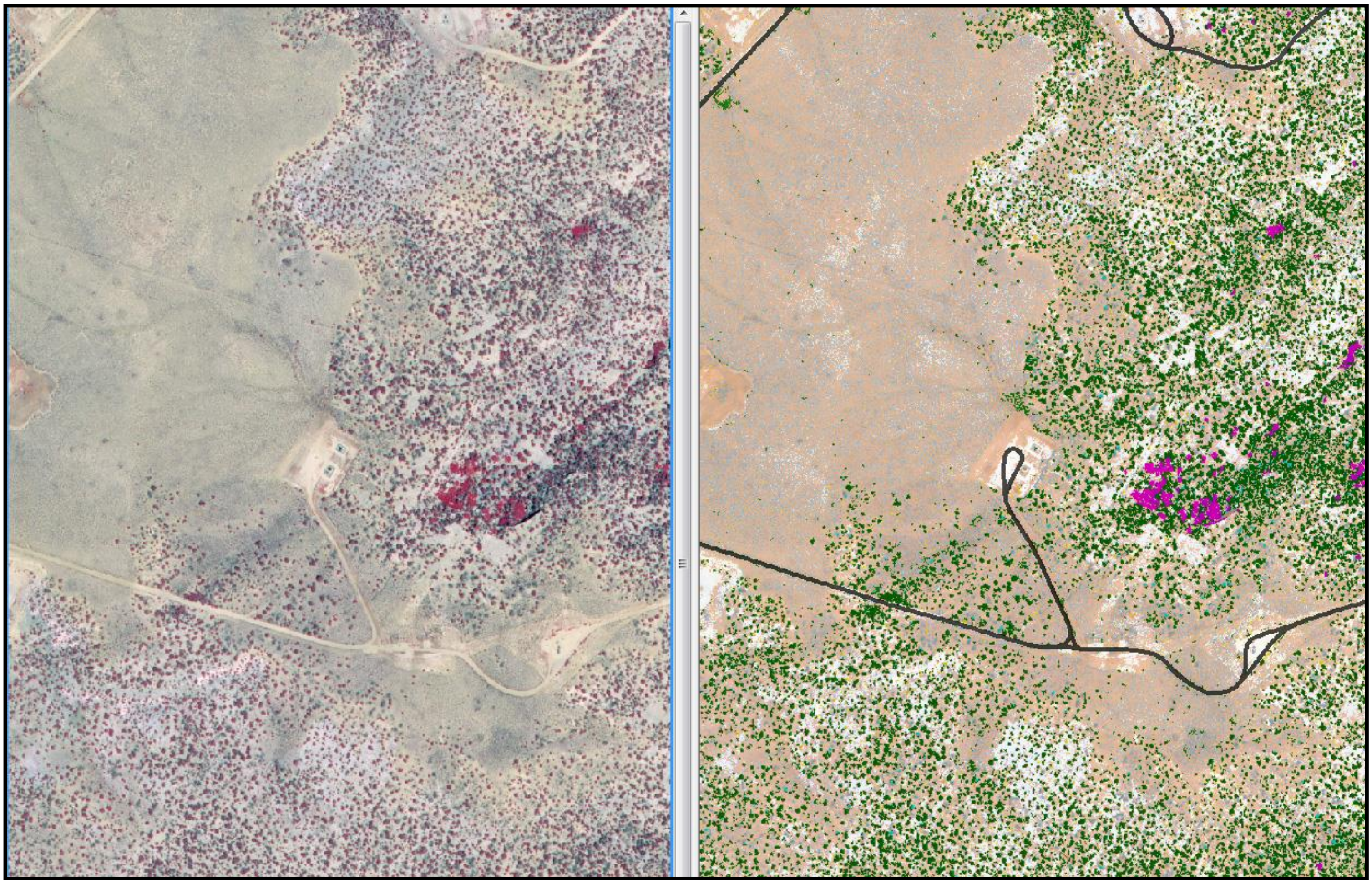

Land Cover Mapping Using Object Oriented Image Analysis in the BLM Carrizo Largo Landscape Area

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Introduction

As high resolution imagery has become more accessible and available the demand for information derived from this imagery has also increased. Land cover classifications are one of the most common derived products of aerial and satellite imagery. As computer hardware power has increased and software systems advanced over the years, current object oriented image analysis have improved our ability to detect landcover features as well as reducing the amount of time needed to derive land cover maps. Object oriented image analysis allows for the automated or semi-automated analysis of high resolution images. This approach divides the image into meaningful homogeneous regions, known as image objects, and then categorizes them based on their spectral properties and also shape, texture, size, and a multitude of other topological features. (Lizarazo and Elsner 2009). In the past pixel based classifiers were used but these methods often lead to a speckle effect it evaluated one pixel at a time without considering its spatial context. Object based classifiers avoid this problem by segmenting an image into homogenous regions before the classification is employed (Willhauck, 2000). Using software packages such as Definiens eCognition, an image object based classification scheme can be employed over small and large areas.

At the New Mexico Forest and Watershed Restoration Institute (NMFWRI), one of our missions is to provide information for better land management practices. Knowing the spatial distribution and density of different vegetation types across a landscape can aid in decision making for habitat restoration or for providing a baseline estimate for future land cover changes over time.

For the Bureau of Land Management (BLM) lands in the Carrizo Largo area of New Mexico we have created a detailed land cover classification using high resolution imagery. This is the second large area for which we have created such a classification, the first large scale project was in the BLM Rosa Landscape area. For both areas we have create a GIS based raster land cover layer. The end results can then to be used for habitat assessment and multiple land management activities and assessments.

The Study Area

The Carrizo Largo study area is located 40 miles north-east of Cuba, NM in Rio Arriba County with its' western edge in San Juan County The study area cover over 405 square miles or 259,000 acres. The study area is found in the ecological province or ecoregion of the Colorado Plateau Semi-Desert as identified by Baily (1995) and is in the San Juan Watershed drainage

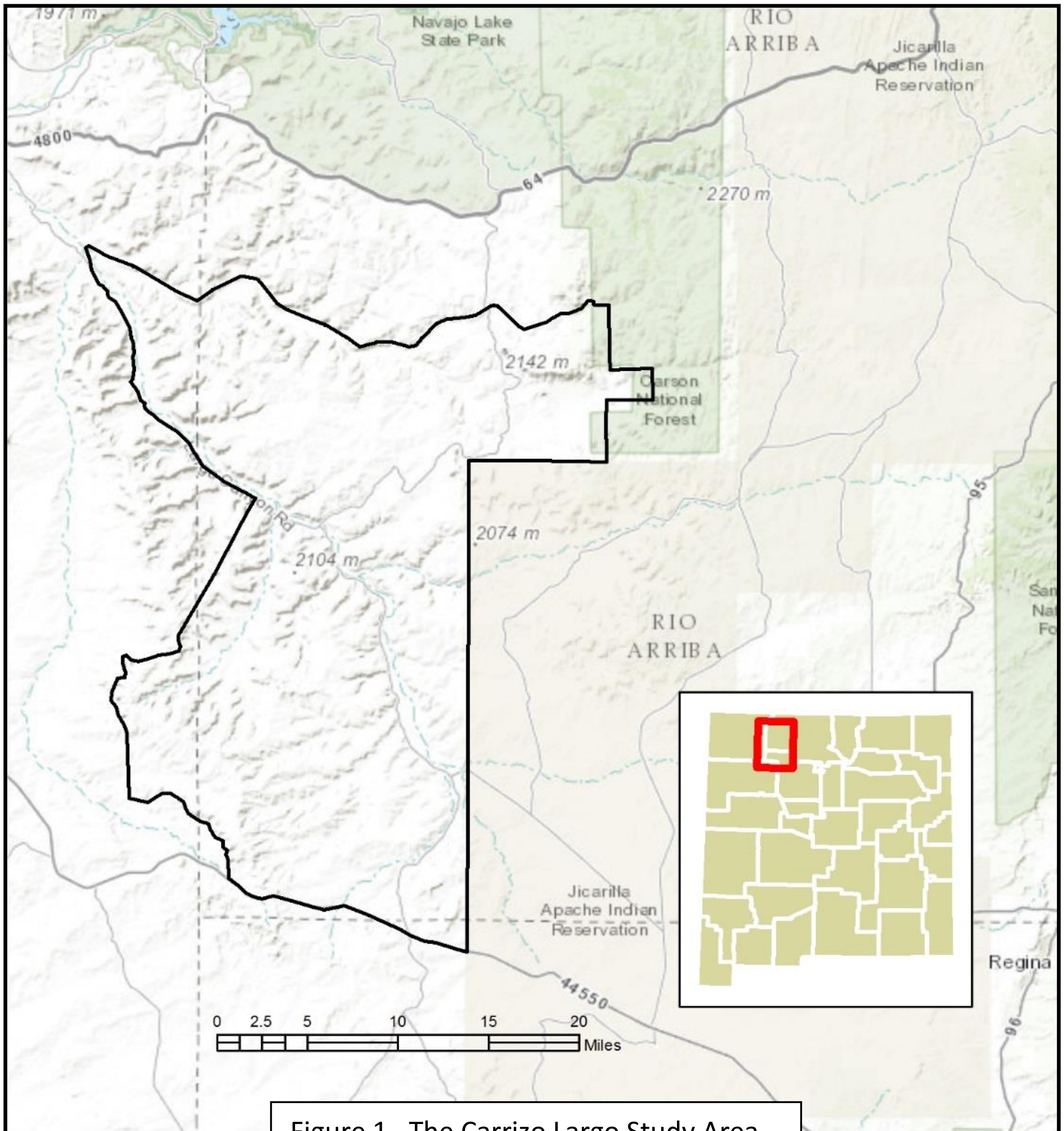


Figure 1. The Carrizo Largo Study Area

area. The Cañon Largo and the Carrizo Canyon Creek flow through the study area hence the name Carrizo Largo. The Colorado plateau Ecoregion is described as a desert with an average yearly rainfall of less than 10 inches with most of the precipitation occurring in winter in the form of snow (Truhy et al. 2002). The Carrizo Largo study area is dotted with well pads and extensive road networks to support oil and natural gas production. Because of the fragmented landscape, habitat for wildlife is a concern. Providing an updated vegetation and land cover geospatial layer is a priority for the BLM. Having a baseline assessment of vegetation cover and diversity is critical to support long term land management activities.

