OGRP Project No. G-051-099

Development of Operational Aerial Analytics for Remotely Measuring Reclamation Success in North Dakota

Final Report

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Introduction

Aerial data collection and analytics offer insights that empower the oil and gas industry and its regulatory agencies to improve economic efficiencies alongside environmental sustainability. In 2018, Director of Mineral Resources Lynn Helms published a memorandum underscoring the North Dakota Industrial Commission's (NDIC) commitment to advancing the use of aerial imagery and analytics as a business and agency decision support tool for improving well site reclamation program efficiencies.[1] However, the widespread adoption of aerial imaging and analysis technology in the oil and gas sector requires two essential actions: 1) validation of the methodology as a means of reducing costs and fulfilling compliance requirements, and 2) automation of data processing and analytics that derive meaningful information from gross aerial data. These needs formed the basis of the project and associated results presented herein.

The primary goal of this project was to develop and validate a suite of automated analytics that bring remote reclamation assessment technology to operational capacity for industry, agencies, and the interested public of North Dakota. Project objectives entailed four central components:

1. *Model Development.* Build upon the findings of OGRC Project G-037-73[2] to develop efficient and scalable imagery analysis tools for remotely measuring the success of well site reclamation, including a broadscale vegetation assessment and a comprehensive suite of aerial reclamation inspection analytics. The analytics suite developed through this project will consist of the following models designed to meet reclamation standards established by North Dakota Administrative Code 43-02-03-34.1: a) vegetative continuity comparison; b) infrastructure identification; c) problematic surface hydrology identification; d) topographic contouring assessment; and e) volumetric measurement.
2. *Model Validation*. Statistically test and validate the accuracy of aerial data and developed analytics with multiple tiers of comparative analysis and ground-truthing field inspections.
3. *Model Automation.* Automate the developed and validated analytics within a GIS platform to enable efficient, repeatable, and scalable deployment of remote reclamation assessment tools.
4. *Cost-Effectiveness Analysis.* Analyze and compare the costs and effectiveness associated with aerial imagery collection and analysis against current well site reclamation inspection procedures.

[1] Helms, L. 2018. Memorandum: NDIC Intent to gain efficiencies and improve procedures concerning the well site reclamation program.

[2] Jackson, M. Collection and Development of Actionable Reclamation Data Using Aerial Remote Sensing, Contract No. G-037-73, Final Report prepared for the North Dakota Industrial Commission. Hell Creek Environmental LLC. Submitted January 15, 2018. Retrieved from https://cms.oilresearch.nd.gov/image/cache/Contract_G-037-73_Final_Report_HellCreek_HESS.pdf

Methods

Data Collection

SolSpec partnered with Whiting Petroleum Corporation to select 100 oil and gas well pads located in the Bakken oil field in northwestern North Dakota that were utilized for aerial data collection and assessment. The well pad locations varied in life stage, from sites with active extraction operations to fully reclaimed sites. Twenty-eight well pads were recorded as active with interim reclamation, 40 were inactive and undergoing reclamation, and 35 were plugged and abandoned. All data were collected during the 2020 vegetative growing season between May and August.

Aerial imagery for the development of the reclamation inspection tools was acquired by ISight RPV Services (ISight). Imagery for the 100 well pad sites in the Bakken oil field was collected using a Inspire 2 Pro UAV made by DJI. The UAV was mounted with a gimbaled 100-megapixel camera capable of capturing red, green, and blue (RGB) 3-band imagery at a resolution of three-to-five centimeters. The images were processed through Pix4D photogrammetry software to develop RGB orthomosaics and digital surface models for each well pad.

Field data were collected by Duraroot Environmental Consulting (Duraroot) for 29 of the 100 well pad sites. Field data for each site consisted of three-to-five photographs used for ocular assessment and two-to-three standard line-point intercept transects[3] for quantifying soil cover, including vegetation, litter, rocks and biotic crusts. This method is commonly used to assess current site conditions and repeated annually as a long-term assessment of the ability of a site to resist and recover from degradation. The purpose of these data were mainly for comparison and model validation, although imagery and field data collection though time on an annual or biannual basis would provide great insight into site trends and vegetative community trajectory. The subset of sites visited consisted of 19 plugged sites that were categorized as in-progress toward or near final reclamation but that the NDIC had not yet certified, and 10 active sites representing partial, or interim, reclamation status.

Model Development

This project involved the development of several analytic models for assessing reclamation success. The suite of analytics was designed to evaluate well site conditions per reclamation standards established by North Dakota Administrative Code 43-02-03-34.1, which requires that the well pad be returned as close as practicable to original conditions. The analytic models were developed to remotely perform the following reclamation inspection functions: classify ground cover; examine vegetation vigor, height, and structure; assess deviation of vegetative community from background conditions; identify the presence of infrastructure; assess deviation of site topography from background conditions; and identify problematic surface hydrology. All analytics were developed in an ESRI ArcGIS environment using Arcpy and Python 2.7 scripting languages for tool creation.

[3] Elzinga, C.L., D.W. Salzer, J.W. Willoughby and J.P. Gibbs. 2001. Monitoring Plant and Animal Populations, Blackwell Publishing. 368 pp.

Vegetation Analysis

Broadscale Vegetation Assessment. SolSpec created a broadscale vegetative vigor and classification comparison model using the most recent National Agricultural Imagery Program (NAIP) at 0.6 meter resolution to analyze the population (n= 2,313) of well pad sites operated by Whiting in North Dakota. This assessment utilized the NAIP four spectral bands (Red, Green, Blue and near-infrared) to build out a broadscale vegetation similarity analysis that examines general vegetation spectral signatures and patterns to provide an approximation of a pad's reclamation status. The most recent NAIP imagery available for the study area was captured in August, 2018.

The broadscale vegetation assessment entailed calculating the Normalized Difference Vegetation Index (NDVI) for the study area and then evaluating the pattern of NDVI values between a given pad area and its associated reference area. The analysis is functionally equivalent to the Continuity Index (CI) implemented throughout this study, which measures the statistical difference in the distributions between two model outputs. The NDVI variable was selected for analysis because the near-infrared band (fourth band) is a good measure of chlorophyll content, making the index optimal for assessing vegetation vigor. The broadscale vegetation assessment was automated by building an ArcToolBox Python 2.7 tool that requires the following inputs: well pad points; pad and reference area boundaries; and NDVI raster layer. The tool iteratively visits each well point, calculates NDVI statistics for the well pad and reference area, directs that information to the CI algorithm to calculate the index between the pad and reference area, and then attributes the output score to the well pad point.

UAV-based Vegetation Cover. Ground cover conditions on and adjacent to well sites were classified into categories of vegetation and bare soil, including litter, gravel, senescent vegetation, and structures (see Figure 1). The differentiation of vegetation from other ground cover types and evaluation of vegetation health (i.e., vigor) were accomplished using spectral relationships between the red, green, and blue spectral bands captured in the UAV-based orthomosaics. A literature review was conducted to determine the most effective current methods of vegetation indices for identifying vegetative spectral signatures. This research yielded the following six vegetation indices that, when combined, are robust across grasslands, shrubland, and forested areas:

- Triangular Greenness Index (TGI)[4]
- Normalized Difference Vegetation Index (NDVI)[5]
- Visible Atmospheric Resistant Index (VARI)[6]
- Green Leaf Index (GLI)[7]

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[4] Hunt, E.R., Doraiswamy, P., McMurtrey, J., Daughtry, C., Perry, E., 2013. A visible band index for remote sensing leaf chlorophyll content at the canopy scale. International Journal of Applied Earth Observation and Geoinformation. 21, pp. 103112.

[5] Rouse, J., Jr., Haas, R., Schell, J., Deering, D. 1974. Monitoring vegetation systems in the Great Plains with ERTS. NASA Special Publication, 351, pp. 309-317.

[6] Gitelson, A.A., Kaufman, Y.J., Stark, R. and Rundquist, D., "Novel Algorithms for Remote Estimation of Vegetation Fraction", Remote Sensing of the Environment, 80, 76-87, 2002.

[7] Gnyp, M.L., Panitzki, M., Reusch, S., 2015. Proximal nitrogen sensing by off-nadir and nadir measurements in winter wheat canopy. In: Stafford, J.V. (Ed.) Proceedings of the European Conference on Precision Agriculture 2015, Tel Aviv. Pp. 43-50.

- Red-Green-Blue Vegetation Index (RGBVI)[8]
- Normalized Green Red Difference Index (NGRI)[9]

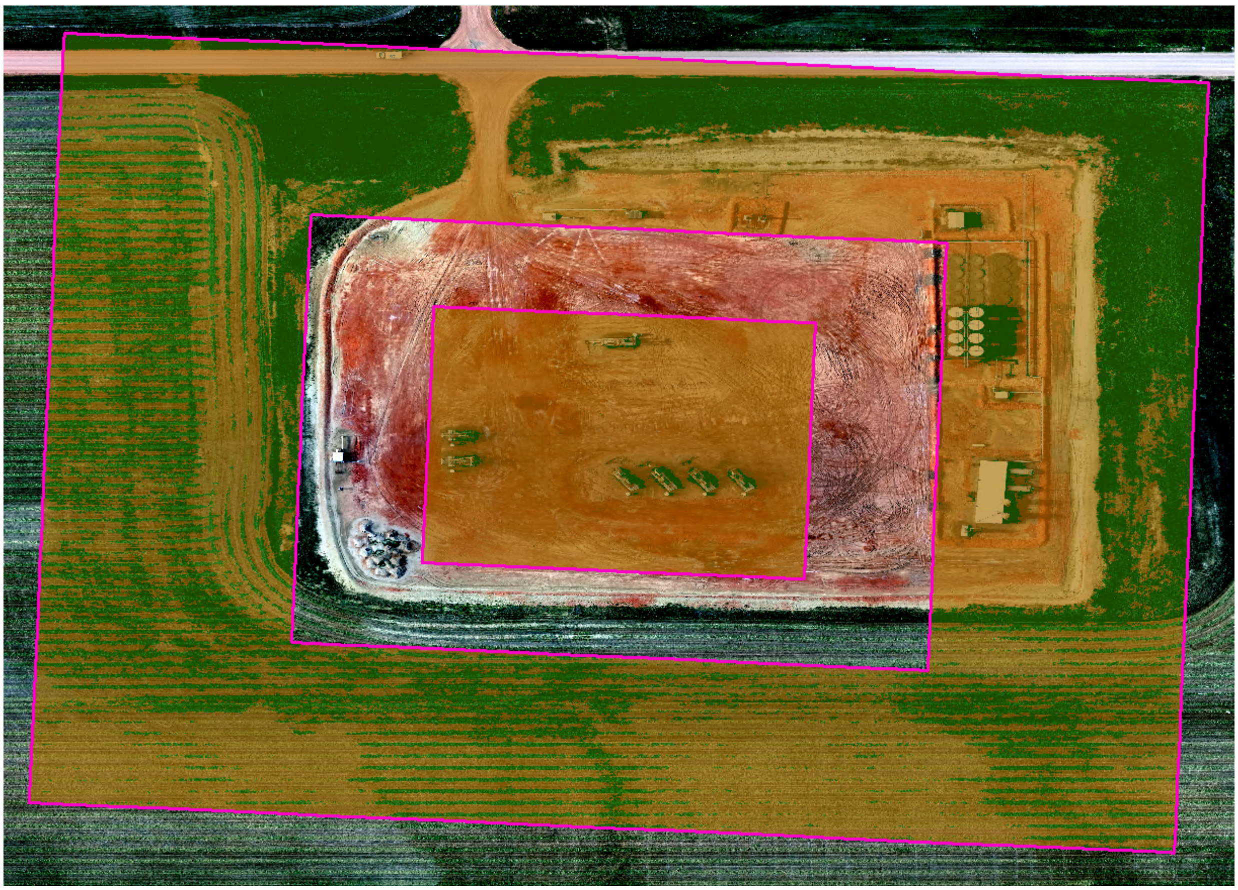

Figure 1. Example of vegetation classification analysis around an operating well pad based on UAV imagery. Green indicates vegetation, and brown indicates bare soil, litter, or gravel. Note that, while effective at classifying vegetation, some structure shadows are erroneously classified as vegetation due to the shadows possessing spectral signatures similar to vegetation spectral signatures.

[8] Bendig, J., Yu, K., Aasen, H., Bolten, A., Bennertz, S., Broscheit, J., Gnyp, M.L., and Bareth, G., 2015. Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley. International Journal of Applied Earth Observation and Geoinformation, 39, pp. 79-87.
[9] Tucker, C., "Red and Photographic Infrared Linear Combinations for Monitoring Vegetation", Remote Sensing of Environment, 8, 127-150, 1979.

The final vegetation model utilizes several vegetation indices in combination with filtering algorithms that eliminate shadows and other anomalies in the imagery and clustering algorithms that account for both spatial distances and spectral values. Once vegetation has been identified, the overall vegetative condition is approximated by examining the spectral signature of chlorophyll, with higher values representing higher vegetative vigor (see Figure 2).

Figure 2. Example of vegetation vigor analysis around an operating well pad based on UAV imagery. Green indicates healthy vegetation (i.e., high levels of chlorophyll), and red and orange colors indicate vegetation that is senescent or has low levels of chlorophyll. This analysis was developed using a modified version of the TGI index that utilizes components of the GLI and NGRI indices.

Vegetation Structure. Vegetation height and structure were examined by first isolating and creating a mask of areas that were dominated by vegetated ground cover in the orthomosaics. The mask was then used to extract elevation values from the digital surface model where vegetation occurred. The model utilizes edge enhancement algorithms and other methodologies that examine variability in the data to determine the degree of heterogeneity in the local vegetation composition. This allows for the extraction of vegetation height, shape, and density information used in determining overall vegetation community classes such as forest, shrubland and grass/forb (see Figure 3).

