MAPPING RIPARIAN VEGETATION CHANGE IN YELLOWSTONE'S NORTHERN RANGE USING HIGH SPATIAL RESOLUTION IMAGERY

by

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Title: MAPPING RIPARIAN VEGETATION CHANGE IN YELLOWSTONE'S NORTHERN RANGE USING HIGH SPATIAL RESOLUTION IMAGERY

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The purpose of this research is to investigate the potential to use high spatial resolution 4-band remote sensing imagery as a tool for mapping riparian vegetation composition, cover and change in northeastern Yellowstone National Park. Using 1-m airborne imagery from 1995 and 1999 and 4-m IKONOS satellite imagery from 2001, this thesis investigates whether these images can be used to: (1) accurately separate riparian from non-riparian vegetation; (2) map individual riparian taxa; (3) determine what parameters control the ability to classify plant taxa; and (4) measure change in riparian vegetation cover throughout the Northern Range of Yellowstone. Maximum Likelihood classification results show that riparian vegetation can be classified as different from non-riparian with an accuracy of 90%. Accuracies decrease to 42% to 77% for individual taxa. Change detection showed an increase of at least 135% in riparian shrub cover from 1995 to 1999 near the Lamar River-Soda Butte Creek confluence.

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CHAPTER 1

Introduction and Study Area Description

Introduction

Riparian zones are the corridors along streams that form the ecotone between aquatic and upland ecosystems (Malanson, 1993). Within these zones, riparian vegetation is a key control on the diversity and productivity of the ecosystems supported by streams. Vegetation stabilizes stream banks (Thorne, 1990; Abernethy and Rutherfurd, 2000), maintains nutrient balances (Lorensen and Andrus, 1994), regulates water temperatures (Poole et al., 2001), and provides food and shelter for fish and wildlife (Haslam, 1978). The linkage of terrestrial and aquatic systems creates a critically important environmental resource patch; the abundance of water allowing for a diversity of plants and other nutrient resources that are unavailable elsewhere in an environment (Malanson, 1993).

In Yellowstone National Park (YNP), riparian vegetation change has been an important consideration in environmental management decisions. In particular, the winter range of the northern elk (*Cervus elaphus*) herd, known as the Northern Range, has a complex and controversial history related to the distribution of riparian vegetation (YNP, 2002). The Northern Range encompasses a 153,000-ha region of forest and grassland in the Yellowstone River and Lamar River basins, two-thirds of which is within

YNP; one-third is north of the park boundary on public and private lands (Houston, 1982; YNP, 2002). In the 20th Century, observers noted declines in riparian shrub vegetation (*Salix sp.* and *Populus sp.*) in the Northern Range and offered several hypotheses to explain the declines, including: (1) overbrowsing and physical damage by ungulates (hoofed mammals) (Grimm, 1939; Kay, 1990; Chadde and Kay, 1991; Wagner et al., 1995); (2) declines in beaver (*Castor canadensis*) populations (Singer et al., 1994); (3) plant succession (Houston, 1982); (4) changes in fire frequency due to human presence (Houston, 1973, 1982); and/or (5) variations in climate that change surface and groundwater levels (Houston, 1982; Singer et al., 1994).

In contrast to historical observations of decline, riparian shrub vegetation has expanded in Yellowstone's Northern Range from 1995 to 2003 (Beschta, 2003; Ripple and Beschta, 2003). By comparing photographs of riparian cottonwood shrubs from pre-2000 and post-2000, Ripple and Beschta (2003) were able to determine locations along Soda Butte Creek and the Lamar River where cottonwoods were beginning to grow past the height at which ungulates can browse. Beschta (2003) used age-diameter relationships on cottonwood trees and belt transects of new seedlings along a 9-km reach of the Lamar River to determine establishment dates and numbers of trees for 20-yr intervals from 1800 to the present. He determined that almost no seedlings had established between the late 1940s and 1990, but thousands of seedlings were counted in his 2001 study. Hypotheses explaining vegetation expansion are the reverse of those proffered about the declines, including: (1) less browsing pressure by ungulates due to predation by wolves (*Canis lupus*) reintroduced in 1995 (Ripple and Beschta, 2003); (2)

changes in fire frequency due to changes in management policy (Beschta, 2003); or (3) variations in climate that change surface and groundwater levels (YNP, 2002, p.54).

The ability to evaluate hypotheses about causes of change in Northern Range riparian vegetation requires careful measurements of vegetation and documentation of locations of specific taxa for multiple years. Maps of vegetation change provide a way of analyzing spatial patterns of these changes (Macleod and Congalton, 1998; Lyon et al., 1998) and delineating potential causal mechanisms such as climate or browsing pressure changes (Green et al., 1994; Jensen, 1996). There is therefore a need in Yellowstone for data on location and amount of riparian vegetation that is accurate, covers a large region, and can measure changes over time. In this study, I examine four questions to evaluate the potential of high spatial resolution (~1 m) multispectral remote sensing imagery for mapping riparian vegetation in Yellowstone's Northern Range:

1. To what degree of accuracy can riparian shrubs (e.g., willow and alder) be classified using aerial and satellite images?
2. To what degree of accuracy can different plant taxa within riparian vegetation communities be distinguished using these images?
3. What size parameters (e.g. shrub diameter, density) control the ability to classify plant taxa with remotely sensed data?
4. To what extent it is possible to detect change in riparian shrub taxa in the Northern Range of YNP using high spatial resolution imagery?

Study Area

The study area was an ~4 km^2 region at the confluence of the Lamar River and Soda Butte Creek in the Northern Range of YNP (Figure 1). Despain (1990) placed this region in the Big Sagebrush/Idaho Fescue (non-forest habitat) vegetation community. Vegetation in the valley bottom outside the modern floodplain consists of sagebrush steppe, dominated by big sagebrush (*Artemisia tridentate*), and grassland interspersed with small stands of trees, primarily Douglas fir (*Pseudotsuga menziesii*). The dominant riparian shrubs and trees in the floodplain are willow (*Salix* sp.), narrowleaf cottonwood (*Populus angustifolia*), and black cottonwood (*Populus trichocarpa*), with lesser amounts of alder (*Alnus incana*) and aspen (*Populus tremuloides)* (Figure 2).

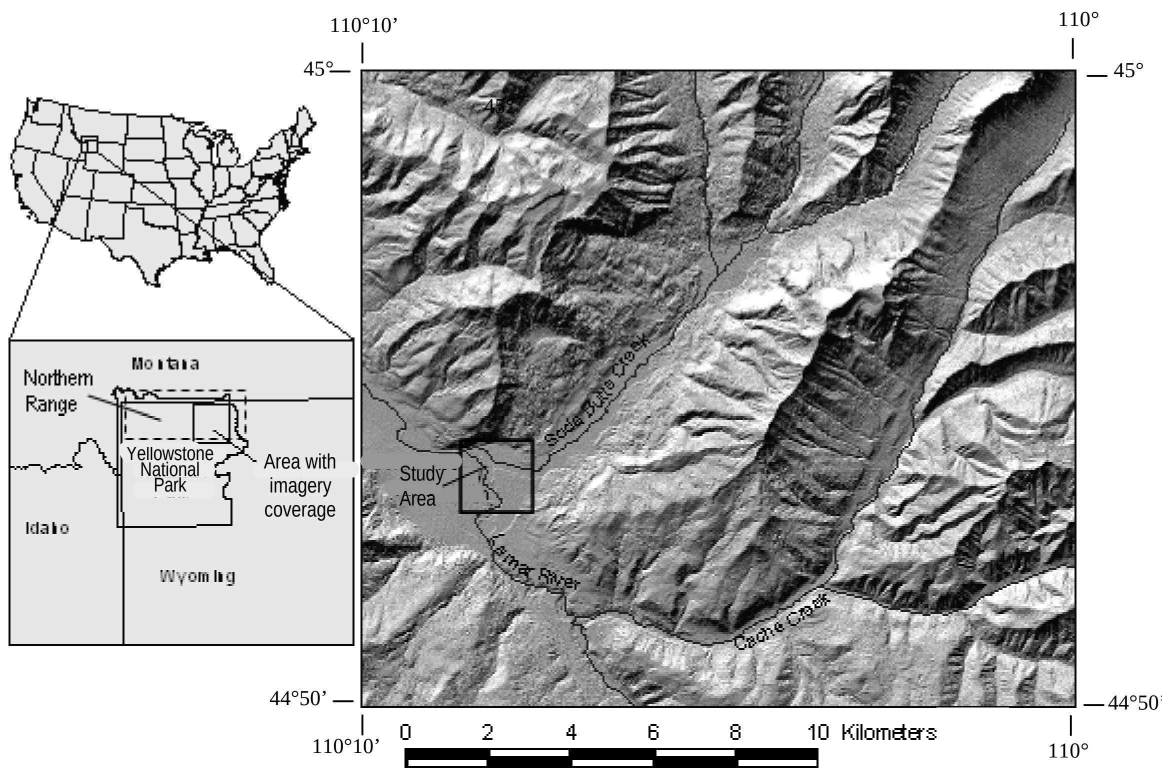


Figure 1: Location of Yellowstone, Northern Range, and confluence study area.

Figure 2: Picture looking south-west to willows along Soda Butte Creek near the confluence with the Lamar River. Trees in the distance are conifers, cottonwoods, and aspens. More distant trees in the floodplain are along the Lamar River.

The Northern Range of Yellowstone National Park is an excellent region for this research because: (1) high spatial resolution imagery has been gathered throughout the region for six years in the past decade (Legleiter et al., 2002; Marcus, 2002; Marcus et al., 2002; Marcus et al., 2003); (2) existing research on the natural history of this region can help inform a change-over-time study (Despain, 1990; YNP, 1997; Bartlein et al., 1997; YNP, 2002); and (3) the remote sensing work will help to inform ongoing research on trophic cascade effects of wolf reintroduction (Ripple et al., 2001; Ripple and Beschta, 2003) and the age structure of aspen and cottonwood (Larsen and Ripple, 2003; YERC, 2003) in the Northern Range ecosystem.

CHAPTER 2

Background Literature

Vegetation research documents a multitude of techniques for mapping and monitoring vegetation change, ranging from field methods to remote sensing methods or combinations of the two. Each method is valuable for certain purposes, from gathering highly detailed species and population data for small plots to summarizing vegetation regimes for large regions. Monitoring riparian vegetation in the Northern Range requires the ability to efficiently gather fine scale measurements on vegetation gather these measurements for a large region. The following section summarizes major methodologies for monitoring vegetation, describes the details of techniques that have been used for Yellowstone National Park vegetation monitoring, and discusses the potential utility of each method monitoring changes in the Northern Range. Terms with superscript numbers are defined in the glossary at the end of this document.

Classical approaches for mapping vegetation change include methods that identify species and their frequency (e.g., Braun-Blanquet, 1964), or methods that measure the structural characteristics for physiognomic categorization (e.g. broadleaf deciduous, graminoids) (Muller, 1997). Both taxonomic and physiognomic studies employ field techniques for measuring plots or transects over time (Cain and Castro, 1959). These classical methods for measuring vegetation require some combination of extensive field measurements, large numbers of personnel, and/or long-term fieldwork (e.g., Bonham, 1989). The process of setting up and repeatedly working on long-term plots can be expensive as well as potentially detrimental to the environment being studied, especially in areas like national parks, where permanent markers and any damage to vegetation are discouraged or prohibited.

In Yellowstone National Park, many conventional field methods have been used to monitor vegetation in the Northern Range. Eight 2-ha exclosures (areas of vegetation protected from browsing) and a series of transects were established in 1958 and 1962 (Parker, 1951; Francis et al. 1972). Measurements of basal area and species composition were used to rapidly assess vegetation condition and trends starting in 1958 and resampled in 1962, 1967, 1974, 1981, 1986 and 1989. Data from Parker's transects are difficult to interpret, however, because the methodology did not take into account effects of plant density, shape, size, and size class distribution of plants (Coughenor et al., 1996). Parker's transects constitute the principal long-term sampling program of herbaceous vegetation in Yellowstone's Northern Range, although the changes in these plots are inadequate to use for determining plant cover changes in the Northern Range due to the difficulty of interpreting the results (Risser, 1984; Coughenor et al., 1996).