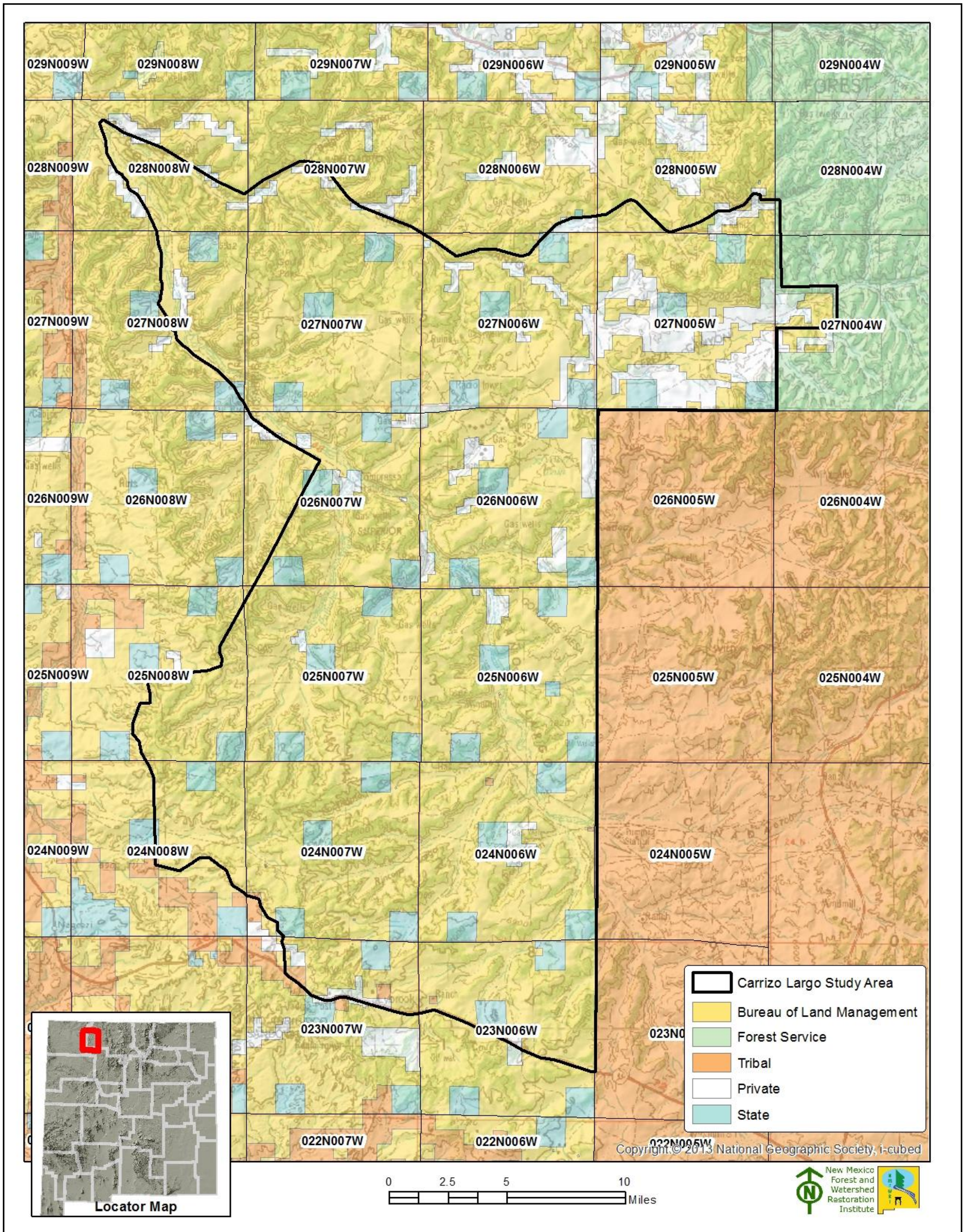


Figure 2. Location and Land Ownership Map

Land ownership in the study area is approximately 81.3% Bureau of Land Management, 10.4% State of New Mexico Lands, 7.4% private, .54 % Tribal, and .32% USFS Lands (see figure 2).

Previous Work

In October of 2013 a land cover classification was finished for the BLM Rosa Landscape Area located north of the Carrizo Largo study area, 45 miles east of Farmington, NM in northern Rio Arriba County.   The land cover classification included over 170 square miles or 111,000 acres. The Rosa Landscape land cover classification included 21 land cover classes and had an overall accuracy of 80.14%. This new classification is twice the size of the Rosa Landscape area but similar classification methodologies were employed.

Methodology

Data Preparation

30 image tiles of True Color and Color Infrared Imagery were purchased from Digital Globe (http://www.digitalglobe.com/). Imagery was acquired on June 18 of 2010 with a sensor attached to an aircraft. True color imagery (visible red, green, and blue bands) were collected at 30 centimeter or 1 foot resolution. Near infrared imagery was collected at 60 centimeter or 2 foot resolution.   The final classification was developed at 30 centimeter resolution. Imagery was projected to the World Geodetic System (WGS), North American Datum (NAD) 1983, Zone 13.

Before running the classification additional spatial layers were created. Roads were not accurately distinguished from the landscape due to a large number of dirt roads. Paved roads could be classified well but not dirt roads. To avoid an incomplete road classification student workers at New Mexico Highlands University were employed to on-screen digitize the entire serviceable road network in the Carrizo Largo area using the 2010 imagery as the base layer (see figure 3). After talks with BLM it was specified that it was important to differentiate well pad versus non well pad areas. In order to distinguish between well pad and non-well pad areas, student workers digitized existing well pads using the 2010 imagery. Well pad areas were identified as cleared areas surrounding well equipment that consist of bare ground and minimal vegetation. Approximately 2,446 well pads were identified across the study area. The well pad and road shapefiles were created before running the classification. These shapefiles were used in eCogniton as part of the automated classification routine. The final well pad shapefiles were provided to the BLM Farmington office even before the classification was finished to aid in their well pad inventory assessment project.

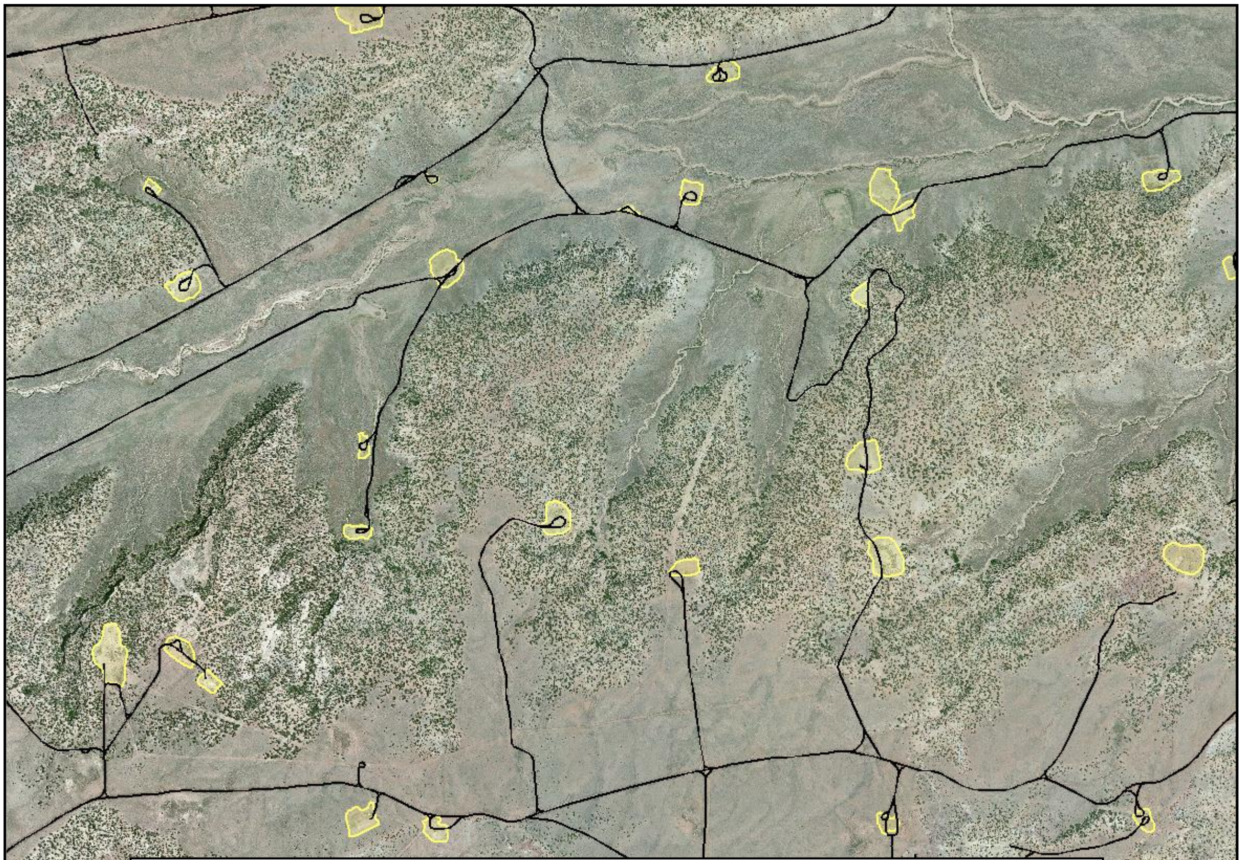


Figure 3. Example of shapefiles created for roads and well pads

As riparian areas were classified separately from the rest of the study area, a shapefile identifying riparian was developed for the Carrizo Largo area. To do this a Riparian GIS Model was employed. This specific model was developed by Michigan Technological University: http://www.sfi.mtu.edu/muses/GIS_Riparian.htm. Inputs to the model included; the National Hydrology Dataset stream network, 10 meter Digital Elevation Model, Soil Survey Geographic database (SSURGO) data, and the National Wetlands Inventory data.

