

APPLICATION OF UNMANNED AUTONOMOUS VEHICLE SYSTEMS:
MAPPING TAMARIX

by

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ABSTRACT

Tamarisk (*Tamarix ramosissima*), commonly known as saltcedar, is an invasive plant that has displaced numerous native riparian species in the southwestern US. Mapping *Tamarix* populations is essential for developing effective eradication programs. Innovative remote sensing technologies such as unmanned autonomous vehicles (UAV), can provide high spatial resolution imagery for assessing vegetative distributions. UAV are able to collect images at affordable rates, flexible schedules, and at no risk to the pilot; therefore, an economic comparison of UAV to satellite and piloted aircraft was assessed. Additionally, an assessment of the accuracy for identifying *Tamarix* using UAV remote sensing was evaluated. UAV imagery was obtained over 8.8 km² of riparian corridor at the Matador Wildlife Management Area to identify *Tamarix* distribution. An unsupervised classification method was utilized to assess spatial surface features by analyzing spectral characteristics. An accuracy assessment of the feature classes was performed to evaluate the overall classification accuracy of the imagery. The accuracy assessment concluded an overall Kappa statistic of 0.62, with a Kappa statistic of 0.21 for *Tamarix*. Therefore, the classification accuracy is found to be moderate ($0.40 > K < 0.79$) for surface features and poor ($K < 0.40$) for *Tamarix*. Low accuracy for *Tamarix* was attributed to use of only RGB imagery (i.e., no NIR) and the unsupervised classification application. The results of this study indicate that UAV-based remote sensing is able to produce high resolution images, moderately accurate in identifying surface features, and

cost-effective. Challenges and considerations for increasing *Tamarix* classification accuracy are addressed in future research recommendations.

CHAPTER I

Introduction

Background

Land cover contains immense environmental information, which is valuable for evaluating land use, determining abiotic and biotic relationships, managing resources, monitoring changes, and developing effective management policies. The need to collect information about and monitor land cover change arose as the need for environmental planning and management increased. In the past, land cover was primarily mapped using field-based surveys; however, this method can be very costly and time consuming. Using remotely sensed datasets and the spectral data collected by satellite and sub-orbital sensors have revolutionized land cover mapping at the local, regional, and global scales. To date, the suite of research and applications on remotely sensed datasets to map land cover comprises a variety of topics including monitoring wildlife habitat (Manier *et al.*, 2011), ecosystem productivity (Liu *et al.*, 1997), ecosystem services (Egoh *et al.*, 2008), hydrologic impacts (Nie *et al.*, 2011), and invasive species management (Kettenring *et al.*, 2011).

Common remote sensing platforms to map land cover include satellite (Cohen and Goward, 2004) and piloted aircraft (Giri, 2012). Choosing the aerial platform and sensor that is appropriate for a particular application is dependent on the type of information and the level of detail desired. If a high level of map classification detail is required, satellites can be used to obtain high spatial resolution imagery (0.6-4.0 m). However, this option can be costly (Klemas, 2011), particularly if repeat acquisitions are required to monitor land cover change over short temporal durations. Additionally, satellite availability can

be an issue if the sensor is not able to obtain imagery within a specific time relevant to vegetation phenology.

Using a piloted aircraft to collect imagery of an area is often a preferable approach for an application that requires a detailed classification of surface features, such as identifying specific plant species across a heterogeneous landscape. Piloted aircrafts provide increased flexibility in terms of scheduling for image acquisition than satellite platforms; however, they still pose challenges with regard to deployment, costs, and risk to human life (Rango *et al.*, 2009).

An emerging alternative to traditional satellite and piloted aircraft image acquisitions is the implementation of unmanned autonomous vehicle (UAV) systems. UAV systems consist of a manual or remote-controlled aerial platform that is capable of acquiring imagery of surroundings with an on-board camera (Jensen *et al.*, 2008). The applications of UAV systems vary considerably from recreational and military use to natural resource management.

In terms of land cover mapping, the timing of image acquisition can be crucial to obtain the necessary information for research. UAVs can be deployed more readily than piloted aircraft, especially since many systems do not require a runway for deployment. In terms of cost effectiveness, many UAVs use a rechargeable battery (Quaritsch *et al.*, 2011), which is a more affordable and sustainable option than piloted, fueled aircrafts. Additionally, due to the size and materials of a UAV, maintenance costs are significantly lower than for satellites or piloted aircrafts. Since high spatial, low spectral resolution satellite images are expensive (Klema, 2011), and piloted aircrafts possess inherent risk, high maintenance costs, and inflexibility, UAVs offer a platform that is effective,

affordable, safe and flexible for a variety of land cover mapping applications that require temporally-specific, high spatial resolution image datasets.

A specific land cover application that may benefit from UAV-based image acquisitions is the mapping and monitoring of invasive species. Invasive species generally distribute in a patchwork pattern throughout the landscape, thus a high resolution remote sensing system is ideal for detecting fragmented vegetation patches. One such invasive in Texas is Saltcedar (*Tamarix ramosissima*). *Tamarix* is native to southern Europe, eastern Asia and northern Africa. In the early 1800s, *Tamarix* was introduced into the U.S. to prevent soil erosion along riparian communities and as an ornamental plant.

Since then, *Tamarix* has spread to become a noxious weed in the U.S. due to its phreatophytic and halophytic nature, as well as undesirable food source for wildlife (North Dakota Department of Agriculture, 2012). One *Tamarix* plant can transpire over 757 liters of water per day, therefore, significantly reducing or depleting water flow along drainages (North Dakota Department of Agriculture, 2012). Native plants are unable to re-establish an area because of the increased salinity exuded from *Tamarix*'s leaves. *Tamarix* can spread by seed (one plant can produce up to 600,000 seeds annually) or vegetative re-growth from the root system. *Tamarix* is challenging and costly to control once established and requires early detection, prevention, monitoring and local eradication, thus monitoring *Tamarix* populations is essential for creating an effective management plan (North Dakota Department of Agriculture, 2012).

Mapping *Tamarix* to identify location and areas of infestation has become a high priority for natural resource researchers and managers (Evangelista *et al.*, 2009). The

ecological impact *Tamarix* has on native plant populations as well as hydrologic regimes is of major concern, thus verifying a need to map this species. Based on the phenological cycle of *Tamarix*, temporal resolution is important to ensure the data collected will consist of unique spectral signatures compared to other vegetation present on the landscape (Everitt *et al.*, 2006). To accurately map *Tamarix*, a high spatial resolution, multispectral, image acquisition during leaf senescence would be ideal. A UAV system would potentially provide the most efficient, affordable, and adequate method for obtaining such imagery.

Problem Statement

A specific area in Texas that has experienced negative consequences of *Tamarix* spread is the Matador Wildlife Management Area (MWMA). Within the MWMA, *Tamarix* has spread aggressively, specifically along riparian corridors by forming thickets (Charles and Dukes, 2007). Since the climate of the MWMA is a semi-arid savanna, water availability is limited and therefore threatened by phreatophytic *Tamarix*. The rapid growth rate and halophytic nature of *Tamarix* reduces habitat for other native riparian plants, such as *Populus deltoides* and *Salix spp.* (Nagler *et al.*, 2011).

The MWMA has a goal to develop a monitoring, management, and eradication plan for *Tamarix*; therefore, a highly detailed vegetation map would be a useful operational dataset for the plan. A map identifying *Tamarix* would serve as a guide to those implementing targeted eradication efforts within the MWMA.

Research Objectives

The overall goals of this research are to produce an UAV image-derived vegetation map of a riparian corridor along the Pease River at the MWMA and assess the cost-effectiveness of implementing the UAV system. To achieve these goals, the following research objectives are listed below.

- 1) Obtain and process UAV-based imagery;
- 2) Classify imagery to map *Tamarix* presence;
- 3) Assess accuracy of classification; and
- 4) Evaluate and compare costs of UAV, satellite, and piloted aircrafts.

Objective 1 addresses obtaining UAV imagery and associated image processing. Objective 2 involves the classification of the imagery produced from Objective 1 in order to identify vegetation, specifically *Tamarix*. Objective 3 consists of an accuracy assessment of the classified imagery compared to *in situ* observations. Objective 4 calculates and compares the costs of UAV, satellite, and piloted aircraft platforms for obtaining remotely sensed data.

Justification

UAV-based remote sensing provides flexible scheduling to correspond with plant phenology, results in ultra-high spatial resolution, and the onboard sensor is able to provide sufficient spectral resolution to map vegetation at the species level. Producing an accurate map of *Tamarix* location, presence, and abundance at the MWMA will be useful information for future monitoring and eradication efforts by MWMA managers.

CHAPTER II

Literature Review

Overview of Remote Sensing for Land Cover Classification

Remote sensing takes the saying “a picture is worth a thousand words” to new heights. Remote sensing is an interdisciplinary science that consists of the use of a sensor platform (e.g., satellite, piloted aircraft, or UAV) that collects information of the target resource from a remote distance. Remote sensing technology has been developing since the 1800s when the infrared and visible wavelengths were discovered (Campbell, 2002). Photography was developed around 1840 (Friedman and Ross, 2003) and the first aerial images were taken from a hot air balloon in the 1850s (Campbell, 2002). By the early 1900s, applications using knowledge of wavelength-specific electromagnetic radiation (EMR) were developed and aerial images were being taken from kites and other aerial platforms. In 1908, Wilbur Wright flew the first aircraft to take a photograph (Geist, 2006). From that point, technology rapidly progressed. Digital image processing resulted in sensor advancements in approximately 1980, including hyperspectral sensor development. Around this same time, new generation satellites were launched into orbit (Campbell, 2005). Finally, the miniaturization of remote sensing systems (platforms and sensors) led to some of the first uses of UAV image acquisitions around 1980 (Eisenbeiss, 2004).

