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Data Driven Stormwater Management for Climate Resilience

Abhijeet Patel | WSP



Disclaimer

- The following presentation on AI applications in hydrology science reflects recent trends and findings from current research.
- I am not an author of the research discussed herein; this presentation is based on my personal interest in the topic.
- The views and opinions expressed are solely mine and do not represent those of WSP.

Contributors



Google Research



University of
Alabama



Johannes Kepler
University



Upstream
Tech, PBC



University of
Arizona



NASA



Frederik
Kratzert



Daniel
Klotz



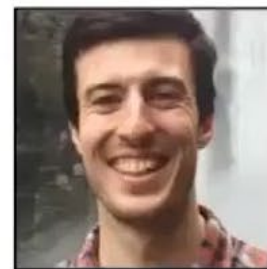
Sepp
Hochreiter



Craig
Pelissier



Grey
Nearing



Alden
Sampson



Jonathan
Frame



Hoshin
Gupta

<https://neuralhydrology.github.io/>

Presentation Outline

- Problem statement
- Case study of ML application in context of Hydrology and Climate Change
- Other avenues to be explored with AI and ML
- Summary, conclusion and Q&A





This
presentation
is NOT
about...



Application of AI /ML for
government policy and regulation
pertaining to climate resilience



Financial aspect of climate resilience
planning using AI/ML



In-depth technical analyses of
concepts discussed however the
github repositories mentioned in the
video will be shared in the end



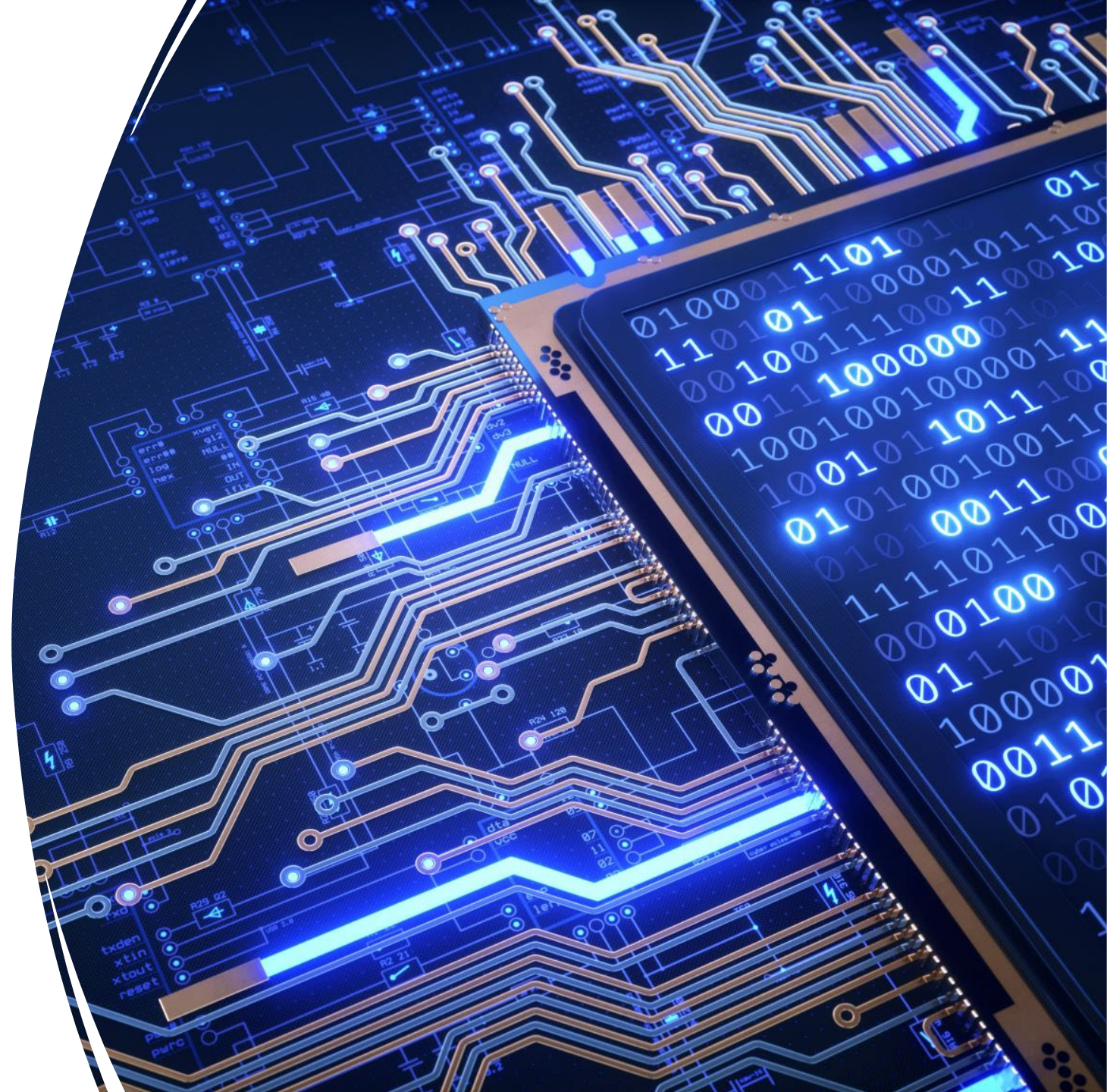
Word Definitions

- Climate resilience: It is the capacity or ability to **anticipate** and **cope with shocks**, and **to recover** from changing climate conditions and disruptions in a timely and efficient manner.
- Examples:
 - Increased Capacity for Water Storage
 - Integration of Nature-Based Solutions
 - Flexible Infrastructure Design
 - Climate-Informed Planning and Decision-Making



Word Definitions

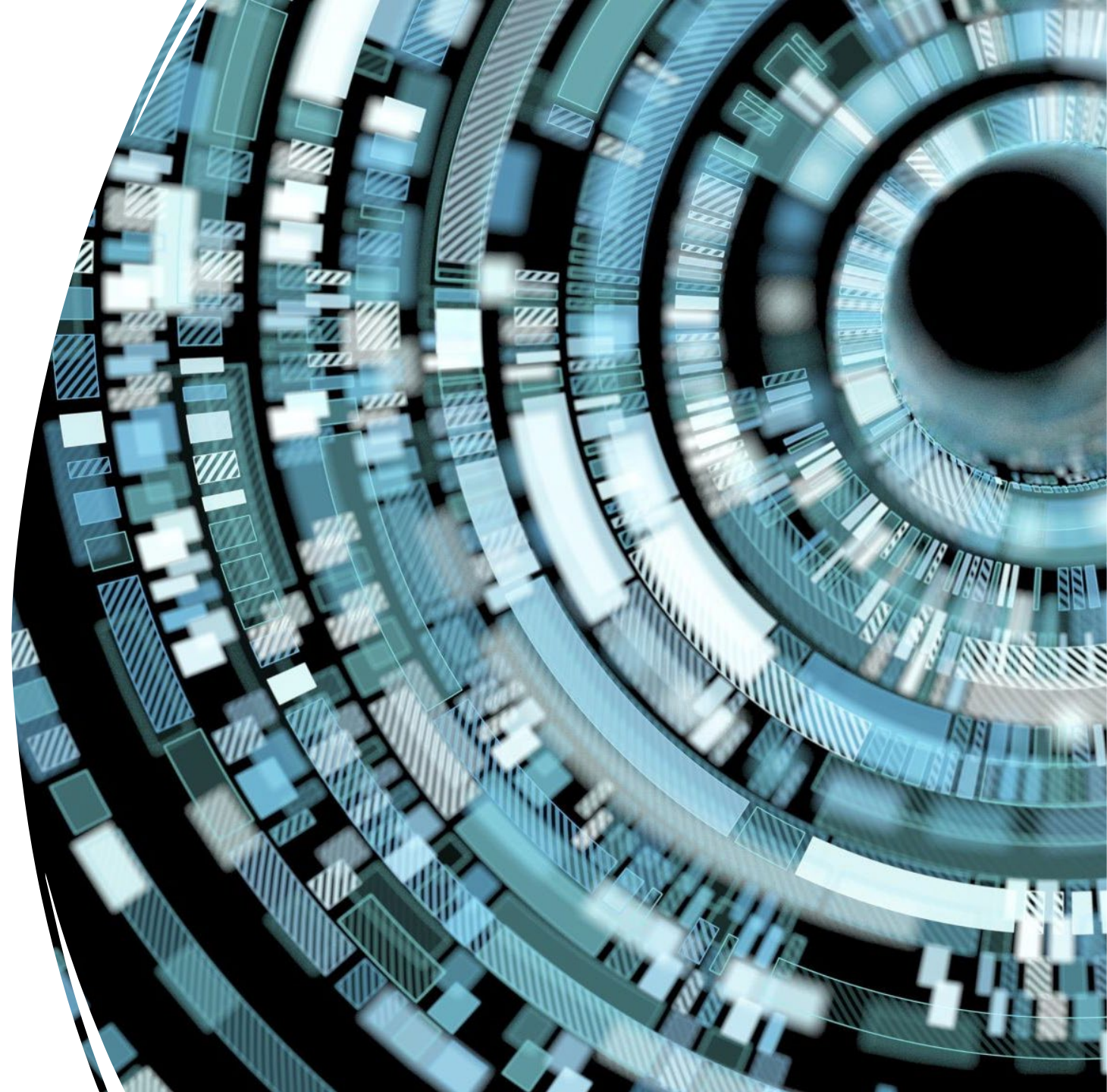
- Artificial Intelligence: AI refers to the development of computer systems or algorithms that can perform tasks typically requiring human intelligence, such as understanding **natural language**, **recognizing patterns in data**, and **making decisions**.
- Examples of AI :
 - Natural Language Processing (NLP)
 - Computer Vision
 - Robotics
 - Expert Systems