Singer et al. (1994) provided an alternative landscape-scale sampling methodology when they used dot grids[1], aerial photographs[1] and circular field plots to survey changes in willow populations between 1987 and 1990. For their study area along the entire lengths of Slough and Soda Butte Creeks, willow stands greater than 0.3 hectares in size were circled on 1:32,000 air photos from 1987. Willow species abundance and production were measured in 15 randomly-located circular plots of 9.3 m in size in each willow stand. Each plot was monitored twice a year for detailed measurements on size, amount of dead material on plants, amount of annual growth, number of rooted stems, and amount of browsing in winter and summer. They combined plots into 42 'communities' based on browse pressure measurements during 3 summers (1988, 1989, 1990) and 4 winters (1987/88, 1988/89, 1989/90, 1990/91) and classified 10 as suppressed, 11 as intermediate and 21 as tall based on changes seen. In their results they note that all of the plants in the study had some evidence of browsing with most of the suppressed willows growing on sites with less water availability, making them more vulnerable to browsing pressure.

Remote sensing technology provides an alternative means to make detailed measurements of changes in vegetation change over broad regions in less time and for less money than traditional ground-based methods require. Aerial photos have been used to supplement vegetation field surveys. The only park-wide vegetation map for Yellowstone was created by combining black and white aerial photo analysis with field ground-truthing[1] (Despain, 1990). These black-and-white images, however, lacked the multispectral[1] visible and infrared reflection data that greatly enhances the ability to identify species of plants. In fact, vegetation mapping is one of the most widely utilized applications of multispectral remote sensing imagery. Researchers in Yellowstone National Park have used multispectral Landsat[1] imagery to extract structural information about lodgepole pine (*Pinus contorta*) forests (Jakubauskas and Price, 1997), map habitats and biodiversity in the Greater Yellowstone Ecosystem[1] (Craighead et al., 1982;

Debinski et al., 1999; Saveraid et al., 2001), and map historical fire patterns based on vegetation stand structure for fire management (Marrs, 1978; Keane et al., 2001).

Extracting information about riparian vegetation from remote sensing imagery, however, provides unique challenges. The first three Landsat satellites launched in 1972, 1975 and 1978 had an average spatial resolution[1] of 80 meters whereas the latest Landsat platforms have a multispectral spatial resolution of 30 meters. These spatial resolutions are too coarse to accurately classify narrow zones of riparian vegetation in small order streams (Hewitt, 1990; Muller et al., 1993; Muller, 1997; Congalton et al., 2002) which are typical of Yellowstone National Park. Kokaly et al. (2003) created a map of willow and sedge along a 16-km reach of the Lamar River in YNP using data from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) with a spatial resolution of ~17 m, but even this resolution missed individual plants and outcrops of brush. Furthermore, they used a pre-existing spectral library[1] of vegetation for classification that did not capture the spectra[1] as they changed through the seasons and this resulted in an inability to perform accuracy assessments on their maps of willow and sedge (Kokaly et al, 2003).

Recent advances in high spatial resolution (< 5 m) remote sensing technology may make it possible to monitor riparian vegetation with reasonable accuracy (Aspinall et al., 2002). In particular, airborne multispectral digital imaging has become more accessible and affordable since the early 1990s. There are a variety of airborne sensors[1] ranging in sophistication and expense from digital color-infrared (DCIR) cameras made by companies such as Kodak© (e.g. Weber and Dunno, 2001 and Williamson et al., 2002) to sensors like NASA’s ATLAS (Airborne Terrestrial Applications Sensor), which have greater spectral coverage and resolution (Rickman and Luvall, 2001). Since the late

1990s, satellite imagery of 1 to 5 m resolution has become publicly available from the IKONOS (Space Imaging Corp., Thornton, CO) and QuickBird (DigitalGlobe, Longmont, CO) satellites (Cook et al., 2001; Nale, 2002). Research from high resolution satellite imagery is just beginning to be published on a broad scope of vegetation applications, ranging from mapping of Arctic vegetation (Stow et al., 2004), to deciduous forests near Brussels, Belgium (Carleer and Wolff, 2004) and African rainforests (Thenkabail et al., 2004).

High spatial resolution sensors have also been used to map vegetation in Yellowstone National Park. A majority of the remote sensing research on riparian zones in YNP has utilized 1 m resolution hyperspectral imagery[1] from the Probe-1 sensor with 128 spectral bands[1] (Legleiter et al., 2002; Marcus, 2002; Marcus et al., 2003). The hyperspectral studies required technology that was expensive and relatively difficult to access, as well as requiring sometimes complex processing techniques. Four-band[1] multispectral imagery, like the type used in this study, is easier to acquire and can often be more easily processed.

Developing accurate maps of vegetation communities from remote sensing imagery is only a first step, however. To understand processes driving riparian vegetation change, one must also be able to overlay images from different years and analyze differences. Change-detection algorithms developed for this purpose include post-classification comparison[1] (Munyati, 2000), multi-temporal or composite change classification[1] (Muchoney and Haack, 1994), principal components analysis[1] (Green et al., 1994), image differencing[1] (Macleod and Congalton, 1998), image ratioing[1] (Lyon et al., 1998), and change vector analysis[1] (Yuan et al., 1998). Project-specific recommendations for choosing change detection algorithms (e.g. Lunetta and Elvidge, 1998) have been made for satellite-based projects with >30 m spatial resolution, but fine spatial resolution imagery generates problems not encountered with coarser resolution imagery (Aspinall et al., 2002) and little research has been done on change detection with this type of imagery. Aerial photographs were the only commonly available images with spatial resolutions of less than 5 m until the 1990s, so many published change detection studies combine recent high spatial resolution multispectral imagery with air photos from the past. For example, Stow et al. (2004) used 2000 IKONOS data and a 1964 aerial photo to assess patch-scale land-cover change over decadal time scales. Unfortunately, these studies do not provide clear guides for choosing change detection techniques when comparing high spatial resolution imagery from different periods.

CHAPTER 3

Methods

Data Collection

For this research, high spatial resolution airborne imagery of the Northern Range was acquired by Positive Systems, Inc.® in August 1995 and September 1999 (Figure 3) using an ADAR 5500 camera with 4 bands that cover the visible to shortwave-infrared portions of the spectrum[1]. Specific band widths on the ADAR 5500 are: band 1 (400-515nm), band 2 (525-605nm), band 3 (610-690nm), and band 4 (750-1000nm). The spatial resolution was 1.0 m in 1995 and 0.78 m in 1999. The 1999 imagery was recent enough that vegetation on the images could be verified in the field in 2002 and 2003.

IKONOS imagery for the study area was acquired in August 2001 and provided courtesy of the Yellowstone Ecological Research Center for this study. The IKONOS imagery has a panchromatic[1] spatial resolution of 0.85 m and multispectral resolution of 4.0 m. The panchromatic image has a bandwidth[1] of 525.8-928.5nm, while the band widths of the 4-band multispectral image are: band 1 (444.7-516.0nm), band 2 (506.4-595.0nm), band 3 (631.9-697.7nm), and band 4 (757.3-852.7nm).

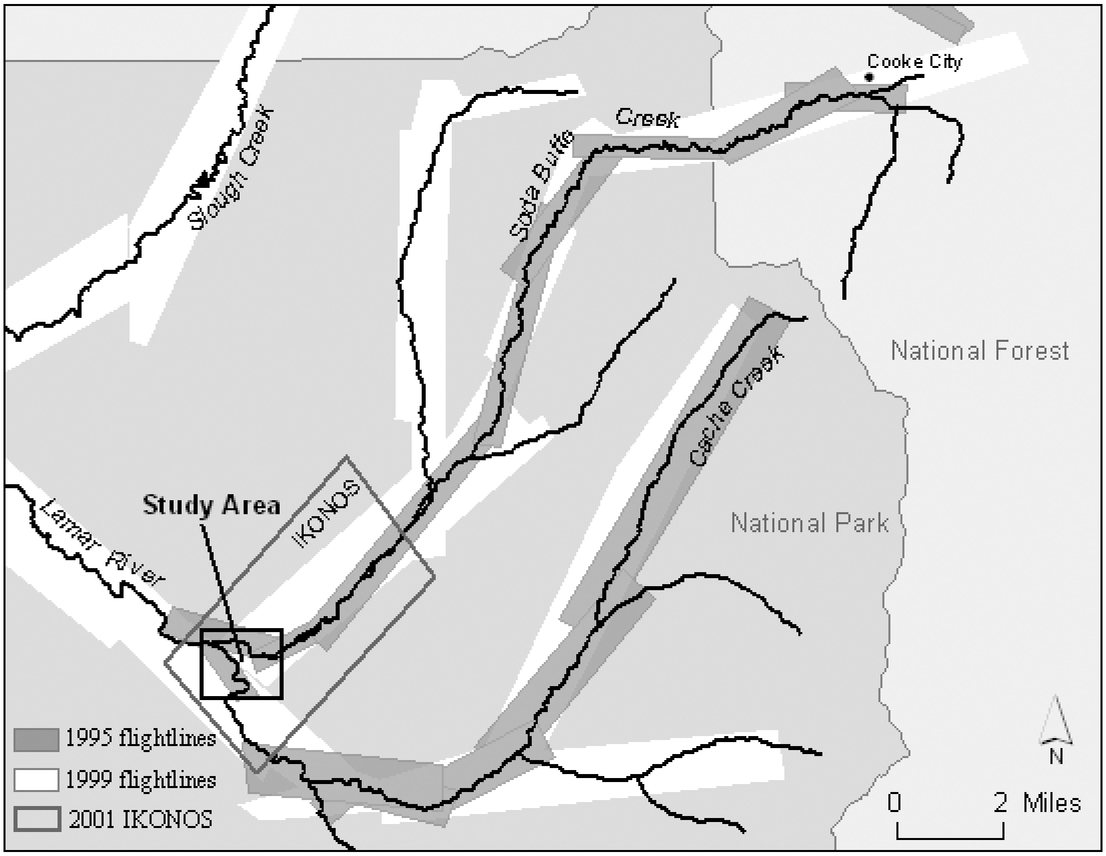


Figure 3: Location of study area relative to 1995, 1999, and 2001 imagery. Polygons representing flight lines are the actual length and width that was flown.

Field data for ground-truthing were collected in September of 2002 and 2003. True color composites[1] of the 1999 imagery were printed and used to map locations and species of vegetation. Because field work was performed three years after the date of image acquisition, I compensated for possible changes in shrubs and trees by only mapping vegetation that could be identified on both the 1999 image and in the field. Noticeable growth or decline in vegetation seen in the field in comparison with the 1999 images was noted. Approximately 400 riparian shrubs and trees were mapped in the confluence region totaling about 4,350 digitized pixels (Table 1).

Table 1: 1999 sample sizes**.** The “mixed” category included pixels at edges of bushes, the “pure” pixels were chosen by avoiding edges and shadows.

Vegetation	Total pixels digitized	"Mixed" training pixels	"Pure" training pixels
Willow	2658	1628	461
Green aspen	659	304	105
Yellow aspen (senesced)	329	152	95
Green cottonwood	474	292	98
Yellow cottonwood (senesced)	237	146	68
Grass/sedge	5610	5610	2581
Sagebrush	5892	5892	2003
Conifer	486	486	314

Detailed measurements on height and stem density of specific plants were made to determine effects of plant size on detection and classification on the 1999 imagery. Measurements included height, number of stems per 0.5 m, leader branch length, age, and x and y axis widths (Figure 4). I collected these measurements for 109 individual willow and cottonwood shrubs that were identifiable on the images of the entire length of Soda Butte Creek and the upper and lower Lamar River (Appendix B). Heights, widths and stem counts were measured with an extendable rod (e.g. stadia rod), marked with decimeter segments.

Figure 4: Locations of X and Y axis measurements. The X axis width measured what was estimated to be the widest part of the shrub, and the Y axis measured the narrowest axis. Shrub crown area was calculated from these measurements.

The density was measured by inserting the rod into the approximate middle of the plant, pushing the rod slightly against the stems, and counting the number of stems touching a 5 decimeter segment of the rod (Figure 5). Age of growth over the last ten years was estimated by counting annual terminal buds and plants with large trunks or rootstocks were documented and photographed. These individuals were digitized onto the 1999 imagery. Forty-seven of these measured plants were located within the confluence study area and were later superimposed onto the 1999 classification image of this region to see which had been classified correctly. Potential issues created by comparing 2002 field measurements of vegetation to 1999 imagery are examined later in the Discussion section.

Figure 5: Method of counting stems per 0.5 meters for density approximation.

