

# *Using Deep Learning to Predict Yearly Wildfire Potential from Antecedent Land Surface and Meteorological Data*

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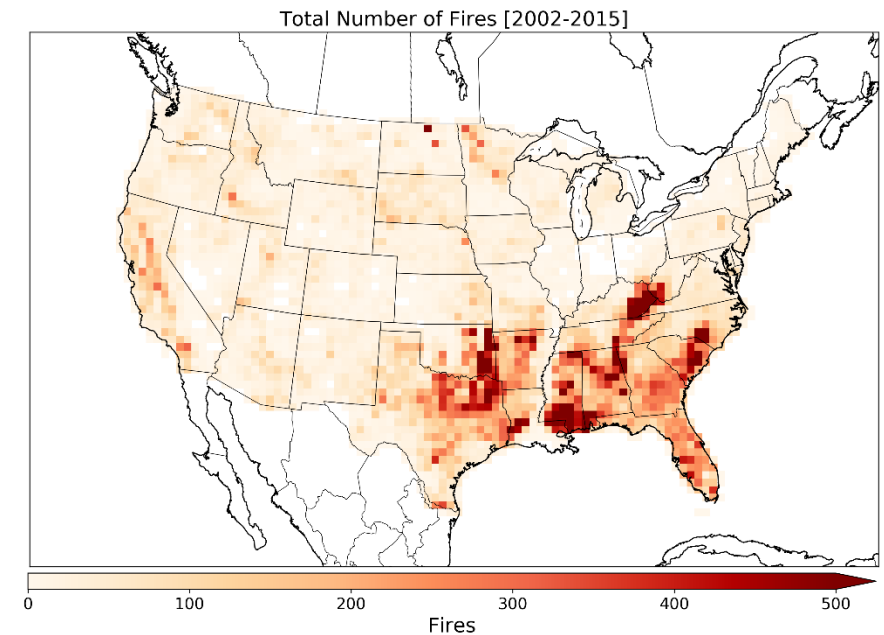
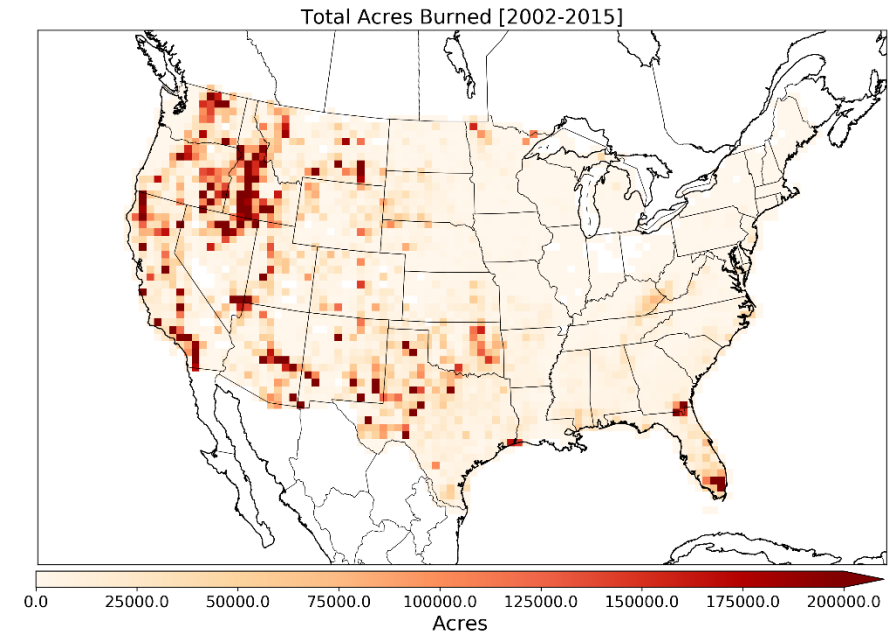
<sup>3</sup>ENSCO, Inc./NASA MSFC SPoRT

<sup>4</sup>NWS/NASA MSFC SPoRT



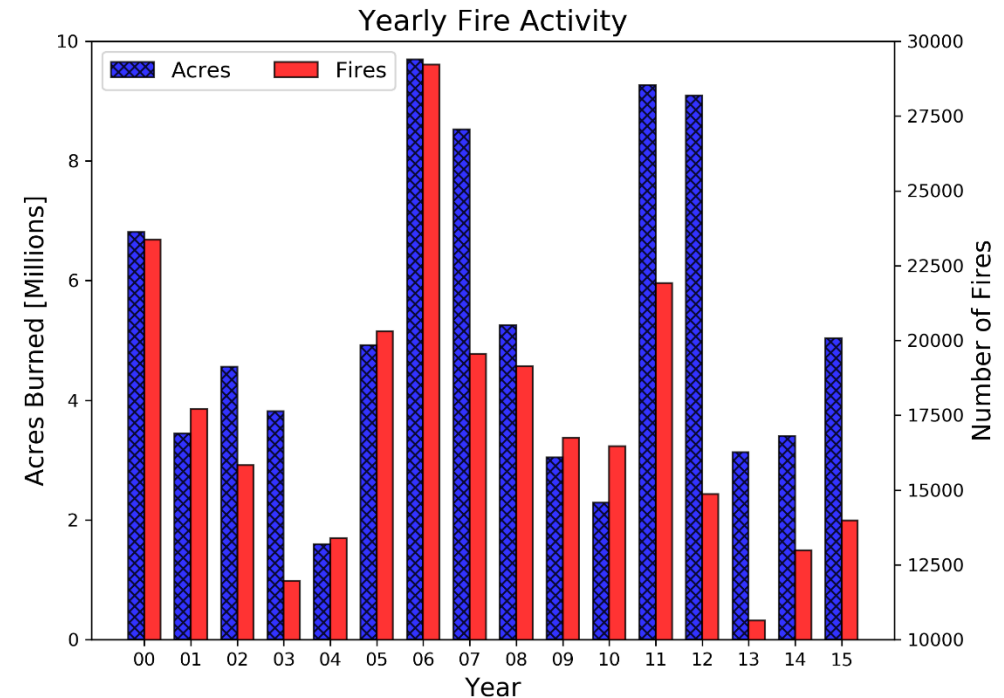
# Wildfires Overview

- Wildfires can have devastating social and economic impacts.
  - Loss of life
  - Air quality impacts
  - Yearly costs are rising
  
- Expansion of the wildland-urban interface (WUI) is leading to increased fire risk.
  
- While much of the wildfire focus is in the west, a significant number of fires do occur in the eastern U. S.