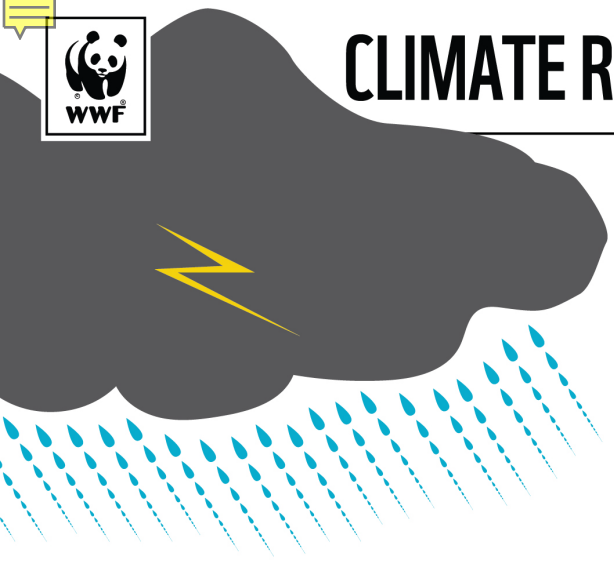
Word Definitions

- Machine Learning: ML is a subset of AI that focuses on algorithms and techniques that enable computers to **learn from data** and improve their performance on **specific tasks over time**, without being explicitly programmed.
- Examples of ML :
 - Supervised Learning
 - Unsupervised Learning
 - Reinforcement Learning
 - Deep Learning





CLIMATE RISKS: 1.5°C VS 2°C GLOBAL WARMING



EXTREME WEATHER

100% increase in flood risk. vs **170%** increase in flood risk.

SPECIES

6% of insects, **8%** of plants and **4%** of vertebrates will be affected. vs **18%** of insects, **16%** of plants and **8%** of vertebrates will be affected.

WATER AVAILABILITY

350 million urban residents exposed to severe drought by 2100. vs **410 million** urban residents exposed to severe drought by 2100.

ARCTIC SEA ICE

Ice-free summers in the Arctic at least once **every 100 years.** vs Ice-free summers in the Arctic at least once **every 10 years.**

PEOPLE

9% of the world's population (700 million people) will be exposed to extreme heat waves at least once every 20 years. vs **28%** of the world's population (2 billion people) will be exposed to extreme heat waves at least once every 20 years.

SEA-LEVEL RISE

46 million people impacted by sea-level rise of 48cm by 2100. vs **49 million people** impacted by sea-level rise of 56cm by 2100.

OCEANS

Lower risks to marine biodiversity, ecosystems and their ecological functions and services at 1.5°C compared to 2°C.

CORAL BLEACHING

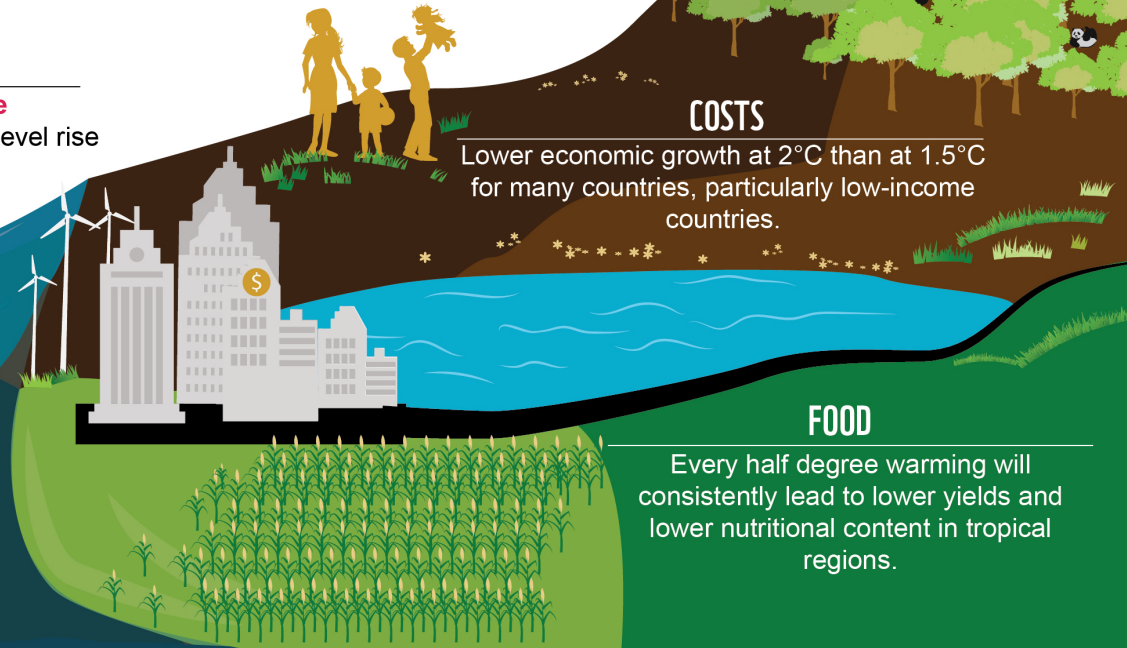
70% of world's coral reefs are lost by 2100. vs **Virtually all coral reefs are lost** by 2100.

COSTS

Lower economic growth at 2°C than at 1.5°C for many countries, particularly low-income countries.

FOOD

Every half degree warming will consistently lead to lower yields and lower nutritional content in tropical regions.



