Near-Term Forecasting of Water Reservoir Storage Capacities Using Long Short-Term Memory

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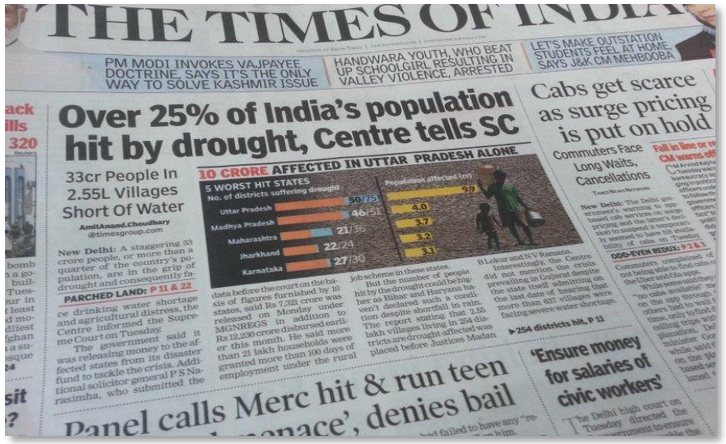
OUTLINE

- Motivation
- Methodology
- Results and Discussion
- Roadmap
- Acknowledgements

MOTIVATION

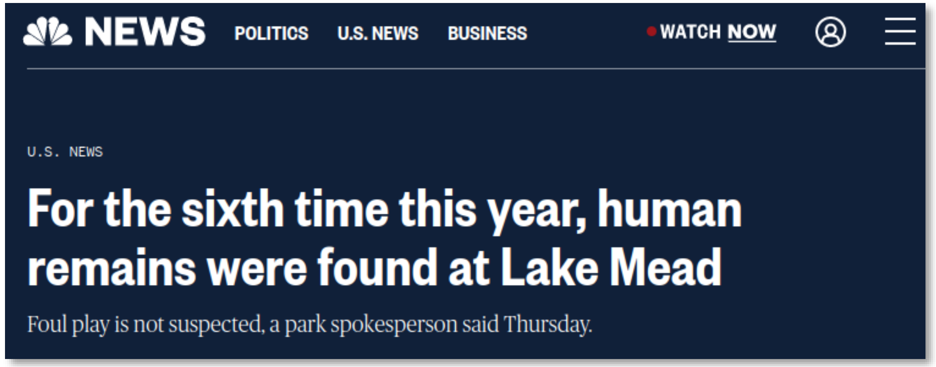
Source: Mercury News (San Jose, CA)

Source: Washington Post



Source: Times of India

Source: Inside Climate News



Source: NBC News

MOTIVATION

- Question: Since surface water won't suddenly appear, how can we manage existing water resources better?