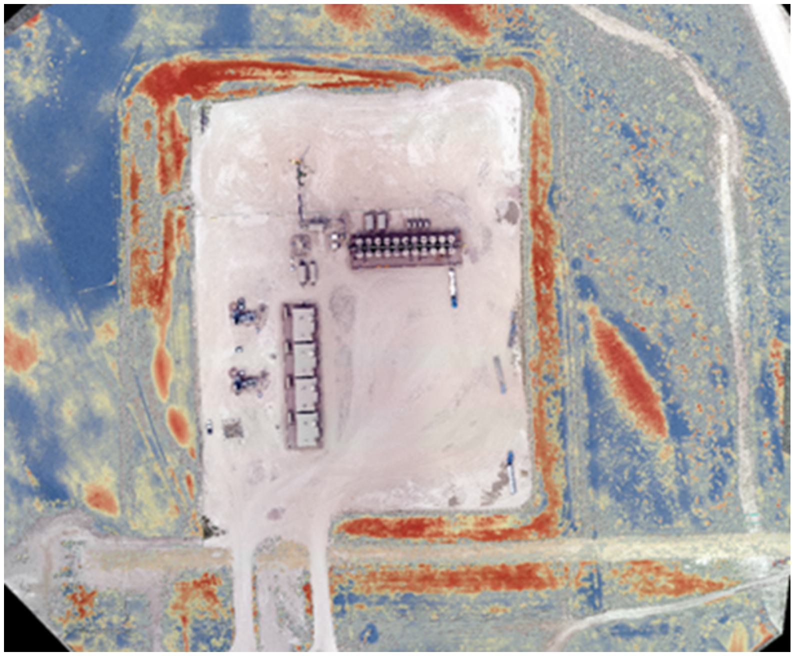

Figure 3. Example of vegetation structure analysis around an operating well pad based on a digital surface model derived from UAV imagery utilizing photogrammetric methods. Red colors indicate taller woody vegetation, while blue colors indicate grass/forb vegetation.

For each of the 100 Whiting well pads included in the study, the vegetation classification, vigor, and structure models were run on the well pad footprint and an undisturbed area 30 meters from the well pad footprint. This design assumes that the adjacent undisturbed area -- or reference area -- represents the original conditions of the well pad location prior to construction and operation activities; however, recent changes in land use near the well pad site may violate this assumption (for instance, conversion from rangeland to cropland). The models outputs were combined to create a CI useful for examining vegetation community deviation from a natural undisturbed state. The CI leverages the Kolmogorov-Sminirnov (K-S) statistic to measure differences in the distributions of the individual models outputs, as well as for the well pad footprint and the reference area.

Model validation was accomplished by comparing the models' outputs against a) 2,000 random sample points and b) 20 randomly located 1-meter plots distributed across all 100 Whiting well pad sites (see Figure 4). For each of the 2,000 points, ground cover was classified as vegetation or bare soil by an ocular assessment of the UAV-based orthomosaic imagery viewed at a 1:1500 scale. Sample plots were classified using the same methodology and ocularly assigned a percent area covered by vegetation within the plot. The point locations and sample plots were then evaluated using the vegetation analytics. The resultant data were summarized and used to assess overall agreement between the model outputs and ocular assessment.

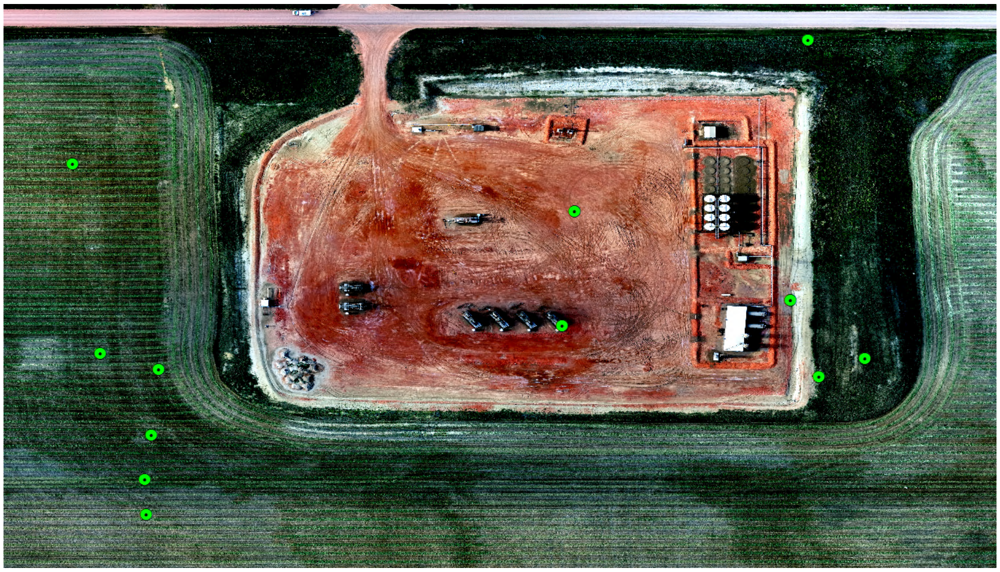

Figure 4. Example depicting remote aerial sampling locations (green points) for on- and off-pad locations.

Infrastructure Analysis

The infrastructure identification analytic leverages the digital surface model for each well pad location clipped to the inverse of the vegetation mask discussed above. Areas classified as vegetation are removed from the digital surface model, and the remainder of the data are used as an input into the infrastructure analytic. A moving window at multiple scales examines variability in elevation and slope, with high variability indicating abrupt changes and thus the presence of infrastructure (see Figure 5). Geometry and shape complexity of the isolated areas were then used to filter out large trees, rock outcroppings, or boulders.

Figure 5. Example of infrastructure identification analytic. Structures or equipment are highlighted in green.

Contouring Analysis

Slope and elevation surfaces were created at multiple scales using the digital surface model. These surfaces were then collapsed into a single surface to remove small features and outliers in the data. The contouring analytic was applied to the well pad footprint and the reference area to assess differences in the topographic profiles. The CI analysis was then applied to determine significant differences in the distribution of topographic values between the well pad footprint and reference area. The resultant K-S statistics were used to determine if the site had been re-contoured to its background conditions.

Surface Hydrology Analysis

The problematic surface hydrology analytic identifies inundation zones with the potential to cause stormwater problems, indicating that an existing pad is not well drained or that a reclaimed pad is not properly contoured. This analysis entailed using terrain and hydrology metrics to find zones without outlets, or pour points, within the digital surface model. These zones' corresponding digital surface model cell values were iteratively increased in elevation until a pour point was identified. Once a pour point was identified, the pour point elevation differential between all other digital surface model elevation cells within the zone was calculated. This elevation differential was then used to calculate the total volume of water associated with the inundation zone (see Figure 6). The problematic surface hydrology analytic results in two datasets: 1) a raster for all inundation zones with depth-of-water calculations and 2) a polygon shapefile that contains all inundation zones identified with total-volume-of-water calculations.

Figure 6. Example of inundation analysis on a functioning pad. Exhibit A is the orthomosaic of the pad, and Exhibit B is the inundation analysis for the pad, with darker blue indicating deeper inundation.

Volumetrics

The volumetrics analytic is the only tool among the reclamation analytics suite that requires user-defined parametrization and thus is not as automated as the other analytics. The major input into the volumetrics analytic is delineated features for which the user wishes to calculate volume. The other input to this analytic is the digital surface model or a folder containing many digital surface models. The analytic uses the delineated feature to establish a series of baseline elevation values as a reference for which to calculate volume. The model then populates the input features with cut or fill cubic yards. The volumetrics analytic has been automated to process multiple delineated features across many different pad locations. This means that multiple features of interest can be delineated for a given period and then simply run across all well pad digital surface models.

Cost-Effectiveness Analysis

A cost-effectiveness analysis is an economic tool for comparing the relative costs and outcomes of different courses of action that aim to achieve a similar goal. In this study, we evaluated the relative costs and outcomes for industry and agencies associated with aerial imagery collection and analysis against manual well site reclamation and inspection procedures. To calculate the costs of the status quo reclamation and inspection process, we conducted brief interviews with both Whiting and NDIC representatives regarding the resources and expenditures each organization estimates it typically spends on manual well site inspections. SolSpec confirmed with both Whiting and the NDIC that the cost-effectiveness data interpretation and comparative summary presented herein are accurate and representative of their reclamation inspection experience.

SolSpec originally anticipated collecting data regarding expenditures that Whiting and the NDIC had allocated to inspecting ten Whiting well sites during the previous five years that were not included in the aerial inspection group. However, record keeping did not support the level of detail needed to retroactively determine costs associated with specific well pads. Instead, SolSpec compiled information regarding the average expenditures, including personnel and equipment, associated with recent manual well pad reclamation inspections for Whiting and the NDIC. SolSpec also recorded opinions offered by Whiting regarding data quality, quantity, and consistency of traditional versus remote inspection methods.

Similarly, SolSpec estimated expenditure data associated with aerial reclamation inspection, including costs of data collection, processing, and analysis. The costs associated with model development, internal validation and automation, as well as ground truthing performed by Duraroot were not included in the cost-effectiveness analysis, as those costs are not representative of what the aerial inspection process would cost operators and agencies once operational. SolSpec then summarized the perceived effectiveness of remote reclamation inspection methods in terms of data quality, quantity, and consistency.

The cost-effectiveness analysis related to data collection and quality topics are based on data collection using the battery-powered, multirotor Inspire Pro UAV made by DJI. The battery-powered, multirotor UAV is among the most commonly used UAV models at present for its maneuverability, dependability, and overall ease of use. The model is limited, however, in the distance, speed, and duration it can fly due to design and battery life. This project originally sought to incorporate the use of ISight's gas-powered, fixed-wing V2 UAV for sampling a portion (n=5) of the sites that were also sampled with the multirotor UAV. The double sampling of sites was intended to support a comparative analysis of the costs and effectiveness between the two UAV models for remote reclamation inspection. However, ISight experienced unforeseen and conflicting business demands for the fixed-wing UAV during leaf-on vegetation conditions. Since the fixed-wing UAV was not available for deployment to the project during the required time window, the comparison between the multirotor and fixed-wing UAVs was excluded from the scope of the project.

Results & Discussion

Orthomosaics and Digital Surface Models

The official resolution of the orthomosaics and digital surface models for the 100 pads is 3 centimeters squared, with a horizontal Root Mean Squared Error (RMSE) of 50 centimeters and a vertical RMSE accuracy of 6 meters. The lower vertical accuracy is because Ground Control Points (GCPs) were not utilized in this study due to their labor- and resource-intensiveness. Doing so would have drastically increased project costs and reduced scalability with limited analytic enhancement. The reclamation success analytics were developed around the *relative* (not absolute) elevations of the digital surface models that capture terrain and vegetation structure accurately.

The digital surface models developed for this project contain elevation values that are a mix of terrain and non-terrain elevations (e.g., trees, shrubs, and structures). This is useful for assessing vegetation structure and detecting infrastructure but poses limitations to terrain-based analytics such as surface hydrology and slope analysis. Drawbacks of the digital surface model derived from photogrammetry (as opposed to LiDAR) are that water features, dark shadowed areas, and homogeneous terrain (e.g., row crops) can have elevation values that are interpolated from surrounding areas. This results in noisy terrain information that can, in turn, cause erroneous artifacts within the analytics (see Figure 7).

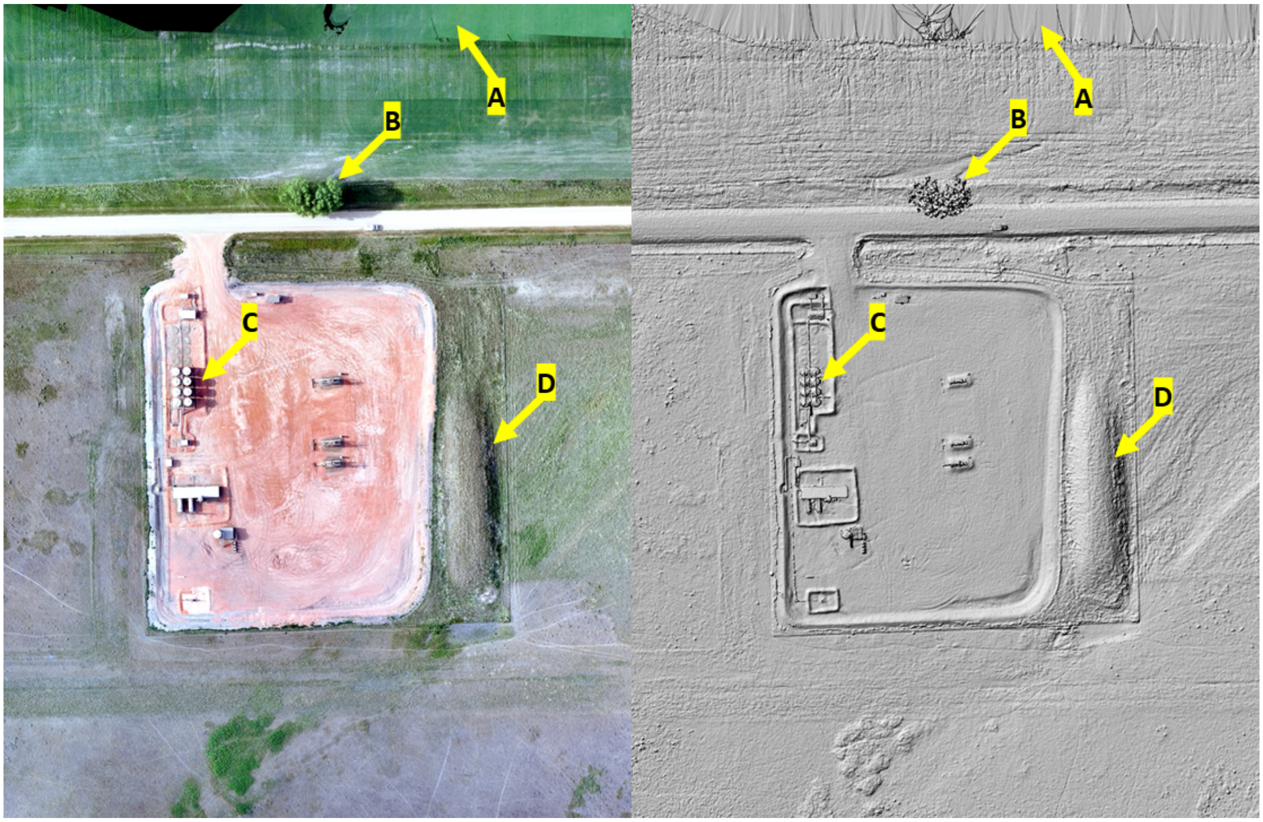

Figure 7. Example of an orthomosaic and associated digital surface model hillshade for a pad with four features highlighted in yellow. Feature A is interpolation noise that is a product of not enough photograph overlap or areas that are very spectrally homogeneous. Feature B is a tree that has higher elevation values than the surrounding terrain, which is useful for calculating tree structure but poses issues when calculating terrain slope or surface hydrology since the tree feature is considered part of the terrain. Feature C is storage tanks on the pad. Notice how infrastructure features have sharp elevation values with homogeneous tops. Feature D is a stockpile for reclamation purposes. This feature can be delineated and total volume calculated with the volumetrics analytic.

The orthomosaics on average contained spectral values that were consistent across all the 100 study sites. This allowed for the vegetation analysis to be stable and reliable for most of the sites. There were several instances where the color balance was skewed (see Figure 8), resulting in RGB values that were inconsistent with the greater population of orthomosaics. This resulted in higher misclassification rates of vegetation for those sites, thus contributing to the lower overall classification rate. To remedy the color balance issues, these images need to be adjusted by hand or subjected to a histogram matching algorithm -- options that were beyond the scope of this study. The color balance artifacts can be minimized during data capture if the imagery is consistently collected across all sites during the same time period and at the highest sun angle during the day.

