Assessment of Using NAIP Imagery Classification to Perform Restoration Monitoring in the Yuma East Wetlands, Yuma, Arizona

Practicum Submittal

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Without my final committee member, Fred Phillips, none of this would be possible. His work leading the restoration of the Yuma East Wetlands and later the Yuma West Wetlands led to the design of this project. We talked of ways to improve the process and ways to save money while doing it, and ultimately, that led to the initial design of this project. I appreciate him providing me first, with a job, allowing me to see the restoration process first hand, and second his continued support with data and information later in the process.

Finally, I want to thank my wife Katy for all of her continued support in all aspects of our life. And her editing skills. They made this a better product.

Thank you.

Kevin Dickinson
07 May 2019

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CHAPTER 1. INTRODUCTION

Background

Seven western states of the United States depend upon the Colorado River for domestic uses, irrigation, and the production of electricity through dams. As the river flows south, less and less water is seen as drought and water entitlements in the United States are filled, until the river eventually runs dry in Mexico (Cohn 2004). As water levels decrease, habitats that were dependent on seasonal flooding and continual groundwater are replaced by upland or invasive populations of plants, altering the landscape (Rood & Mahoney 1990; Poff et al. 1997; Stromberg 2001). Historically between the Hoover Dam and the Sea of Cortez, approximately 400,000 hectares of wetlands, forests, and intertidal habitat consisting of cottonwood and willow gallery forests, mesquite bosques, wetlands, intertidal salt flats, lakes, and channels occurred, stretching up to 24 km wide during flood stages (Phillips et al. 2009). Today these habitats are limited to approximately 109,000 hectares (Phillips et al. 2009).

The Yuma East Wetlands is a 570-hectare restoration site that, as recently as 2004, was an ecologically compromised area (Figure 1). Approximately half of the area is owned by the Quechan Indian Tribe with the remainder owned by the City of Yuma, the State of Arizona, private landowners, and the Bureau of Land Management (Figure 2). Prior to restoration, the area was composed of non-native species, filled with garbage from illegal dumping, was home to a large homeless population, and showed signs of channelization of the nearby Colorado River. This environment led to a reduction and loss of native habitat for wildlife species and was unsightly for the local riverfront. Fred Phillips Consulting, LLC (FPC) was hired by the Yuma Crossing National Heritage Area to design, construct, and monitor the restoration activities, which included removing non-native species, recontouring side channels of the river, and planting a variety of native plants including wetland and upland species (Figure 3). Vegetation monitoring occurred at 12 sites within the restoration area to identify quantitative and qualitative measures of success, with surveys conducted multiple times a year for 8 years (2005-2012).

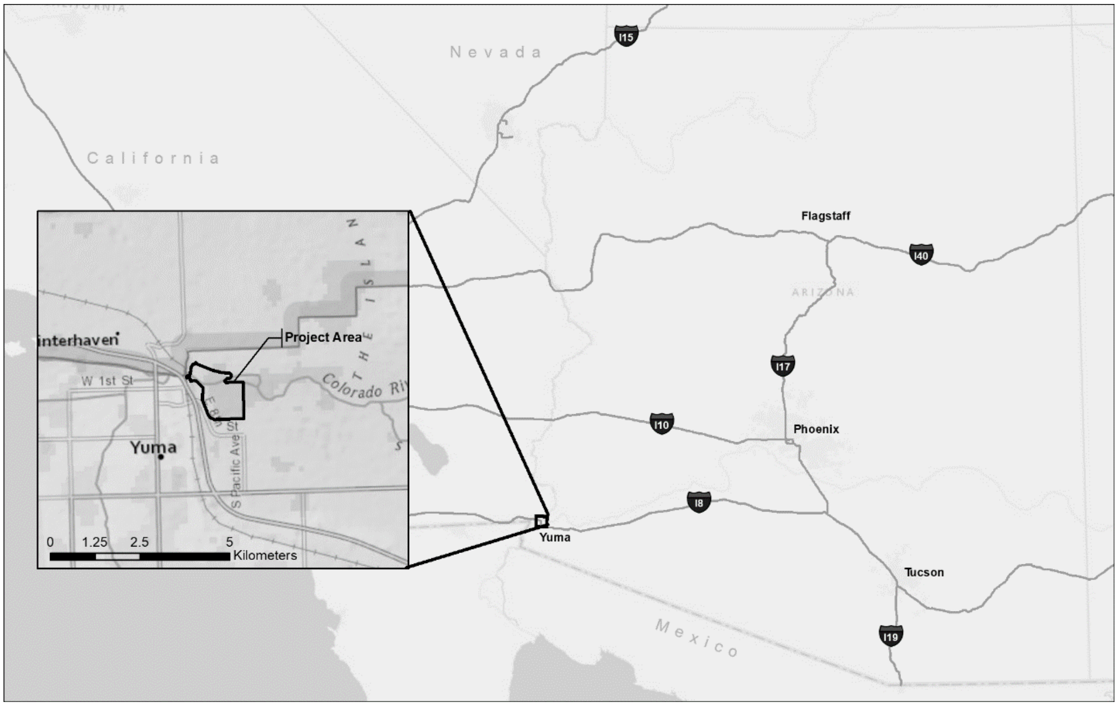

Figure 1. Location of Yuma East Wetlands, Yuma, Arizona

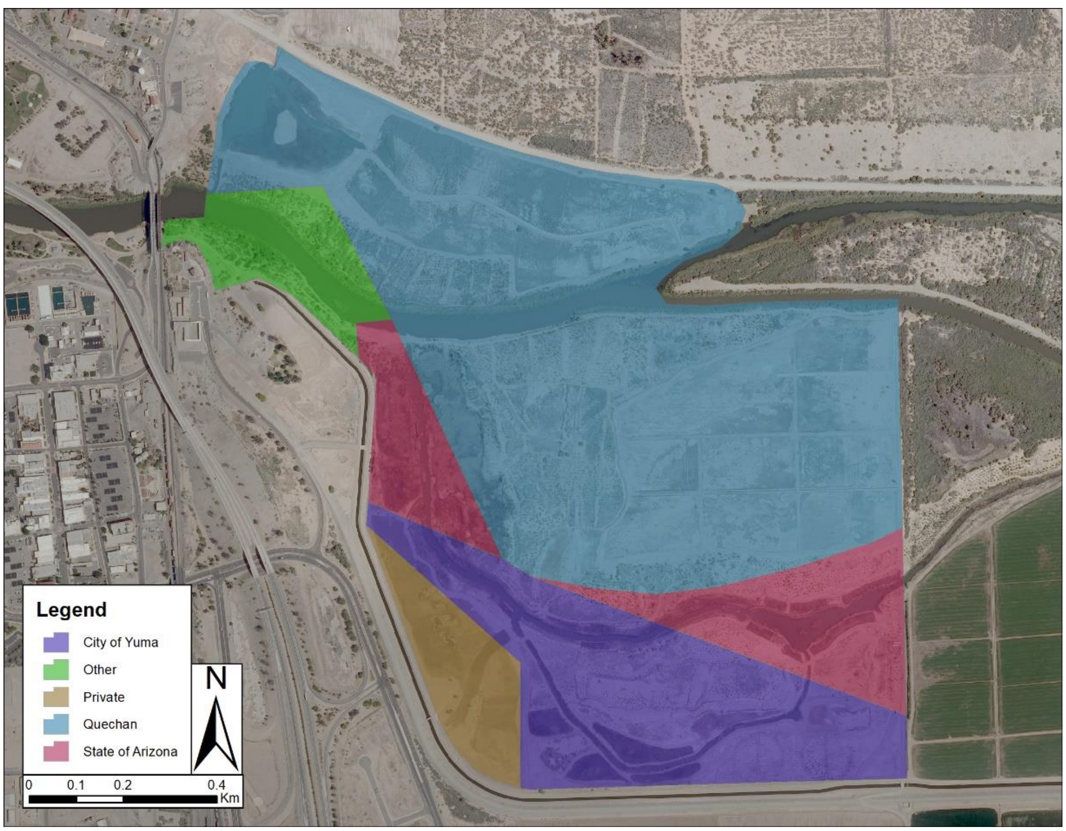

Figure 2. Project extent and approximate land ownership in the Yuma East Wetlands

