IDENTIFYING DUNE HABITAT THROUGH THE USE OF REMOTE SENSING

CLASSIFICATIONS

by

Lucas John Chavez, B.S.

A thesis submitted to the Graduate Council of
Texas State University in partial fulfillment
of the requirements for the degree of
Master of Science
with a major in Geography
December 2019

Committee Members:

Jennifer Jensen, Chair

Thom Hardy

Edwin Chow

FAIR USE AND AUTHOR'S PERMISSION STATEMENT

Fair Use

Duplication Permission

ACKNOWLEDGEMENTS

First, I would like to thank my advisor and committee chair Dr. Jennifer Jensen, whose guidance and teachings led me into the field of remote sensing. Ever since I walked through her office door asking about my semester project, I would have never seen myself where I am today. The opportunities she has provided me from my undergraduate through graduate degree I may never repay her, but I am just extremely grateful that she believed in me and motivated me to apply for a graduate degree. The completion of this thesis would not have been possible without her never-ending encouragement and relentless ability to help me solve any problem I ran into.

I would also like to thank, Drs. Thomas B. Hardy and Edwin Chow. Dr. Hardy provided me the opportunity to work on multiple projects involving different research interests and have hands-on experience as a graduate student. He allowed me to work with a talented team and travel to West Texas for my research which entailed into an amazing experience. Dr. Chow's valued recommendations were essential to incorporate into my research. His teachings of GIS was my introduction into the field of GIS and led me to pursue a bachelors in Geographic Information Science.

In addition, I would like to thank my parents Richard and Annabelle Chavez for providing me every opportunity to further my education. The sacrifices they have made to give me every opportunity to experience life to the fullest. They have been my source of encouragement and biggest supporters, and without them none of this would have been possible.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

Figure **Page**

LIST OF ABBREVIATIONS

Abbreviation	Description
OBIA	Object-based Image Analysis
PBIA	Pixel-based Image Analysis
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infared
DSL	Dunes Sagebrush Lizard
NAIP	National Agriculture Imagery Program
ETM	Enhanced Thematic Mapper
IDM	Inverse Difference Moment
ENT	Entropy

1. INTRODUCTION

1.1 BACKGROUND

The Southern High Plains and Permian Basin are semi-arid regions composed of sandy loam soils (Holliday, 1990) and known for the large amount of oil reserves. Over the past decade, heavy development due to oil and gas exploration has resulted in habitat loss and landscape fragmentation, both of which impact biodiversity. Additionally, the more recent implementation of hydraulic fracturing has created a market to use local sand and has accelerated construction of large sand plants and sand mines throughout the region.

The dunes sagebrush lizard (DSL) (*Sceloporus arenicolus*) is an endemic species to this region of southeastern New Mexico and West Texas. The DSL is a habitat specialist because of its preference to dune blowouts in shinnery dune habitat (Fitzgerald, 1997). A dune blowout is formed when erosion from wind creates a bowl-shaped depression (Dzialak, 2013) and blowout features are characterized by large depressions that develop as sand is eroded from the windward slope and crest of a sand dune and deposited on the leeward slope as a depositional lobe (Pethick, 1984; Hesp, 2002). Accurate identification of dune landscape is critical for understanding the spatial distribution of potential DSL habitat.

Remote sensing analysis is a common method to identify land cover and associated landscape features and has potential to aid in identification of land covers relevant to the DSL. However, classification accuracies are oftentimes dependent on the spatial resolution of the data as well as the classification method used for analysis. For example, high resolution imagery exhibits higher levels of detailed features which may cause the classification to identify features incorrectly (Myint, 2010). Pixel-based classifications can be accurate, but with high resolution imagery, pixel-based classification methods confuse spectrally similar features which become difficult to differentiate relative to the size of a pixel and spatial extent of the landscape feature (Dzialak, 2013). In general, as spatial resolution increases, the spectral response from certain features may be difficult to identify because pixel-based methods only use spectral information and may misidentify a group of pixels that should be grouped together as one object (Myint, 2010).

Object-based image analysis (OBIA) classification is used in remote sensing to partition the imagery into meaningful image-objects and assess their characteristics through spatial and spectral scales (Chen et. al 2012). Implementing an object-based approach for classification uses segmentation to produce homogenous objects that are then classified as a group of pixels. Depending on the environment being classified, parameters are adjusted to account for spectral, shape, spatial, and context characteristics of the segments to classify based on land cover classes. The selection and combination of suitable objects for identification for an object-based classification depends on the specific land cover classes. The analyst must identify land cover training sites to which the object-based iterative process will configure the pixels into objects that share similar values. Once these objects have been grouped the analyst can identify which objects belong to each land cover class. With increased spatial resolution the potential for OBIA to outperform pixel-based will become an occurring theme across remote sensing.

According to Blaschke (2010), numerous studies show where OBIA has produced better classification accuracies compared to a pixel-based approach. These studies indicated that being able to incorporate spatial photo interpretive elements (i.e., texture, context, shape) into their segments allowed for better feature identification (Hay and Castilla, 2006). As stated earlier, pixel-based image classifications organize pixels based solely on spectral signatures which can lead to spectral mixing. Given the heterogeneity of ideal DSL habitat and the broader Southern High Plains and Permian Basin ecoregions, accurate landscape classification may benefit from texture, shape, or elevation inputs during the classification process.

1.2 PROBLEM STATEMENT

This research focuses on habitat classification for the dunes sagebrush lizard. Due to the dynamic nature of sand dunes, it is important to know the land cover and land-use (LULC) for this region. Dune fields exhibit a shifting dynamic by which dunes emerge and recede over time due to various factors such as prevailing wind, shin oak (*Quercus havardii*) encroachment, and anthropogenic development such as sand plants and well pads. Additionally, activity for the clearing of shin oak for caliche road placement and well pad construction has caused the dunes to be more dynamic, potentially isolating the DSL through habitat fragmentation (Fitzgerald, 2012). Leavitt (2013) demonstrated that increased fragmentation in the region has contributed to DSL community disassembly. Using image classification, we will classify the LULC and develop a model that will use the classification to determine potential DSL habitat. Being able to locate potential sites of where DSL may inhibit is crucial in trying to halt development that could devastate this ecosystem.

1.3 RESEARCH OBJECTIVES

The purpose of this research is to compare two different classification methods, pixel- and object-based, to determine which method accurately classifies LULC across this region. To carry out this comparison, the following objectives will be addressed:

1. Produce a pixel-based classification of National Agricultural Imagery Program (NAIP) imagery using supervised classification.
2. Produce an object-based classification of NAIP imagery.
3. Calculate accuracy assessments for both map products.
4. Compare classification accuracies to determine which method performs best.

1.4 SIGNIFICANCE

This is a comparative study to examine how various classification methods can be used to identify suitable DSL habitat. Producing high accuracy land cover classifications is necessary to accurately map the extent of suitable habitat for the DSL. The use of both object-based and pixel-based image classifications to analyze this region will provide a spatial assessment of the distribution, extent and composition of important landscape features (Dzialak, 2013).

2. LITERATURE REVIEW

2.1 REMOTE SENSING METHODS FOR LAND COVER CLASSIFICATION

Over the past two decades the need to extract tangible information from remotely sensed data has increased steadily. This is due in part to the increased availability of satellite data collected from satellite families such as Landsat satellite system, SPOT satellite system, and Sentinel satellites to name a few. With new satellites being launched (i.e. Landsat-8 (2013), Sentinel-1 (2014), Worldview-3 (2014)) and increased spatial and radiometric resolutions, new applications to characterize and monitor land cover have been identified (Blaschke et al., 2009). The demands for environmental monitoring, assessing and meeting conservation goals, spatial planning, and ecosystem-oriented natural resource management have led to the increased incorporation of remote sensing data to help with these efforts.

With anthropogenic land-use/land-cover change proceeding much faster than natural change, this has become an environmental concern worldwide. Understanding the distribution and dynamics of land cover is crucial to gain a better understanding of the earth's fundamental characteristics and processes, including productivity of the land, diversity of plant and animal species, and biogeochemical and hydrological cycles (Giri, 2012). The need for better land-cover information is being addressed by several national and international programs interested in land-change science. The United States Global Change Research Program (USGCRP) have identified five strategic questions that are important for future research on land cover and land-cover change (Giri, 2012). These questions include: 1)What tools and methods can be applied to better characterize land-use and land-cover?, 2) What are the primary drivers of land-use-land-cover change?, 3) What will the land-use and land-cover patterns and characteristics be in 5-50 years?, 4) How do climate variability and change affect land use and land cover, and what are the potential feedbacks of changes in land use and land cover to climate?, and 5) What are the environmental, social, economic, and human health consequences of current and potential land-use and land-cover change over the next 5-50 years? (Giri, 2012). Addressing questions like these in an environment that is experiencing rapidly increasing anthropogenic development can help guide researcher's intent on answering these questions.

Land-cover classifications using remotely sensed data is an abstract representation of features of the real-world using classes to group them based on their relationships (Giri, 2012). Aside from Arctic and Antarctic landscapes and deserts, most surfaces are covered by vegetation. Therefore, many studies investigating land-cover using remote sensing classification are analysing some form of vegetation in their study area (Di Gregorio and O'Brien, 2012). Land-cover classification schemes are generalized to reflect specific needs of the data producer or areas of interest. Large-area land-cover mapping applications can use the Anderson land use and land cover classification system that meets the needs of U.S. agencies, but there is no internationally accepted approach (Franklin and Wulder, 2002). The Anderson land use and land cover classification system was developed to set specific standards and guidelines to be followed when analysing land use and land cover. This system also defined how to categorize different land covers and what constituted them to those classes.

