

DISSERTATION

MAPPING *TAMARIX*: NEW TECHNIQUES FOR FIELD  
MEASUREMENTS, SPATIAL MODELING AND REMOTE SENSING

Submitted by

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In partial fulfillment of the requirements

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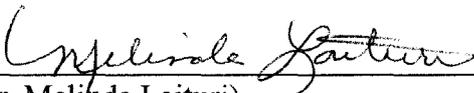
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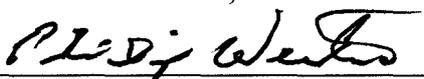
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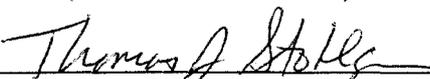
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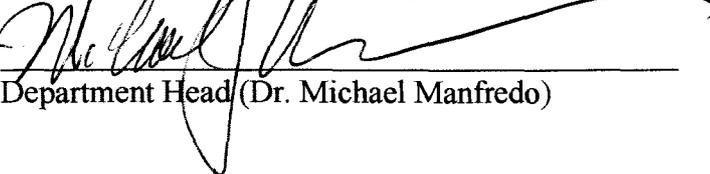
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## ABSTRACT OF DISSERTATION

### MAPPING *TAMARIX*: NEW TECHNIQUES FOR FIELD MEASUREMENTS, SPATIAL MODELING AND REMOTE SENSING

Native riparian ecosystems throughout the southwestern United States are being altered by the rapid invasion of *Tamarix* species, commonly known as tamarisk. The effects that tamarisk has on ecosystem processes have been poorly quantified largely due to inadequate survey methods. I tested new approaches for field measurements, spatial models and remote sensing to improve our ability measure and to map tamarisk occurrence, and provide new methods that will assist in management and control efforts. Examining allometric relationships between basal cover and height measurements collected in the field, I was able to produce several models to accurately estimate aboveground biomass. The best two models were explained 97% of the variance ( $R^2 = 0.97$ ). Next, I tested five commonly used predictive spatial models to identify which methods performed best for tamarisk using different types of data collected in the field. Most spatial models performed well for tamarisk, with logistic regression performing best with an Area Under the receiver-operating characteristic Curve (AUC) of 0.89 and overall accuracy of 85%. The results of this study also suggested that models may not perform equally with different invasive species, and that results may be influenced by species traits and their interaction with environmental factors. Lastly, I tested several approaches to improve the ability to remotely sense tamarisk occurrence. Using Landsat7 ETM+ satellite scenes and derived vegetation indices for six different months of the growing season, I examined their ability to detect tamarisk individually (single-scene analyses) and collectively (time-series). My results showed that time-series analyses were

best suited to distinguish tamarisk from other vegetation and landscape features (AUC = 0.96, overall accuracy = 90%). June, August and September were the best months to detect unique phenological attributes that are likely related to the species' extended growing season and green-up during peak growing months. These studies demonstrate that new techniques can further our understanding of tamarisk's impacts on ecosystem processes, predict potential distribution and new invasions, and improve our ability to detect occurrence using remote sensing techniques. Collectively, the results of my studies may increase our ability to map tamarisk distributions and better quantify its impacts over multiple spatial and temporal scales.

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limit myself as an observer, and for inspiring me to follow a life-long path of environmental work. Last, but not least, I thank my father, Noli Evangelista, for encouraging me to follow my dreams and supporting my life visions. I hope that I have made them proud.

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## INTRODUCTION

Riparian ecosystems throughout the southwestern United States are being threatened by the rapid invasion of *Tamarix* species, also known collectively as tamarisk or saltcedar. Introduced from Eurasia in the early 1800s for use in erosion control, as windbreaks and as ornamentals, tamarisk was acclaimed for its ability to withstand drought, heat, and diverse soil conditions (Carleton 1914, DiTomaso 1998). These views began to change by the mid 1900s as resource managers witnessed tamarisk's remarkable ability to spread and dramatically affect native flora, wildlife habitat, and hydrologic processes (Christensen 1962, Robinson 1965, Harris 1966). It is generally reported that the rapid spread of tamarisk between the 1920s and 1960s was correlated with increased regulations of stream flows associated with dam construction and water diversions used to facilitate agriculture (Everitt 1980, Everitt 1998). Its estimated distribution in the southwest grew from 40 km<sup>2</sup> in 1920 to over 4,800 km<sup>2</sup> by the mid-1960s (Robinson 1965). Initially, tamarisk infestation was primarily confined to regions of the American southwest (i.e., Colorado, Arizona, New Mexico, Utah, and Texas) but is now a major threat to riparian ecosystems from California to Washington and has become established in at least 38 states (Morissette *et al.* 2006, NIISS 2008, USDA Plants Database 2008). There is no evidence that tamarisk invasion has subsided. New invasions have been reported throughout the U.S. and tamarisk is now found in several Canadian provinces, throughout Central America, and as far south as Brazil and Peru (Baum 1967, NIISS 2008, USDA Plants Database 2008).

## Species Profile

Tamarisk species are members of the family *Tamaricaceae*, which consists of four genera totaling about 100 species (Mozingo 1987). None of the species are native to North America and only the genus *Tamarix* can be found in North America. Currently, there are 11 species of tamarisk in the U.S. (USDA Plants Database 2008) and at least three new forms that have resulted from hybridization (Gaskin and Schaal 2002). The most pervasive species are *T. chinensis* (native to Mongolia, China, and Japan), *T. gallica* (native to Europe and northern Africa), *T. parviflora* (native to southern Europe and Asia Minor) and *T. ramosissima* (native to the Middle East, China, and Korea; Baum 1967, Mozingo 1987). Analyses of DNA sequence data by Gaskin and Schaal (2002) found that the most common type of tamarisk found in the U.S. is a hybrid involving the combination of *T. ramosissima* and *T. chinensis*. Other less common hybrids identified include crosses of *T. ramosissima* and *T. chinensis* with *T. gallica* and *T. parviflora* (Gaskin and Schaal 2002).

Tamarisk may exhibit varying growth forms, generally growing as a large shrub that can reach heights up to 6 m tall with multiple stems. Its deciduous leaves are scale-like, alternately arranged, and grow 1.5 to 3.5 mm long. Its flowers are pinkish purple in color and have five sepals, five petals, five stamens, and a five-carpellate pistil arranged on a flowering stalk that is 2 to 7 cm long (Welsh *et al.* 1993). Flowering may begin one to three years after germination and generally peaks between April and August. The seeds are produced in a lance-ovoid capsule, are viable for up to 45 days under ideal conditions, and can germinate within 24 hours after moistening (Carpenter 1998).

Tamarisk is a prolific seed producer that can generate as many as 600,000 seeds annually;

the seeds are easily dispersed over long distances by wind or water (Robinson 1958). Reproductive success is further enhanced by its ability to sprout from branches and its ability to develop adventitious roots from pieces of the plant in wet soils (Horton 1977). Tamarisk possesses several other important characteristics that contribute to its success as a riparian invader. The genus has a greater tolerance to saline soils than native vegetation. Salts from deep in the soil are assimilated by roots and deposited on the soil surface in leaf litter where the salts may accumulate at high concentrations, inhibiting the persistence of many native species (Carman and Brotherson 1982, DiTomaso 1998). Tamarisk is also resilient to a variety of natural and anthropogenic disturbances such as fire, drought, flooding, and cutting, creating a dilemma for resource managers trying to control or eradicate it (Busch and Smith 1995, Smith *et al.* 1998). These physiological characteristics and interactions with riparian communities make tamarisk a superior invader that can successfully compete with most native plant species.

### **Impacts of Tamarisk on Native Ecosystems and Natural Resources**

Although researchers have been actively examining the effects of tamarisk on a number of ecological processes (Campbell and Dick-Peddie 1964, Carman and Brotherson 1982, Stromberg 1998, Sher *et al.* 2002), there is still little quantitative information to provide a complete picture of its impacts. This is of particular concern for western states such as Colorado, where water yield is heavily managed for human consumption, agriculture, and maintenance of biodiversity. Tamarisk is a facultative phreatophyte and can extend its root system as deep as 50 m, desiccating flood plains and water tables (Blackburn *et al.* 1982, Pinay *et al.* 1992). Observations from resource

managers and results from several small-scale studies show that tamarisk uses water more efficiently than native cottonwoods (*Populus* spp.) and willow (*Salix* spp.; Busch and Smith 1993, Cleverly *et al.* 1997). Research efforts attempting to quantify water loss from tamarisk infestation have yielded varying results; however, it is evident that large stands of tamarisk utilize significantly more water than ecosystems dominated by native species.

The impacts of tamarisk on hydrological processes are further compounded by the extent of infestation. Many studies show that tamarisk now dominates a larger area of many southwestern riparian ecosystems than native riparian species (Christensen 1962, Harris 1966, Busch and Smith 1995, DiTomaso 1998, Everitt 1998). Anderson *et al.* (1977) reported that tamarisk comprises 95 to 100% of the total trees one small portion of the lower Colorado River, while Briggs and Cornilius (1998) reported that cottonwood stands have decreased from over 20 km<sup>2</sup> in the 1600s to less than 2 km<sup>2</sup> in 1998 in the same area. Throughout riparian ecosystems of the Colorado River Basin, tamarisk may account for as much as 40% of the total ground cover (Zamora-Arroyo *et al.* 2001). Along the Arkansas River Basin in eastern Colorado, tamarisk was first observed in 1913 by R. Niedrach near the present-day city of Lamar. On a return visit to the area in 1921, he reported that the species had spread considerably (Lindauer 1985). Today, tamarisk covers 117 km<sup>2</sup> between the Pueblo Dam and Colorado/Kansas state line with an additional 60 km<sup>2</sup> along the tributaries of the Arkansas River (Tamarisk Coalition 2008). Similar rates of infestation have been reported on other Colorado rivers, and mapping initiatives and predictive models indicate potential tamarisk expansion into new riparian ecosystems (Morisette *et al.* 2006, Tamarisk Coalition 2008).

Riparian ecosystems in the southwest are of particular importance to plant diversity. Because tamarisk infestations often result in dense monotypic stands, native plant diversity is greatly reduced as tamarisk increases in dominance (Lindauer 1983, Stromberg *et al.* 1993, Busch and Smith 1995, Smith *et al.* 1998, Briggs and Cornilius 1998, Horton *et al.* 2001, Bhattacharjee *et al.* 2002). Besides its ability to outcompete native plants for water, tamarisk utilizes other strategies to increase its competitive advantage. First, the species is more tolerant to drought than most native species (Horton 1977, Busch and Smith 1995, Cleverly *et al.* 1997). This not only includes tolerance to natural variations in climate but also to artificial conditions created by altered flow regimes from anthropogenic activities (Dick-Peddie 1993, Everitt 1998). Second, tamarisk foliage contains high concentrations of salts which can alter soil chemistry as litter accumulates in the understory inhibiting the establishment and growth of native plants (Decker 1961, Wilkinson 1966, Carman and Brotherson 1982, DiTomaso 1998). Increased salinity in the soil can enhance the establishment of other invasive species such as cheatgrass (*Bromus tectorum*), hairy whitetop (*Cardaria pubescens*), Russian knapweed (*Acroptilon repens*), and Canada thistle (*Cirsium arvense*), which are also known to be highly competitive with native species (Akashi 1998, Simberloff and Von Holle 1999). Third, tamarisk is unpalatable to most domestic livestock and wild ungulates, while native cottonwood and willow are grazed by cattle, deer, and elk (Horton 1977, Stromberg 1998). Finally, tamarisk is capable of sprouting from the root crown after a fire; native plants and seed banks are less tolerant of fire. Dense stands of tamarisk tend to be highly flammable at certain times of the year resulting in high-intensity fires that cause high mortality in native plant populations and the destruction of

seed banks. Aboveground tamarisk stems are burned, leaving the roots intact, allowing the plants to rapidly reestablish (Busch 1995, Hohlt *et al.* 2002). The physiological characteristics of tamarisk allow the species to compete successfully with native plants, but its ability to withstand wide-ranging environmental conditions and to alter ecosystem processes further enhances its ability to reduce native plant diversity and establish itself as a dominant species over time.

The impacts of tamarisk on wildlife and critical habitat have not been fully examined. Studies on specific wildlife species have shown that infestations may have varying effects. In some cases, habitat quality is greatly reduced by the presence of tamarisk (Cohan *et al.* 1979, Anderson *et al.* 1984, Meents *et al.* 1984, Jake and Gatz 1985), while other cases have shown that some wildlife species have the ability to adapt with little or no effects (Hunter *et al.* 1989). Riparian habitats generally provide two broad functions for wildlife: cover for breeding and protection, and as a source of food. The greatest concern with changes in riparian habitats is with avian species that rely heavily on riparian corridors for nesting, migrant use, and food (e.g., insects, berries). Although many bird species are known to use tamarisk (Brown *et al.* 1987, Hunter *et al.* 1988, Livingston and Schemnitz 1996), several studies show that they prefer native vegetation or, at the least, require native vegetation to be in close proximity (Rosenberg *et al.* 1991, Young and Finch 1997). The yellow-billed cuckoo (*Coccyzus americanus*), for example, is known to require native riparian forests but will utilize tamarisk stands in defining territories and breeding activities (Hunter *et al.* 1988, Kunzmann *et al.* 2000). Reduced reproductive fitness has been observed in the endangered southwestern willow flycatcher (*Empidonax traillii*) in tamarisk-dominated habitats; however, they are able to

maintain fledgling survivorship rates similar to those recorded in native habitats (Dudley *et al.* 2000, Sogge *et al.* 2003). Although many studies show that avian diversity and abundance are not significantly impacted by tamarisk (Brown *et al.* 1987, Hunter *et al.* 1988, Finch and Stoleson 2000), some species simply require large native trees (e.g., cavity nesters, drillers, granivores; Cohan *et al.* 1978, Rosenberg *et al.* 1991, Ellis 1995). The impacts of tamarisk on avian species must be assessed on a case-by-case basis; however, a general rule would be that specialist species have a higher likelihood of being negatively impacted by tamarisk replacement. These species are also more likely to be rare or endangered.

