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Using Remotely Sensed Data to Detect Tamarisk along Colorado's San Miguel River

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Abstract

Tamarisk, an invasive tree native to Eurasia, has become widespread in river corridors across the southwestern United States. Accused of excessive water consumption and degradation of native habitats, it has been the target of extensive eradication and restoration efforts. Identifying its ever-changing distribution and extent benefits natural resource managers tasked with planning and prioritizing invasive plant management activities.

The use of GIS tools and remotely sensed data offers the potential to speed and improve our ability to locate tamarisk distributions. This project searches for tamarisk by classifying land cover vegetation (including tamarisk) based on spectral reflectance values from three-band natural color digital orthophotos. The study area is a section of the San Miguel River in western Colorado, where an extensive tamarisk eradication and restoration project was completed in 2008. Recent site survey reports indicate that a few small, scattered tamarisk trees are beginning to reappear in the study area. While the overall classification was relatively accurate, it was unable to reliably classify the tamarisk category.

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Project Definition

Tamarisk is a shrub-like tree that has invaded riparian zones across the southwestern United States. Native to dry regions of Africa and Eurasia, tamarisk was brought to the United States in the 1800's as an ornamental and provider of shade and river bank stabilization. It has thrived and expanded its territory to river corridors across America's arid southwest, in some cases forming dense monoculture thickets. Environmental scientists and natural resource managers have multiple concerns about tamarisk's impacts, including excessive water consumption, diminished accessibility to rivers, degraded wildlife habitat, and displacement of native vegetation.

Along Colorado's San Miguel River, an extensive multi-year tamarisk eradication and restoration project was completed in 2008. At the San Miguel River Preserve, a Colorado State Natural Area, regular site visits are conducted to monitor and record the recovery process and identify tamarisk recurrences. An increasing number of tamarisk specimens have been identified during recent site surveys. Supporting and enhancing this monitoring work with GIS tools and remotely sensed data forms the basis for this research project.

The primary research goal is to test the ability of these systems and data to discern the early stages of tamarisk recurrence at the San Miguel Preserve. A consistently successful method offers multiple benefits including a reduced need for site visits, the ability to focus onsite work to specific high-probability problem areas, and reduced mitigation costs resulting from early detection.

The project methodology uses a supervised classification approach with three-band natural color aerial photographs to classify study area vegetation (including tamarisk), based on pixel reflectance values. This method has previously demonstrated the ability to successfully detect tamarisk, albeit in somewhat different contexts (Akasheh, Neale, and Jayanthi 2008, Everitt et al. 1996, Everitt et al. 2007). Tamarisk distribution and characteristics in the San Miguel Preserve differ fundamentally from the study areas in prior studies. Most research has focused on study areas containing relatively large dense tamarisk concentrations. In contrast, most tamarisks at the San Miguel Preserve are scattered, with no expansive concentrations or dense thickets. Many specimens are located below an intermittent cottonwood canopy and at least partially shielded from the view of airborne or satellite-based sensors. Most are smaller trees - two to three meters tall, thin, and spindly in appearance. There are a small number of larger more robust trees, including a small cluster beneath an open sky.

As a result, I hypothesize that the classification will not be able to discriminate the smaller, scattered tamarisk trees. The larger specimens, and especially the small cluster, represent a more reasonable target for sensors. I hypothesize that the classifier is more likely to successfully identify this group.

For the researcher, a fundamental benefit of the research process is the acquisition and synthesis of new knowledge, understanding, and insight about the topic at hand. Thus the secondary research goal is to identify data, techniques, and tools beyond those employed in this project and evaluate their ability to provide effective solutions.

The approach used in this study is not at the cutting edge of current research. It represents a foundational starting point from which to continue investigating the topic with different combinations of data and methods. The use of remotely sensed data to detect tamarisk and other invasive plants is a work in progress, still needing additional research to identify consistently accurate, cost-effective solutions (Fletcher, Everitt, and Yang 2011). This is especially true for San Miguel Preserve-like scenarios, in which tamarisk is in the early stages of establishing a foothold or repopulating (Shafroth et al. 2005).

Project Foundations

Invasive Species

The term "globalization" often brings to mind an economic perspective regarding transnational corporations and financial institutions, international trade, and job offshoring. In truth, globalization is many-faceted concept encompassing political, social, cultural, and ecological dimensions. Although we tend to think otherwise, globalization is not new. Certain aspects are as old as our planet. Nevertheless, its rate is accelerating, fueled by increasingly ubiquitous transportation and communication systems. For environmental scientists, ecological globalization might represent an environmental version of Pandora's Box, particularly with respect to the problems associated with invasive species.

