Athabasca Lake West - Remote sensing

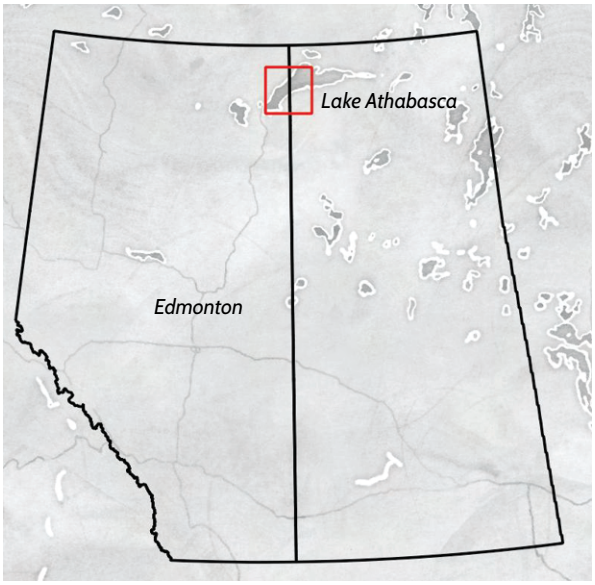

Figure 1: Location of the study area

Figure 2: "Natural colour" view (Band, 4-3-2)

Figure 3: Near-Infrared view (Band 8-4-3). The more active vegetation appears more red.

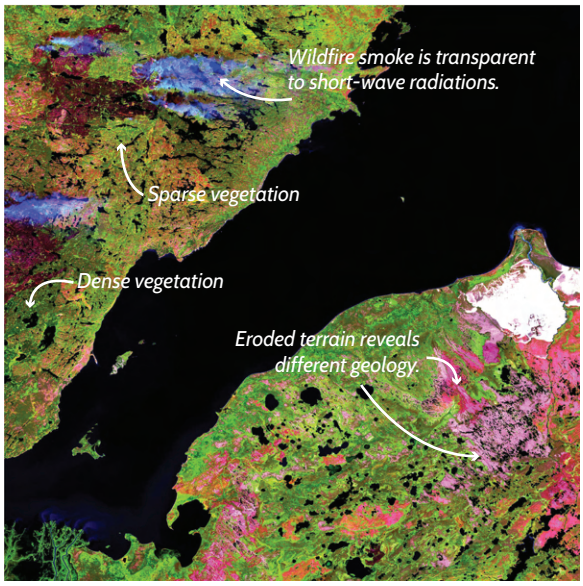

Figure 4: "Agriculture" view (Band 11-8-2) showing vegetation density (darker green = denser vegetation) and geological composition variations (redish colours).

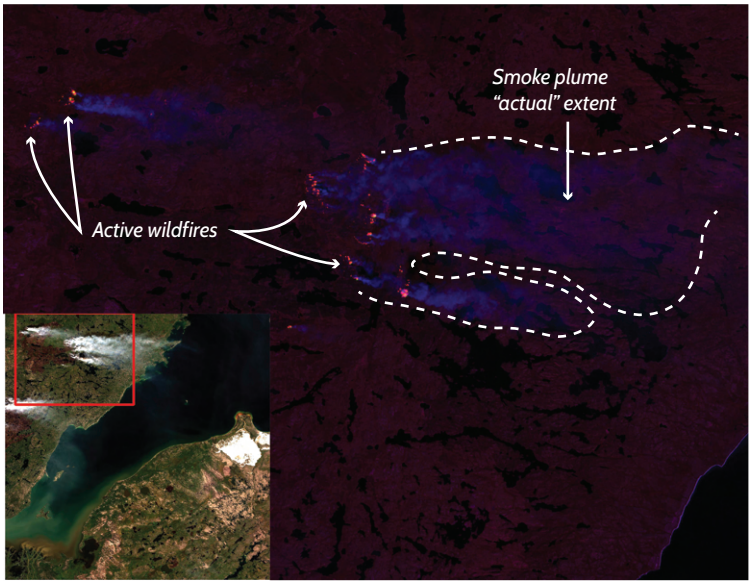

Figure 5: "Geological" view (Band 12-11-4) highlighting the active wildfire positions (white to bright red colours) and extent of the smoke generated (blue plume).

