MAPPING AND CHANGE DETECTION OF WETLAND AND RIPARIAN ECOSYSTEMS IN THE GALLATIN VALLEY, MONTANA USING LANDSAT IMAGERY

by

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Abstract

The location and distribution of wetlands and riparian zones influences the ecological functions present on a landscape. Accurate and easily reproducible landcover maps enable monitoring of land management decisions and ultimately a greater understanding of landscape ecology. Multi-season Landsat ETM+ imagery from 2001 combined with ancillary topographic and soils data was used to map wetland and riparian systems in the Gallatin Valley of Southwest Montana. Classification Tree Analysis (CTA) and Stochastic Gradient Boosting (SGB) decision-tree based classification algorithms were used to distinguish wetlands and riparian areas from the rest of the landscape. CTA creates a single classification tree using a one-step-look-ahead procedure to reduce variance. SGB utilized classification errors to refine tree development and incorporated the results of multiple trees into a single best classification. The SGB classification (86.0% overall accuracy) was more effective than CTA (61.7% overall accuracy) at detecting a variety of wetlands and riparian zones present on this landscape.

A change detection analysis was performed for the years 1988 and 2001. The change detection used Landsat-based Tasseled Cap (TC) components and change vector analysis (CVA) to identify locations of wetland/riparian gain or loss in the 13-year period. CVA of TC brightness, greenness, and wetness components reduces the compound errors of multi-date classifications by using a threshold value to separate land cover change from spectral variability between 1988 and 2001 imagery. Only the highly changed pixels were classified using 1988 Landsat imagery and ancillary data. These change pixels were then merged with the 2001 classified image to develop a wetland/riparian map for 1988. The high overall accuracy of the 1988 classification (81%) developed with this procedure showed the benefits of this technique for mapping historical landcover features. Comparison of the 1988 and 2001 classifications identified locations where wetlands/riparian areas increased, decreased, or remained stable between these years. TC based CVA had an overall change detection accuracy of 75.8% and was able to identify areas of isolated and contiguous wetland/riparian change.

CHAPTER 1

INTRODUCTION

Wetlands and riparian zones provide unique ecological functions such as wildlife habitat and hydrologic purification. These ecosystems occupy the transitional areas between aquatic and terrestrial environments and are vital to the buffering of materials transferred across these ecotones (Sader et al., 1995). The ecological importance of wetland/riparian ecological functions requires that our society monitor the quality and quantity of wetland/riparian ecosystems. Wetlands and riparian zones account for less than 5% of the total landscape in the western United States (Lewis et al., 2003). Unfortunately, few effective techniques have been developed for locating and monitoring these ecologically under-represented ecosystems (Semlitsch & Bodie, 1998).

An accurate resource inventory map provides greater understanding of the current ecological features present on the landscape, however this might not tell the whole story. Wetland and riparian zone location and distribution are controlled by hydrologic, topographic, and geologic conditions and are subject to change in response to shifting environmental conditions (Tiner 2003). Detection and identification of landscape-scale changes has been a difficult task with traditional techniques. Landscape mapping using remotely sensed data has improved human understanding of landscape ecology and increases our ability to compare historic and current conditions.

The impacts of environmental changes on wetland and riparian ecosystems (from both natural and human causes) are poorly understood due to our limited knowledge of riparian and wetland ecology. The first step in deciphering the intricate ecological activities of wetlands and riparian systems is to locate these areas on the landscape. Many wetland and riparian communities are inaccessible due to property boundaries or unstable substrate that prohibits traditional means of transportation (Kindsher et al., 1998). The synoptic nature of remote imaging provides a complete sample of the variability present in diverse ecosystems, thus allowing many types of wetlands and riparian areas to be distinguished from the surrounding landscape features. Once an effective and reproducible detection method has been established, wetland and riparian areas can be monitored using multiple years of remotely sensed imagery. Periodic monitoring can then be used to analyze wetland/riparian distribution and evaluate the impacts of land management decisions on these important ecosystems (Muller et al., 1993; Semilitsch & Bodie, 1998; Whigham, 1999).

The project discussed in this thesis was a unique opportunity to combine the interests and resources of several local organizations to create a valuable wetland and riparian resource inventory. A concurrent photo interpretation-based wetland mapping project conducted by the Gallatin Local Water Quality District (GLWQD) provided vital image and on-site survey data that was used as reference data for this project and for comparison of inventory results. The development of an accurate, reproducible, and automated procedure for locating wetland and riparian zones was the project goal and was supported by numerous local resource management agencies.

The purpose of this research was twofold: 1) to evaluate wetland/riparian mapping procedures using remotely sensed data with automated land cover classifications and 2) to conduct a change detection analysis of wetland/riparian areas using automated classifications and change thresholding. Chapter 2 is a literature review that discusses several remote sensing data sources, classification procedures, and change detection techniques. Chapter 3 contains the analysis of two Landsat-based wetland/riparian classifications, written in traditional manuscript format. Chapter 4, also written in manuscript format, is an evaluation of change detection analysis utilizing 1988 and 2001 Landsat imagery with change vector analysis.

CHAPTER 2

LITERATURE REVIEW

The management and conservation of wetlands and riparian areas remain as two of the most hotly debated issues in the United States and across the globe. Once considered wastelands, the value of wetlands is now considered in terms of human use and ecological contribution. The concentration of urban development and ecological interests involving wetlands ensures that these systems remain at the forefront of ecological research and management.

Ecological Role and Importance of Wetlands & Riparian Zones

Wetlands are highly variable ecosystems that exist in a variety of forms across various climatic zones and topographic positions. The diversity in form and function of these ecosystems is evident in the range of definitions that have been developed to describe wetlands. Since the 1970s the U.S. Environmental Protection Agency (EPA) has been responsible for regulations concerning wetlands and has therefore developed a working wetlands definition.

> "Wetlands are areas that are inundated or saturated by surface or ground water at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions. Wetlands generally include swamps, marshes, bogs, and similar areas." (U.S. EPA, 2003. p.1)

Wetlands exist in a variety of forms, including vernal pools, playas, prairie potholes, and wet meadows. The common thread between all of these wetland types is that these systems are driven by hydrologic conditions that result in the growth of hydrophytic vegetation and development of hydric soils (U.S. EPA, 2003).

Similar to wetlands, the size, shape, and ecological characteristics of riparian areas vary greatly among different climatic, topographic, and geologic conditions (U.S. EPA, 1983). The range of ecological conditions and species diversity within riparian ecosystems has proven difficult to capture in a single definition. Riparian systems are not as heavily regulated as wetlands but have been the focus of federal resource inventories and land management plans conducted by the Natural Resources Conservation Service (NRCS). The NRCS defines riparian areas as,

> "…ecosystems that occur along watercourses and water bodies. They are distinctly different from the surrounding lands because of unique soil and vegetation characteristics that are strongly influenced by free or unbound water in the soil. Riparian ecosystems occupy the transitional areas between the terrestrial and aquatic ecosystems. Typical examples would include floodplains, streambanks, and lakeshores." (Montgomery, 1996. p.2)

This version of the definition has been expanded to include areas along most fresh water bodies, but has eliminated specific measurements of soil or vegetation conditions that were used in earlier NRCS definitions (Montgomery, 1996).

The riparian zone filters sediments and nutrients from surface and subsurface flows moving toward the river. The width and density of the riparian vegetation zone has a dramatic effect on the efficiency of sediment and nutrient filtering. Previous studies have established that riparian zones in excess of 30 m wide are most effective in this capacity (Thibault, 1997; Wang et al., 2000). The riparian zone also slows river flows to create deposition zones for sediment and organic matter transported in the river corridor. These depositional locations are often sites of concentrated organic matter decomposition and subsequent nutrient uptake by riparian vegetation (Thibault, 1997).

Both wetlands and riparian areas provide habitats that wildlife frequently use for nesting, feeding, and as transportation corridors (Thibault, 1997; Rotterborn, 1998). With an estimated 46% of U.S. endangered species and over 50% of waterfowl species dependent on wetland ecosystems, preservation of these areas will help maintain or increase national biodiversity (Gress et al., 1993; Whigham, 1999). The abundance of water and nutrients in wetlands allows a wide variety of species to thrive, even in arid regions. Unfortunately, the moist, fertile condition of wetlands also makes them susceptible to infestations of exotic species that readily establish and disperse in wetland environments (Tabacchi et al., 1998).

The ecological importance and human interaction between wetlands and riparian zones (including riparian wetlands) are similar enough to allow synonymous discussion of these ecosystems. The term wetland, therefore, will be used to describe both wetland and riparian areas for purposes of this thesis, unless deliberately specified.

Wetlands provide a variety of ecological services that contribute to ecosystem function at local, watershed, and regional scales (Table 1) (Semlitsch & Bodie, 1998; Tabacchi et al., 1998; Mitsch & Gosselink, 2000; Ehrenfeld, 2000). The ecosystem functions performed by wetlands are valuable to the purification and recycling of aquatic and terrestrial resources utilized by humans. Typically, land values are determined by tangible production from a parcel of land, not from ecological contribution. Wetlands perform fundamental ecological processes, that if factored into land values would dictate that wetlands are more economically and ecologically valuable than other ecosystems (Table 2) (Mitsch & Gosselink, 2000).

Table 1. Ecological and anthropogenic benefits of wetland and riparian zone functions.

Ecosystem	Ecological Scale	Value
Wetlands	Human Population	Fish & shellfish collection
		Timber harvesting
		Endangered species habitat
	Greater ecosystem	Flood mitigation
		Storm abatement
		Aquifer recharge
		Improvement of water quality
	Biosphere	Nitrogen, sulfur, carbon, and phosphorus recycling

Adapted from: Mitch & Gosselink, 2000

Table 2. Financial value of ecosystem units, based on value of ecological functions.

Ecosystem Type	Unit Value ($/ha/yr)
Estuaries	22,832
Wetlands	14,785
Lakes/rivers	8,498
Forest	969
Grasslands	232

Source: Mitch & Gosselink, 2000

Urban planners are learning that large, highly diverse wetlands located in moderate intensity urban developments can perform many ecosystem services that would be cost prohibitive for humans to perform. In these locations, wetlands are able to effectively minimize sediment loss, control runoff volume, purify surface water, and concentrate aquifer recharge (Ehrenfeld, 2000; Tiner, 2003). Additionally, these wetlands serve as recreation sites for humans and critical habitat for a large percentage of avian, terrestrial, and aquatic species (Gress, 1993; Semilitsch & Bodie, 1998; Lewis et al., 2003). High densities of impervious surfaces (i.e. concrete) dramatically increase surface flows into wetlands and overwhelm the systems, thereby diminishing or destroying ecological functions (Ehrenfeld, 2000; Mitsch & Gosselink, 2000; Wang et al., 2001).

Wetland Inventory Procedures

Currently the two most common wetland mapping approaches are on-site analysis and aerial photograph interpretation. In most cases the method used to map wetlands depends on the size of the study area and the desired resolution, or minimum mapping unit, of the resulting land cover map (Tiner, 1993; Muller, 1997). The resolution of the data source used will determine if the resulting map distinguishes individual wetland types or provides a generalized wetland inventory (Finlayson & van der Valk, 1995).

On-site Analysis

Wetland mapping projects utilizing on-site measurements of environmental conditions provide highly detailed data sets. Data collected in this procedure includes lists of floral and faunal species, water chemistry, and soil characterization information (Tiner, 1993). Gaining access for wetlands study can be difficult due to factors such as uncooperative landowners, impassable roads, limited mobility on saturated soils, and dense vegetation. The soils, hydrologic, and vegetation data collected from accessible sites are often extrapolated to describe the conditions of similar environments in the surrounding landscape (Thompson, et al., 1997). This is a common practice in ecosystem mapping that might not provide an accurate account of current ecological conditions. When mapping wetlands at a landscape or watershed scale, the added expense of personnel, equipment, and time for on-site analysis rarely justifies the more detailed level of data collected (Harvey & Hill, 2001).

