Asset Management of the Piñon Gas Field Using Imagery

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Abstract

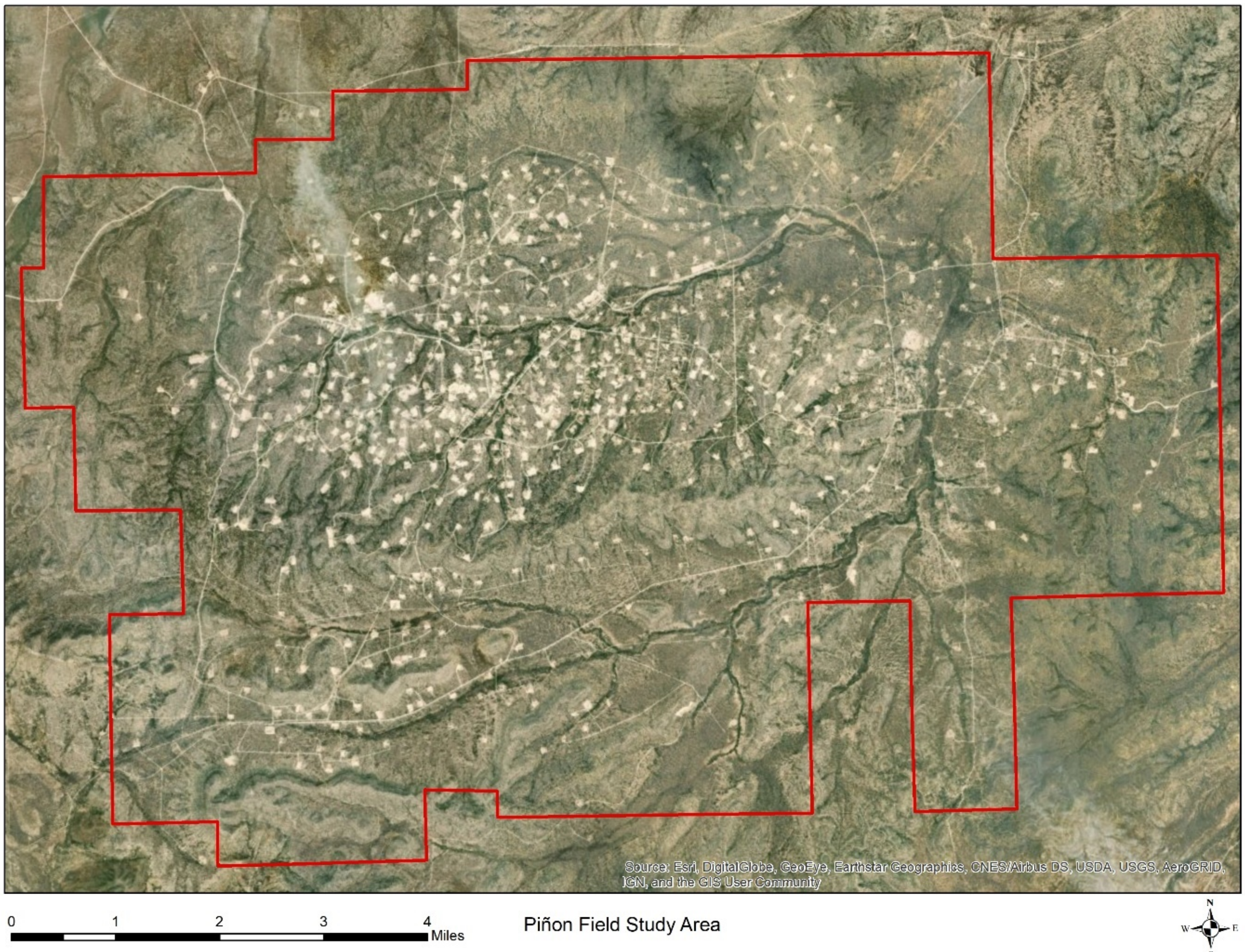
Determining the developed area of an oil and gas field is an important step to evaluating the economics of the field. There are requirements to reclaim the well pad and access road to its natural state once the well stops producing. A field with hundreds of sites can be evaluated by visiting each site as part of a manual field survey, although this method is very time intensive. By using a remote sensing approach, feature extraction of well pads and access roads of the oil and gas field can be accomplished through an object-based image analysis (OBIA). This is an analysis of a gas field for the purpose of accomplishing an inventory of the estimated reclamation liability of the access roads and well pads. An attempt to extract the larger surface equipment on the well pads was also attempted. It was a two-phase analysis of the well pad features in the Piñon gas field in southern Pecos County, West Texas. The first phase is the extraction of the well pads and access roads. The second phase is the extraction of the features on the well pad; tanks, separators, heater treaters, and possibly wellheads and other surface equipment. It used a multi-resolution segmentation of multi-spectral imagery to create objects which were then analyzed and classified into features. The features are then connected to the oil and gas wells, so the reclamation costs is known when the well becomes uneconomic. By using remote sensing instead of the manual field survey, the time and cost requirements are drastically reduced, while also providing accurate spatial data.