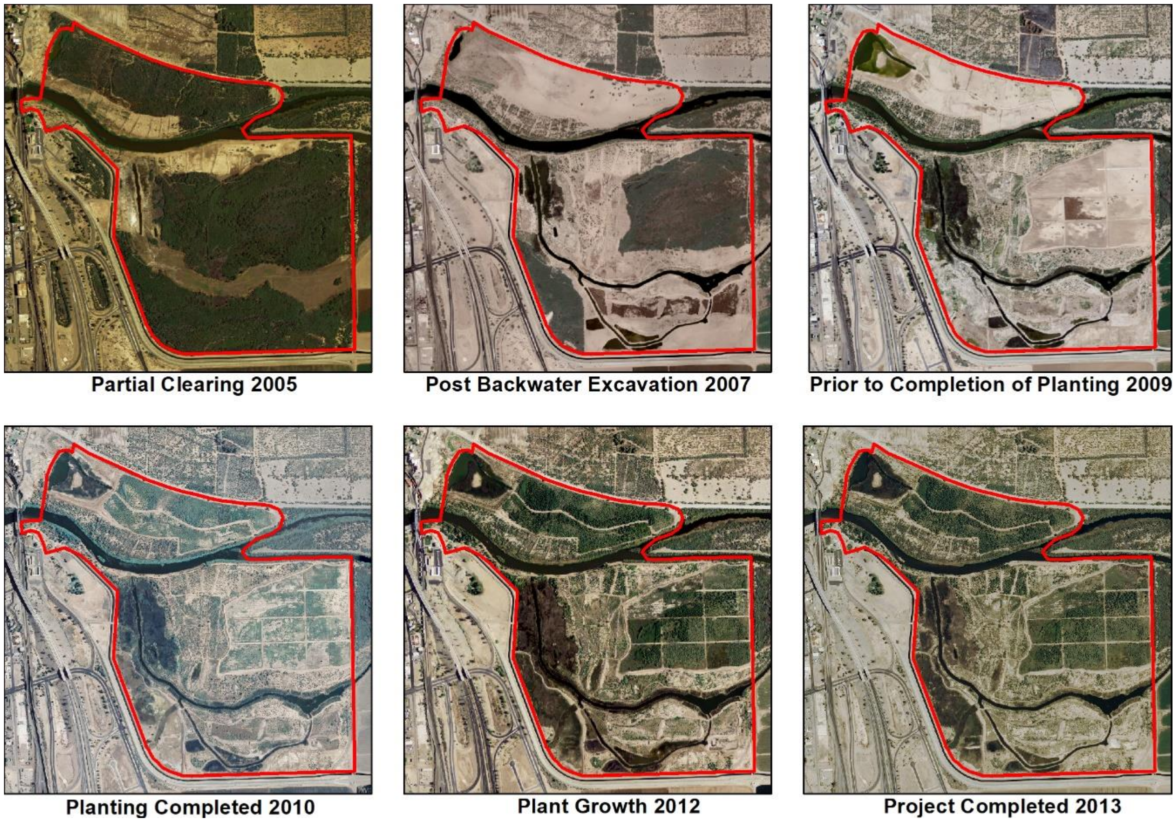

Figure 3. Project Timeline Using Available NAIP Imagery

INTRODUCTION

Tools available for use in landscape studies have varied over time as a function of increased accessibility and overall technological advancement. In the 1930s, aerial photography offered a series of photos available for comparison over an extended time period, but these photo series, collected over variable flight lines, were limited in spatial coverage and contained subjective results due to manual interpretation (Morgan et al. 2010). As a result, standardized imagery was developed, with data collected by airplanes, drones, and satellites that can be postprocessed to ensure horizontal and vertical accuracy. Current available imagery can provide high spatial resolution data (sub-meter or greater); be specific to times, dates, and locations; be multi- or hyperspectral and allow for bands that are outside of the visible spectrum; and be highly repeatable and accessible to a wide audience, often for free (Morgan et al. 2010).

Satellite data can deliver large scale coverage, with recent satellites, such as Landsat 8, providing image swath widths of 185 km. However, a detriment to this wide coverage is that spatial resolution often declines as image swath width increases; for example, Landsat 8 only has a spatial resolution of 30 m. Although free satellite data is an appropriate tool for monitoring large areas undergoing restoration through prescribed burns and reseeding, it is not appropriate for small scale projects (Malmstrom et al. 2009).

Imagery is used to classify vegetation, soils, geology, etc. by type using a combination of multiple spectral bands. The information embedded in the spectral band data can be manipulated through algorithms and other data analysis techniques to further identify tree density, canopy size, size of stands, composition of stands, stem density, or canopy cover, otherwise unidentifiable to the casual viewer (Pouliot et al. 2002; Leckie et al. 2003; Wang et al. 2004; Davies et al. 2010). Remote imagery, such as digital aerial photography, can provide imagery at varied spatial resolutions and time scales of locations around the world, with many sets of imagery available free to the general public. As such, the cost of conducting vegetation monitoring or inventories in a wide range of systems is significantly reduced using digital aerial photographs; in several cases, time spent assessing a system was reduced by almost 90% through the use of aerial imagery over on the ground methods (Paine & Kiser 2003; Booth et al. 2006). In addition, unlike the use of 3- and 4- band imagery which can provide high spatial resolution but low spectral resolution, leading to confusion among vegetation classes during the classification, digital aerial photographs can be used to map smaller project areas and show levels of details as small as individual trees or riparian features (Fensham & Fairfax 2002; Tuominen & Pekkarinen 2005; Cleve et al. 2007; Morgan et al. 2010).

The use of digital aerial photography as well as imagery such as that produced through the National Agriculture Imagery Program (NAIP), has been used to analyze landscape changes at both national and smaller scales, with NAIP imagery, in particular, being applied for its wide availability and coverage of the United States, free cost, rigorous orthorectification procedures, and high spatial resolution (1 x 1 m pixels) (Taylor et al. 2000; Rogan & Chen 2004; Davies et al. 2010). Analyzing a combination of classified imagery and vegetation indices can produce an output that can be compared with ground data to determine how effective the aerial imagery model corresponds to that found through line intercept ground monitoring.

When landscape restoration projects occur, most grant funding agencies, as well as the people who conduct the restoration, want some indicator other than visual cues to identify the success of the project (Hobbs & Norton 1996; Tischew et al 2010; Hagan & Evju 2013). This generally involves field biologists visiting the field site numerous times over a specified time period to collect data on vegetative growth, canopy cover, wildlife sightings, soil conditions, or other information. This process can be expensive, both in cost and person hours, which begs the question: is there a more efficient option that provides comparable data?

