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LOOKNorth

Project

Development of Remote Sensing Techniques for Regional Reclamation Monitoring of Peatlands in Alberta

Report

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Acronyms and Abbreviations

ABMI - Alberta Biodiversity Monitoring Institute

AEP - Alberta Environment and Parks

AHFP - Alberta Human Footprint

AISA - Airborne Imaging Spectrometer for Applications

AMW - Alberta Merged Wetlands Inventory

AVI – Alberta Vegetation Inventory

EnMAP – Environmental Mapping and Analysis Program

ENVI - ENvironment for Visualizing Images

ESA – European Space Agency

GIS - Geographic Information System

GPS - Global Positioning System

IRECI - Inverted Red-Edge Chlorophyll Index

K-means - Unsupervised Classifier

LAI – Leaf Area Index

LiDAR - Light Detection And Ranging

LSD - Legal Subdivision

MCARI2 - Modified Chlorophyll Absorption Ratio Index - Improved

MESMA - Multiple Endmember Spectral Mixture Analysis

MNF - Minimum Noise Fraction

NDVI - Normalized Difference Vegetation Index

NIR - Near Infrared spectral region

NRCan - Natural Resources Canada

OSE - Oil Sands Exploration

RS - Remote Sensing

SNAP - Sentinel Application Platform

SWIR - Shortwave Infrared spectral region

VI – Vegetation Index

VIS - Visible spectral region

ZM - Zarco and Miller Index

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Executive Summary

Assessing condition of reclaimed wellsites in wetlands usually involves intensive field visits that are often constrained by the human and economic resources available. Field surveys are maybe one of the most accurate way to characterize these sites but they are mainly effective in small areas and are not manageable when regular monitoring is required at a large scale. The scope of this work is to assess the value of hyperspectral remote sensing technologies for mapping vegetation condition in a number of reclaimed or like-reclaimed wetlands in Alberta in support of field-based assessments. A set of methods to derive information related to vegetation composition and health from remote sensing data is investigated. Furthermore, Hyperspectral technologies were also assessed against spaceborne multispectral remote sensing data.

Two flight lines of the AISA airborne hyperspectral data acquired at 2-meter spatial resolution in August 2013 over the Stoney Long Lake area forms the foundation of this study. Field data related to vegetation composition and fractional cover were collected in July/August of 2014 and 2015 in a set of wellsites and adjacent areas. Furthermore, Sentinel-2 multispectral data acquired at a 10/20-meter spatial resolution were collected over the Stoney Long Lake area in August 2016. Assessment of Sentinel-2 data was also conducted in the MATRIX study area, where ground measurement were collected across a range of natural and project disturbances related to seismic lines and oil sands exploration pads.

The K-means unsupervised classification was applied to AISA and Sentinel-2 data to map landcover types in the selected study areas. A set of landcover classes were determined based on visual interpretation of remote sensing data, Google Earth and StreetView. Furthermore, the Multiple Endmember Spectral Mixture Analysis (MESMA) was applied to the AISA data to determine fractional cover at a sub-pixel level for a set of vegetation and background targets. Accuracy assessment was conducted for Sentinel-2 and AISA landcover maps using ground data over the MATRIX site, and a set of validation data extracted from orthophos for the Stoney Long Lake due to a limited size of ground measurement over the latter site. In addition, fractional cover per landcover type in wellsites and control adjacent areas was extracted for each of AISA and Sentinel-2 in the Stoney Long lake area and compared to ground data.

Hypespectral narrow-band and multispectral broad-band indices such as NDVI, MCARI2, ZM, and IRECI were derived using AISA and Sentinel-2 data to assess vegetation condition within wellsite and adjacent areas in the Stoney Long Lake area.

Landcover classification using K-means was achieved with moderate to high accuracies using the 2013 AISA data, except for grass/herbaceous and black spruce classes depending on the AISA flight lines assessed. Different types of misclassification errors due to confusion between classes were observed. Shaded areas in wellsites and adjacent areas tends to be classified as water or conifers. Open areas dominated by wetland background tend to be classified as black spruce. Some confusion was also observed between trees and shrubs. Moderate to high accuracies were also achieved using Sentinel-2 data over the Stoney Long Lake and MATRIX study areas. The classes having the lowest accuracies differs between the two study areas. Low accuracies were

observed in white spruce, deciduous and regeneration classes. In the Stoney Long Lake, the average fractional cover for the 45 wellsites in wetland areas was found about 0.5 for grass/herbaceous with an average fractional cover of 0.5. The average fractional cover for shrub and black spruce was 0.13 while it equals 0.1 for bareground/builtup. In adjacent areas, vegetation composition included black spruce, deciduous, shrub, and grass/herbaceous with average fractional cover values of 0.5, 0.15, 0.10, and 0.10 respectively.

Some of the causes behind classification errors include class labeling in the K-means classification process using visual interpretation, and assigning a landcover class to test sites based on the interpretation of ground measurements. The K-means classification seems to identify the same landcover classes observed in the field. However, quantifying the agreement between the measured and observed fractional cover was not achievable due to conceptual differences in the ground- and remote-sensing-based methods used. In addition, errors in wellsite boundaries delineation and discrepancies between the areas sampled on the ground and the one assessed in the remote sensing products all prevent a quantitative measure of the agreement between mapped and measured fractional cover.

Compared to K-means, MESMA classification revealed a number of issues such as unclassified pixels scattered throughout the mapped area, and larger classification errors. Deciduous are overestimated at the expense of shrubs and up to 30 % of wellsite and control areas were unclassified. The image-based selection of endmember is possible source of errors due to the lack of pure pixels and/or the unrepresentativeness of the endmember spectral variability.

Assessment of vegetation condition using vegetation indices was conducted for both AISA and Sentinel-2 data based on a spatial subset of the Stoney long lake that was not affected by the 2016 wildfire. NDVI, MCARI2 and ZM vegetation indices were calculated using the AISA hyperspectral data. MCARI2 is more sensitive than NDVI to vegetation biomass and tend to show a wider variation range suggesting MCARI2 is a better indicator of revegetation progress. For a similar MCARI2 magnitude, the ZM index was found to be different between vegetation communities, which could be due to inherent variations in chlorophyll content between these communities. Differences in the ZM and IRECI indices were observed within and between wellsites and could be attributed to the chlorophyll variation between different vegetation communities and/or other factors such as senescence or stress.

Difference in spatial resolution between AISA and Sentinel-2 resulted in a high proportion of shaded pixels in the former, and mixed pixels in the latter, both causing misclassification errors. Furthermore, landcover type with low fractional cover tends to be underestimated in Sentinel-2 data. Assessment of chlorophyll-related indices also suggested the Sentinel-2 IRECI vegetation index to be less sensitive than ZM. Possible causes of the differences observed between AISA and Sentinel-2 could be a reduction in vegetation productivity due to senescence, disturbance, vegetation stress and/or inconsistency between AISA and Sentinel-2 data due to differences in their spectral sampling and resolution.

1. Background

Vegetation composition, its abundance and distribution as well as vegetation productivity and stress are examples of some of the information relevant for a sustainable management of wetlands. Traditionally, this type of information is gathered through intensive field visits that are often constrained by the human and economic resources available. Although very accurate and effective in small areas, field-based assessments remain very limited for a regular large-scale monitoring as this process is time-consuming and can suffer from poor site-accessibility. Overcoming such limitations has been the ultimate goal pursued in remote sensing studies arising questions such as:

i) What type of information is retrievable from Remote Sensing (RS)?

ii) Which type of sensors provides an appropriate accuracy?

iii) What is the best method to extract such information?

A number of remote sensing studies (Lee and Lunetta 1996; May et al. 1997; Harvey and Hill 2001; Nagler et al. 2001; Ozesmi and Bauer 2002; Yang 2007) have focused on mapping wetland vegetation, because it represents an important component of this ecosystem and changes in its composition and condition can be a sign of wetland degradation (Dennison et al., 1993). Discrimination of vegetation communities has been investigated using multispectral and hyperspectral remote sensing technologies. The use of spaceborne multispectral data (e.g., Landsat, SPOT) for discriminating vegetation types in wetlands was relatively successful depending on the complexity of the vegetation composition, its spatial variability and the level of detail pursued (Johnston and Barson, 1993; Harvey and Hill, 2001; McCarthy et al., 2005). While discrimination of shrubs and meadow was better achieved with Landsat TM than SPOT, both sensors were found to be not effective in mapping meadow subtypes (May et al., 1997). Spatial resolution and the number and width of spectral bands of such sensors are considered one of the major reasons for their poor performance. In fact, a 20/30-m pixel size may encompass more than one type of vegetation, resulting in species mixture that would require a finer spatial resolution or advanced algorithms for a better discrimination of vegetation composition. Compared to multispectral remote sensing, the use of hyperspectral sensors has been found to considerably improve species discrimination due to the large number and narrow bands they offer (Vaiphasa et al. 2007; Schmidt and Skidmore 2003; Li et al. 2005; Wang et al. 2007). Most of these studies identified the red-edge, a spectral region sampled by hyperspectral sensors, as a critical parameter to capture the spectral variation in wetland vegetation. Finally, combining spectral and structure/topography-related information as provided by LiDAR remote sensing was also found valuable for improving species discrimination (Zhang, 2014). While most efforts were oriented towards mapping vegetation composition, the benefits of remote sensing technologies for assessing wetland-vegetation health are still unknown. The use of narrow spectral indices derived from hyperspectral data for mapping vegetation stress has been widely applied in agriculture and forested areas. However, this aspect still needs to be investigated for wetland vegetation.

The combined use of hyperspectral and LiDAR remote sensing for mapping vegetation condition in reclaimed wetland promises to be of value and needs to be demonstrated. Having access to large-scale information about vegetation composition, health and stress would facilitate the assessment of wetland reclamation efficiency and enhance reclamation assessment in the field. Within this context, the scope of this work is to assess the value of hyperspectral remote sensing technologies for mapping vegetation condition in a number of reclaimed or like-reclaimed wetlands in Alberta in support of field-based assessments. Three main objectives are pursued including:

- Development of hyperspectral technology to retrieve information related to vegetation type and condition in reclaimed wetlands;
- Validation of the developed procedures on revegetated areas resulting from several reclamation strategies;
- Performance assessment of the developed hyperspectral technology against multispectral technology

2. Methodology

Two study areas were selected due to the availability of ground and remote sensing data over these areas. The Stoney Long lake study area was part of the airborne hyperspectral mission championed by Natural Resources Canada (NRCan) in 2012/2013 where AISA airborne hyperspectral, Light Ranging Detection (LiDAR) and ortho-photos were acquired. In addition, ground data collected in summer of 2014 and 2015 in reclaimed wellsites and undisturbed adjacent areas were also available through Circle T Consulting. The second study area encompasses the MATRIX Solutions field plots where ground measurements were collected in summer 2016. A spaceborne Sentinel-2 scene was acquired over both study areas in August 2016. Figure 1 illustrates the locations of the selected study areas overlaid on a Google Earth baseline image.

The methodology development addresses the following three aspects:

- Identification of a classification method for mapping vegetation composition
- Assessment of spectral indices for mapping vegetation health
- Intercomparison of airborne hyperspectral and spaceborne Sentinel-2 data for mapping vegetation composition and health

While the above mentioned aspects were all addressed for the Stoney Long Lake, only the first one was addressed for the Matrix Solutions study area.

Figure 1: Location of the Stoney Long Lake and MATRIX study areas

2.1. Mapping Vegetation Composition

Two different classification techniques were selected to map vegetation composition. The first technique is a pixel-based unsupervised classification that relies on a pattern recognition process. Unsupervised classification uses a similarity measure to organize the remote sensing data in a series of clusters that are spectrally separable. The k-means clustering algorithm was applied to the data using 100 clusters and 50 iterations using the ENVI image processing software. The resulting clusters were successively merged to produce a set of landcover-type classes that were labeled using visual interpretation of orthophotos, Google Earth images and/or street view. The landcover classification schemes used for both Stoney Long Lake and MATRIX study areas are summarized in Table 1. Eight and seven classes were identified for the Stoney Long study area using AISA and Sentinel-2 data respectively and nine classes were defined for the MATRIX study area using Sentinel-2 data.

Table 1: Landcover classes adopted for Stoney Long Lake and MATRIX study areas using AISA, and Sentinel-2 data.

Stoney Long Lake		MATRIX
AISA	**Sentinel-2**	**Sentinel-2**
Grass/Herbaceous	Grass/Herbaceous	Grass/Herbaceous
Shrub	Shrub	Shrub
Bareground	Bareground	Bareground/Builtup
Water	Water	Water
Deciduous	Deciduous	Deciduous
Black Spruce	Black Spruce	Black Spruce
White Spruce	Burned	Jack Pine
Conifer 1		Wetland Background
		Regeneration

The second technique is the Multiple Endmember Spectral Mixture Analysis (MESMA). Contrary to the unsupervised classification which basically maps the dominant target within a pixel, MESMA is a sub-pixel classification that can provide the abundance of multiple targets within a pixel. MESMA models the pixel reflectance as the sum of the reflectance values of all pure targets also known as endmembers (e.g., soil, grass, water etc…) and their corresponding shadow within a pixel, weighted by their fractional cover. The spectral mixture model is formulated as following:

$$\boldsymbol{R_{pixel}} = \sum_{\boldsymbol{B_i=1}}^{\boldsymbol{N}} \boldsymbol{\rho_i} * \boldsymbol{f_i} + \boldsymbol{\rho_{Shadow}} * \boldsymbol{f_{Shadow}} + \boldsymbol{\epsilon}$$

where $\boldsymbol{R_{pixel}}$ is the pixel reflectance, $\boldsymbol{\rho_i}$ is reflectance of endmember i, $\boldsymbol{f_i}$ is the fractional cover of endmember i, $\boldsymbol{\rho_{Shadow}}$ is the shadow reflectance, $\boldsymbol{f_{Shadow}}$ is the shadow fractional cover , ϵ is a residual error term and N is the number of enedmembers within a pixel.

In addition to shadow, three endmember categories were defined including non-woody vegetation, woody vegetation, and trees. Under each category a set of endmember targets (Table 2) were identified based on visual assessment of orthophotos, AISA and Sentinel-2 data. The endmember target selection aims to isolate pixels that are representative of a pure target. To refine the selection process, canopy closure derived from the 2013 airborne LiDAR data acquired over the Stoney Long Lake was examined to isolate forested areas with more than 80% canopy closure and minimize the understory and background contribution to the pixel reflectance.
To capture the spectral variability within endmembers, a set of endmember reflectance was extracted from each of the AISA and Sentinel-2 scenes for each endmember target and ingested in MESMA for these two sensors.
AISA and Sentinel-2 reflectance data as well as endmembers reflectance were normalized before executing MESMA. Fractional cover for each endmember target was constrained between 0 and 1 while the shadow maximum fractional cover was limited to no more than 0.8.

Table 2: Endmembers categories and corresponding endmember targets identified based on visual inspection of remote sensing data and LiDAR canopy closure.

Non-Woody	Woody	Tree
Bareground	Shrub	Deciduous
Grass/Herb		Black Spruce
Water		White Spruce
		Conifer-1
		Conifer-2

2.2. Mapping Vegetation Health

Spectral indices have been widely used from local to global scales to determine vegetation condition in various canopies such as crops, forests and grasslands (Jordan 1969, Rouse et al. 1973, Brown et al., 2000). These indices have been developed to infer information related to biophysical and biochemical variables such as leaf area index (LAI), fractional cover, biomass, canopy water content or chlorophyll content. Spectral indices are a set of mathematical formulations that involve different spectral bands located in the visible (VIS), near infrared (NIR) and shortwave infrared (SWIR) spectral regions. The location and width of the spectral bands that formulate the spectral index determines the index sensitivity to the canopy biophysical/biochemical variables of interest as well as their resistance to external factors such as soil background and atmosphere that can affect the consistency of the spectral indices values. A set of narrow-band and broad-band spectral indices that were developed and assessed in the literature with hyperspectral and Sentinel-2 data were selected (Zarco et al., 2001, 2005, Haboudane et al., 2004, Frampton et al., 2013).