Introduction

The Piñon gas field, with an area of interest (AOI) of about 67 mi², lies completely within the Longfellow Ranch (Figure 1). In the summer of 2018, a manual field survey was done to evaluate the status of the well pads and access roads, with an inventory of the surface equipment being acquired at the same time. The field analysis took approximately 450 hours to complete, or about 30 minutes to visit and record details of each of the more than 900 well pads in the field.

A similar analysis was done on the Piñon gas field for a previous class in the MGIS program, Geography 883: Remote Sensing Image Analysis and Applications. The final project for the class was a change detection analysis using National Agriculture Imagery Program (NAIP) air photo mosaics from 2012 and 2016 to attempt to quantify the change over the four-year span. This analysis was partially successful. Change was measured between the two vintages, but the segmentation and classification rulesets were not able to capture the well pad features in enough detail to make the change detection meaningful. There were too many errors of commission and omission of the extracted feature when compared to known well pads to accomplish the goals of the project. This was partially due to data limitations; no elevation data was used in the segmentation analysis and the 4-band NAIP imagery didn't have the spatial and spectral resolution to complete the analysis. Another limitation of this analysis was time constraints for refining the segmentation and classification rulesets. While the analysis didn't accomplish the project goals, it did provide a good basis to expand upon for further evaluation.

Elevation data point cloud covering the AOI was acquired by the US Geological Survey in 2018. This data was still being processed by the USGS during my analysis and is set for release in late 2020 or early 2021, so it was not available for the analysis. Other elevation data, with the required spatial and temporal resolution was available for a cost starting at $12,000. With the economic downturn and oil price crash caused by the COVID-19 pandemic, there was not an available budget to acquire data for this analysis, so elevation data was not incorporated.



(Figure 1: Satellite Image of the Piñon gas field showing the approximately 900 well pads and their access roads with the AOI outline in red.)

This main reason for the survey was because the operator of the field has the responsibility to reclaim the well pads to their original land cover. The landowner wanted to know the reclamation costs based on the size and number of well pads. The landowner also wanted to know the number of surface facilitates on each well site. This capstone attempted to automate the time-consuming site visit methodology by using object-based feature extraction from remotely sensed data and GIS technology.

Previous research relates to OBIA feature extraction from remotely sensed data. OBIA incorporates the context of the pixel, which the pixel-based approach does not. It evaluates the values of the pixel, but then looks at the surrounding pixels, grouping all pixels of similar value into an object. The relationship between these objects can then be evaluated. Well pads are rectangular objects connected to access roads. Well pad facilities will be contained within a well pad and so forth. Blaschke 2009 demonstrates that an object-based approach can be superior to a pixel-based approach when feature extraction is the goal, especially when using variable data sources in the multi-resolution segmentation, such as elevation and imagery. He also outlines how the texture and shape of these objects can be used in the classification.

Dacre et al., 2017 and Brodrick et al., 2014 both attempt to use remotely sensed data to identify well pads. Brodrick et al., 2014 uses an object-based approach trying to identify well pads in the Bakken oil field in North Dakota using national agriculture imagery program (NAIP) 2012 imagery. The detail provided in the paper about the multi-resolution segmentation parameters and well pad object reflectance values of the NAIP imagery help guide this analysis. Dacre et al., 2017 uses a pixel-based approach for a supervised classification of oil sands wellsite reclamation in Northern Alberta. This study had detailed results on the quantification of remote sensing data in relation to the assessment of reclamation success. The methods used were applicable to determining if a well pad was reclaimed or still active in the Piñon AOI.