Aerial Photography

Aerial photographs have been used to map wetlands at watershed, regional, and even national spatial scales. Aerial photographs provide synoptic views of the study area, allowing “big picture” understanding of hydrologic and vegetation patterns (Harvey & Hill, 2001). Additionally, archives of aerial photographs are available for many regions of the United States, providing a valuable historical record of past landscape conditions. Improved resolving capabilities of aerial cameras and the incorporation of color infrared (CIR) imagery into mapping projects, has enabled more distinct separations of wetlands from other land cover (Figure 1). The use of CIR film during the dry season creates a visible distinction between actively growing wetland vegetation and senescent non-wetland communities. Aerial photographs captured on film are subsequently scanned into digital format, drastically increasing versatility for Geographic Information System (GIS) analyses (Muller, 1997). Recent developments in digital camera technology have promoted the use of digital aerial photography in GIS mapping efforts. So far conventional digital images have not provided consistently accurate separations of landcover classes when used with automated land cover classification techniques (Thomas et al., 2002).

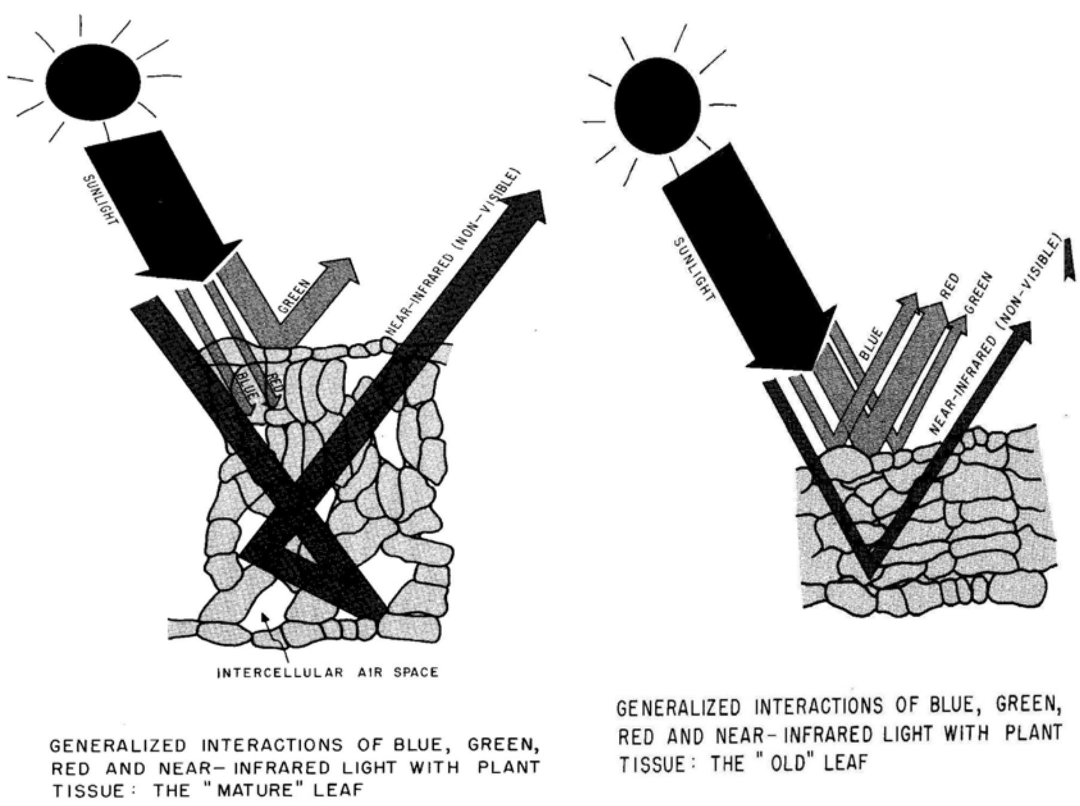

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Figure 1. Illustration of interaction differences of visible and near infrared light with healthy and senescent leaf structures.

Many concerns are still associated with the utilization of aerial photos, despite many improvements in this form of data. Improvements in the spatial and radiometric resolutions of aerial photographs are not sufficient for accurate delineation of gradual or indistinct ecotones, such as those surrounding many wetlands (Thompson et al., 1997). In other cases, climate variations allow adaptive vegetative species to establish in unexpected locations within and immediately surrounding wetlands. In prolonged droughts or wet periods, hydrophytic vegetation is frequently mixed with terrestrial vegetation, thus concealing isolated or marginal wetlands (Tiner, 1993).

The National Wetlands Inventory (NWI) was initiated by the U.S. Fish and Wildlife Service in 1974 to create a national map of wetland areas in the United States. The NWI project utilized 1:58,000 scale CIR aerial photographs as the primary data source since low-altitude photographs would be cost prohibitive and satellite imagery was not considered reliable (Sader et al., 1995). Mapping wetlands with such small-scale imagery limits accurate identification of small, isolated wetlands or wetland areas occluded by tree or shrub canopies (Stolt & Baker, 1995). A primary concern with NWI wetland maps is the extensive time lapse between acquisition of the imagery and production of the final wetland map, often in excess of 10 years (Ramsey & Laine, 1996). Wetlands change frequently in response to variable landscape conditions, relegating deeming newly created NWI maps to historical records of wetland distribution. Another concern with NWI maps and other forms of photo interpretation products is repeatability. Differences in the skill or bias of photo interpreters cause inventory errors that can result in inconsistent resource monitoring. As the concern over global wetland resources continues to escalate, so does the need for automated and reproducible wetland maps (Finlayson & van der Valk, 1995). Without statistically derived wetland inventory maps, change detection methods lack the power to differentiate actual wetland changes from differences in human interpretation.

Space-borne Sensors

Increasingly, space-borne sensors such as multi-spectral detectors and microwave (i.e., radar) imaging instruments are being utilized as data sources for wetland and riparian zone mapping. Factors such as repetitive flight paths, high temporal resolution, relatively low imagery costs, unbiased observation methods, and ability to sample variability at a landscape scale have contributed to the increasing popularity of these data sources (Kasischke et al., 1997; Lakshmi et al., 1997; Harvey & Hill, 2001; Toyra et al., 2001). The utility of many satellite imagery systems is limited by spatial resolution and inability to collect imagery due to cloud cover (Bagdadi et al., 2001; Toyra et al., 2001). These data sources, however, have provided accurate and reliable wetland inventory maps, despite the concerns associated with space-borne imaging systems (Sader et al., 1995; Naramulani et al., 1997; Baghdadi et al., 2001).

Radar instruments are active imaging systems that transmit and detect energy in the microwave portion of the electromagnetic spectrum (Figure 2). Passive microwave sensors exist (e.g., Scanning Multi-Channel Microwave Radiometer and Advanced Microwave Scanning Radiometer) and have been used to map regional and global hydrology and vegetation. These sensors often provide unreliable data due to inconsistent response sensitivities and extremely low spatial resolution (Guha & Lakshmi, 2002; Njoku et al., 2003). More dependable data is collected from active imaging radars that transmit microwave energy toward the Earth's surface and measure the intensity of the energy returning to the radar sensor. The wavelength and polarization of the energy transmitted by the radar can be adjusted to determine the size and orientation of the objects that are detected. The degree to which microwave energy is scattered, attenuated, or reflected by earth objects depends on characteristics such as hape and surface texture (Kasischke et al., 1997).

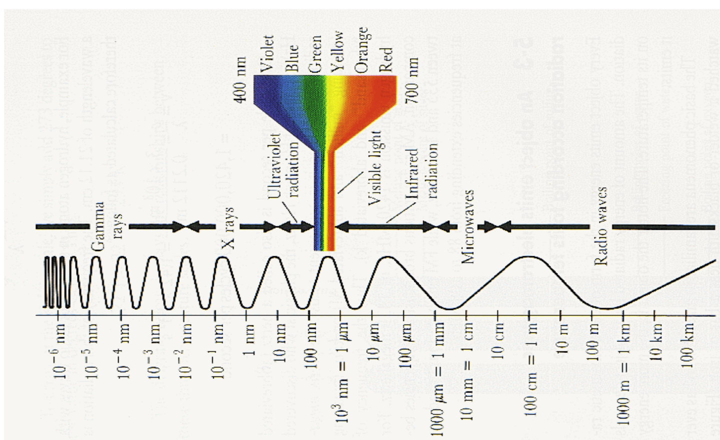

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Figure 2. Electromagnetic spectrum, wavelength ranges and energy groups.

Microwaves are comprised of longer wavelength energy than that of visible or infrared (IR) energy (Figure 2) and thus are able to penetrate atmospheric water vapor in clouds. This provides a significant advantage to resource mapping projects in tropical or boreal regions that remain significantly cloud covered for most of the year (Kasischke et al., 1997). Although C-band (5.7 cm wavelength) radar is insensitive to water vapor, the polar nature of water in liquid form makes C-band frequency highly sensitive to surface, soil, and vegetation moisture (Lakshmi et al., 1997). Longer wavelength radar (P- and L-bands) are useful for flood mapping since these frequencies are able to penetrate vegetation but are less sensitive to surface and soil moisture.

Interactions of microwave energy with objects on the earth surface are dictated by the reflective and conductive characteristics, or dielectric constant, of that object. The dielectric constant of water is 10 times greater than dry materials, thus making radar a logical moisture detection technique (Lillesand & Kiefer, 1994, p, 673; Kasischke et al., 1997). The strong interaction between moisture and microwave frequency energy has spawned many wetland mapping projects using a variety of radar wavelengths and polarizations. Previous wetland and flood monitoring projects have identified measurably different responses of water to different radar polarizations (Guha & Lakshmi, 2002). Early radar based wetland mapping efforts using ERS-1 data were significantly limited by the vertical polarization of this C-band system. Boundary detection of horizontally oriented features, such as standing water, is most effectively determined with horizontally polarized systems (Kasischke & Bourgeau-Chavez, 1997; Baghdadi et al., 2001). More recently, wetland mapping projects have used the horizontal polarization of Radarsat C-band radar data to map the extent of flooded wetlands with overall classification accuracies ranging from 66% - 80% (Toyra et al., 2001, Toyra et al., 2002). A similar project utilized multiple polarizations of airborne C-band radar data to map wetlands at 73% and 86% accuracies for June and October data, respectively. This same study also found that cross-polarized images were most sensitive to wetland features, followed by horizontal and then vertical polarizations (Baghdadi et al., 2001).

Radar systems hold great promise for the detection of wetland moisture and vegetation, however some significant concerns exist that limit the applicability of this technology. First, the sensitivity of C-band radar to surface moisture is severely compromised in the presence of woody vegetation and makes forested wetland mapping a difficult endeavor (Kasischke & Bourgeau-Chavez, 1997). Second, radar systems require low incidence angles to provide distinctive land cover responses, thus creating shadowed images in mountainous regions. Third, radar detection of patch sizes less than 200 m x 200 m is generally not practical, due to coarse spatial resolutions of space borne satellite instruments. Last, well calibrated, digital radar data has only been available since the early 1990s, which limits the applicability of this data for change detection studies (Kasischke et al., 1997).

Recent efforts have combined radar and multispectral (Landsat and SPOT) sensors to map wetlands. Overall classification accuracies were 66% - 80% when SPOT or Radarsat data was used individually and increased to 92% when these two data sources where used in unison (Toyra et al., 2001, Toyra et al., 2002). The nature of the data collected by these two sensors is fundamentally different, allowing each data source to compensate for the other’s weaknesses (Toyra et al., 2002). This is a developing field of study that holds great promise for the future of wetland monitoring, but is currently limited by cost, availability, and logistical complications in the handling of radar data.

Multispectral data from satellite mounted remote sensing instruments, such as Landsat, have been available for more than 3 decades and can be purchased from several commercial and government distributors. Space-borne multispectral instruments detect the intensity of reflected solar energy in visible, near infrared, and thermal bandwidths. These sensors were specifically designed to detect variations in spectral reflectance of earth objects for purposes of land cover mapping (Goward et al., 2001). More recent multispectral sensors, including SPOT and Landsat 7, have further modified the spectral bandwidths detected to increase the spectral separation of different vegetative systems (Jensen, 1996, p. 37 & 49, Goward et al., 2001).

