

HydroSlopeNet: Learning Landslide Risk via Hydrological–Geomechanical Coupling

Ren Ozeki^{1,2}, Hamada Rizk^{1,3}, Hirozumi Yamaguchi¹

1. The University of Osaka
2. Japan Meteorological Agency
3. Tanta University





Ren Ozeki: PhD Student in Osaka University / JMA

Education

- 2019 B.Sc., Meteorological College
- 2024 M.Sc., Osaka University
- 2025- Ph.D. Student, Osaka University

Experience

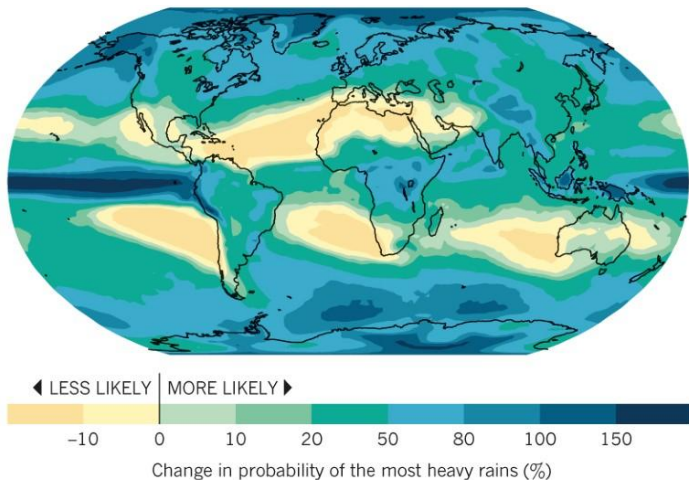
- 2020- Technical Official, Japan Meteorological Agency
- 2023- Visiting Researcher, Osaka University
- 2024- Ph.D. Student, Osaka University



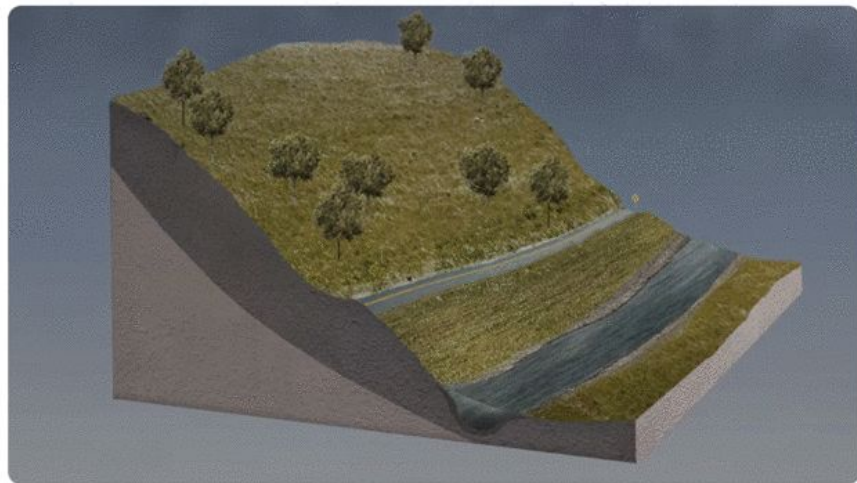


Background - Climate Change

- Landslide disasters are becoming more frequent and severe
- Even areas that were once considered safe are now facing higher disaster risks
- We need reliable landslide predicting systems as social infrastructure



