Post-Fire Debris Flow Likelihood Prediction

Graduate Students:
Alejandro Hohmann
Bhanu Muvva
Chunxia Tong

Faculty Advisors:
Dr. Daniel Roten
Dr. Ilkay Altintas

UCSD

Jacobs School of Engineering

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Project Abstract

Debris Flows are a distinct type of landslide that suddenly occur without warning. They are fast-moving channels of water and soil that carry large natural objects like boulders and trees, or human-made objects including cars. In the American West, Debris Flows have directly caused death and property damage. Debris Flows often occur after rain events and the burn scars left behind by wildfires increase their likelihood. Given the increasing frequency of extreme weather events, it is critical to predict Debris Flows and take precautionary action before they occur. This project builds upon prior research of predicting Debris Flows using additional geological features and more advanced machine learning techniques. The project also includes an intuitive interface for decision makers to access these probability estimates.

Pine Gulch Fire burn scar, Colorado, USA

75mm rain triggered this debris flow

Project Team

Alejandro Hohmann
Data Scientist

Bhanu Muvva
Data Engineer

Chunxia Tong
Data Analyst

Dr. Daniel Roten
Computational Scientist

Dr. Ilkay Altintas
Chief Data Science Officer

Presentation Overview

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User Interface

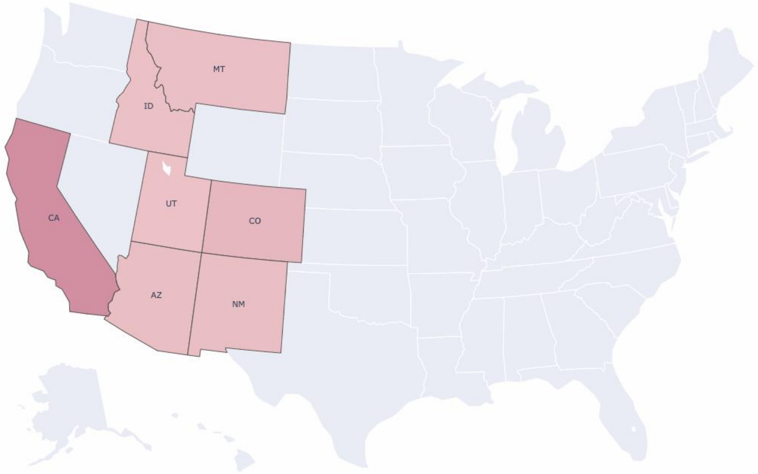
Prior Work

Staley et al. (2016)

Staley Exploratory Data Analysis

1,550 observations across 716 sites in 7 states

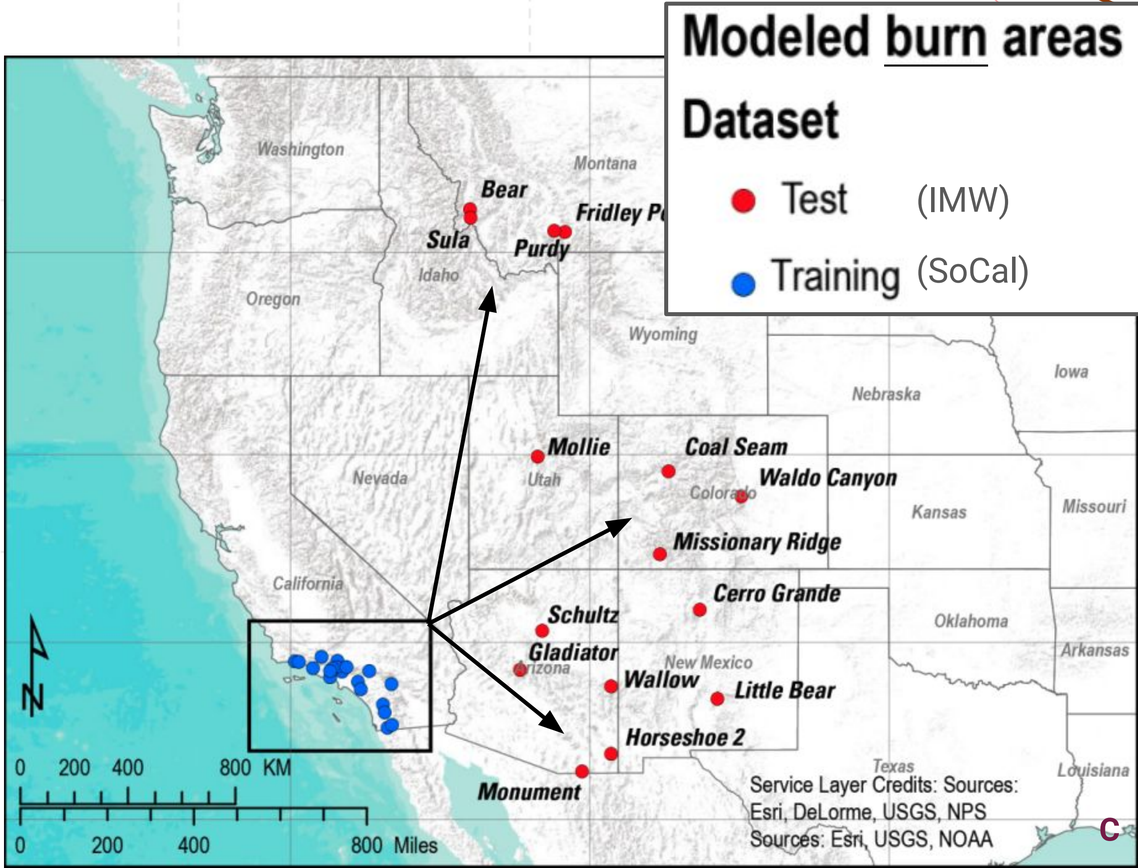
- ~20% of observations with a debris flow
- Drainage areas ranging from 0.2 - 8 km^2
- History of wildfire in each area between years 2000 - 2012
- Rain events between years 2000 - 2014
  - Rain gauges up to 4 km from DF sites
  - Collected by USGS, NOAA, local gov't
  - Rain has highest correlation with DF response



Logistic Regression Trained on SoCal

Staley Features (4 total)

- 15-minute rainfall accumulation
  - multiplied by subsequent features
- Proportion of watershed with slope > 23°
- Difference Normalized Burn Ratio
  - Change in landscape from pre-fire to post-fire
- Soil Erodibility Factor



Briefly Defining Model Metrics

Accuracy	Overall proportion correctly classified
Precision	Proportion of <u>positively classified</u> that are actually correct
Recall	Proportion of <u>actual positives</u> that are correctly classified (true positive rate)
F1 Score	Harmonic mean between Precision and Recall
AUC	~True Positive Rate vs False Positive Rate at varying classification thresholds