The inherent compromise with conventional space-borne sensors is a loss of spatial resolution in exchange for increased spectral and radiometric resolutions. In many cases, the additional dynamic range of multispectral sensors enables accurate classification of broad landscape cover types (Masek et al., 2001). More rigorous tests of resolving power used moderate resolution sensors, with 15 to 60 m ground resolution, to map narrow and linear or small and isolated ecosystems. Both SPOT and Landsat 7 data have produced accurate maps for a variety of wetland types in Australia, Canada, and the United States (Sader et al., 1995; Narumalani et al., 1997; Kindscher et al., 1998; Harvey & Hill, 2001; Townsend & Walsh, 2001; Toyra et al., 2002). Data from the Indian IRS LISS-II multispectral sensor was used to map wet meadows in Grand Teton National Park, Wyoming. The overall accuracy of this project was 70% using an unsupervised classification algorithm and the visible and near infrared (NIR) data provided by the IRS sensor (Kindscher et al., 1998). The lack of middle infrared (MIR) detection on the IRS instrument inhibits the detection of surface and soil moisture, which are unique features of wetland areas (Mahlke, 1996; Johnston & Barson, 1993).

Other wetland mapping studies suggest that Landsat based classification procedures provide greater overall accuracies than other space-borne sensors (Civco, 1989; Hewitt, 1990; Bolstad & Lillesand, 1992b). A test of this theory on forested wetlands in Maine found that Landsat-TM based classifications provided wetland maps with 82% accuracy (Sader et al., 1995). A similar overall accuracy (80%) was achieved when mapping riparian ecosystems in Eastern Washington with Landsat-TM data (Hewitt, 1990). In Australia, a comparison of generalized wetland classifications using aerial photos, SPOT, and Landsat image data was conducted to determine the accuracy and applicability of each data source. This analysis determined that the sensitivity of Landsat band-2 (green), band-3 (red), band-4 (NIR), and band-5 (MIR) was sufficient to overcome the decreased spatial resolution when compared to the other two data sources. The overall classification accuracies for this study were 90.6% for aerial photos, 90.2% for Landsat, and 84.3% for SPOT (Harvey & Hill, 2001).

Wetlands are notoriously dynamic ecosystems that are subject to drastic seasonal changes in shape, size, and distribution resulting from variations in water quantity. Due to the frequent return interval of many satellite based sensors, multidate imagery can be collected for a given landscape to capture vegetation and hydrologic conditions during both wet and dry seasons. The resulting multidate set of imagery is used to provide a range of spectral response values for multiple dates. Alternatively, calculating spectral difference values for these dates provides another dimension of land cover data that characterizes variations in seasonal response. The incorporation of multiple season datasets improves separation of land cover classes and has improved overall accuracies in previous classification studies (Bolstad and Lillesand, 1992a; Miller et al., 1991; Shriever & Congalton, 1993; Wolter et al., 1995, Horn & Milne, 2002). Multidate images maximize detection of differences in phenological conditions and surface hydrology of wetland ecosystems (Horn & Milne, 2002). The additional time required for processing these larger data sets is offset by the increased explanatory power of resulting wetland maps (Townsend & Walsh, 2001).

The potential of a site to retain surface or soil moisture is largely determined by topographic and soil characteristics. Locating such specific site conditions using a combination of spectral data and ancillary environmental data has provided improved classification accuracies over classifications using only spectral data (Civco, 1989; Bolstad & Lillesand, 1992a; Bolstad & Lillesand, 1992b; Sader et al., 1995; Lawrence & Wright, 2001). Soils and/or elevation data provided ancillary information regarding the vegetative or hydrologic conditions on the landscape, thus improving classification accuracies (Sader et al., 1995).

Multispectral Image Classification Procedures

Unsupervised Techniques

The variation of spectral responses provided by different wetland types creates a challenge for image analysts. This challenge is frequently addressed through the use of unsupervised clustering algorithms. Unsupervised classification algorithms, such as

ISODATA and K-means, are statistical clustering algorithms that classify pixels based on a selected number of spectral clusters and are refined iteratively to reduce the spectral variation within each cluster. Land cover classes with highly variable spectral responses, such as wetlands, have been effectively classified using the ISODATA clustering algorithm (Kindscher et al., 1998). ISODATA can split or combine clusters to develop numerous “wetland” clusters that capture a range of spectral responses within the wetland class (Evans, 2004). ISODATA based wetland classifications using SPOT and Landsat data with ancillary data yielded overall accuracies of 84% to 86%, respectively (Henderson, et al., 1998; Harvey & Hill, 2001).

Several inherent problems with unsupervised classification algorithms limit the accuracy and efficiency of this classification procedure. Adaptive clustering programs (i.e., ISODATA) can create hundreds of clusters, just to identify wetland classes (Henderson et al., 1998). Assigning each cluster to a land cover class is a time consuming process that requires the analyst to decipher inter-cluster spectral confusion (Kershaw & Fuller, 1992). Unsupervised grouping algorithms are also sensitive to the range and variability of spectral values used to develop the initial clusters (Thomas et al., 2002).

Supervised Techniques

Supervised classification procedures are employed when a priori knowledge of specific land cover characteristics is available. This knowledge is then used to select training sites that sample the variability existing within each land cover class. Numerical grouping algorithms are used to statistically place each pixel into one of the predetermined land cover classes (Lillesand & Kiefer, 1994, p. 586). The accuracy of supervised classifications strongly depends on how well the designated training sites represent the variability within each land cover type. Additionally, selection of the proper classification technique depends on the nature of the expert knowledge resources available and the distinctiveness of each land cover type. Conventional parametric classification algorithms, such as maximum likelihood, assume that the data is normally distributed for each ground cover class (Ghedira et al., 2000). This statistical assumption is rarely met in highly variable ecosystems, and severely limits the applicability of this method for wetland classification.

Density slicing is a technique that requires the image analyst to determine the minimum and maximum reflectance intensities of a given cover type and each pixel is then classified based on these reference values. A test of this procedure used the strong interaction between MIR energy and surface moisture to map inundated wetlands (Johnston & Barson, 1993). Isolating the responses of wet meadows in this study was ineffective and correctly identified only 50% of these sites. The subjective nature of the slicing process, combined with dependency on one spectral bandwidth are significant shortcomings of this technique.

The use of neural networks for image classifications is an evolving procedure that has proven capable of mapping wetland landscapes with high accuracy (Ghedira et al., 2000). The benefits of neural networks include the ability to incorporate ancillary data sources, insensitivity to non-normally distributed data, and the utilization of relationship data between the various classification nodes. The applicability of neural networks is limited by inconsistencies of classifications and difficulties interpreting classification results.

Decision Tree Classifications

The combination of readily interpretable classification results and accurate class separations has contributed to the increasing popularity of rule-based and decision tree methods. Interpretation of classification rules enables the image analyst to identify inconsistencies in the data or validate ecological conditions existing on the landscape. The training data can then be modified to better represent the existing variability for each land cover class. In a classification of forested wetlands in Maine, a rule-based method produced an overall accuracy of 80%, an 8% improvement over unsupervised classifications (Sader et al., 1995).

Classification tree analysis (CTA) is a rule-based technique that has produced highly accurate classifications based on a variety of spectral and ancillary data sources (Lawrence et al., 2004). This non-parametric technique does not assume normal distributions in the available datasets and can effectively form dichotomous decision trees with fundamentally unique datasets of either continuous or categorical nature (Lawrence et al., 2004). The CTA algorithm works to reduce both intra-class and inter-class variability through recursive binary splitting of training data values (Venables & Ripley, 1997). The results of such binary splits are displayed as branching dichotomous trees that serve as readily interpretable illustrations of variability within the data sources.

These splits are then applied to the classification of an entire image through knowledge based classification rules (Lawrence & Wright, 2001).

Some recently acknowledged concerns with CTA have shown that more accurate trees might be produced, albeit at some sacrifice of classification interpretability. Since CTA trees are formed using a one-step-look-ahead, initial splits to reduce the greatest variability largely determine the effectiveness of the tree to distinguish more detailed separations further down the tree (Venables & Ripley, 1997; Lawrence et al., 2004). Problems with CTA develop when outliers are present in the data or when attempting to classify highly variable classes within a diverse landscape. Additionally, if the class of interest represents a small portion of the landscape and the training data is collected in similar proportions, the less dominant landcover types might be under-classified with CTA (Lawrence et al., 2004). Both of these issues are applicable to wetland classification within a large landscape and thus encouraged a closer examination of these issues as part of this project.

Recent advancements in computer processing speed and data storage capacities have facilitated the development of data mining programs designed for improving classification accuracies of decision trees. These techniques use iterative tree development to address some of the previously mentioned shortcomings inherent in the one-step-look-ahead algorithm utilized in CTA. Arguably, the most powerful data mining algorithm to emerge is stochastic gradient boosting (SGB), which combines the beneficial aspects of bagging and boosting techniques. Bagging and boosting techniques are individually subject to inaccurate classification rules due the methods used to select sample data in each iteration of tree development (for comprehensive discussion see Lawrence et al., 2004). SGB minimizes classification errors by using results of previous classifications to influence new tree development (boosting) and using randomly selected data to develop new trees (bagging) (Lawrence et al., 2004). Broad applicability of SGB for purposes of land cover classification has yet to be tested due to the recent development of this technique and limited software distribution. This technique has the potential to identify distinctive characteristics of small, yet highly diverse, ecosystems such as wetlands from spectral or topographic data.

Addressing Landscape Change

Hydrologically driven systems, such as wetlands and riparian zones, are often located in low-lying landscapes and influence the location of human structures and land use patterns (Wehrwein, 1942). The price for anthropogenic activities such as urban development and agricultural practices in low-lying areas has been the significant loss of wetland and riparian areas (Syphard & Garcia, 2001). At the time of European settlement the United States contained approximately 220 million acres of wetlands, by the mid-1980s only 103 million acres of wetland remained (Brown & Lant, 1999). The majority of these wetlands were drained or filled to create agricultural land, however since the 1980's over 80% of all wetland conversions have been for non-agricultural uses.

Programs to convert wetland areas into more economically productive uses, primarily agriculture, have dominated the past 200 years. Wetland conversion policies were abandoned with the creation of the Clean Water Act in the early 1970's (Brown &

Lant, 1999). Section 404 of the Clean Water Act requires completion of a permit process prior to alteration of any wetland area. The permitting process allows wetland alterations to continue, although this legislation drastically reduced the rate of wetland destruction. Less than 1% of permit applications are rejected by the Corps of Engineers and only 25% of state wetland management agencies are able to track wetland impact permits issued in their jurisdiction (Brown & Lant, 1999; La Peyre et al., 2000).

Monitoring Wetlands

Human activities such as agriculture, road building, and urbanization often lead to severe hydrological alterations that affect water supply and the drainage patterns of surface and subsurface moisture. In many cases such activities result in drastic changes to wetland size and spatial distribution (Ehrenfeld, 2000). As wetlands are increasingly surrounded by urban structures, the wetland functions are increasingly needed to counteract the effects of human induced conditions. Urban wetlands will often continue to provide effective water purification and storage functions until they are overwhelmed by pollution or excessive runoff (Ghermay et al., 2000; Mitsch & Gosselink, 2000; Wang et al., 2001). Effective monitoring of these changing ecosystems helps to determine the susceptibility of wetlands to human activities (Ghermay et al., 2000). An issue of equal importance to wetland health is determining the importance of wetland distribution across increasingly urbanized landscapes. (Semilitsch & Bodie, 1998; Tiner, 2003).

Change Detection Procedures

Aerial photographs were first utilized over 100 years ago and provide a rich historical record of imagery that can be used to identify land cover changes. By the 1960s CIR film was widely available and commonly used to photograph landscapes across the globe. Since that time CIR photographs have been used to monitor changes in the species composition or relative ecological health of wetlands (Ramsey & Laine, 1997). Identifying wetland sites on multiple years of photos requires a significant time investment. The accuracy of this approach is often detrimentally influenced by inconsistent interpretations that inhibit the separation of interpretation differences from ecological changes. The accuracy of change detection through photo interpretation is vulnerable to differences in the spatial resolution of images and spectral sensitivity of film used for each set of photography.

High temporal resolution, precise spectral bandwidths, and accurate georeference procedures are factors that contribute to the increasing use of satellite image data for change detection analysis (Jensen, 1996, pp. 257-262). Much of the subjectivity inherent in photo interpretation is eliminated through the use of quantified spectral response values from digital images. These data values may be mathematically corrected for atmospheric variability, radiometric differences between sensors, or variability in spectral sensitivity. Furthermore, automated procedures have been developed to create reproducible classifications and change detection algorithms. The aptitude of multispectral sensors for wetland classification has spawned the development of many change detection techniques using these data sources. A rich historical record of landscape conditions has been captured in the approximately 80,000 Landsat images collected over the 32-year history of this program (Goward et al., 2001).