# Yearly Variation

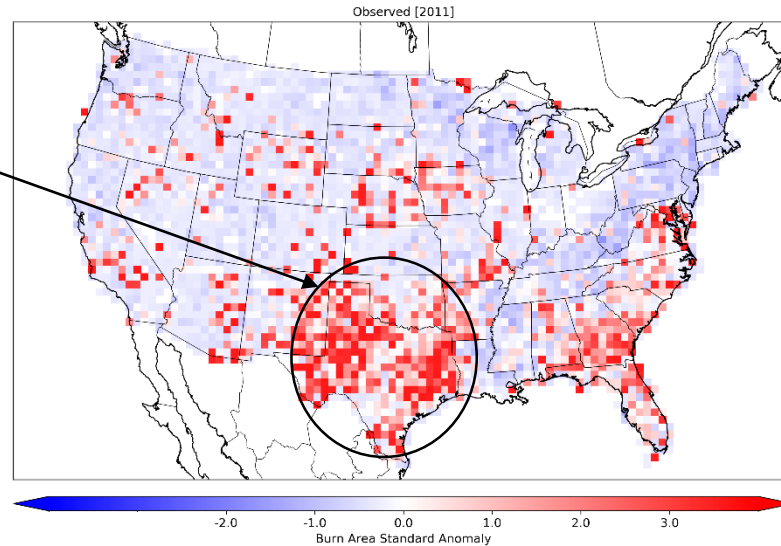
- Fire activity is highly variable from year to year.
- Yearly changes in fire activity are related to changes in both atmospheric and land surface conditions.
  - Numerous amounts of available data related to fire potential (i.e. dead fuel moisture, soil moisture, precipitation, temperature, moisture, etc.)
  - Antecedent conditions provide an indication about potential fuel availability and dryness.



Yearly number of fires and acres burned across the CONUS domain. Indicates high year to year variability.

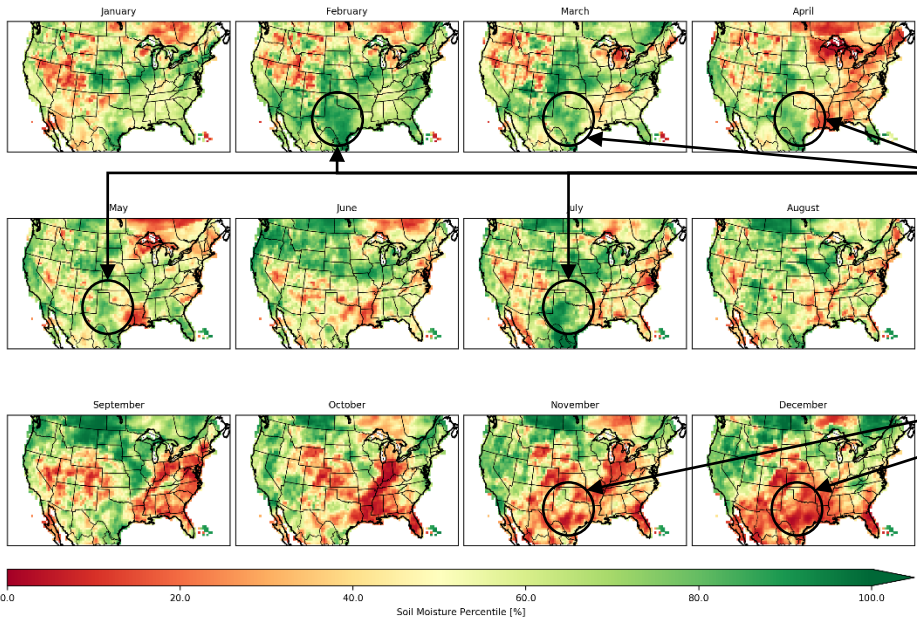
# Antecedent Relationships

- Standardized burn area anomaly for 2011 shows anomalous wildfire activity over much of Texas.
- SPoRT LIS 0 – 40 cm Soil Moisture percentile is high for much of the previous year (2010), especially over the growing season.



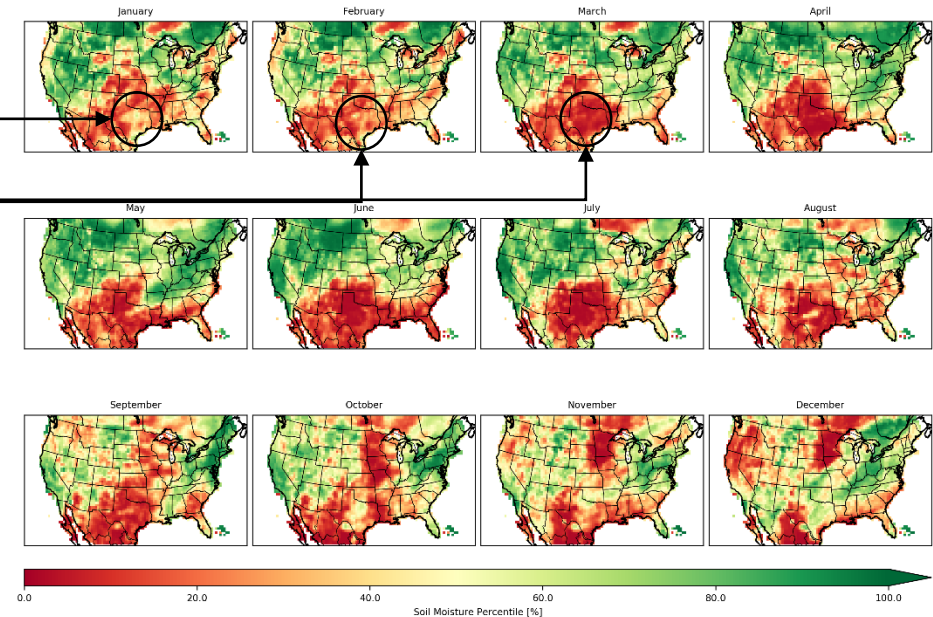
- Drying then occurred from late fall 2010 and continued through 2011.
- High antecedent soil moisture during growing season can lead to a build up of fuel.
- Low soil moisture leading up to fire season continually dries the available fuel.

Monthly LIS 0-40 cm Soil Moisture Percentile [2010]



High antecedent (2010) soil moisture during growing season.

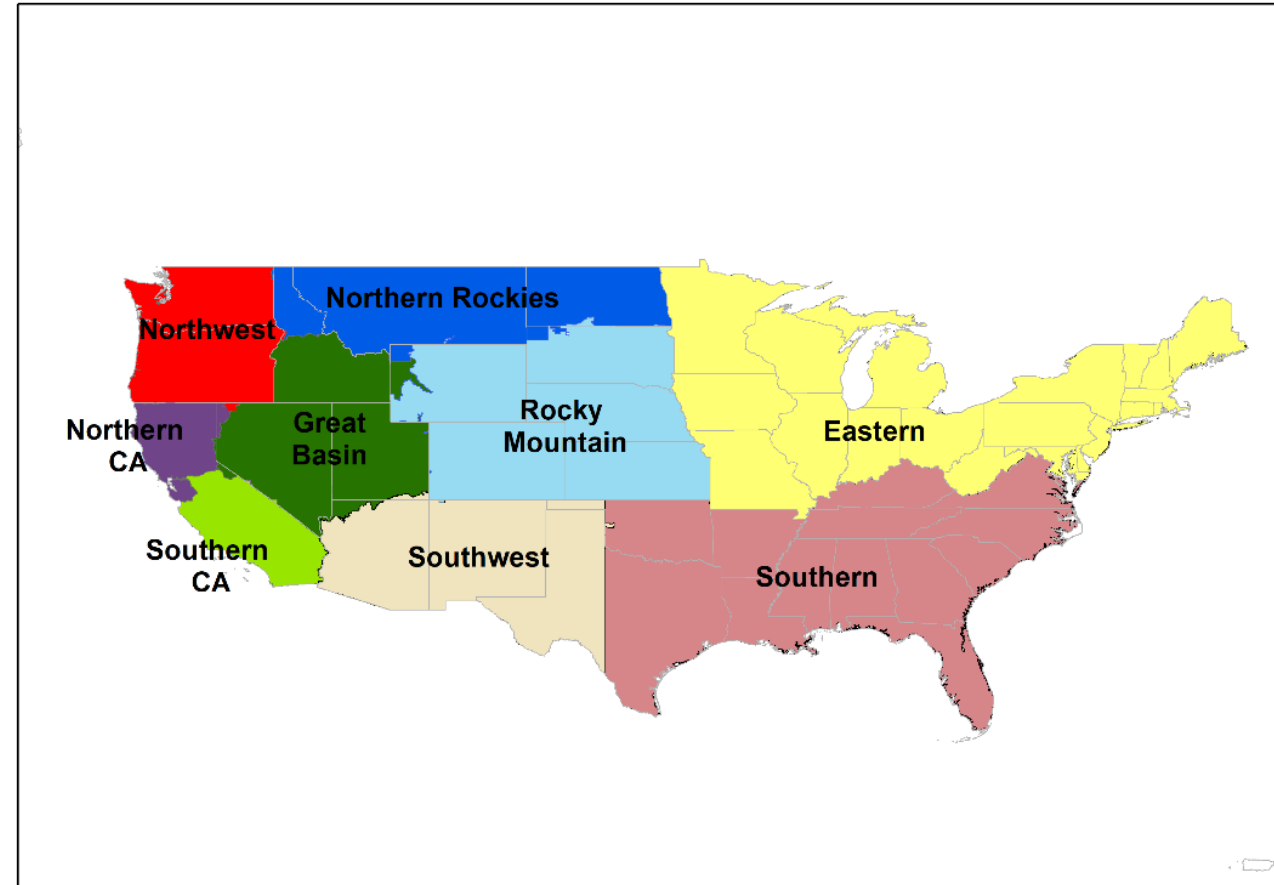
Monthly LIS 0-40 cm Soil Moisture Percentile [2011]



