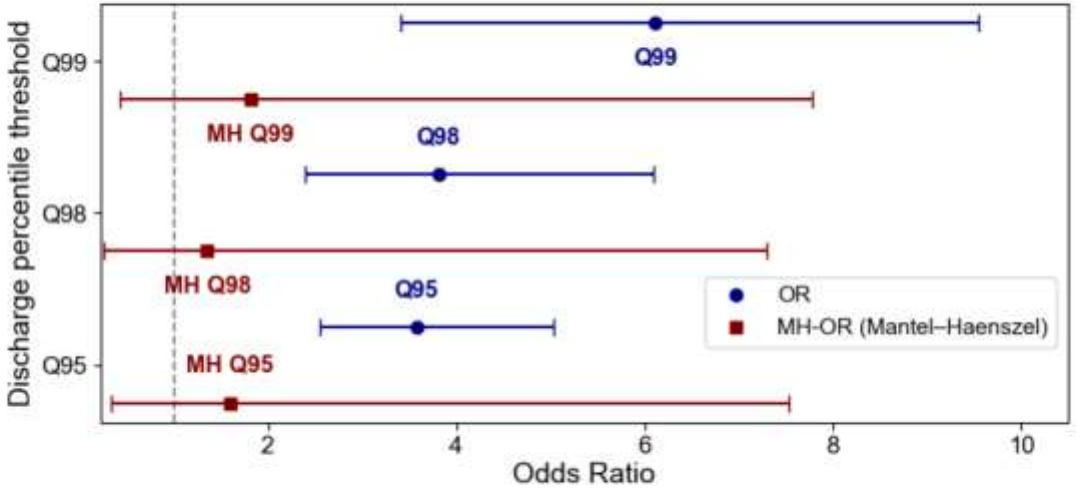
Hydrologic consequences: To what extent is sub-seasonal temporal clustering of extreme precipitation associated with increased likelihood of high-discharge events?

Clustered precipitation episodes increase the likelihood of high discharge events

Prob. of extreme discharge following precipitation episodes



Clustered precipitation increases the odds of 99th-percentile discharge exceedance by nearly six-fold

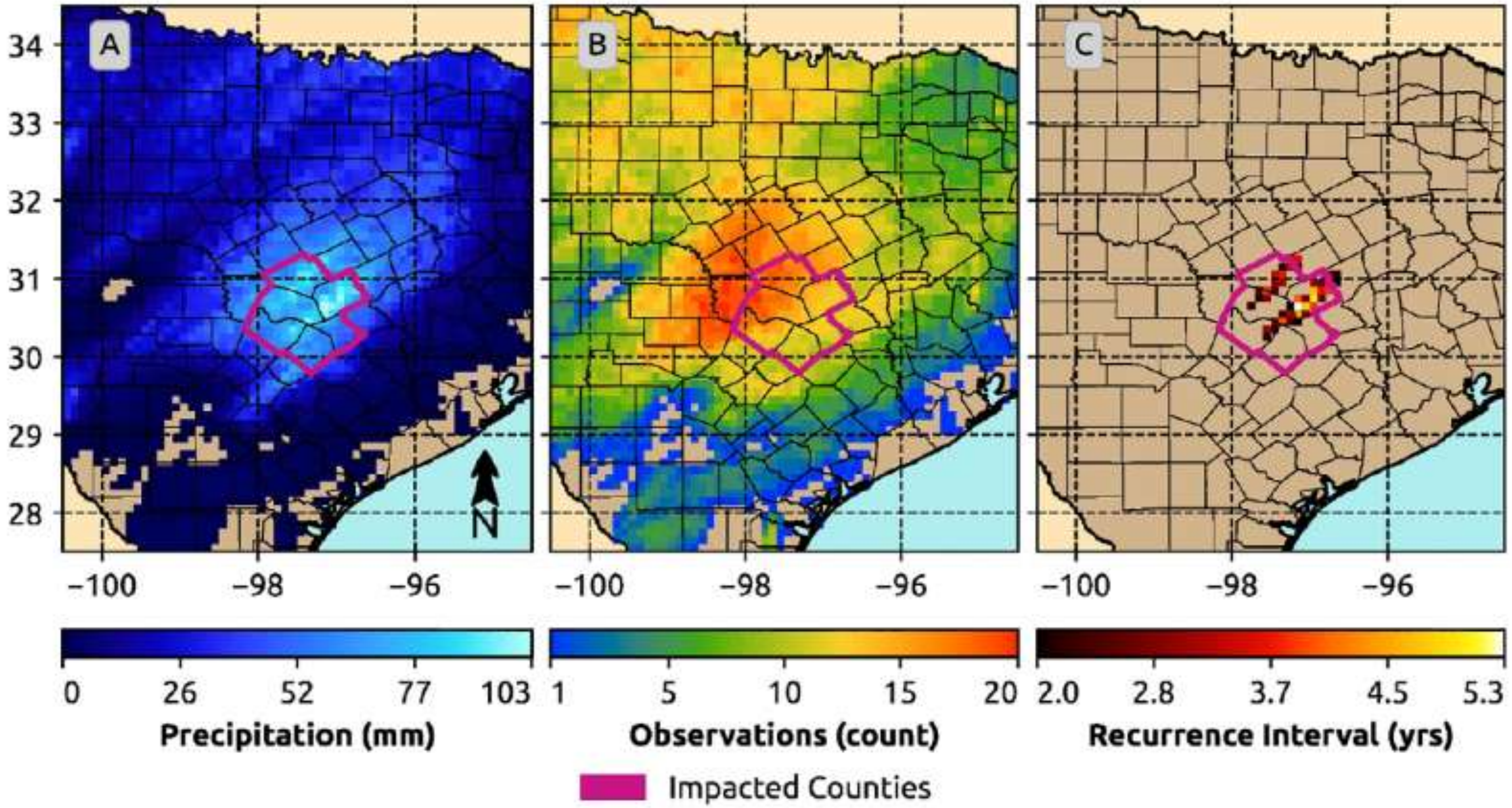


- Identify non-overlapping clustered episodes (moving window)
- Select seasonally matched control windows
- Compute extreme-discharge probability (clustered vs non-clustered)
- Evaluate Odds Ratio (OR) for clustered episodes
- Compute Mantel Haenszel Odds Ratio (MH-OR) stratified over cumulative precipitation (MH-OR tests whether there is an association between exposure and outcome after controlling for stratification)

Detecting multi-hazard events: number of days an area experiences a heat hazard within 30 days of an extreme precipitation event

Compounded heat and rain: How many heat and precipitation events happen within the same 30 days window?

- Used daily precipitation (IMERG-GPM) satellite data
- Identified precipitation events with single day average recurrence interval of 2 years
- Merged events within 200 km and 3 days from each other

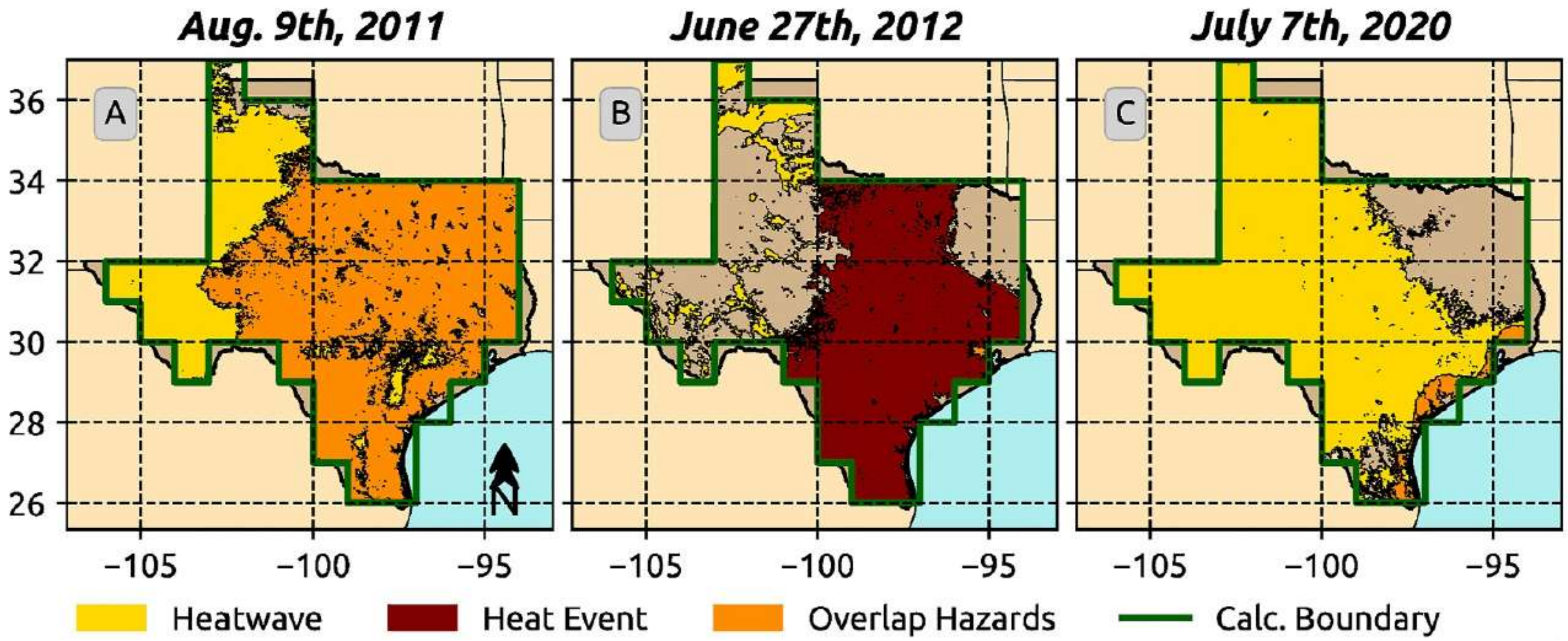


Example of proxy flood hazard boundary delineation for 25 May 2015
(A) daily precipitation depth (mm)
(B) count of half hourly observations with more than 0.01 mm of precipitation
(C) average recurrence interval for rainfall (comparing with NOAA precipitation frequency estimates)

Preisser and Passalacqua, AGU Advances, 2025

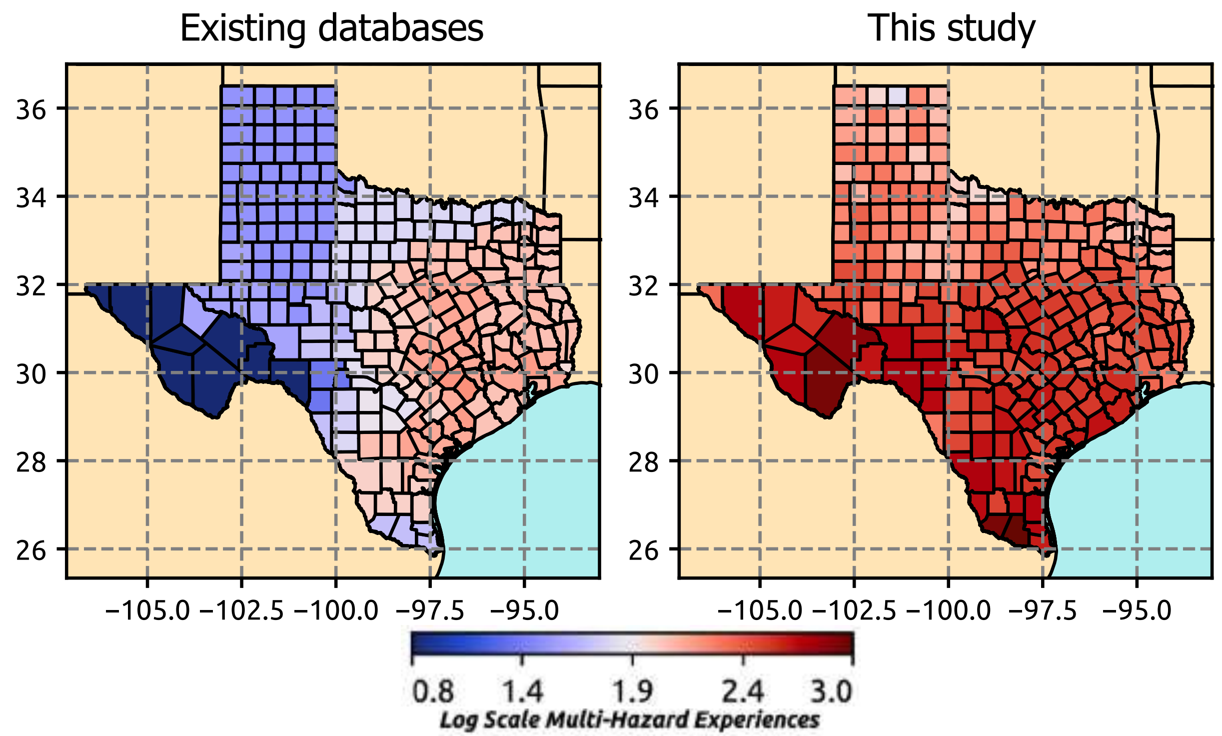
Heat hazards: combinations of 95th percentile heatwave and 30C wet bulb globe temperature