Transformations and Standardizations for Image Data

Landsat data contains substantial noise from atmospheric interference with electromagnetic energy and changes in illumination geometry, with lesser effects from instrument noise. Performing absolute corrections for all of these factors is a daunting task that would require substantial amounts of additional data collected in unison with each sensor overpass. As a result, collection of comprehensive atmospheric correction data is not feasible for most images.

Landsat scenes are converted to at-sensor reflectance values that are calibrated to adjust for sun angle, earth-sun distance, solar irradiance, and instrument noise (Huang et al., 2001; Huang et al., 2002b). A standardized equation was developed by the United States Geological Survey (USGS) through the use of over 100 pseudo-invariant targets from 10 Landsat scenes. These pseudo-invariant targets were used to test the stability and accuracy for reflectance conversions across a variety of landscapes and seasons. This normalization technique is physically based, readily automated, does not introduce extraneous noise, and removes more than half of noise present in raw digital number data. The converted at-sensor reflectance values are normalized for the majority of radiometric and solar illumination differences. Reliable and accurate conversion factors have been developed for both ETM+ and TM sensors (Huang et al., 2001; Masek et al., 2001; Huang et al., 2002b; Chandler & Markham, 2003).

The Tasseled Cap (TC) transformation was originally developed for crop development studies (Kauth & Thomas, 1976) but has seen more widespread use as a predictable method for compressing scene characteristics into 3 orthogonal spectral bands (Huang et al., 2002a). Unlike principle components analysis (PCA), TC transformations produce reliable spectral bands that can be directly associated with physical scene characteristics (Crist & Cicone, 1984; Collins & Woodcock, 1994). TC-Component 1 is a measure of brightness, TC-Component 2 is a measure of greenness, and TC-Component 3 is a measure of wetness. The coefficients used to derive these components were collected through samples of water, vegetation, soil, and impervious surface extracted from 10 Landsat scenes (Crist & Cicone, 1984; Huang et al., 2002a). Through widespread application and detailed development of current TC procedures, this transformation has proven to be efficient and highly effective. The invariant nature of TC transformations allows direct comparisons of TC bands for multiple Landsat scenes (Crist & Cicone, 1984). The brightness, greenness, and wetness components generally account for over 97% of spectral variability present in a given scene and have been widely used for quantifying spectral changes (Lawrence & Wright, 2001; Huang et al., 2002a).

Change Detection Techniques for Image Processing

The variety of image data sources and classification techniques has led to the development of numerous change detection techniques, ranging from simple image comparisons to spectral vector measurements. Post classification comparison is a basic image comparison technique that provides readily interpretable results of changes between land cover classes between multiple classified images. This technique has been applied to wetland studies to determine the total area of wetland change and identify specific locations of such ecosystem changes (Choung & Ulliman, 1992; Ramsey & Laine, 1997; Munyati, 2000). The compound error of comparing individually classified images has resulted in unreliable change detection with notoriously low accuracy. Identification of the spectral endmembers for each class is a change detection procedure that isolates minimum and maximum spectral responses for various landcover types on individual images. These endmember values are then used to classify each image and the classified images are compared to identify changes in landcover (Oki et al., 2002). Classifications using endmember values can require intensive image interpretation and can result in high compound errors.

More mathematically dependent methods use the differencing of individual standardized spectral bands or transformations of spectral data. Although differencing non-transformed Landsat bands is an intuitive process, this method often provides spurious results due to influence of data noise and variable sensitivity of individual sensors (Nielsen et al., 1998). Simple differencing of more basic vegetation indices (e.g. Normalized Difference Vegetation Index) is less susceptible to noise interference, but is heavily dependent on the resolution of very few Landsat bands (Hayes & Sader, 2001; Stefanov et al., 2001).

Orthogonal transformations have proven to be an effective technique for detecting changes of diverse ecosystems using differencing techniques (Nielsen et al., 1998; Oetter et al., 2001; Parmenter et al., 2003). To increase the accuracy and applicability of change detection, techniques have been created to measure the magnitude of spectral changes observed. Defining spectral threshold values to separate true landscape changes from inherent spectral variation is particularly beneficial for studies of broadly diverse wetland ecosystems (Houhoulis & Michener, 2000).

Change vector analysis (CVA) (similar to pixel vector modulus and cross correlation analysis) has been used to detect the magnitude of changes in spectral space (Collins & Woodcock, 1994; Allen & Kupfer, 2000; Houhoulis & Michener, 2000; Civco et al., 2002). CVA measures the Euclidean distance of spectral change using the three vertices of TC-brightness, TC-greenness, and TC-wetness.

Combining TC brightness, greenness, and wetness data with CVA procedures can effectively detect definitive biophysical differences (Allen & Kupfer, 2000; Parmenter et al., 2003). CVA overcomes problems associated from within-class sensitivity to phenologic or hydrologic differences between image dates (Civco et al., 2002). The combination of using physically interpretable data transformations (i.e., TC) and quantifying determinations of change (i.e., CVA) reduces much of uncertainty of previous techniques while providing more ecologically interpretable results.

CHAPTER 3

MAPPING WETLANDS AND RIPARIAN AREAS USING ETM+ IMAGERY AND DECISION TREE-BASED MODELS

Introduction

Wetland and riparian zones provide a variety of ecological services that contribute to ecosystem functions at local, watershed, and regional scales (Semlitsch & Bodie, 1998; Tabacchi et al., 1998; Mitsch & Gosselink, 2000; Ehrenfeld, 2000). Wetlands can effectively minimize sediment loss, control runoff volume, purify surface water, and enhance aquifer recharge (Ehrenfeld, 2000; Tiner, 2003). The shape, size, and distribution of wetland and riparian zones are largely determined by geologic, topographic, and hydrologic conditions (Peck & Lovvorn, 2001; Toyra et al., 2002). If factored into land values, the ecological contributions of wetlands and riparian zones would dictate that these ecosystems are more economically and ecologically valuable than other land uses (Mitsch & Gosselink, 2000).

Riparian zones and wetlands are highly diverse ecosystems that exist in a variety of forms across different climatic zones and topographic positions. The definition of wetlands used for this project was adapted from the U.S. Environmental Protection Agency (EPA) definition that describes wetland as "[areas] that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions" (U.S. EPA, 2003. p.1). Riparian areas often have size, shape, and ecological characteristics similar to those of wetlands. The Natural Resource

Conservation Service (NRCS) defines riparian areas as “ecosystems [that] occupy the transitional areas between the terrestrial and aquatic ecosystems” (Montgomery, 1996. p.2). Several fundamental ecological differences exist between wetlands and riparian zones; however, the ecological importance and human interaction between these ecosystems are very similar. These common characteristics enable synonymous discussion for purposes of landscape resource mapping. The term wetland, therefore, will be used to describe both wetland and riparian areas unless specified.

Accurate wetland mapping is an important tool to understand wetland function and monitor wetland response to natural and anthropogenic actions. Wetlands are often damaged or overwhelmed by increased surface flows in urban or suburban areas with high densities of impervious surfaces (i.e. buildings and paved surfaces) (Ehrenfeld, 2000; Mitsch & Gosselink, 2000; Wang et al., 2001). Wetland mapping is used to evaluate land use decisions and monitor the effectiveness of mitigation efforts (Muller et al., 1993). Wetlands also serve as recreation sites and critical habitat for a large percentage of avian, terrestrial, and aquatic species (Gress, 1993; Lewis et al., 2003). Landscape scale mapping of these scarce habitats facilitates understanding of floral and faunal population dynamics (Semilitsch & Bodie, 1998).

The susceptibility of wetlands to human activities and human dependence on the ecological contributions of wetlands illustrate the importance of mapping wetland resources. Establishing the role of wetlands in increasingly urban landscapes requires an understanding of wetland density and distribution (Tiner 2003). Is a broad distribution of wetlands across a region more ecologically important than a small number of large wetlands (Semilitsch & Bodie, 1998)? How does the methane and carbon dioxide released from decomposition in wetlands factor into atmospheric conditions on local and global scales (Prigent et al., 2001)? Questions of this nature have spawned the development of more efficient and accurate methods for mapping wetlands and riparian ecosystems.

The three primary inventory techniques currently used to map wetland ecosystems are on-site evaluations, aerial photo interpretation, and digital image processing. Wetland mapping projects utilizing on-site measurements of environmental conditions provide highly detailed data sets including lists of floral and faunal species, water chemistry, and soil characterization information (Tiner, 1993). The added expense of personnel, equipment, and time rarely justifies the more detailed level of data collected acquired through on-site evaluations when mapping wetlands at a landscape or watershed scale (Harvey & Hill, 2001).

Aerial photographs provide synoptic views of the study area, allowing "big picture" understanding of hydrology and vegetation patterns (Harvey & Hill, 2001). Additionally, archives of aerial photographs are available for many regions of the United States, providing a valuable historical record of past landscape conditions. Many concerns are still associated with the utilization of aerial photos for wetland mapping, despite improvements in the quality of photo data. A primary concern with landscape-scale wetland maps derived from aerial photos is the extensive time lapse between acquisition of the imagery and production of the final wetland map (Ramsey & Laine, 1996). Repeatability is another concern with human derived photo interpretation products. As concerns over global wetland resources continue to escalate, so does the need for automated and reproducible wetland maps (Finlayson & van der Valk, 1995). Without quantitatively derived wetland inventory maps, change detection methods lack the power to differentiate actual wetland changes from inconsistent human interpretation.

Multispectral sensors provide data with increased spectral and radiometric resolutions and decreased spatial resolutions compared to conventional aerial photography. Systeme Pour l'observation de la Terre (SPOT) and Landsat are two sensors that have been used to produce accurate maps of a variety of wetland types in Australia, Canada, and the United States (Sader et al., 1995; Narumalani et al., 1997; Kindscher et al., 1998; Harvey & Hill, 2001; Townsend & Walsh, 2001; Toyra et al., 2002). Data from the Indian IRS LISS-II multispectral sensor was used to map wetland meadows in Grand Teton National Park, Wyoming. The lack of middle infrared (MIR) detection on the IRS instrument inhibited the detection of vegetation and soil moisture, which are distinctive features of wetland areas (Mahlke, 1996; Johnston & Barson, 1993).

Several wetland mapping studies suggest that Landsat-based classifications provide greater overall accuracies than other space-borne sensors (Civco, 1989; Hewitt, 1990; Bolstad & Lillesand, 1992a). A test of this theory found that Landsat-TM based classifications provided wetland maps with 82% accuracy for forested wetlands in Maine (Sader et al., 1995). A similar overall accuracy (80%) was achieved when mapping riparian zones in xeric ecosystems of Eastern Washington with Landsat-TM data (Hewitt, 1990). Wetlands classifications using aerial photos, SPOT, and Landsat image data were compared to determine the accuracy and applicability of each data source (Harvey & Hill, 2001). This analysis determined that the sensitivity of Landsat band-2 (green), band-3 (red), band-4 (NIR), and band-5 (MIR) provided a more accurate classification than SPOT, and overall accuracy comparable to that of aerial photos. These results demonstrate that accuracy is not sacrificed with automated wetland identification methods or coarser spatial data.

The combination of readily interpretable classification results and accurate class separations has contributed to the increasing popularity of rule-based and decision tree methods (Bolstad & Lillesand, 1992b; Sader et al., 1995; Lawrence & Wright, 2001). Interpretation of classification rules enables the image analyst to identify inconsistencies in the data and validate true ecological variation existing on the landscape. The rule-based method produced an overall accuracy of 80% in wetland specific classifications of forested wetlands in Maine, an 8% improvement over the statistical clustering functions of unsupervised classifications (Sader et al., 1995).

Classification tree analysis (CTA) is a rule-based technique that has produced highly accurate classifications based on a variety of spectral and ancillary data sources (Lawrence et al., 2004). Similar to neural networks, CTA is a non-parametric technique that does not assume normal distributions in the available datasets. CTA forms dichotomous decision trees using fundamentally unique datasets of continuous or categorical data (Lawrence et al., 2004). The CTA algorithm works to reduce both intra-class and inter-class variability through recursive binary splitting of training data values (Venables & Ripley, 1997). The results of such binary splits are displayed as branching dichotomous trees that serve as readily interpretable illustrations of variability within the data. Splits are applied to the classification of an image through knowledge-based classification rules (Lawrence & Wright, 2001). Combinations of multispectral and ancillary data have been used in decision trees to produce highly accurate land cover classifications. Decision trees are easily interpreted and can provide valuable insight into ecological conditions.

