Cloud to Street

Deep Hydrology

Hourly, Gap-Free Flood Maps Through Joint Satellite and Hydrologic Modelling

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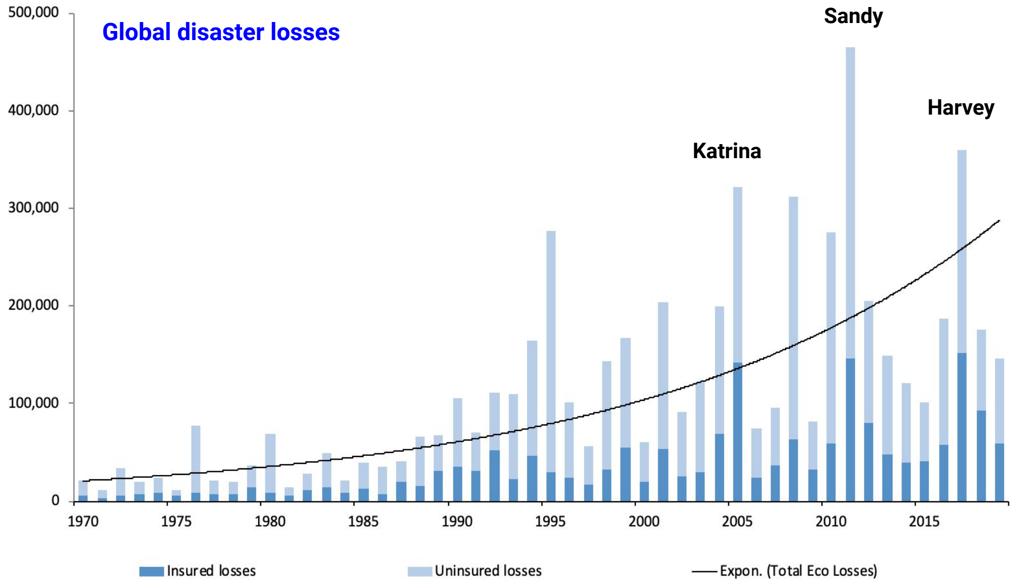
Flood disasters are increasing in frequency and magnitude

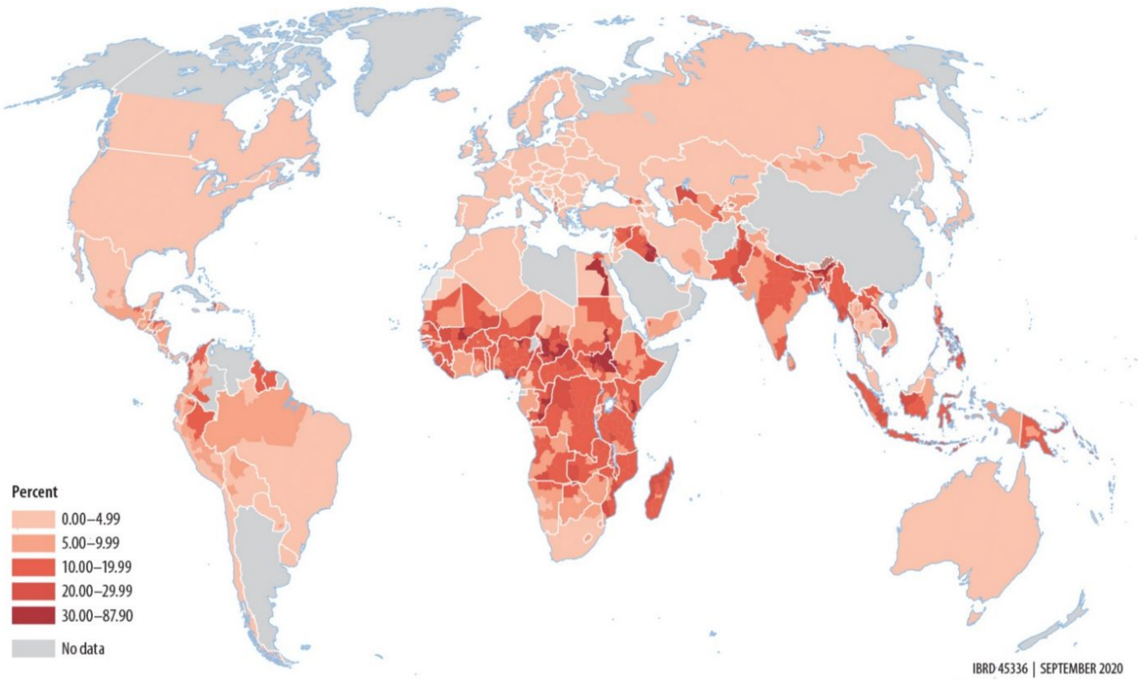
$40B+

Annual Losses due to flood



SwissRe Institute

Places with social vulnerability have the greatest flood risk



Share of total population that is exposed to significant flood risk and living

Cloud to Street

Rentschler and Salhab, 2020

Near Real-Time Flood Mapping

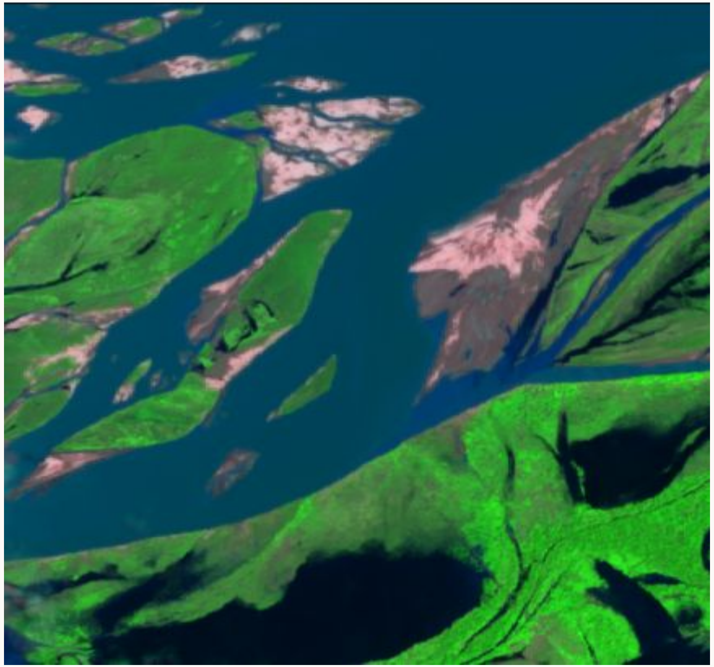
>> Enables decision makers, relief agencies, and citizens to make informed decisions and provide direct relief where it is needed most.