Aerial photography and remote sensing can provide imagery at varied spatial resolutions and time scales at locations around the world, with many sets of imagery available free to the general public. Aerial photographs can be used to map smaller project areas and show levels of detail as minor as individual trees or riparian features (Fensham & Fairfax 2002; Tuominen & Pekkarinen 2005, Morgan et al. 2010). Researchers have shown that aerial photographs can reduce the cost of conducting vegetation monitoring and inventories in a wide range of systems (Paine & Kiser 2003). As a result, I am interested in remote sensing methods that can be employed to reduce the number of visits required for landscape restoration monitoring, while producing similar results to on the ground efforts.

PRACTICUM PURPOSE

The purpose of this applied research is to identify whether classified aerial imagery can be a tool to replace or supplement on the ground vegetation monitoring. Successful environmental consulting firms rely on identifying methods that will improve their output, reduce their costs, and still produce quality results that are within their contract parameters. Field monitoring can be expensive in terms of employee time, with survey time and travel costs included, and generally requires the surveyors to collect a subset of data and extrapolate it across the project site. If aerial imagery can replace part of the required monitoring, while producing similar or better results, it will provide consultants another tool to satisfy the client and reduce costs.

Research Goals

1. Identify methods for classifying riparian vegetation from National Agricultural Imagery Program (NAIP) imagery within the project area using ArcGIS software
2. Validate this classification using data collected from on the ground surveys conducted by FPC during the 2006-2011 field seasons
3. Correlate the GIS model to field-collected data to identify how effective the model is at replicating field collected results.

Deliverable

For this project, I propose to fully satisfy the above-mentioned Research Goals for eventual submission to the peer-reviewed journal *Ecological Restoration*. Fred Phillips Consulting, LLC has published articles about the Yuma East Wetlands within this journal, making it an appropriate avenue for continued dissemination of this this work (Phillips et al. 2009; Kleoppel Thathnigg & Phillips 2015). Additionally, as this target journal is directed towards landscape restoration practitioners, identifying methods that could save projects money could be useful to many readers.

CHAPTER 2. ARTICLE FOR SUBMISSION TO ECOLOGICAL RESTORATION

Assessment of Using NAIP Imagery Classification to Perform Restoration Monitoring in the Yuma East Wetlands, Yuma, Arizona.

Authors: Kevin Dickinson, Erik Schiefer*, and Fred Phillips*
Word Count: 3848

ABSTRACT

Conducting on the ground vegetation monitoring for restored landscapes can be labor intensive and cost prohibitive, yet it is a requirement for many restoration activities conducted on private and government owned parcels. Utilizing Geographic Information Systems (GIS), imagery can be classified into vegetative classes and change analysis can be conducted to examine temporal patterns in vegetation cover from image to image. The free and widely available National Agriculture Imagery Program (NAIP) provides one-meter resolution aerial imagery through the agricultural growing season that is acquired on a three-year cycle beginning in 2009. This presents an opportunity to determine if GIS and NAIP aerial imagery can be an appropriate tool to replace or supplement on the ground monitoring for vegetative success in areas that have undergone restoration. Using the 152-hectare Yuma East Wetland restoration project in Yuma, Arizona as a case-study, we attempted to develop a method to create additional bands from the NAIP imagery as a means of increasing the capability of supervised classification for planted vegetation in restored wetlands. Other color models and imagery products were combined with the NAIP imagery to produce a 9-band composite which was then classified. While this method did not produce accurate classifications, it offered examples of why multi- or hyperspectral imagery might be needed to conduct classifications in this complex landscape.

Key Words: *4-Band Imagery; Geographic Information Systems; Lower Colorado River; Supervised Classification; Vegetation Monitoring; Wetland Restoration; Yuma, Arizona*

*Anticipated additional authors

INTRODUCTION

Tools available for use in landscape studies have varied over time as a function of increased accessibility and overall technological advancement. In the 1930s, aerial photography offered a series of photos with limited spatial coverage and produced subjective results due to manual interpretation, while current, standardized imagery that is collected by airplanes, drones, and satellites that can be postprocessed to ensure horizontal and vertical accuracy (Morgan et al. 2010). Current available imagery can provide high spatial resolution data (sub-meter or greater); be specific to times, dates, and locations; be multi- or hyperspectral and allow for bands that are outside of the visible spectrum; and be highly repeatable and accessible to a wide audience, often for free (Morgan et al. 2010).

The information embedded in the spectral band data of imagery can be manipulated through algorithms and other data analysis techniques to identify tree density, canopy size, size of stands, composition of stands, stem density, or canopy cover, otherwise unidentifiable to the casual viewer (Pouliot et al. 2002; Leckie et al. 2003; Wang et al. 2004; Davies et al. 2010). Utilizing digital aerial photographs has significantly cut the cost of conducting vegetation monitoring or inventories in a wide range of systems; in several cases, time spent assessing a system was reduced by almost 90% through the use of aerial imagery over on the ground methods (Paine & Kiser 2003; Booth et al. 2006). In addition, unlike the use of 3- and 4-band imagery which can provide high spatial resolution but low spectral resolution, leading to confusion among vegetation classes during the classification, digital aerial photographs can be used to map smaller project areas and show levels of details as small as individual trees or riparian features (Fensham & Fairfax 2002; Tuominen & Pekkarinen 2005; Cleve et al. 2007; Morgan et al. 2010).

When landscape restoration projects occur, most grant funding agencies, as well as the people who conduct the restoration, want some indicator other than visual cues to identify the success of the project (Hobbs and Norton 1996; Tischew et al. 2010; Hagan & Evju 2013). Employing remote sensing techniques, a tool shown to provide rapid, inexpensive, and nondestructive techniques to study vegetation and soils of rangelands and forests, can enhance the ability of restoration firms to conduct landscape restoration processes, primarily through the reduction in costs of monitoring (Joshi et al. 2004; Mirik & Ansley 2012). Free satellite data is an appropriate tool for monitoring large areas undergoing restoration through prescribed burns and reseeding, it is not appropriate for small scale projects (Malmstrom et al. 2009). The use of digital aerial photography as well as imagery such as that produced through the National Agriculture Imagery Program (NAIP), has been used to analyze landscape changes at both national and smaller scales, with NAIP imagery, in particular, being applied for its wide availability and coverage of the United States, free cost, rigorous orthorectification procedures, and high spatial resolution (1 x 1 m pixels) (Taylor et al. 2000; Rogan & Chen 2004; Davies et al. 2010).

Analyzing a combination of classified imagery and vegetation indices can produce an output that can be compared with ground data to determine how effective the aerial imagery model corresponds to that found through line intercept ground monitoring. Limited research however has been conducted on classification and analysis of remote imagery as a model for riparian areas, due to their inherent vegetation class complexity (Vande Kamp et al. 2013). In this study, I aim to supplement the literature by modeling a riparian restoration, the Yuma East Wetlands, through a combination of classification techniques and the incorporation of vegetation indices and additional methods of viewing visible band imagery.

METHODOLOGY

STUDY AREA

Yuma, Arizona is in far southwestern Arizona, situated on the southern shore of the Colorado River from California. Yuma has a hot, desert climate, with warm winters and extremely hot summers with an average of less than 100mm of rain annually. The Yuma East Wetlands restoration area is located near downtown Yuma, Arizona east of the Historic Yuma Crossing, and west of the confluence of the Gila and Colorado Rivers between River Miles 29.0 and 34.0. The land is owned by a series of stakeholders, including the Fort Yuma Quechan Indian Tribe, the City of Yuma, the State of Arizona, and private landowners. The project area encompasses approximately 152 hectares and is located in Yuma County, Arizona (Figure 4).