ST16 Model Performance Summary

Test Set Performance (IMW)	Logistic Regression (Staley)
Accuracy	0.6258
Precision	0.3544
Recall	0.7671
F1	0.4848
AUC	0.7178

Problem Statement & Proposed Solution

B

Problem	Proposed Solution
Training on SoCal inserts bias into predictive model	Implement random splitting between training and testing sets
Imbalanced class, 20% observations with DF, means a model that always predicts NO-FLOW would be correct 80% of the time	Train models with additional features and architectures to achieve better performance
Decision Makers need fast and accessible predictions; typically don't have the capacity to calculate Logistic Regression outputs	Build an intuitive user interface that is publicly accessible

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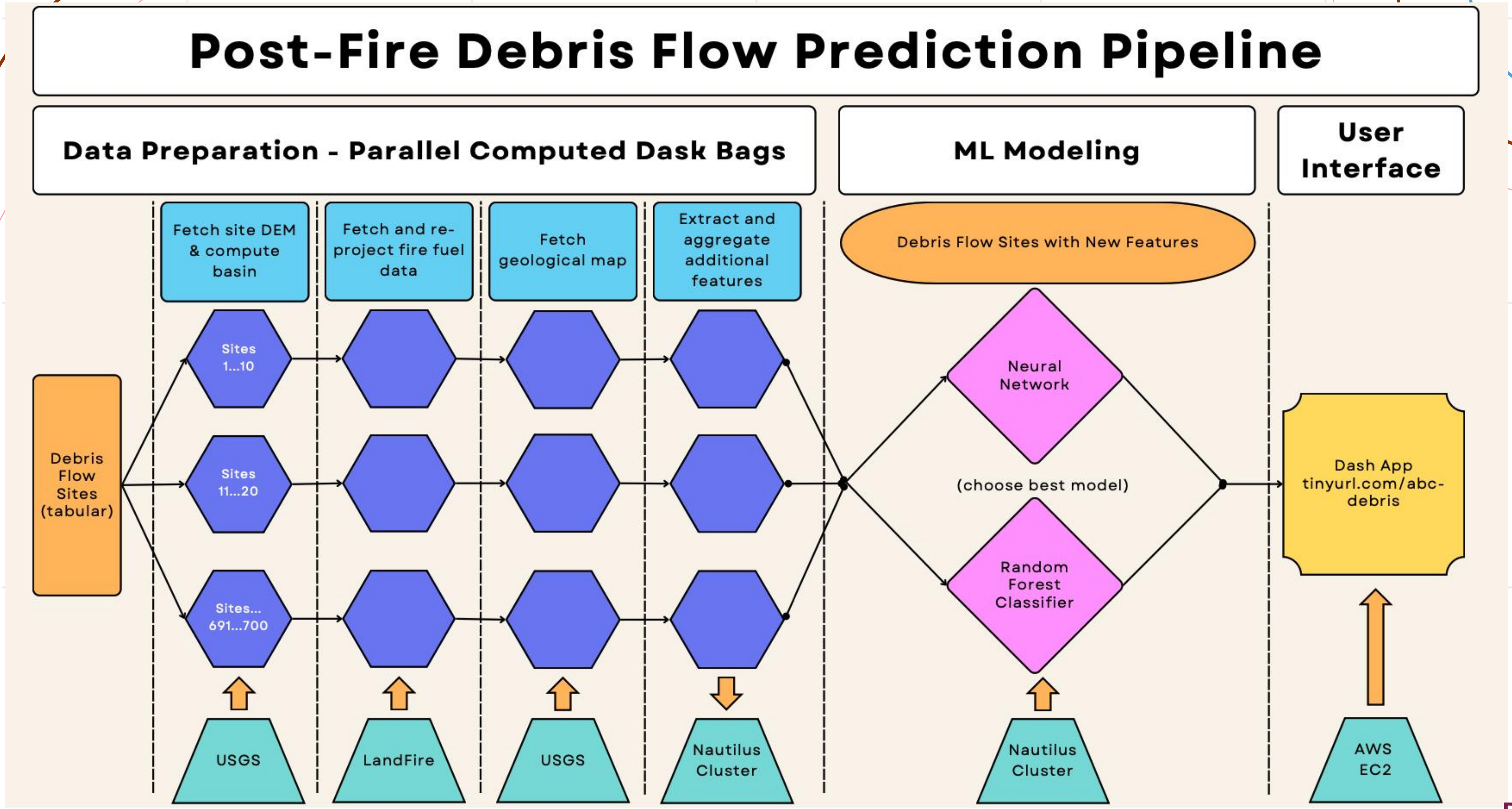
Data Pipeline & Feature Development


Post-Fire Debris Flow Prediction Pipeline
Data Preparation - Parallel Computed Dask Bags
ML Modeling
User Interface
Fetch site DEM & compute basin
Fetch and re-project fire fuel data
Fetch geological map
Extract and aggregate additional features
Debris Flow Sites with New Features
Debris Flow Sites (tabular)
Sites 1...10
Sites 11...20
Sites... 691...700
Neural Network
(choose best model)
Random Forest Classifier
Dash App tinyurl.com/abc-debris
USGS
LandFire
USGS
Nautilus Cluster
Nautilus Cluster
AWS EC2
B

Feature Development

- Staley model started with four features (three with cross product of rain)
- 6 new features were added from publicly available USGS, FBFM40 & FEMA databases

1) Add site ids and clean data
2) Extract contributing region
3) Extract rock type
4) Randomize storm data
5) Query geological age
6) Query FEMA county landslide risk
7) Calculate time between fire and DF
8) Consolidate certain features & universal split
   - E.g. multiple rock features become "Dominant rock type"
   - Consistent Train-Test split for all models

Modular, organized, reproducible python code

Name	Last commit message
..	
.ipynb_checkpoints	dash app
.DS_Store	folder reorg
01_add_site_ids.ipynb	prep notebooks finalized
02_extract_contributing_region.ipynb	dash app
03_extract_rock_type.ipynb	dash app
04_randomize_storm_data.ipynb	prep notebooks finalized
05_geological_age.ipynb	dash app
06_landslide_risk.ipynb	prep notebooks finalized
07_fire_interval.ipynb	prep notebooks finalized
08_feature_consolidation_and_split.ipynb	dash app
README.md	folder reorg