Shifts in Heavy Rainfall Areas



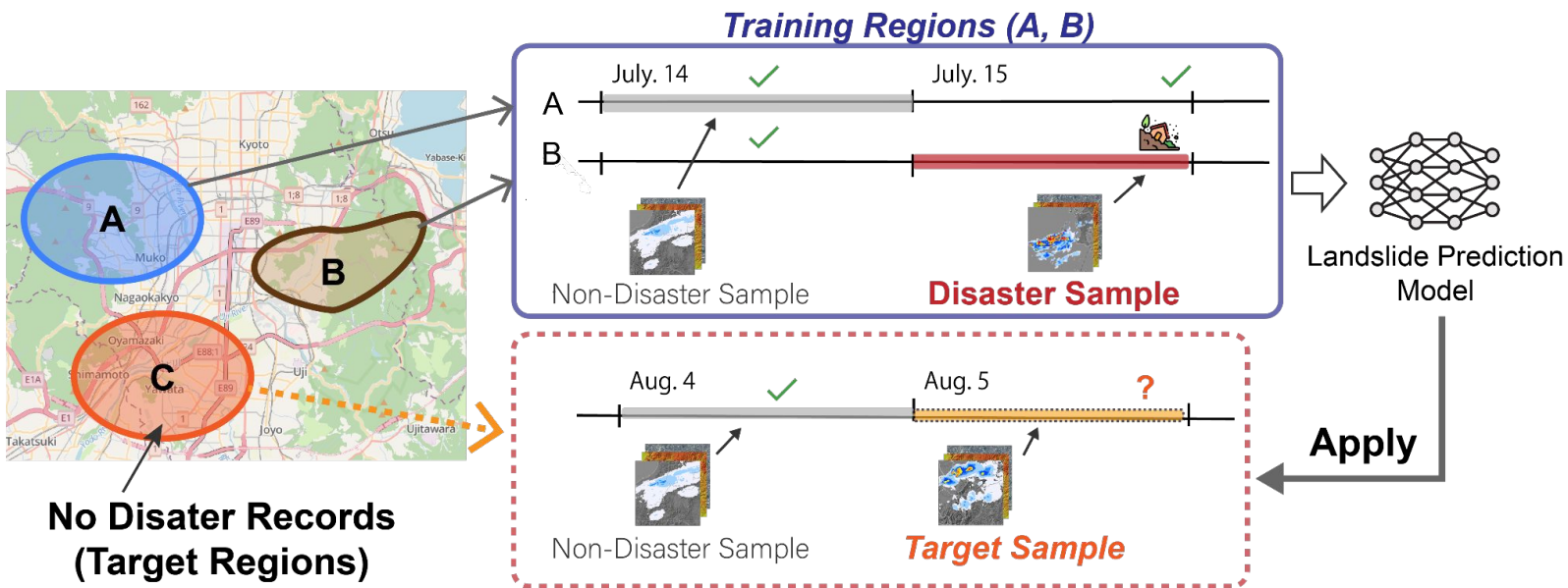
What is a landslides?



Problem Statement

4

- Accurately Landslide Predictions are required **even in unseen regions** (previous safe regions)
- We aim to provide **day-level landslide predictions** that support timely evacuation decisions





Technical Challenge

1. Scarce & Imbalanced Data

- Since disasters are extreme events, limited data hinders data-driven approaches

2. Data heterogeneity among regions

- Disaster event significantly depends on region characteristic
- Some Regions haven't experienced disaster => No positive case data



Japan only has **200 positive cases** for
2years!!



Steep slope



Lack of plants



Heavy rain





Related Works

Method	Limitation
Statistical / ML ^[11]	low capacity to capture spatial/temporal dependencies
Deep Learning Model ^[17]	small amount of data may lead to region-specific correlations
Pure Physics Model	Observability Gap: subsurface parameters are hard to measure in this application

HydroSlopeNet bridges the observability gap via data-driven estimation within a physics-constrained architecture, enabling generalization to unseen regions

