

# PREDICTION AND INFERENCE OF LARGE WILDFIRE BURN AREA IN THE CONTIGUOUS UNITED STATES

2023 TAMIDS Student Data Science Competition

*Team – Sam's Strikers*

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TEXAS A&M UNIVERSITY  
Water Management &  
Hydrological Science

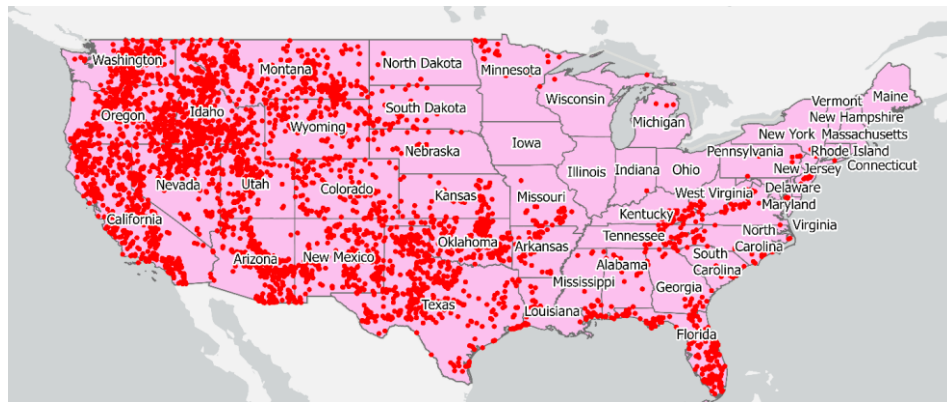


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Picture Courtesy:  
[kqed.org](http://kqed.org)

# Introduction

- Primary focus on two challenges: **wildfire behavior** prediction and effective communication of research findings
- Wildfire behavior is complex, and predicting it accurately is challenging
- Effective communication of research findings to end-users is critical in addressing the wildfire problem
- In last decade, the US witnessed **70,000** wildfires per year, burning **7 million acres** of land on average
- Texas had **3,700** wildfires in 2021, burning around **200,000** acres of land
- Data-driven approaches can help in predicting wildfire spread and ultimately reducing their impact
- A **Deep Learning** approach is used to predict burn area for large wildfire occurrences based on **climate forcings** and **geological characteristics**



*Map of large wildfire incidents in the contiguous US between 2011 and 2020 (4538 incidents)*

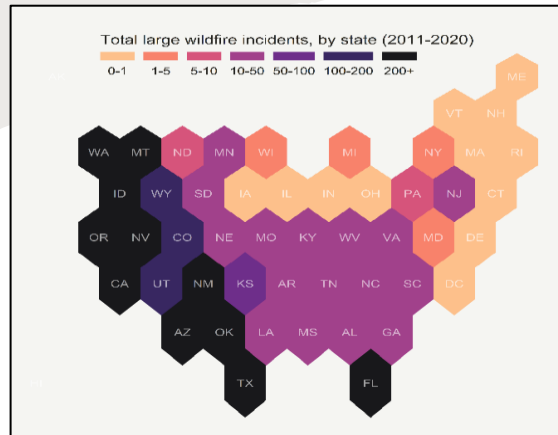
# Wildfire Data



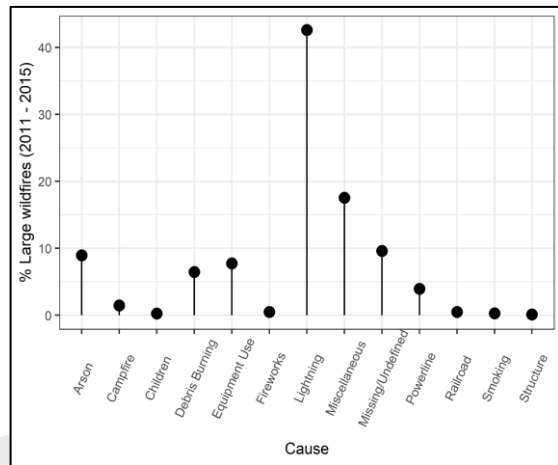
- GIS data for large wildfire locations and burn area boundaries downloaded from **Monitoring Trends in Burn Severity Program**.
- Large wildfire thresholds – **1000** acres in Western US and **500** acres in Eastern US.
- 10 years of data collected (**2011 – 2020**)
- **4,538** incidents covering **87,305 square miles** of burn area used in analysis