Data Dictionary

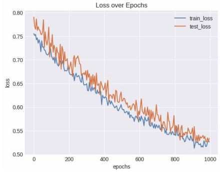
Data-Dictionary	
Feature name	**Description**
Fire Name	Name of wildfire
Year	Year of wildfire occurrence
Fire_ID	Abbreviation of fire name
Fire_SegID	Concatenated fire abbreviation and unique segment ID generated during processing
Database	Database type: "Training" indicates data used to calibrate model equation, "Test" indicates data used to test model performance
State	State in which wildfire occurred
UTM_Zone	UTM zone containing majority of wildfire area
UTM_X	UTM X coordinate (Easting, in meters from zone origin)
UTM_Y	UTM Y coordinate (Northing, in meters from zone origin)
Response	Field-verified hydrologic response. 0 = no debris flow. 1 = debris flow
StormDate	Date of storm that produced the debris-flow response (in YYYY-MM-DD format)
GaugeDist_m	Distance (in meters) from rain gauge to documented response location
StormStart	Date and time (24-hour format, GMT) that storm began (in YYYY-MM-DD HH:MM format)
StormEnd	Date and time (24-hour format, GMT) that storm ended (in YYYY-MM-DD HH:MM format)
StormDur_H	Total duration of storm, in hours
StormAccum_mm	Total rainfall accumulation of storm, in millimeters
StormAvgI_mm/h	Average storm intensity, in milllimeters per hour
Peak_I15_mm/h,Peak_I30_mm/h,Peak_I60_mm/h	Peak 15-minute,30-minute, 45 minute rainfall intensity of storm, in millimeters per hour respectively
ContributingArea_km2	Contributing area of observation location, in square kilometers
PropHM23	Proportion of watershed burned at high or moderate severity and with gradients in excess of 23 degrees
dNBR/1000	Average differenced normalized burn ratio (dNBR) of watershed, divided by 1000
KF	Average KF-Factor (erodibility index of the fine fragments of the soil) of the watershed
Acc015_mm, Acc030_mm, Acc045_mm	Peak 15-minute, 30 minute, 60 minute rainfall accumulation of storm, in millimeters respectively
NB, GR, GS, SH, TU, TL	FBFM40 fuel category /Vegetation type in catchment area - grassland/ grassland shrubs, shrubs, timber
Fine Fuel Load	FBFM40 Fuel characterstic
SAV	FBFM40 Fuel characterstic
Packing Ratio	FBFM40 Fuel characterstic
Extinction moisture content	FBFM40 Fuel characterstic
Igneous, Metamorphic, Sedimentary, Unconsolicated	Rock Category
dom	Dominant FBFM40 Fuel sub-category
domrt	Dominant rock type
LNDS_RISKS, LNDS_RISKR	Landslide Risk score for country from FEMA
fire_interval	Time between the events (wildfire and rain-storm)

Neural Network

Hyperparameter Tuning & Model Selection

PyTorch

scikit learn



Created Sequential NN classes with varying hidden layers

Trained models with all features to extract feature importance

Shapely Additive Explanations (SHAP) values for ranking

GridSearch for best combination of features and hyperparameters

Up to 1,000 combinations per run

Evaluate models, balancing performance metrics

Priority on maximizing Recall and AUC

A

More than 50 models trained and evaluated

Subset of model with performance metrics

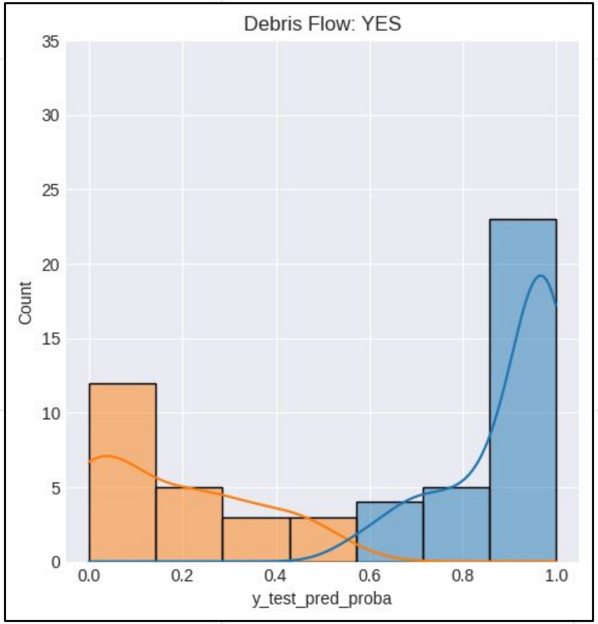
	hidden_size	lr	dropout_rate	epochs	model_class	grid_search_metric	train_loss	val_loss	train_accuracy	test_accuracy	test_precision	test_recall	test_f1_score	test_auc
ThreeLayer_500_epochs_optimized_roc_auc_score	250	0.0100000	0.0500000	500	ThreeLayer	roc_auc_score	0.0203263	1.8640250	0.9916107	0.8856089	0.7222222	0.7090909	0.7155963	0.9226852
TwoLayer_250_epochs_optimized_roc_auc_score	250	0.0100000	0.2000000	250	TwoLayer	roc_auc_score	0.1100651	0.7525712	0.9505034	0.8745387	0.7142857	0.6363636	0.6730769	0.9216751
TwoLayer_750_epochs_optimized_roc_auc_score	100	0.0100000	0.2000000	750	TwoLayer	roc_auc_score	0.0325475	0.8078681	0.9899329	0.8597786	0.6666667	0.6181818	0.6415094	0.9136364
TwoLayer_100_epochs_optimized_roc_auc_score	500	0.0100000	0.0500000	100	TwoLayer	roc_auc_score	0.1446602	0.7158454	0.9395973	0.8671587	0.6792453	0.6545455	0.6666667	0.9128788
ThreeLayer_750_epochs_optimized_roc_auc_score	100	0.0100000	0.2000000	750	ThreeLayer	roc_auc_score	0.0170232	1.2795470	0.9932886	0.8671587	0.6938776	0.6181818	0.6538462	0.9114057
OneLayer_750_epochs_optimized_roc_auc_score	250	0.0100000	0.1500000	750	OneLayer	roc_auc_score	0.1220149	0.4372137	0.9521812	0.8708487	0.7083333	0.6181818	0.6601942	0.9092593
OneLayer_500_epochs_optimized_roc_auc_score	250	0.0100000	0.2000000	500	OneLayer	roc_auc_score	0.1050764	0.5184278	0.9614094	0.8450185	0.6274510	0.5818182	0.6037736	0.9002525
ThreeLayer_250_epochs_optimized_roc_auc_score	100	0.0100000	0.1500000	250	ThreeLayer	roc_auc_score	0.0420898	1.1421973	0.9890940	0.8523985	0.6470588	0.6000000	0.6226415	0.8961279
ThreeLayer_250_epochs_optimized_f1_score	250	0.0100000	0.0500000	250	ThreeLayer	f1_score	0.0193442	2.1054745	0.9949664	0.8597786	0.6666667	0.6181818	0.6415094	0.8960017
TwoLayer_500_epochs_optimized_roc_auc_score	500	0.0100000	0.1000000	500	TwoLayer	roc_auc_score	0.0189185	2.0523396	0.9924497	0.8634686	0.6800000	0.6181818	0.6476190	0.8946970
OneLayer_250_epochs_optimized_roc_auc_score	500	0.0100000	0.1500000	250	OneLayer	roc_auc_score	0.1099459	0.5147722	0.9597315	0.8450185	0.6274510	0.5818182	0.6037736	0.8926768
TwoLayer_1000_epochs_optimized_f1_score	250	0.0100000	0.1000000	1000	TwoLayer	f1_score	0.0077226	3.2219794	0.9949664	0.8708487	0.6851852	0.6727273	0.6788991	0.8899411
OneLayer_100_epochs_optimized_roc_auc_score	500	0.0100000	0.0500000	100	OneLayer	roc_auc_score	0.1607866	0.4363066	0.9362416	0.8560886	0.6428571	0.6545455	0.6486486	0.8849327
TwoLayer_750_epochs_optimized_recall_score	100	0.0100000	0.0500000	750	TwoLayer	recall_score	0.0117989	2.1628008	0.9949664	0.8634686	0.6451613	0.7272727	0.6837607	0.8841751
ThreeLayer_100_epochs_optimized_f1_score	250	0.0100000	0.1000000	100	ThreeLayer	f1_score	0.0958066	0.7082357	0.9588926	0.8376384	0.6037736	0.5818182	0.5925926	0.8696128
TwoLayer_500_epochs_optimized_recall_score	10	0.0001000	0.1500000	500	TwoLayer	recall_score	0.5179337	0.4779459	0.7911074	0.7970480	0.5000000	0.0545455	0.0983607	0.7951178
ThreeLayer_1000_epochs_optimized_recall_score	10	0.0001000	0.2000000	1000	ThreeLayer	recall_score	0.4655180	0.4563868	0.7860738	0.7970480	0.0000000	0.0000000	0.0000000	0.7950337
OneLayer_1000_epochs_optimized_recall_score	10	0.0001000	0.2000000	1000	OneLayer	recall_score	0.4948710	0.5049611	0.7734899	0.7453875	0.2083333	0.0909091	0.1265823	0.7292088
TwoLayer_250_epochs_optimized_recall_score	10	0.0001000	0.0500000	250	TwoLayer	recall_score	0.5069298	0.4701360	0.7860738	0.7970480	0.0000000	0.0000000	0.0000000	0.7229377

