DUNE FEATURE EXTRACTION USING IMAGE TEXTURE AND PATCH METRICS

by

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1. INTRODUCTION

1.1 Background

Human interaction with sensitive physical environmental features can result in lasting effects that negatively impact ecosystems. With an ever-increasing need for resources, the potential for physical environmental damage will only increase. To manage and prevent ecosystem degradation or destruction, sensitive features need to be identified along with areas prone to potential impacts. Remote sensing analysis techniques can identify and inform mitigation of those effects.

In the Permian Basin of West Texas, there exists a large region of active and inactive sand dunes, a part of the Mescalero-Monahans dune system. This area is dominated by vegetation, such as Shin Oak (*Quercus havardii*), that helps stabilize most of the sands, though there are large areas with bare, unstable dunes. Resource extraction in and around this region disturbs natural dune processes and can fragment the landscape. Specific features present in this environment are dune blowouts. These features are first formed when areas of stabilized dunes are disturbed, which allows wind to erode the underlying sand. Over time, the area eroded by the sand will increase, thus creating depressed areas of bare sand surrounded by Shin Oak. Dune blowouts and associated vegetation structure can be indicative of suitable habitat for native species and consequently, areas where human induced land use change could potentially affect native species populations such as the Dunes Sagebrush Lizard (*Sceloporus arenicolus*). Therefore, identification of blowouts is important for understanding the relationship between human induced land change, the dune ecosystem, and dune dwelling fauna.

1.2 Problem Statement

Identifying a dune blowout with traditional spectral classifications is difficult in dune fields located in the Permian Basin. Blowouts themselves are a structure of the dune ecosystem and appear spectrally similar when compared to other dune features such as active dune fields. Due to this similarity, any barren sand will be grouped into a single spectral class. Additionally, misclassification of developed (i.e., crushed caliche surfaces) and sandy areas is common. This is due to the spectral properties of sand compared to the crushed caliche road material used for access to resource extraction operations. Both exhibit high reflectance across all bands available in National Agriculture Imagery Program (NAIP) imagery and additional band ratios do not separate out these land covers. What is different between these objects are various spatial attributes such as size, shape, and how the features occur relative to the area around each feature. Caliche surfaces and dune blowouts exhibit distinct geometry as well as connectedness to same feature types. Dune blowouts, compared to dune fields, occur within large patches of vegetation and are smaller than dune fields. With the incorporation of texture-based measures these differences may be accounted for and assist in identification and classification of dune blowouts.

1.3 Objective

Remote sensing analyses have proven to be viable methods to extract information from landscapes. Common applications of remote sensing analysis include the identification of land cover types and features. For this study, texture analysis will be applied to remotely sensed images to investigate an alternative method of classifying dune blowouts. Identification of blowouts is informative when studying sensitive dune environments. These features are vital habitat to some species, such as *S. arenicolus*, and can serve as an indicator of presence and quality of habitat . Improving identification of blowouts will also aid in identifying areas where human induced land use change has or will potentially affect those species. My research question asks whether texture-based measures can be used to identify dune blowout features in the Permian Basin. To answer this question, the following objectives will be addressed:

1. **Using NAIP imagery, identify image texture measures that work best to highlight dune features.**
2. **Generate patches and assign metrics that describe variability in texture output.**
3. **Utilize patch metrics to classify dune blowouts and other landscape features.**

1.4 Justification

Within both fragmented and non-fragmented habitats, *S. arenicolus* shows significant preferences for microhabitat variables such as steep slopes, open sand, and lower amounts of leaf litter. (Hibbitts et. al. 2013). This indicates that microhabitats with the presence of blowouts tend to be most ideal. Hibbitts et. al. (2013) discussed these preferences, reinforcing that *S. arenicolus* prefers a narrow range of habitat conditions and can be classed as a habitat specialist. This would infer that the presence of dune blowouts within Shin Oak dominated sands can indicate high likelihood of the presence of *S. arenicolus.*

2. LITERATURE REVIEW

2.1 Dune habitat fragmentation

Disturbance of sensitive habitats has the potential to negatively affect species that reside in these areas. The most damaging is habitat loss and fragmentation, both of which have direct negative effects on biodiversity (Fahrig 2003). Along with the effects of fragmentation, landscape composition can influence the presence of native species (Herse, With, and Boyle 2018). As human development increases and more land is converted, changes in habitat will be a common reason for the reduction of native species populations.

A study conducted by Vega, Bellagamba, and Fitzgerald (2000) examined the effect development had on lizard populations (*Liolaemus multimaculatus* and *Liolaemus gracilis*) in Argentina and they observed a direct reduction in lizard populations because of dune habitat loss and fragmentation. Several probable connections were theorized which included direct removal of habitat through construction and indirect erosional effects due to increased human presence. Although the research was conducted within a coastal dune environment, the effects of fragmentation identified by Vega et al (2000) are similar to those found in the Permian Basin and known to impact *S. arenicolus* populations within the sands (Young, Ryberg, Fitzgerald, and Hibbitts 2018).

Smolensky and Fitzgerald (2011) sought to determine the effects of oil and gas development on dune dwelling lizard populations in eastern New Mexico. They found the relationship between presence of caliche surfaces and the variation in lizard population was not significant. What was significant was how area and occurrence of blowouts served as a predictor for habitat presence and quality. Their conclusions indicate that the detection of dune blowouts can be vital in estimating quality and occurrence of suitable habitat.

Specific fragmentation effects from resource extraction within dune habitat impact *S. arenicolus* (Leavitt and Fitzgerald, 2013; Young, Ryberg, Fitzgerald, and Hibbitts 2018). Leavitt and Fitzgerald (2013) noted important differences between fragmented and non-fragmented landscapes. Within a fragmented landscape, dune blowouts are more dispersed, smaller, and less likely to occur while the total area of flat sand covered areas increases. In these areas, the presence of *S. arenicolus* is lower than in non-fragmented landscapes. Leavitt and Fitzgerald (2013) explained that a large amounts of sand covered area within non-fragmented landscapes showed increased detections of *S. arenicolus* and noted sand was present in the form of dune blowouts.

Landscape variation within *S. arenicolus* habitat as discussed by Ryburg et.al (2013) reinforce findings of blowouts association with lizard populations. They found that blowout attributes such as area, contiguity, and geographic orientation showed significant relationships with the size of S. *arenicolus* neighborhoods. Additionally, variations in recruitment into neighborhoods showed associations with blowout configuration within continuous habitat.

2.2 Remote sensing of dune environments

The application of remote sensing for classification of dune environments and identification of specific features within them has taken several approaches. Jones (1985) digitized dune hollows in a coastal island from monochromatic aerial imagery. The digitized features were used to analyze clustering of these the dune hollows, and they concluded that remotely sensed imagery can be used to effectively identify dune features. Bertacchi and Loambardi (2014) tracked changes in coastal dune vegetation and morphology as well as anthropogenic development between 1954 and 2010. They employed methods that included traditional photointerpretation using stereoscopic pairs, *in-situ* observations, and topographic surveys. Using these techniques to study the roughly 4 km long coastline provided evidence that the coastal dunes were being fragmented and transformed over the observed time period.

Paisley et. al. (1991) examined spectral differences between active and inactive sand dunes serves as an instance where spectral characteristics of bare sand were examined. Using Landsat 5 TM data of the Kelso Dunes in the Mojave Desert of California, the spectral response of inactive and active dune sand was found to be different. Differences were discerned using Bands 3 (red) and 7 (shortwave infrared) which were able to detect the variations in the amount of magnetite between active and inactive dunes. This permitted the conclusion that active and inactive sand can be tracked with remotely sensed imagery.

A study by Hugenholtz et. al. (2012) took a deeper look into the application of remote sensing technology to study dune environments. Geomorphological approaches to investigating dune features were studied where primary focus was on dune activity, dune patterns, and vegetation. In-depth analysis did not involve advanced image statistics; instead, the researchers analyzed digitized features and highlighted the advantages of band ratios. The consensus was that remote sensing methods they examined showed promise, but more development was needed in data availability and analysis techniques.

