IDENTIFICATION AND CHARACTERIZATION OF ABANDONED PADDED WELLSITES USING REMOTE SENSING

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EXECUTIVE SUMMARY

In 2018, the Petroleum Technology Alliance of Canada (PTAC) initiated a multi-stage project on the reclamation certification process for sites that were constructed using imported mineral soil pads in peatlands (padded sites). Stage 1 of the project has been completed and identified knowledge gaps for making decisions to accept or reject requests for a change in land use for padded sites during the reclamation certification process. Stage 2 is nearing completion and includes a decision framework and support tools for making decisions related to reclamation certification of padded sites; however, some of the factors that the framework and support tools are based upon are knowledge gaps.

Stage 3 is the field research component of the project to address the knowledge gaps. The objective of Phase 1 of Stage 3 is to evaluate abandoned padded sites (between 1940 and 2020) in peatlands within Alberta using well databases, company records, environmental reports, and remote sensing data and techniques to identify and characterize available padded sites.

For the project, sites of interest consisted of abandoned wellsites found in peatland areas in the Boreal and Foothills Region of the Green Area. Using wellsite information and ecoregion layers, the list of all wells licensed in Alberta between 1900 and 2021 were initially filtered down to 103,531 wellsites located in the Boreal and Foothills Region of the Green Area. To avoid redundancy, wells with the same surface location (defined as being within 30 m of one another) were consolidated into one site; oil sand exploration wells were excluded (as these are unlikely to be padded) and only abandoned wellsites were included, resulting in 47,920 sites.

Sites with no available LiDAR data coverage before the drill (spud) date, as noted in the AbaData information, were excluded. In addition, any wellsite that fell within certain active dispositions was excluded, such as a road or pipeline, where the topography was likely to have been disturbed. Finally, only sites found in peatland areas in a buffered query of the ABMI and DEP wetland datasets were retained. This resulted in a final count of 15,083 sites for evaluation.

A supervised classification was run on the assembled datasets. To train the classifier, a set of 181 identified padded and unpadded sites was assembled from a combination of existing wellsite records augmented by expert visual interpretation of airborne and spaceborne imagery. The independent variables consisted of the derived spectral features and ancillary data whereas site type (pad/no pad) acted as the dependent variable. The output consisted of a binary classification of padded/unpadded sites. The classification procedure achieved 81.2% accuracy when predicting no pad and 73.9% accuracy when predicting a pad, for an overall classification accuracy of 78%. As a result, a total of 7,077 padded sites and 8,006 unpadded sites in peatland areas were obtained from the supervised classification.

The accuracy of the classification may be increased through several options:

- Increasing the size of the training dataset used to parameterize the supervised classification would likely improve accuracy and result in more predictive power. This would require additional effort and expert knowledge to visually interpret new sites and re-run the classification.

- Including other predictor variables in the classification, such as side aperture radar or LiDAR-derived texture metrics, additional wetness and greenness indices from different Sentinel-2 acquisition dates, and alternate spectral indices not previously considered.
- Implementing different classification techniques. For instance, a Logistic Regression model could be used to predict the probability of a pad (as a numerical output), which could be further classified into semantic probability classes.

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ACRONYMS

ABMI	Alberta Biodiversity Monitoring Institute
AEP	Alberta Environment and Parks
AER	Alberta Energy Regulator
DEP	Derived Ecosite Phase
DEM	Digital Elevation Model
DIDs	Alberta Digital Integrated Dispositions
ELC	Ecological Land Classification
GEE	Google Earth Engine
LiDAR	Light Detection and Ranging
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NTS	National Topographic System

PTAC	Petroleum Technology Alliance Canada
TCB	Tasseled Cap Brightness
TCG	Tasseled Cap Greenness
TCW	Tasseled Cap Wetness
USGS	United States Geological Survey
UWI	Unique Wellsite Identifier

GLOSSARY

Classifier

A classifier is a type of machine learning algorithm used to assign a class label to a data input.

Cloud mask

In optical remote sensing, a cloud mask enables cloudy and cloud-free pixels to be identified. Cloud masking of Earth Observation images is one of the first required steps in optical remote sensing data processing.

Confusion matrix

A confusion matrix is a technique for summarizing the performance of a machine learning classifier.

Grid tiles

A grid is a network of evenly spaced horizontal and vertical lines used to identify locations on a map. Grid tiles are the individual squares in a grid.

Machine Learning (ML)

Machine Learning (ML) is a branch of Artificial Intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving accuracy. Using statistical methods, algorithms are trained to make classifications or predictions, uncovering key insights within data mining projects.

Mosaiced

In remote sensing, a mosaiced image is a raster dataset composed of two or more merged raster datasets. For example, one image created by merging several individual images or photographs of adjacent areas is a mosaiced image.

Orthogonal components

In Principle Component Analysis (PCA), orthogonal components are the result of an orthogonal transformation of a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables.

Point cloud data

In LiDAR remote sensing, point cloud data are a collection of hundreds of millions, or sometimes billions of highly accurate 3-dimensional x, y, z points and component attributes.

Spectral index

A spectral index is a combination of the pixel values from two or more spectral bands in a multispectral image. Spectral indices are designed to highlight pixels showing the relative abundance or lack of a land-cover type of interest in an image. The most common index is the Normalized Difference Vegetation Index (NDVI), which provides an indication of abundance of vegetation by comparing the different reflectance values of the red and near-infrared bands (normalized such that the minimum value is -1.0, and the maximum is +1.0). There are many other indices that have been developed, using a variety of spectral bands to highlight different phenomena, such as vegetation, water, snow, and soil.