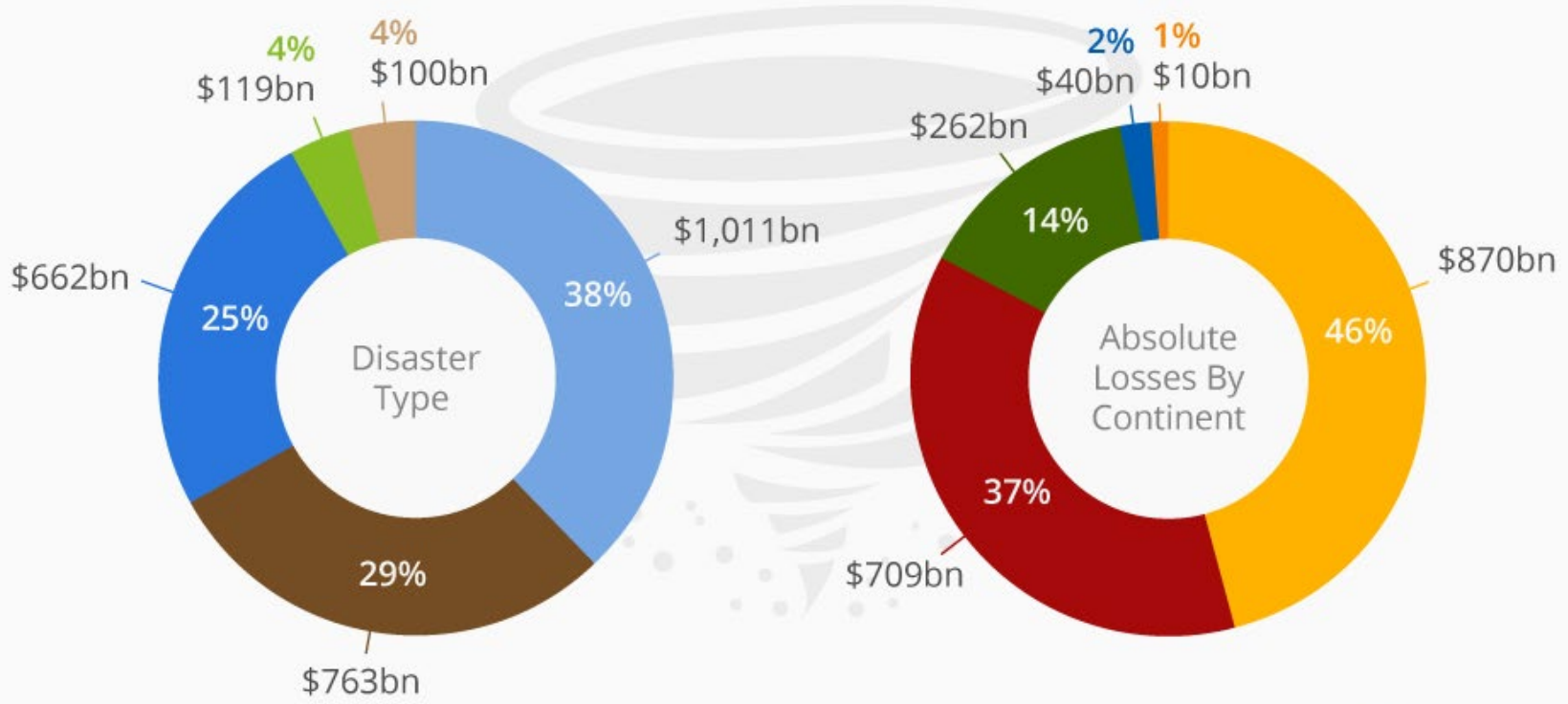
Problem statement

Problem Statement

The Natural Disasters That Inflict The Most Economic Damage

Economic damage by disaster type and region from 1995 to 2015

- Storm
- Geophysical
- Flood
- Americas
- Asia
- Europe
- Weather related-other
- Drought
- Oceania
- Africa



CC BY ND
@StatistaCharts

Source: UNISDR

statista

Accurate predictions and planning are one of the most successful predictors of survival
Better forecasting models are needed For climate resilience



27-1400=87?

SENIOR WOODCHUCK COUNCIL



MOTHER

Matilda



FATHER

Hortense

GRANDPA



Good for the Goose

CLAN McDUCK

SCROOGE'S WORST NIGHTMARE



friend of F.O.W.L

Beagle Burg

Beagle Boy Names:
• Burger
• Bigtime

What Looms Larger than McDuck's Shadow?



SCROOGE McDUCK



Hortense

Neither World War I nor World War II

who is D.B.?

Scotty McDuck - Alternate Timeline???

- Sir Roast McDuck
- Seafoam McDuck
- Malcol McDuck
- Sir Stuf
- Sir Quacklet
- Sir Elder



Quackmore Duck

DUCKBURG DAILIES
SKYPIRATES SPOTTED ABOVE PLAIN AWFUL!

10d = 11

The Last TREASURE

friends



Granny

ME!!!
WEBBY!!!

GRANNY

Disney DUCKTALES



Huey, Dewey, Louie



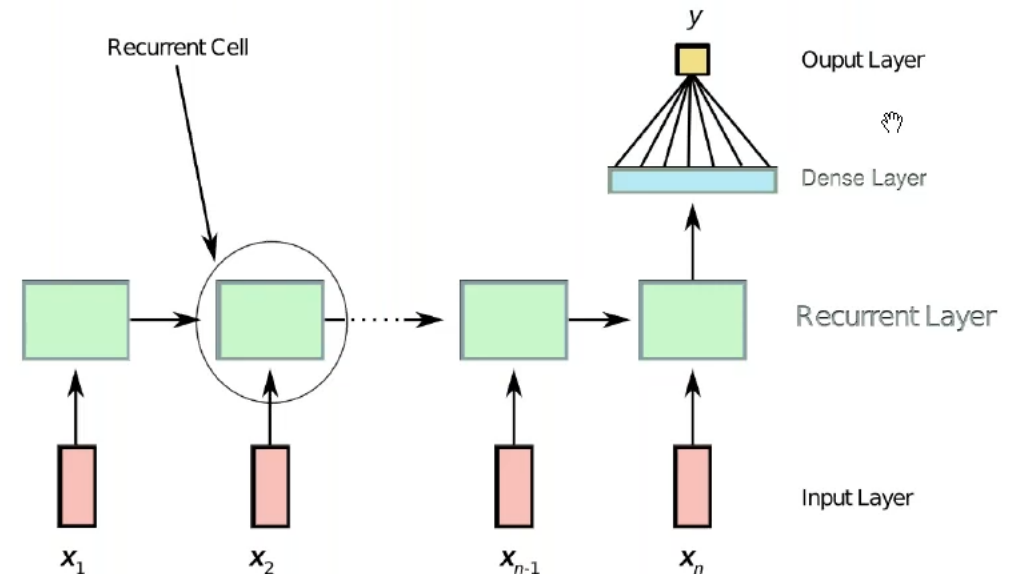
What's Cleaning My Room??

Disney CHANNEL

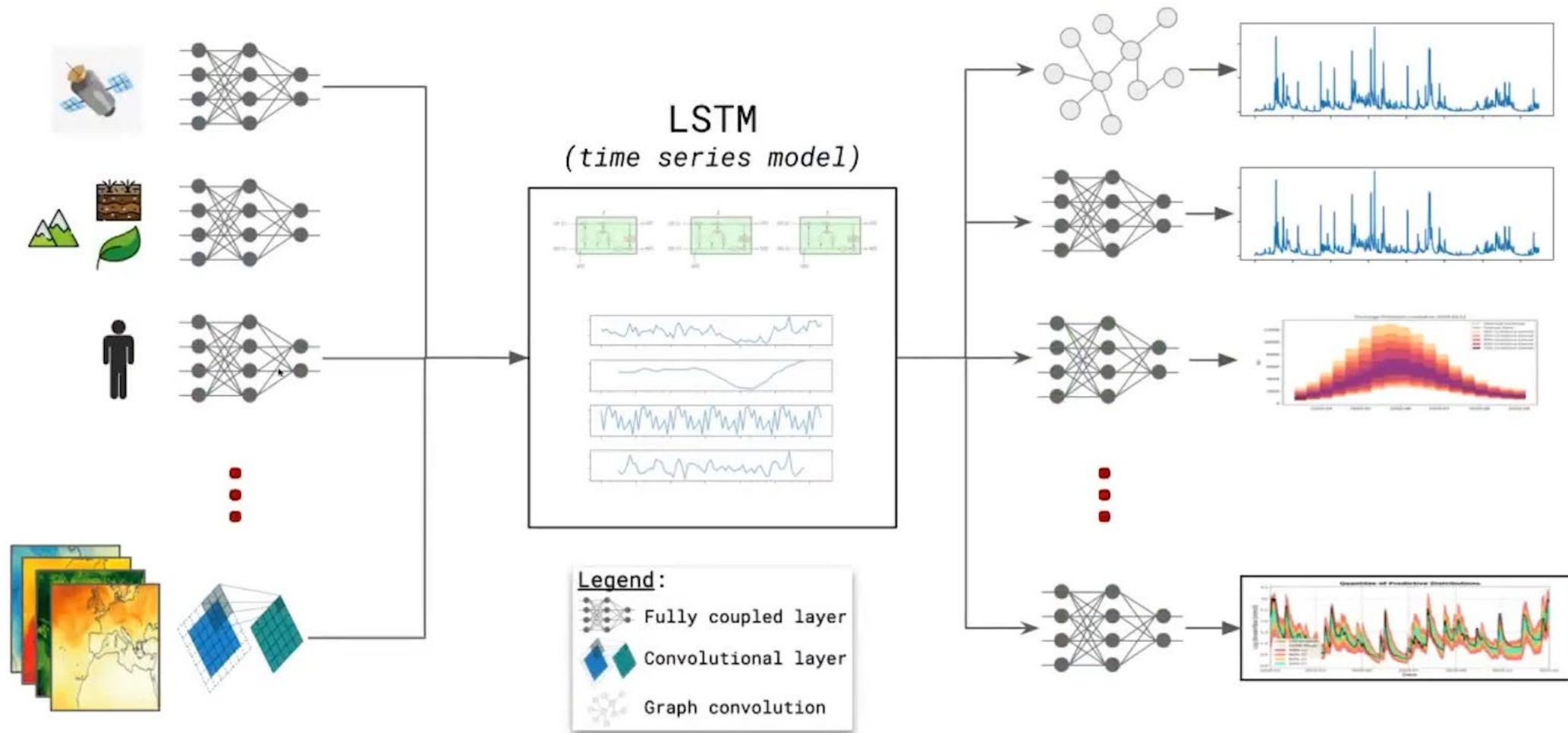
© Disney

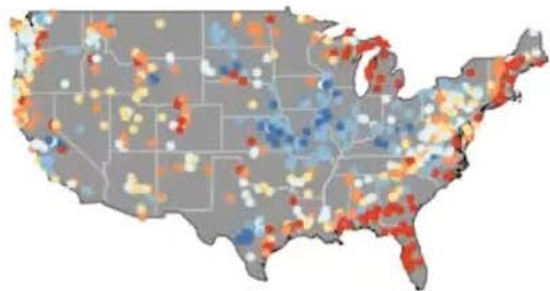
The LSTM

- **R**ecurrent **N**eural **N**etwork with explicit memory (Hochreiter and Schmidhuber, 1997)
- Used across a wide range of applications
 - E.g. language modeling, machine translation, image captioning, etc.