Additional wildfire data obtained from **Fire Program Analysis Fire-Occurrence Database (FPA-FOD)** for information on wildfire causes


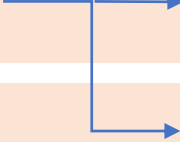










*Large wildfire incidents by state*

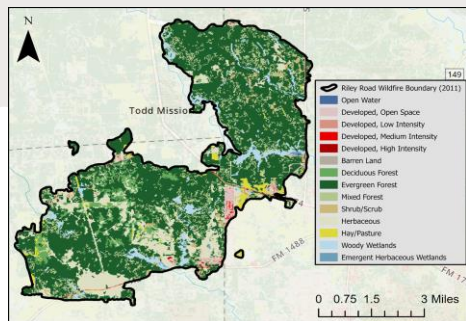


*Major causes of large wildfires in US*

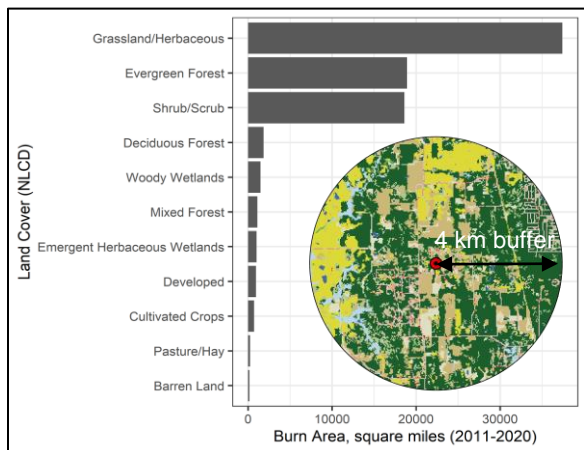
# Meteorological and Topography Data

	Climate		PRISM	Precipitation, Temperature, Vapor Pressure Deficit (Minimum and Maximum)
			GRIDMET	Palmer Drought Severity Index (PDSI), Potential Evapotranspiration (PET)
	Land cover		National Land Cover Database (NLCD 2016)	Open Water, Developed, Barren, Forests, Shrub/Scrub, Hay/Pasture, Cultivated Crops, Wetlands
	MODIS		MOD13A3 Version 6	Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI)
	Topography		USGS DEM	Elevation (meters)
	Ecoregion		US EPA Ecoregions	Level I and Level IV ecoregion boundaries

