McMaster University

School Of Earth, Environment and Society

Carbon Emission Mapping from Disturbnaces in Canada and Alaska Using Synthetic aperture radar (SAR), Landsat and Lidar

By

Chinyere Ottah

A Thesis Submitted to the School of Graduate Studies in Partial Fulfillment
of the Requirements for the Degree Doctor of Philosophy
in Earth and Environmental Sciences

December 2023

Abstract

Wildfire is the major standing disturbance in Canada.The area burned in Canada over the years has continued to progress with climate change as well as carbon released due to fire mediated disturbances for the year 2023. Here, statistical models will be established between field combustion and remotely sensed data from Landsat imagery as well as other environmental and climate variables obtained from the GEE datasets to estimate carbon emitted from the 2023 wildfires in order to derive a combustion map for 2023. The combustion datasets described here can be used across local and global scale for fire combustion science. The combustion datasets which will be described here [github.com/ChinyereRuth/Thesis] can be used for local to continental-scale applications of boreal fire science.

Keywords: Wildfire, carbon, spatial modelling, boreal forests

Contents

Acknowledgements

I am profoundly grateful to my dedicated supervisor, Dr. Alemu Gonsamo, whose unwavering guidance and support have been invaluable throughout my entire PhD journey. His expertise, encouragement, and commitment to excellence have significantly enriched my academic experience.

I extend my sincere appreciation to Dr. Anthonio Paeza for imparting his expertise and providing a comprehensive introduction to R and GitHub. His insightful teaching has equipped me with essential skills that have proven instrumental in my research endeavors.

1.0 Introduction

Worldwide, forests are vital carbon sinks and they store carbon belowground and aboveground. The boreal forest is the largest forest biome in the world and more than 20% of this zone is in Canada contributing to 8% of the world's forests (Brandt 2009). Canada's boreal forests accumulate over 28 Pg of Carbon (Kurz et al. 2013) making them important global C reservoirs. A vast amount of Carbon has accumulated within this zone because of slow decomposition from cold temperatures and from their anoxic conditions (Kurz et al. 2013).

Although this zone has been known for a very long time to be a C sink, drier air temperatures attributed to climate change are now making them vulnerable to wildfire by enhancing drier fuels below and aboveground. Wildfire is currently the dominant disturbance impacting the boreal forest and accounting for vast amounts of C (Potter et al. 2023). Carbon loss is the release of particles, gases, and aerosols into the atmosphere. Wulder et al. (2020) estimated that about 1.79 Pg of biomass had been lost as a result of fire disturbance from 1985–2016. In addition to this, fire regimes are also changing, and these trends are projected to increase as climate change progresses. Changes to fire regimes in Canada include an increase in area burned, fire intensity, and fire severity leading to more carbon emission from fires both aboveground and belowground. For example, over 17 Mha have burned just from the fires in 2023 alone in Canada. This is 5 times higher than the 2.37 Mha annual burn reported by Potter et al. (2023) in the past two decades. Changes in Canada's fire regime (fire frequency, intensity, burned area, fire severity) have the ability to convert some of these forest biomass C stocks to carbon sources, and this ecosystem might not return to its original biomass carbon storage.

To understand the impact of fires on Canada's boreal forest where small fluctuations in temperature are already noted and projected to have a significant effect on climate change, there is a critical need to estimate and understand the carbon loss from fire. This will not only help to improve carbon modeling and reporting but also provide mitigation measures for the areas where these trends are expected to be high.

There are two approaches to estimating carbon loss from fires. The first is the more traditional approach where the area burned, the fuel load (biomass consumed), the combustion completeness, and the fraction of carbon are taken into account (French et al. 2011). The second approach is the remotely sensed method where statistical techniques are used to model combustion by establishing a relationship between field combustion and remotely sensed variables. For the more traditional approach of C emissions, a lot of uncertainties arise when accounting for fuel load and combustion completeness as it differs from landscape to landscape (Hook et al., n.d.; Rogers et al. 2014). The latter is now used widely because of the availability of satellite imagery and the integration of field C measurements. Fuel load can be mapped with remote-sensed observations, and C loss information can cover a larger extent both spatially and temporally. Typically, remote sensing estimates of C loss rely on a statistical approach between field measurements of C loss and absorption properties from either active or passive sensors. Several studies have found a significant relationship between remote sensing observation and carbon combustion across the boreal forests (Veraverbeke, Rogers, and Randerson 2015). The difference normalized burn ratio along with other environmental spectral inputs, topographic, and climate variables are derived to explain C loss. For example, Rogers et al. (2014) was able to estimate the amount of below and aboveground carbon loss from fire disturbance in Alaska using dNBR and field combustion. Veraverbeke et al. (2015) using geospatial data and environmental variables reported that elevation, the day of burning, burn severity (dNBR), and tree cover were the drivers of carbon emission from boreal fires in Alaska. Similarly, Potter et al. (2023) related fire combustion measurements with predictor variables of climate, fire weather indices, environmental variables, and remotely sensed variables. He reported that the period where a larger fire year was witnessed and later season burning generally accounted for a higher mean combustion. Tree cover, relative humidity, Normalized Difference Infrared Index (NDII), and dNBR were the most important variables for aboveground combustion, while silt, slope, solar radiation, tree cover, and sand were the drivers of combustion for belowground combustion.

Carbon emission mapping, such as our studies here, will allow for improving C emission accounting, modeling, and reporting and also more accurate prediction of C losses, which is a very key importance discussion within the United Nations framework accounting.

Most of the research modeling carbon emission from disturbances such as wildfire only looked at Alaska and sometimes a combination of Alaska and western Canada. This research will be the first to provide belowground, soil, and aboveground C emissions for the entire Canada. Here, we are looking at the carbon emission from fire for the entire Canada considering that this year, Canada had the worst fire seasons compared to other years. It is, therefore, important to understand the C that has been released from this disturbance and mitigation measures that can be carried out to help this ecosystem recover from this disturbance. And also, carbon emission modeling of Canada will help in improving Canada's C loss emission report and modeling and also to understand the drivers of C emission within Canada's forest.

1.1 Research Aim & Objectives

The primary goal of this study is to estimate the amount of carbon loss from wildfire disturbance within Canada's forests. The specific objectives include:

2.0 Methods

2.1 Study area

The study area (Figure 1) is Canada's forests region which comprises of boreal, great lakes, acadian, carolinian, subalpine, columbia, montane and coastal forest. Tree species within the zone are generally conifers such as black spruce, white spruce, Tamarack, balsam fir and jack pine while deciduous trees within the zone includes Aspen, balsam poplar and paper bitch. The climate of Canada's forest varies but it is mainly characterized by cold winters and short summer (Brandt, 2009), although we are beginning to observed more warmer winter due to climate change. The mean temperature in Canada's boreal forests ranges 10ºC- 20ºC and this varies from region to region (Zhang et al., 2019)