Supervised image classification

Supervised image classification is a procedure for identifying spectrally similar areas on an image by identifying training sites of known targets and then extrapolating those spectral signatures to other areas of unknown targets.

Tasseled Cap linear transformation

Tasseled Cap linear transformation is a type of principle component analysis method, where the spectral information of satellite data is transformed into spectral indicators. The Tasseled Cap coefficients used in the linear equation of the Tasseled Cap transformation are sensor-specific and are therefore derived for each unique sensor system.

Training set

In machine learning classifications, the training set is a set of examples used for learning, i.e., for fitting the parameters of the classifier.

Test set

In machine learning classifications, the test set is the sample of data used to provide an unbiased evaluation of a final classifier fit on the training set.

Vector digital data

Vector digital data are a coordinate-based data model that represents geographic features as points, lines, and polygons in a computer file. Each point feature is represented as a single coordinate pair, while line and polygon features are represented as ordered lists of vertices. Attributes are associated with each vector feature, as opposed to a raster data model, which associates attributes with grid cells.

1.0 INTRODUCTION

1.1 PROJECT OVERVIEW

In 2018, the Petroleum Technology Alliance of Canada (PTAC) initiated a multi-stage project on the reclamation certification process for sites that were constructed using imported mineral soil pads in peatlands, and upland sites with vegetation on a trajectory to approximate natural forest vegetation but with one or more reclamation deficiencies according to the applicable wellsite criteria. These sites cannot receive a reclamation certificate without additional scrutiny and professional justification under current regulatory criteria and policies. The goal of the project is to ensure that decisions made during the reclamation certification process result in the best possible ecological outcome (i.e., net environmental benefit) for these sites and surrounding region.

1.2 STAGE 1 LITERATURE REVIEW AND IDENTIFICATION OF KNOWLEDGE GAPS

Stage 1 of the project was completed in 2019. It identified that there was limited guidance on how decisions were being made to accept or reject requests for a change in land use for sites constructed using imported mineral soil pads in peatlands (Tokay et al., 2019). Stage 1 also identified key factors to consider when assessing the ecological implications of a change in land use request (hydrology, cumulative effects and regional considerations, upland function, status of the borrow pit, site location, and land use considerations) and several knowledge gaps related to these key factors.

1.3 STAGE 2 DRAFT WELLSITE CERTIFICATION GUIDANCE DOCUMENTS

The outcome of Stage 1 led to the development of two draft reports (Stage 2):

- one focused on decisions and justifications for variances on upland sites (Tokay et al., 2019) and
- the other on decisions related to leaving mineral soil pads in place in peatlands (Drozdowski et al., 2020).

Both documents will be updated with feedback from industry (energy companies and practitioners) and government (Alberta Environment and Parks (AEP) and Alberta Energy Regulator (AER)).

1.4 STAGE 3 RESEARCH PROGRAM

The overall goal of Stage 3 is to **address key priority areas for research and refine the draft reports based on results of the research program.**

Priority areas for research were identified from the knowledge gaps identified in Stages 1 and 2 for sites that were constructed using imported mineral soil pads in peatlands. A summary of these knowledge gaps is provided in Appendix A.

Based on the priority areas for research, the following research objectives were developed:

- Determine factors that result in sustainable forest ecosystem development on padded sites, including access roads, in peatlands
- Develop a mechanism for detecting and evaluating the effects of pads off-site

- Determine factors that result in padded sites impacting surrounding peatland ecosystems in the long term and the extent and severity of these impacts
- Evaluate the effectiveness of partial reclamation activities for alleviating off-site impacts resulting from pads left in place in peatlands

1.4.1 *Inventory of Padded Sites*

To inform the knowledge gaps and research objectives, an inventory of padded sites is required that can be used to select representative sites for the field research program. The objective of the pad inventory phase of the research program (Stage 3, Phase 1) was to evaluate abandoned padded sites (between 1940 and 2020) in peatlands within Alberta. A desktop exercise using well databases, company records, environmental reports, and remote sensing to identify and characterize available padded sites was conducted.

This report describes the results of the inventory work.

2.0 METHODS

2.1 DATA

2.1.1 *LiDAR*

LiDAR (Light Detection and Ranging) imagery, acquired between 2004 and 2015, was provided by AEP in eight delivery phases. The LiDAR imagery (Figure 1) is spatially represented by a set of National Topographic System (NTS) grid tiles. Note that only partial LiDAR coverage of each NTS tile was available. The imagery has a spatial resolution and vertical accuracy of 1 m and was provided as bare Earth digital elevation models (DEM) in ASCII or TIFF files. The point cloud data were provided along with the DEMs, but not used in this project.

2.1.2 *Optical Imagery*

Sentinel-2 satellite imagery, supplied by the Copernicus Open Access Hub (European Space Agency, 2022) and accessed via the Google Earth Engine (GEE) platform (Gorelick, 2017), has 13 optical bands in the visible, near infrared, and short-wave infrared part of the electromagnetic spectrum. The imagery has wavelength-dependent spatial resolution of 10 m, 20 m, and 60 m, that can be used to measure several different characteristics of land cover, such as vegetation and moisture content. Sentinel-2 data were used for this project because (a) they are free and open data, (b) have a high revisit time (5 d), which increases the likelihood of acquiring cloud-free scenes, and (c), the pixel size of the Sentinel-2 optical bands that we employed has finer spatial resolution than Landsat data (30 m). For this project, we used imagery acquired in 2018 over the spring and summer seasons.