Field Work

To validate our classification and to supplement our accuracy assessment field work was carried out in August of 2013. Rick McNiell, a consultant Botanist, was hired to go to specific areas and take photographs and to document the vegetation species found at each location and to identify the variety of species found throughout the study area. Areas were selected to represent a variety of landscape areas and elevations. A total of 85 sites were sampled and six 100 meter line intercept vegetation transects of Pinon-Junper and Big Sagebrush landscape dominated areas were assessed. Vegetation transects were collected in order to compare field measured percent cover values and then compare those same areas with image classification derived percent cover values. A list of all species identified in this area during his field study is found in Appendix A. Pictures taken during field work of dominate vegetation types are found in Appendix C.

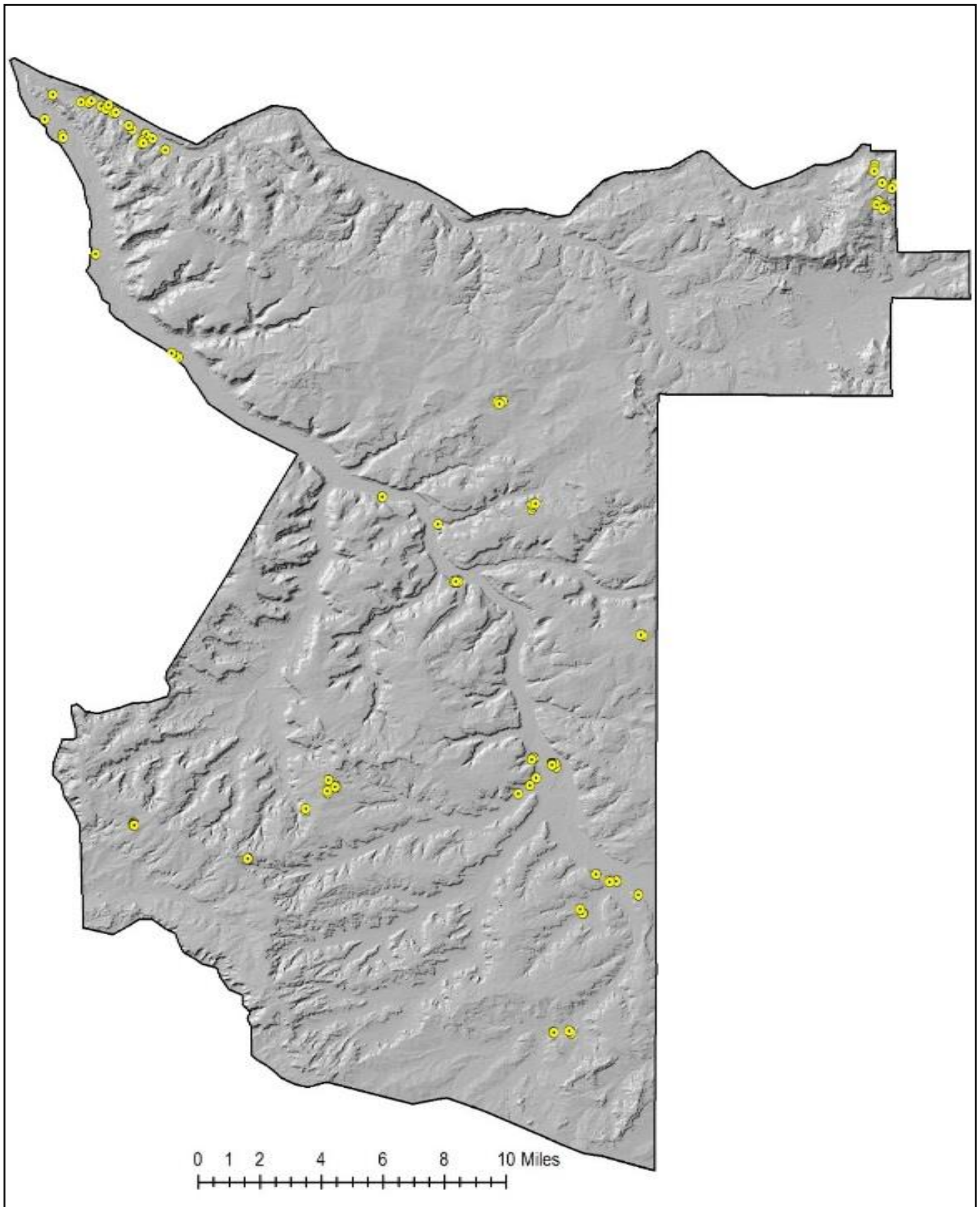


Figure 4. Field data locations in the Carrizo Largo Study Area
(85 sites and six 100m transects)

eCognition- Object Oriented Image Analysis

Automatic processing of digital imagery has advanced in recent years due to software such as Definiens eCognition. ECognition software incorporates object based image analysis. The most common approach for creating these objects is with image segmentation. Image segmentation divides the image into homogenous objects. These objects are determined by scale and other input parameters that the user identifies, plus the imagery and any ancillary GIS layers.

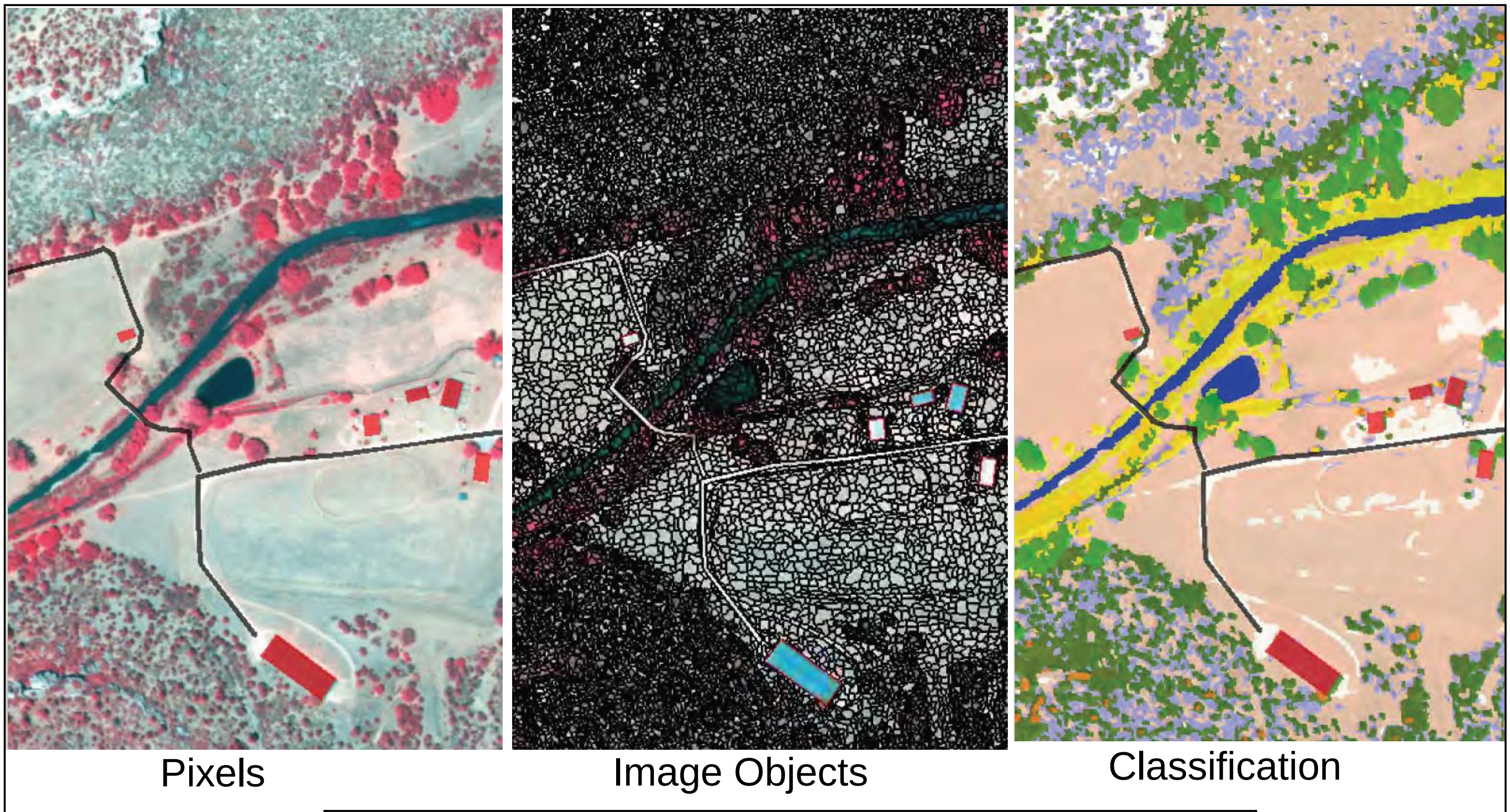


Figure 5. Example of Image Objects Used to develop a classification

Object based image classification is especially suited for high-resolution imagery. The basis of the object-oriented technique is to process of a set of pixels as a unit, known as the image object. These image objects group pixels that are adjacent to each other and are spectrally similar. Once image objects are created, they provide a great deal of information from which an image classification can be developed. Full use can be made of the various kinds of information contained in the images, such as spectral, size, shape, texture, pattern, shadow, site, and association characteristics. Processing image objects instead of working at the pixel level can remove redundant details resulting in higher spatial resolution (Y. Tang, 2011). For the

Carrizo largo landscape area, image objects were created and image classifications were developed using field information in combination with the spatial and spectral information of the segmented image objects.