Some recently discovered concerns with CTA acknowledge that more accurate trees can be produced, albeit at some sacrifice of classification interpretability. Since CTA trees are formed using a one-step-look-ahead, initial splits to reduce the greatest variability largely determine the effectiveness of the tree to distinguish more detailed separations further down the tree (Venables & Ripley, 1997; Lawrence et al., 2004). Less effective splitting occurs when outliers are present in the data or when attempting to classify landcover containing high within-class variability. Additionally, if the class of interest represents a small portion of the landscape and the training data is collected in similar proportions, the less dominant landcover types can be under-classified with CTA (Lawrence et al., 2004). Both of these issues are applicable to wetland classification within a large landscape and thus encouraged a closer examination of these issues as part of this analysis.

Bagging and boosting techniques use iterative tree development to address some of the previously mentioned shortcomings inherent in the one-step at a time CTA algorithm. Stochastic gradient boosting (SGB) has the potential to provide improved classification accuracies over CTA by combining the beneficial aspects of bagging and boosting techniques (for comprehensive discussion see Lawrence et al., 2004). SGB can reduce classification errors by incorporating the classification errors from previous trees into the development of subsequent trees (boosting). SGB also uses bagging to increase separation of distinguishing land cover characteristics by using randomly selected data to create new classification trees. The most difficult classification problems are emphasized in iterations of tree development and the resulting collection of trees (a grove) vote on the correct classification using a plurality rule (Lawrence et al., 2004). Broad applicability of SGB for purposes of land cover classification has yet to be tested due to the recent development of this technique and limited software distribution. This technique has the potential to identify distinctive characteristics of small and highly diverse ecosystems, such as wetlands, from spectral and topographic data.

The purpose of this project was to develop an accurate and easily reproducible procedure for mapping wetlands across natural and human dominated landscapes. Ancillary environmental data was incorporated into spectrally based classifications to improve the detection of isolated or ecologically unique wetlands (Sader et al., 1995). The applicability and accuracy of two decision tree algorithms, CTA and SGB, were compared to determine the efficacy of both techniques for wetlands mapping.

Methods

Study Area

The 135,570 ha study site was the lower basin of the Gallatin River watershed, located in the Gallatin Valley of Southwestern Montana (Figure 3). The project area boundary generally follows the boundary of the Gallatin Local Water Quality District.

The foothills and mountainous terrain of the Bridger, Gallatin, and Madison ranges surround the plains of the Gallatin Valley. The Gallatin and East Gallatin rivers have formed the majority of landscape features on the valley floor (Willard, 1935 p.226). A semiarid climate and fertile soils support the prevalence of irrigated and dryland agriculture in the valley. Primary crops of the region are alfalfa, barley, wheat, and hay for livestock. Population growth over the past 50 years has resulted in localized conversions of agricultural land to residential and commercial development (Kendy, 2001).

Precipitation averages range from 40 cm in the valley (1,250 m) to over 100 cm in the higher elevations (3,350 m) (Custer et al., 1996; Western Regional Climate Center, 2002). Snow and rain from March through June provide the majority of yearly precipitation. Surface and subsurface flow regimes have been altered through the widespread construction of irrigation canals. Canals reduce in-stream flows and distribute water throughout the interior and periphery of the valley. The perennial streams contain much herbaceous and woody vegetation, including chokecherry *(Prunus virginiana)*, willow (*Salix* spp.), cottonwood (*Populus trichocarpa, P. augustifolia*), aspen (*Populus tremula)*, and several other native and non-native species. Vegetation strips along the ephemeral natural streams and artificial canals are narrower with less vegetation density and species diversity than perennial systems.

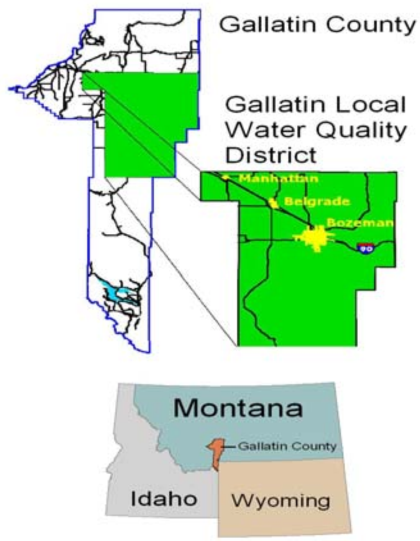

Figure 3. Location map for the Gallatin Local Water Quality District.

Image Pre-processing

Landsat ETM+ images from May 22, 2001 and September 11, 2001 were the spectral data sources used in the classification procedure. The ETM+ sensor has 30 m spatial resolution and records 7 bands of spectral data in the visible, infrared, and thermal portions of the electromagnetic spectrum. Multi-date imagery was used to capture the extent of seasonal variation between wet (May) and dry (September) conditions. The May image was geo-registered to the September scene (registration error less than 6.0 m). Both scenes were corrected to at-sensor reflectance using the United States Geological Survey (USGS) equation (Huang et al., 2001) and ETM+ gain/bias header file data. Tasseled Cap (TC) transformations were performed using the at-sensor reflectance values and USGS TC coefficients (Huang et al., 2002a). Ancillary data used in this project included a 30 m USGS digital elevation model (DEM), slope map (calculated from the 30m DEM), and digital hydric soils data from the 1985 NRCS soil survey for Gallatin County. Training sites were developed for wetland, riparian, and other landcover using recently digitized wetland and riparian data acquired from 2001 color infrared (CIR) aerial photography of the study area.

Classification Procedures

Seven land cover types were identified in the primary classification procedure. The cover types included were open water, forest, urban, agriculture, grass/shrub, riparian, and wetland. The first five cover classes were collapsed into the "non-wet" class that was used for the remainder of the analysis. The "wetland" class was primarily composed of marshes, wet meadows, and slope wetlands. The "riparian" class included riparian wetlands, ephemeral drainages, and woody riparian vegetation (i.e., cottonwood and willow).

CTA decision trees were created using a combination of S-Plus statistical software and ERDAS Imagine image processing software (Insightful, 2001; ERDAS, 2001). Overfitting of CTA decision trees was avoided through cross validation of the training data (Lawrence & Wright, 2001). Cross validation develops classification trees for nine random data subsets and validated against a tenth. Plots of this validation are used to determine the number of terminal tree nodes that provides the lowest average deviance. SGB decision tree groves were created using TreeNet™ software (Salford

Systems, 2001). The TreeNet™ grove file was then used to predict an ASCII text version of the image file that was later converted to image pixels.

Accuracy assessment

The accuracy assessment points were randomly generated in a stratified random format to define approximately 100 points for the wetland and riparian classes and 150 points for the more predominate non-wetland/non-riparian class. On-site evaluations, 1:24,000 CIR photographs, and a 5 m digital image derived from the 2001 CIR photos were used as reference data for classification accuracy assessments. Landcover class assignments were determined using a modification the 50% vegetation rule (Tiner, 1993). In this project at least 20% of an area (i.e., a pixel) had to contain hydrophytic vegetation in order to be classified as wetland or riparian.

A spatial analysis of classification sensitivity was performed to determine the accuracy of the two classification techniques on different landscapes. The first subset was located in a primarily rural setting with abundant agricultural land, and the second subset included the urban/sub-urban regions surrounding the town of Bozeman. These two subsets were located in physically and ecologically contrasting valley locations and were selected based on the range of spectral variability present in each landscape. Accuracy assessment of the sensitivity analysis also used a stratified random design to identify reference points for each of the three land cover classes. A focused accuracy assessment of these areas was used to determine which of the two techniques had greater overall accuracy and what spectral or environmental factors contributed to the classification differences.

Results

Overall classification accuracy was 73.1% for CTA and 86.0% with SGB, a 12.9% improvement over CTA results (Table 3). Producer accuracies for wetland and riparian classes in the SGB classification (93.2% and 88.3%, respectively) were markedly higher than CTA (58.3% and 57.5% respectively). The producer's accuracy is a measurement of omission error and is calculated by determining the probability that a reference pixel for each class is correctly classified (Jensen, 1996, p. 250). The majority of the error in the CTA classification resulted from wetland and riparian areas that were misclassified as non-wet. Conversely, the majority of error in the SGB classification resulted from non-wet areas mistakenly classified as wetland.

The user's accuracy is used to measure commission errors and represents the mapping accuracy for each class (Jensen, 1996, p. 250). The user's accuracy of SGB (94.5%) was 28.1% higher than CTA (66.4%) for the non-wet class. The tendency of CTA to underestimate wetland and riparian areas was the primary cause of the large difference. The user's accuracy values for the wetland and riparian classes were similar for the two classifications. The primary source of error in the wetland class for both classifications was the inclusion of non-wet sites into the wetland class. Commission errors in the riparian class were more evenly distributed, with approximately equal numbers of non-wet and wetland sites erroneously placed in this class.

Table 3. Error matrices using classified and reference data pixels for CTA and SGB classifications.

CTA Classification

Classified Data	Reference Data			
	Non-wet	Wetland	Riparian	Users Accuracy
Non-wet	142	38	34	66.4%
Wetland	10	60	6	79.0%
Riparian	1	5	54	90.0%
Producers Accuracy	92.8%	58.3%	57.5%	
Overall Accuracy	73.1%		Kappa =	0.569

SGB Classification

Classified Data	Reference Data			
	Non-wet	Wetland	Riparian	Users Accuracy
Non-wet	122	3	4	94.5%
Wetland	23	96	7	76.2%
Riparian	8	4	83	87.4%
Producers Accuracy	79.7%	93.2%	88.3%	
Overall Accuracy	86.0%		Kappa =	0.788

A notably smaller percentage of classification errors resulted from confusion between riparian and wetland pixels. The presence of woody vegetation in riparian zones appeared to minimize confusion, despite the hydrologic similarities of these sites. The over inclusion of wetlands in the non-wet class was primarily attributed to the prevalence of flood irrigated fields with elevation, soils, and spectral values similar to those of wetlands. Differences in the vegetation patterns between these two land covers were visible in the CIR photographs, although this variability was not discernable in the coarser resolution Landsat images.

The classified images created through CTA and SGB contain substantially different proportions of wetland and riparian areas. CTA classified 6.8% of the pixels as wetland and 2.3% as riparian. The SGB classification placed 13.1% of the pixels in the wetland class and 5.3% in the riparian. These percentages, however, cannot be used to estimate the total area occupied by wetlands and riparian areas, since each pixel classified as wetland or riparian can be comprised of as little as 20% wetland or riparian vegetation. The buffers surrounding most wetland and riparian zones were therefore notably larger than aerial photo based inventories. The purpose of this project was to determine the accuracy of classification procedures designed to distinguish wetland and riparian areas from other land cover types. It was advantageous, therefore, to locate all areas potentially containing wetlands or riparian areas rather than to neglect marginal or smaller hydrologic ecosystems.

Results of the sensitivity analysis for the rural subset had an overall accuracy of 90.0% for SGB and 66.0% for CTA (Table 4). The SGB method was more apt to include marginal wetlands and moist ecotones in the wetland class. Inclusion of marginal and degraded wetlands is advantageous when performing comprehensive wetland inventories. SGB more successfully classified altered or impaired wetlands, such as cropped wetland sites that were partially converted to agriculture or heavily grazed.

Both classification techniques produced lower accuracies in the urban dominated landscape subset. While the increased sensitivity of SGB to wet conditions was beneficial for rural landscapes, this served as a source of error in the urbanized areas. Classification errors of SGB in the urban subset partially resulted from irrigated forests (e.g., city parks and cemeteries) erroneously classified as riparian areas. Similarly, heavily irrigated suburban yards and pastures were mistakenly classified as wetlands.

Table 4. Summary accuracy data for classification sensitivity analysis of urban and rural data subsets.