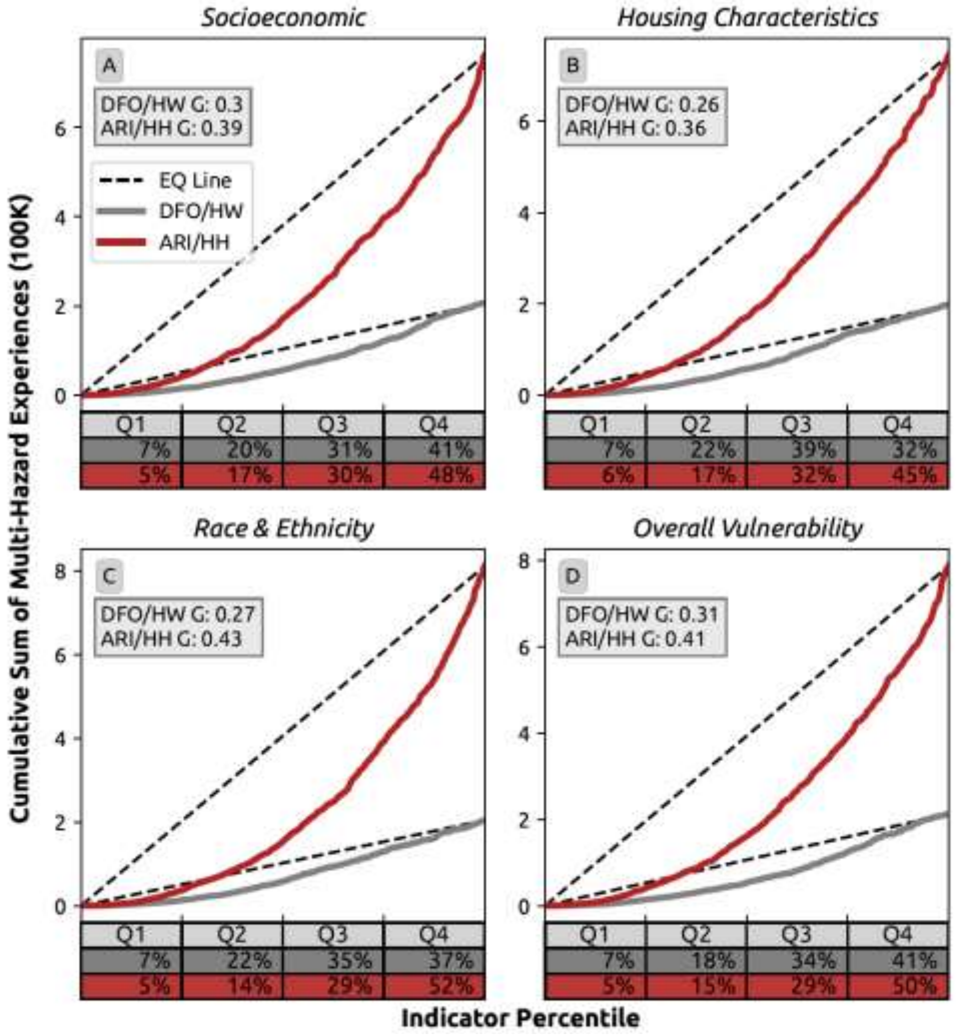
- Used daily temperature (AIRS + MODIS) satellite data
- Heat wave: minimum of 3 consecutive days where both min and max temperature are above 95th percentile
- Wet bulb globe temperature accounts for additional meteorological variables (solar radiation, humidity, wind speed) – computed from air temperature and relative humidity
- Aggregated heat events based on 200 km and 3 days as for precipitation



Preisser and Passalacqua, AGU Advances, 2025

Remote sensing improves multi-hazard flooding and extreme heat detection by fivefold over current estimates





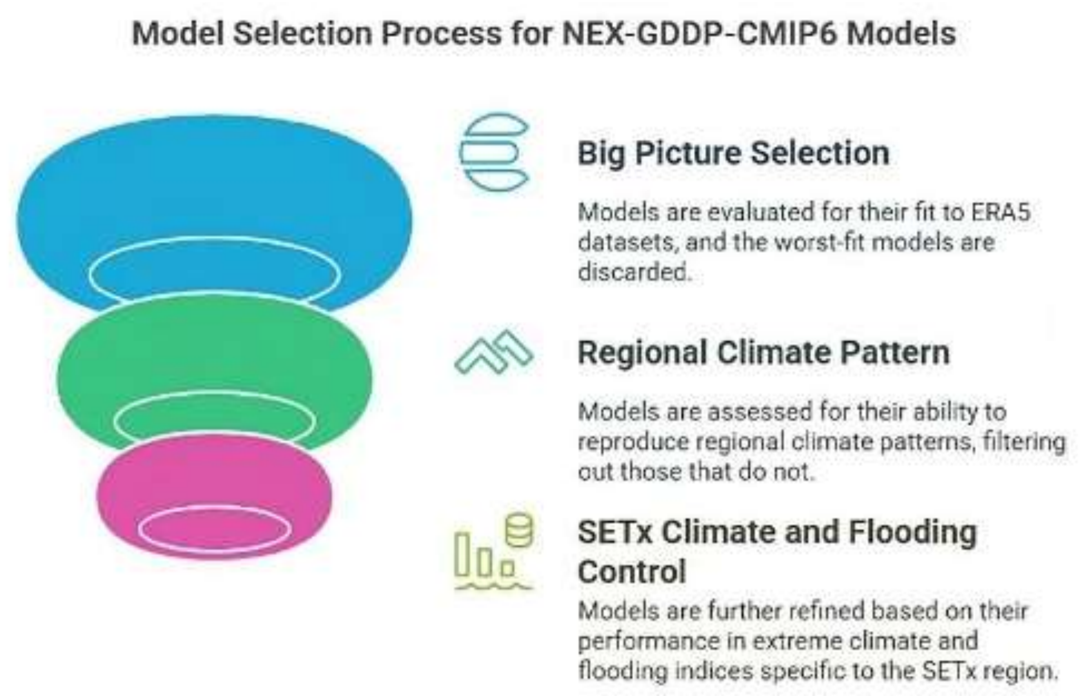
- Computed multi-hazard experiences: number of heat hazard days that occur within a given time-lag of each flood event.
- Inequities detected regardless of method and vulnerability metric
- Data resolution limits detection of inequities

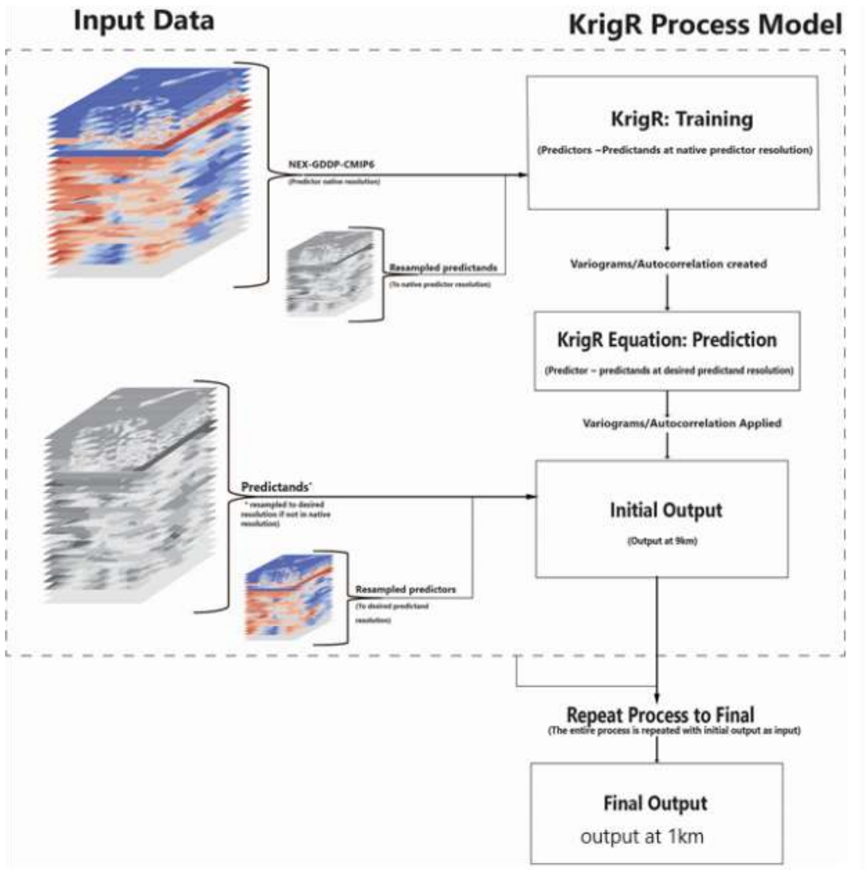
Preisser and Passalacqua, AGU Advances, 2025

How does the future look like?

Future climate scenarios: Which GCMs work best in southeast Texas and can we obtain high resolution projections?

- Identified global climate models that best capture climate conditions over SETx
- Developed algorithm to create ultra-high resolution climate projections for SETx
- Piloted new techniques for capturing and projecting rainfall events that drive flood risk over SETx