Many native flora and fauna rely on insects and other arthropods as pollinators or as a food base. Most studies comparing invertebrate populations living in tamarisk stands to those living in native vegetation suggest that diversity and abundance are only minimally reduced (Liesner 1971, Stevens 1985, Miner 1989, Ellis *et al.* 2000). Only a few native insects will feed on tamarisk (Glinski and Ohmart 1984, Ellingson and Andersen 2002). Those that do are usually pollinators, such as bees and butterflies (Nelson and Andersen 1999, Drost *et al.* 2001). Because tamarisk retains its flowers longer than many native plants, life cycles for insects may be extended, which in turn may provide longer foraging opportunities for birds and other fauna (Drost *et al.* 2001, Yard *et al.* 2004).

Herpetofauna appear to be at greater risk from tamarisk invasion. A few studies have shown herpetofauna populations to be significantly lower in tamarisk stands than in native vegetation (Jakle and Gatz 1985, Szaro and Belfit 1986, Konkle 1996). These studies were largely focused on species diversity and abundance, and offered no

conclusive evidence of the exact cause of population declines. The decrease in populations could be related to habitat structure (e.g., loss of thermal cover) or alterations in hydrological processes (e.g., decreased water levels; Szaro and Belfit 1986). For some species, such as the western pond turtle (*Actinemys marmorata*), reduced water levels appear to be responsible for population declines (Lovich and DeGouvenain 1998). Food supplies (e.g., insects, small mammals), for the most part, remain intact. Studies by Ellis *et al.* (1997) and Hink and Ohmart (1984) found that diversity and abundance of rodent populations in tamarisk stands were comparable to those in native vegetation. Some populations, such as deer mice (*Peromyscus* spp.), have been observed to increase in tamarisk stands (Ellis *et al.* 1997), while habitat alterations (e.g., reduced herbaceous vegetation and water) can be conducive to kangaroo rats (*Diodomys* spp.) and pocket mice (*Perognathus* spp.; Anderson and Nelso 1999)

### **Research and Management Needs**

Tamarisk infestation is now widespread and continues to expand throughout the U.S. If tamarisk is to be successfully controlled, new research is required to better support the needs of resource managers. Specifically, resource managers need detailed distribution maps of tamarisk to determine its impacts on an ecosystem, formulate control strategies, and monitor ecosystem recovery. Spatial models are proving to be useful in predicting the potential spread of tamarisk and other invasive species; however, they are a better measure of risk and do not always accurately reflect where current infestations occur. As a tool, spatial modeling software and techniques can be fit with real-time data, such as satellite imagery, to detect current tamarisk distributions. Most spatial models

rely on landscape features (e.g. elevation, slope, distance from water) to predict tamarisk occurrence, where remote sensing data measures spectral properties (e.g. reflectance, green-up, wetness) of a landscape at the time of data acquisition. In previous studies, remote sensing of tamarisk has not always produced the results desired. Detailed information on tamarisk distribution is increasingly compromised with ecosystem heterogeneity, coarse data resolution, and at large spatial scales. When used in combination, spatial models and remote sensing may greatly enhance our ability to detect tamarisk better than either technique used independently.

Perhaps the greatest constraint to spatial modeling and remote sensing applications is the methods used to map tamarisk in the field. Field surveys are generally conducted by collecting location points where tamarisk is either present or absent. This method is not only costly and labor intensive, but provides little information on stand structure and is soon outdated as new infestations emerge, young stands become mature, and control treatments are conducted. Improved methods for collecting data on stand structure are required to facilitate new spatial modeling and validate remote sensing data, in addition to addressing some general research and management concerns. The impacts of tamarisk on native ecosystems are difficult to quantify. Information on tamarisk occurrence (e.g. presence, absence) offers little insight on the effects an infestation may be having on ecosystem processes. Field surveys that can estimate tamarisk biomass accumulation over a given area would be more useful to resource managers. In addition to clarifying potential transpiration and water use, biomass measurements provide critical information to a suite of ecological processes and facilitate better control and restoration strategies. In particular, they can be helpful in developing cost projections and for

planning logistical requirements related to control efforts, and be implemented in long-term monitoring programs.

## **Overview**

This dissertation consists of three chapters, each with the objective of improving our ability to detect, map, and monitor tamarisk invasion. My work has been an iterative learning process that examines tools and techniques that can be employed under a variety of conditions with significant accuracy. My research question is “How can we improve our ability to detect tamarisk distributions at different scales and geographic regions using existing knowledge and technology?” To answer this question, I had three objectives:

- (1) Develop field techniques for measuring tamarisk infestation that will provide better information on the stand structure and ecosystem impacts, while improving the performance of spatial modeling and remote sensing efforts.
- (2) Test and compare a suite of spatial models to evaluate their performance in predicting tamarisk occurrence.
- (3) Examine different remote sensing approaches to detect phenological characteristics of tamarisk and help distinguish the species from other vegetation and landscape features.

Each of these objectives is addressed in a chapter of this dissertation. Chapter 1 describes field and laboratory methods that can be used for estimating aboveground

biomass of tamarisk at the stand level. The species' irregular growth form has prevented the use of traditional biomass measurements and formulas; as a result, most surveys only record its presence or absence. By adding estimated basal cover and height measurements, allometric relationships are developed to enhance information collected in the field. In Chapter 2, I examine the utility of five spatial models in predicting the occurrence and potential distribution of tamarisk occurrence and another highly invasive plant species. With an increasing number of spatial models available to researchers, my aim in this study was to identify the best model(s) for predicting tamarisk occurrence using varying types of field data. In Chapter 3, I investigate different techniques in remote sensing to detect phenological attributes of tamarisk by comparing satellite data from six different months of year, independently and collectively. I also test the applicability of some commonly used vegetation indices in an effort to determine the best times of the growing season for distinguishing tamarisk from other vegetation.

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# CHAPTER 1: ESTIMATING ABOVEGROUND BIOMASS OF TAMARISK IN THE ARKANSAS RIVER BASIN OF SOUTHEASTERN COLORADO

## 1.0 Abstract

Predictive models of aboveground biomass of non-native tamarisk of various sizes were developed using destructive sampling techniques on 50 individuals and four 100 m<sup>2</sup>-plots. Each sample was measured for average height (m) of stems and canopy area (m<sup>2</sup>) prior to cutting, drying, and weighing. Five competing regression models ( $P < 0.05$ ) were developed to estimate aboveground biomass of tamarisk using average height and/or canopy area measurements and evaluated using Akaike's Information Criterion corrected for small sample size ( $AIC_c$ ). My best model ( $AIC_c = -148.69$ ,  $\Delta AIC_c = 0$ ) successfully predicted tamarisk aboveground biomass ( $R^2 = 0.97$ ) using average height and canopy area as predictors. My second best model, using the same predictors, was also successful in predicting aboveground biomass ( $R^2 = 0.97$ ,  $AIC_c = -131.71$ ,  $\Delta AIC_c = 16.98$ ). A third model demonstrated high correlation between aboveground biomass and canopy area only ( $R^2 = 0.95$ ), while two additional models found high correlations between aboveground biomass and average height measurements only ( $R^2 = 0.90$  and  $0.70$ , respectively). These models illustrate how simple field measurements, such as height and canopy area, can be used in allometric relationships to accurately predict aboveground biomass of tamarisk. Although a correction factor may be necessary for predictions at larger scales, the models presented will prove useful for many research and management initiatives.

## 1.1 Introduction

Researchers have been actively examining the effects of tamarisk on a number of ecological processes (Campbell and Dick-Peddie 1964, Carman and Brotherson 1982, Stromberg 1998, Sher *et al.* 2002). However, there is still little quantitative information on biomass or transpiration rate, and predictive regression models or allometric equations have not been previously developed. This is of particular concern to resource managers who work where water yield is intensively managed and biomass estimates are required for many research, monitoring, and restoration efforts. In addition to clarifying potential transpiration and water use (Sala *et al.* 1996), biomass measurements are commonly utilized in evaluating leaf area (Nagler *et al.* 2004), nutrient flow and productivity (Kelly *et al.* 1974, Cannell *et al.* 1987), wildlife habitats (Wiens and Rotenberry 1981; Rea and Gillingham 2001), fire effects and hazard (Abrams *et al.* 1986), disturbance (McWilliam *et al.* 1993), impacts of non-native plant invasions (Haase and Haase 1995, Standish *et al.* 2001), and monitoring the effectiveness of restoration efforts (Johnson *et al.* 1986, Oomes 1992). Many resource management agencies are also actively engaged in tamarisk mitigation efforts (Personal communication, A. Hughes, Grand Staircase-Escalante National Monument; F. Pannebaker, National Park Service; S. VanLandingham, Colorado State Forest Service). A reliable method for estimating biomass would enhance their ability to plan budgets and identify the necessary labor and equipment required for tamarisk removal.

Although there are several methods available for estimating the biomass of various tree species (Whittaker and Woodwell 1968, Monk *et al.* 1970, Swank and Schreuder 1974, Young 1976, Crow 1983, Pastor *et al.* 1984), there is yet to be an

adequate method for estimating biomass of tamarisk and other multi-stem shrubs and trees. Diameter measurements (DBH, diameter at breast height) are frequently used and have strong correlations with biomass (Prescott *et al.* 1989, Arthur and Fahey 1990, Harcombe *et al.* 1993); however, DBH measurements are difficult to acquire for tamarisk due to its irregular growth patterns, multiple stems, and tendency to persist in dense stands. A single tamarisk tree may have a single bole or dozens of stems protruding from the ground. Variations in growth patterns are often related to species characteristics, fluctuations in resource availability, or various disturbances. These discrepancies in stem growth, and labor associated with collecting field measurements, have discouraged the collection of DBH measurements and limit most tamarisk surveys to presence or absence, and occasionally basal cover (Campbell and Dick-Peddie 1964, Wilkinson 1966, Nagler *et al.* 2004).

There are two methods that are generally employed for measuring biomass of single-bole trees. The first is complete harvesting, or destructive sampling, where an individual or area is measured, cut, dried, and weighed (Grier and Logan 1977, Gholz 1980, Jenkins *et al.* 2001). Although this method produces accurate results, it is often labor intensive, costly, and impractical, while limiting possibilities of temporal studies. The second method uses regression models based on other tree dimensions that are more easily measured, such as stem diameter, height, and canopy cover (Swamy *et al.* 2006). Due to the constraints of associated with DBH measurements, I examine the potential of modeling tamarisk biomass using only height and cover measurements.

## **1.2 Methods**

### ***1.2.1 Study area***

Biomass data were collected from two different areas in the Arkansas River basin of southeastern Colorado, USA. In October 2005, I collected data from the Oxbow State Wildlife Area (SWA) and in February 2005 from Grenada SWA. Oxbow SWA is in Otero County (38.04<sup>0</sup> N, 103.41<sup>0</sup> W) on the south bank of the Arkansas River near Bent's Old Fort National Historic Site. The SWA covers approximately 164 ha at 1,219 m elevation and contains large expanses of mixed-sized tamarisk. The Colorado Division of Wildlife, Colorado State Forest Service, and National Park Service have been removing tamarisk at Oxbow SWA since 2001. Grenada SWA is located east of Oxbow SWA and also borders the south bank of the Arkansas River. Located in Prowers County (38.04 N<sup>0</sup>, 102.22<sup>0</sup> W), Grenada SWA has an elevation of about 1,036 m and covers about 2,226 ha. Tamarisk at this site is largely evenly sized with more than 90% categorized as mature (height > 3 m). Since 2003, the Colorado Division of Wildlife has aggressively removed tamarisk to open river access and promote cottonwood regeneration. This region is believed to be one of the earliest tamarisk infestations in Colorado. First reported in the early 1900s, tamarisk has since become the dominant species along much of the Arkansas River, its tributaries, and neighboring reservoirs (Robinson 1965, Lindauer 1985, Pannebaker 2005).

### ***1.2.2 Field sampling and laboratory analyses***

During my first field campaign at Oxbow SWA, I selected 25 tamarisk trees of various height classes ranging from 0.6 m to 5 m for complete harvesting and biomass measurements. At the time of sampling, tamarisk trees were in full foliage and had only

remnant flowers. Before cutting, I established a scale-dependent plot around each tree to determine area and percent canopy cover. The scale-dependent plot is a square or rectangular design that is adjustable to the dimensions of an individual tree or stand of interest. The area of each plot varied in size, having different lengths and widths based on the size and canopy cover of the tree (or stand) being measured. The length and width of each plot were measured to determine the plot's area ( $m^2$ ). I estimated average height (m) and the total percent canopy cover for all sampled trees including dead stems. Individual trees were then cut at the ground surface and carefully moved to tarps to ensure that all parts were collected and weighed. Each tree was weighed using a portable scale immediately following cutting for total green weight. Foliage (including small-diameter green stems) was then separated from woody parts and each weighed separately to determine weight distribution and ratios.

Next, I sub-sampled both foliage ( $n = 20$ ) and woody parts with mixed diameters ( $n = 20$ ) for drying. Larger woody parts were split or cut into smaller pieces to hasten the drying process. Each sub-sample was placed in a 20 x 30 cm pre-weighed burlap bag and transported to the Natural Resource Ecology Laboratory, Colorado State University, Fort Collins. Sub-samples were oven dried at 60° C and weighed regularly until weights became constant. Foliage sub-samples took seven days for weights to stabilize while woody parts took 14 to 18 days.

