Wildfire Mapping in Interior Alaska Using Deep Neural Networks on Imbalanced Datasets

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April 10, 2019

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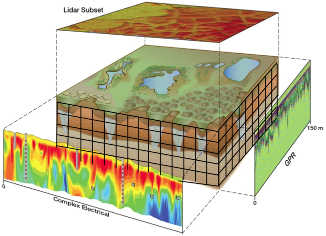
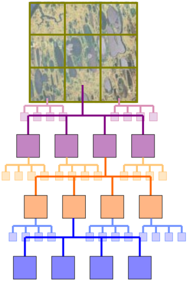
Motivation

- US Department of Energy's **Next Generation Ecosystem Experiments (NGEE) Arctic** project goal is *to advance a robust predictive understanding of Earth's climate and environmental systems by delivering a process-rich ecosystem model, extending from bedrock to the top of the vegetative-canopy and atmospheric interface, in which the evolution of Arctic ecosystems in a changing climate can be modeled at the scale of a high-resolution ESM grid cell.*
  - Develop datasets to constrain modeled Arctic ecosystem responses to environmental change
  - Quantify the carbon cycle effects of disturbance at high latitudes
  - Understand how wildfire alters the physical and ecological structure and function of Arctic ecosystems





Research Questions

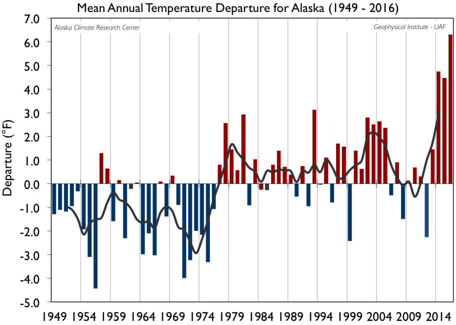
- Can we map wildfires in Alaska based on imbalanced classes (wildfire vs. no-wildfire)?
- Can we apply a convolutional neural network (CNN) for supervised classification of MODIS imagery as input and historical fire boundaries as the target?
- Can a weight-selection strategy on a deep CNN model based on imbalanced classes improve performance?

Class Imbalance Problem

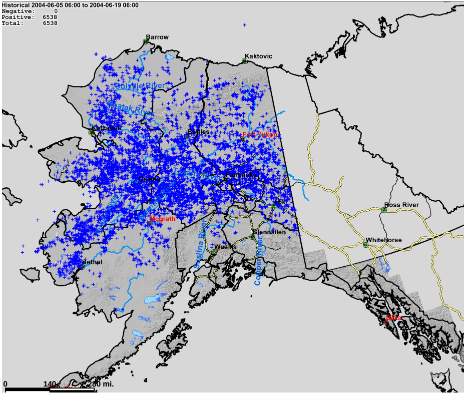
- Imbalanced data classification exists where one class (e.g., burned areas) contains a much smaller sample size than the others (e.g., unburned areas). It poses a challenge for DNN architectures in recognizing the minority class (Sze-To and Wong, 2017).
- However, there has been a significant amount of research performed on the class imbalance problems using dataset resampling (Chawla et al., 2002), cost-sensitive weighting (Ting, 2000), and few-shot learning (Ravi and Larochelle, 2017).
- Newer meta-learning methods (Ren et al., 2018) perform a meta gradient descent step on the current mini-batch example weights to minimize the loss on a clean unbiased validation set.

Alaska Wildfires – 2004

- One of the warmest and driest summers on record.
- Most lightning strikes recorded during summer.
- Wildland fires burned the largest area in recorded Alaska history.
- Total fires were 701 and area burned 6,600,000 acres.



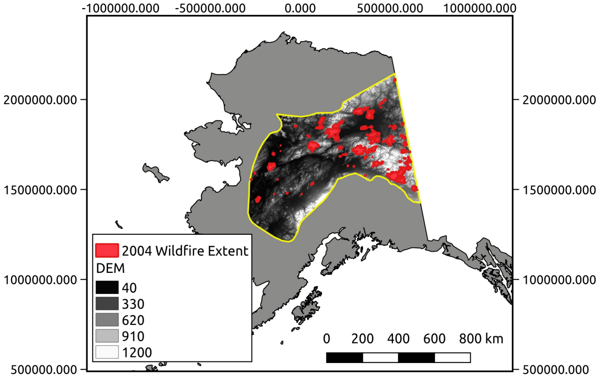
Departure from average temperature across Alaska for every year since 1949. (Image Source: Alaska Climate Research Center)



Number of lightnings strikes (6,538) in Alaska from June 5–19, 2004. The grand total was over 147,642 strikes.