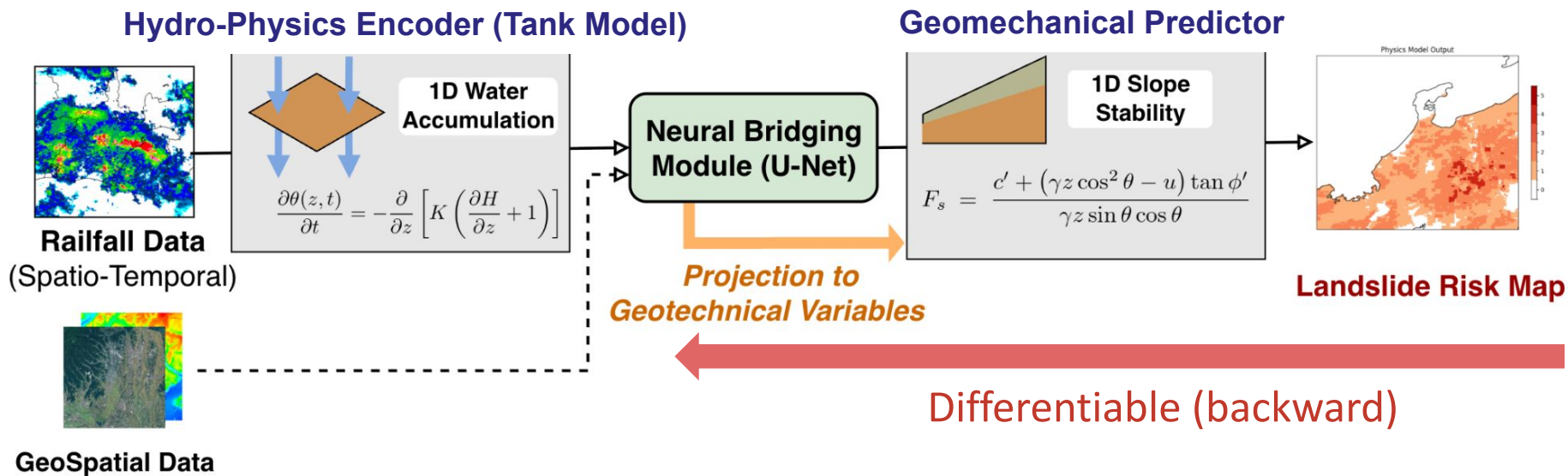
[11] Determination of rainfall thresholds for landslide prediction using an algorithm-based approach: Case study in the darjeeling himalayas, india

[17] Litetransnet: An interpretable approach for landslide displacement prediction using transformer model with attention mechanism



Proposed System - HydroSlopeNet

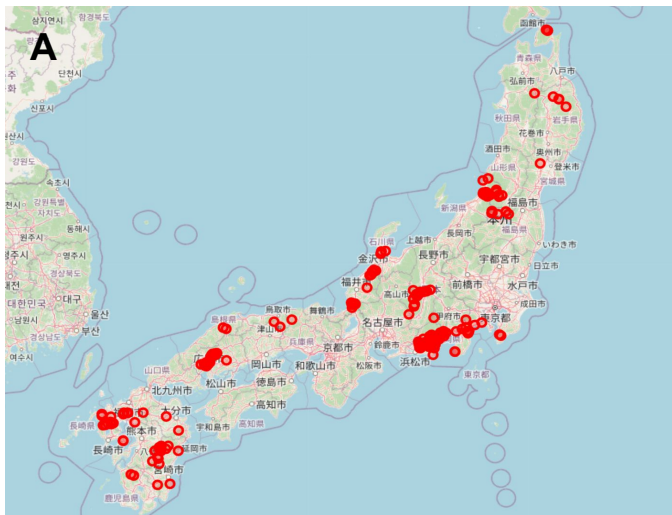
- Our proposed system bridges hydrological and geomechanical process models (two physics model) using a Neural Bridging Module
- Physics constraints are imposed by the downstream slope stability model
- **INPUT:** Rainfall and GeoSpatial Data; **OUTPUT:** Landslide Risk in target regions



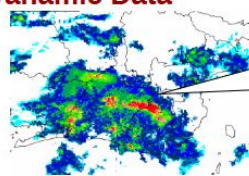


Evaluation -Dataset

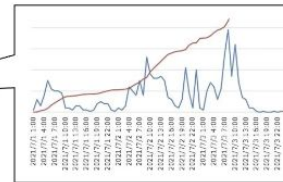
- Spatial Resolution: 1x1km, Our Dataset consists of 13 regions data (10x10km)
- We Collected Data for Landslide Prediction (Japan, 2021–2022)
 - A. Landslide occurrence records (positive: 253 cases, whole dataset: about 3000)
 - B. Spatio-temporal Rainfall data (48 hour Rainfall data for one sample)
 - C. Geospatial data: soil, terrain, vegetation