A second field campaign was conducted in Grenada SWA to collect additional samples of individual trees at a stand level. At the time of sampling, nearly all of the foliage had fallen or was only weakly attached. My intention was to collect biomass data on the woody parts only, applying previous results from my weight distribution analyses

to estimate lost foliage. Using the same methods previously described (without foliage measurements), I harvested and measured an additional 25 tamarisk individuals, which ranged from 1.8 to 6.1 m tall. Because leaves were absent, careful consideration was given when estimating foliar percent coverage. My estimates reflected probable cover if full foliage were present. Ten sub-samples of woody parts with mixed diameters were collected for oven drying. Additionally, I established four 10 x 10 m (100 m<sup>2</sup>) plots for measurements. Prior to complete harvest of the 100-m<sup>2</sup> plots, I recorded number of trees, average height, and total percent canopy cover of tamarisk within each plot. Tamarisk trees on the edges of each plot were carefully cut along the 100-m<sup>2</sup> plot perimeters to determine whether branches were to be included in the sample. Woody parts and remnant foliage were separated and only the woody parts were saved; the foliage and deadwood were discarded. All standing woody parts were weighed in the field and summed to determine total green woody weight for each stand. No litter or dead parts were considered.

### ***1.2.3 Statistical analyses***

The canopy area (m<sup>2</sup>) for each tree or plot was calculated by multiplying plot area (m<sup>2</sup>) by the percent canopy cover (%) recorded in the field. My analyses included all 50 individual tree samples and the four 100-m<sup>2</sup> plots (n = 54). A suite of candidate regression models for total aboveground biomass was developed using average height (m) and canopy area (m<sup>2</sup>) and their interaction terms as predictor variables. In all cases I used  $P < 0.05$ , and tolerance levels  $< 0.95$ , as criteria to include a variable as a significant predictor. Regression analyses were conducted using the PROC REG procedure in SAS

software (SAS Institute 2004). Residuals from the models were plotted against fitted values to check nonlinearity, unequal variances, and outliers in the data (Zar 1999). Prior to regression analyses, total oven-dry aboveground biomass (TAGB; kg) of tamarisk and canopy area were log-transformed to normalize these variables and meet the assumption of normality for regression models (Neter *et al.* 1996).

The candidate models were evaluated using Akaike's Information Criterion (AIC) and the information-theoretic approach (Burnham and Anderson 2002). Normally distributed errors with a constant variance were assumed for least-squares regressions. Since the number of observations was small ( $n = 54$ ), we used AIC adjusted for small sample size (i.e.,  $AIC_c$ ; see Burnham and Anderson 2002: 66). I identified the best model with the lowest  $AIC_c$  and calculated  $AIC_c$  differences ( $\Delta AIC_{c_i}$ ) across all candidate models in the set. The best model has  $\Delta AIC_{c_i} = 0$  (Burnham and Anderson 2002: 70-71).

For log-log regression models, taking antilogs of the previously transformed data to estimate total aboveground biomass induces an inherent bias "because the largest values are compressed on the logarithmic scale and thereby tend to have less 'leverage' than small values in making such an estimate" (Beauchamp and Olson 1973). Therefore, a correction factor (CF) has been recommended to account for this bias (Sprugel 1983). The CF for the models was calculated as follows (Sprugel 1983):

$$CF = \exp [(SEE \times 2.303)^2/2]$$

where SEE is the standard error of the estimate of the regression model. The biomass estimates should be multiplied by the CF for unbiased estimation of total aboveground biomass (Sprugel 1983).

### 1.3 Results

Sampled trees from both sites ranged from 0.6 m in average height and canopy area of 0.03 m<sup>2</sup>, to 6.1 m in average height and canopy area of 69.5 m<sup>2</sup>. At the Oxbow SWA site, total green weights of foliage were higher than green weights of woody parts on the six smallest tamarisk samples (< 1.5 m average height and < 1.1 m<sup>2</sup> canopy area), while total green woody material constituted greater weights for 19 larger samples (> 1.5 m average height and > 1.1 m<sup>2</sup> canopy area). Total oven dry weights of foliage were higher than oven dry weights of woody parts for only four samples (< 1.2 m average height and < 1.7 m<sup>2</sup> canopy area) and greater for 21 samples (> 1.2 m average height and > 1.7 m<sup>2</sup> canopy area). Mean dry weights from foliage collected at Oxbow SWA on average were reduced to 47.1% ( $\pm 2.3$ ) and woody parts to 63.6% ( $\pm 0.6$ ) of their green weights. Foliage represented on average 9.3% and woody material represented 90.7% of the total oven-dry weights for all samples collected at Oxbow SWA. The total oven-dry aboveground biomass for the individual tamarisk trees varied from 0.007 kg to 375.81 kg.

Five competing regression models were evaluated from a suite of candidate models (Table 1.1). The best model ( $AIC_c = -148.69$ ,  $\Delta AIC_c = 0$ , Table 1) explained 97% of the variation in total oven-dry aboveground biomass (TAGB) of tamarisk and was highly significant ( $P < 0.0001$ ). It included both canopy area and average height as variables with canopy area being the strongest predictor of TAGB (partial  $R^2 = 0.95$ ). Similarly, the second-best model ( $AIC_c = -131.71$ ,  $\Delta AIC_c = 16.98$ ) also included canopy area and average height and explained 95% of the variation of TAGB. Canopy area for this model was equally as strong a predictor as the first model (partial  $R^2 = 0.95$ , Table

1.1). Other candidate models utilized either canopy area or average height only and explained 70% to 95% of the variation in tamarisk TAGB (models 3-5, Table 1.1). The third model related only canopy area to TAGB (Fig. 1.1) and explained 95% of the variation ( $\Delta AIC_c = 21.93$ , Table 1.1). My fourth model considered average height (Fig. 1.2) and square of average height as predictors to TAGB explaining 90% of the variation ( $\Delta AIC_c = 57.01$ ), whereas a fifth model that also considered only average height as a predictor was the weakest model explaining only 70% of the variation in tamarisk TAGB. The results from my best model found a strong agreement between tamarisk observed TAGB and predicted TAGB (Fig. 3,  $Y = 0.0261 + 0.9674 X$ ,  $R^2 = 0.97$ ).

#### **1.4 Discussion**

I was extremely encouraged to be able to accurately predict tamarisk aboveground biomass from simple field measurements of cover and height (Table 1.1, Fig. 1.3). While additional destructive sampling in other areas will be needed to generalize the models, the individuals and stands used here are indistinguishable from many of my study sites elsewhere in Colorado, New Mexico, and Utah. Because there are high costs associated with collecting and analyzing this type of field data, the models presented here may serve as a first approximation of aboveground biomass of tamarisk until additional samples are gathered from fringe populations.

Although my models succeeded in identifying strong relationships between aboveground biomass and average height and canopy area (Fig. 1.3), there are still important caveats to consider. The models may be strongest when applied to tamarisk within the geographical vicinity of my study area, and results may differ in other

landscapes or at larger scales, or may not be applicable throughout the species' distributional range. Ecological variables, such as climate, water availability, or disturbance regimes, are likely to affect growth formations and stand structure of tamarisk. Therefore, my best model would provide much better biomass estimates if applied to the areas that have the range of variation in average height and canopy area similar to this study; this model may underestimate or overestimate biomass outside these ranges. Furthermore, in an effort to preserve simplicity, my models do not consider diameter, age, or stem numbers of sampled trees, all of which may contribute to varying biomass estimates. Also, my study measured actual foliage weights from only half of the sampled trees, using the results to estimate the other half. Although dry weights of foliage are unlikely to vary much, I should acknowledge that some bias in the model can be expected.

These models may not be suited for all species of tamarisk and should be evaluated prior to application, or new models should be developed using similar methodology. In particular, the models that utilized average height and canopy area measurements independently to predict aboveground biomass (models 3, 4 and 5) are limited to the site of sampled trees. For example, model 3 (which utilizes canopy area as the only predictor variable) does not distinguish an area infested by new seedlings and an area infested by mature stand; yet there will be obvious differences in aboveground biomass between the two sites. Despite these limitations, my best model, which utilizes both average height and canopy area (model 1, Table 1.1) has the strongest potential in providing researchers and resource managers with a rapid and easy method to determine aboveground biomass of tamarisk. However, this model is also sensitive to canopy area

and a correction factor for canopy area may be necessary for biomass predictions over larger areas (e.g., > 100 m<sup>2</sup>).

These models can be integrated with a variety of research initiatives, such as determining water usage and productivity, monitoring the effectiveness of bio-control agents, and developing remote sensing capabilities. Resource managers can employ these models to assess fire risks, changes in riparian habitats, and calculate costs of herbicides and other control treatments. With some additional field work, these biomass models can also be applied to mapping landscape-level tamarisk biomass using remotely sensed data (e.g., Hall *et al.* 2006). To broaden the applicability of aboveground biomass models, similar research initiatives are needed throughout the distribution range of tamarisk to assess the variability associated with geography and climate. Additionally, large-scale sampling in other invaded areas that have trees of varying height and canopy area would further enhance the model's utility for stand estimates and its application across the western United States.

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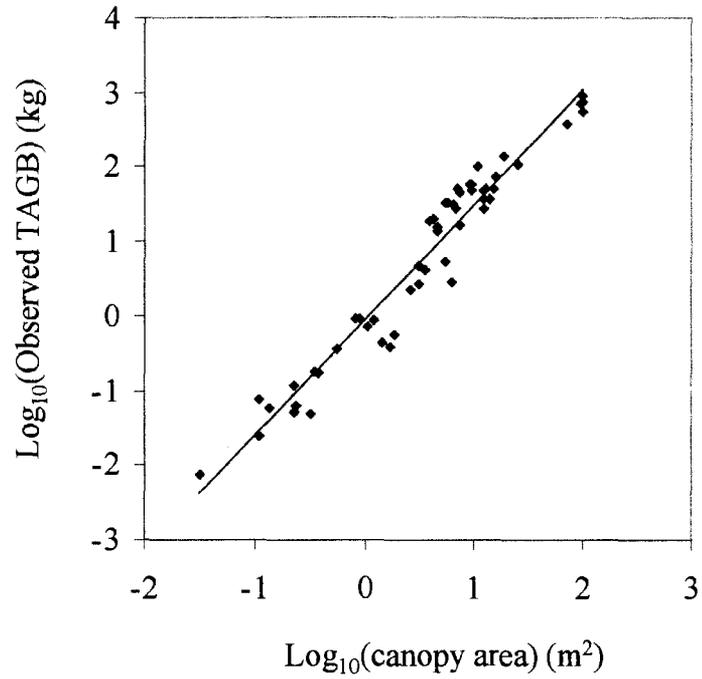
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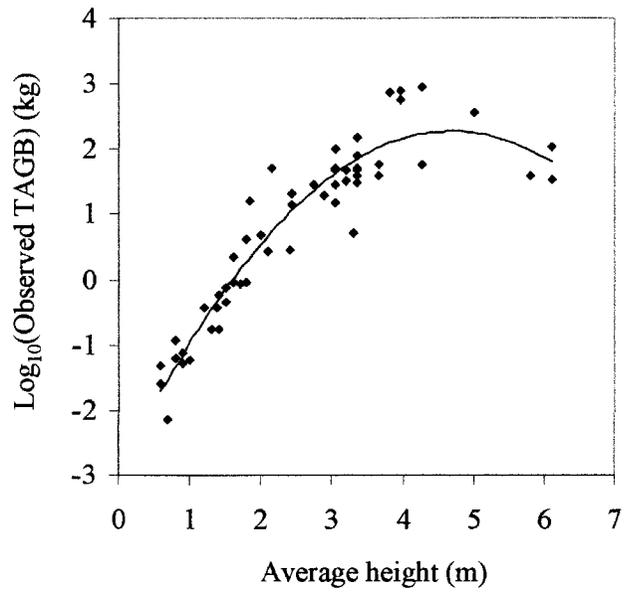
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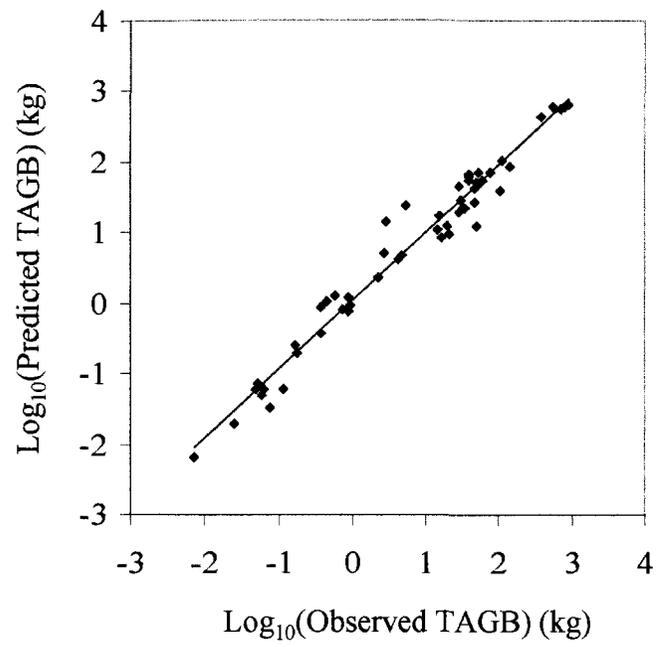
## 1.6 Figures and tables



**Figure 1.1.** Relationship between *T. ramosissima* canopy area (m<sup>2</sup>) and predicted total oven dry aboveground biomass (TAGB) (kg) (Model 3).



**Figure 1.2.** Relationship between *T. ramosissima* average height (m) and predicted TAGB (kg) (Model 4).



**Figure 1.3.** Relationship between *T. ramosissima* observed TAGB (kg) and predicted TAGB (kg).

**Table 1.1.** Regression models for estimating *T. ramossissima* total oven dry aboveground biomass (TAGB) (kg) using canopy area (CA) (m<sup>2</sup>) and average height (Ht) (m) as predictors.  $P < 0.0001$  for all models,  $n = 54$ . Note:  $AIC_c$  is Akaike's Information Criterion corrected for small sample size; and  $\Delta AIC_{ci} = AIC_{ci} - \text{minimum } AIC_c$ , CF is correction factor. The final estimates of *T. ramossissima* biomass (kg) should be multiplied by CF to correct for bias; see text for details.