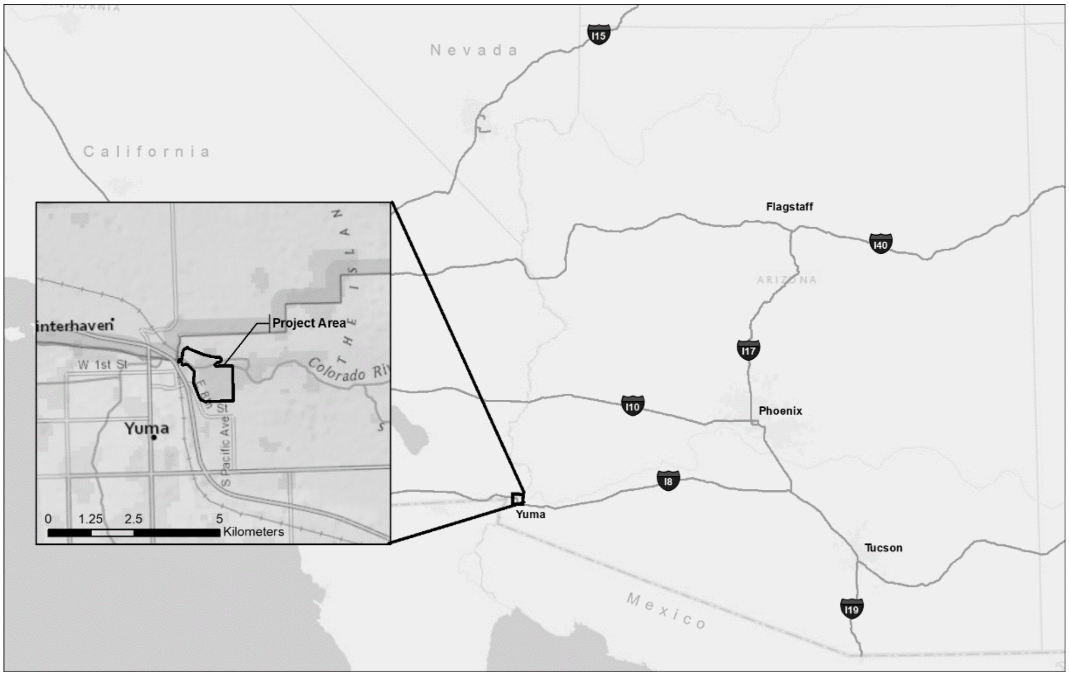

Figure 4. Location of the Yuma East Wetlands, Yuma, Arizona

As recently as 2004, the Yuma East Wetlands was an ecologically compromised area. Prior to restoration, the area was composed of non-native species, primarily tamarisk (*Tamarix* spp.) and giant cane (*Arundo donax*), filled with garbage from illegal dumping, was home to a large homeless population, and showed signs of channelization of the nearby Colorado River (Phillips et al. 2009). This environment led to a reduction and loss of native habitat for wildlife species and was unsightly for the local riverfront. The Yuma Crossing National Heritage Area began a process to create a Master Plan that detailed the design, construction, and monitoring of the restoration activities. The Master Plan included removing non-native species, performing intensive soil and site analysis to understand the salinity of the project landscape, recontouring side channels of the river, and planting a variety of native plants including wetland and upland species, including salt tolerant species in areas of high salinity (Phillips et al. 2009). Clearing, grading, and contouring of the area was completed by 2009, and planting was completed by April 2010.

METHODS

Four digital orthophoto quarter quads (DOQQ) of the project area were obtained from the United States Geological Survey (USGS) Earth Explorer website (www.earthexplorer.usgs.gov) for dates within our study range (Table 1). These images were downloaded in GeoTIFF format and contain four bands: blue, green, red, and near infrared (NIR). NAIP imagery has a vertical accuracy of +/- 5m through the use of ground control points. The images used in this study were in the center of the DOQQ and did not appear to be shifted from one image to the next, so no vertical shifting was needed to ensure accuracy.

The imagery corresponds to when planting was completed in April 2010, wherein trees are sapling size or smaller and bare ground is a primary cover class. By June 2013, a large percentage of the vegetation was successfully transplanted, currently covering most of the restored area, and the intensive monitoring had ceased. Mesquite (*Prosopis* sp.) and cottonwood (*Populus fremontii*) have crowns that are fully leafed out, and bare ground is replaced by planted vegetation in all areas other than roads and channels (Figures 5 and 6).

Table 1. Dates of NAIP Imagery

Year	Date
2010	04/26/2010
2010	07/04/2010
2012	04/28/2012
2013	06/09/2013

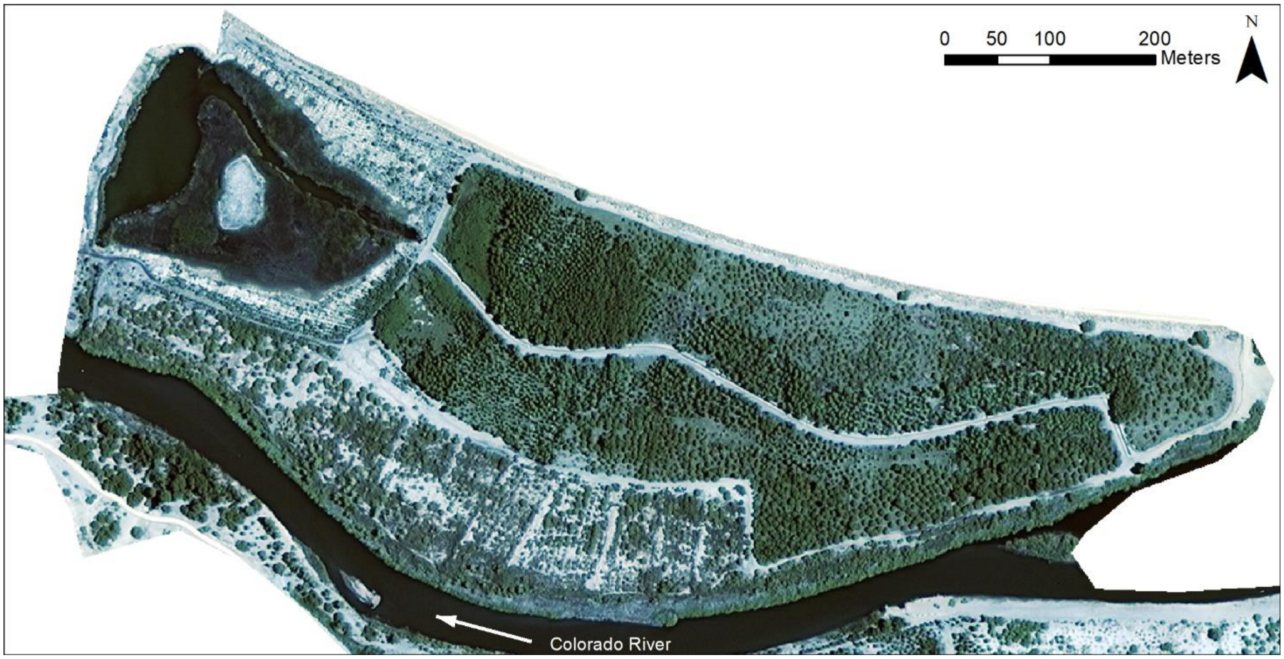

Figure 5. June 2013 NAIP Imagery of northern portion of project location.