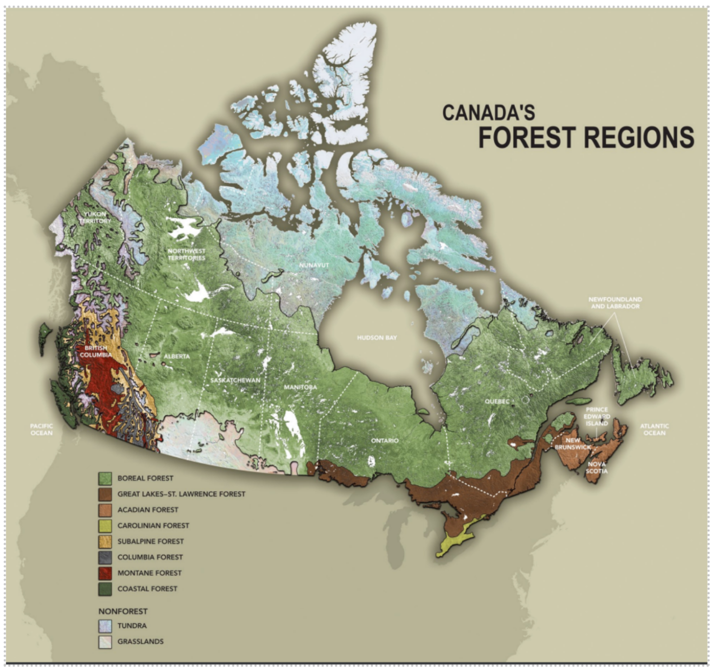


Figure 1: Canada's forests regions (Natural resource Canada)

Wildfire is the major standing disturbance within Canada's boreal forest and also other forest region with more than 2 Mha burn annually on average (Stocks et al., 2002) although this range varies from year to year.o determine areas that burned, a burned area map derived using a support vector machine learning algorithm will be used to identify area burned. To determine the areas that are primarily forests, a land cover map will be used to stratify the various land cover types. a land cover map will be used to stratify the areas of various landcover classes.

2.2 Field data

2.2.1 Field combustion area

To estimate the amount of C loss across Canada's major disturbances, Field combustion measurements for the year 2014 and 2015 as shown in Figure 2 were acquired from a number of publications that carried out combustion measurement within Canada's boreal forests and published online as a single database (Walker et al., 2020a).

This field measurements resulted in 456 plots and were used with other predictor variables to estimate C loss from Canada 's boreal forest fires.

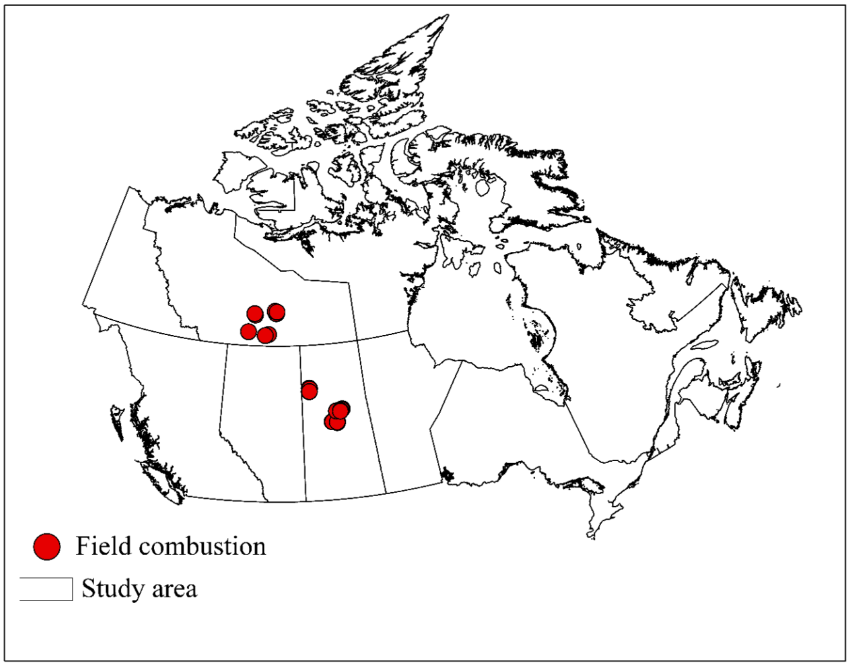


Figure 2: Field combustion area

2.2.2 Burned-area, harvest and insect disturbance mapping

Disturbnace map across the entire sty area will be drive using a random forest approach where we integrated different spectral indices, spectral bands and environmental variables. A threshold value established from literature and other filed collected disturbance site will be used on the final disturbance product to identify each disturbance types(fire, harvest and insect infestation) within Canada's forests.

2.3 Combustion models

2.3.1 Predictor variables

Field combustion measurements for aboveground and belowground C loss was obtained from Walker et al. (2020) and related to gridded environmental, fire severity and remotely sensed variables of combustion (Figure 3).

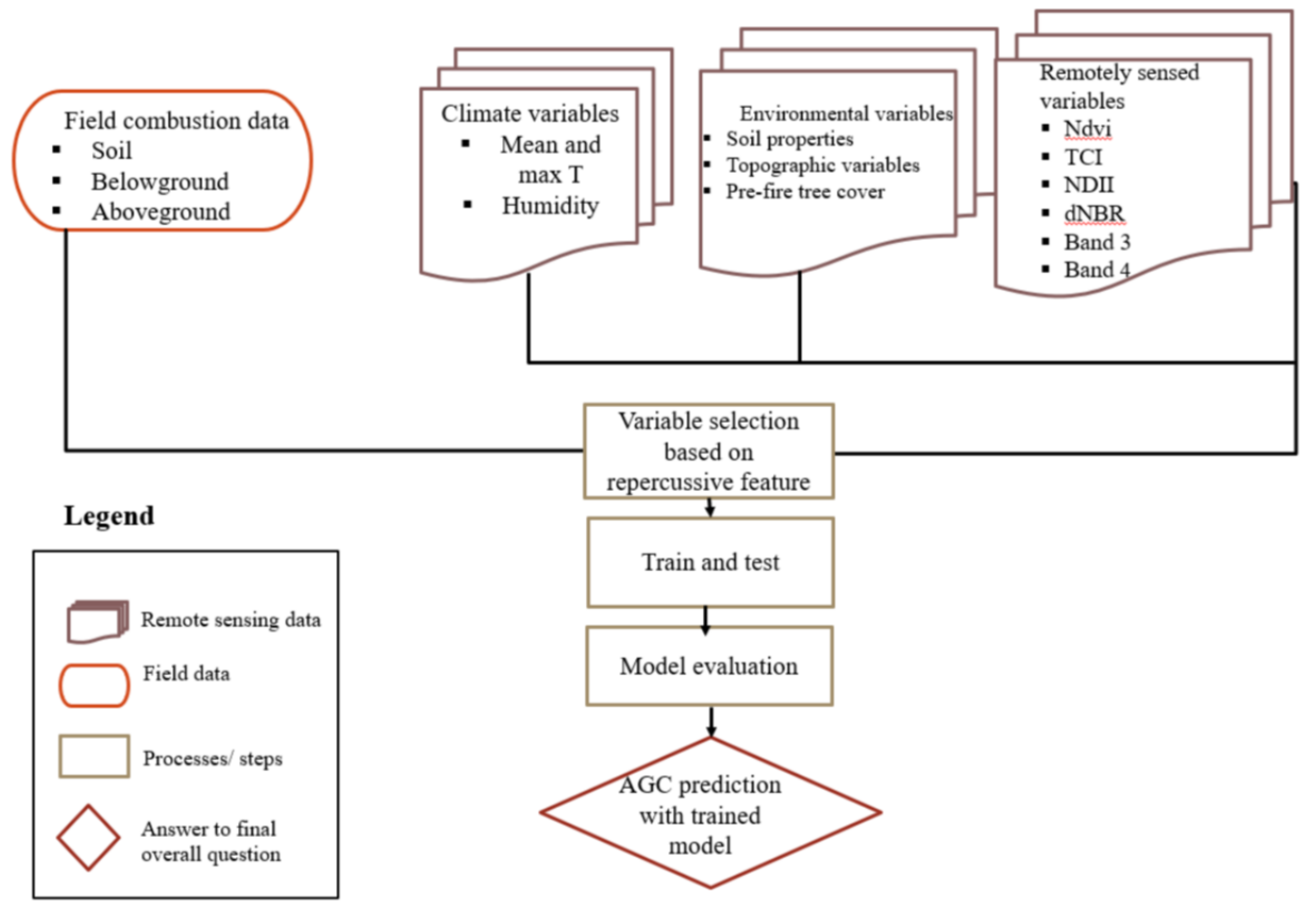


Figure 3: method to map C emissions from disturbance

The predictor variables of combustion used in this study was selected first by spanning across the literature and also discussing with experts and also further validated with a selection from random forests.