Image Analysis

Preprocessing

The goal of preprocessing was to prepare the images so that classification and change detection results were as accurate and reliable as possible. The image processing, classification, and change detection analysis were performed with ENVI (Environment for Visualizing Images) version 4.0 software (RSI, 2003). The 1999 images were georeferenced[1] (UTM Zone 12, North American Datum 1927) and mosaicked[1] by Positive Systems, Inc®. The mosaicking of the 1999 imagery altered the underlying reflectance[1] values and created problems with classification that are presented in the Discussion section. The 1995 images consisted of individual scenes of ~1 km^2 each that I georeferenced to the 1999 imagery (RMSE[1] = 0.9-1.3 m). Like the 1995 Postive Systems imagery, the 2001 IKONOS imagery was also coregistered[1] to the 1999 imagery (RMSE = 0.99 m) to maintain a consistent coordinate system for the analysis.

I investigated different data transformations that might highlight the signal to noise ratio[1] for plants (Aspinall, 2002; Zhang et al., 2003; Carleer and Wolff, 2004), including principal components and minimum noise transformations[1]. Classification accuracies with transformed data were significantly lower than those reached with the untransformed data (Table 2), so all of the subsequent classifications were performed on untransformed 4-band images.

Table 2: Comparison of maximum classification accuracies achieved for transformed and untransformed data on the 1999 4-band imagery.

Classification Algorithm	**Data Transformation**	**Overall Accuracy**
Spectral Angle Mapper (SAM)	none	82.5%
	PCA	67.6%
	MNF	14.7%
Maximum Likelihood	none	90.0%
	PCA	80.7%
	MNF	80.7%

Classification

The objective of classification was to automate the identification of vegetation taxa on the images. Field maps of species were digitized onto the 1999 imagery to create training[1] and accuracy assessment pixels[1] for classifications. Conventional remote sensing practice is to choose training pixels away from the edges of features, thus avoiding transitional areas where class types are indistinct and creating homogenous sets of training spectra (Congalton and Green, 1999). Choosing "pure" training pixels for vegetation was difficult because the high spatial resolution images captured a wide variety of light and dark shadow within the crowns (Figure 6).

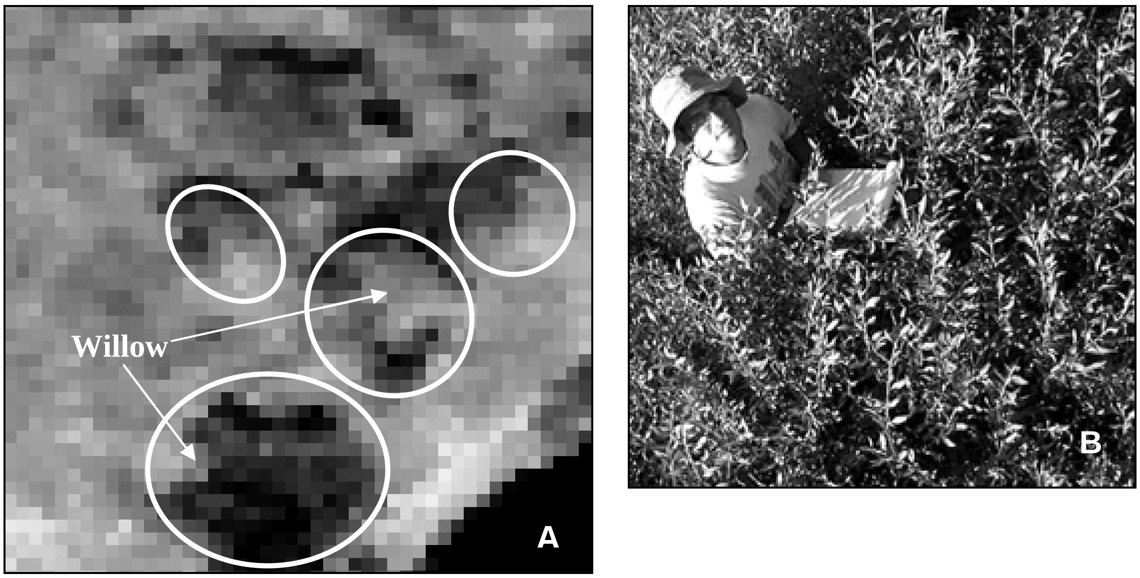


Figure 6: A) Heterogeneity of pixels within one taxa on the 1999, 0.78 m resolution image. Willows are circled. B) Photo of willow at the same site from above in 1999. Note large proportion of shadow.

Two sets of training pixels were therefore developed for classification purposes. In the "pure" set, pixels were chosen conservatively, including only bright green pixels without obvious shadow effects and located away from edges. A second set of "mixed" training pixels included the shadowed portions of tree and shrub crowns and some edge areas. The sample size was larger for the mixed set of pixels, but enough areas had been field mapped to have approximately a minimum of 100 training pixels in each category, even within the pure pixel training set (Table 1).

The research goals for classification were to determine the ability to: (1) discern riparian vegetation from other features; and (2) discern individual taxa of interest from each other. I therefore created two sets of classification categories, one grouping willow, cottonwood, aspen and alder taxa into a single riparian vegetation category, and one separating key taxa of interest into individual categories (Table 3). Alder were included in the willow category when mapping taxa.

<table>
<tr><th colspan="6">Table 3: Classification categories for 1995, 1999, and 2001.</th></tr>
<tr><th colspan="2">1995</th><th colspan="2">1999</th><th colspan="2">2001</th></tr>
<tr><td rowspan="5">riparian shrubs and trees</td><td>willow</td><td rowspan="5">riparian shrubs and trees</td><td>willow</td><td rowspan="5">riparian shrubs and trees</td><td>willow</td></tr>
<tr><td>aspen</td><td>green aspen</td><td>aspen</td></tr>
<tr><td></td><td>yellow aspen</td><td></td></tr>
<tr><td>cottonwood</td><td>green cottonwood</td><td>cottonwood</td></tr>
<tr><td></td><td>yellow cottonwood</td><td></td></tr>
<tr><td>grass/sedge</td><td>grass/sedge</td><td>grass/sedge</td><td>grass/sedge</td><td>grass/sedge</td><td>grass/sedge</td></tr>
<tr><td>sagebrush</td><td>sagebrush</td><td>sagebrush</td><td>sagebrush</td><td>sagebrush</td><td>sagebrush</td></tr>
<tr><td>conifer</td><td>conifer</td><td>conifer</td><td>conifer</td><td>conifer</td><td>conifer</td></tr>
</table>

Several classification methods were applied. Based on preliminary accuracy assessments, Spectral Angle Mapper (SAM) and Maximum Likelihood approaches were chosen for further study. SAM often works best when only a few representative pixels (i.e., spectral endmembers[1]) are used as training pixels for each classification category (Zhang et al., 2003). Based on scatter plots and spectral profile graphs, I chose 5-10 endmember training pixels for each category to serve as training sites for SAM classification. For the maximum likelihood classification, I randomly selected 10% of the ground-truth data as training pixels. Pixels not used as training pixels were used for validation for both the SAM and maximum likelihood classifications.

The same methodology was used to classify the 1995 imagery. However, I had no field or other validation data for 1995, so it was necessary to use the training data from the 1999 image. The 1995 image was coregistered to the 1999 image as closely as possible using 54 ground control points and a 2nd order polynomial transformation (RMSE = 0.90 m). Despite this tight fit, visual analysis indicated residual offset between the 1999 training pixels and the corresponding vegetation locations on the 1995 image. This offset varied across the image from zero to about 4 pixels (Figure 7). In addition, some of the riparian training sites for 1999 contained different cover (e.g., sedge) on the 1995 image. Because the fine spatial resolution made it possible to identify such sites visually on the images, I manually removed the offset training pixels from the 1995 training data.

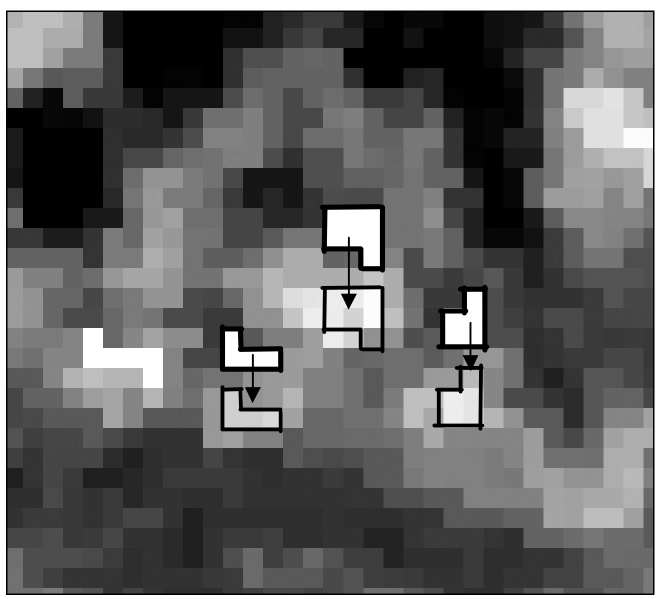


Figure 7: Offset of 1999 training pixels (outlined white polygons) on 1995 image due to coregistration error. This figure demonstrates the largest offsets encountered in the project; in some portions of the imagery there was zero offset.

The 1995 image was taken in August, prior to senescence, which made it difficult to distinguish the riparian vegetation from the green background of sedge and grasses. Initial classification results were poor using the 1995 image, so I used a mask[1] to limit the area of analysis and improve the ability to distinguish shrubs from background grasses. The mask was created from the 1999 classification of riparian brush and overlaid onto the 1995 image. In this way, only areas that were classified as riparian brush in 1999 could be classified as riparian brush in 1995. This approach was justified because unpublished field observations (Marcus, personal communication, 2004) documented that riparian shrubs in 1995 were smaller than those in 1999. Visual inspection showed that portions of the 1995 image not masked out contain riparian shrubs surrounded by background grasses (Figure 8).

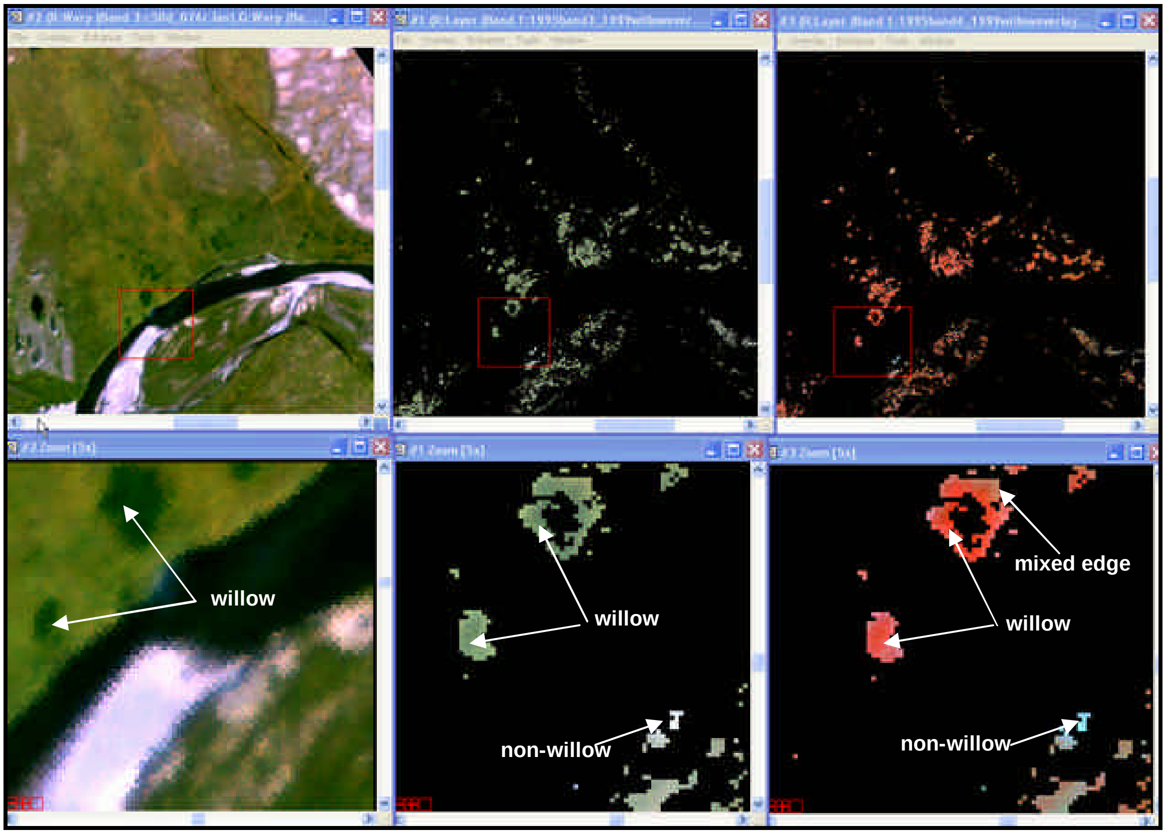


Figure 8: 1995 image without mask (left), with mask (middle), and 1995 false color with mask (right). Mask covers everything in the image except for the areas that were classified as riparian brush in 1999. Brightest red in false color image are 1995 riparian brush within the mask.

