Quantifying Wildfire Susceptibility in Utah with a Neural Network

ERIK NEEMANN

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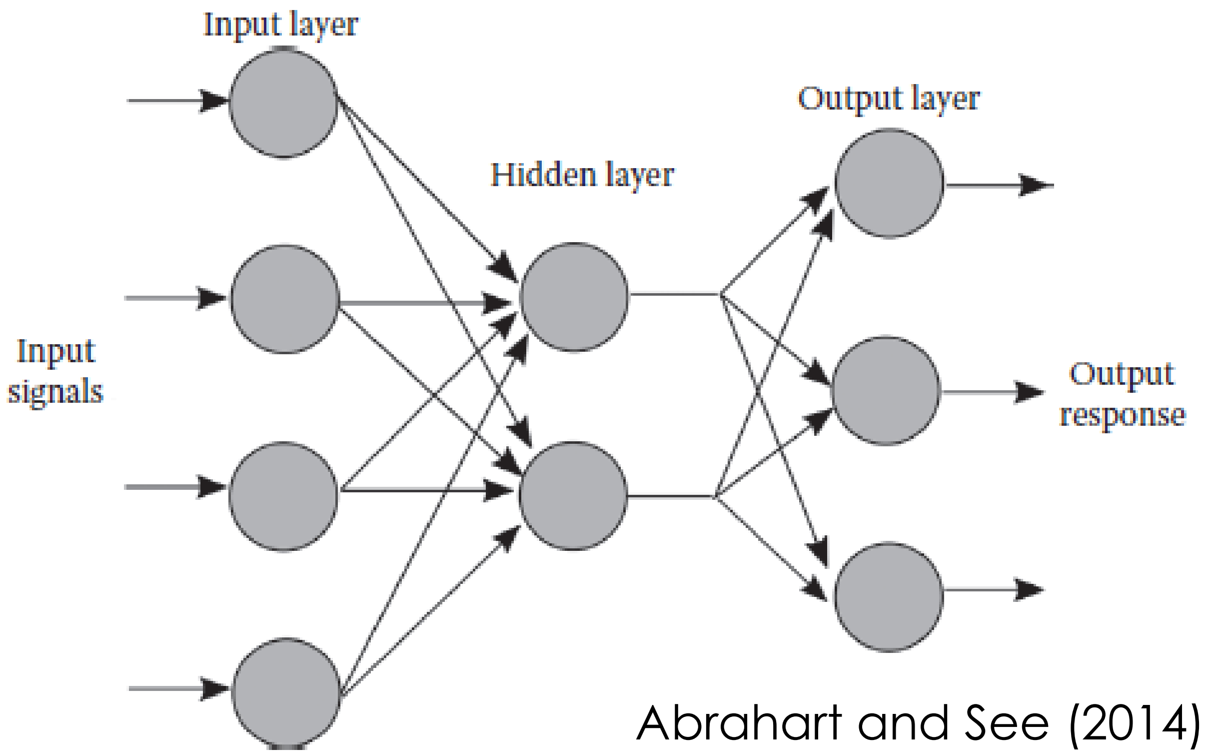


Abrahart and See (2014)

Overview

- Research Background
- Study Aims
- Methodology
- Results
  - Qualitative
  - Quantitative
  - Demographics
- Conclusions
- Future Work
- References

Research Background

- Wildfire is a common hazard in the Western US
  - Vegetation/fuels
  - Climate
  - Topography
  - Population growth into urban-wildland interface
- Size and occurrence of wildfire increased since 1980s (Dennison et al., 2014)
- Changing Climate may lead to continued increase in future due to greater fuel aridity (Abatzoglou et al., 2016)

Research Background

- Wildfires will continue to pose a significant threat to communities and populations
  - Loss of life
  - Major property damage/financial cost
  - Environmental destruction
- Best method of identifying risk areas is to produce maps combining a variety of wildfire parameters
- Info can then be used to target outreach, education, and preparedness planning to minimize exposure

Study Aims

- Apply geographic techniques to better understand wildfire threat in Utah
- Implement neural network to quantify wildfire susceptibility
- Examine demographics of highly susceptible communities to look for characteristics, patterns, and/or trends

Methodology

- Gather data sets related to past fire occurrence, infrastructure, terrain, vegetation/land use, and climate
- Combine disparate data sets onto uniform grid via GIS
- Implement a neural network
  - Trained NN on past fire occurrence and severity to identify wildfire susceptibility
- Summarize demographic data in high-threat areas to identify persons most at-risk from wildfire

Methodology

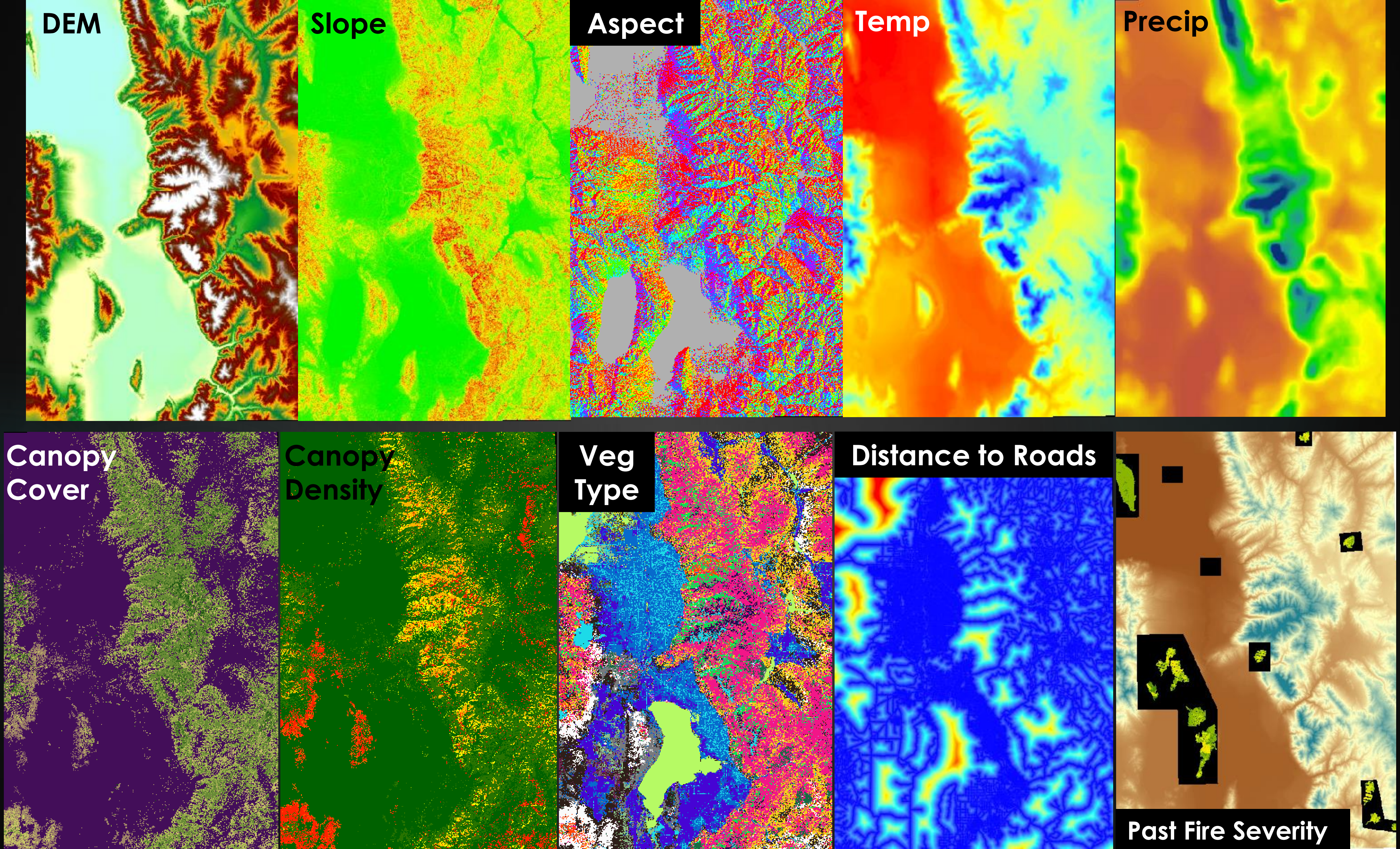
- Studies have shown Multi-layer Perceptron (MLP) neural networks may be a successful method for characterizing wildfire probability (Satir et al., 2015; Bui et al., 2012)
  - Good at approximating complex functions
  - Capture linear and nonlinear relationships between predictors and fire occurrence
- Proposed NN architecture (9:25:1)
  - 9 input layers (nodes)
  - Single hidden layer w/ 25 nodes
  - Single output node [0, 1]
  - Fully connected
  - Backpropagation learning

Data sets

- Fire data: Monitoring Trends in Burn Severity (MTBS)
- Terrain DEM: Utah Wildfire Risk Assessment Portal (WRAP)
  - Calculated Slope and Aspect
- Vegetation: WRAP
  - Canopy Cover
  - Canopy Density
  - Vegetation Type
- Climate: Oregon State PRISM Climate Group
  - Monthly normal temperature
  - Monthly normal precipitation
- Demographic Data: U.S. Census Bureau