Milkmen wade through a flooded road after Cyclone Amphan, in North 24 Parganas district.
(Photo: PTI)

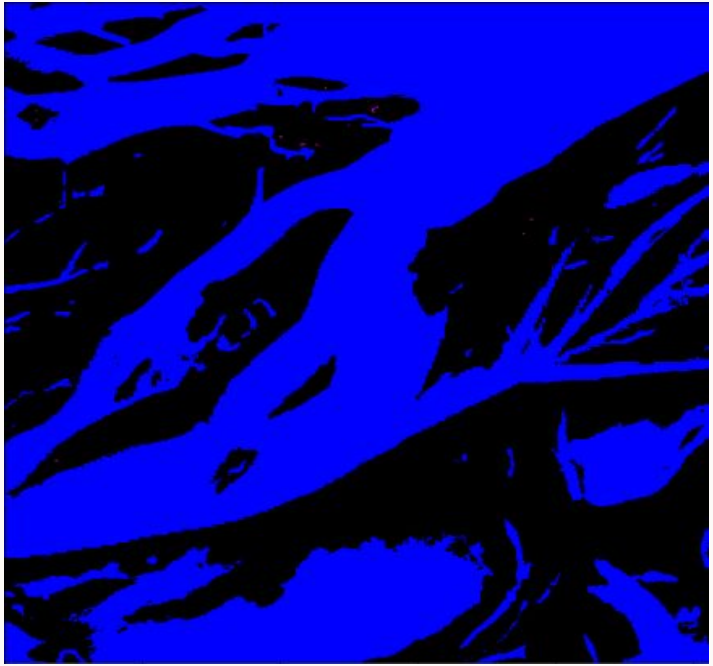
Cloud to Street

Satellite can observe surface flooding

Optical Satellite Observation

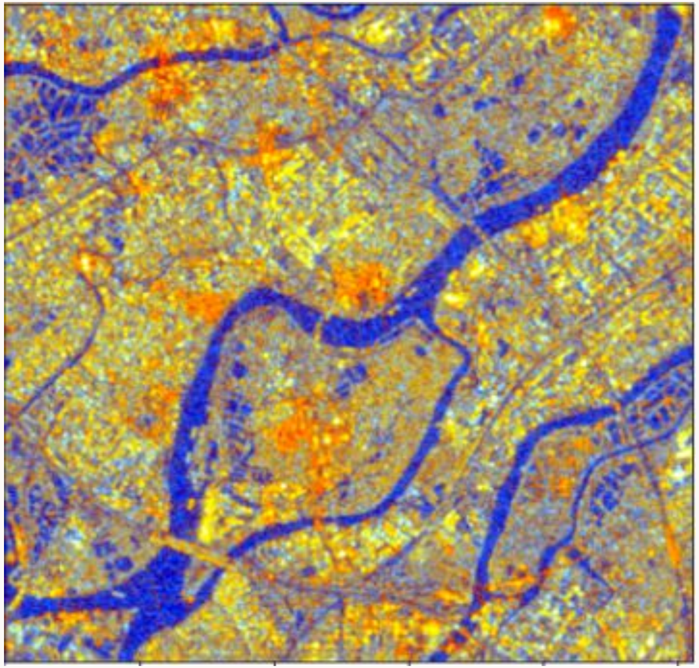


Floodmap

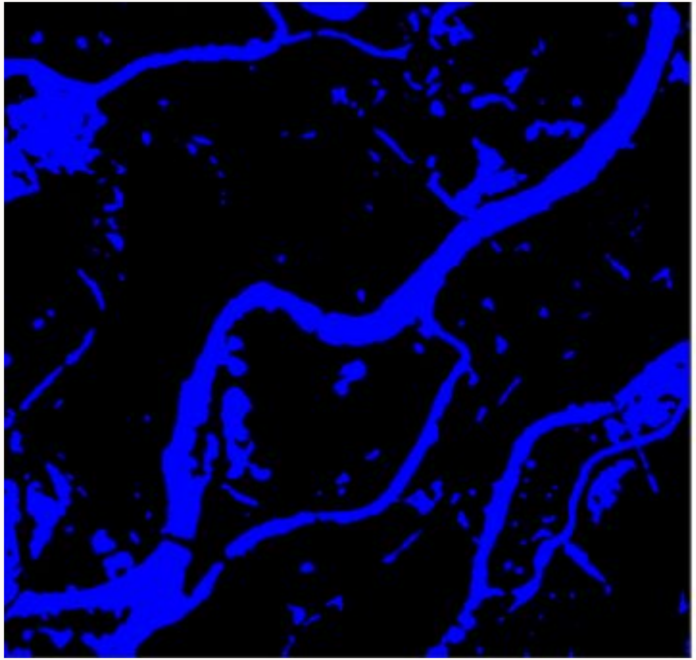


Satellite can observe surface flooding

RADAR Satellite Observation

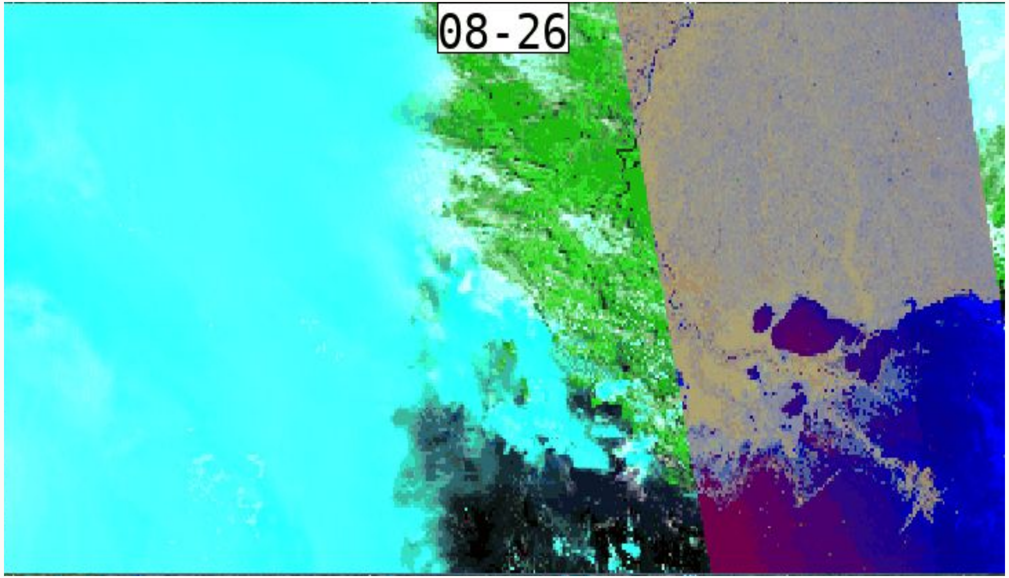


Floodmap



Clouds and low-revisit periods limit satellite reliability

Cloud to Street



Southern Texas, Louisiana during Hurricane Harvey

Cloud to Street

Flood Mapping Technology

	Public Satellite Observations	Hydraulic and Hydrologic Models