Passive remote sensing systems collect spectral information by recording the quantity of EMR emitted by the sun that is reflected within defined wavelength intervals (e.g., blue [450-515 nm], green [525-605 nm], red [640-690 nm], or near-infrared [750-1,300 nm]; Jensen, 2005) of the electromagnetic spectrum. Each wavelength of EMR has

a relatively unique interaction with different surface features, and so remotely sensed data can be used to identify various surface features, and vegetation in particular. Mapping land cover is essential for resource management (Friedl *et al.*, 2010) as land cover data (derived from imagery) provide useful information about the environment on local and global scales, which is important for sustainable land management, water quality and quantity, as well as ecosystem health.

Advantages of UAV Remote Sensing for Natural Resource Management

UAV popularity for natural resource management has been rising due to a reduction in sensor size, greater availability, as well as faster and low-altitude deployment. There are a variety of emerging applications of UAV remote sensing for natural resource management and ecological research. Remote sensing via UAV is a sound approach for obtaining information at low-altitudes, particularly for plant community distributions. Booth *et al.*, (2003) concluded that UAV systems are effective economically, scientifically, and provide increased efficiency. Since ground-based monitoring of landscapes is time consuming and resource intensive, remote sensing can be an alternative solution to accurately assess an ecological state or change. According to Kettenring *et al.* (2011), UAV remote sensing for acquiring high-spatial resolution imagery can offer valuable information as to the rate of invasion and location of invasive (wetland) species.

The advantages of UAV over using piloted aircrafts for remote sensing and rangeland monitoring include: improved safety, low cost, more flexible flight plans, and closer proximity to target (Hardin and Hardin, 2010). Five centimeters (cm) UAV sensor image resolution may be used to measure gap and patch size of canopy type, and

vegetation ground cover as well as bare soil (Rango *et al.*, 2006). Less than one cm image resolution may be used for ground truth or reference data (Rango *et al.*, 2006). UAV image acquisition is an effective means of obtaining remotely sensed data for repeatable studies, such as data that are obtained for the same site on different days at the same relative time (Laliberte *et al.*, 2010). Lightweight UAV have the potential to be used by rangeland consultants, resource management agencies, and private land managers in order to acquire affordable data for making resource management assessments (Rango *et al.*, 2006).

UAV based remote sensing platforms have been used not only to inventory natural resources, such as agriculture, vegetation, hydrology, but also to map natural disasters. Digital imagery obtained from a UAV sensor has been found to be accurate for producing a Digital Terrain Model from the imagery, which is useful for systems managing natural disasters (Udin *et al.*, 2012). Mapping floods, for instance, can be dangerous and challenging if performed through ground surveying and costs associated with satellite and piloted aircraft remote sensing for mapping floods may be too expensive. UAV based remote sensing systems offer an affordable, flexible means for acquiring flood map data that can be useful for determining pay compensation of an area that has been flooded (Lee *et al.*, 2013).

Utilizing UAV systems to monitor controlled or wild fires poses an important developing application for natural resource management. UAV based remote sensing systems are feasible for monitoring forest fires because of the close proximity to the ground (compared to satellites) and the flexibility of deployment (compared to piloted aircrafts). Using UAV based systems can assist fire-fighting operations in monitoring

fires from safe locations and developing plans for controlling fires as well as develop routes of evacuation (Merino *et al.*, 2011).

Remote Sensing Considerations to Identify *Tamarix*

Remote sensing has been employed for decades to map and monitor invasive plant species such as *Tamarix* (Everitt *et al.*, 2006). The characteristics of *Tamarix*'s spectral reflectance have been described in various studies to identify riparian infestations using normal color aerial photography (Everitt *et al.*, 2006). The timing of remote sensing *Tamarix* is crucial to accurately identify and classify the plant among other plant species. During leaf-out season in mid-April, *Tamarix* reflects a similar spectral response as plants such as mesquite (*Prosopis spp.*). *Tamarix* begins the defoliation process in early fall and total litter fall occurs by late December, therefore, to collect data that distinguish *Tamarix* from other vegetation depends on the season of the year (Yang *et al.*, 2013).

The phenological cycle of plants influences spectral characteristics depending on the phase of the cycle due to changes in pigment production. If the images are taken during a phase of the phenological cycle when the plant of interest is exhibiting unique spectral characteristics to that of other plants within the study area, then a single-date image may suffice for identifying that particular species. The phenological cycle of individual plants is affected by genetic and environmental factors (e.g., weather, climate, temperature, and nutrient availability). Members of the same species may vary individually in their development through the phenological cycle, which may necessitate multi-temporal imagery (Koch *et al.*, 2007).

The timing of image acquisition is critical for providing useful imagery that can be used to map specific vegetation species. In an effort to predict optimal timing for

acquiring imagery to classify vegetation, a time-series of conventional color satellite images have been utilized in previous research. Research has concluded that fall is the ideal time in Texas for identifying *Tamarix* based on the unique spectral response produced by the yellow-orange leaves prior to defoliation. Satellite images were acquired in the lower Arkansas River in Colorado for six months of the year (April – October). The images were classified to identify *Tamarix* and other vegetation. September and October were found to produce the most specific and accurate classification for *Tamarix* (Evangelista *et al.*, 2009). Thus, single-date imagery should be obtained between September and October in Texas in order to maximize *Tamarix* detectability.

Utilizing single-date imagery may not be sufficient in addressing all research objectives; therefore, multi-temporal imagery is often necessary. In a study performed by Everitt *et al.* (2007), multi-temporal imagery was acquired in order to assess the biological control of *Tamarix*. The *Tamarix* population was exposed to the leaf beetle (*Diorhabda elongata*) on various occasions in 2004 and aerial images were acquired using a piloted aircraft on three separate dates: August and September, 2005 and August 2006. A supervised classification was performed on all three images to classify the surface features (i.e., vegetation type). The overall accuracy of the classification was 95%, which indicates that sensors on aerial vehicles are an accurate system for collecting vegetative composition data. Multi-temporal remotely sensed data were also found to be useful for assessing and monitoring the effect *D. elongata* had on *Tamarix* (Everitt *et al.*, 2007). Further, in another study, Evangelista *et al.*, (2009), successfully used time series Landsat 7 ETM+ satellite data with the Maxent model to map *Tamarix* in Colorado.

UAV-specific Research to Map Plant Species

High spatial resolution remotely sensed data are valuable in detecting invasive species throughout a landscape (Ge *et al.*, 2005). Invasive species generally distribute in a patchwork pattern throughout the landscape, thus a high resolution remote sensing system, such as an UAV with a high resolution sensor, is ideal for collecting spatial data (Ge *et al.*, 2005). An aerial image can be accurately classified to identify vegetation types and detecting changes over time, both of which are vital for monitoring ecological changes and invasive species progression (Kettenring *et al.*, 2011).

The high-spatial resolution of UAV based remote sensing systems (sensor with high-spatial resolution capabilities) is useful for accurately locating or mapping invasive plant species (Kettenring *et al.*, 2011). In a study conducted at Bear River Migratory Bird Refuge in Utah, a UAV based sensor system was deployed to geographically and spectrally analyze 130 km² for *Phragmites australis* expansion. The images acquired consisted of RGB and NIR spectral wavelengths with a spatial resolution of 25 cm. The images were classified to identify the vegetation using a multi-class relevance vector machine. The overall classification was 95% accurate. These results indicate that UAV remote sensing systems can provide accurate results for mapping vegetation in general and specific plant species, such as invasives.

Invasive, non-native plant species are challenging for natural resource managers to monitor. However, high spatial resolution images, such as those acquired by UAV systems, can provide a viable source of information to classifying vegetation and detecting change over time. Previous research has determined the spectral, spatial, and temporal (e.g., single-date or multi-temporal) factors influencing data acquisition. Sensor

capabilities vary among UAV platforms, therefore, determining the resolution needs to address research objectives and identifying the appropriate sensor and UAV platform is essential. At this point, image classification of *Tamarix* has been successful using satellite and aerial imagery, however, the use of image data from UAV systems for classifying *Tamarix* have not been explored.

CHAPTER III

Data and Methodology

Study Area

The MWMA includes 114 km² and is located in the Rolling Plains (Figure 1). The Texas Parks and Wildlife Department (TPWD) purchased the MWMA in 1959 to research and manage the wildlife as well as allow public use of the land. Hunting, fishing, bird watching, hiking, camping and nature study are some of the public use activities that draw tourists to this area.