Invasive species, both plants and animals, are a growing phenomenon across the globe. As international transportation systems pick up and deliver goods across the world, they unintentionally provide new import/export pathways for non-natives. In other cases, non-native species are purposefully imported into a new region as, for example, pets or ornamental plants. If the characteristics of the non-native's new territory suit its needs, it has an opportunity to thrive and spread. The absence of natural enemies or other native deterrents frequently enhances these newcomers' opportunities.

The impact of an invasive species can vary, depending on the nature of the species and its newfound territory. Potential negative impacts can include changes to the makeup and function of native ecosystems, reduction of biodiversity, and displacement of native species (Ge et al. 2006, Mack et al. 2000). In the United States, the economic impact of invasive plants is estimated to be losses of tens of billions of dollars annually (Pimental et al. 2001).

Tamarisk

A shrub-like tree named tamarisk, colloquially called salt cedar, is one such invasive. Tamarisk is the subject of this research. Introduced to North America in the 1800's, tamarisk was embraced for its perceived benefits as an ornamental plant, as well as more practical qualities including a provider of shade, wind protection, and stream bank stabilization. Native to arid regions of Africa and Eurasia, tamarisk thrived in the dry climate of the southwestern United States, primarily in riparian zones along river corridors (Robinson 1965, deGouvenain 1996). It broadened its presence in North America through the twentieth century. By the late 1980's, tamarisk was estimated to have extended its coverage to more than 600,000 hectares, and was increasing at a rate of 3 to 4% annually (Brotherson and Field 1987, Di Tomaso 1998). Today it is thought to be the most abundant non-native tree in southwestern riverine systems (Friedman et al. 2005).

Somewhat concurrent with Tamarisk's expansion across the southwest, America's population began a southwesterly migration, in part enabled by widespread dam building and the resulting availability of water. Soon, tamarisk began to be recognized as a problem (Brotherson and Winkel

1986), eventually becoming demonized in both peer-reviewed and popular publications (Sher and Quigley 2013). Its perceived negative impacts are extensive, including excessive water consumption, reduction of plant and wildlife diversity, increased wildfire frequency, and increased flood potential (Di Tomaso 1998, Hughes 1993). As a result, widespread eradication efforts were initiated. Today, with increased knowledge, a more holistic approach appears to be taking hold. Management efforts focus primarily on dense monoculture infestations, emphasizing ecosystem restoration versus a single-minded eradication. We have learned that restoration reduces the likelihood of recurrence by tamarisk or invasion of other non-natives. Meanwhile, scientists continue re-assessing many aspects of tamarisk ecology including water consumption, habitat suitability, and competition with its riparian neighbors (Sher and Quigley 2013).

In Colorado, the Noxious Weed Act defines noxious weeds as: "… non-native plants that are disrupting our native vegetation and ecosystems." Tamarisk is listed on the B List of Noxious Weeds. The B List is includes plants whose continued spread should be stopped. Both the state and local governments are required by state law to develop and implement management plans to stop the continued spread of the List B species (Doran, Anthony, and Shelton 2009).

Remote Sensing to detect tamarisk

Given the importance of identifying the locations and extents of tamarisk populations, what is the most effective way to obtain such information? Field surveys can identify and measure invasive species, albeit with limitations. They are a good solution for limited areas, but they can be time-consuming and labor-intensive. They are also impractical for remote areas, for assessment of large areal expanses, and for areas having difficult, limited, or restricted access (Griffith, McKellip, and Morisette 2005). The successful use of remote sensing methods to identify tamarisk (as well as other invasives) has the potential to overcome these limitations and provide information not previously available.

In addition to providing new data, remote sensing methods can become a valuable tool to supplement field work. These methods could enhance the efficacy of site surveys by identifying explicit high-probability target locations. Tools could also provide more timely information, allowing earlier detection of invasions. Ultimately, these capabilities can lead to more well-informed and improved decision-making by our natural resource managers.

Remote sensing has been used to detect tamarisk since 1936 (Robinson 1965). Since then, techniques have evolved, driven by technology advances including sensor instruments, sensor platforms, and computer technologies that support analyses (Griffith, McKellip, and Morisette 2005). Improvements to remotely sensed imagery, a product of these technologies, represent a prime example. Modern sensor systems are capable of fine spectral and spatial resolution, thereby providing highly granular data to analysts.