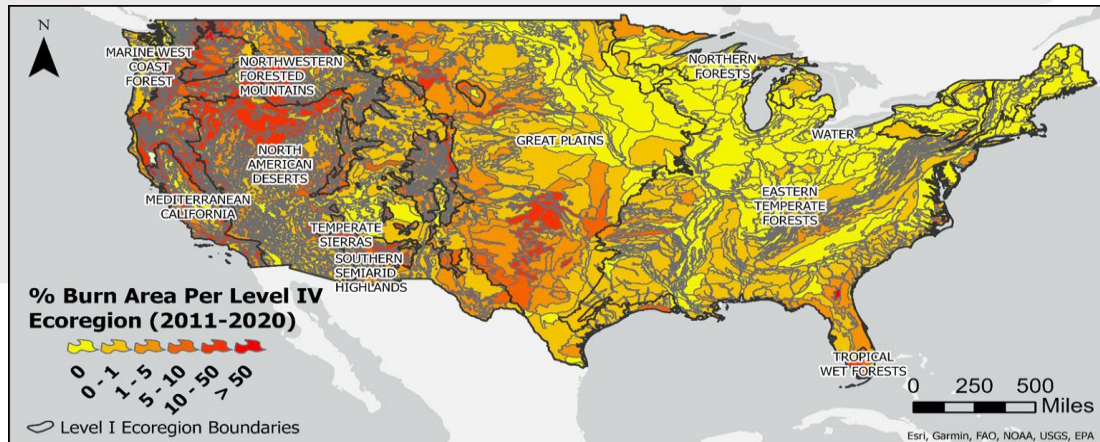
# Data Exploration



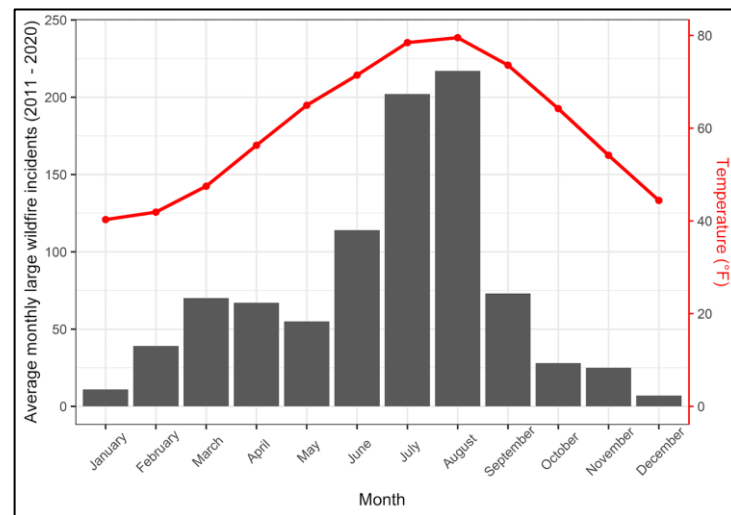
*NLCD land cover for area burned in Riley Road wildfire northwest of Houston burning 19,000 acres of land*



*Burn area by NLCD land cover in large wildfires between 2011-2020*



*Percent of Level IV Ecoregion land burned in large wildfires between 2011 - 2020*

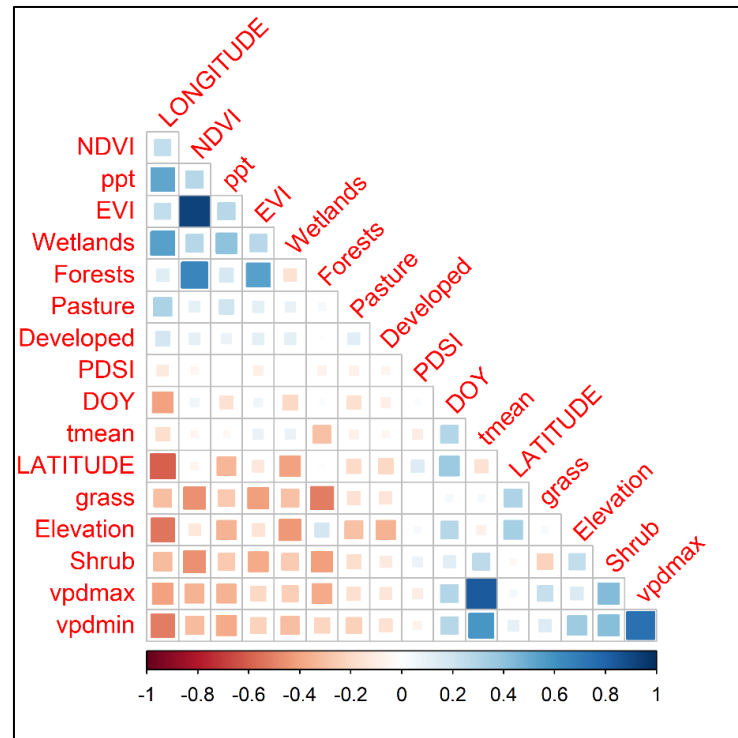


*Average monthly large wildfires (bar) in the contiguous US and the mean monthly temperature (line).*