Image Classification Workflow

Since the study area covers a large area and includes 30 separate image tiles, separate rule sets were developed to assign classes based on properties inherent within the image objects and GIS layers. Rule sets are the processing script that eCogntion uses to automate the classification. Rule sets can be very complicated and are set to flow sequentially so that when the rule set is executed it goes through many steps before resulting in a final classification. Rule set development accounted for a large amount of time in the project as new ruleset were developed for each separate image tile. Each land cover class had specific thresholds that had to be tested and re-evaluated for each image tile. The ruleset development followed a hierarchal approach. Parts of the image were classified separately, then other areas were re-segmented and re-classified as they met certain threshold levels. These threshold levels differed according to each scene so rule sets were continually re-worked in order to develop the most accurate classification.

Due to limitations found within eCognition there are only so many image segments that could be created. We were creating over ten million image segments within each scene and the software would crash. To solve this problem each image tile was diced into smaller scenes of 1000 meters by 1000 meters. Within Definiens Developer Workstation each diced image was loaded into a workspace. By setting the work environment and specifying the location of the rule set, each diced image was classified one after the other until they were all finished. These processes were set to run overnight as it would take anywhere between 8-26 hours to complete. In the end all of the separate classified diced images were mosaicked together

The flowing steps outline the general workflow of the eCognition Ruleset for all scenes.

1. The first step was to convert the road and wellpad shapefiles into image objects and classify them using their vector extents. Road polygons were loaded and their associated area on the image was converted to image objects classified as roads. This was also done for wellpads.
2. With the roads and wellpads initially classified, all other areas were segmented using a multi-resolution segmentation. The multi-resolution segmentation used the 4 band imagery plus a separately derived image texture layer. The segmentation was set with a

scale parameter of 3. The composition of homogeneity criterion for shape was .8 and compactness .2. After the multi-resolution segmentation, a spectral difference segmentation was applied which merges neighboring objects according to their mean layer intensity values using a maximum spectral difference of 4.

3. Shadow areas were distinguished between non-shadow areas based on image brightness values and Normalized Difference Vegetation Index (NDVI) values. (The Normalized Difference Vegetation Index (NDVI) was calculated as a ratio of visible red and near infrared layers of the imagery).
4. Resulting areas of non-shadow were split into two categories, highly vegetative areas and low vegetative areas based on Hue, Saturation, and Intensity values and NDVI values.
5. Resulting low vegetative areas were split into two categories, Bare Ground and Sparse Vegetation and Rangelands using a threshold of specific brightness calculation values. Bare ground and rock had much higher brightness values than sparse vegetation and rangeland areas.
6. Image objects classified as highly vegetative areas were then broken down into the majority of the vegetation classes. First Gamble Oak was classified due to its characteristically high NDVI values. Next dead vegetation was pulled out using a threshold that identified low NDVI values and specific mean ratio blue values (due to the grey/bluish color of the dead piñon and juniper trees).
7. Piñon and Juniper trees were the two dominate woodland species in the study area. Ponderosa and Douglas fir were distinguished from Piñon and Juniper using the length of associated shadow to try to estimate the taller tree height. When this failed Ponderosa and Douglas fir species (Dry Mixed Conifer Woodlands) were manually digitized as it was easily distinguished using the high resolution imagery due to shadow patterns. Spectrally it was not possible to tell the difference between the two woodland species.
8. Big sagebrush shrublands were identified using a separately derived image texture layer that provided lower values for smooth features and higher values for rough features. This allowed for sagebrush (rough) to be identified from the surrounding rangeland areas (smooth). The full explanation of the image texture layer creation and development can be found in a later section titled *Project Enhancements -Big Sagebrush Classification Improvements*.
9. Greasewood and chamisa shrublands were distinguished from big sagebrush shrublands by slightly higher NDVI values and higher greenness index values.
10. A separate image segmentation was performed only on the wellpad areas in order to identify landcover features found within the well pad extents. Similar threshold values as those previously mentioned were applied to distinguish between Wellpad piñon-

juniper areas, wellpad big sagebrush shrublands, wellpad bare ground, and wellpad sparse vegetation and rangelands. Unique to wellpad areas was the wellpad equipment class (see figure 6). This class was identified by negative NDVI values and a standard deviation of the blue band of the imagery.

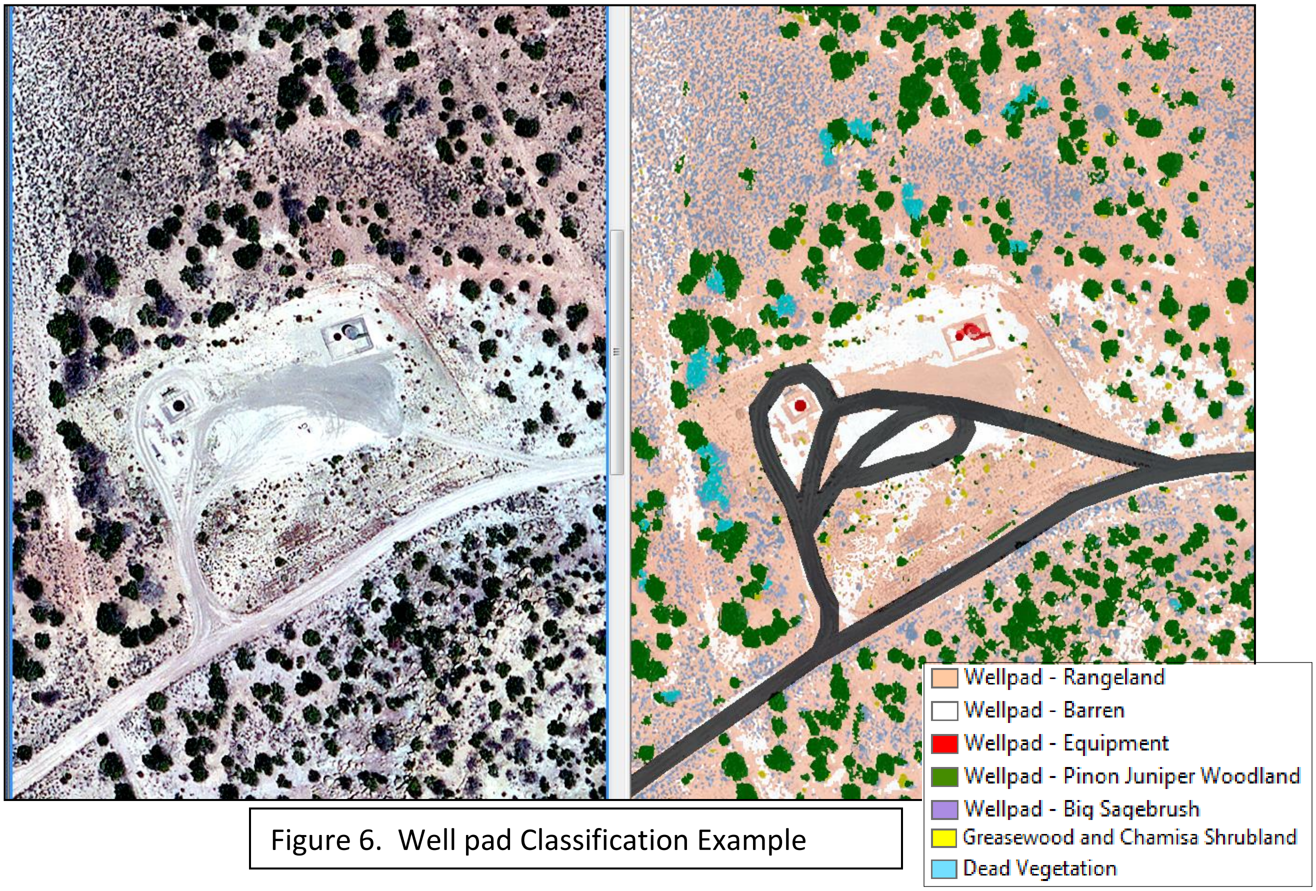


Figure 6. Well pad Classification Example

11. As the landscape had significant cliff and canyon areas there were large shadows associated in steep canyon due to the time of day of the imagery acquisition. To fix this problem, shadow areas that were larger than 1,000 square meters were classified as cliff shadow. Cliff shadow classified image objects were then exported as a vector shapefiles. These shapefiles were used to clip 2011 NAIP Digital Orthophotos and an image classification was performed on these shadow area extents using 2011 NAIP imagery. When the cliff shadow areas were classified they were mosaicked onto the final classification of the scene replacing the cliff shadow areas.
12. All other small shadow areas (less than 1,000 square meters) were classified using the 2010 digital globe imagery. These smaller areas were not as difficult to classify. NDVI was used to pull out two classes, vegetative shadow and non-vegetative shadow. Areas

of vegetative shadow were classified based on the proximity of a surrounding vegetation type. If a vegetative shadow area shared a border with a piñon-juniper image object then it would be classified as piñon-juniper. If a vegetative shadow shared a border with gamble oak then it would be classified as gamble oak and so on. Non-vegetative shadow image objects were most often classified as sparse vegetation and rangelands since it was impossible to get a brightness value in shadow areas to distinguish barren areas.