The Normalized Difference Vegetation Index (NDVI, Rouse et al., 1974)

This index has been widely used in part because it requires only the red and NIR bands that are the most common bands in remote sensing systems. This index is sensitive to green vegetation and tends to increase in response to vegetation growth. However, NDVI does exhibit some saturation problems at high LAI values and sensitivity to soil background variations.

$$\boldsymbol{NDVI} = \frac{(\boldsymbol{\rho_{800}} - \boldsymbol{\rho_{670}})}{(\boldsymbol{\rho_{800}} + \boldsymbol{\rho_{670}})}$$

where $\boldsymbol{\rho_{800}}$ and $\boldsymbol{\rho_{670}}$ are reflectance values at 800 nm and 670 nm respectively

The Modified Chlorophyll Absorption in Reflectance Index 2 (MCARI2, Haboudane et al., 2004)

A narrow-band index that has been tested using hyperspectral data over closed crops to estimate LAI. The MCARI2 index tend to have a better responsiveness to LAI changes than NDVI, be less sensitive to chlorophyll content variations and soil background effects.

$$\boldsymbol{MCARI2} = \boldsymbol{1.5}[\boldsymbol{2.5}(\boldsymbol{\rho_{800}} - \boldsymbol{\rho_{670}}) - \boldsymbol{1.3}(\boldsymbol{\rho_{800}} - \boldsymbol{\rho_{550}})](\boldsymbol{2\rho_{800}} + \boldsymbol{1})^{\boldsymbol{2}} - (\boldsymbol{6\rho_{800}} - \boldsymbol{5\rho_{670}}) - \boldsymbol{0.5}$$

where $\boldsymbol{\rho_{800}}$, $\boldsymbol{\rho_{670}}$ and $\boldsymbol{\rho_{550}}$ are reflectance values at 800 nm, 670 nm and 550 nm respectively

The Zarco and Miller index (ZM, Zarco et al., 2001)

A narrow-band index that uses Red-Edge (RE) bands and was tested for chlorophyll content estimation in a closed forest using hyperspectral data (Zarco et al. 2001). In this study, The ZM was found to be correlated with leaf and canopy chlorophyll content and be one of the best indices for chlorophyll estimation at canopy level.

$$\boldsymbol{ZM} = \frac{\boldsymbol{\rho_{750}}}{\boldsymbol{\rho_{710}}}$$

where $\boldsymbol{\rho_{750}}$ and $\boldsymbol{\rho_{710}}$ are reflectance values at 750 nm and 710 nm respectively

The Inverted Red-Edge Chlorophyll index (IRECI, Frampton et al., 2013)

This index was originally developed for Sentinel-2 data and uses both sensor RE-bands (Frampton et al. 2013). IRECI was found to have a highly correlated relationship with canopy chlorophyll content and LAI using field dataset acquired in cultivated areas.

$$IRECI = \frac{(\rho_{783} - \rho_{665})}{\rho_{705}/\rho_{740}}$$

Where ρ_{783} , ρ_{665} , ρ_{705} and ρ_{740} are reflectance values at 783 nm, 665 nm, 705 nm and 740 nm respectively.

NDVI index was calculated for both AISA and Sentinel-2 data, while MCARI2 and ZM indices were computed for AISA and IRECI was derived for Sentinel-2.

2.3. Vegetation Composition Product Validation

Validation of the vegetation composition maps produced using hyperspectral and Sentinel-2 data relied on the ground data collected by Circle T Consulting and Matrix Solutions over the Stoney Long Lake and MATRIX study areas respectively. Because the Circle T Consulting data lacked exact GPS locations and sampled only a limited numbers of sites, additional validation data were collected for the Stoney Long Lake based on visual interpretation of orthophotos and Sentinel-2 data.

A confusion matrix was calculated for the vegetation composition maps produced and a set of accuracy measures were derived. The confusion matrix is a table that uses a set of validation data to determine for each landcover class the number of instances that are correctly or incorrectly mapped. The accuracy measures used are as following:

- Overall accuracy: the probability that pixels in the land-cover map have been correctly classified,
- Kappa coefficient: an accuracy measure that compensates for chance agreement
- User's accuracy: the probability that pixels for a given class of the land-cover map have been correctly classified, and
- Producer's accuracy: the probability that a given land-cover class on the ground was correctly represented in the land-cover map.

Before conducting the accuracy assessment, ground measurements for both study sites were reviewed and a landcover class as defined in Table 1 was assigned to each test site. In addition, fractional cover of remote-sensing-based landcover in wellsite and adjacent areas was compared to the ground data collected in the Stoney Long lake area. The adjacent control area was defined in the remote sensing data by a 30-meter buffer around the wellsite boundaries.

3. Data

3.1. Ground Data

3.1.1. MATRIX Study Area

The study area is located in the Connacher Oil and Gas Ltd's Great Divide Lease along Highway 63 about 77 km South of Fort McMurray. The area is characterized by peatland and upland ecosystems and contains regenerating ecosystems and unburned remnant as a result of the 1995 Mariana Lake fire. A field campaign was conducted in July 2016 at 448 vegetation plots through ground and helicopter visits and 61 camera monitoring stations. Data collection was conducted across a range of natural and project disturbances related to seismic lines and Oil Sands Exploration (OSE) pads. Tree species composition and canopy closure and height in canopy and subcanopy were measured within 10 m x 10 m plots. Common tree species found in the study area included trembling Aspen, balsam poplar, white birch, white spruce, black spruce and jack pine. Percent cover of ground components (e.g., bare soil, mulch, moss and sphagnum), sedge, willow, forbs, shrub, and grass species were measured in 2 m x 2 m plots. A subset of these data, where clear-sky Sentinel-2 data were available was selected. Figure 2 illustrates the location of the selected test plots overlaid on top of Google Earth image.

3.1.2. Stoney Long Lake Area

The study area is located in the Central Mixedwood natural subregion near Anzac Alberta. Test sites are distributed from Townships 82 to 86 between Ranges 6 and 8 west of the 4th Meridian and are mainly located in uplands ecosystems. A set of 33 research wellsites were reclaimed between 2004 and 2006 using different soil handling and woody debris management methods (Frerichs et al., 2017). Most of wellsites were 70 x 70 m in size where planted and non-planted treatments were established on each half of the wellsite respectively. In addition, various soil handling and woody material management such as spread of mulched or whole non-merchantable vegetation and windrow of whole slash vegetation were used. For each wellsite and within each treatment four plots of 10 m x 10 m or 12 m x 12 m depending on their reclamation year, were established. In July/August 2014 and 2015 vegetation assessment was conducted within five 1 m x 1 m quadrats randomly located in each plot. In addition control transects were also established about 25 to 30 from all four wellsites edges where five 1 m x 1m quadrats were set 15 to 20 meter apart along each transect. Percent cover of ground component (e.g., bare soil, litter, woody debris, moss and lichen), forbs, shrubs, and tree species (e.g., trembling aspen, white spruce, black spruce, balsam poplar, white birch, tamarack) was visually estimated. Eight Legal Subdivisions (LSD's) covering ten wellsites were selected since they fall in the two AISA data flight lines assessed in this work (Figure 2).

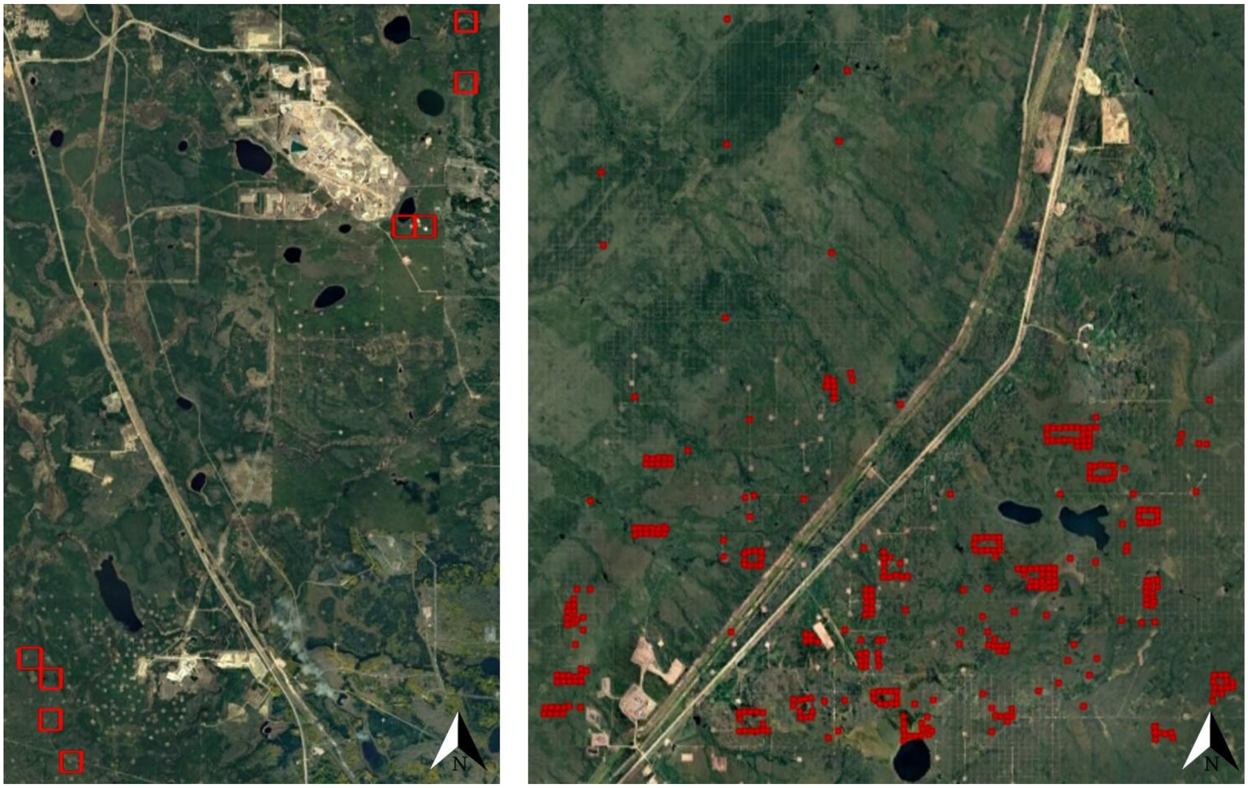

Figure 2: Selected LSD's for Stoney Long Lake (left) and point locations for MATRIX (right) study areas.

3.2. Remote Sensing Data

3.2.1. Airborne Data

The airborne AISA hyperspectral data acquired on August 23, 2013 over the Stoney Long Lake area were first inspected to determine any issues with data quality. Two flight lines where ground data were available, were selected and spatially subset (Figure 3). The hyperspectral data were delivered in surface reflectance format at a 2-meter spatial resolution and were projected in the 1983 North American Datum (NAD83) Universal Thematic Mapper zone 12 Northern hemisphere (UTM-12N). AISA data had 212 spectral bands ranging from 397 nm to 1007.8 nm. Inspection of the spectral profile for various targets showed inconsistency in the data beyond 880.67 nm. To minimize any impact of noise contamination in AISA data on the study results, the methodology development was restricted to the first 169 bands comprised within the 397nm – 880.67 nm range. The Minimum Noise Fraction (MNF) data-reduction process was applied to the AISA surface reflectance data to remove inherent noise and data redundancy. The first 20 MNF bands were selected as they contain most of the data information and less noise than in the bands beyond the 20th MNF band. An inverse MNF process was also applied to the first 20 MNFs to reconstruct reflectance data with minimum noise. The unsupervised classification was executed on the first 20 MNF while the MESMA process was only applied to the inverse reflectance data. Orthophotos and LiDAR data simultaneously acquired with AISA data were also processed. Othophotos were mosaicked and used to support the selection of validation data, labeling process of the K-means classification and the selection of endmember spectra. The LiDAR data were processed using the LDV/FUSION software (McGaughey, 2016) to derive canopy closure. The endmember selection process was limited to pixels with an 80% canopy closure or higher.

3.2.2. Sentinel-2 data

Four 100 km x 100 km Sentinel-2 scenes with clear-sky conditions over the selected study areas were available in 2016 (Table 3). The August 30th scene, collected over both study areas was downloaded from the European Space Agency (ESA) Copernicus site for further processing (Figure 4 - top). Sentinel-2 raw data are acquired in 13 spectral bands with a spatial resolution of 10 m, 20 m and 60 m depending on the spectral band (Table 4). The scene projection was in the 1984 World Geodetic System (WGS1984) Universal Thematic Mapper zone 12 Northern hemisphere (UTM-12N). Sentinel-2 data were atmospherically corrected using the SEN2COR package embedded in the ESA SNAP image processing tool (http://step.esa.int/main/toolboxes/snap/). The surface reflectance data were produced for ten spectral bands (2-8A, 11-12) and resampled to 10-meter spatial resolution using the nearest neighbor method. Geometric accuracy of the Sentinel-2 scene using the National Road Network was less than half a pixel. Sentinel-2 surface reflectance data were reprojected to NAD83 and a spatial subset was extracted for each of the two study areas (Figure 4 - bottom).

Table 3: Sentinel-2 data availability over the Stoney Long Lake and MATRIX study areas in 2016

Acquisition Date	July 18th	August 30th	September 29th	November 15th
Stoney Long Lake	x	x	x	x
MATRIX	N/A	x	x	N/A

Table 4: Spectral and Spatial characteristics of Sentinel-2

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

3.3. Ancillary Data

The Alberta Merged Wetland (AMW) inventory available through Alberta Environment and Parks (AEP, 2016), and the 2014 Alberta Human Footprint (AHFP) database available through the Alberta Biodiversity Monitoring Institute (ABMI, 2014) were queried to determine the availability of these data over the two study areas. The 2014 AHFP provides a set of Geographic Information System (GIS) layers that delineates areas of anthropogenic activities such as wellsites, pipelines and seismic lines. The AHFP data were used to identify the location and boundaries of wellsites in the selected study areas. Furthermore, The AMW which provides a delineation of wetlands and their type, served as a basis for selecting wellsites located in wetland areas.

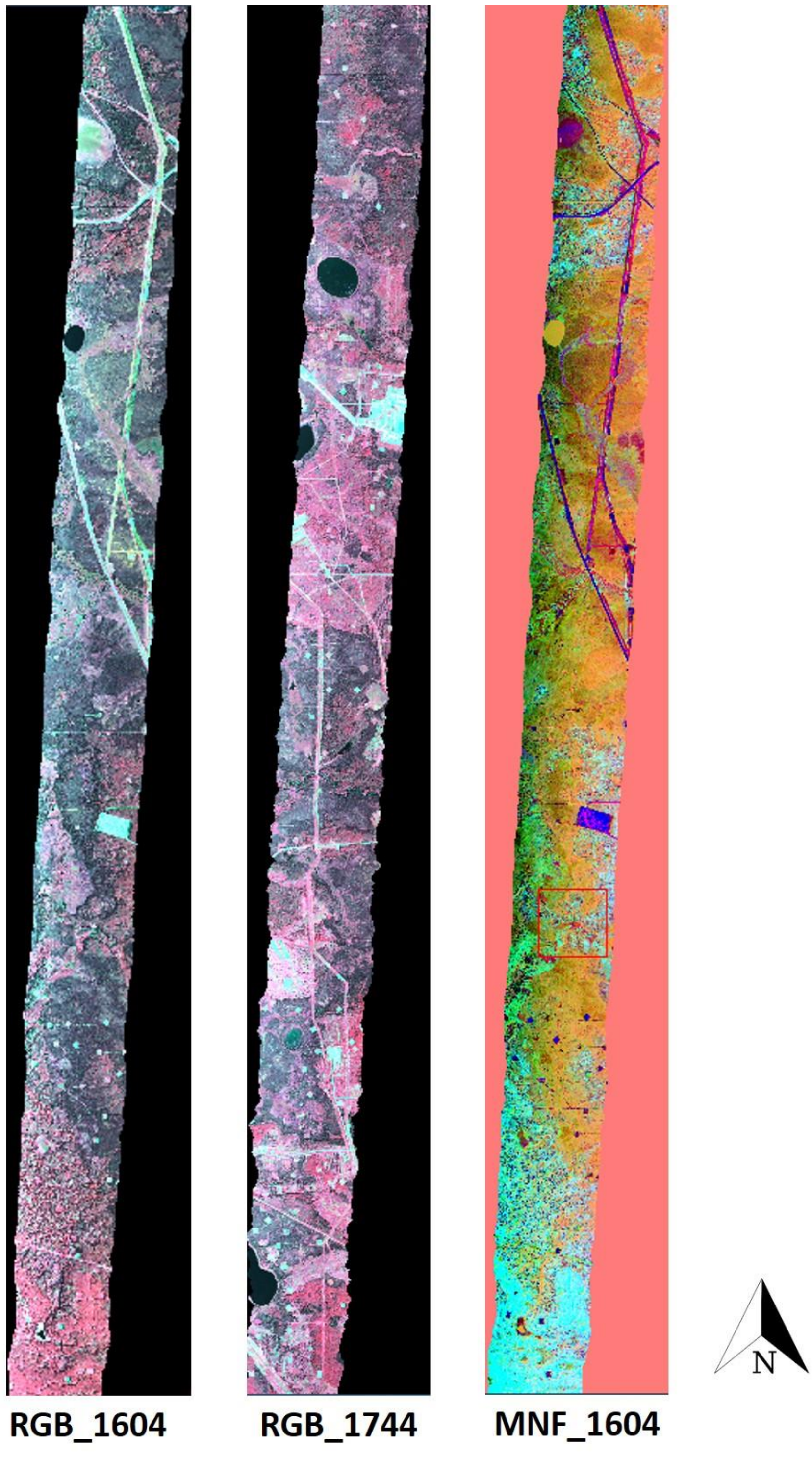

Figure 3: R(NIR), G (Red), B(Green) colour composites for the AISA fight lines 1604 and 1744 acquired on August 23rd, 2013 over the Stoney Long Lake area and the MNF R(MNF1), G (MNF2), B (MNF3) colour composite for flight line 1604.