# Predicting Burn Area

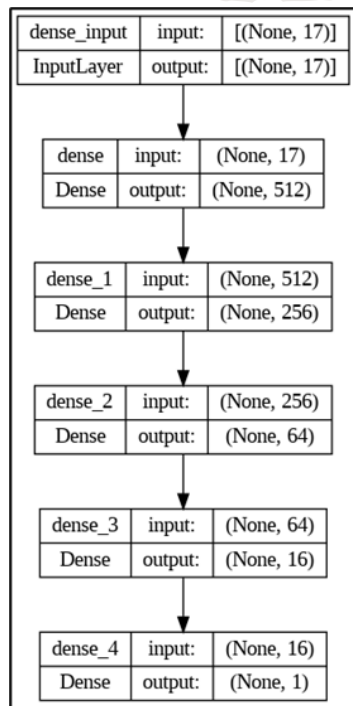
*Features gathered for 4,536 large wildfires*

Feature	Description	Min	Max
<b>LATITUDE</b>	Latitude coordinates of wildfire occurrence (decimal degrees)	25.2	49
<b>LONGITUDE</b>	Longitude coordinates of wildfire occurrence (decimal degrees)	-124.1	-72.8
<b>DOY</b>	Wildfire ignition day of year	1	365
<b>ppt</b>	Total monthly precipitation for month of wildfire ignition	0	1063.2
<b>tmean</b>	Average monthly temperature for month of wildfire ignition	-5.3	36.8
<b>vpdmax</b>	Maximum vapor pressure deficit for month of wildfire ignition	2.7	81.8
<b>vpdmin</b>	Minimum vapor pressure deficit for month of wildfire ignition	0	35.3
<b>PDSI</b>	Palmer Drought Severtiy Index during ignition date	-8.1	7.6
<b>Developed</b>	% NLCD developed around 4-kilometer buffer of wildfire ignition	0	64.2
<b>Forests</b>	% NLCD forests around 4-kilometer buffer of wildfire ignition	0	99.8
<b>Shrub</b>	% NLCD shrub/scrub around 4-kilometer buffer of wildfire ignition	0	100
<b>grass</b>	% NLCD grasslands/herbaceous around 4-kilometer buffer of wildfire ignition	0	100
<b>Pasture</b>	% NLCD hay/pasture around 4-kilometer buffer of wildfire ignition	0	74
<b>Wetlands</b>	% NLCD wetlands around 4-kilometer buffer of wildfire ignition	0	100
<b>NDVI</b>	Normalized Difference Vegetation Index for month of wildfire occurrence	0.1	0.9
<b>EVI</b>	Enhance Vegetation Index for month of wildfire occurrence	0	0.7
<b>Elevation</b>	Elevation of wildfire occurrence	-2	3507

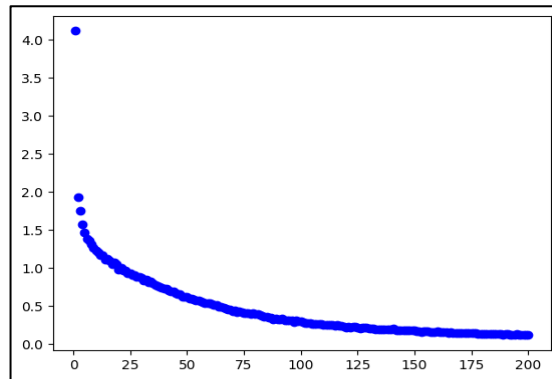


*Correlation plot for features used in the study*

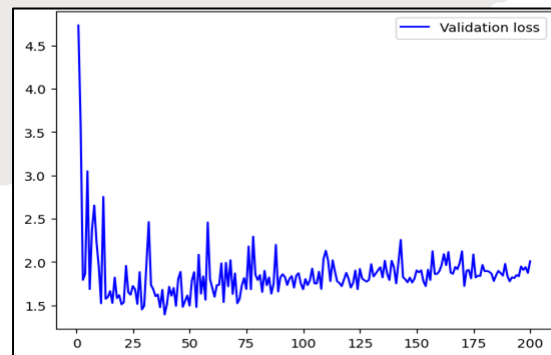
# Modeling and Analysis



DNN architecture used in the study



Training loss for the DNN model



Validation loss for the DNN model

## Model Specifications:

- Train/Test split ratio – **80/20**
- Number of repeats: **3**
- Activation function: **ReLU**
- Learning rate: **0.001**
- Batch size: **32**
- Number of Epochs: **200**
- Test Error (MSE): **0.055 to 0.06**