Spectral resolution refers to the number of spectral bands that can be detected by the sensor system, and the bandwidth of each band (Akasheh et al. 2008). Early data was acquired with single-band black-and-white photography. It progressed to three-band color and four-band color infrared versions, and migrated from film to digital systems. Today, three- and four-band digital sensors remain in widespread use. In addition, multispectral sensors capture data representing a wider range of the electromagnetic spectrum including thermal infrared bands. Hyperspectral systems generally collect data from the same overall frequency/bandwidth ranges as multispectral systems, but in significantly greater numbers of bands (typically 200 or more) consisting of much smaller wavelength slices. This level of specificity eliminates spectral confusion associated with wider wavelength sampling, enabling precision identification and analysis (Lillesand, Kiefer, and Chipman 2008).

Spatial resolution is the ground area represented by one pixel in the remotely sensed image (Akasheh, Neale, and Jayanthi 2008). Spatial resolution of remotely sensed data ranges from centimeter-level up to one kilometer. Generally, spatial resolution is related to the sensor platform. UAV (drone) and aerial systems provide the finest resolutions, while resolution from satellite-based systems is typically coarser. Larger pixel sizes, somewhat similarly to large-wavelength spectral bands, result in spectral confusion (commonly called the 'mixed pixel problem') because each pixel value represents the average reflectance of its areal extent.

The earliest efforts to identify tamarisk via remote sensing were visual examinations of black and white aerial photographs. Subsequent efforts have applied automated classification algorithms to images of various spatial and spectral resolutions.

In one earlier study, tamarisk were successfully identified by using images captured during autumn, when its foliage progresses through a distinctive yellow-orange to orange-brown color change, prior to leaf drop (Everitt and Deloach 1990, Everitt et al. 1996). While the approach is useful, it is limiting due to the restrictive timing considerations for data acquisition.

More sophisticated methods have since evolved, with increased numbers and types of data sources and more powerful software tools. Ge et al. (2006) demonstrated an effective method that applied texture-based classification to one-meter resolution natural color photographs. Time-series approaches have been used to detect invasions and to monitor tamarisk mitigation efforts (Anderson et al. 2005, Everitt et al 2007). Groenveld and Watson (2008) were able to discern leafless wintertime tamarisk using Landsat 5 Thematic Mapper data, based on the low reflectance values of bare branches.

A number of projects have used image data combining high spatial resolution with multispectral/hyperspectral bands, using data from commercial sources such as QuickBird (Carter et al. 2009, Nagler et al. 2009) or 'fly to order' solutions using airborne sensors (Akasheh, Neale, and Jayanthi 2008, Everitt et al. 2007, Hamada et al. 2007). These solutions have been generally successful. Study area extent, data acquisition timing, and sensor capabilities (spatial and spectral resolution) can be customized to the needs of the project. While this flexibility is a great advantage, commercial solutions also represent a more costly approach.

The most current published research methods apply techniques such as sub pixel classification (Silvan-Cardenas and Wang 2010) and advanced classification algorithms (Fletcher, Everitt, and Yang 2011, Wang et al 2013). One such classification algorithm, SVM (support vector machines), is a machine learning method that does not require normally distributed training samples and does not impose limitations on the number of bands that can be used in the classification, potentially enabling more effective use of hyperspectral data.

Research studies investigating the ability to detect tamarisk with remotely sensed data use two fundamentally different approaches. One general approach uses standard classification methods, based on pixel reflectance values, applied to image data with increasingly higher resolutions. The second approach uses more standard data, such as Landsat, but applies more sophisticated classification algorithms to the data.

These methods, considered as a whole, highlight some of the difficulties involved in using remotely sensed data to detect tamarisk. While most have successfully located tamarisk, most also have limitations. Many solutions use commercial data sources in the form of satellite based data or 'fly to order' airborne solutions. While these data can provide greater resolution and therefore yield better classification results, they are costly. Other classification approaches impose limitations to the timing of data capture.

A fundamental problem has to do with variations in the extent and density of the target species we are trying to identify. The majority of studies attempting to detect tamarisk used study areas in which the invader is densely populated in a relatively large area, creating an extensive, homogeneous environment. As a result, imagery of the study areas contains groups of adjacent 'pure' pixels known to represent tamarisk (Evangelista et al. 2009). In the early stages of an infiltration or repopulation, tamarisk does not exist in these large, dense clusters. Rather, it consists of smaller, scattered specimens, often growing below the understory of larger trees. The ability to detect these invasions or recurrences while still in their early stages can give natural resource managers the opportunity to initiate mitigation while the scope of the problem is still small, thereby minimizing mitigation costs and reducing potential negative impacts to the affected ecosystem.