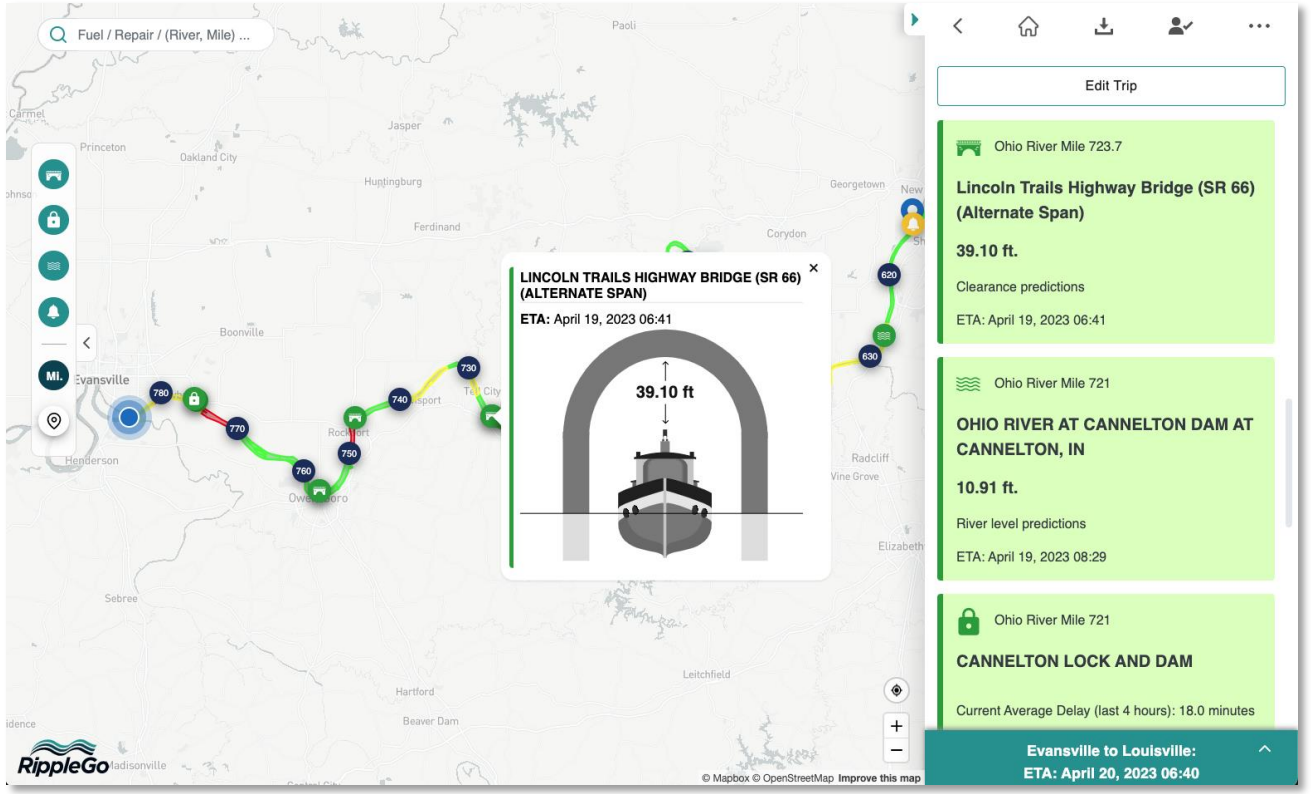
- Existing hydrological models can accurately model fluid flow with extreme detail, but:
  - Require extensive computational resources to use their full capabilities
  - Are not suited to rapid prototyping and simulation of various scenarios

- How do rain events impact reservoir levels?

- Can similar results be obtained using numerical models?
  - Then, can we use these models for rapid simulation?