Embedding into Deep Learning Models

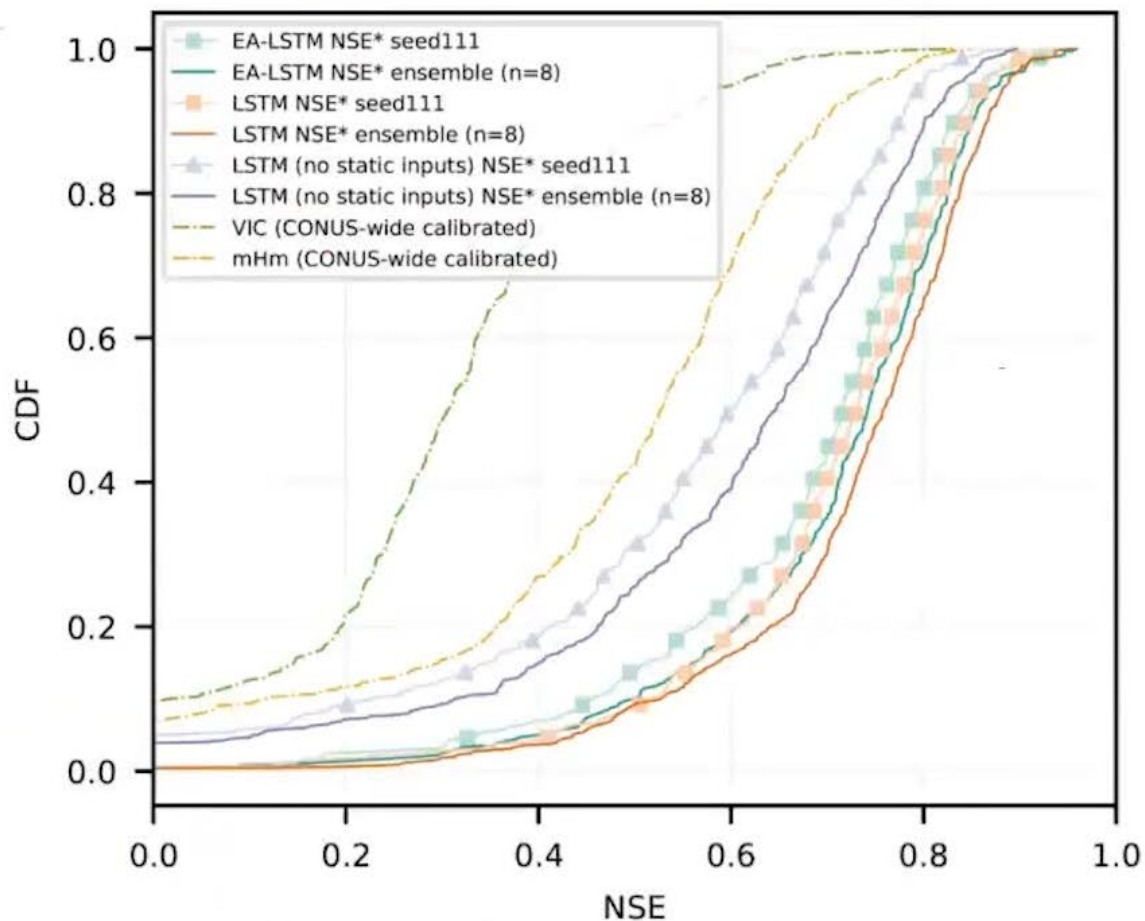




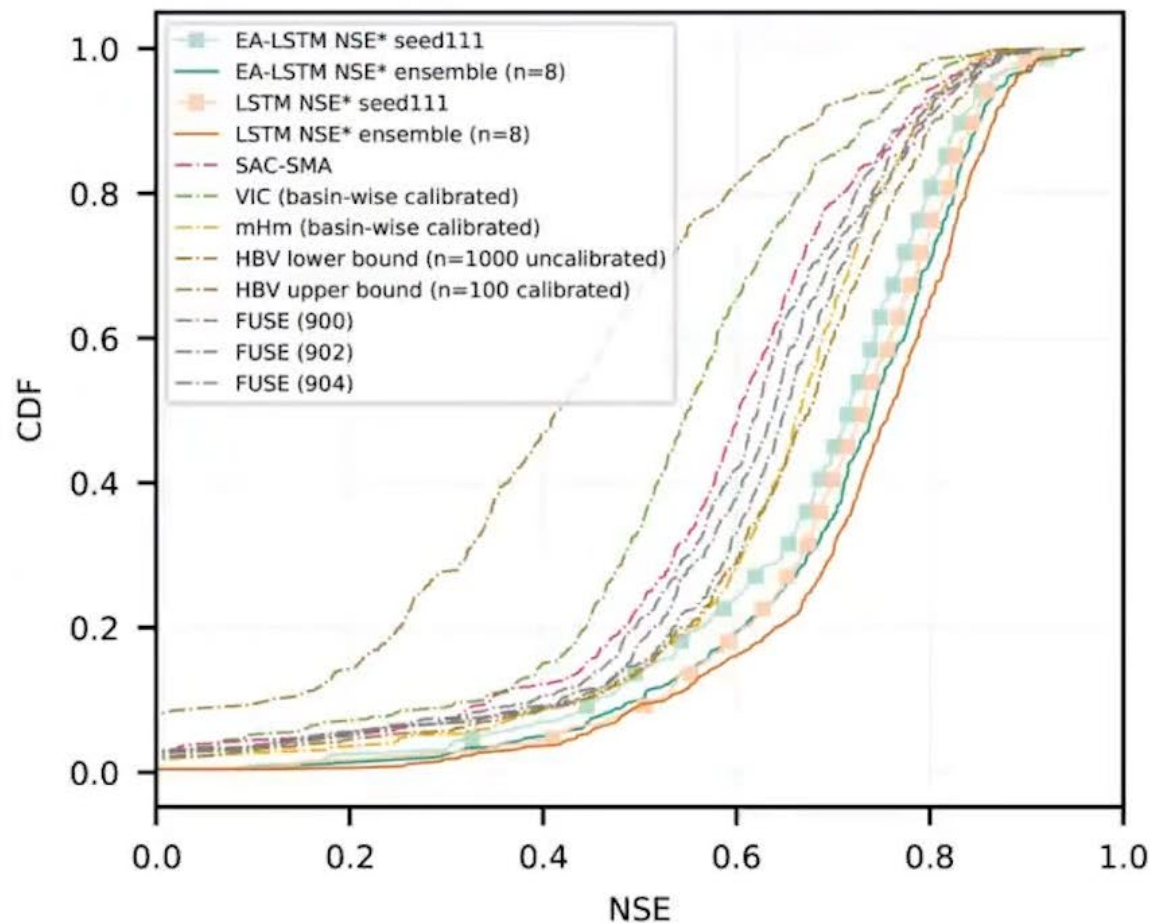
Regional Modeling

Regional LSTMs are better than catchment-specific hydro models.