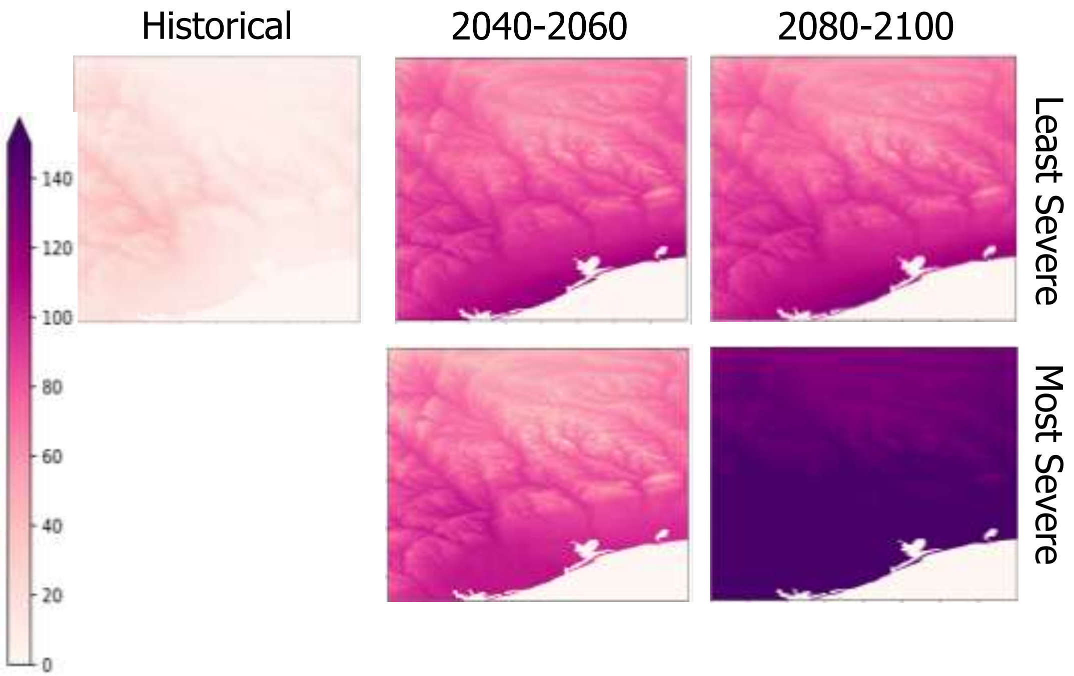
Nduka, Persad, et al., in preparation

We produced daily projections 1950-2100 for 5 SSPs from 10 GCMs

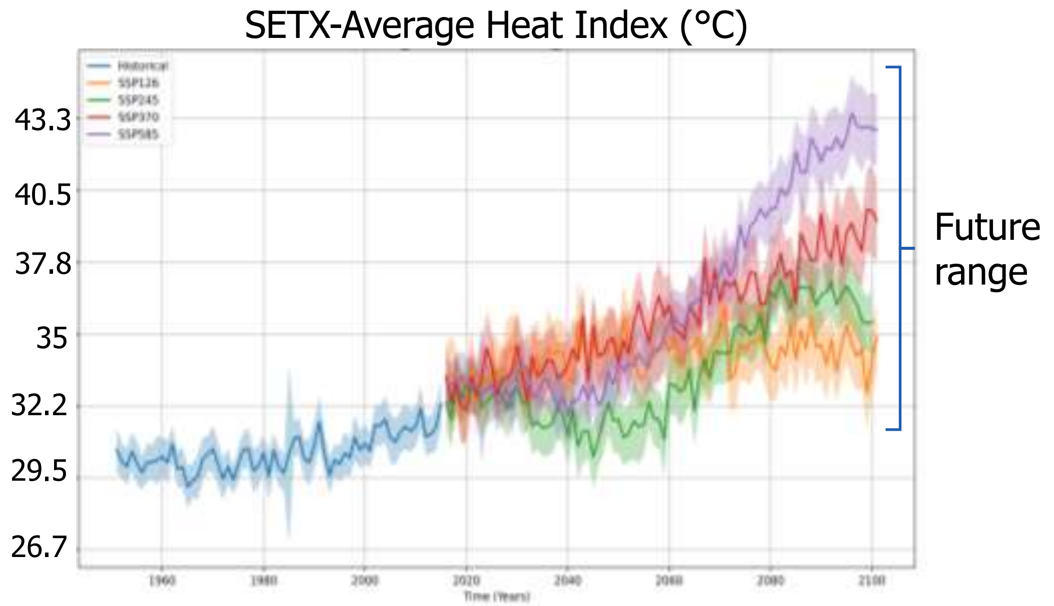
Daily
- avg., max., min. temperature
- avg. rainfall rate
- avg. relative humidity
- avg. specific humidity
- avg. wind speed
- avg. surface solar radiation
- Total precipitation

City by city heat stress projections

Average number of days/year with heat index above 90°F	Historical (1980 - 2014)	End of Century (2080-2100) *Least Severe Scenario*	End of Century (2080-2100) *Most Severe Scenario*
Port Arthur	8	115	159
Beaumont	8	106	157
Houston	13	103	162
Galveston	9	123	162
Orange	9	109	158
Kountze	9	97	155
Silsbee	9	97	155
Lumberton	8	99	156
Bridge City	8	111	158
Port Neches	8	111	158



Days/year with heat index ≥32.2°C



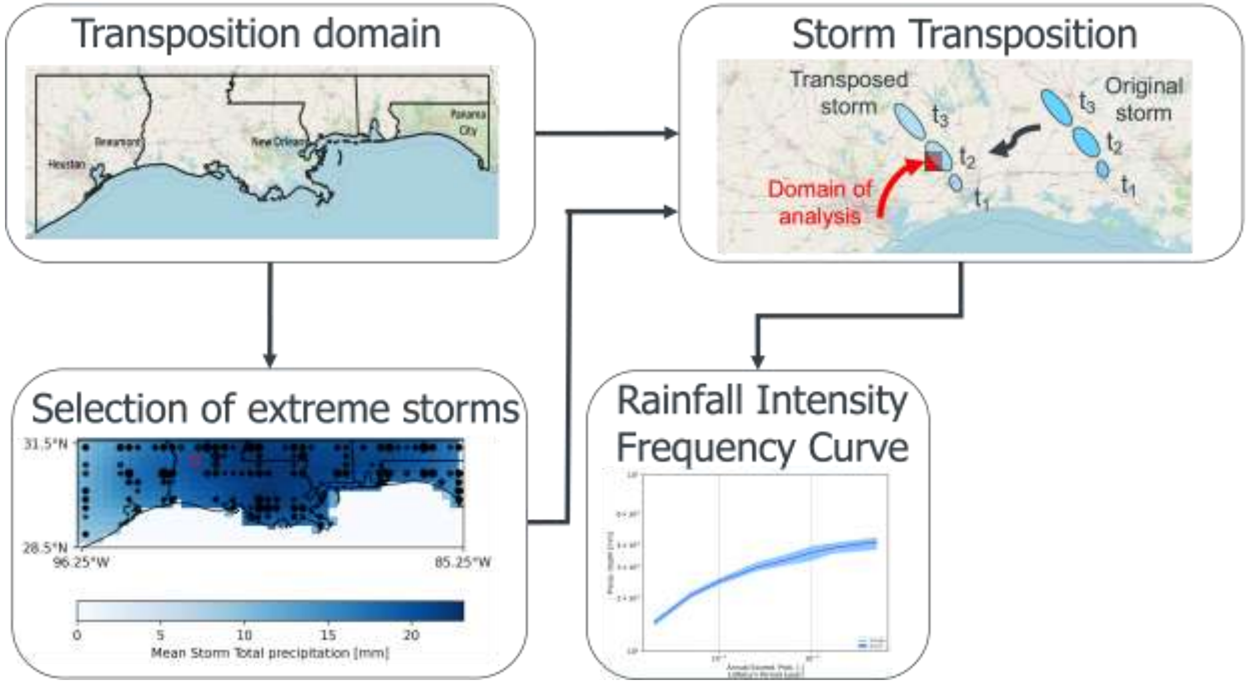
Nduka, Persad, et al., in preparation

Interactions: Precipitation-discharge patterns, heat-flooding events, and future projections

Impacts: Compound flood inundation mapping and downscaling of hydrological predictions

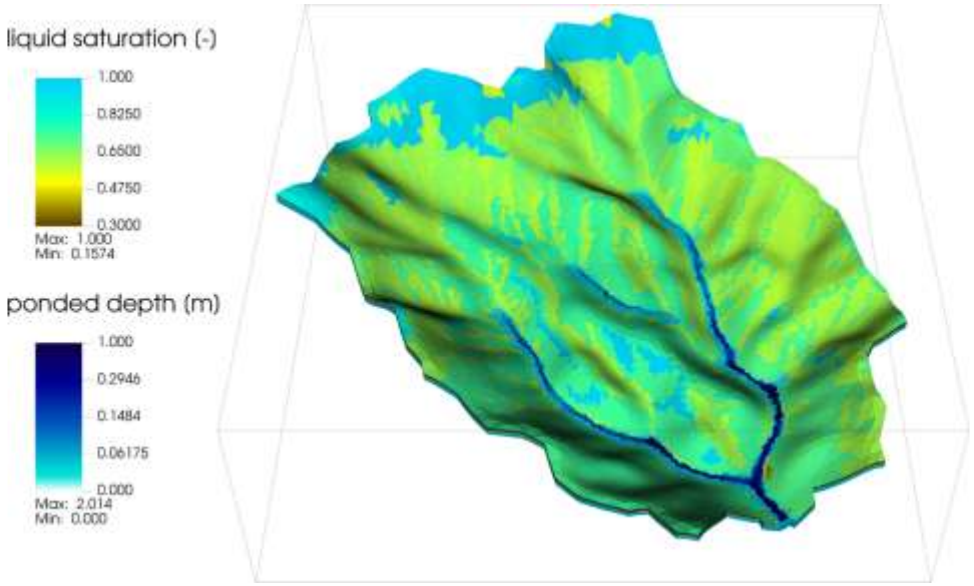
Adaptation: Co-design of adaptation strategies, activities, projects, and communication of results

We built a synthetic database of storms using storm transposition



Storm transposition: identify the most severe storms within a homogeneous region and transpose them to the analysis watershed

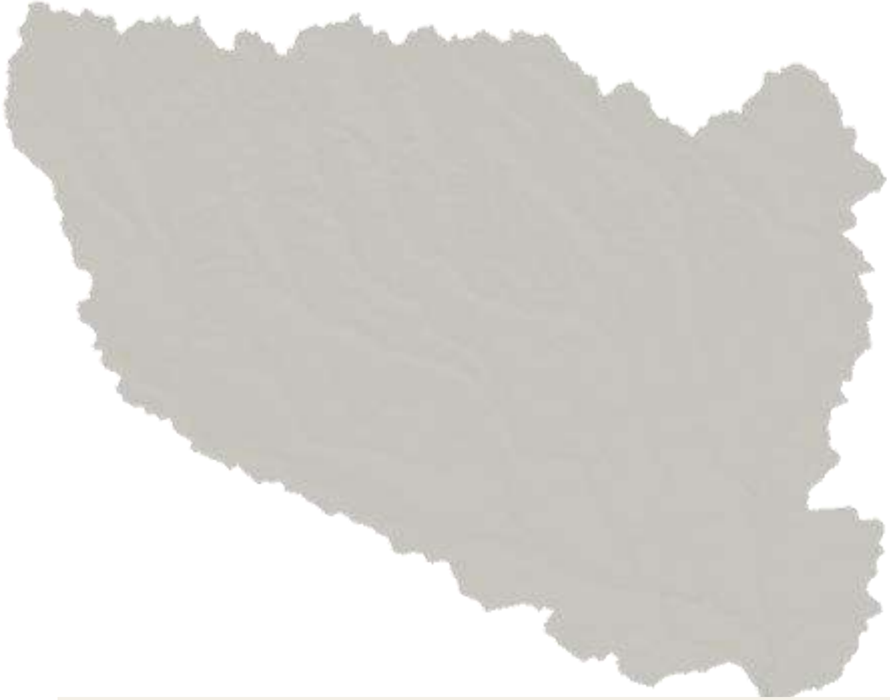
Perez, Coon, Rathore, Le, Journal of Hydrology, 2024



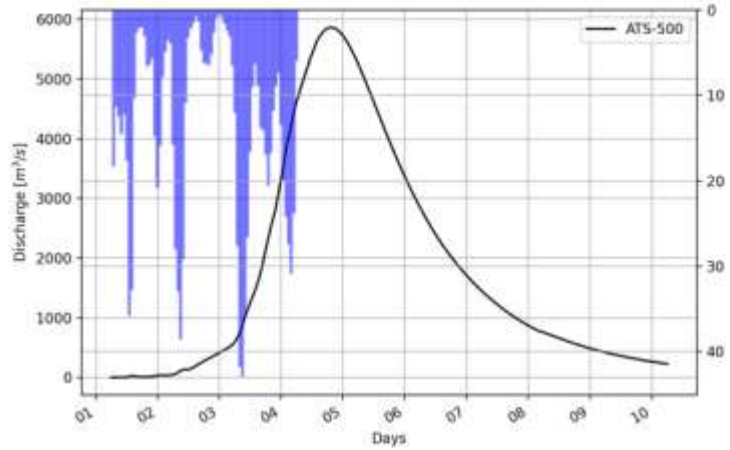
ATS: fully coupled, watershed-scale surface-subsurface hydrologic model for pluvial-fluvial flooding
Expensive to run: mesh elements O(100 m)