B Dynamic Data



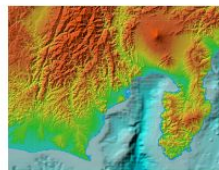
Rain fall



Rainfall data at the landslide site

C Static Data

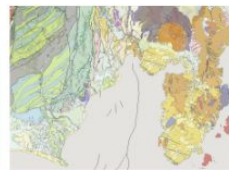
C



Elevation



Vegetation

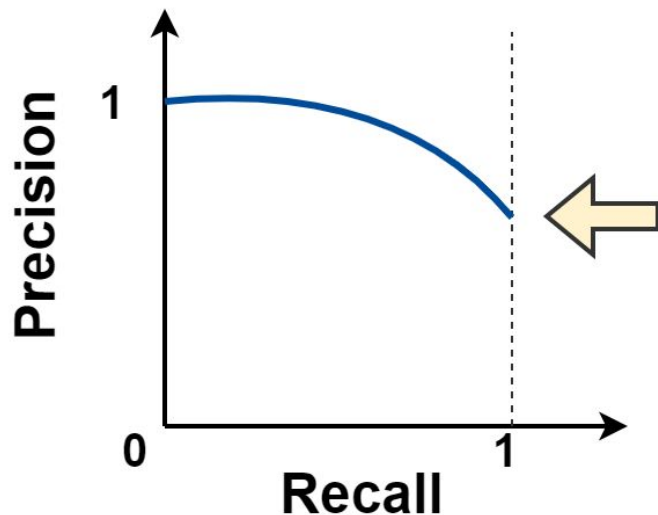


Soil



Evaluation - Experimental Settings

- We evaluate the proposed system under two settings:
 - (1) **All-in:** all regions included and evenly split
 - (2) **Leave-K-Region-Out:** K regions excluded from training (6-folds cross-validation)
- **Metrics:** PR-AUC and Precision@80% Recall
=> These metrics reflect practical and socially relevant requirements





We select comparison methods for predicting landslides

	Integration of Physics Model	Spatio-Temporal Feature	Regional Generalization
SWI-EWS [7]	Only Physics	X	O
CTLGNet [32]	X	X	X
PGNN-0 [33]	Input Feature	O	X
MMD-AAE [34]	X	O	O
Proposed	Input Feature & Physics-Head	O	O



- Our method outperforms state-of-the-art approaches
- It maintains strong generalization even on unseen regions (**Leave-K-Out**)
- On known regions, it achieves 34% higher Precision than SOTA baselines

Method	All-in		Leave-K-Out	
	PR-AUC	Precision	PR-AUC	Precision
SWI-EWS [44]	0.21	0.08	0.21	0.08
CTLGNet [45]	0.62	0.29	0.53	0.16
TNDNN [46]	0.61	0.27	0.60	0.37
MMD-AAE [47]	0.58	0.19	0.42	0.17
LiteTransNet [17]	0.51	0.45	0.38	0.27
Proposed	0.86	0.83	0.72	0.60
+TTA	0.86	0.83	0.76	0.65



Conclusion & Future Works

- We proposed a physics integrated ML framework
- Integration of Hydro-Physics Encoder and Geomechanical Predictor improves stability of learning process under limited and imbalanced data
- Across 13 regions, our system achieves **up to +34%** Precision@80%recall over SOTA
- Future work: subsurface data integration and Continual Learning Framework to deal with climate change