In a geologic application, Emerson et al., 2015 used elevation data and thematic shapefiles in conjunction with multi-spectral imagery with OBIA methods to correctly identify fossil bearing formations. Details about the segmentation parameters and rule sets used in eCognition were outlined in high detail in this paper. I was able to compare the extraction of bright fossil bearing formations to the extraction of bright well pads and access roads. Ghimire et al., 2014 used OBIA to identify windbreaks in Kansas. This analysis incorporates NAIP imagery. The analysis outlines the process of thresholding, or excluding of objects in the OBIA that have properties that exclude them from the analysis, which I used as part of the segmentation analysis.

There are two objectives to this study. First the well pads and the associated roads were identified. Second, the features on the well pads such as storage tanks, heater treaters, separators, and wellheads were attempted to be extracted from imagery with the elevation data. Unfortunately, the USGS 2019 lidar survey was not available for this analysis.

Data Sources

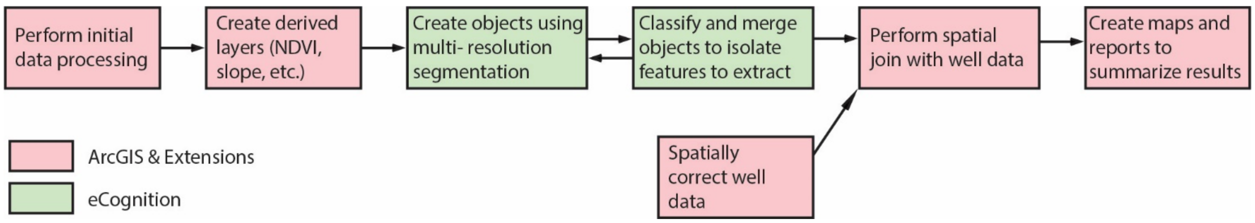
This analysis used high resolution multi-spectral imagery. It is 4-band (R, G, B, NIR) (NAIP) imagery with a spatial resolution of 60cm (approximately 2 ft) from 2018. This freely available imagery has enough spatial and spectral resolution to identify the pads and access roads but can’t be used to identify all features on the pad.

Elevation data would also benefit this study. Lidar or satellite-based radar has the resolution to help identify the well pads and features on them. Well pads are flat, while the features on them will be vertical. As mentioned in the introduction, USGS point-cloud data collected in 2018 was being processed when I was conducting the study, but it was not released in time to incorporate it into the study and has still not been released.

The IHS well database allows spatial joins from the well data to the pad and feature data. This data was spatially corrected prior to use.

Methodology

This analysis had multiple parts. Pre-processing of the data was required and followed by the generation of derived layers in ArcGIS. eCognition was then used to segment and classify the data into objects over multiple iterations. Then the corrected well data was joined back the objects and exported into maps and reports. Figure 2 outlines the software and the major methodology steps in order to perform the analysis. The first part of the analysis was to finalize the data sources.



(Figure 2: generalized methodology and software used)

Pre-processing before eCognition includes the creation of derived layers, such as NDVI from aerial imagery. (De Souza et al., 2017)

The derived layers and other data was loaded into eCognition and used in the multi-resolution segmentation. This segmentation created objects based on the pixel values from each layer loaded. These values were then used to classify the objects into features. (Brodrick et al., 2014)

The classification was based on the average brightness value of the red, green and blue bands. Average brightness values > 190, on a scale of 0-255, were the first objects classified as bright. Objects with lower brightness values, > 175 > 190 and with high "relative border to" the brighter objects were added to the bright class. This added less bright objects that shared 80% of their border to the bright objects. Roads were then extracted based on the high asymmetry values > 0.8, on a scale of 0 - 1. This provided the basis of the classification. It also included other objects in the classification that needed to be manually edited to remove the objects from the pad and road classes.

