Coanda
Research & Development Corporation

Wildfire Prediction Using Satellite Data and Machine Learning

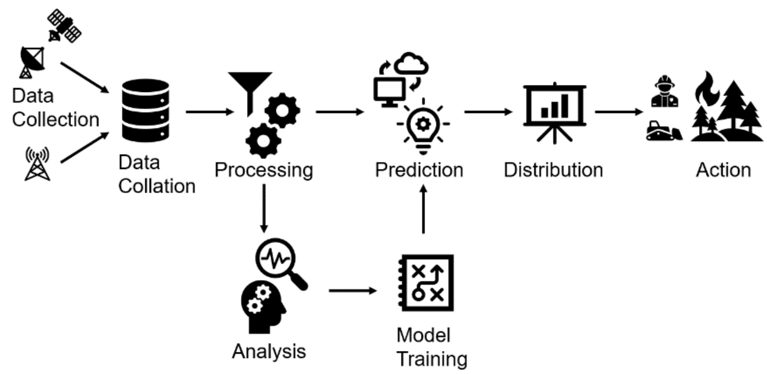
Wildfires have severe impacts in Canada and worldwide and present a significant challenge for management agencies. While wildfires are a natural phenomenon that play an important role in our ecosystems, they can threaten communities, destroy timber resources, degrade air quality, and cause other harmful effects. Currently Natural Resources Canada (NRCan) collects data from a network of weather stations and calculates fire related indices to create maps and other resources used by wildfire management professionals.

Coanda recently completed a project to investigate the use of machine learning (ML), also known as artificial intelligence, and satellite data to improve wildfire occurrence prediction in Canada. The work was performed through the Innovative Solutions Canada program and the "Artificial Intelligence and Big Data Analytics for Advanced Autonomous Space Systems" challenge sponsored by the Canadian Space Agency. The project successfully demonstrated a proof of concept model that improved wildfire occurrence prediction.

Satellites gather large quantities of data over wide geographic regions and can therefore be used to augment the current ground-based weather station network, filling in gaps between stations, and providing additional variables. ML is uniquely suited to handling these large data volumes and can identify complex patterns in varied data sets.

Proof of Concept Study Parameters

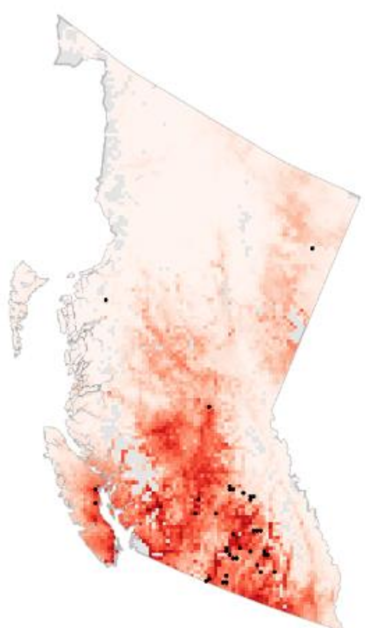
- Province of British Columbia
- 10 km by 10 km grid
- Data from July and August, 2011-2018
- Model input data from (see next page for details):
    - Canadian Wildland Fire Information Service
    - MODIS instrument on NASA satellites
    - Population density, road locations



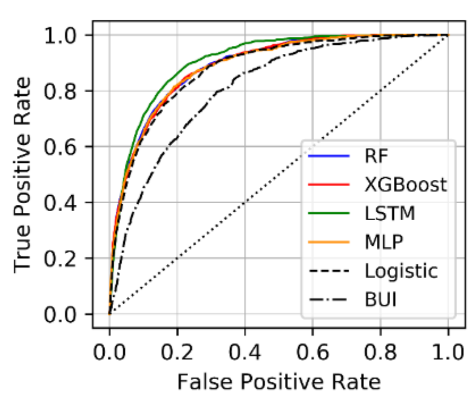
Wildfire prediction pipeline with machine learning

To evaluate the performance of the ML models, we used established NRCan indices such as the Fire Weather Index (FWI) as a baseline. Commonly used ML metrics, such as the area under the receiver operator characteristic curve (AUROC) and the average precision, were used to assess models. Several ML approaches, including decision tree methods, and time series neural networks were found to provide improved wildfire prediction performance compared to the baseline. The best AUROC was achieved by the LSTM model with a value of 0.907 for the year of 2015 (omitted from training the model and used only for testing performance), compared to the FWI value of 0.783, or 0.825 for the build up index (BUI) another NRCan index. The random forest model had an average precision of 0.0324 for 2015, compared with 0.0050 for FWI and 0.0059 for BUI.

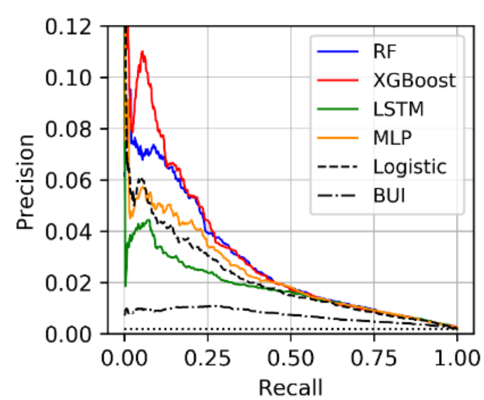
Analysis of the feature importance in the ML models showed that satellite derived variables such as the atmospheric stability measures of lifted index and K-index helped to improve model performance, demonstrating the promise of adding satellite data to the predictions.



Coanda fire danger map example from July 19, 2015. Black dots are actual fire starts.



Receiver Operating Characteristic



Precision-Recall Curve

These results demonstrate a successful proof of concept and achievement of TRL level 3. Future work can include full automation of the calculations, extending coverage to all of Canada, and refinement through the use of supplementary data from a longer historical period. Additional consultation with government agencies can better inform the creation of products that are most useful to wildfire personnel and identify other useful data sources. It may also be possible to apply ML methods to other aspects of wildfire science, such as fire behaviour prediction.

Data used for proof of concept study. MODIS data products are from the Aqua and Terra satellites operated by NASA.

Data Source	Variables
Natural Resources Canada (NRCan), Canadian National Fire Database	historic fire records
NRCan	elevation, temperature, dew point temp., wind speed, 24-h precipitation, snow on ground, sea-level pressure, mixing ratio, fine fuel moisture code (FFMC), Duff moisture code (DMC), drought code (DC), pressure at altitude, relative humidity, build up index (BUI), initial spread index (ISI), fire weather index (FWI)
MODIS Atmospheric Profiles	temperature, pressure, elevation, total ozone, total totals, lifted index, K index, water vapour (abs., direct, low, high)
MODIS Vegetation Index Products)	normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), vegetation index quality, red reflectance, near-infrared (NIR) reflectance, blue reflectance, mid-infrared (MIR) reflectance
MODIS Leaf Area Index/FPAR	leaf area index (LAI), fraction of photosynthetically active radiation (FPAR)
MODIS Evapotranspiration	evapotranspiration (ET), latent heat flux (LE), potential ET, potential LE
MODIS Land Cover Products	land cover type
BC Data Catalogue	population density, forest service roads
Statistics Canada	roads

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