Model No.	Model	Coefficient symbol	Coefficient value	Partial R <sup>2</sup>	CF	Adjusted R <sup>2</sup>	AIC <sub>c</sub>	$\Delta AIC_c$
1	$\text{Log}_{10}(\text{TAGB}) = c + \alpha \text{Log}_{10}(\text{CA}) + \beta \text{Ht} + \gamma \text{Ht}^2$	c	-1.1993		1.17	0.966	-148.69	0.00
		$\alpha$	1.1090	0.947				
		$\beta$	0.8595	0.007				
		$\gamma$	-0.0927	0.014				
2	$\text{Log}_{10}(\text{TAGB}) = c + \alpha \text{Log}_{10}(\text{CA}) + \beta \text{Ht}$	c	-0.2968		1.24	0.952	-131.71	16.98
		$\alpha$	1.3621	0.947				
		$\beta$	0.1324	0.007				
3	$\text{Log}_{10}(\text{TAGB}) = c + \alpha \text{Log}_{10}(\text{CA})$	c	-0.0518		1.28	0.946	-126.75	21.93
		$\alpha$	1.5445					
4	$\text{Log}_{10}(\text{TAGB}) = c + \alpha \text{Ht} - \beta \text{Ht}^2$	c	-2.9543		1.58	0.898	-91.68	57.01
		$\alpha$	2.2312	0.707				
		$\beta$	-0.2380	0.195				
5	$\text{Log}_{10}(\text{TAGB}) = c + \alpha \text{Ht}$	c	-1.2616		3.82	0.701	-34.61	114.07
		$\alpha$	0.7902					

## CHAPTER 2: MODELING INVASION FOR A HABITAT GENERALIST AND A SPECIALIST PLANT SPECIES

### 2.0 Abstract

Predicting suitable habitat and the potential distribution of invasive species is a high priority for resource managers and systems ecologists. Most habitat suitability models are designed to identify habitat characteristics that define the ecological niche of a species with little consideration to individual species' traits. I tested five commonly used modeling methods on two invasive plant species, the habitat generalist cheatgrass (*Bromus tectorum*) and habitat specialist tamarisk (*Tamarix chinensis*), to compare model performances, evaluate predictability, and relate results to distribution traits associated with each species. Most of the tested models performed similarly for each species; however, the generalist species proved to be more difficult to predict than the specialist species. The highest Area Under the Receiver Operating characteristic (ROC) Curve (AUC) values with independent validation datasets of cheatgrass and tamarisk were 0.503 and 0.885, respectively. Similarly, a confusion matrix for cheatgrass had a maximum overall accuracy of only 55%, while the overall accuracy for tamarisk was 85%. Models for the generalist species had varying performances, poor evaluations, and inconsistent results. This may be a result of a generalist's capability to persist in a wide range of environmental conditions that are not easily defined by the data, independent variables, or model design. Models for the specialist species had consistently strong performances, high evaluations, and consistent results among different model applications. This is likely a consequence of the specialist's requirement for explicit environmental resources and ecological barriers that are easily defined by predictive

models. Although defining new invaders as generalist or specialist species can be challenging, model performances and evaluations may provide valuable information on a species' potential invasiveness.

## **2.1 Introduction**

Invasion of non-native plant species continues to be a high-priority issue for natural resource managers throughout the United States. The impacts that these species have on the landscape include the loss of native biodiversity (Rosentreter 1994, Randall 1996), alteration of ecosystem processes (Vitousek *et al.* 1997, D'Antonio *et al.* 1999, Mack *et al.* 2000), and reduced availability of resources (Busch & Smith 1995, Olson 1999, Si *et al.* 2005). Only a small percentage of plant species introduced to the U.S. become invasive, and a species' success is generally attributed to species traits and the availability of resources that enable it to survive and flourish within a system (Baker 1974, Lodge 1993, Cronk and Fuller 1995, Planty-Tabacchi *et al.* 1996, Thebaud *et al.* 1996, Williamson and Fitter 1996, Mack *et al.* 2000, Lee 2001, Stohlgren *et al.* 2003, Pysek and Richardson 2007). The success of an invasive species may be dependent on a single trait that facilitates a competitive advantage under specific ecosystem conditions or multiple traits that allow widespread dispersal across environmental gradients. Given the potential range of survival strategies associated with non-native species, and diverse ecosystem characteristics across North America, identifying or predicting attributes that drive or prohibit invasions can be challenging.

The diversity of survival strategies exhibited by invaders has led some researchers to categorize species as generalists or specialists, and subsets within (e.g., dominant

generalist, subdominant generalist; Chong *et al.* 2006). These categories are loosely defined by the interaction between a species and its environment. Although comparisons between generalist and specialist species are common in biological studies (Adler 1999, Arens 2001, Bohn and Amundsen 2001, Lambrinos 2002), they are rarely considered when forecasting invasions or testing model applications (Seoane *et al.* 2005, Chong *et al.* 2006). Most studies use a single model to make predictions for a species of interest (Ficetola *et al.* 2007, Zhu *et al.* 2007), while model comparisons tend to test multiple models for a single species (Phillips *et al.* 2006, Stockman *et al.* 2006, Pearson *et al.* 2007) or test individual models for multiple species (Bonn and Schoeder 2001, Thuiller *et al.* 2005). In any case, considerations of species traits or dispersal strategies are extremely rare (Segurando and Araujo 2004, Elith *et al.* 2006). This is especially common with invasives, where detailed species information is often lacking on autecology and inter-specific competition over large and small spatial scales.

Alternatively, models are generally designed to identify ecosystem characteristics that can predict habitat suitability on the landscape and can be broadly applied to different species (Phillips *et al.* 2004, Payne and Stockwell 2006). The “one size fits all” approach may be applicable for species that have evolved within restricted or native ranges but may not always meet the challenges presented by invasive species (Lee 2001, Doyle *et al.* 2003, Saura-Mas & Lloret 2005, Stohlgren *et al.* 2005, Ellstrand and Schierenbeck 2006). Most invasive species are new arrivals lacking sufficient residence time to define their ecological niche, reveal biotic and abiotic interactions, or demonstrate species traits that would characterize them as generalist or specialist species (Chong *et al.* 2006, Stayer *et al.* 2006). As a result, predictive models for new invaders are often

believed to underestimate the potential distribution and habitats at risk (Wilson *et al.* 2007).

In this study, I hypothesized that model performance can be influenced by species-specific traits and that the ecological niche of habitat specialists can be better predicted than those that are characterized as habitat generalists. As a result, models do not perform equally with all species; however, model performance, whether weak or strong, may provide resource managers and researchers with clues on how a particular invader will interact with potential habitats. To test my hypotheses, I selected five common modeling methods to predict the potential distribution of two highly invasive species; a habitat generalist, cheatgrass (*Bromus tectorum*; Mack 1981, Knapp 1996) and a habitat specialist tamarisk (*Tamarix chinensis*; Horton, 1964; Everitt, 1980).

## **2.2 Methods**

### **2.2.1 Study area**

My study site is the Grand Staircase-Escalante National Monument (GSENM), located in south-central Utah, USA. The monument covers an area of approximately 769,000 ha with elevations ranging from 1,160 to 2,620 m. High plateaus and deeply incised canyons are characteristic of the landscape. The climate of the region is generally temperate and arid with the average annual precipitation approaching 250 mm and mostly occurring during winter months. Mean summer temperatures range from 16 to 32° C, and winter temperatures range from -9 to 4° C (National Climatic Data Center 2003). Despite its extreme climate, the monument is rich in floral diversity and vegetation types. Over 984 plant species have been recorded within the monument's boundaries, of which 174

(19%) are regionally endemic and 98 (10%) are non-native (Fertig *et al.* 2002). Only a small proportion of the non-native species exhibit invasive characteristics, while most do not appear to pose a significant threat to the monument's diverse ecosystems and vegetation types (Waters *et al.* 2004).

### **2.2.2 Field data collection**

For this study, I used four independent datasets collected by the Bureau of Land Management (BLM), the Natural Resource Ecology Laboratory (NREL) at Colorado State University, and the U.S. Geological Survey (USGS). BLM datasets included the results from a Noxious Weeds Inventory (N = >24,000) conducted by the BLM Utah State Office in 1997 and from the Rangeland Health Monitoring Program (N = 285) conducted by resource managers at the GSENM between 1999 and 2003 (Pellant *et al.* 2000). Datasets collected by the NREL and USGS include a six-year landscape-scale vegetation assessment of GSENM (N = 380) conducted between 1998 and 2004 (Waters *et al.* 2004), and a research project titled Fingerprinting Biodiversity (N = 380) conducted between 2005 and 2007 (Stohlgren & Evangelista, *work in progress*). I randomly chose a selected number of samples from each dataset to achieve balance between sample sizes and to limit samples to within the monument's boundaries. For cheatgrass, I used a total of 366 samples (246 present and 120 absent) for training and 450 samples (218 present and 232 absent) for validation of the models. For tamarisk, a total of 449 samples (226 present and 223 absent) were used for training and 464 samples (227 present and 237 absent) were used for validation of the models.

### **2.2.3 Environmental variables**

I generated six different environmental variables from a 10-m Digital Elevation Model (DEM) in ArcGIS 9.1, Arc Toolbox (ESRI 2004) to represent resource availability and topographic features on the landscape that may facilitate invasion (Davis *et al.* 2000, Stohlgren *et al.* 2003). Each variable had a 10-m pixel size and was generated in a grid format that extended over the entire study area. All six candidate variables were considered for each model and for both species. These variables were overland distance to water, slope (degrees), solar insolation, soil wetness index, eastness, and northness. A raster dataset for overland distance from water was generated using FlowS Geoprocessing tools (version 1.0; Theobald *et al.* 2006) and slope was generated using Spatial Analyst in ArcGIS 9.1 (ESRI 2004). A solar insolation grid was generated using the Shortwave program developed by Kumar *et al.* (1997). Soil wetness index was calculated using the formula  $[\ln(A/\tan \beta)]$ , where  $\ln(\cdot)$  is the natural logarithm,  $A$  is the area drained per unit contour or specific area, and  $\beta$  is the topographic slope (Moore *et al.* 1991, Wolock 1993). Eastness and northness were generated in ArcGIS 9.1 (ESRI 2004) using the formulas  $\sin(A)$  and  $\cos(A)$ , respectively, where  $A$  is aspect in degrees (Guisan *et al.* 1999, Gutierrez *et al.* 2005, Kumar *et al.* 2006). Previous studies have demonstrated that these landscape characteristics often play significant roles in species distributions and patterns of invasions (Lambrinos 2002, Stohlgren *et al.* 2003, Kumar *et al.* 2006)

### **2.2.4 Statistical analyses and modeling**

The first model tested was a simple envelope design that has no statistical basis but simply defines the parameters of the independent variables for presence-only data (Envelope; <http://www.niiss.org/cwis438/gather/Envelope.php>). For each presence point, the value of each independent variable is extracted, with the minimum and maximum values of all presence points defining the probability range of occurrence. The highest probability value for the Envelope model cannot exceed the number of independent variables tested. I also tested maximum entropy (Maxent, version 2.3.18; [www.cs.princeton.edu/~schapire/maxent/](http://www.cs.princeton.edu/~schapire/maxent/); Phillips *et al.* 2004, Phillips *et al.* 2006) and genetic algorithm rule-set prediction models (Desktop GARP, [www.nhm.ku.edu/desktopgarp/](http://www.nhm.ku.edu/desktopgarp/); Stockwell and Nobel 1992; Anderson *et al.* 2003) which have gained popularity because of their ability to predict species occurrence with presence-only data and small datasets. Finally, I tested two commonly employed regression models: logistic regression (Evans *et al.* 2000, Pearce and Ferrier 2000) and classification tree analysis (Breiman *et al.* 1984, Lewis 2000), both of which require presence and absence data. Both regression models were analyzed using SYSTAT software (version 10.0, SSI 2004). For logistic regression models, all variables were assessed for multicollinearity and normality. The variables were transformed using  $\text{Log}_{10} + 1$  where appropriate. Significance of predictors in the logistic regression model was assessed at alpha 0.05.

The performance of all the models was evaluated using threshold-dependent and threshold-independent measures. Threshold-dependent evaluation was measured by specificity and sensitivity and Cohen's maximized Kappa (Cohen 1960). There are two possible errors that may occur in prediction models: false-negatives (under-prediction)

and false-positives (over-prediction; Fielding and Bell 1997). Using the independent validation data for each species, I present the relative proportions of these errors in a confusion matrix. Specificity, the proportion of true-positive and false-positive absences, and sensitivity, the proportion of true-positives and false positive presences, are reported for the best two models of each species as defined by the Area Under the Curve values described below. Overall accuracy was calculated using the formula  $[(a + b)/N]$ , where  $a$  is the number of correctly classified absences,  $b$  is the number of correctly classified presences, and  $N$  is the total number of samples (Fielding and Bell 1997).

Next, I used Cohen's maximized Kappa (Cohen, 1960) to measure the proportion of correctly classified points (i.e., presence, absence) after accounting for the probability of chance agreement. Kappa statistic values range from -1 to +1, where +1 is perfect agreement and any value less than 0 indicates a performance no better than random (Cohen 1960, Allouche *et al.* 2006). Landis and Koch (1977) rank analysis performances as poor when Kappa values are  $<0.40$ , good when the Kappa values range from 0.40 to 0.75, and excellent when Kappa values are  $> 0.75$ .