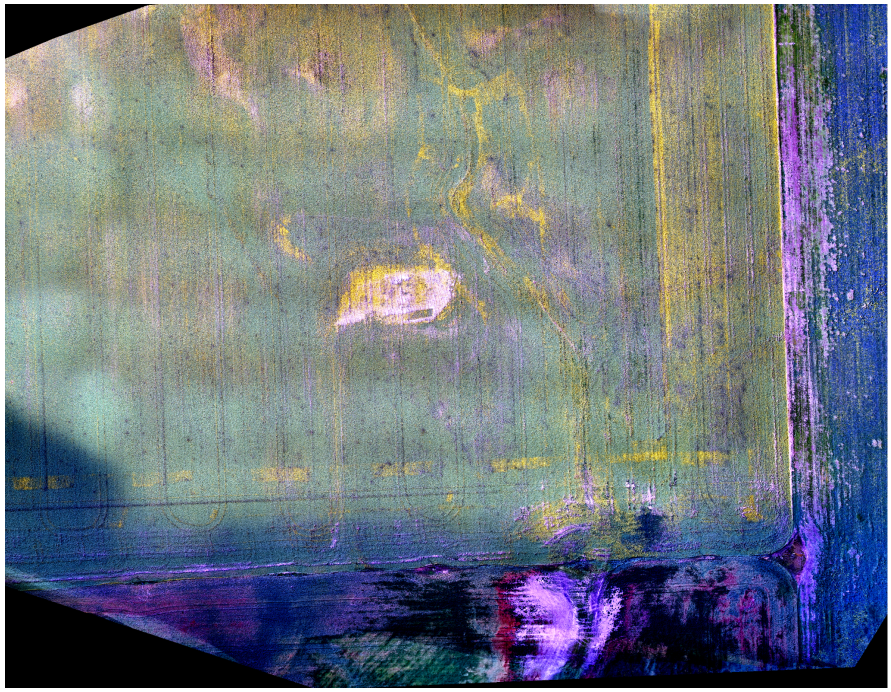

Figure 8. Example showing an orthomosaic that has a skewed RGB color balance, resulting in the magenta and yellow tones. Note that the beige feature at center is a reclaimed well pad.

Model Development & Automation

One of the main objectives of this study is to investigate and develop analytics and workflows that allow operators and inspectors to accurately evaluate reclamation success based on high-resolution imagery obtained from UAV technology. The other main objective of this study is to automate and standardize the analytics so that large geographies can be assessed quickly and cost effectively for streamlined reclamation inspection processes.

The development of the analytics for this study focused on probabilistic and deterministic modeling techniques. The probabilistic models rely on training data to inform a statistical model that predicts a phenomenon based on a set of covariates. This modeling approach was utilized to inform the vegetation cover analytic and is powerful when the complex nuances between covariates that predict a phenomenon are largely unknown. For instance, the covariates that went into development of the vegetation cover model include spectral and structural derivatives from the orthomosaics and digital surface model. The development of the covariates that inform a statistical model need to be informed based on known deterministic processes that can explain the presence or absence of a phenomenon. The probabilistic modeling approach becomes more predictive with time as more training data elements allow the statistical model to gain more numeric leverage on the covariate interactions and reduce the unknown biases limiting prediction rates.

The deterministic models that were generated for this study include the surface hydrology, contouring, vegetation structure, volumetric, and infrastructure models. These models used mathematical relationships to predict or assess a variable of interest. The surface hydrology analytic fits strongly into this category because it purely identifies low areas where water would accumulate and iteratively increases the elevation until a pour point is detected. There is very little randomness within the surface hydrology model, but it does assume that the digital surface model accurately represents the area of interest. The contour assessment analytic is another good example of a deterministic model because it directly measures the slope and terrain on a pad and within the reference area to then assess the numeric difference between them.

The infrastructure model also falls into the deterministic category for the purpose of this study, though it could be classified as a probabilistic model because it is predictive in nature. The reason why the infrastructure analytic was folded into the deterministic modeling approach is because the generalized hard-edge finder and convolution analytics relationships performed well, and further training was deemed unnecessary. To fold the infrastructure model into a probabilistic modeling approach, training data needs to be collected and incorporated into a statistical modeling process.

Automation of the reclamation success analytic suite involved building a Python-based toolbox in ArcGIS. Each analytic within the suite was initially tested on a pad-by-pad basis to ensure its operational feasibility. When a built analytic was determined operational, it was incorporated into the automated toolbox that sequentially executes the analytics for all pads within a given dataset and arrives at a summary of reclamation success metrics for each well pad. Once the toolbox is directed to the well pad points and imagery datasets, any and all of the reclamation success analytics can be executed for any number of well pads in a single step. The toolbox stores all analytic outputs in a standardized data structure with a standardized naming convention. This allows for the final summarization of all analytics to a well pad to be automated by pointing to the data structure and executing to derive the final assessment product in one step (see Figure 9). The only analytic that is not automated is the volumetrics analytic because areas of interest need to be defined by the user for the tool to calculate volume.

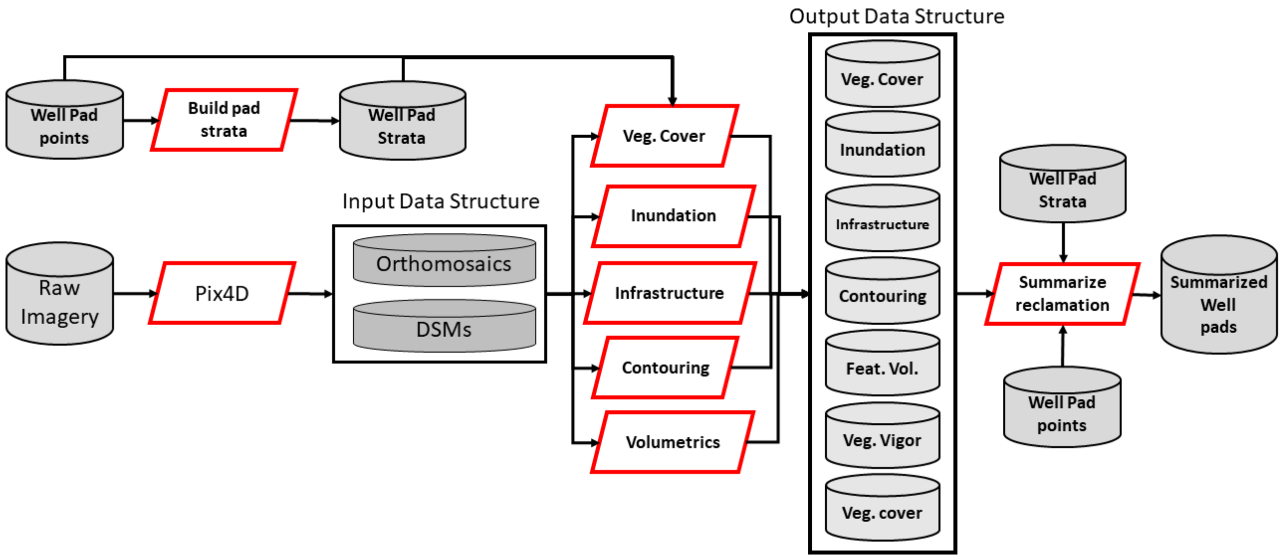

Figure 9. Example showing the automation workflow beginning with ingesting raw UAV imagery; building processing strata; executing models that run for all pad locations; storage of outputs in standardized data structure; and summarization of each of the individual analytics to their corresponding well pad. Note that the raw imagery and well pad points datasets are the only two datasets required to run this workflow.

Vegetation Analysis

Broadscale Vegetation Assessment. The broadscale vegetation assessment was performed on 2,313 well sites operated by Whiting in North Dakota using the NAIP 0.6-meter-resolution dataset. This assessment analyzed vegetation vigor and classification to identify hot spots for further analysis (see Figure 10). The results of the broadscale assessment enable streamlined prioritization of field visits or aerial data collection, thus reducing time, labor, and other resources associated with field inspections. Figure 11 depicts 650 Whiting well pads in Mountrail county (Exhibit A), followed by the same well pads ranked according to their CI vegetation vigor metric (Exhibit B). In Exhibit B, greener points indicate more similar vegetation vigor between the pad and the off-pad reference area. The analytic outputs can be further ranked into percentiles to identify the top Nth percentile pads to be prioritized for field visits.

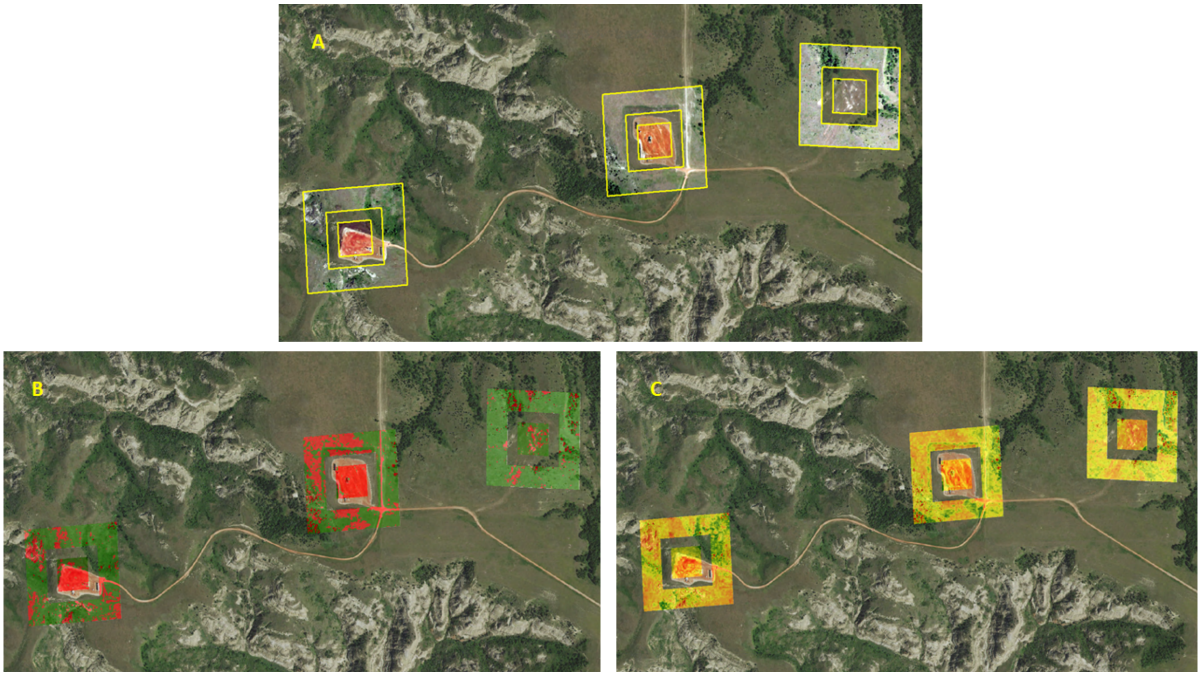

Figure 10. Broadscale vegetation assessment using NAIP 0.6-meter resolution data. Exhibit A displays estimated well pad footprint and reference area with NAIP imagery; Exhibit B displays vegetation classification; and Exhibit C displays vegetation vigor. These metrics can be used to prioritize well pads for further in-field or remote analysis.

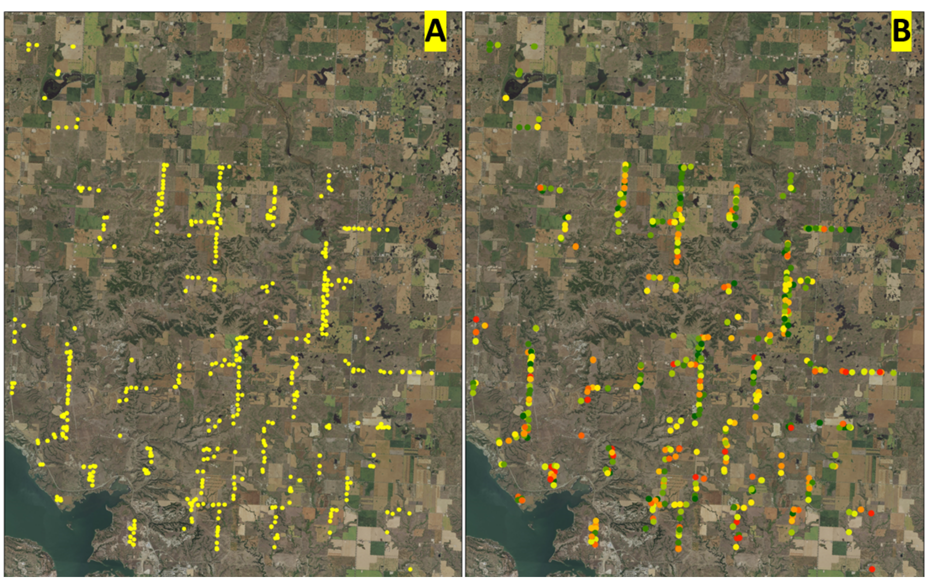

Figure 11. Example of the broadscale vegetation assessment for Whiting well pads in Mountrail County, ND. Exhibit A shows the pads locations, and Exhibit B shows the well pads ranked according to their CI vegetation vigor score. In Exhibit B, greener points indicate the pads most similar to their reference area, while red-to-yellow points indicate that the well pad is active or very different from the reference area.

Although publicly available and budget-friendly, the most recent NAIP dataset available at the time this broadscale assessment was performed dated to August, 2018. The date posed a problem for this analysis since it relies on the near-infrared chlorophyll relationship with some grasses and forbs in senescence during August and represents vegetation characteristics from 2018 -- two years prior to the study start. While the NAIP data in North Dakota is refreshed more frequently than in other parts of the country, the refresh timeline can span up to five years.

The NAIP dataset is useful for preliminarily assessing reclamation success across a large population of well pads. However, NAIP-based assessment has several notable limitations that make it unfit for annual reclamation condition inspections: 1) it fails to account for changes to the well site that have occurred since the imagery acquisition; 2) its coarse resolution is insufficient for detecting subtle variability in well pad conditions and reference areas; and 3) NAIP imagery does not support photogrammetric processes necessary for producing digital surface models. The central benefit of the broadscale assessment is the ability to quickly and cost-effectively prioritize problematic or certification-ready well pads for further action.