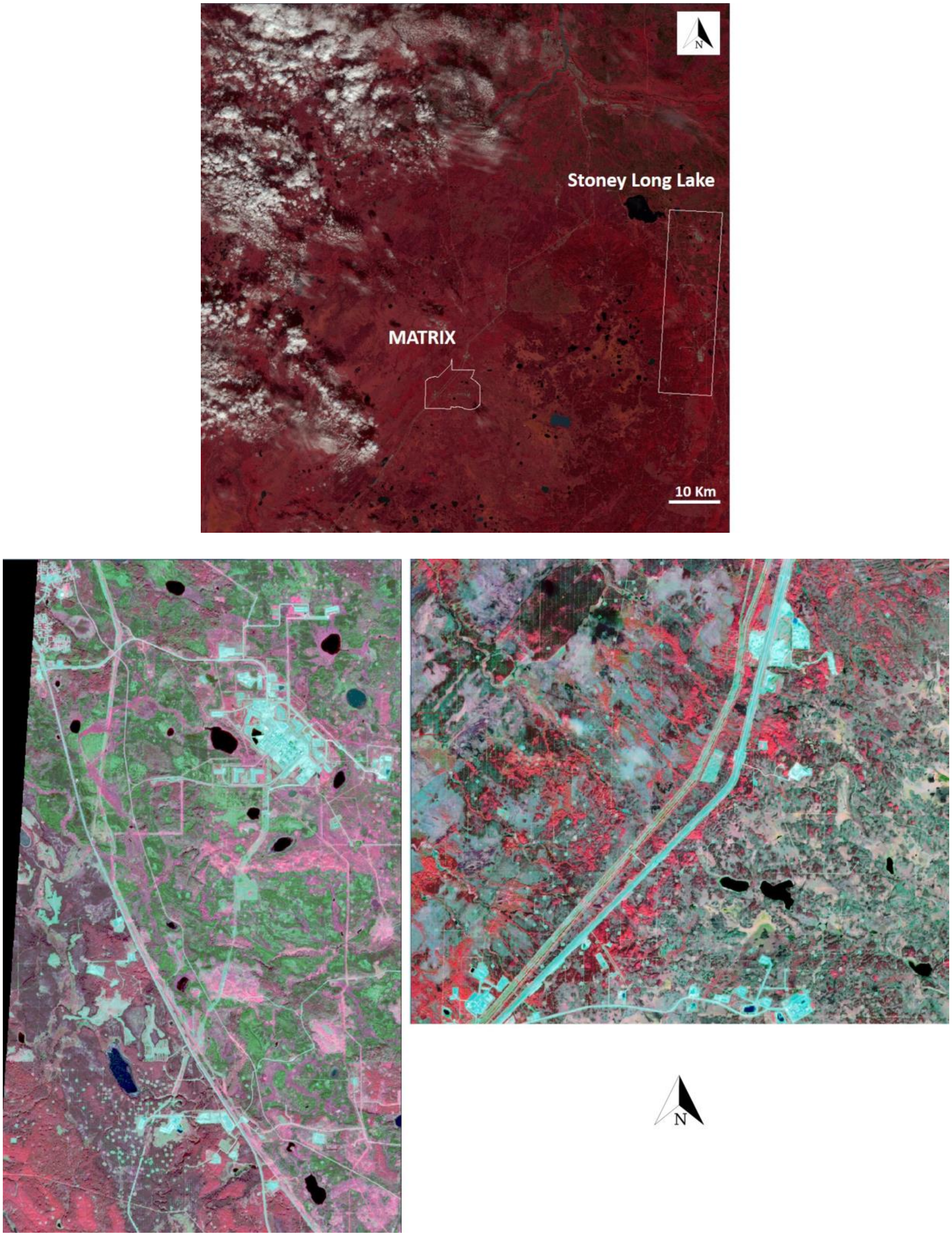

Figure 4: R(NIR), G(Red), B(Green) colour composites for the full Sentinel-2 scene (~ 100 km x 100 km – top) and subsets of the Stoney Long Lake (left - bottom) and MATRIX (right - bottom) acquired in August 30th, 2016

4. Results

4.1. Vegetation composition

The K-means results are discussed for both the Stoney Long Lake and MATRIX study areas. The MESMA results are reported only for AISA hyperspectral data.

4.1.1. Hyperspectral Unsupervised Classification

A landcover classification map was produced for each of the two 2013 AISA hyperspectral flight lines using the K-means unsupervised classifier (Figure 5). Eight land cover classes were identified including water, bareground/builtup, grass/herbaceous, shrub, deciduous, black spruce, white spruce and conifer-1. Identification of the tree species associated with the conifer-1 was not possible due to the lack of ground data and a low confidence in the visual interpretation of this class.

Accuracy assessment was conducted for each flight line using a set of validation data produce based on visual interpretation of orthophotos (Table 5). The overall accuracy for flight lines #1604 and #1744 were 72.3 % and 88.9 % and the Kappa coefficient was 0.67 and 0.86, respectively. Producer's accuracy was above 80 % for deciduous, bareground/builtup, grass/herbaceous, black spruce and conifer-1. Producer's accuracy for water was 71.2 % in #1641 mainly due to misclassification of eutrophic water as black spruce. Shrub producer's accuracy for both flight lines was moderate not exceeding 72 % partially due to its misidentification as grass and deciduous which seem to occur in open areas where there is a mixture of these classes as well as in senescent deciduous trees that seem to be common in both flight lines. White spruce producer's accuracy was less than 50% and seems to be confused with black spruce and to a lesser extent with deciduous and shrub especially in an open mixed stand. User's accuracy was moderate to high with values ranging from 67.7 % to ~ 100 % except for grass/herbaceous in #1477 and black spruce in #1604. In this case, user's accuracy was 49.6 % and 58.4 % respectively. Four examples of landcover types in wellsites and surrounding undisturbed areas are summarized in Figure 6 for four different areas. In this case, bareground/builtup, grass/herbaceous and shrub are common in wellsites while deciduous and black spruce are overall dominant in undisturbed adjacent areas.

Assessment of the AISA classification over the ten wellsites surveyed in 2014 and 2015 showed grass/herbaceous, shrub and deciduous classes occurring in all wellsites followed by conifer-1 present in five wellsites and water, black spruce and white spruce classes present in two sites (Figure 7). Bareground/builtup class was absent from all wellsites. For undisturbed adjacent areas, similar results were found with an increase in the number of sites where water, black spruce, white spruce and bareground classes were present.

Figure 7 summarizes the median, mean, minimum and maximum fractional cover of each landcover class for wellsites and adjacent areas respectively for the ten wellsites selected. Average fractional cover in wellsites was close to 0.43, 0.27, 0.19, and 0.07 for shrub, deciduous grass/herbaceous and black spruce respectively. Maximum fractional cover for these classes was 0.80, 0.48, 0.46 and 0.36 respectively. For undisturbed adjacent areas, average fractional cover was about 0.31, 0.47, 0.09, and 0.11 for these four classes respectively while it did not exceed 0.01 for white spruce and conifer classes. Finally, maximum values were 0.50, 0.73, 0.21, 0.57, 0.05 and 0.04 for shrub, deciduous, grass/herb, black spruce, white spruce and conifer-1 respectively.

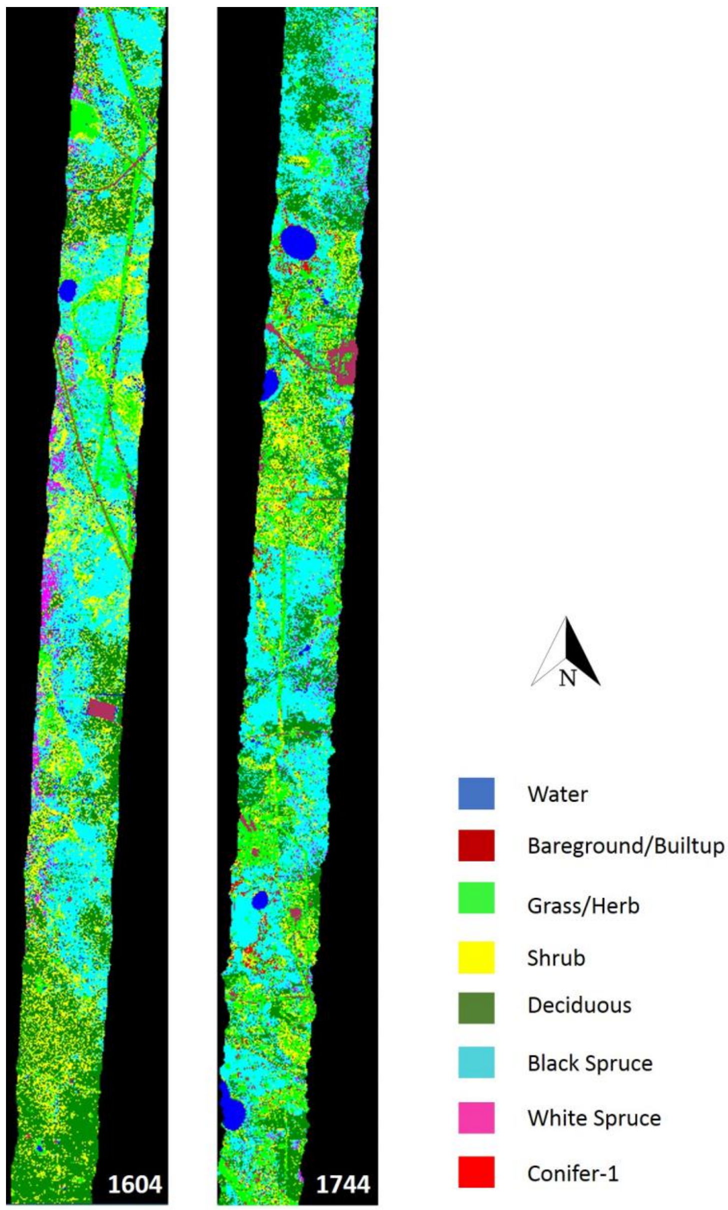

Figure 5: Landcover maps of the Stoney Long Lake area derived from AISA flight lines #1604 and #1744 using the K-means unsupervised classification.

Table 5: Accuracy assessment measures for the K-means classification maps of AISA #1604 and #1744 flight lines over the Stoney Long Lake area.

Landcover Class	**AISA-1604**		**AISA-1744**	
	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Deciduous	80.1	76.6	83.3	95.6
Bareground	91.8	99.8	98.1	99.5
Shrub	72.1	67.7	66.1	89.2
Grass/herbaceous	92.7	70.4	99.1	58.4
Water	71.2	94.1	99.1	99.5
Black Spruce	84.6	49.6	96.4	70.2
White spruce	42.0	86.9	48.0	95.7
Conifer-1			82.8	87.0
Overall Accuracy (%)	72.3		88.9	
Kappa	0.67		0.86	

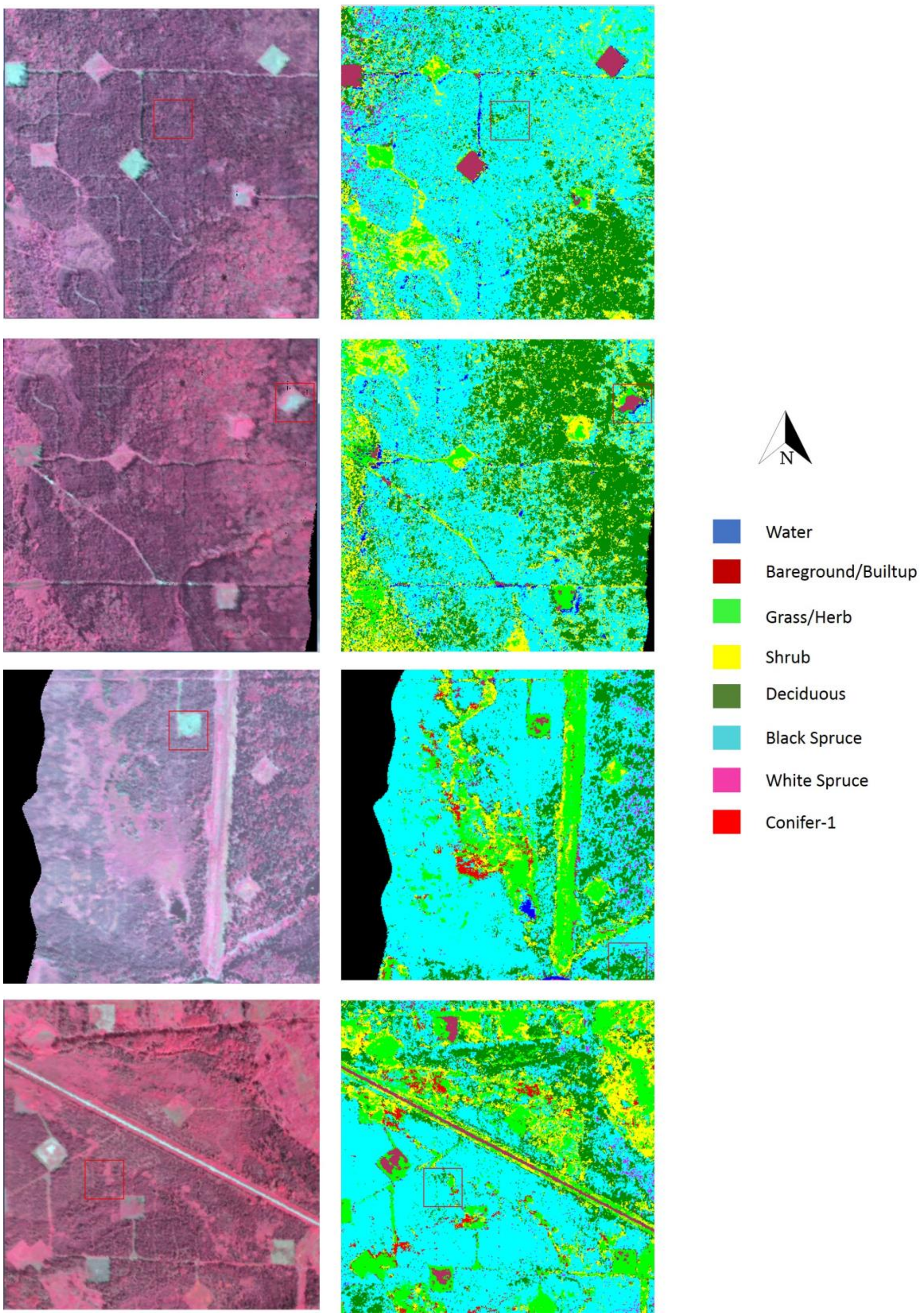

Figure 6: R (NIR), G (Red), B(Green) colour composite subsets of AISA data and their K-means landcover classification for the Stoney Long Lake area.