The threshold-independent evaluation required a receiver operating characteristic curve (ROC), where sensitivity is plotted against 1-specificity for all possible thresholds (Pearce and Ferrier 2000). From the ROC analysis, I calculated the Area Under the ROC Curves (AUC) using true presence and absence observations to measure the probability that a random, positive point falls within the predicted range of occurrence and a random negative point falls outside (Fielding and Bell 1997). The Maxent model generates AUC values using pseudo-random absence points on its own (Phillips *et al.* 2006), but I do not report these because I chose to maintain consistency with all models tested.

The independent variables used in the model comparisons play different roles of importance in predicting the potential habitat and distribution of each species. The Maxent, logistic regression, and classification tree models provide the contributions of each independent variable. The evaluations cannot be directly compared to each other, but are reported to serve as a general guide for ranking the importance of each environmental variable in model predictions.

## **2.3 Results**

### ***2.3.1 Generalist species***

Models tested for the habitat generalist cheatgrass generally did not perform as well as those tested for the habitat specialist tamarisk (Table 2.1). Evaluation of model performances for the cheatgrass training data showed that logistic regression was the best with an AUC value of 0.590. The GARP and Maxent models had slightly weaker predictive strength, while the Envelope model had the lowest performance. The classification tree analysis was unable to make any predictions using the independent variables tested. Evaluation of model performances for the cheatgrass validation data rank GARP the best with an AUC value of 0.503 (Table 2.1) which is no better than random, and all the models were within a range of 0.01 from each other. The Maxent, Envelope, and logistic regression models had only slightly weaker performances, respectively. For cheatgrass, the GARP model had an overall accuracy of 54.7%, while Maxent was 54.0% (Table 2.2). The predictive contributions of each independent variable for cheatgrass were ranked differently for each model. The Analysis of Variable Importance provided by the Maxent program ranked solar insolation as the most

important contributor (55.9%), slope as second (24.2%), and overland distance to water as third (12.4%). For logistic regression, soil wetness index was the only significant variable at  $p < 0.05$ .

### ***2.3.2 Specialist species***

For the specialist species tamarisk, the Maxent model performed best with the training data, having an AUC value of 0.773 (Table 2.1). The logistic regression, classification tree, and GARP models also performed strongly while the Envelope model had considerably lower predictive performances than the other models. Model evaluations using the validation data had higher performances overall (Table 2.1). Logistic regression performed the best with an AUC of 0.885 (Table 2.1). The GARP, classification tree, and Maxent models performed equally well, while the Envelope model performed poorly. The overall accuracy for the two best models for tamarisk, logistic regression and classification tree, was 84.7% and 87.2%, respectively (Table 2.2).

The predictive contributions of the independent variables for the models of tamarisk favored overland distance to water for the Maxent, logistic regression, and classification tree models. Maxent ranked overland distance to water as the most important contributing variable (82.1%), slope as second (8.3%), and soil wetness index as third (2.9%). Logistic regression found overland distance to water as the only significant predictor at  $p < 0.05$ . Similarly, the classification tree analysis found overland distance to water as the only predictor for tamarisk and split the tree at two different distances. Seventy percent of the presence points (mean = 0.70, standard deviation =

0.45) occurred when overland distance to water was <314m, and tamarisk was not found in the training data when the overland distance to water was >1731m.

## **2.4 Discussion**

### ***2.4.1 Predictability of a generalist versus a specialist***

As a generalist species, cheatgrass has become widely distributed throughout the GSENM and persists in a broad range of habitat types and environmental conditions (Evangelista *et al.* 2004, Guenther *et al.* 2004, Crall *et al.* 2006, Chong *et al.* 2006). Field data collected during the landscape-scale vegetation assessment found cheatgrass in 93% of the plots, making it the second most common species recorded in GSENM (Waters *et al.* 2004). Therefore, it was not surprising to see that the models tested in this study did not effectively distinguish cheatgrass's ecological niche or identifying specific landscape characteristics that may inhibit the species' distribution (Fig. 2.1, Fig. 2.2). All the models had consistently weaker performances for the habitat generalist cheatgrass than for the habitat specialist tamarisk (Table 2.1). Other modelling efforts for cheatgrass (Alley *et al.* 2004, Crall *et al.* 2006) and tamarisk species (Morissette *et al.* 2006, Davern 2006) have had similar results. Some of the models, such as Envelope, appear to have over-predicted the range of cheatgrass, which has been a concern with other generalist species (Dettmers *et al.* 2002, Hepinstall *et al.* 2002, Seoane *et al.* 2005). However, given the pervasiveness of cheatgrass, the predicted surface from Envelope appears to match field observations better than the more conservative model surfaces (Fig. 2.1, Fig. 2.2).

In contrast, most of the models for the habitat specialist tamarisk had stronger predictive performances. This trend might be expected because specialist species tend to have sharply defined niches and environmental barriers that are easier to distinguish by model analyses (Bohn *et al.* 2001, Caley and Munday 2003). In my model comparisons, overland distance to water was the most significant independent variable in the three models that provided predictive contributions of independent variables (Fig. 2.3, Fig. 2.4), which further highlights the specialist nature of tamarisk that largely confines it to riparian ecosystems.

#### ***2.4.2 Model performance and interpretation***

Despite varying performances, I believe that all the models tested still have promising applications in predicting suitable habitat and the potential distribution of generalist and specialist invasive species. The results from this study suggest that no single model is superior in all circumstances (Table 2.1), supporting reviews from other studies (Elith *et al.* 2006). Most of the models I tested performed similarly with each species, suggesting that the varying results between the generalist and specialist species are likely correlated to species traits or the independent variables tested. On average, the models for cheatgrass performed no better than random, while the predictive contributions of each independent variable tested for cheatgrass fluctuated considerably between the Maxent and logistic regression models. In contrast, most of the models for tamarisk performed strongly. The Maxent, logistic regression, and classification tree models agreed that one independent variable (i.e., overland distance to water) was highly significant in predicting the habitat specialist tamarisk.

Closer examination of the predicted surfaces for tamarisk suggests that Maxent performed slightly better at a finer scale than the other models (Fig 2.4). For example, the lower portion of Hackberry Creek is cradled by steep canyon walls that are prohibitive to most plant establishment. Above the canyons are flat xeric landscapes dominated by pinyon pine (*Pinus edulus*), Utah juniper (*Juniperus osteosperma*), and big sage (*Artemisia tridentata*). Tamarisk is absent from these communities (Evangelista, *personal observation*), and these communities are highly unlikely to support future establishment of the specialist species. The sensitivity of Maxent was able to distinguish canyon walls from the riparian system but incorrectly predicted potential tamarisk habitat on the xeric plateau above Hackberry Creek. The logistic regression, classification tree, and GARP models made coarser predictions and did not account for the steep slopes of the canyon walls while predicting tamarisk to occur on the xeric plateaus.

Improved predicted surfaces for both species may have been likely with inclusion of additional independent variables. For example, tamarisk models may be improved by including variables related to stream flow, native species richness, or climate (Horton 1977, Brotherson and Field 1987, Morissette *et al.* 2006). Similarly, the performance of models for cheatgrass may have been improved had variables for fire history, livestock grazing, and recreational use been available (Evangelista *et al.* 2004, Crall *et al.* 2006). Many studies have found that model performance greatly relies on the particular independent variables tested, spatial resolution, or inadequate field data (Suarez-Seoane *et al.* 2002, Gibson *et al.* 2004, Barry and Elith 2006). I do not suggest that the independent variables selected for this study are completely representative of ecological niches for each species; however, they are known to have significant influences on

invasive plant species in general (Stohlgren *et al.* 2003) and were selected with consideration of my objectives in comparing models and species.

When models perform strongly, it is generally indicative that key variables associated with habitat suitability and species traits were successfully identified for the analyses (Boyce *et al.* 2002, McKenney *et al.* 2003, Gibson *et al.* 2004). It is also reasoned that when models perform poorly, the analyses were lacking significant variables to predict suitable habitats (Waters *et al.* 2004) or relied on inconclusive field data (Hernandez *et al.* 2006, Real *et al.* 2006). Although these are rational interpretations in the model process, they are not easily corrected when assessing risk or modelling distribution of invasive species. If model performances are influenced by species traits (e.g., habitat generalist or specialist), then a broader interpretation of results may provide important insight to species traits, thus gauging the potential distribution of new invaders. I suggest that predictive models that perform poorly may not always be a shortcoming in methodology, the independent variables selected, or the completeness of occurrence data. An alternative interpretation might consider weak model performances as a clue to species traits and an early warning of a generalist's positive response to new habitats. Although this is demonstrated by the poor performances of all the models tested with cheatgrass, it is highlighted by the inability of the classification tree analysis to produce any results. Overall results of my analyses of cheatgrass further highlight the pervasive nature of the species and the models' inability to define any significant barriers to invasion among the independent variables tested. My results were consistent with those from other studies on cheatgrass (Evangelista *et al.* 2004, Waters *et al.* 2004), but a

thorough review of the literature examining different species and model responses was inconclusive since poor model performances are rarely published.

### **2.4.3 Conclusion**

Although most of the models I tested generally performed similarly with both species, there were some discrete differences noted. The models tested each have unique analytical approaches that may function better or worse with different species and datasets (Segurado & Araujo 2004, Pearson *et al.* 2007, Ward 2007). For this reason, I recommend that users select several models to test their data. The scientific literature offers numerous model comparisons suggesting that some models are superior to others. I do not discount the results of any individual study; however, collectively they reveal that model performances can exhibit different degrees of variability.

My study also demonstrates the importance of model functions and evaluations in interpreting results. I recommend the selection of models that have built-in functions that evaluate the performance of results (e.g., R-square, AUC). Although model evaluations can be conducted independently of models, they require access to different software and a comprehensive understanding of statistical methodology. Additionally, models that measure the predictive contributions of the independent variables (e.g., standardized regression coefficients, jackknife) will provide users with valuable clues regarding environmental conditions that may prohibit or facilitate species dispersal and establishment. Maxent and classification tree models, for example, provide user-friendly and comprehensive operations that quantify the predictive strength of each independent variable tested. Users should consider the results from all the available functions when

evaluating model performances or making predictions on a species' potential distribution, while considering expert knowledge whenever possible.

Because this study only examined two species, I cannot conclude that model performance alone can be used to gauge species traits or potential distribution risks of invasive species. However, this study offers several insights to model performances and their relationships to species traits. Only a few studies on these relationships have been conducted in any depth (Chong *et al.* 2006, McPherson and Jetz 2007), leaving a large gap in our understanding of the effects that autecology has on predictive modelling. My results also demonstrate the need for further studies that include a wide array of species (native and non-native) that exhibit different traits and dispersal strategies. Specifically, increased research may prove to be especially useful in assessing the risk of new invasive species.