A project to construct *S. arenicolus* habitat maps and models in New Mexico by Johnson et. al (2016) demonstrates the extent of remote sensing habitat research for the lizard. The team used NAIP imagery, unsupervised classifications, and manual editing to develop land cover maps for relevant cover types, including dune blowouts. Accuracy of the final land cover map was reported at 84% for vegetation cover types, however, accuracies relating to direct dune blowout identification were not reported. The report mentioned that human-disturbed areas were distinguished from blowouts by the initial classification but that manual editing was required to increase overall accuracy, though to what extent was not clearly described. The report further discusses habitat modeling at dune blowouts scale where the land cover map was used to inform site selection. These sites, which contained blowouts as per the land cover map, then had blowouts attributes measured manually for inclusion into the model.

Brownett and Mills (2017) developed a procedure for classification of coastal dune environments in England using hyperspectral imagery, Light Detection and Ranging (lidar), and object-oriented image analysis. Their data processing methods were able to extract over 20 different classes of habitat with 0.84 overall accuracy, at resolutions down to about 1 meter. They concluded the workflow they developed was successful in mapping coastal dune habitats and then applied it at multiple sites. The methods they used provide an example of what can be done in this type of landscape when multiple data sources and types are available.

The methods and results discussed in these papers show that remote sensing techniques and analysis can be very useful in change detection, analysis of landscape structure, and identification of features in dune environments.

2.3 Overview of image texture and incorporation of texture to feature identification

Texture statistics calculated from a grey level co-occurrence matrix (GLCM) indicate spatial relationships between pixel values (Haralick, Shanmugam, and Dinstein 1973). GLCMs perform statistical analysis on an image to characterize pixel values occurrences within a moving window and provide additional raster data that can be used to improve classification (Jones and Vaughan 2010).

Texture measures that will be applied in this study are classified as second order as they operate over the GLCM rather than the original image. According to Hall-Beyer (2017), these measures can be grouped to provide a general expectation of their output and aid in results interpretation and discussion (Table 1). Contrast measures look to identify and enhance contrast variation reported via the GLCM, or lack of variation (i.e., homogeneity). Orderliness measures characterize the regularity of GLCM values. Descriptive measures are like those used in descriptive statistics but operate on the GLCM. The use of any specific measure listed here is dependent on what textures are within a scene, what texture the researcher is looking to capture, and variability in each measures output.

Table 1: Hall-Beyer's grouped texture measures (Hall-Beyer 2017)

Contrast	**Orderliness**	**Descriptive**
Contrast	Angular Second Moment	Mean
Dissimilarity	Entropy	Variance
Homogeneity		Correlation

Research into texture statistics has resulted in guidelines and recommendation on the use and interpretation of texture. Hall-Beyer (1336, 2017) suggested, “For classification problems, choose Mean and, where a class patch is likely to contain edge-like features, Con [Contrast]. Cor [Correlation] is an alternative for Mean in these situations; Dis [Dissimilarity] may similarly be used in place of Con. For more detailed texture study, add Ent [Entropy].” These findings were the result of extensive principal components analysis of several texture statistics to find which metric would characterize and contrast differing patches of landcover. The resulting recommendations serve as considerations for initial investigations utilizing texture. Ferro and Warner (2002) employed texture statistics on simulated data and concluded that window size was a crucial consideration when utilizing texture statistics with issues specifically concerning edge effects and misclassifications.

Studies indicate that texture analysis is a viable method that can identify objects from remotely sensed data (St-Louis et al., 2005) and that texture analysis can be used to extract additional information from a remotely sensed data set to potentially improve classification results (Jones & Vaughan, 2010). Texture analysis adds a mechanism of human perception to image processing, meaning when humans perceive an object, characteristics such as color, texture, patterns, etc. are used to assist in object identification (Haralick et al., 1973). Additionally, information regarding specific texture measures has been published which helps to understand the theory behind texture analysis as well as recommendations as to what measures would be most useful (Hall-Beyer. 2017). Overall, the literature suggests that inclusion of texture variables is a viable approach for analysis and detection of specific landscape features.

In general, application of texture analysis in remote sensing studies has applied the technique to classification of land cover types. To date, automated large-scale identification of inland dune blowouts has not been investigated, although feature detection has been done on status of dune sand levels in coastal regions (Ryu & Sherman, 2014). Though texture-based analysis in dune habitats is lacking, other studies have used texture in arid habitats with successful results (St-Louis et al. 2005). The apparent lack of direct investigation into identifying dune blowouts via remote sensing and texture analysis indicates a study such as this is needed, and knowledge will be gained from the investigation which will inform further analyses.

3. METHODOLOGY

3.1 Study area

The study area encompasses over 100,000 hectares of sandy shrubland, part of the Mescalero-Monahans dune system, in the Permian Basin north of the Pecos River in West Texas (Figure 1). Dominated by Shin Oak and other shrubs, this area serves as vital habitat for species which include *S. arenicolus*. Primary disruption of this landscape originates from development and operation of resource extraction activities. The primary focus of this study will be areas with Shin Oak, dune blowouts, and well pads which will be reflected in the site selection.

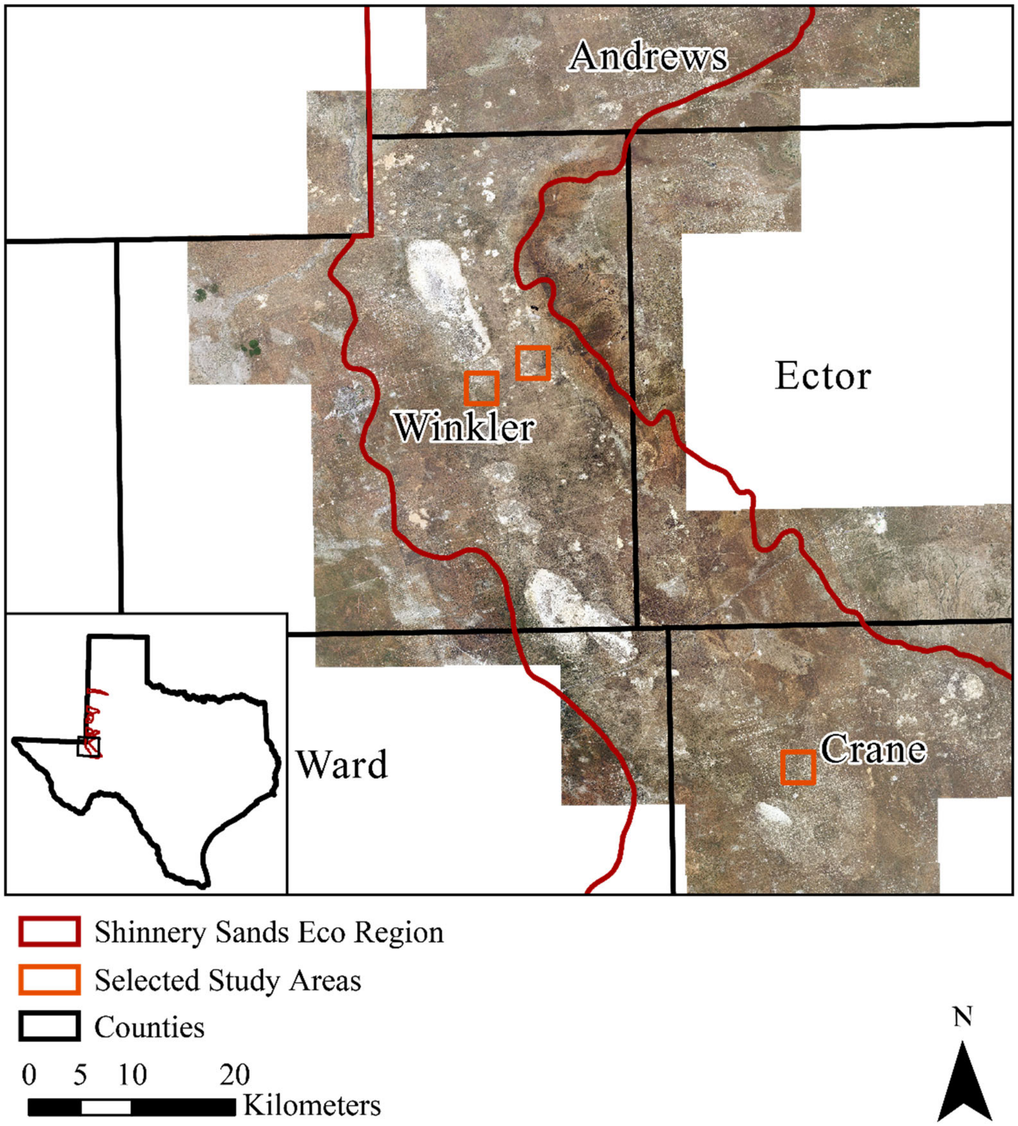

Figure 1: Overview of study area

3.2 Site selection

Within the study area, three 3 x 3 km sites in the shinnery sands ecosystem were selected (Table 2). Each site was selected based on features present, data available, and representativeness within the overall landscape. Site selection also considered capturing as much variation in the landscape while keeping data produced during the analysis manageable.