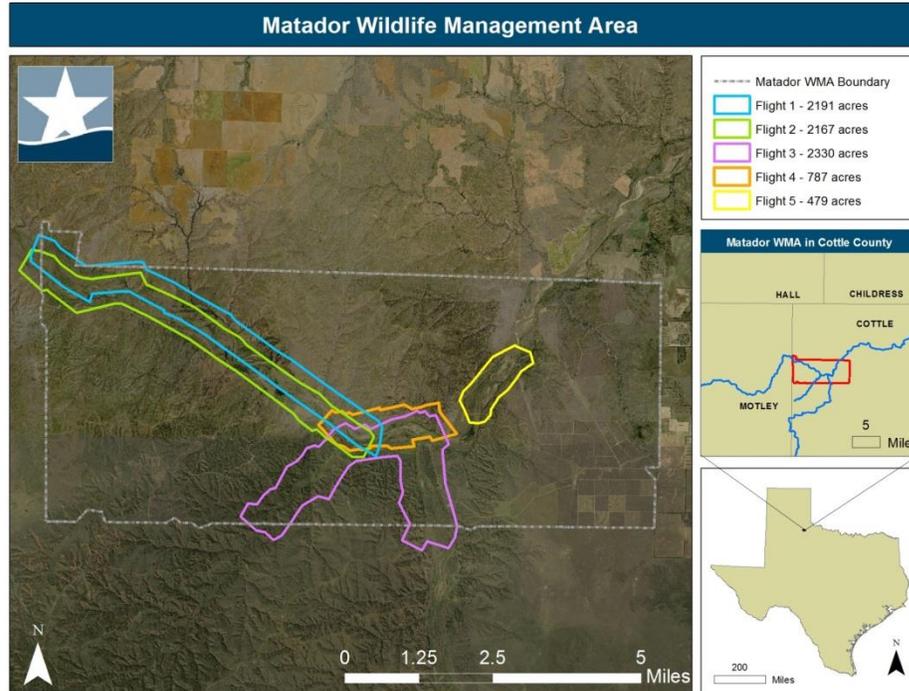


Figure 1. Matador Wildlife Management and UAV flight paths.
(Map Courtesy of Kristina Tolman, 2013)

This area of the Rolling Plains consists of mesas, red hued canyons and badlands where most of the region is semiarid rangeland and sub-humid grassland. The natural vegetative composition includes escarpment bluffs with juniper-scrub oak-midgrass

savanna (Griffith *et al.*, 2007). The landscape is dominated by shinnery oak (*Quercus havardii*) rangeland and mesquite uplands with gravelly hills accompanied by a mesquite mix and red berry juniper (*Juniperus pinchotii*; Texas Parks and Wildlife Department, 2012). Native plant species, such as, sand sagebrush (*Artemisia filifolia*), willow (*Salix* spp.), and cottonwood (*Populus* spp.) are being displaced by invasive *Tamarix* (Griffith *et al.*, 2007).

Geospatial Data Collection

Imagery was acquired for the MWMA in the Fall of 2012 using an AggieAir UAV platform (Figure 2). Refer to Table 3 for a summary of the individual flight dates and parameters. Images were acquired during October in order to capture *Tamarix* during senescence while the plants exhibited unique spectral characteristics relative to the other plants on the landscape.

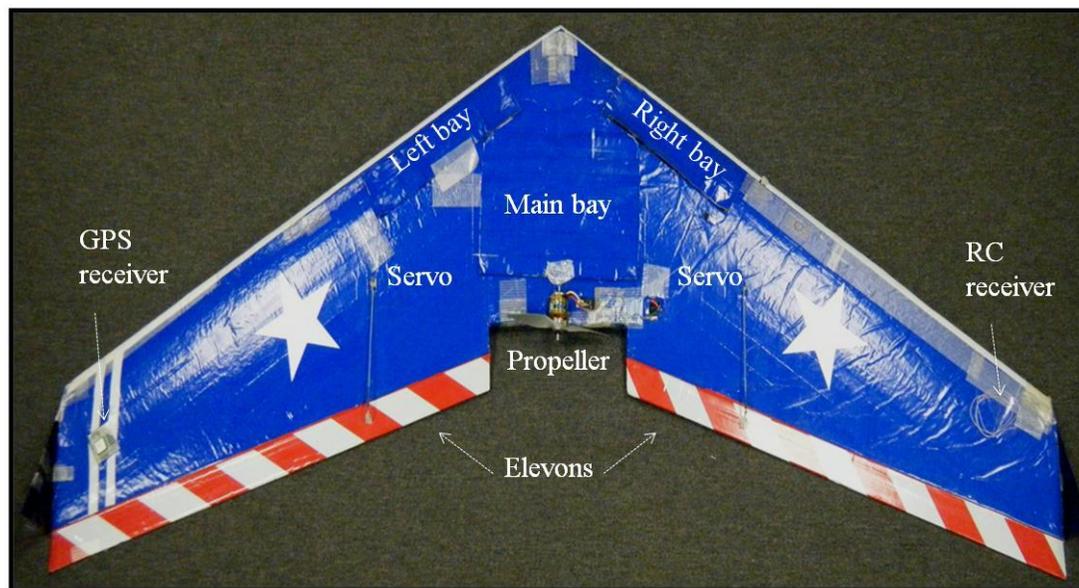


Figure 2. External view of the AggieAir Unmanned Autonomous Vehicle. (Photo courtesy of the Meadows Center for Water and the Environment, 2012)

The AggieAir UAV is a fixed wing aircraft composed of Styrofoam, which houses an onboard computer and remote sensor system. The onboard computer system (Figure 3) or bay contains the sensors: two digital Canon cameras. One of the Canon cameras measures spectral wavelengths between 400 – 700 nm (RGB wavelength intervals) and the other camera measures spectral wavelengths between 700 – 1,300 nm (NIR wavelength intervals).

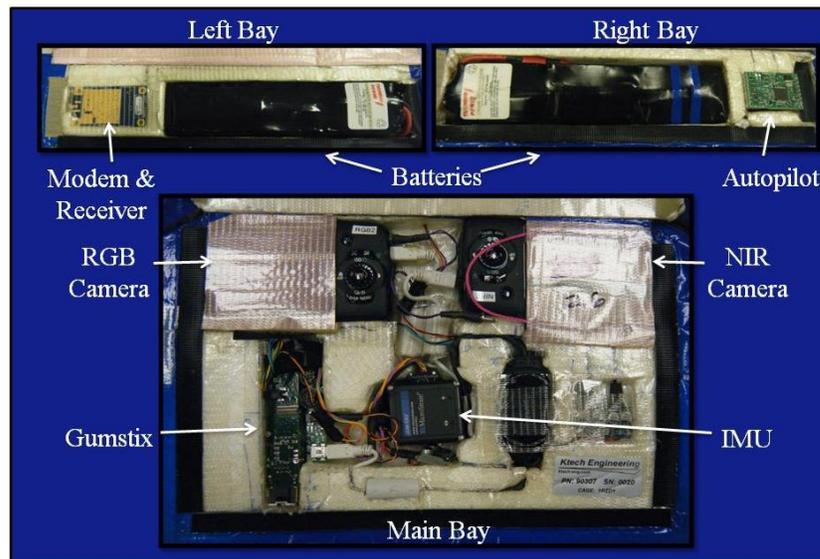


Figure 3. Internal view of the AggieAir Unmanned Autonomous Vehicle's components. (Photo courtesy of the Meadows Center for Water and the Environment, 2012)

The flight plans were configured using Google Pro (refer to Figure 1 for flight locations). Paparazzi software (Brisset *et al.*, 2006) was used to collect the real-time data of the UAV and the imagery data. The MWMA flight plan consisted of five flight paths over a riparian community along the Middle Pease River to map the distribution of *Tamarix*. Even though five flight paths acquired imagery, only flight path two was used in this study.

***In Situ* Data Collection**

In situ data were collected in February of 2013. Numerous variables were measured in a random sampling manner to collect *in situ* data at GPS locations. The variables recorded at each *in situ* data location included: surface feature type (i.e., bare ground or vegetation), plant species (if applicable), tree height (if applicable), diameter at breast height (DBH; if applicable), photo of GPS point/surface feature, 360° videos made at approximately 50 locations, and any additional comments. Photos and videos of the *in situ* data locations were created to provide reference data for the classification and accuracy assessment process. Additionally, each *in situ* data location was georeferenced using a Trimble GeoXH GeoExplorer 2008 series Global Positioning System receiver. Other landscape features were recorded and measured, such as: forbs, shrubs, rock/soil, and roads. A total of 88 *in situ* data locations were recorded for flight path two (Figure 4).

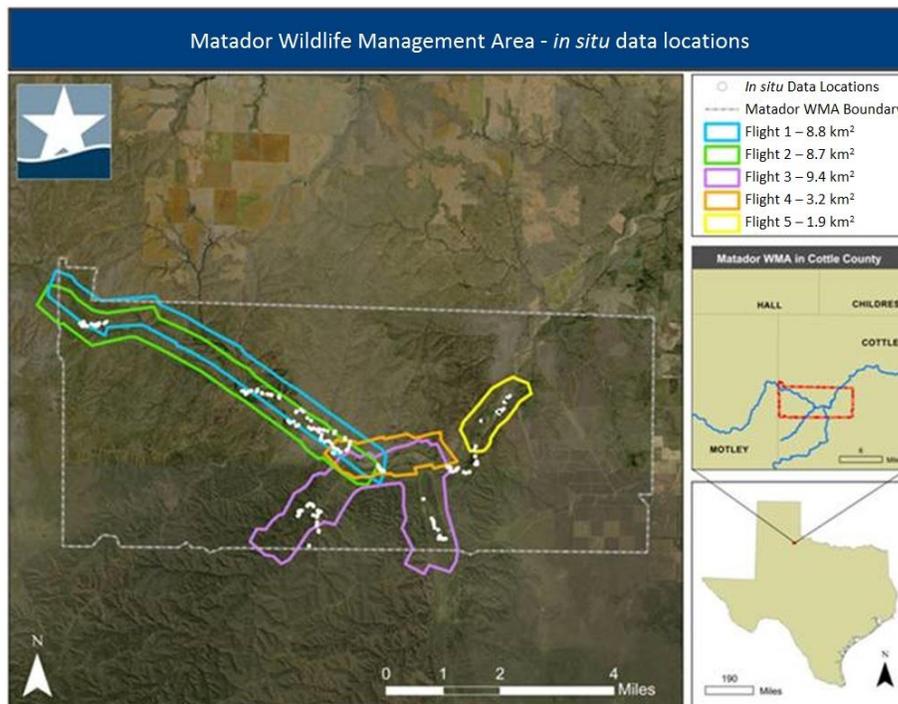


Figure 4. Matador Wildlife Management Area *in situ* data flight paths 1-5. (Map created by Kristina Tolman, 2012)

The *in situ* data were collected in order to assist the analyst in the classification process as well as the validation of the accuracy assessment. There were a variety of surface features and vegetative species collected for the *in situ* data locations in order to best represent the heterogeneous landscape. This data were valuable as a visual reference for the analyst to determine which pixels represented which surface features on the ground.