The current characteristics and distribution of tamarisk at the San Miguel Preserve represent an excellent example of an early stage tamarisk re-population scenario. Due to its remoteness and size, the preserve is also a location at which a remote sensing detection approach can lead to cost savings. An effective, reliable remote sensing solution would have the potential to reduce the frequency of time-consuming site visits. Such a solution should also enhance the efficiency of field work by focusing attention to specific locations within the preserve.

Approach

Study Area

The study area is the riparian zone of Colorado's San Miguel River within the boundaries of the San Miguel Preserve, a Colorado State Natural Area. The Preserve, remotely situated in western Colorado, encompasses approximately seven miles of the San Miguel River. Conveniently, State Highway 141 parallels the river through the preserve, providing multiple access points. The nearest city is Grand Junction, 100 miles to the north. From a mapping standpoint, the study area is neatly contained within the extent of a single USGS 1:24,000 map (Uravan, CO).

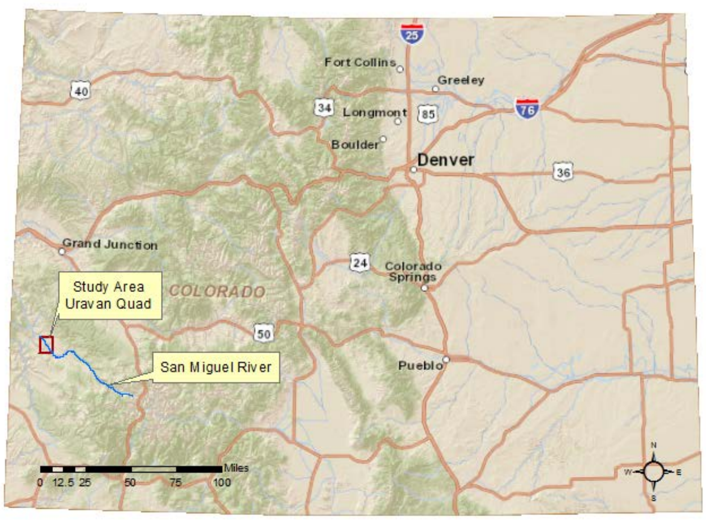

Figure 1. Study Area Location

The San Miguel River is Colorado's only naturally functioning river system, with no dams and minimal irrigation diversions to disrupt its natural riverine processes. The river begins in the San Juan Mountains near Telluride and flows approximately 90 miles to the northwest, where it joins the Dolores River immediately north of the San Miguel Preserve study area.

The primary vegetation in the San Miguel Preserve's riparian zone consists of cottonwood, oak, willow, various shrubs, and grasses. Most tamarisks are small and somewhat scattered, with only a few larger occurrences.

Data

A fundamental element of any GIS-based analysis is its data. This project relied on primary and secondary data to support the analyses.

Primary Data

Site data, itemized and described in Table 1, was collected over the course of three site visits: October 7, 2012; April 21, 2013; and May 11, 2013. Data was recorded with GPS units, written notes, and photographs. Data included tamarisk locations, identities of representative vegetation and land cover categories, spatial extents for sample land cover categories, and locations of useful landmarks. Notes and sketches were recorded on 1:1,500 scale digital orthophoto maps. The maps were created beforehand as reference aids to evaluate and document representative land cover categories. Photographs were taken to supplement written notes and GPS data, and as evidence to confirm and document the verity of tamarisk observations. Notes, maps, GPS data, and photos were subsequently used as references to help visualize and digitize training samples during the classification workflow.

Eight land cover categories were identified:

1. Water (San Miguel River)
2. Bare ground (dirt, rock, and asphalt)
3. Shadow (primarily shadows of large cottonwood trees)
4. Shrubs
5. Willow
6. Cottonwood
7. Oak
8. Tamarisk

Two handheld GPS receivers were used for data collection. One unit was a consumer grade Garmin GPSMap 76CSx handheld. GPSMap 76 accuracy is typically in the five- to ten-meter range (Trimble 2005). The second was a professional grade Trimble Juno SB unit. The Juno SB unit supports post-processed differential correction (DGPS) and provides accuracy between two and five meters (Trimble 2008).