Land use and land cover classifications have been transformed into a panacea for land inventory and has been adopted by a wide range of disciplines (Comber et al. 2005). A study done by Weiss et al. (2003) looked at land cover over long time scales in semi-arid ecosystems to detect climate variation effects on vegetation. Using Advanced Very High-Resolution Radiometer (AVHRR) data they calculated the Normalized Difference Vegetation Index (NDVI) to detect areas of vegetated surfaces. Regarding semi-arid environments, vegetation canopies do not achieve complete coverage, making NDVI susceptible to the spectral influence of the soil in gaps between vegetation (Weiss et al., 2003). A study done by Civco et al., (2015) looked at (LULC) classifications using five different methods that detected change using Landsat Thematic Mapper. These methods included: traditional post-classification cross-tabulation, cross-correlation analysis, neural networks, knowledge-based expert systems, and image segmentation and object-oriented classification. They wanted to compare the results from each method to see how each method identified LULC and how well each performed in identifying change using multi-temporal imagery. Their study showed that a comparison between several methods to identify LULC change could be applied, but that no single best method was identified.

Using remotely sensed data to monitor fundamental processes of landscape change has been implemented for over five decades and image analysis applied to landscape ecological questions, species conservation, and other sustainability efforts has been growing (Pasher et al. 2007). Landscape analyses are concerned with how changes in landscape scale, resolution, and classification can have complex consequences for landscape pattern, analysis, and interpretation (Comber et al. 2005). Remote sensing for landscape planning can be applied for multiple purposes that can include targeting locations for reclamation, identifying important areas for connectivity of a species, or focusing on areas where human activity is encroaching on monitored habitat.

2.2 REMOTE SENSING OF DUNE HABITATS

Understanding the dynamics of dune lands for habitat conservation can help with monitoring endemic species movement throughout a region. Moreover, image classification allows for identification of how soil interacts with vegetation where endemic species can be found throughout an entire ecosystem (Dzialak et al. 2012). Monitoring of dune landscapes requires an understanding that change can occur gradually or rapidly depending on certain factors that can be assessed when it comes to environmental and habitat conservation (Boyaci et al.2015).

According to Hesp et al. (2002), dune blowouts are saucer-, cup- or trough-shaped depressions or hollows formed by wind erosion on a pre-existing sand deposit. Dunes are susceptible to a multitude of factors that can contribute to the initiation of becoming a blowout including: topographic acceleration of airflow over the dune crest, climate change, vegetation variation in space or vegetation clearance over time, high velocity wind erosion, and human activity (Hesp et al., 2002). The main factors contributing to blowouts in the Permian Basin region involve human development (oil and gas exploration) and high velocity wind erosion which can be attributed to the sparse vegetation cover on the dune crest.

The literature related to classification of dune landscapes is mostly focused around coastal dune features, and few publications focus on semi-arid regions where dunes occur inland, although Jewell et al. (2014) suggests that the same effects that would occur inland, such as human activity near dune features may increase the number of dune blowouts in each area.

2.3 LANDSCAPE STUDIES SPECIFIC TO THE DUNES SAGEBRUSH LIZARD

The Mescalero-Monahans shinnery sands ecosystem is home to the dunes sagebrush lizard (DSL) (*Sceloporus arenicolus*) which has emerged as a focal species of conservation. It has the second-most restricted geographic distribution among North American lizards (Painter et. al. 1999). A study by Dzialak et al., (2013) applied an object-based image classification to produce and validate a spatially- explicit estimate of the shinnery oak soil-vegetation association throughout the range of the DSL. They collected 458 sample points distributed throughout the study area which were used to delineate 242 training polygons for the object-based classifiers. They used (NAIP) 1-m orthophotography for Texas and New Mexico for training polygon development. They developed a mask based on soil type due to the DSL preference for sand soil types using the Soil Survey Geographic Database. They then used Feature Analyst for image classification of Landsat 5 TM data collected across the study area and incorporated a digital elevation model (DEM) into the process to provide additional contextual information for object classification. Their results indicated a 10.3 percent reduction in the geographic extent of sand shinnery oak soil vegetation from 1986 to 2011. This translated into a rate of 0.41% annually. Over time, patch size and total extent increased through time in portions of Texas but decreased in New Mexico.

The Mescalero-Monahans Sandhills region has been heavily impacted by development and a study done by Walkup et al. (2017) shows how landscape fragmentation can impact a species' population. Networks of roads built for oil and gas development result in persistent landscape fragmentation which cause species like the DSL, who rely on shinnery oak dunes, to be negatively impacted by fragmentation. Walkup et al. (2017) identified the demographic structure of species in a dune-dwelling lizard community and the effects that landscape fragmentation has on this community. The goal was to capture lizards on 27 pitfall grids in the Mescalero sands ecosystem, where nine grids were classified as fragmented and the other 18 grids were in unfragmented areas as control areas. Areas identified as fragmented consisted of 13 or more well pads in a section of 259 hectares, based on prior research that demonstrated a negative correlation between lizard densities and oil well density (Leavitt, 2012). All the trapping grids were located in shinnery oak dunes with blowouts that were known to be occupied by DSL. The 27 independent sites were similar in landscape characteristics with shinnery oak dune habitat that is required by the DSL in all trapping grids. This allowed for statistically independent capture data, while testing for the effects of landscape fragmentation. Each trapping grid had 30 pitfall traps spaced 20 m apart covering an area of 1.2 ha. Sampling was done from May to August 2009, from April to August in 2010, and from April to September in 2011-2013. For each lizard captured, they recorded species, trap number, sex, and assigned a unique permanent mark by toe-clipping. Results from the capture sites for the DSL gave insight of how a specialist species is affected by isolation and habitat degradation following fragmentation. Capture rates of DSL in fragmented sites were very low across all years of capture compared to unfragmented sites and consistently declined across the 5 years of trapping. In the 18 unfragmented sites, capture rates of DSL increased from 2009 to 2011 and then decreased from 2011 to 2013. From the capture rates reported, the results suggest that this specialist species has a relatively high susceptibility to local extinction following fragmentation of habitat.

A study done by Smolensky and Fitzgerald, (2011) looked at study sites in the Mescalero Sands ecosystem in New Mexico counties. This ecosystem is characterized by stabilized and semi-stabilized dunes interspersed with shinnery-oak, sand sagebrush, bunchgrasses, and sandy hammocks with honey mesquite. They quantified the abundance of lizards at 11 sites based on the presence of shinnery-oak-sand-dune-habitat, presence of dunes sagebrush lizard, and amount of oil and gas development. They assessed oil and gas development on the landscape by total surface area of caliche, which is the surface type of well pads and roads in a 259-ha, area of shinnery-oak dune habitat. They used GIS data from the New Mexico State Land Office to quantify total surface area of caliche and locations of oil pads and roads. They also looked at total area of blowouts at sites to measure the quantity of habitat for the dunes sagebrush lizard (DSL). The DSL inhabits blowouts, so the area of blowouts was integral in identifying suitable habitat. They measured area within the 11 sites within the 259 ha. Study area using ArcMap to determine average size of blowout available to dune-dwelling lizards. They created a polygon shapefile of all blowouts from aerial photographs taken in 2004. They quantified encounters of lizards by time from line transects in May-July 2005-2006. The number of transects at each site varied between 8-48 and each transect were 25 minutes in duration. These transects were located randomly within shinnery-oak-sand-dune habitat. They used a linear regression to test for a relationship between mean size of blowout and total area of blowouts, with total area of blowouts as the independent variable. Abundance of dunes sagebrush lizard varied across the study area and suggested that the extent of sand-dune blowouts in the surrounding landscape was an important determinant of these abundances. There was no clear statistical evidence to support their hypothesis that oil and gas development correlated to reduced abundances of dune-dwelling lizards, or of the dunes sagebrush lizard.

2.4 OBJECT VS. PER PIXEL LAND COVER CLASSIFICATION

The availability of high-resolution remote sensing data has brought about debate within the remote sensing community as to whether object-based image analysis (OBIA) should be used rather than the traditional pixel-based image analysis for land cover classification. Numerous studies and peer reviewed articles have been published comparing the two analysis methods with recommendations for various approaches. According to Blaschke et al. (2013) we are entering a new paradigm in remote sensing with the increase of spatial resolution in satellite imagery and the increased implementation of OBIA classification in recent research. Since the early 2000s there has been an increase in literature that states OBIA provides more accurate classifications when compared to pixel-based methods (Blaschke et al., 2010).

Gao and Mas (2008) performed a study looking at how OBIA and PBIA classified different images at multiple spatial resolutions to determine accuracies. Using SPOT-5, LANDSAT-7 ETM+ and MODIS images, with four different spatial resolutions of 10, 30, 100, and 250 m. The results from the classification analysis showed that at OBIA performed better than PBIA at higher spatial resolution, but as spatial resolution decreased and smoothing filters were applied, the PBIA increased while object-based accuracies decreased. Cleve et al. (2007) compared PBIA and OBIA using high-resolution aerial photography to classify wildland-urban interface. The study showed that object-based performed better than pixel-based, with an improvement of 17.97% higher overall accuracy. The object-based approach recognized contextual values, such as texture and spatial context, where pixel-based only accounts pixel value. This allowed for OBIA to develop better image objects for the different classes to allow for higher accuracies (Cleve et al. 2007). Whiteside et al. (2011) mapped savannas in Australia using object-based and pixel-based classifications and compared accuracies. The ability of OBIA to use objects to reduce spectral variability in land cover types that are heterogenous, attributed primarily to the improved classification results. With 1-m high spatial resolution NAIP imagery, it is difficult with per-pixel approaches due to sensitivity to the discontinuous and variable nature of mesquite, sandy shrubland type of landscape.

Unlike per pixel-based approaches, OBIA uses spectral, textural, spatial, topological, and hierarchical object characteristics to model features on the landscape (Hussain et al., 2013). For example, Aryaguna et. al. (2016) provided weights to wavelengths to improve their segmentation method and incorporated similarity, tolerance, mean, and variance to the segments to improve the representation for floristic composition. They also looked at how time intensive each image analysis was and reported OBIA being far more time intensive compared to PBIA. Even with the amount of time invested for OBIA classification their results reported the pixel-based analysis provided a better classification accuracy. Research results like this are subjective to the landscape being observed but shows that the debate between OBIA and pixel-based analysis is not settled.