2.3.1.2 Climate variables Climate variables used in this study was obtained from Climate NA. Climate NA provides monthly, seasonal and yearly gridded climate data. This data was used to generate climate impact of C combustion within Canada's boreal forests.

2.3.1.3 Environmental variables Aboveground combustion from fire depends on a lot of top tree influence. The environmental variables that we will use for this research includes elevation, Soil properties , slope, aspect, and pre-fire tree cover. The elevation data will be obtained from the Advanced Spaceborne and Thermal Emission and Reflectance Radiometer Global Digital Elevation Model (ASTER GDEM), and then slope and aspect will be derived in ArcGIS or R USING THE DEM.

Prefire tree cover plays a huge factor and influences below and aboveground combustion. Tree cover influences biomass fuel for burning and it is also a measure of tree stand. Studies have found out that tree cover correlates with C loss (Rogers et al., 2014). The pre-fire tree cover used in this study will be obtained rom Sexton et al et al. (2013) for the year201 and it will serve as the pre- fire tree cover for our combustion model

The differenced normalised burn ratio (dNBR) assess changes in fire impacted vegetation using the near and shortwave infrared reflectance (Key & Benson, 2004). dNBR will also be included as a predictor variable as studies have found out the dNBR correlates significantly with biomass loss. Spectral bands of Landsat 1- 9 wil be downloaded from the USGS and the NIR and SWIR band s will be used for deriving NBR (NIRSWIR)/(NIR + SWIR). dNBR will be computed as the difference between pre-fire and post fire NBR.

2.3.1.4 Remotely sensed variables Remotely sensed variables used for this studies were all derived from Landsat 7 and 8. This include Landsat band 1 -9, the normalised differenced vegetation indices(NdVI), the topographic wetness index, Tasseled cap indices, and the Landsat dNBR

3.0 Results

3.1 Minimum Tempertaure

Across Canada in the month of May, the minimum temperatures (Figure 5) before the fire varied from -8 to 20 degrees Celsius. Notably, the provinces of the Northwest Territories, Alberta, British Columbia, Saskatchewan, and Ontario exhibited high minimum temperature values exceeding 10 degrees Celsius, while locations such as Yukon experienced lower minimum temperatures.

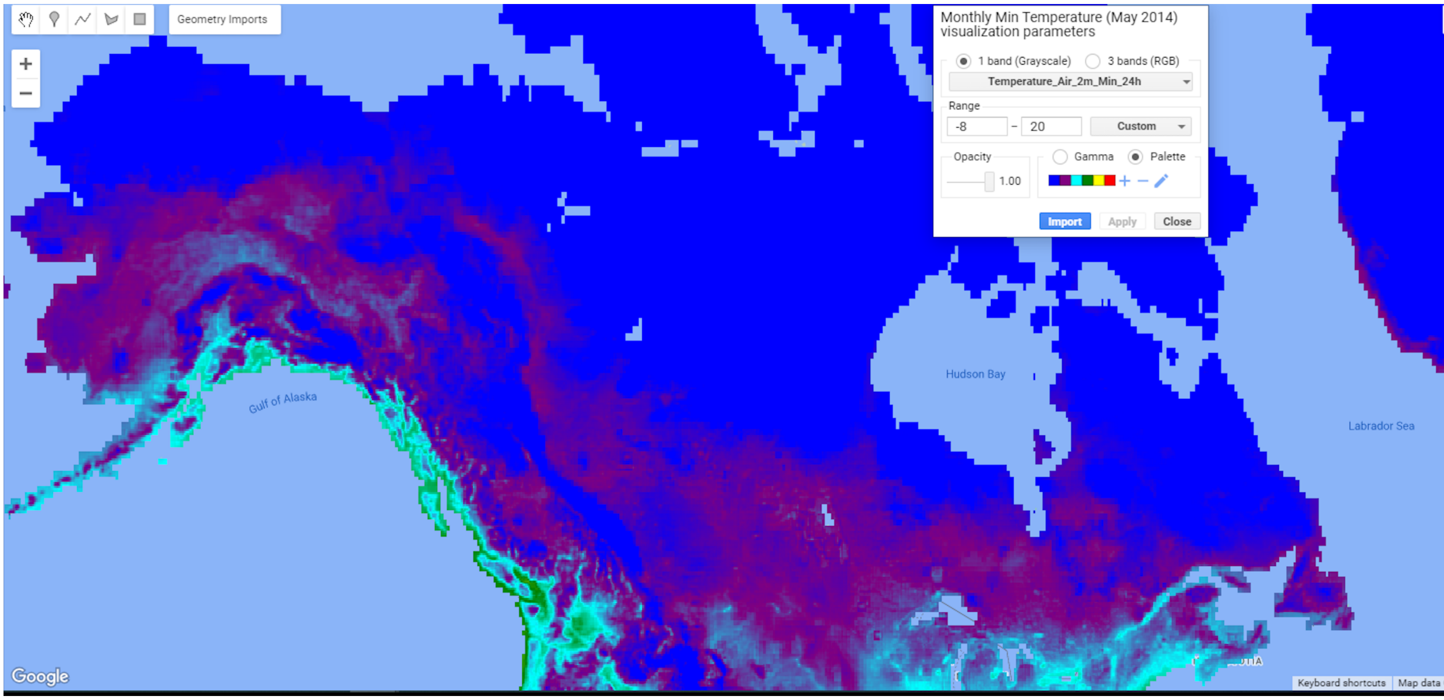


Figure 4: Minimum Air Temperature in Canada for the month of May, 2014

3.2 Mean Tempertaure

The mean temperature values, as depicted in Figure 5 for the month of May, closely paralleled the minimum temperature. Across lakes and rivers, the mean temperature values were lower. In contrast, regions such as the Northwest Territories, Alberta, British Columbia, Saskatchewan, and Ontario exhibited notably higher mean temperature values exceeding 20 degrees Celsius.