Within these un-masked areas riparian shrub, mixed shrub/grass-sedge and grass/sedge areas were classified. These categories helped determine a range of possible changes over time, as is discussed later. A drawback to the masking method was that it could miss riparian shrubs that existed in 1995 and did not in 1999. Issues related to coregistration errors and possible masking out of 1995 riparian shrubs are presented in the Discussion section.

The 4-band 2001 IKONOS image was classified into vegetation categories using training pixels from the same locations as the 1999 image. I chose identical vegetation categories as were used on the 1995 image (Table 3). In addition, classification of shadow on the 2001 imagery improved the ability of SAM to identify vegetation, but is not included in the list of categories because it was used only to remove the shadow pixels from the categories of interest. Pan-sharpening[1] has been used in recent classification work with IKONOS imagery (Thenkabail et al., 2004). Pan-sharpening, however, changes the spectral data and initial classifications with pan- sharpened data generated poor results, so I did not use it for vegetation mapping.

After classification accuracies were optimized for the 1999 image, I extracted the classification data for sites where plants had been measured in the field. Each individual was represented by between 1 and 5 pixels on the imagery. I analyzed the image to determine correlations between the classification of individuals and field measurements of width, density, and height. The 1999 image was chosen for this comparison because it had the highest spatial resolution, which maximized the ability to distinguish individual shrubs.

Change Detection

The goal for change detection in this study was to establish a quantitative and spatially explicit measurement of riparian vegetation change between imagery dates within the study area. Effective riparian vegetation change detection requires techniques that control for variables such as phenology, illumination differences, and coregistration errors (Green et al., 1994). After experimenting with multiple change detection approaches, such as image ratio[1] and PCA compositing[1], post-classification change detection[1] was used to control for differences in phenology and to document magnitude and direction of change.

I applied post classification change detection to the 1995 and 1999 imagery for the entire study area without a mask and to the masked image that showed only areas classified as riparian shrub in 1999. When the unmasked classification images for 1995 and 1999 were superimposed, the change results were obviously skewed due to the large amount of grass/sedge area on the 1995 image that was misclassified as riparian shrub. Use of the masked images significantly improved upon these results, limiting change to areas that were classified as riparian shrub in 1999. This change detection scheme allows for some "fuzziness" in the results, because the pixels classified as "mixed shrub/grass-sedge" pixels could have been pure sedge, pure shrub, or some mix of the two categories. Change detection between 1999 and 2001 generated exceedingly poor results due to the differing spatial resolutions of the Positive Systems and the IKONOS data and was not pursued beyond the exploratory phase.

CHAPTER 4

Results

Maximum Likelihood[1] and Spectral Angle Mapper (SAM)[1] returned the highest overall classification accuracies with the images used in this research (Table 2). Both SAM and Maximum Likelihood offer the user the option of adjusting the angle or probability threshold[1] (respectively) for each classification category. For the 1999 imagery, SAM returned slightly higher accuracies[1] than Maximum Likelihood using fixed thresholds for all categories, but Maximum Likelihood was more responsive to changing riparian vegetation class thresholds (Table 4). For this reason, the maximum likelihood classifier was used for the 1995 and 1999 images.

Table 4: Varying maximum likelihood probability to attain maximum accuracy.

	# of pixels in field	# classed as that type	# correct	producer's accuracy[1]	user's accuracy[1]	probability used
willow	415	309	274	66%	89%	0.8
green aspen	94	126	39	42%	31%	0.76
yellow aspen	85	86	65	77%	76%	0.8
green cottonwood	88	83	50	57%	60%	0.87
yellow cottonwood	61	67	32	53%	48%	0.8
grass & sedge	121	114	114	94%	100%	0.7
conifer	283	261	249	88%	95%	0.75
sagebrush	251	240	240	96%	100%	0.75

For the 2001 IKONOS image, however, Maximum Likelihood did not work, returning an overall accuracy of ~5%. Using SAM with a constant angle threshold of 0.1 radians returned a higher overall classification accuracy of 80.5%. The following sections report on the results as they relate to each of the four research questions.

Question 1 - Classification accuracy for riparian taxa as one category

The classification results (Table 5) show that it is possible to achieve relatively high accuracies for riparian vegetation when treating shrubs as one category. Using maximum likelihood classification with 4-band, 0.78 m resolution imagery, only 2.7% of the riparian vegetation pixels on the 1999 airborne image were incorrectly classified. However, the 2001 and unmasked 1995 images had relatively high errors due to confusion between grass/sedge taxa and riparian shrub and tree taxa (willow/alder, cottonwood and aspen). Use of a mask to screen out obvious areas without riparian brush on the 1995 image improved the accuracy of riparian brush to 96% by eliminating grass/sedge pixels that were misclassified as riparian shrubs. Classification accuracy of riparian brush on the 2001 IKONOS 4 m resolution image, however, was only 58%, with 33% of the riparian shrubs misclassified as grass/sedge (Table 5).

Table 5: Error matrix showing raw pixel counts of correctly and incorrectly classified pixels using the 1995, 1999 ADAR5500 images and the 2001 IKONOS image. The 1995 classification used a mask to screen out areas that were not shrubs in 1999.

Class	**riparian shrubs**	**conifer**	**grass/sedge**	**sagebrush**	**Total**
1995 (overall accuracy 37%)					
unclassified	2	12	425	1	440
riparian shrubs	**299 (96%)**	0	6331	0	6630
conifer	0	**83 (87%)**	19	0	102
grass/sedge	11	1	**3271 (33%)**	1	3284
sagebrush	0	0	0	**249 (99%)**	249
Total	312	96	10046	251	10705
1999 (overall accuracy 90%)					
unclassified	91	15	5	10	121
riparian shrubs	**632 (85%)**	8	0	0	640
conifer	20	**260 (92%)**	0	0	280
grass/sedge	0	0	**116 (96%)**	0	116
sagebrush	0	0	0	**241 (96%)**	241
Total	743	283	121	251	1398
2001 (overall accuracy 81%)					
unclassified	28	0	0	0	28
riparian shrubs	**364 (58%)**	0	42	0	406
conifer	20	**27 (44%)**	0	73	120
grass/sedge	204	10	**404 (91%)**	0	618
sagebrush	9	25	0	**907 (93%)**	941
Total	625	62	446	980	2113

Question 2 – Classification accuracy for individual riparian taxa

Overall accuracies decreased for all of the classified images when the riparian category was separated into willow, cottonwood and aspen (Table 6). The 1995 classification had a 92% accuracy for willow and a 98% accuracy for deciduous tree taxa, although there was a significant error of commission related to background greenness (i.e., grasses and sedges). For the 1999 and 2001 images, percent accuracies for all of the categories decreased when trying to distinguish between willow, cottonwood and aspen taxa.

On the 1999 September imagery, classification accuracies for riparian taxa ranged from 42 to 77%. Separating the 1999 taxa into senesced and green stages of each taxa improved the willow accuracy from 53 to 66%, aspen from 29 to 42%, and cottonwood from 35 to 57%. The remaining non-senescing shrubs and trees were all confused with each other to some extent. Misclassifications of willows and cottonwoods were mainly due to confusion with one another or with green aspen, a common error with these vegetation types (Wirth et al., 1996) (Table 6).

The SAM classification of the 2001 IKONOS image also showed a weak ability to discern taxa, with percent correct classifications ranging from 47% for cottonwood to 66% for willow (Table 6). Furthermore, the IKONOS imagery displayed high errors of commission, classifying 43% of the grass/sedge as aspen or cottonwood.

Table 6: Classifying vegetation taxa – raw pixel count error matrices.

Class	willow	green aspen	yellow aspen	green cwd	yellow cwd	conifer	grass/ sedge	sage-brush	Total
1995 (overall accuracy 34%)									
unclassified	2	0				13	401	1	417
willow	**185 (92%)**	2				0	6550	0	6737
aspen & cottonwood	1	**108 (98%)**				0	87	0	196
conifer	0	0				**82 (85%)**	6	0	88
grass/sedge	14	0				1	**3002 (30%)**	1	3018
sagebrush	0	0				0	0	**249 (99%)**	249
Total	202	110				96	10046	251	10705
1999 (overall accuracy 77%)									
unclassified	23	27	10	3	15	18	5	11	115
willow	**274 (66%)**	12	0	18	0	5	0	0	309
green aspen	58	**39 (42%)**	0	17	1	11	0	0	126
yellow aspen	7	1	**65 (77%)**	0	13	0	0	0	86
green cwd	24	9	0	**50 (57%)**	0	0	0	0	83
yellow cwd	18	5	10	0	**32 (53%)**	0	2	0	67
conifer	11	1	0	0	0	**249 (88%)**	0	0	261
grass/sedge	0	0	0	0	0	0	**114 (94%)**	0	114
sagebrush	0	0	0	0	0	0	0	**240 (96%)**	240
Total	415	94	85	88	61	283	121	251	1493
2001 (overall accuracy 73%)									
Unclassified	2	11		0		0	0	0	13
willow	**184 (67%)**	17		42		0	0	0	301
aspen	30	**97 (49%)**		10		10	154	0	184
cottonwood	36	35		**71 (47%)**		0	42	73	120
conifer	3	10		7		**27 (44%)**	0	0	243
grass/sedge	19	21		21		0	**250 (56%)**	0	311
sagebrush	0	9		0		25	0	**907 (93%)**	941
Total	274	200		151		62	446	980	2113

Question 3 – Relationship between plant size and classification accuracy

Field data for 47 individual shrubs indicate the approximate size thresholds necessary to classify riparian brush correctly on the 1999, 0.78 m resolution 4-band imagery (Figure 9). In general, shrubs having long axis widths above 2 m and heights above 1.7 m are most likely to be classified correctly. The influence of the short axis on classification accuracy is less pronounced than the long axis. Density of stems did not appear to make a difference in classification accuracy (Figure 9e), a statement that appears to hold true regardless of plant size (Figure 10).

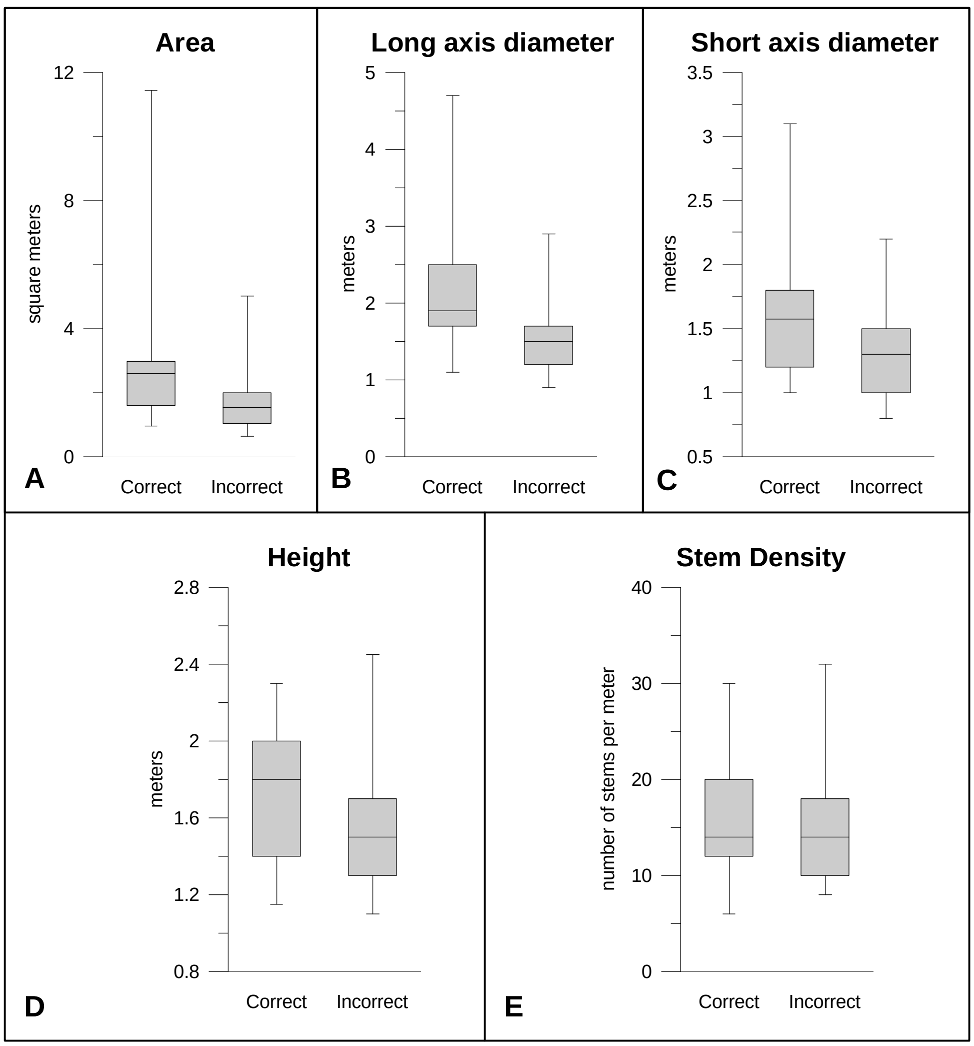


Figure 9a-e: Measurements of individual riparian shrubs. Correct (N=24), classified correctly; Incorrect (N=23), classified incorrectly.