TRABUS TECHNOLOGIES

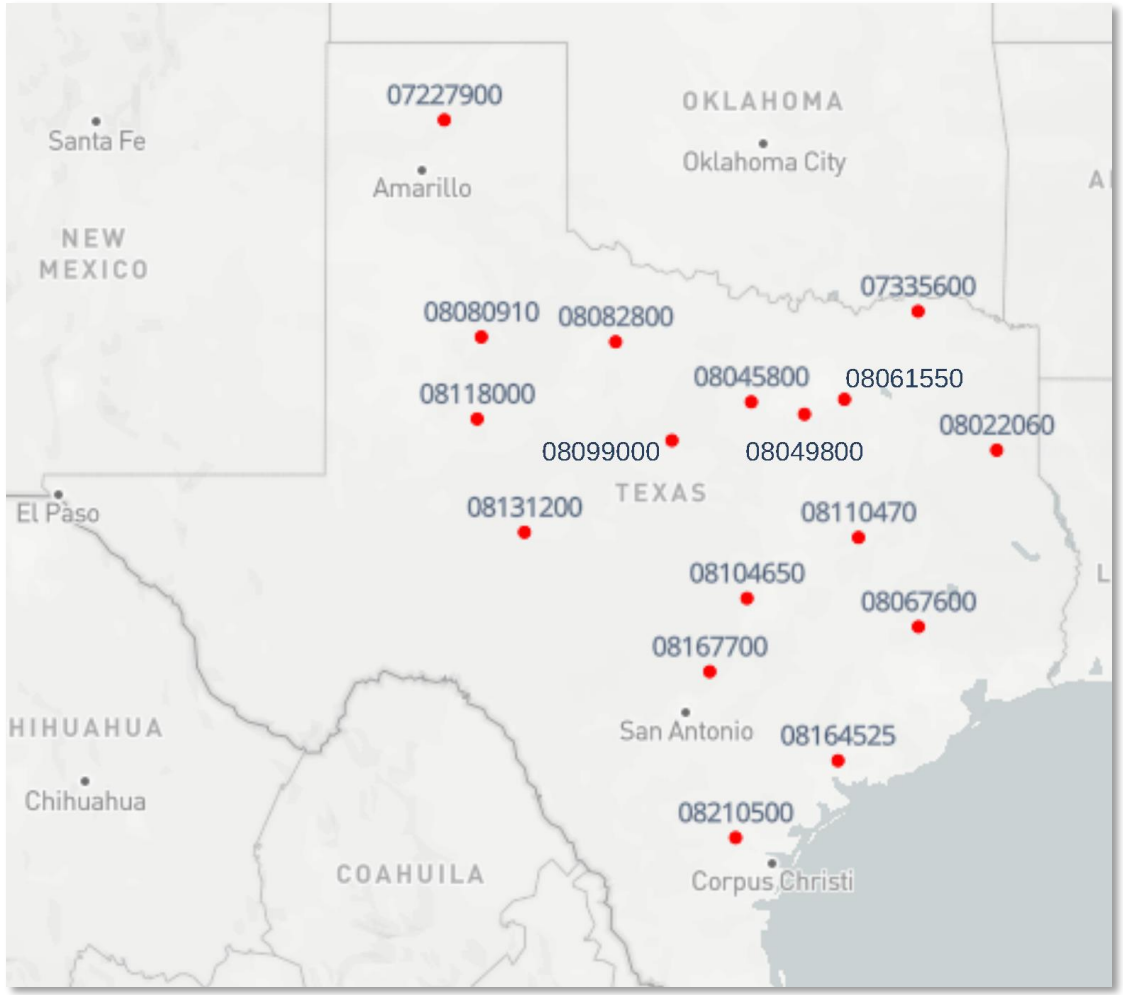
- Small business headquartered in San Diego, CA
- AI/ML/data science experience in hydrological, climate, maritime transport and wireless domains
- Provides data analytics services and IT for the Southern Regional Climate Center
  - Partnered with Texas A&M University
  - 1 of 6 National RCCs
  - ACIS – Applied Climate Information System