The accuracy assessment uses random sample points across the two categorized feature classes (well pads and access roads) and the uncategorized area. The level of confidence indicates if a feature is correctly classified (producer's accuracy) and that points correspond to the classification (user's accuracy). For example, the producer's accuracy will quantify how many roads were included in the road category, while user accuracy will quantify how many other objects where incorrectly classified as roads. (Campbell and Wynne, 2011)

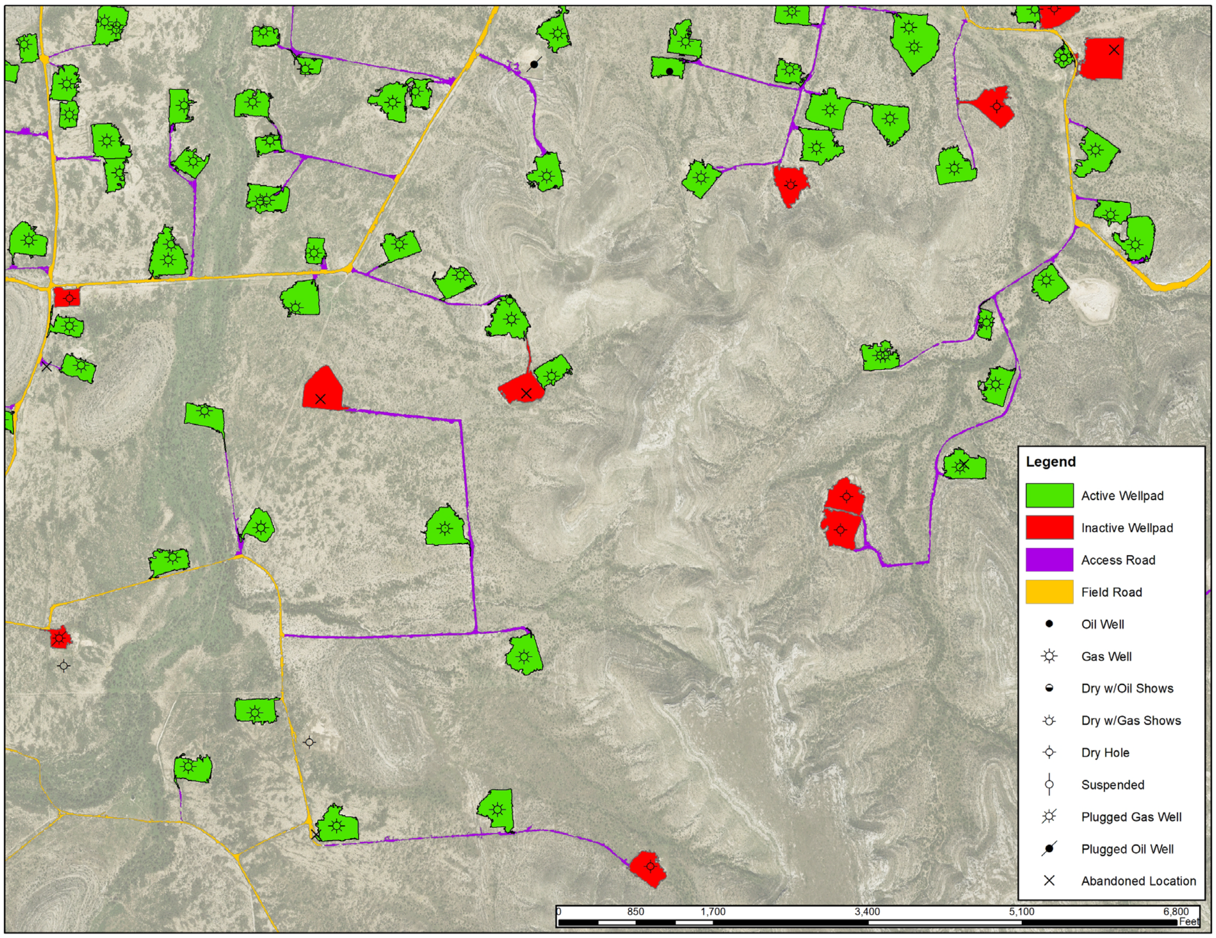
As the elevation data was not available, a second AOI was evaluated in Andrews County, Texas that did have point-cloud and NAIP 2018 coverage. This second AOI was analyzed to determine the procedures and analysis in order to extract the well pad features in relation to secondary objective.

Results and Discussion

Examples of the resulting inventory of well pads and access roads joined to the well data are summarized in Figure 3 and 4. This allows for better estimation of the reclamation costs for each well pad and access road.