Strengths	Low runtime computational complexity Scalable “observed truth”	High temporal resolution High spatial resolution
Limitations	Cloud, canopy cover Low revisit time	Need high-quality geographic features and infrastructure information Runtime computational complexity Slow to scale to new regions

Flood Mapping Technology

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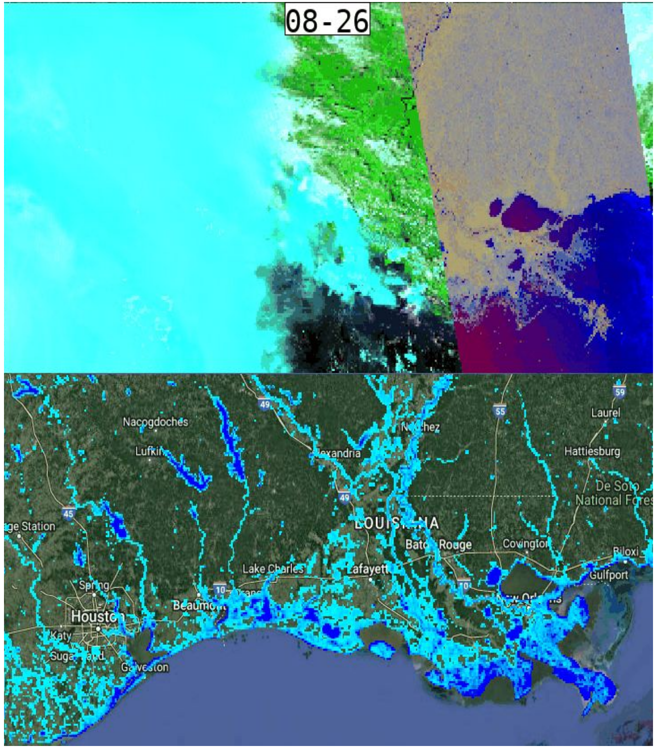
Moving Beyond Direct Observations

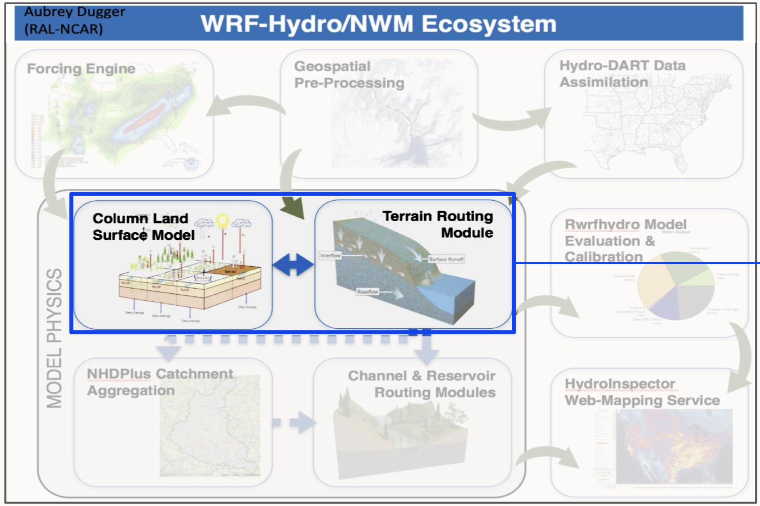
>> How can we fuse state-of-the-art flood maps from direct observation with more frequent (hourly, daily) modeled products to produce the necessary daily flood maps for disaster monitoring?