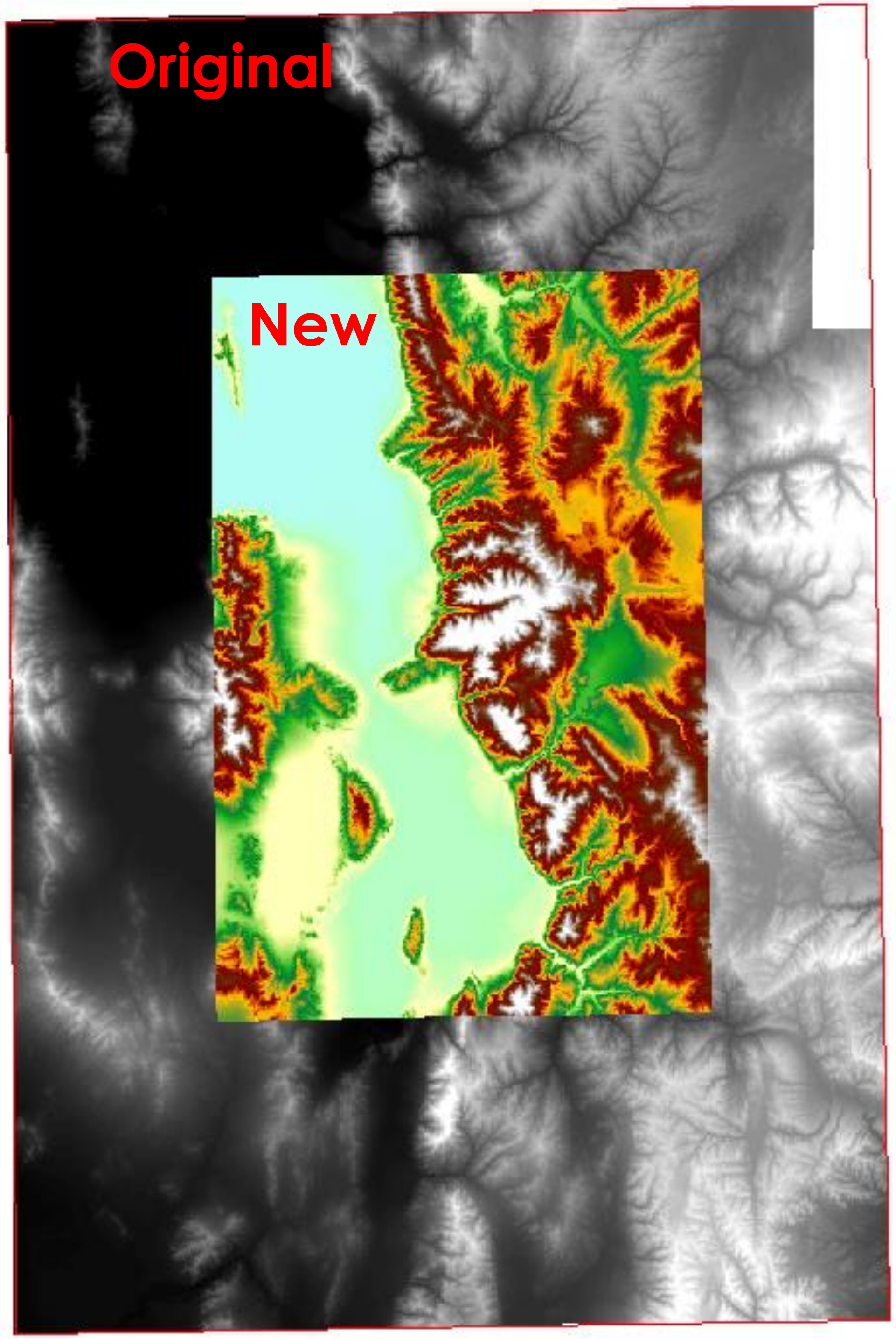
Data Preprocessing

- Matched data sets to the same grids
  - Projection (UTM 12N)
  - Cell size ~~(30m)~~ **(90m)**
  - Cell alignment
  - Same dimensions ~~(2867 by 4251)~~ **(956 by1417)**
- Summed MTBS fire severity plots for 2007-2016
  - Emphasis on most recent fire data
- Averaged temp/precip normals for Jun-Oct
  - Emphasis on wildfire season
- Calculated Euclidean distance to roads raster
- Scaled all data from 0 to 1


DEM
Slope
Aspect
Temp
Precip
Canopy Cover
Canopy Density
Veg Type
Distance to Roads
Past Fire Severity

Challenges

- Original study area → New study area
  - Original:
    - 5088 by 7527 = 38.2 million pixels
    - 34,467 sq km
  - First Update:
    - 2867 by 4251 = 12.2 million pixels
    - 10,968 sq km
  - Final:
    - 956 by 1417= 1.35 million pixels
    - 10,968 sq km
- New area still too large
  - Resampled cells **90m**

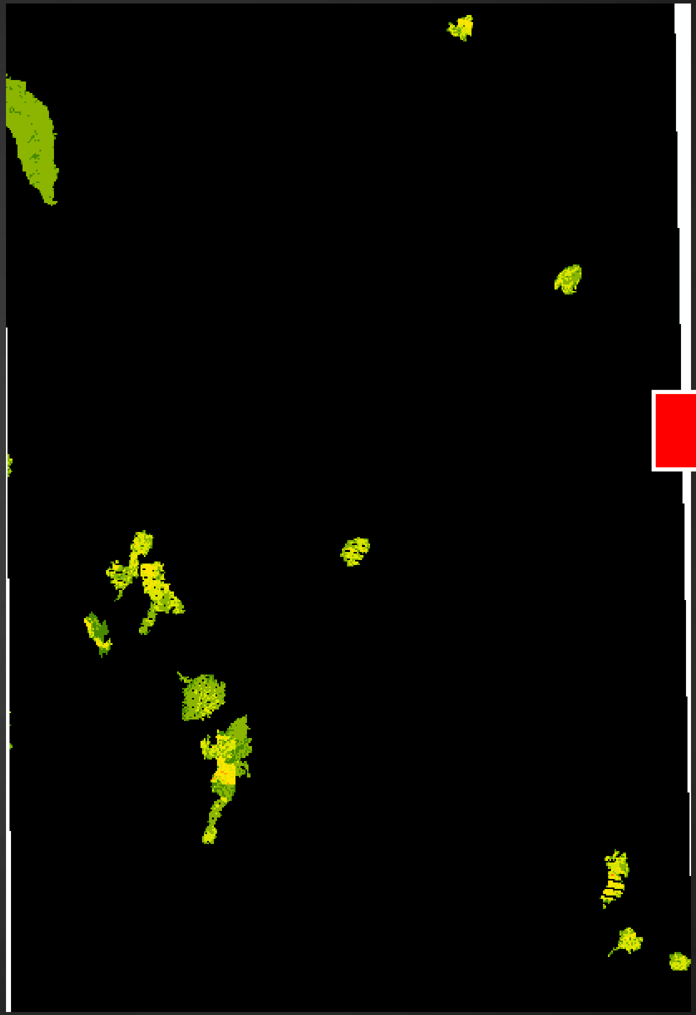


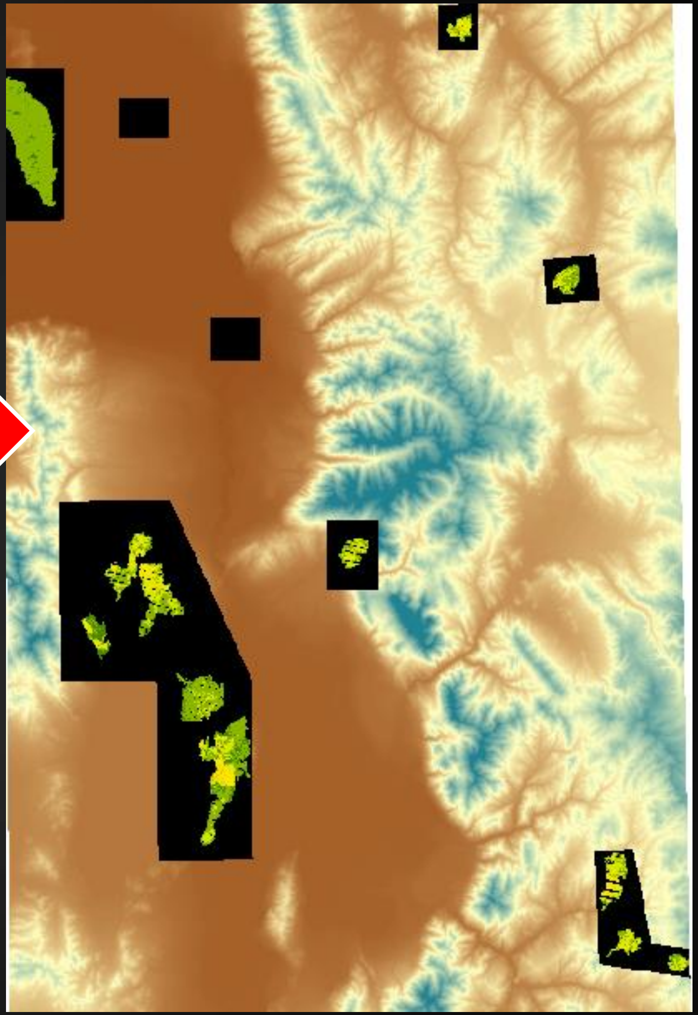
Neural Network Challenges

- Numerous issues encountered during NN training
  - Very slow NN training process
    - Initially 36+ hours on full training data set, 25 nodes in hidden layer
  - Model couldn't decrease error function below threshold (0.01)
    - Resulted in NN exiting without applying model weights!
- Improved NN training efficiency with several modifications
  - Reduced hidden layer nodes to 15
  - Increased error function threshold between 0.75-1.0
  - Decreased training iterations from 100k to 50k
  - Decreased size of training data (by 90%)