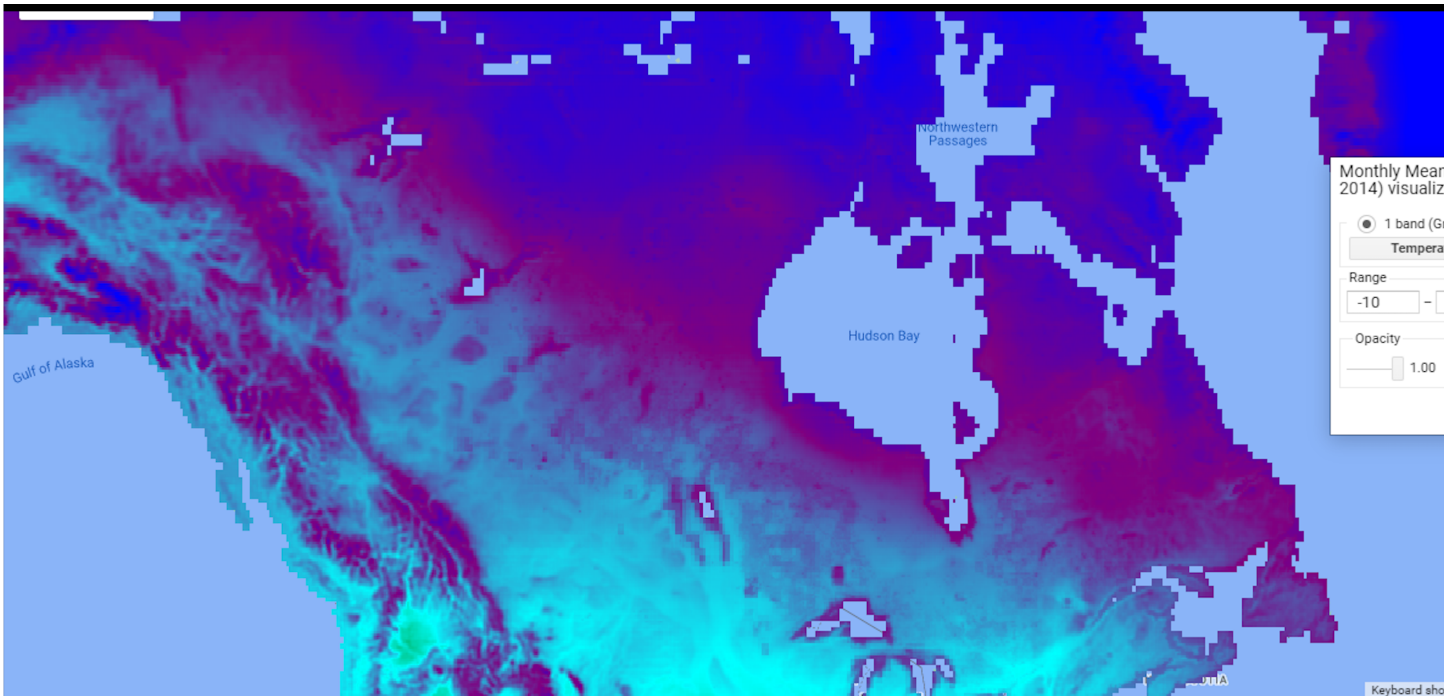


Figure 5: Mean Air Temperature in Canada for the month of May, 2014

3.3 Maximum Tempertaure

3.4 Prefire Tree Cover

According to Figure X, regions surrounding the boreal forests exhibited elevated prefire tree cover. Specifically, the provinces of Ontario and British Columbia demonstrated higher pre-fire tree cover compared to other provinces in Canada, as illustrated in the figure. In contrast, the prefire tree cover in the vicinity of the unmanaged boreal forest was notably lower.