Table 1. Primary Data

Description:	Data Type:	Method:	Purpose:
Tamarisk Ground Truth	Points & Polygons	GPS	Accuracy Assessment
Land Cover Ground Truth	Polygons	GPS	Accuracy Assessment
Land Cover Training Samples	Polygons	Digitized	Classification
Study Area Riparian Zone	Polygon	Digitized	Analysis & Basemap
Landmarks	Points	GPS	Basemap

Secondary Data

Readily-available public domain data was collected via the internet from a U. S. Government data portal, the Natural Resource Conservation Service's Geospatial Data Gateway. A National Agricultural Imagery Program (NAIP) digital orthophoto directly supported the classification. In Colorado, the most current NAIP datasets were acquired in the summer of 2011. The specific image that includes the study area was recorded on July 14, 2011. Although most NAIP products are four-band color/infrared images, only three-band versions are freely available.

Additional datasets were used as basemap layers, providing map readability and context. Where possible, data was downloaded based on the extent of the Uravan, Colorado quad. Datasets with larger extents were clipped to the Uravan quad's extent. Datasets were projected to NAD83 UTM12N as needed. Pertinent information for secondary data is described in Table 2.

Table 2. Secondary Data

Description:	Data Type:	Purpose:
NAIP Orthophoto	3-band natural color, 1m resolution Acquired: July 14, 2011 11:31 am > 11:54 am MDT	Analysis
National Land Cover Database	NLCD 2006, 30m resolution	Basemap
Digital Raster Graphic	USGS Topo	Basemap
TIGER Transportation	Highways, roads	Basemap
National Elevation Dataset	10m resolution	Basemap
National Hydrography Dataset	Rivers, streams, water bodies	Basemap

Workflow

Preprocessing

After acquisition, GPS data was downloaded and processed with each device's corresponding software. All GPS data was captured and downloaded in the WGS84 coordinate system.

Garmin data were downloaded to Garmin's Pathfinder Office application and reviewed for coherence. The data were then exported to Microsoft Excel for preprocessing. Pathfinder Office displays a point location's latitude and longitude values as a single attribute called "Position". A decimal degree point, for example, appears as: *N38.35480 W108.71060*. Excel was used to split "Position" into two attribute fields (latitude and longitude), remove the "N" and "W" characters from the fields, and convert west longitude to a negative value. When preprocessing was completed, the Excel worksheet was converted to an ESRI shapefile and projected to NAD83 UTM12N.

Comment [SRH1]: I think you mean some other Garmin software. Garmin Trip and Waypoint Manager maybe?

Just an FYI but you could have used DNR GPS and moved the data directly to shapefile of geodb.

Trimble data was downloaded to Trimble's Pathfinder Office application and reviewed for reasonability before preprocessing. In this case, the processing applied DGPS corrections to the data. Following DGPS correction, the Trimble data were exported to an ESRI shapefile and projected to NAD83 UTM12N.

Map Production

A series of study area maps were created in ArcGIS Desktop. A location map shows the study area location, relative to the State of Colorado (Figure 1). As a starting point for classification, a "Uravan Quad" map was created, using the NAIP digital orthophoto as a base layer and displaying points representing tamarisk and landmark locations. The 1:1,500 scale maps used in the site survey were derived from the Uravan Quad map.

An explicit study area map was created for analysis and classification purposes. The study area was limited to the San Miguel River's riparian zone, clearly visible in the NAIP image. Using the distinct boundary of the riparian zone, a polygon was digitized and used to clip the NAIP image, creating the study area image used for classification. By focusing in the river corridor, the processing demand and complexity of classification was significantly reduced. Figure 2 depicts the study area, bounded in red, and includes a sample of detailed feature annotations.