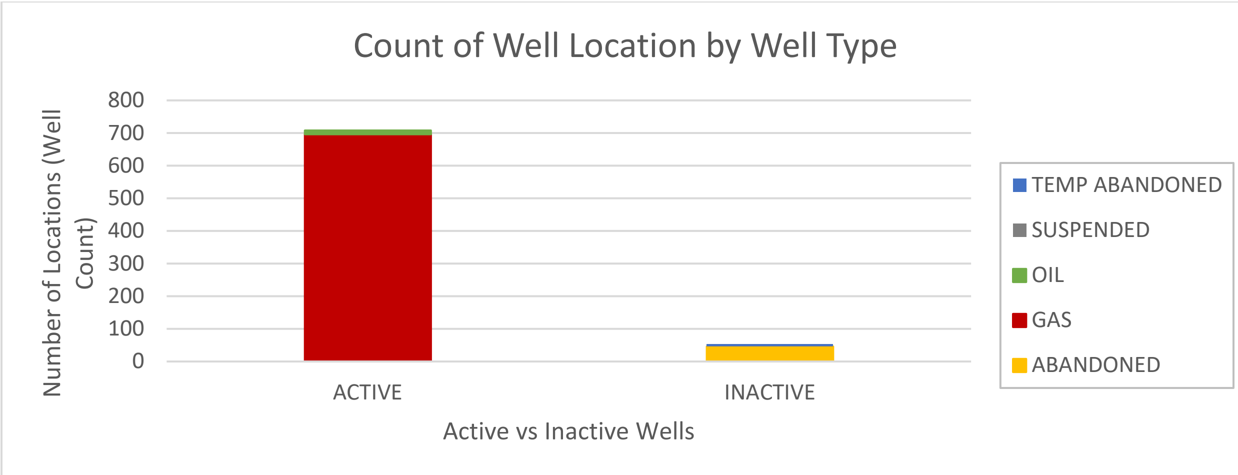
UWI	API UNIQUE	WELL NUM	LEASE	WELL_NAME	FINAL STAT	Pad Acreage	Road Acreage	Total Acreage
42371380340000	38034	6068	WEST RANCH	6068 WEST RANCH	GAS	2.6		2.6
42371381890000	38189	6072	WEST RANCH	6072 WEST RANCH	GAS	1.5	0.6	2.1
42371384100000	38410	2421	WEST STATE	2421 WEST STATE	GAS	2.2	0.1	2.3
42371381690000	38169	5077	WEST RANCH	5077 WEST RANCH	GAS	2.6	0.3	2.9

(Figure 3: table showing pad and well detail)