Probability Distribution of Confusion Matrix

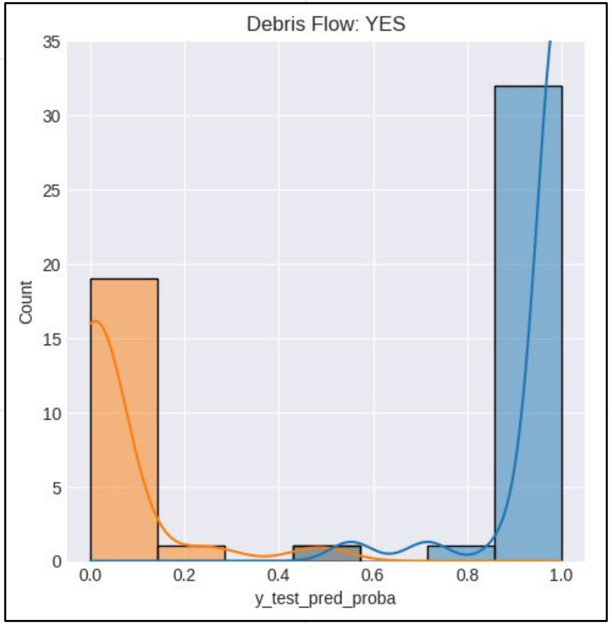
TP
FN

500 epochs

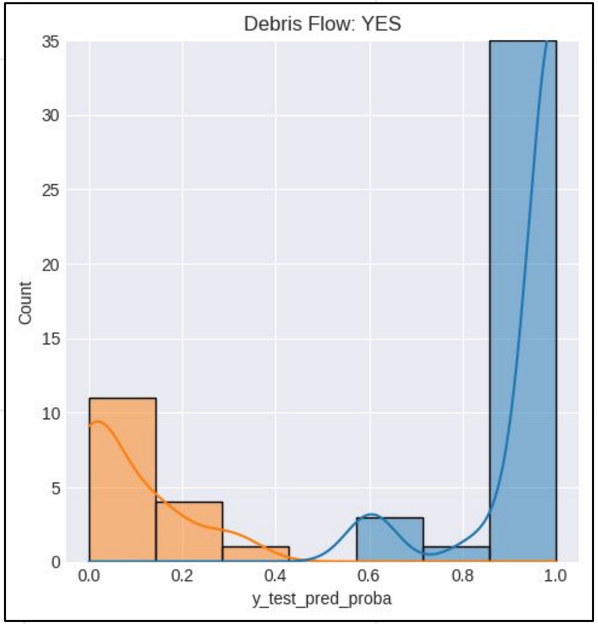
1 Hidden Layer



2 Hidden Layer

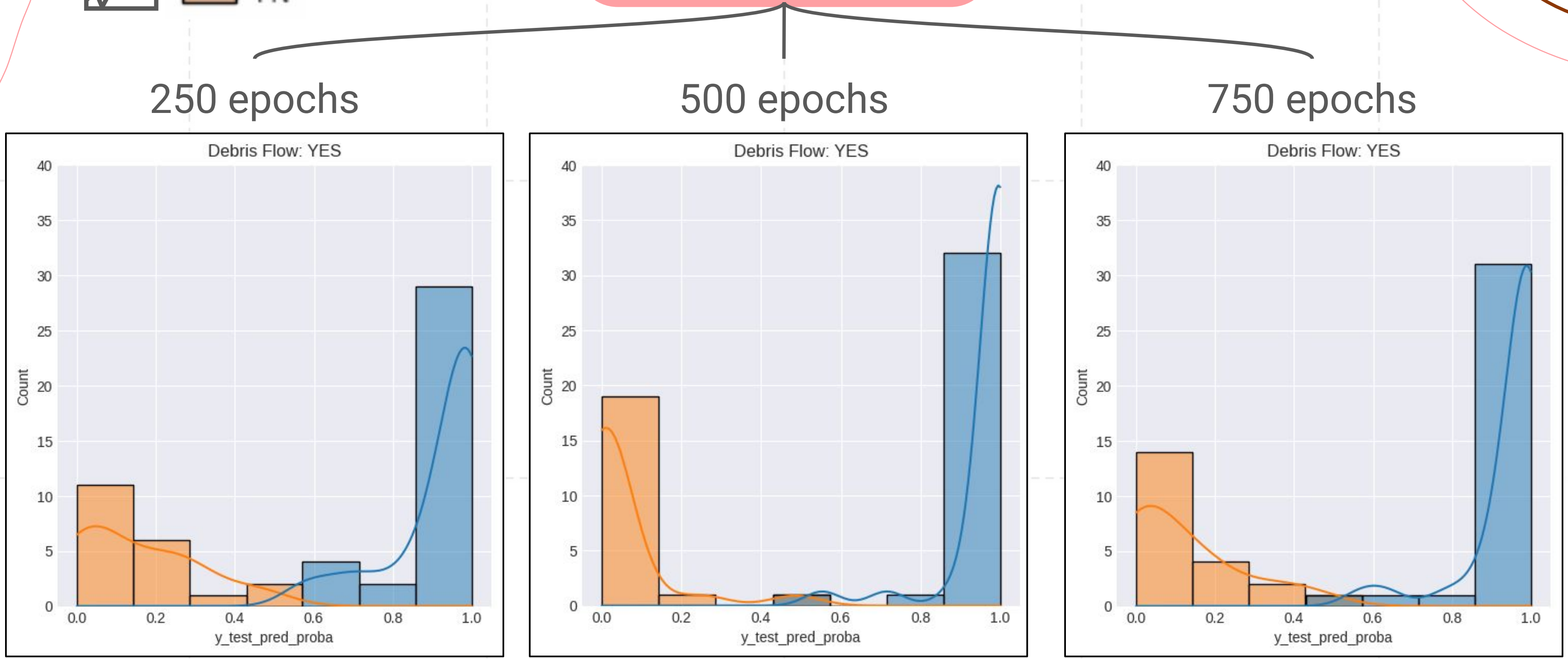


3 Hidden Layer



Probability Distribution of Confusion Matrix

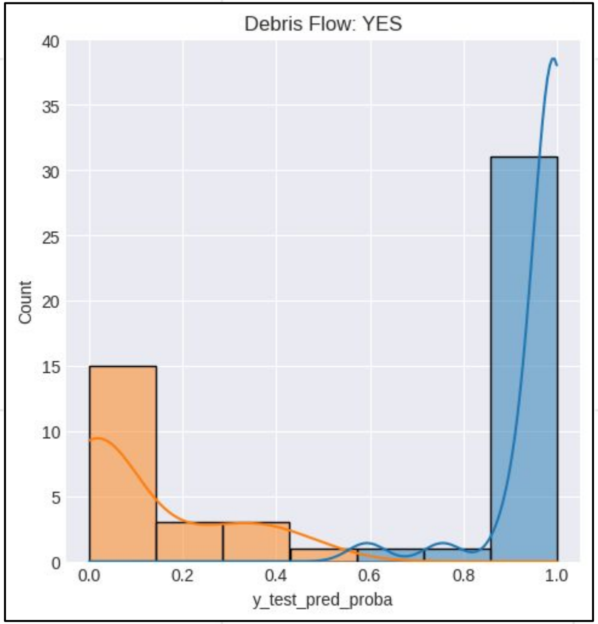
Two Hidden Layers



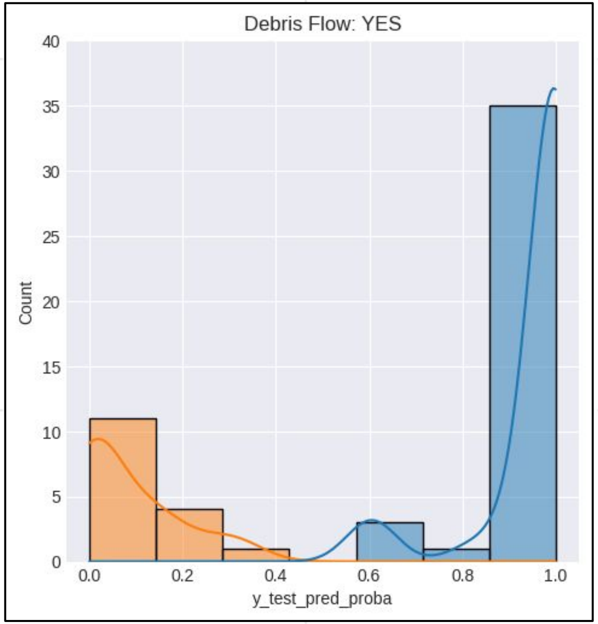
Probability Distribution of Confusion Matrix