Low antecedent soil moisture during late Fall 2010 into early Spring 2011.

# Project Overview

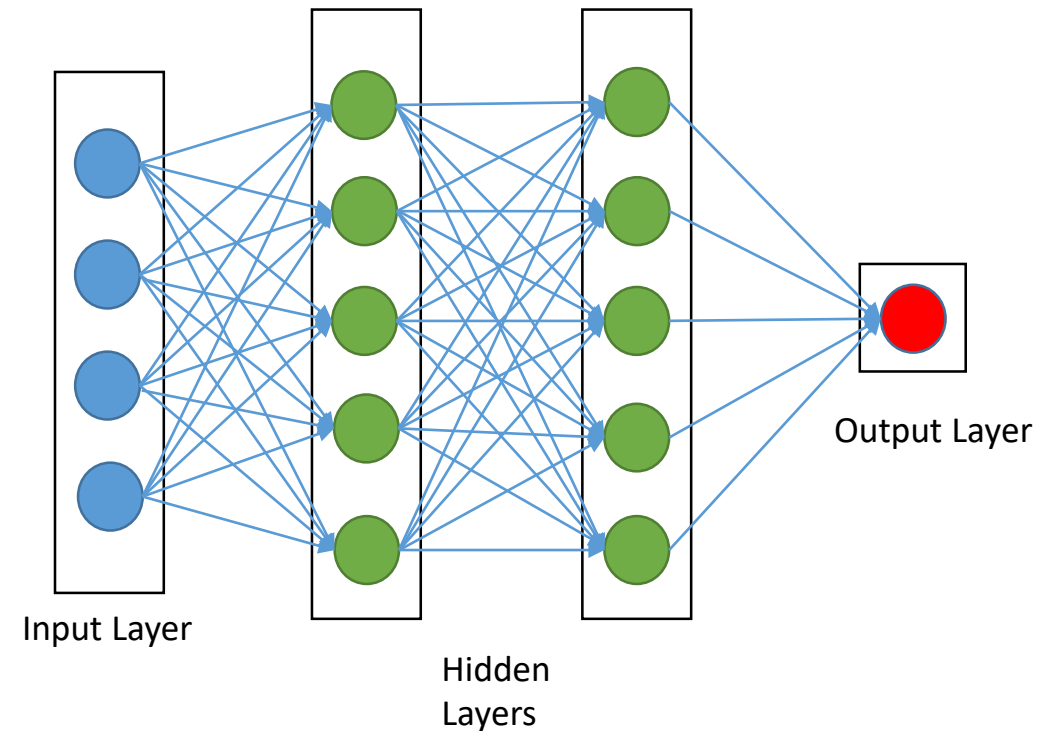
- **Goal:** Use deep learning to develop a predictive model for yearly number of fires and acres burned across each Geographic Area Coordination Centers (GACC) region.
  - Study predictability by region.
  - Study the predictor variable importance by region.
  - Study time-lag importance by region.



GACC Regions

# Deep Learning

- Deep Neural Network (DNN)
  - Learn representations from the data through hierarchical layers.
  - Works by determining the weights which effectively map the inputs to their targets.
- Each DNN was built using Keras with the tensorflow backend.
  - 5 layers (4 hidden layers and the output)
  - 500 nodes per hidden layer.



# Input Data

- A plethora of data corresponding to the antecedent land surface, atmospheric and fuel conditions are used.
- The 4<sup>th</sup> edition Fire Program Analysis – Fire Occurrence Database (FPA-FOD) is used as the truth dataset (Short 2017).
  - Point data is gridded and smoothed to represent a continuous wildfire truth dataset.

Input Features	
SPoRT LIS Volumetric Soil Moisture (0 – 10 cm, 10 – 40 cm, 40 – 100 cm)	SPoRT LIS Soil Moisture Percentiles (0 – 10 cm, 0 – 40 cm, 0 – 100 cm)
Dead Fuel Moisture (100-hr and 1000-hr)	Precipitation
Daily Minimum and Maximum Temperature	Daily Mean Vapor Pressure Deficit
Daily Minimum and Maximum Relative Humidity	Energy Release Component
Daily Average Downwelling Shortwave Radiation	Wind Speed
<u>Planned Addition</u> MODIS LAI/GVF	<u>Planned Addition</u> Evaporative stress index