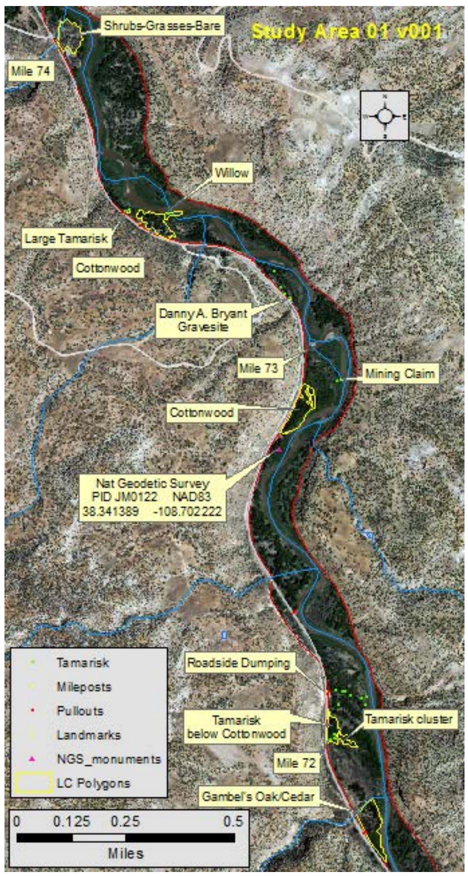

Figure 2. Riparian Zone Study Area

Classification

Image classification is the process of defining information categories in a raster image. Supervised classification uses training samples to create the categories. Training samples are analyst-defined areas within the image that are characteristic of the category they are intended to represent, based on pixel values. The classification software "learns" to classify an image from the training samples. For this project, training samples were digitized while referencing the first subset of ground truth data (Lillesand, Kiefer, and Chipman 2008).

ESRI ArcGIS Desktop 10.1 was used to perform the supervised classification for both analyses. The Multivariate toolset, in the Spatial Analyst extension, contains the tools for supervised and unsupervised classification. Classification, a multi-step iterative workflow, is visually depicted in figure 3.

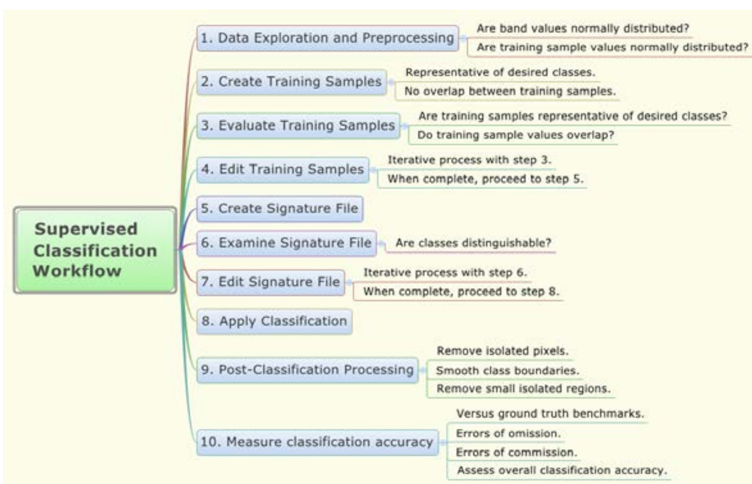

Figure 3. Supervised Classification Workflow

ArcGIS uses the maximum likelihood classification algorithm. This method assumes the image band and training sample data are normally distributed, usually a reasonable one for spectral response distributions (Lillesand, Kiefer, and Chipman 2008). Histograms and descriptive statistics were examined for the NAIP image bands representing the study area image. While not perfect, each band displayed a generally normal distribution pattern.

Creating, evaluating, and editing the training samples is an iterative process. The idea is to create samples comprised of pixels whose value ranges are representative of the desired classification categories. It is important to create samples with discrete value ranges that do not overlap. Overlapping values blur the distinctions between classes and reduce the accuracy of the classification (Lillesand, Kiefer, and Chipman 2008). In the end, 168 training sample polygons were digitized, with multiple polygons representing each of the eight classes. Digitizing was done from two versions of the study area NAIP three-band image. The natural color version was the primary reference image. In addition, a principal components analysis was applied to the natural color image, creating a secondary reference image in which band correlation has been removed. The principal components image enhanced the appearance of certain features and generally facilitated the digitization process.

A subset of the information collected during site survey visits (referred to as the training sample data) was the fundamental basis for digitizing the training samples. A second subset of the site survey data (referred to as the ground truth data) was set aside and used as a baseline during the post-classification evaluation process. Training samples were sized to include between 30 and 300 pixels, the optimal range for a three-band image (Lillesand, Kiefer, and Chipman 2008).

After multiple iterations, training samples were finalized and the study area image was classified. Finally, post-classification processing was performed to eliminate isolated pixels and smooth class boundaries. The nature of this analysis, attempting to detect small and somewhat isolated tamarisks, dictated the use of small parameter values for these steps.

Results

An accuracy assessment, comparing classification results to ground truth observations, was the final stage of the workflow. The first step was a visual examination of the classification map, with particular attention to classified and ground truth tamarisk locations. In general, areas classified as tamarisk were small and widely scattered across the entire study area. They did not appear to have any spatial relationship to the ground truth tamarisk locations. Figure 4 shows detail of the study area containing a number of tamarisk, several of which are grouped together with a clear view to the sky. The classification indicates only a few scattered specimens, consistent with the classified distribution across the entire study area. An accurate classification should have somewhat duplicated the ground truth concentration in this area.