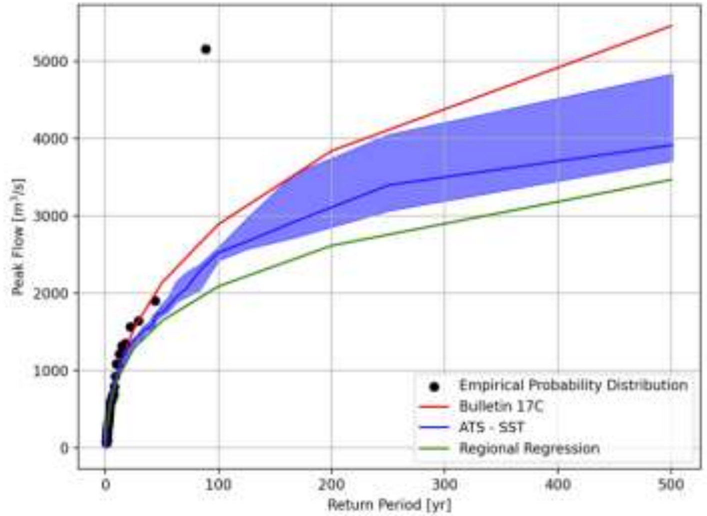
Coon and Shuai, 2022

The hydrological model was run for all 5000 storm events



ATS results are too coarse to inform local planning





Flood frequency curve derived from 5000 storm events in Village Creek

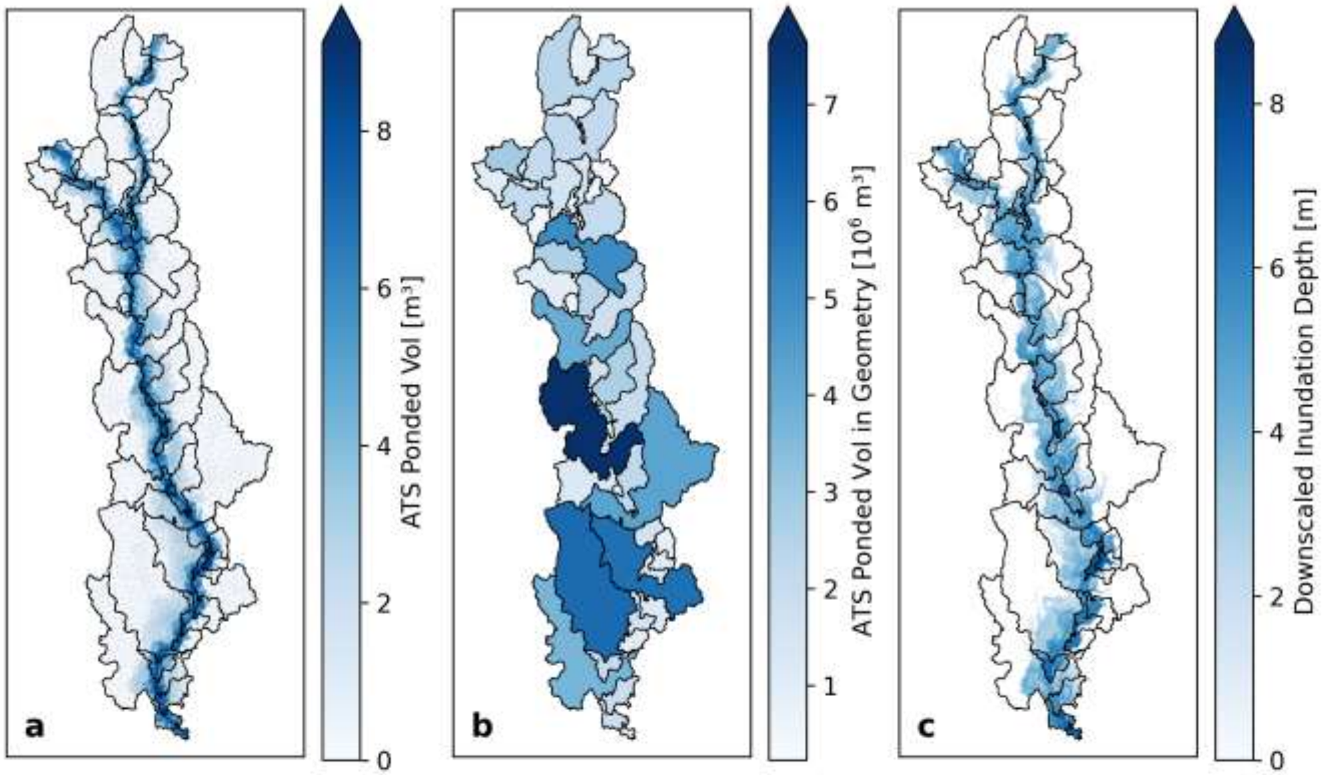
We apply volume conservation to distribute water from ATS on high-resolution terrain

Downscaling: How do we downscale modeling predictions to scales relevant to stakeholders?

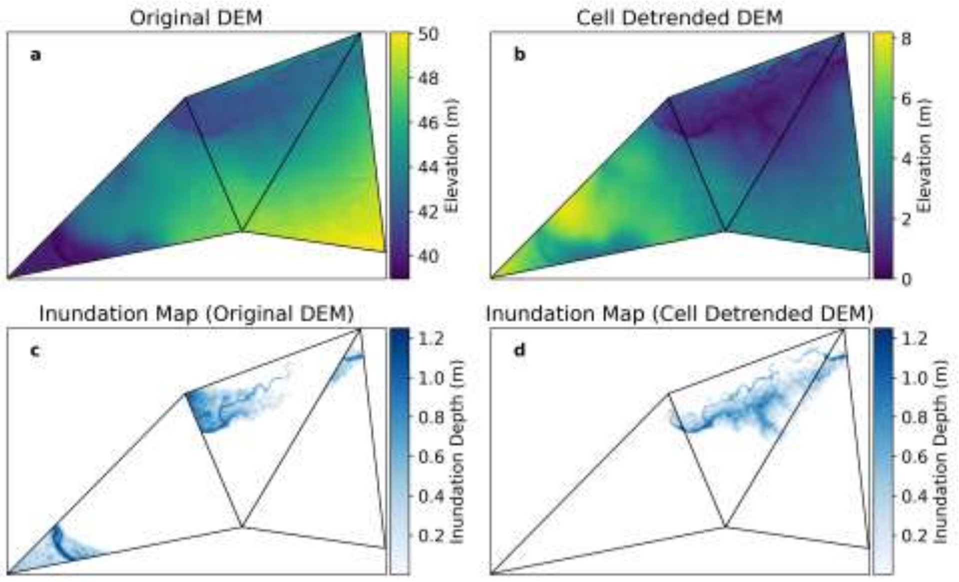
(1) Overlay downscaling geometry on coarse mesh

(2) Sum volume in geometry

(3) Distribute the volume on high-resolution terrain

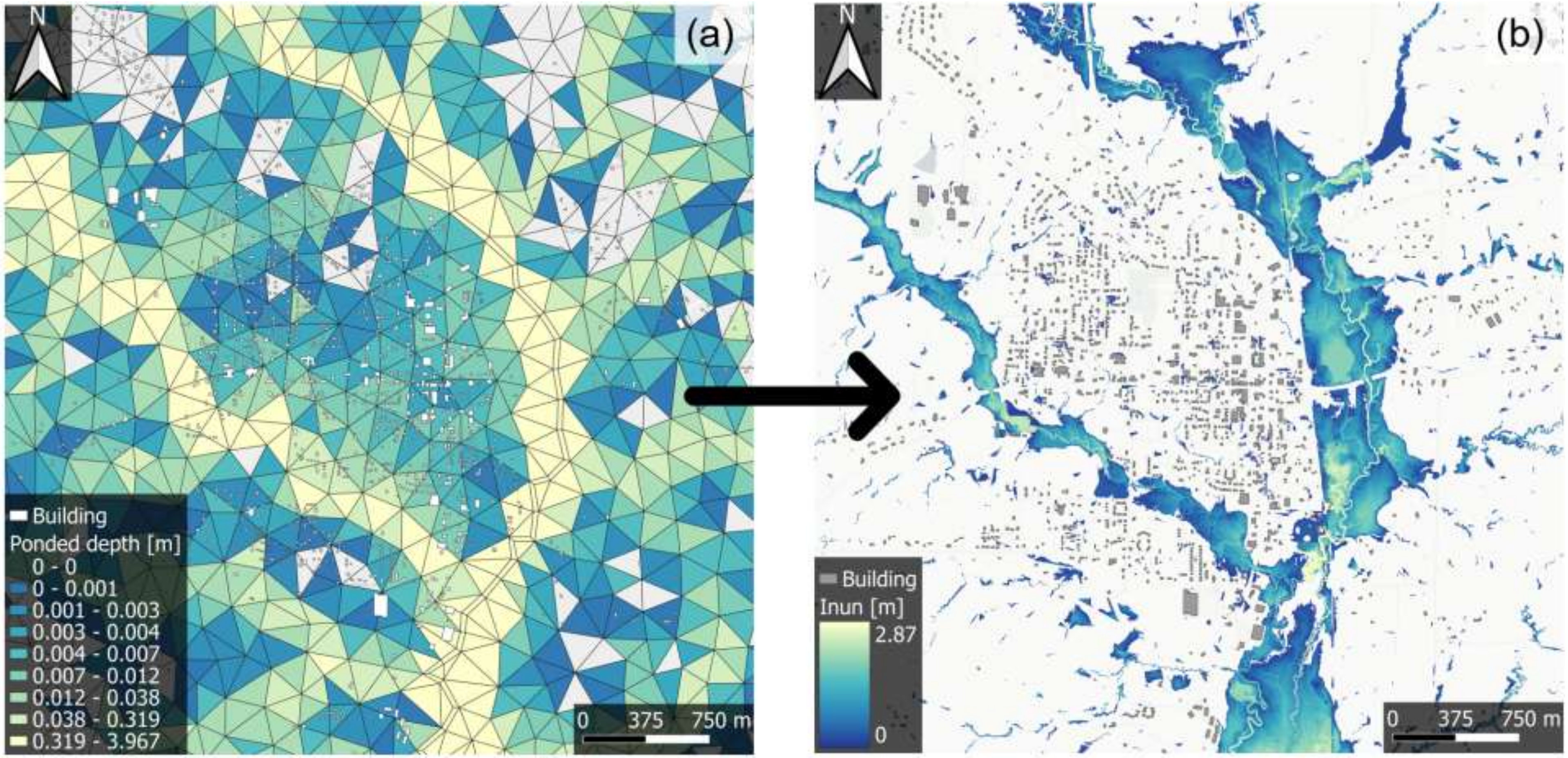


Wang, Passalacqua, et al., in preparation



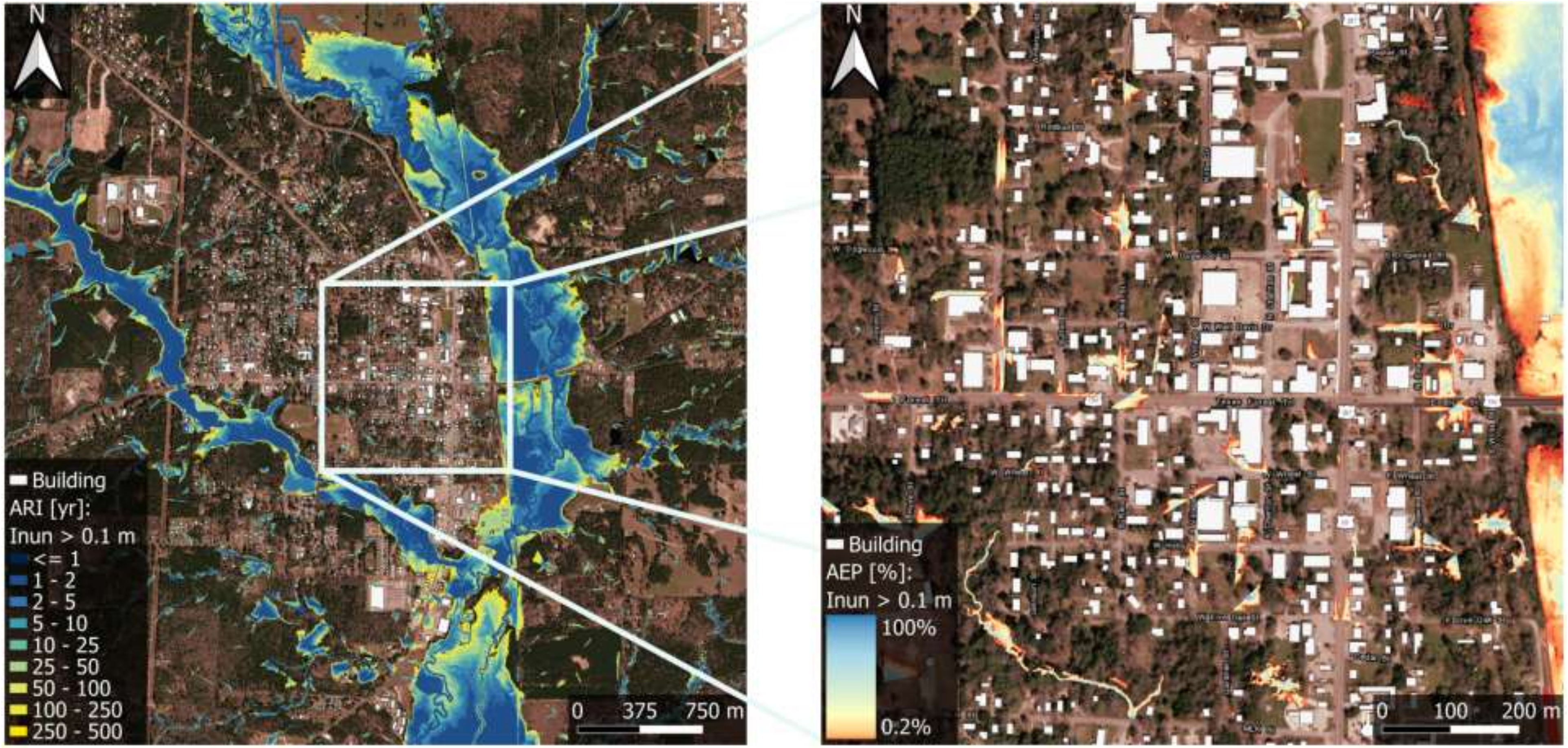
We use a detrended DEM to avoid discontinuities at the boundaries between elements