Benchmarking vs CONUS-wide calibrated models

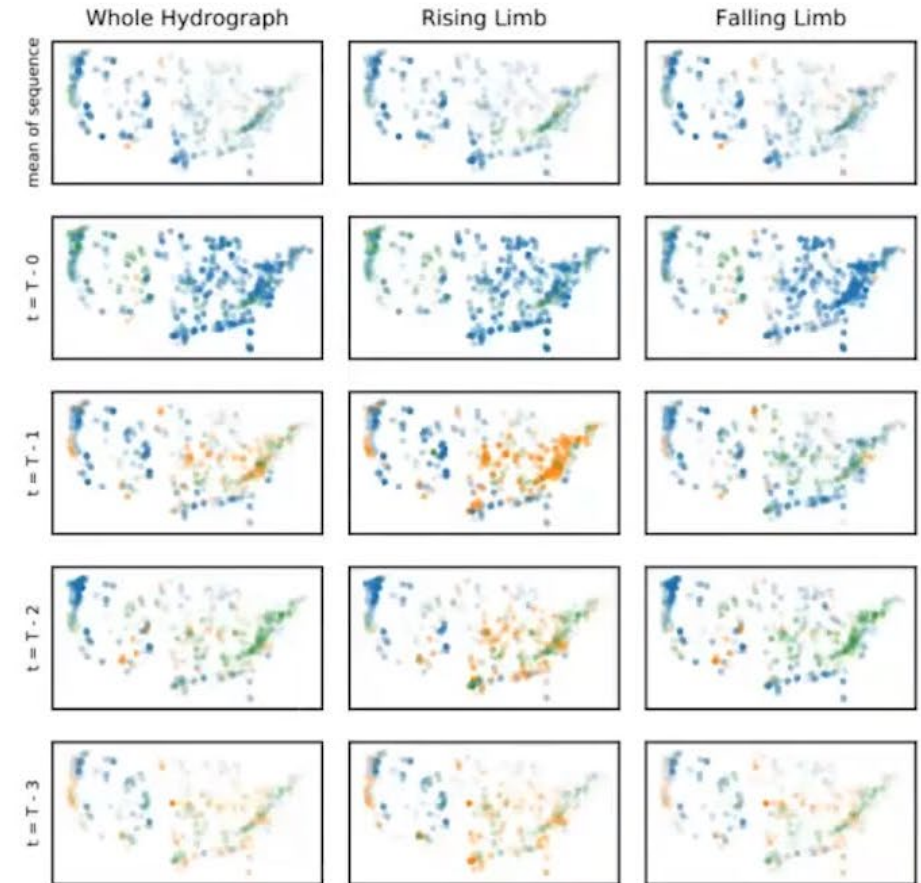
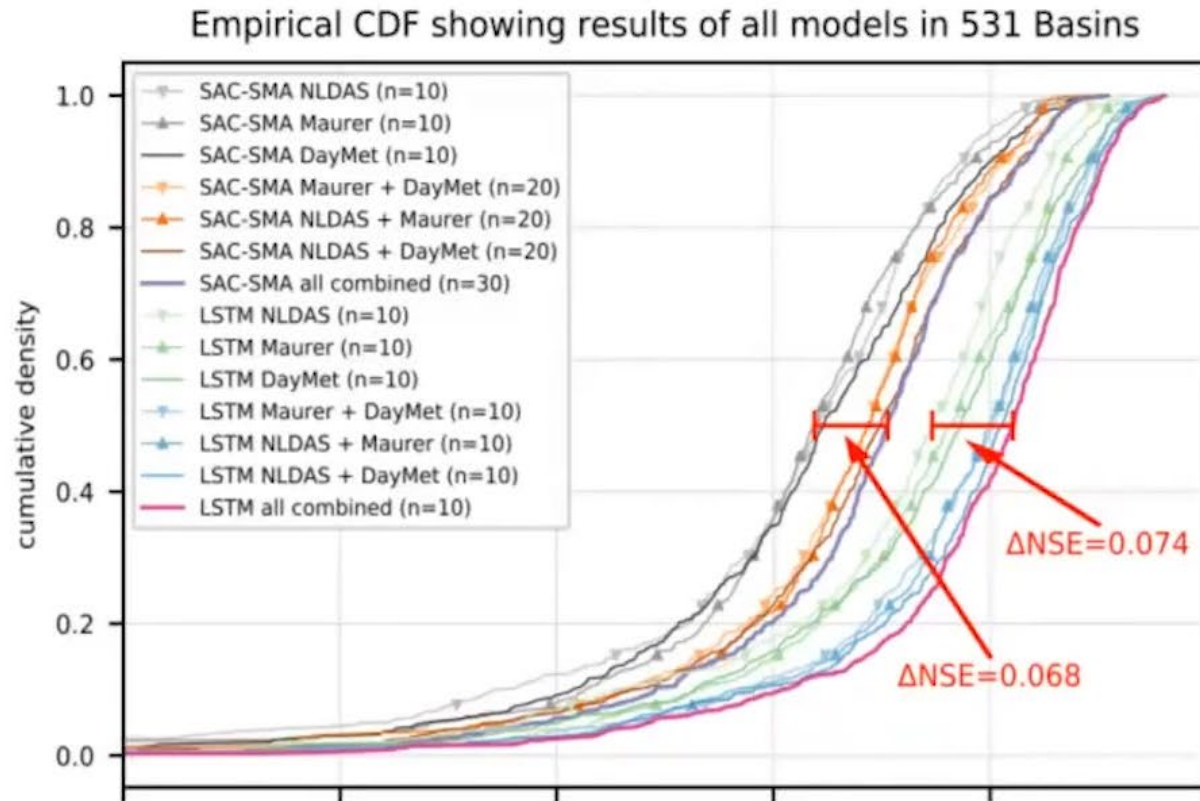


Benchmarking vs. basin-wise calibrated models



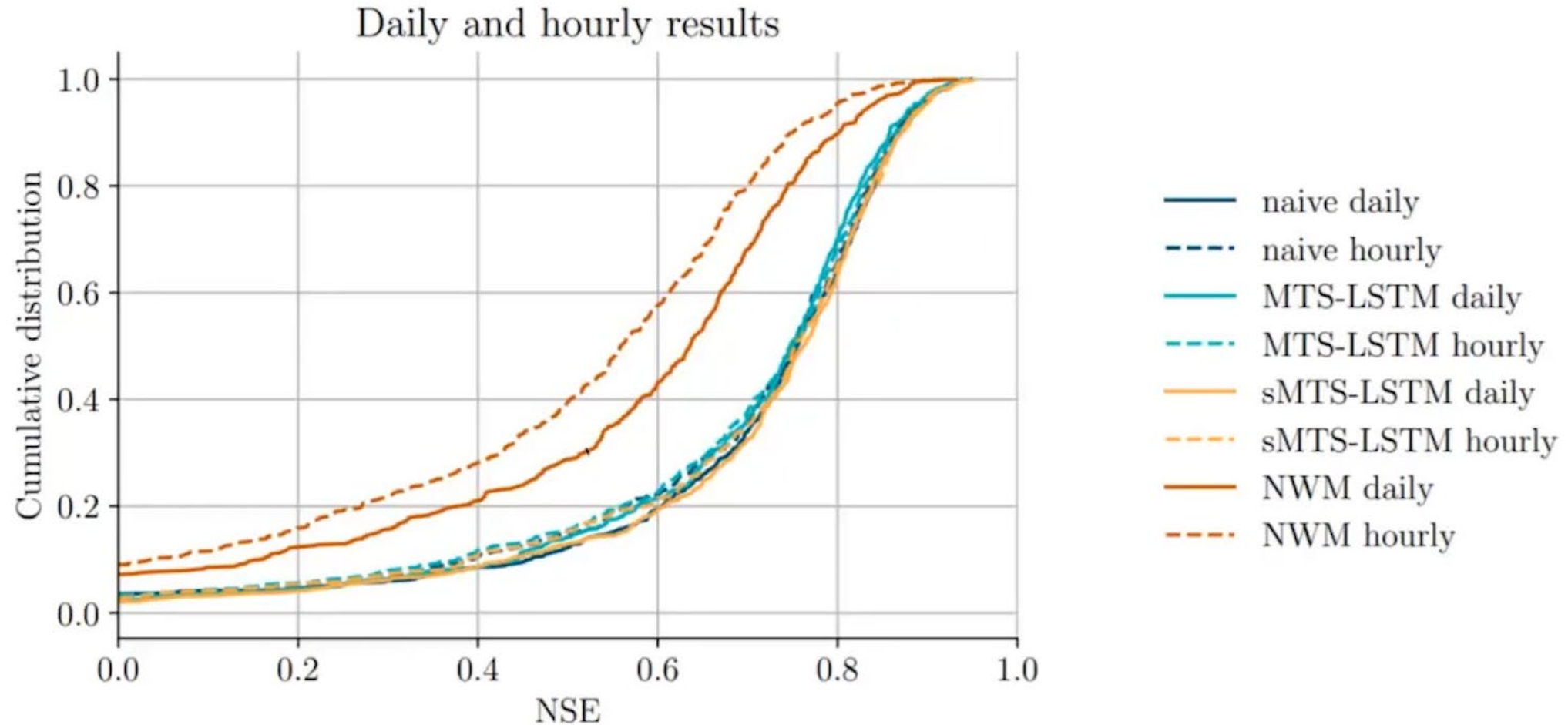
Certain “hard” tasks are easy with DL

Multiple Forcings w/o Ensembles



Certain “hard” tasks are easy with DL

Multiple Time Scales



Physics into Deep Learning Models

Table 1: Benchmarking Results. All values represent the median over the 447 basins.