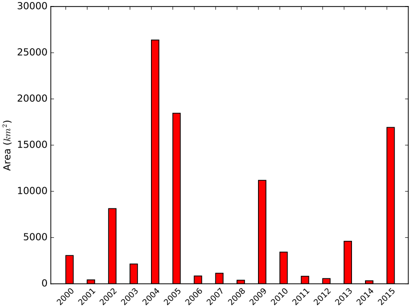
Study Area Overview

- Bounded by Interior Alaska, based on climate conditions.
- Background class (no-wildfire) significantly outnumbers the wildfire class.
- 1,742,618 no-wildfire pixels and 105,072 wildfire pixels (500×500 m).
- Select CNN weights during training that reflect the imbalanced class.

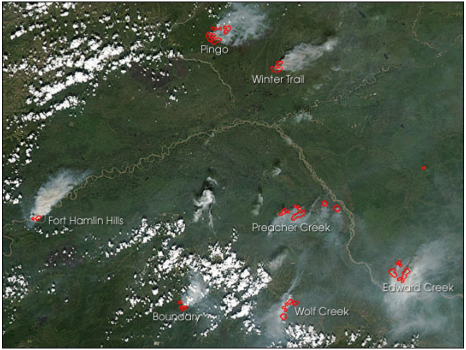


Monitoring Trends in Burn Severity (MTBS)

- Includes all reported fires 1,000 acres or larger in the western United States and greater than 500 acres in the eastern US.
- Developed and managed by the USGS, USDA, and NASA using Landsat datasets.

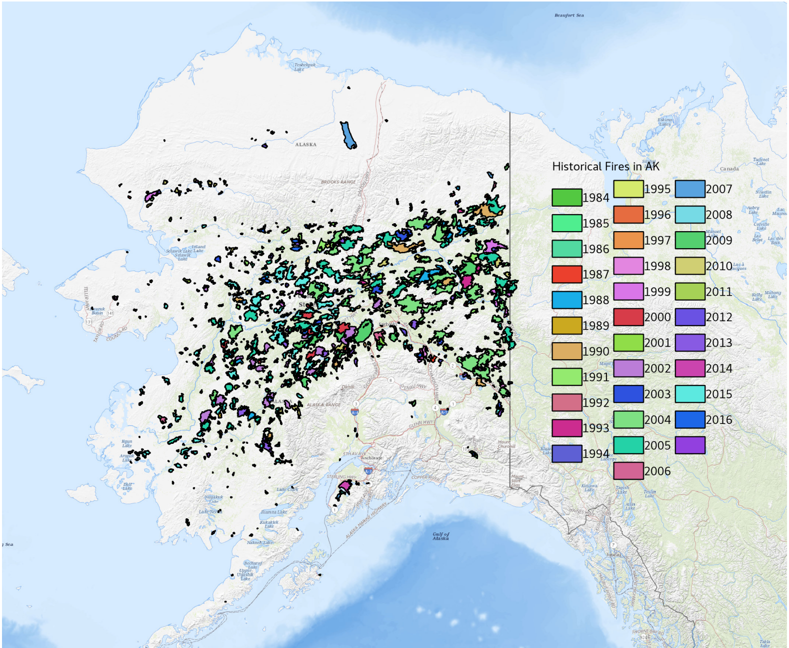


MTBS Burned Area for Interior Alaska



NASA Landsat 7 Image Over Interior Alaska

Wildfires in Alaska from MTBS

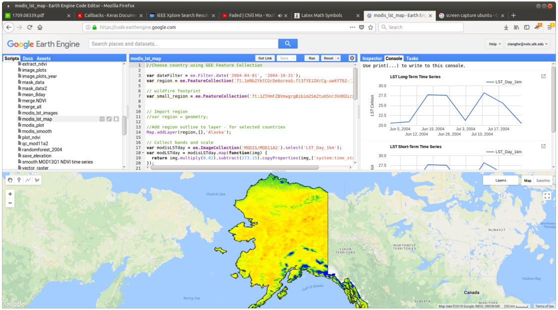


Remote Sensing Datasets

We used Google Earth Engine (GEE) for processing images. Two types of datasets were used (only April 1–October 31):

- MODIS: MOD09A1 (Surface Reflectance 8-Day L3 Global 500m)
- MODIS: MOD11A2 (Land Surface Temperature and Emissivity 8-Day L3 Global 1 km)