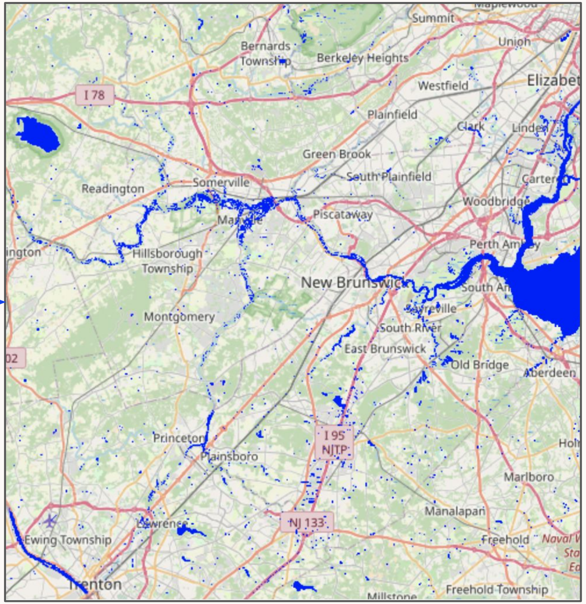
Deep Hydrology:
Leveraging strengths of Observations and Models

Cloud to Street

Dynamic Inputs



Deep Network



Static Geographical Inputs

Gochis, D.J., et al., (2020)

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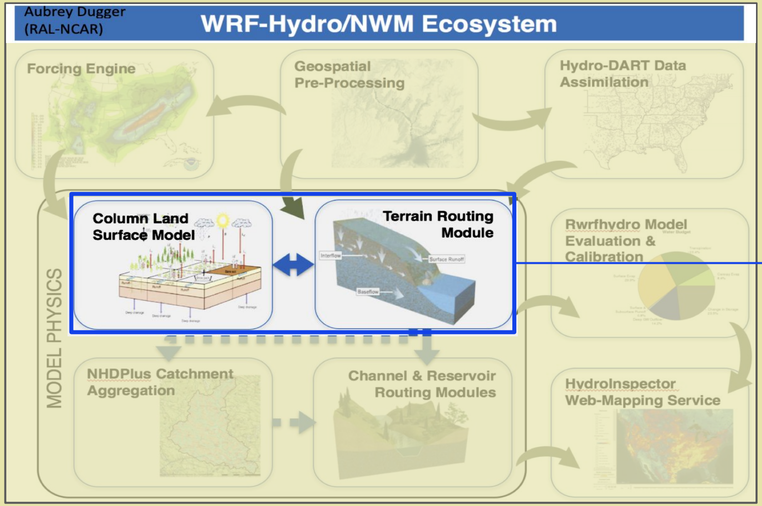
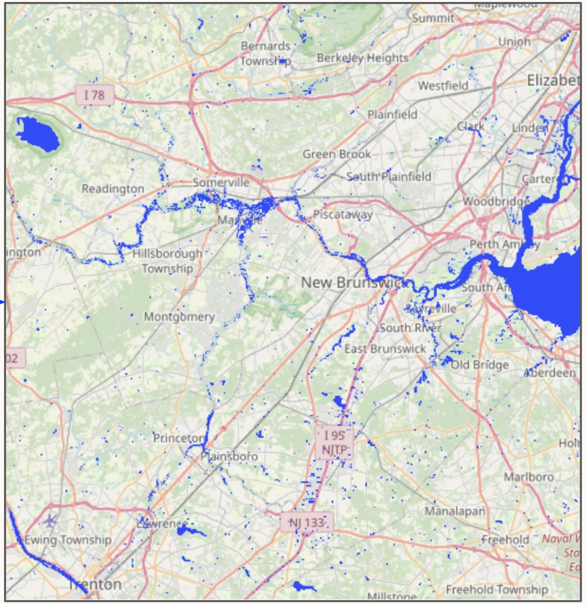
Cloud to Street

Dynamic, physically modelled inputs: Updated hourly



Deep Network



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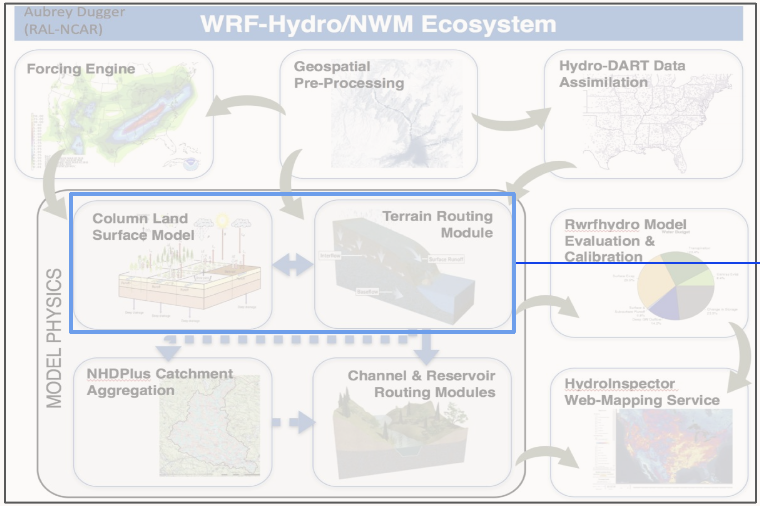

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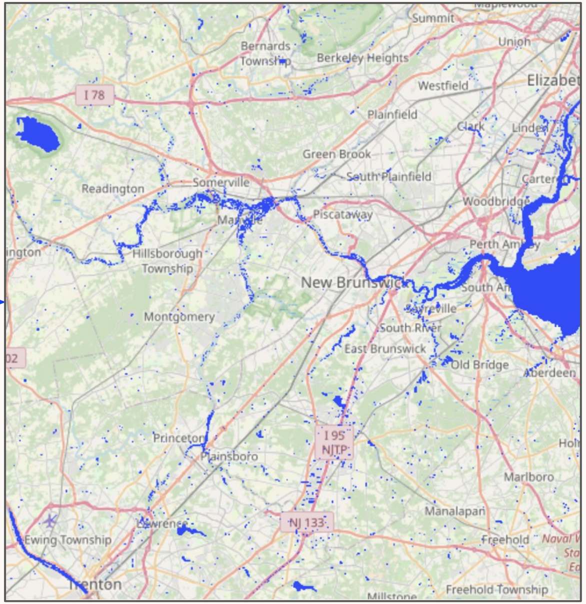