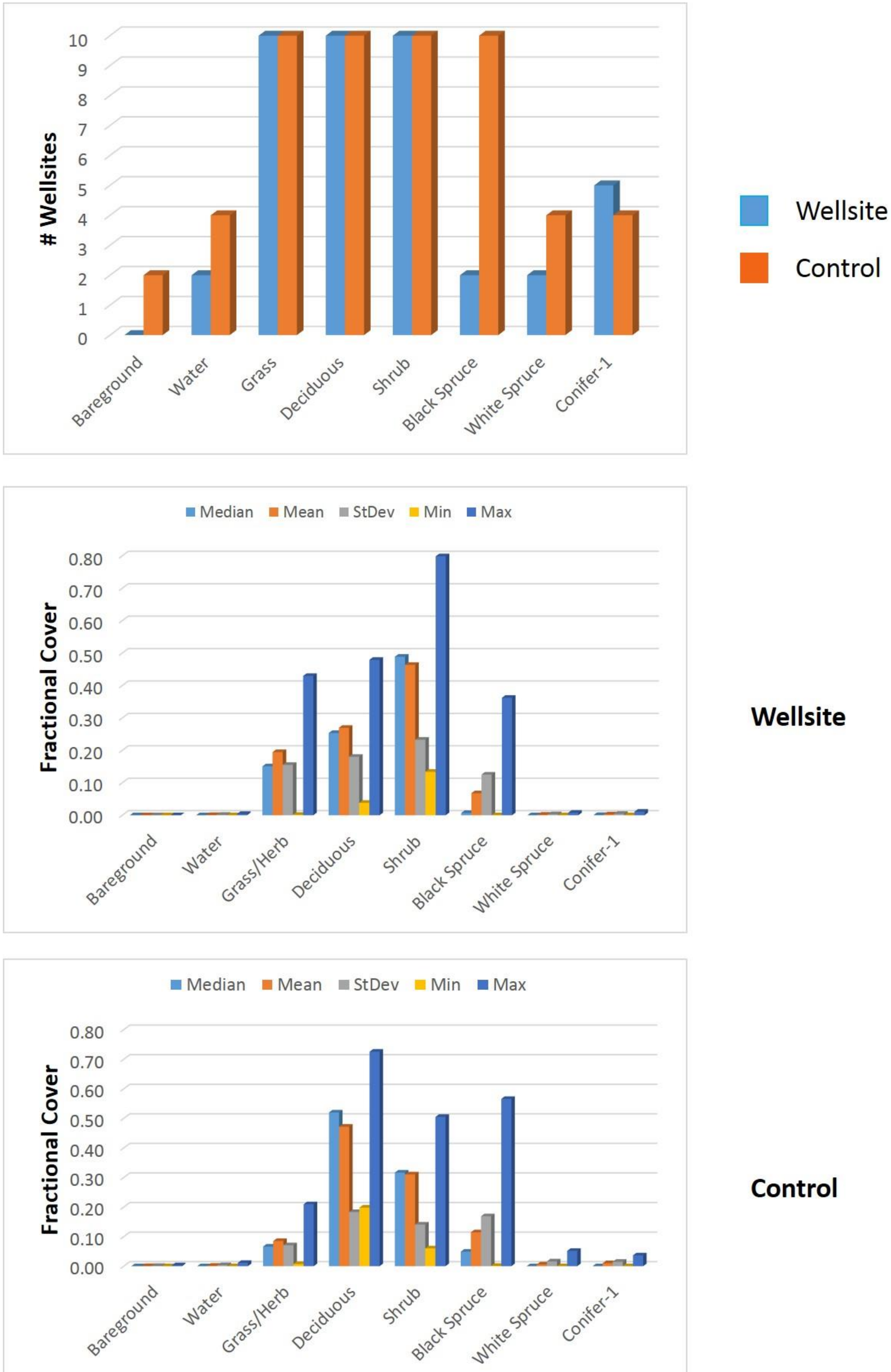

Figure 7: Occurrence of landcover type in ten wellsites and their adjacent areas (control) based on the AISA/K-means landcover map of the Stoney Long Lake area (top). Median, mean, minimum, and maximum fractional cover for the ten wellsite (middle) and control areas (bottom).

Because no geoghraphic coordinates were available for the surveyed wellsites, comparison of AISA fractional cover estimates to ground data excluded LSD's that covered more than one wellsite. Therefore, out of the ten wellsites located in the two AISA flight lines only seven were considered (Figure 8). The SPUD date and status associated with each of the seven wellsites are summarized in Table 6. Overall, both ground measurements and AISA estimates seems to identify grass/hebaceous, shrub, deciduous and black spruce as the most dominant classes. Differences between AISA estimates and ground data are partially due to the differences in the fractional cover definition used in each approach. While field fractional cover is independently estimated for each landcover class including areas of overlapping between different landcover classes, remote sensing based fractional cover correspond to projected areal coverage of each landcover class and overlapping areas are excluded. Consequently, the sum of fractional cover for all classes is equal to 1 in remote sensing-based estimates while it can exceed 1 in ground data. This is especially the case for the grass/herbaceous class where ground measurements were larger than AISA estimates in six wellsites with differences in fractional cover reaching up to 0.6. Similar results were observed for undisturbed adjacent areas with fraction cover differences in the [0.02, 0.4] range. For the shrub class, differences between ground measurements and AISA estimates did not exceed 0.04 for two wellsites. For the remaining five sites, fractional cover differences range from 0.07 to 0.44 and AISA overestimated ground measurements in two sites. For adjacent areas, differences in fractional cover were between 0.03 and 0.36 and ground measurements were larger in five sites. For the black spruce class, differences in wellsites were less than 0.02 except for wellsites # 5 and # 6 where differences were 0.08 and 0.23 respectively. In adjacent undisturbed areas, differences were between 0.05 and 0.40 for wellsite # 5 to # 7 with ground measurements larger than AISA estimates in two of these sites. Differences for the white spruce class were under 0.14 while they were under 0.05 for the conifer-1 class except for site #5 where ground measurement in wellsite was 0.86 higher than AISA estimate. In this case, ground data for conifer-1 was derived by summing fractional cover measurements for all coniferous species observed, with the exception of black spruce and white spruce.

Table 6: The SPUD date and status of the seven wellsites surveyed in the Stoney Long Lake areas

Welliste #	SPUD Date	Status
#1	13/02/2006	Abandoned
#2	15/02/2006	Abandoned
#3	31/01/2006	Abandoned
#4	06/03/2006	Abandoned
#5	19/01/2004	Abandoned
#6	16/01/2004	Abandoned
#7	25/01/2004	Abandoned

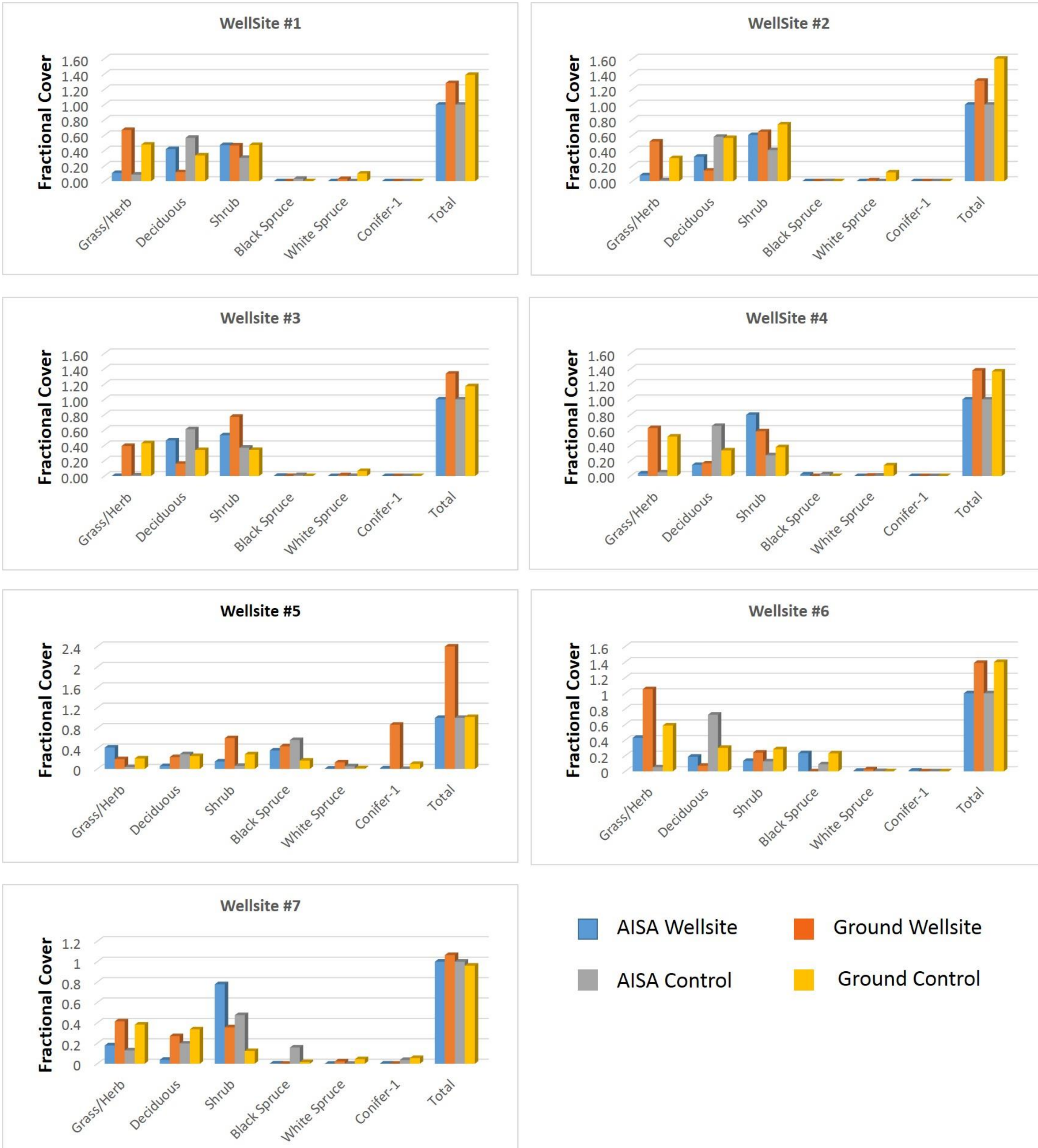

Figure 8: comparison of AISA fractional cover per landcover type to ground data in wellsite and adjacent areas (control) for seven wellsites surveyed on the ground in the Stoney Long Lake area.

4.1.2. Hyperspectral MESMA

A set of three abundance maps corresponding to the three endmembers categories defined, were produced for each of the two AISA flight lines. Subpixel fractional cover for background, shrub and tree endmembers categories were determined for ~ 95 % of each flight line and ~ 5 % remained unclassified. A preliminary assessment of the MESMA fractional cover estimates was conducted by first generating a majority abundance map where each pixel was labeled by the endmember target that had over 0.51 fractional cover. Endmember targets were then merged to produce a set of nine landcover classes: water, bareground/builtup, grass/herbaceous, shrub, deciduous, black spruce, white spruce, conifer-1, and conifer-2. The tree species for these last classes were not identified due to the lack of ground data and the low-confidence in the visual interpretation of orthophotos. Figure 9 illustrates two examples of the MESMA-based classification map, AISA colour composite and K-means classification map. The MESMA classification seems to be noisy due to scattered unclassified pixels. Furthermore it tends to map bareground in wellsites as water and misclassify deciduous areas as shrub. In addition, it seems to identify the conifer-2 class not mapped in the K-means classification.

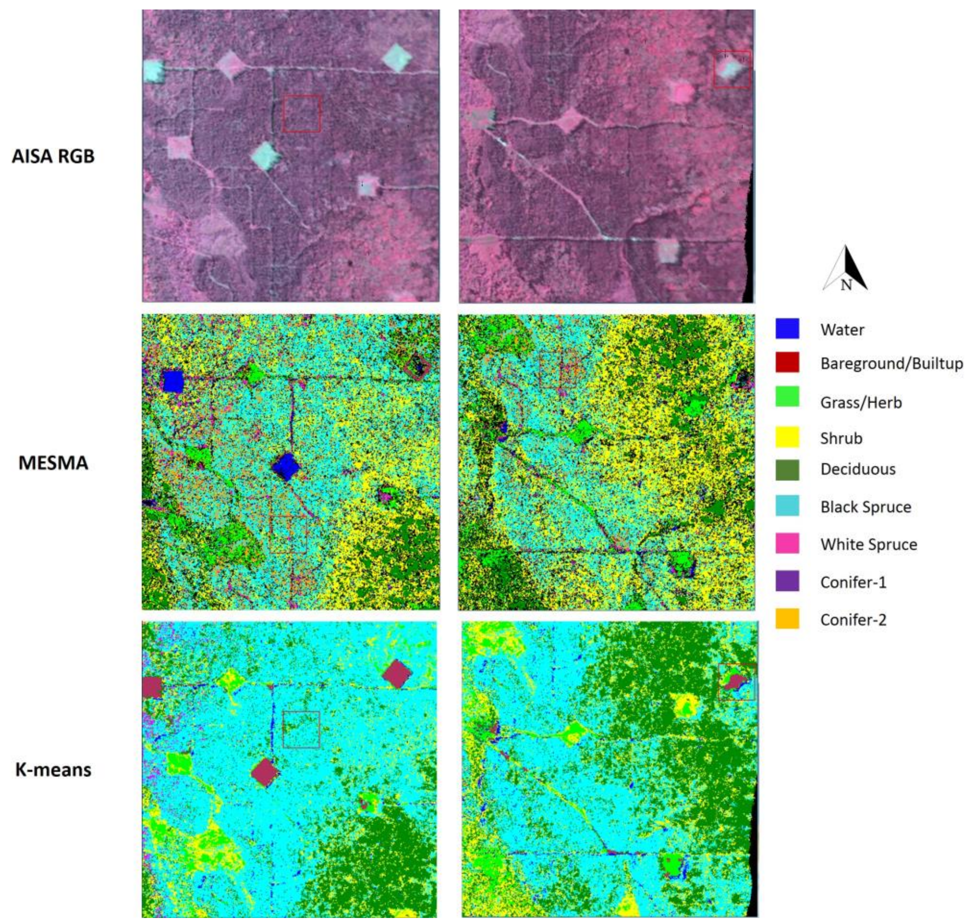

Figure 9: R (NIR), G (Red), B (Green) colour composite subsets of AISA data (top) and their MESMA (middle) and K-means (bottom) landcover classifications for the Stoney Long Lake area.

Assessment of the fractional cover estimates from the MESMA-based classification was conducted using ground data in surveyed wellsites and adjacent areas. Figure 10 shows the number of sites where the landcover classes were present as well as the median, mean, minimum and maximum values calculated using four sites located in the #1604 flightline. Unclassified pixels were found in all wellsites and adjacent areas. Dominant land cover classes in wellsites were grass/herbaceous, shrub and deciduous while for undisturbed adjacent areas all four conifer classes were also found. Deciduous class was dominant in all wellsites with fractional cover values ranging from 0.66 to 0.97 and an average value of 0.85. Similar results were found in adjacent areas with an average value of 0.56 and minimum and maximum values of 0.35 and 0.75 respectively. Shrub fractional cover did not exceed 0.05 in wellsites and was under 0.32 in adjacent areas with an average value of 0.17. Grass/herbaceous fractional cover was under 0.12 in all wellsites and adjacent areas. Unclassified fractional cover was between 0.02 and 0.27 with average values of 0.07 and 0.23 in wellsites and adjacent areas respectively.