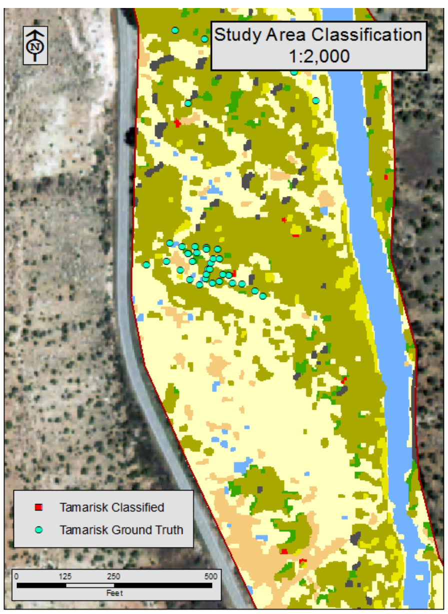

Figure 4. Tamarisk: Classification and Ground Truth

An error matrix (Table 3) provides a more objective evaluation of classification accuracy by comparing the relationship between ground truth data and classification results for each classification category. Columns represent ground truth pixel counts. Rows represent classification pixel counts. Pixels that were correctly classified are along the diagonal where ground truth and classification categories intersect (Lillesand, Kiefer, and Chipman 2008).

Table 3. Classification Error Matrix and Statistics

Category:	Ground Truth:								Classification
Classification:	Water	Bare	Shadow	Shrub	Willow	Cottonwood	Oak	Tamarisk	Totals:
Water	**16,183**	0	0	28	1	11	17	0	16,240
Bare Ground	0	**2,573**	0	0	0	381	397	0	3,351
Shadow	0	0	**899**	0	0	854	139	0	1,892
Shrub	447	3	1	**3,609**	232	2,755	2,874	6	9,927
Willow	0	0	0	0	**1,783**	1,480	187	31	3,481
Cottonwood	0	0	5	0	492	**13,547**	5,472	209	19,725
Oak	0	0	0	0	0	328	**1,042**	1	1,371
Tamarisk	0	0	0	0	0	10	49	**18**	77
Ground Truth Totals:	16,630	2,576	905	3,637	2,508	19,366	10,177	265	56,064

Total Pixel Count:	56,064
Correctly classified:	39,654
Overall accuracy:	70.7%
K_{HAT} Value:	0.62

Producer's Accuracy:	
Water	97.3%
Bare	99.9%
Shadow	99.3%
Shrub	99.2%
Willow	71.1%
Cottonwood	70.0%
Oak	10.2%
Tamarisk	6.8%

User's Accuracy:	
Water	99.7%
Bare	76.8%
Shadow	47.5%
Shrub	36.4%
Willow	51.2%
Cottonwood	68.7%
Oak	76.0%
Tamarisk	23.4%

The overall classification accuracy, the quotient of correctly classified pixels divided by total pixels, was 71%.

Producer's accuracy estimates the probability that a known land cover area is properly classified (Lillesand, Kiefer, and Chipman 2008). It is calculated for each classification category. Producer's accuracy for the water class (97%) is calculated by dividing the number of correctly classified water pixels (16,183 – water diagonal) by the number of pixels known to be water (16,630 – water column total). This measurement is primarily meaningful to the producer of the classification.

User's accuracy is more meaningful to prospective users of the classification. It estimates the probability that a pixel labeled as a certain category really is that category (Lillesand, Kiefer, and Chipman 2008). User's accuracy for water (99%) is the quotient of the number of correctly classified water pixels (16,183 – water diagonal) divided by the number of pixels classified as water (16,240 – water row total).

The K_{HAT} statistic compares the classification results to results that would have been obtained by random chance. Its value ranges from zero to one. A K_{HAT} value of zero suggests that the classification results are no better than a random assignment. A value of 0.62 indicates that the classification is 62% better than one resulting from chance (Lillesand, Kiefer, and Chipman 2008).

It is worth noting that error matrices and their resulting statistics report on the classification accuracy of the ground truth data, not the accuracy for the entire study area (Lillesand, Kiefer, and Chipman 2008).