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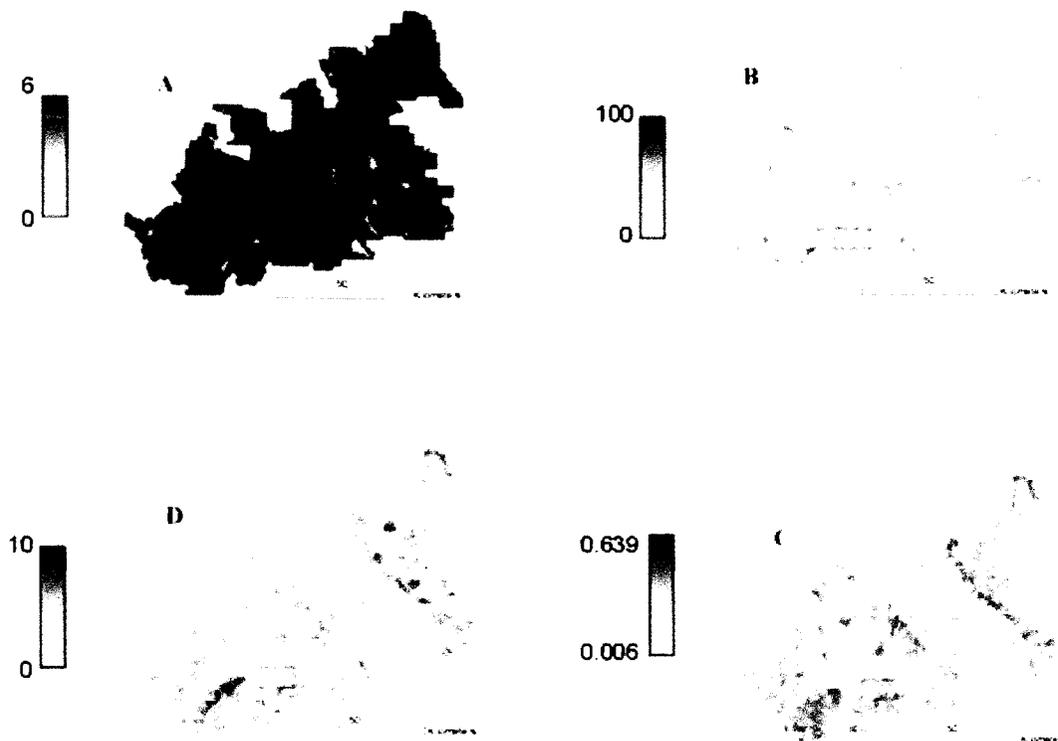
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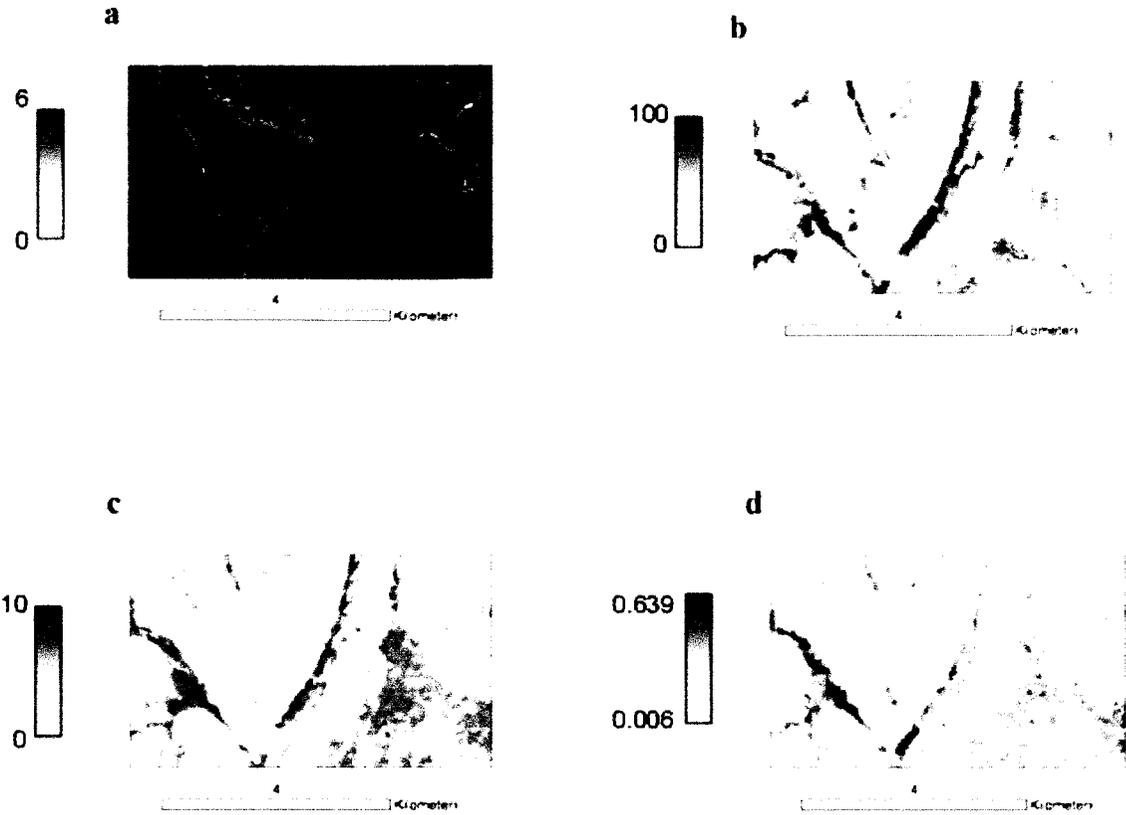
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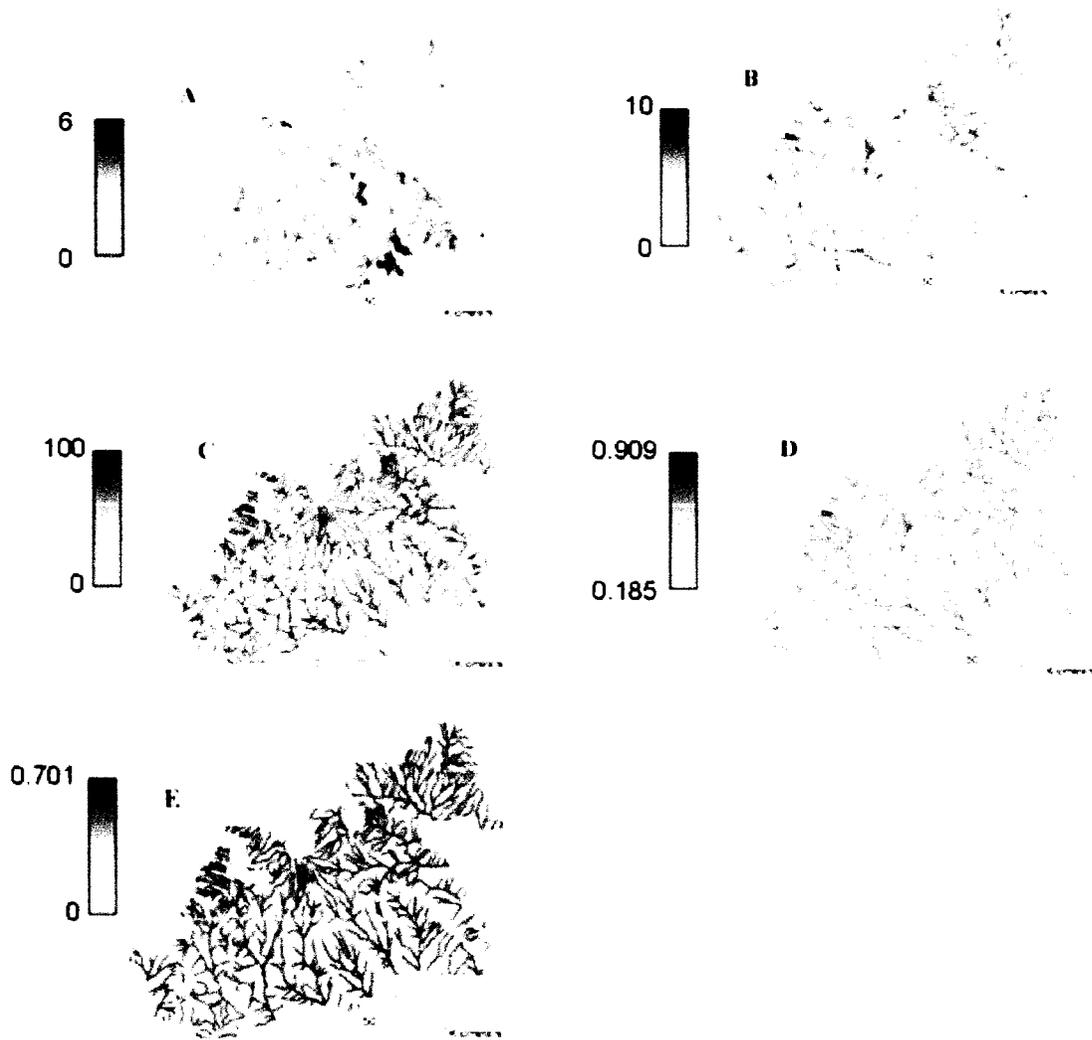
## 2.6 Figures and tables



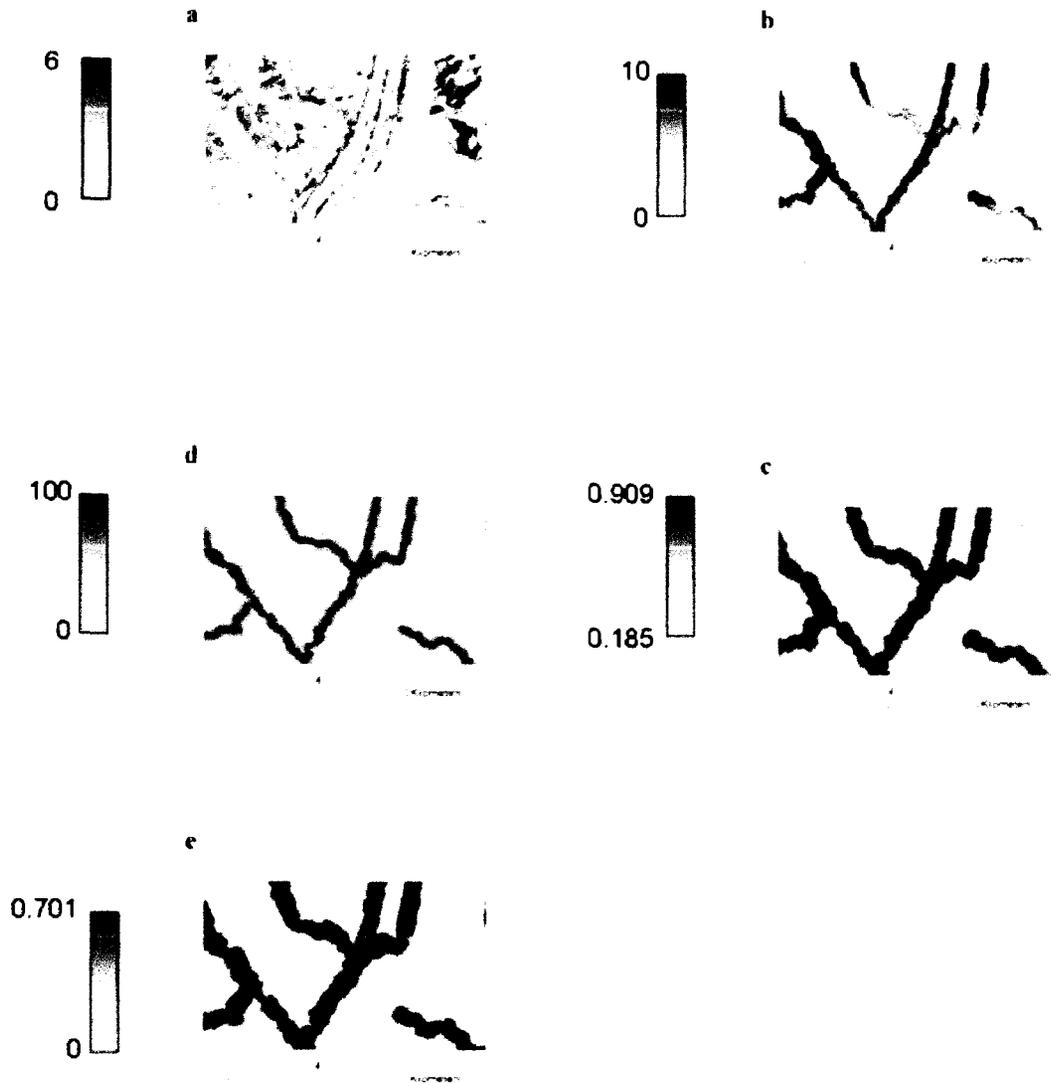
**Figure 2.1.** Predicted habitat and potential distribution of *B. tectorum* in the Grand Staircase-Escalante National Monument (A-D). Models compared are Envelope (A), Maxent (B), GARP (C), and logistic regression (D).



**Figure 2.2.** Predicted habitat and potential distribution of *B. tectorum* at a finer resolution along the Hackberry Creek, Cottonwood Creek and Paria River confluences (a-b). Models compared are Envelope (a), Maxent (b), GARP (c), and logistic regression (d).



**Figure 2.3.** Predicted habitat and potential distribution of *T. chinensis* in the Grand Staircase-Escalante National Monument (A-E). Models compared are Envelope (A), Maxent (B), GARP (C), logistic regression (D) and (E) classification tree.



**Figure 2.4.** Predicted habitat and potential distribution of *T. chinensis* at a finer resolution along the Hackberry Creek, Cottonwood Creek, and Paria River confluences (a-d). Models compared are Envelope (a), Maxent (b), GARP (c), logistic regression (d), and (e) classification tree.

**Table 2.1.** Performances of different models for *Bromus tectorum* and *Tamarix chinensis* based on training and validation data evaluated by area under the curve (AUC) values and Cohen's maximized kappa.

Model	<i>B. tectorum</i>				<i>T. chinensis</i>			
	Training data		Validation data		Training data		Validation data	
	AUC	kappa	AUC	kappa	AUC	kappa	AUC	kappa
Envelope	0.513	0.034	0.499	-0.002	0.542	0.096	0.458	-0.073
MaxEnt	0.559	0.055	0.502	0.055	0.773	0.452	0.828	0.612
Garp	0.582	0.212	0.503	0.077	0.721	0.421	0.830	0.63
Classification Tree	n/a	n/a	n/a	n/a	0.741	0.393	0.829	0.66
Logistic Regression	0.590	0.151	0.495	0.029	0.744	0.416	0.885	0.694

**Table 2.2.** Confusion matrix tables for the two best models of *B. tectorum* and *T. chinensis* with cut-off at maximized kappa value.

		GARP ( <i>B. tectorum</i> )			Maxent ( <i>B. tectorum</i> )		
		Predicted		Correct	Predicted		Correct
		0	1		0	1	
0		192	40	82.8 %	219	13	94.4 %
1		164	54	24.8 %	194	24	11 %
Overall				54.7 %			54.0 %
Cut-off threshods				0.85			0.84

		Logistic regression ( <i>T. chinensis</i> )			Classification Tree ( <i>T. chinensis</i> )		
		Predicted		Correct	Predicted		Correct
		0	1		0	1	
0		200	37	85 %	187	50	78.2 %
1		34	193	84.4 %	29	198	87.2 %
Overall				84.7 %			87.2 %
Cut-off threshods				0.50			0.55

# CHAPTER 3: MAPPING TAMARISK (*TAMARIX*) BY REMOTE SENSING: A COMPARISON OF SINGLE-SCENE AND TIME-SERIES ANALYSES FOR DETECTING PHENOLOGY

## 3.0 Abstract

Previous attempts to map invasive tamarisk (*Tamarix* sp.) using remote sensing techniques have had varying results. Most successful remote sensing studies have taken advantage of phenological characteristics that distinguish tamarisk from other vegetation, such as its extended growing season and unique coloration during different times of the year. I tested six Landsat 7 ETM+ satellite scenes and several vegetation indices at different times of the growing season for their ability to detect tamarisk along the Arkansas River in Colorado. Satellite scenes were selected for April, May, June, August, September, and October. Using bands 1-5, band 7, Normalized difference vegetation index (NDVI), Soil-adjusted Vegetation Index (SAVI), Ratio Vegetation Index (RVI), and tasseled cap transformations (brightness, greenness, and wetness) for each month, I conducted single-scene and time-series analyses using the Maxent model. The time-series analyses were conducted in two modeling processes: the first model using all spectral variables ( $n=72$ ), and second model using only the top predictors ( $n=7$ ) from the results of the first model and removing those variables that were cross-correlated. Models were evaluated by using area under the receiver-operating characteristic curve (AUC), specificity, sensitivity, and Cohen's maximized Kappa. The best model was the time-series analysis fit with all spectral variables, which had an AUC = 0.96, overall accuracy = 0.90, and Kappa = 0.79. The top three predictor variables were June tasseled

cap wetness (25.8%), September tasseled cap wetness (16.4%), and October band 3 (11.6%). The second best model was the time-series analysis with the reduced number of spectral variables, followed by single-scene analyses for June, September, and August. Although several vegetation indices were strong predictors, the tasseled cap wetness index was one of the top three predictors in all but the April single-scene analysis. My results suggest that a time-series analysis of remotely sensed data is better for detecting phenological characteristics of tamarisk than a single-scene analysis. However, studies relying on a single time for data acquisition may have better results in June or late summer months.