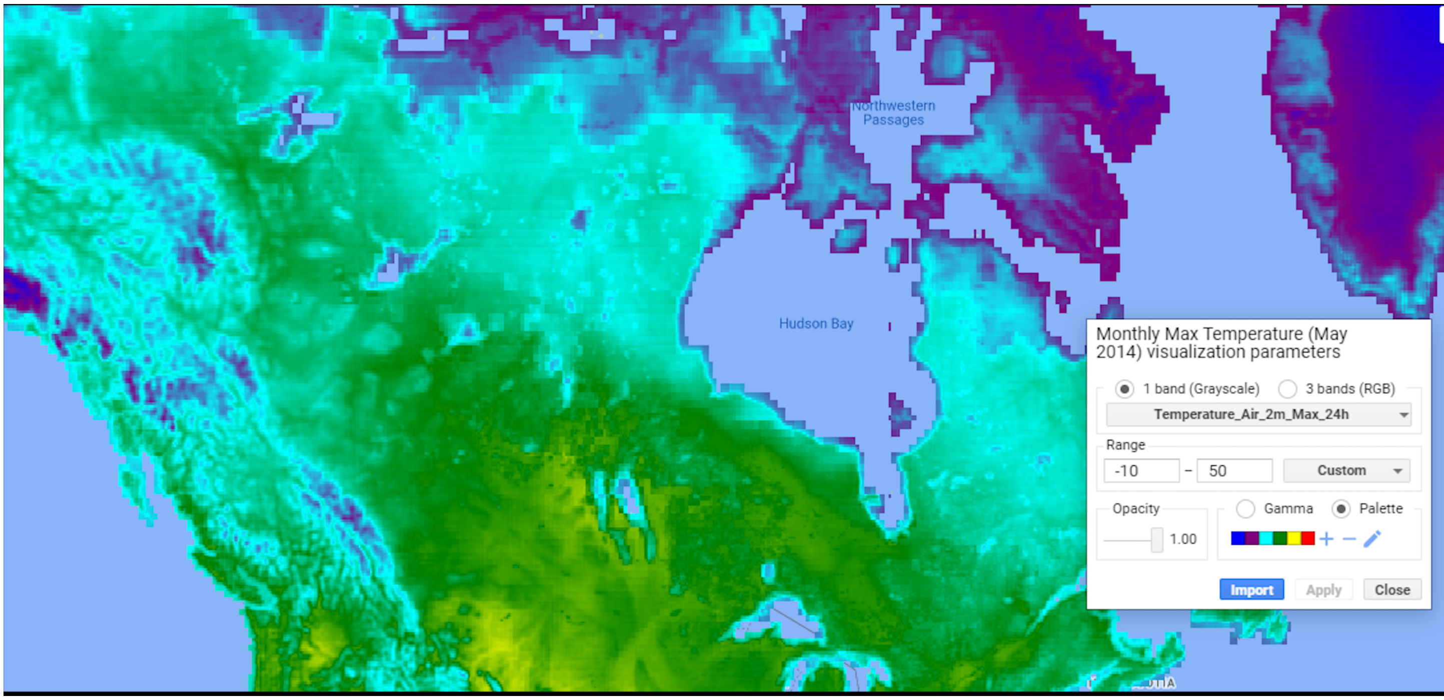


Figure 6: Minimum Air Temperature in Canada for the month of May, 2014

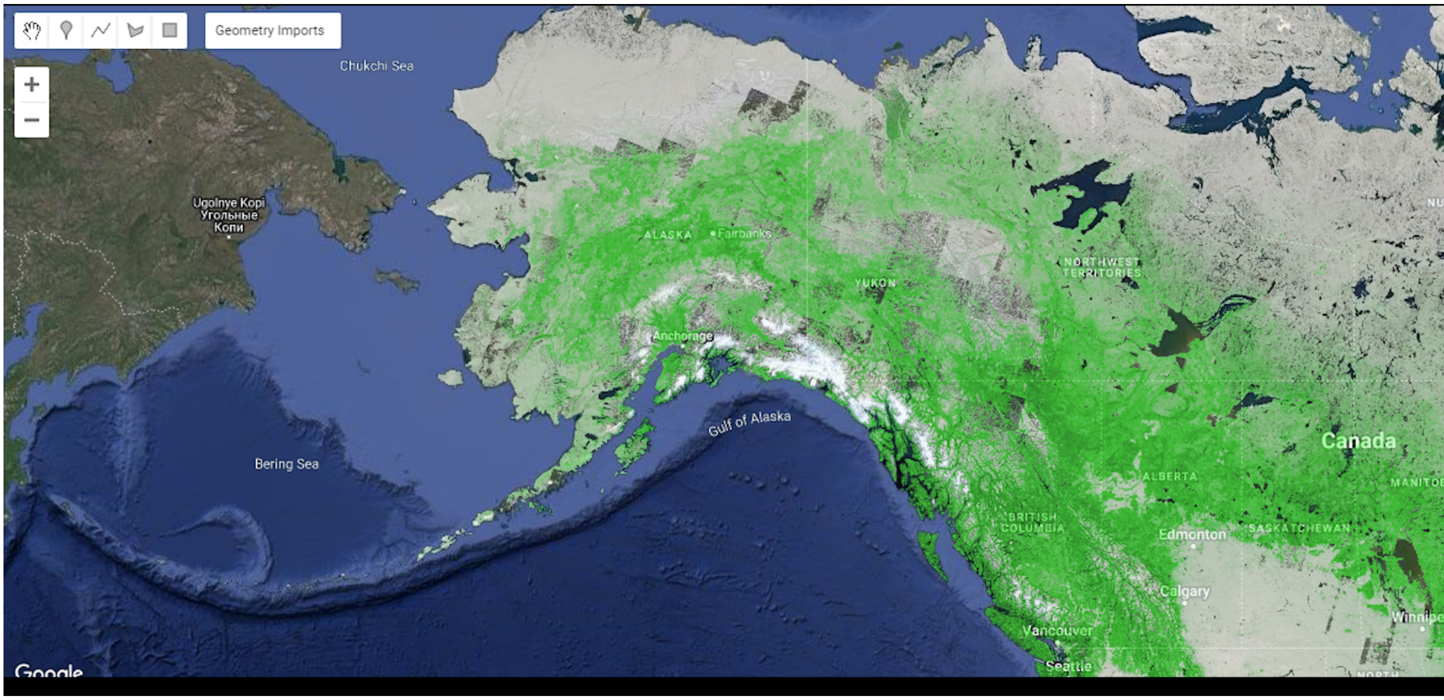


Figure 7: Minimum Air Temperature in Canada for the month of May, 2014

3.5 Mean Area burned

When the fire ignited in May, the Slave Lake region in the provinces of the Northwest Territories was affected. The extent of the burned area varied across the provinces in Canada, as depicted in Figure X. The severity of the burn was more pronounced in the provinces of Alberta, the Northwest Territories, and Saskatchewan, where dNBR values higher than 0.5 were observed.

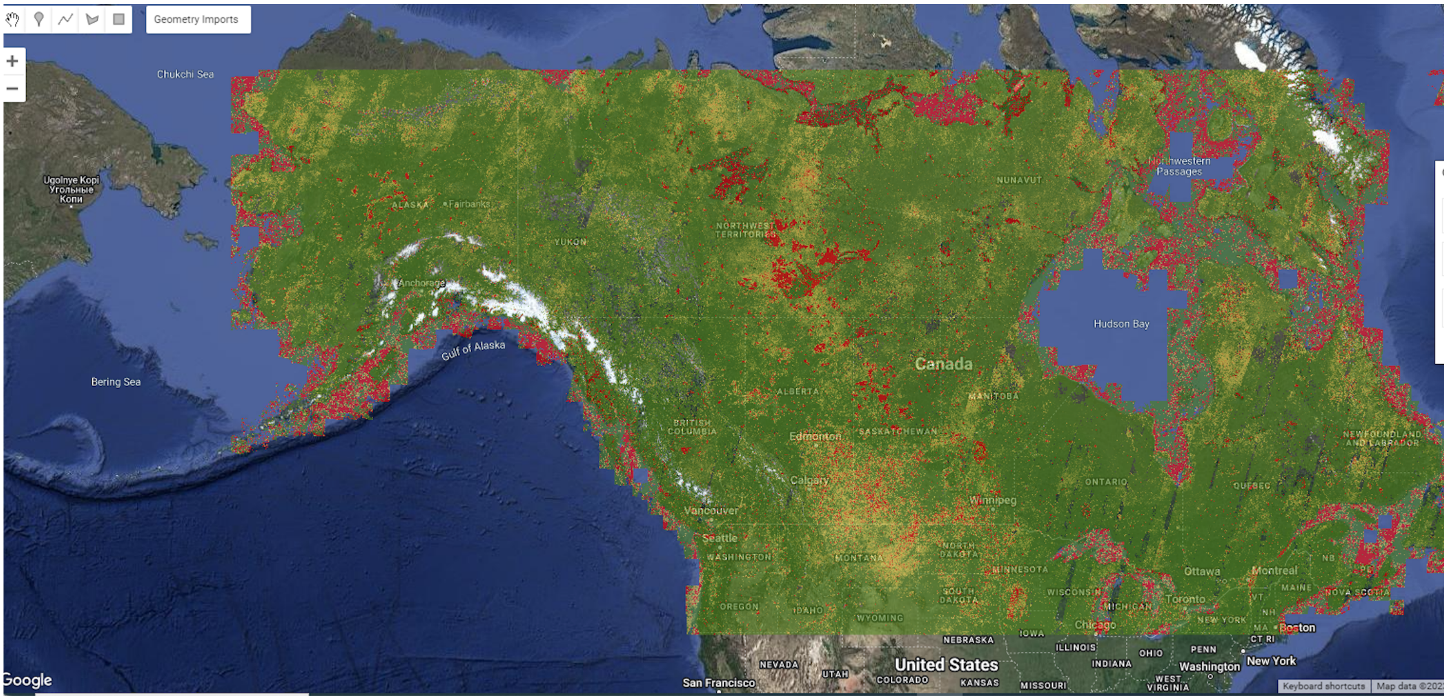


Figure 8: Area burned in Canada for the month of May, 2014

In contrast, regions such as Ontario, British Columbia, and Yukon experienced lower burn severity during the month of May 2014.

Carbon emitted and variable of importance for predicting C emissions

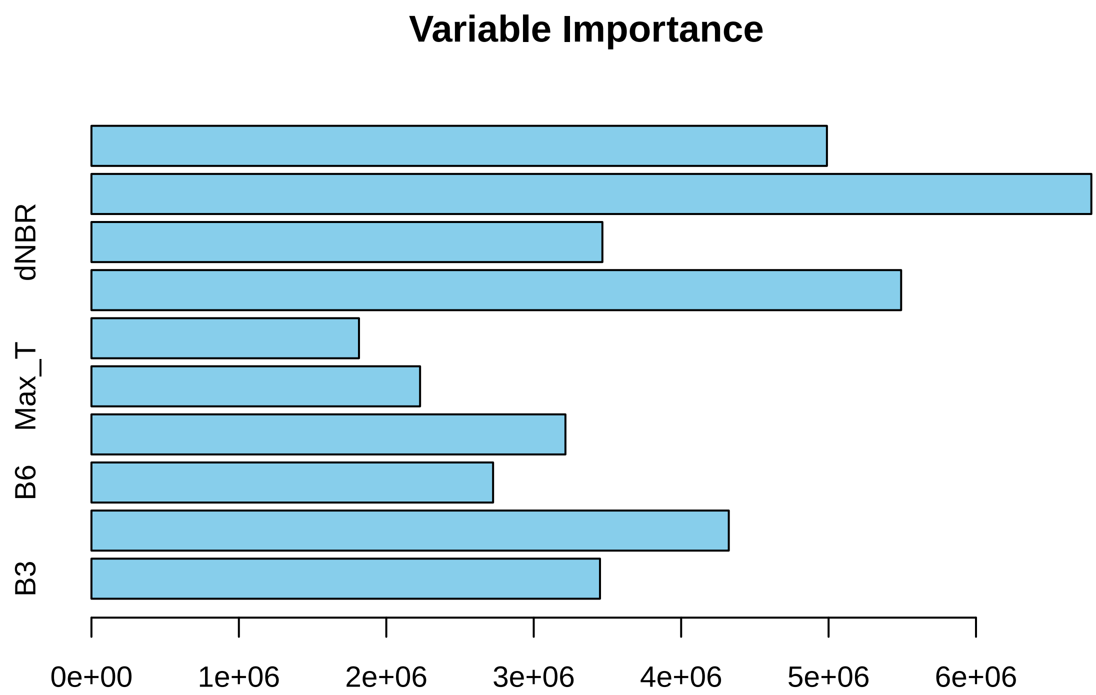
Utilizing a Random Forest regression model with ranger for predicting carbon emissions across fires in Canada revealed that prefire tree cover, Landsat band 3, Landsat band 5, maximum temperature, and dNBR (difference Normalized Burn Ratio) emerged as the most influential variables in explaining carbon emissions within Canada's boreal forest (refer to Figure X). The model demonstrated a mean and explained 38% of the variance in combustion events.

```
## Warning: package 'ranger' was built under R version 4.2.2

## Mean Absolute Error (MAE): 205.0964

##          B3        B5        B6     Gness     Max_T   Mean_RH    Mean_T
##     3449623   4323137   2724332   3215046   2229160   1814798   5492183
```

```
##       dNBR Canopcover       GDEM
##    3465845    6782424    4988881
```




```
## R-squared: 0.3843798
```