UAV-based Vegetation Cover. The orthomosaic-based vegetation cover analytic assesses the degree of vegetation regrowth over the disturbed well pad with a higher degree of temporal relevance and accuracy than afforded by the NAIP-based analysis. The vegetation cover analytic automatically discerns vegetative- from non-vegetative cover for an area of interest and determines the total area and percentage of each cover type (see Figure 12).

The accuracy of the model was determined as described in the validation methods above. Out of the 2,000 test points, bare soil was classified in agreement with human ocular assessments at a rate of 77.27 percent, while 72.40 percent of the points classified as vegetation were classified in agreement with human ocular assessments (see Table 1). A total of 35 points were classified as vegetation by the model that were classified as bare soil by the observer. A total of 374 points were classified as bare soil by the model but classified as vegetation by the observer. The large amount of false negatives for vegetated ground cover points is due to the classification of senescent vegetation as litter or bare soil by the model, whereas the observer correctly classified these points as vegetation.

On-pad vegetative cover was compared to that of off-pad reference areas represented by the large “frame” surrounding the well pad (see Figures 1 and 12). Vegetation cover ranged from 0.02 to 99.0 percent for well pads and from 8.74 to 100 percent for reference areas. Similarly, vegetation vigor was calculated for each well pad and its corresponding reference area and compared using the CI tool (see Figures 2, 13, 14). The vegetation CI output values range from 0.052 to 0.959, where smaller values represent more similarity between reference conditions and well pad ground cover.

Figure 12. Image at left is the unaltered orthomosaic and image at right is the model output where classified bare soil is red and classified vegetation is green.

Table 1. A confusion matrix describing vegetation cover model performance in which accuracy of observer-classified imagery is compared against model-classified imagery.

Model Accuracy				
		Model Classified		
		Bare Soil	Vegetation	Percent Model Accuracy
Human Classified	Bare Soil	273	35	88.6%
	Vegetation	374	673	64.3%
	Percent Model Accuracy	42.2%	95.1%	

Veg Positive	1047		Soil Positive	308
Veg Negative	308		Soil Negative	1047
Veg True Positive	673		Soil True Positive	273
Veg True Negative	308		Soil True Negative	35
Veg False Positive	35		Soil False Positive	374
Veg False Negative	374		Soil False Negative	35
Accuracy Veg	72.40%		Accuracy Soil	77.27%

Figure 13. The Blacktail Federal BN_1_25_100MSDCF well location imagery (at left), vegetation classification with vegetation in green and bare soil in red (at center), and vegetation vigor (at right) where green represents higher vegetation vigor or health.

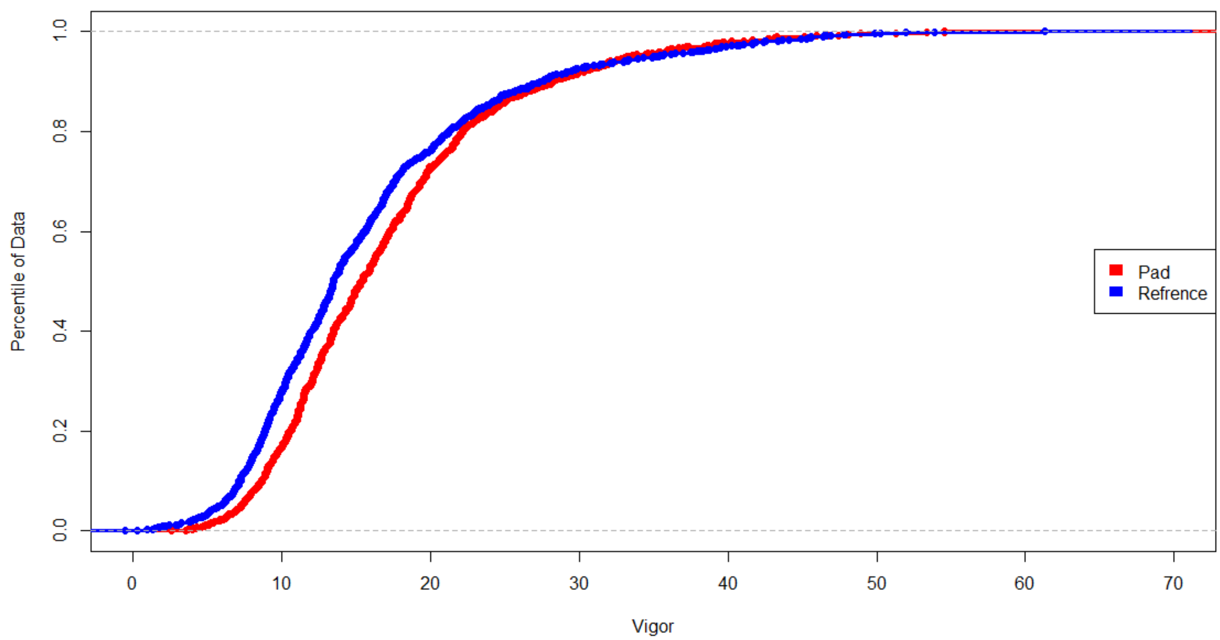

Figure 14. Continuity Index test performed on vegetation vigor for the Blacktail Federal BN_1_25_100MSDCF well location (see Figure 11), the D(n) = 0.121. The distribution of vegetation vigor values on the well pad are represented in red and those for the off-pad reference area are in blue.

The vegetation spectral analytics (i.e., cover, classification, and vigor) have an accuracy rate of greater than 70 percent -- a performant predictive rate in the realm of probabilistic models -- and will further improve with additional iterations and exposure to more training data. However, some limitations did surface during the development phase. Temporal variability in the data capture can greatly impact model performance. Differences in the time of day and the time of year can introduce shadow, senescent vegetation, rain, snow, and sun angle issues that change the spectral signature of objects. These issues highlight the necessity for careful planning and consistent methods for data collection.

For development of the vegetation analytics, data were used from two different locations: the DJ basin and the Bakken formation. Different methods were used to process the imagery and create the orthomosaics and digital surface models. Although similar, the slightly different processing methods produced different spectral signatures, which in turn could have influenced analytic results. This emphasized the need for a standardized workflow for data processing to ensure that inputs into the models are consistent and accurate.

Vegetation model validation was performed on 2-centimeter-resolution imagery whereby points were classified and compared between the model and human ocular assessment. At that resolution, spaces between vegetation foliage can be detected by the model and classified as bare soil even though they are not detected at a 1:1,500 scale by the human eye. This issue resulted in an artificially high number of false-negative predictions.

Lastly, differentiation between litter and senescent vegetation using imagery alone is exceedingly difficult for both an automated process and for remote human classification. For these reasons, data collection should be limited to the growing season when the presence of senescent vegetation is minimal.

Vegetation Structure. The purpose of the vegetation structure analytic is to remotely evaluate vegetation community types for reclamation assessment. The vegetation classification and vigor models are solely based on spectral values, whereas the vegetation structure model relies on elevation data derived from the digital surface model to measure vegetation community composition. The vegetation structure analytic use ground cover classified as vegetation as a mask to examine the height and texture of the vegetation community which could be used to classify grassland, shrubland, forest and other communities (see Figure 15).

Similar to the methodology described above, vegetation structure on a well pad was compared to vegetation structure within the reference area using a CI analysis to examine the difference between the distribution of values between areas. The CI output values range from 0.004 to 0.621, where smaller values represent more similarity between reference conditions and well pad vegetation height and texture.

One potential limitation of the analytic is that during the creation of the digital surface models, different methods of interpolation could have been used to fill gaps in the data that would alter elevation values. This would introduce bias into the results if consistent data processing methods were not followed.

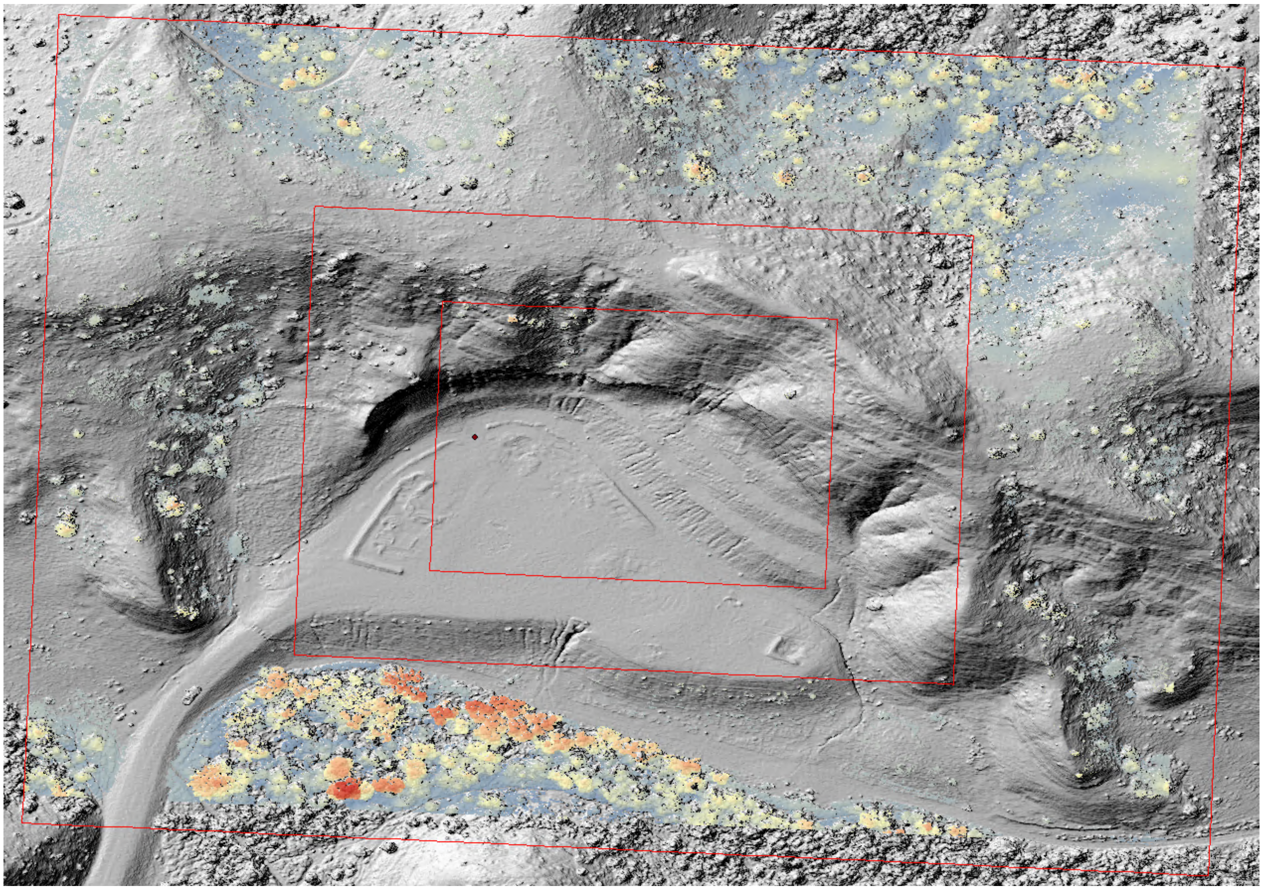

Figure 15. Vegetation structure output from the Federal 14_7H_100MSDCF well pad. The red center square represents the estimated well pad footprint. The outer red "frame" represents the reference area. Blue represents low height and texture (likely grasses), while red indicates higher height and texture values (woody vegetation).

Infrastructure Analysis

The purpose of the infrastructure analytic is to identify the presence of any infrastructure that has not been removed during reclamation such as meter houses, tanks, risers, etc. The analytic utilizes elevation values from the digital surface model to extract structures and anomalous features (see Figure 5). The output of the model is a determination of the presence of structures or materials and the overall count located on the well pad. The amount of structures ranged from 0 to 33 for a given well pad. Although the model performs well, further improvement could be achieved by masking out vegetation, as large woody vegetation can be misclassified as infrastructure (see Figure 16).

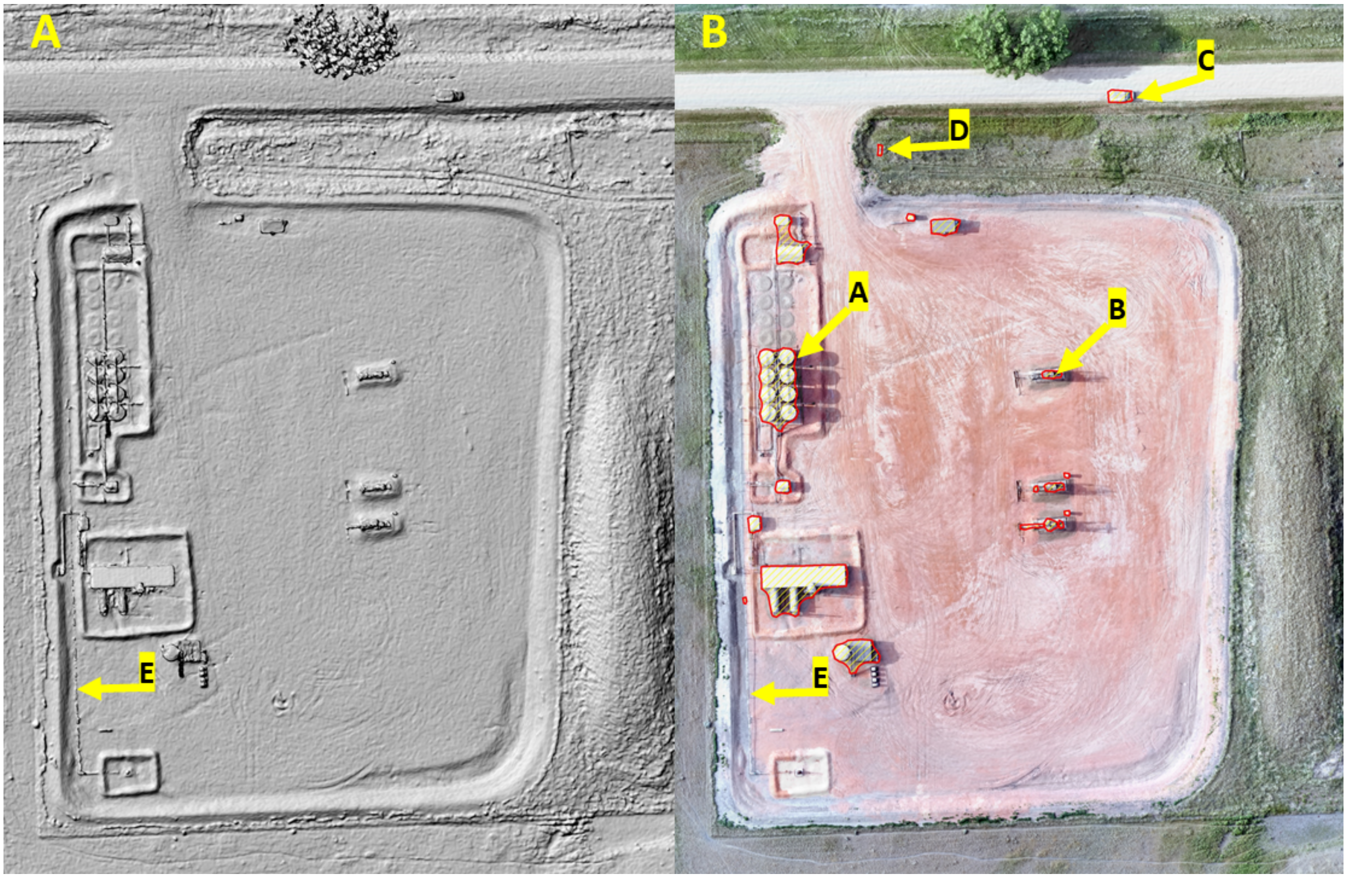

Figure 16. Example showing infrastructure identification on an operating well pad with Exhibit A being the digital surface model hillshade and Exhibit B being the orthomosaic with identified infrastructure. Feature A is a stock tank bank that is lumped into one feature; Feature B is a well head; Feature C is a truck; and Feature D is a misidentified infrastructure feature. Feature E depicts where pipeline and other small diameter features are fragmented and close to the ground, resulting in not being identified as infrastructure.