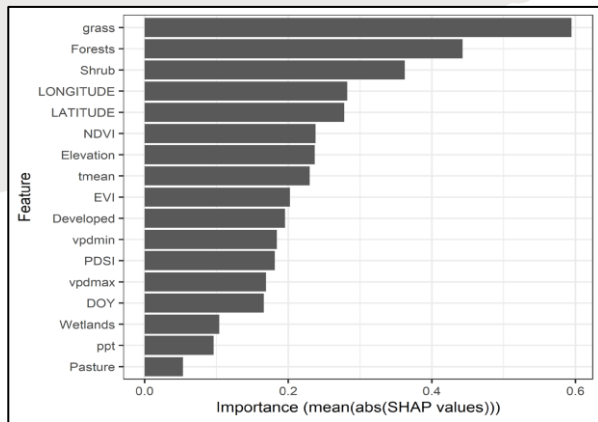
$$\text{Error rate} = \frac{\sum_1^N |y_{obs} - y_{pred}|}{\sum_1^N |y_{obs}|}$$



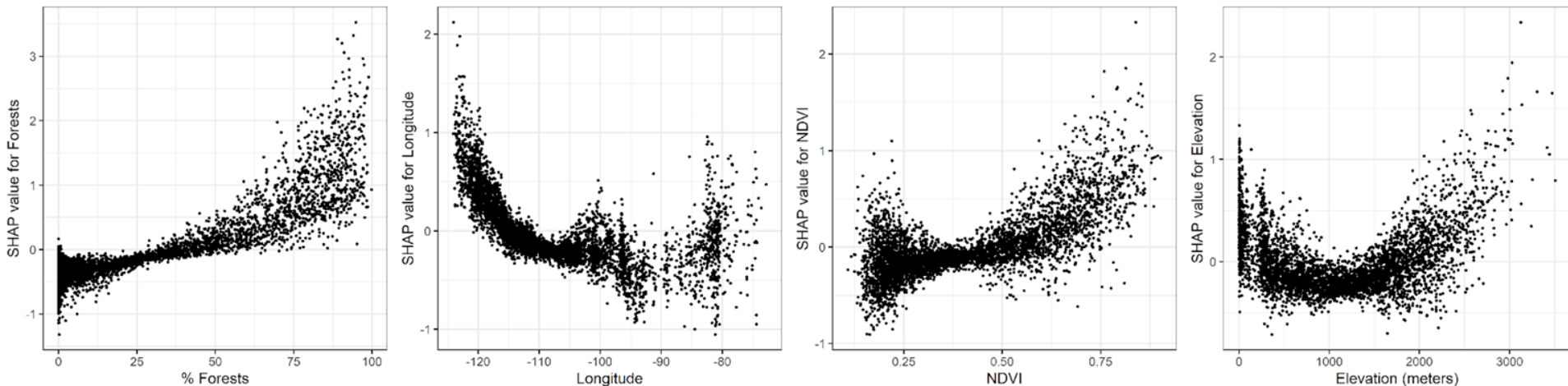
# Model Inference

- Using **shapley values** (from game theory) for feature interactions and importance
- Positive SHAP value indicated increase in model's prediction due to the feature in analysis, and vice-versa for negative values

- For any observation -  
*Model prediction = Average prediction + sum of all SHAP values*