The model had a (MAE): 205.7412. Using this model output, C emitted across the 2023 fires will be predicted for Canada's forest.

4.0 Discussion

4.1 Burned area

The application of Landsat-derived Normalized Burn Ratio (dNBR) proved instrumental in identifying areas affected by wildfires within Canada's forested regions throughout the month of May. Analyzing the resulting burned area map, generated with Landsat imagery, unveiled notable instances of high burn severity in proximity to the boreal shield and boreal plains, where dNBR thresholds surpassed 0.5. The severity of these burns during the 2014 incidents was found to be intricately linked to a range of influencing factors, such as prefire tree cover, temperature, and vegetation.

These factors, as previously highlighted by Wang et al. (2014), have demonstrated a significant influence on fire behavior. By integrating this knowledge into our analysis, we gain valuable insights into the complexity of wildfire dynamics. Notably, prefire tree cover, ambient temperature, and the type of vegetation contribute substantially to the severity of wildfires in these regions.

The significance of employing dNBR maps extends beyond mere detection; they prove indispensable in the realm of carbon accounting and the implementation of models designed for assessing and managing the ecological and environmental impacts of wildfires. This comprehensive understanding of burn severity factors enhances our ability to develop effective strategies for mitigating the impact of wildfires on forest ecosystems and facilitating informed decision-making in resource management.

4.2 Carbon emission model

The aboveground carbon emission model in this study was influenced by prefire tree cover, Landsat dNBR, band 3, band 5, and maximum temperature. Veraverbeke et al. (2015) had previously identified dNBR, elevation, and pre-fire tree cover as crucial factors driving combustion. Additionally, Barrett et al. (2011), using spectral and non-spectral indices, also reported dNBR as one of the top three predictors of combustion.

Future research for this study will involve applying this model to explain the combustion events that occurred in Canada in 2023. This endeavor will contribute to a deeper understanding of the dynamics of combustion fires and further refine our ability to predict and manage such incidents.

5.0 Concluson

In conclusion, the utilization of Landsat-derived dNBR for mapping burned areas within the Canadian forest in May 2014 has proven to be pivotal for carbon emission accounting and enhancement strategies. Complementing this approach, we incorporated mean, minimum, and maximum temperatures to formulate a robust carbon emission model. The results indicated that our Random Forest model effectively explained 38% of the variability in carbon loss. This valuable insight not only underscores the significance of accurate burned area mapping but also sets the stage for future studies to refine and expand upon our model, contributing to a more comprehensive understanding of carbon dynamics within forest ecosystems. As we continue to advance our methodologies, the implications for carbon management and environmental conservation are promising.

References

Brandt, James P. 2009. "The Extent of the North American Boreal Zone." *Environmental Reviews* 17 (NA): 101–61.

French, Nancy HF, William J De Groot, Liza K Jenkins, Brendan M Rogers, Ernesto Alvarado, Brian Amiro, Bernardus De Jong, et al. 2011. "Model Comparisons for Estimating Carbon Emissions from North American Wildland Fire." *Journal of Geophysical Research: Biogeosciences* 116 (G4).

Hook, Simon, Nancy French, Louis Giglio, James Randerson, David Roy, David Schimel, Wilfred Schroeder, Sander Veraverbeke, and Martin Wooster. n.d. "Carbon Emissions from Biomass Burning."

Kurz, Werner A, CH Shaw, Celine Boisvenue, G Stinson, J Metsaranta, David Leckie, Andrew Dyk, Caroline Smyth, and ET Neilson. 2013. "Carbon in Canada's Boreal Forest—a Synthesis." *Environmental Reviews* 21 (4): 260–92.

Potter, Stefano, Sol Cooperdock, Sander Veraverbeke, Xanthe Walker, Michelle C Mack, Scott J Goetz, Jennifer Baltzer, et al. 2023. "Burned Area and Carbon Emissions Across Northwestern Boreal North America from 2001–2019." *Biogeosciences* 20 (13): 2785–2804.

Rogers, Brendan M, S Veraverbeke, G Azzari, CI Czimczik, SR Holden, GO Mouteva, F Sedano, KK Treseder, and JT Randerson. 2014. "Quantifying Fire-Wide Carbon Emissions in Interior Alaska Using Field Measurements and Landsat Imagery." *Journal of Geophysical Research: Biogeosciences* 119 (8): 1608–29.

Veraverbeke, S, BM Rogers, and JT Randerson. 2015. "Daily Burned Area and Carbon Emissions from Boreal Fires in Alaska." *Biogeosciences* 12 (11): 3579–3601.

Appendix

Documentation of the data used in this project

Specification Table

Subject	Geography, Environmental Science, Remote Sensing, Computer Science, Climate studies
Specific subject area	Tree Carbon in boreal forests, Remote Sensing modelling, Environmental Science climate processing
Type of data	Raster data (Tif file type) Excel data (CSV) Code files (html)
Method of data acquisition	Predictor and Explana tory data were acquired online Field combustion data was acquired: The ABoVE Fire Emissions Database USGS Earth Explorer: Landsat 8 band 1-9 GEE Climate variables: Precipitation, humidity, minimum and maximum temperature. ASTER DEM: Digital elevation
Data format	Processed
Description of data acquisition	Field combustion dataset were acquired from the above fire emissions derived from Potter et al. 2023 [ˆ1ˆ].
For prediction of Carbon emissions, we used different covariate layers:	• Time-series 2014 and 2015 : USGS Landsat bands [ˆ7ˆ], Optical vegetation indices, GEE Climate variables (Humidity, precipitation, mean, min. and max. air temperature, ASTER DEM
Location of data source	Landsat bands: [ˆ2ˆ] GEE climate dataset: [ˆ3ˆ] ASTER DEM: [ˆ4ˆ]
Accessibility of data	The predicted carbon emission dataset will be found at 30 m resolution in the following repository [ˆ5ˆ] : Repository name: Chinyereruth Data identification number: Still in progress Direct URL to data: Still in progress Detailed code associated with the data analysis is available from the Github repository [ˆ5ˆ]

VALUE OF DATA

- The map provides the amount of carbon emission from trees from Canada's boreal forests, using statistical methods such as regression and machine learning.

- The map will support research on Carbon emission models, and climate change assessment and can be used to inform climate and fire scientists on carbon accounting and reporting, and also recommend measures to reduce carbon emission footprints. It can also be used to compare carbon emissions from other boreal forest zones.
- The methods that will be outlined and code that will be provided can also be replicated in other locations and zones to derive carbon emission maps.