Model	MC? ^a	KGE ^b	Bias ^c	σ_{rat} ^d	r^2	FHV ^e	FLV ^f
Deep Learning Models							
MC-LSTM Ens.	yes	0.764*	-0.020*	0.842	0.873*	-14.689*	-24.651*
LSTM Ens.	no	0.762	-0.034	0.838	0.886	-15.740	36.267
Conceptual Hydrology Models							
SAC-SMA	yes	0.632	-0.066	0.779	0.792	-20.356	37.415
VIC (basin)	yes	0.588	-0.018	0.725	0.760	-28.139	-74.769
VIC (regional)	yes	0.257	-0.074	0.457	0.651	-56.483	18.867
mHM (basin)	yes	0.691	-0.040	0.807	0.832	-18.640	11.433
mHM (regional)	yes	0.468	-0.039	0.589	0.793	-40.178	36.795
HBV (lower)	yes	0.391	-0.023	0.584	0.713	-41.859	23.883
HBV (upper)	yes	0.681	-0.012	0.788	0.833	-18.491	18.341
FUSE (900)	yes	0.668	-0.031	0.796	0.815	-18.935	-10.538
FUSE (902)	yes	0.690	-0.047	0.802	0.821	-19.360	-68.224
FUSE (904)	yes	0.644	-0.067	0.783	0.808	-21.407	-67.602

What does it mean for Climate change?

^aMass conservation (MC).

^bKling-Gupta Efficiency: $(-\infty, 1]$, values closer to one are desirable.

^cBias: $(-\infty, \infty)$, values closer to zero are desirable.

^dVariance Ratio: $(-\infty, \infty)$, values closer to one are desirable.

^eTop 2% high flow bias: $(-\infty, \infty)$, values closer to zero are desirable.

^fBottom 30% low flow bias: $(-\infty, \infty)$, values closer to zero are desirable.

*MC-LSTM is significantly different than the LSTM by Wilcoxon rank test at $\alpha = 0.05$.

Slight performance increase over LSTM, but currently the best peak-flow model we've tested.

Output flood inundation map



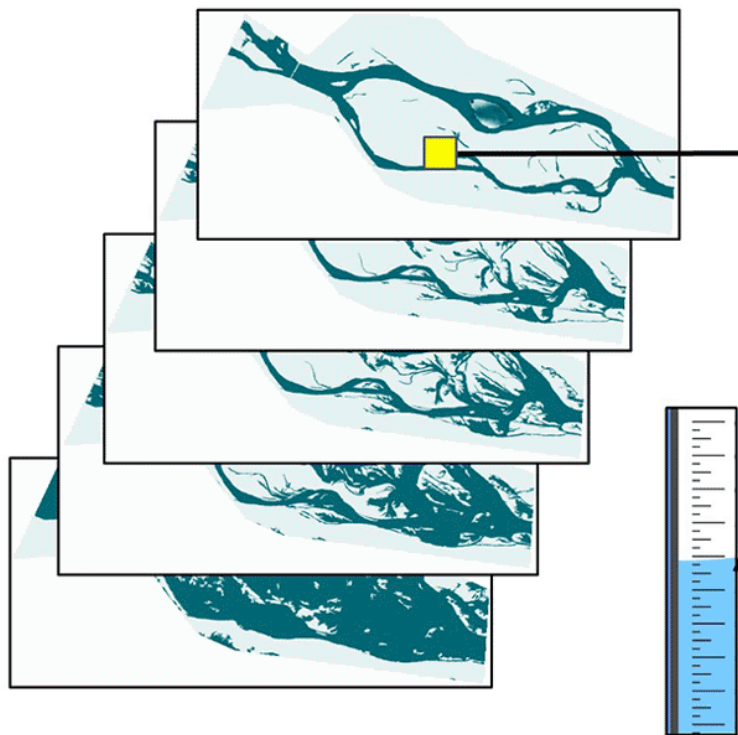
4.2m Gauge stage

Optimized stage threshold for the pixel

Historic pixel state for each flood event



Historic gauge stage for each flood event



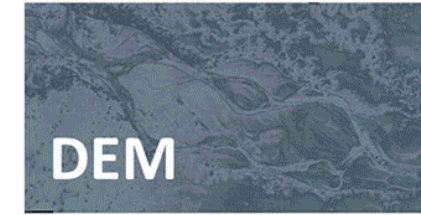
Historic inundation maps and gauge stage data

(a) Thresholding model

Output flood inundation map and water depth map



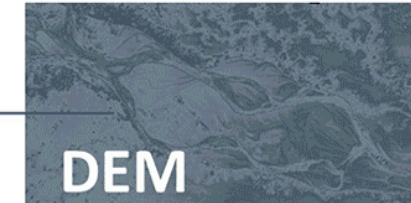
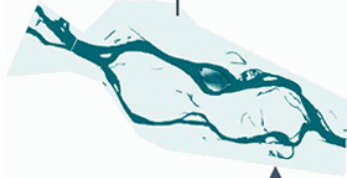
Interpolated and smoothed water height map



Physically-constrained water height maps



Computed inundation maps (Thresholding model)



Historic gauge stage for each flood event



2.1m

3.1m

...

5.7m

...

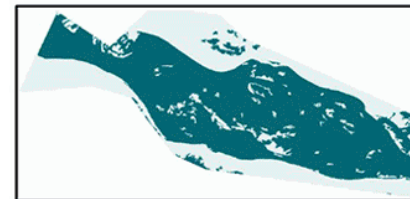
7.3m

4.2m

Gauge stage

(b) Manifold model

Simulated
inundation maps



Simulated
gauge stage

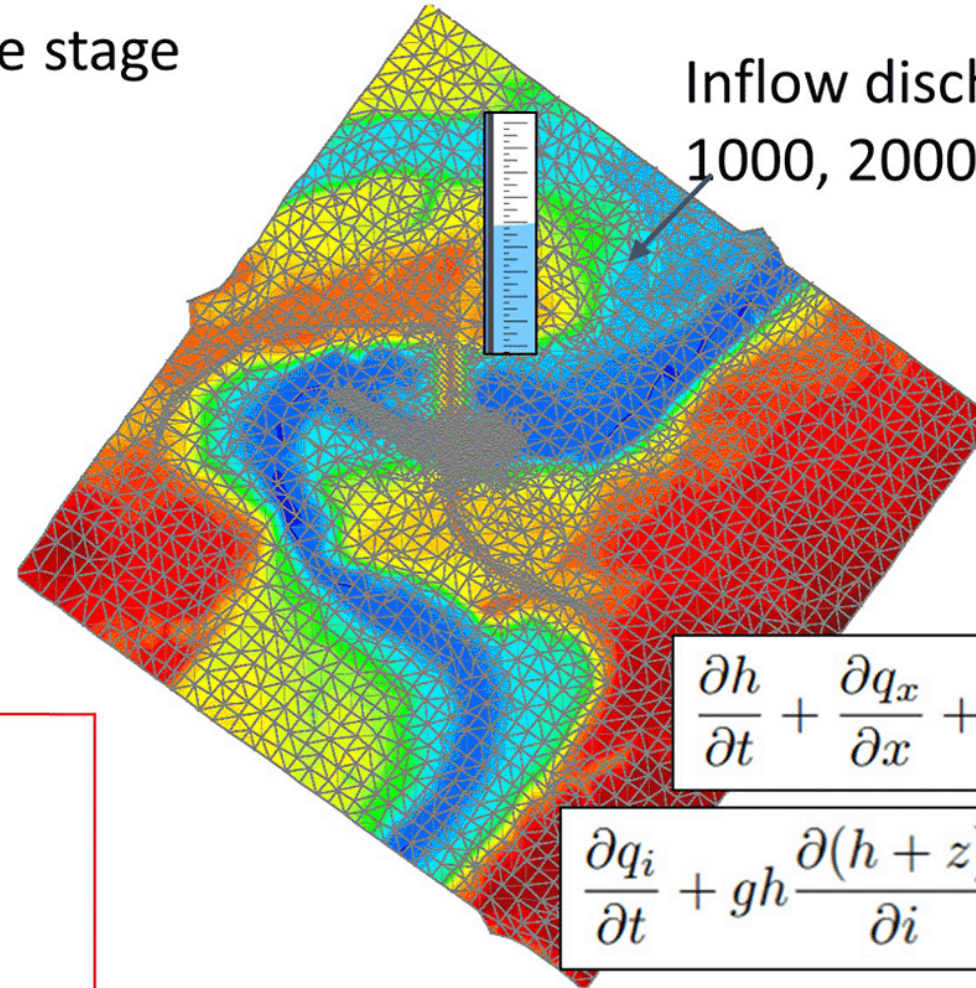
2.1m

2.3m

3.1m

4.5m

4.8m



Inflow discharge:
1000, 2000, ... m³s⁻¹

$$\frac{\partial h}{\partial t} + \frac{\partial q_x}{\partial x} + \frac{\partial q_y}{\partial y} = 0$$