Training Data Modifications

- Using the entire AOI for training was extremely slow
  - Also a potential over-influence by non-burned pixels
- Decreased size of training data by masking data to small polygons around burned areas
  - Included small polygons in 2 unburned areas (GSL and SLC)



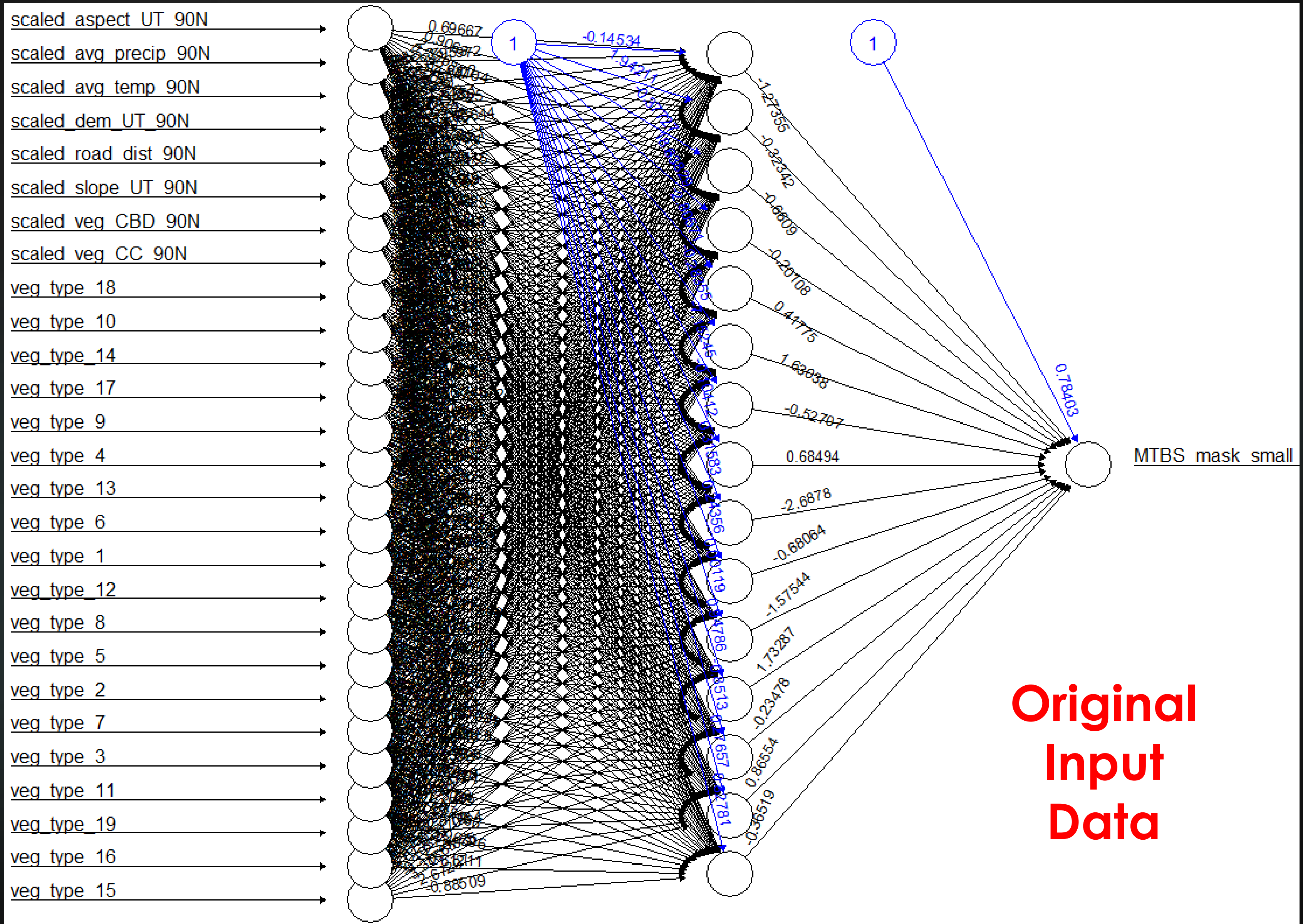


Results

- Successfully implemented NN model for wildfire
  - Final Architecture of 9:15:1
    - Reduced hidden nodes to speed up training process
  - Output node scaled from -1 to 1 (generally -0.8 to 0.8)
  - Rescaled output with min-max normalization [0, 1]
  - Resilient Backpropagation learning
- Two primary model runs:
  - 1 - Original Input Data (dummy vegetation variables)
  - 2 - No Vegetation Data