Contouring Analysis

The purpose of the contouring analytic is to identify large differences in topographic relief between the disturbed well pad area and the background landscape (reference area). If well pad construction required flattening of a site located among rolling hill topography, the analytic will determine the extent to which the site has been recontoured to its original state for reclamation purposes. The analytic utilizes elevation values from the digital surface model to extract topographic patterns (see Figure 17). The output of the model is a raster with slope contouring values representing terrain for the pad and reference areas.

This analytic is summarized to the pad by calculating the average and standard deviation and CI for the pad and reference area. The contouring CI values for the 100 pads analyzed range from 0.068 to 0.621, where smaller values represent more similarity between reference area and well pad topography. These results are skewed due to the fact that the well pads in this study are at various stages of operation.

The countering analytic would be enhanced by polygons delineating the edge of the pad disturbance so that the contouring metrics are more reflective of the actual pad contouring. Figure 17 demonstrates what can happen in the absence of edge-of-disturbance boundaries: A pad was cut into a hillslope with the pad strata capturing only a small section of the actual pad due to an offset well pad point. This resulted in a contouring CI value of .23, which is lower than expected because the pad strata is capturing some of the hillslope, causing the tool to interpret similar contouring values between the pad and the to reference strata.

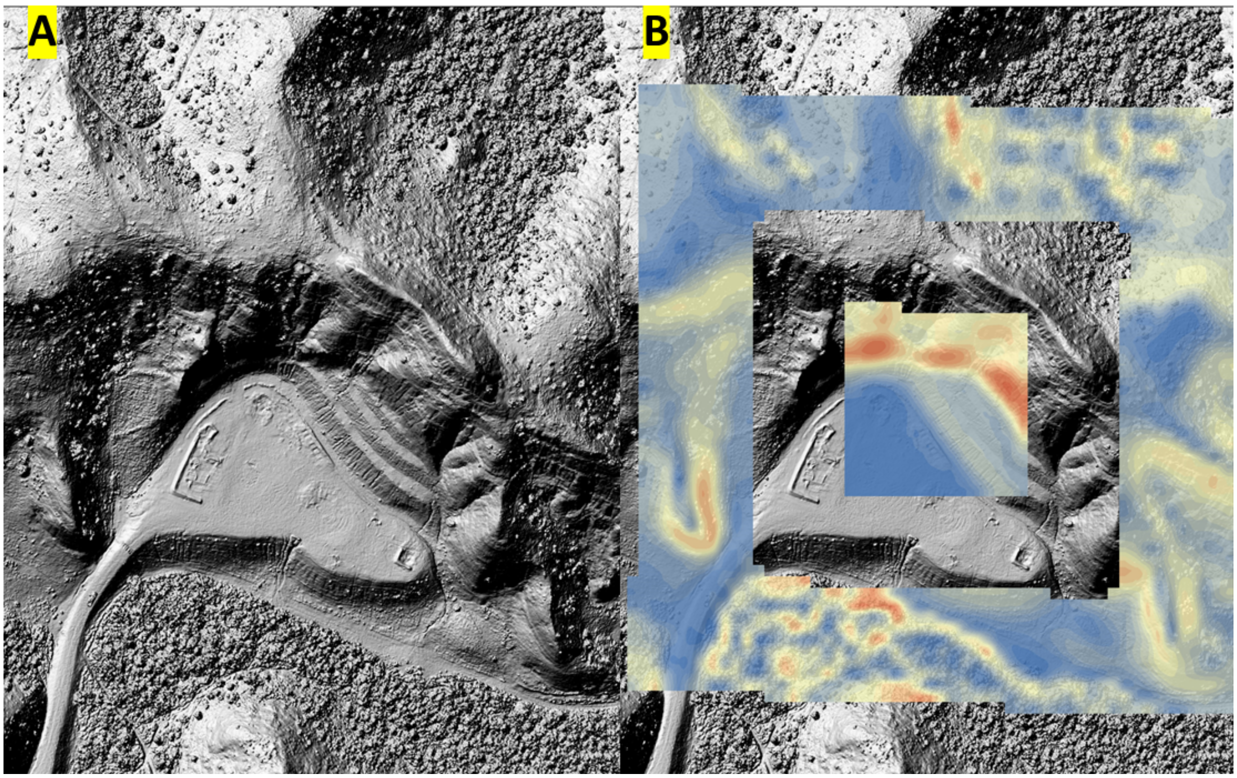

Figure 17. Example showing the contouring assessment for the pad and reference area. Exhibit A is the digital surface model hillshade with the pad in middle. This example has a high amount of terrain relief with a lot of tree canopy elevation variability that influences local slope estimates. Exhibit B shows the generalized slope analysis for the pad and reference areas with tree canopy muted. Blue indicates shallow slopes and red indicates steeper slopes.

Surface Hydrology Analysis

The results of the surface hydrology inundation analytic proved robust for on-pad inundation assessments of ponding issues for active pad and pads that have been reclaimed. In the case of an active pad, the model can be used to identify previously unknown inundation areas, monitor stormwater hazards (see Figure 6), and visualize where off-pad hydrology may flow onto the pad during heavy rainfall events (see Figure 18). For well sites in reclamation progress, the model is useful for evaluating if recontouring activities are successful in properly draining the site.

Figure 18. Example showing inundation zones on- and off-pad. On-pad inundation zones occur within the spill containment zones. Off-pad inundation zones depict where water will accumulate following heavy rainfall events. The surface hydrology analytic can be used to assess the effectiveness of stormwater mitigation devices on and around the well pad.

A limitation of the inundation analytic is that vegetation or interpolated areas may return false-positive zones. This is due to the nature of the digital surface model, in which it is difficult to discern ground elevation beneath heavily vegetated areas. Additionally, the model can be misleading for fully reclaimed areas in flat terrain with ketel ponds or naturally occuring closed basins. For example, Figure 19 depicts a fully reclaimed well pad site for which the model returned the highest inundation volume out of the 100 well pads in the study. Upon further ocular examination of the imagery, it is evident that the high inundation value is not a problem and that the site was reclaimed properly.

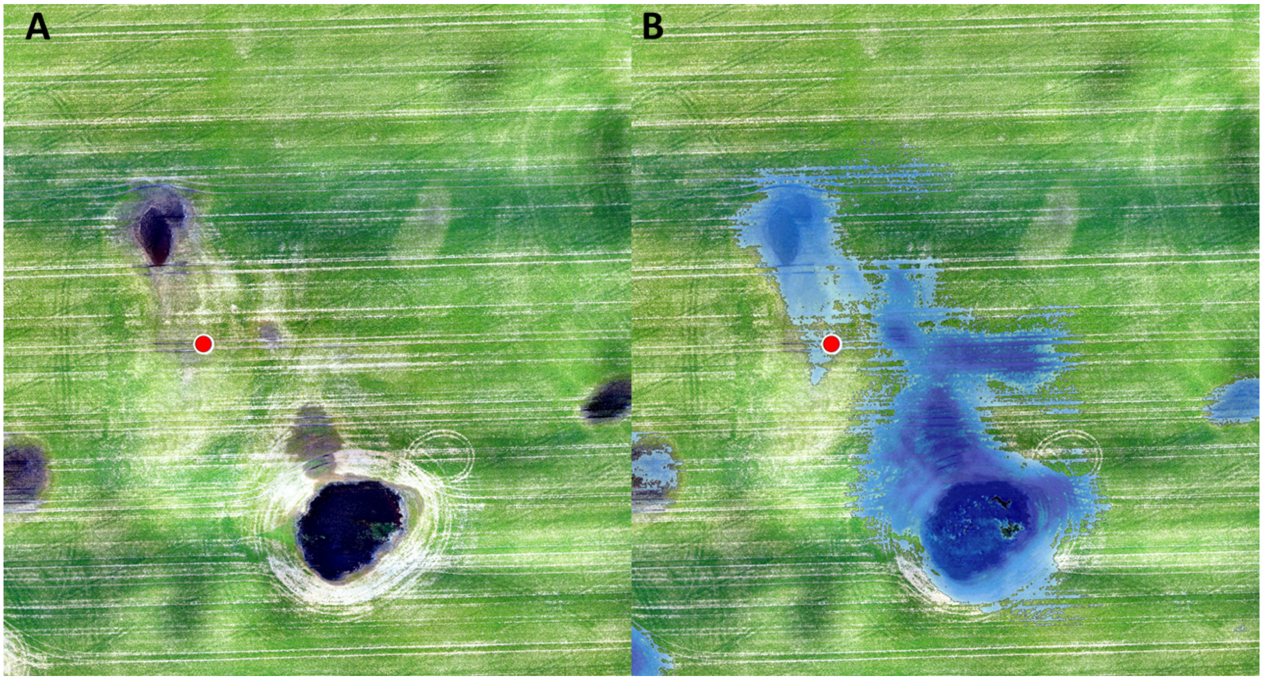

Figure 19. Exhibit A depicts the orthomosaic with the reclaimed pad center indicated by the red dot. Kettle ponds or potholes are naturally occurring in this area. Exhibit B shows the inundation analysis detecting large amounts of inundation on the pad site (darker blue indicates deeper inundation). The analytic correctly identified the inundation, though in this case the zone is likely a result of natural terrain and hydrology and not a product of well pad modification.

Volumetrics

The volumetrics analytic was developed as an interactive tool that enables users to demarcate and measure the volume of above-ground or below-ground material. The analytic requires that a user first defines the feature(s) to be measured. Once features have been delineated, the tool mathematically interpolates a theoretical elevation of the user-defined circumference to calculate the volume of the material or pit. The volumetrics tool can be run on a single pad or a set of pads at once.

The accuracy of this analytic is not impacted by the large z-value RMSE error, because it functions off of the relative elevation value to calculate total volume. When the volumetric tool estimates were compared to known volumes of stock tanks, trucks, and other infrastructure features for validation, the volumetric tool underestimated volumes by 5-to-10 percent. Figure 20 shows several delineated features on a pad and their associated volumes in cubic yards. The estimated volume for the building feature (Feature A) is 89.4 cubic feet, but its dimensions correspond with a volume of 93.1 cubic meters -- about a 4 percent error. This is because the edges of these features are rounded or dampened during the photogrammetric process (see Figure 21), thus diminishing its size. However, the tool's intended use is the estimation of soil stockpile volumes, and it is able to provide more accurate volumetric measurements when applied to earth material because its boundaries are more accurately interpreted in the photogrammetric process. An accuracy assessment was not executed for these features due to a lack of field-based observations upon which to base a full numeric comparison.

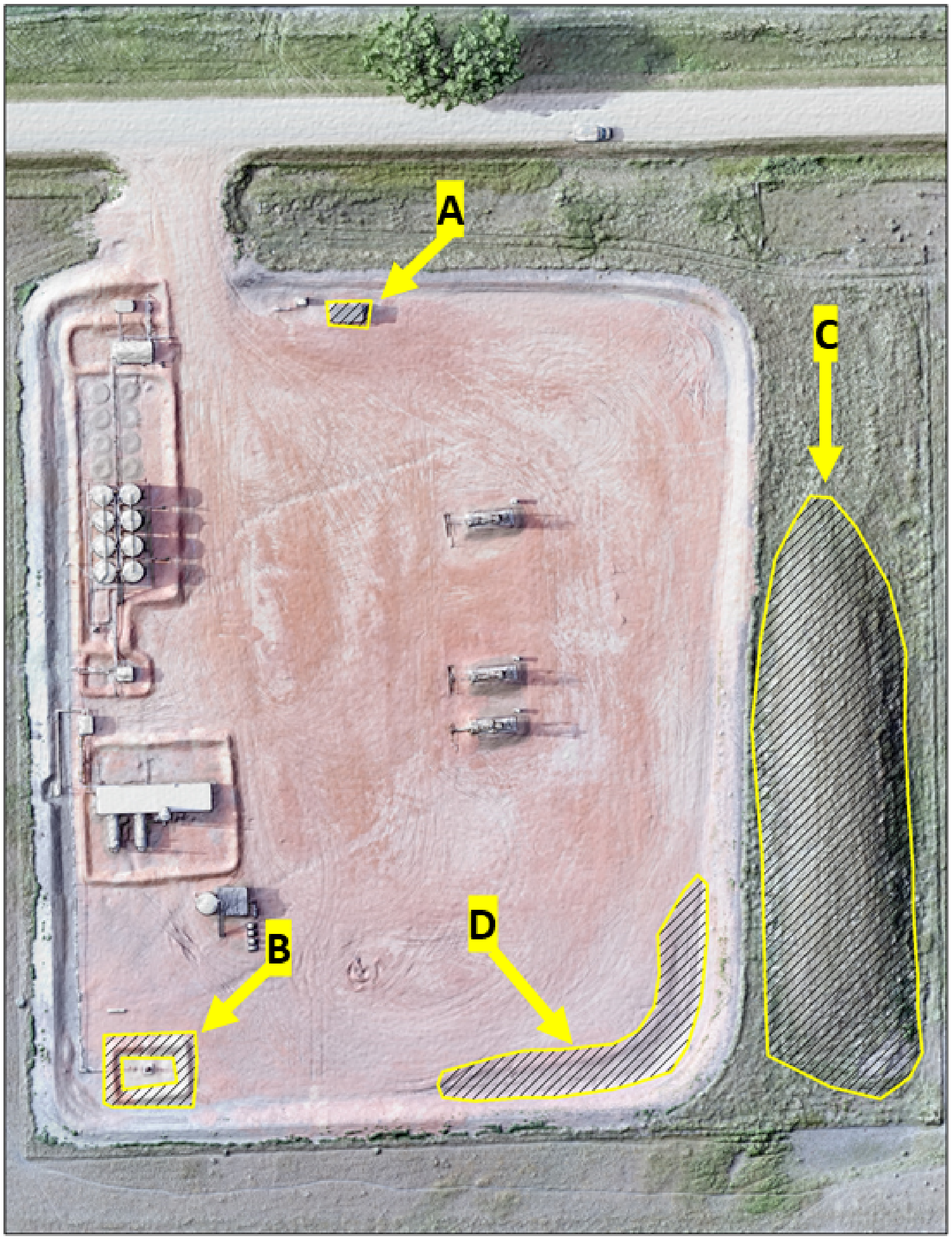

Figure 20. Example of volumetrics delinations on the Cherry State 21 well pad. These delinatioins are processed through the batch volumetrics tool to calculate volume in cubic yards. Feature A is a small building 387 square feet in size that is approximately 6.5 feet tall and has a volume of 89.4 cubic yards. Feature B is a bermed area that is 1,690 square feet in size with an average height of 1.1 feet and volume of 56.3 cubic yards. Feature C is a topsoil stockpile that is 27,168 square feet in size with an average height of 6 feet and volume of 5,116 cubic yards. Feature D is concave area that accumulates water with an area of 4,757 square feet, average depth of 0.8 feet, and a volume of -175 cubic yards.