Feature importance in the DNN model obtained from SHAP values



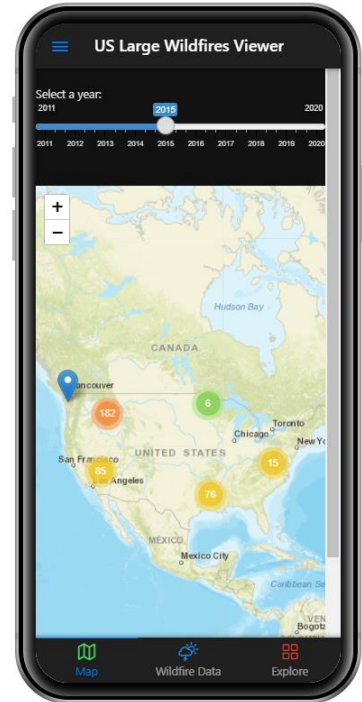
Partial Dependence Plots showing the interactions between features and burn area using SHAP values



# Conclusion and Recommendations

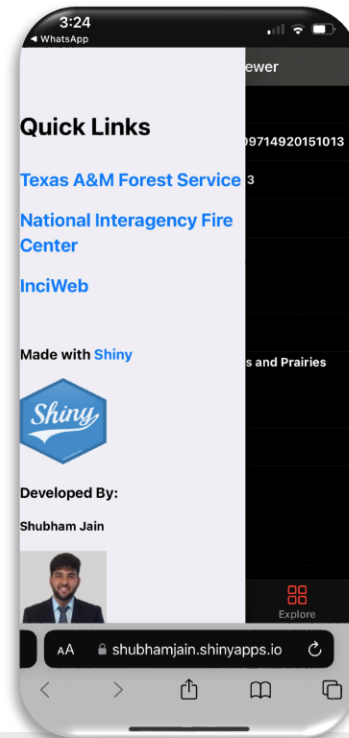
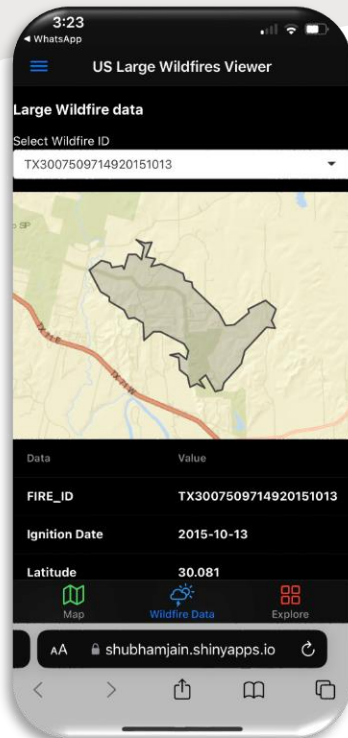
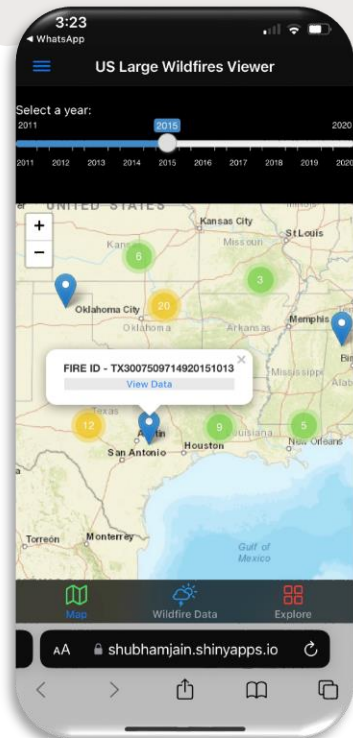
- The **DNN** model performed reasonably well with an average test MSE of **0.055**
- **Land cover** and **location of wildfire occurrence** were most influential in determining burn area
- Future work could involve learning the effects of other features such as **soil characteristics** and **dead fuel moisture** on burn area
- **Data collection, modeling** and **on-ground action** need to be looked together for an effective strategy to mitigate impact of forest fires
- Promoting **interdisciplinary research** with more collaboration between Natural Sciences and Data Science
- A prototype interactive web-tool to visualize wildfire data and characteristics for end-users

<https://shubhamjain.shinyapps.io/Wildfires/>



*Mobile friendly data visualization tool*

# Web tool



# Team – Sam's Strikers



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# Hearty gratitude:



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Thank You!

**Questions?**