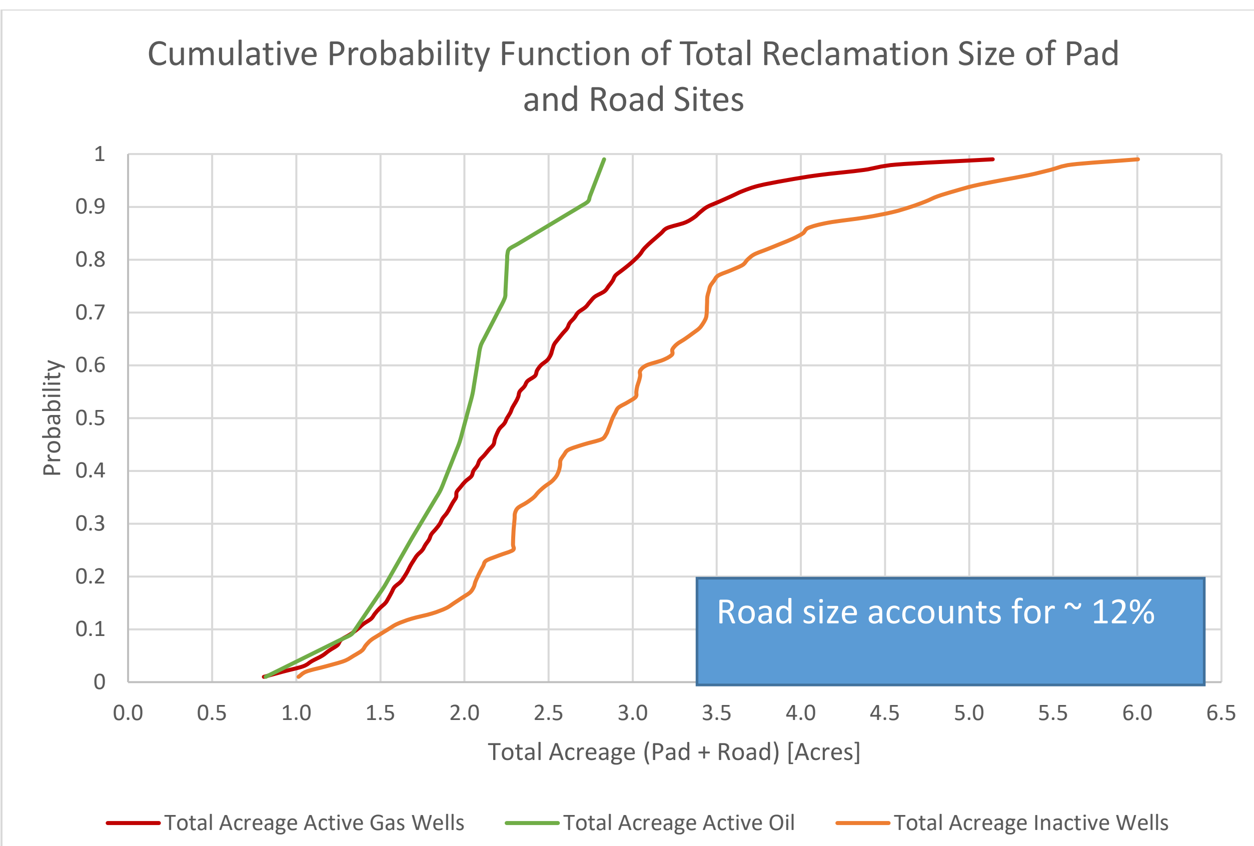
(Figure 4: map of well pads and roads)

The count and size of the pads is shown in the Figures 5 and 6 respectively. There are 708 active well pads and 546 active access roads along with 53 inactive well pads and 35 access roads to inactive pads.



(Figure 5: chart counting the number of pads by type)

The size distribution is graphed in the chart below (figure 6). Oil pads are the smallest, but had the lowest count. The inactive pads were the largest. Gas wells have the most normal distribution, based on the shape of the curve, but also have the highest count with the average size of the pad being 2.25 acres.



(Figure 6: chart counting the number of pads by type)

An overall accuracy of 77% was achieved on the initial object based image analysis (figure 7), not the final manually edited classes. Accuracy was lower than anticipated, as the missing elevation data did not allow for the inclusion of slope. Slope is a key attribute for well pads, as the pads are required to be flat to avoid any spills leaving the pad or rainwater channeling potential contaminants off the pads during a storm event. Most of the errors were errors of commission, including objects in the classification that should not have been included. In the road class, these errors mostly consisted of edge features on the pad that had lower spectral values and high asymmetry values. Another cause of this error was geologic stratification with high spectral and asymmetry values, but far from existing road and well pad features. Well pads also had errors of commission where excavation pits, storage yards or gas facilities were mistaken for well pads. All of these mistaken features were bright and had a similar size to the well pads. Of these errors, the excavation pits and the rock outcrops could be corrected by using the slope data as part of the classification analysis.

Count of FID	Column Labels				
Row Labels	Other	Pad	Road	Grand Total	User's Accuracy
Other	94			94	100%
Pad	11	87	7	105	83%
Road	25	27	49	101	49%
Grand Total	130	114	56	300	
Producer's Accuracy	72%	76%	88%		77%

(Figure 7: error matrix)

Conclusions

The analysis was successful in that the GIS inventory of well pads and access roads was constructed, but the quality of analysis could be improved by incorporating the elevation data and further refining the segmentation and classification algorithms to remove the need for manual classification of the objects. The analysis did produce a detailed dataset of the pad and road areas, and by tying these areas and the estimated cost per acre back to the well, the cost to reclaim the site can be better estimated and modelled into the economics of the field.

In total, I estimate the disturbed areas encompassing the well pads and access roads to be 2,111.6 acres. Out of the total 42,764 acres in the AOI this accounts for 4.9% of the total area of the AOI.

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