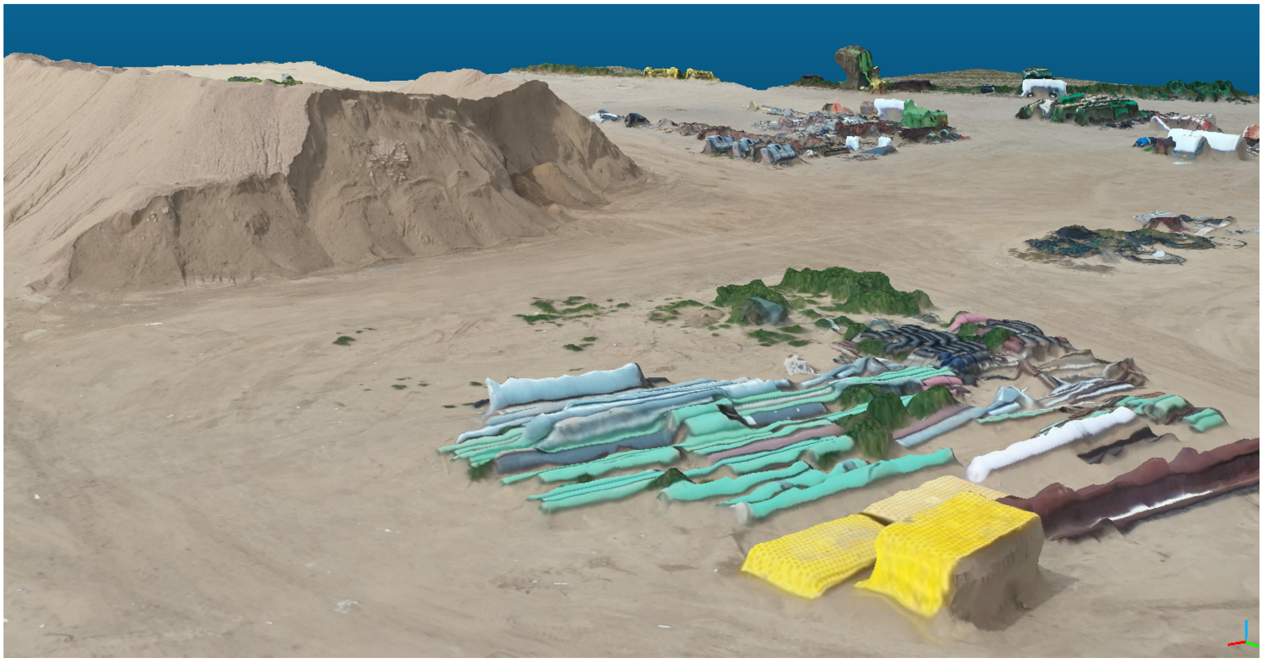

Figure 21. Example depicting a 3-D orthomosaic perspective of a stockyard with various infrastructure features and a large sand stockpile. Note the amount of elevation variability associated with each non-earth-material infrastructure feature, which introduces error in the volumetrics model when used for purposes other than measuring earth material.

Reclamation Success Assessment

The reclamation success assessment tool integrates the well pads, reference areas, and the full suite of reclamation analytics (see Figure 9) to assign each well pad a set of reclamation success metrics. These metrics compare the vegetative and topographic conditions of each well pad to its corresponding reference area, as well as summarize each pad's potential hydrologic inundation and infrastructure conditions. The attributes summarized to each well pad include: percent vegetative cover on the pad; percent vegetative cover in the reference area; average contouring metric on the pad; standard deviation of contouring metric; average contouring metric in the reference area; standard deviation of contouring metric for the reference area; total inundation volume (cubic meters); number of infrastructure features identified; total area (square meters) of infrastructure features identified; CI for vegetation vigor; vegetation vigor CI p-value; CI for vegetation structure; vegetation structure CI p-value; CI for contouring; and contouring CI p-value.

Figure 22 visualizes the well pad vegetation vigor CI metric, with red indicating well pads that are very different from their corresponding reference areas and green indicating pads very similar to their reference areas. The analytic allows for a large amount of well pads to be assessed at once for streamlined reclamation success investigations.

The pad and reference area vegetation cover metric utilizes the vegetation cover analytic to summarize total vegetation cover for each site. The contouring metric summarizes the scaled slope metric for the pad and the reference area with calculated average and standard deviation, which allows for the averages between the two zones to be evaluated based on the context between the two averages provided by the standard deviation. The inundation metric outputs the inundation volume and area totals for each well pad. The infrastructure metric reports the total number of infrastructure features per well pad.

The CI for vegetation vigor and associated p-value provide a metric of similarity between the pad and the reference area (see Figure 22). The CI value ranges between 0 and 1, with 0 being the exact same and 1 being very different. Figures 23, 24, 25, and 26 offer examples of the vegetation vigor CI analysis applied to two well pads and demonstrate how the reclamation analytics with CI metrics (vegetation vigor, vegetation structure, and contouring) may be interpreted.

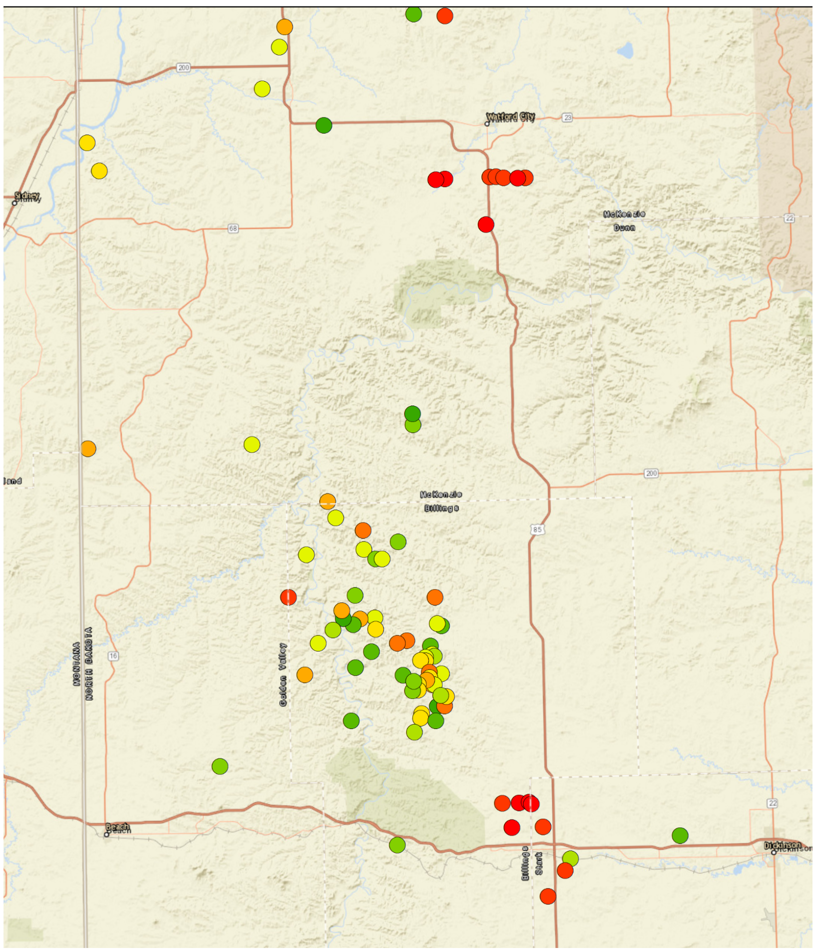

Figure 22. Example showing a subset of the well pads involved in the study with vegetation vigor CI values displayed. The redder points are pads that have high vegetation vigor CI values, indicating low correlation between on- and off-pad vegetation vigor and thus lower reclamation success. Greener points are pads with low vegetation vigor CI values, indicating high correlation between on- and off-pad vegetation vigor and thus greater reclamation success.

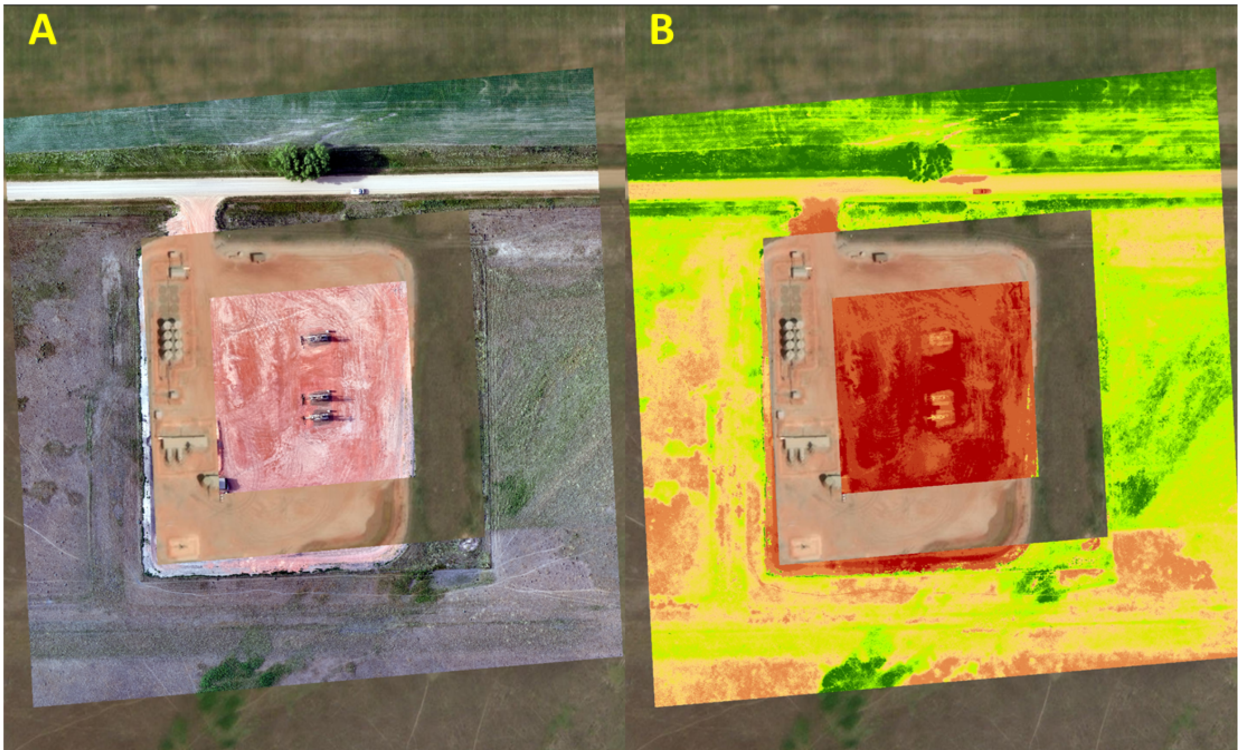

Figure 23. Example showing the Cherry State 21 pad orthomosaic (Exhibit A) and associated vegetation vigor analytic (Exhibit B), with green indicating high vegetation vigor. This pad has the highest vegetation vigor CI value (.95) of the study population because it is an active site with no vegetation on the pad.

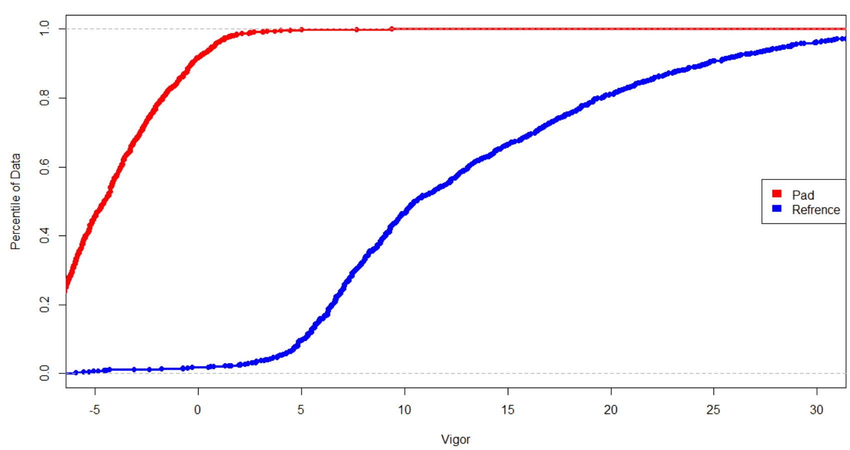

Figure 24. Cumulative Distribution Function (CDF) of vegetation vigor for the Cherry State 21 pad. The CDF demonstrates how different the pad (indicated by red line) is from the reference area (indicated by blue line). The difference between these two lines is what the CI metric measures. Notice that the pad line hits 100 percent of the data before 0, indicating all bare soil.