We obtain an inundation map at 1 m resolution



Wang, Passalacqua, et al., in preparation

The operation can be repeated with the ensemble of storms to obtain probabilistic maps



$$AEP_{pixel} = \frac{j}{n+1}$$ Annual exceedance probability of inundation > 0.1 m [%] (j: rank; n: # simulations)

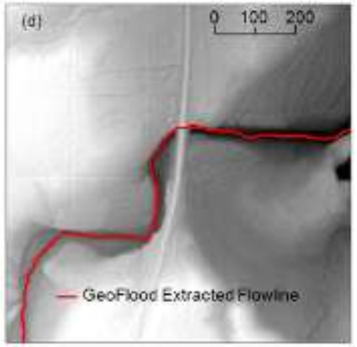
$$ARI_{pixel} = \frac{1}{AEP_{pixel}}$$ Annual recurrence interval of inundation > 0.1 m [years]

Wang, Passalacqua, et al., in preparation

pygeoflood: A simple near real time approach for mapping fluvial, pluvial, and coastal flooding

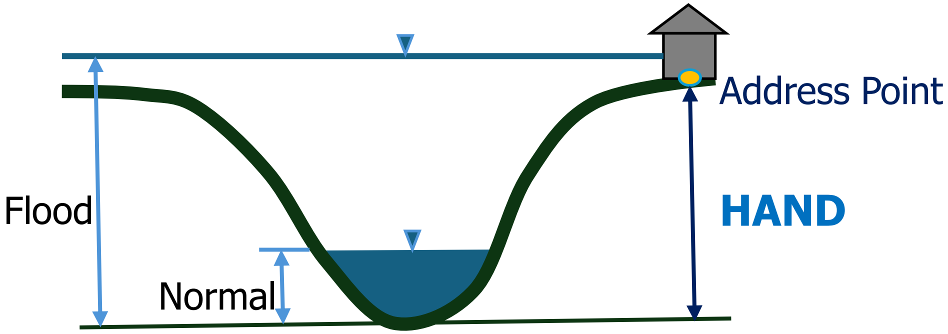
Flood inundation mapping: Is a high-fidelity model always needed?

- GeoFlood (Zheng et al., 2018) computes the **fluvial** component based on HAND on lidar with retraced centerlines via GeoNet



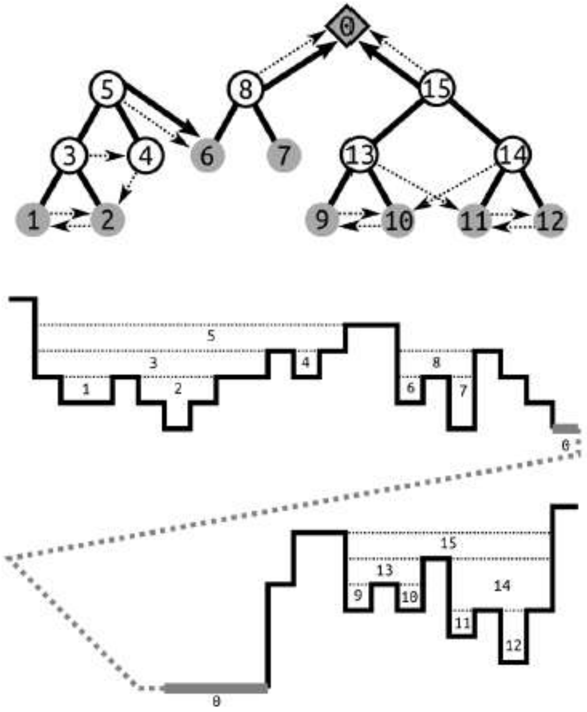
$$\Psi = \frac{1}{\alpha \cdot A + \delta \cdot \kappa}$$

$$g(a,b) \coloneqq arg\left(\min_{C \in \Omega} \int_a^b \Psi(s)ds\right)$$



Passalacqua et al., JGR-ES, 2010; Zheng et al., WRR, 2018

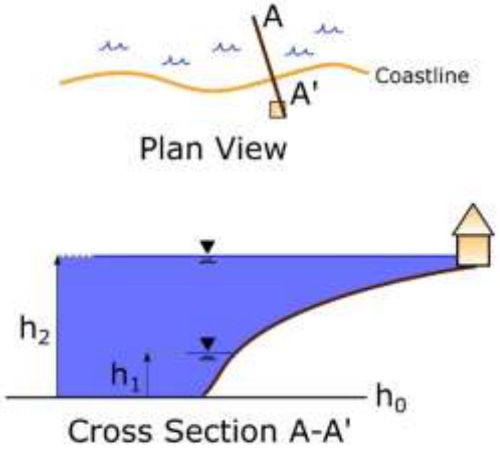
- **Pluvial** inundation is estimated with FillSpillMerge routing flows through depressions

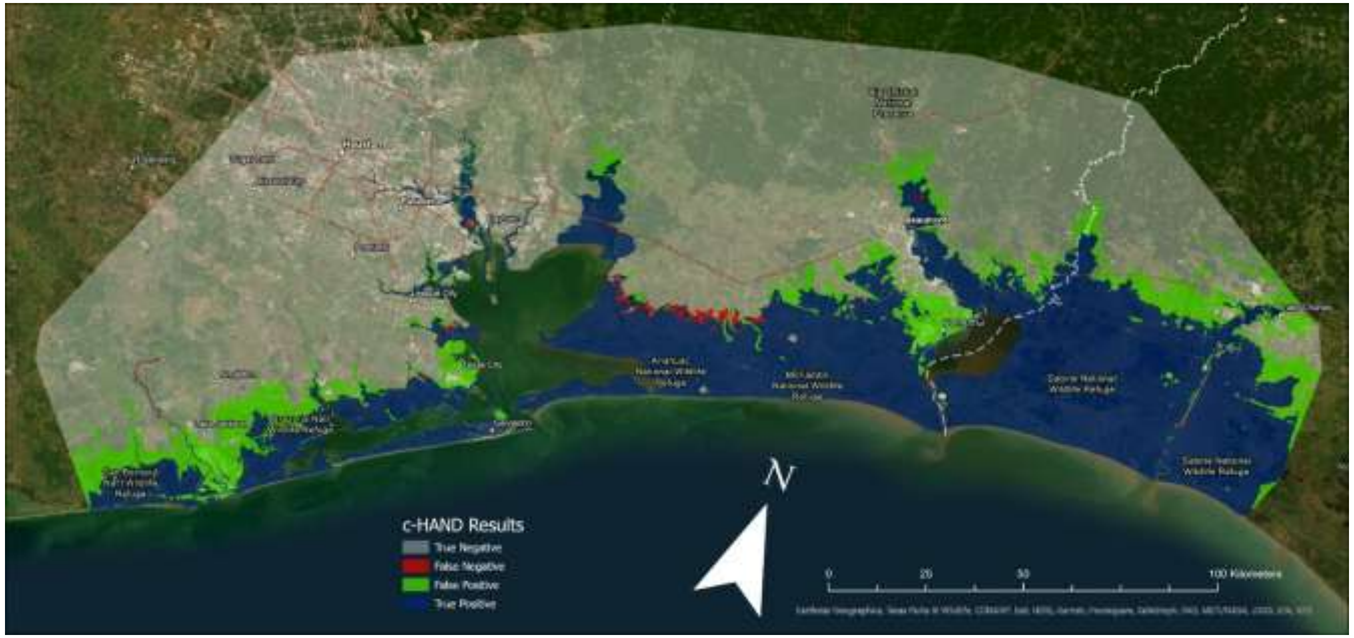


Barnes et al., eSurf, 2019; Preisser, Passalacqua, et al., HESS, 2022

pygeoflood: A simple near real time approach for mapping fluvial, pluvial, and coastal flooding

- Coastal inundation is computed with a HAND-like approach that accounts for connectivity of water bodies

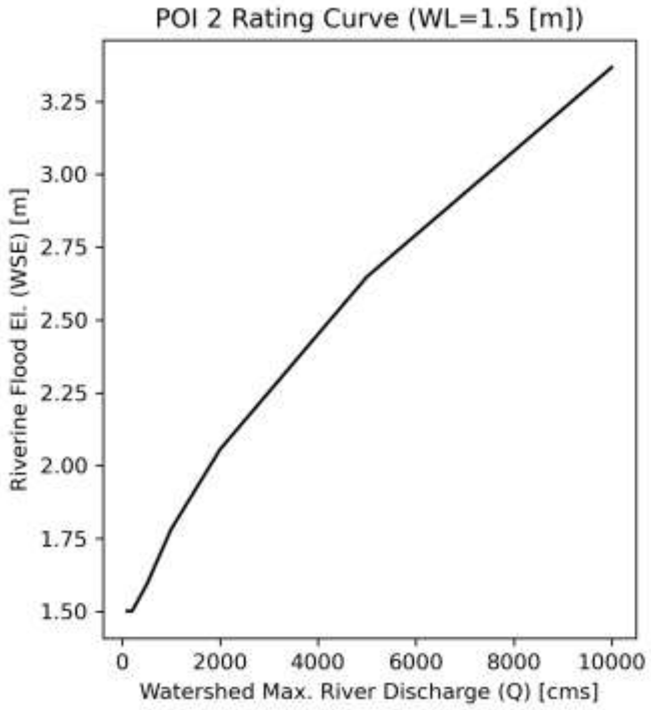


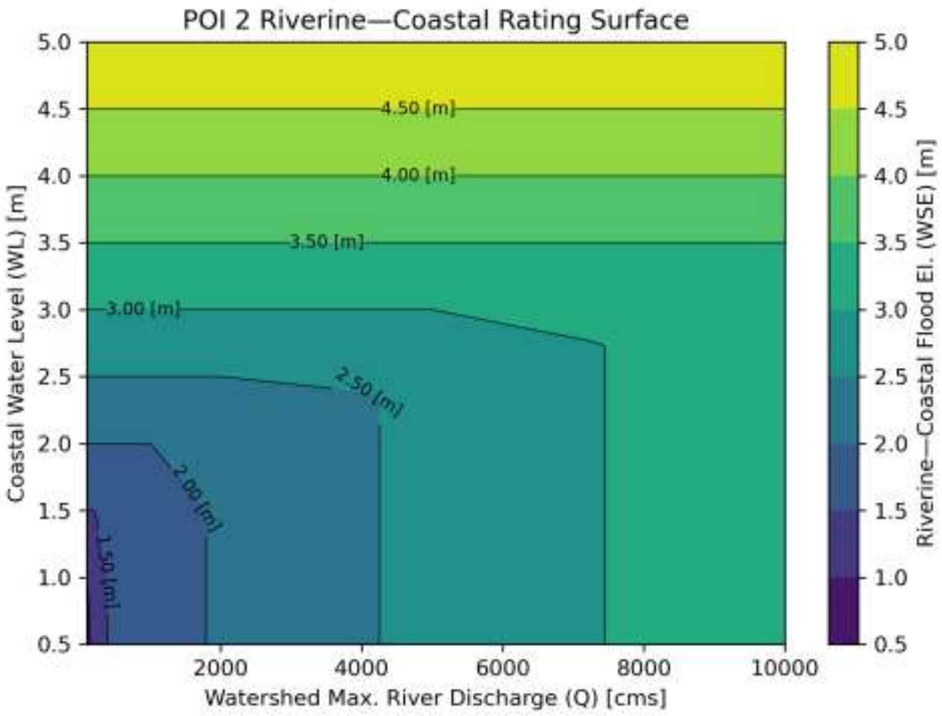



```
$ pip install pygeoflood
```

Wang, Passalacqua et al., Frontiers in Water, 2024; Wang, Preisser, and Passalacqua, in preparation; https://github.com/passaH2O/pygeoflood

We compute rating surfaces that provide the inundation depth under a range of forcing combinations