Rural Subset

SGB	Users Accuracy	Producers Accuracy
Non-wet	100.0%	89.3%
Wetland	86.0%	86.0%
Riparian	84.0%	95.5%
Overall Accuracy	90.0%	
Kappa	0.850	

CTA	Users Accuracy	Producers Accuracy
Non-wet	57.8%	100.0%
Wetland	81.8%	36.0%
Riparian	80.7%	56.8%
Overall Accuracy	66.0%	
Kappa	0.476	

Urban Subset

SGB	Users Accuracy	Producers Accuracy
Non-wet	96.0%	53.3%
Wetland	36.0%	69.2%
Riparian	56.0%	82.4%
Overall Accuracy	62.7%	
Kappa	0.440	

CTA	Users Accuracy	Producers Accuracy
Non-wet	78.5%	93.3%
Wetland	27.6%	30.8%
Riparian	71.4%	29.4%
Overall Accuracy	68.0%	
Kappa	0.381	

SGB developed 80 total decision trees, which was later reduced to 29 trees to avoid overfitting. Overfitting of the single CTA decision tree was avoided using cross validation to reduce the number of terminal nodes from 56 to 39. Despite the distinctive statistical approaches of CTA and SGB, both algorithms relied on several common spectral and ancillary datasets. SGB utilized data from 19 of the 23 available datasets while CTA used 18 of the 23 datasets.

Elevation (DEM), hydric soils, NIR-Band 4 (September), TC-Brightness (September), TC-Wetness (September), and thermal-Band 6 (September) were used in the primary splits of the CTA tree and were among the top 10 most important variables listed for SGB. Topographic position and moisture content provided the greatest reductions in deviance on the CTA output and were the most distinguishable characteristics between the riparian or wetland sites and the rest of the landscape. Spectral data from the September image was more frequently used by both classification algorithms to separate landcover types than the May image. Moisture and vegetation vigor was sharply contrasting in the September image between moderately to extremely moist wetlands and the senescent vegetation of most other land cover. Such contrasts were not visible in the May image, where the majority of the landscape was irrigated by spring rains and snowmelt.

Discussion

The results of this study supported the hypothesis that applying SGB techniques to decision trees can improve classification accuracy. Using a combination of Landsat imagery and ancillary environmental data with a SGB classification algorithm proved to be a highly effective technique for distinguishing a variety of wetland conditions from the surrounding landscape. Wetland and riparian areas were classified with minimal omission errors and an aptitude for detecting isolated and marginal wetland areas.

Mapping this landscape with 86% accuracy provides a valuable resource inventory map of hydrologically dependent ecosystems.

The accuracy of decision tree-based classifications were potentially dependent on the inherent variability within a landscape, as demonstrated by the sensitivity analysis. The modest performance of CTA and SGB on the urban landscape subset was not necessarily indicative of limitations with either technique, rather a result of inadequate training for complicated urbanized wetland and riparian areas. Furthermore, the 30 m spatial resolution of ETM+ limited the detection of small, yet ecologically healthy, wetland and riparian systems that were present in the highly fragmented framework of urban and suburban areas. Higher spatial resolution data and a concerted effort to sample the variability of urban wetland and riparian sites would likely improve identification of these areas in spectrally diverse landscapes.

Both classification techniques classified some wet and/or heavily vegetated upland areas as wetlands, although the inclusion of marginal and severely impaired wetlands was intentional. Detection of wetland and riparian sites was a source of error in both classifications, however the overall and class accuracies were lower with CTA. Recent investigations of CTA classifications indicate that high within class variability might positively influence the performance of SGB classifications compared to CTA (Lawrence et al., 2004). This theory would apply to the diversity of wetland and riparian systems in the Gallatin Valley and might explain the markedly improved producer's accuracies of these classes with SGB. The SGB tree development method concentrates on correcting classification errors on the most similar data and separating more distinctive classes on subsequent iterations of tree development. In this manner, SGB has proven more adept at separating spectrally similar classes (Lawrence et al., 2004).

The ability of SGB to detect isolated and drier-end wetlands also served as a source of error for irrigated pastures and cropland. CTA was less susceptible to the inclusion of wetlands in the non-wetland class, but more likely to exclude drier wetland and riparian areas. Evidence of such predictable differences might allow analysts to select a classification technique based on the level of hydrologic sensitivity desired in the classification. It is possible that classification of broad and spectrally distinctive landcover types might be more accurately performed with CTA while detection of under-represented or highly variable land cover will require the increased sensitivity of SGB. Choosing between classification methods (such as CTA or SGB) or data sources (moderate spatial resolution or high spatial resolution) could enable stakeholders to select the level of classification detail.

Wetlands and riparian areas are highly diverse ecosystems that exhibit significant variability of physical and chemical properties. The results of this analysis provide further evidence that highly accurate detection of such diverse landcover is feasible using automated classification procedures. Repeat temporal coverage, unbiased data collection, and effective sampling of landscape variability are advantages provided by remotely sensed data that enable systematic inventories of these ecosystems (Lakshmi et al., 1997). Combining automated classifications with recently acquired remote sensing data can quickly and accurately determine the location of small, isolated, and highly variable ecosystems, thus enabling the systematic monitoring of these important ecological resources.

CHAPTER 4

CHANGE DETECTION OF WETLAND AND RIPARIAN ECOSYSTEMS USING CHANGE VECTOR ANALYSIS

Introduction

Anthropogenic activities such as urban development and agricultural management have caused a significant loss of wetland and riparian areas (Syphard & Garcia, 2001). Historically, the majority of lost wetlands were drained or filled to create agricultural land; however, over 80% of all wetland conversions since 1980 have been non-agricultural (Brown & Lant, 1999). The 1972 Clean Water Act drastically decreased the rate of wetland loss, although wetland and riparian alterations still continue (Brown & Lant, 1999).

Activities such as agriculture, road building, and urbanization often cause indirect damage to wetland and riparian systems. The hydrological alterations associated with these activities affect water supply and drainage patterns of surface and subsurface moisture, reducing the size and distribution of ecosystems dependent on these water sources (Ehrenfeld, 2000; Winter et al., 2001). Wetlands and riparian zones often continue to provide effective water purification and storage functions until they are overwhelmed by pollution or excessive runoff (Ghermay et al., 2000; Mitsch & Gosselink, 2000; Wang et al., 2001). Monitoring these changing ecosystems helps to determine the tolerance of wetlands and riparian ecosystems to human activities (Ghermay et al., 2000).

Aerial photograph interpretation has traditionally been used to monitor changes in wetland and riparian resources. Identifying wetland sites on multiple years of photos can require a significant time investment (Ramsey & Laine, 1997). The spatial resolution of aerial photos can enable more precise change detection, although replicating these interpretations is difficult and can be inconsistent (Coppin et al., 2004). The accuracy of change detection through photo interpretation is vulnerable to human error and variability between photographic images.

High temporal resolution, precise spectral bandwidths, repetitive flight paths, and accurate georeferencing procedures are factors that contribute to the increasing use of satellite image data for change detection analysis (Jensen, 1996, pp. 257-262; Coppin et al., 2004). Landsat-based classification procedures can provide equal or greater overall accuracies than other comparable space-borne sensors (Civco, 1989; Hewitt, 1990; Bolstad & Lillesand, 1992b). Landsat data have produced accurate maps for a variety of wetlands in Australia, Canada, and the United States (Sader et al., 1995; Narumalani et al., 1996; Kindscher et al., 1998; Harvey & Hill, 2001; Townsend & Walsh, 2001; Toyra et al., 2002). The broad dynamic range of multispectral sensors enables accurate classification of narrow riparian systems and isolated wetland patches, despite moderate spatial resolutions (Hosking, et al., 2001; Masek et al., 2001).

The variety of image data sources and classification techniques now used has led to the development of numerous change detection techniques ranging from simple image comparisons to spectral vector measurements (Coppin et al., 2004). Post classification comparison has been applied to wetland studies to determine the total area of wetland change and identify specific locations of such changes (Choung & Ulliman, 1992; Ramsey & Laine, 1997; Munyati, 2000). The compound error of comparing individual classified images, however, has resulted in unreliable change detection with notoriously low accuracy (Coppin et al., 2004).

Simple differencing of spectral bands is a common technique for quantifying spectral change. This method can provide spurious results due to influence of data noise, inconsistencies between individual sensors, and limitations of detecting change with a single spectral band (Nielsen et al., 1998; Coppin et al., 2004). Simple differencing of vegetation indices (e.g., Normalized Difference Vegetation Index) is less susceptible to noise interference (Hayes & Sader, 2001). Index differencing is more spectrally dynamic than simple differencing, although these techniques are also heavily dependent on the resolution of only two spectral bands (Stefanov et al., 2001; Dymond et al., 2002).

Change vector analysis (CVA) (similar to pixel vector modulus and cross correlation analysis) is a change detection technique that can determine the magnitude of changes in multidimensional spectral space (Collins & Woodcock, 1994; Allen & Kupfer, 2000; Houhoulis & Michener, 2000; Civco et al., 2002). CVA was first used to identify changes in forest vegetation through measures of change magnitude (Malila, 1980; Coppin et al., 2004). The CVA method identifies a change magnitude threshold that is used to separate actual land cover changes from within-class variability. Defining spectral threshold values to separate true landscape changes from inherent spectral variation is particularly beneficial for studies of broadly diverse ecosystems, such as wetlands and riparian zones (Houhoulis & Michener, 2000).

Since only highly changed pixels are reclassified with CVA, problems associated with within-class sensitivity to phenologic or hydrologic differences between image dates are reduced (Civco et al., 2002).

Orthogonal spectral data transformations compress spectral data into a few spectral components that can accurately detect diverse ecosystems (Collins & Woodcock, 1994; Nielsen et al., 1998; Oetter et al., 2001; Dymond et al., 2002; Parmenter et al., 2003). Principle components analysis (PCA) and Tasseled Cap (TC) are two commonly applied orthogonal data transformations. PCA maximizes the spectral variability detected by decreasing the redundancy of information contained in multiple spectral bands (Armenakis et al., 2003). PCA components are based on statistical relationships that are difficult to interpret and are variable between different landscapes (Collins & Woodcock, 1994).

TC components are based on the physical characteristics present in an image and are therefore ecologically interpretable and comparable between image dates (Collins & Woodcock, 1994). TC transformations rotate Landsat spectral data onto brightness, greenness, and wetness axes that correspond to the physical characteristics of vegetation (Parmenter et al., 2003). TC-Component 1 is a measure of image brightness derived from the responses of all but the thermal (Band 6) Landsat bands (Armenakis et al., 2003). TC-Component 2 is a measure of greenness calculated through differencing near infrared with visible bands. TC-Component 3 is a measure of wetness determined by comparing visible and near infrared responses with shortwave infrared response. The invariant nature of TC transformations allows direct comparisons of TC bands for multiple Landsat scenes (Crist & Cicone, 1984). The brightness, greenness, and wetness components generally account for over 97% of spectral variability present in a given scene and have been widely used for quantifying spectral changes (Collins & Woodcock, 1994; Allen & Kupfer, 2000; Lawrence & Wright, 2001; Huang et al., 2002; Parmenter et al., 2004). TC transformations have effectively isolated wet sites on a landscape (Dymond et al., 2002) and improved distinctions between moist and senescent vegetation (Crist et al., 1986). The CVA technique was developed using Landsat-based TC brightness, greenness, and wetness components to describe specific biophysical differences (Allen & Kupfer, 2000; Coppin et al., 2004).

We used CVA with Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data to identify and locate areas of wetland and riparian change between 1988 and 2001 in the Gallatin Valley of southwestern Montana. CVA was performed for wetlands, riparian areas, and non-wet areas using the first three TC components derived from Landsat images. Wetland/riparian landcover inventory maps were developed for the years 1988 and 2001, and a map of changed wetland/riparian sites was also produced.

Methods

Study Area

The 135,570 ha study site was the lower basin of the Gallatin River watershed, located in the Gallatin Valley of Southwestern Montana (Figure 3). The project area boundary generally follows the boundary of the Gallatin Local Water Quality District.

The Gallatin and East Gallatin rivers have shaped the majority of landscape formations on the valley floor (Willard, 1935, p.226). The population of Gallatin County increased from 50,000 in 1985 to nearly 64,000 in 1999 (Census & Economic Information Center, 2004). Agricultural land across the state of Montana is increasingly being converted into residential and commercial development as a result of population growth (Kendy, 2001; Census & Economic Information Center, 2004). In contrast to wetland losses from agriculture, wetland and riparian increases could result from the increasing construction of private ponds across the Gallatin Valley.