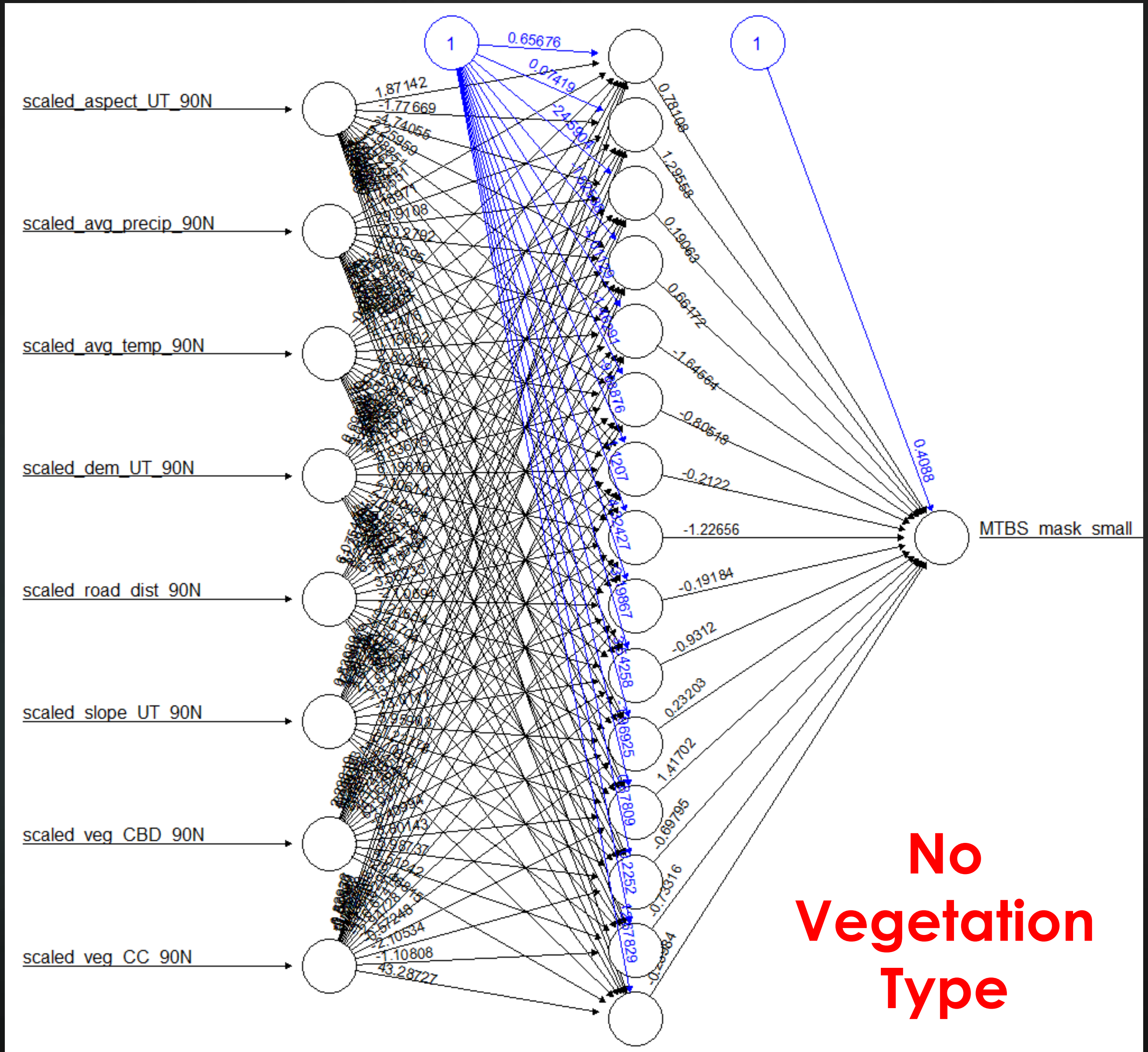
Results

- Original Inputs



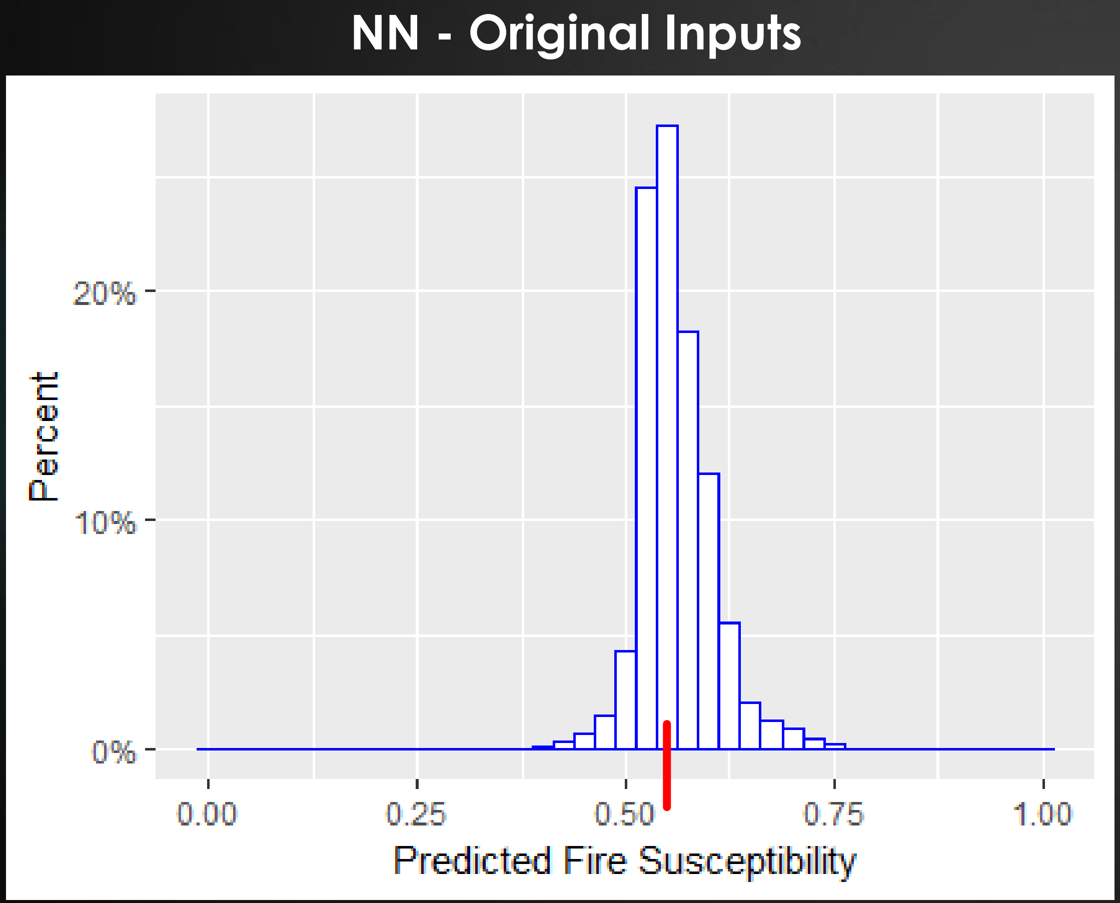
Results

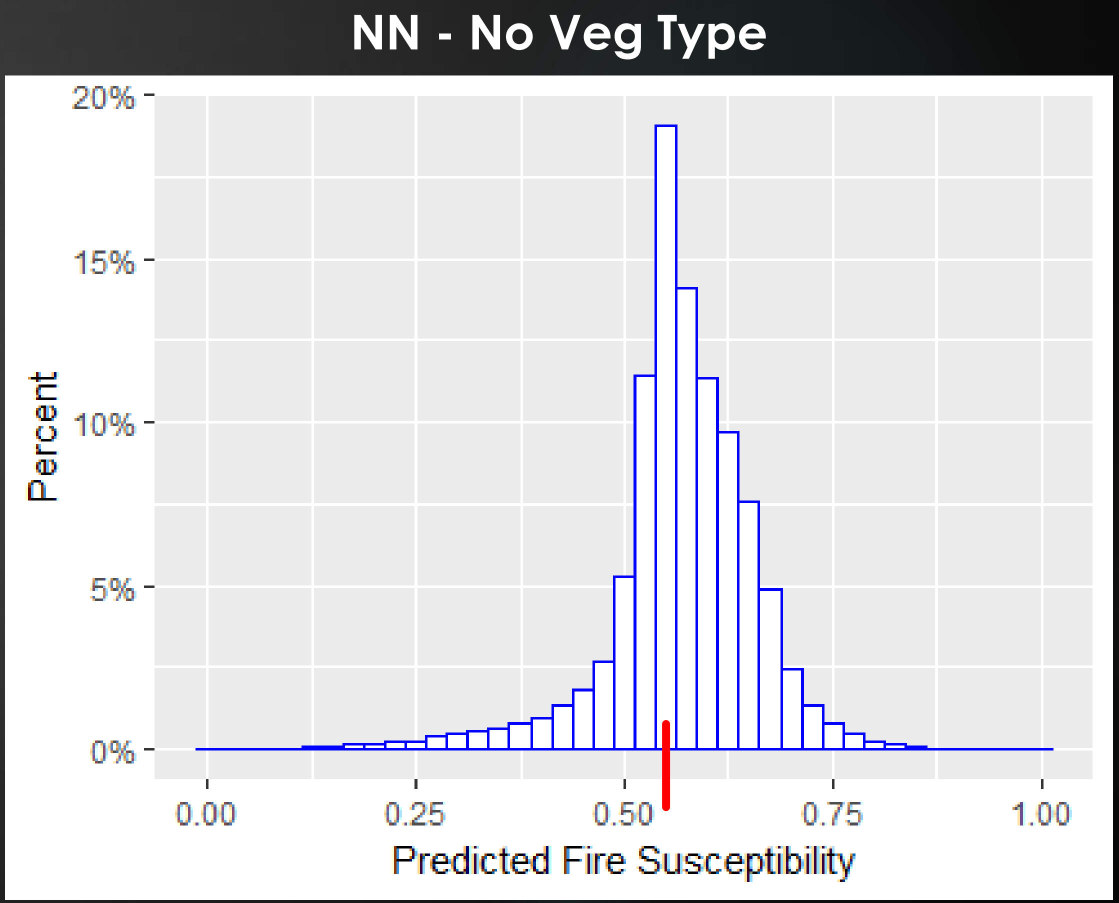
- No Vegetation Type



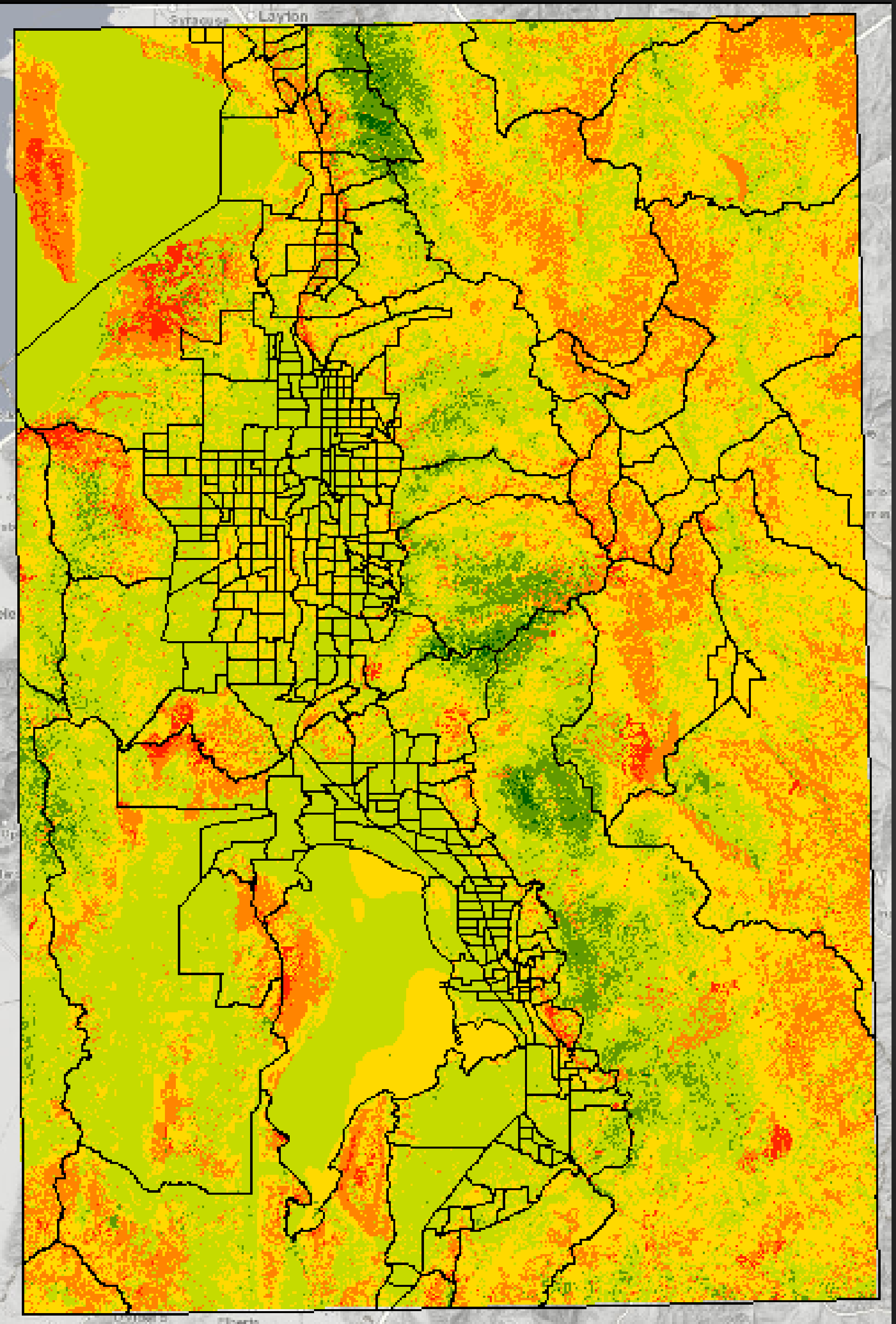
Results – Qualitative

- Histograms





NN - Original Inputs



Subjective Comparison