Table 2: Study area, selected sites

County	Quad name	1/4 Quad Name	Focus
Winkler	Wheeler Ranch	Wheeler Ranch NW	Wells and blowouts
Crane	Penwell SW	Penwell SW SE	Dense wells and blowouts
Winkler	Notrees NW	Notrees NW SE	Wells, blowouts, and large open sand

3.3 Geospatial data collection

Data used in this analysis consists of NAIP quarter-quads captured in 2016 with 1-meter spatial resolution and four wavelength bands (near-infrared, blue, green, and red).

3.3 Data processing and analysis methods

Texture measures were calculated using the r.texture tool available in GRASS GIS (GRASS Development Team). The texture measures tested in the analysis were second-order measures based on the GLCM as defined in Haralick's Textural Features for Image Classification. These measures operate on single layers of data and for this study the primary focus for texture-based feature extraction were the red, near-infrared, and normalized difference vegetation index (NDVI) layers. These layers were of interest as they sufficiently capture tonal differences of surface features in the study area. Final implementation used only the NDVI layer for each study area. NDVI was selected after assessing image contrast and texture output at the selected study sites for texture measures including Contrast, Angular Second Moment (ASM), and Correlation at varying window sizes. The texture values were then grouped and filtered into patches.

This involved a three-step process using the GRASS GIS tools r.clump and r.neighbors. The r.clump tool groups raster cells into similar regions based on digital numbers of the raster, a threshold parameter, and a minimum clump size. Clumping threshold values were adjusted for each site in order to sufficiently group high contrast values from the texture outputs. These clumps represented areas that could possibly be dune blowouts. The output of the r.clump tool was then processed with a 7-cell circular moving window variance filter using the r.neighbors tool. This was performed to transform the areas of clumped cells into continuous individual patches. The last step involved using ArcMap 10.6 (ESRI) test tool to designate resulting patches as one (1) and background values as zero (0) using a logical expression where values other than the background value were evaluated as a value of one.

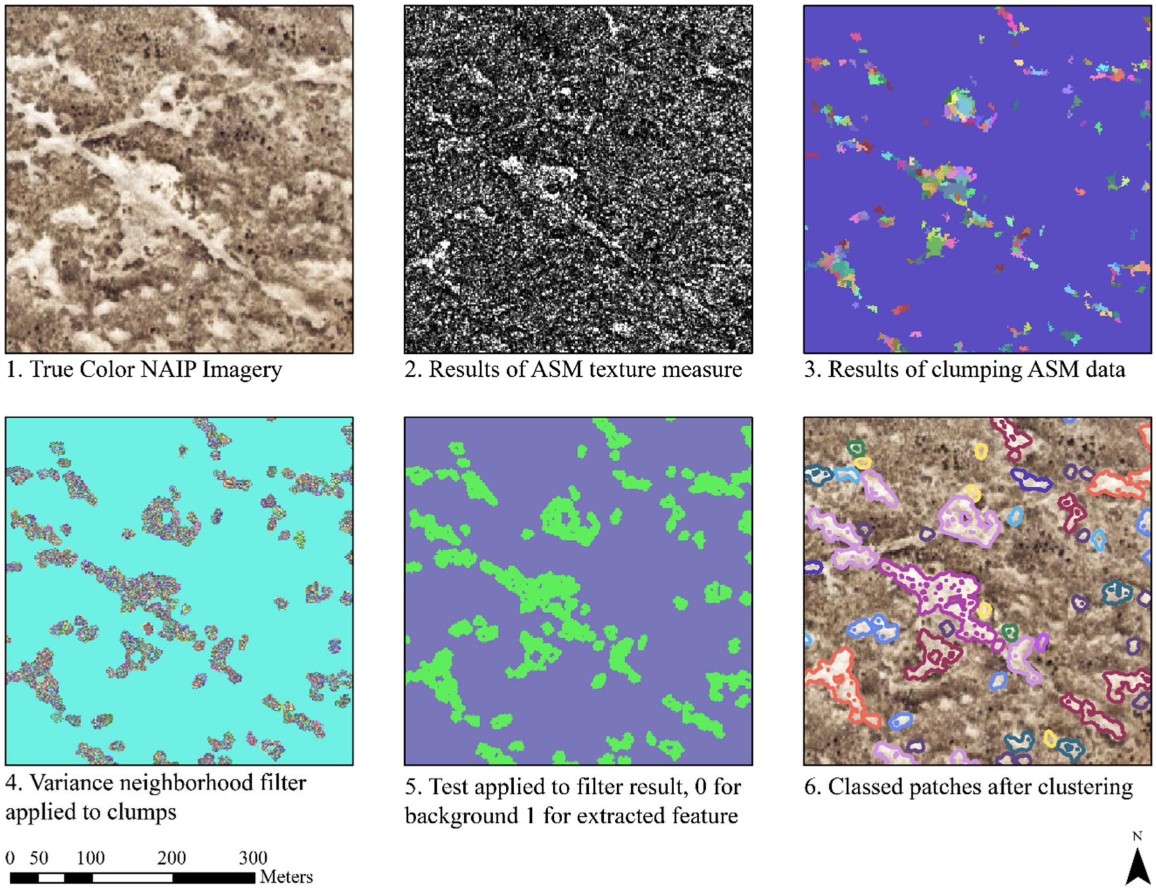

Figure 2: Illustrated analysis method

FRAGSTATS 4.2.1.603 was used to calculate patch metrics on the resulting filtered texture raster. Patch analysis consisted of nine distinct patch metrics chosen to best describe the variation between patches (Table 3). These metrics were chosen for their ease of use, requiring no additional data, and their applicability to this study. Applicability was based on a review of online documents describing what each patch metric computes. The results from FRAGSTATS consisted of a table of unique patches with columns of metric values and a patch ID raster. The patch ID raster was converted to a polygon vector file and the metric values were joined to the unique patch IDs. The table was processed with JMP Pro 13 (SAS Institute) and a hierarchical cluster analysis was performed using the nine metrics as input, Ward as the method, and cluster level set at 20. Clusters were assigned to the table of unique patches and then joined to the vector polygon patch ID file.

Table 3: Selected FRAGSTATS Patch Metrics

Metric Group	**Metric**	
Area	AREA	Patch Area
	PERIM	Patch Perimeter
	GYRATE	Radius of Gyration
Shape	SHAPE	Shape Index
	FRAC	Fractal Dimension Index
	CIRCLE	Related Circumscribing Circle
	CONTIG	Contiguity Index
Aggregation	ENN	Euclidean Nearest Neighbor Distance
	PROX	Proximity Index

3.4 Statistical Analysis Procedures

To determine if this analysis procedure correctly extracts dune blowout features, a contingency table was produced to determine if output clusters were associated with specific cover types. Each of the three sites had tables constructed where patch cover types were fit by cluster class. Refer to Table 4 for a list of cover types. For each cluster output, 10 randomly selected patches were assessed for patch cover types. Clusters with less than five features were omitted from the analysis. Contingency tables were processed using JMP and Chi-square (χ^2) values were assessed based on Pearson probability.