13. Riparian areas near the Cañon Largo and the Carrizo Canyon Creek areas were subset and classified using different riparian rule sets. These areas were classified separately to capture the variety of plant species and allow for the classification of willow, salt cedar, cottonwood, chamisa and greasewood species. Imagery was clipped using a riparian shapefile layer that was developed at NMFWRI and specific rules sets were developed. Rio grande cottonwood was classified based on NDVI values and the size of the image objects. Cottonwoods made rather large homogenous clumps that would be easily identified. Salt Cedar image objects were identified based on a combination of texture feature values and NDVI values. Willow and rush areas were identified due to their high NDVI values compared to surrounding vegetation. The sandy wash areas were originally classified as barren but the sandy wash areas were identified by the large size and shape as compared to other small barren areas (see figure 7).

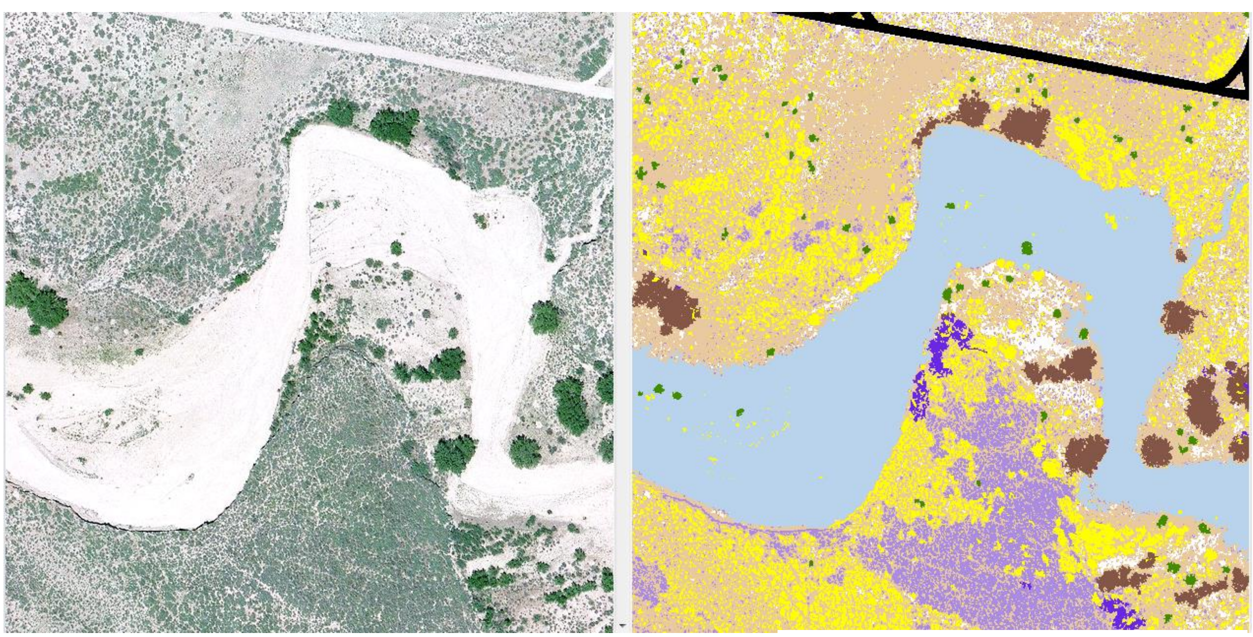


Figure 7. Riparian Areas Classification Example

14. After running the rule sets and exporting the classification as raster files, all files were mosaicked together. After the final mosaic final edits were done to the scene to fix small errors in the classification.

To determine specific threshold values for land cover features, information about each image object could be displayed and tested to determine if those values were appropriate for the given land cover feature. For example after running a multi-resolution segmentation to generate image object, there is a wealth of information associated with the generated image objects. In the example provided in Figure 8, within eCogntion software an image object was selected representing a gamble oak tree. Gamble oak has a very high vegetative response and we are able to capture based on its' associated NDVI value. In figure 8 we identify the gamble oak image object and once selected we can display all of the associated information of that object on the left side. In this case gable oak has an NDVI value of .416. Other gamble oak areas were selected to determine average NDVI values and the classification was tested to find the threshold were the greatest number of gamble oak could be identified without miss-classifying other classes. In this instance and we were able create a condition in the rule set that if vegetation with a Ratio NDVI greater than or equal to .40 then that class is gamble oak.

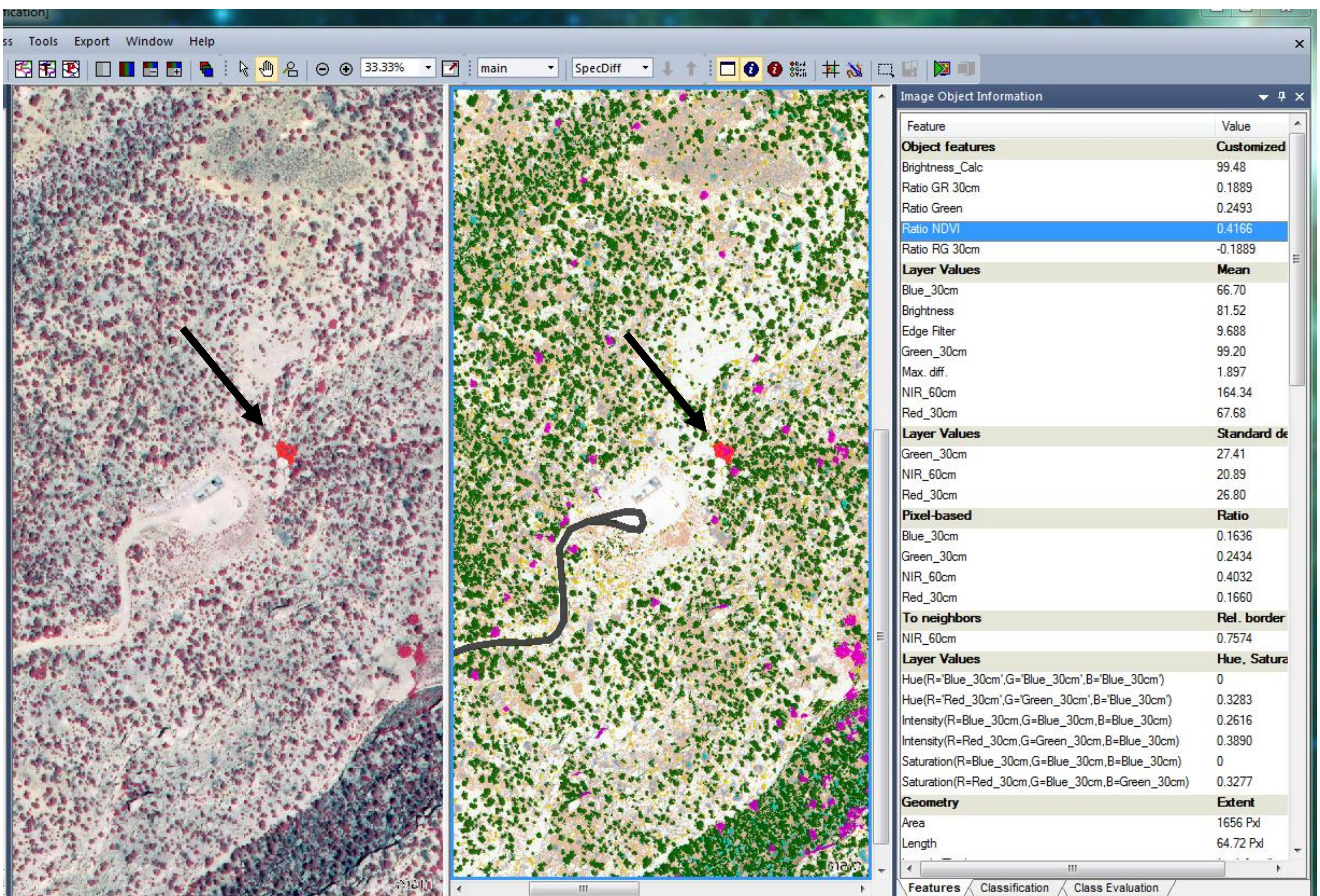


Figure 8. Identifying NDVI threshold values for Gamble Oak

Project Enhancements – Big Sagebrush classification improvements

After deriving percent cover for big sagebrush it was determined that in some cases big sagebrush was over and underestimated. Previous classification methods using eCognition software used classification thresholds for brightness and and polygon size. Because low brightness values also included areas of darker soils these areas were sometimes classified as sagebrush instead of range. Areas that were dominate with sagebrush but with bright soil backgrounds were often under represented. John Hansen, of the BLM Farmington office, did several sagebrush transects in the Rosa in the summer of 2013. These transects were used to determine percent cover in order to improve the sagebrush classification.