2.1.3 *Ancillary Data*

Wellsite information (including well coordinates, unique wellsite identifier (UWI), spud date, and abandoned date) was extracted from AbaData (Abacus Datagraphics, 2022). Digital ecoregions and wetland layers used to filter wellsites were obtained from the Derived Ecosite Phase (DEP) (Alberta Agriculture and Forestry, 2020) and the Alberta Biodiversity Monitoring Institute (ABMI) Wetland Inventory (Alberta Biodiversity Monitoring Institute, 2021). Vector digital data of public land dispositions were obtained from the Alberta Digital Integrated Dispositions (DIDs) dataset (Alberta Energy Regulator, 2022).

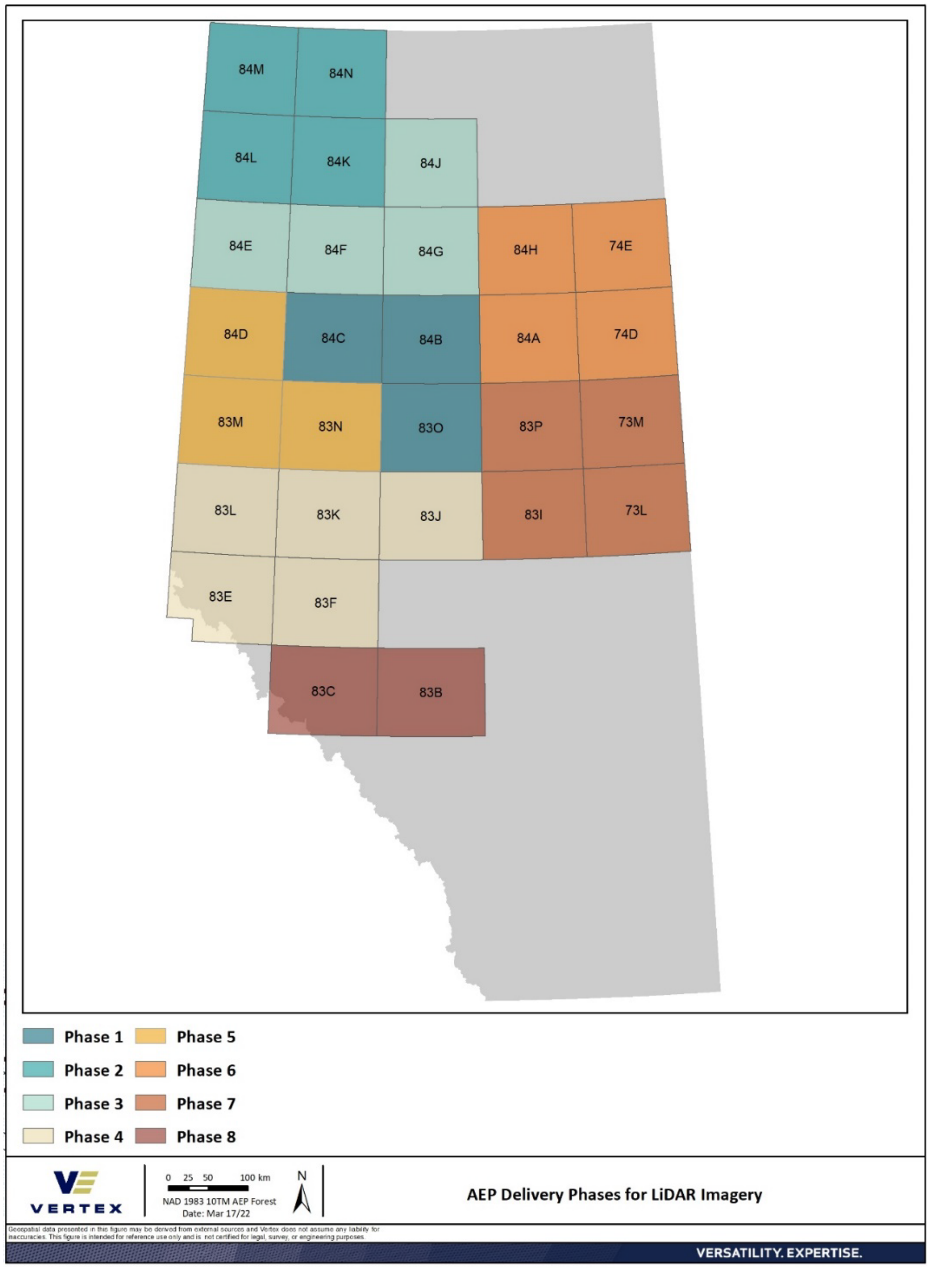

Figure 1. LiDAR delivery phases and their corresponding National Topographic System grid tiles.