Table 4: Cover types for feature identification

Cover Type	Description
1	Dune blowout or open sand surrounded by vegetation
2	Well infrastructure interconnected with open sand
3	Well infrastructure
4	Other

4. RESULTS

4.1 Angular Second Moment to highlight dune features in NAIP imagery

Of the three texture measures tested, ASM was shown to differentiate dune features from the surrounding landscape in NDVI imagery (Figure 3). Dune blowouts and open sand areas bordered by vegetation were identified by continuous DNs at or near values of one, while surrounding vegetation had values nearing zero. Disruptions within sandy areas or blowouts by vegetation caused reductions of interior values where the disruption occurred. The two additional measures tested, Contrast and Correlation, served as edge detectors. Though these additional measures did detect a component of dune sand, ASM captured the feature in a manner consistent with the goal of the question. For all measures, adjusting the window size for texture measures to values higher than the default value of three pixels served to only smooth landscape detail. Overall, dune features were easily distinguished from the landscape with the use of the texture measure ASM. However, petroleum well infrastructure built using crushed caliche was also highlighted. With this result ASM can be characterized in this analysis as a texture method that will differentiate surfaces defined by continuous values in single layer imagery (Figure 4).

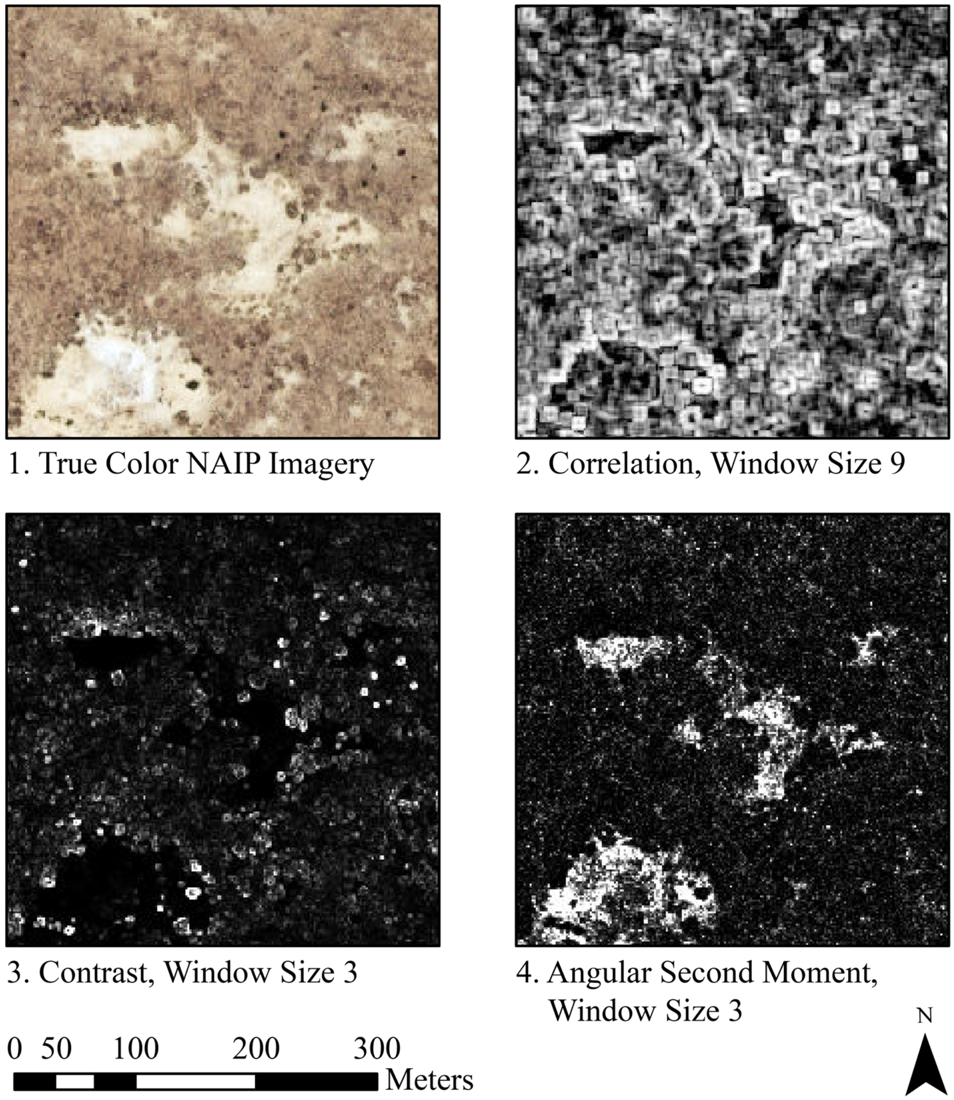

Figure 3: Texture results using NDVI for a sub-section of Notrees

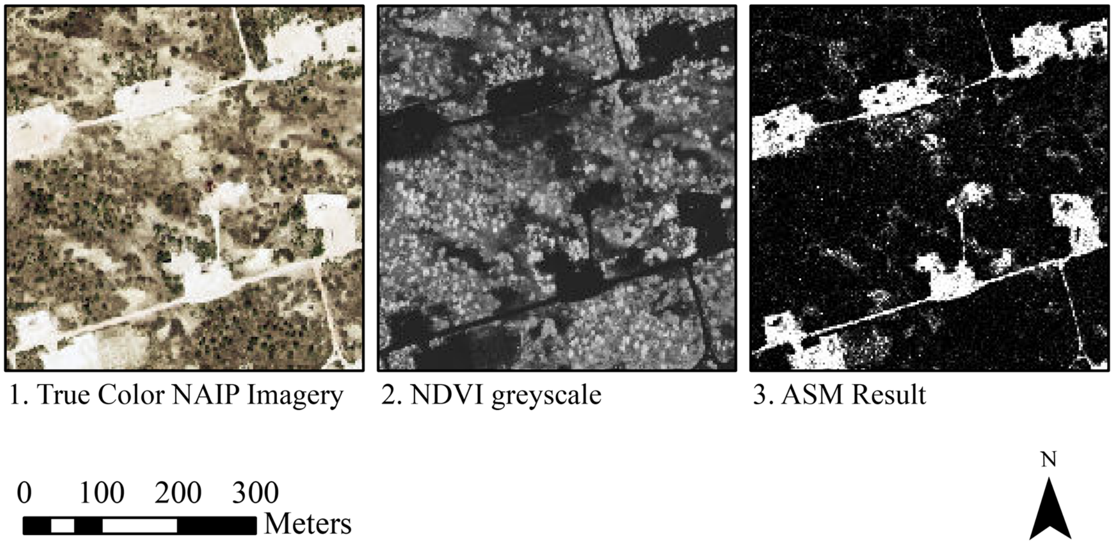

Figure 4: Texture output for Penwell subset using NDVI and ASM to calculate texture

4.2 Patches from texture output and assigning patch metrics

Transforming texture output using clumping and filtering methods effectively identified continuous independently defined patches. Clumping was able to identify areas of similar texture values and group those values, as seen in map three of Figure 2. Each study site required fine adjustment of the clumping threshold in order to identify as many open sand and dune blowout features as possible and extract well defined feature edges. Minimum clump size was adjusted to 25 meters for all sites to limit complexity of data extracted and reduce noise. Final clumping parameters are outlined in Table 6. Processing of final clumping data necessitated the application of a moving window variance filter to ensure all background values were assigned the same value (Figure 5). Application of the test tool resulted in defined patches that were identified by FRAGSTATS and the selected patch metrics were applied. Data produced from these steps resulted in patches with associated patch ID in raster format along with a table contain patch IDs and their respective patch metric column. Visual assessment indicated patch metrics describe variations in identified features (Figure 6).