Legend

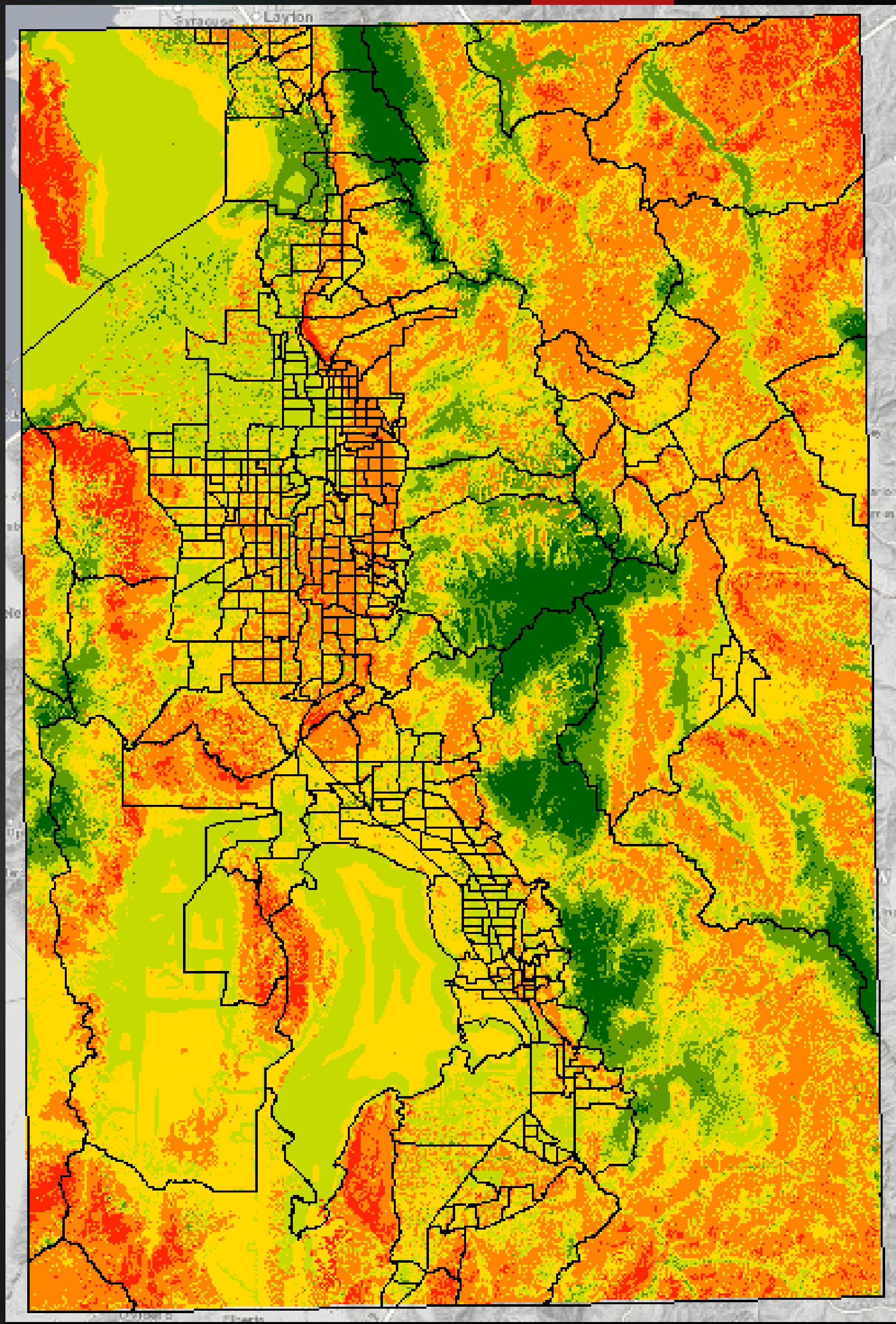
Fire Susceptibility

- Very Low [0 - 0.4]
- Low [0.4 - 0.5]
- Moderate [0.5 - 0.55]
- High [0.55 - 0.6]
- Very High [0.6 - 0.7]
- Extreme [0.7 - 1]
- Census Tracts

Differences:

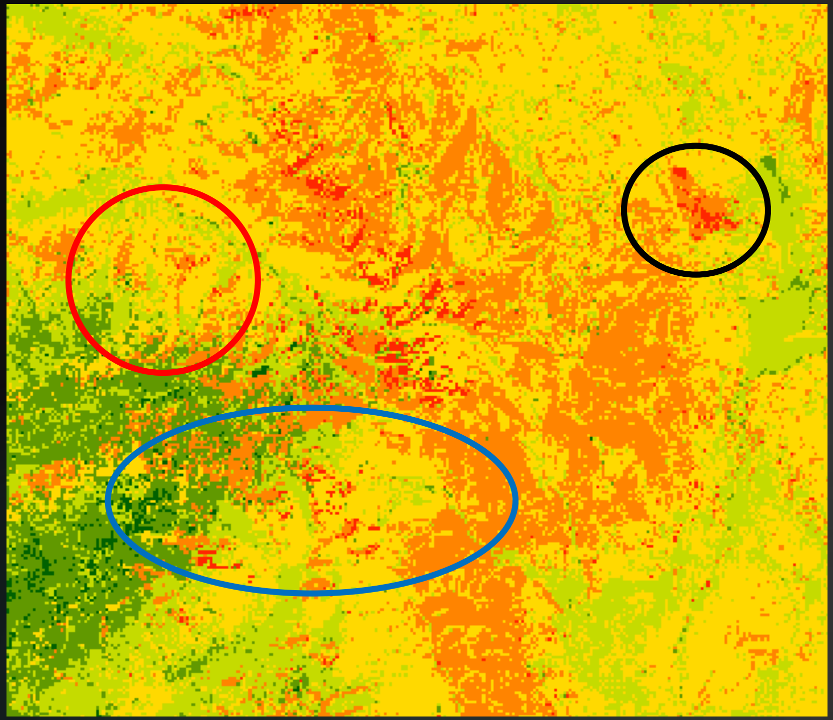
- Range of values
- Noise/variance
- Veg influence