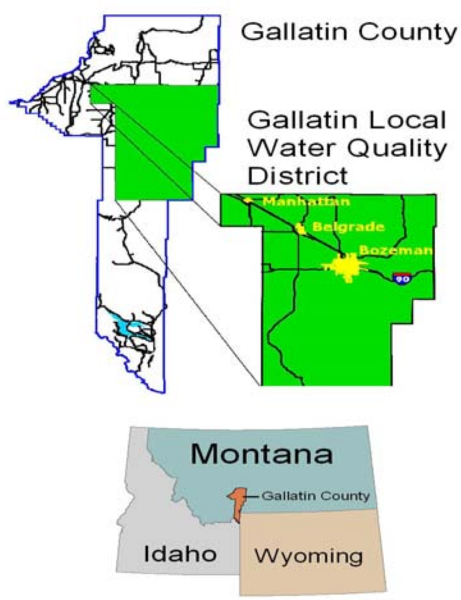

Figure 4. Location map for the Gallatin Local Water Quality District.

CVA Change Detection Overview

A conceptual model of the change detection process is used to illustrate the image processing steps required to perform the CVA change detection analysis (Figure 5). The 2001 ETM+ images and ancillary data were used with a stochastic gradient boosting (SGB) decision tree classification algorithm (Lawrence et al., 2004) to develop a 2001 image classification of wetland/riparian and non-wet landcover types. The CVA equation was then used to calculate the magnitude of spectral change among the three TC components between September 1988 and September 2001. A change threshold value was established using areas of known wetland/riparian changes as a guide. Potentially changed locations (i.e., high change threshold values) were reclassified with the SGB algorithm utilizing 1988 spectral and ancillary data. The potentially changed pixels that were classified differently in 1988 than 2001 were then merged with the unchanged pixels from the 2001 classification. Each procedural step is described in more detail below.

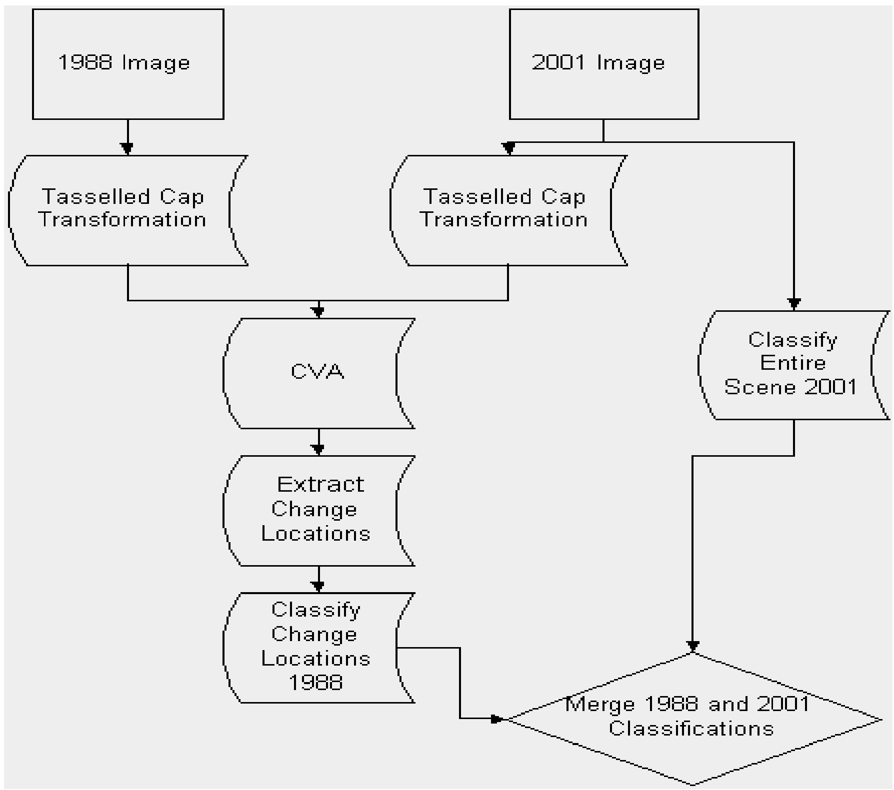

Figure 5. Conceptual model of CVA change detection procedure.

Image Pre-Processing

Landsat images acquired on May 22, 2001 and September 11, 2001 were used to create the wetland/riparian classification for 2001. A Landsat TM image from September 15, 1988 was selected as the historical image and used for change detection against the September 2001 image. The 2001 imagery dates were selected to sample the seasonal extent of wetland/riparian sites in the wet season and to maximize the contrast of wetland/riparian locations from other land cover types during the dry season (Munyati, 2000; Coppin et al., 2004). Color infrared (CIR) photos acquired on September 9, 2001 were also available as a reference data source for the 2001 landcover classes. Selection of the Landsat image from 1988 was selected based on similarities in hydrologic and temperature regimes between 1988 and 2001 as well as the availability of a cloud-free, anniversary date image. CIR photos acquired in July 1985 were used as the reference data for the 1988 classification. Geometric errors were reduced through geo-registering the 1988 Landsat image to the 2001 Landsat image (registration error = 8.2 m).

When comparing two image scenes, steps must be taken to reduce exogenous errors such as atmospheric differences, sensor calibrations, and illumination angle differences that might cause inaccurate detection of spectral change (Collins & Woodcock, 1994). Differences between Landsat TM and ETM+ sensors were standardized through established radiometric correction procedures prior to change detection analysis (Ramsey & Laine, 1997; Masek et al., 2001). Both Landsat scenes were corrected to at-sensor reflectance using the United States Geologic Survey (USGS) equation. Sensor corrections were made using gain/bias header file data for ETM+ and the USGS Multi-Resolution Land Characteristics (MRLC) gain/bias values for TM (Huang et al., 2001; Huang et al., 2002b; Chander & Markham, 2003). Conversion to reflectance is a method of radiometric calibration that incorporates solar illumination distance, solar illumination angles, and the differences in sensor characteristics (i.e. gain and bias) for each spectral band. Atmospheric variability is difficult to correct without comprehensive data acquired at the time of image acquisition. Reasonable assumptions regarding similarities in atmospheric conditions were made based on visual inspection of the image characteristics and analysis of the image histograms.

Tasseled Cap (TC) transformations were performed using the at-sensor reflectance values and USGS TC coefficients (Huang et al., 2002a). Ancillary data used in this project included a 30m USGS digital elevation model (DEM), slope gradient map (calculated from 30m DEM), and digital hydric soils data from the 1985 Natural Resource Conservation Service (NRCS) soil survey for Gallatin County.

Change Detection Procedure

The CVA equation is a variation of the Pythagorean Theorem that calculates the Euclidean distance of spectral change among the three vertices of brightness, greenness, and wetness (Equation 1, as applied to TC) (Parmenter et al., 2003).

Equation 1. CVA equation used to determine spectral change magnitude using the first three Tasseled Cap components.

$$Cm = \sqrt{(Brightness_1 - Brightness_2)^2 + (Greenness_1 - Greenness_2)^2 + (Wetness_1 - Wetness_2)^2}$$

Cm = Change magnitude (Euclidean TC component distance)
$*_{1,2}$ Refer to respective TC component value for separate imagery dates

The CVA change detection technique required consideration of some ecological and spectral conditions in regard to threshold selection and overall change sensitivity. A lower change threshold value would allow inclusion of slightly changed wetlands into the change analyses, while a high threshold value would only include the locations of significantly changed areas. We opted for a lower change threshold value to increase the sensitivity to minor wetland/riparian ecosystem alterations. The change magnitude values ranged from 0 – 0.944 and the change threshold was established at 0.130. Pixels with change values less than 0.130 were assumed to have remained unchanged between the image dates and were excluded from the change analysis.

The potentially changed pixels were used to create a mask that extracted the 1988 spectral data for only these locations. Training locations for wetland/riparian and non-wet classes were identified using 1985 color infrared (CIR) photographs. The data sources for this classification were 1988 Landsat spectral data combined with topographic and hydric soils ancillary data. Only 3.4% of the study area had to be reclassified for 1988 using the CVA threshold technique, thus reducing compound errors created by independent classifications.

Accuracy Assessment

CIR photography from September 2001 and on-site inventories were used as reference data for the 2001 classification. CIR photographs from 1985 were the reference data sources for the 1988 classification. Land cover determinations were based on vegetation and hydrology characteristics and used a variation of the 50% rule (Tiner 1999). In this study, 20% was the confidence level above which wetlands and riparian areas could reliably be detected, based on comparisons of classified images and reference data.

The change detection error matrix for this analysis was comprised of two change classes and two non-change classes (Table 5). Error matrices were also compiled for the 1988 and 2001 SBG classifications as part of the change detection accuracy procedure.

Table 5. Designations for land cover change classes

Class in 1988	**Class in 2001**	**Change Class Designation**	**Ecological Interpretation**
Non-wet	Non-wet	No change – non-wet	Unchanged non-wet/riparian
Non-wet	Wetland/Riparian	Wet/Rip Increase	Wetland/riparian increase
Wetland/Riparian	Non-wet	Wet/Rip Decrease	Wetland/riparian decrease
Wetland/Riparian	Wetland/Riparian	No change – wet	Unchanged wet/riparian

Results

Overall accuracy of the change detection analysis using the SGB classification was 75.8% (Table 6). The high user (97.2%) and producer (88.3%) accuracies for the unchanged wetland/riparian (wet/rip) class showed that SGB was able to effectively distinguish stable wetland/riparian sites on both image dates. The unchanged non-wetland/riparian class had markedly lower user (50.0%) and producer (76.0%) accuracies. The low user accuracy for the no-change, non-wet class provides evidence that the CVA threshold value was too high, thus excluding a variety of wetland/riparian changes from the analysis (Table 6). Compound errors in the wetland/riparian class for the 1988 and 2001 classifications also contributed to change detection misclassifications.

Table 6. Error matrix for 1988 –2001 change detection analysis.

Reference Data

	No-change (non-wet)	Wet/Rip Increase	Wet/Rip Decrease	No-change (wet)	Users Accuracy
Classified Data					
No-change (non-wet)	38	14	24	0	50.0%
Wet/Rip Increase	4	55	6	9	74.3%
Wet/Rip Decrease	8	3	39	5	70.9%
No-change (wet)	0	3	0	106	97.2%
Producers Accuracy	76.0%	73.3%	56.5%	88.3%	
Overall Accuracy	75.8%				

The 2001 SGB classified image had 86.0% overall accuracy and the overall accuracy of the 1988 classification was 81.0% (Table 7). The decrease in the 1988 classification accuracy was partially the result of intensive sampling of underrepresented land cover types (wetland/riparian) during the accuracy assessment. Both of these accuracy values showed that the SGB classification algorithm distinguished the majority of wetland/riparian sites from other land cover. In both classifications, the majority of error resulted from non-wet locations incorrectly classified as wetlands. This over-classification of wetlands is advantageous for inventories designed to locate all possible wetlands, however such misclassifications likely caused some errors in the change detection analysis.

A total of 331,038 pixels (22.0% of the study area) had change magnitude values greater than the 0.139 change threshold and were considered potentially changed sites

(Table 8). Only 50,651 pixels (3.4% of the study area) of these potential change pixels were classified differently in 1988 than in 2001 and thus represented estimated ecological change. The landscape area classified as wetland/riparian was somewhat inflated since each pixel can be comprised of as little as 20% wetland or riparian vegetation. As a result, the size of most wetlands and riparian zones were notably larger in these classifications than previous ecosystem inventories of this region.

Table 7. Error matrices of 1988 and 2001 wetland/riparian classifications.