2.2 WELLSITE SELECTION

For the project, sites of interest consisted of abandoned wellsites found in peatland areas in the Boreal and Foothills Region of the Green Area. Using wellsite information from AbaData and the ecoregion layers from the DEP and ABMI, the list of all wells licensed in Alberta between 1900 and 2021 were initially filtered down to 103,531 wellsites located in the Boreal and Foothills Region of the Green Area. To avoid redundancy, wells with the same surface location (defined as being within 30 m of one another) were consolidated into one site; oil sand exploration wells were excluded (as these are unlikely to be padded) and only abandoned wellsites were included, resulting in 47,920 sites.

Sites with no available LiDAR data coverage before the drill (spud) date, as noted in the AbaData information, were excluded. In addition, any wellsite that fell within certain active dispositions was excluded, such as a road or pipeline, where the topography was likely to have been disturbed. Finally, only sites found in peatland areas in a buffered query of the ABMI and DEP wetland datasets were retained. This resulted in a final count of 15,083 sites for evaluation (Table 1 and Figure 2).

Table 1. Breakdown of site selection criteria and number of sites.

Criteria	Number of Sites
All wells or well events licensed in Alberta between 1900 and 2021	611,737
Located in the Green Area and Boreal and Foothills Region of Alberta	226,078
Excluding exploration wells	188,404
Consolidating multiple wells at same surface location into one	103,531
Surface locations with only abandoned wells (no active well on-site)	47,920
With LiDAR coverage and in peatland areas	15,083

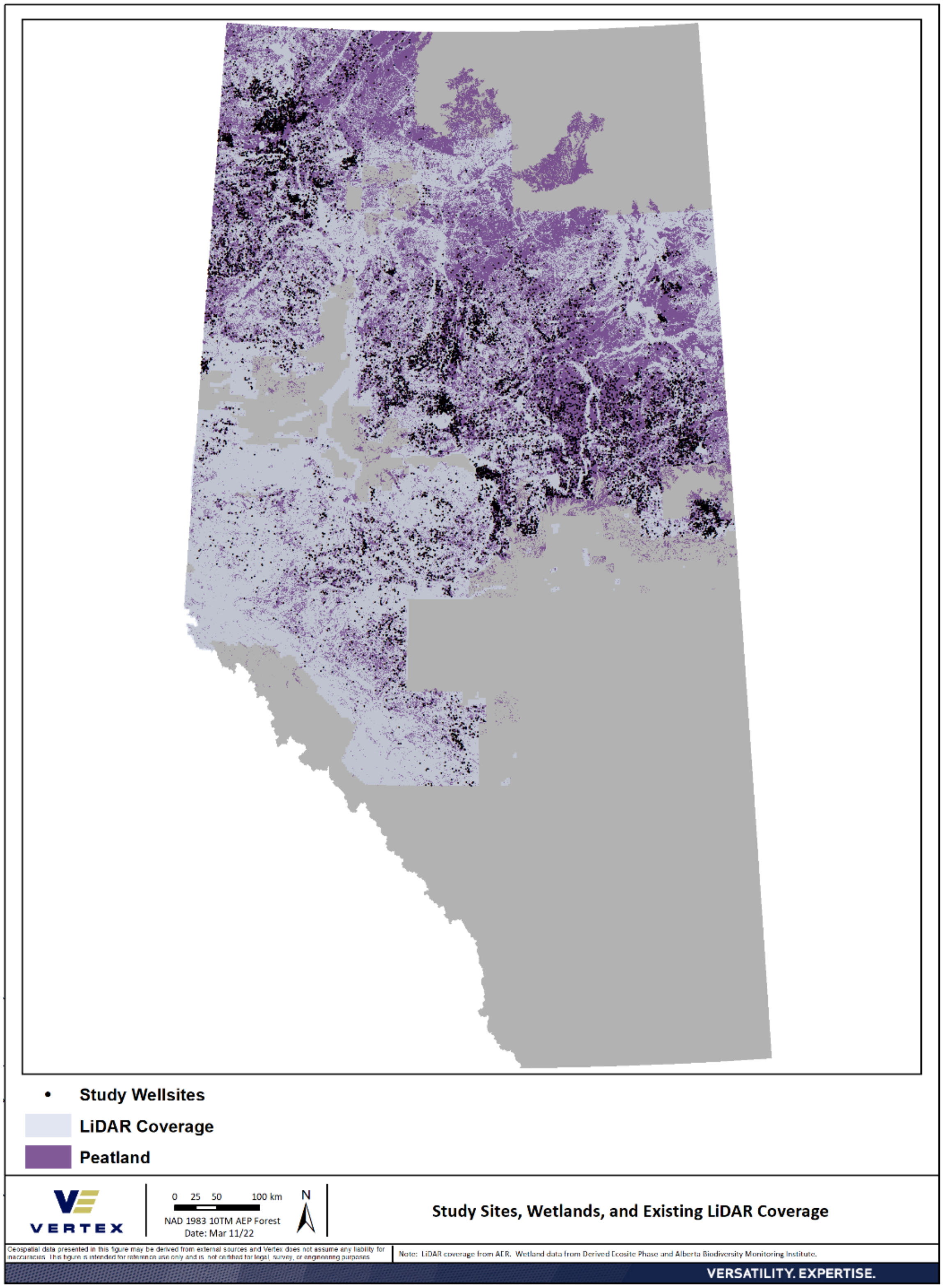

Figure 2. Map detailing the locations of study sites and wetlands within existing LiDAR coverage.