Geospatial Data Processing

The individual flight paths resulted in a series of images that needed to be mosaicked to a single image for classification. EnsoMOSAIC, a proprietary mosaicking program from Finland developed by MosaicMill, was used to perform this task. Files required for processing are the: raw imagery, camera calibration, GPS file, and ground control points that are typically extracted from reference imagery. EnsoMOSAIC performs a series of alternating steps that shift between assigning tie points to link images and converging tie points to reduce error (Figure 5). The initial automatic aerial triangulation (AAT) generates tie points for every image based on overlapping features. After the initial AAT, the bundle block adjustment (BBA) converges tie points and checks the image orientation. This process is repeated until the final BBA. Coordinate locations are selected based on features found within reference NAIP imagery from TNRIS, Google Earth, as well as the UAV imagery. Additional BBA iterations are often needed to adjust points and reduce the level of error. Upon completion, a digital elevation model (DEM) is created and used as an input for the mosaicked image. The final spatial resolution of the mosaic is based on the altitude the UAV was flown. All

aerial orthorectified images were projected and assigned the WGS 1984 UTM Zone 14N coordinate system.

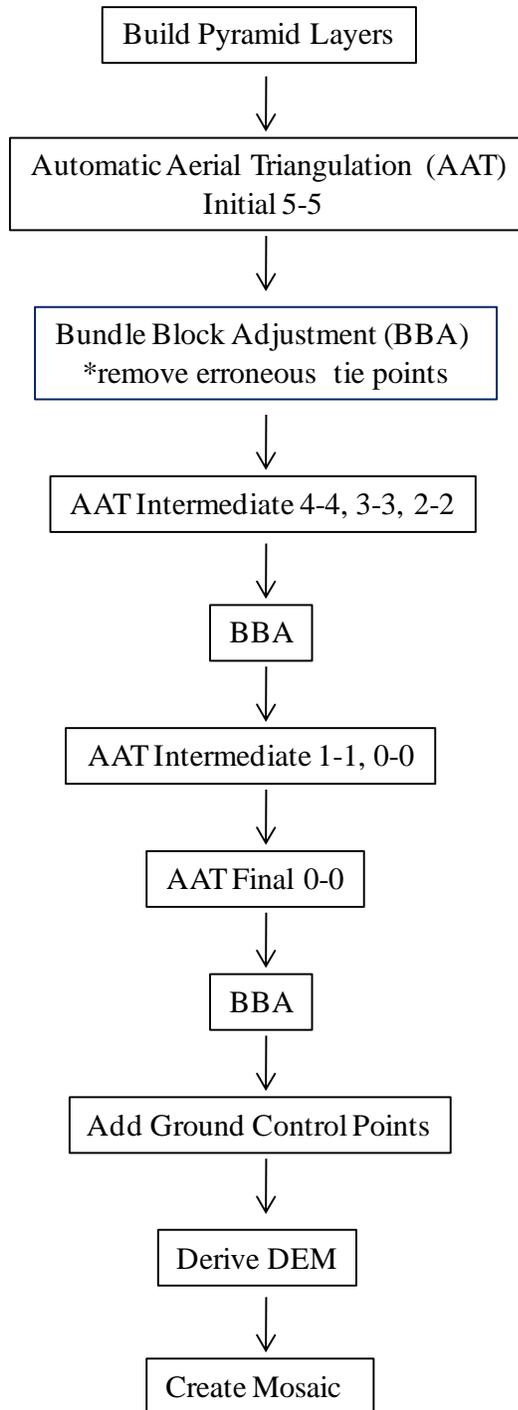


Figure 5. Organizational flow chart for the processes involved for generating mosaics with EnsoMOSAIC software. (Developed by Kristina Tolman, 2013)

Statistical/Analysis Procedures

Data Classification

The RGB and NIR mosaicked imagery did not line-up with one another for flight path two, which caused surface features between the RGB and NIR to not overlap correctly and result in a blurred image; therefore, only the RGB imagery was used in this study. Prior to classification, water features were removed from the image by digitizing a shapefile of water features in ArcGIS and using it as a mask to exclude water bodies (Figure 6). It was necessary to remove water features because *Tamarix* was exhibiting similar spectral signatures to that of water, which was confusing the unsupervised classification algorithm and thus the resultant output. Classifying the water features was not needed, since identifying water features was not an objective of this research.

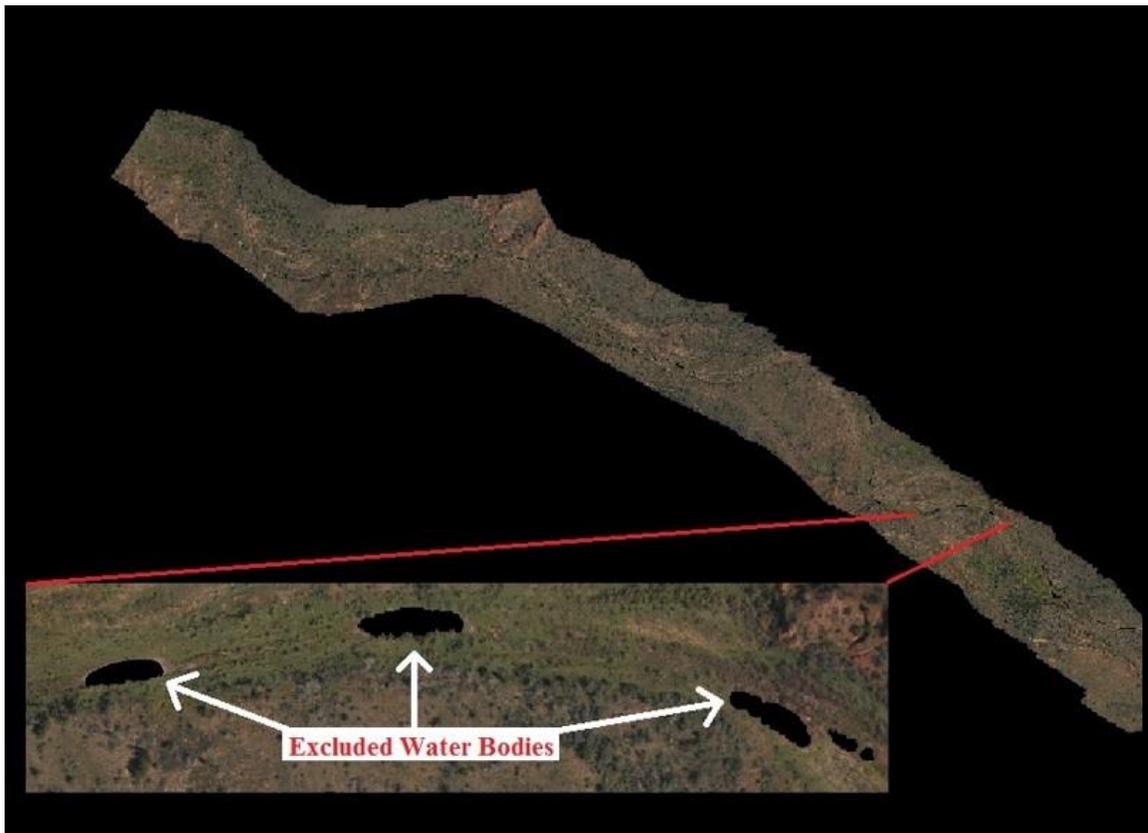


Figure 6. Blue, green red image with water bodies excluded.

Several external variables influence vegetation spectral response such as sun angle, atmospheric constituents, and the attitude of the UAV during flight. Significant spectral variation was observed in adjacent mosaicked images in flight path two (Figure 7). The two adjacent mosaicked images displayed in the inset map in Figure 7, exhibit a divisional line circled in yellow. This line is created because the mosaicked image on the left has slightly different (darker) radiometric characteristics than the image on the right (lighter). This variation between the adjacent mosaicked images was most likely due to clouds blocking direct sun exposure to surface features, sun intensity (time of day) at the time each image was obtained, or the direction of the aircraft during image acquisition leading to one of the images having direct sun exposure (image to the left) to that of the adjacent one (image to the right).



Figure 7. Blue, green red mosaicked image variation.

To mitigate illumination issues and varying image brightness along the flight path, the RGB image with the masked water bodies was subset in ERDAS Imagine into radiometrically-similar sections (i.e., separate sections of the image mosaic that did not exhibit brightness variation due to external factors). The clipped sections were determined by optical evaluation of the spectral consistency within the image. A total of three subset images (clipped sections) were created for the classification process (Figure 8). In Figure 8, the subset images were overlaid on the original RGB imagery.