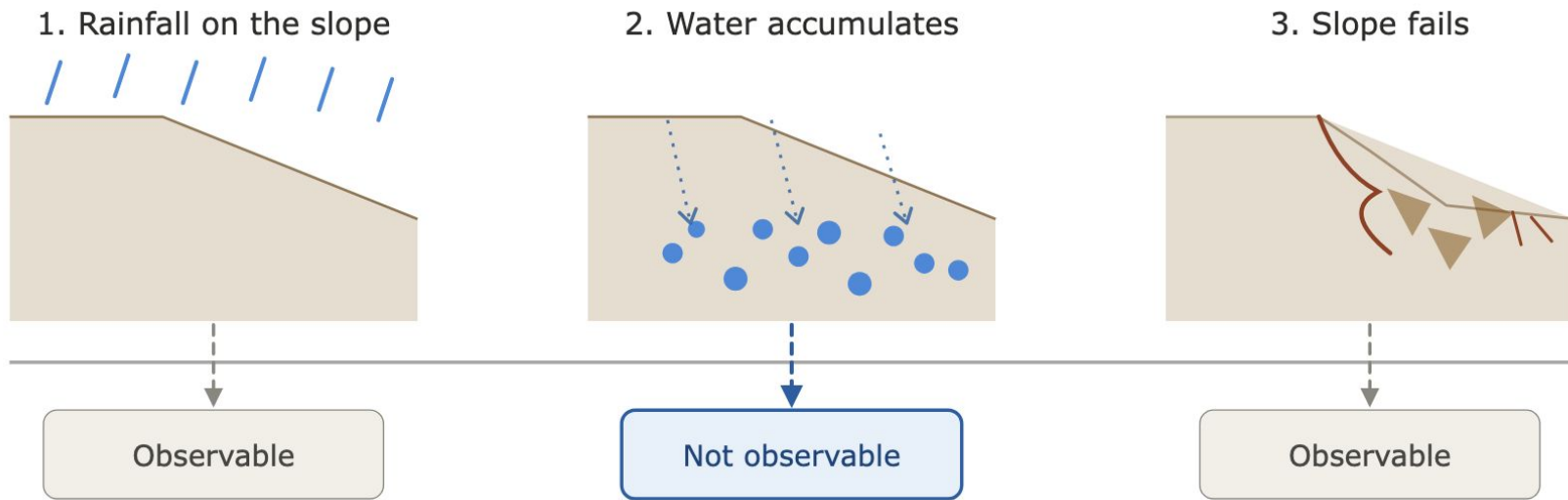
Appendix





Landslide occurrence can be explained in two main steps:

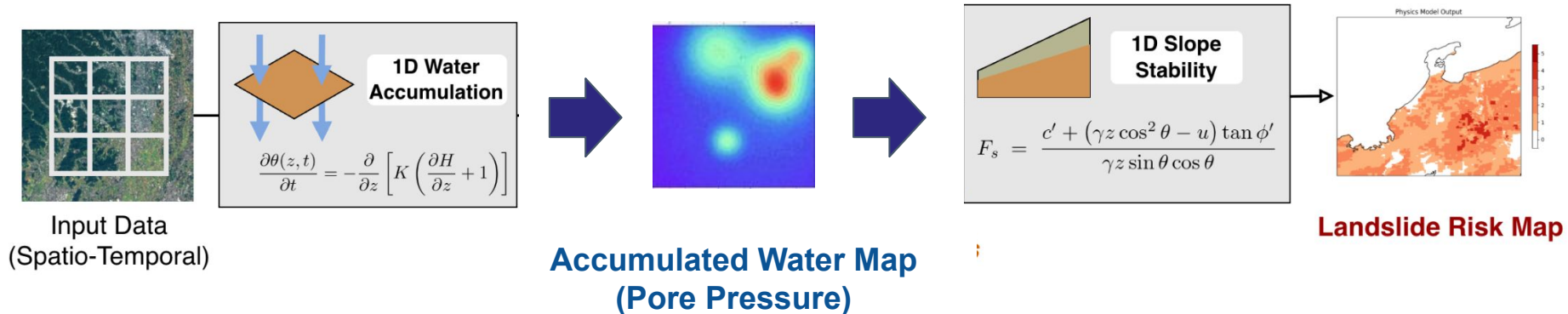
- Water infiltrates into the soil and accumulates underground
- Increased subsurface water pressure reduces slope stability





General Prediction Flow of physics model

- To assess landslide risk, a separate model simulates water infiltration and slope stability
- Complex 3D models are difficult to apply over large areas
- Therefore, simplified and fixed parameter models are generally used for large-scale prediction