### **3.1 Introduction**

Mapping invasive plants has become a high priority for resource managers and researchers across the U.S. Ground surveys are still commonly used for most mapping projects despite intensive labor requirements, associated economic costs, and incomplete coverage of the landscape (Crosier and Stohlgren 2004, Dewey and Andersen 2004). Improved methods to accurately determine the current distribution of invaders are required to better assess their environmental impacts, formulate effective control strategies, and forecast potential dispersal. Remote sensing has played an important, but limited, role in mapping and detecting invasive plants (Anderson *et al.* 1993, Everitt *et al.* 1995, Rowlinson *et al.* 1999, Noujdina and Ustin 2008) or for mapping potential habitat (Morissette *et al.* 2006). It is more commonly applied to mapping weeds in agricultural environments where species richness and diversity are minimal (Medlin *et al.* 2000, Lopez-Granados *et al.* 2006). Detecting a specific plant species in forests, rangelands,

riparian areas and natural landscapes using remote sensing techniques has proved to be a greater challenge. Large-scale infestations, where invaders are clearly the dominant species and environmental heterogeneity is reduced, tend to be easier to detect remotely (Anderson *et al.* 1993, Lass and Prather 2004, Laba *et al.* 2005).

One invasive species that is especially problematic in the western U.S. is tamarisk. Tamarisk's impacts to native ecosystems in the U.S. include the desiccation of water tables, displacement of native plant communities, alteration of soil chemistry and ecosystem processes, and loss of critical wildlife habitat (Christensen 1962, Robinson 1965, Harris 1966; See Introduction). Infestations often begin discretely among species-rich riparian ecosystems before abruptly overwhelming and displacing competitor species. Once tamarisk establishes dominance, control and restoration efforts can be extremely labor intensive and costly. Detecting tamarisk in the early stages of infestation and mapping its distribution are essential to resource management and stewardship. Remote sensing of tamarisk distributions has been only marginally effective (Lass *et al.* 2002, Hirano *et al.* 2003, Hamada *et al.* 2007, Asner *et al.* 2008). New airborne and satellite sensors promise to improve our ability to spectrally distinguish tamarisk from other species, but the techniques remain inadequate and are not yet economically practical.

The detection of invasive plants using remote sensing may be improved if the target species has phenological attributes that are distinctive from native vegetation. For example, leafy spurge (*Euphorbia esula* L.) has yellow-green inflorescences that are spectrally unique when compared to associated flora (Everitt *et al.* 1995, Parker Williams and Hunt 2002, Hunt *et al.* 2004). Similarly, yellow starthistle (*Centaurea solstitialis*),

tamarisk (*Tamarix* spp.), yellow hawkweed (*Hieracium pratense*), oxeye daisy (*Chrysanthemum leucanthemum*), and Chinese tallow (*Sapium sebiferum*) also have distinctive colorations that can facilitate remote sensing (Everett and Deloach 1990, Lass *et al.* 1996, Lass and Callihan 1997). Other species have been detected by their extended growing periods. Broom snakeweed (*Gutierrezia sarothrae*), a perennial sub-shrub, has been remotely sensed during its early-season greening (Peters *et al.* 1992). Cheatgrass (*Bromus tectorum*), an invasive annual grass, has also been successfully detected because it germinates in winter months prior to most native grasses (Bradley and Mustard 2005). The distinctiveness of any phenological attribute can vary widely with regional climate, latitudinal gradients, and species richness within an ecosystem. As a result, the timing of acquiring remotely sensed data is critical and can be difficult to predict.

Time-series analyses of remotely sensed data are increasingly being used for detecting broad-scale invasions (Pavri and Aber 2004, Robinson *et al.* 2008) and monitoring the impacts of mitigation treatments (Anderson *et al.* 2005, Everett *et al.* 2007). A few studies using time-series analyses have reported success in identifying cheatgrass. Bradley and Mustard (2005) demonstrated how inter-annual data collected from Landsat and Advanced Very High Resolution Radiometer (AVHRR) can detect cheatgrass responses to precipitation. Peterson (2005) was able to distinguish cheatgrass from other vegetation by using scenes from Landsat 7 ETM+ on two different dates within a single year. In both cases, the researchers were able to exploit subtle phenological differences (i.e., extended growing season, rapid response) between the invaders and associated native flora within a growing season. To determine the optimal time of the year to conduct remote sensing surveys, Everitt and Deloach (1990) used a

time-series of conventional color and color infrared aerial photographs for tamarisk and native riparian vegetation. From their study sites in Texas and Arizona, they found that tamarisk could best be identified in late fall and early winter months when foliage turned a yellow-orange color before dropping.

Remote sensing of tamarisk has had limited success, and conventional methods (e.g., supervised and unsupervised classification) have not proved to be reliable. Ge *et al.* (2006) analyzed color aerial photographs at 1-m<sup>2</sup> resolution using a texture analysis for tamarisk in northern California. The photographs were acquired in April and the mean grey-level values were calculated for 60 pixels representing eight cover types. They found that color (grey tones) alone could not distinguish tamarisk from associated vegetation; however, the use of textural classifiers greatly improved separability of cover types. In southern California, Hamada *et al.* (2007) used discriminant analyses of presence/absence data and hierarchical clustering with hyperspectral imagery collected in October. Overall accuracy of their research varied by scene and minimum patch size, and results tended to over classify tamarisk distribution. Akasheh *et al.* (2008) used an iterative classification procedure to map riparian vegetation with high-resolution multi-spectral airborne sensors in July on the Rio Grande River, New Mexico. The vegetation in their study site was largely dominated by four riparian species: tamarisk, cottonwood, willow, and Russian olive. Using 24 validation plots for tamarisk, they were able to achieve 86% classification accuracy.

These studies demonstrate an evolution of remote sensing and image processing for detecting tamarisk and other invasive species. The development of new airborne and satellite sensors and platforms, coupled with advanced statistical software, geographic

information systems (GIS), and predictive models, give researchers a variety of tools to detect and predict the distribution of invasive species (Elith *et al.* 2006, Liu *et al.* 2006, Morisette *et al.* 2006, Evangelista *et al.* 2008, Noujdina and Ustin 2008). I explored new methods in remote sensing and image processing to map the distribution of tamarisk while incorporating some previous strategies that have proven to be effective. I tested six satellite scenes and derived vegetation indices from different months of the growing season to detect tamarisk using single-scene and time-series analyses. My objectives for this study were to compare each analysis and determine which month of the growing season was the best time for detecting tamarisk. I also examined the effectiveness of several vegetation indices derived from remote sensing data that have proven useful in other remote sensing studies. My analyses were conducted using the Maxent model (v3.2.1; [www.cs.princeton.edu/~schapire/maxent/](http://www.cs.princeton.edu/~schapire/maxent/)), which uses presence points to predict the potential range and habitat distribution of a species (Phillips *et al.* 2004, 2006). In several recent studies, Maxent has been found to be especially useful for mapping invasive species (Ficetola *et al.* 2007, Kumar *et al.* 2009) and ranked high when compared to other models for predicting tamarisk distributions (Evangelista *et al.* 2008).

## **3.2 Methods**

### ***3.2.1 Study area***

This study was conducted in the lower Arkansas River in southeastern Colorado. The Arkansas River is the sixth longest river in the continental U.S. Its headwaters begin in the Rocky Mountains of central Colorado and it flows east 2,364 km through Kansas, Oklahoma and Arkansas before emptying into the Mississippi River. In Colorado, the

river drops 1,400 m in elevation from its origin to the edge of the Great Plains near the city of Pueblo (Kammerer 1990). From Pueblo, the river flows approximately 400 km to the Kansas state line and sustains a wide belt of irrigated agriculture through a series of ditches and channels. Elevations and mean annual precipitation range from 1,417 m and 29.7 cm at Pueblo to 1,021 m and 38.3 cm at the state line (Lindauer 1983). Tamarisk was first reported in this region in 1913, and observers noted the species' rapid spread as early as 1921 (Lindauer 1983). Today, tamarisk infestation along the Arkansas River between Pueblo and the state line is estimated to be more than 120 km<sup>2</sup> resulting in the estimated loss of 47,000 acre-feet of water annually (Tamarisk Coalition 2008).

My study area was defined by the boundaries of the Landsat7 Enhanced Thematic Mapper Plus (ETM+) scene (Path 32, Row 34) used in my analyses. The study area includes approximately 175 km of the Arkansas River in southeastern Colorado between the town of Avondale and the City of Lamar (Figure 3.1). Also included in the scenes are John Martin Reservoir, the lower sections of the Purgatoire and Apishapa rivers, developed agriculture, and a significant area of semi-arid rangeland that extends into New Mexico.

### ***3.2.2 Field data collection***

This study relied on the results of an intensive inventory and mapping effort by the Tamarisk Coalition ([www.tamariskcoalition.org](http://www.tamariskcoalition.org)) and other groups in 2005. Stands of tamarisk were inventoried by field crews using global positioning systems (GPS) and transformed into geographical information systems (GIS) polygons with the aid of aerial photography (Tamarisk Coalition 2008). These data are now stored and available on the

National Institute of Invasive Species Science website ([www.niiss.org](http://www.niiss.org)). From these data, I randomly generated 400 presence points from tamarisk polygons that had a percent basal cover >50%. Of these, 250 points were used for training (62.5%) the models and 150 points were reserved for testing (37.5%). An additional 150 tamarisk absence points were randomly generated using GIS from cottonwood (*Populus* sp.) stands, agriculture, and rangeland land cover types for model testing.

### ***3.2.3 Remotely sensed data***

I used six Landsat7 ETM+ scenes for my analyses. Each scene and derived vegetation indices were processed using ERDAS Imagine v9.0 (Leica 1991-2005) and ArcGIS 9.1 (ESRI 2004) software. The scenes, selected for their seasonal variance, were acquired on April 16, 2000; May 11, 2003; June 23, 2001; August 12, 2002; September 7, 2000; and October 23, 1999. From each scene, bands 1-5 and band 7 were used in my analyses. Additionally, I generated several vegetation indices from each scene that are commonly used for estimating vegetation and land-cover features. Normalized difference vegetation index (NDVI) is a non-linear transformation of the ratio between the visible (red) and near-infrared bands (NIR: Rouse *et al.* 1974). The NDVI index is commonly used to measure vegetation canopy characteristics such as biomass, leaf area index, and canopy cover (Kriegler *et al.* 1969, Myneni *et al.* 1997, Todd *et al.* 1998). I calculated NDVI using the following expression:

$$\text{NDVI} = (\text{band 4} - \text{band 3}) / (\text{band 4} + \text{band 3})$$

The Ratio Vegetation Index (RVI) was calculated by dividing near infrared (band 4) by visible red (band 3) reflectance values (Jordan 1960). The RVI and NDVI are very similar in that they are a measure of the slope of the line between the origin of red-NIR space and the red-NIR value of each pixel. The major difference between the two is the range of values given by the calculations. Some studies have used RVI and NDVI together (Liu *et al.* 2006), while other studies have elected to use one or the other (Lopez-Granados and Garcia-Torres 2006).

Tasseled Cap transformations were conducted for each scene using the coefficients reported by Huang *et al.* (2002). Originally developed for understanding changes in crop development, tasseled cap transformations are weighted composites of the six Landsat bands into three bands that have been useful in measuring soil brightness (tasseled cap, band 1), vegetation greenness (tasseled cap, band 2), and soil/vegetation wetness (tasseled cap, band 3; Kauth and Thomas 1976). These transformations have been described as a guided and scaled principal components analysis and have been shown to be useful in identifying forest attributes such as species composition, age class, and structure (Cohen *et al.* 1995, Todd *et al.* 1998, Jin and Sader 2005).

I also calculated the Soil-adjusted Vegetation Index (SAVI; Huete 1988), a ratio-based index developed to minimize the effects of the soil background. The formula used for calculating SAVI is:

$$\text{SAVI} = [(\text{band 4} - \text{band 3}) * (1 + L) / (\text{band 4} + \text{band 3} + L)]$$

where  $L$  is a correction factor ranging from 0 (high vegetation cover) to 1 (low vegetation cover). Each month had twelve potential predictor variables used for single-scene analyses, while the time-series analysis used a total of 72 potential predictor variables.

### **3.2.4 Data analyses**

I conducted my analyses using the Maxent model v.3.2 ([www.cs.princeton.edu/~schapire/maxent/](http://www.cs.princeton.edu/~schapire/maxent/)), which is a general-purpose method for estimating probability of distributions based on the principle of maximum entropy (Phillips *et al.*, 2004, Phillips *et al.* 2006). Maxent uses presence-only data to define known conditions within the parameters of the independent variables to predict a species' distribution and excludes all conditions that are unfounded or undefined. The model is nonlinear, nonparametric, and not sensitive to multicollinearity. Besides having several evaluation features built into the program, Maxent also provides the percent contribution of each variable. Several recent studies have found the Maxent model to perform as well, or better, when compared to other modeling methods (Elith *et al.* 2006, Evangelista *et al.* 2008, Kumar *et al.* 2009).