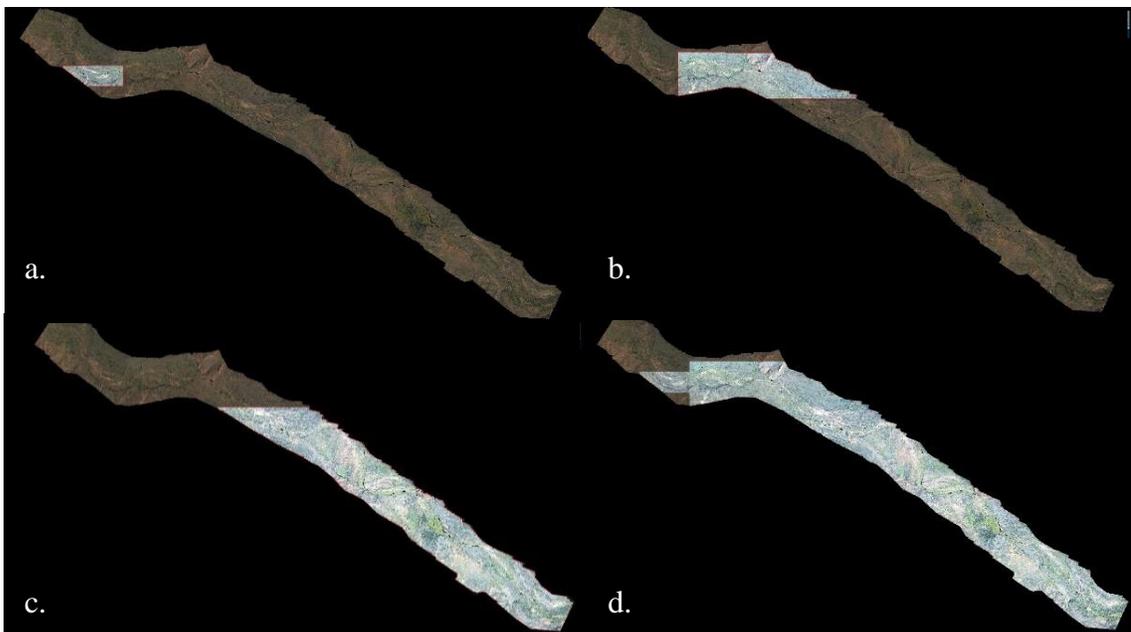


Figure 8. Blue, green, red subset images. a) Subset 1. b) Subset 2. c) Subset 3. d) Combination of subsets used for classification.

Once the entire image was clipped into spectrally similar sections, each section was then classified in ERDAS Imagine using the Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA). ISODATA is an unsupervised classification process for identifying land cover features, whereby the computer system identifies clusters of pixels with analogous spectral characteristics. Pixels with similar spectral characteristics

are assigned to a class based on modified k-means clustering, which is constructed using pixel vector characteristics and their proximity in multispectral space.

ISODATA is an iterative process and therefore passes through the entire remote sensing dataset repeatedly until the specified results are achieved. The first pass through the data is analyzed; however, ISODATA does not assign the initial mean vectors, instead, there is an initial arbitrary assignment of clusters throughout the n -dimensional vectors that run along certain feature space points. The feature space region of a cluster is defined using the values of the criteria below. Once the first iteration of comparing each candidate pixel to each cluster mean and assigning pixels to a cluster with a mean closest in Euclidean Distance (distance between two points) is complete, the second to M th iterations are calculated. During the second to M th iterations, a new mean is calculated for each cluster based on the exact spectral position of pixels that are assigned to the respective cluster. This process repeats the comparison of each candidate pixel with new cluster means and assigns them to the closest cluster mean. This method may be more thorough than a supervised classification method since every pixel is analyzed and designated to a spectrally-similar cluster.

ISODATA parameters to classify the three image subsets are as follows (Table 1). The clustering options were set to “Initialize from Statistics” and 30 clusters were specified to differentiate between distinct surface features while also allowing for spectral variability within the same land cover type. The maximum iterations were set to 50 for the maximum number of times the ISODATA algorithm re-clusters the data. The maximum standard deviation was set to 5.0. The Convergence Threshold was set to 0.95 in order to specify that 95% or more of the pixels do not change clusters between

iterations. ISODATA stopped processing when the 50th iteration was reached. The output clusters of the unsupervised classification were evaluated by referring to the *in situ* data to determine which surface features the pixel groupings represented: Bare ground, Vegetation, Shadows/Null, Tamarix, or Tamarix Mix. The “Vegetation” class contains all vegetation except for Tamarix. The “Tamarix Mix” class includes Tamarix and other vegetation pixels. Due to the morphology of *Tamarix*, pixels near, under, and around the plant contribute to the spectral response contained in the pixel, thus the "Tamarix Mix" class was included to account for the variation.

Table 1. ISODATA criteria and values.

ISODATA Criteria	Value
number of classes	30
convergence threshold	0.95
maximum iterations	50
minimum percentage of members in a cluster	0.01
maximum standard deviation	5.0
maximum merges	1.0
minimum distance between cluster means	4.0

Accuracy Assessment

To evaluate the classification output of land cover data for the MWMA imagery, an accuracy assessment was performed to determine how well the classified map corresponded to field-based observations. The *in situ* data were used in the accuracy assessment as a visual reference for whether the classes in the unsupervised classification output were correct or not. The *in situ* data were not collected prior to the production of the validation stratified random sampling of the accuracy assessment, therefore, the *in situ* data were used as a visual reference instead of coinciding reference points in validation of the accuracy assessment.

A validation sample size, or number of observations required for the accuracy assessment, was based on a binomial probability with an expected accuracy of 80% and allowable error of 5%.

Equation 1:

$$N = \frac{z^2 (p) (q)}{E^2} = 256$$

where: $z = 2$, which denotes a confidence level of 95%; $p =$ expected accuracy or 0.80; $q = 1.0 - p$; and $E =$ allowable error or 0.05. The 256 validation points obtained from Equation 1 were distributed throughout the original imagery using a stratified random sampling technique with no minimum points per class. The *in situ* data were then referenced to determine what each validation point represented on the ground. The validation points and *in situ* data locations did not have the same GPS location; therefore, the *in situ* data were used as a visual reference for validation of the classification.

Overall classification accuracy, as well as producer and user accuracies for individual classes were calculated. The error matrix was produced by the accuracy assessment tool. Overall accuracy was determined by dividing the total number of correctly classified pixels by the total number of pixels used for the accuracy assessment (Table 2). In addition, the Kappa Coefficient of Agreement (K) was calculated as well. Producer accuracy, a measure of how well the area is classified, was calculated by dividing the total number of correct pixels in a category by the class column total. User accuracy, a measure of the reliability of the classified pixel on the map representing that category on the ground, was calculated by dividing the total number of correct pixels in a category divided by the row total for that class.

Table 2. Example of an error matrix between two classes (A and B). (RS/GIS Laboratories, 2003)

	Reference Data		
Classified Data	A	B	Row Total:
A	9	2	11
B	3	7	10
Column Total:	12	9	21

Kappa analysis is considered a discrete multivariate statistical method used to quantify categorical class agreement and is considered robust because Kappa (K) accounts for agreement occurring by chance alone. K is calculated by measuring the accuracy or agreement among the reference data and the remotely sensed classification map (Equation 2). The measure of agreement is determined by the major diagonal and the chance agreement specified by column and row totals and their corresponding products. The equation for calculating K is as follows:

Equation 2:

$$K = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} \times x_{+i})}$$

where r represents the number of rows or land-cover classes in the matrix, N represents the total number of observations, x_{ii} represents the number of observations in column i and row i , and x_{+i} and x_{i+} represent the marginal totals for column i and row i . A Kappa statistic ranges from 0 – 1.0; < 0.40 (i.e., 40%) exhibits a poor agreement, 0.40-0.79 (i.e., 40-79%) signifies a moderate agreement, and > 0.80 (i.e., 80%) exhibits a strong agreement between the classification and reference data (Jensen, 2005).

Cost Comparison Analysis

The costs for AggieAir flight/image acquisition as well as image processing were calculated and compared to the calculated costs of satellite and piloted aircraft. The available pricing for satellite, piloted aircraft, and UAV platforms varies on the research objective as well as the platform and sensor capabilities. To account for the variation in remote sensing platform and sensor pricing, the AggieAir UAV prices were converted accordingly to the costs of comparison, such as comparing image acquisition among satellites and the AggieAir UAV. If the platform and sensor being compared to the AggieAir UAV included post-processing costs, then AggieAir UAV post-processing pricing was included within the comparisons.

CHAPTER IV

Results

Objective 1 - Obtain and Process UAV-based Imagery

A total of five flight paths were flown at the MWMA in October 2012 (Figure 1), resulting in a total of 1,448 images. The raw images had a spatial resolution of 18 cm (from October 2, 2012) and 12 cm (from October 5, 2012; Table 3). After mosaicking the images together, the resulting images had a spatial resolution of 21 cm (from October 2, 2012) and 20 cm (from October 5, 2012; Table 3). Due to variation of altitude from wind turbulence, the mosaic resolution is lower than the raw imagery. During flight, the wind influences the attitude of the plane; therefore, the resolution of the final mosaic is restricted to the lowest resolution of the imagery obtained. Thus, if the raw images have an approximate resolution of 18cm, then the final mosaic may be set to 20cm to account for variation during image acquisition. In order to address research objectives 2 and 3, only flight path two was used (Figure 9).

Table 3. Matador Wildlife Management Area flight information.

Flight Dates	Altitude (m)	Resolution (cm)	Mosaic Resolution (cm)	Time of Day Flown	Number of Images Acquired
October 2, 2012	650	18.0	21.0	9:30 am – 3:15 pm	1276
October 5, 2012	450	12.0	20.0	9:30 am – 10:00 am	172



Figure 9. True color image mosaic for flight path two along the Pease River in the Matador Wildlife Management Area.

Flight path two was used to evaluate a protocol for classifying *Tamarix* via UAV derived remote sensing data since the altitude of the plane (dependent on weather conditions) produced high quality imagery; the flight path encompassed the largest area, and was representative of varying surface features throughout the MWMA landscape. Flight path two consisted of 8.8 km², with a length of 11 kilometers and a swath of 0.80 kilometers (Figure 9).

Objective 2 - Classify Imagery to Map *Tamarix*

An analysis of the spectral response of the feature classes was performed to determine how *Tamarix* spectral response differs from other surface features. The spectral profile indicated that the greatest variation in vegetation types was evident in the green band. However, *Tamarix* and water were spectrally similar in the green band. Therefore, all water bodies were masked from the image prior to classification (Figure 10).