2.3 Data Pre-processing

2.3.1 *Wellsite Sampling Areas*

Each selected wellsite was buffered into on-pad and off-pad areas to sample the LiDAR and Sentinel-2 raster data. A circular buffer of 20 m was created to extract on-pad data, and a 2-m-wide ring buffer 140 m away from the well centre was created to extract off-pad or control data (Figure 3). To avoid sampling data from modified surfaces, portions of the off-pad sampling polygons that overlapped with existing dispositions that may have altered the topography were removed.

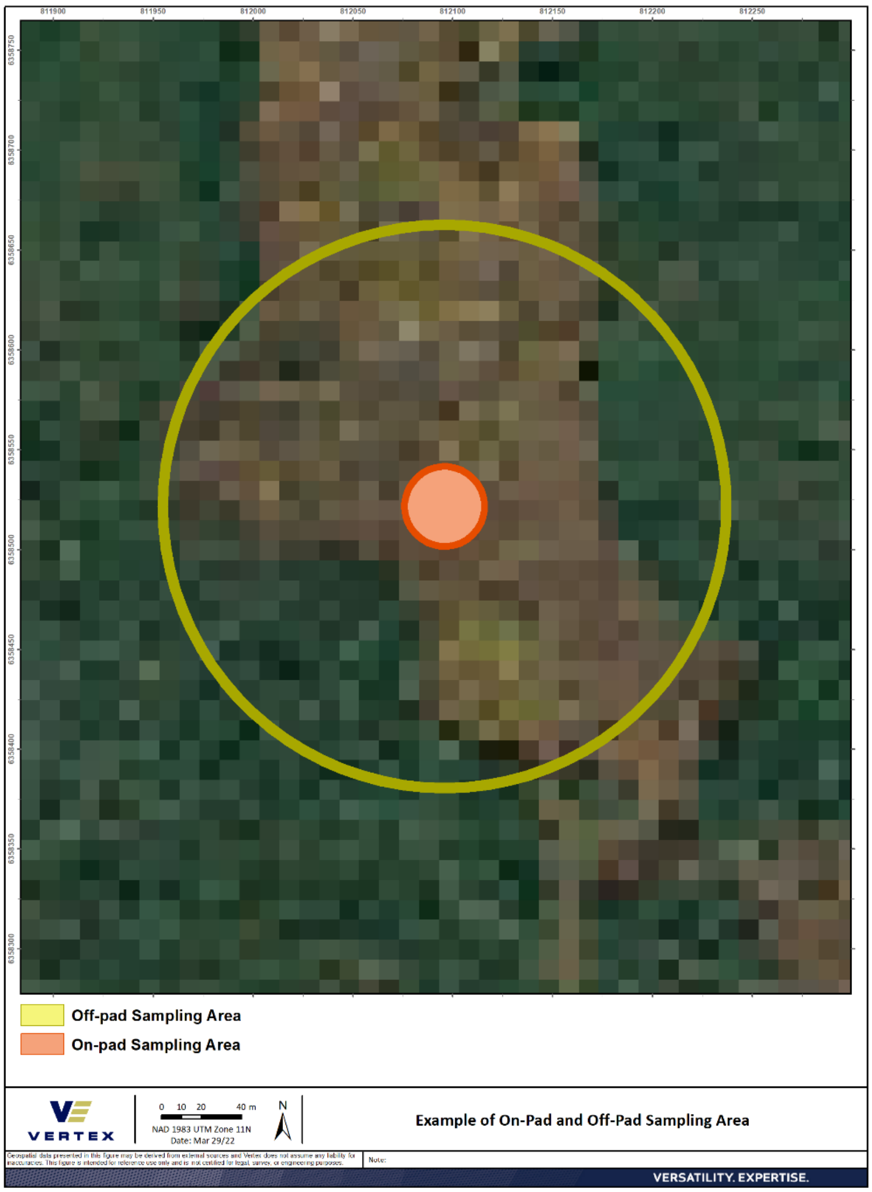

Figure 3. Example of on-pad and off-pad sampling areas.

2.3.2 *Image Pre-processing*

Sentinel-2 and LiDAR data were processed in GEE. LiDAR DEM images were mosaiced and converted to GEOTIFF. Open-access archives of Sentinel-2 were queried using three filters:

- Locational: intersection with sampling polygons
- Temporal: summer (July 1 to Aug 30) and spring (April 1 to May 31)
- Cloud cover percentage: < 10%

This yielded a catalog of 578 and 533 summer and spring scenes, respectively, overlapping the 15,083 wellsites spread across the study area. To remove clouds and shadows, a rule-based cloud mask solution was applied to each image. The cloud-free images were then reduced to a summer and spring composite by computing the median reflectance for each input band. Both the native 10-m and 20-m bands were retained for processing. From the Sentinel-2 composites, we calculated three spectral indices: the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Moisture Index (NDMI), and the Normalized Difference Water Index (NDWI). In addition, we calculated the Tasseled Cap components – Brightness (TCB), Greenness (TCG), and Wetness (TCW). The Tasseled Cap linear transformation of Sentinel-2 optical bands was used to obtain orthogonal components that reduce data volume and redundancy, while capturing 95% or more of the data variability.

2.3.3 *Feature Extraction*

Several features associated with physical characteristics of the land surface, which may discriminate padded from unpadded wellsites, were extracted from the LiDAR DEMs and the optical imagery. From the DEMs, mean, minimum, maximum, and standard deviation of each sampling area was extracted. From the optical imagery, the mean value of each of the indices calculated was extracted for each sampling area (Table 2).