RippleGo: An AI-based Voyage Planner for Inland Water Transportation

METHODOLOGY – SITE SELECTION

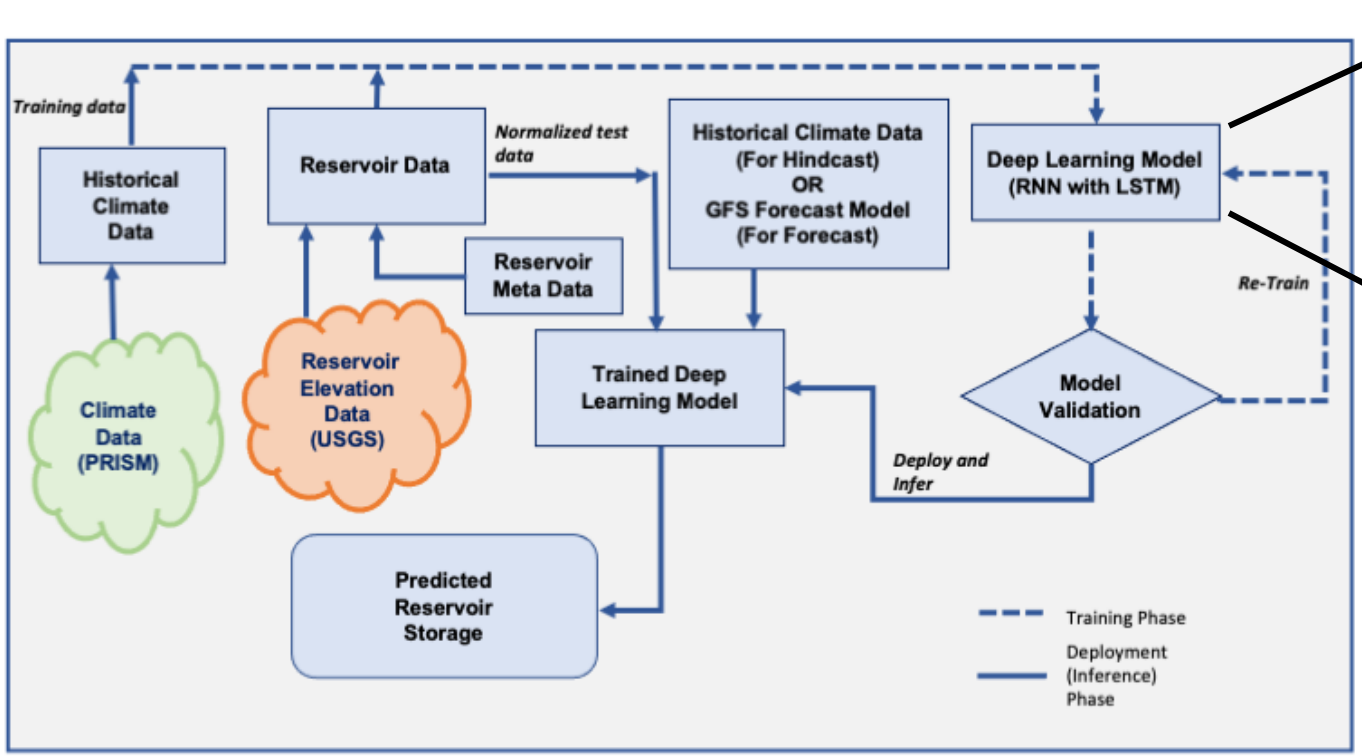
- 17 reservoirs located in Texas, USA
  - Period of record for reservoir elevation or storage: at least 1 Jan. 2010 – 31 Dec. 2022
  - Sites continually report during study period
  - Data available through USGS Water Data for the Nation API
  - Elevation-area-capacity curve information available through Texas Water Board
- Spans 9 of 10 climate divisions in Texas, 16 different watersheds

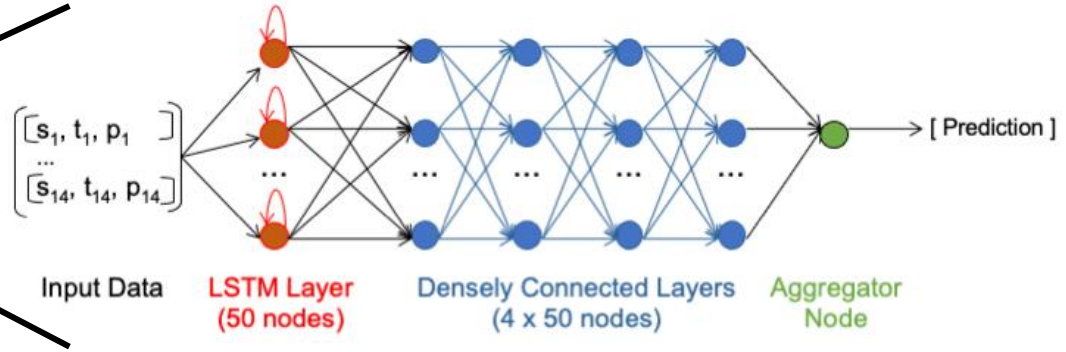


METHODOLOGY – PREPROCESSING

- 14 days of reservoir data augmented with gridded climate data - Parameter-elevation Regressions on Independent Slopes Model (PRISM)
- Data divided sequentially into model training, validation, and test sets
  - Sequential division preserves time series nature of data
  - Sets chosen to capture a wide range of long-term weather conditions
- Separate datasets/models developed **for each reservoir**