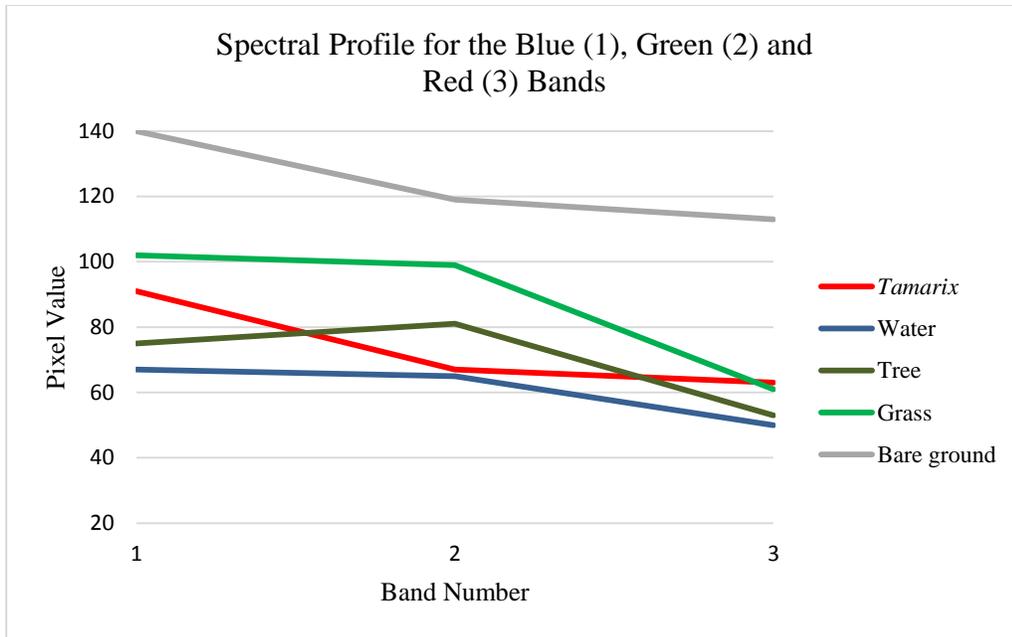


Figure 10. Spectral profiles of blue, green red bands for various surface features sampled in the Matador Wildlife Management Area.

Figure 11 provides an overview and inset graphic of the classified vegetation map for flight path two in the MWMA. Based on the classification results, 8.23% of the area was classified as Shadows/Null, 9.74% as Tamarix, 15.82% as Tamarix Mix, 59.07% as Vegetation, and 7.14% as Bare ground. These results do not allow the separation of the Tamarix Mix class into Tamarix and other vegetation in order to determine the total percent area of Tamarix and other vegetation. Considering the Tamarix Mix class includes Tamarix as well as other vegetation, the amount of Tamarix within flight path two is most likely higher than 9.74%.



Figure 11. Final classification output from UAV-derived true color imagery.

Objective 3 - Accuracy Assessment of Classified Imagery

Three separate accuracy assessments were performed, one for each subset unsupervised classification output (Table 4 and Appendix A). Overall classification accuracy for classified images one, two, and three were 79%, 79%, and 82 percent, respectively (Table 4). The overall Kappa Statistic (K) was 0.62 (Table 4), which indicates poor agreement between the classification and the true surface features ($0.80 > K < 0.40$).

Table 4. Accuracy assessment results.

Subset Image	Overall Accuracy (%)	Overall Kappa Statistic
1	79.3	0.67
2	78.9	0.55
3	82.0	0.64
Average:	80.1	0.62

Individual class accuracies were also calculated. The producer's accuracy measures how well an area has been classified by determining which pixels are not assigned to the class they belong. The Vegetation class exhibited the highest producer's accuracy of 89% (Table 5), followed by Shadow/Null (84%), Bare ground (81%), Tamarix (50%), and Tamarix Mix (41%). The Tamarix Mix class had the greatest number of pixels that were not assigned to the class they belong (i.e., an error of omission). The low producer's accuracy for Tamarix Mix is mostly attributable to the fact that the Tamarix Mix class did contain some vegetation pixels that were not a Tamarix Mix pixel and were therefore referenced as "Vegetation" during the accuracy assessment, instead of Tamarix Mix.

The user's accuracy measures how well the map represents the surface features by determining which pixels are assigned to the wrong class (i.e., an error of commission). The Bare ground class exhibited the highest user's accuracy of 90%, which is interpreted as Bare ground being represented most accurately in the classification (Table 5). The second most accurately represented class is Vegetation (88%), followed by Shadow/Null (83%), Tamarix Mix (62%), and Tamarix (25%). The Tamarix class had the most pixels that were assigned to the wrong class. This may be attributed to the similarities of spectral characteristics found among Tamarix and other vegetation. Some dry grasses near bare ground (clay-iron rich soil with a prominent visible red wavelength reflectance) exhibited similar spectral characteristics to Tamarix and were therefore grouped with the Tamarix class during the unsupervised classification process.

Kappa statistic values for each class are reported in Table 5 as well. Two classes resulted in a strong agreement between the classification and the true surface feature ($K > 0.80$): Shadow/Null and Bare ground. Tamarix resulted in a poor agreement ($K < 0.40$).

Table 5. Class average producer and user accuracy for subset images 1-3.

Subset Image Number	Class	Average Kappa (k)	Producer Accuracy (%)	User Accuracy (%)
Subset 1	Shadow/Null	0.70	72.2	72.2
	Tamarix	0.50	82.8	55.8
	Tamarix Mix	0.74	51.9	79.4
	Vegetation	0.68	89.4	85.8
	Bare ground	0.92	80.0	92.3
Subset 2	Shadow/Null	0.94	85.7	94.7
	Tamarix	0.10	50.0	11.1
	Tamarix Mix	0.22	40.7	30.6
	Vegetation	0.63	84.1	90.3
	Bare ground	0.80	76.5	81.3
Subset 3	Shadow/Null	0.82	93.8	83.3
	Tamarix	0.04	16.7	6.7
	Tamarix Mix	0.73	29.4	76.9
	Vegetation	0.59	93.0	86.4
	Bare ground	0.96	86.2	96.2
All Subsets Combined and Averaged	Shadow/Null	0.82	83.9	83.4
	Tamarix	0.21	49.8	24.5
	Tamarix Mix	0.56	40.7	62.3
	Vegetation	0.63	88.8	87.5
	Bare ground	0.89	80.9	89.9

Objective 4 - Cost Comparison

The total AggieAir UAV costs for collecting and processing the imagery at the MWMA were determined by assessing the following factors:

UAV Flight Cost: \$120/hour

UAV Flight Crew Cost: \$30/hour/person

Post-flight Image Mosaicking: \$33/hour

Post-flight Image Classification: \$14/hour

The MWMA UAV image collection consisted of 2.5 hours of UAV flight, 40 hours for each person of the UAV flight crew (three people total), 80 hours for post-flight image mosaicking, and 160 hours for post-flight image classification. Therefore, the total cost for obtaining and processing the imagery at the MWMA is:

$$(120 \times 2.5) + (30 \times 40 \times 3) + (33 \times 80) + (14 \times 160) = \mathbf{\$8,780.00}$$

The cost for just obtaining the imagery is calculated as follows:

$$(120 \times 2.5) + (30 \times 40 \times 3) = \mathbf{\$3,900.00}$$

Even though only flight path two was used in this study, the UAV costs are for collecting imagery for flights 1-5. Therefore, all of the flight paths recorded at MWMA are included in the cost. To be able to compare the UAV among satellite and piloted aircraft, the cost was converted to USD/km². The total area recorded was 32.2 km² (7,954 acres; Table 6).

Table 6. Flight paths and total square kilometers recorded.

Flight	km²
1	8.9
2	8.8
3	9.4
4	3.2
5	1.9
Total:	32.2

Taking into account the total cost to obtain and post-process imagery from MWMA using the UAV and the total square kilometers, the total cost per square kilometer was calculated to be \$272.67/km²:

$$\frac{\$8,780.00}{32.2 \text{ km}^2} = \$272.67 / \text{km}^2$$

The total cost for acquiring imagery alone, minus the post-processing costs, relative to the km² was calculated to be \$121.19/km²:

$$\frac{\$3,900.00}{32.2 \text{ km}^2} = \$121.19 / \text{km}^2$$

In order to adequately compare pricing for image acquisition among varying platforms, the costs were converted to USD/km². Satellite and piloted aircraft pricing were compared to the AggieAir UAV platform (Table 7). There are substantial differences in the pricing among different platforms for acquiring aerial imagery due to the basic maintenance and operating expenses as well as sensor capabilities. The costs for acquiring imagery using satellite, piloted aircraft, and UAV range from \$0-383.39/km² (Porter *et al.*, 2006). The most affordable rate is using the satellite platform, Landsat TM, which is at no cost; however, the spatial resolution is the lowest (30 m) of all platforms presented in Table 7 (Porter *et al.*, 2006). Landsat is available at no cost for image acquisition because it is tax-payer subsidized (U.S. Geological Survey, 2014). The second most affordable platform is the IKONOS satellite, which costs \$30.00/km² and has a much higher spatial resolution (1-4 m) to that of Landsat TM (Table 7; Porter *et al.*, 2006). The costs for satellite acquired imagery are the most affordable rates, although, at the expense of spatial resolution. For research objectives that require a higher spatial resolution than 30 m or even 3.0 m, a piloted aircraft may be more appropriate than using a satellite platform.

Piloted aircraft present the most expensive costs for acquiring aerial imagery, although, they are capable of acquiring significantly higher spatial resolution than some satellite platforms. The high costs for piloted aircrafts is attributed to paying the pilot,

insurance, licensures, fuel, as well as costly maintenance and operational expenses. The most affordable piloted aircraft was found to be AISA (Table 7; Porter *et al.*, 2006), with a rate of \$175/km² and a spatial resolution of 2.3 m. The most expensive (\$383.39 km²) piloted aircraft is the CASI (Mumby *et al.*, 1999), which has the lowest spatial resolution (3.0 m; Table 7). The ADS40 has the highest spatial resolution of 0.3 m and is not the most expensive or affordable piloted aircraft platform (Table 7). A spatial resolution of 0.3 m provides significantly greater detail than a 2.0 m or lower spatial resolution. However, a higher spatial resolution than even the ADS40 piloted aircraft can be acquired using an UAV platform (as used in this study).