Three Hidden Layers

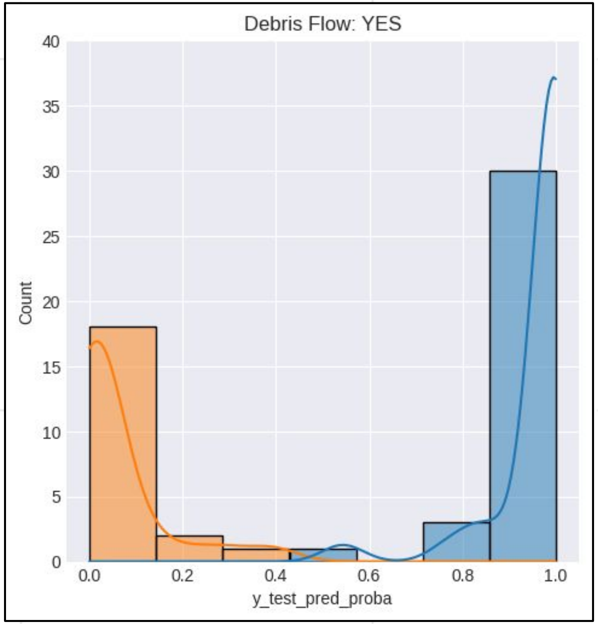
250 epochs



500 epochs



750 epochs



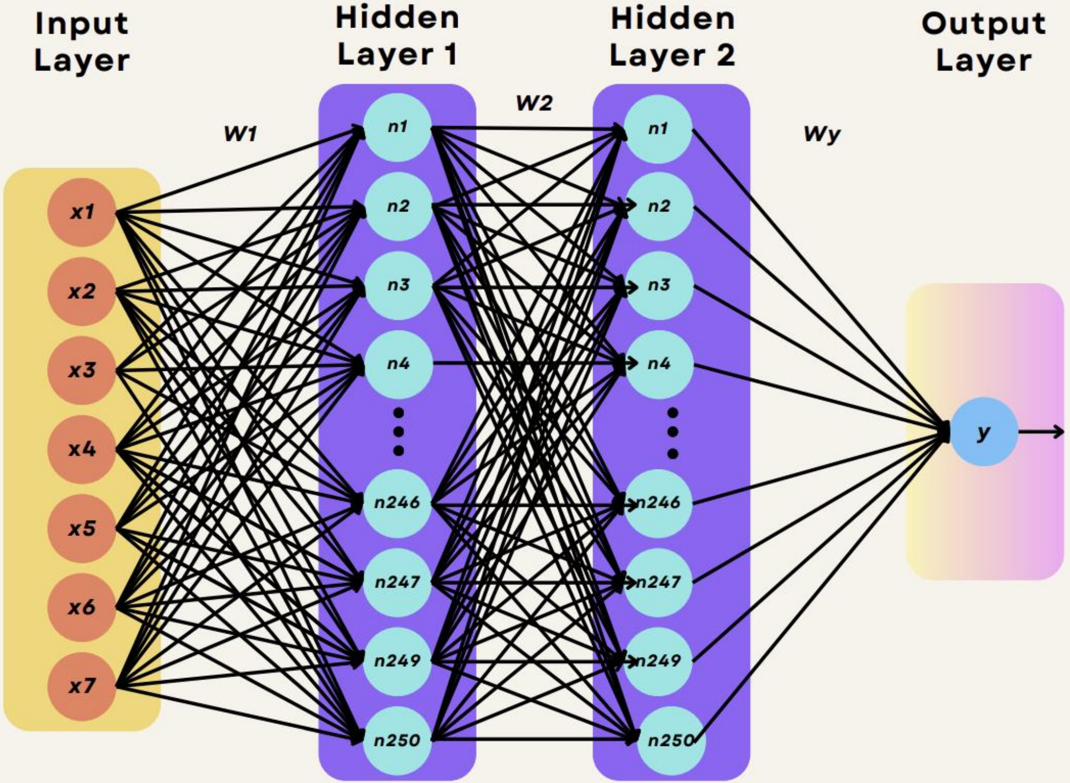
Fully Connected Neural Network Architecture

Architecture

Weight Initialization: Xavier Uniform

Activation Function: ReLu

Output Function: Sigmoid



Training Parameters

LR: 0.01

Dropout: 0.20

Epochs: 250

Loss Function: Binary Cross Entropy

Feature Subset

Rain: rain in mm/h

Fire Interval: time since wildfire

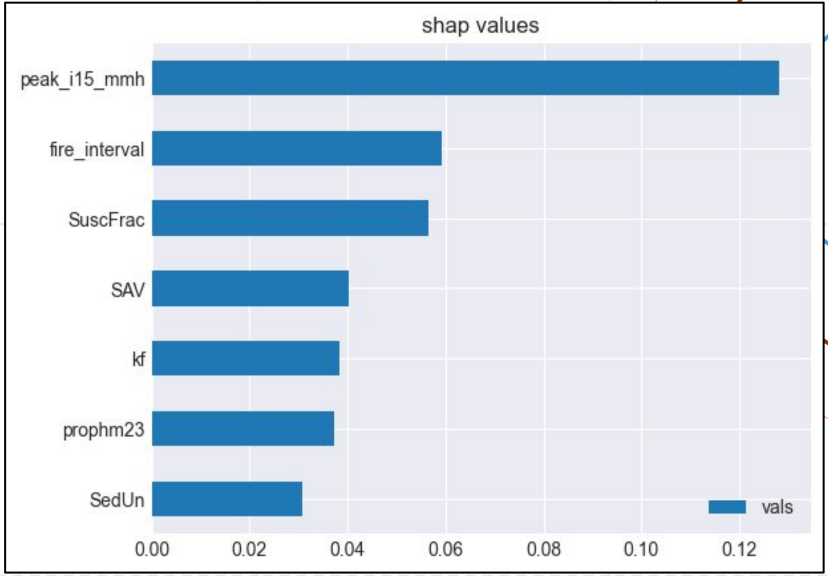
SuscFrac: fraction of watershed covered by burn susceptible vegetation types

SAV: Avg Surface Area to Volume across fuel categories

KF: Fine Fragment Soil Erodibility of watershed

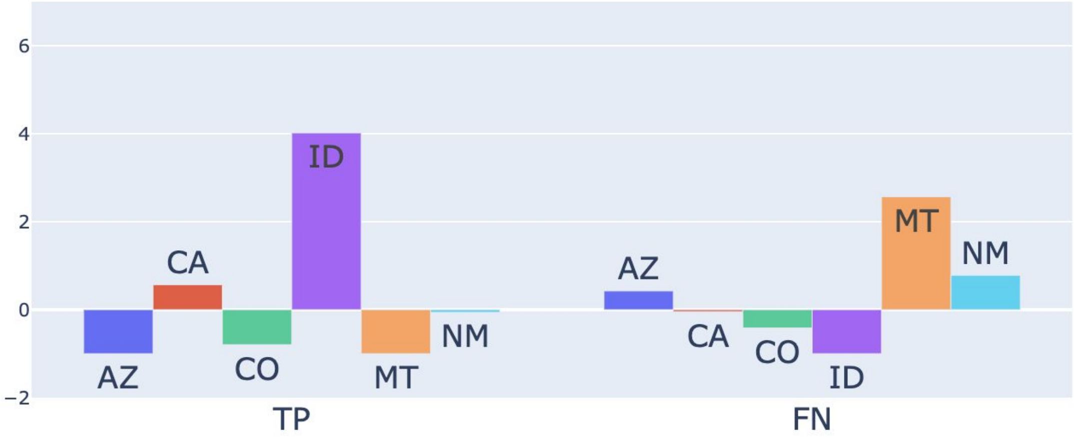
Prophm23: Proportion of watershed with slope > 23°