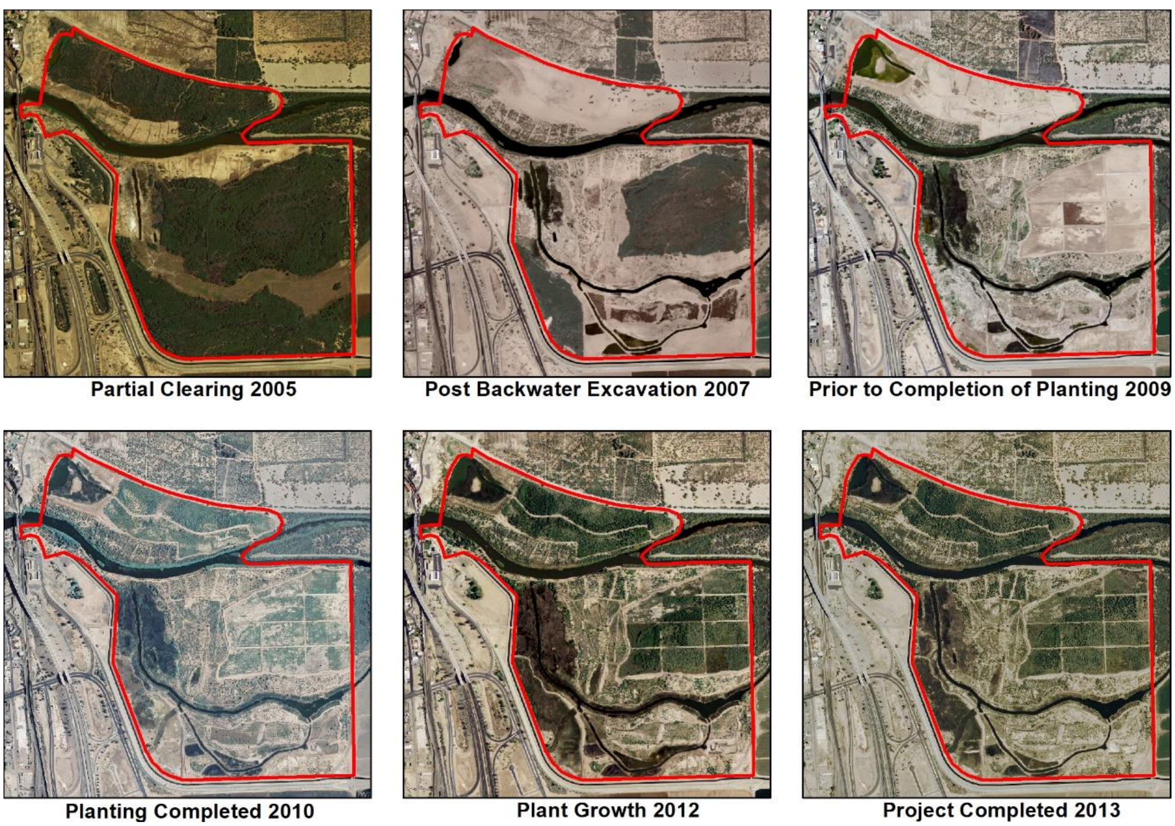

Figure 6. Project Timeline Using Available NAIP Imagery

To supplement the information contained with the NAIP images, other color models and image analysis tools are used to create more “bands” for the classification to analyze. Transforming the original RGB (red, green, blue) image to its corresponding HSV (hue, saturation, value) color model has been shown to provide additional information than what is available in the RGB colorspace (Ezequiel et al. 2014; Sugiura et al. 2016).

Vegetation indices, such as Normalized Difference Vegetation Index (NDVI), can be used to separate the non-vegetated areas from vegetation, as NDVI is a common remote sensing method that assesses the “greenness” of a pixel as it correlates to actively photosynthesizing material (Rouse et al. 1974; Burgan & Hartford, 1993; Glenn et al. 2008; Vande Kamp et al. 2013). NDVI is the ratio of near-infrared radiation minus visible radiation to near-infrared radiation plus visible radiation ((NIR band – R band)/(NIR band + R band)).

While NDVI separates vegetation from non-vegetation, it does not distinguish between different types of vegetation or manage shadows. Further, texture analysis can help highlight the spatial variation in image tone that results from the variability between vegetative species in their leaf arrangements and vegetative structure (Franklin et al. 2000; Cleve et al. 2007). Texture examines the spatial information of neighboring cells to determine how much or little variation there is in their spectral values. If the standard deviation of these neighborhood values is low, we identify that as low texture, like a field of corn, but if the standard deviation is high, we identify that as high texture, like the crown of a mature tree.

Additional “bands” were created within ArcGIS 10.6 software (ESRI 2018) to increase the potential for more classes to be accurately identified during classification. These additional bands were HSV, NDVI, and texture. The NIR band was removed from each NAIP image and using the color model conversion function in the Image Analysis toolboox, the RGB image was converted to HSV. Using the NDVI function in the Image Analysis toolbox, an NDVI raster was created from the 4-band NAIP image. A texture model from the green and NIR bands was developed using the Focal Statistics tool in ArcToolbox

(Ziegler 2016). Each band was put through the Focal Statistics tool twice, once using Rectangular neighborhood analysis (3 m x 3 m) and once using Circular neighborhood analysis (3 m radius). The Raster Calculator tool was then used to average the four resulting rasters to create the final texture band. The final nine “bands” (blue, green, red, NIR, hue, saturation, value, NDVI, and texture) were then stacked using the Composite Bands tool.

A grid of 3 m x 3 m blocks was created that covered the northern region of the project area (everything north of the river) using the Create Fishnet tool in ArcToolbox. A random sample of 500 points was created within this grid using the Create Random Points tool with a tolerance that limited points to no closer than 15 m proximity to each other. The grid locations that intersected with the random points were exported to a new shapefile to be used to create random training locations for training samples (Figure 7). This created a potential of up to 4500 pixels being used in training for the classification of each image.