1988 Classification — Overall Accuracy 81.0%

Classified Data	Reference Data: Non-wet	Wetland	Riparian	Users Accuracy
Non-wet	119	6	8	89.5%
Wetland	19	71	8	98.0%
Riparian	8	8	53	76.8%
Producers Accuracy	81.5%	83.5%	76.8%	

2001 Classification — Overall Accuracy 86.0%

Classified Data	Reference Data: Non-wet	Wetland	Riparian	Users Accuracy
Non-wet	122	3	4	94.5%
Wetland	23	96	7	76.2%
Riparian	8	4	83	87.4%
Producers Accuracy	79.7%	93.2%	88.3%	

Table 8. Histogram values of change classes and quantity of pixels included in study area

Change Classes	# of pixels	% of study area	hectares (ha)
No-change (non-wet)	1194843	79.3%	107536
Wet/Rip Increase	13395	0.9%	1206
Wet/Rip Decrease	37256	2.5%	3353
No-change (wet)	261935	17.4%	23574
Total # of pixels =	1507429		135669
potential change pixels =	331038	22.0%	29793

The results of this change detection analysis (Table 8) showed that wetlands and riparian areas have generally decreased within the Gallatin Valley. Wetland/riparian change locations occurred in the interior of existing wetland/riparian clusters and around the peripheral areas of unchanged wet sites (Figure 6). Many relatively large, contiguous change clusters were visible for both positive and negative change classes. CVA accurately detected shifts of large areas, such as sub-irrigated wet meadows converted to residential development.

The majority of land cover changes occurred in the northern and the southeastern sections of the study area. The East Gallatin and West Gallatin rivers converge in the northern end of the valley and produce a matrix of surface and sub-irrigated wetland and riparian ecosystems. Decreasing wetland/riparian area accounted for the majority of landcover change in this region, although the direct cause was not apparent. The southeastern portion of the valley contained the rapidly growing urban and suburban communities that surround the city of Bozeman. This section of the Gallatin

Valley was also dominated by decreasing wetland/riparian area, although some smaller wetland/riparian areas have developed in this fragmented landscape.

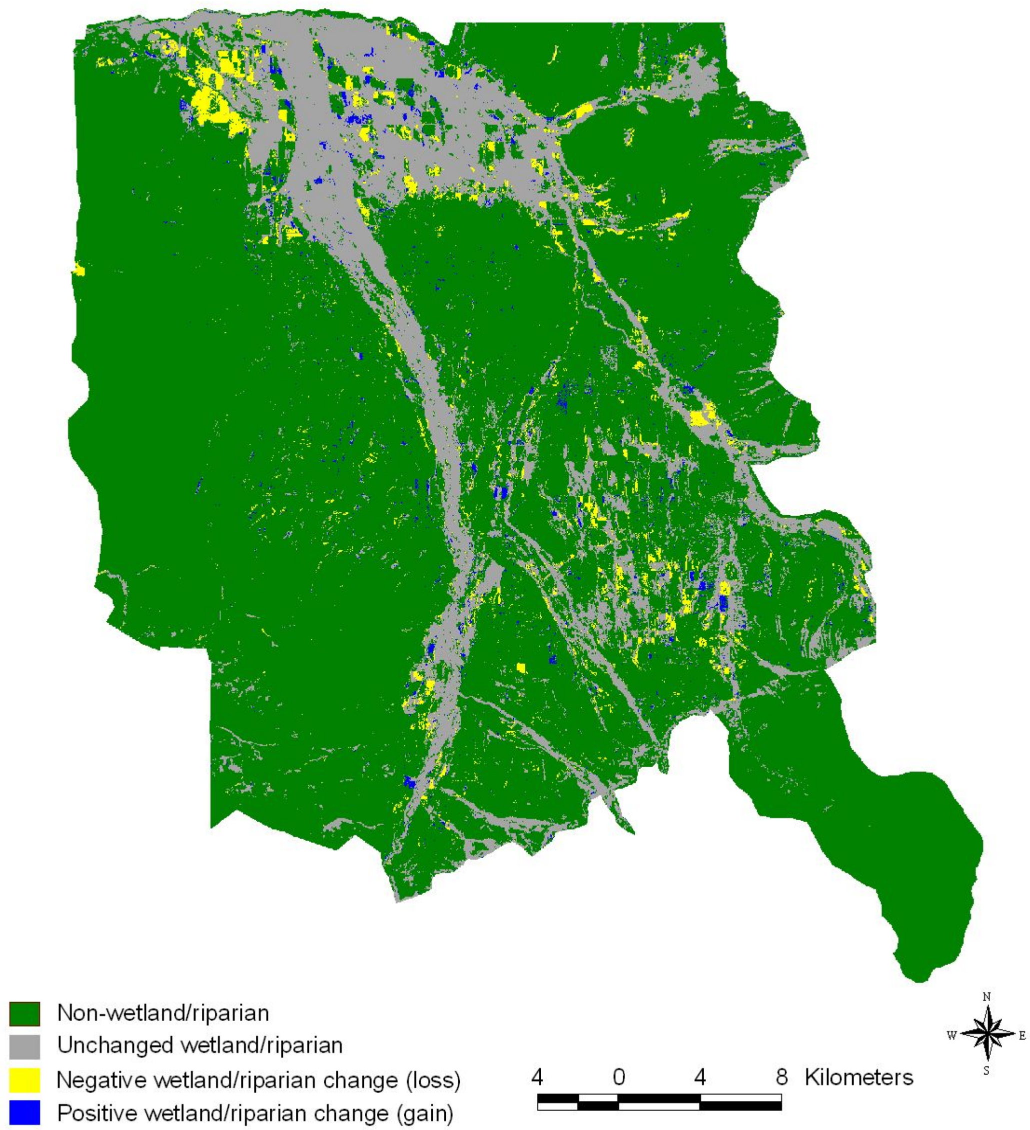

Figure 6. Map of wetland/riparian change sites (1988-2001) in the Gallatin Valley, as identified by CVA

Discussion

Overall change detection accuracy of nearly 76% indicated that CVA was an effective method for identifying changing ecosystems across a landscape. This accuracy was comparable to a forest monitoring project that used CVA to perform change detection with 72% accuracy (Allen & Kupfer, 2000) and much improved over 58.8% accurate wetland change detection using image differencing (Choung & Ulliman, 1992). The dynamic nature of wetland and riparian ecosystems requires an equally dynamic change detection procedure. These ecosystems can exhibit a variety of vegetative or hydrologic changes (Whigham, 1999; Mitsch & Gosselink, 2000) that might not be detected when using one or two spectral bands. The ability of CVA to measure change using several spectral components is advantageous when mapping rapidly changing and highly diverse landscapes (Coppin et al., 2004).

The pattern of landcover change across the Gallatin Valley identified locations of changing wetland/riparian vegetation and/or altered surface and sub-surface hydrology. The 0.9% increase in wetland/riparian area might represent a portion of the natural ecological fluctuation in these systems. The 2.5% decrease could result from anthropogenic alteration of hydrologic or vegetative systems in addition to natural ecological succession. Large contiguous change areas highlighted the urban areas of Bozeman and Manhattan, where residential development was the primary source of wetland and riparian alteration. Small isolated sites of both positive and negative change were broadly distributed across the valley and were likely representative of natural ecological fluctuation. Large areas of wetland/riparian gain also had broad distribution across the valley. The largest wetland/riparian increases were primarily located within established riparian corridors. Vegetation response to flood scouring and deposition within the West and East Gallatin River corridors accounted for some of these increases.

The individual 1988 and 2001 image classification accuracies (86.0% and 81.0%, respectively) indicated that the SGB algorithm effectively distinguished wetland/riparian sites from other land cover types. Analysis of the change detection error matrix also showed a lack of confusion between the unchanged classes. These results supported the theory that reducing the number of reclassified pixels using CVA thresholding helps to maintain the integrity of classification accuracies between multiple images. This combination of CVA and SGB proved to be an accurate and efficient method for locating historical wetland and riparian communities.

Thresholding can also be a source of change detection error that must be considered against the benefits this technique provides. The use of thresholding has been debated in regards to statistical analysis, although many studies have opted for the higher accuracies thresholding can provide (Allen & Kupfer, 2000; Coppin et al., 2004). It was difficult in this complex landscape to establish a threshold value that was sensitive to the ecological change of interest without including extraneous land use changes, such as differences in agricultural practices. The thresholding sensitivity might be more readily identified if a specific type of landcover change (e.g., conifer mortality) was the subject of analysis.

The results of this study showed that under-estimating the threshold value might be advantageous when detecting changes in highly diverse ecosystems. A lower threshold would identify more locations as potential change sites and include these locations in the change detection analysis. The overall accuracy should not be jeopardized by a lower threshold value since most of these potential change sites (locations above the change threshold) were classified the same in 1988 and 2001. A lower change threshold would likely increase overall change detection accuracy by identifying more change locations to be incorporated into the 1988 classification.

The two change classes and the non-change wetland/riparian class were heavily sampled in the stratification of the accuracy assessment. This sampling method thoroughly tested the accuracy of the areas associated with wetland and riparian areas. Overall accuracies would be substantially higher if a proportionate number of the more prevalent unchanged non-wet pixels had been sampled, instead of intensively sampling the changed locations. This study, however, was conducted specifically to identify changes regarding riparian and wetland ecosystems and thus the accuracy assessment was a reflection of that focus.

Capturing the nature of rapidly changing ecosystems such as wetlands and riparian areas is a difficult proposition. These ecosystems occupy a wide variety of habitats and display and equally expansive range of vegetation and hydrology. Using the CVA technique, future research should help establish procedures for empirical determination of change threshold values. Using CVA with TC spectral information and established change thresholds holds potential for effective monitoring of specific biophysical characteristics within a landscape.

CHAPTER 5

CONCLUSIONS

The wetland and riparian classification analysis evaluated two decision tree algorithms for purposes of identifying small and diverse landscape features. SGB proved to be an effective method for classifying wetlands and riparian zones in the Gallatin Valley. The overall accuracy of this classification met the 85% accuracy goal that was established during project development. Classification errors were low and primarily resulted from over-classification of wetland and riparian areas. We determined that this form of error was acceptable since it is more efficient to dismiss incorrect wetland/riparian sites than to omit marginal locations.

The SGB classification procedure was intuitive and image pre-processing can be promptly performed using automated procedures. The development of tree groves and image classification were straightforward, although some processing time was required to convert image files to ASCII text files and back into classified image format. TreeNet™ is a commercially available software package that offers many options for stochastic gradient boosting classifications. The price of this software, however, is likely to be cost prohibitive for most applications. More moderately priced boosting and bagging software packages (e. g., C5) exist that are more compatible with image processing software (Homer et al., 2004).

Both decision tree classifications performed well in rural environments and were able to distinguish wetlands and riparian areas from other vegetation. Heavily irrigated agricultural areas were difficult to distinguish from wet meadows and were only discernable on the higher resolution aerial photos by studying vegetation patterns. Detecting wetlands in urban and suburban areas was problematic and will require further research. The use of more specific urban wetland training sites and/or higher spatial resolution data would likely remedy many inaccuracies in this landscape. This is an important research topic that should be pursued to help establish a more thorough understanding of the role wetlands play in urban environments (Ehrenfeld, 2000; Wang et al., 2001).

Establishing an effective wetland and riparian mapping procedure is an important first step to the ultimate goal of monitoring ecosystem changes. Monitoring techniques that measure change magnitudes allowed us to select the desired level of ecological change to be included in the analysis. Using TC components with CVA selected a specified level of spectral changes that would reduce confusion between image variability and physical changes. CVA detected riparian and wetland change with reasonable accuracy and was an effective way of maintaining classification accuracy for the historical (1988) wetland/riparian classification.

The CVA procedure was intuitive and can be performed with rapid turn around time. Establishing an accurate change threshold value was a complex issue that would require a thorough understanding of known ecological changes in wetland and riparian communities. Once the threshold values are established and tested, these thresholds will help guide other change detection studies. Reducing the threshold value in this project would have included more wetland/riparian change sites and would likely reduce the omission errors in this class. The accuracy of the 1988 classification would not have been jeopardized since CVA selected only a small percentage of the image to be re-classified using the 1988 data. I suggest using a lower threshold value in future studies to allow more of the image to be considered in change analysis.

The results of this project showed that the SGB classification algorithm and moderate spatial resolution spectral imagery, combined with ancillary environmental data, can produce accurate and reproducible wetland and riparian classification. This methodology can be used in conjunction with the CVA change detection method to accurately locate wetland and riparian ecosystems on historic Landsat images. The low cost and high availability of Landsat imagery were primary reasons this data was used in this analysis. Combining SGB and CVA techniques with higher spatial and spectral resolution image data will foster the development of highly accurate and detailed resource inventories.

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