Applying different classifiers (fuzzy or nearest neighbour methods) for OBIA and pixel-based analysis can improve the classification accuracy depending on features being observed (Boyaci et al., 2017). With landscapes like urban city centers, OBIA classifications outperform pixel-based due to the segmentation being able to delineate features with less confusion (Myint et al., 2011). Liu et al. (2010) mentions that OBIA has potential limitations related to segmentation scale. The segmentation process has the potential for under-segmentation and over-segmentation errors, which could create objects that do not represent real-world features (Hussain et al. 2013). Segmentation algorithms that are cluster-based such as K-means, region growing techniques, and mean-shift schema are dependent on the scale of the feature being segmented (Zehtabian et al. 2014). Therefore, OBIA approaches to image classification should integrate field data to allow for comprehensive and accurate identification of features. Integrating field data with a cluster-based segmentation method can facilitate accurate analysis by merging small similar segments iteratively until the object reaches the user-defined threshold (Su et al. 2015). However, segmentation of dune landscapes can be difficult due to the object geometries; dunes tend to become mixed with vegetation and this requires proper scale parameters to control the output object size (Hussain et al. 2013). Each of the aforementioned studies compared PBIA and OBIA within a specific environment and the results show that accuracy of the classification is dependent on the features on the landscape. Parameters set for one environment may not be able to be applied for a similar landscape but could benefit by applying the same methods for classification purposes.

3. METHODOLOGY

3.1 STUDY AREA

The study area consists of portions of the Southern High Plains and Permian Basin region located in West Texas. Although the entire region is comprised of 14 counties, I selected two (NAIP) quadrangles for image classification. The two quadrangles selected were Doodle Bug Well located in Crane County (Figure 1) and North Cowden NW located in Andrews County (Figure 2). These sites were selected based on field data collected and based on previous studies indicating suitable habitat for the DSL.

The landscape of West Texas consists of broad basins, mesas, and valleys bordered by sloping alluvial fans. This region is a part of the Chihuahuan desert that extends from Mexico towards southern New Mexico. Known for its rich deposits of petroleum and natural gas, the region is well- studied because of its geologic and economic importance. The West Texas Basin, also known as the Permian Basin, is composed of the eastern Midland Basin, the Central Basin Platform, and the western Delaware Basin. The sands in this region of West Texas seem to be derived from low-lying border lands south of the Midland Basin (Warn and Sidwell, 1953).

The climate of West Texas is influenced by many factors, one of them being the North American Cordillera. This set of mountain ranges and plateaus are a barrier to air traveling from west to east. Precipitation in West Texas is more common in areas with higher elevation than lower elevations because of upslope flow and summertime thunderstorms. West Texas has a well-defined wet season and dry season. The dry season is November through May, and the wet season is June through October. The peak rainfall months of July and August are due to the Southwest Monsoon, which is a flow pattern that brings moist tropical air and convection to West Texas. Rainfall changes over extended periods are closely related to changes in the pattern of the Southwest Monsoon. Depending on the amount of rainfall this region receives the vegetation coverage can change from year to year.