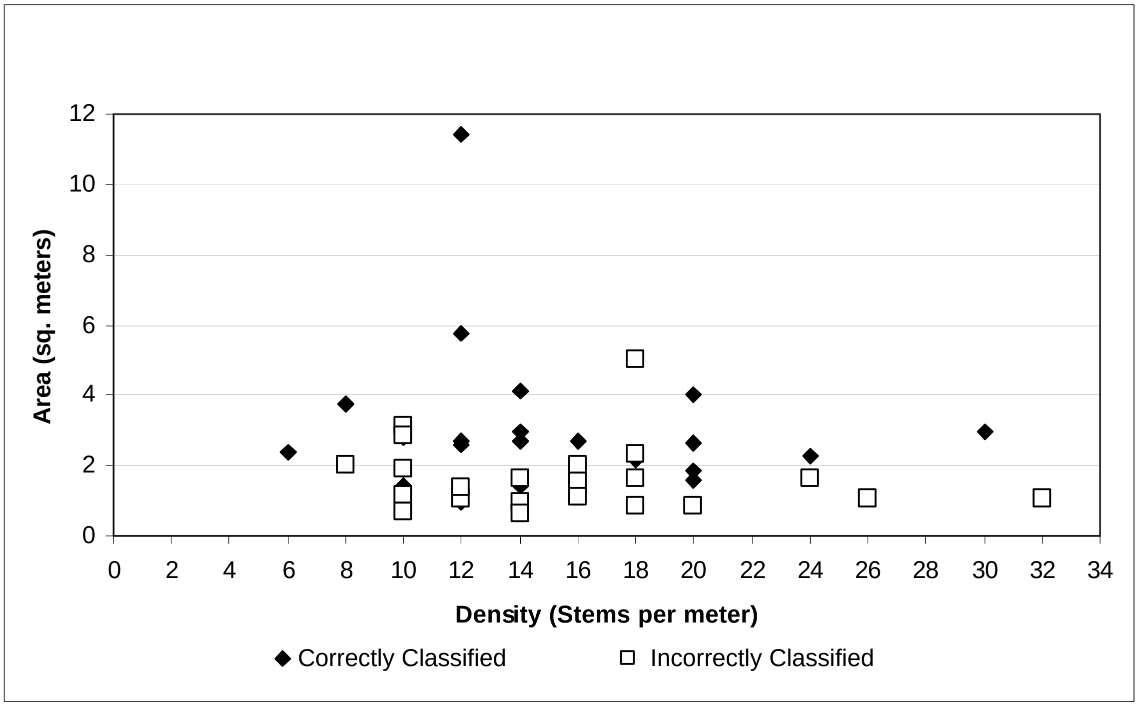


Figure 10: Scatter plot of stem density vs. area of crown for correctly and incorrectly classified riparian shrubs.

Question 4 – Ability to detect change in riparian vegetation cover

The results in this study provide three estimates of change in riparian brush between 1995 and 1999 for the Lamar-Soda Butte confluence area (Table 7). The minimum possible increase of 135% was estimated by assuming that all of the pixels classified as mixed sedge/grass/riparian brush in 1995 were entirely riparian brush, so that only the pixels classified as pure grass/sedge changed to riparian brush. The maximum possible change of 1011% was estimated by assuming that all of the pixels classified as mixed were entirely grass/sedge, which significantly increased the number of 1995 grass/sedge pixels that changed to riparian brush in 1999. It is more likely that the actual change is somewhere in between the minimum and maximum estimates. The “estimated probable” result assumes that 50% of the mixed pixels were riparian brush and 50% were grass/sedge, which results in an 239% increase in riparian shrub cover. In terms of area, this intermediate estimate indicates that riparian shrub in 1995 covered 3,500 m^2 and had grown to cover 8,358 m^2 of the study area by 1999.

Table 7: Change detection between 1995 and 1999. Refer to text for explanation of categories.

	minimum	estimated probable	maximum
Change in area (m^2)	2185	4858	7531
Percent cover change	135%	239%	1011%

Accurate change detection to 2001 was not possible due to the poor classification accuracies achieved with the IKONOS imagery (Table 5). The 1999 mask could not be used to improve accuracies, because the mask for 1999 would exclude the new areas of growth.

CHAPTER 5

Discussion and Conclusions

Controls on Classification Accuracy

Results from this study indicate that the ability to classify riparian brush is a function of the time of year and associated vegetation phenology, as well as the sizes of the riparian shrubs relative to the spatial resolution of the imagery. In addition, the amount of pixel heterogeneity is a major limiting factor on accuracy as is discussed in more detail in the following section on high spatial resolution (HSR) imagery.

Image Resolution and Size of Vegetation

Analysis of the field data for individual shrubs and associated classification accuracies on the 1999 imagery (Figure 9) indicate that shrubs having long axis widths above 2 m and crown areas over ~2 m^2 are most likely to be classified correctly with the 0.78 m resolution imagery. Comparison of figures 9b and 9c indicates that long axis width may be more significant than short axis width. This may be because the 0.78 m resolution allows the sensor to capture a shrub that has one axis >2 m (approximately twice the length of any given pixel), regardless of the corresponding axis width. Plant heights are typically correlated with widths, so it follows that taller plants (>1.6 m) were classified correctly more often than shorter plants (Figure 9d).

Based on Figure 10, it appears that a small dense shrub is not any more likely to be classified correctly than an equal sized, less dense shrub. There were doubts during fieldwork, however, as to the accuracy of the density measurements because the measurement method did not seem to account for the range of variability in the riparian shrubs. Different species of plants had different growth patterns and leaf densities, so that counting stems in the center of the plant did not necessarily capture the spectral thickness of a bush when compared with other plants of similar sizes. Based only on the data in this study, however, it appears that the key vegetative component controlling accuracy is the long axis of the bush and that densities, at least within the ranges documented in this study, are not a significant factor.

At 0.78 m pixel resolution, a 2 m^2 plant is 3.3 times the area of a pixel. This finding that most shrubs bigger than 2 m^2 were classified correctly is consistent with other research on object identification by remote sensing imagery, which suggests that a feature should be approximately four times larger than the pixel size to be consistently classified correctly with multispectral imagery (Woodcock and Strahler, 1987). Fine resolution imagery is therefore necessary to identify small patches of riparian shrubs with multispectral imagery. This is especially important in a setting like Yellowstone's Northern Range where willows tend to have a patchy growth pattern on the landscape. Fine resolution imagery enables detection of recent riparian growth rather than detecting only changes for large established stands.

Timing of Imagery

The high classification accuracies on the 1999 imagery relative to the 1995 imagery (Table 5) were achieved largely because of the time of year in which the imagery was acquired. In September, 1999 the grasses and sedges were senesced, whereas the riparian shrubs were still green, thus allowing the maximum likelihood classifier to easily separate the categories. Since riparian brush does not usually senesce until October in this region of Yellowstone, one can use this reflectance difference in an early Fall image to maximize the ability to discern these taxa from others.

The 1995 ADAR 5500 and 2001 IKONOS images had lower overall accuracies and high errors of commission and omission due to the overall greenness of August vegetation. Much of the grass/sedge regions were classified as riparian brush on the 1995 image, whereas the reverse happened on the 2001 image, with the riparian brush being classified as grass and sedge (Table 5). This commission/omission reversal could be result of using different classification algorithms for 1995 and 2001; regardless, it indicates that these categories have similar spectral signatures and that achieving high accuracies with these image types requires careful timing of imagery.

Seasonal variation in vegetation phenology is a widely documented issue when using multispectral imagery for vegetation classification (Wirth et al., 1996, Mas, 1999; Coulter et al., 2000; Asner and Warner, 2002; Goetz et al., 2003). Strategies to improve classification accuracies of vegetation during seasons when phenology is not ideal include masking (Weber and Dunno, 2001), decision tree analysis (Goetz et al., 2003), spectral mixture analysis (Roberts et al., 1993), or using variations in amount of shadow within canopies to tease out structural variations (Roberts et al., 1993; Asner and Warner, 2003). In this study a combination of these approaches was necessary, with masking of the 1995 imagery, separation of sensescing vegetation on the 1999 imagery, and classification of shadow on the 2001 imagery providing the highest classification accuracies for each of these dates. Furthermore, in this study, high spatial resolution imagery enabled working around misclassifications due to phenology differences, because details such as variations within a senescing crown could be visually identified on the image and incorporated into selection of training sites and development of masks.

Although the mask based on the 1999 classification significantly improved the 1995 classification accuracies, its use required assumptions that will not be reasonable in many applications. The assumption that all riparian brush in 1999 occurred in the same locations that had riparian shrubs in 1995 was reasonable in this setting (Marcus, personal communication, 2004), but could not be used for monitoring of locations without field observations or where vegetation is migrating rather than expanding in place. On the other hand, this technique can be applied quickly and easily to any taxa of interest as long as one has an accurate classification of that taxa from one image and the direction of change between images is generally known.

Issues Exacerbated by High Spatial Resolution (HSR) Imagery

Many of the issues affecting accuracy of classifications in this study are symptomatic of issues that will affect all users attempting to map vegetation with similar high resolution imagery. The following comments focus on the identification of issues related to HSR imagery, possible solutions to some of these problems, and alternatives to approaches used in this study. Although all of these issues have been documented in studies using coarser resolution imagery, the use of high spatial resolution imagery exacerbates some of these problems.

Coregistration and Problems Associated with HSR Imagery

In order to achieve reliable change detection statistics, remote sensing literature suggests that one should achieve sub-pixel accuracy during coregistration, the ideal being ¼ of a pixel (Lillesand and Kiefer, 2000). The 4-band IKONOS image (4 m pixels) with 49 ground control points had an acceptable RMS error of 0.99 m (equals ~1/4 pixel size). However, this level of coregistration accuracy was impossible to achieve with the 1 m or smaller pixel sizes on the 1995 and 1999 images used in this research. Several weeks were spent coregistering 8 individual 1995 scenes (1 m pixels) to the 1999 mosaic (0.78 m pixels). With 40 to 50 ground control points on each image and a 2nd polynomial transformation, root mean squared errors ranged from 0.94 to 1.28 m. Higher order transformations and different transformation approaches did not improve upon this accuracy. Similar obstacles can be anticipated in any natural landscape, where the absence of discrete points common to urban landscapes (e.g. buildings, street corners) make it difficult to unambiguously find the exact locations of features on images from different dates. The apparent location of features such as trees can also change between years due to growth, changes in viewing angle, and/or changes in sun angle that altered the appearance of the features. Finally, aircraft pitch, yaw and roll, create nonsystematic variation that can be hard to correct for with high resolution imagery (Aspinall et al., 2002).

Furthermore, resampling the images when coregistering them can lead to the loss of entire pixels. At landscape scales, such changes may not alter overall patterns, but at the scale of the individual riparian shrub, pixel-sized bushes can entirely disappear on the resampled image. Individual images in the 1999 imagery were resampled at least twice by Positive Systems, Inc. in order to georectify and mosaic the entire stream reaches (Figure 2). The additional resampling of 1995 and 2001 images when coregistering them to the 1999 imagery introduced more error to the overall classification and change detection analysis.