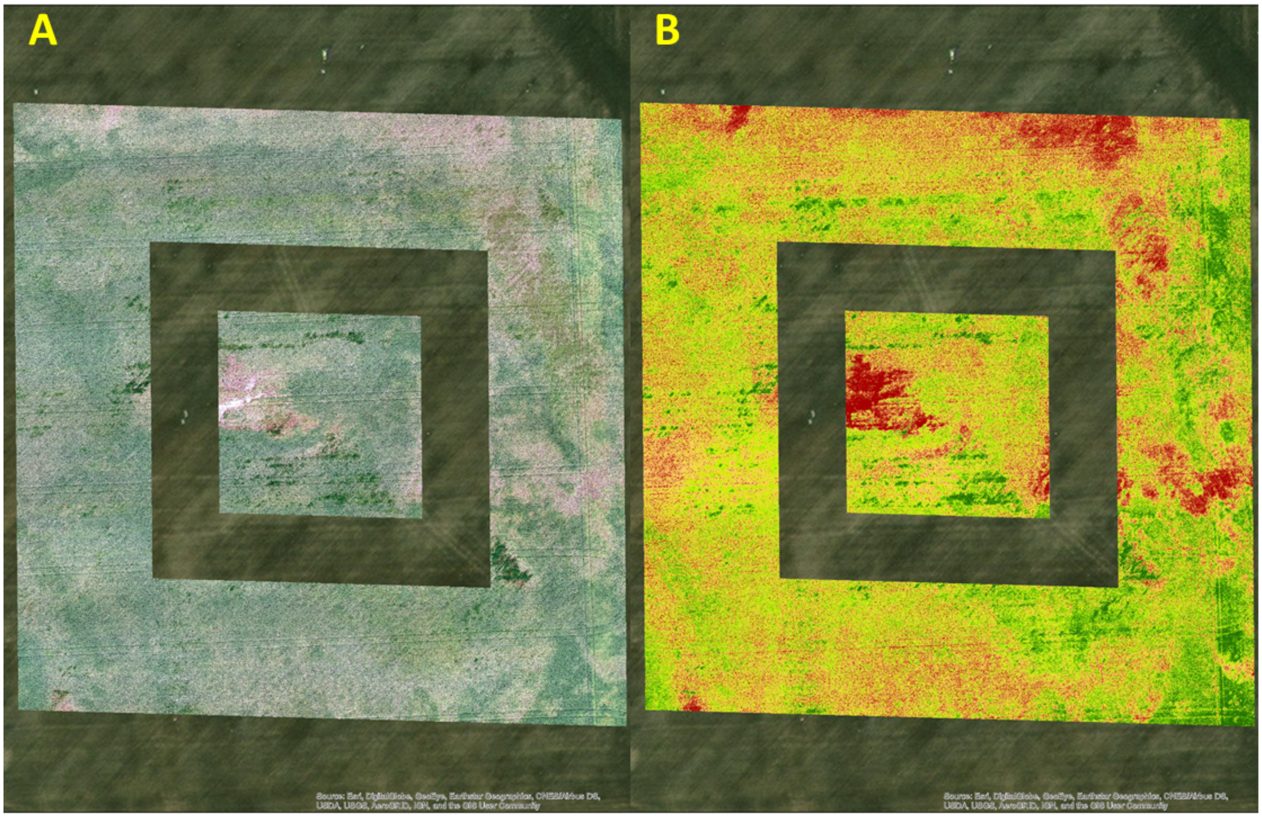

Figure 25. Example depicting the Scheer 24 27 pad orthomosaic (Exhibit A) and associated vegetation vigor analytic (Exhibit B), with green indicating higher vegetation vigor. This reclaimed pad has the lowest vegetation vigor CI value (.06) of the study population.

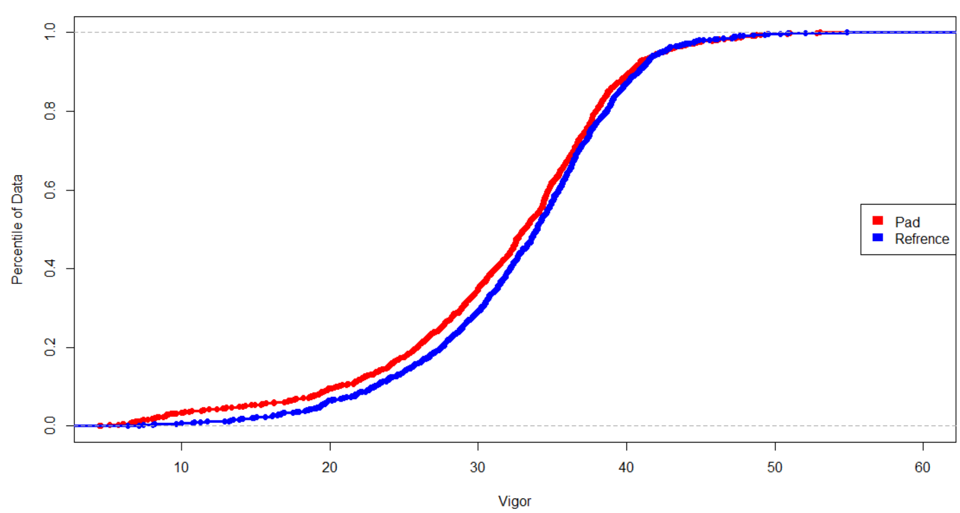

Figure 26. Cumulative Distribution Function (CDF) of vegetation vigor for the Scheer 24 27 pad showing how similar the pad (indicated by red line) is to the reference area (indicated by blue line). Notice the small gap between the two curves, indicating that the composition of bare soil and vegetation are close to identical on- and off-pad.

The reclamation success assessment summarizes the suite of reclamation success analytics to well pad locations, allowing users to remotely query details regarding the specific reclamation conditions at sites of interest. For instance, an operator or inspector could use the reclamation success assessment tool to evaluate sites through an initial “virtual visit”, then prioritize field inspections at those sites needing special attention or where a field visit would verify readiness for interim reclamation status or reclamation certification. The current version of this analytic summarizes the individual reclamation success analytics to a well pad location (point), but does not generate an overall reclamation success score. The development of a reclamation success scoring system would require industry and regulators to work together to develop a weighting schema that would collapse the summarized analytics into a standardized index. Doing so would allow an operator or regulator to understand and compare a well pad’s reclamation progress against all other well pads in a population using a single numerical indicator.

Case Study

This section walks users through a case study demonstrating how the remote reclamation success analytics compare to and can be used in conjunction with field-based inspection methods. The Christen 24-10 well pad was selected as an ideal case study site for evaluating the reclamation success analytics against Duraroot’s transect survey and NDIC inspection notes. The Christen 24-10 is a plugged and abandoned well pad that was ready for inspection for bond release in Summer of 2020. Table 2 depicts the reclamation success assessment metrics summarized to the Christen 24-10 well pad (see Figures 27 and 28), with the pad exhibiting 77.4 percent vegetation cover and the reference area exhibiting 95.2 percent vegetation cover. Field-based vegetation transects performed for the same pad by Duraroot show an average vegetation cover of 80.5 percent on the pad and 90 percent in the off-pad reference area (see Table 3). The NDIC inspector field notes state that although the pad is plugged and abandoned with no infrastructure, the vegetation was insufficient to pass the site for bond release at the time of inspection.

Table 2. Reclamation success assessment’s summarized metrics for the Christen 24-10 well pad.

Pad Veg. Cover (%)	Ref. (Off-Pad) Veg. Cover (%)	Pad Contouring Avg/STD	Ref. (Off-Pad) Contouring Avg/STD	Inundation	Infrastructure	CI Veg. Vigor	CI Veg. Structure	CI Contouring
77.4	95.2	2.5/0.9	3.4/1.8	0	0	.29	.15	.26

Table 3. Field transect results for vegetation cover at the Christen 24-10 pad. Transect names correspond to transect labels in Figure 25.

	Pad Transect 1	Pad Transect 2	Off-Pad Transect
Grass (%)	80	78	85
Forb (%)	2	3	5
Shrub (%)	0	0	0
Bare Ground (%)	18	19	10

Figure 27. The Christen 24-10 orthomosaic (at left) and digital surface model hillshade (at right) with pad and reference areas considered in the vegetation cover analytic outlined in yellow and in-field vegetation cover transects depicted in red.

Figure 28 shows the vegetation cover analytics for the Christen 24-10 pad and reference areas, with green indicating vegetation cover greater than 15 percent and brown indicating bare ground. The model summarizes vegetation cover to the pad and reference areas by calculating the proportion of pixels classified as vegetation cover (e.g., 77.4 and 95.2, respectively). The results between the vegetation cover analytic and Duraroot's transects are strongly correlated, validating the model's accuracy.

Ocular assessment of the well pad using the orthomosaic revealed that the Christen 24-10 pad and access road are still prominent. The CI values (see Table 2) for contouring, vegetation structure, and vegetation vigor show that vegetation structure is the most similar between the pad and references area, while vegetation vigor differs the most. The vegetation vigor CI value of .29 indicates that there is a ~30 percent difference between the pad and reference area. Figure 29 supports that the pad has a low vegetation vigor compared to the reference area because the well pad values (in red) are skewed toward lower vegetation vigor or more exposed soil than the reference area values (in blue). Figure 30 shows the vegetation vigor analytic for the Christen 24-10 well pad and reference area with the pad and access road highlighted in redder colors, indicating lower vigor values.

Figure 28. Vegetation cover analytics for the Christen 24-10 pad and reference areas. Green indicates vegetation cover greater than 15 percent cover and brown areas being bare ground. This analytics is then summarized to the pad and reference area (Table 2) by calculating the proportion of vegetation pixels within an area.

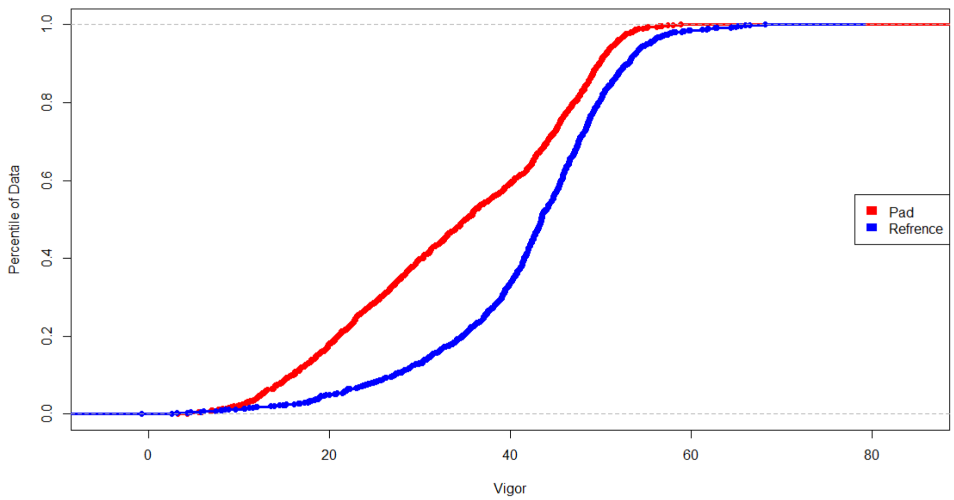

Figure 29. Cumulative Distribution Function (CDF) comparing vegetation vigor between the well pad (indicated by red line) and the off-pad reference area (indicated by blue line).

Figure 30. Vegetation vigor analytic for the Christen 24-10 well pad and reference area with greener colors indicating high vegetation vigor and dark brown colors being bare soil or scensent vegetation.

The inundation and infrastructure metrics for the Christen 24-10 well pad show that there are no hydrology or infrastructure issues with the pad (see Table 2). The contouring metrics entail two separate summaries that measure the average contouring slope for the pad and references area and a contouring CI between the two areas. The average contouring metric (see Table 2) shows that on average there is a 0.9 percent difference between the pad and the reference area with standard deviations that show significant overlap. The contouring CI tells a slightly different story with a value of .26 indicating that the two areas are not as similar as the averaged value indicates. The CDF graph (see Figure 31) shows that the contouring slopes for the pad area are much lower than the reference area, which is evident in Figure 32.

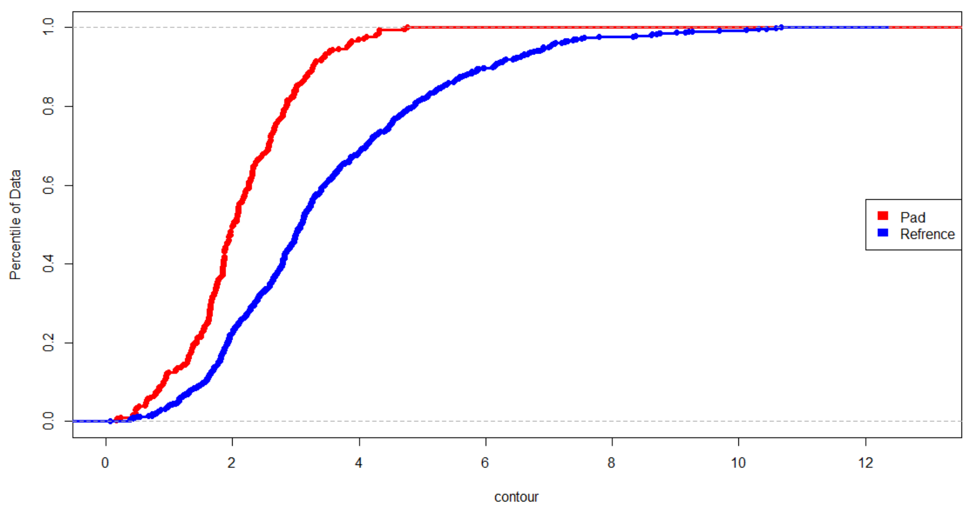

Figure 31. Cumulative Distribution Function (CDF) comparing contouring metrics between the Christen 24-10 pad (red line) and reference area (blue line).