The AggieAir UAV platform and sensor used in this study was able to produce an ultra-high spatial resolution of 0.12 m and 0.18 m for the aerial images acquired (Table 3). This is the highest spatial resolution of all platforms and cost less than all of the piloted aircrafts that were reviewed (Table 7). Even though satellite acquired imagery is the most cost-effective, the spatial resolutions are considerably lower than the UAV platform and sensor. The Landsat TM platform is able to acquire imagery in the Mid-IR and thermal wavelengths, which would increase the cost since this technology is more expensive. The UAV costs \$121.19/km², which relative to the spatial resolution, appears to be the most affordable option for acquiring particularly high spatial resolution.

Table 7. Platform image acquisition pricing. (Porter *et al.*, 2006; U.S. Geological Survey, 2014; and Mumby *et al.*, 1999).

Platform	Spatial Resolution (m)	USD / km²	Bands/Channels
Satellite – IKONOS	1-4	30.00	RGB and NIR
Satellite – Landsat TM	30	0.00	RGB, NIR, Mid-IR, and Thermal
Piloted Aircraft - AISA	2.3	175.00	RGB and NIR
Piloted Aircraft – ADS40	0.3	330.00	RGB and NIR
Piloted Aircraft – CASI	3.0	383.39	RGB
AggieAir UAV	0.12-0.21	121.19	RGB and NIR
<p>*Satellite – IKONOS, Satellite – Landsat TM, Piloted Aircraft – AISA, Piloted Aircraft – ADS40 data provided by Porter <i>et al.</i>, 2006 and U.S. Geological Survey, 2014 * Piloted Aircraft – CASI data provided by Mumby <i>et al.</i>, 1999. *AggieAir UAV data provided by the MCWE, 2012.</p>			

CHAPTER V

Discussion

Challenges Associated with Acquiring and Processing UAV-based Imagery

Many aspects of UAV based remotely sensed image acquisition are important, such as considering sensor capabilities, when to fly and how often; however, it is highly contingent on weather as well as work accommodations (scheduling for all personnel). Wind is a variable that can influence the quality of the collected imagery. Due to the phenological cycle of *Tamarix*, the time of which to collect aerial imagery was limited to October. In order to obtain quality imagery given the time constraints for collecting data, the UAV was flown before and after solar noon for some of the image acquisition to avoid high winds; therefore, shadows resulted throughout the imagery. To avoid shadows in future research, the UAV should be flown near to solar noon. Although, when the UAV is flown near to solar noon, uncontrollable variables still may influence results of the remotely sensed data such as, cloud cover. A flight near solar noon on a sunny day versus an overcast day will result in varying spectral reflectance values.

Spectral characteristics of specific surface features can vary throughout an image due to differences in the solar radiance of which is influenced by cloud cover, the time of day the imagery was obtained, incidence angle of the wavelength, intensity, atmospheric composition, and polarization (MicroImages, 2012). Two potential avenues for resolving these issues include: Performing a radiometric correction of the image (discussed further on page 41); and acquiring multi-temporal imagery. Multi-temporal imagery may resolve issues of identifying surface features based on varying spectral characteristics. Additionally, members of a plant species in a population (i.e., plant species) may have

spectral variation due to physiological characteristics, such as plant height, pigment, and leaf water content. In this case, multi-temporal imagery may be necessary in order to account for spectral variations among one species (Civco *et al.*, 2008).

Leaf senescence is a temporal variable that can significantly increase the accuracy of classifying *Tamarix*. *Tamarix* was undergoing leaf senescence at the time the data were collected. Most of the *Tamarix* population's leaves had changed from green to yellow-orange, however, some plants had not changed yet, and some plants were only partially senesced (Figure 12). Therefore, *Tamarix* plants that had not changed yet were likely grouped into the general "vegetation" class in the classification. Using multi-temporal data would assist with correcting errors in classification due to variations in leaf senescence.

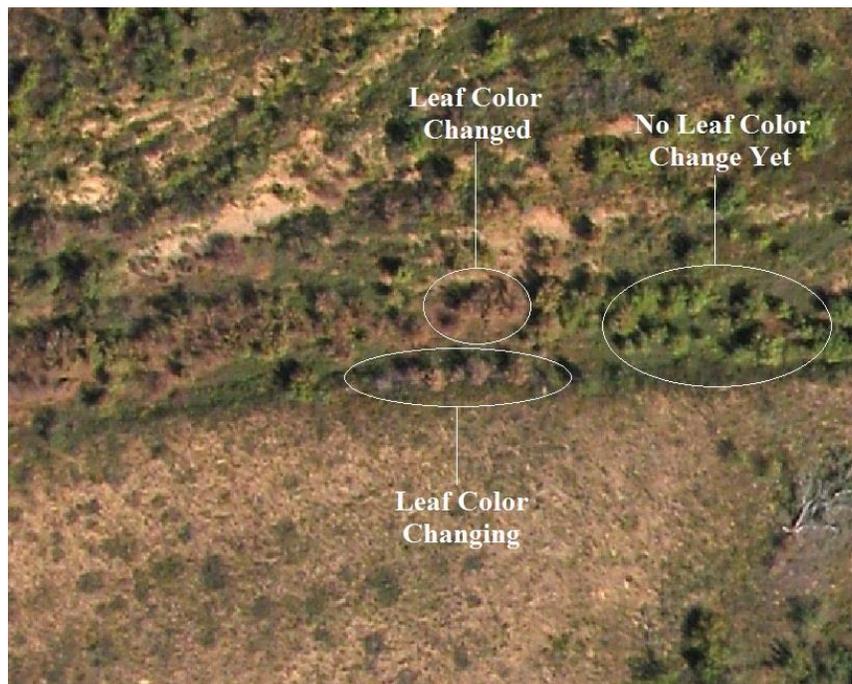


Figure 12. *Tamarix* leaf color variation.

The *in situ* data used in the classification and accuracy assessment validation process for this research were unable to be collected during the time the images were

obtained. Since the *in situ* data were collected during the winter when the plants were senesced, there may have been some discrepancies in the *in situ* data with live and dead plants. A dead plant would have been leafless during image acquisition, which may have lead those pixels to be inappropriately classified or validated incorrectly during the accuracy assessment. Collecting *in situ* data when the plants were senescing (at the time of image acquisition) would have provided information as to whether a plant was living or dead (based on whether leaves were present or not), thus allowing more accurate reference data for the classification and accuracy assessment validation than were collected in this study. Also, there may have been some discrepancies in the classification since the leaf coverage was not able to be recorded due to the time of the year the *in situ* data were collected (February). Leaf coverage would be useful reference data for the classification and accuracy assessment especially considering the significant variation among *Tamarix* senescence (Figure 12). Leaf coverage as well as leaf spectral signatures in other seasons (multi-temporal imagery) would be valuable in increasing the accuracy of mapping *Tamarix*. For future research, the *in situ* data would ideally be collected during the time the images were acquired.

The physiology of *Tamarix* with leaf-off allows for pixels near and around the plant in the imagery to “blend” with the pixels of *Tamarix* causing unique spectral characteristics of mixed *Tamarix* and bare ground as well as *Tamarix* and other vegetation. Obtaining multi-temporal data would be a solution to this issue, since the seasons with leaf-on would not allow as much vegetation near the plant to influence its spectral reflectance then the vegetation could be more accurately classified.

Image Classification and Accuracy Assessment Considerations

Since the RGB and NIR mosaicked imagery did not overlap properly, only the RGB imagery was used in this study which limited the accuracy of the classification. The amount of NIR reflectance from plant foliage is dependent on the anatomy, water, and nutrient content of the plant, which results in a unique spectral response among varying plant species and even the variation among members of the same species. The image classification of this study would have benefited from the use of NIR, specifically for identifying specific plant species such as *Tamarix*, thus resulting in a more accurate classification than what resulted from the sole use of RGB wavelengths.

The ISODATA algorithm did prove to be an accurate method for classifying certain surface features, however *Tamarix* was not accurately classified with this method. This algorithm analyzed every pixel within the image acquired for flight path two and grouped the pixels into spectrally similar classes. A supervised classification would have also been another potential classification method, which consists of the analyst creating training data for spectrally similar pixel groupings and every pixel being analyzed and grouped based on the assigned training data. Even though *Tamarix* was the only specific plant species that was identified, there is potential to identify other plant species. In order to classify additional plant species with an unsupervised classification method, a greater maximum iteration value should be set in order to increase the likeliness of reaching a 0.95 convergence threshold combined with more *in situ* data collection. Additionally, since the maximum iterations for ISODATA were set to 50 in this study, the convergence threshold of 0.95 may have never been achieved, which would lead to errors in pixel groupings and resulted in lower classification accuracy. There were many challenges

faced in the unsupervised classification process, which enabled the analyst to identify solutions to these problems for future research inquiries similar to this study.

To minimize confusion within the classification process for future research of this type, first evaluate the spectral profile of surface features that are to be classified. Evaluating the spectral profile is a quick tool for determining which classes may spectrally overlap and thus cause confusion within the classification. If the surface feature of interest is spectrally overlapping with another feature, perhaps consider removing or masking the feature that is overlapping the feature of interest.