Pixel heterogeneity and spectral signatures

Another important parameter that affected classification accuracy was the amount of variation between pixels within the same feature. High spatial resolution imagery exacerbates the problem of pixel heterogeneity as compared with traditional satellite images, because the finer spatial resolution captures more subtle variations in phenology, mixed pixels on edges, and shadows within shrubs (Carleer and Wolff, 2004). As a result, the process of manually choosing training pixels that had the purest possible reflectance signature for each category of interest was very time consuming, taking approximately 50 hours for the 4 km^2 image. A potential solution to this could be the use of spectral unmixing, to get sub-pixel measurements of multiple taxa that make up one pixel's reflectance value. Unmixing, however, requires a season-specific spectral library of reflectance signatures for riparian vegetation (Kokaly et al, 2003), and it is questionable whether the 4-band imagery provides sufficient spectral information to drive an unmixing-based approach.

Cross-image brightness variations

Brightness and reflectance differences across airborne images are a well documented phenomenon (Lillesand and Kiefer, 2000). With the preprocessed 1999 mosaic, the brightness differences caused misclassification of vegetation less than 1 km away from the region where training sites were chosen (Figure 11).

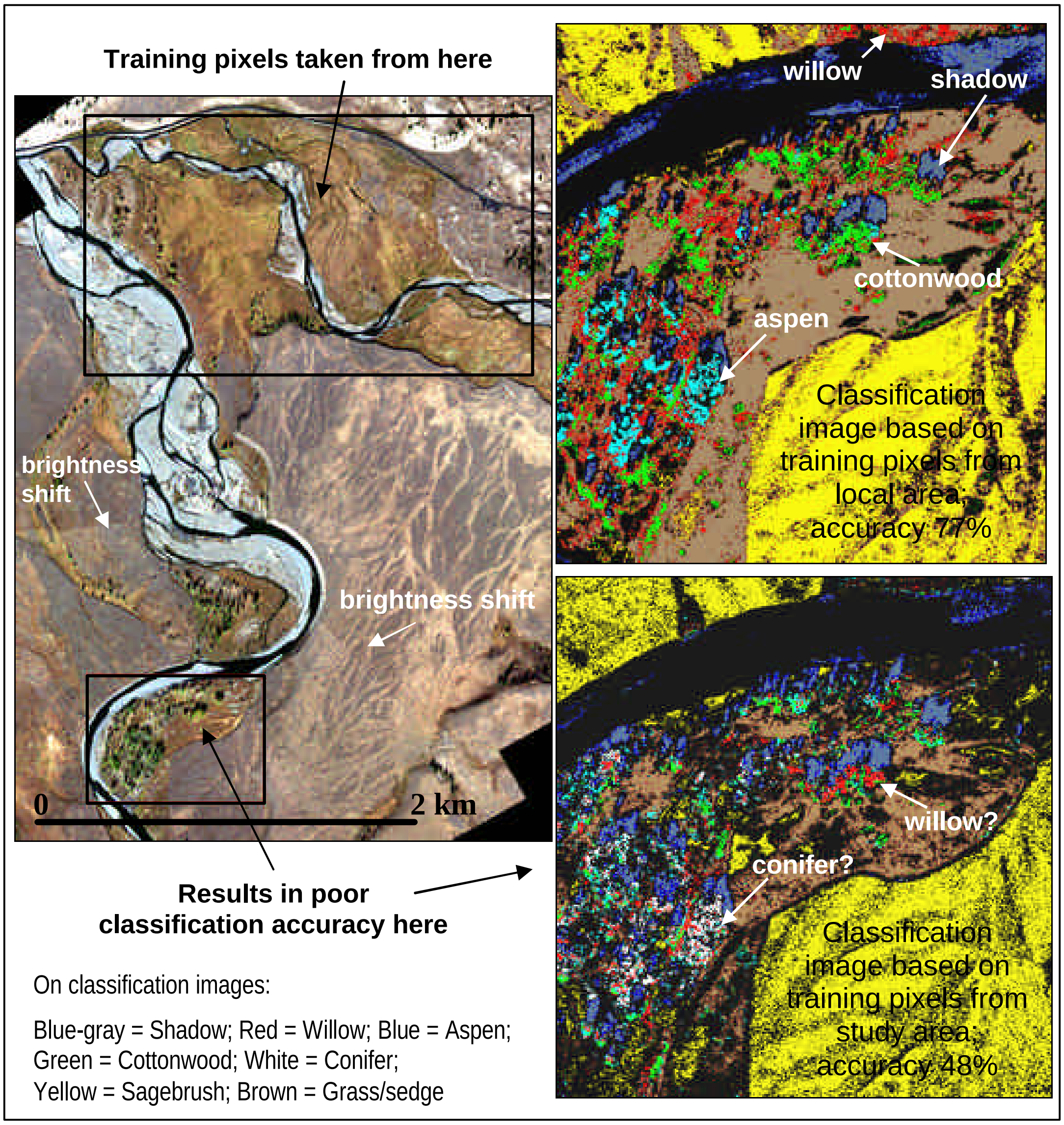


Figure 11: Brightness variation on 1999 mosaic causing misclassification

High spatial resolution imagery is typically taken as a series of small scenes, each of which have their own radiometric characteristics. Airborne platforms add to the variations in radiometric properties because the aircraft often changes it viewing angle relative to the sun, local topography results in a variety of viewing angles relative to the earth surface, and time of flight relative to solar noon is less consistent than with satellite imagery. Radiometric correction algorithms can partially correct for viewing geometry, time of day differences, and topography, but are mathematically complex (Jensen, 1996; Lillesand and Kiefer, 2000) and very time consuming to apply when dealing with multiple scenes that need to be corrected and mosaicked. Satellite imagery provides a potential solution to the brightness issue because of the satellite's constant position relative to the earth's surface and the larger field of view (e.g. Congalton et al., 2002), although satellites have their own potential problems as is discussed below.

Utility of HSR imagery for mapping riparian vegetation change in the Northern Range

Due to the time involved in achieving coregistered, classified images, this research did not expand the classification and change detection outside of the Soda Butte-Lamar confluence area. Additionally, there is a limit on the reliability of post-classification change detection with high spatial resolution imagery due to accuracy issues related to coregistration and brightness variations between images. In applications that have field data for all of the years in which imagery is taken, a more exact estimate of change could be made (Lunetta and Elvidge, 1998); unfortunately, this is not the case across Yellowstone's Northern Range.

The 1995 imagery was taken along most of Soda Butte and Cache Creeks, so it is possible to apply the methods from this study to calculate changes in riparian vegetation along the entire lengths of those streams. Calculating those changes, however, would require using more than 100 airborne scenes taken by the ADAR 5500 sensor in 1995, each of which needs to be coregistered to the 1999 imagery and radiometrically corrected. Additionally, due to the lack of 1995 field data, there continues to be no way to adequately assess the accuracy of 1995 classifications and the amount of subsequent change that is calculated.

Nonetheless, because of the growing interest in the riparian vegetation expansion in the Northern Range (Ripple and Beschta, 2003; Robbins, 2004), there will continue to be a need for accurate landscape scale data on the location and amount of riparian vegetation. The findings from this research indicate that using airborne imagery to continuously monitor vegetation change for the Northern Range may not yet be worth the time and effort relative to other techniques.

The above obstacles suggest that satellite imagery might provide a preferred alternative to airborne imagery for change detection, because satellite imagery is more geometrically and spatially consistent than airborne imagery. High spatial resolution satellites such as IKONOS and QuickBird provide 4 spectral bands at approximately 3-4 m resolution, with a field of view of approximately 11 km^2. Alternatively, satellite platforms such as ASTER (Jet Propulsion Laboratory, Pasadena, CA) have more spectral bands, which could compensate for lower spatial resolution in their ability to distinguish between vegetation taxa (JPL, 2001).

The results of this study indicate, however, that even ~4 m resolution will miss many areas of riparian brush that are significant to the Northern Range. In addition, cloud cover can block out an area of interest during an anniversary date for change detection. Atmospheric path length leads to lower signal to noise ratios and interference from humidity and other atmospheric components alters reflectance values in a non-systematic manner. Finally, high spatial resolution satellite imagery is not available for most locations on an historic basis, limiting its use to the present time and future monitoring. Nonetheless, the benefit of having a larger field of view with less brightness difference may outweigh the drawbacks to using satellites, especially as these satellites are improved and the acquisition of imagery becomes less expensive (Table 8).

Table 8: Price comparison based on township size area of 121km^2 or 46.7 mi^2. DCIR aerial photo estimates are based on the approximate price of aircraft rental with pilot, use of digital infra-red camera (DCIR) equipment and 2 people for data support (Lake et. al, 1997). Probe-1 airborne imagery estimates are based on the approximate price of aircraft rental with pilot, use of 128-band imaging spectrometer and processing to produce a precision geocoded product (Marcus et al., 2000).

(modified from Finley, 2003)	**Product**	**Coordinate Accuracy**	**Resolution**	**Product Type**	**Price**
Aerial Photo (scanned, non-rectified)	9-inch	n/a	1-meter	Color	$4 - 5,000
Aerial Photo (orthorectified)	9-inch	custom	1-meter	Color	$10 - 15,000
DCIR Aerial Photo (custom acquisition)	custom	n/a	1-meter	Multispectral	$13,500
Probe-1 airborne imagery	custom	custom	5-meter	Hyperspectral	$13,000
IKONOS	Reference	25-meter	1-meter and 4-meter	panchromatic & multispectral	$5,300
	Precision	4-meter	1-meter and 4-meter	panchromatic & multispectral	$10,000
QuickBird	Standard	23-meter	.61 meter and 2.44 meter	panchromatic & multispectral	$3,600
	Orthorectified	10-12 meter or custom	.61 meter and 2.44 meter	panchromatic & multispectral	$7,800

Conclusion

The major findings in this research answer four key questions about the application of high spatial resolution imagery to riparian vegetation classification and change detection in Yellowstone's Northern Range: (1) it is possible to achieve accuracies as high as 90% when classifying riparian brush as one category; (2) accuracies decrease to 42% to 77% when trying to distinguish between riparian taxa; (3) vegetation that is approximately 4 times the size of the imagery resolution are more likely to be classified correctly than smaller plants; and (4) increases in riparian brush cover in the study area range from 135% to 1011% .

These numbers provide the first quantitative measurements of change in riparian shrubs for the Soda Butte Creek-Lamar River confluence between 1995 and 1999. Expanding this analysis of riparian vegetation change along Soda Butte Creek and Cache Creek between 1995 and 1999 could give resource managers in Yellowstone National Park order of magnitude estimates of changes in riparian vegetation and locations of change. In this way, important patterns may become apparent and help focus researchers' efforts in determining factors driving the changes.

As remote sensing imagery with spatial resolutions of less than 5 m become more affordable and accessible, this imagery will be applied to increasingly fine scale research questions (Aspinall et al., 2002). This application of high spatial resolution imagery for riparian vegetation mapping, has defined some strategies for successful use of this imagery:

- Set up sites for field monitoring and ground-truth data where features of interest are 3 to 4 times the pixel resolution.
- Plan imagery acquisition for the season when vegetation phenology offers the maximum contrast.
- Concentrate rectification ground control points around areas of interest to compensate for RMS errors greater than ¼- ½ of a pixel.
- Avoid resampling images that have pixel-sized features of interest.
- Coregistration and classification of ~1 m resolution airborne imagery should be performed on regions no larger than 2 km^2 to maintain optimum accuracy.
- Acquire images for change detection from the same week and at the same time of day to minimize loss of features due to shadow and seasonal changes in reflectance.

All of these strategies speak to the need for a coordinated funding and monitoring effort that is planned well in advance of imagery acquisition. In order to successfully monitor riparian vegetation with HSR remote sensing imagery at the scale of the Northern Range, decisions about the amount of area coverage and timing will affect what type of imagery should be acquired. Knowledge of whether the same type of imagery can be acquired for the entire region and for all the years of the project should be taken into consideration as well. The process may not follow the remote sensing ideal of being able to quickly digitize training pixels and apply classifications to very large regions all at once, but with more effort on the front end of a project, classifications and change analyses can be performed over large regions to a level of detail that has previously not been seen from remote imagery.

Appendix A – Glossary

(Definitions are modified from Lillesand and Kiefer (2000) unless otherwise noted.)

Accuracy assessment- Quantification of the accuracy of digital land-cover classifications by comparing the relationship between known reference data (ground-truth) and the results of an automated classification. A classification accuracy of 90% means that 90% of the digitally classified pixels were classified into categories that matched the ground-truthed categories.

Aerial photography- The first airborne remote sensing technique were photographs taken from an aircraft. Geometrically reliable systematic aerial photography surveys of the United States began in the 1930s so that topographic maps could be created for the country. Standard aerial photos are taken with panchromatic, black and white film, which captures ultraviolet and visible wavelengths of light.