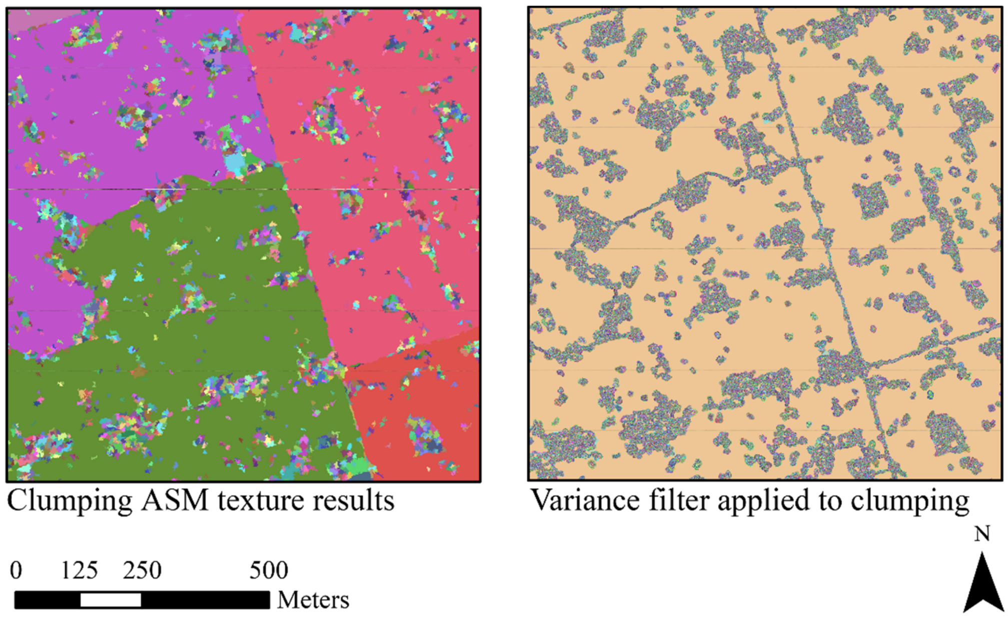

Figure 5: Clumping and variance filter on subset of Penwell SW SE

Table 5: Clumping parameters

County	Quad Name	1/4 Quad Name	Threshold	Minimum Clump Size (meters)
Winkler	Wheeler Ranch	Wheeler Ranch NW	0.013	25
Crane	Penwell SW	Penwell SW SE	0.004	25
Winkler	Notrees NW	Notrees NW SE	0.007	25

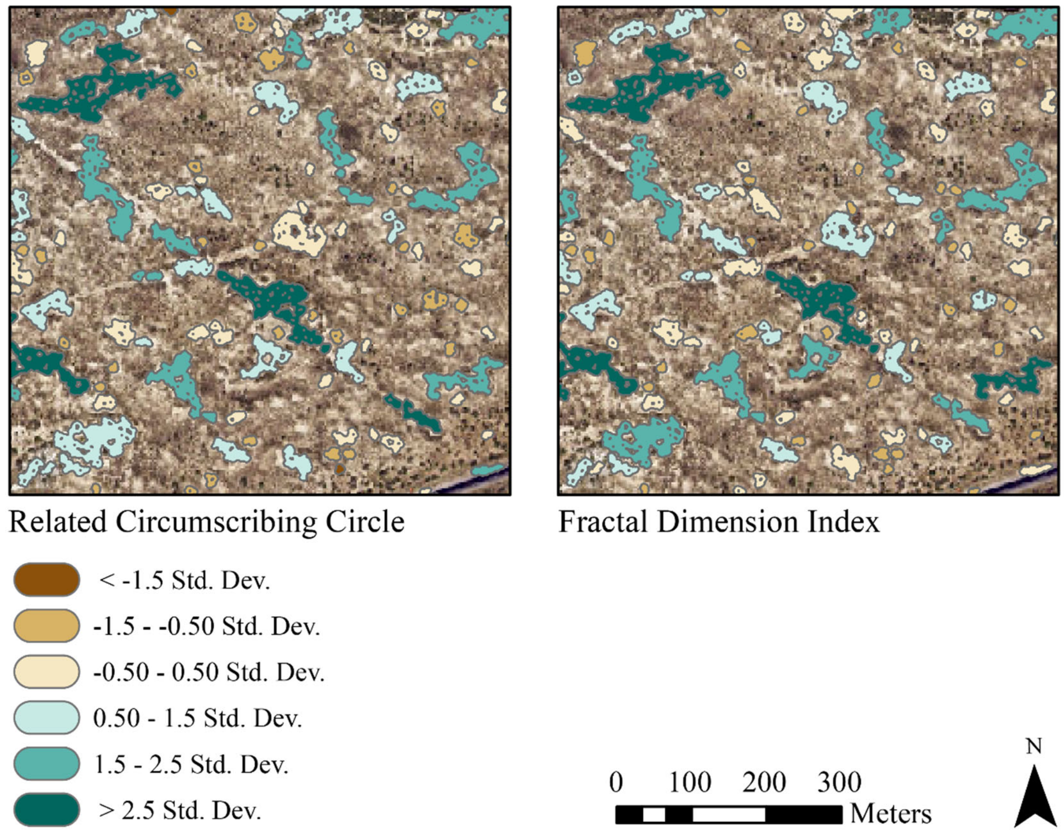

Figure 6: Patch metrics visualized for subset in Wheeler Ranch

4.3 Clustering is dependent on patch metrics

Setting the cluster break point to 20 clusters was the result of a visual interpretation of the cluster results at 10, 20, and 30 clusters. It was observed that a setting of 10 did not separate patches with similar area measurements, causing similar sized well pads and dune blowouts to be included in the same class. Setting the break point at 30 would separate small patches into cluster groups regardless of feature structure. Chi-square testing of the contingency table produced from cluster samples indicated statistically significant clustering depending on cover type (Table 7). This indicates for the 20 clusters in each of the three sample sites, assignment of features to specific classes was not random and based on differences detected in the patch metrics.

The cluster identification of features based on the cover types established is summarized in Table 8. Cover type 1 (Dune Blowout or Open Sand Surrounded by Vegetation) was the dominant cover identified for Wheeler Ranch NW. Cover type 4 (Other) was the majority cover for both Penwell SW SE and Notrees NW SE. In all sites, clusters with less than five features present were either large areas of open sand (>200 sq. km.) or large well infrastructure and open sand mixtures (>1 sq. km.).

Table 6: Chi-square test results of the cover type assignments to clusters for the three study sites

	Pearson	
1/4 Quad Name	**Chi Square**	**Prob>ChiSq**
Wheeler Ranch NW	97.029	0.0001
Penwell SW SE	121.188	0.0001
Notrees NW SE	75.436	0.0004

Table 7: Percentages of cover types identified for the three study sites

1/4 Quad Name	**Cover Type 1**	**Cover Type 2**	**Cover Type 3**	**Cover Type 4**
Wheeler Ranch NW	57.31%	5.85%	3.51%	33.33%
Penwell SW SE	30.73%	3.35%	26.82%	39.11%
Notrees NW SE	31.85%	0.74%	4.44%	62.96%