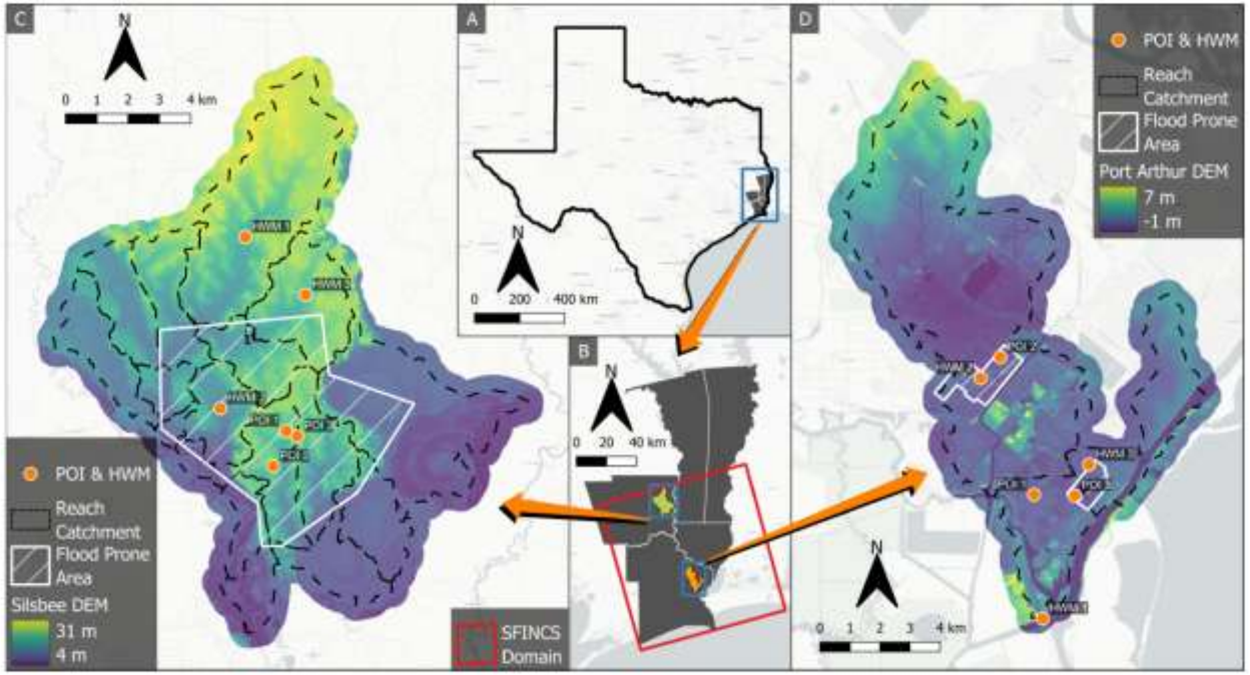


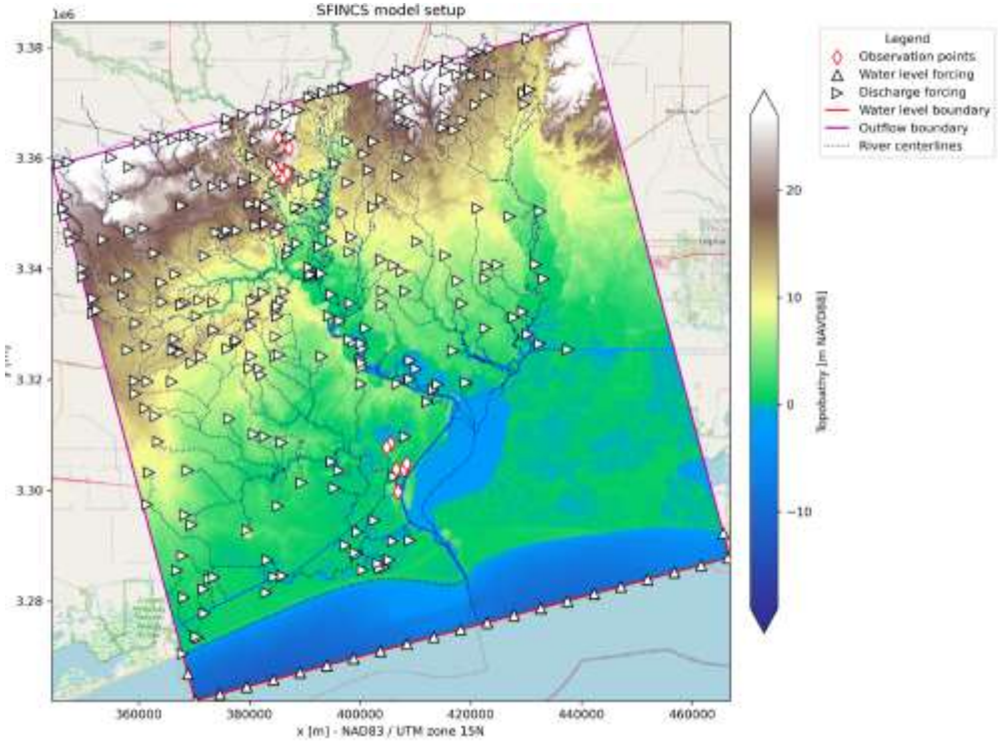


A Rating Surface is a Rating Curve with an extra dimension

Wang, Passalacqua, Moftakhari, Hardage, in submission.

We built Rating Surfaces at points of interest identified by the stakeholders and with HWMs and compared the results to SFINCS





SFINCS Leijnse et al., 2021

Hydrodynamic model that captures fluvial, pluvial, and coastal flooding

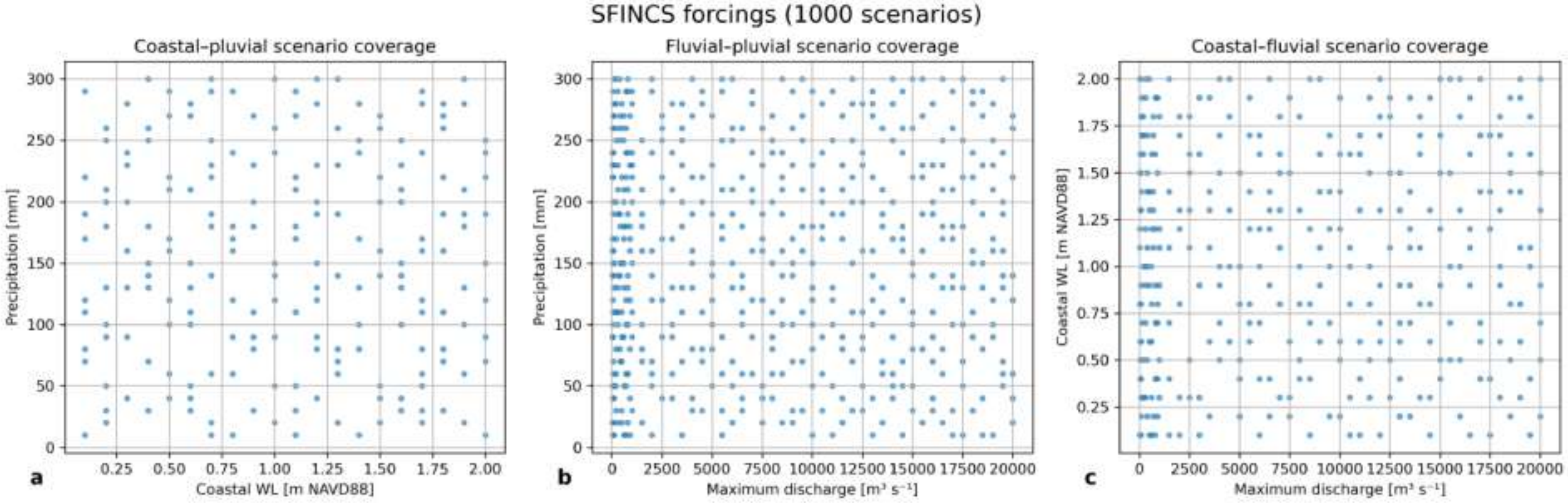
Definition of range of forcings

- Coastal: water levels from 0.1—2 m
  (max observed: 1.1 m)
- Fluvial: max. discharges from 25—20k m^3/s
  (Harvey: 14k cms)
- Pluvial: precipitation rates from 0.01—0.3 m/hr
  (Harvey: 0.17 m/hr)
- 100 total coastal, fluvial, and pluvial scenarios are calculated

Table 2: SFINCS compound scenario types and corresponding forcing ranges.

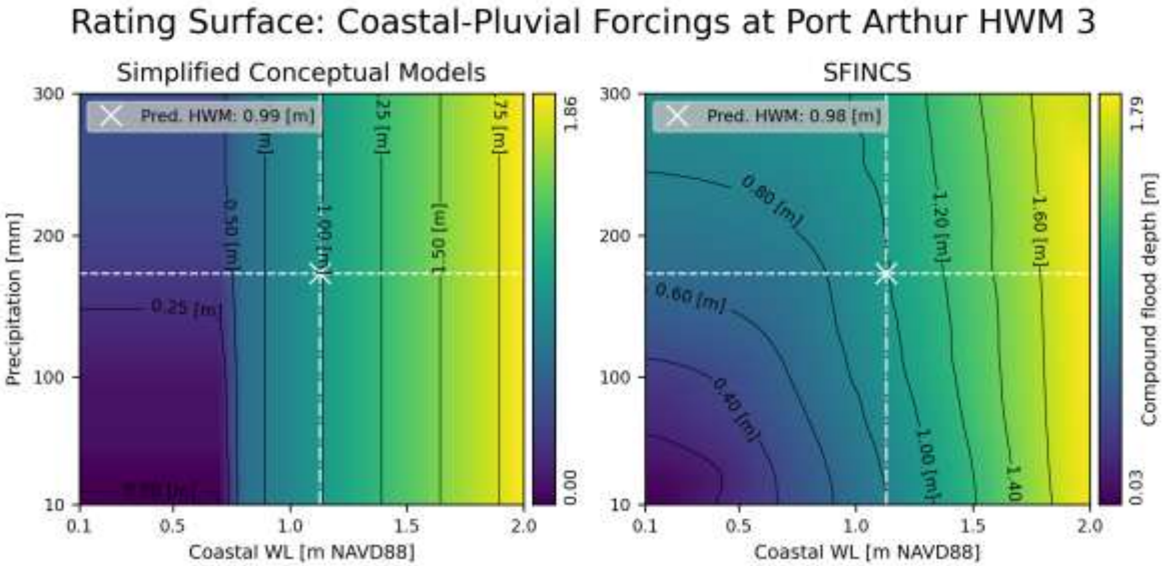
	Forcings		
Scenario type	Coastal [m NAVD88]	Fluvial[a] [$m^3 s^{-1}$]	Pluvial [mm]
Fluvial–pluvial	0	25 to 20 000	10 to 300
Coastal–pluvial	0.1 to 2.0	baseflow	10 to 300
Fluvial–coastal	0.1 to 2.0	25 to 20 000	0

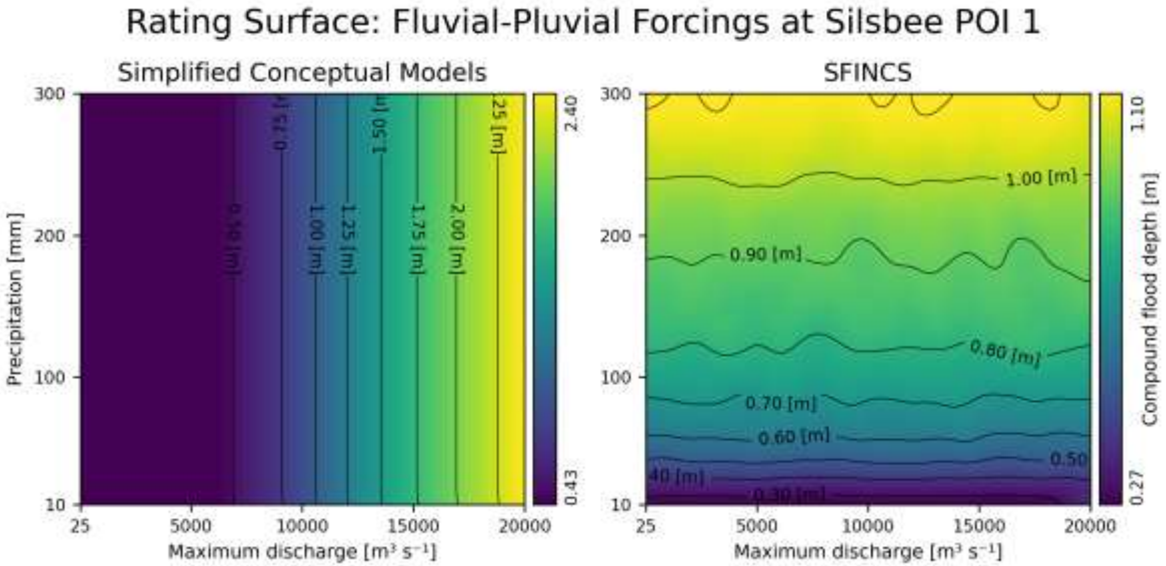
[a] Represents maximum discharge within the watershed.