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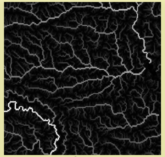
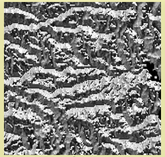
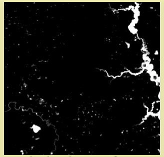


Flow Accumulation



Flow Direction



Global Surface Water

Gochis, D.J., et al., (2020)

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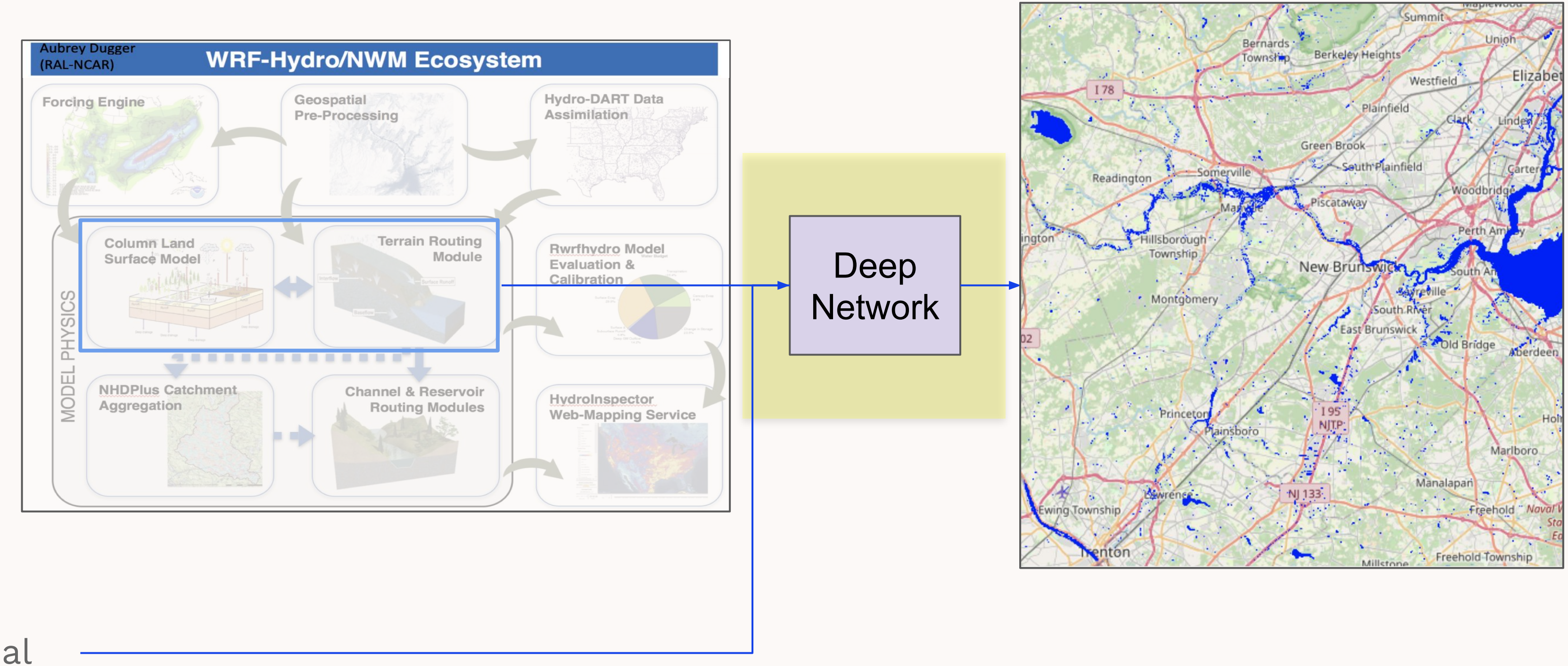

Static Geographical Inputs

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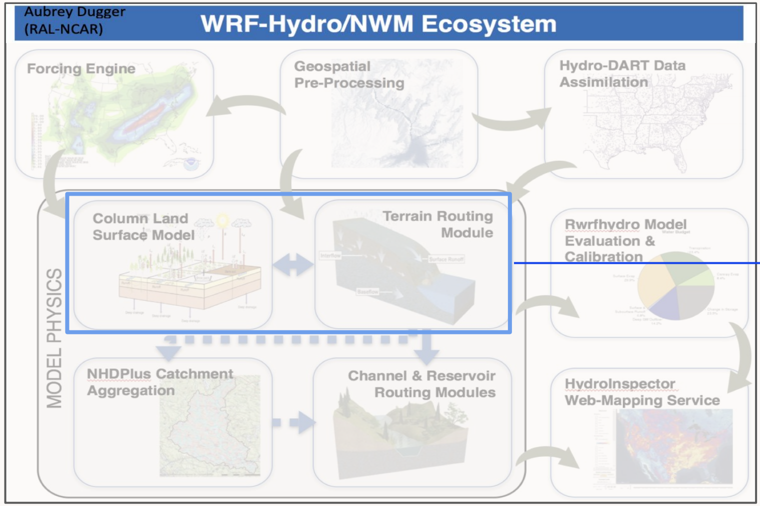
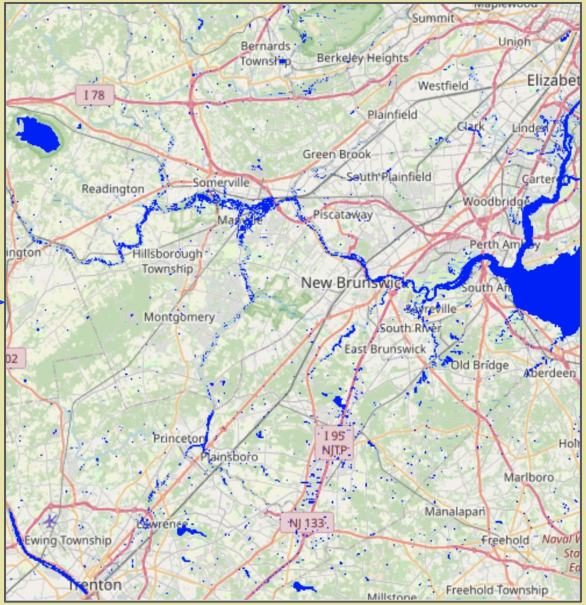