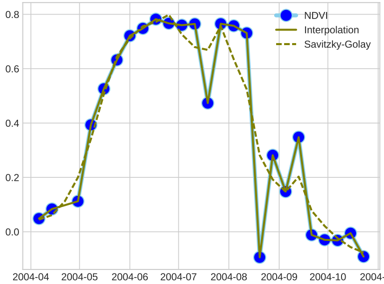
Description	Resolution	Variable
MOD09A1	500 m at 8 days	NDVI
	500 m at 8 days	EVI
	500 m at 8 days	SAVI
	500 m at 8 days	Bands 1–7 (459–2155 nm)
MOD11A2	1 km at 8 days	Daytime LST (Kelvin)



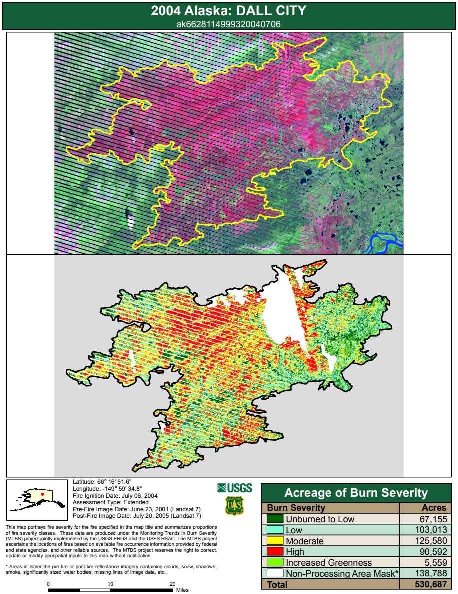
Google Earth Engine JavaScript API

Image Processing

- Increased resolution to 500 m for all datasets, GEE performs nearest neighbor resampling.
- Linear interpolation for missing values.
- Savitzky-Golay filter was applied to smooth out noise.
- Converted MTBS vector boundary to raster pixels.

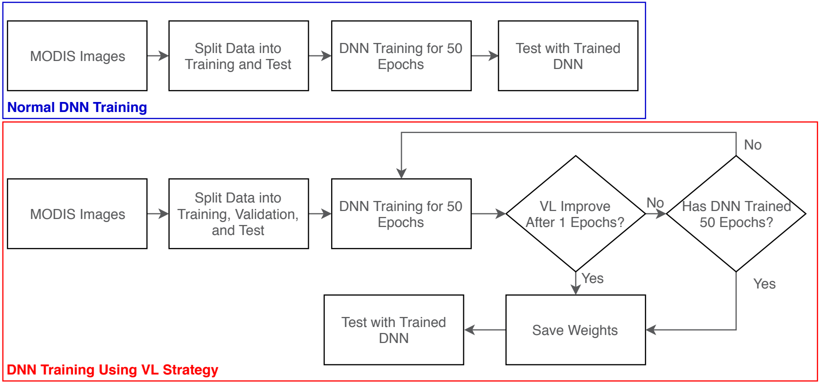


Example image processing workflow applied to a large wildfire, which occurred on July 6, 2004.



Fire severity for the Boundary fire based on Landsat 7. (Source: USGS and US Forest Service)

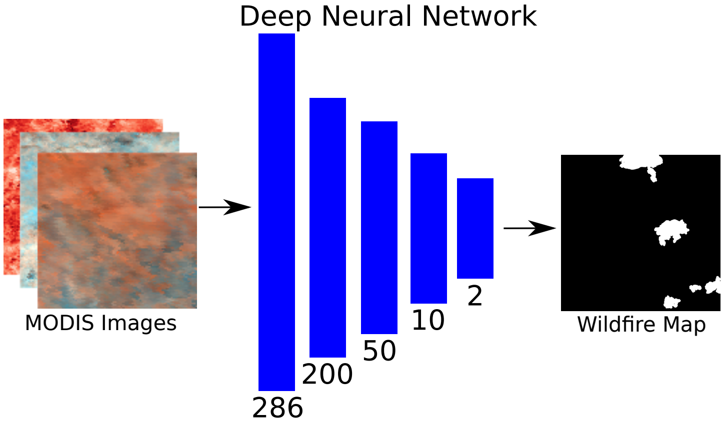
Validation-Loss (VL) Strategy



- Weight selection strategy from Sze-To and Wong (2017).
- Normal DNN training loss/accuracy measured on training data.
- Validation-Loss (VL) strategy splits data into equal parts by class for **selecting** weights.
- Split data equally between classes for measuring VL.
- Done by: keras.callbacks.ModelCheckpoint(filepath, monitor='val_loss', verbose=0, save_best_only=False, save_weights_only=False, mode='auto', period=1)