Data Description

Predictors will be provided within the domain of the boreal forest in a folder called the "carbon-emission-modelling-2023.zip". Carbon emitted from each province will be named according to its geographic location (i.e. 059E_14N corresponds to 59E to 60E, 14N to 15N). The "pronvince_carbon_emission_2023.Tif"file will contain carbon emissions for each province within Canada and the "Canada_Carbon_emission_2023.tif"file contains the final carbon emission map for the entire Canada . The detailed code associated with this project will be found in the Github repository (https://github.com/Chinyereruth/carbon-emission), allowing for the prediction applied here to be replicated. In addition, the code used for this folder will be found in "carbon-emission-Canada-2023- code. Rmd" which will be located in the main GitHub repository folder.

Table 1 Files used in the study for wildfire carbon emission modelling in Canada for the year 2023

File description	File name
Predicted Carbon emitted for Canada 2014	Carbon-emiss-Can_ JanDec_2014-30m.tif
Minimum temperature for Canada 2014	Min-temp-Can_ JanDec_2014-30m.tif
Maximum temperature for Canada 2014	Max-temp-Can_ JanDec_2014-30m.tif
Soil data for Canada 2014	Soil-Can_ JanDec_2014-30m.tif
NDVI data for Canada 2014	NDVI-Can_ JanDec_2014-30m.tif
Tree cover for Canada 2014	Treecov-Can_ JanDec_2014-30m.tif
DEM for Canada 2014	ASTER-dem-Can_JanDec-2014-30m.tif

Experimental Design, Materials and Methods

Training data I used a compilation of field carbon combustion data obtained from the ABoVE Fire Emissions Database (n=467). This field combustion data that were collected across Alberta, Saskatchewan, Manitoba and North Western Territories.

Covariate layers Combustion measurements that were obtained from ABoVE fire database were related to covariates of remotely sensed variables for fire severity, elevation, soil and climate.

Climate variables Climate data for minimum and maximum temperature were obtained from Climate ClimateNA using the GEE climate hub portal for the year 2023. The climate data used here provided the climate point estimate in degrees Celsius which was imported in the spatial environment. The data upscaled to a 30 m grid. This helped to capture the climate impact on vegetation, fuel loads, and fuel moisture, which affect combustion losses.

Environmental variables I used a variety of environmental variables. This includes soils, topography and vegetation category. The soil data was gotten at 250 m resolution but this was upscaled. Topographic variables that will be derived include aspect in degrees, elevation (m),

and slope at a 30 m pixel size.

Remotely sensed variables Here, I derived various remotely sensed vegetation indices from Landsat, and this includes NDVI, the normalized difference infrared index (NDII) and the dNBR. All images used were atmospherically and geometrically corrected using the correction and geometric tool in R.

Model training For the model training, remotely sensed variables, climate and environmental variables were used. Areas of clouds, cloud shadows, and snow were extracted out using an extraction function in R.

Spatial carbon modelling The results from this research are still in progress. Preliminary results are displayed here.

Ethic statement This study did not use human subjects, experiments carried out on animals, and did not also acquire any data from social media platforms.

Data availability

Carbon emission modelling from wildfire disturbances in Canada at 30 m resolution for the year 2023 will be available at Github/ChinyereRuth/carbon-emission.

Goggle Earth Engine (Google Earth Engine) used in deriving dNBR, minimum,mean and maximum tempertures.

GEE code for differenced normalised burn ratio (dNBR)

// Assuming you've uploaded the CSV to Google Drive and have the file ID var myPoint = ee.FeatureCollection('projects/ee-ottahchinyereglcf/assets/Burnedpoint'); // Add points to the map Map.addLayer(myPoint, { color: 'blue' }, 'CSV Points');

//Set up Region of Interest var albertaGeometry = ee.FeatureCollection('FAO/GAUL_SIMPLIFIED_500m/2015/level1').filter(ee.Filter.eq('ADM1_NAME','Alberta')); var albertaBounds = geometry.bounds();

// Function to mask clouds using Landsat band. var fun = require('users/ottahchinyere2/biomass:PrepFunctions');

//The preprocess function takes an input start year, and end year, followed by a start month and end month var PreFireImg = fun.preprocessHLS([2013, 2013], [6,9], albertaBounds).median(); var DurFireImg = fun.preprocessHLS([2014, 2014], [6,9], albertaBounds).median(); var PostFireImg = fun.preprocessHLS([2015,2015], [6,9], albertaBounds).median();

//Calculate NBR before, during and after 2015 fire var preNBR = PreFireImg.select('nir').subtract(PreFireImg.select('swir2')) .divide(PreFireImg.select('nir').add(PreFireImg.select('swir2'))); var durNBR = DurFireImg.select('nir').subtract(DurFireImg.select('swir2')) .divide(DurFireImg.select('nir').add(DurFireImg.select('swir2'))).rename('NBR'); var postNBR = PostFireImg.select('nir').subtract(PostFireImg.select('swir2')) .divide(PostFireImg.select('nir').add(PostFireImg.select('swir2'))).rename('NBR');

//Calculate dNBR between pre- and post- fire images var dNBR = preNBR.subtract(postNBR).rename('dNBR');

print(dNBR.projection().getInfo()) //Prints out the projection of the dataset to the console

var sample = dNBR.reduceRegions({ collection: myPoint, //The point dataset scale: 30, //This forces it to sample at 30m resolution, This is important as the default is very very very large. crs: ee.Projection('EPSG:4326'), //This is the projection of the original landsat data, so we aren't reprojecting anything reducer: ee.Reducer.median().setOutputs(["dNBR"]), //to use a mean, change this to ee.Reducer.mean() (the setOuput part just renames the band to dNBR instead of 'median' or 'mean') tileScale: 5 //This prevents out of memory errors by splitting the analysis into tiles that can run in parallel (I think) });

print(sample.getInfo()) //Prints out 'sample' to the console. This should contain the same points as the imported geometry, but with the dNBR data appended.

Export.table.toDrive({ //This sends the 'collection' to your own Google Drive. Set the fileNamePrefix and folder options to save to a specific place in your drive. collection: sample, //The 'feature collection' to export description: 'sampleTable', //just a description for the task manager in the GEE console (not important) folder:'GEE4', //folder on your google drive fileNamePrefix: 'burnedarea', //filename essentially fileFormat: 'csv' });

//Add layers to the map: var visualization = { bands: ['red', 'green', 'blue'], min: 0.0, max: 0.3, };

Map.addLayer(PreFireImg, visualization, 'Pre Fire - True Color (321)'); //Map.addLayer(DurFireImg, visualization, 'During 2015 Fire - True Color (321)'); Map.addLayer(PostFireImg, visualization, 'Post Fire - True Color (321)'); Map.addLayer(dNBR,{palette : ['green','white','Red'], min: -0.3, max: 0.3},'dNBR');

//dNBR

2. Prefire Tree cover // Assuming you've uploaded the CSV to Google Drive and have the file ID var myPoint = ee.FeatureCollection('projects/ee-ottahchinyereglcf/assets/AGC-rangerforests_Nov'); // Add points to the map Map.addLayer(myPoint, { color: 'blue' }, 'CSV Points');

//Set up Region of Interest var albertaGeometry = ee.FeatureCollection('FAO/GAUL_SIMPLIFIED_500m/2015/level1').filter(ee.Filter.eq('ADM1_NAME','Alberta')); var albertaBounds = geometry.bounds();