NN - No Veg Type

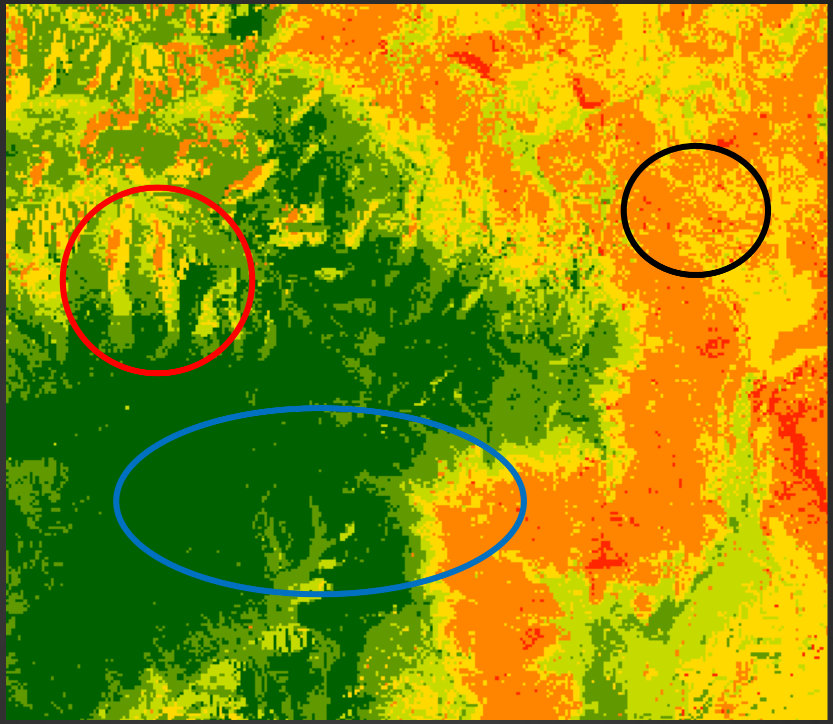


Subjective Comparison - Cottonwood Canyons to Jordanelle Reservoir

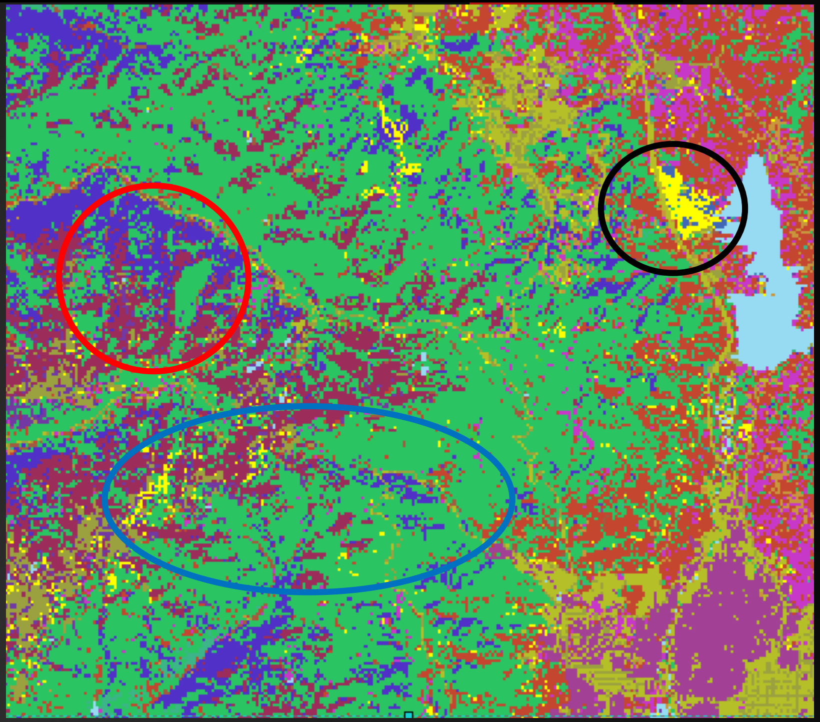
NN - Original Inputs



NN - No Veg Type



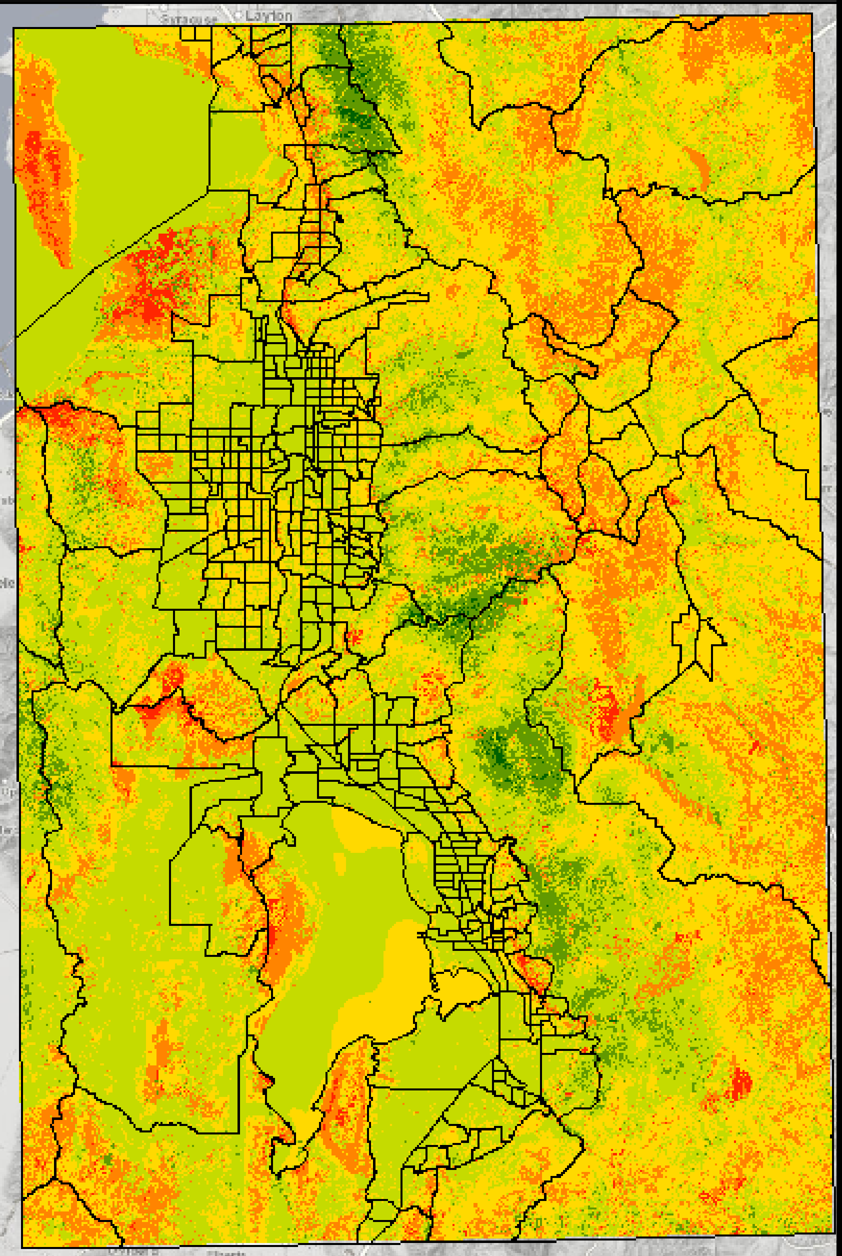
Vegetation Type Class



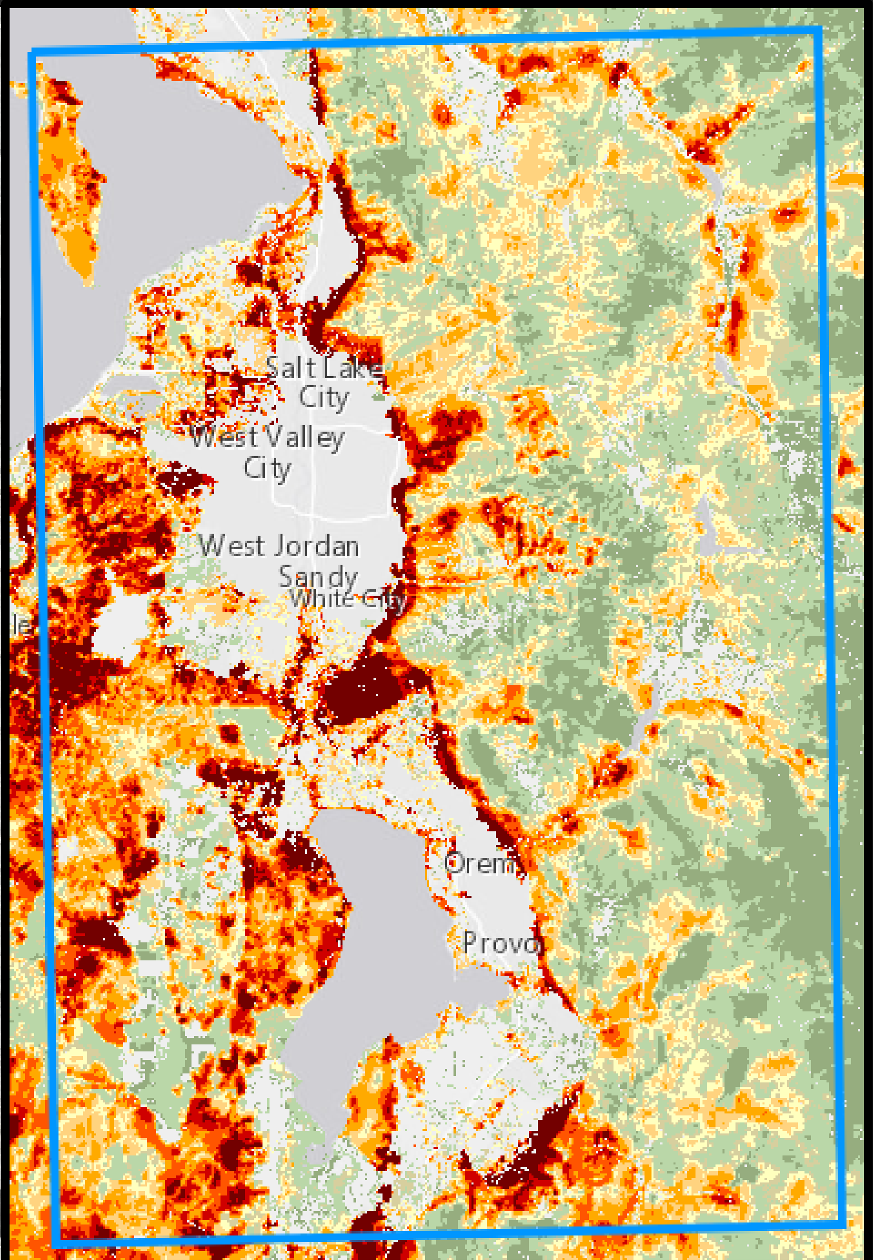
Possible Significant Influences:

- Black - Vegetation Type (Grassland and Exotic Herb)
- Red - Aspect
- Blue - Elevation