Wheeler Ranch NW Study Site

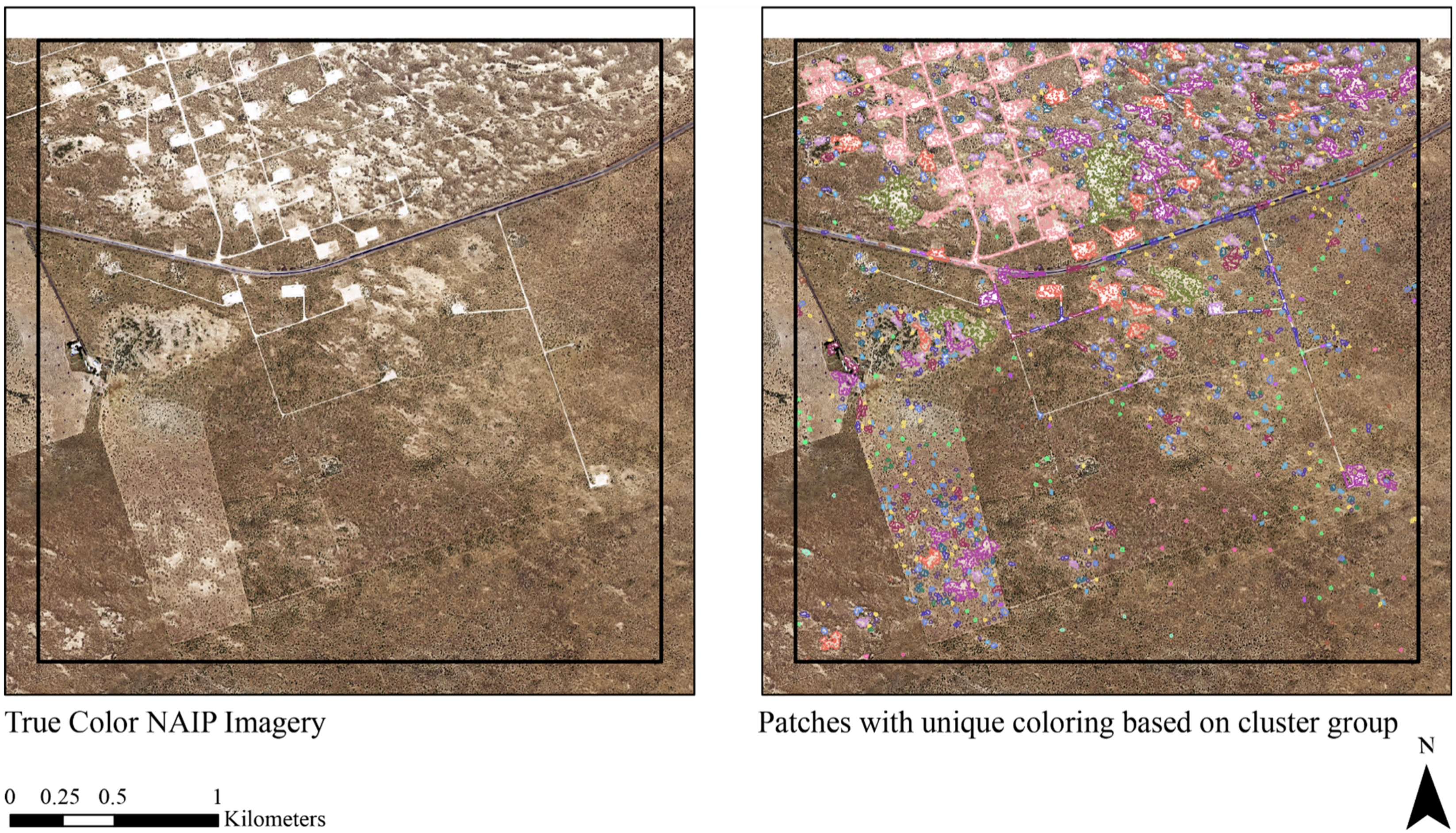

Figure 7: Patches overlaid on NAIP imagery for Wheeler Ranch NW study site

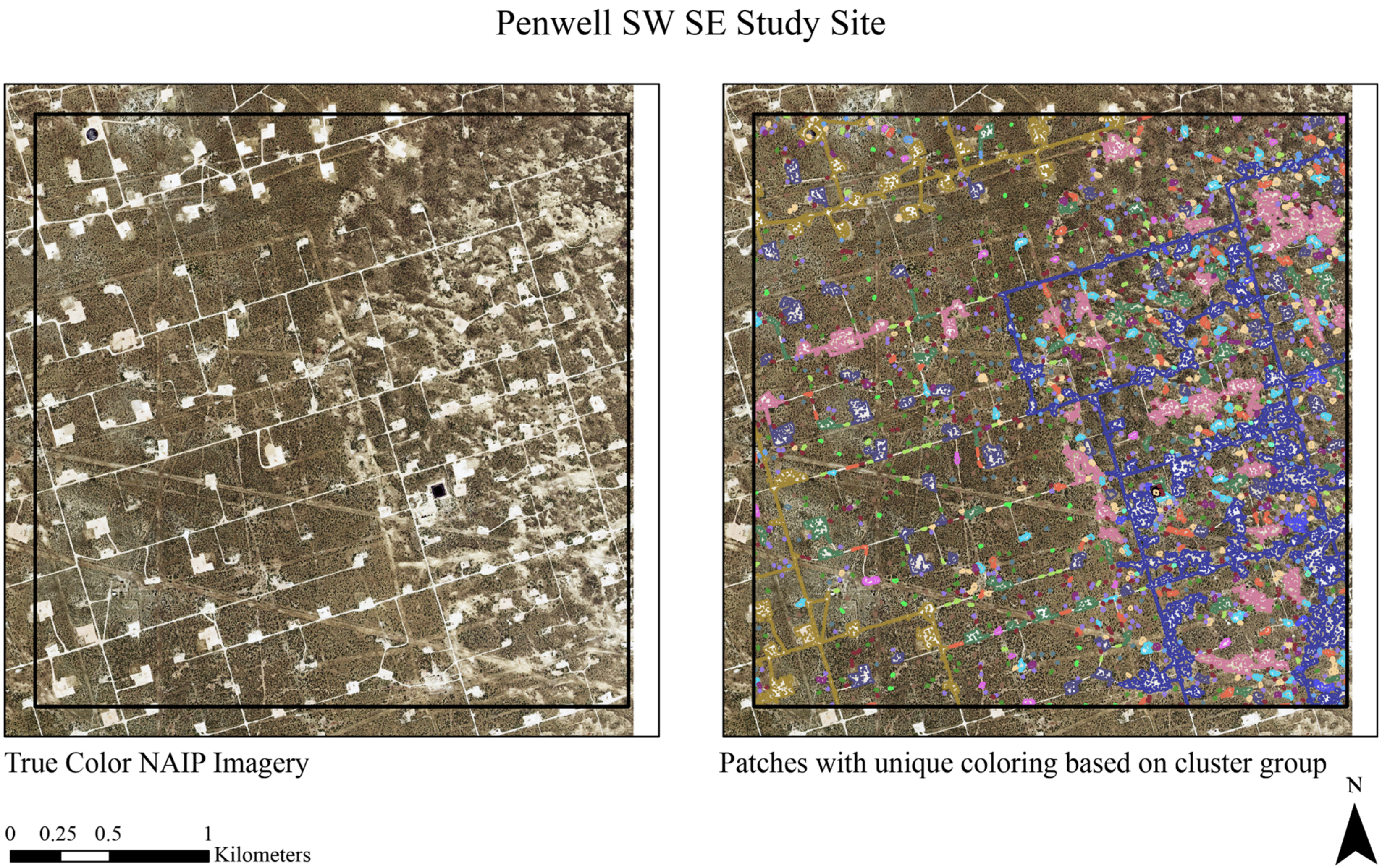

Figure 8: Patches overlaid on NAIP imagery for Penwell SW SE study site

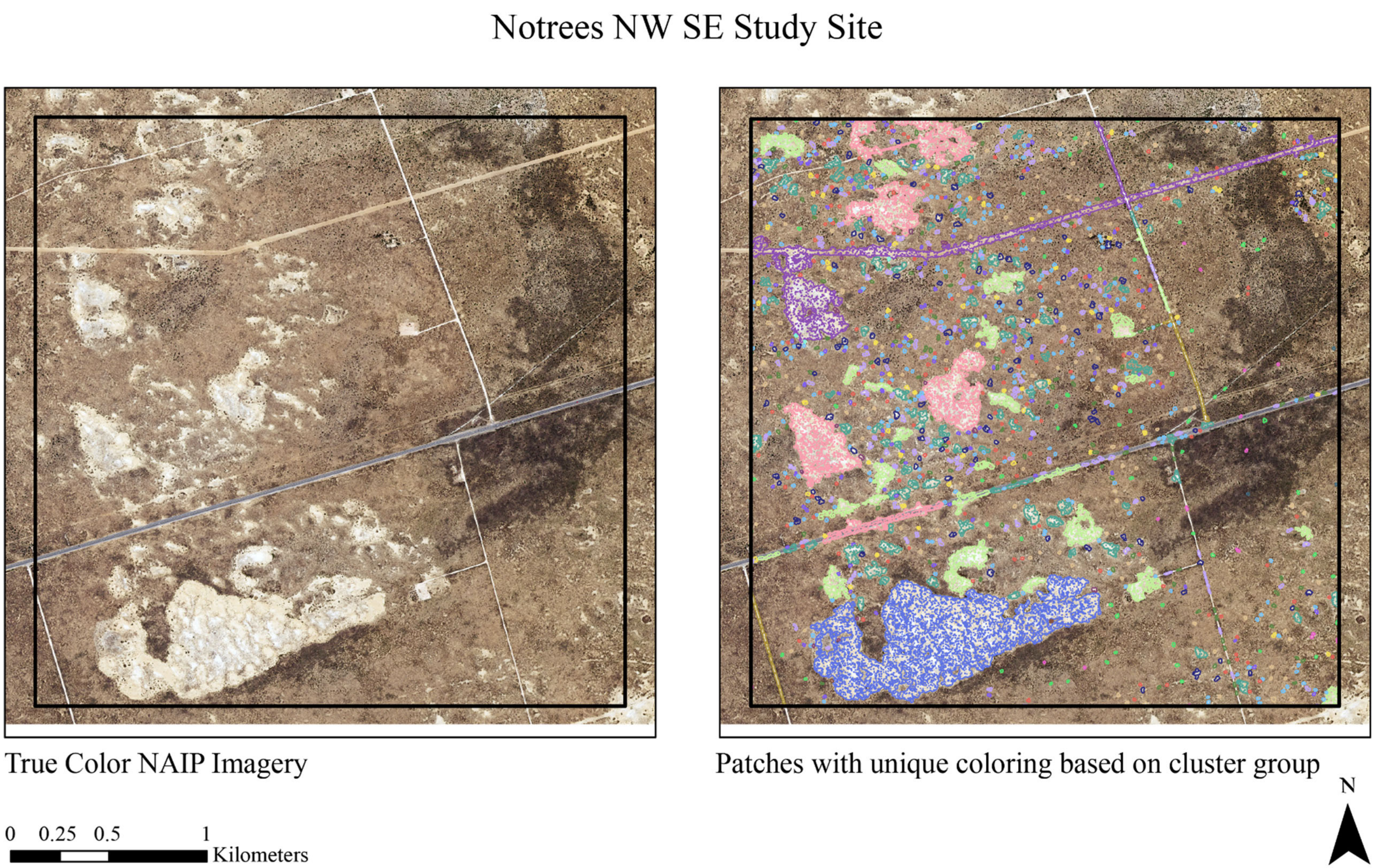

Figure 9: Patches overlaid on NAIP imagery for Notrees NW SE study site

5. DISCUSSION

5.1 Texture and processing the output for features in dune systems

The three tested texture measures were able to extract information from the dune landscape. The information gathered from Contrast and Correlation texture measure both reported changes in contrast across a spatial extent. This effect is good for identifying edges of sufficiently contrast features within the landscape but does not identify continuous patches (Figure 3). ASM performed best in identifying patches in this landscape as areas of continuous DN were assigned high values from the algorithm. Additionally, ASM was sensitive to changes within these patches. This would result in low values assigned to disturbances within the feature. These characterizations were similarly reported by Hall-Beyer (2017) where Contrast and Correlation resulted in high values where abrupt changes in DN occurred, and ASM reported interior patch variations. Since the measure was executed on the NDVI band ratio, vegetation was the primary cause of interior patch disturbance. Features contrasted by the ASM texture measure were not primarily dune blowouts or open sand areas. Caliche well pads and roads were consistently assigned values nearing the maximum output for ASM. For this analysis, additional steps were needed to address the extra features extracted. What these results have indicated is that ASM can identify and report tonal variations within areas of continuous DN in a vegetation dominated dune environment. Dune blowouts and open sand are primary features identified when excluding well infrastructure, thus texture measures such as ASM could be used to monitor dune activity over temporal scales and discriminate within dune properties. This observation of texture method’s sensitivity to within dune properties, such as vegetation coverage, adds to Hugenholtz et al. (2012)

review of RS applications in the understanding of aeolian processes. In their review, multispectral imagery along with band ratios were methods to investigate vegetation-dune relationships. Difficulty was noted when attempting to quantify measures over temporal scales. Texture measures executed on multidate NDVI imagery could be a solution, where each dune feature could have parametric statistics from texture values associated and changes of these statistics noted over a temporal scale.