Table 2. List of extracted features used as inputs in the analysis.

Input	Source	Rationale
NDVI	Sentinel-2	The NDVI can be used to estimate the density of green vegetation and plant health.
NDMI	Sentinel-2	The NDMI is a measure of vegetation moisture content and can be used to estimate vegetation's water stress level.
NDWI	Sentinel-2	The NDWI can be used to detect and highlight water bodies on land surfaces.
TCB	Sentinel-2	TCB measures the relative brightness of the surface, which can be used to detect bare or partially covered soil, and natural features such as rock outcrops and other bare areas.
TCG	Sentinel-2	TCG captures variability in vegetation and is correlated to green leaf area.
TCW	Sentinel-2	TCW captures variation in surface water and has been shown to be sensitive to soil and plant moisture condition.
Elevation	LiDAR	Padded wellsites will often have a higher elevation than surrounding peatland areas in their unmodified state. Unpadded sites will have more equivalent elevation to their surrounding landscape.

2.4 Remote Sensing Analysis

A supervised classification was run on the assembled datasets described in the previous section. To train the classifier, a set of 181 identified padded and unpadded sites was assembled from a combination of existing wellsite records augmented by expert visual interpretation of airborne and spaceborne imagery. The independent variables consisted of the derived spectral features and ancillary data whereas site type (pad/no pad) acted as the dependent variable. The ground-truth dataset was split into a training set (70%) and a test set (30%), and the performance of the classification was evaluated through a confusion matrix. The output consisted of a binary classification of padded/unpadded sites.

3.0 RESULTS

Based on the training dataset, the classification procedure achieved 81.2% accuracy when predicting no pad and 73.9% accuracy when predicting a pad (Figure 4), for an overall classification accuracy of 78%. As a result, a total of 7,077 padded sites and 8,006 unpadded sites in peatland areas were obtained from the supervised classification. The results reflect abandoned wellsites with LiDAR coverage that was acquired prior to the spud date of the well.

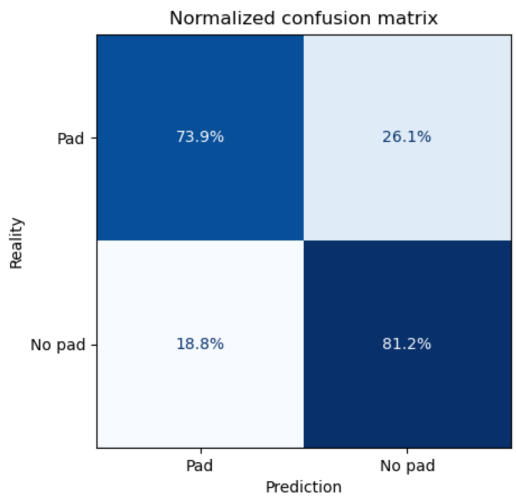

Figure 4. Accuracy assessment of the supervised classification using a normalized confusion matrix.

The results were broken down by drill (spud) year and well abandonment year (Figure 5), and there appears to be a tendency for more recently built sites to be unpadded.

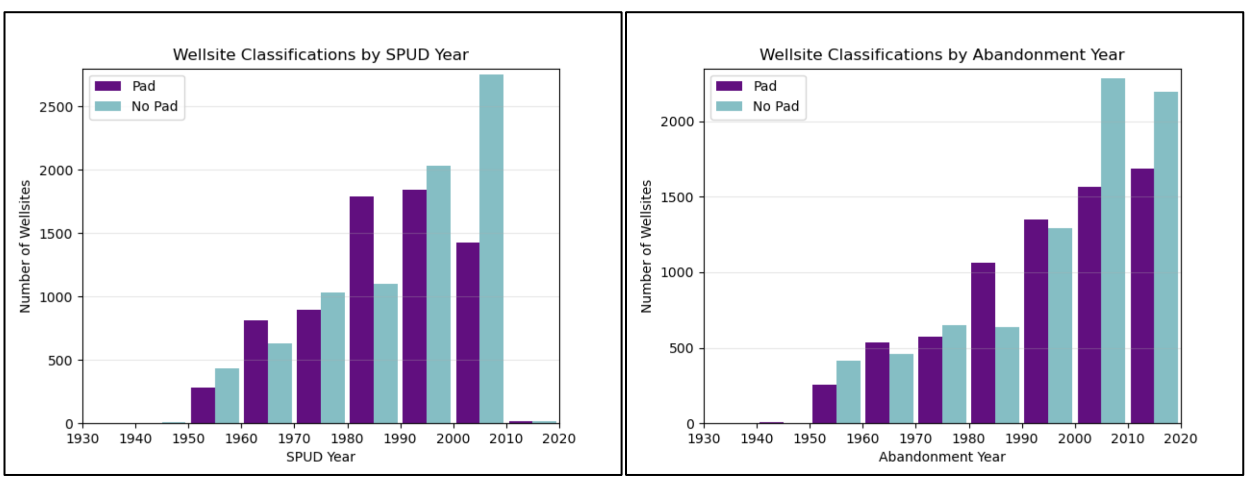

Figure 5. Classification results by spud year (left) and abandonment year (right) indicate a larger proportion of unpadded sites in recent years.