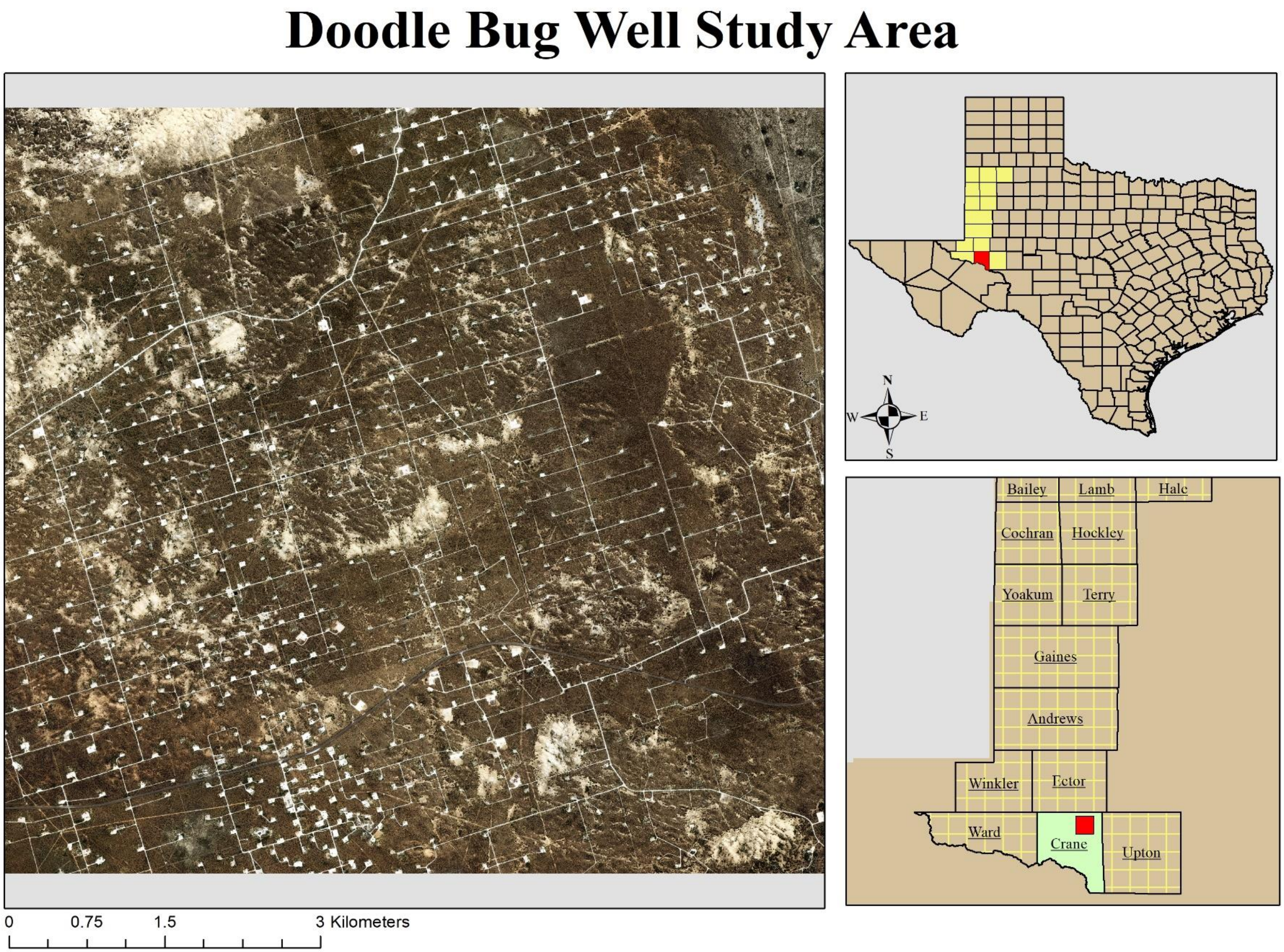

Figure 1. Doodle Bug Well NAIP imagery

North Cowden NW SW Study Area

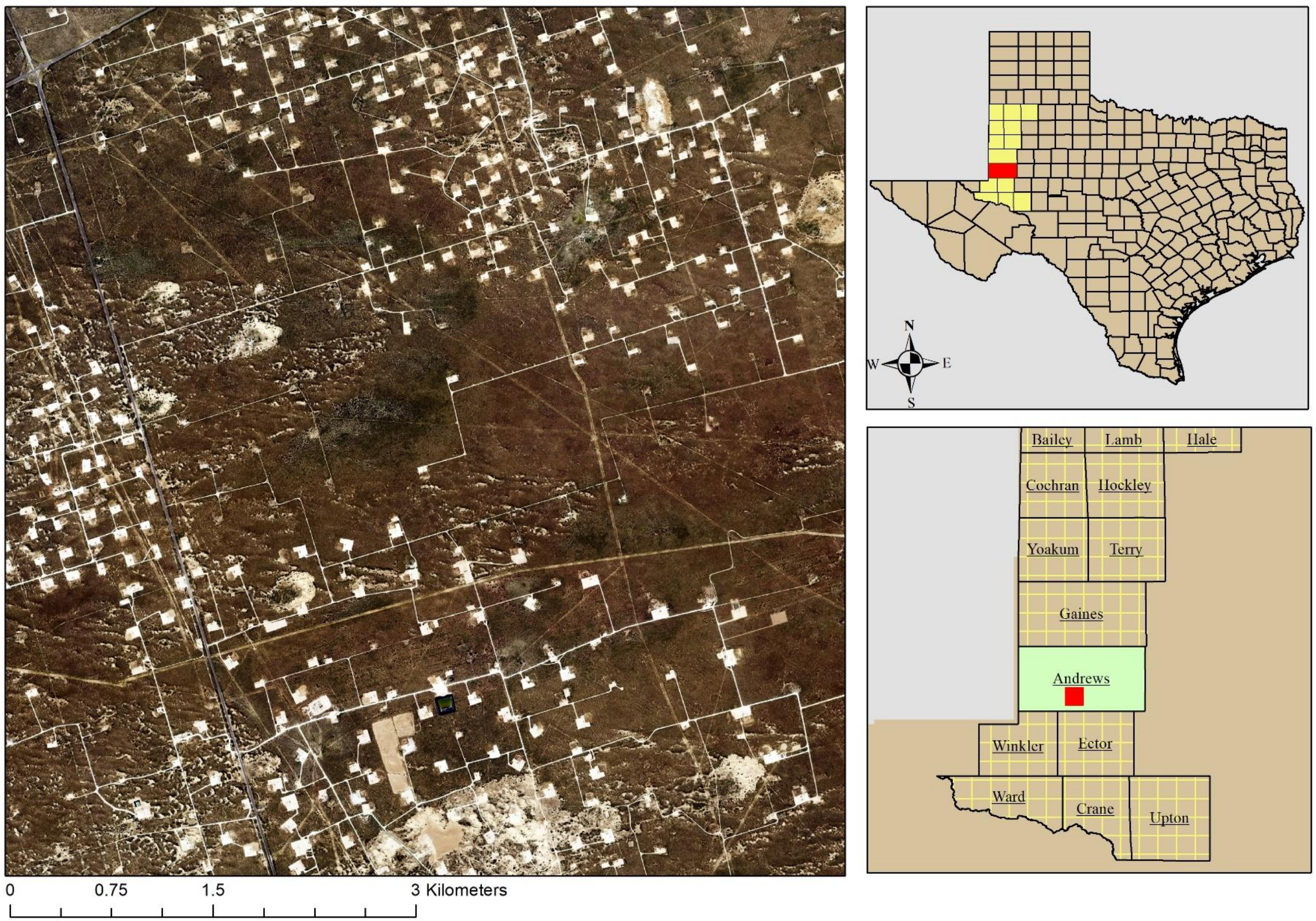

Figure 2. North Cowden NW SW NAIP Imagery

3.2 SITE SELECTION

3.2.1 GEOSPATIAL DATA COLLECTION AND PROCESSING

One-meter spatial resolution quarter quadrangles of NAIP imagery were downloaded from the Texas Natural Resources Information System (TNRIS) for both locations. NAIP imagery was not radiometrically corrected prior to analysis. Imagery for Doodle Bug Well and North Cowden NW images were clipped to include field data collected within each image and to contain deposits of sand mixed in with vegetation and developed well pads. The data are showing digital number values due to lack of methods for retrieving surface reflectance from NAIP digital number values. Images selected for both sites consist of red, green, blue, and near-infrared (NIR) bands. Calculation of a NDVI layer was done using ERDAS indices tool. The NDVI band were layer stacked with the other bands to help identify vegetation covers and improve classification. NDVI was used to separate vegetated areas from sand dune features, due to the high contrast of vegetation and the low contrast of sand in NDVI outputs. Features that can be easily distinguished using NDVI are developed areas and sand, which have low NDVI compared to vegetated areas.

The use of grey level co-occurrence texture features were added to each of the images used for classification. Grey level co-occurrence textures are based on co-occurrence probabilities which provide a second-order method to generate texture features (Haralick, 1973). The probabilities “represent the conditional joint probabilities of all pair wise combinations of grey levels in the spatial window of interest, given two parameters: interpixel distance and orientation" (Clausi, 2002, page 46). A grey level co-occurrence matrix (GLCM) characterizes the configuration of grey scales in an image and is used to quantify textural variation in images (Sonka, 1999). Second-order statistics were chosen due to the relation between neighboring pixels being a key texture feature. Multiple second-order textures were calculated using GRASS GIS to determine which measures would contribute to the identification of features on the landscape.

Inverse Distance Moment (IDM) and Entropy (ENT) texture measures were chosen for both images. IDM shows larger values for windows with little contrast. This will highlight features showing homogeneity across the landscape. ENT shows values with complex variability within an image. Entropy will identify areas where confusion between classes may occur. IDM and ENT were both tested at different window sizes for each image to determine which texture measure provided spatial separability between landscape features. The North Cowden NW SW quarter quad was layer stacked with IDM of NDVI band, with a window size of 31, and ENT of the NDVI band with a window size of 17. The larger window sizes allowed for the capture of larger image elements that fit within these texture scales. Doodle Bug Well used IDM and ENT of NIR band, with a window size of 3, which depicted the variation in neighboring pixels between the different vegetation and landscape features in the image.

3.3 ANALYSIS

3.3.1 OBJECT-BASED CLASSIFICATION

OBIA involves the identification of image objects that contain similar pixel values based on texture, color, and tone through the process of segmentation. I used a mean-shift segmentation using ArcGIS Pro, which requires parameters such as spatial detail, spectral detail, minimum segment size, and band indices. The segmentation parameters for North Cowden NW SW and Doodle Bug Well are provided in Table 1.

Table 1.Spatial detail, Spectral Detail, Minimum Segment Size for each image

Images	North Cowden NW SW	Doodle Bug Well
Bands	NIR, IDM, ENT	Red, NIR, NDVI
Spatial Detail	19	18
Spectral Detail	12	13
Minimum Segment Size	500	500

Spatial detail defines the size of the neighborhood, the spectral detail defines the radius in multispectral space, and minimum segment size which allows for the image to not be over segmented. The band indices used for N Cowden NW SW were NIR, IDM, and ENT bands to identify segments. The band indices used for Doodle Bug Well were the red, NIR, and NDVI bands. The mean shift algorithm segmented each image and training segments were identified for object-based supervised classification in ArcGIS Pro. The training classes used were developed, developed caliche roads, developed well pads, developed roads, shin oak dune land, open sand, shin oak (light), shin oak (dark), mesquite shrubland, mesquite shrubland (dry), mesquite shrubland (healthy), grassy shrubland, and other vegetation. Mesquite shrubland was identified as segments consisting of a mesquite tree with grasses. Grassy shrubland was classified as various grasses interspersed with shrubs. The reason for this number of classes was to allow the classifier to differentiate between spectrally-similar classes and reduce confusion.

Once the segments were selected for training data for each class, the selected segments were exported as shapefiles to be used for the pixel-based classification. This allowed the use of same training data across both classification methods. A maximum likelihood classification was used in ArcGIS Pro, to follow the same algorithm used for the pixel-based approach.

3.3.2 PIXEL-BASED IMAGE ANALYSIS

Supervised pixel-based image classification was implemented to compare how well pixel-based could classify the high spatial resolution imagery compared to the object-based approach. The first step was to set up the training data that were used to perform the object-based approach. Each training site was selected by creating an area of interest from the selected segments used for the object-based approach, to classify the same signatures for each classification. A supervised pixel-based classification was performed using maximum likelihood decision rule, which is based on the probability that a pixel belongs to a class by using the covariance matrix. The equation assumes that these probabilities are equal for all classes and that the input bands have normal distributions. Each signature had equal weight to allow equal probability across all classes. After the classification was completed, the 12 classes were recoded to five classes including developed land, shin oak dune land, mesquite shrubland, grassy shrubland, and other vegetation.

3.4 ACCURACY ASSESSMENTS AND COMPARISONS

After both OBIA and the pixel-based classifications were completed, accuracy assessments were conducted for both maps. The accuracy assessments determined how well each classification performed compared to reference data using aerial photo interpretation by the user. The multinomial distribution formula was used to calculate the number of sample points that were required per image to achieve an accuracy of 85 percent with a 5 percent error. A stratified random sample of 546 assessment points was calculated for N Cowden NW SW, and 646 points for Doodle Bug Well. For N Cowden NW SW and Doodle Bug Well, the same assessment points were used for pixel and object-based classifications. This was done using the update accuracy assessment points tool in ArcGIS Pro to transfer the same points and reference data to the next classification.

An accuracy assessment error matrix was calculated using the compute confusion matrix tool in ArcGIS Pro and resulted in, reported user accuracies, producer accuracies, overall accuracies and Kappa coefficients of agreements for all classifications. Producer's accuracy and user's accuracy are related to commission and omission error, respectively. Commission error refers to misclassification by the user by labeling pixels of another class as belonging to the class of interest. Omission error happens when pixels belong to the proper class but are assigned a different class. Overall accuracy is calculated by adding the diagonal of correctly identified classes between user and producer by the total assessment points. Kappa coefficient is a measure of agreement between two individuals. Kappa is calculated by the observed level of agreement, compared to the value of what is expected if two individuals identifying a classification were completely independent. That is then divided by the maximum level of agreement for Kappa being 1 minus expected probability. Error matrices for each classification were produced and compared.

3.5 STATISTICAL ANALYSIS

The overall accuracy for each OBIA and PBIA classification was compared by producing a test statistic and the difference in accuracy between the two thematic maps. I used a z test to compare proportions (equation 1) with alpha at 0.05 of significance

$$z = \frac{\pi_1 - \pi_2}{\sqrt{\frac{\pi_1(1-\pi_1)}{n_1} + \frac{\pi_2(1-\pi_2)}{n_2}}}$$

if |z| > 1.96. The z test provides an objective measure to determine if the accuracies between the two different classifications is statistically significant where the null hypothesis is that there are no significant differences between the two overall accuracies.

4. RESULTS

4.1 RESULTS OF PBIA AND OBIA CLASSIFICATIONS

The PBIA for North Cowden NW SW used a total of 3,417,432 pixels across the entire image for training data. A total of 321 signatures were selected based on segments that were classified for the OBIA of North Cowden NW SW (Figure 3). The OBIA for North Cowden NW SW assigned a total 750 segments across the image to identify each class. The OBIA used a total of 826,548 pixels across the entire image of North Cowden NW SW for training data (Figure 4). Table 2 shows the number of training sites, number of pixels, and percent of pixels used to train the PBIA and OBIA classifications for North Cowden NW SW.