Deep Network



Static Geographical Inputs

Target:
Satellite observed flood maps

Gochis, D.J., et al., (2020)

Experimental Setup

- Inputs
  - 72 hour routing aggregate
  - 72 hour soil moisture aggregate
  - static flow direction, flow accumulation
  - global surface water (gsw)*
- Target: MODIS Constellation Flood Maps in the United States
  - Selected based on geographic distribution, visibility
- 6865 examples divided in 3 cross-validation folds and a test set
- Model selection:
  - Take best models based on held-out validation metrics and evaluate on unseen case studies. Select best based on case study performance (qualitative + quantitative)

*Pekel, Jean-François, et al. "High-resolution mapping of global surface water and its long-term changes." Nature 540.7633 (2016): 418-422.

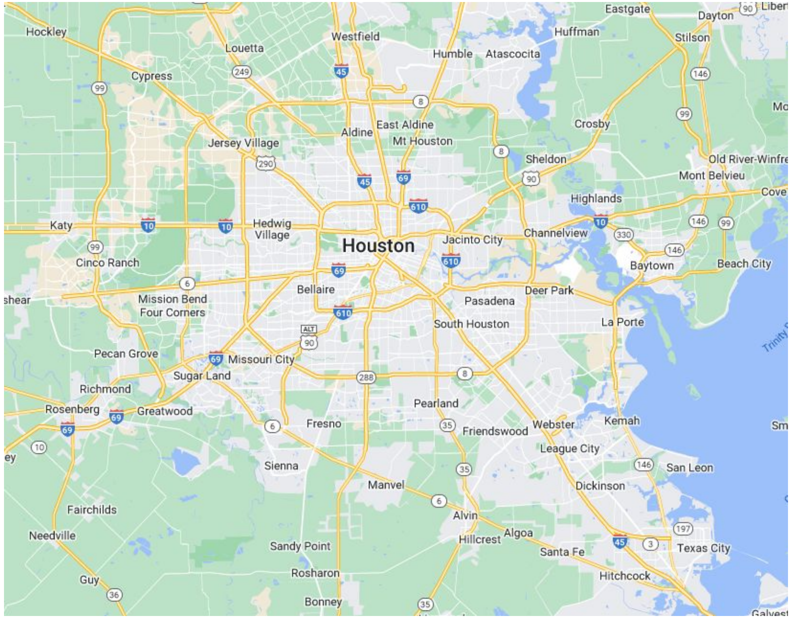
Quantitative Results

>> **RMSE excluding True Negatives**

Pixel Grouping	RMSE
Never-Flooded	0.063 +/- 0.014
Flooded Before	0.069 +/- 0.02

Case Study: Houston

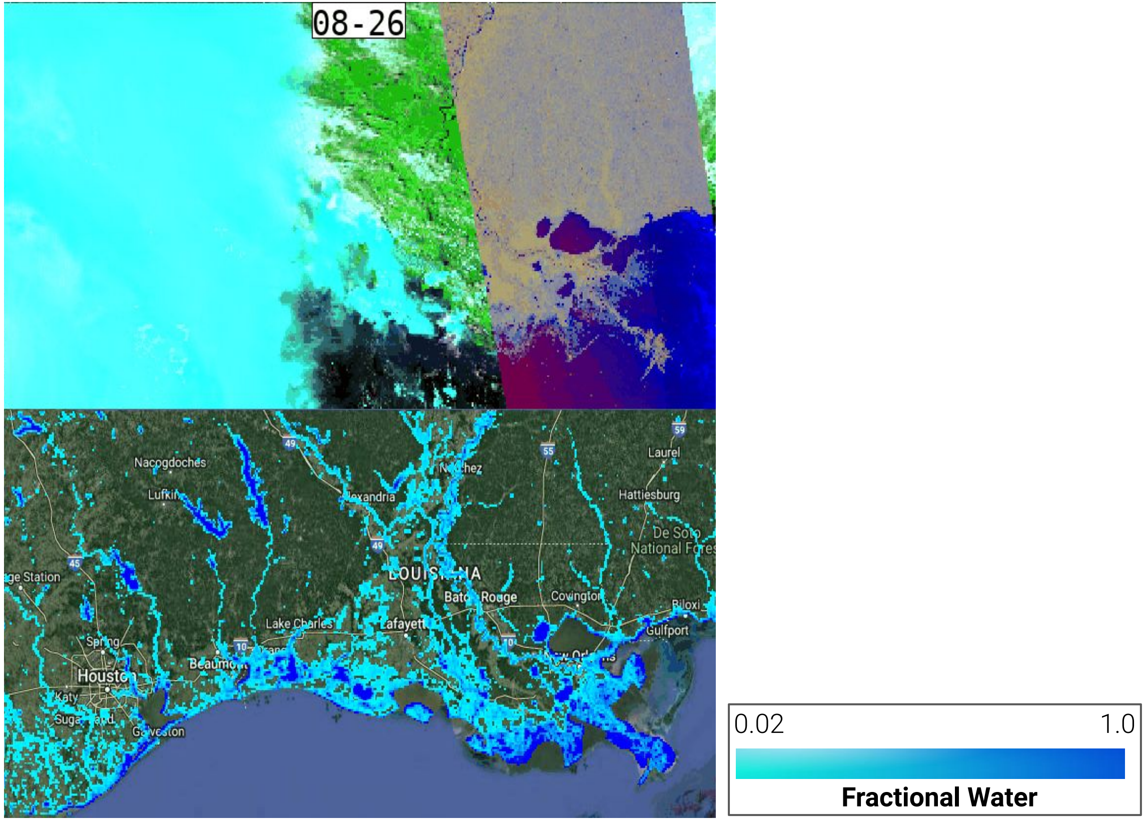
>> Can our model separate storms that caused flooding from those that did not?