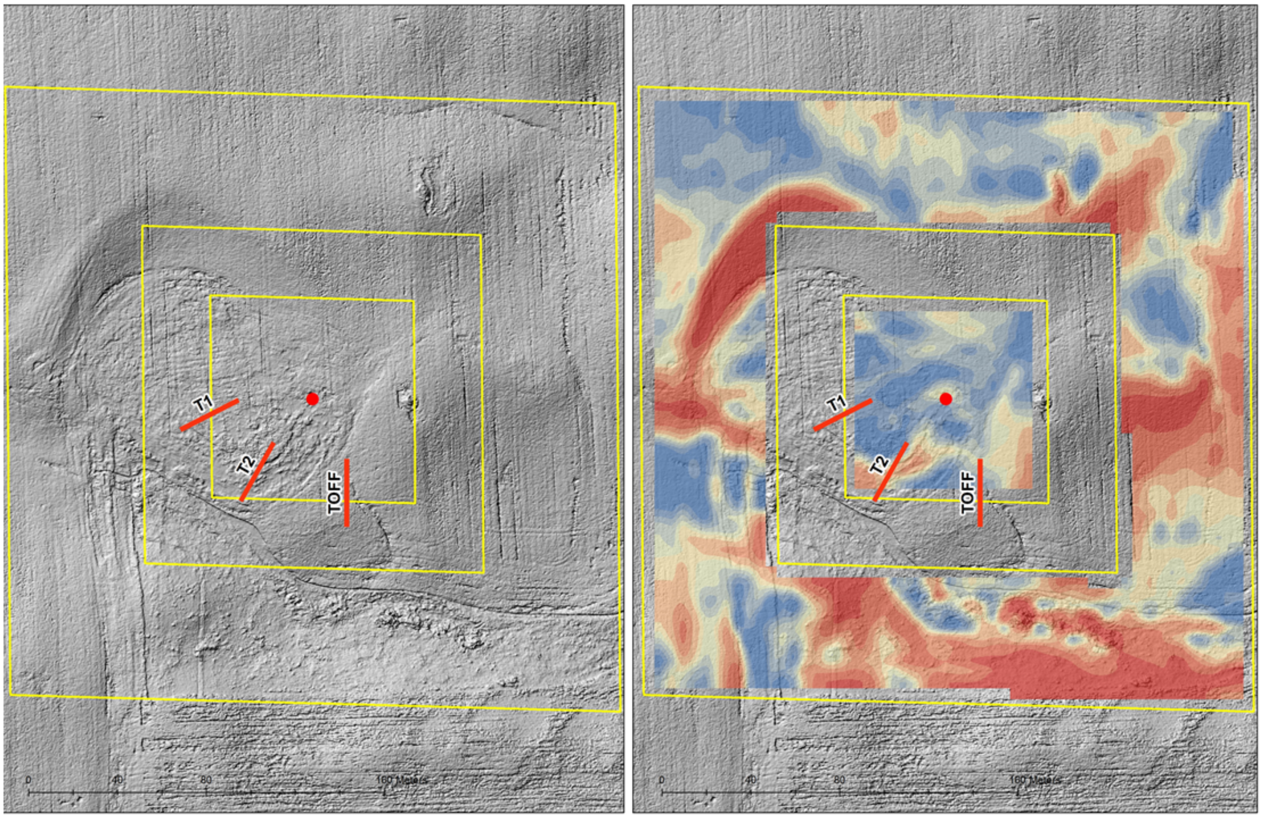

Figure 32. Contouring analytic for Christen 24-10 well pad and associated reference area with blue representing low-gradient slope and red representing high-gradient slope.

In summary, the reclamation success assessment toolbox revealed the following conditions for the Christen 24-10 well pad:

- Well pad vegetation cover has been returned to at least 80 percent of the site's original conditions.
- Well pad vegetation vigor (a proxy for vegetation health) is about 30 percent different from the site's original conditions.
- Well pad vegetation structure (a proxy for vegetation community) is about 15 percent different from the site's original conditions. (The site is located in a wheat field with little structural variability.)
- Well pad contouring is about 25 percent different from the site's original conditions.
- The well pad has no problematic inundation zones.
- The well pad has no remaining infrastructure.

Cost-Effectiveness Analysis

Manual Inspection Costs. To understand Whiting's costs associated with manual reclamation processes, SolSpec briefly interviewed Whiting Field Regulatory Manager Kyle Waggoner. Waggoner explained that Whiting conducts approximately 60-100 well inspections throughout the Bakken annually, with the number of inspections trending upward every year. Field inspection consultant rates average $75 per hour (about $600 per 8-hour day), with field transportation costing $110 per day. Consultants typically inspect 5 sites in a day. For 80 well sites visited over a span over 16 days in a year, Whiting spends roughly $9,600 on personnel and $1,760 on equipment, totalling $11,360 per year in expenditures. If the sum annual expenditures is split evenly among the 80 well sites, Whiting spends approximately $142 to inspect each well pad.

Regarding data quality, quantity, and consistency, Waggoner explained that the quality of manual inspection deliverables is not nearly as good as that of digital-based inspection because of the subjective nature of human observation. Waggoner described the manual inspection process as a judgement call, while the aerial inspection and analytics approach offers an objective, dependable dataset upon which to make better business decisions.

Similarly, SolSpec briefly interviewed NDIC Reclamation Specialist Cody VanderBusch to gather information regarding the costs associated with the agency's manual inspection methods. As of September 2019, the NDIC counted approximately 1,500 well pads in some stage of reclamation, with NDIC's 32 field inspectors splitting field inspection visits to each. According to VanderBusch, field inspection personnel rates average about $50 per hour, with 32 trucks averaging 200 miles per day at $0.28 per mile (about $56 per day). The inspection field season lasts approximately 90 days, with 30 working field days during that time frame. If each of NDIC's 32 inspectors worked 8-hour days at $50 per hour for 60 days, personnel costs would total $384,000 for the field season. Vehicle costs would represent another $53,760. Given these variables, the estimated annual expenditures for NDIC's field inspection activities equate to approximately $437,760. If the sum annual expenditures is split evenly among the 1,500 sites, the NDIC spends approximately $292 to inspect each well pad.

For well sites located in native grassland environments, the reclamation process -- and thus associated annual inspections -- can continue for 5 to 10 years. Thus, operators and agencies may incur repeated inspection costs for up to a decade per well site.

Remote Inspection Costs. Aerial imagery acquisition with the battery-powered, multirotor UAV typically costs $800 per well pad, in addition to a $20,000 mobilization fee. (ISight donated mobilization costs and a discount of $100 per well pad to the project.) Data acquisition using the limited-range, battery-powered UAV was the most cost-intensive component of this remote inspection project. The battery-powered UAV's restricted distance, speed, and flight duration mean that the machine is not well-suited for large-scale projects. Other aerial data acquisition methods better suited to capture data over large distances and reduce costs through economies of scale include use of a fixed-wing UAV capable of BVLOS flights or a camera-mounted plane. For instance, an aviation company deploying a small manned aircraft mounted with an image sensor could charge approximately $0.48 per acre, or $14.40 per 30-acre well pad, in addition to a $15,000 mobilization fee.

Once the imagery is captured, acquisition firms or imagery analytics providers utilize software such as Pix4D to process the images into an orthomosaic and digital surface model upon which analytics can be applied. Imagery processing costs can average $0.20 per acre, or $6 per 30-acre well pad. (SolSpec did not charge for the cost of processing imagery for this project).

The one-time costs associated with model development, validation, and automation have already been covered during the course of this project. Thus, the suite of remote reclamation success analytics is available to the market at a price unencumbered by research and development costs. Pricing for the remote reclamation success analytic suite, data hosting and visualization, and data content curation may be offered at a cost of $1.67 per acre, or $50 per 30-acre well pad. Assuming a single data collection effort per year, SolSpec offers the $50-per-pad pricing as part of an annual data subscription service that it provides to operators and agencies for measuring change in well pad reclamation success through time.

Table 4 below presents estimated costs per well pad for RGB imagery data collection, processing, and reclamation success analytics (assuming 30 acres of imagery for each well pad and associated reference area) in the cases of UAV data collection and manned aircraft data collection. Those numbers are compared against estimated manual field inspection costs.

Table 4. Cost scenarios for manual field inspection, RGB imagery data collection via UAV and manned aircraft, data processing, and reclamation success analytics.

	Manual Field Inspection	**UAV Data Collection & Processing**	**Manned Aircraft Data Collection & Processing**	**Reclamation Success Analytics**
Cost Per Pad - Whiting	$142	$806	$217*	$50
Cost Per Pad - NDIC	$292			
Mobilization Rate	N/A	$20,000	$15,000	N/A

*Assumes flying 50 square miles with a density of 100 well pads at a cost of $435 per square mile, or $0.68 per acre.

The manual reclamation inspection process produces largely qualitative data based on site observations. The inspector ocularly estimates vegetation cover and community at the ground level, and scans the scene for remaining infrastructure, stockpiles, noxious weeds, or other obvious-to-the-eye conditions impeding reclamation success. Inspector notes are ideally logged in a digital spreadsheet for data tracking and as a reference for subsequent field visits, which will likely be performed by different inspectors. Though field protocols and inspection forms help to control for subjectivity and variation among many different field inspectors' assessment techniques, it is still extremely difficult to standardize human interpretations of a landscape. Qualitative inspection notes may provide a rich narrative about a particular site; however, the depth and subject of the details captured are inconsistent across the population of well pad inspections, which limits system-wide comparison, resource prioritization, and monitoring of trends over time.

Manual field inspections are resource- and time-intensive, and the resultant data outputs are inherently subjective due to the nature of ocular inspection. Boots-on-the-ground monitoring means that a site's reclamation progress -- and whether or not a site is deemed sufficiently reclaimed for bond release -- is determined by visually assessing and summarizing if the site has been restored as closely as practicable to original conditions. The "original conditions" standard written into North Dakota law[10] challenges the

[10] North Dakota Administrative Code Section 43-02-03-34.1 and North Dakota Century Code Section 38-08-04.12.

human eye at ground level to evaluate a well pad's context, imagine what the site's original conditions might have been, and deduce how close the current conditions are to the imagined standard. The manual inspection process is unavoidably exposed to subjectivity, human error, and inconsistencies. These conditions can impede consistent and accurate site monitoring through time and, in turn, produce misinformed decisions affecting budgets, penalties and bond releases, and environmental quality.

In comparison, aerial data inspection and automated analytics can produce more consistent, standardized, and objective data for decision makers. When data collection, processing, and analysis steps are standardized, then data outputs are consistent and comparable across space and time. Instead of the rich and varying narrative produced during manual field inspections, the remote inspection process generates a variety of quantitative metrics that, together, provide a comprehensive evaluation of reclamation success for either an individual well pad or an entire population.

Data acquisition is the most cost-intensive component of the remote reclamation inspection process. Making acquisition more affordable is a matter of economies of scale. If well pad density is low with substantial distance between disparately located pads, then mobilizing between sites with a vehicle and acquiring imagery using a UAV is likely most cost-effective. However, if well pads are densely located in a region, then economies of scale favor data acquisition via manned aircraft. Planes collect imagery continuously along a flight path, allowing for larger data collections over contiguous areas in a shorter amount of time. The reclamation success analytics are designed for scalability and performance with photogrammetric imagery captured either from UAVs or manned aircraft.

Limitations & Caveats

Several limitations and opportunities for improvement were discovered during the model development phase. Although the vegetation cover analytic is currently fairly accurate (>70 percent), and the vegetation structure analytic was verified using an ocular assessment of imagery, the classification of vegetation communities may be further refined by quality field data. A spatially explicit, statistically rigorous methodology was not used during initial field data collection, and because the vegetation data is temporally sensitive the areas were unable to be resampled.

Furthermore, different methods were used to capture images and create the orthomosaics for well pads in the DJ basin for initial model development than for well pads in the Bakken formation for model refinement. The different methodology produced different spectral signatures and emphasized the need for a standardized workflow for data processing to ensure inputs into the models are consistent and accurate. Temporal variability in the data capture can also greatly impact model performance. Careful planning and consistent methods of data collection are important to minimize differences in the spectral signature of objects arising from data collection at different times of the day and year, which introduce variable shadowing, senescent vegetation, rain, snow, and sun angle challenges.

In addition to imagery challenges, challenges arose due to inaccurate well pad location data and unknown well pad footprints (i.e., true edge of disturbance polygons). The model uses well location data as the center point and estimates the well pad footprint by generating a square around the point that equates to the average size of well pads in the area. If the well location point is inaccurate or the well pad varies significantly in size from the average pad, the analytic results could be skewed. The process of the automated reclamation assessment would be greatly improved with access to accurate well location and well pad footprint data.

Even though high-resolution (3 centimeters squared) imagery can be difficult to assess by an observer at the pixel level, the analytic models can detect minute details within vegetation (e.g. branches, roots, gaps in foliage). For this reason, space between vegetation foliage (such as gaps between branches where bare soil is visible) can be detected by the model and classified as bare soil even though they are not detected in orthomosaics at a 1:1,500 scale by the human eye. This situation resulted in an artificially high number of false negatives for this project.

Also, differentiation between litter and senescent vegetation using imagery alone is exceedingly difficult for both automated and human classification processes, making viable field data necessary for refining and improving model classification of senescent vegetation from litter. For these reasons, data collection should be limited to the growing season when the presence of senescent vegetation is minimal.

Lastly, the difference in the angle of observation from which the UAV and on-the-ground reclamation inspector examine the landscape can also generate very different results for vegetation cover. While furrows and gaps between plants correctly appear as bare ground from an aerial viewpoint, they erroneously appear as vegetation to a ground observer. Thus, vegetation cover estimates are often inflated when performed on the ground.

Conclusions

The vegetation, infrastructure, contouring, and problematic hydrology analytics developed during the course of this project demonstrated that an unbiased, automated reclamation assessment is possible using remote sensing technology. The outputs of these analytics provide decision makers with quantitative data paired with geospatial information and imagery that assist in more accurate assessments of current reclamation status and trends through time. This information empowers managers to identify and prioritize problematic areas that may be deviating from the desired outcome or well pads eligible for bond release. More informed prioritization of limited personnel and resources improves economic efficiencies for industry and agencies. The population of well pads can be categorized and ranked according to individual reclamation success metrics (e.g., presence of infrastructure, vegetation cover, or problematic hydrology) or by overall progress towards each site's original conditions.

Industry leaders and agencies stand to benefit from supplementing manual reclamation inspection programs with remotely sensed data and analytics at multiple spatial and temporal scales to optimize field visits where they are needed most. This study focused on building a suite of automated reclamation success analytics that provide accurate and consistent quantitative intelligence for measuring well pad change through time. For this technology to be operationalized, industry leaders and agencies must adopt remote reclamation inspection technologies and, importantly, contribute to developing a standard set of metrics and measurable objectives for defining reclamation success. If efforts are made to clearly define reclamation success with measurable targets and metrics aligned with North Dakota law,[11] then inspection practices will evolve to adopt new technologies and more robust data capture, management, and analysis. Defined reclamation targets -- combined with operational tools for measuring and documenting progress toward those targets -- will improve well site reclamation program efficiencies and outcomes.

A remote reclamation inspection program would enable industry and operators to streamline and prioritize resource-intensive field visits to only those sites ready for final certification or problematic sites in need of special attention. The suite of reclamation success metrics pinpoint the exact conditions hindering reclamation progress to enable judicious and targeted environmental restoration efforts. The metrics also make evident and clear when successful reclamation has been achieved. The remote reclamation success analytics developed, validated, and automated as a result of this project offer a fully operational decision support tool ready for immediate use in improving economic efficiency alongside environmental sustainability for the benefit of all North Dakotans.

Expenditures

The project was funded in-part by the NDIC at $163,200 with $0 remaining (expense documentation and invoice sent separately). Cost Share (In-Kind) was $167,600 with $0 remaining. Cost-share was as follows: Whiting - $41,600, ISight - $34,000, and SolSpec - $92,000. Total project cost was $330,800 with $0 remaining.

[11] North Dakota Administrative Code Section 43-02-03-34.1 and North Dakota Century Code Section 38-08-04.12.