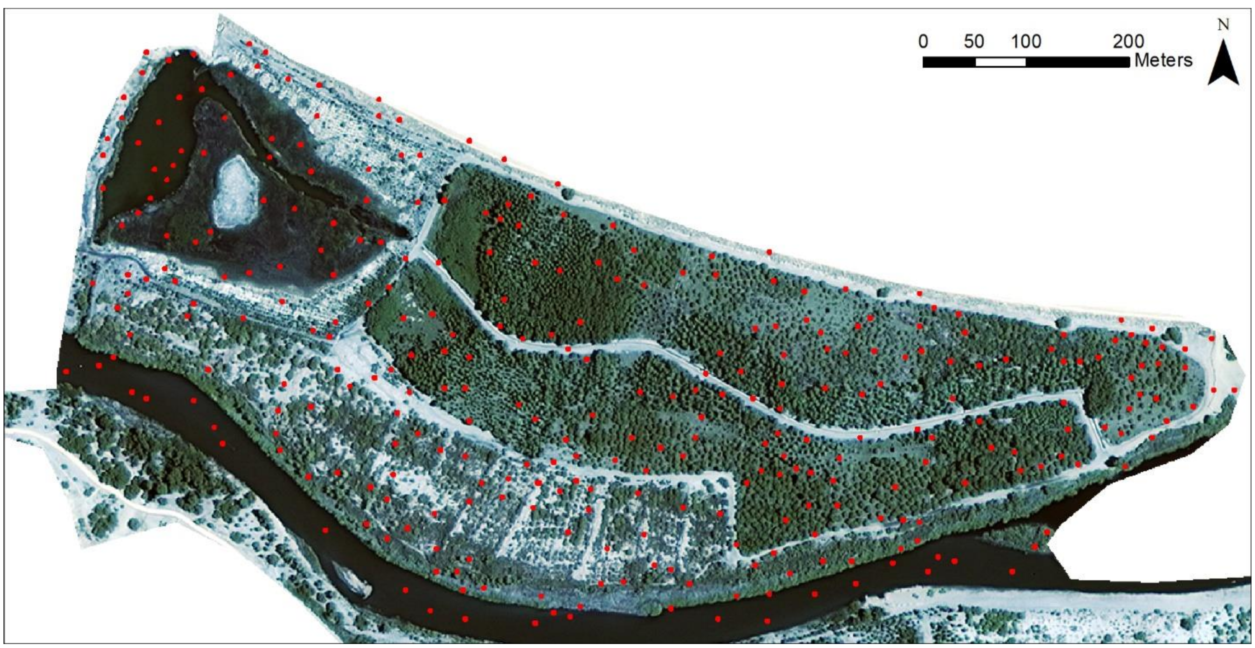

Figure 7. Training data locations

Chen and Stow (2002) stated that it is reasonable to derive training data for classification directly from an image if the user has *a priori* knowledge of the scene. Access to planting plans and institutional knowledge about this site allowed us to directly place the 500 grid locations directly on the NAIP image and determine what class falls within each block for inclusion in the training samples. Training data was collected for seven classes: mesquite, cottonwood, willow (*Salix gooddingii* and *S. exigua*), upland ground cover, wetland ground cover, open water, and bare ground. Only the training locations that were wholly one class or another were classified and included in the training data. This process was done for each of the four NAIP images. The training data then was saved as a signature file for the composite band, and Maximum Likelihood Classification was conducted (Figure 8).

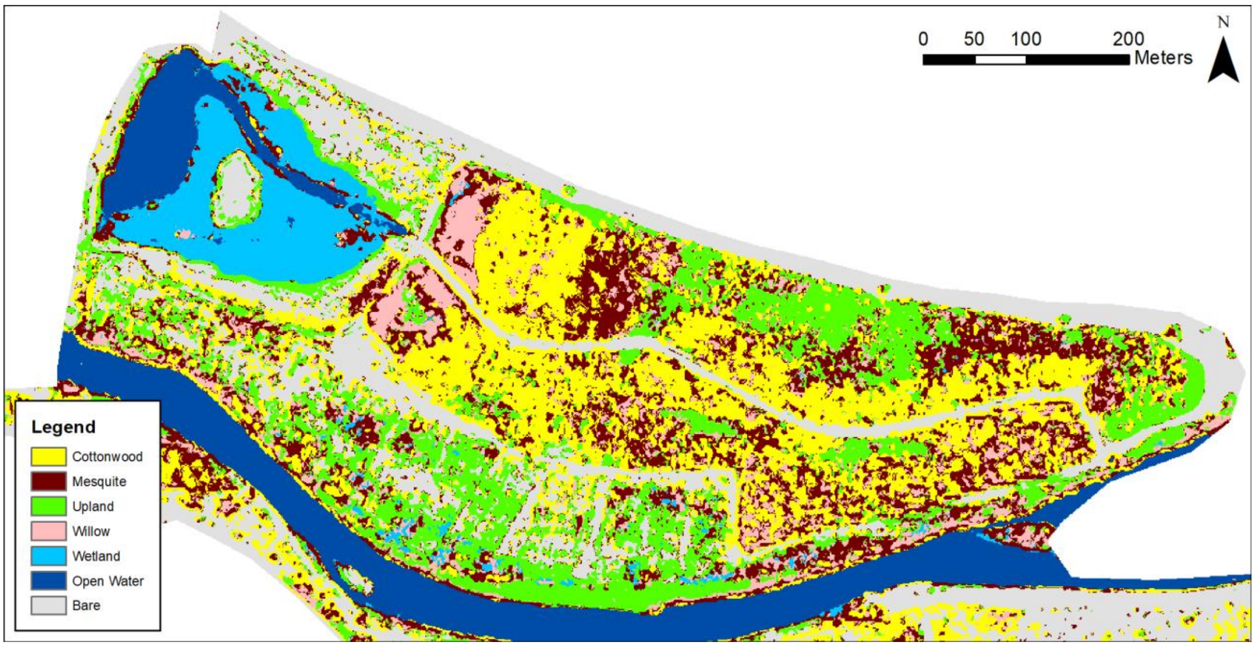

Figure 8. June 2013 Classification results for northern portion of project area.

Accuracy assessments were conducted on each of the classifications to create an error matrix that identifies Producer's Accuracy, User's Accuracy, and Overall Accuracy (Congalton 1991). The Producer's Accuracy measures how accurately a certain area is classified, the User's Accuracy measures the accuracy of a certain category across the classification, and the Overall Accuracy identifies the probability of a single reference pixel being accurately classified. An Overall Accuracy of greater than 85% is expected for a classification to be considered accurate (Anderson et al. 1976; Foody, 2000; Wilkinson, 2005). Transect data from surveys conducted by FPC during the month closest to the imagery data was compared to the classified image to determine accuracy. None of the transect locations overlapped areas where signature data was collected.

RESULTS

Following the process to create the composite image, classifications were created for each of the four NAIP images and accuracy assessments were performed. Table 2 shows the Producer's, User's, and Overall Accuracies for each of the images. While trends were increasing across the study's time period, the Overall Accuracy for each classification was far below the 85% accuracy standard needed.

Table 2. Accuracy Assessments for Imagery Classifications

	Producer's Accuracy				**User's Accuracy**				**Overall Accuracy**	
	April 2010	July 2010	April 2012	June 2013	April 2010	July 2010	April 2012	June 2013		
Bare	30%	53%	N/A	N/A	67%	73%	N/A	N/A	April 2010	39%
Willow	43%	25%	18%	46%	25%	40%	42%	**87%**	July 2010	46%
Cottonwood	44%	44%	62%	65%	51%	33%	**88%**	63%	April 2012	60%
Mesquite	43%	41%	76%	60%	15%	65%	31%	44%	June 2013	61%
Upland	36%	69%	79%	78%	41%	40%	81%	**90%**		

The Producer's Accuracy values allow us some insight into why this process failed. Inaccuracy or confusion in the signature file will produce low production accuracy number. This shows that differentiation of the species was not correctly occurring preventing the model from accurately identifying the different vegetations (Figure 9).