Table 2. Number of training signatures, number of pixels used per training class for pixel-based and object-based classification, percentage of pixels per total image pixels for North Cowden NW SW

Image	North Cowden NW SW (PBIA)			North Cowden NW SW (OBIA)		
	# of training sites (signatures)	# of pixels per training class	Percent of total image pixels	# of training sites (signatures)	# of pixels per training class	Percent of total image pixels
Developed	18	662,202	1.4	37	68,947	0.14
Developed Caliche Road	14	21,779	0.05	31	45,388	0.10
Developed Road	47	843,268	1.8	30	71,730	0.15
Grassy Shrubland	45	761,012	1.6	153	131,203	0.28
Mesquite Shrubland	45	404,907	0.86	81	84,277	0.18
Mesquite Shrubland (healthy)	10	29,172	0.06	8	26,273	0.06
Mesquite Shrubland (dry)	11	45,087	0.09	18	25,306	0.05
Open Sand	28	46,188	0.10	67	78,749	0.17
Other Vegetation	7	106,073	0.23	12	6,438	0.01
Shin Oak Duneland	37	238,969	0.51	68	78,981	0.17
Shin Oak Dark	40	179,465	0.38	120	83,646	0.18
Shin Oak Light	19	79,310	0.17	125	70,177	0.15
Total number of signatures	321	Number of pixels per image	46,731,108	Total number of segments	750	

The Doodle Bug Well OBIA assigned a total of 1,258 segments across the image for each of the classes selected (Figure 6). The purpose behind selecting this many segment samples was to have an adequate amount to be used for training data per class in the pixel-based classification. The PBIA for Doodle Bug Well classified a total of 1,050,257 pixels across the entire image. A total of 486 signatures were selected based on the segments that were classified for the OBIA of Doodle Bug Well (Figure 5). Table 3 shows the number of training sites, number of pixels, and percent of pixels used to train the pixel-based and object-based classifications for Doodle Bug Well. These classes were then reclassified into the five classes of developed, shin oak dune land, mesquite shrubland, grassy shrubland, other vegetation. Tables 4 and 5 explain the distribution of pixels per classification after condensing the training classes into the five final classes for North Cowden NW SW and Doodle Bug Well, respectively.

Table 3. Number of training signatures, number of pixels used per training class for pixel-based and object-based classification, percentage of pixels per total image pixels for Doodle Bug Well

Image	Doodle Bug Well (PBIA)			Doodle Bug Well (OBIA)		
	# of training sites (signatures)	# of pixels per training class	Percent of total image pixels	# of training sites (signatures)	# of pixels per training class	Percent of total image pixels
Developed	46	115,550	0.17	29	81,225	0.12
Developed Caliche Road	26	103,822	0.15	54	86,625	0.12
Developed Road	56	95,115	0.14	87	94,673	0.14
Grassy Shrubland	42	90,694	0.13	202	121,695	0.17
Mesquite Shrubland	40	71,310	0.10	87	66,514	0.09
Mesquite Shrubland (healthy)	23	47,168	0.07	107	71,069	0.10
Mesquite Shrubland (dry)	43	85,258	0.12	74	54,881	0.08
Open Sand	62	149,748	0.21	122	126,760	0.18
Other Vegetation	6	9,132	0.01	10	1,259	0.002
Shin Oak Duneland	52	97,484	0.14	148	108,719	0.16
Shin Oak Dark	37	74,783	0.11	166	109,671	0.16
Shin Oak Light	53	110,193	0.16	124	119,373	0.17
Total number of signatures	486	Number of pixels per image	70,034,832	Total number of segments	1,258	

Table 4. North Cowden NW SW classes, pixels per class, percent of total image pixels per class

Image	North Cowden NW SW (PBIA)		North Cowden NW SW (OBIA)	
	Pixels per class	Percent of total image pixels	Pixels per class	Percent of total image pixels
Developed	4,023,379	8.61	4,800,188	10.27
Shin Oak Duneland	14,093,324	30.16	26,859,705	57.47
Mesquite Shrubland	18,472,230	39.53	3,431,075	7.34
Grassy Shrubland	9,757,422	20.88	11,589,183	24.79
Other Vegetation	384,753	0.82	49,957	0.11
	Number of pixels per image	46,731,108 pixels		

Table 5. Doodle Bug Well classes, pixels per class, percent of total image pixels per class

Image	Doodle Bug Well (PBIA)		Doodle Bug Well (OBIA)	
	Pixels per class	Percent of total image pixels	Pixels per class	Percent of total image pixels
Developed	3,593,514	5.13	3,366,231	4.81
Shin Oak Duneland	33,492,998	47.82	26,301,758	37.56
Mesquite Shrubland	17,044,037	24.34	35,535,861	50.74
Grassy Shrubland	15,359,400	21.93	4,782,516	6.82
Other Vegetation	544,883	0.78	48,466	0.07
	Number of pixels per image	70,034,832 pixels		