Processing the texture results with the goal of feature identification necessitated the transformation of greyscale raster into data that defined individual patches. The first step to achieve this goal was using r.clump to group similar texture values. This tool was successful in grouping like values, but the threshold adjustment was very sensitive for these datasets. The threshold had to be set to capture as much dune and open sand features but still retain individual patches as identified in the originating texture measure output. This processing step is where many of the cover type 4 (other) patch identifications originated. Further processing was successful in transforming the original texture output into patches FRAGSTATS could interpret and assign metrics.

5.2 Patch metrics inclusion

The primary goals for incorporating patch metrics into the analysis was to describe variation in dune structure and separate well infrastructure from patches identified by FRAGSTATS. Previous analyses have used patch and landscape metrics to describe ecological properties (Linke et al. 2008) and asses available habitat to actual distribution of species residing in these areas (Hokit, Stith, and Branch 1999). This analysis had patch metrics describe both dune structure variations and well infrastructure. I hypothesized that well infrastructure structure was different enough from dune features that data clustering would separate these features into distinct classes based on patch metrics. Though the statistics indicate cluster output is dependent on cover type, there are issues with mixtures of cover types within clusters. Penwell SW SE has features in group 6 that can be identified as cover type 3 (well infrastructure) and cover type 1 (dune blowouts or open sand) (Figure 10). This is not unlike misclassification in traditional pixel-based analysis methods.

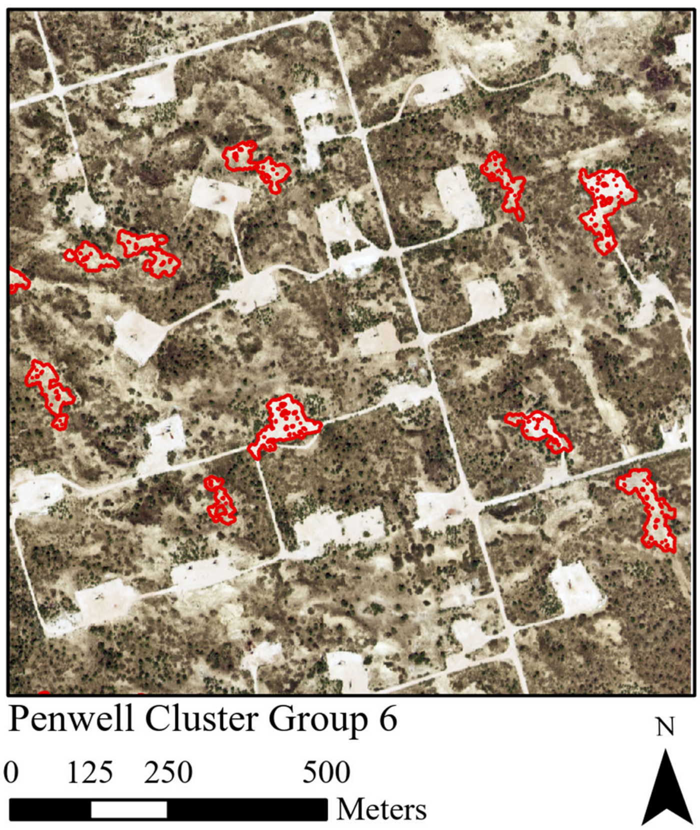

Figure 10: Cluster group 6 in Penwell SW SE showing dune blowouts and well infrastructure mixing

5.3 Building upon analysis results

Extracting dune blowouts from this region is made complex by the presence of well infrastructure, these features are seen as high contrast pixels from the surrounding vegetation just as dune blowouts are. If these features could be made to be more distinguishable from one another purely in initial imagery, identification and separation could be easier. Thus, improving the viability of the results gathered in this analysis exist in primarily in additional data and data processing steps.

Remotely sensed imagery with higher than the 8-bit radiometric resolution available with NAIP imagery could help distinguish color variations between well infrastructure and dune blowouts. Additionally, increasing the spectral resolution by using sensors that can detect soil variations could also improve separation. Production and inclusion of well infrastructure masks to prevent the identification of these features could also improve results, similar to masking steps taken by St-Louis et al. (2006) to remove dirt roads before texture analysis although generating masks manually would be a time intensive process for this region. As such, a combination of manual digitization and feature extraction using methods like those in this analysis is recommended.