SedUn: fraction of watershed covered by sedimentary and unconsolidated rocks

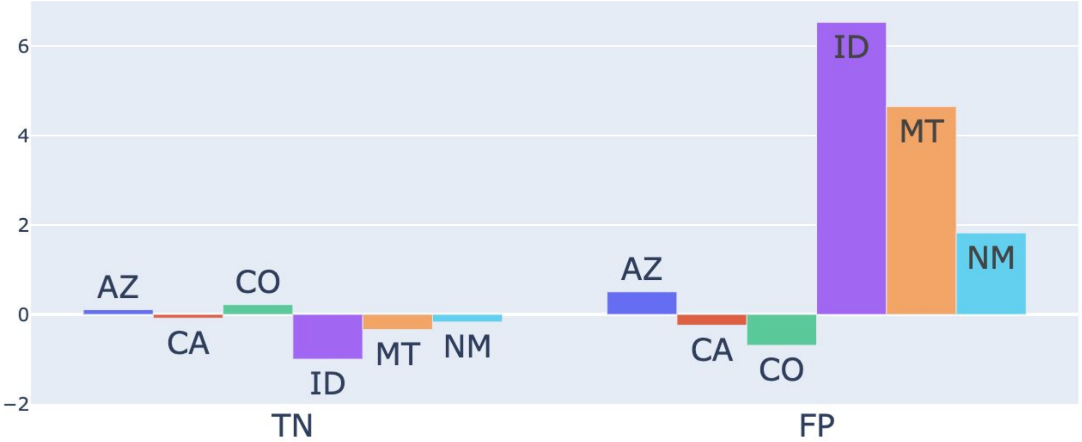


State Confusion Index

True Positive Cases



True Negative Cases



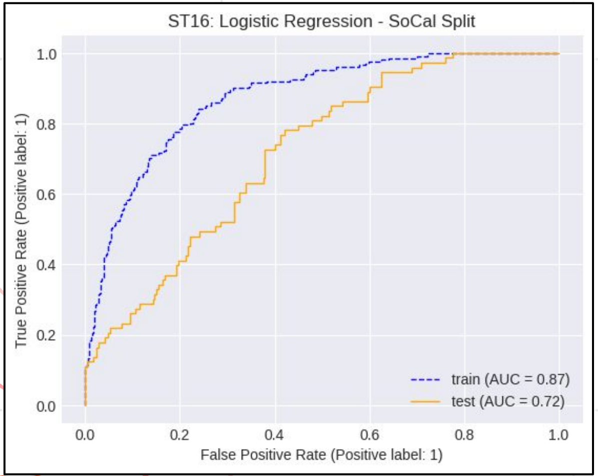
Tuned Model Comparison

Model Comparison
Performance Metrics

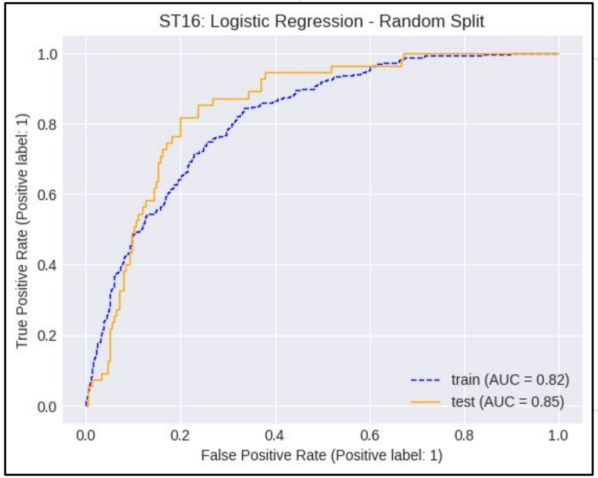
Test Set Performance	Logistic Regression (SoCal)	Logistic Regression (Random-Split)	Neural Network (Random-Split)
Accuracy	0.6258	0.8007	0.8745
Precision	0.3544	0.5200	0.7143
Recall	0.7671	0.2364	0.6264
F1	0.4848	0.3250	0.6731
AUC	0.7178	0.8476	0.9217

Model Comparison AUC (ROC)