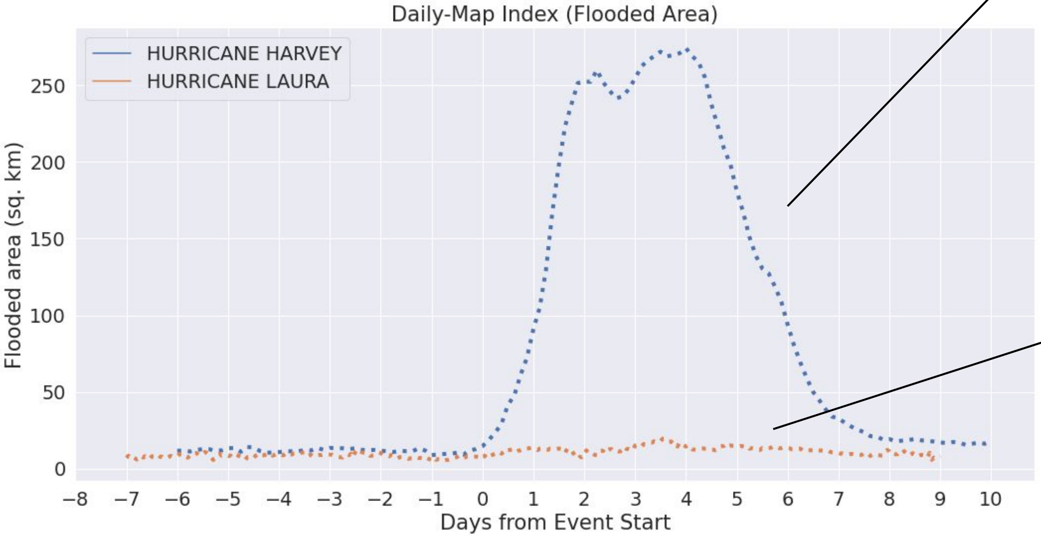
Case Study: Hurricane Harvey

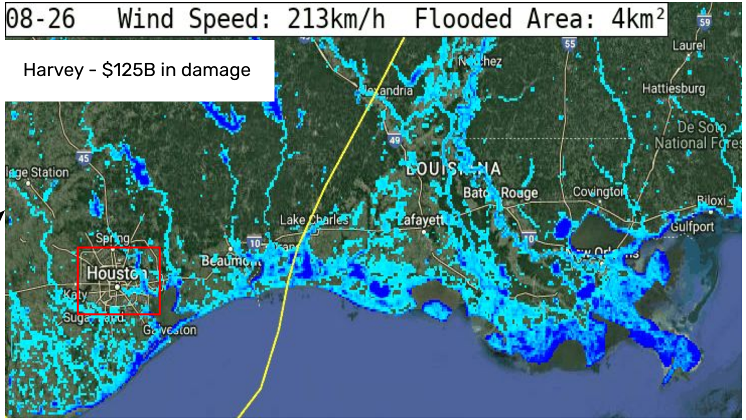
Daily Satellite observations from public sensors