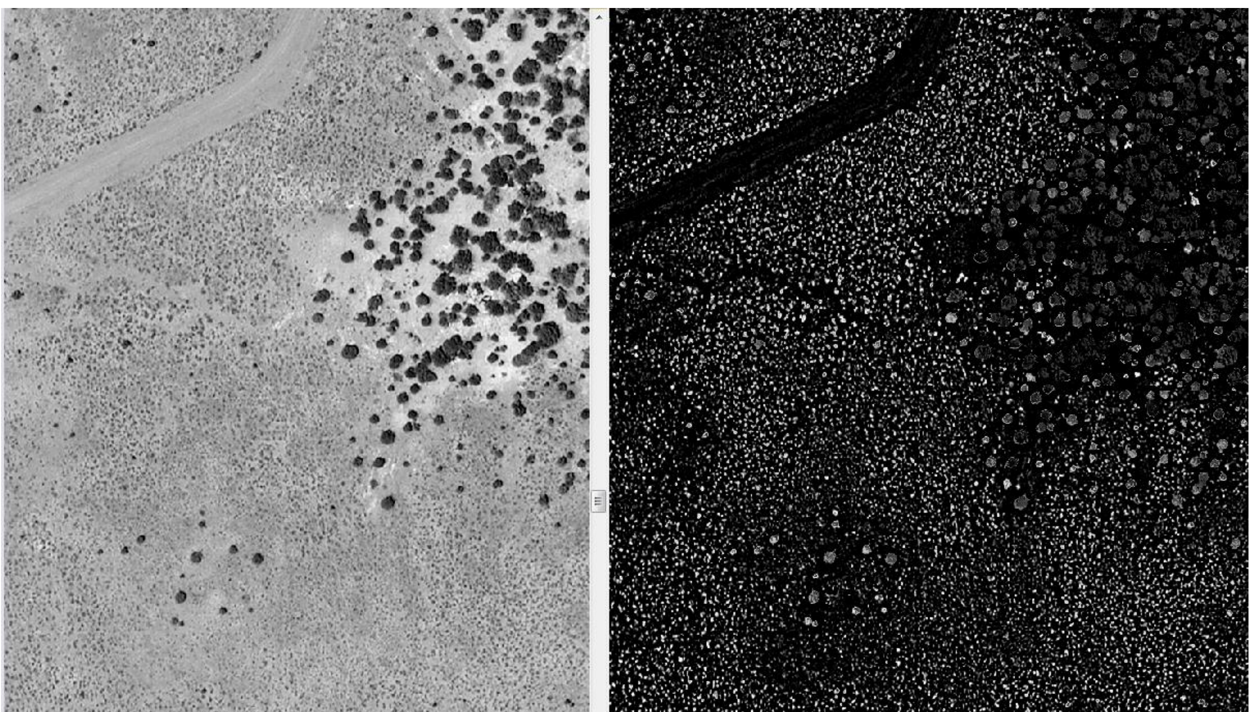
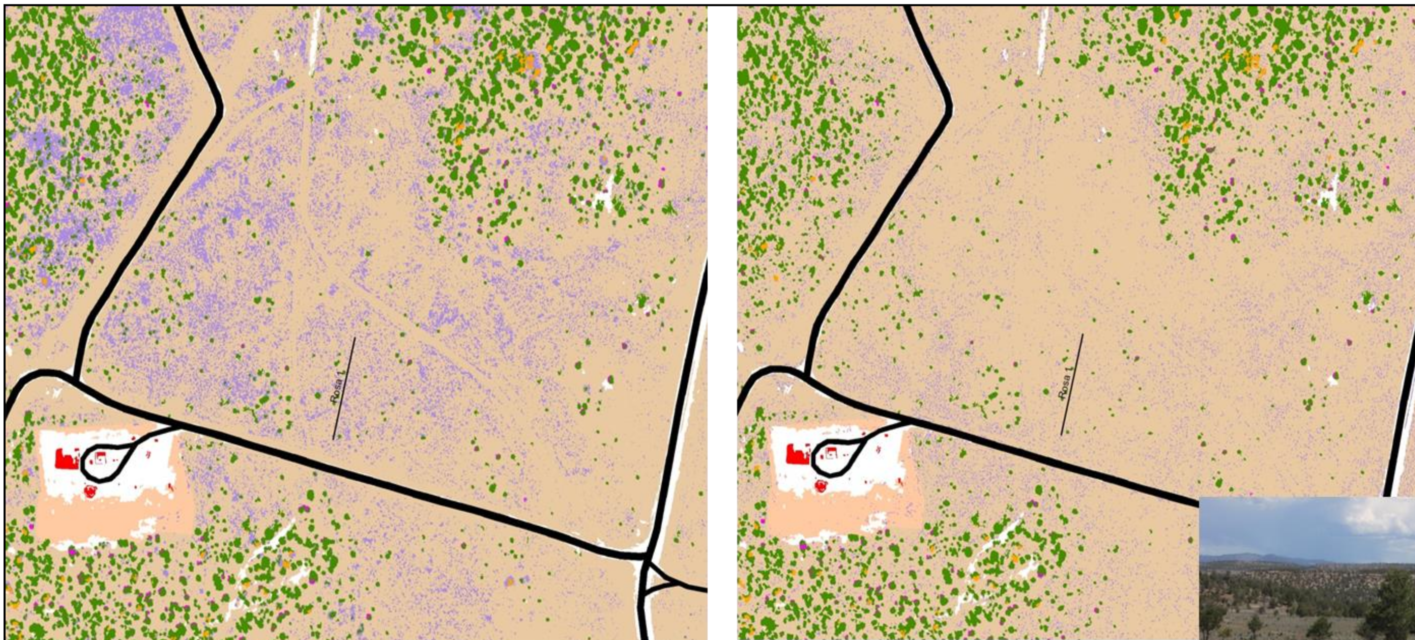


Figure 9. Left image is of first Principal Component Analysis (PCA) Image, Right image is of the final texture image where the PCA image was subtracted from Lee Sigma filter image.

Upon further research it was determined that we could create a separate texture layer using Erdas Imagine software. In order to create this layer a Principal Component Analysis (PCA) Image was created using only the 30cm RGB imagery. The first Principal Component image was then smoothed using a Radar Speckle Suppression Filter with a Lee Sigma algorithm. This smoothed speckle suppression image was then subtracted from the first Principal Component image. The final file created a texture layer where low values were given to smooth features and high values given to rough features. In figure 9 you can see the resulting image where the sagebrush areas have a higher or brighter pixel value compared to the sparse vegetation and rangeland class.

The new texture layer was employed in both the Rosa and the Carrizo Largo Landscape areas. Areas where big sagebrush were overestimated due to darker soil backgrounds and topography were corrected when simply using values of the texture layer to identify threshold values for the classification. In figure 10 the percent cover of sagebrush reduced from 20.4% percent cover (classification with no texture layer) to 4.2% cover (with texture layer) compared to the field measurement of 2.5% percent cover.



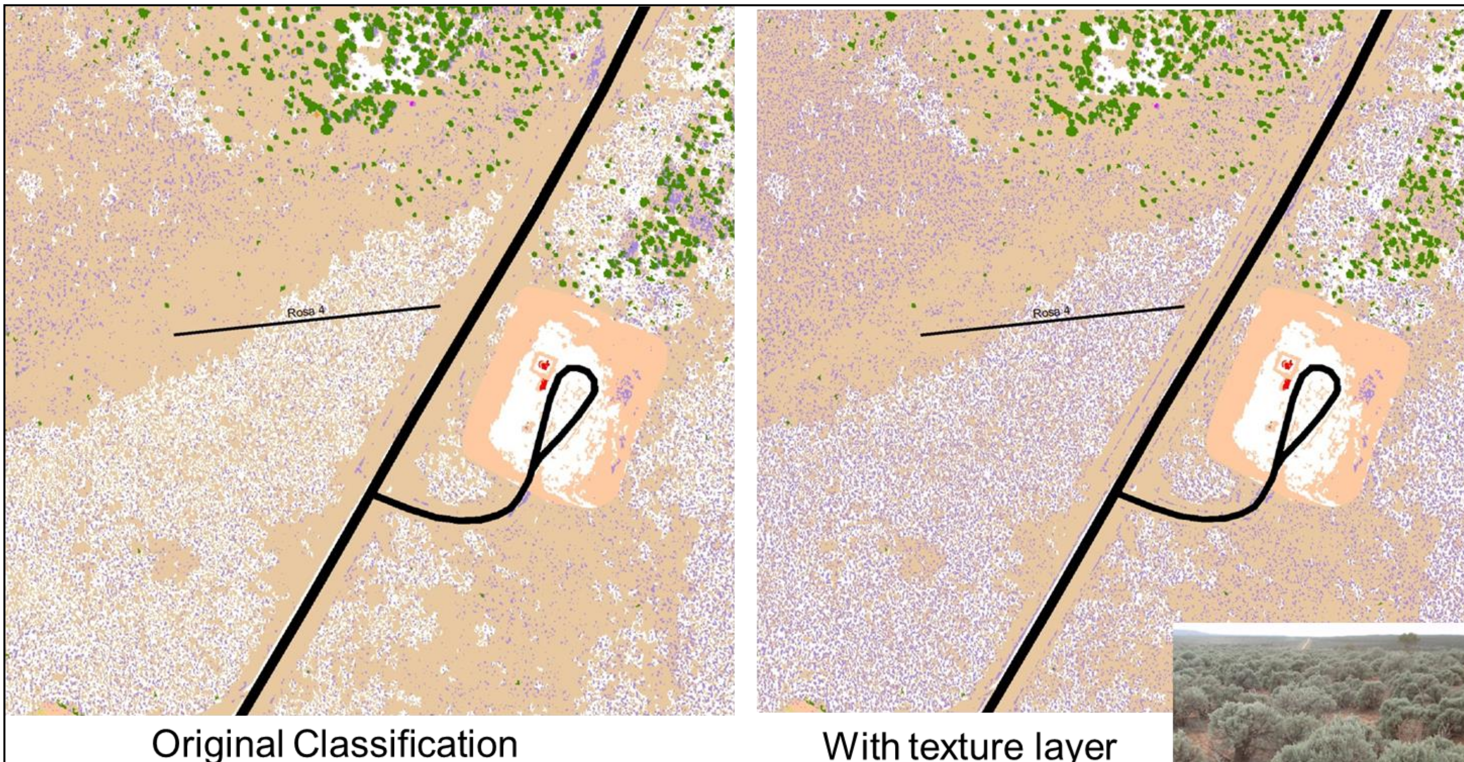
Classification without texture Layer

With texture layer

Percent Cover Rosa 1 Transect	
Original Classification	20.40%
With Texture	4.20%
Actual Transcet Percent Cover Sagebrush	2.50%