# Model Training

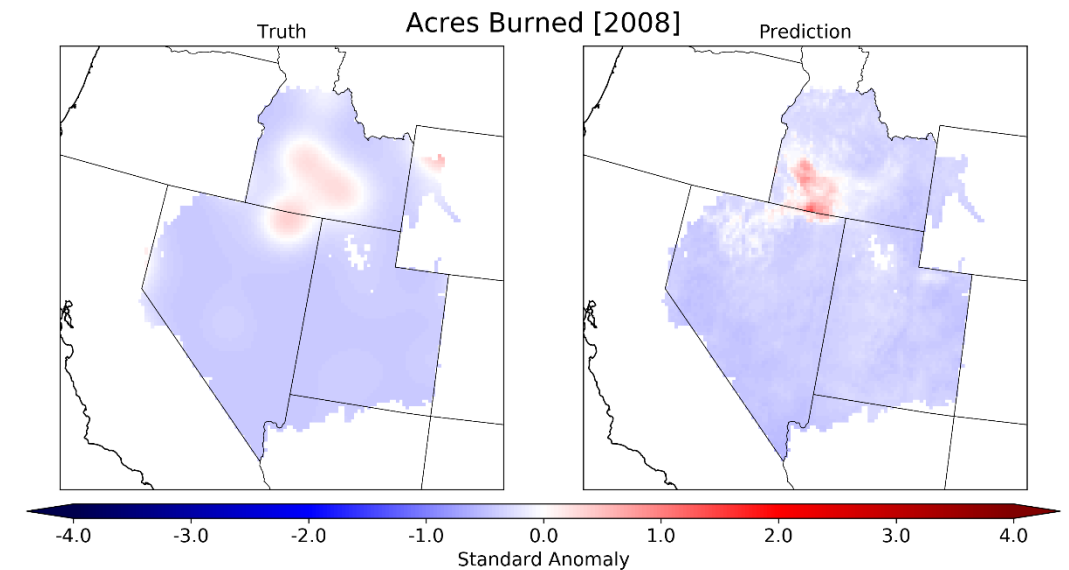
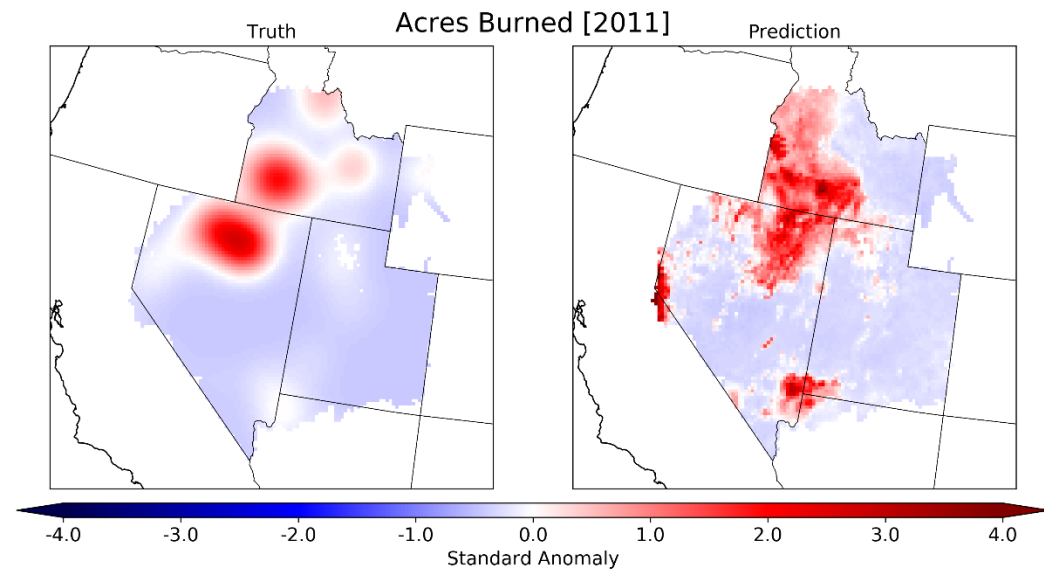
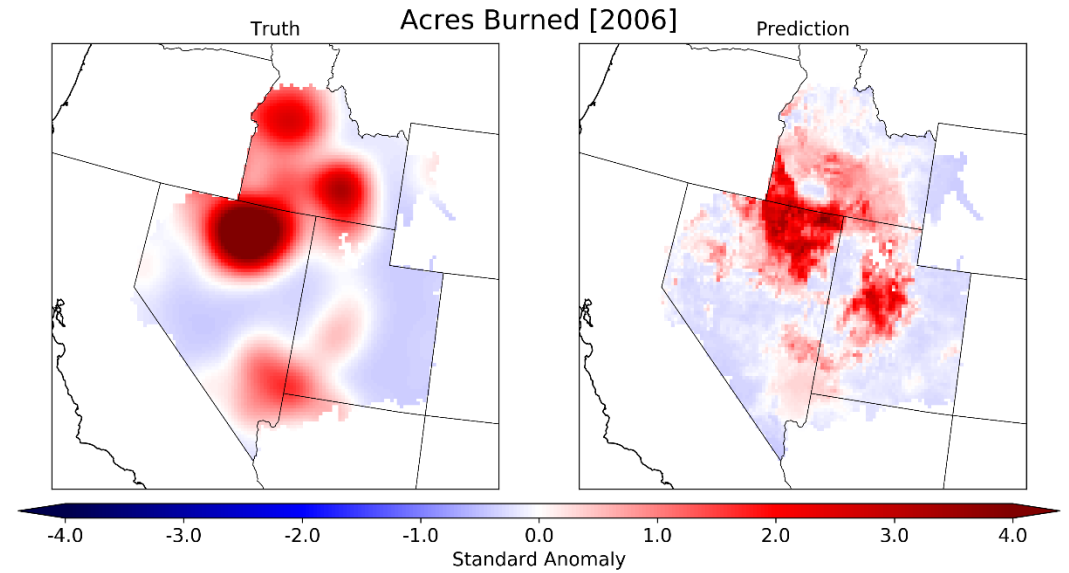
- Monthly averages of each feature from the previous three years through the start of fire season were used.
  - Feature scaling was completed on a GACC region basis.
- DNN models were trained over the 2002 – 2015 time period.
  - Individual years were held out for testing.

GACC	Start Date (5%)	Median (50 %)	End Date (95%)
Eastern	47 (Feb)	103 (Apr)	317 (Nov)
Northern CA	127 (May)	206 (Jul)	297 (Oct)
Northern Rockies	90 (Mar/Apr)	211 (Jul/Aug)	284 (Oct)
Northwest	102.9 (Apr)	211 (Jul/Aug)	286 (Oct)
Rocky Mountain	43 (Feb)	181 (Jun/Jul)	305 (Nov)
Southern CA	101 (Apr)	196 (Jul)	296.7 (Oct)
Southern	20.5 (Jan)	95 (Apr)	332 (Nov/Dec)
Southwest	28 (Jan/Feb)	158 (Jun)	310 (Nov)
Great Basin	128 (May)	205 (Jul)	270 (Sep)