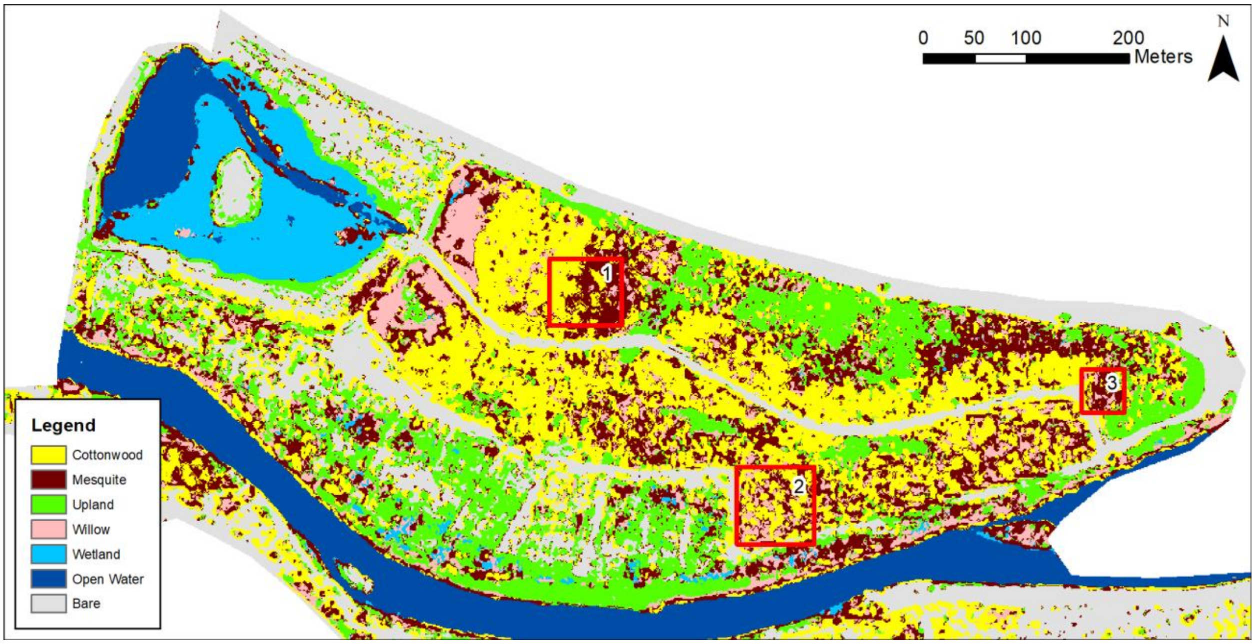

Figure 9. June 2013 Classification with three areas of incorrect classification. Blocks 1 and 3 should be entirely classified as cottonwood while Block 2 should be entirely mesquite.

Reviewing the spectral values for Cottonwood, Mesquite, Willow, and Upland across each of the bands details more of the story (Figure 10). It is expected when creating signatures for a class that one will be able to obtain values generally independent of other classes so that any value that falls within the range of the signature will correctly assign. In this case, the spectral values for cottonwood, mesquite, and willow, and upland fall within the standard deviation for each band, preventing clean, accurate classification.

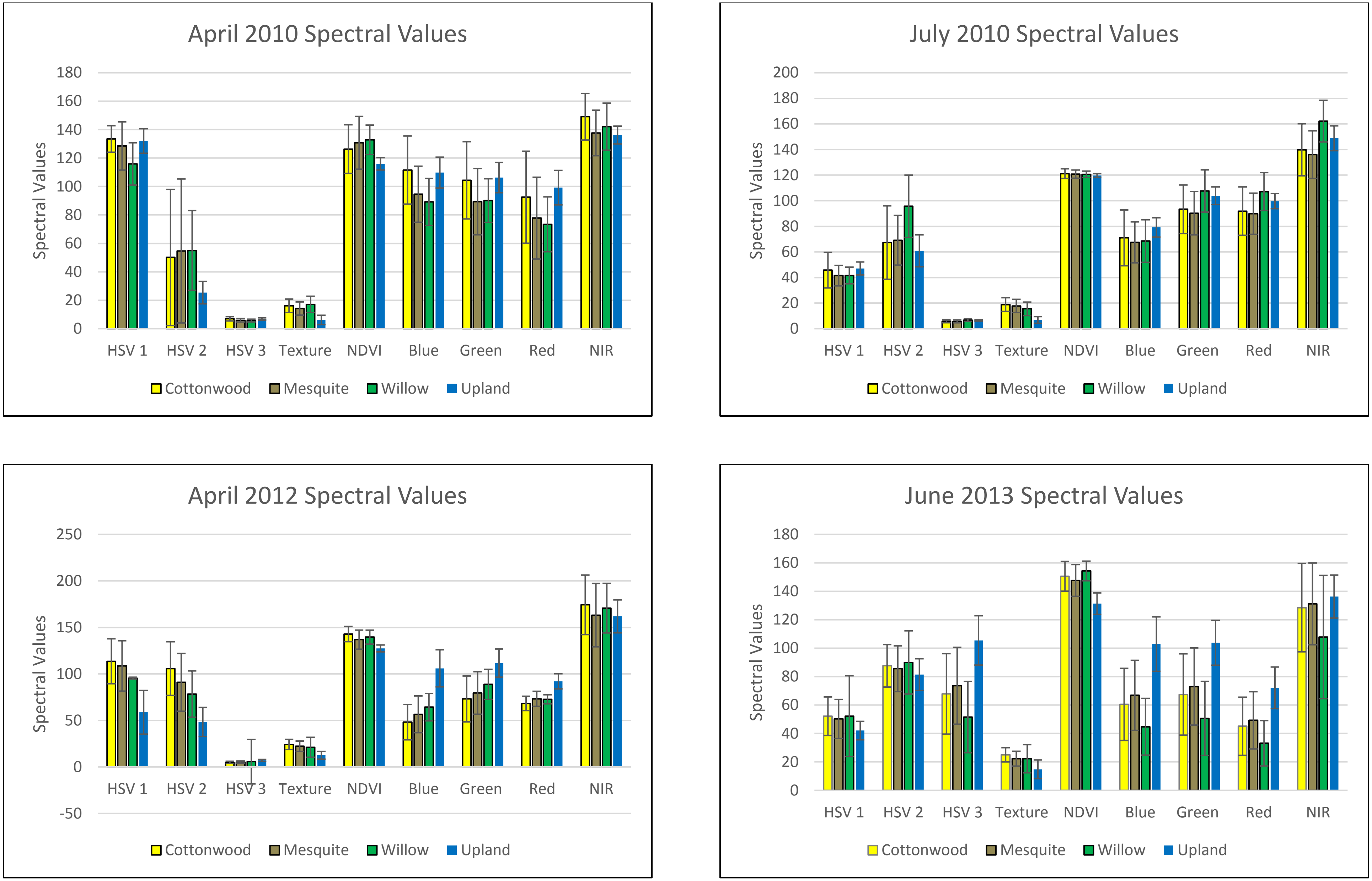

Figure 10. Spectral values for each of the vegetation types within each band of the composite image.

DISCUSSION

The results suggest that NAIP imagery is not a viable tool to create classifications that will decrease the need for on the ground monitoring of vegetation in riparian restoration sites. Spectral signatures for vegetation types were too similar and the inclusion of additional bands did not add the additional information needed to the model. The 8-bit data in NAIP imagery limits the values for it or any products created from it to values that range from 0-255. This limits the level of spectral information encased in the imagery needed to accurately discriminate between vegetation types in wetland areas. The use of 3m x 3m blocks for identification of signatures was an attempt to incorporate object-based classification, but a more intensive object-based classification approach might be more suitable than the pixel-based classification I used. Furthermore, the complex nature of riparian systems makes conducting classification from imagery difficult.

An additional difficulty arose from the multiple age classes and intermingling of species throughout the planted areas. Planting plans that I referenced showed monotypic stands, but in reality, a more complex system was seen that may have muddied the signatures. While this, in effect, resembles what one might see within a mature riparian system, for most restoration projects, during the monitoring period, age classes will likely be closer to each other, and stands will be possibly more monotypic. Large scale restoration locations that are using only one or two tree species throughout the entirety of the project might be able to use this technique as there is limited variability in the vegetation and small pockets of variability will not have as large of an impact on the overall results.

Imagery that contains higher spatial and spectral imagery could cost hundreds to thousands of dollars with requirements for minimum orders that cover at least 25-100 km^2. While this imagery may have centimeter scale resolution and contain multispectral bands, this imagery will increase the cost of the process, have a large amount of extraneous data, and require the purchase of multiple data sets to correspond to the dates that you want to survey.