Figure 10. Big Sagebrush Classification Comparisons – Overestimation Correction

Other areas that were misclassified were in low vegetative areas where the bright soil background was so dominate that it was hard to distinguish individual big sagebrush plants. Using texture instead of brightness or RGB values, sagebrush could be distinguished between bare ground and rangeland areas. In figure 11 the percent cover of sagebrush increased from 6.7% percent cover (classification with no texture layer) to 20.5% percent cover (with texture layer) compared to the field measurement of 21% percent cover.



Percent Cover Rosa 4 Transect	
Original Classification	6.74%
With Texture	20.59%
Actual Transcet Percent Cover Sagebrush	21%

Figure 11. Big Sagebrush Classification Comparisons – Underestimation Correction

Land Cover Classes

The final land cover classification included 20 land cover classes including Gamble Oak, Piñon-Juniper Woodlands, Dead Vegetation, Water, Barren, Sparse Vegetation and Rangeland, Dry Mixed Conifer Woodlands, Big Sagebrush Shrubland, Roads, Willow, Sandy Wash, Salt Cedar, Rio Grande Cottonwood, Greasewood and Chamisa Shrublands, Wellpad Rangeland, Wellpad Barren, Wellpad Equipment, Wellpad Piñon Juniper Woodlands, Wellpad Big Sage Brush, and Exotic Vegetation. Table 1 lists the class description and the acreage totals for each land cover class, Appendix C provides field photographs of the dominate vegetation types found in the Carrizo Largo study area.

Table 1. Carrizo Largo Land Cover Classes with Acreage Totals

Class Name	Class Description	Acres	Total Area Percent of
Sparse Vegetation and Rangeland	Low vegetative areas including grasslands	135,579.0	52.16%
Pinyon Juniper Woodlands	Twoneedle pinyon (Pinus edulis), Oneseed juniper (Juniperus monosperma) and Rocky Mountain juniper	43,984.5	16.92%
Big Sagebrush Shrubland	Big sagebrush (Artemisia tridentata) shrublands	35,959.6	13.83%
Barren	Non-vegetative areas including rock	27,157.3	10.45%
Greasewood and Chamisa Shrubland	Greasewood (Sarcobatus vermiculatus), chamisa (Ericameria nauseosa) and some four wing saltbrush	4,368.1	1.68%
Roads	Developed and semi-developed roadways	3,345.8	1.29%
Water	Open water areas	2,779.2	1.07%
Wellpad - Rangeland	Low vegetative areas found on well pad areas	2,004.5	0.77%
Sandy Wash	Intermittent stream channels	1,233.6	0.47%
Wellpad - Barren	Non vegetative areas found on well pad areas	1,050.5	0.40%
Dead Vegetation	Areas of dead vegetation that have no photosynthetic activity	694.7	0.27%
Salt Cedar	Salt Cedar (Tamarix chinensis)	500.2	0.19%
Gambel Oak	Quercus gambelii shrubland	371.1	0.14%
Dry Mixed Conifer Woodlands	Ponderosa Pine (Pinus ponderosa) and Douglans Fir (Pseudotsuga menziesii) woodlands	279.6	0.11%
Rio Grande Cottonwood	Rio Grande Cottonwood (Populus deltoides var. wislizeni)	225.8	0.09%
Wellpad - Big Sagebrush	Big sagebrush (Artemisia tridentata) found on well pad areas	137.3	0.05%
Exotic Vegetation	Introduced species (weeds) often found in disturbed areas	83.7	0.03%
Willow	Salix species	67.5	0.03%
Wellpad - Equipment	Hardware, wells, buildings, and other developed material found on well pad areas	35.5	0.01%
Wellpad - Pinon Juniper Woodland	Twoneedle pinyon (Pinus edulis), Oneseed juniper (Juniperus monosperma) found on well pad areas	16.2	0.01%

Accuracy Assessment

In order to validate the results of our classification 320 reference points were used to develop an accuracy assessment of our land cover classification. Producer's, User's and Overall Accuracy were calculated (Table 2). The producer's accuracy refers to the probability that a certain land cover of an area on the ground is classified correctly and reflects errors of omission. The user's accuracy or errors of commission indicate the probability of a class that is included into a category when it should have been excluded (Lunetta and Lyons, 2004). The overall accuracy for the entire classification was assessed at 85.63%. The full error matrix is found in Appendix B. This provides more information on how classes were misclassified. In the error matrix each column represents the instances in a predicated class, while each row represents the instances in an actual class (how it was actually classified).

Table 2. Accuracy Assessment for the BLM Carrizo Largo Land Cover Classification

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
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Gambel Oak	18	18	16	88.89%	88.89%
Pinyon Juniper Woodlands	77	80	75	97.40%	93.75%
Dead Vegetation	18	11	11	61.11%	100.00%
Water	8	7	7	87.50%	100.00%
Barren	21	25	20	95.24%	76.92%
Sparse Vegetation and Rangeland	37	37	31	83.78%	83.78%
Dry Mixed Conifer Woodlands	11	12	10	90.91%	83.33%
Big Sagebrush Shrublands	61	58	50	81.97%	86.21%
Roads	4	6	4	100.00%	66.67%
Willow	3	1	1	33.33%	100.00%
Sandy Wash	7	8	7	100.00%	87.50%
Salt Cedar	9	11	7	77.78%	63.64%
Rio Grande Cottonwood	11	12	11	100.00%	91.67%
Greasewood and Chamisa Shrubland	25	25	16	64.00%	64.00%
Wellpad - Equipment	4	4	4	100.00%	100.00%
Exotic Vegetation	5	5	4	80.00%	80.00%
Totals	320	320	274		
Overall Classification Accuracy = 85.63%					

In Appendix B, the highlighted cells of the error matrix on the diagonal represent the number of times the class was classified correctly. Looking at big sagebrush for example, 50 out of 61 accuracy points were correctly classified resulting in a producer's accuracy of 81.97%. The other 11 points were misclassified: 4 points were classified as sparse vegetation and rangelands, 7 points were classified as greasewood and chamisa shrublands. The error matrix provides more information about how classes were misclassified.

Results and Carrizo Largo Deliverables

Carrizo Largo hard copy final maps, digital datasets and metadata were provided to the BLM Farmington Office and BLM Albuquerque Office. The final land cover raster data was clipped by Township and Range extents to keep file sizes manageable. All geospatial data were provided in UTM, WGS 84 spheroid, Zone 13 projection system. In addition percent cover datasets were provided for the following land cover classes; Big Sagebrush, Piñon-Juniper Woodlands, Gamble Oak, Sparse vegetation and rangelands, and Dry Mixed Conifer Woodlands.

The final land cover classification was derived at 1 foot or 30cm grid cells, while this provides a great amount of detail it is in some cases too much detail. For modeling and assessment purposes the 30 centimeter land cover classes were converted to percent cover rasters using 30 meter grid cells. To derive percent cover, each of the 30 centimeter grid cells were tallied in order to get a total count of each land cover class within a 30 meter vector lattice using the Zonal Attribute function within Erdas Imagine software. The counts were then divided by one hundred to get percentages. The 30 meter vector lattices will be then converted to raster. An example of the conversion process is found in figure 12 for determining percent cover for piñon juniper woodlands.