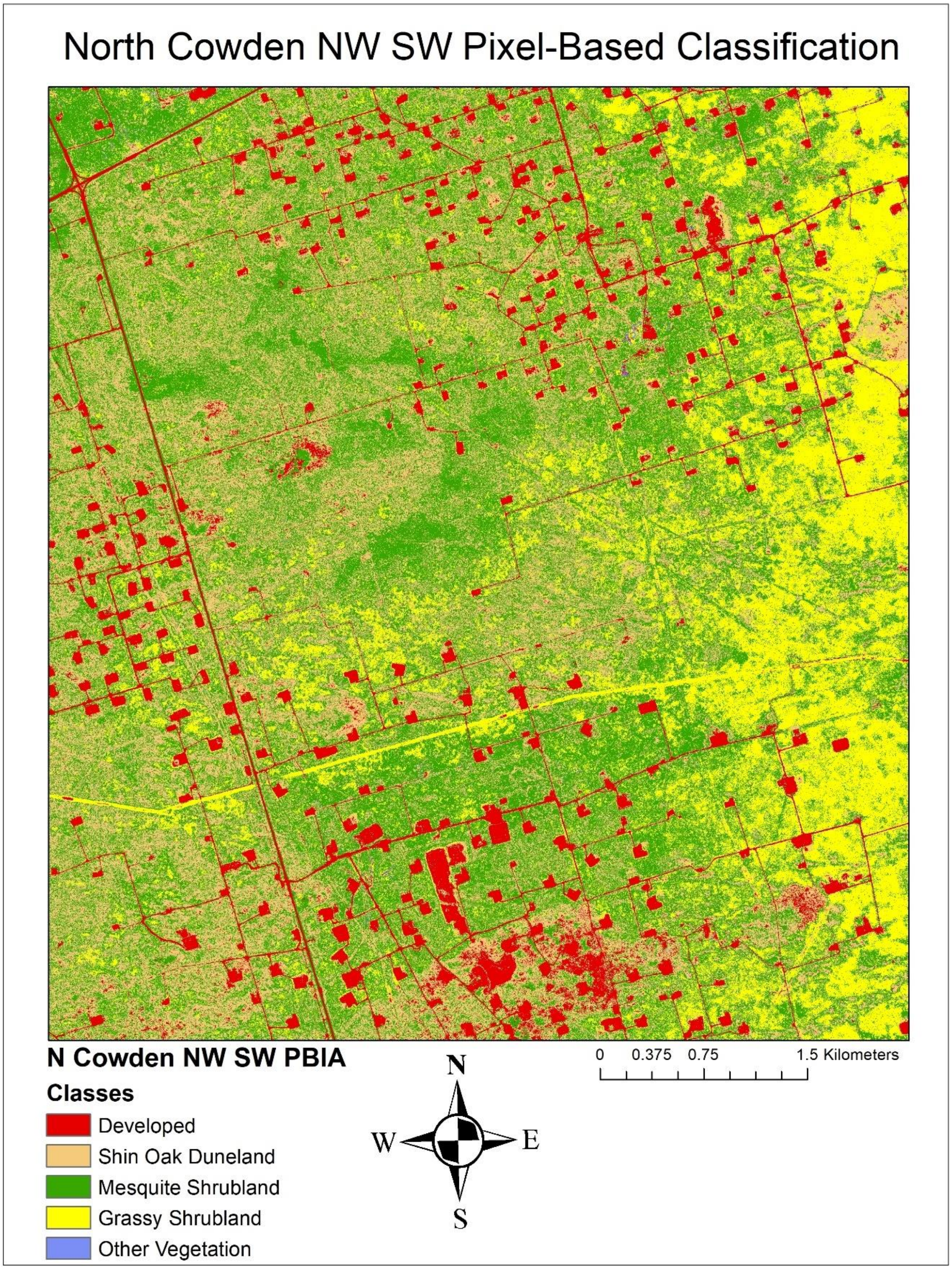

Figure 3. North Cowden NW SW Pixel-based classification

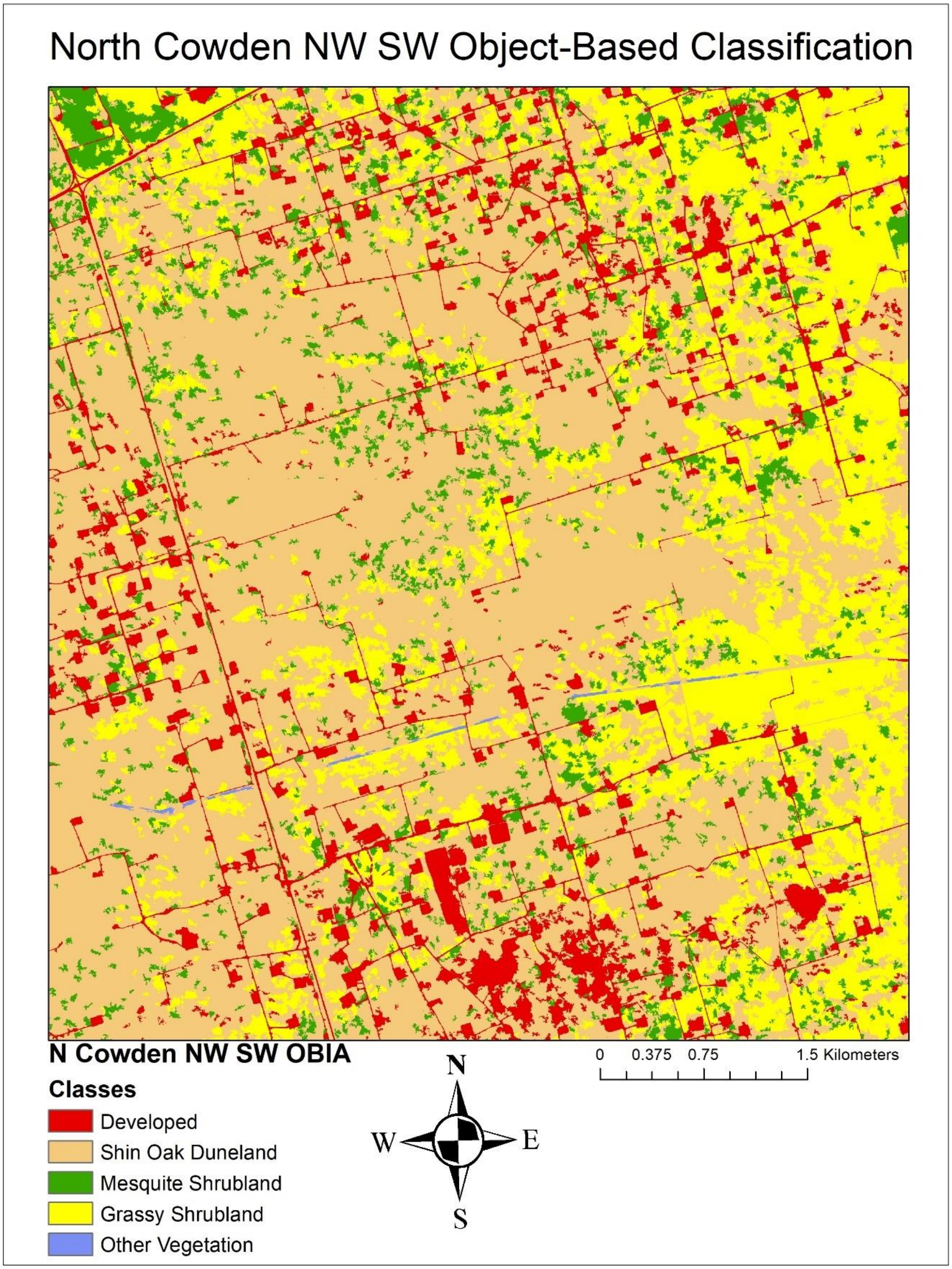

Figure 4. North Cowden NW SW Object-based classification

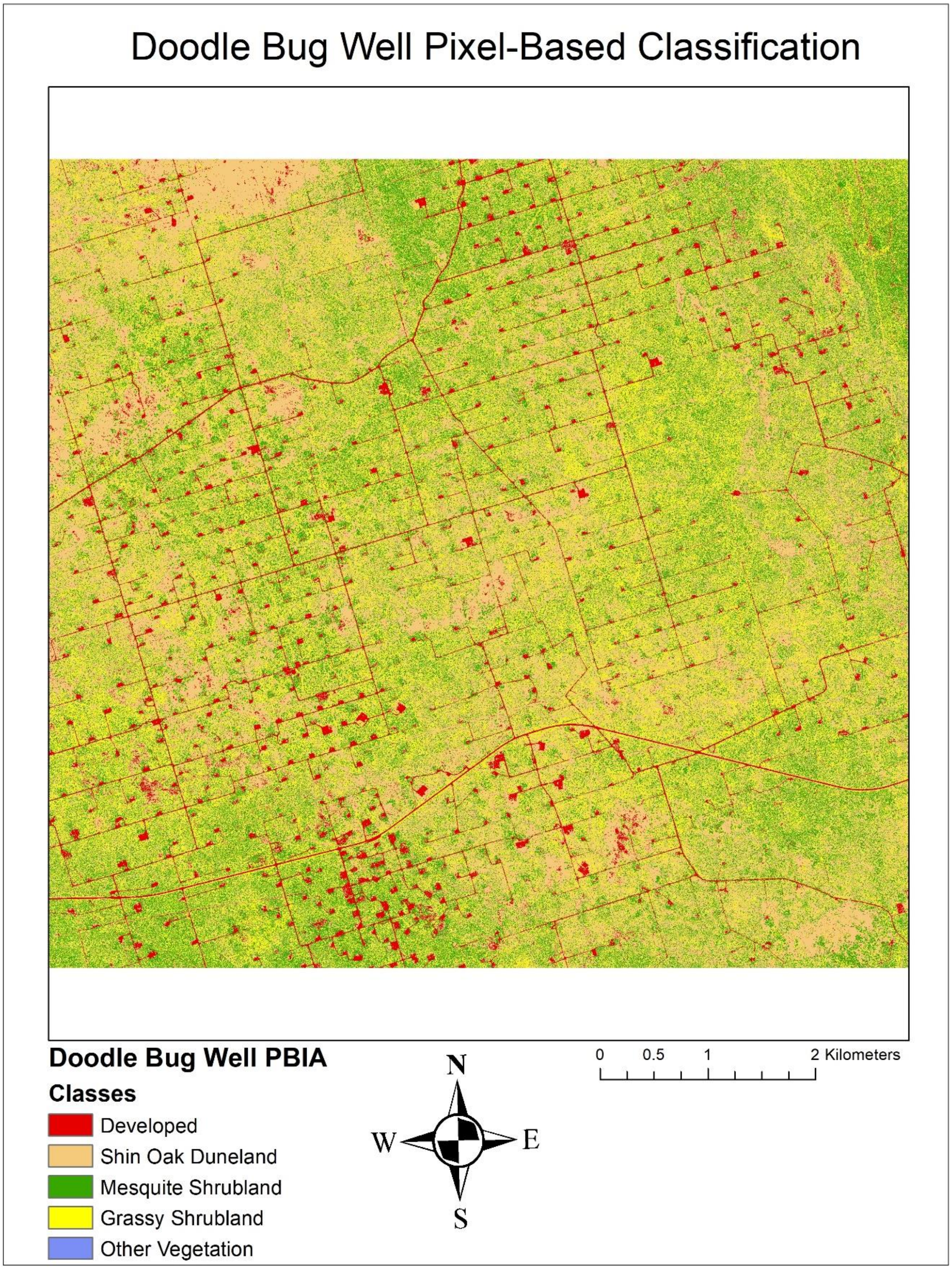

Figure 5. Doodle Bug Well Pixel-based classification

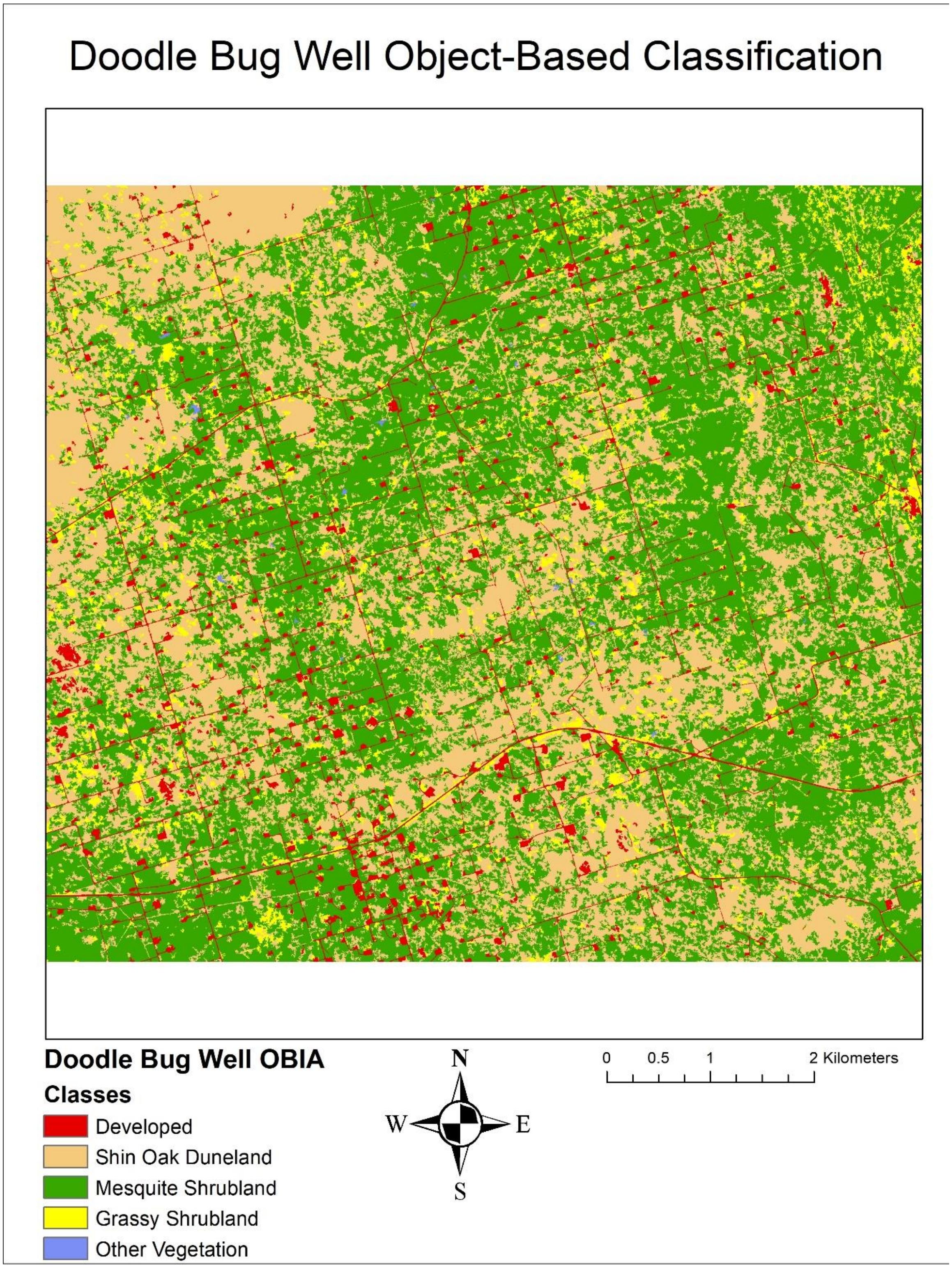

Figure 6. Doodle Bug Well Object-based classification

4.2 ACCURACY RESULTS OF PBIA AND OBIA CLASSIFICATION

Table 6 shows the resulting values for both pixel-based and object-based classifications for each of the images. The PBIA for North Cowden NW SW resulted in an overall accuracy of 43.60%. Most class specific accuracies were poor as the overall accuracy shows, but a one class was able to be identified with moderate agreement. Class with moderate agreement was Developed, which had a producer's accuracy of 70%, as well as a user's accuracy of 67%. Grassy shrubland resulted in poor agreement but with similar producer's accuracy (44%) and user's accuracy (45%). Shin oak dune land, mesquite shrubland, and other vegetation had poor agreement between producer's and user's accuracy.