Bands- The channels that a sensor has to record a range of reflected wavelengths. A 4-band multispectral sensor typically records a range of wavelengths in the infra-red portion of the spectrum as 1 band, red wavelengths as another, and green and blue wavelengths as the 3^{rd} and 4^{th} bands.

Bandwidth- The range of wavelengths in the spectrum that a particular band in a sensor records.

Change vector analysis- The change vector of a pixel is defined as the vector difference between the multi-band digital vectors of the pixel on two different dates (Yuan et al., 1998).

Classification accuracy- see Accuracy assessment.

Coregister- Lining up multiple images of the same region and selecting common points that allow a digital algorithm to warp the images so that they overlay as exactly as possible.

Dot grids- A method to measure irregularly shaped features on a photograph. A transparent grid of uniformly spaced dots are placed over an area of interest and the knowledge of the dot density of the grid allows for computation of the area of a region.

Endmembers- Pure spectral signatures of materials that are used as reference signatures to help digitally separate categories that are mixed together in the pixels of an image (see spectral library).

Errors of commission and omission- Commission errors are those that are due to *more* pixels being classified in a particular category than actually belong in that category, whereas omission errors are those that are due to *less* pixels being classified in a category than should be.

Georeference- A process of applying a geographic coordinate system to an image that previously did not have any connection with coordinates on the surface of the earth.

Greater Yellowstone Ecosystem (GYE)- A rich temperate ecosystem that includes Yellowstone and Grand Teton National Parks and six surrounding National Forests and two National Wildlife Refuges in Idaho, Montana, and Wyoming (YNP, 2002).

Ground-truthing- The acquisition of reference data that involves collecting measurements and observations about the areas being remotely sensed. These measurements are typically used for accuracy assessments.

Hyperspectral imagery- Imagery with more than 100, very narrow, contiguous spectral bands throughout the visible, and infrared portions of the spectrum (Marcus, 2002).

Image differencing- coregistered images from two dates are subtracted, pixel by pixel, toproduce a new image that represents the digital change between the two dates (Yuan et al., 1998).

Image ratio- coregistered images from different dates are ratioed, band by band. The idea is that areas without spectral change in any bands will all yield similar ratio values and in areas of change, the ratio would either be higher or lower than the no-change ratio (Yuan et al., 1998).

Landsat imagery- Imagery from a series of 7 polar-orbiting satellites called Landsat 1, 2, 3, 4, 5, 6 and 7.

Mask- A mask is a binary image that consists of values of 0 and 1. When a mask is used in a processing function, the areas with values of 1 are processed and the masked 0 values are not included in the calculations (RSI, 2003).

Maximum Likelihood- A classification algorithm that considers the relative probabilities that a given pixel should be classified in a particular category based on the variance and covariance of that category’s spectral response patterns.

Minimum Noise Transformation- An algorithm within remote sensing software programs that is applied to determine the inherent dimensionality of image data, to segregate noise in the data, and to reduce the computational requirements for subsequent processing. The MNF transform as modified from Green et al. (1988) and implemented in ENVI, is essentially two cascaded Principal Components transformations (RSI, 2003).

Mosaic- An overlay of two or more images that have overlapping areas (RSI, 2003).

Multispectral imagery- Imagery with 4-7 spectral bands covering portions of the visible and near infrared portions of the spectrum; typically not contiguous bands (Wright et al., 2000).

Multi-temporal or composite change classification- a change detection technique in which two image scenes of the same area, recorded on different dates, are superimposed and treated as a single image with all the bands of both of the superimposed images. This multi-band image can then be classified in such a way that areas in which the bands of both dates are most different from each other are highlighted.

Panchromatic- black-and-white photographs that contain ultra-violet and visiblewavelength information.

Pan-sharpening- a technique that sharpens coarse spatial resolution spectral image data with high spatial resolution data (RSI, 2003).

PCA composite- see Principal Components Analysis.

Post-classification comparison- land cover change is detected as a change in land cover label (the classification of each pixel) between two image dates. These are based on independent land cover classifications that are superimposed (Yuan et al., 1998).

Principal Components Analysis (for change detection)- used either as a way to bring out areas of change on a composite image (see multitemporal or composite change), or as a preprocessing technique on each individual image (Yuan et al., 1998). PCA reduces the data dimensionality in such a way that it highlights uncorrelated bands of information within the image.

Principal Component Transformation- PC transforms are used to produce uncorrelated output bands, to segregate noise components, and to reduce the dimensionality of data sets. Because multispectral data bands are often highly correlated, the Principal Component (PC) Transformation is used to produce uncorrelated output bands. This is done by finding a new set of orthogonal axes that have their origin at the data mean and that are rotated so the data variance is maximized (Richards, 1999; RSI, 2003).

Producer’s Accuracy- The number of correctly classified pixels in each category divided by the number of training set pixels used for that category.

Reflectance- Wavelengths of light that are not absorbed by an object are reflected and recorded by a sensor as values for each band of light.

RMSE (Root Mean Squared Error)- After georeferencing or coregistering images, RMSE reports the standard deviation of actual locations of points on an image as compared to the desired coordinates.

Sensors- The remote sensing term for the camera that records reflectance values from the ground.

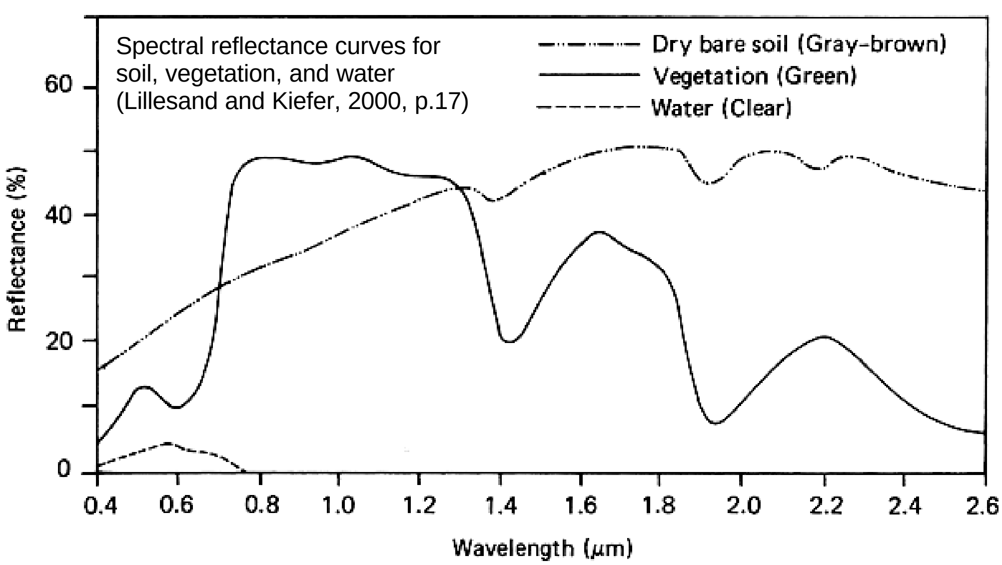
Signal to noise ratio- The relationship between the amount of actual reflectance information a sensor is recording as compared to background electronic noise. Typically, the larger the field-of-view a sensor has, the higher the signal to noise ratio.

Spatial resolution- The amount of ground that each pixel in an image displays.

Spectral Angle Mapper- A classification algorithm that is based on the idea that an observed reflectance spectrum can be considered as a vector in a multidimensional space, where the number of dimensions equals the number of spectral bands. To compare two spectra, the multidimensional vectors are defined for each spectrum and the angle between the two vectors is calculated. If this angle is smaller than a given tolerance level, the spectra are considered to match.

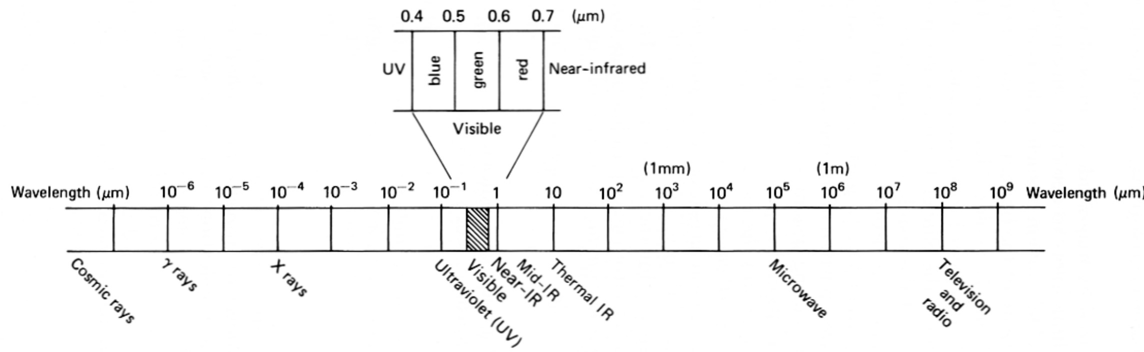
Spectral bands- See Bands.

Spectral library- data sets of specific spectral reflectance curves for particular materials, as below:



Spectrum (Electromagnetic spectrum) / spectra is plural-

Lillesand and Kiefer, 2000, p.5



Thresholds (in classification categories)- a user-defined probability requirement for classifying a pixel into a given category. For example, if 0.8 is the defined threshold for pixels to be classified as willow, only those pixels with an 80% probability of being willow based on their band values will be classified as willow. Those under 80% will either be classified as something else or left unclassified.

Training pixels- Pixels that are chosen and digitized in order to assemble a set of statistics that describe the spectral response pattern for each land-cover type to be classified in an image.

True-color composite- A color image that mimics what the human eye sees, created fromcombining the red, green and blue spectral bands from a remote sensing image.

User’s Accuracy- The number of correctly classified pixels in each category divided by the total number of pixels that were classified in that category.

Appendix B - Field measurements of individual riparian shrubs

Aug. 2002- Hitching Post Vegetation Measurements (Soda Butte Creek)										
Plant #	Average Maximum Height (in meters)	Stems per 0.5m	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	Classified correctly? (Y/N)
1	1.50	9	1.80	2.90	2.20	N	6			N
2	1.40	7	2.00	1.20	1.00	1	5	evidence of past browsing-minimal current browsing	20020910 - #10	N (pixel next to this one is willow)
3	1.35	8	2.00	1.40	1.40	1	6		20020910 - #11 (rootwad)	N
4	1.35	7	2.05	1.05	0.90	1	6	damaged plant - crown folded over - changing color		n/a
5	1.70	8	2.30	1.70	1.50	1	6		20020910 - #14	N
6	1.90	10	2.30	1.10	1.00	2	5	no recent browse	20020910 #12 #13	N
7	2.00	6	2.60	2.00	1.65	1	6			Y(3/4 - one sage)
8	2.30	6	2.80	4.70	3.10	1	5	huge willow bush		Y
9	n/a							no measurements - edge of #8 - offshoot?		n/a
10	1.75	13	2.25	1.20	1.10	2	6	2001 heavy browsing activity - along major game trail		N (shadow)
11	1.90	7	2.50	1.40	1.30	1	5	2001 heavy browsing activity - along major game trail		Y (1/1)
12	1.80	5	2.40	1.40	1.20	2	5	2001 heavy browsing - 1m b/t 12 and 13 - looks like 1 plant on '99 imagery		Y (1/1)

Hitching Post continued (2002)										
Plant #	Average Maximum Height (in meters)	Stems per 0.5m	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
13	2.00	12	2.55	1.80	1.60	2+	6	2001 heavy browsing - 1m b/t 12 and 13 - looks like 1 plant on '99 imagery	20020910 #15 #16	Y (2/2)
14	1.60	10	2.20	1.20	1.00	1	6			n/a
15	1.80	10	2.30	1.70	1.40	1	5			Y (3/3)
16	1.60	16	2.30	1.20	1.10	2	6	2000-2001 heavy browsing		N
17a	2.20	15	3.00	2.50	1.50	1+	7	east - looks like 1 willow		Y
17b	1.55		2.20					west - this one shorter and lighter - different species than east		Y
18	2.45	5	3.00	2.50	1.60	2	7	2 willows - larger one (west) used for measurements - 2000-2001 heavy browsing		N
19	1.70	9	2.30	1.80	1.55	1	6	heavy browsing in all previous years		Y (1/2)
20	1.20	9	1.70	1.50	1.40	N	4	2002 heavy browse		N
21	1.80	7	2.50	2.10	1.80	1	6			Y (3/3)
22	2.00	7	2.60	2.90	1.80	1	5	2 willows - darker species on east - lighter on west		Y (6/6)
23	1.40	3	2.15	1.80	1.70	1	7	heavily browsed - turning color - looks ill		Y (2/2)
24	1.80	6	2.20	1.90	1.80	1	4	caterpillar/insect holes in leaves?		Y (2/2)
25	1.40	7	1.80	1.10	0.90	N	4			n/a