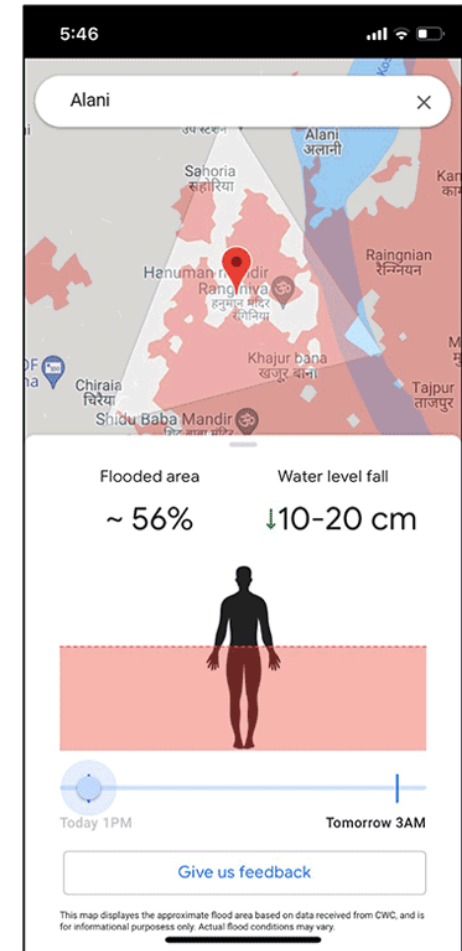
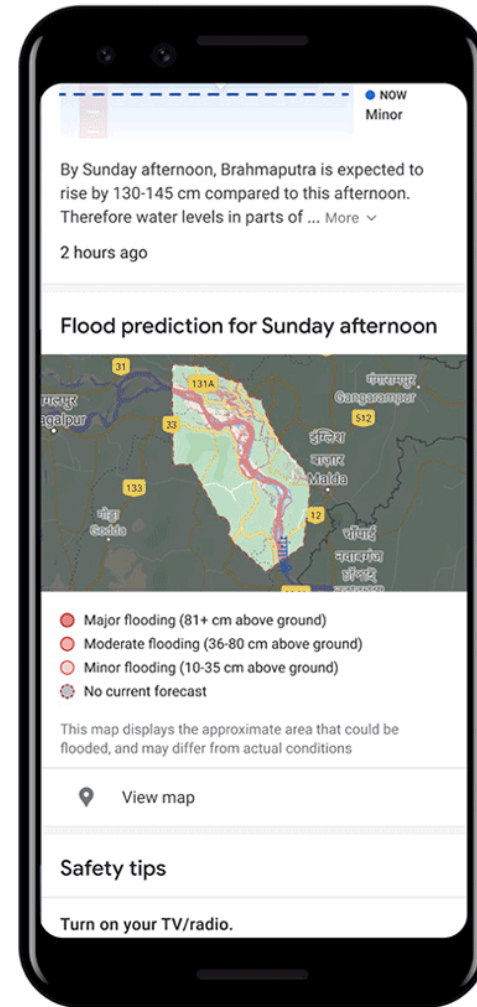
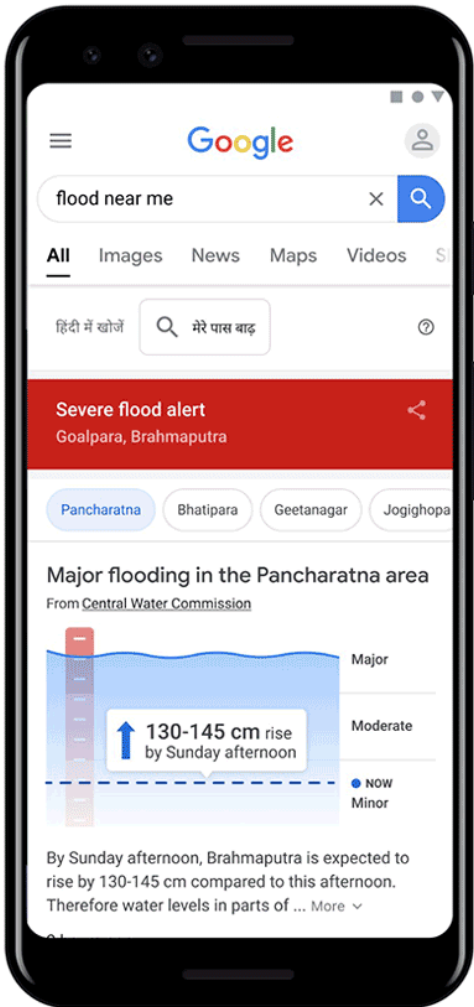
$$\frac{\partial q_i}{\partial t} + gh \frac{\partial(h+z)}{\partial i} + \frac{gn^2}{h^{7/3}} \|\mathbf{q}\| q_i = 0$$