The results were also split by the surrounding wetland types (Table 3 and Figure 6) and the Alberta Environment and Parks land division districts (Table 4 and Figure 7). Due to the coarseness of the wetland datasets associated with the fuzziness in boundaries between land cover classes, wellsites in transitional areas between forests and wetland areas may have also been included in other classes.

Table 3. Classification results of pad presence/absence categorized according to wetland class.

Wetland Class	Classification	Count	Percentage	Total
Bog	No Pad	2,133	14.2%	3,548
	Pad	1,415	9.4%	
Fen	No Pad	1,962	13.0%	3,506
	Pad	1,544	10.2%	
Marsh	No Pad	15	0.1%	41
	Pad	26	0.2%	
Swamp	No Pad	987	6.5%	1,718
	Pad	731	4.8%	
Other Wetland	No Pad	240	1.6%	468
	Pad	228	1.5%	
Transitional	No Pad	2,669	17.7%	5,802
	Pad	3,133	20.8%	

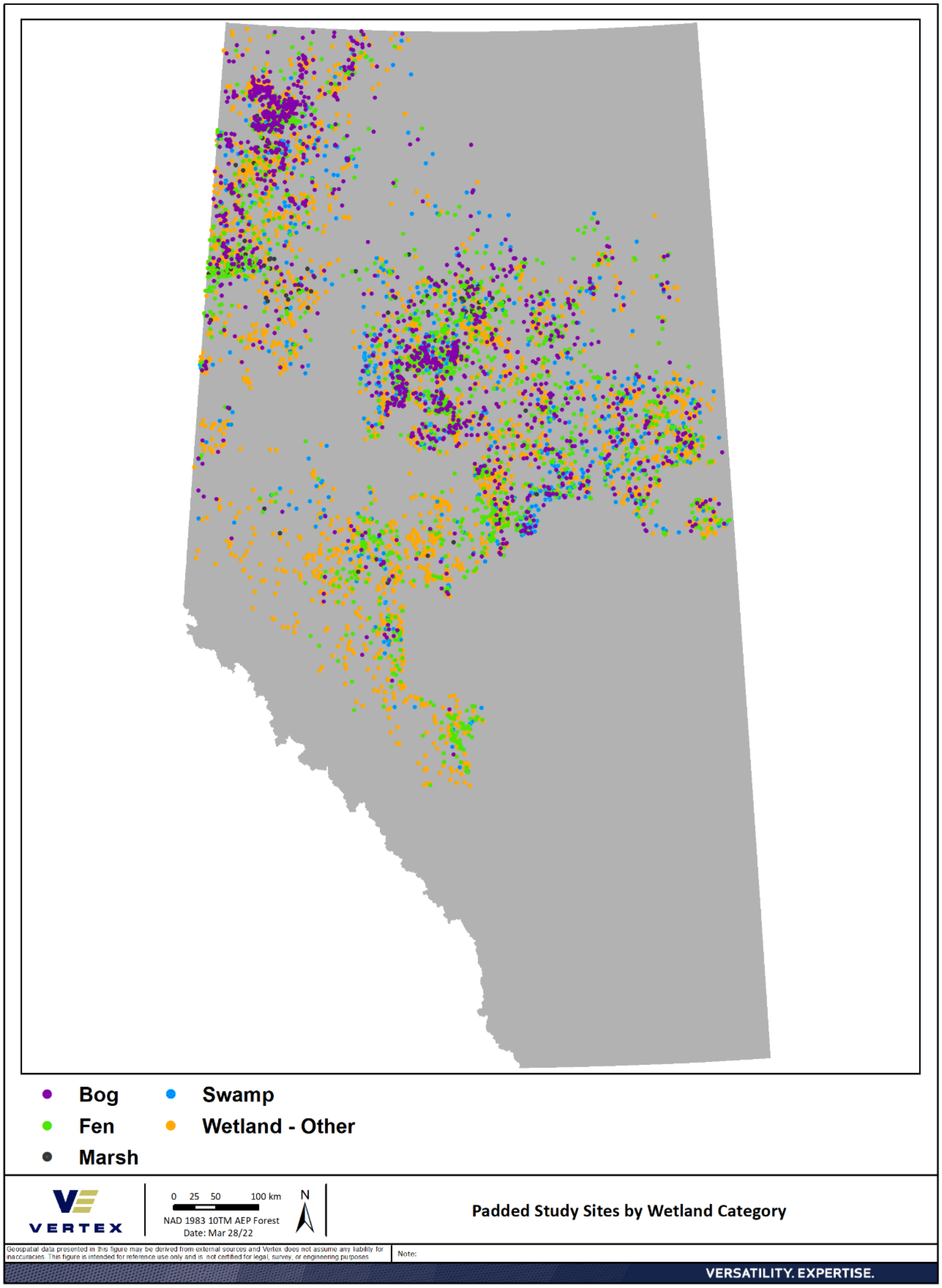

Figure 6. The study sites were categorized by wetland type to provide a better understanding of their distribution within the study area.

Table 4. Classification results by AEP Land Division Districts.