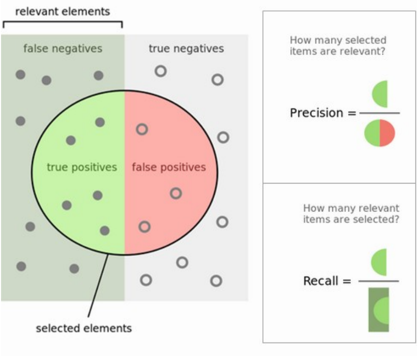
Deep Convolutional Neural Network Models

```
self.model = Sequential()
self.model.add(Dense(60, activation=relu, kernel_initializer=normal, input_dim=nb_bands))
self.model.add(Dense(30, kernel_initializer=normal, activation=relu))
self.model.add(Dense(10, kernel_initializer=normal, activation=relu))
self.model.add(Dense(nb_classes, kernel_initializer=normal, activation=softmax))
self.model.summary()
self.model.compile(optimizer=Adam(), loss=sparse_categorical_crossentropy, metrics=[accuracy])
```



Training/Testing/Validation Datasets

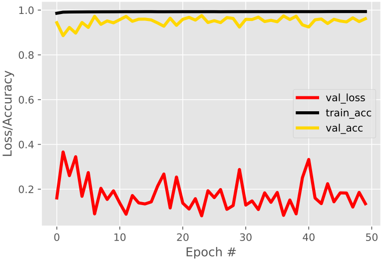
Dataset	No-Fire	Fire	Percentage
Dataset-0 Train	1,154,333	70,493	75%
Dataset-0 Test	427,115	26,356	25%
Dataset-0 Validation	7,947	7,947	10%
Dataset-1 Train	384,375	23,477	25%
Dataset-1 Test	1,282,862	78,702	75%
Dataset-1 Validation	2,617	2,617	10%
Single Wildfire	9,724	276	<1%



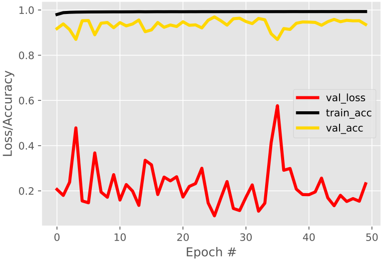
Source:
https://en.wikipedia.org/wiki/Precision_and_recall

- Number of pixels (500×500) used for training, testing, and validation.
- The validation column was only applied when using the VL strategy.
- Precision – high value means that an algorithm returned substantially more relevant results than irrelevant ones.
- Recall – high value means that an algorithm returned most of the relevant results.

Results – CNN Training



Dataset-0 training



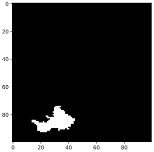
Dataset-1 training

- Showing scores during VL mode when classes are split equally for validation.
- Weights selected using lowest VL.
- Dataset-0 Validation Samples (7,947) for each class.
- Dataset-1 Validation Samples (2,617) for each class.

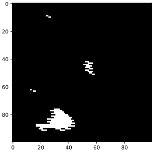
Results – Conventional DNN Training

Conventional DNN training method precision, recall, and number of test samples

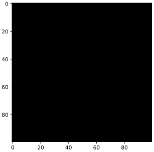
Dataset	Class	Precision	Recall	Samples
0	Fire	0.90	0.90	26356
	No-Fire	0.99	0.99	427115
1	Fire	0.00	0.00	78702
	No-Fire	1.00	1.00	1282862



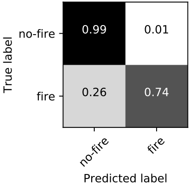
Test Image



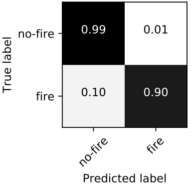
Dataset-0



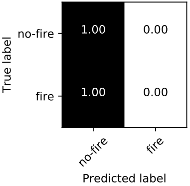
Dataset-1



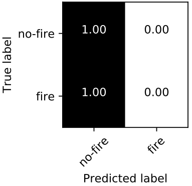
Dataset-0 single fire



Dataset-0 all



Dataset-1 single fire

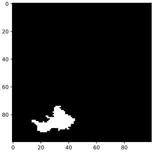


Dataset-1 all

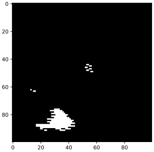
Results – Validation-Loss (VL) DNN Training