// Load NASA MEaSUREs GFCC Tree Canopy Cover dataset for 2010 var tcDataset = ee.ImageCollection('NASA/MEASURES/GFCC/TC/v3') .filter(ee.Filter.date('2010-01-01', '2010-12-31')) .filter(ee.Filter.bounds(albertaBounds)); var treeCanopyCover = tcDataset.select('tree_canopy_cover'); // Print the number of images in the ImageCollection var count = tcDataset.size(); print("Number of images in the ImageCollection:", count); // Load ASTER Global Digital Elevation Model (GDEM) var asterGDEM = ee.Image("projects/sat-io/open-datasets/ASTER/GDEM").clip(albertaBounds); print(asterGDEM) // Visualization parameters for tree canopy cover var treeCanopyCoverVis = { min: 0.0, max: 100.0, palette: ['ffffff', '00ff00'] // Adjust the palette as needed }; // // AGCpoints2 code // var AGCpoints2 = asterGDEM.addBands(treeCanopyCover.median()) // .reduceRegions({ // collection: myPoint, // scale: 30, // crs: ee.Projection('EPSG:4326'), // reducer: ee.Reducer.median().setOutputs(["tree_canopy_cover"]), // tileScale: 5 // }); var AGCpoints2 = asterGDEM .select(['b1']) .rename(['GDEM']) .addBands(treeCanopyCover.median()) .reduceRegions({ collection: myPoint, scale: 30, crs: ee.Projection('EPSG:4326'), reducer: ee.Reducer.median(), tileScale: 5 }) // .select(['GDEM', 'tree_canopy_cover']); // Export the 'sample' feature collection to Google Drive Export.table.toDrive({ collection: AGCpoints2, description: 'AGCpoints2', folder: 'outputFolder', fileNamePrefix: 'GDEM_TreeCover', fileFormat: 'CSV' }); // Add the DEM layer to the map for Alberta only Map.addLayer(asterGDEM, { min: 0, max: 3000, palette: ['0000ff', 'ffffff'] // Adjust the palette as needed }, ‘ASTER GDEM - Alberta’); // Add the tree cover layer to the map for Alberta only Map.addLayer(treeCanopyCover.median(), treeCanopyCoverVis, ‘Tree Canopy Cover - Alberta’); // Add the Region of Interest (Alberta) to the map Map.addLayer(albertaBounds, {color: ‘FF0000’}, ‘Alberta’); // Center the map on the Region of Interest Map.centerObject(albertaBounds, 3);

// Calculate slope var slope = ee.Terrain.slope(asterGDEM);

// Calculate Topographic Position Index (TPI) var tpi = asterGDEM.subtract(ee.Image(asterGDEM.reduceNeighborhood({ reducer: ee.Reducer.mean(), kernel: ee.Kernel.square(5, ‘pixels’), }))).rename(‘TPI’);

// Add layers to the map for slope, TPI, and TWI Map.addLayer(slope, {min: 0, max: 45, palette: [‘blue’, ‘yellow’, ‘red’]}, ‘Slope’); Map.addLayer(tpi, {min: -100, max: 100, palette: [‘blue’, ‘white’, ‘red’]}, ‘TPI’);

3. Minimum, maximum and mean temperature code

Assuming you’ve uploaded the CSV to Google Drive and have the file ID var myPoint = ee.FeatureCollection(‘projects/ee-ottahchinyereglcf/assets/Burnedpoint’); // Add points to the map Map.addLayer(myPoint, { color: ‘blue’ }, ‘CSV Points’);

//Set up Region of Interest var albertaGeometry = ee.FeatureCollection(‘FAO/GAUL_SIMPLIFIED_500m/2015/level1’).filter(ee.Filter.eq(‘ADM1_NAME’,‘Alberta’)); var albertaBounds = geometry.bounds();

// Read in Image Collection and get first image var agera5_ic = ee.ImageCollection(‘projects/climate-engine-pro/assets/ce-ag-era5/daily’); var agera5_i = agera5_ic.first(); var Proj = ee.Projection(‘EPSG:6931’); // Print first image to see bands print(agera5_i);

// Filter Image Collection by date range (May 2014) var startDate = ee.Date(‘2014-05-01’); var endDate = ee.Date(‘2014-05-31’);

var agera5_ic_may = agera5_ic .filterDate(startDate, endDate);

// Calculate monthly maximum, minimum, and mean temperature var agera5_monthly_max = agera5_ic_may.max(); var agera5_monthly_min = agera5_ic_may.min(); var agera5_monthly_mean = agera5_ic_may.mean();

// Define a color palette for temperature visualization var temp_palette = [‘blue’, ‘purple’, ‘cyan’, ‘green’, ‘yellow’, ‘red’];

// Visualize monthly maximum, minimum, and mean temperature for May 2014 Map.addLayer(agera5_monthly_max.select(‘Temperature_Air_2m_Max_24h’).selfMask().subtract(273.15), {min: -10, max: 50, palette: temp_palette}, ‘Monthly Max Temperature (May 2014)’);

Map.addLayer(agera5_monthly_min.select('Temperature_Air_2m_Min_24h').selfMask().subtract(273.15), {min: -10, max: 50, palette: temp_palette}, 'Monthly Min Temperature (May 2014)');

Map.addLayer(agera5_monthly_mean.select('Temperature_Air_2m_Mean_24h').selfMask().subtract(273.15), {min: -10, max: 50, palette: temp_palette}, 'Monthly Mean Temperature (May 2014)');

// Mypoint code var myPoint_max = agera5_monthly_max .select(['Temperature_Air_2m_Max_24h']) .rename(['Max_Temperature']) .reduceRegions({ collection: myPoint, scale: 30, crs: Proj, reducer: ee.Reducer.median(), tileScale: 5 });

var myPoint_min = agera5_monthly_min .select(['Temperature_Air_2m_Min_24h']) .rename(['Min_Temperature']) .reduceRegions({ collection: myPoint, scale: 30, crs: Proj, reducer: ee.Reducer.median(), tileScale: 5 });

var myPoint_mean = agera5_monthly_mean .select(['Temperature_Air_2m_Mean_24h']) .rename(['Mean_Temperature']) .reduceRegions({ collection: myPoint, scale: 30, crs: Proj, reducer: ee.Reducer.median(), tileScale: 5 });

// Print the resulting FeatureCollections print('Max Temperature:', myPoint_max); print('Min Temperature:', myPoint_min); print('Mean Temperature:', myPoint_mean);

// Add points with temperature information to the map Map.addLayer(myPoint_max, { color: 'red' }, 'Max Temperature Information'); Map.addLayer(myPoint_min, { color: 'green' }, 'Min Temperature Information'); Map.addLayer(myPoint_mean, { color: 'blue' }, 'Mean Temperature Information');

print(myPoint_mean);

// Export the feature collections to Google Drive Export.table.toDrive({ collection: myPoint_max, description: 'MaxTemperature', // Description for the task manager folder: 'outputFolder2', // Specify the folder on your Google Drive fileNamePrefix: 'MaxTemperature', // Set the filename fileFormat: 'CSV' // Choose the file format });

Export.table.toDrive({ collection: myPoint_min, description: 'MinTemperature', // Description for the task manager folder: 'outputFolder2', // Specify the folder on your Google Drive fileNamePrefix: 'MinTemperature', // Set the filename fileFormat: 'CSV' // Choose the file format });

Export.table.toDrive({ collection: myPoint_mean, description: 'MeanTemperature', // Description for the task manager folder: 'outputFolder2', // Specify the folder on your Google Drive fileNamePrefix: 'MeanTemperature', // Set the filename fileFormat: 'CSV' // Choose the file format });