Halton sequence used to select 1000 scenarios for SFINCS simulations

Rating Surfaces are an efficient way to evaluate compound flooding





The pygeoflood-based approach and SFINCS provide comparable ranges of flood inundation depth but SFINCS captures interactions between the forcings not detectable with a simple superposition of flood inundation depth resulting from single forcings.

Wang, Passalacqua, Moftakhari, Hardage, in submission.

Interactions: Precipitation-discharge patterns, heat-flooding events, and future projections

Impacts: Compound flood inundation mapping and downscaling of hydrological predictions

Adaptation: Co-design of adaptation strategies, activities, projects, and communication of results

We developed and implemented a co-design process

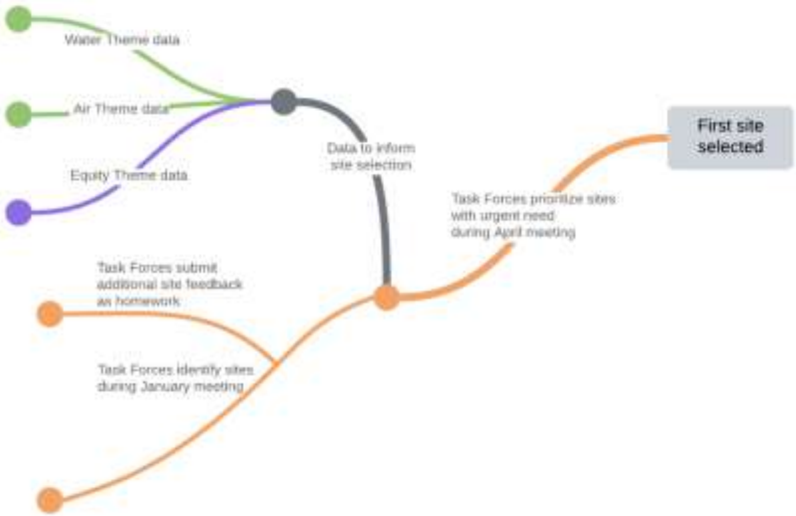
- How do residents define and prioritize environmental problems in their community?
- What processes can we use to integrate that knowledge with scientific knowledge?
- How effective and equitable are the strategies that we develop from that integrated process?

Collaborative work joined by researchers, residents, and decision makers to link air, hydrologic, & climate modeling & observations with residents' knowledge & preferences for developing equitable adaptation strategies focused on flooding & air quality.

Selected sites with task force members and developed ways to visualize co-designed strategies

Activities with Technical Task Force & Community Organization Task Force:

- Community engagement strategy that is sensitive to community context
- Quarterly meeting with task force members
- Selected sites of interest with task force members and gathered + integrated data + site visits
- Developed workflow to generate visualizations of co-designed strategies
- Performed interviews and surveys

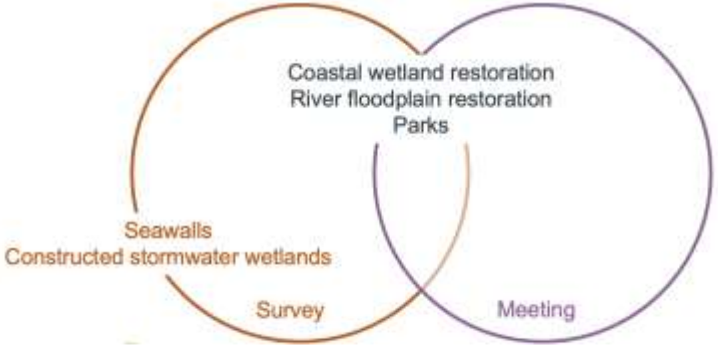


Co-created strategies to address flooding and air quality

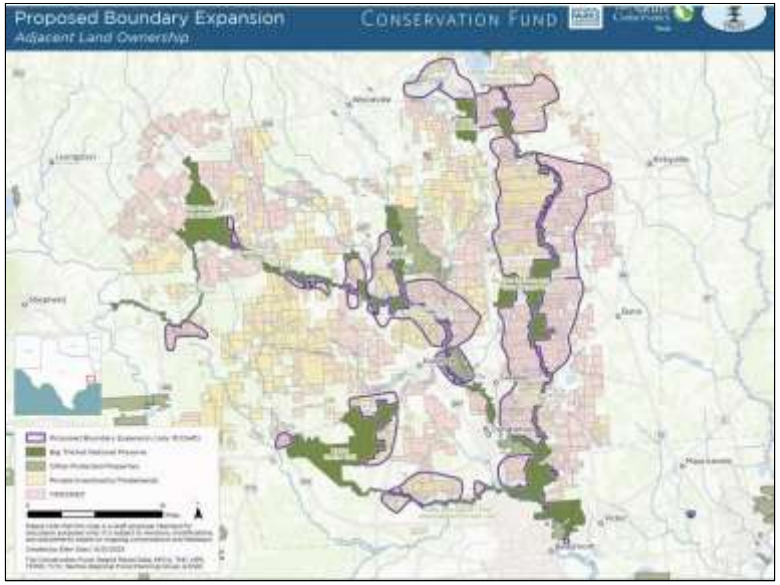
Developing 6 scenarios of river floodplain restoration focused on expansion of Big Thicket National Preserve, using:

- Data that The Conservation Fund, The Nature Conservancy, Big Thicket National Heritage Trust, and the National Parks Conservation Organization used to create a priority expansion plan;
- Future impervious cover projections;
- Flood modeling

Modeling scenarios of expansion of Halbouty pump station.



Proposed floodplain (Big Thicket) expansion



Proposed pump station (Halbouty) expansion

Moving forward


Cattail Marsh boardwalk, Beaumont

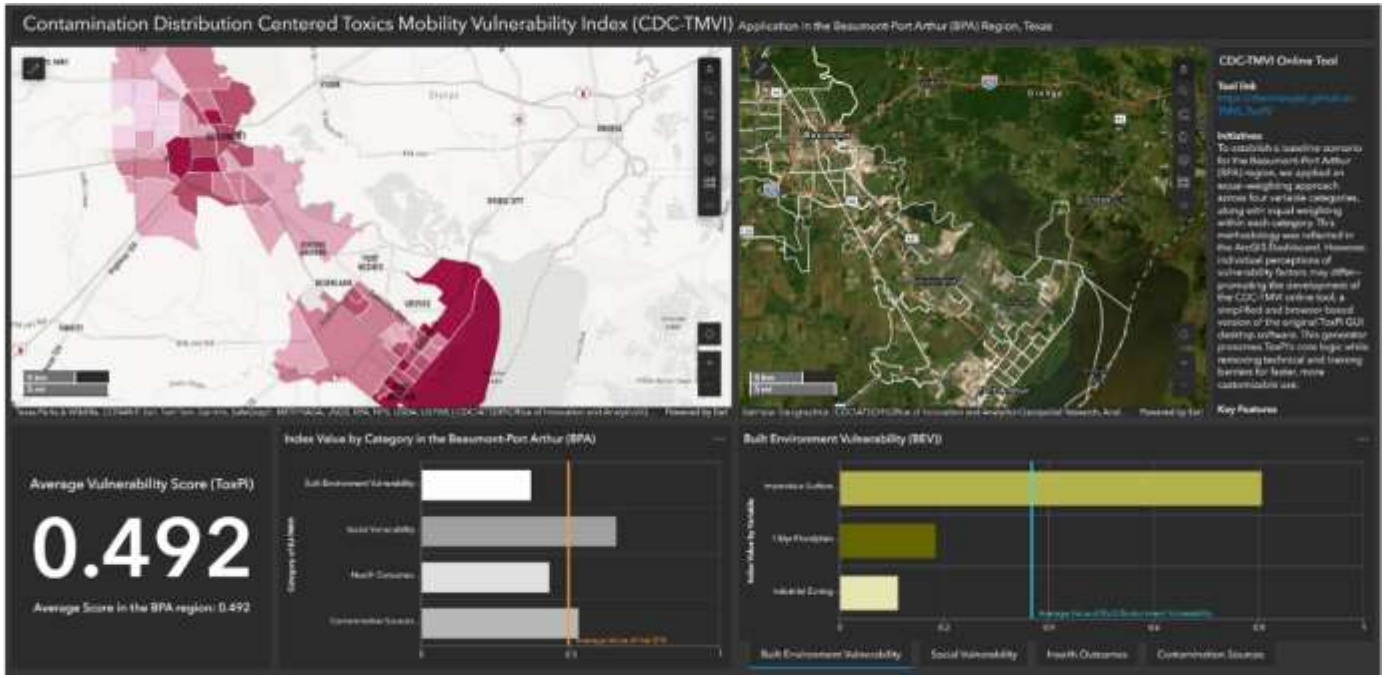
Communication: visualization, data access, opportunities

River floodplain restoration/preservation

Example: Floodplain before and during a flood event (Thomas Borchers' presentation, NWRM Workshop 1 [from: Nora Künkler])

- **Description of strategy:** Preserving forested or natural areas adjacent to rivers
- **Scale:** Neighborhood to regional
- **Benefits:** Habitat restoration, recreational opportunities, carbon sequestration, and flood risk reduction by absorbing excess water. They also improve downstream water quality by filtering pollutants and sediments.
- **Challenges:** High land acquisition costs, complex regulations, potential community resistance, and the need for ongoing maintenance to control invasive species and sediment buildup.
- **Costs/return on investment:** Research by the National Institute of Building Sciences (NIBS) finds that for every $1 spent on flood resilience, communities save $5 to 7 in disaster response and recovery.
- **Local example:** The River Road Ecosystem Restoration Project in San Antonio (construction to begin 2027).

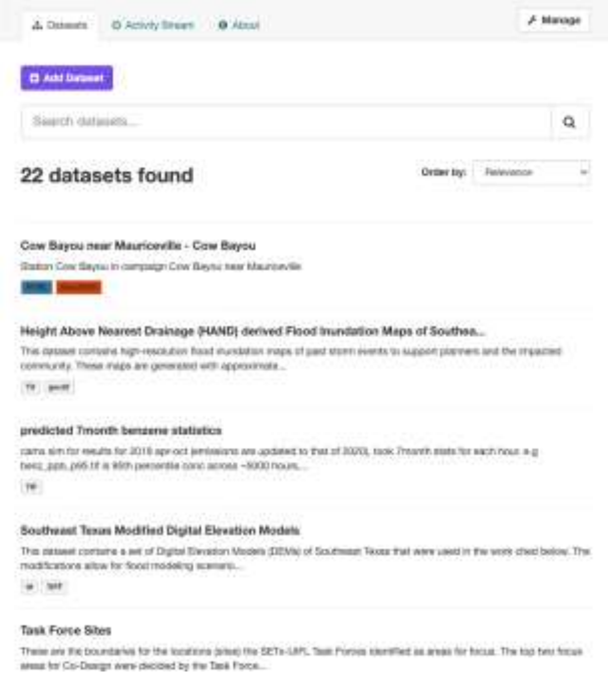
Example Strategy Card from Task Force meetings and survey



CDC-TMVI Dashboard that integrates vulnerability indices into knowledge platform
Developed by G. Newman's group at Texas A&M.