Output flood
inundation map



3.2m Gauge stage

(c) Hydraulic model



Grand River

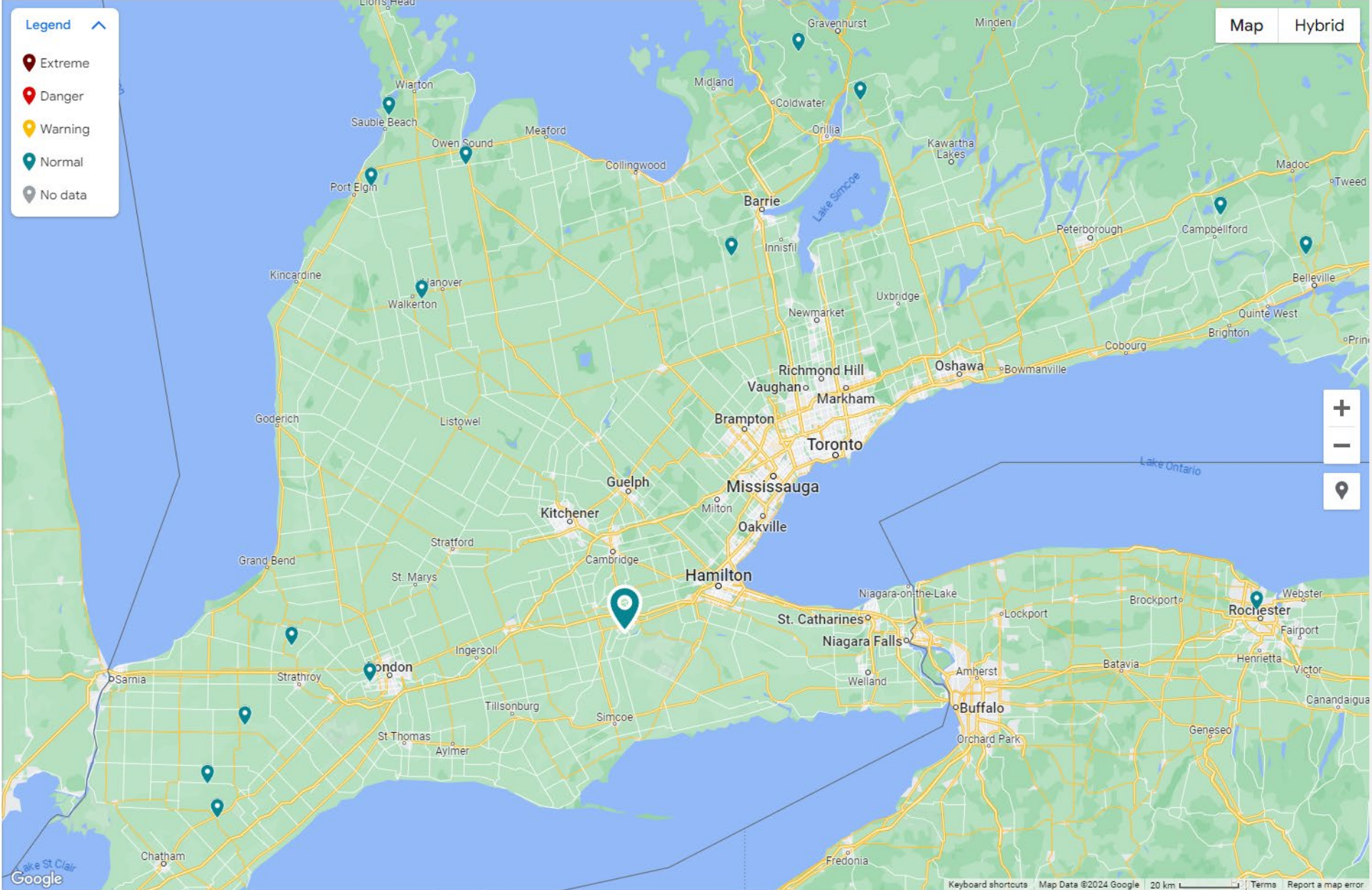


Legend

- Extreme
- Danger
- Warning
- Normal
- No data



Give us feedback



Flood conditions are approximate and are for informational purposes only. Check official sources for more information. Learn more

Other Applications

- **Urban Flooding Prediction and Management:** AI algorithms can analyze historical flood data, urban topography, and land use patterns to predict areas at high risk of urban flooding during heavy rainfall events.
- **Water Quality Monitoring and Contamination Detection:** ML algorithms can analyze water quality data collected from sensors and monitoring stations to detect contaminants, pollutants, and harmful bacteria in stormwater runoff.



Other Applications

- **Smart Irrigation Systems:** AI-powered irrigation systems can optimize water use efficiency in urban landscapes, parks, and green spaces by analyzing weather forecasts, soil moisture levels, and plant water requirements.
- **Floodplain Mapping and Risk Assessment:** ML algorithms can analyze remote sensing data, LiDAR imagery, and elevation models to map floodplains and assess flood risk levels in vulnerable areas.



Other Applications

- **Green Infrastructure Performance Monitoring:** AI-powered sensors and IoT devices can monitor the performance of green infrastructure assets, such as bioswales, retention ponds, and permeable pavements, in real-time.
- **Dynamic Stormwater Management:** AI algorithms can optimize stormwater management strategies by dynamically adjusting stormwater storage, detention, and infiltration systems based on forecasted weather conditions and anticipated runoff volumes.



Other Applications

- **Community Resilience Planning:** AI-powered decision support tools can facilitate community engagement and participatory planning processes to develop climate resilience strategies at the neighborhood level.
- **Infrastructure Maintenance and Upgrades:** AI-powered image recognition can analyze CCTV footage and aerial imagery to assess the condition of stormwater infrastructure, such as culverts, pipes, and drainage channels.



Some other examples...

-
- **Hydroinformatics Institute**: applying AI techniques such as ML and DL to address water-related challenges such as hydrological forecasting, water supply optimization, and climate change impact assessment. Read More: h2i.sg
 - **HydroLabs**: provides AI-powered solutions for water quality monitoring, pollution detection, and environmental assessment, using sensors, drones, and satellite imagery for data collection and analysis. Read More: hydrolabs.co
 - **Aquaoso**: develops AI-powered software solutions for water risk management in agriculture and real estate by utilizing ML algorithms to analyze water data, identify water-related risks, and facilitate informed decision-making for water resource management. Read More: aquaoso.com

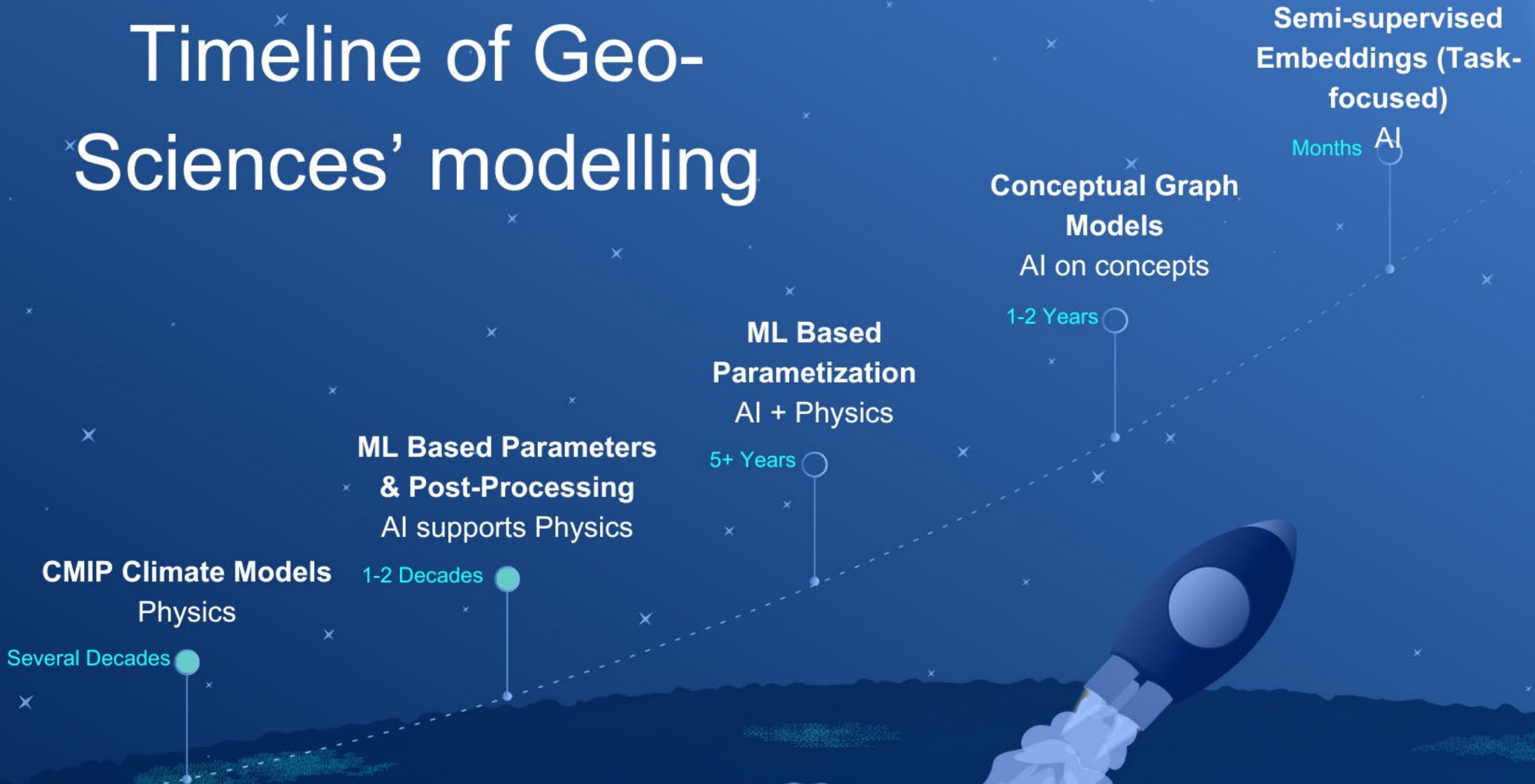
City of Peterborough builds integrated flood model with updated land cover data

Ecopia® is using AI to build a digital twin of the world, converting high resolution geospatial imagery into comprehensive, accurate, and up-to-date vector maps for use in data-driven decision-making across industries.



A sample of land cover data extracted by Ecopia for use in the City of Peterborough's integrated flood model

Timeline of Geo-Sciences' modelling



What are the conclusions?

The background of the image is a dense field of 3D question marks. These question marks are rendered in a dark blue-grey color with a slight gradient and a soft shadow, giving them a three-dimensional appearance. They are scattered across the entire frame, creating a textured, repetitive pattern. In the center of this pattern, the word "Questions?" is written in a clean, white, sans-serif font. The text is centered both horizontally and vertically, standing out clearly against the darker, busy background.

Questions?