# Initial Results for Different GACC Regions

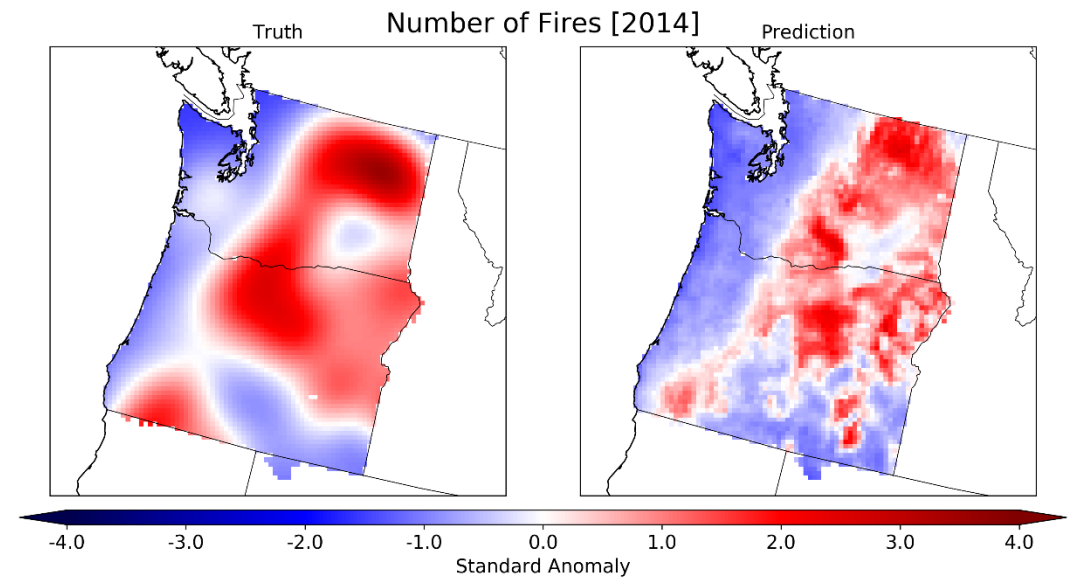
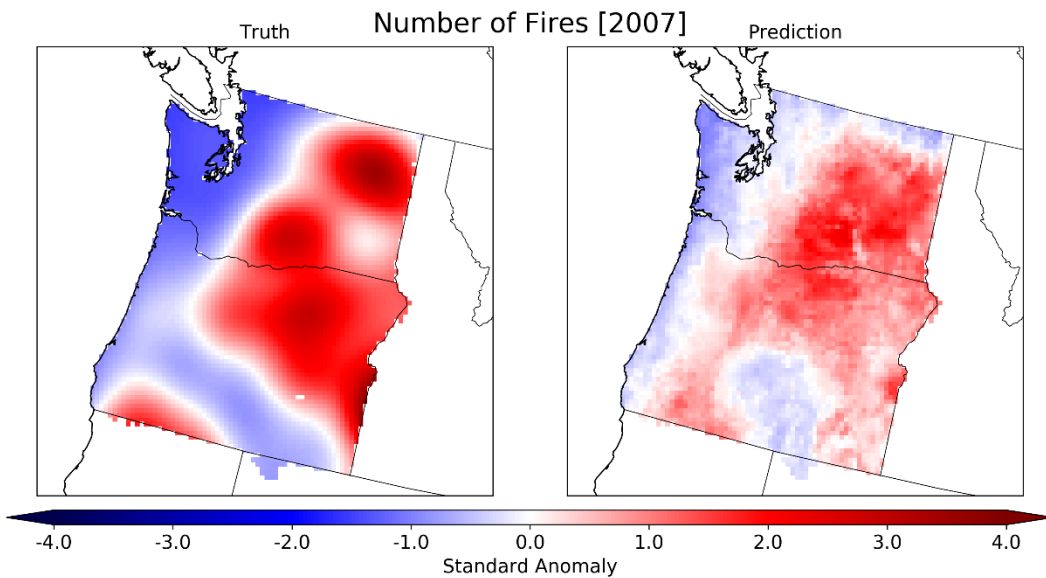
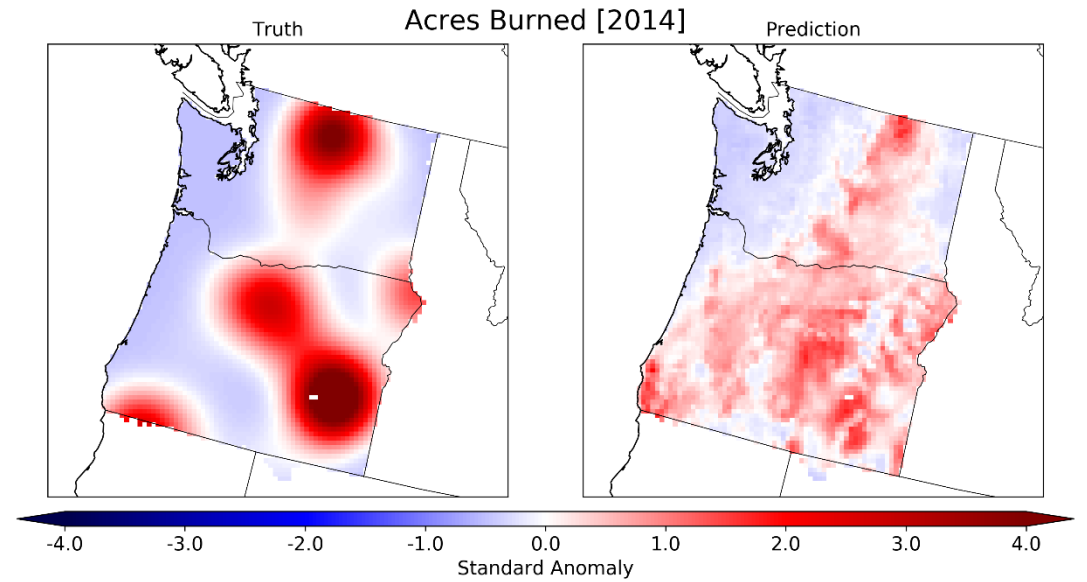
# Great Basin

- The model shows skill in capturing the yearly variability in acres burned across the region.