Large volumes of data and modeling results pose challenges for data storage and model integration

CKAN (Inter-team Data Sharing)



Example Theme 1 Data

Air Pollution

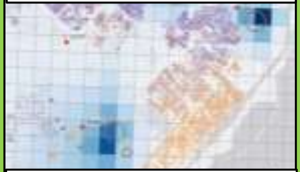


Image Source Yosuke Kimura

Flooding

Image Source Christa Brelsford

Any other raster, NETCDF, polygon dataset

Heat

Image Source Geeta Persad

KMP CKAN Cookbook

Example Theme 3 Data

Population Study Site

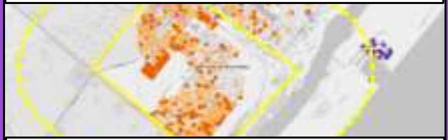


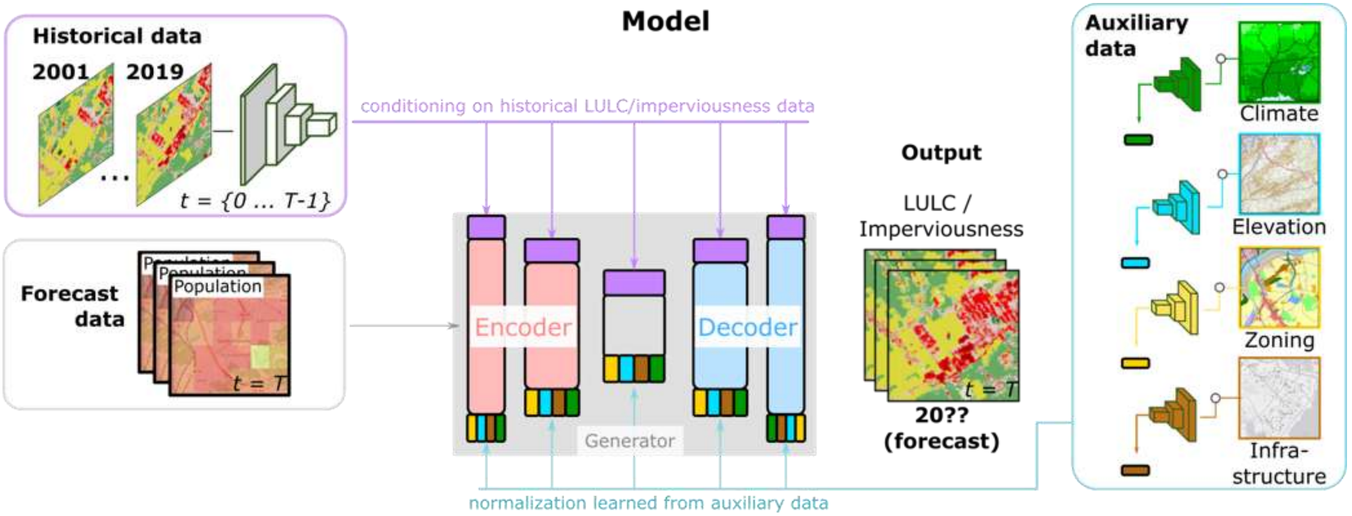
Image Source Nathanael Rosenheim

Spring 2026 Present Data to Taskforce

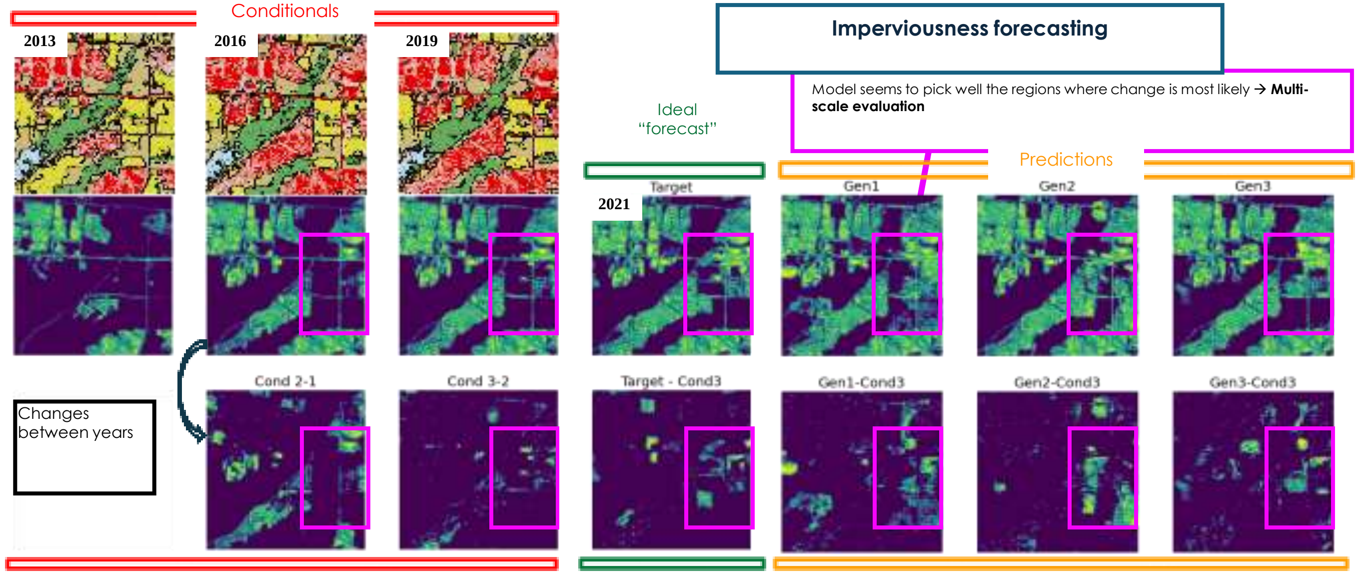
Receive questions and feedback

TACC
TEXAS ADVANCED COMPUTING CENTER

We don’t know what future land cover will look like



The model is conditioned on historical and auxiliary data



Example of LULC forecasting approach:

- National Land Cover Database (NLCD):
  30m/px, historical LULC & imperviousness maps
- Test Case: learn from [2013,2016,2019], predict 2021

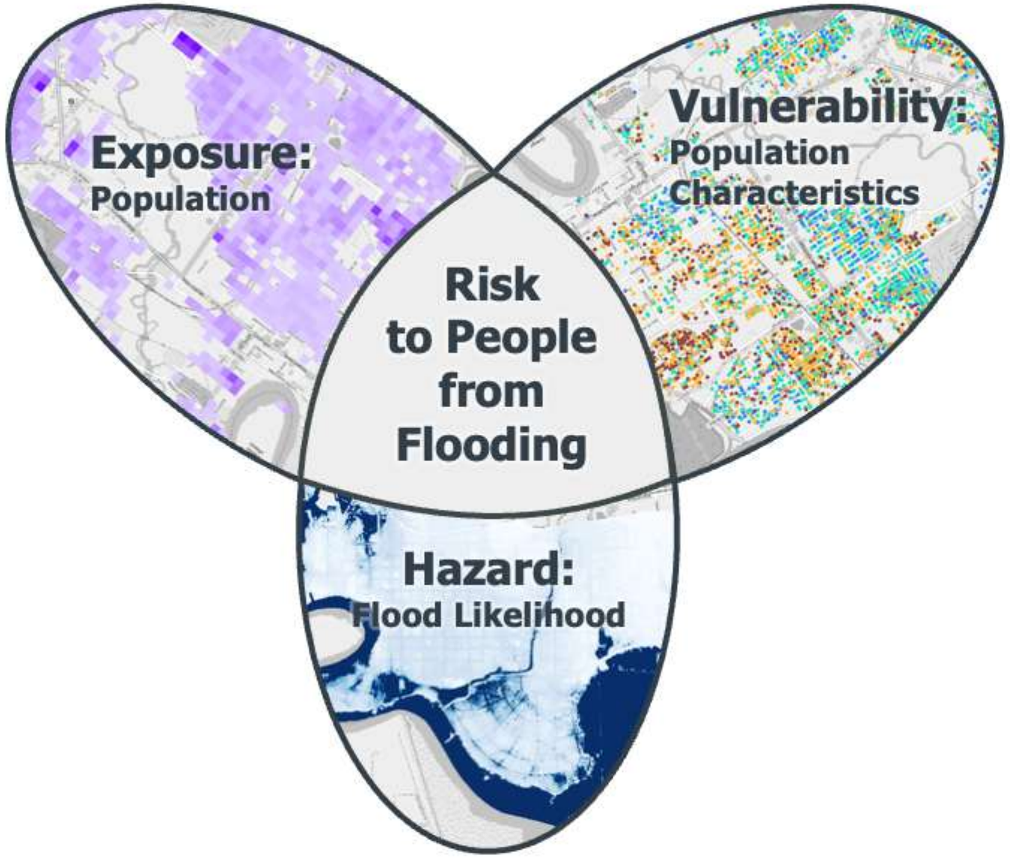
Dias et al., 2025

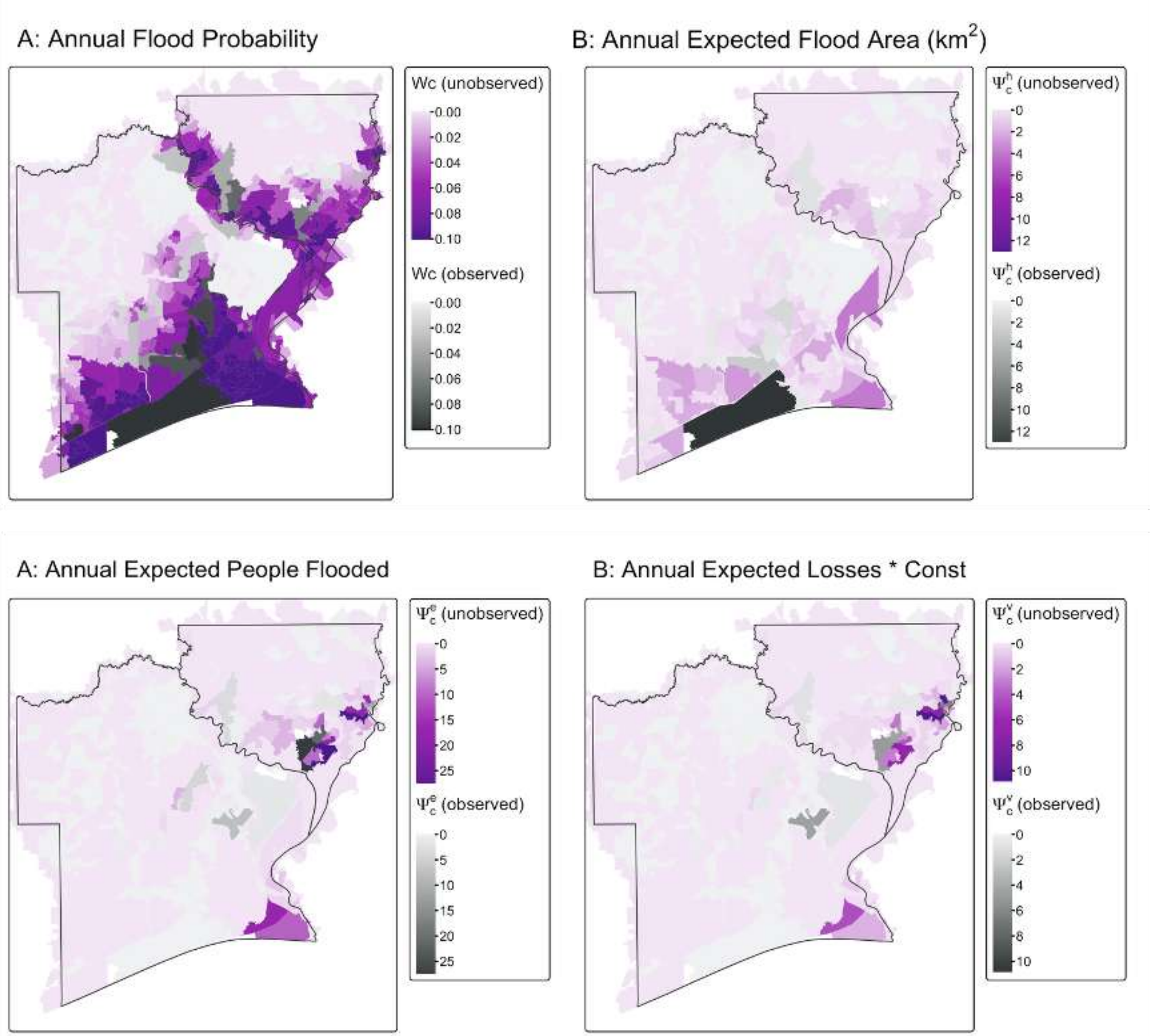
We don't know the geomorphic change resulting from climatic and hydrological changes

Multispectral imager and Lidar on Alta-X drone

We have instrumented the wetlands with a flux tower, and we are running numerical modeling simulations with E3SM Land Model and collecting lidar data and multispectral imagery.

Risk results from the interactions across multiple systems





Brelsford et al., Water Resources Research, 2026

- We quantified risk to people from flooding accounting for hydrological and socio-demographic information
- Based on the analysis, we informed the placement of new sensors
- This risk mapping can be used to prioritize specific objectives in the expansion or design of sensor networks

Building community trust and integrating local knowledge are key

TEXAS A&M UNIVERSITY
Texas Target Communities

Christiaan Brunings devoted his life to being

“...raad en beschermer tegen de woede der zee en der stormen”

That challenge is still with us today, and we continue to improve our understanding and our ability to anticipate, manage, and adapt to these events.

SETx-UIFL approach: top-down and bottom-up