The use of drones and digital photogrammetry to create higher resolution images that can be processed to create structure-from-motion photogrammetric images for smaller sites such as the Yuma East Wetlands might be a more appropriate approach to take. Studies have used small, commercial grade, RGB digital cameras on lightweight drones to create centimeter resolution orthophotos and near-centimeter digital elevation models of riparian systems that were able to be classified for vegetation and geomorphological type (Puttock et al. 2015; Woodget et al. 2017). This system is limited by flying ability of the user and the large amount of imagery data that you collect, but purchasing the system to conduct this is similar in costs to one session of monitoring a project of the Yuma East Wetlands. For projects that require multi-year monitoring plans, investing in a system such as this, may ultimately reduce costs in the long run.

This model was unsuccessful in identifying classified NAIP imagery as a tool to supplement or replace on the ground vegetation monitoring in restoration setting. Confusion within spectral signatures of vegetation types led to classifications that were no greater than 61% accurate, precluding the use of these classifications. Increases in the availability of quality, low-cost or free imagery and the tools to collect this imagery appear to be quickly advancing, offering future avenues to explore that may aid companies in limiting costs and the labor necessary to conduct monitoring surveys.

CHAPTER 3. CONCLUSION AND RECOMMENDATIONS

The results of this project suggest that NAIP imagery is not a viable tool to create classifications that will decrease the need for on the ground monitoring of vegetation in riparian restoration sites. Spectral signatures for vegetation types were too similar and the inclusion of additional bands did not add the additional information needed to the model. The 8-bit data in NAIP imagery limits the values for it or any products created from it to values that range from 0-255. This limits the level of spectral information encased in the imagery needed to accurately discriminate between vegetation types in wetland areas. Furthermore, the complex nature of riparian systems makes conducting classification from imagery difficult.

An alternate approach to conducting vegetation monitoring would save restoration firms money and time in their efforts to restore landscapes. It has been estimated that for a project of the scale of the Yuma East Wetlands, it would require two biologists to conduct vegetation monitoring, a mid-to-senior level biologist and a biological technician, with a combined hourly wage of approximately $125-$150/hr (assuming $85/hr for mid-level and $50/hr for technician). Assuming the surveys take a day and a half, plus analysis and report writing, it would cost approximately $3,000 for each monitoring session. This cost is without any necessary equipment costs, gas, travel time or hotel/per diem costs, which could raise the costs another $500. If a GIS analyst could perform this work remotely with free imagery, these costs could be lowered by approximately 75%.

The approach I took to creating signature files for each vegetation class was more stringent than what would be assumed for restoration firms. It is assumed firms would create signature files from large swaths of the study area as planting plans that identify the composition and density of vegetation across each area of the landscape would be readily available. I wanted to remove any bias in the training samples to ensure that the methodology we used would stand up to critique and statistics. By creating a random sampling of training areas and setting the training locations in only the northern third of the project area removed this bias from our signature files. Any classification created would rely heavily on the signature files instead of *a priori* knowledge of what was on the ground ensuring our accuracy assessments would provide details about the accuracy of the classification and whether this approach was successful.

There were inherent limitations with the use of NAIP imagery: there is limited availability of imagery which is only collected during the growing season, and each area only has imagery collected once every 2-3 years. While 1 m spatial resolution is excellent for free imagery, spectral resolution is poor, as only four bands are collected in an 8-bit format, limiting the data potential. We attempted to improve the information available by creating “bands” to uncover additional hidden information. In addition, the use of texture and conversion to other color models have proven successful in other studies and deserve more analysis for their potential in uncovering hidden data. Ultimately, we were unable to get the separation in values needed to delineate one vegetation type from another accurately.

The use of multi- or hyperspectral imagery from companies such as DigitalGlobe (the owner of WorldView satellites [www.digitalglobe.com]), provide greater spectral (8 band), temporal, and spatial (30 cm) resolution, but they are outside of what would be economically feasible for most firms. Imagery companies require a minimum order area of 25-100 km^2, and with prices ranging from \$14 to \$60/km^2, this is an expense outside the range of providing cost savings, particularly for project areas that are as small as the Yuma East Wetlands (1.52 km^2). For projects that are in the 25-100 km^2 range, this type of imagery may be appropriate, as vegetation monitoring on the scale of that conducted in the Yuma East Wetlands would cost approximately \$60,000 to \$240,000, equal to or more than the cost of multi- or hyperspectral imagery.

With the decrease in cost of user-friendly drones, small, commercial grade, RGB digital cameras on lightweight drones have been used to create centimeter resolution orthophotos and near centimeter digital elevation models of riparian systems that were classified for vegetation and geomorphological type (Puttock et al. 2015; Woodget et al. 2017). A large array of photos is collected over the project area and stitched together using structure-from-motion software that produces a type of point cloud, enabling elevation modeling and increased ability to better classify vegetation. This system is better suited and more cost efficient for projects on the scale of the Yuma East Wetlands, necessitating additional work to determine the efficiency and accuracy of such a system.

Ultimately, we were unable to meet our stated goals of using NAIP imagery to conduct or supplement vegetation monitoring in restoration projects. Our method of trying to improve the available information within the 4-band image was unsuccessful, and for projects that are small scale in nature, continuing to conduct vegetation surveys in person may continue to be the best approach to take in terms of accuracy and value. Values in the Overall Accuracy in the Accuracy Assessment showed an increase in accuracy from April 2010 to June 2013. Further study on NAIP imagery that shows more mature restoration areas is suggested and may show that while this method is not capable of use on early restoration projects, but more suited to monitoring later in the process.

More research and experimentation are also needed on the use of drones to acquire data for similar scale projects, as this approach is likely to offer improved results and decreased costs. For large-scale restoration, depending upon the scale, classification of multi- or hyperspectral imagery should prove to be cost-effective, as increases in on the ground survey costs will ultimately allow imagery expenses to decrease.

CHAPTER 4. LITERATURE CITED

LITERATURE CITED

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APPENDIX: OTHER APPROACHES EXPLORED

Multiple variations of the methodology identified in Chapter 2 were explored, but not included in the final product. The table below highlights these other methods and identifies why these methods were not included.

Approach	Outcome
Focal statistics with different pixel radius or block size (2m, 4m)	There was no change in results when using these distances compared with 3m, and I felt that they underestimated or overestimated the crown and neighborhood if individual trees, limiting the accuracy of this approach for more mature trees. It might have been worthwhile to explore using smaller neighborhood sizes with less mature stands (i.e. April and July 2010 imagery) as the vegetation was much smaller, but this study was looking at limiting the variables in the methodology for widespread use.
Only attempt to classify the NAIP image, and not incorporate the additional bands from other color models and imagery analysis	This was done initially to see whether I needed to explore the creation of other bands in the model. Classifications were even less accurate and muddied that the classifications created from the composite band. Just visually looking at the classification created from only the NAIP image showed that the classification did not work.
Principal Component Analysis (PCA) instead of Composite Band	PCA allows the user to take a large set of data and distill it down to only data the is relevant and removes the redundant data. I attempted to combine the 9-bands this way, reducing it to 5 bands that contained 95% of the data. While it sped up analysis, there was no discernable difference in the results when compared with the Composite Band classifications, and ultimately, I felt that the additional data found in the Composite Band was more likely to work. Additionally, this additional data also showed us why this methodology did NOT work.
Unsupervised Classification	Using the Maximum Likelihood Classification required the use of signature files that were created from planting plans and aerial photographs and images, so work was conducted prior to classification. Unsupervised classification requires post processing to clean up the classification and combine classes. This was attempted and no clear approach to combining of classes was found that produced a clean result.