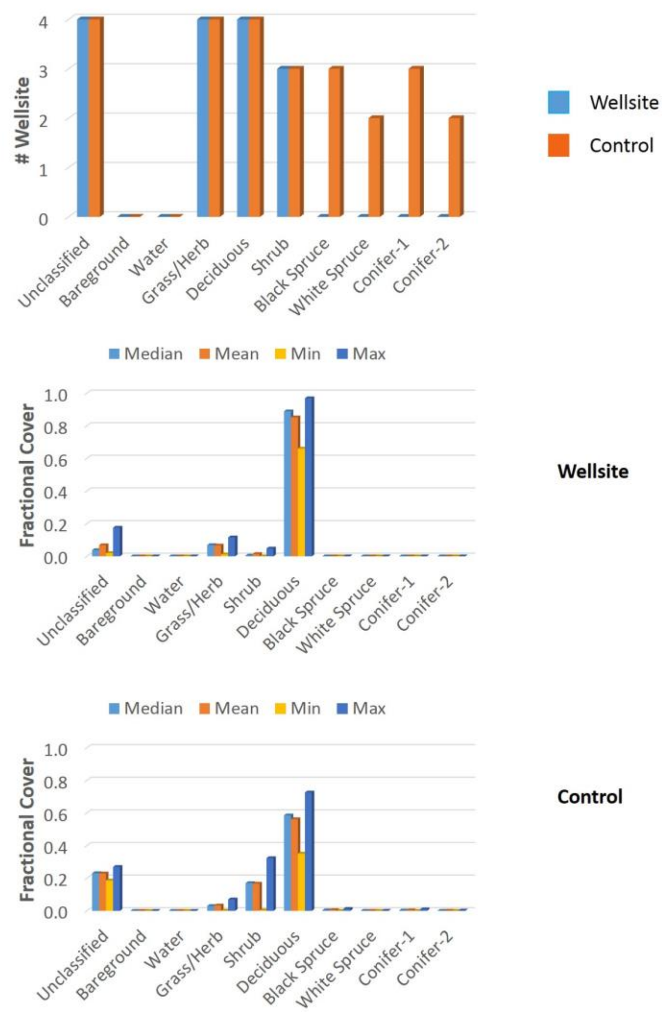

Figure 10: occurrence of landcover type in four wellsite and adjacent areas (control) in the Stoney Long Lake area based on MESMA landcover map of AISA #1604 (top). Median, mean, minimum, and maximum fractional cover for wellsite (middle) and control areas (bottom).

Figure 11 summarizes the fractional cover per landcover class for each of the four wellsites and adjacent areas together with K-means estimates and ground measurements. Compared to K-means, larger discrepancies were observed between MESMA estimates and ground data with an overestimate of deciduous fractional cover in the 0.5-0.8 range for wellsites and the 0.02-0.39 range for adjacent areas. Shrub fractional cover was underestimated using MESMA with differences from ground data ranging from 0.46 to 0.77 for wellsites and 0.05 to 0.65 for adjacent areas.

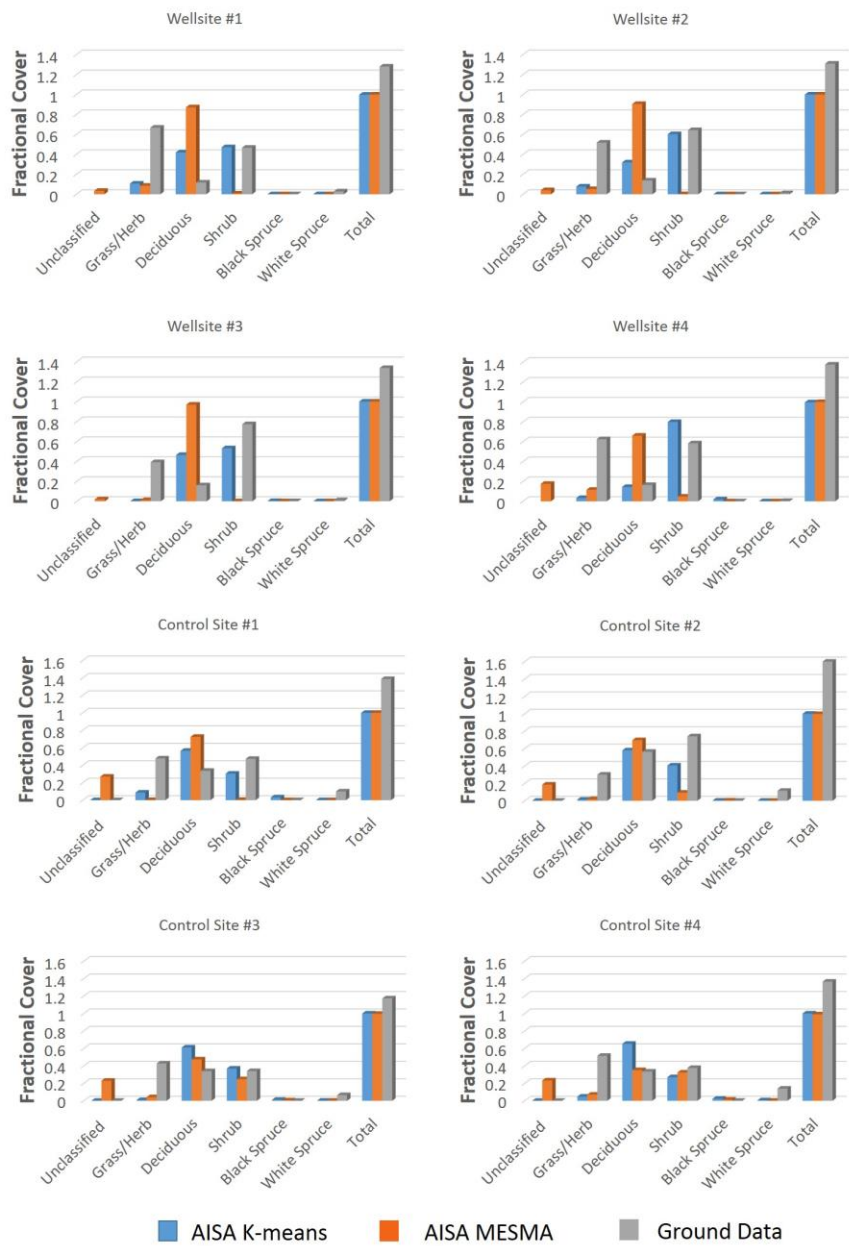

Figure 11: Comparison of AISA/MESMA fractional cover per landcover type to AISA/K-means and ground data in wellsite and adjacent areas (control) for four wellsites surveyed on the ground in the Stoney Long Lake area.

4.1.3. Sentinel-2 Unsupervised Classification

1- Stoney Long Lake Site

A landcover classification map was generated for the Stoney Long Lake area using the 2016 Sentinel-2 data and the K-means unsupervised classifier with seven landcover classes including water, bareground/builtup, grass/herbaceous, shrub, deciduous, black spruce and burned areas (Figure 12). Accuracy Assessment of the Sentinel-2 classification was conducted using a validation dataset selected based on visual interpretation of the Sentinel-2 scene (Table 7). Overall accuracy was 91.0 % and kappa coefficient was 0.89. For all classes with the exception of white spruce, producer's accuracy was above 81.5 % and user's accuracy was moderate to high with values in the 69.8 % -100% range. Accuracies for white spruce were very low not exceeding 3 % due to misclassification of this class as black spruce. A set of three examples is illustrated in Figure 13. Bareground/builtup, grass/herbaceous and shrubs were the most common landcover types present in wellsites while black spruce, deciduous and burned areas dominated the undisturbed adjacent areas.

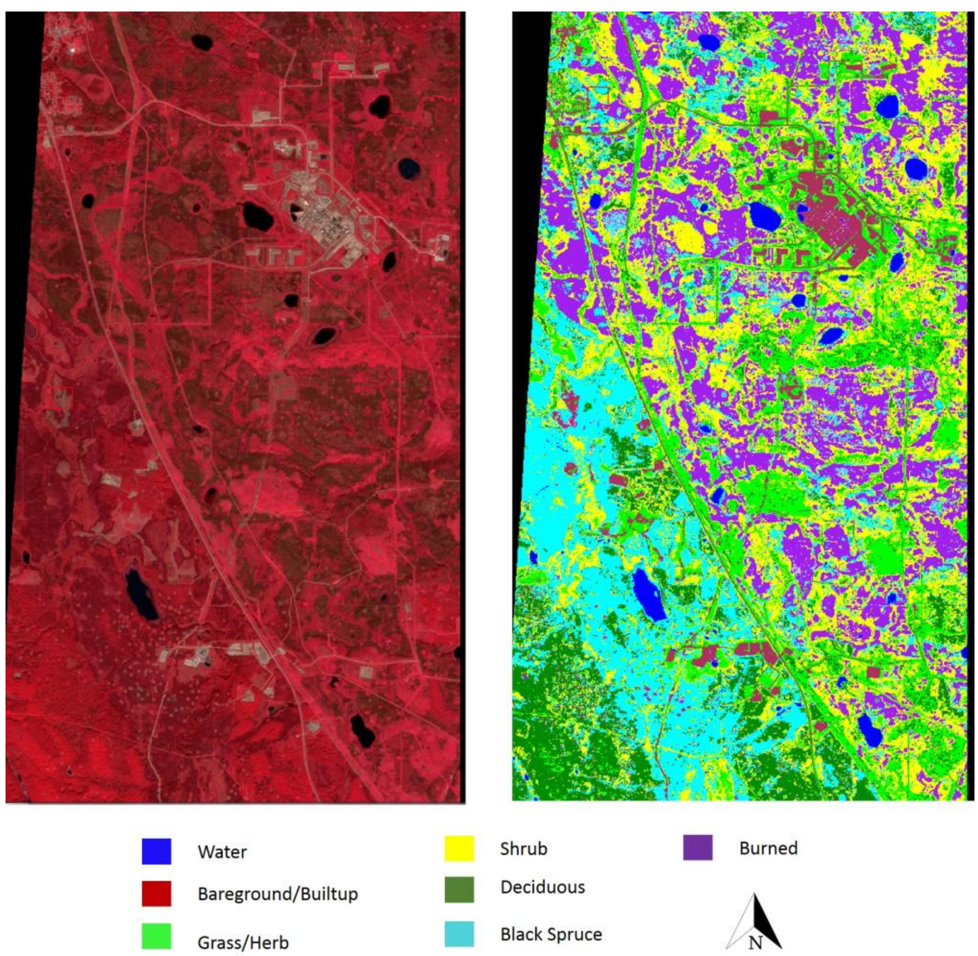

Figure 12: **R (NIR), G (Red), B (Green) colour composite of** Sentinel-2 and the Landcover map of the Stoney Long Lake area produced using the K-means unsupervised classification.

Table 7: Accuracy assessment measures for the K-means classification of Sentinel-2 data over the Stoney Long Lake area

Landcover Class	Sentinel-2	
	Producer's Accuracy (%)	User's Accuracy (%)
Deciduous	88.5	93.4
Bareground	89.9	100
Shrub	88.9	73.7
Grass/herbaceous	81.5	93.2
Water	99.5	89.6
Black Spruce	99.9	69.8
White spruce	0.6	2.6
Burned	99.9	89.3
Overall Accuracy (%)	91.0	
Kappa	0.89	

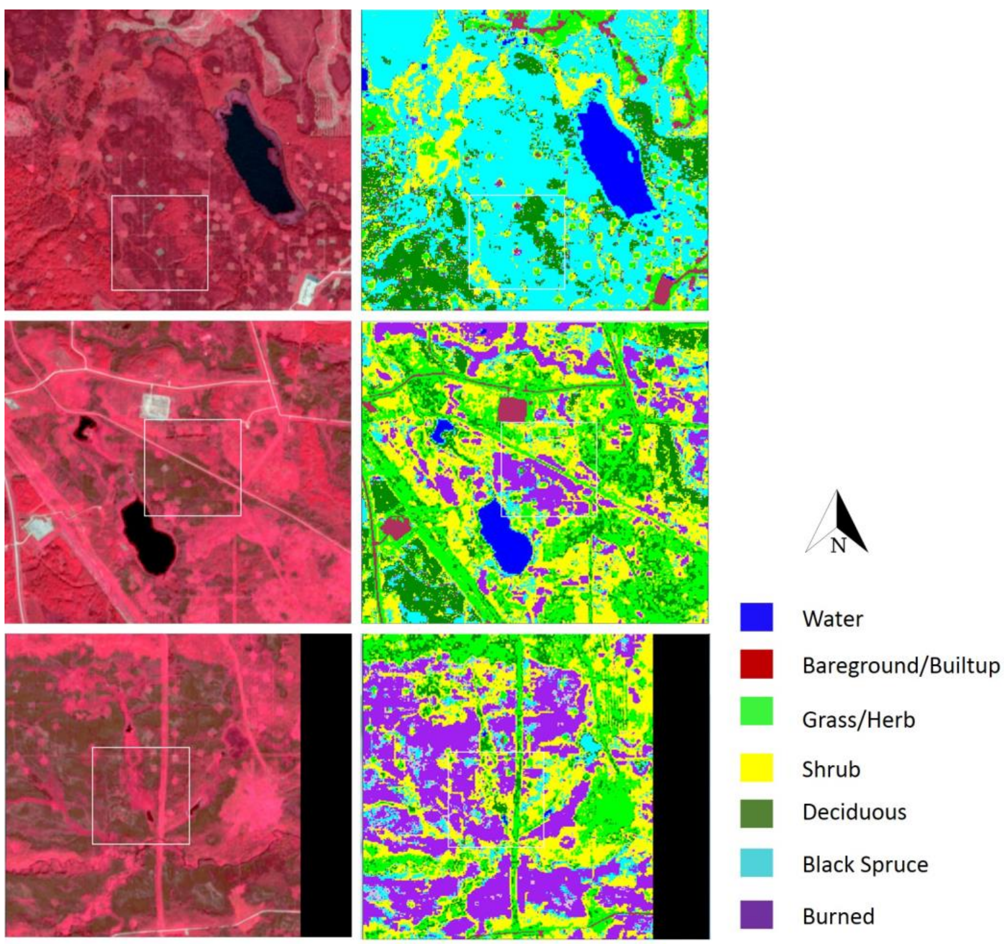

Figure 13: R (NIR), G (Red), B (Green) colour composite subsets of Sentinel-2 data and their K-means landcover classification for the Stoney Long Lake area.

For the ten sites where ground data were available, K-means classification identified deciduous in nine wellsites and grass/herbaceous and shrub classes in seven wellsites (Figure 14 - top). Black spruce and white spruce classes were present in five wellsites and burned areas in three. For adjacent areas, shrub, black spruce, and grass/herbaceous were present in 10, 9, and 7 sites respectively while deciduous, white spruce and burned classes occurred in 5 sites. The median, mean, minimum and maximum values of fractional cover for each landcover calculated for all 10 sites are shown in Figure 14. Shrub was dominant in both wellsites and adjacent areas with average values of 0.57 and 0.48 respectively and values ranging from 0.15 to 0.92. Deciduous fractional cover had an average value of about 0.20 in both wellsites and adjacent areas and values in the 0.03-0.55 range. For grass/herbaceous, the average fractional cover was 0.23 and 0.07 in wellsites and adjacent areas respectively and fractional cover values were not higher than 0.59 and 0.22 respectively. Burned fractional cover reached up to 0.69 with average values of 0.04 and 0.15 in wellsites and adjacent areas respectively. Black spruce fractional cover did not exceed 0.06 in wellsites and 0.28 in adjacent areas with average values of 0.02 and 0.08 respectively. Finally, white spruce had low fractional cover values not exceeding 0.07 in both wellsites and adjacent areas.