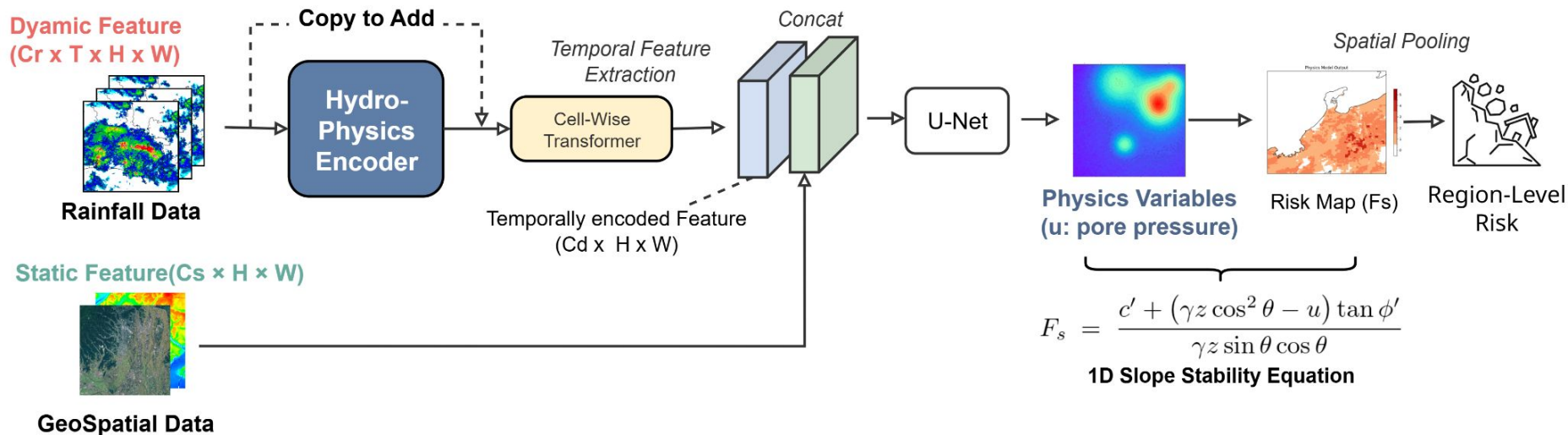
Proposed System - Network Architecture

16

INPUT: Rainfall and GeoSpatial Data; **OUTPUT:** Landslide Risk in target regions

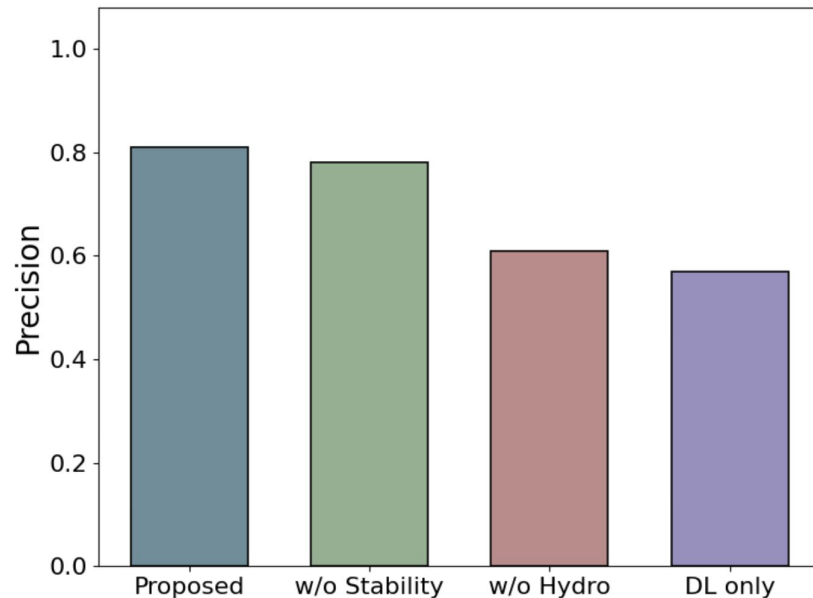
Loss Function: PairWise Ranking Loss (disaster case = 1, non-disaster case = 0)

- Our system predict physics variables instead of labels, and let stability equations handle the rest





- Our system consists of Hydro-Physics Encoder, Neural Bridging Module, and Geomechanical Predictor
- We validate effect of each component
- These components contributes improvement of accurate prediction respectively





- We compare our proposed approach with other physics-hybrid methods
- Our method outperforms other related methods
- Performance gains through effective integration, not merely by incorporating physics knowledge