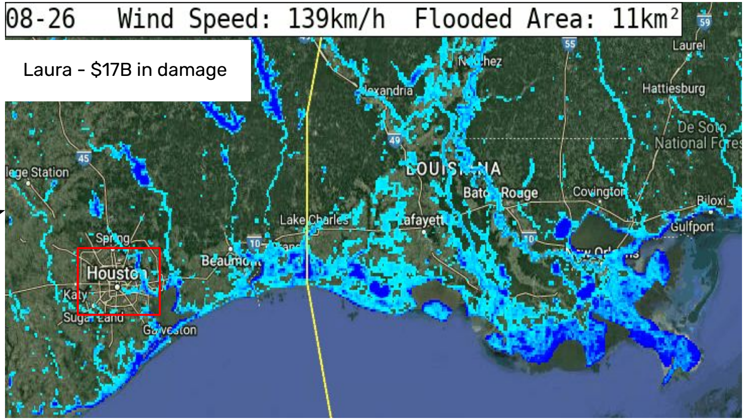
Daily Modelled Flooding



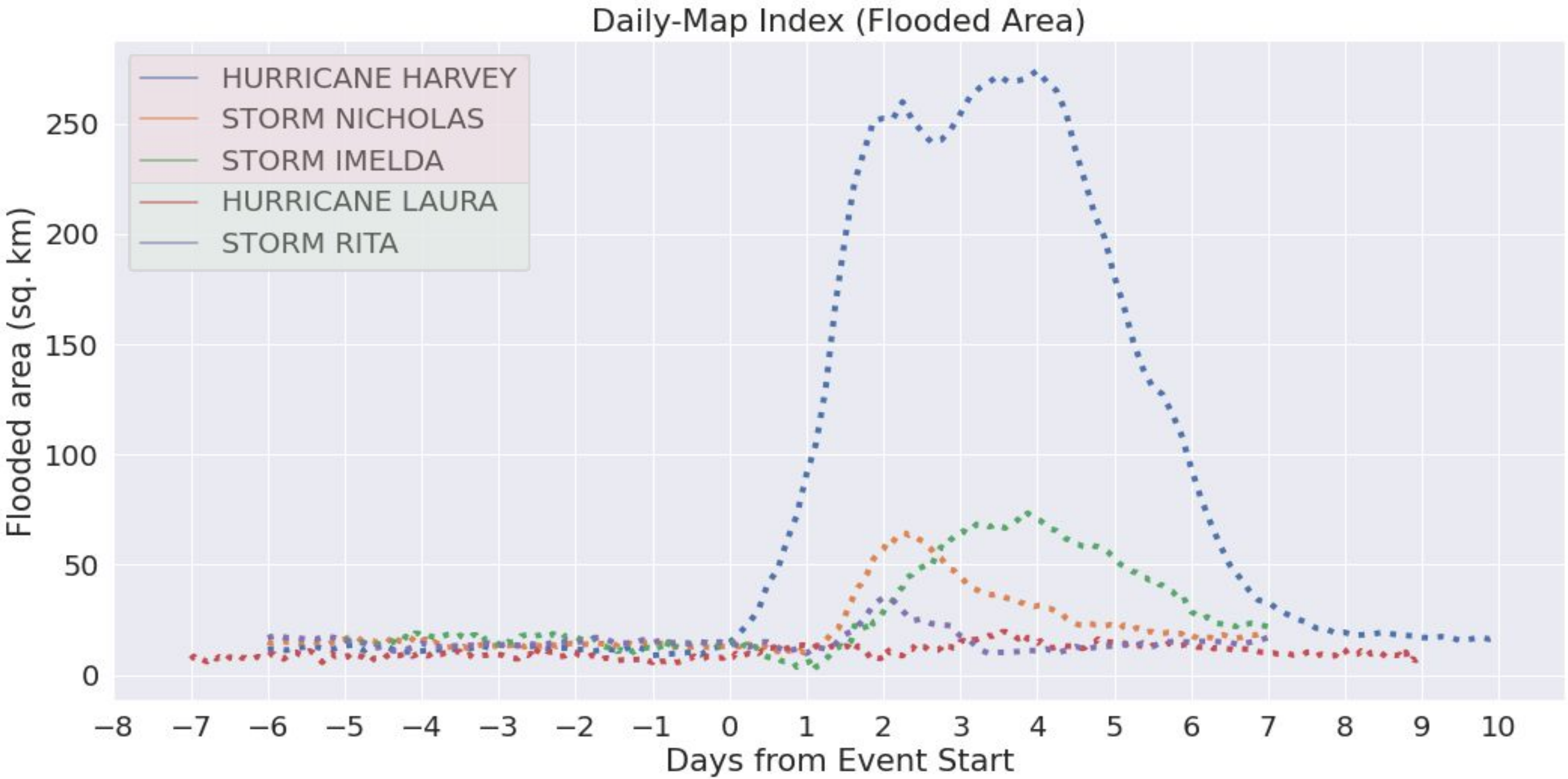
Our model can capture exposure to flood damage where other hurricane risk factors do not (ex. wind)







Within the Houston AOI, we can separate events that cause flooding (Harvey, Nicholas, Imelda), from those that do not (Laura, Rita)



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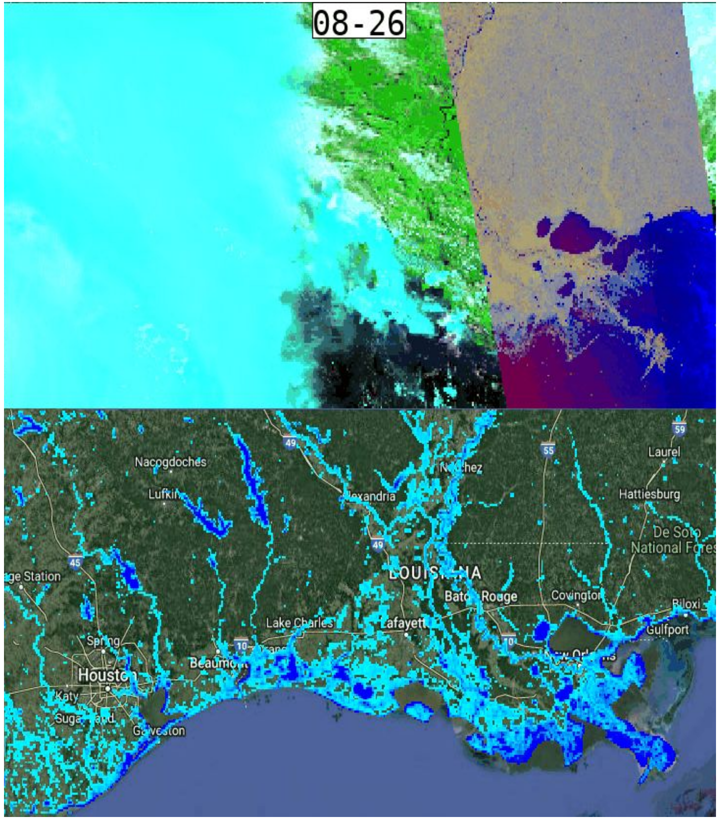
Daily Flood Monitoring

>> Using high-quality, satellite-derived flood maps, we are able to produce hourly flood extent maps from the hydrological states produced by the National Water Model that mirror the extent and intensity of major flood events in the US.

We can distinguish the severity of different flooding events across history.



Future Work

1. Integrating sources of flooding beyond precipitation-driven data
2. Increased resolution
3. Globalization

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Built in Brooklyn

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