Sentinel-2 estimates of fractional cover were compared to ground data and AISA K-means estimates using four test sites that were not affected by the 2016 Fort McMurray fire (Figure 15). In wellsites, Sentinel-2 fractional cover for grass/herbaceous was closer to ground measurements than AISA estimates, with differences lower than 0.3. Conversely, in adjacent areas fractional cover differences from ground data of the two sensors were relatively similar, with values not exceeding 0.4. For the shrub class, absolute differences between Sentinel-2 fractional cover and ground measurements were within the 0.11 – 0.44 range for both wellsites and adjacent areas. Absolute differences of AISA estimates were overall smaller with values varying between 0.01 and 0.34. For deciduous, absolute differences of Sentinel-2 fractional cover from ground data ranged from 0.02 to 0.38. Sentinel-2 fractional cover was overall smaller than AISA estimates. For black spruce, Sentinel-2 fractional cover in adjacent areas was larger than ground data with up to a 0.28 difference, while for white spruce differences from ground data were within 0.10 in both wellsite and surrounding areas.

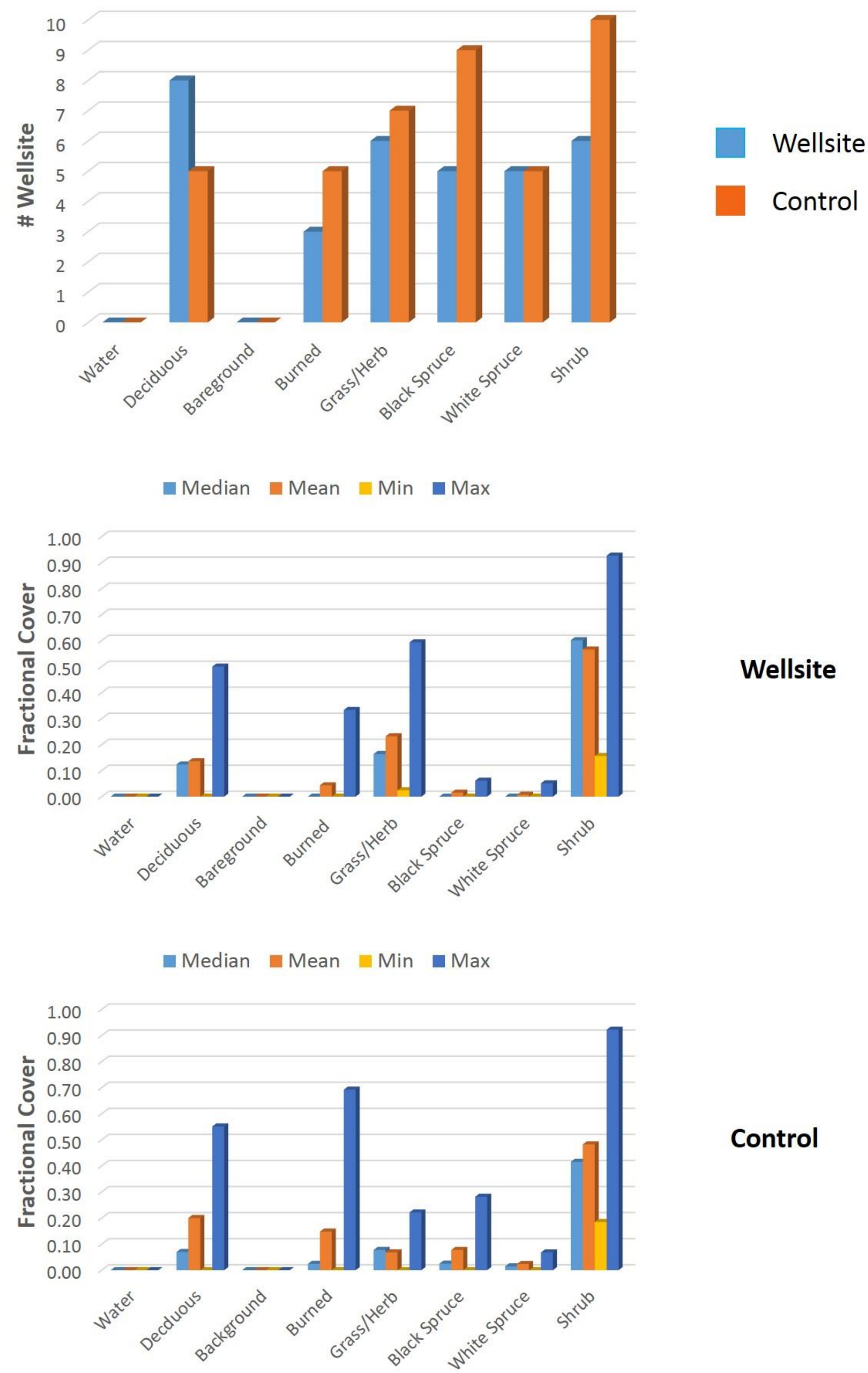

Figure 14: occurrence of landcover type in ten wellsites and their adjacent areas (control) based on Sentinel2/K-means landcover map in the Stoney Long Lake area (top). Median, mean, minimim, and maximum fractional cover per landcover type for wellsite (middle) and control areas (bottom).

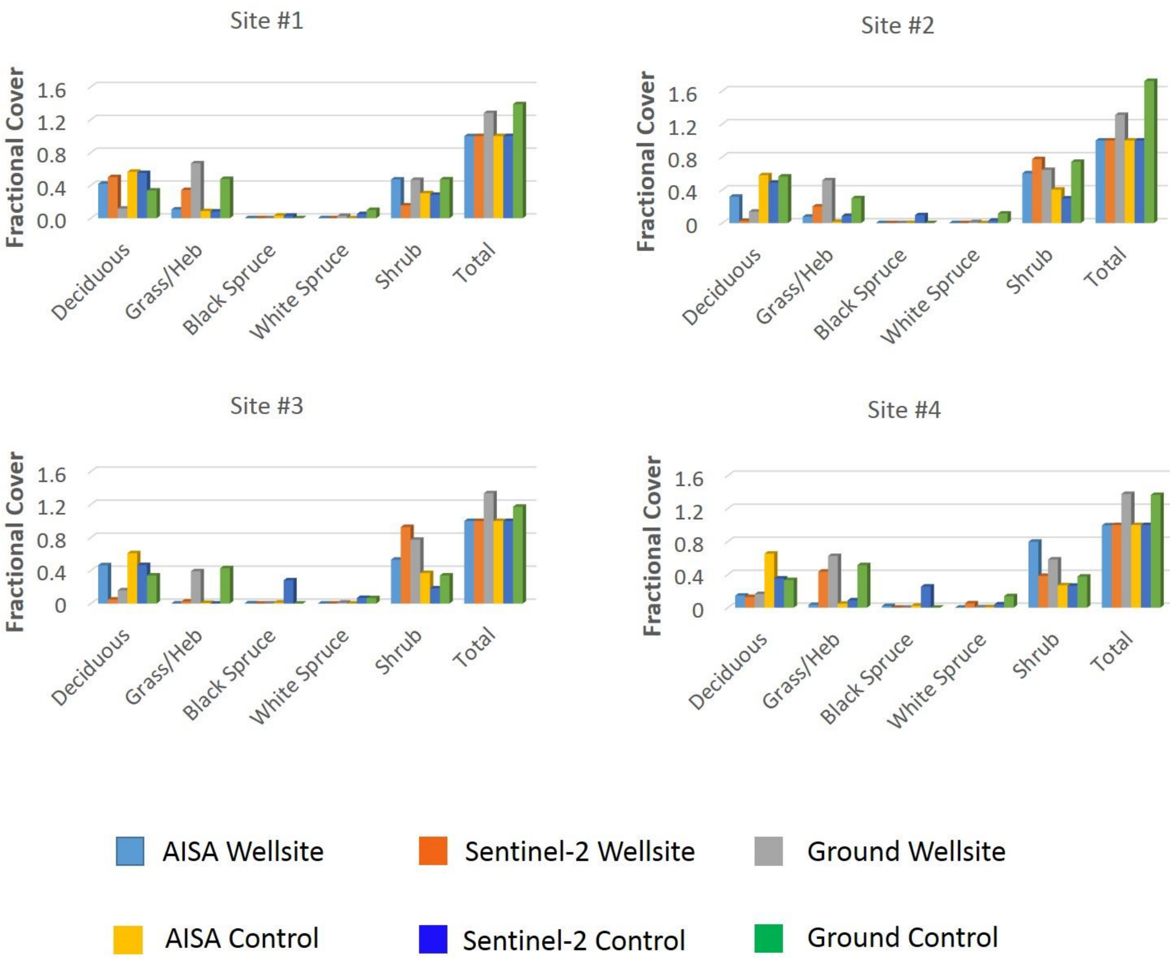

Figure 15: Comparison of Sentinel2/K-means fractional cover per landcover type to AISA/K-means and ground data in wellsite and adjacent areas (control) for four wellsites surveyed on the ground in the Stoney Long Lake area.

2- MATRIX Site

A landcover classification was produced for the MATRIX site using the K-means classifier and eight landcover classes including water, bareground/builtup, grass/herb, shrub, deciduous, black spruce, jack pine, wetland background and regeneration (Figure 16). The regeneration landcover class seems to be dominant with deciduous, black spruce and jack pine classes scattered throughout the study site. A set of subsets showing landcover in wellsites and adjacent areas is shown in Figure 17. Grass/herbaceous, shrub and bareground/builtup were the most common landcover types in wellsites and adjacent areas were dominated by deciduous, regeneration and conifer species.

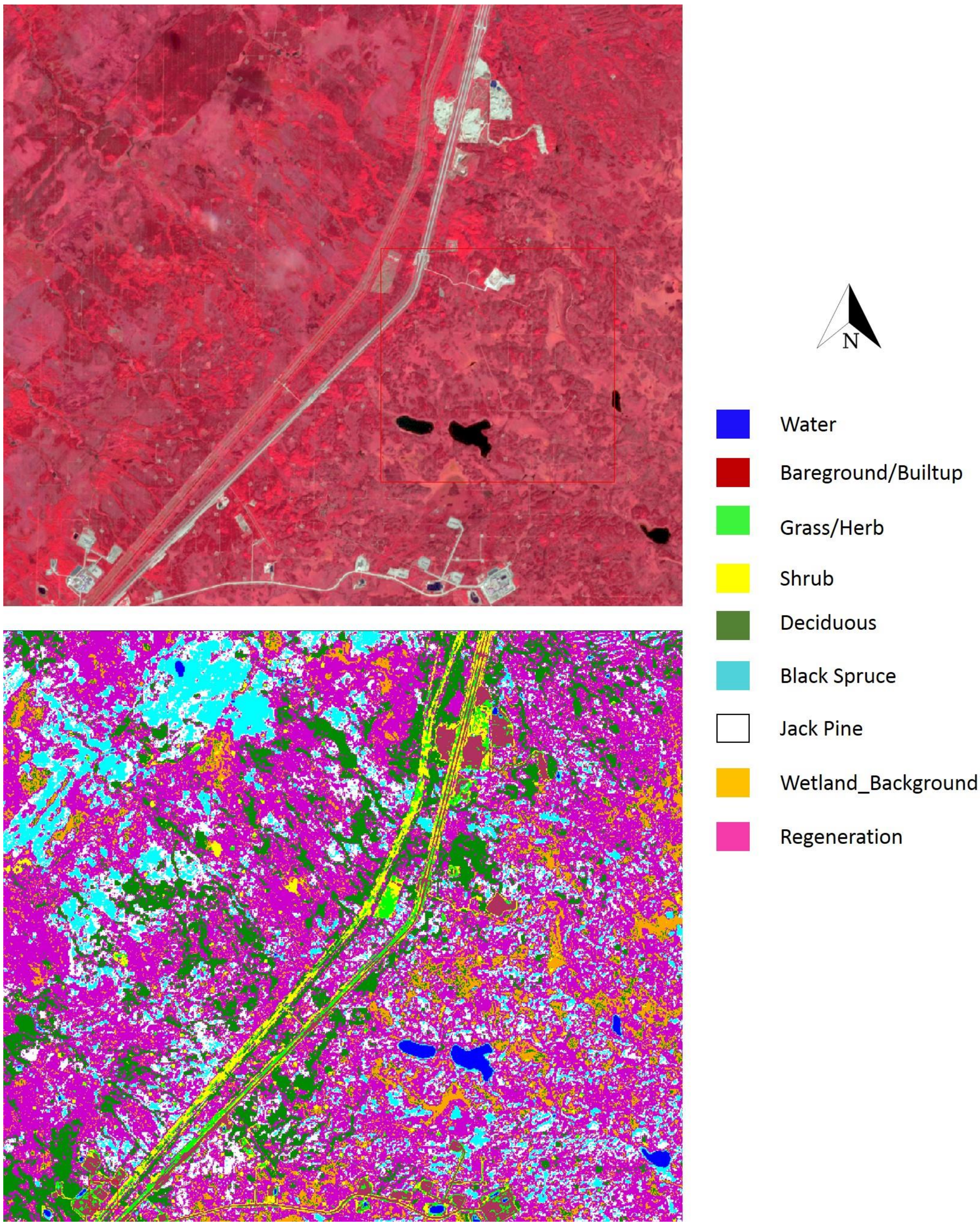

Figure 16: Sentinel-2 R (NIR), G (Red), B (Green) colour composite and Landcover map of the MATRIX site produced using the K-means unsupervised classification.

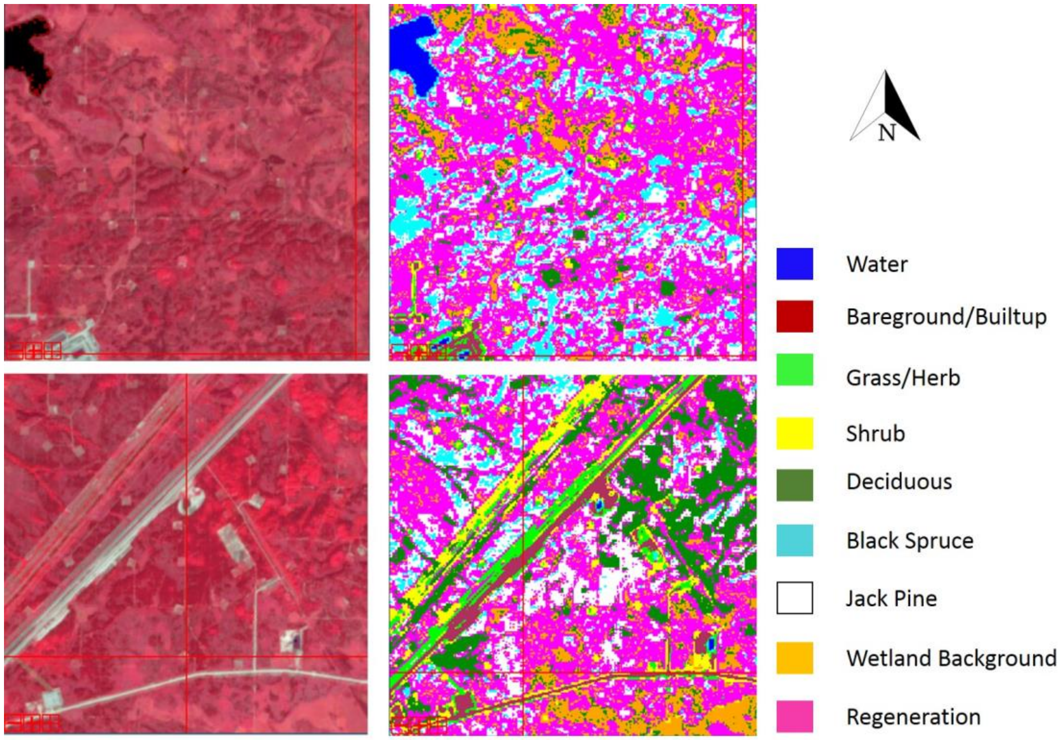

Figure 17: R (NIR), G (Red), B (Green) colour composite subsets of Sentinel-2 data and their K-means landcover classification for the MATRIX Site.