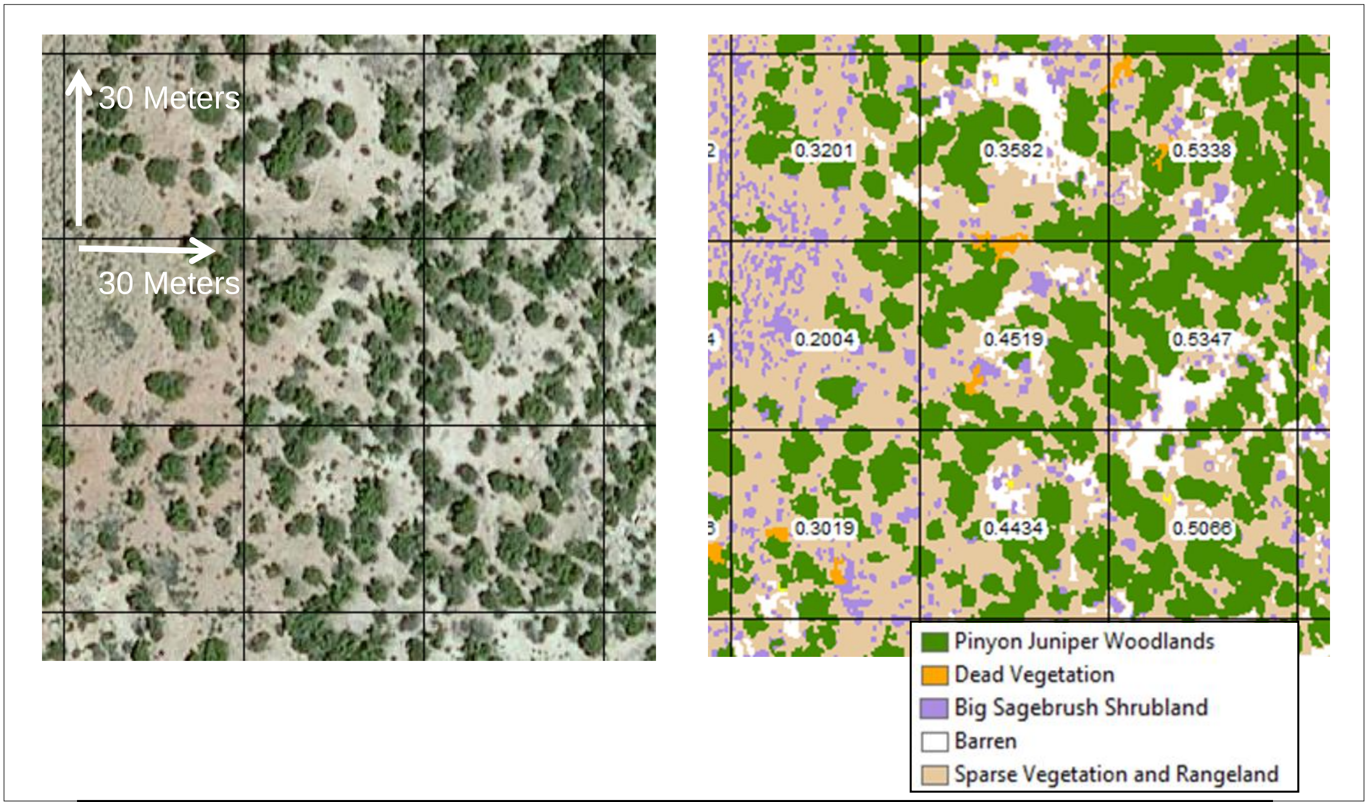

Figure 12. Estimating Percent Cover for Piñon-Juniper Woodlands at 30 meter grid cells

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Appendix A. List of Plant Species Field Identified in the Carrizo Largo Landscape Area

Species	Common Name
Achliea millifolium	Common Yarro
Acnatherum hymenoides	Indian Rice Grass
Agropyrum cristatum	Crested Wheat Grass
Amaranthus sp.	Spiny Amaranth
Ambrosia grayi	Wollyleaf Bur Ragweed
Amelanchier utahensis	Service Berry
Arctium sp.	Burdock
Aristata purpurea	Purple three-awn
Artemisia biglovii	Bigelow Sagebrush
Artemisia frigida	Fringed Sagebrush, Prairie Sagewort, Pasture Sage
Artemisia ludoviciana	White Sage Brush, Grey Sagewort
Atrtemisia nova	Black Sage Brush
Artemisia tridentata	Big Sagebrush
Artemisia tridentata-mortis	Dead Big Sagebrush
Atriplex canescens	Four-wing saltbrush
Boutaloua gracilis	Blue Grama Grass
Boutloua curtipendula	Side Oats Grama
Boutloua hirsuta	Hairy Grama
Bromus anomolus	Nodding brome
Bromus inermis	Smooth Bromegrass
Bromus tectorum	Cheatgrass, Downy Brome
Carduus nutans	Musk Thistle, Nodding Thisle
Cercocarpus montanus	Mountian Mohagany
Ericameria nauseosa	Chamisa, Rubber Rabbitbrush, Grey Rabbitbrush
Chenopodium album	Lamb's Quarters
Cirsium arvense	Creeping Thistle
Cleome serrulata	Skunkweed
Conyza canadensis	Horseweed
Cryptantha sp.	Cryptantha
Cuscuta sp.	Dodder
Disticulus spicata	Inland Saltgrass, Desert Saltgrass
Elymus elymoides	Squirreltail
Elymus spicata	Bearded Wheatgrass
Ephedra viridis var. viridis	Green Ephedra
Ericameria parryi	Parry's Rabbitbrush
Eriogonum ramossisimum	Buckwheat

Species	Common Name
Eriogonum sp.	Rock Buckwheat
Erodium cicutarium	Redstem Filaree, Common Storks Bill, Pinweed
Grindelia squarosa	Curly-top(cup) gumweed
Guterizia sarothae	Broomweed, Snakeweed
Helianthus sp.	Sunflower
Heterotheca villosa	Hairy False Goldenaster
Hilaria jamesii	James' Galleta
Hordeum jubatum	Foxtail Barley
Hymenopappus filifolius	Fineleaf Hymenopappus, Columbia Cutleaf
Juncus balticus	Baltic Rush
Juniperus monosperma	One Seed Juniper
Juniperus scopulorum	Rocky Mountian Juniper
Kocia scoparia	Ragweed, Summer Cypress, Mexican Fireweed
Koleria macrantha	Prarie Junegrass
Lolium perrinis	Ryegrass
Lycium sp.	Wolfberry
Melilotus officinalis	Yellow Sweet Clover, Yellow Melilot
Mirabilis sp.	Four o'clocks
Mirabilis multiflora	Colorado four o'clock
Lycium pallidum	Pale wolfberry, pale desert thorn
Opuntia sp.	Prickly pear cactus
Penstemon crandellii	Cardwell's Penstemon
Philidelphus microphylus	Littleleaf mock-orange
Phragmites australis australis	Common reed
Pinus edulis	Two Needle Piñon
Poa sp.	Bluegrass
Populus wislizeni	Rio Grande Cottonwood
Portulaca oleracea	Purslane
Pseudotsuga menzeseii	Douglas Fir
Purshia tridentata	Antelope brush, Antelope bitterbrush, buckbrush
Quercus gambelii	Gambel Oak
Ranunculus sp.	buttercups, spearworts, water crowfoots
Rhus trilobata	Three leaf sumac
Salix exigua	Narrowleaf willow
Salix sp.	low growing willow shrubs
Salsola tragus	Russian thistle, wind witch, common saltwort
Sarcobatus vermiculatus	Greasewood
Sphralcea concina	Scarlet Globemallow
Eleocharis palustris	Common spike rush
Sporobolus sp.	Sheathed Dropseed
Tamarix chinensis	Salt ceder
Tribulus terrestris	Goathead
Typha sp.	Cattail
Krascheninnikovia lanata	Winterfat
Tetraneuris ivesiana	Bitterweed
Yucca baccata	Banana Yucca
Yucca glauca	Soapweed yucca, narrowleaf yucca
Halogeton glomeratus	Saltlover, Aral barilla, halogeton
Eriogonum effusum	Spreading buckwheat

Appendix B. Accuracy Assessment Error Matrix

Each column represents the instances in a predicated class, while each row represents the instances in an actual classified class

									Reference Data												
Classified Data	Gambel Oak	PJ	Dead Veg.	Water	Barren	Rangelands	Dry MCW	Sage	Roads	Willow	Sandy Wash	Salt Cedar	Cottonwoo	Greasewood	Wellpad - Rang	Wellpad - Barren	Wellpad - Equip.	Wellpad - PJ	Wellpad- Sage	Exotic Veg	Row Total
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Gambel Oak	16	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	18
Pinyon Juniper	1	75	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80
Dead Vegetation	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11
Water	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
Barren	0	0	0	0	20	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25
Rangelands	0	0	0	0	1	31	0	4	0	0	0	1	0	0	0	0	0	0	0	0	37
Mixed Conif Wood	1	1	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	12
Big Sagebrush	0	0	3	0	0	0	0	50	0	0	0	0	0	5	0	0	0	0	0	0	58
Roads	0	0	0	0	0	1	0	0	4	0	0	0	0	0	1	0	0	0	0	0	6
Willow	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
Sandy Wash	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	8
Salt Cedar	0	0	0	0	0	0	0	0	0	1	0	7	0	3	0	0	0	0	0	0	11
Rio Grande Cott	0	0	0	0	0	0	0	0	0	0	0	0	11	1	0	0	0	0	0	0	12
Greasewood and	0	0	0	0	0	0	0	7	0	0	0	1	0	16	0	0	0	0	0	1	25
Wellpad - Range	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wellpad - Barre	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wellpad - Equip	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	4
Wellpad - Pinon	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Wellpad - Big S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Exotic Vegetati	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	4	5
Column Total	18	77	18	8	21	37	11	61	4	3	7	9	11	25	1	0	4	0	0	5	320

Appendix C. Field Photographs of Dominate Land Cover Types found in the Carrizo Largo Study Area

Big Sagebrush (*Artemisia tridentata*)
Classified as Big Sagebrush Shrublands

Piñon Pine (*Pinus edulis*)
Classified as Piñon Juniper Woodlands

Dead Piñon Pine (*Pinus edulis*)
Classified as Dead Vegetation

Willow (*Phragmites australis*), Classified as Willow

Greasewood (*Sarcobatus vermiculatus*)
Classified as Greasewood and Chamisa Shrublands

Salt Cedar (*Tamarix chinensis*), Classified as Salt Cedar

Chamisa (*Ericameria sp.* and Russian Thistle (*Salsola sp.*)
Classified as Greasewood and Chamisa Shrublands

Bosque Cottonwood (*Populus wisilizeni)*
Classified as Rio Grande Cottonwood

Ponderosa Pine (*Pinus ponderosa)*
Classified as Dry Mixed Conifer Woodlands

Gambel Oak (*Quercus gambelii)* Classified as Gambel Oak