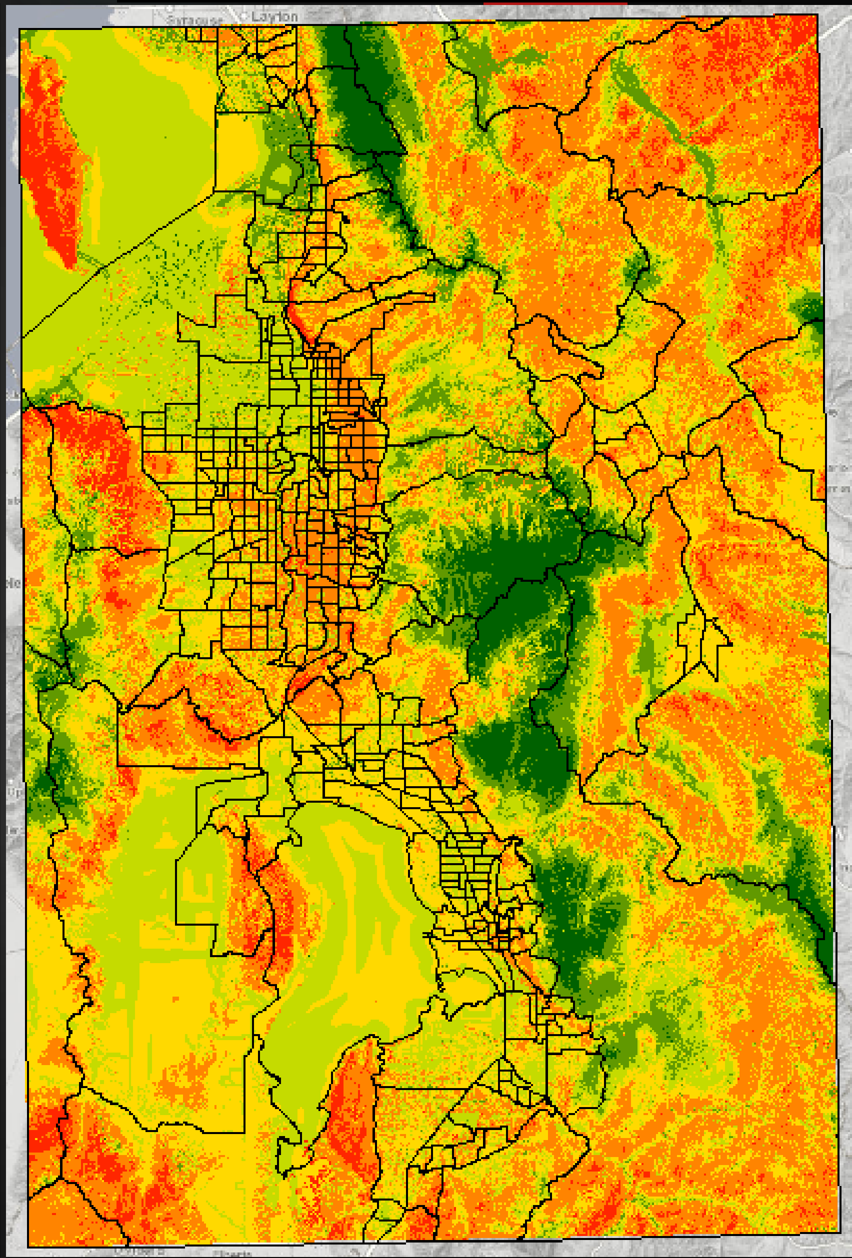
NN - Original Inputs



Utah DNR Wildfire Risk Assessment Portal



NN - No Veg Type



Results - Quantitative

	Original Inputs	No Vegetation Type
Mean Squared Error (MSE)	2.1398	0.8981
Mean Absolute Error (MAE)	4.4087	1.8097
Area Under the Curve (AUC)	0.8875	0.8127

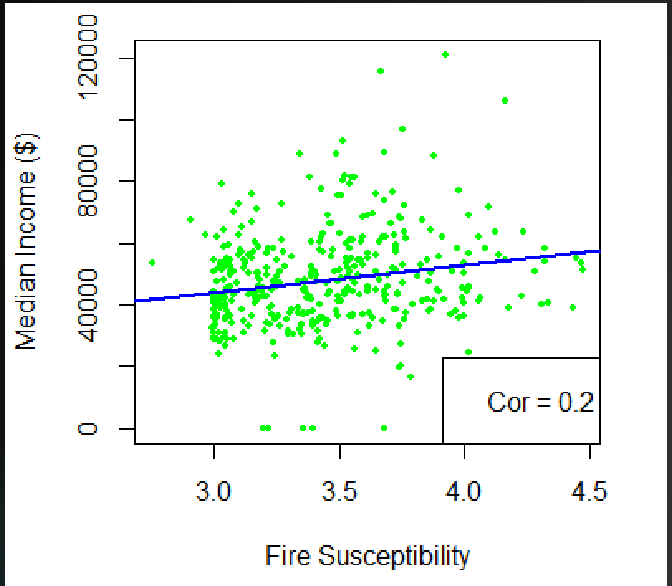
Original Inputs

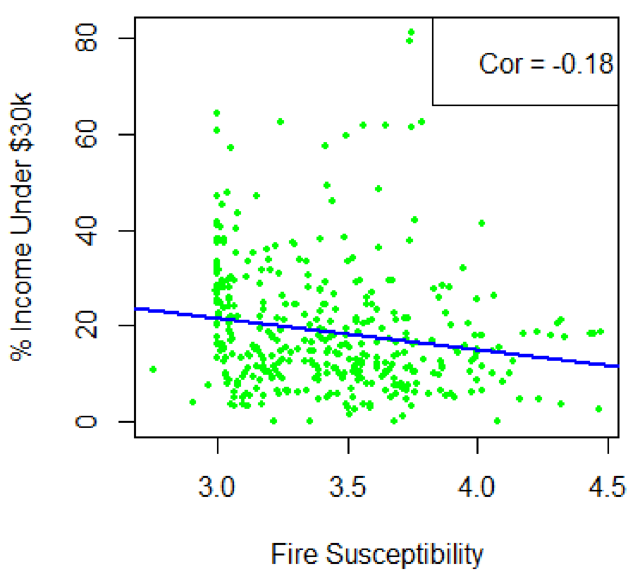
Category	Total Pixels	Fire Density (%)
Very Low	3250	0.00%
Low	52494	0.02%
Moderate	535672	0.15%
High	470312	1.47%
Very High	188226	7.96%
Extreme	15581	27.01%

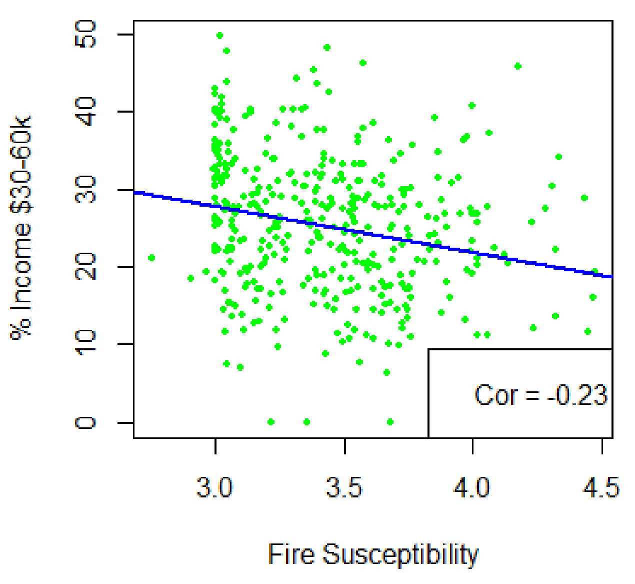
No Vegetation Type

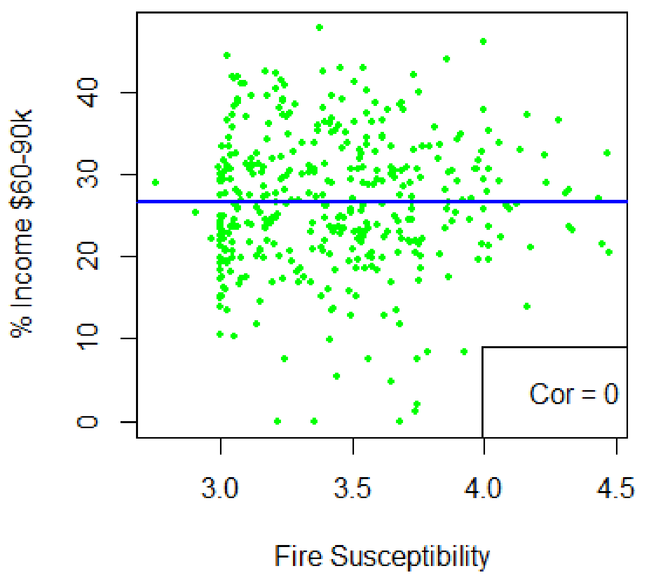
Category	Total Pixels	Fire Density (%)
Very Low	56313	0.00%
Low	104867	0.02%
Moderate	311982	0.21%
High	372354	0.94%
Very High	367234	3.71%
Extreme	52785	17.27%