Discussion and Recommendations

The methods used in this project, supervised classification of a three-band one-meter image, yielded reasonable results for certain classification categories: water, bare ground, cottonwood, and oak. It did not, however, successfully detect the principal target, tamarisk.

Retrospectively, and as somewhat expected, the nature of tamarisk distribution in the study area made it difficult to discern when using the traditional remote sensing methods and data employed in this study.

Due to its limited and scattered distribution across the study area, the number and size of tamarisk training samples was limited (265 pixels). In spite of numerous iterations through the training sample development and testing process and several unsupervised classifications, the spectral distributions of tamarisk training samples continued to overlap with other categories. Classification is ineffective when these distributions overlap – there is no bargaining with statistics. Figure 4 shows the vegetation class histograms and overlaps: yellow is shrub, bright green is willow, olive is cottonwood, green is oak, and red is tamarisk.

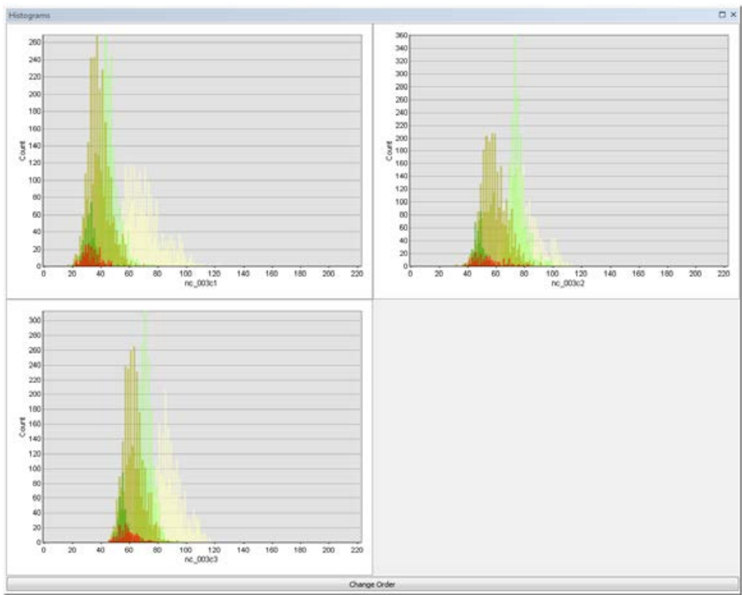

Figure 4. Training Sample Histograms – Vegetation Classes

A second factor potentially impacting the tamarisk classification accuracy relates to the time difference between the classified image and the data that was collected for training samples and ground truth. The NAIP image was acquired on July 14, 2011, almost two years before most of the onsite data gathering took place. Considering that most tamarisks located in the recent site surveys were young, small plants, it is reasonable to assume that they would have been smaller, or nonexistent, in 2011. The "2011 size" of the larger tamarisks is difficult to estimate. Colorado's next appearance on the NAIP schedule is in 2014.

Comment [SRH2]: It would be interesting to time field data collection with collection of aerial photography. Then all you have to do is wait for release of the imagery.

Looking forward, it is apparent that a successful solution will require advanced methods combined with data providing greater spatial and spectral resolution. One goal of the project was to identify, through the literature review and by working through the analysis and classification, ideas for new and different methods and data. That goal has been successfully achieved.

Journal articles revealed a variety of analysis techniques and datasets that have been used to detect invasive plants. Because the techniques are discussed in the literature review section, they are summarized here in bullet form:

- Texture analysis (Ge et al. 2006)
- Evapotranspiration (Nagler et al. 2009, Dennison et al. 2009)
- Maximum Entropy Model: Maxtent (Evangelista et al. 2009)
- SVMs using hyperspectral data (Fletcher, Everitt, and Wang 2011)
- Sub pixel mapping (Silvan-Cardenas and Wang 2010)
- Comparison of multiple classification algorithms (Wang et al. 2013)
- OBIA – Object Based Image Analysis using image data and LiDAR (ASPRS Seminar 2012)

This project represents the foundation from which I will continue researching remote sensing methods and data that can reliably identify invasive plant species, especially in their early stages of infestation. Although this project's specific approach was unsuccessful, I view the project as a great success – made so by the gained knowledge and experience. This is the goal of research.

- Bill, nice work overall. While I'm reading I imagine floating down the river. Maybe someday. It appears that you have established a firm foundation for further research. Nothing is as easy as we would like it to be and we don't have magic bullet to collect and analyze data. Will you carry on with this work? I hope so.
- It has been a privilege working with you over the years. Congratulations on completing the program!

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