VL DNN training method precision, recall, and number of test samples

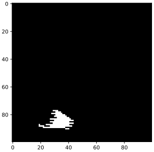
Dataset	Class	Precision	Recall	Samples
0	Fire	0.68	0.95	26356
	No-Fire	1.00	0.97	427115
1	Fire	0.61	0.96	78702
	No-Fire	1.00	0.96	1282862



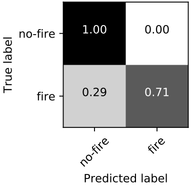
Test Image



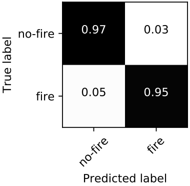
Dataset-0



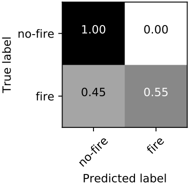
Dataset-1



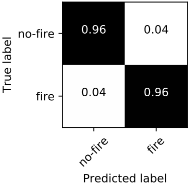
Dataset-0 single fire



Dataset-0 all

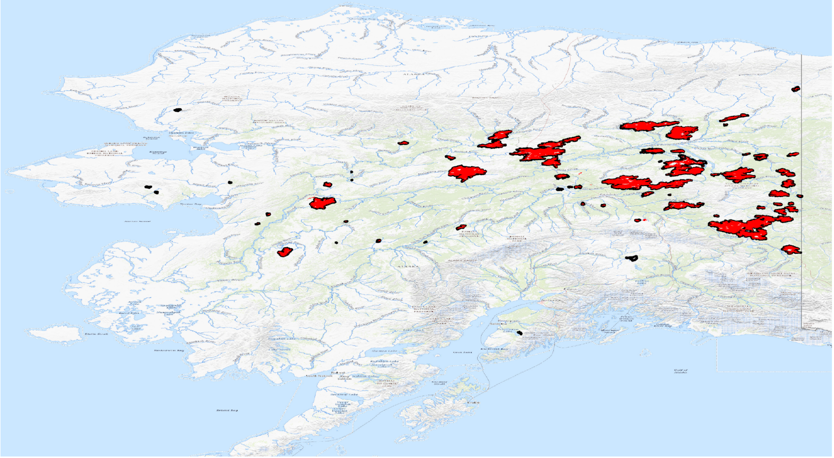


Dataset-1 single fire

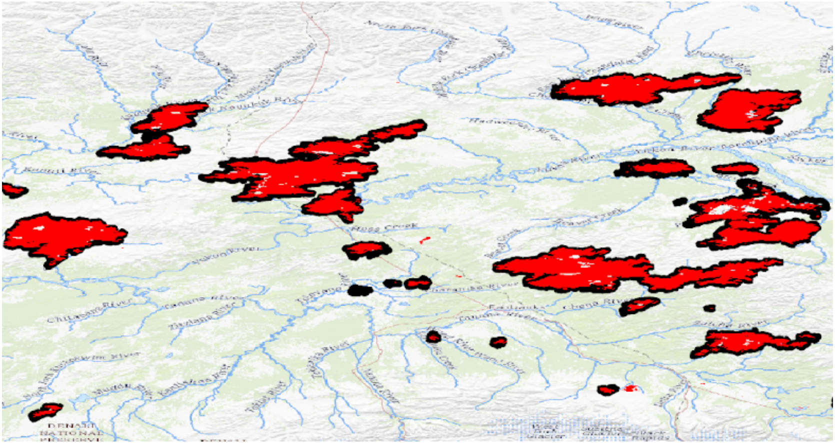


Dataset-1 all

Burn area detection in Alaska during 2004



Burn area detection in Alaska during 2004



Conclusions and Next Steps

- MODIS bands can be used to predict the spatial extents of wildfire with good accuracy.
- Google Earth Engine provides a powerful platform for processing and analyzing datasets without moving data.
- Validation-Loss (VL) DNN training strategy significantly improves performance and possibly captures unknown wildfires outside MTBS dataset.
- Next steps: More sophisticated algorithms utilizing sequential data and meta-learning approaches.

Acknowledgments

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This research was supported by the Next-Generation Ecosystem Experiments (NGEE Arctic) and the Reducing Uncertainties in Biogeochemical Interactions through Synthesis and Computation (RUBISCO) Scientific Focus Area (SFA), which are sponsored by the Climate and Environmental Sciences Division (CESD) of the Biological and Environmental Research (BER) Program in the US Department of Energy Office of Science. Oak Ridge National Laboratory (ORNL) is managed by UT-Battelle, LLC, for the US Department of Energy under Contract No. DE-AC05-00OR22725.

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