Texture statistics, clumping techniques, filtering methods, and patch metrics not tested in this analysis could potentially extract features with better detail and accuracy. I noted that the output of the clumping step grouped texture output in areas of light vegetation, further refinement of clumping threshold and texture output could remove these areas. The inclusion of additional patch metrics to assist in cluster separation might reduce cover type mixing. A different classifying algorithm or using supervised classification could also provide better the results.

6. CONCLUSION

This research attempted to identify a workflow that can overcome challenges of dune blowout detection. Analysis used NAIP imagery, NDVI band ratio, image texture statistics, and patch metrics to extract and describe features present within each study area. Extracted features, referred to as patches, were then grouped based on patch statistics using hierarchical clustering. Statistical significance was indicated when reviewing clusters resulting from GLCM texture based feature extraction ($p < 0.001$). Angular Second Moment (ASM) texture measure contrasted dune features from surrounding vegetation in the Permian Basin region, in addition to petroleum well infrastructure. Patches extracted from the texture result were able to be described by patch metrics. Those patches and associated metrics were able to be classified into distinct clusters based on patch metrics. Classifying using hierarchical based clustering successfully clustered patches into four distinct groups based on 4 cover types outlined.

When evaluating patches within the clusters, it was observed that errors equivalent to misclassification are present in the clusters when attempting to select a cluster according to a cover type of interest, for example dune blowouts. This indicates the analysis procedure used can produce statistically significant results, but those results would be difficult to use from a production standpoint. To improve results using similar analysis procedures one could investigate the application of higher spectral or radiometric resolution imagery. Additional patch metrics could be characterized and their applicability for automated classification into well-defined groups. Sensitivity analyses could be conducted to determine if there are better cluster break points for this data.

The extraction of dune feature and well pads with these analysis steps provide information for researchers investigating environmental changes in the Permian Basin region. Using texture statistics vegetation interaction within sand dunes can be identified with high sensitivity and could potentially be quantified, thus forming an additional technique for time series monitoring of dune areas. Patch metrics assigned to the dune areas alone could enable comparison and monitoring of dune structure throughout the region. With further refinement of a processes to extract dune and well features, the impact on Dunes Sagebrush Lizard habit by petroleum well development could be monitored. Inferences about impact to lizard populations could be made and relationships modeled.

This analysis introduced a unique procedure for extracting features in a dune ecosystem intermixed with anthropogenic features. With additional refinement, the methods used here could result in well-defined and accurate features useful for habitat research.

REFERENCES

Bertacchi, A., and Lombardi, T. 2014. Diachronic analysis (1954–2010) of transformations of the dune habitat in a stretch of the Northern Tyrrhenian Coast (Italy). *Plant Biosystems - An International Journal Dealing with all Aspects of Plant Biology.* 148(2):227-236. doi:10.1080/11263504.2013.788572

Brownett, J., and Millis, R. 2017. The development and application of remote sensing to monitor sand dune habitats. *Journal of Coastal Conservation.* 21(5):643-656. doi;10.1007/s11852-017-0504-x

Fahrig, L. 2003. Effects of Habitat Fragmentation on Biodiversity. *Annual Review of Ecology, Evolution, and Systematics.* 34(1):487-515. doi:10.1146/annurev.ecolsys.34.011802.132419

Ferro, C., and Warner, T. 2002. Scale and Texture in Digital Image Classification. *Photogrammetric Engineering & Remote Sensing.* 68(1):51-63. doi:10.1080/01431161.2016.1278314.

Hall-Beyer, M. 2017. GLCM TEXTURE: A TUTORIAL V 3.0. http://dx.doi.org/10.11575/PRISM/33280

Hall-Beyer, M. 2017. Practical guidelines for choosing GLCM textures to use in landscape classification tasks over a range of moderate spatial scales. *International Journal of Remote Sensing.* 38(5):1312-1338. doi:10.1080/01431161.2016.1278314

Haralick, R., Shanmugam, K., and Dinstien, I. 1973. Textural Features for Image Classification. *IEE TRANSACTION ON SYSTEMS, MAN AND CYBERNETICS.* SMC-3 (6):610-621.

Herse, M. R., K. A. With, and W. A. Boyle. 2018. The importance of core habitat for a threatened species in changing landscapes. *Journal of Applied Ecology.* 55 (5):2241–2252. doi:10.1111/1365-2664.13234

Hibbitts, T. J., W. A. Ryberg, C. S. Adams, A. M. Fields, D. Lay, D. Lay & M. E. Young. 2013. Microhabitat selection by a habitat specialist and generalist in both fragmented and unfragmented landscapes. *Herpetological Conservation and Biology*. 8. 104-113.

Hokit, D. G., B. M. Stith, and L. C. Branch. 1999. Effects of Landscape Structure in Florida Scrub: A Population Perspective. *Ecological Applications* 9 (1):124. doi:10.2307/2641173

Hugenholtz, C., et al. 2012. Remote sensing and spatial analysis of aeolian sand dunes: A review and outlook. *Earth-Science Reviews.* 111(3):319-334. doi:10.1016/j.earscirev.2011.11.006

Johnson, K., M. Horner, E. Muldavin, P. Neville, T. Neville, and J. Smith. 2016. Dunes sagebrush lizard habitat map and models, New Mexico. Natural Heritage New Mexico Publ. No. 15-387. Natural Heritage New Mexico, University of New Mexico, Albuquerque, NM.

Jones, H., and Vaughan, R. 2010. *Remote Sensing of Vegetation: Principles, Techniques, and Applications.* Oxford University Press

Jones, J. R. 1985 Analysis of Coastal Dunes: A Remote Sensing and Statistical Approach, *Journal of Geography*, 84 (3):111-113, doi: 10.1080/00221348508979041

Leavitt, D. J., and L. A. Fitzgerald. 2013. Disassembly of a dune-dwelling lizard community due to landscape fragmentation. *Ecosphere.* 4 (8):1-15. doi:10.1890/ES13-00032.1

Linke, J., S. E. Franklin, M. Hall-Beyer, and G. B. Stenhouse. 2008. Effects of cutline density and land-cover heterogeneity on landscape metrics in western Alberta. *Canadian Journal of Remote Sensing* 34 (4):390–404. doi: 10.5589/m08-034

Paisley, E. C., N. Lancaster, L. R. Gaddis, and R. Greeley. 1991. Discrimination of active and inactive sand from remote sensing: Kelso dunes, Mojave desert, California. *Remote Sensing of Environment* 37 (3):153–166. doi:10.1016/0034-4257(91)90078-K

Ryberg, W. A., M. T. Hill, C. W. Painter, and L. A. Fitzgerald. 2013. Landscape Pattern Determines Neighborhood Size and Structure within a Lizard Population. *PLoS ONE* 8 (2).

Smolensky, N. L., and L. A. Fitzgerald. 2011. Population Variation in Dune-Dwelling Lizards in Response to Patch Size, Patch Quality, and Oil and Gas Development. *The Southwestern Naturalist* 56 (3):315–324. doi:10.1894/f03-mlk-21.1

St-Louis, V., A. M. Pidgeon, V. C. Radeloff, T. J. Hawbaker, and M. K. Clayton. 2006. High-resolution image texture as a predictor of bird species richness. *Remote Sensing of Environment.* 105(4):299-312. doi:10.1016/j.rse.2006.07.003

Vega, L., and Bellagamba, P. and Fitzgerald, L. 2000. Long-term effects of anthropogenic habitat disturbance on a lizard assemblage inhabiting coastal dunes in Argentina. *Canadian Journal of Zoology.* 78(9):1653-1660. doi:10.1139/z00-095

Young, M. E., W. A. Ryberg, L. A. Fitzgerald, and T. J. Hibbitts. 2018. Fragmentation alters home range and movements of the Dunes Sagebrush Lizard (Sceloporus arenicolus). *Canadian Journal of Zoology*. 96(8):905-912. doi:10.1139/cjz-2017-0048