AEP Land Division Districts	Classification	Count	Percentage
Bighorn/Edmonton	Pad	87	2.2%
Headwaters	Pad	128	3.2%
North Athabasca	Pad	972	24.6%
Peace	Pad	1,909	48.4%
South Athabasca	Pad	845	21.4%
No district	Pad	3	0.1%

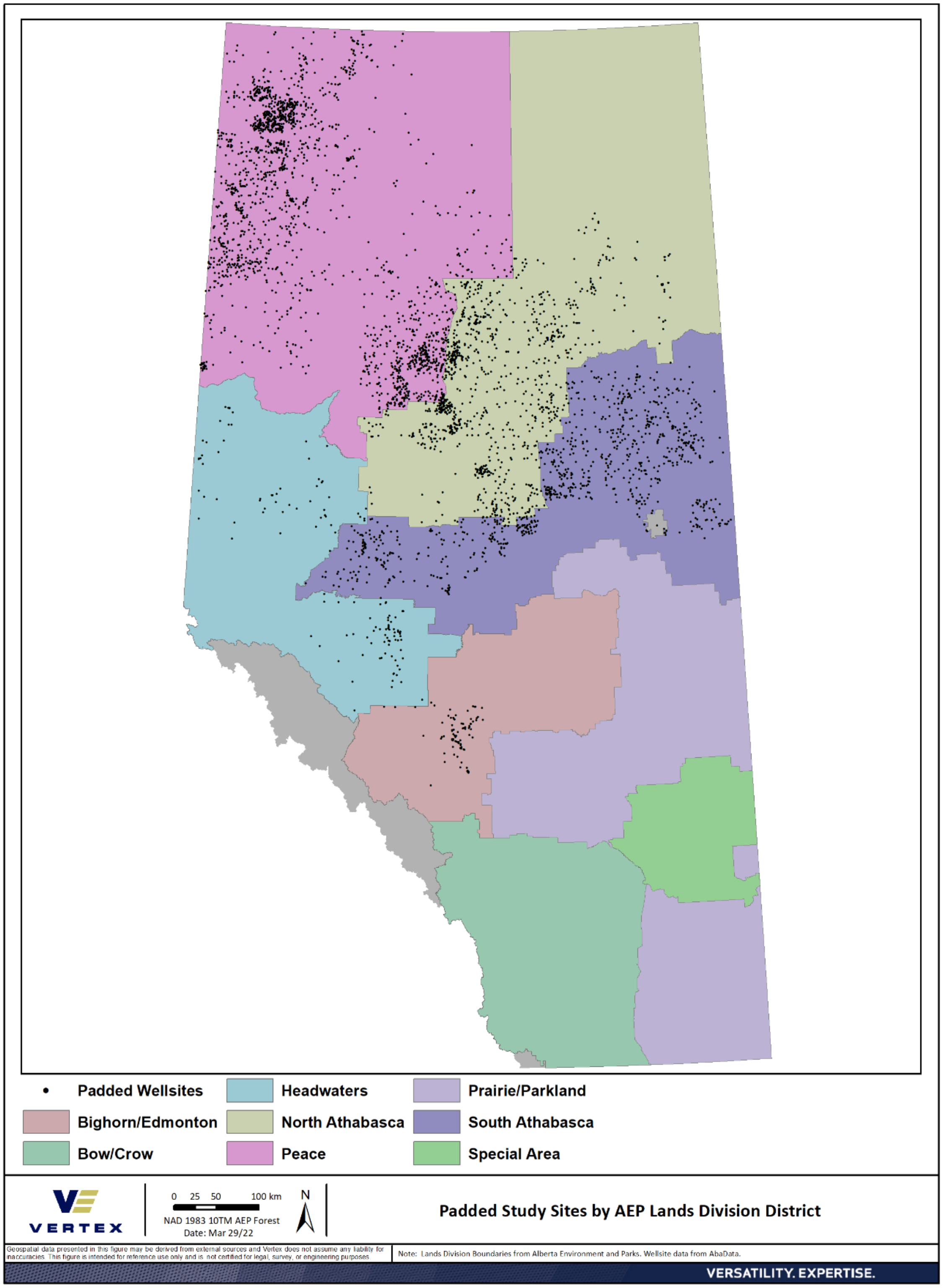

Figure 7. Location of wellsites segregated by AEP Land Division Districts.

4.0 LIMITATIONS AND RECOMMENDATIONS

When interpreting the results of the classification, the following data limitations should be acknowledged:

- Small training dataset size (181 sites, which is just around 1% of the sites).
- The available DEP and ABMI wetland layers have different spatial extents, so both were used to identify wellsites. The two data sources occasionally offered conflicting wetland classifications and we defaulted to the ABMI classification in such cases.
- Many wellsites overlapped existing polygons in the DIDs layer and many of those may represent modified topography that could influence the off-pad sampling. We erased those DIDs polygons from the off-pad sampling polygons that were most likely to have modified elevations such as roads or pipelines.
- Low vertical accuracy of the LiDAR data (1 m), whereas the observed changes between onsite and offsite elevations was only a few centimetres.

The accuracy of the classification may be increased through several options:

- Increasing the size of the training dataset used to parameterize the supervised classification would likely improve accuracy and result in more predictive power. This would require additional effort and expert knowledge to visually interpret new sites and re-run the classification.
- Including other predictor variables in the classification, such as texture metrics derived from synthetic aperture radar (SAR) or LiDAR data, additional wetness and greenness indices derived from different Sentinel-2 acquisition dates, and alternate spectral indices not previously considered.
- Implementing different classification techniques. For instance, a Logistic Regression model could be used to predict the probability of a pad (as a numerical output), which could be further classified into probability classes (e.g., 'High Likelihood' and 'Low Likelihood') based on chosen probability thresholds.

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