Each monthly scene, and the associated vegetation indices, were analyzed and tested independently (six models); while the time-series analyses were conducted using two modeling procedures. The first time-series model used all 72 predictor variables generated from the six scenes. From these results, I selected all the variables that had a predictive contribution >1.0 percent ( $n = 17$ ) and used them as predictor variables for my second time-series model. The 17 variables were tested for cross-correlations using SYSTAT (version 12; SYSTAT Software, Port Richmond, California, USA). For

variables that were highly correlated (Pearson correlation coefficient > 0.80), I removed the ones that had the least predictive cross-contribution in first-time series analysis model. This further reduced my number of variables to seven potential predictors.

I tested the models with threshold-dependent and threshold-independent measures using Schroder's ROC/AUC software (<http://brandenburg.geoecology.uni-potsdam.de/users/schroeder/download.html>). The ROC/AUC software was specifically developed for assessing the predictive performance of habitat models and requires presence and absence data. Threshold-dependent evaluations, using the ROC/AUC software, were measured by specificity, sensitivity and Cohen's maximized Kappa (Cohen 1960). Specificity is the proportion of true-positives and false-positive absences, and sensitivity is the proportion of true-positives and false-positive presences. The maximized Kappa statistic (K) measures the proportion of correctly classified points (i.e., presence, absence) after accounting for the probability of chance agreement. Kappa statistic values range from -1 to +1, where +1 would be perfect agreement and any values less than 0 would indicate a performance no better than random (Cohen, 1960; Allouche *et al.*, 2006). Landis and Koch (1977) ranked analysis performances as poor when Kappa values are <0.40, good when the Kappa values range from 0.40 to 0.75, and excellent when Kappa values are > 0.75.

The threshold-independent evaluation required a Receiver Operating Characteristic (ROC) curve, where 'sensitivity' is plotted against '1-specificity' for all possible thresholds (Pearce & Ferrier 2000). From the ROC analysis, the Area Under the ROC Curve (AUC) is calculated using presence and absence observations to measure the probability that a random, positive point falls within the predicted range of occurrence,

and a random negative point falls outside (Fielding and Bell 1997). The AUC value can vary from 0.5 (no better than random) to 1.0 (perfect discrimination; Hosmer and Lemeshow 2000). AUC evaluations for each model are presented in the results.

### **3.3 Results**

All the models generally performed well, further highlighting the applicability of remote sensing and vegetation indices for detecting tamarisk. The best model was the first time-series analyses that used all 72 variables (Figure 3.2). The AUC evaluation was 0.96, while the percent of correct predictions was 0.90 and kappa statistic was 0.79 (Table 3.1). The next best models were the second time-series analyses with the reduced number of variables and the October single-scene analysis. The AUC evaluations for these models were 0.93 and 0.89, respectively. The percent of correct predictions and kappa statistics for the second time-series analyses and October single-scene analyses were 0.84 and 0.85, and 0.69 and 0.71, respectively. The June, August, and September single-scene analyses had slightly lower but similar evaluations. Generally, the results from the single-scene analyses improved toward the later part of the growing season and into the fall months when most native plants go into dormancy.

The best predictor variables for the first time-series analyses were the June tasselled cap wetness (25.8%), September tasselled cap wetness (16.4%), and October wetness (11.6%; Table 3.2). Similarly, the best predictors for the second time-series analyses were the June tasselled cap wetness (63.1%), April NDVI (9.7%), and October band 3 (7.8%). It should be noted that the September tassled cap band 3 was found to be highly correlated with the June tasselled cap wetness, thus it was omitted from the second

time-series analyses. With the exception of the April NDVI, the best predictors for both time-series analyses were from the months that performed the best of the six single-scene analyses. Of the eight models, seven had at least one tasselled cap transformation as one of the top predictors.

### **3.4 Discussion**

My results suggested that the time-series analyses can better distinguish phenological differences between tamarisk and native flora than a single-scene analysis. Spectral data from the months of June, September, and October consistently had the greatest capability for detecting tamarisk in all of the models. I speculate that the peak in tamarisk green-up and its purple-white flowers contribute to the spectral uniqueness during June, while its extended growing season and the yellow foliage late in the year are conspicuous in September and October. Collectively, data from these months produced the strongest results in the time-series analysis; I was encouraged to see that they each performed exceptionally well with the single-scene analyses. My findings are also in agreement with results from previous remote sensing studies on tamarisk (Everitt and Deloach 1990, Akasheh *et al.* 2008). Although spectral data from these months performed best in my study area, they may not necessarily be the best candidates in other ecosystems, geographic regions, or spatial scales.

Vegetation indices used in my analyses made considerable predictive contributions to the final results. Most notable were the tasselled cap transformations for soil/vegetation wetness (tasselled cap band 3). The tasselled cap wetness index have been shown in other studies to be reliable for detecting change in forest structure and

biomass using single-scene and time-series analyses (Franklin *et al.* 2005, Jin and Sader 2005, Healey *et al.* 2006). Tamarisk biomass in my study site is quite extensive and significantly higher than native vegetation (Evangelista *et al.* 2008). Further study may be required to test the effectiveness of the tasselled cap wetness index on low densities of tamarisk; however, my results indicate the index may perform well with the remote sensing of large tamarisk stands or when used in a time-series analyses.

I was also encouraged by the performance of the Maxent model in analyzing remote sensing data. I am confident that my model results could be improved if additional geospatial variables that characterize the physical landscape were integrated (e.g., distance from water, slope), but I elected to analyze monthly scenes and vegetation indices exclusively to better identify temporal trends with tamarisk's phenology in relation to the spectral reflectance.

In conclusion, my study revealed several important factors that may significantly improve remote sensing efforts for tamarisk and other invasive species. I have identified at least three different times during the growing season when phenological attributes of tamarisk can help distinguish the species from native vegetation. I have also demonstrated that phenological differences may be better detected using a time-series analysis than a single-scene analysis. Biomass indicators, such as the tasselled cap wetness index, may prove useful for remotely sensing large tamarisk infestations or for detecting landscape change in a time-series analysis. Finally, the Maxent model proved to be a sufficient tool for analyzing remote sensing data and can easily integrate other geospatial variables that may enhance modeling efforts. These findings may prove useful

for most remote sensing studies including those that employ new, advanced sensors and across multiple spatial scales.

### **3.5 Literature**

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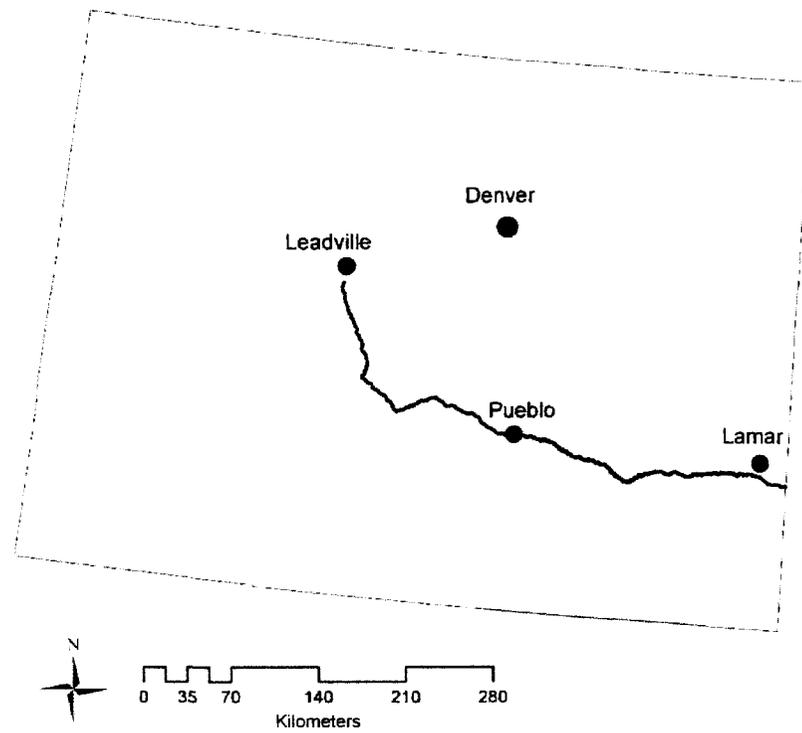
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### 3.6 Figures and tables



**Figure 3.1.** Map of study area (in grey) and the Arkansas River in Colorado.



**Figure 3.2.** An enlarged view of tamarisk detected along the Arkansas River and irrigation ditches near the town of Riverdale in southeastern Colorado. The results shown here are from a time-series analysis that used 72 remotely sensed data sets from Landsat7 ETM. Tamarisk distributions are shown from moderate (orange) to high (red) densities.

**Table 3.1.** Tamarisk model evaluations of single-scene and time-series analyses of Landsat7 scenes and associated vegetation indices. AUC values are presented from the Maxent model (Max) and the ROC/AUC Calculator (ROC), while sensitivity, specificity, percent correct, and the Kappa statistic were generated using the ROC/AUC Calculator.

<b>Scene analysis</b>	<b>Num. variables</b>	<b>AUC<sup>ROC</sup></b>	<b>Sensitivity</b>	<b>Specificity</b>	<b>% Correct</b>	<b>Kappa</b>
April	12	0.89	0.75	0.89	0.82	0.64
May	12	0.88	0.83	0.84	0.83	0.67
June	12	0.92	0.93	0.76	0.84	0.69
August	12	0.91	0.91	0.79	0.85	0.70
September	12	0.91	0.83	0.89	0.86	0.71
October	12	0.89	0.77	0.94	0.85	0.71
Time-series <sup>1</sup>	72	0.96	0.93	0.86	0.90	0.79
Time-series <sup>2</sup>	7	0.93	0.85	0.84	0.84	0.69

**Table 3.2.** The predictive contributions of the top three variables for each model generated from Maxent.

<b>Scene analysis</b>	<b>Variable</b>	<b>Contribution (%)</b>
April	band 7	25.5
	band 4	20.6
	NDVI	17.8
May	band 7	37.7
	tasseled cap wetness	31.9
	band 1	9.9
June	tasseled cap wetness	78.5
	band 1	8.6
	band 4	5.5
August	tasseled cap wetness	59
	band 4	13.6
	band 1	9.6
September	tasseled cap wetness	42.2
	band 5	16.1
	band 7	14.3
October	band 3	30.2
	tasseled cap wetness	21.4
	band 7	17.9
Time-series <sup>1</sup>	(June) tasseled cap wetness	25.8
	(Sept) tasseled cap wetness	16.4
	(Oct) band 3	11.6
Time-series <sup>2</sup>	(June) tasseled cap wetness	63.1
	(April) NDVI	9.7
	(Oct) band 3	7.8

## CONCLUSION

As researchers and resource managers continue to recognize the threats and impacts that invasive species can have on ecological processes, biodiversity, hydrology, and our society, there are a few critical research needs that must be explored before we can effectively address these issues. To direct and set priorities for control efforts, and to assess the environmental impacts of invaders, there is one fundamental question that remains to be answered: Where are they? Although an obvious question, the answer in regard to most invasive species remains unknown. Today, we have a better understanding of ecology than ever before; and advanced technology has equipped us with a variety of tools that can facilitate research and provide answers in regard to species distribution. In this research project, I have demonstrated that new and old methodologies can be integrated to detect the distribution of invasive tamarisk and predict its potential spread. I have tested multiple approaches to determine the best combinations of field measurements, spatial models, and remote sensing that can be applied over space and time.

In Chapter 1, I demonstrated how two easy field measurements (basal cover and height) can be used to make reasonable estimates of aboveground biomass. This measure will not only help researchers and resource managers in determining the ecological impacts of tamarisk but will also be used to produce better predictive models and advance remote sensing capabilities. The importance of this study has been demonstrated by the high volume of tamarisk research that now employs the allometric models presented in my results. For example, the Tamarisk Coalition has modified their field protocols to

include measurements for biomass estimation. They have used the methods for their statewide surveys in Colorado (see Chapter 3), and for new tamarisk surveys for the entire Colorado River watershed. Similarly, my results are being tested in tamarisk research examining water usage, impacts on avian habitat, and for potential bio-fuel programs. The study in Chapter 1 was also helpful in providing me with high-quality field data used for my remote-sensing research presented in Chapter 3.

In Chapter 2, I tested which of the most commonly used spatial models worked best for tamarisk. Although there are a few similar studies reported in the literature, where researchers test the performance of different models, the results have varied considerably. I have also found with my other research studies that models do not perform the same with different species, as further demonstrated by the results presented in Chapter 2. Based on the types of survey data commonly collected in the field and geospatial predictor variables that can be developed with GIS and remote sensing, it was important to identify the appropriate models best suited for tamarisk. The models that were ranked highest in my study have continued to perform well with other tamarisk studies (see Chapter 3). However, for research on other species, I would recommend that several models be tested to determine which performs the best for the species of interest and the data available.

Finally, in Chapter 3, I examined different remote sensing approaches to detect phenological characteristics of tamarisk that can distinguish it from other vegetation and landscape features. This was a temporal study that specifically targeted tamarisk's extended growing season in southwest Colorado and its green-up and flowering stages during the peak times of the year. There have been a few remote-sensing studies that

have successfully detected tamarisk using different sensors and techniques, but they are not necessarily applicable throughout tamarisk's range in the U.S. Varying climatic conditions and environmental heterogeneity have impeded widespread use of most of these methods. However, the methods I used in Chapter 3 have the potential to be broadly applied throughout the range of tamarisk. Although I elected to use data from the Landsat 7 ETM+, an older satellite platform, the principles of my study can be applied with other remotely sensed data and at different spatial resolutions.

In conclusion, I present in this study several important building blocks that will allow scientists and resource managers to better detect tamarisk distributions. Further testing of all my results are recommended as species adaptations, changes in ecological conditions, and new technology are likely to occur. For the time being, I believe that the results of this work will greatly facilitate new research and help provide some critical answers to questions surrounding the impacts of tamarisk invasion.