METHODOLOGY – MODEL CONSTRUCTION





RESULT – ALL RESERVOIRS

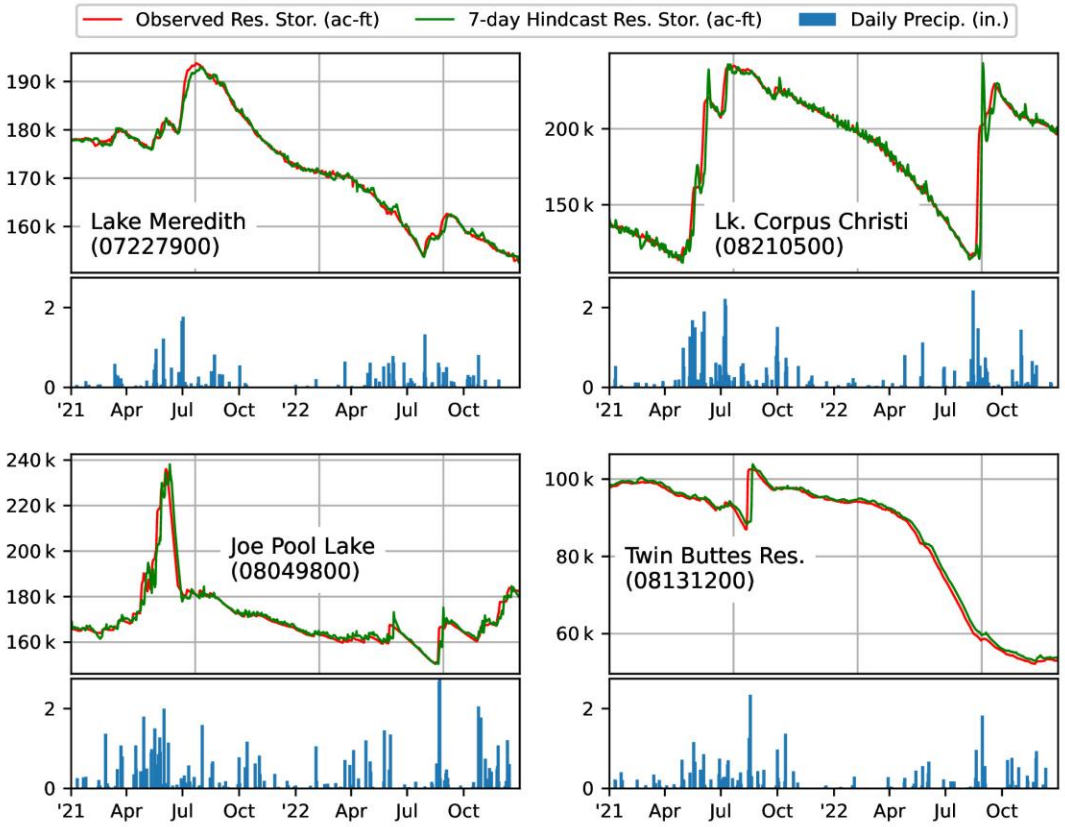
Reservoir	7-day MAPE (%)	7-day RMSE (ac-ft)	14-day MAPE (%)	14-day RMSE (ac-ft)
Meredith	0.32	786	0.54	1339
Weatherford	0.95	203	2.04	353
Joe Pool	1.01	3331	1.83	5883
Martin	0.84	1146	1.40	1731
Ray Hubbard	0.81	4985	1.29	7186
Conroe	0.75	5435	1.09	7073
Georgetown	1.55	535	3.16	955
White River	1.85	263	3.14	377
J.B. Thomas	2.10	3975	3.84	6380
Corpus Christi	1.92	8720	3.17	13876
Texana	1.37	3232	2.31	4797
Limestone	1.36	3340	2.11	4961
Twin Buttes	1.18	1572	2.33	2519
Millers Creek	0.82	305	1.49	458
Crook	1.52	214	2.07	261
Canyon	0.42	2402	0.86	4020
Leon	0.97	531	1.64	699