The OBIA for North Cowden NW SW produced an overall classification accuracy of 74.41% and demonstrated a stronger agreement between reference and classified objects for most of the classes. Shin oak dune land showed strong agreement with a producer's accuracy of 78%% and a user's accuracy of 88%. Developed had a moderately strong agreement with producer's accuracy of 88% and a user's accuracy of 68%. Grassy shrubland showed a moderate agreement with producer's accuracy of 68% and a user's accuracy of 59%. Mesquite shrubland resulted in a weak agreement with producer's accuracy of 42% and a user's accuracy of 35%.

The PBIA for Doodle Bug Well performed better than the North Cowden NW pixel-based method with an overall accuracy of 51.83% and had better agreement between classes. Developed showed a moderately strong agreement with a producer's accuracy of 73% and a user's accuracy of 75%. Shin oak dune land showed a moderate agreement with a producer's accuracy of 64% and a user's accuracy of 59%. Mesquite shrubland, grassy shrubland, and other vegetation all indicated weak agreement with varying accuracies among producer's accuracy and user's accuracy.

The OBIA of Doodle Bug Well performed better than the pixel-based classification with an overall classification accuracy of 65.55%. Compared to the PBIA, the agreement between reference data and classified objects the agreement is stronger for most of the classes. Developed had a moderately strong agreement with a producer's accuracy of 78.37% and a user's accuracy of 93.55%. Shin oak dune land had a moderate agreement with a producer's accuracy of 63.25% and a user's accuracy of 73.66%. Mesquite shrubland showed a greater agreement than the pixel-based approach having moderate agreement with a producer's accuracy of 76.10% and a user's accuracy of 63.11%. Grassy shrubland showed a weak agreement with a producer's accuracy of 22.22% and a user's accuracy of 31.82%.

Kappa coefficient of agreement statistics for all the classifications across both images indicates weak agreement for both of the OBIA classifications. The overall Kappa statistic for North Cowden NW SW for the OBIA classification of 0.5531 indicates a moderate agreement, whereas the value of 0.2368 for the PBIA of North Cowden NW SW shows a poor agreement. The Kappa coefficient for Doodle Bug Well indicates better agreement for the OBIA classification when compared to the PBIA classification. The overall Kappa coefficient for Doodle Bug Well OBIA showed a moderate agreement of 0.4476, while the Kappa coefficient for the pixel-based classification shows a poor agreement of 0.2849.

The difference between two proportions was assessed by comparing PBIA and OBIA overall accuracy for each image to produce a z-score. The null hypothesis was that we will reject if the test statistic z is greater than z =1.44 and confidence interval of .85. North Cowden NW SW test statistic was equal to 11, and Doodle Bug Well test statistic was equal to 5.1. Since the z statistic was greater than 1.96, we can reject the null hypothesis that the two proportions were the greater than the test statistic. Concluding that the accuracies between the two map classifications are significantly different (Ott, 2016).

Table 6. Accuracy results for pixel-based and object-based for North Cowden NW SW and Doodle Bug Well

Image	North Cowden NW SW (Pixel-Based)		North Cowden NW SW (Object-Based)		Doodle Bug Well (Pixel-Based)		Doodle Bug Well (Object-Based)	
	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy
Developed	69.77	66.66	88.37	67.86	72.97	75	78.37	93.55
Shin Oak Duneland	38.1	84.47	77.59	88.22	63.96	58.58	63.25	73.66
Mesquite Shrubland	75.75	10.82	42.42	35	40.44	71.43	76.10	63.11
Grassy Shrubland	43.58	44.74	67.52	58.52	34.92	14.19	22.22	31.82
Other Vegetation	0	0	100	0.5	0	0	0	10
Overall Classification Accuracy	43.60		74.41		51.83		65.55	
Overall Kappa Coefficient	0.2368		0.5531		0.2849		0.4476	

5. DISCUSSION

5.1 NAIP IMAGERY AND FIELD DATA COLLECTION

The 2016 NAIP imagery utilized in this research allowed to produce a land-use land cover dataset with a high spatial resolution (1-m). However, the low spectral resolution of the NAIP imagery limited some land cover class separability. Shin oak dune land and developed classes were misclassified throughout the image. This could be solved with the implementation of imagery with better spectral resolution. This would increase class separability and accuracy of identifying land covers. The high spatial resolution also causes confusion in that certain features on the ground are larger than the 1-m spatial resolution provided by the NAIP imagery. This caused certain features to be mixed in with other classes or misidentified in the accuracy assessment. This research supports the implementation of other imagery with better spectral resolution and radiometric resolution to improve identification of land cover. This was implemented by Johnson (2016) in a DSL study that incorporated Landsat 5 Thematic Mapper (TM) satellite imagery with NAIP imagery to show multi-temporal scenes to capture seasonal vegetation change. Their study tried to combine TM data with NAIP to improve classification of shin oak during seasonal “green-up” but were unable to produce the results they were expecting.

Additionally, field data images for this research were collected in 2018 and the NAIP imagery was acquired in 2016. This temporal discrepancy made identifying land covers challenging due to vegetation being different colors when the aerial imagery was acquired. Certain landcovers, mesquite and shin oak, showed seasonal vegetation change, where the images used showed these landcovers varying in color. The images collected for field data were taken in June, which under normal climatic conditions would capture the seasonal shin oak "green-up" (Johnson, 2016). GPS ground truth points were collected in certain locations around my study area to help identify vegetation. This GPS data were helpful but with the size of the pixels and the accuracy of the GPS units, the data was hard to determine what the line or polygon was identifying or if the feature was what was identified. The GPS data were used for validating certain landcovers that were delineated properly by my interpretation, if not the data was not used.

5.2 INFLUENCE OF TEXTURE MEASURES ON SEGMENTATION

Using the high spatial resolution NAIP imagery, the use of texture measures were implemented due to the poor spectral resolution. This allowed for additional information to be stacked with the fine spatial resolution of the NAIP imagery. Texture operators are beneficial to a segmentation using a region growing method. The use of the inverse distant moment (IDM) and entropy (ENT) texture measures were used for each of the images to help with the segmentation.

Chen, 2004, added texture measures for multiple spatial resolutions with differing window sizes to determine how classification accuracies and transformed divergence values were affected. The transformed divergence values determined that texture improves the values substantially as the window size increases. The use of multiple texture measures from different window size did not result in significant improvement of classification accuracy. Texture features derived from high spatial resolution imagery can be used to increase land-cover classification accuracy (Franklin and Peddle, 1990). The information derived from the texture features can be used to increase land-cover classification from high spatial resolution imagery.

The use of texture for this landscape can be improved by implementing different measures additionally to the one's chosen for this research. The use of different window sizes could be another factor that could be assessed depending on what is trying to be identified. The purpose of inputting texture was because pixel-based classifier does not consider texture or spatial information (Blaschke 2010). Texture was specifically used for the segmentation process for OBIA, which helped with delineating objects to be identified as training segments. The use of the texture measures did help with classification by providing additional context that provided separation between land cover classes.

5.3 INFLUENCE OF CLASSIFICATION METHOD ON OUTCOMES

Object-based image analysis creates meaningful statistic and texture calculation, an increased uncorrelated feature space using shape and topological features, and the close relation between real-world objects and image objects (Benz, 2004). OBIA can implement spatial concepts into the classification approach, whereas pixels only contain individual spectral values. Including contextual information such as shape and texture to objects produces objects that are indicative of what is on the ground and can help to reduce the "salt and pepper effect" (Blaschke 2010). The appropriate segmentation parameters must be set before classification due to over-segmentation and could produce the "salt and pepper effect" at a larger scale.

When comparing PBIA and OBIA, the amount of time that went into the object-based classification to test different texture measures and variations of segmentations required more work and time than the supervised pixel-based approach. Around fifty texture measures were produced at different window sizes using different bands to see which measure was optimal for each image. Segmentations were produced multiple times to make sure the features were segmented properly for each image. If this amount of time was put into the PBIA by applying additional image post-processing methods, the accuracy of the pixel-based results could have been improved.

6. CONCLUSION

This research performed a comparative analysis between OBIA and PBIA to assess the accuracy of each method for mapping endangered species habitat with heterogenous vegetation in a sandy ecosystem. The analysis used NAIP imagery stacked with NDVI and texture measures to perform OBIA and PBIA classifications. OBIA implemented IDM and ENT texture measures to enhance segmentation of objects. Segments used to train classes for OBIA were also used to train signatures for PBIA. The maximum likelihood algorithm was used for both classification methods to organize the image into twelve intermediate classes, which were recoded into five final classes. To perform accuracy assessments, the multinomial distribution formula was used to calculate the number of sample points required per image to achieve an accuracy of 85 percent with 5 percent error. A stratified random sample of 546 assessment points was calculated for N Cowden NW SW, and 646 points for Doodle Bug Well. Overall accuracies for both OBIA classifications, have moderate accuracies compared to PBIA overall accuracies. This indicates that even with the added steps required for OBIA the improvements are not significantly greater. The difference between two proportions was assessed by comparing OBIA and PBIA overall accuracy for each image to produce a z-score. After calculating the difference between both classifications, I rejected the null hypothesis that the two proportions were the same.

This research proves that OBIA will produce higher accuracies than PBIA but is not accurate enough to be reliable for this study area. To potentially improve results and classification accuracy, additional field data to train and validate the classifications would be helpful, especially if the training samples were collected around the time imagery was acquired. The use of imagery with higher spectral and radiometric resolution could also be used to improve accuracies. Finally, additional texture measures could be implemented to the segmentation for improved delineation between objects. Future work should consider these improvements to the existing research.