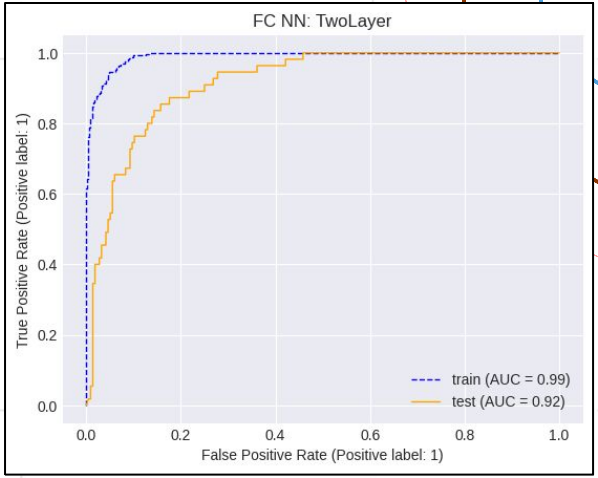
ST16 - SoCal



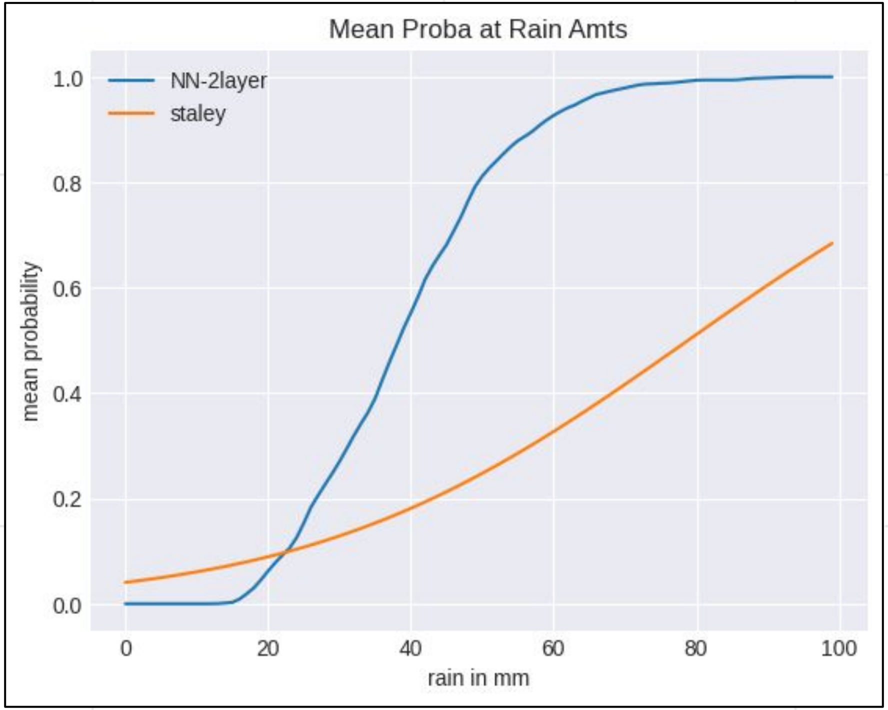
ST16 - Random Split



FC NN - Random Split

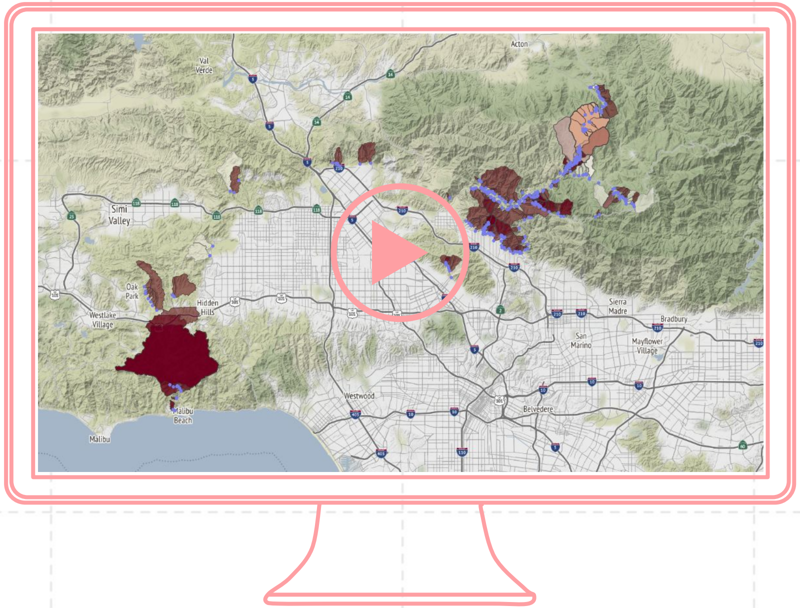


Model Comparison
Probability Curve



A

User Interface



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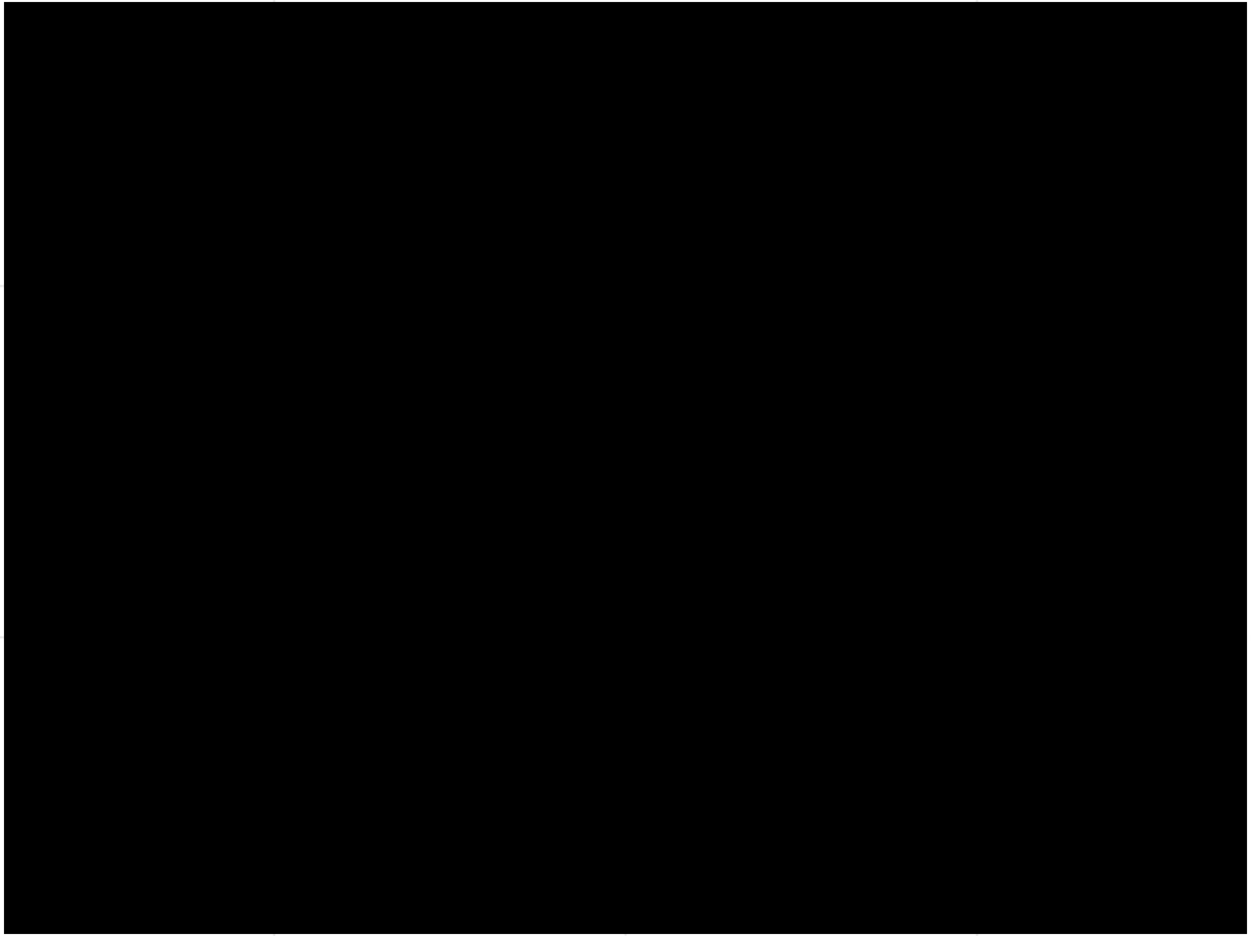
Visualization app Development & Deployment

- Dash is an open-source framework for building data visualization interfaces.
- Three technologies constitute the core of Dash: Flask, React.js, Plotly.js
- App developed in python and is hosted on Amazon EC2
- Server used is a t2.xlarge with Ubuntu OS , 4 Cores and 32 GB RAM.
- Once the instance is up and running, below are main steps for getting the app run
- SSH into the server and clone the Git repo
- Repo has all the libraries required to create a virtual environment (requirements.txt) file and the code base