An accuracy assessment was conducted using a set of 352 ground measurements acquired in summer 2016. Two types of assessment were used. The first type was a single-pixel-based where only the pixel where the GPS coordinates of a single ground location falls was used. The second type also included all eight surrounding pixels to minimize geolocation errors between Sentinel-2 data and ground measurements. The confusion matrix for type-1 assessment is summarized in Table 8. A low overall accuracy of 42.1 % and a kappa coefficient of 0.29 were found. User's accuracy was low with values in the 29.9 % - 58 % for all landcover classes except the Jack pine class that had a moderate accuracy of 67.5 %. Similar results were found for producer's accuracy with a moderate value of 69.7 % for deciduous and low accuracies ranging from 13.5 % to 57.1 % for the other classes. The regeneration class seem to be overestimated and tends to be mistaken for the remaining landcover classes. In addition, confusion errors are also present between each of the deciduous, shrub, jack pine and wetland-background classes. Classification accuracy tends to improve when using type-2 assessment (Table 9). The overall accuracy and kappa coefficient were noticeably higher and equaled 60.8 % and 0.52 respectively. Confusion errors between classes decreased, resulting in higher user's and producer's accuracies. Moderate to high user's accuracies were achieved for black spruce, grass/herbaceous, shrub, jack pine, wetland-background with values ranging from 60.0 % to 82.0 %. User's accuracy for deciduous and regeneration classes remained relatively low with values equal to 54.0 % and 45.2 %, respectively. Producer's accuracy was moderate to high for deciduous, wetland-background and regeneration classes with values varying between 70.3 % and 81.8 %. For black spruce, grass/herbaceous, shrub and jack pine, accuracy values were low within the 29.7 % - 56.0 % range. Based on type-2 assessment, regeneration class remains to a lesser extent overclassified. Bareground accuracies equals zero in both type-1 and type-2 assessments.

Table 8: Confusion matrix and accuracy measures for type-1 assessment of the Sentinel-2 landcover classification over the MATRIX site, produced using K-means. Columns correspond to ground data and rows to mapped classes

	Bareground	Deciduous	Black Spruce	Grass/Herb	Shrub	Jack Pine	Wet_Background	Regeneration	Total
Bareground	0	0	1	1	1	0	0	0	3
Deciduous	1	23	1	1	9	7	7	7	56
Black Spruce	1	0	7	1	1	3	0	2	15
Grass/Herb	2	0	0	4	2	0	1	0	9
Shrub	0	0	0	1	5	0	8	2	16
Jack Pine	2	3	2	0	3	27	2	1	40
Wet_Background	0	1	0	0	1	5	38	21	66
Regeneration	1	6	8	5	15	33	35	44	147
Total	7	33	19	13	37	75	91	77	352
Overall Accuracy (%)	42.1								
Kappa	0.29								
User's Accuracy (%)	0.0	41.1	46.7	44.4	31.3	67.5	57.6	29.9	
Producer's Accuracy (%)	0.0	69.7	36.8	30.8	13.5	36.0	41.8	57.1	

Table 9: Confusion matrix and accuracy measures for type-2 assessment of the Sentinel-2 landcover classification over the MATRIX site, produced using K-means. Columns correspond to ground data and rows to mapped classes

	Bareground	Deciduous	Black Spruce	Grass/Herb	Shrub	Jack Pine	Wet_Background	Regeneration	Total
Bareground	0	0	1	0	1	0	0	0	2
Deciduous	1	27	1	1	8	6	0	6	50
Black Spruce	1	0	8	1	1	1	0	1	13
Grass/Herb	2	0	0	6	1	0	1	0	10
Shrub	0	0	0	1	11	0	5	1	18
Jack Pine	2	1	2	0	3	42	1	0	51
Wet_Background	0	1	0	0	1	5	64	13	84
Regeneration	1	4	7	4	11	21	20	56	124
Total	7	33	19	13	37	75	91	77	352
Overall Accuracy (%)	60.8								
Kappa	0.52								
User's Accuracy (%)	0.0	54.0	61.5	60.0	61.1	82.4	76.2	45.2	
Producer's Accuracy (%)	0.0	81.8	42.1	46.2	29.7	56.0	70.3	72.7	

4.2. Vegetation Health

Assessment of vegetation condition using vegetation indices was conducted for both AISA and Sentinel-2 data based on a spatial subset of the Stoney Long Lake that was not affected by the 2016 wildfire. NDVI, MCARI2 and ZM vegetation indices were calculated using the AISA hyperspectral data. The NDVI, MCARI2 and ZM maps are illustrated in Figure 18. NDVI and MCARI2 are sensitive to foliage amount and tend to increase with LAI. The lowest values for these indices are observed in areas with low vegetation cover where bareground is dominant such as in wellsites. The highest values are observed in areas with dense vegetation such as grass/herbaceous, shrub and closed forested areas. MCARI2 and NDVI maps showed different spatial patterns. The MCARI2 variation range over the area covering coniferous and deciduous areas is wider than the NDVI range. This is due to the difference in the sensitivity to leaf area index of these spectral indices. In fact, for high LAI values NDVI tends to saturate while MCARI2 is more sensitive and tends to increase as LAI gets higher. In such a case, MCARI2 is considered a better indicator of foliage amount and tend to show a larger difference between conifer and deciduous than NDVI does. The ZM vegetation index varies between 0 and 5 and showed a different spatial pattern from the one observed for MACRI2 and NDVI indices. The ZM index seems to be higher over deciduous and shrubby areas than in coniferous and grass/herbaceous dominated areas. This might be caused by differences in chlorophyll content between these classes. In fact, ZM index was found to correlate to both leaf and canopy chlorophyll content in a previous study focused on closed forested areas (Zarco et al., 2001). The lowest ZM index was observed in areas where bareground is dominant and vegetation cover is minimal.

NDVI and IREC indices were derived for the 2016 Sentinel-2 data (Figure 19). The NDVI magnitude is relatively close to the one observed using AISA data with some differences in the spatial pattern. Higher Sentinel-2 NDVI values were observed in wellsites that were dominated by bareground in the 2013 AISA data suggesting an increase in vegetation cover. Lower Sentinel-2 NDVI values caused by vegetation clearance and establishment of new wellsites between 2013 and 2016 were also observed. In wetlands areas, Sentinel-2 NDVI values were lower. This could be caused by a decrease in vegetation productivity or due to senescence. Finally compared to AISA, differences in Sentinel-2 NDVI between conifers and deciduous were smaller. This could be due to differences in the spectral bands characteristics of the two sensors. The IRECI index correlates to canopy chlorophyll and was found to vary between 0 and 4. IRECI tends to have low values over conifers, shrubby areas and grass/herbaceous. With the lowest value found in wellsites where bareground is common and vegetation cover is low. IRECI values over deciduous tends to be moderate to high.

Figure 20 shows a set of subsets of the Sentinel-2 and AISA spectral indices over six wellsites showing different reclamation conditions that translate in different VI’s magnitude. Wellsite #4 and #5 show the largest variation range in AISA-NDVI due to the presence of both bareground and vegetated areas in these sites. This variation range tends to substantially decrease for wellsite #4 in the Sentinel-2 NDVI indicating an increase in vegetation cover between 2013 and 2016. A slighter decrease is also observed for wellsite # 5. Wellsites #2 and # 3 show the lowest variation range in AISA NDVI and high NDVI values indicating a more homogeneous site with higher vegetation productivity. Sentinel-2 NDVI suggest wellsite #2, # 3 and #4 have undergone an increase in vegetation growth between 2013 and 2016. Vegetation condition in wellsite #1 seems to be stable during this period. MCARI2 shows a similar wellsite ranking than NDVI in terms of average value per site, and a wider variation range. Differences in the ZM and IRECI indices exist within and between wellsites sites and could be attributed to the chlorophyll variation between different vegetation communities and/or other factors such as senescence or stress. This possible causes cannot be assessed within this work due to the lack of ground observations related of vegetation stress.

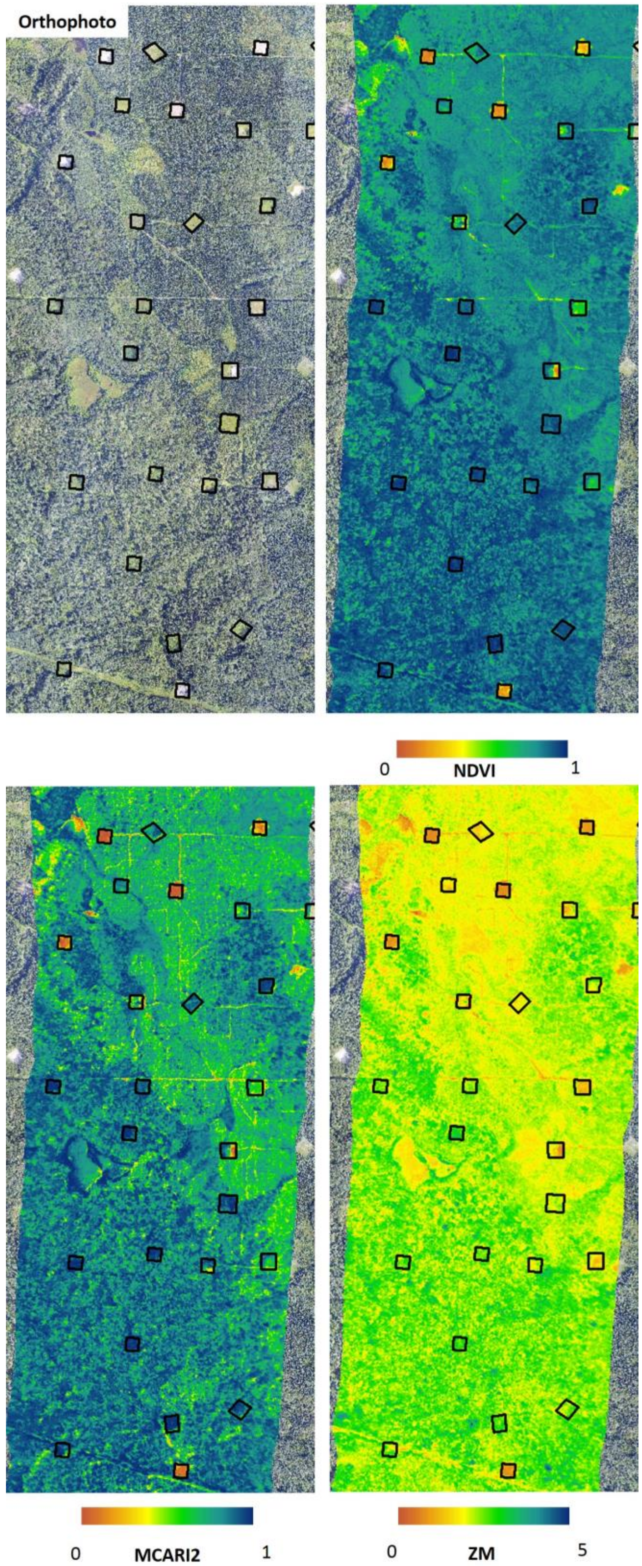

Figure 18: Airborne orthophoto and NDVI, MCARI2, ZM indices derived using AISA flight line #1604 over the Stoney Long Lake area.

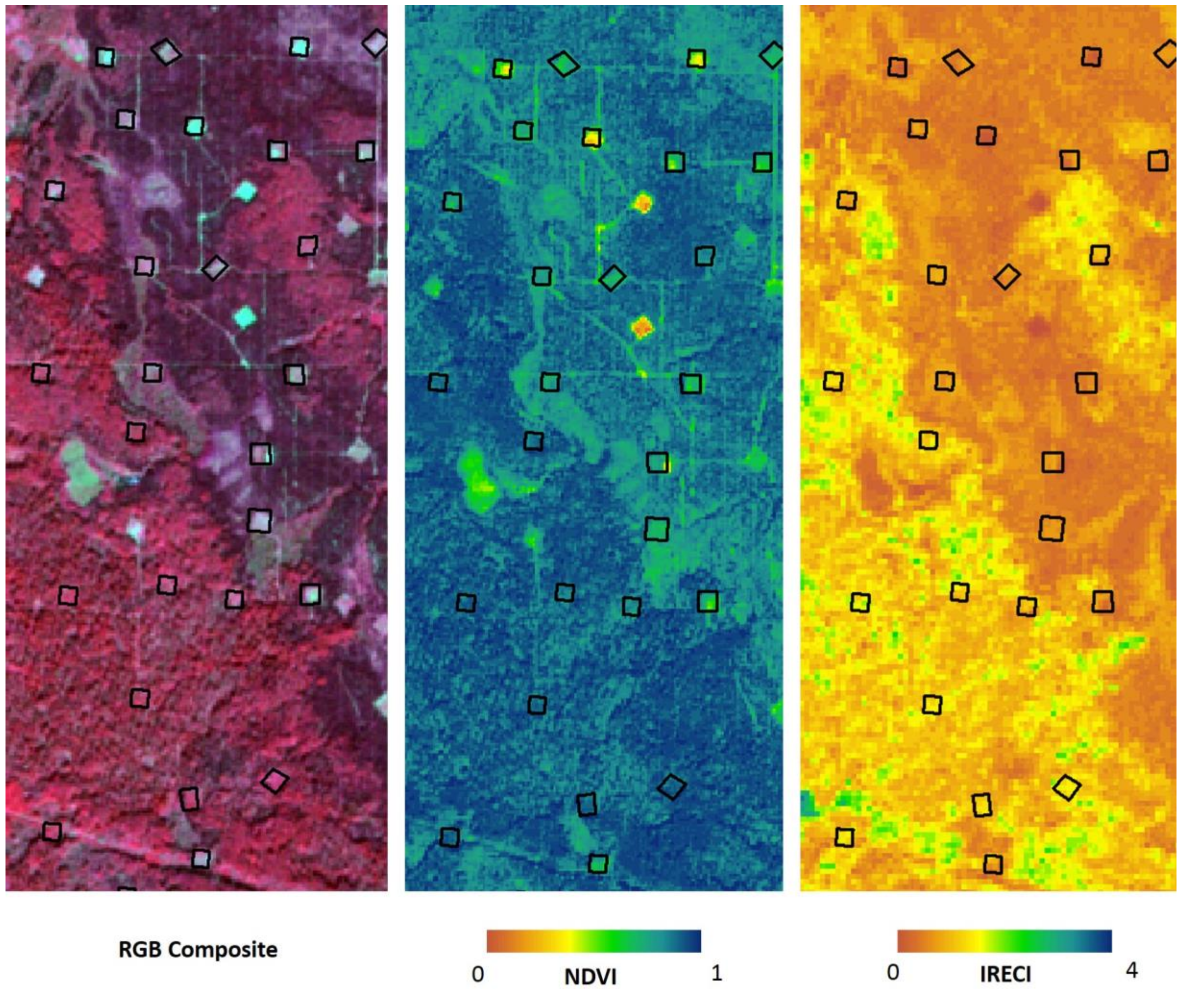

Figure 19: Sentinel-2 R (NIR), G (Red), B (Green) colour composite and NDVI and IRECI maps for the Stoney Long Lake area.