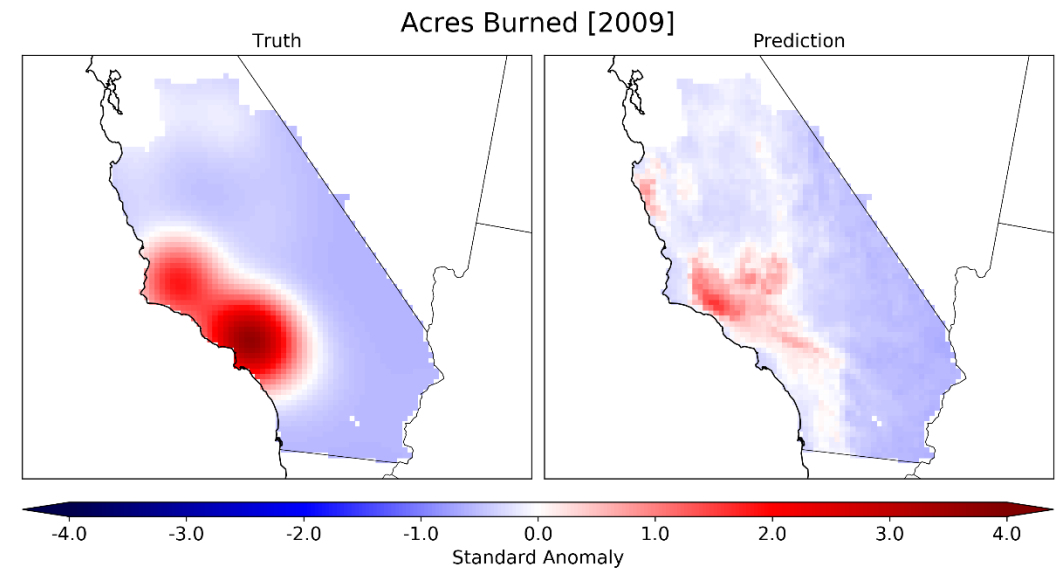
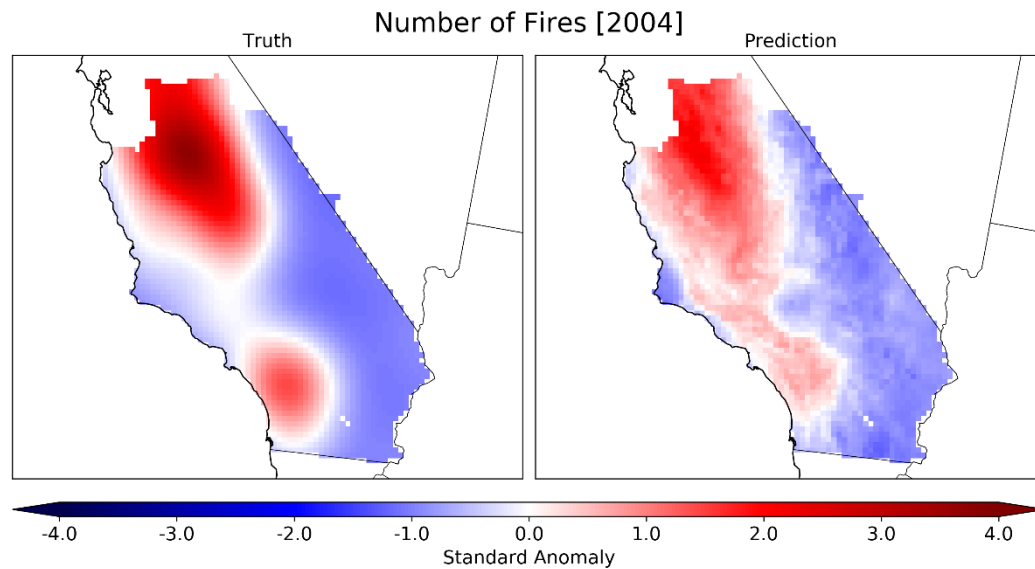
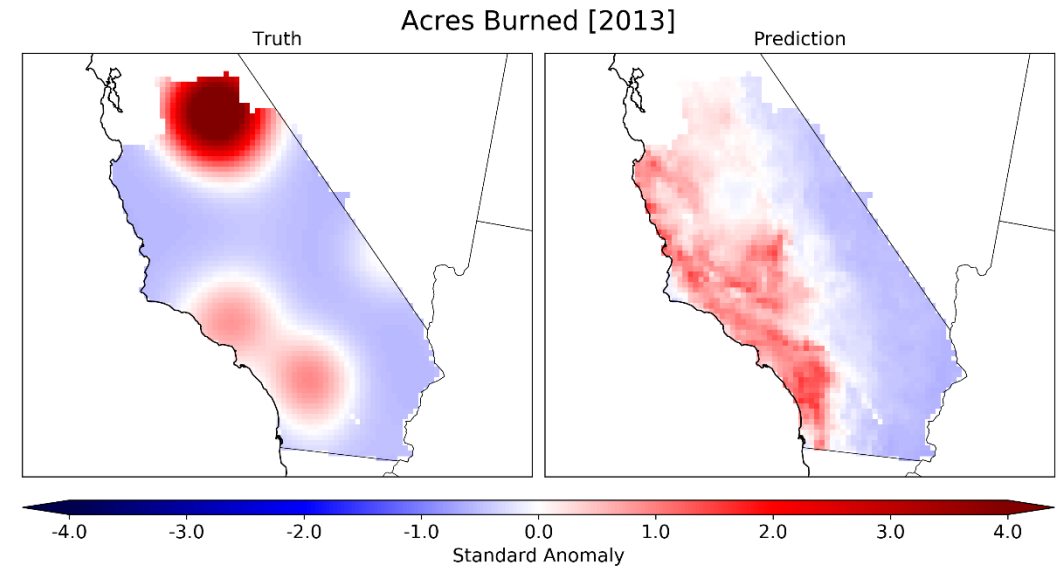
# Northwest

- The model currently shows more skill at predicting the number of fires over acres burned.



# Southern CA

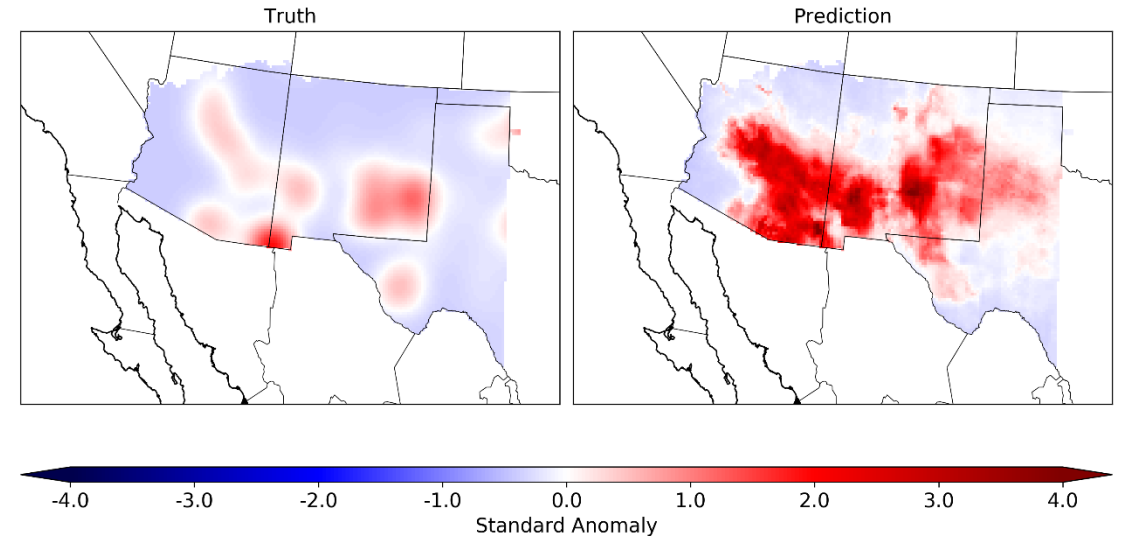
- The model shows better agreement when predicting the number of fires.



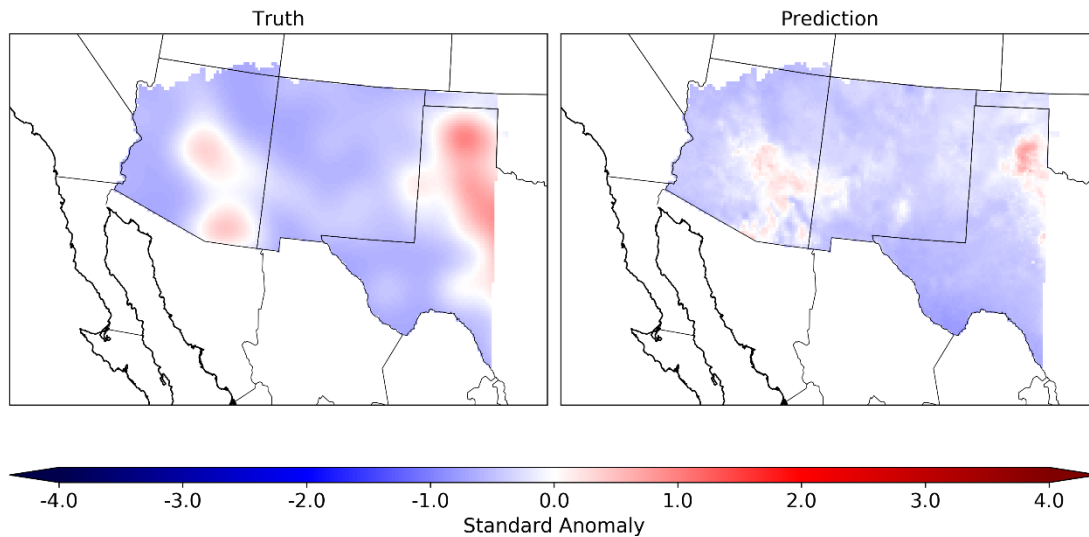
# Southwest

- In the Southwest region, the developed model shows more skill in predicting number of fires over the acres burned.