Imaging platform: Sentinel - 2A

Sensing date: Auguest 19th, 2022, 18:39:31 GMT

Granule designation: S2A_OPER_MSI_L1C_TL_A-TOS_20220819T222723_A037390_T12VWL_N04.00

Center coordinates: 59.041806374°N - 110.04359248°W

Processed with: QGIS 3.26.2 and SCP 7.10.6 plugin.

This scene from Sentinel 2, taken in late August 2022, is centred around the west end of Lake Athabasca at the border between Alberta and Saskatchewan (Figure 1).

Wildfires are present in the north part of the image. On this page of my portfolio, I show a quick visual analysis of the scene using different combination of bands from the Sentinel-2A imagery. Figure 2 (in visible light) gives an overview of the different elements present in the scene (lake, wildfires, sand dunes and water streams). Using a combination of visible light bands and near-infrared band, Figure 3 gives an opportunity to acquire more details on the burned areas, vegetated areas and on the sediment mixing happening in the SW part of Lake Athabasca.

Using a combination of short-wave, near-infrared and visible bands (Figure 4), we can peer through the smoke of the wildfire to discover that the terrain that was hidden before is partially burned already. Another remarkable element is the different lithology present near the sand dunes area in the east of the scene. Finally, Figure 5 focus on the wildfires. Using short-wave bands with the red band, and by cancelling the display value stretching, it is possible to see individual active wildfire centres and the "real" extent of the smoke plume.

On this page, I present the results of an unsupervised classification of the scene. I choose this type of classification for the following reasons:

1. When working in an unknown area, an unsupervised classification (clustering) shows how the data group "naturally" and with the expertise of a remote sensing specialist, this information could be harnessed to conduct a supervised classification (using machine learning or not) and establish the classes presenting the more differentiated spectral signatures.

2. The calculated clusters can be directly using as training areas for a supervised classification.

3. Hardware constraints forced me to use the classification requiring minimum input (spectral signatures calculation and display were showing important lag) from the user and minimum computation power (machine learning algorithms are power hungry).

Figure 6 shows the direct output of the unsupervised classification with interpretation of the different clusters. Figure 7 uses the same output but showing how the clusters can be repurposed as basic classes for a supervised classification. If it was not for the hardware constraints, I would have performed a classification using a machine learning algorithm which takes into account the texture of the training area (e.g. present in L3Harris ENVI software), allowing a better separation between ground and smoke.

To conclude, Figures 8 and 9 are simple index calculation to quantify the health of the vegetation (NDVI, Fig. 8) and the water present in the soil (NDWI, Fig. 9).

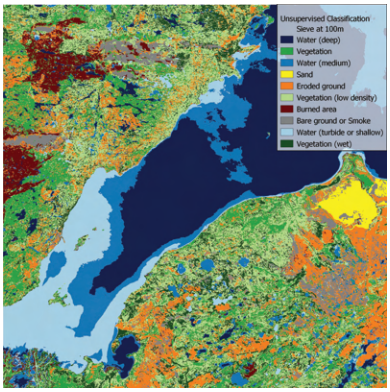

Figure 6: Results of unsupervised classification using 10 clusters.

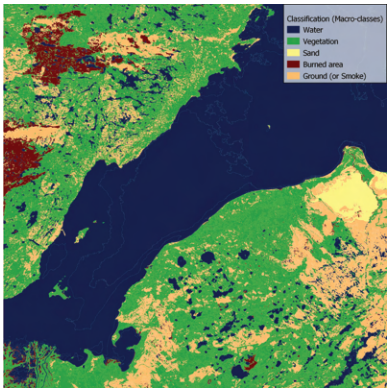

Figure 7: Interpretation in macro-classes of the clusters of the unsupervised classification.

Figure 8: Normalized difference vegetation index (NDVI).

(B8-B4) / (B8+B4)

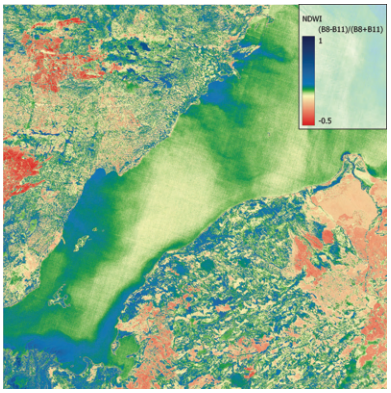

Figure 9: Normalized difference water index (NDWI).

(B3-B8) / (B3+B8)