WORKS CITED

Aggarwal, Nikita, Mohit Srivastava, and Maitreyee Dutta. 2016. "Comparative Analysis of Pixel-Based and Object-Based Classification of High-Resolution Remote Sensing Images – A Review." *International Journal of Engineering Trends and Technology* 38 (1): 5–11.

Aryaguna, Prama Ardha, and Projo Danoedoro. "Comparison Effectiveness of Pixel Based Classification and Object Based Classification Using High Resolution Image In Floristic Composition Mapping (Study Case: Gunung Tidar Magelang City)." *IOP Conference Series: Earth and Environmental Science,* vol. 47, 2016, 12-42.

Aguirre-Gutiérrez, Jesus, Arie C. Seijmonsbergen, and Joost F. Duivenvoorden. 2012. "Optimizing Land Cover Classification Accuracy for Change Detection, a Combined Pixel-Based and Object-Based Approach in a Mountainous Area in Mexico." *Applied Geography* 34: 29–37.

Blaschke, T. "Object based image analysis for remote sensing." *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 65, no. 1, 2010, 2–16.

Blaschke, Thomas, et al. "Geographic Object-Based Image Analysis – Towards a new paradigm." *ISPRS Journal of Photogrammetry and Remote Sensing*, vol.87, 2014, 180–191.

Boyaci, Dijle, Mustafa Erdoğan, and Ferruh Yildiz. 2017. "Pixel- versus Object-Based Classification of Forest and Agricultural Areas from Multiresolution Satellite Images." *Turkish Journal Of Electrical Engineering & Computer Sciences* 25: 365–375.

D. Chen, D. A. Stow, and P. Gong, “Examining the effect of spatial resolution and texture window size on classification accuracy: an urban environment case,” *International Journal of Remote Sensing*, vol. 25, no. 11, pp. 2177–2192, 2004

Civco, Daniel, James D. Hurd, Emily H. Wilson, Mingjun Song, Zhenkui Zhang, 2002. A Comparison of Land Use and Land Cover Change Detection Methods, ASPRS-ACSM Annual Conference and FIG 22nd Congress, p.2.

Cleve, Casey. Maggi Kelly, Faith R. Kearns, and Max Moritz, “Classification of the wildland-urban interface: A comparison of pixel- and object-based classifications using high-resolution aerial photography,” *Computers, Environment and Urban Systems*, vol. 32, no. 4, pp. 317–326, 2008

Comber, Alexis, Peter Fisher (2005). "What is Land Cover?" *Environment and Planning B: Planning and Design*, 32(2): 199-209.

Di Gregorio, Antonio and Douglas O’Brien. “Overview of Land-Cover Classifications and Their Interoperability.” *Remote Sensing of Land Use and Land Cover and Applications*, 37-46. Boca Raton, Fla: CRC Press.

Dzialak, Matthew R., Dean J. Houchen, Seth M. Harju, James P. Mudd, John J. Wondzell, Stephen L. Webb, Nicholas P. Gould, Jennifer E. Hess, and Jeffrey B. Winstead. 2013. “Ecosystem-Level Dynamics of Soil-Vegetation Features, with Implications for Conserving a Narrowly Endemic Reptile.” *Landscape Ecology* 28 (7): 1371–1385.

Fathizad, Hassan, Mohammad Ali Hakimzadeh Ardakani, Ruhollah Taghizadeh Mehrjardi, and Hamid Sodaiezadeh. 2018. "Evaluating Desertification Using Remote Sensing Technique and Object-Oriented Classification Algorithm in the Iranian Central Desert." *Journal of African Earth Sciences* 145: 115–130.

Foody, Giles M. 2004. "Thematic Map Comparison." *Photogrammetric Engineering & Remote Sensing* 70 (5): 627–633.

Franklin, S. E., and M. A. Wulder. 2002. "Remote Sensing Methods in Medium Spatial Resolution Satellite Data Land Cover Classification of Large Areas." *Progress in Physical Geography: Earth and Environment* 26 (2): 173–205.

Gao, Yan, Jean Francois Mas, Norman Kerle, and Jose Antonio Navarrete Pacheco. 2011. "Optimal Region Growing Segmentation and Its Effect on Classification Accuracy." *International Journal of Remote Sensing* 32 (13): 3747–3763.

Giri, Chandra P. 2012. *Remote Sensing of Land Use and Land Cover: Principles and Applications*. Boca Raton, Fla: CRC Press

Hesp, Patrick. "Foredunes and Blowouts: Initiation, Geomorphology and Dynamics." *Geomorphology*, vol. 48, no. 1-3, 2002, 245–268.

Holliday, Vance T. "Soils and Landscape Evolution of Eolian Plains: the Southern High Plains of Texas and New Mexico." *Geomorphology*, vol. 3, no. 3-4, 1990, 489–515.

Hugenholtz, Chris H., Noam Levin, Thomas E. Barchyn, and Matthew C. Baddock. 2012. "Remote Sensing and Spatial Analysis of Aeolian Sand Dunes: A Review and Outlook." *Earth-Science Reviews* 111 (3-4): 319–334.

Hussain, Masroor, Dongmei Chen, Angela Cheng, Hui Wei, and David Stanley. 2013. "Change Detection from Remotely Sensed Images: From Pixel-Based to Object-Based Approaches." *ISPRS Journal of Photogrammetry and Remote Sensing* 80: 91–106.

Jewell, Mallorie, Chris Houser, and Sarah Trimble. 2014. "Initiation and Evolution of Blowouts within Padre Island National Seashore, Texas." *Ocean & Coastal Management* 95: 156–164.

Kacoliris, Federico P., Melina A. Velasco, Camila Kass, Nicolas Kass, Verónica Simoy, Pablo G. Grilli, Tomas Martínez Aguirre, Diego O. Di Pietro, Jorge D. Williams, and Igor Berkunsky. 2017. "A Management Strategy for the Long-Term Conservation of the Endangered Sand-Dune Lizard Liolaemus Multimaculatus in the Pampean Coastal Dunes of Argentina." *Oryx*, 1–9.

Leavitt, Daniel J., and Lee A. Fitzgerald. 2013. "Disassembly of a Dune-Dwelling Lizard Community Due to Landscape Fragmentation." *Ecosphere* 4 (8).

Liu, Desheng, and Fan Xia. "Assessing Object-Based classification: advantages and limitations." *Remote Sensing Letters*, vol. 1, no. 4, 2010, 187–194.

Ott, Lyman, and Michael Longnecker, *An introduction to statistical methods & data analysis*. Boston, MA: Cengage Learning, 2016

Soe W. Myint, Patricia Gober, Anthony Brazel, Susanne Grossman-Clarke, & Qihao Weng (2011). Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. *Remote Sensing of Environment*, *115*(5), 1145-1161.

Miyasaka, Takafumi, Toshiya Okuro, Xueyong Zhao, and Kazuhiko Takeuchi. 2016. “Classification of Land Use on Sand-Dune Topography by Object-Based Analysis, Digital Photogrammetry, and GIS Analysis in the Horqin Sandy Land, China.” *Environments* 3 (4): 17.

Painter CW, Sias DS, Fitzgerald LA, Pierce LLS, Snell HL (1999) Management plan for the sand dune lizard, Sceloporus arenicolus, in New Mexico. New Mexico Department of Game and Fish, Santa Fe

Pasher, J, D King, and K Lindsay. 2007. “Modelling and Mapping Potential Hooded Warbler (Wilsonia Citrina) Habitat Using Remotely Sensed Imagery.” *Remote Sensing of Environment* 107 (3): 471–483.

Ryberg, Wade A., Michael T. Hill, Charles W. Painter, and Lee A. Fitzgerald. 2014. “Linking Irreplaceable Landforms in a Self-Organizing Landscape to Sensitivity of Population Vital Rates for an Ecological Specialist.” *Conservation Biology* 29 (3): 888–898.

Smolensky, Nicole L., and Lee 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.

Su, Tengfei, et al. “Image Segmentation Using Mean Shift for Extracting Croplands from High-Resolution Remote Sensing Imagery.” *Remote Sensing Letters*, vol. 6, no. 12, 2015, 952–961.

Treitz, Paul, and John Rogan. 2004. “Remote Sensing for Mapping and Monitoring Land-Cover and Land-Use Change—an Introduction.” *Progress in Planning* 61 (4): 269–279.

Walkup, Danielle K., Daniel J. Leavitt, and Lee A. Fitzgerald. 2017. “Effects of Habitat Fragmentation on Population Structure of Dune-Dwelling Lizards.” *Ecosphere* 8 (3).

Weiss, Jeremy L, David S Gutzler, Julia E.allred Coonrod, and Clifford N Dahm. 2004. “Long-Term Vegetation Monitoring with NDVI in a Diverse Semi-Arid Setting, Central New Mexico, USA.” *Journal of Arid Environments* 58 (2): 249–272.

Whiteside, Timothy G., et al. “Comparing Object-Based and Pixel-Based Classifications for Mapping Savannas.” *International Journal of Applied Earth Observation and Geoinformation*, vol. 13, no. 6, 2011, pp. 884–893.

Young, Megan E., Wade A. Ryberg, Lee A. Fitzgerald, and Toby J. Hibbitts. 2018. “Fragmentation Alters Home Range and Movements of the Dunes Sagebrush Lizard (Sceloporus Arenicolus).” *Canadian Journal of Zoology* 96 (8): 905–912

Yu, Qian, Peng Gong, Nick Clinton, Greg Biging, Maggi Kelly, and Dave Schirokauer, “Object-based Detailed Vegetation Classification with Airborne High Spatial Resolution Remote Sensing Imagery,” *Photogrammetric Engineering & Remote Sensing*, vol. 72, no. 7, pp. 799–811, Jan. 2006