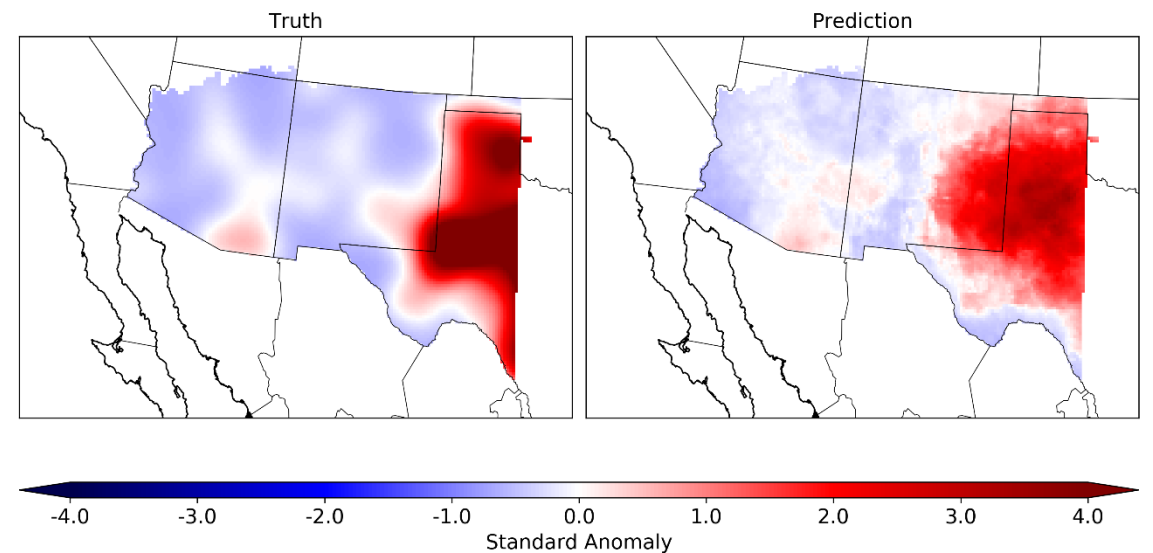
Acres Burned [2009]



Number of Fires [2015]

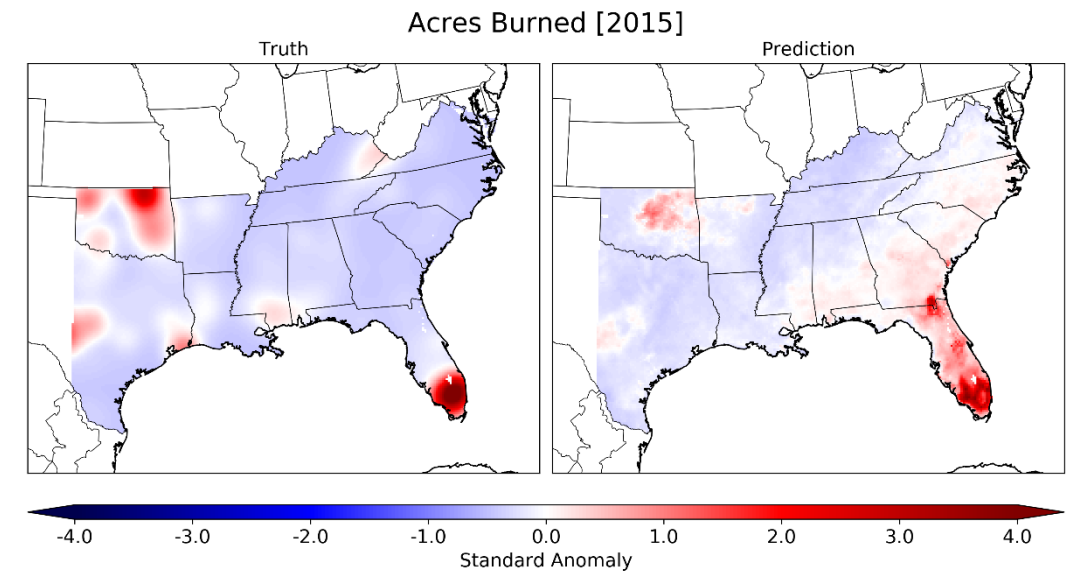
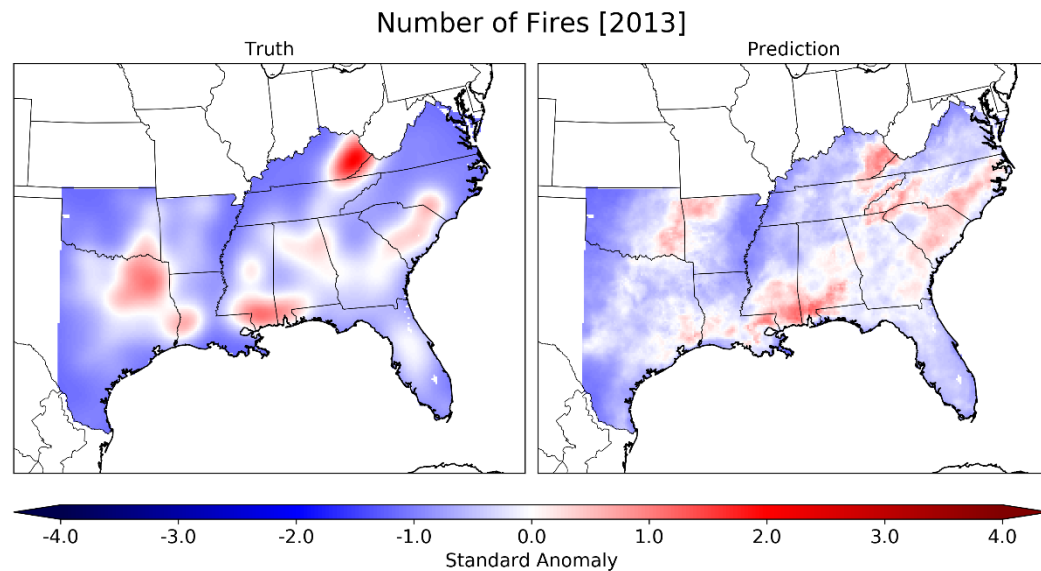
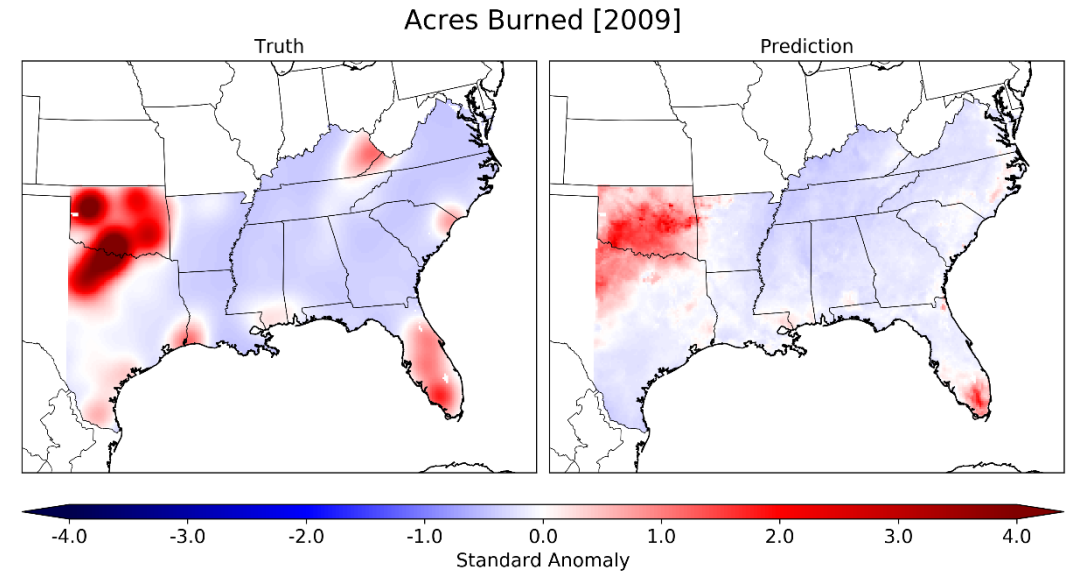