- MAPE = Mean Absolute Percent Error
- RMSE = Root Mean Squared Error
  - Lower = Better

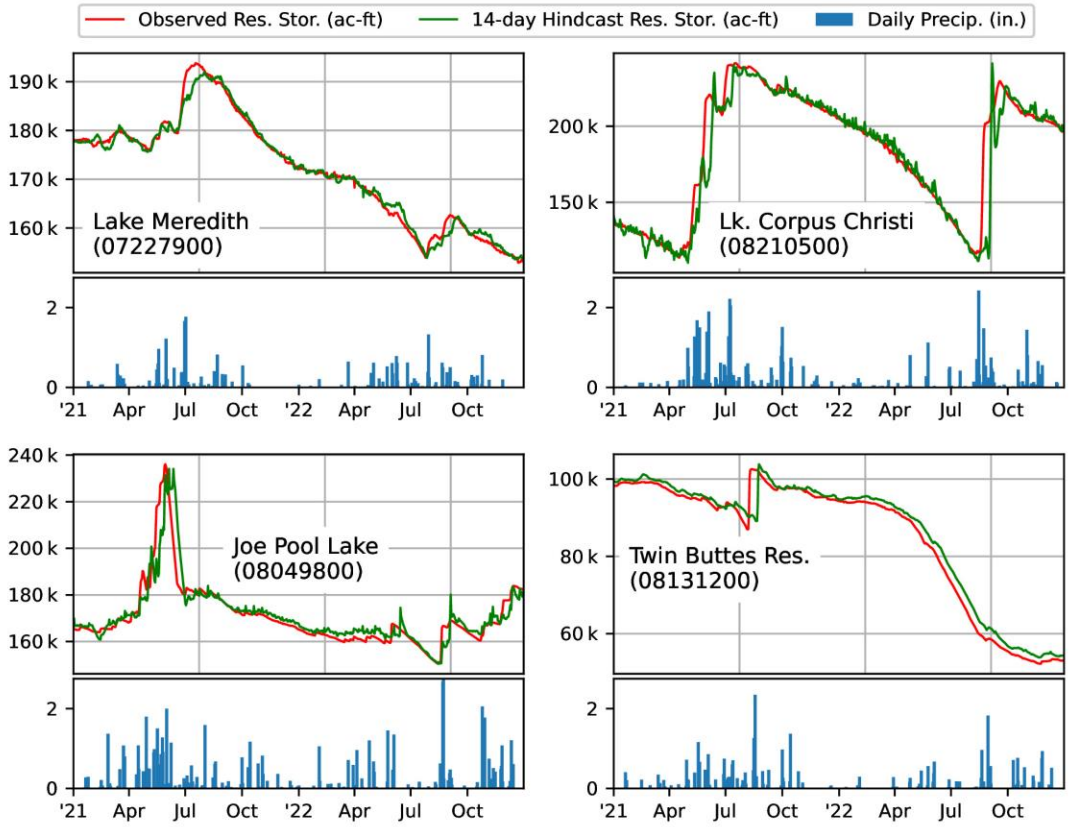
- Best: Lake Meredith, Lake Canyon
- Worst: Lake J.B. Thomas, Lake Corpus Christi

- All 14-day results within 4% error. This suggests generalizing to any reservoir in study area.