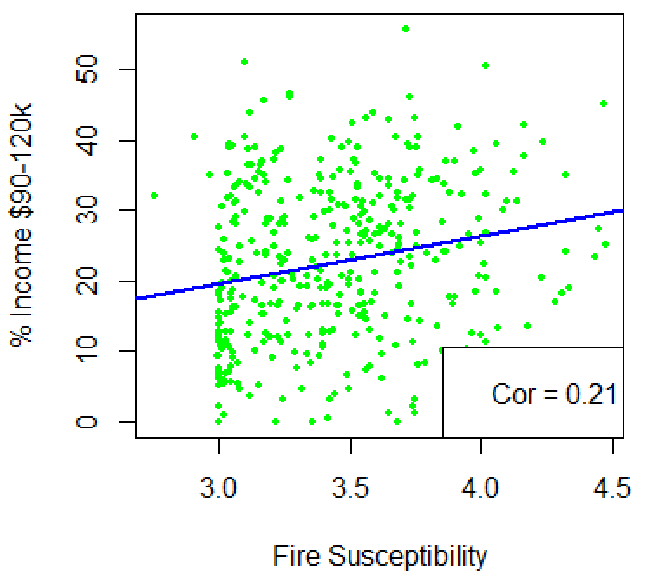
Results – Income Demographics

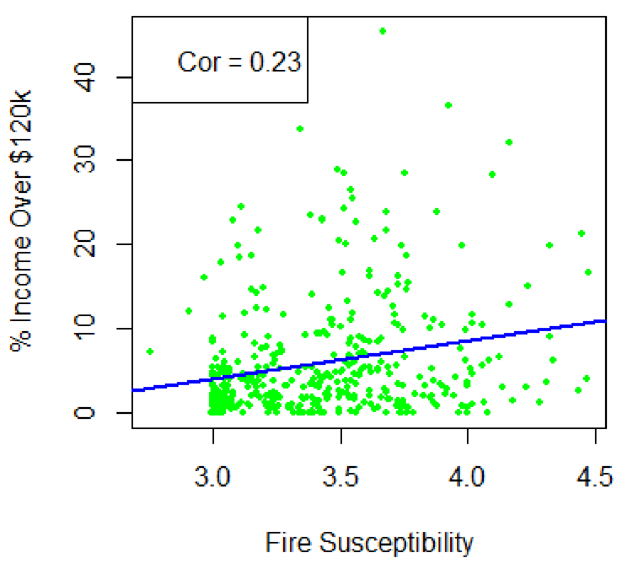




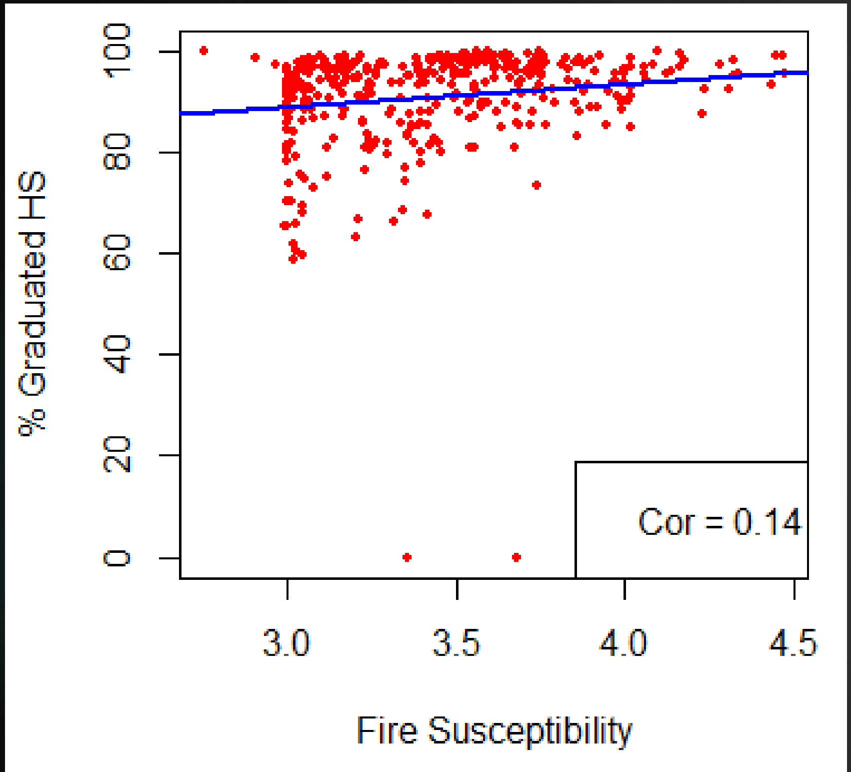


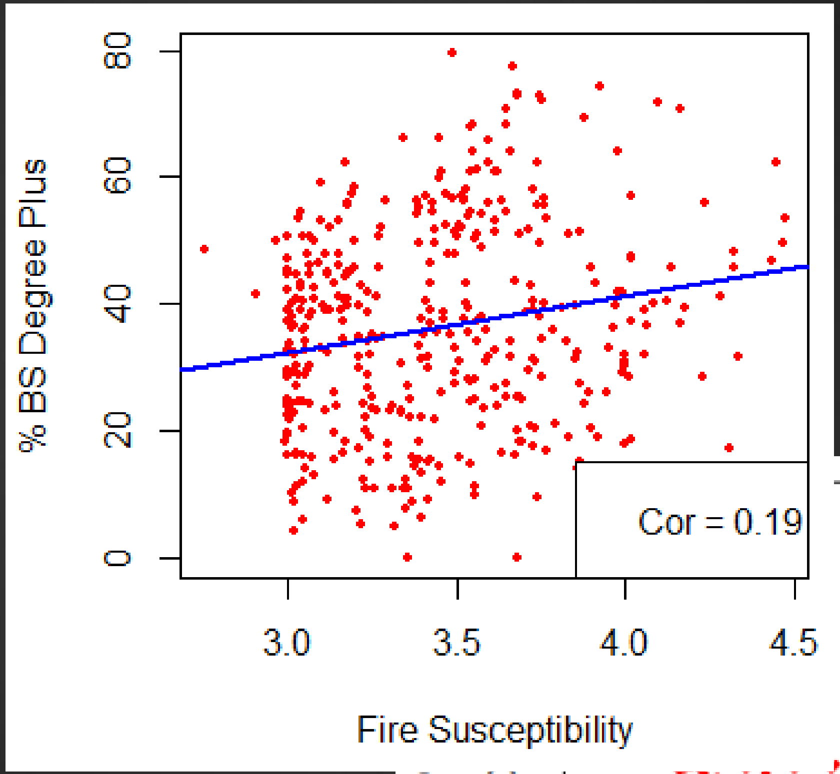


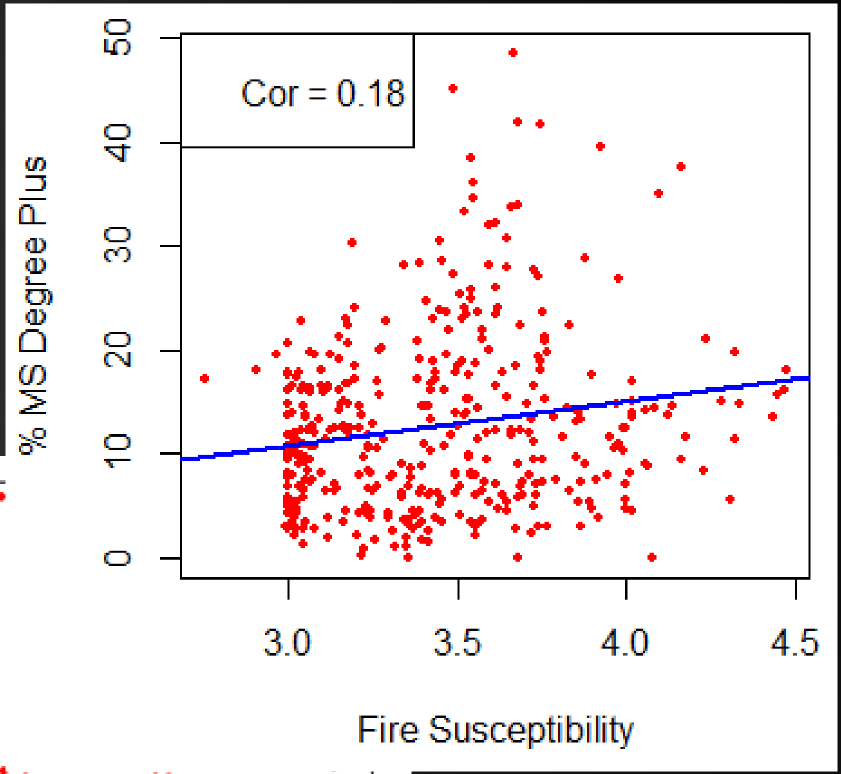


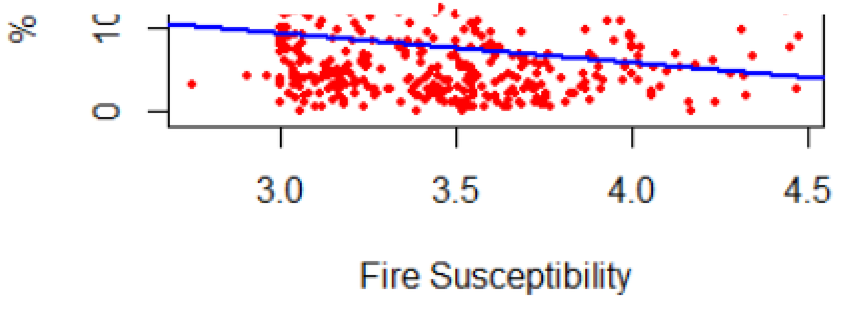


Results – Education Demographics









Conclusions

- Neural Networks appear to produce reasonable results in quantifying wildfire susceptibility along the Wasatch Front
  - Vegetation Type may play a prominent role – noisier results
  - Low Threat: water, high elevation
  - High Threat: grassland, sage/scrub, chaparral
- Brief demographic analysis indicated no real trends
  - Very weak correlations for education/income at census tract level
  - Nothing statistically significant
  - Size of census tracts might contribute to insignificance

Future Work

- Further tweak NN architecture to optimize results
  - Likely would require HPC resources to efficiently train the model
- Include additional geographic/vegetation variables
- Combine climate variables into single fire weather index
  - Humidity and wind speed data needed
- Provide more comprehensive accuracy evaluation
- Examine more demographic variables

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