Number of Fires [2008]



# Southern

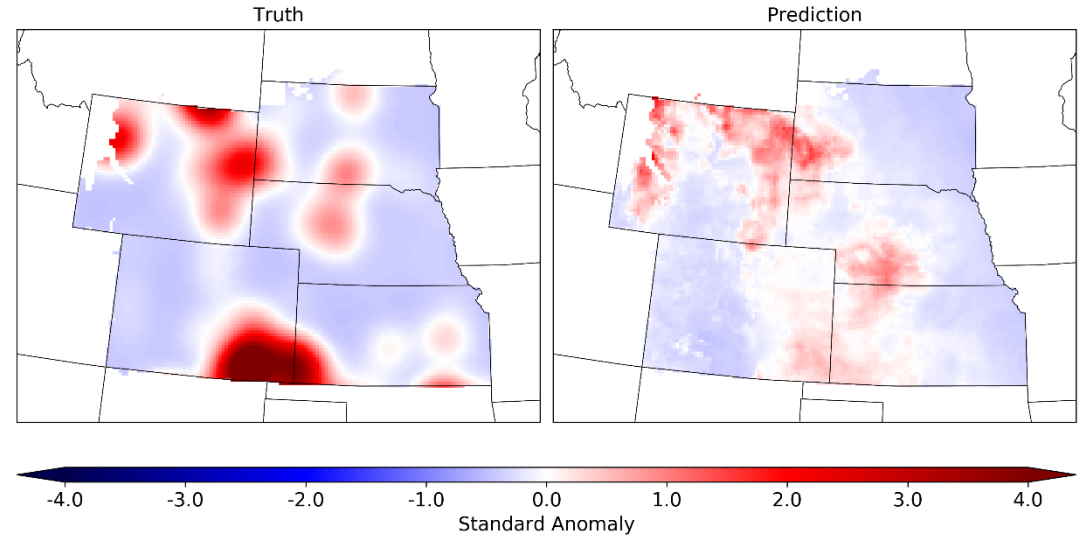
- For acres burned, the model tends to capture the spatially larger anomalies, while missing the smaller ones.
- For number of fires, the model shows better overall spatial agreement.



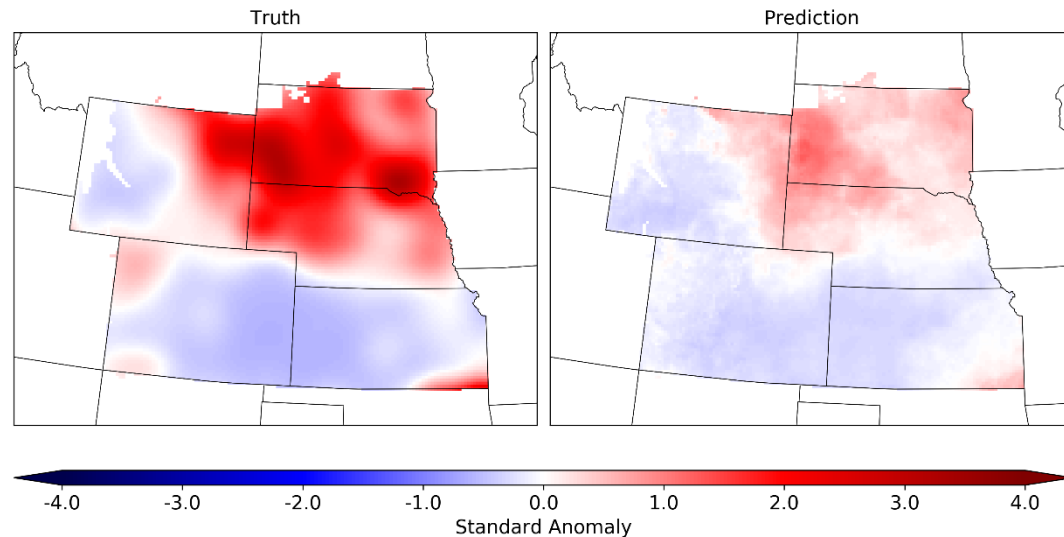
# Rocky Mountain

- The model does reasonably well at predicting the locations of the positive anomalies even though the magnitudes are under-predicted.

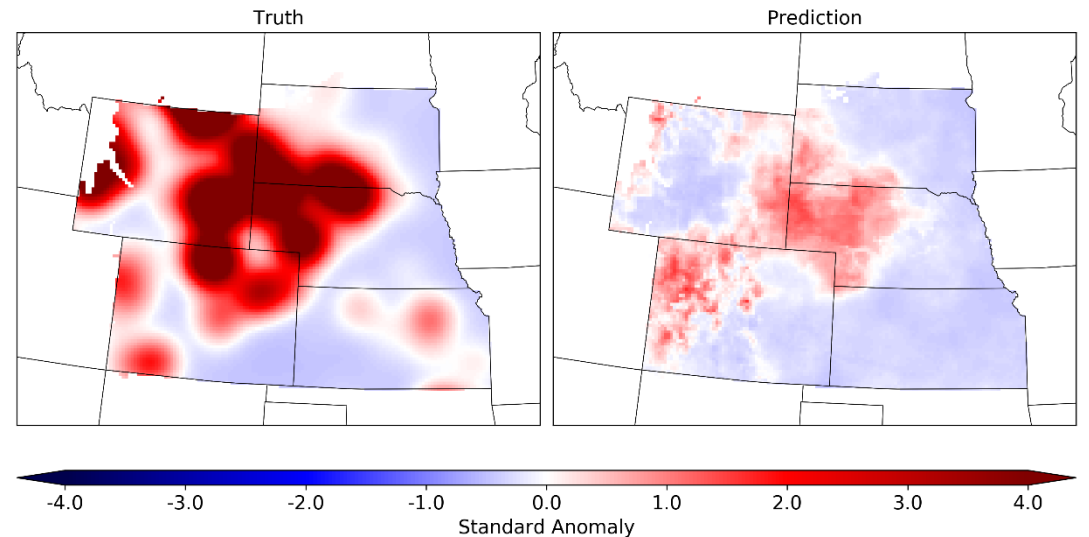
Acres Burned [2011]



Number of Fires [2012]



Acres Burned [2012]



# Summary

- The deep learning model shows promise for predicting areas of high wildfire potential.
  - Full evaluation of the model performance is ongoing.
- Currently, the developed deep learning model is better overall at predicting the number of fires over the acres burned.
  - Acres burned is dependent on location, suppression plan, and current conditions.
- Antecedent conditions are only one piece of the equation.
  - In-season changes are not accounted for.
  - An ignition source is required, which further complicates the model training and prediction.

Thank you!

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