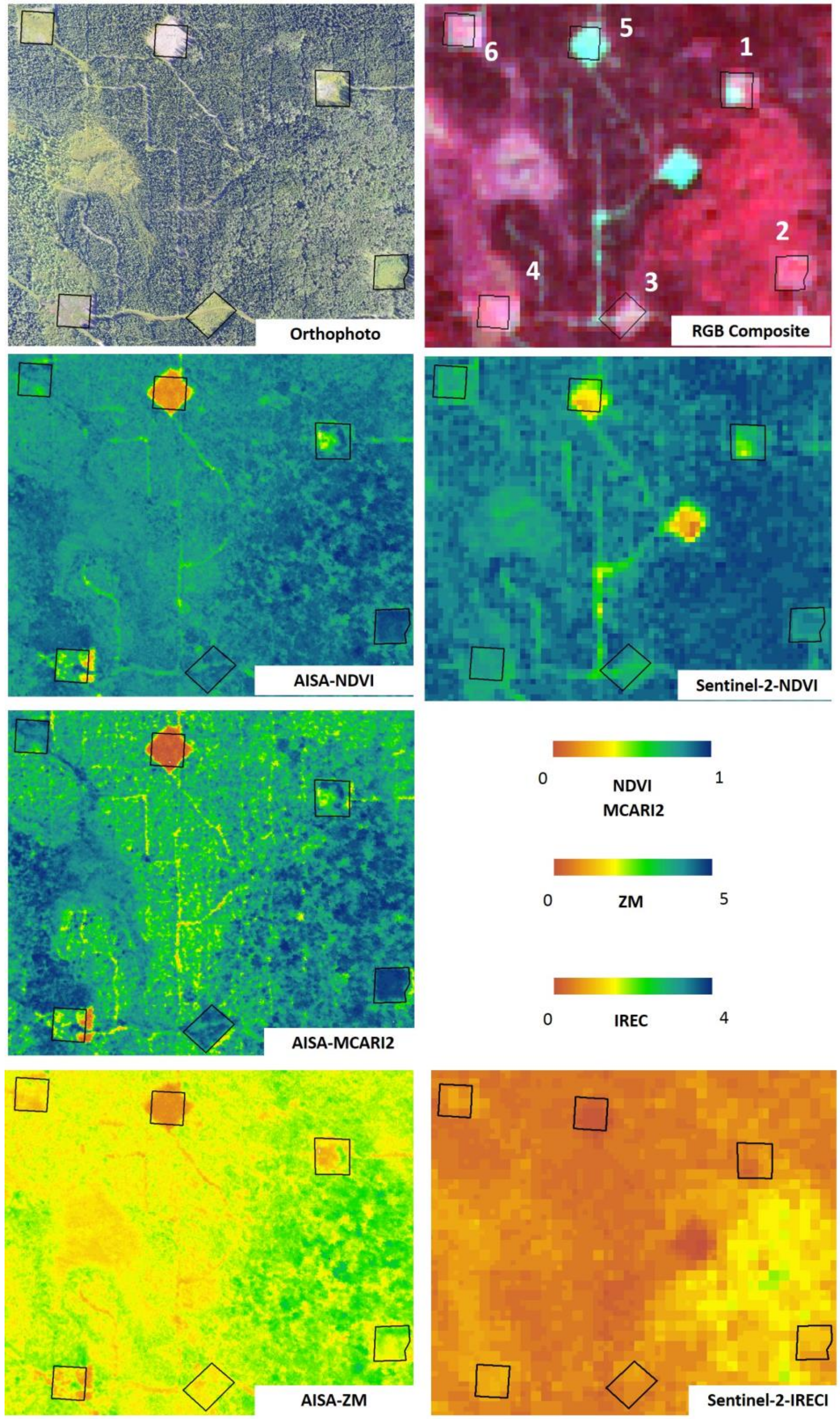

Figure 20: Orthophoto, R (NIR), G (Red), B (Green) colour composite of Sentinel-2 and NDVI, MCARI2, ZM, and IRECI spectral indices for a subset of the Stoney Long Lake area.

5. Discussion

5.1. K-Means *versus* MESMA

Landcover classification using K-means was achieved with moderate to high accuracies using the 2013 AISA data. User's accuracies were greater than 67.7 % for all classes except grass/herbaceous in flight line #1744 and black spruce in #1604. The 45 wellsites located in wetland areas were dominated by grass/herbaceous with an average fractional cover of 0.5. The average fractional cover for shrub and black spruce was 0.13 while it equals 0.1 for bareground/builtup. Vegetation composition in adjacent areas included black spruce, deciduous, shrub, and grass/herbaceous with average fractional cover values of 0.5, 0.15, 0.10, and 0.10 respectively. Visual inspection and accuracy assessment of AISA K-means classification pointed out some misclassification errors due to confusion between classes. Shaded areas in wellsites and adjacent areas tend to be classified as water or conifers. Open areas dominated by wetland background tend to be classified as black spruce. Eutrophic water bodies tends to be classified as grass/herbaceous or black spruce. Some confusion were also observed between trees and shrubs. Further refinement of this method is required to improve the results. Tuning of the K-means parameters, water masking and a multi-stage process where a nested set of classifications is sequentially produced moving from a broad to a more specific class labeling are some of the options that can be explored.

The K-means classification seems to identify the same landcover classes observed in the field. However, quantifying the agreement between the measured and observed fractional cover was not achievable due to conceptual differences. On one hand, field fractional cover is independently estimated for each landcover class including areas of overlapping between different landcover types. On the other hand, remote sensing based fractional cover correspond to projected areal coverage of each landcover class where overlapping areas are excluded. Furthermore, the areal coverage that forms the basis of this assessment is not necessarily representative of the area sampled in the field and was arbitrarily defined due to the lack of exact geographic coordinates of ground measurements. The wellsite boundaries as defined in AHFP are another possible cause of the differences between fractional cover estimates and measurements. In fact, the actual wellsite boundaries seem to not always be accurately delineated resulting in a linear or angular shift. Consequently the areal coverage for each of the wellsite and control buffer used in the assessment tend to include pixels from both wellsite and undisturbed adjacent areas. Finally, labeling test sites using the classification system adopted in this work, was inferred from ground data and is prone to errors.

MESMA classification showed a number of issues such as unclassified pixels scattered throughout the mapped area. Compared to K-means it showed larger confusion errors between classes. Soil is misclassified as water, and deciduous, shrub and grass/herbaceous are interchangeably confused. Assessment of the MESMA fractional cover using ground data showed larger differences than with K-means. MESMA tends to overestimate deciduous at the expense of the shrub class and was unable to classify up to 30 % of wellsite and control areas. The poor performance of MESMA is possibly due to the lack of endmember spectra that are representative of different vegetation types in the pixel or to the use of endmember spectra not representative of a pure target. In fact, endmember selection based on remote sensing image is not only limited by the availability of homogeneous pixels but also by the representativeness of the endmember spectral variability in the area mapped. This is even more problematic for Sentinel-2 data which has a larger pixel size than AISA. Furthermore, the image-based selection is prone to errors in target identification. Improvement of the MESMA results would require refinement of the endmember spectra used through the assessment of a new set of endmember spectra that are collected in the field or extracted from an existing spectral library that is representative of the vegetation communities present in the study area.

5.2. Sentinel-2 *versus* AISA

Landcover classification of the 2016 Sentinel-2 data using the K-means unsupervised classifier achieved high accuracies over the Stoney long lake for all landcover classes except for white spruce whose user's and producer's accuracies did not exceed 3%. The Stoney Long Lake 45 wellsites located in wetland areas were dominated by grass/herbaceous and shrub with an average fractional cover close to 0.38. The average fractional cover for grass/herbaceous and burned areas was close to 0.10 while it did not exceed 0.05 for bareground/builtup and deciduous. Vegetation composition in adjacent areas mostly included shrub, black spruce and burned areas with average fractional cover values of 0.34, 0.28, and 0.23 respectively. Average fractional cover for grass and deciduous classes did not exceed 0.08. Sentinel-2 classification over the MATRIX site showed a moderate accuracy when using a type-2 assessment. This type of assessment is less affected by geolocation errors since it uses a window of 3 x 3 pixels around a given ground point measurement, to determine landcover map accuracy. User's accuracy was between 60.0 % and 82.4 % for black spruce, grass/herbaceous, shrub, wetland background and Jack pine.

Lower accuracies were achieved for deciduous and regeneration classes. Ground measurements in MATRIX study area depicts a very heterogeneous vegetation cover that makes class labeling of K-means clusters challenging when using image interpretation. In addition, assigning a landcover class to a test site using the classification scheme in Table 2 based on the interpretation of ground measurement is also subject to errors. Although for similar canopy structure and condition, interpretation confidence for MATRIX sites would be relatively higher than for Stoney Long Lake since the MATRIX grounddata included canopy closure and height for both the canopy and sub-canopy.

Furthermore, ground measurements were collected in test plots of 2 m x 2 m for shrub/herbaceous/baregound communities and a 10 m x 10 m for tree species and might be limiting for assessing the 10-meter Sentinel-2 products. This difference in the sample areal coverage explains the low accuracies observed for the bareground class. In fact, visual assessment of the Sentinel-2 classiffication suggests large user's and producer's accuracies for the bareground/builtup class. Assessment of high-resolution sensors with a 2 meter pixel would be recommended for the MATRIX site.

Comparison of Sentinel-2 and AISA classification using four surveyed wellsites and adjacent areas showed up to 0.40 difference in grass/herbaceous, shrub and deciduous classes. Sentinel-2 classification was also found to overestimate black spruce ground estimate in adjacent areas. Differences in fractional cover estimates between AISA and Sentinel-2 could be caused by the difference in spatial resolution. In fact, the size of an AISA pixel is 25 times finer than Sentinel-2. Such a difference could cause Sentinel-2 to underestimate or even miss landcover classes that have a low fractional cover. Furthermore, the fractional coverage of mixed pixel along wellsite boundaries is greater for sentinel-2 than AISA. This results in less misclassification errors along the wellsite edges due to a reduction in shaded pixels in the Sentinel-2 data. However, Sentinel-2 mixed pixels tend to be classified as shrub in presence of a mixture of tree and bareground and/or grass/herbaceous leading to an overestimation of shrubs in wellsites. Furthermore, spectral sampling differences between Sentinel-2 and AISA, and the three years time-lapse between their acquisition dates are all possible causes of the differences between Sentinel-2 and AISA landcover maps. Further investigations are required to assess the difference between these two sensors using data that are acquired during the same season.

5.3. Vegetation Health

NDVI and MCARI-2 are both sensitive to foliage amount and tend to increase with LAI. Areas with low vegetation cover where bareground is dominant such as in wellsites exhibit low values while areas with dense vegetation such as grass/herbaceous, shrub and closed forested areas have higher values. However, MCARI2 is more sensitive than NDVI to vegetation biomass and tend to show a wider variation range suggesting MCARI2 is a better indicator of revegetation progress. This is consistent with a previous study where similar behavior was observed for cultivated canopies using model simulations and ground data (Haboudane et al., 2004). The ZM vegetation index showed a different spatial pattern from the ones observed for MACRI2 and NDVI indices. For a similar MCARI2 magnitude, the ZM index was found to be different between vegetation communities, which could be due to inherent variations in chlorophyll content between these communities. Furthermore, lower ZM values were also observed in deciduous areas where senescence was noticeable. Similar behavior was also observed for the Sentinel-2 IRECI, which showed a different spatial pattern than ZM suggesting that the sensitivity of these indices to chlorophyll content might be different. Differences in the ZM and IRECI indices exist within and between wellsites sites and could be attributed to the chlorophyll variation between different vegetation communities and/or other factors such as senescence or stress.

Differences between the 2013 AISA and 2016 Sentinel-2 were attributed to establishment of new wellsites and vegetation progress in reclaimed sites. In wetlands areas, Sentinel-2 NDVI values were lower than AISA NDVI. A Possible cause for this decrease could be a reduction in vegetation productivity due to senescence, disturbance, vegetation stress and/or inconsistency between AISA and Sentinel-2 data due to differences in their spectral sampling and resolution.

6. Conclusion

Airborne AISA hyperspectral acquired in August 2013 and spaceborne Sentinel-2 multispectral data collected in August 2016 were assessed for mapping vegetation composition and vegetation health. The Circle T Consulting and Matrix Solutions Inc. ground data in the Stoney Long Lake and MATRIX study areas were collected in August 2014/2015 and August 2016 respectively, and used to assess landcover classification maps generated from AISA and Sentinel-2 data.

The K-means unsupervised classifier performs better than MESMA for mapping landcover in the Stoney Long Lake area. Improvement of the MESMA results would require refinement of the endmember spectra used through the assessment of a new set of endmember spectra either collected in the field or extracted from an existing spectral library representative of the vegetation communities present in the study area.

The K-means classification accuracies were overall moderate to high with few exceptions depending on the study area and data used. Further refinement such as tuning of the K-means parameters, a multi-stage process where a nested set of classifications is sequentially produced moving from a broad to a more specific class labeling, and incorporation of vegetation indices in the classification process need to be investigated.

In addition, access to the Alberta Vegetation inventory (AVI) is expected to help improving the labeling process in K-means, and endmember selection in MESMA especially in terms of tree species identification.

Assessment of remote sensing estimates against ground measurement in wellsites and adjacent areas, overall showed consistency in the dominant landcover types. However, quantifying the agreement between the fractional cover estimates and measurements was not achievable due to conceptual differences between the remote sensing-based and field approaches. Furthermore, the lack of geographic coordinates of ground measurements and linear/angular shift in AHFP wellsite boundaries are all factors that prevent this evaluation. These aspects will need to be addressed through a manual delineation of wellsite boundaries, and a field strategy that deals with the needs of the remote sensing approach.

Hyperspectral vegetation indices such as MCARI2 and ZM seems to capture differences in vegetation condition. Sensitivity of spectral indices to biophysical variables such as LAI or leaf/canopy chlorophyll content seem to vary between vegetation communities. Anomaly detection in these indices would be recommended on a vegetation community basis. Further research is needed to determine the relationship between these indices and biophysical variables at leaf and canopy scales. In addition, the effect of soil background variability on ZM needs to be investigated since early-stage reclamation tend to have a large contribution of background.

Difference in spatial resolution between AISA and Sentinel-2 resulted in a high proportion of shaded pixels for the former, and mixed pixels for the latter, that caused misclassification errors. Furthermore, landcover type with low fractional cover tends to be underestimated in Sentinel-2 data. Assessment of chlorophyll-related indices also suggested Sentinel-2 IRECI to be less sensitive than ZM. Further investigations are still needed to determine the effect of spectral and spatial characteristics of these sensors on vegetation composition and health. To allow the comparison of these technologies, acquisition of Sentinel-2 and airborne hyperspectral within a 2/3 week window is recommended to minimize differences due to phenology, and natural and anthropogenic disturbances.

7. Recommendations

While the present work still needs further refinement and assessment of the data and the algorithms used, it does indicate potential uses that can benefit and enhance field-assessment efforts of reclamation condition. Integration of remote sensing will potentially support monitoring reclaimed and disturbed wetland by providing the following information:

- ***Access to large-scale information*** that is unachievable otherwise. A Sentinel-2 scene coverage is ~ 100 km x 100 km. Assuming the wellsite density found in the MATRIX study area of about two wellsites per Kilometer square, a clear-sky Sentinel-2 scene would provide information for ~20200 wellsites.

- ***Multi-temporal information*** that will provide the recovery trajectory in reclaimed and disturbed areas. The 2-3 days revisit time in mid-latitudes, projected with the two Sentinel-2 satellites jointly in operation since 2017, would allow both seasonal and annual monitoring.

- ***A priori information in support of best management practices***. Access to multi-temporal information at a large scale would support sites screening and field visit prioritization. This would avoid unnecessary visits and point out to sites where monitoring efforts should be directed. It will also increase the information frequency over challenging sites where accessibility is an issue.

- ***A cost-effective tool for regular monitoring.*** The no-cost policy of Sentinel-2 data and the availability of open-source image processing tools such as the ESA-SNAP software, offer a unique opportunity for a cost-efficient assessment. This also applies to the EnMAP toolbox, another open-source software that has been developed for processing the data to be acquired with the future EnMAP hyperspectral sensor scheduled to be launched in 2019.

- ***Enhanced information in support of the Alberta Wetland Classification System (AWCS)***. Sentinel-2 data temporal availability and spatial coverage would provide information related to change in vegetation composition and health in Alberta's wetlands. The Sentinel-2 10/20-meter pixel size is in fact in accordance with the minimum mapping unit recommended by the Alberta Wetlands Mapping Standard.

The finding of this work has pointed out some conceptual differences between remote sensing information and ground measurements (e.g., fractional cover definition, lack of GPS information). Furthermore, the comparison between ground measurements and remote sensing information can be challenging when a test plot (e.g., 2 m x 2 x m, 10 m x 10 m) is equal or smaller than the pixel size (e.g., Sentinel-2 10/20-meter pixel), especially in a heterogeneous site like the MATRIX study area. An effective use of remote sensing technologies, within the context of reclamation monitoring would require consultations involving both remote sensing and reclamation-field experts in order to address differences and define standards that would harmonize field and remote-sensing based Information. On one hand this will assure that remote sensing products are properly validated. On the other hand, it will guarantee consistency between remote sensing products and field-based information.

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