- Install the libraries and then run the dash app
- Dash app will be rendered on port 8050 of the EC2 server
- This app can now be accessed from EC2 IP & Port 8050.

B

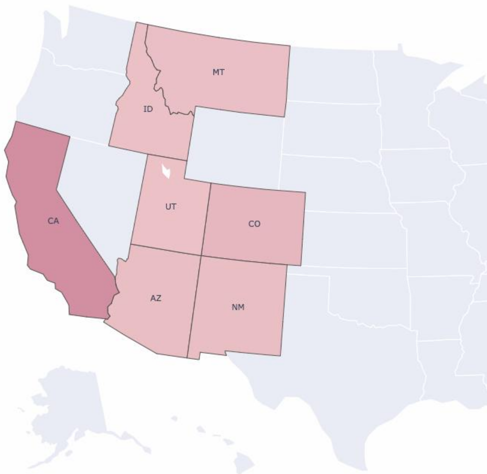
Demo



Conclusion

Conclusion

- Using new features and models developed as part of this project, we developed a model that works better at scale with greater predictive power of Debris Flows
- The User Interface is a demo of what can be a great visualization tool for decision makers for swift action when rain events are in the forecast



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References

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[5] https://prdtnm.s3.amazonaws.com/StagedProducts/Elevation/13/TIFF/current/n35w119/USGS_13_n35w119.ti

[6] https://nwschat.weather.gov/lsr/#LOX,MTR,EKA,SGX,STO,REV,HNX,MFR,VEF/202301040800/202301080759/11

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