Aug. 2002- between Hitching Post and Confluence Vegetation Measurements (Soda Butte Ck)

Plant #	Average Maximum Height (in meters)	Stems per 0.5m	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
26	2.20	6	2.80	3.20	2.30	1	8			Y (14/16 pixels)
27	1.30	6	1.90	1.25	1.10	N	4			N
28	1.40	10	2.00	2.90	1.15	1	4	may be 2 plants - 2 root areas - heavily browsed		Y (5/11 pixels)
29	1.15	5	1.50	1.70	1.00	1	4			Y (1/3)
30	1.10	5	1.50	1.50	1.00	N	4			N
31	2.00	5	2.50	2.40	1.50	2	5	has fruit on it		N (aspen)
32	1.40	5	2.00	1.50	1.20	1	5	2000-2001 heavy browsing - fruit	20020911 - #43	Y
33	1.55	6	1.90	1.60	1.10	1	3			N
34	1.50	7	2.00	0.90	0.90	2	6	2000-2001 heavy browsing - 1999 growth spurt		N (aspen)
35	1.60	12	2.20	1.60	1.30	2	3	heavily browsed in past years - very close to 36		N (aspen)
36	1.40	8	1.90	1.90	1.80	2	6	2000-2001 heavy browsing - very close to 35		Y (1 will&1 asp)
37	1.15	9	1.45	1.10	1.00	2	6	1999, 2000, 2001 heavy browsing evidence - maybe prior to 1999 too		N

Hitching Post to Confluence continued (2002)

Plant #	Average Maximum Height (in meters)	Stems per 0.5m	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
38	1.30	6	1.90	1.10	1.10	1	5	2000-2001 heavy browsing		Y
39	1.40	7	1.70	1.90	1.80	2	5	2000-2001 heavy browsing - maybe prior to 2000 too - 1.5m b/t 39 & 40		Y
40	1.35	7	1.65	1.60	1.30	2	8	2000-2001 heavy browsing - 1.5m b/t 39 & 40		N (conifer)
41	1.20	5	1.50	1.10	0.80	1	8	1999, 2000, 2001 heavy browsing evidence - next to this plant is a root stump - heavily browsed honeysuckle in area		N
42	1.30	8	1.70	1.90	1.30	1	7	1999-present heavy browsing - possible insect damage as well - heavily browsed honeysuckle in area		Y
43	1.25	10	1.60	1.70	1.20	2	6	2000-2001 heavily browsed - heavily browsed honeysuckle in area		Y (1 will&1 asp)
44	1.30	8	1.70	1.20	1.20	1	7	1998, 99, 2000, 01 heavily browsed - heavily browsed honeysuckle in area - 44 & 45 close together		N

Hitching Post to Confluence continued (2002)										
Plant #	Average Maximum Height (in meters)	Stems per 0.5m	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
45	1.50	5	2.15	1.60	1.50	2	6	2002 mechanical damage - 2000-2001 heavily browsed - heavily browsed honeysuckle in area		N
46	1.40	4	2.00	1.70	1.50	2	7	2000-2001 heavily browsed - may have been browsed in 2002 and prior to 2000 as well		N
47	1.40	9	2.00	2.10	1.40	2	6	2000-2001 heavily browsed - has berries		N
48	1.80	10	2.80	3.20	1.60	3	6	1999, 2000, 01 heavily browsed - has berries	20020911 #44 #45 (root)	Y (4/5 - one shadow)
49	2.20	5	2.70	2.80	1.30	1	7	actually 2 plants		N (conifer)
50	2.00	6	2.50	2.30	1.50	2	6	2000-2001 heavily browsed - honeysuckle mixed in on stream-side and west side		Y (4/4)
51	1.70	4	2.50	2.40	2.00	2	8	browsing in most past years - honeysuckle growing around and in this plant		Y (2/3 - one conifer)

Aug. 2002- Footbridge Vegetation Measurements (Soda Butte Ck)

Plant #	Average Maximum Height (in meters)	Stems per 0.5m	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
52	2.05	8	2.70	2.50	2.20	N	6	Willow - browsed throughout life - possible disease - yellowed leaves		
53	1.25	12	1.65	1.30	0.90	N	4	Cottonwood (angustifolia) - insect damage		
54	1.00	4	1.40	1.10	0.80	2	4	Cottonwood (trichocarpa) - next to two more CWs (angust. and tricho.) - browsing/mech. damage		
55	1.50	6	2.10	1.40	1.25	N	4	Cottonwood (trichocarpa) - past browsing/mech. damage		
56	1.50	8	2.15	2.40	1.55	N	5	Willow - hanging over water - 2001, 2002 browsing		
57	1.35	7	1.85	1.80	1.60	1	4	Cottonwood (trichocarpa) - 2000, 01, 02 browsed		
58	1.40	19	1.85	2.40	2.10	N	8	Willow - very healthy - 2000, 01, 02 browsed		
59	1.60	10	2.35	3.10	1.60	N	4	Willow - 2001, 02 browsed - yellowing color - 59 & 60 are representing a group of 5 willows		
60	1.70	6	2.60	2.10	1.80	N	5	Willow - 2001, 02 browsed - yellowing color - disease/insect damage - 59 & 60 are representing a group of 5 willows		

Footbridge continued (2002)

Plant #	Average Maximum Height (in meters)	Stems per 0.5m	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
61	1.20	5	1.60	1.70	1.30	1	4	Cottonwood (Angustifolia?) - Caterpillar observed on leaf (see Pfaff's journal) - 2002, 2001 browsing		
62	1.15	7	1.60	1.60	1.30	1	5	Cottonwood (angustifolia)		
63	1.10	9	1.60	2.50	1.30	N	5	browsing evidence every year		
64	1.30	8	1.70	2.20	1.40	N	7	Cottonwood - browsing evidence every year		
65	1.30	16	1.75	2.00	1.80	N	5	Willow - 2002, 2001 browsing		
66	1.20	7	1.55	2.40	1.70	1	5	Cottonwood (trichocarpa) - browsed throughout life		
67	1.10	4	1.50	1.25	1.20	1	5	Cottonwood (angustifolia?) - browsed throughout life		
68	1.15	6	1.70	1.60	1.50	N	5	Cottonwood (trichocarpa) - browsed throughout life		
69	1.20	6	1.50	1.40	1.10	1	4	Cottonwood (trichocarpa)		
70	1.30	7	1.60	2.70	1.70	N	3	Willow - no browse evidence at all		
71	1.20	4	1.60	1.00	1.00	1	5	Cottonwood (trichocarpa) - browsed throughout life		

Footbridge continued (2002)										
Plant #	Average Maximum Height (in meters)	Stems per 0.5m	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
72	1.00	3	1.55	1.10	1.00	N	4	Cottonwood (trichocarpa) - 2002, 2001 browsed		
73	1.20	3	1.50	1.20	1.15	N	4	Cottonwood (trichocarpa?) - lots of growth - disease and insect damage evident		
74	1.20	6	2.00	1.70	1.00	N	5	Cottonwood (angustifolia) - 1/3 of plant is dead		
75	0.90	5	1.20	1.30	1.20	1	4	Cottonwood (trichocarpa)		
76	1.10	7	1.85	1.80	1.60	N	4	Cottonwood (angustifolia)		
77	1.00	6	1.55	1.50	1.50	N	4	Cottonwood (trichocarpa) - 2002, 2001 browsed		
78	0.80	2	1.25	1.30	1.00	N	3	Cottonwood (trichocarpa) - heavy browsing throughout life		

General Comments:

20020910: Measuring stick is 2.45m, Attempting to measure to the densest portion of bush ("pruning width"), Axes are at breast height, Smaller bushes seem to have more branches but are questionably more dense, 1999 looks like growth spurt year.
20020911: Nos. 31-38 are in one clump - see Pfaff's notes for shape and dimensions.
20020912: Root wad is hard to rate on cottonwoods - seems different than on willows.

Sept. 2003 Crystal Creek (tributary of Lamar R. near Slough Ck)

Plant #	Average Maximum Height (in meters)	Stems per 0.5m (leader density)	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
cr1	1.6	15	1.87	1.5	1.3	2 (2 roots)	7	much large dead root material - one large willow with surrounding upstarts	andrew's camera 08032003	
cr2	1.95	7	2.45	3.5	3	N	7	3 major willows in a group the largest is light in color and furthest east	andrew's camera 08032004-- 2 pics 74-75	
cr3	2.05	21	2.35	1.2	1.3	2-3 coming out of north bank	8	Base stump in creek - center density = 6 stems per 0.5m		
cr4	2.25	9 (alder)	2.65	3.75	2.8	3+ (alder)	8? To alder root	3 young willows and 1 wide alder - alder is denser and darker - 10 is central density		
cr5	1	13	1.3	3.6	1.4	1	5	group of 3 willows - 1 darker species; 9= center density		
cr6	1.5	14	1.7	2.5	2.1	N	5-8? Est. 8 yrs old	11 = center density; mostly dead branches		

Crystal Creek continued (2003)										
Plant #	Average Maximum Height (in meters)	Stems per 0.5m (leader density)	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
cr7	4.7	center 13 (alder)	5.3	3.7	2.9	3++	8 to trunk	~3 willows surrounding giant ALDER		
cr8	1.95	28	2.35	2.5	1.3	7stems at size 1	6-8, gnarled and stumpy	this year's growth = 1.1m leaders at top; center density = 20		
cr9	2.2	20	2.45	2.4	2.4	1	8-11 thick base	growing around granite boulder - 3 different willow species; cent dens. 18		
cr10	3.2	center 22	3.8	4.3	3.4	multiple 1s	7-10 - sprouts everyw here	1-meter growth 3 yrs ago (2001)		
cr11	1.3	27	1.45	3.1	1.25	1	6 to 7	4-5 willows against rock; 18= center density; gooseberry on west side, rose on east		

Sept. 2003 Blacktail Deer Creek										
Plant #	Average Maximum Height (in meters)	Stems per 0.5m (leader density)	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
bd1	3.5	5	4.2	~4	4.2	N	not determinable	low density but huge	20030729 - 53,54	
2	2.5	7	3	3	2.9	N	5+	in group next to stream not visible individually		
3	2.6	n/a (5 bushes)	3.6	circumference 39.6		N	6+	large bunch of willows used to be 5 individuals; see image - X = measure stick	55,56 - creek side; 57 - parkinglot side; left bush = BD1; all center = BD3	
4a	2.4	5	2.75	1.6	1.8	N	6	2 species of willow		
4b	1.8	13	2.3	2.6	2.7	N	7			
5	2.6	7	2.9	3.4	2.8	almost 1	6	root pic	58	
6	1.6	6	1.9	1.6	1.7	N	5	whitestem gooseberry growing at base		
7	1.7	9	2.1	2.6	2.3	undeterminable				

Blacktail Deer Creek continued (2003)

Plant #	Average Maximum Height (in meters)	Stems per 0.5m (leader density)	Maximum leader height (meters)	Long and Short Axis Diameter X & Y (meters)		Root Wad/Stump 1 Small, 2 Med, 3 Large	Age (in years) (from rootstock up)	Notes	Picture date & number	
8	1.35	7	1.65	1.4	1.7	N	3 to 4	stump till last 2-3 years; some leaders allowed to grow		
no #			3.0+					shadowed on 99 imagery	pics 59 & 60	
9	3.4	11	3.8	3.2	3	3+	11		61,62	
10	3.2	4	3.5	2.4	2.2	1	6		65	
11	2.8	9	3	1.8	2.1	N	8			
12	2.9	18 (only 3 alive)	3.3	2.2	2.5	2 TO 3	undeterminable		66,67	
13	2.4	9	2.6	2.6	2.5	1	8			
14	2.9	12	3.2	3.3	3.4	N	9			
15	2.5	4	3	2.6	2	N	7?	EVIDENCE OF BURN	68, 69	
16	2.3	11	2.7	2.1	2.55	N	10	no burn evidence		
17	2.3	4	3	2.6	1.5	N	11	75% of bush dead	70	
18	2.5	6	3	2.5	1.9	N	6+	alder buckthorn next to willow on east		
19	1.4	12	1.8	2.9	3.6	1	6+	beaver cut on creek side	71, 72	

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