RESULTS – DEEPER DIVE

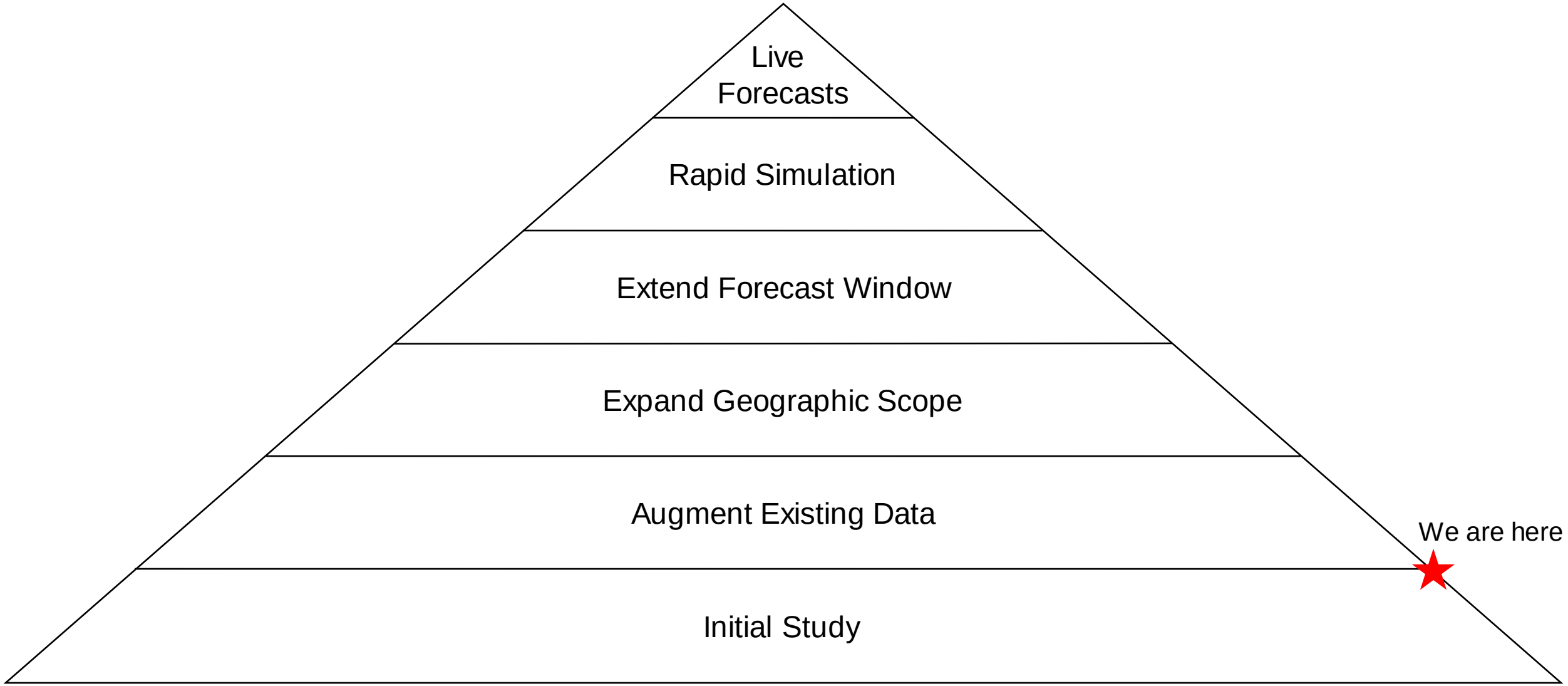


7-day



14-day

ROADMAP


Live
Forecasts
Rapid Simulation
Extend Forecast Window
Expand Geographic Scope
Augment Existing Data
We are here
Initial Study

APPLICATIONS

- Help reservoir managers better plan for extreme climate hazards

- Better understand reservoir responses to rainfall events

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