Initial unsupervised classifications of flight path two exemplified the spectral variation of adjacent mosaicked images provided in Figure 11. Spectral variation is attributed to an assortment of factors: sun angle, sun intensity, atmospheric constituents, weather (i.e., cloud cover), attitude of aircraft, and flight line angle relative to time of day. During image acquisition for flight path two, the UAV flight path began collecting imagery in the Northwest portion of the flight path. The UAV flew southeast along the Pease River and then turned 180° at the bottom southeast portion of the flight path and continued northwest to the aircraft deployment location. The imagery acquired during the initial southwest route was captured before the return flight, thus each set of images were acquired at minimally different times. Even a minimal difference in the timing of image acquisition can lead to spectral inconsistency throughout the resultant mosaicked image due to sun angle, sun intensity, and cloud cover. The comparison among multi-temporal imagery of a given area would assist in accounting for spectral variations throughout mosaicked images.

Another method to account for atmospheric constituent interference and spectral variation throughout the mosaicked images is to perform a radiometric correction. A radiometric correction normalizes the spectral signatures in order to improve radiometric accuracies. This technique is useful when comparing images from different dates in order to normalize them for comparison to one another, primarily by accounting for differences in atmospheric constituents and varying sun/sensor angles. However, depending on the research objectives, this may not be an appropriate option. In order to normalize the spectral variation of adjacent mosaicked images in flight path two, a radiometric correction could have been used. Since using an UAV is an emerging approach to classify vegetation, a radiometric correction was not performed in order to evaluate the raw data and determine appropriate methodologies for this platform relative to these specific research objectives.

A total of 88 *in situ* data locations for flight path two were collected, although, more reference data were needed for visualization during the validation of the classification (accuracy assessment) of flight path two. In retrospect, at least 256 *in situ* data locations should have been collected for flight path two in order to correlate to the validation sample size of 256. Also, the *in situ* data were not collected at the same time the imagery was obtained which created challenges for the analyst in identifying surface features. The MWMA has experienced many wild fires as well as prescribed fires, so some trees were dead; however, the *in situ* data were collected in the winter when the trees were leaf-less, so it was difficult to tell during the *in situ* data collection which were living and dead.

For future research in monitoring the biocontrol of the saltcedar beetle, *in situ* data need to be collected for numerous plants that are infested with the beetle as well as plants with no beetle exposure. Also, multi-temporal imagery would assist with better monitoring the effects of the saltcedar beetle as opposed to single-date imagery.

The accuracy assessment results from this study suggest that the UAV platform and sensor as well as classification methods in this study produced a strong to moderately accurate method for obtaining natural resource data/imagery and associated land cover classification, despite the low classification accuracy for *Tamarix*. The overall classification accuracy of this UAV based remote sensing system is lower compared to other studies that have used piloted aircraft (Everitt *et al.*, 2007) or satellite (Evangelista *et al.*, 2009) platforms, which is most likely due to the differences in sensor capabilities, classification methods, and temporal resolution. A study found an 83% accuracy using a piloted aircraft as the platform and an ISODATA algorithm to identify *Tamarix* (Narumalani *et al.*, 2013). A study performed by Yang *et al.* (2013), performed multiple accuracy assessments of satellite images taken on different dates and found accuracies of 60-91% for identifying *Tamarix*. Perhaps, the poor accuracy value for the *Tamarix* is attributed to the conventional classification algorithms used in ERDAS Imagine as seen in Kettenring *et al.* (2011) or issues associated with sensor resolutions (spectral and spatial), temporal resolution, multiple subset imagery, varying sun angle, or image acquisition vs. *in situ* data collection of *Tamarix*.

The overall classification accuracy for this research using AggieAir UAV platform and Canon camera sensors did result in 80% accuracy, indicating that the sensors and classification method are an accurate method for mapping certain surface

features. The overall kappa statistic of 0.62 signifies that the accuracy assessment resulted in a moderate agreement of the classification among the true surface features. Moreover, the average kappa statistic for *Tamarix* resulted in 0.21, which is a poor agreement; therefore, *Tamarix* was not accurately identified with the methods used in this research. The sensor capabilities, *in situ* data collection, classification methods, and single-date image acquisition are the major factors that most likely contributed to the low classification accuracy of *Tamarix*.

The error matrix produced from the accuracy assessment provided insight to the overall accuracy and what changes could have been made to increase the accuracy of the unsupervised classification throughout the accuracy assessment process. The error matrix provides the analyst with understanding pertaining to each class and the associated inaccuracies. This information is useful for determining which classes specifically were evaluated accurately or inaccurately. There were errors in one of the bare ground classes being evaluated as vegetation, when there is a strong possibility the pixels were small, sparse plants. Pixels of this nature were challenging to evaluate in the classification and validate in the accuracy assessment due to the color of the pixel being affected by bare ground behind the small, sparse plant.

The cost comparison exemplified that the AggieAir UAV is the most affordable platform for acquiring aerial imagery at a high spatial resolution to that of satellites and piloted aircrafts for this study. Weighing the 80% accuracy of using UAV technology for identifying surface features with the costs associated with purchasing such imagery, does portray this technology to be cost-effective and able to produce accurate results. When taking into consideration the factors that could potentially increase the accuracy

combined with the costs, this technology proves to be an accurate method for identifying surface features, and potentially invasive species.

Cost Comparison Considerations

However, the cost comparison does have some limitations. Comparing UAV, satellite and piloted aircraft costs are challenging and does not entail all of the factors that weigh-in on pricing. This research only compared spatial and spectral resolutions as well as USD/ km² per platform, whereas, other factors in comparing the cost should be considered such as, radiometric resolution and temporal resolution. For instance, the radiometric resolution will vary among sensors, and radiometric resolution needs depend on research objectives; therefore, there are challenges in placing a price or value on differences in the radiometric resolutions of sensors. Also, temporal resolution can be highly dependent on research objectives and there are significant variations in costs associated with the timing of image acquisition among varying platforms. Such as, a satellite may not orbit the study area during the time needed to acquire imagery. In regard to piloted aircrafts, the aircraft may not be available during the time for image acquisition or may increase the cost relative to convenience and scheduling of the aircraft and pilot. A challenge arises in considering costs of the temporal resolutions of varying platforms and how to compare them to one another. Additional costs that should be taken into consideration for a full comparison of remote sensing platforms include: deployment, maintenance, fueling, repair (materials), and updating (updating computer systems, software, cameras, etc.). This research does provide a basic cost comparison to portray the image acquisition costs among platforms; although, further detailed information on

platform capabilities and associated costs would demonstrate a comprehensive comparison of remote sensing platform rates.

CHAPTER VI

Conclusion

This study utilized an UAV platform with two digital cameras to collect aerial imagery along the Pease River at the Matador Wildlife Management Area with spectral bands blue, green, red, and NIR. The collected imagery was mosaicked using EnsoMOSIAC software, which produced a high spatial resolution of 21 cm. The RGB based imagery was classified using an unsupervised classification method in ERDAS Imagine software in order to identify *Tamarix* and surface features. The accuracy assessment validated that the UAV sensors combined with the classification methods used in this study are accurate means for mapping certain surface features and not accurate for identifying *Tamarix*. The low accuracy found in identifying *Tamarix* is most likely attributed to sensor capabilities, exclusion of NIR, insufficient *in situ* data collection, classification methods, temporal resolution, and solar radiance variations. This research addresses the challenges and provides solutions of UAV remote sensing for mapping *Tamarix* in the various stages of this process, from image acquisition and classification to the statistical analysis of the accuracy assessment. The cost comparison found that UAV remote sensing is an affordable means to collect aerial imagery. The findings of this study parallel findings of other research; in that, UAV remote sensing was found to be a cost-effective and accurate method for mapping certain surface features.

CHAPTER VII

Future Work

Tamarix is a problem species in the entire Southwest region of the United States and mapping this species is a useful tool for resource managers. Through the findings of this study, researchers and resource managers can employ UAV technology as an affordable, accurate method for mapping surface features. Mapping specific plant species is possible depending on the capabilities of the sensor on the UAV platform, classification methods, and the ability to collect multi-temporal imagery. The same methods used in this research could be applied to mapping and identifying other invasive terrestrial plant species as long as the imagery was obtained at a time of the species' phenological cycle in which the plant exhibited unique spectral signatures to that of neighboring plant species. The research findings of this study present the potential to use UAV remote sensing for other natural resource management needs that require high spatial resolution and low-cost data collection. UAV remote sensing offers many advantages for collecting high spatial resolution for natural resource management and as this technology continues to develop, the challenges faced throughout the process will further be identified to assist in future research.

APPENDIX SECTION

APPENDIX A

Error Matrix for unsupervised classification subset 1.

	Reference Data					
Classified Data	Tamarix	Tamarix mix	Shadow	Vegetation	Bare ground	Row Total
Tamarix	24	8	0	11	0	43
Tamarix mix	1	27	3	3	0	34
Shadow	3	1	13	1	0	18
Vegetation	1	15	2	127	3	148
Bare ground	0	1	0	0	12	13
Column Total	29	52	18	142	15	256

Error Matrix for unsupervised classification subset 2.

	Reference Data					
Classified Data	Tamarix	Tamarix mix	Shadow	Vegetation	Bare ground	Row Total
Tamarix	1	3	0	5	0	9
Tamarix mix	0	11	3	22	0	36
Shadow	0	0	18	1	0	19
Vegetation	1	12	0	159	4	176
Bare ground	0	1	0	2	13	16
Column Total	2	27	21	189	17	256

Error Matrix for unsupervised classification subset 3.

	Reference Data					
Classified Data	Tamarix	Tamarix mix	Shadow	Vegetation	Bare ground	Row Total
Tamarix	1	8	1	5	0	15
Tamarix mix	0	10	0	3	0	13
Shadow	0	0	15	3	0	18
Vegetation	5	16	0	159	4	184
Bare ground	0	0	0	1	25	26
Column Total	6	34	16	171	29	256

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