VEGETATION DYNAMICS IN YELLOWSTONE'S

NORTHERN RANGE: 1985-1999

by

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A thesis submitted in partial fulfillment
of the requirements for the degree

of

Master of Science

in

Land Resources and Environmental Sciences

MONTANA STATE UNIVERSITY
Bozeman, Montana

November 2005

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of a thesis submitted by

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21 November 2005

ACKNOWLEDGEMENTS

I would like to thank my major advisor, Rick Lawrence, for his unwavering support, guidance, and especially patience during this longer than expected project. I've learned so much about remote sensing and the research world and I'm very excited to continue my education at MSU with a Ph.D. project. Much gratitude goes to my committee, Lisa Graumlich and Bret Olson, for their comments and willingness to help. Also, thanks to Andy Hansen for his initial comments on the project proposal. I'm especially grateful to the staff at the Yellowstone Center for Resources not only for their assistance, but for putting up with me trying to work and go to school at the same time for so many years. Thanks to Tom Olliff for helping to get funding for the project, Roy Renkin for providing so much vegetation expertise and guidance, and Ann Rodman for being supportive even when school got in the way of work. I am indebted to the Upper Midwest Aerospace Consortium and NASA for the funding they provided. And finally, I want to thank my family and friends for their encouragement, support, and a meal here and there to help me get through the all-nighters to achieve this accomplishment.

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ABSTRACT

The Northern Range (NR) of Yellowstone National Park (YNP) is currently a critical area of analysis in the Greater Yellowstone Ecosystem (GYE). The complex dynamic ecosystems in the NR provide outstanding field laboratories for long-term scientific investigations to evaluate management techniques. Grassland and shrubland ecosystems serve as important habitat for a wide variety of animal species in the NR and empirical knowledge of these systems enables managers to better understand the ecological complexities and make informed management decisions. Accurate vegetation maps are useful tools for these land managers, as is the ability to detect changes in vegetation over time.

An inexpensive and easily reproducible method for mapping rangelands over the NR was developed utilizing Landsat Enhanced Thematic Mapper Plus (ETM+) satellite imagery. A classification hierarchy of non-forest vegetation was produced with 5 levels, ranging from very broad vegetation types such as woodland, shrubland, or herbaceous vegetation (Level 1) to specific vegetation types such as aspen (*Populus tremuloides*), tufted hairgrass/sedge (*Deschampsia cespitosa*/*Carex spp.*), or big sagebrush/Idaho fescue (*Artemisia tridentata*/*Festuca idahoensis*) (Level 5). A 1999 base map of non-forest vegetation in the NR was created using classification tree analysis (CTA) combined with boosting. Overall accuracies of the final maps ranged from 72.30% for Level 5 to 83.65% for Level 1, providing evidence that this method can be successful for mapping non-forest vegetation in the NR.

A 1985 Landsat Thematic Mapper (TM) satellite image was chosen for performing a change detection analysis from 1985 to 1999. Tasseled Cap space was utilized to choose a threshold of change in a change vector analysis (CVA). Areas of no change in the 1999 image were used to train areas of potential change on the 1985 image to produce a final map of the NR for 1985. Overall accuracies of the final maps ranged from 72.60% for Level 5 to 88.73% for Level 1. Managers are able to analyze this change information and modify their management techniques as needed. With the 1999 base map the CVA method enables managers to detect vegetation change in the NR on a regular basis.

CHAPTER 1

INTRODUCTION

Grassland and shrubland ecosystems (referred to herein as rangelands) serve as important habitat for a wide variety of animal species in the Rocky Mountain west (Despain, 1990; Kershaw et al., 1998). Grass and shrub species provide food for wintering and migrating ungulates, particularly in lower elevations where there is often less snow, while woodland species such as aspen (*Populus tremuloides*), cottonwood (*Populus spp.*), and willow (*Salix spp.*) are “candy” for ungulates as evidenced by their strong preference for this woody browse (Renkin, 2002). These woodland species are found along edges and riparian corridors within rangelands and are consistently browsed by ungulate species in Yellowstone National Park (YNP), leading at least one observer to the conclusion that ungulates have overpopulated the area (Despain, 1990).

Non-forested plant communities are present throughout YNP but are more prevalent in the lower elevations of the northern range (NR) (Despain, 1990). The NR (which extends north of the YNP boundary) is currently a critical area of analysis in the Greater Yellowstone Ecosystem (GYE). The National Academy of Sciences has suggested that much more study of the area needs to be done: “Given the complexities involved in managing Yellowstone’s dynamic ecosystems, there is a continuing need for rigorous research and public education.” (National Research Council, 2002, pp. 10) And: “There is insufficient scientific knowledge available to enable us to predict the consequences of different management approaches. Thus long-term scientific investigations and experiments are needed to provide solid scientific evidence for evaluating management options." (National Research Council, 2002, pp. 11)

Many years were invested in creating a vegetation cover type and habitat type map for YNP (Despain, 1990), however, the data do not extend beyond the YNP political boundary. Ungulates, on the other hand, do not recognize political boundaries and thus move beyond them at will. Scientists need to extend their studies across boundaries to understand and predict the effects of different management approaches. An attempt to combine several agencies' vegetation data for the Cumulative Effects Model (CEM) (Dixon, 1997) provided a vegetation map based on ecosystems rather than political boundaries. Political boundaries that reflect inconsistencies in data development unfortunately are quite visible in the data because the agencies did not work with one another to produce these data. Additionally, my personal experiences searching for vegetation data that cross political boundaries in the GYE have met with mixed success.

A proven technique for mapping large areas over political boundaries is remote sensing. Remote sensing uses satellite or airborne imagery to collect information over great expanses of land. One study of primarily avian diversity, for instance, produced a cover map for the GYE using Landsat TM imagery (Lawrence and Wright, 2001), and another study classified plant communities in the intermountain west using SPOT 3 HRV and Landsat TM imagery (Clark et al., 2001).

The first Landsat satellite, carrying the Multi Spectral Scanner (MSS), was launched in 1972. Subsequent satellites including those launched in 1984 (carrying Thematic Mapper (TM)) and 1999 (carrying Enhanced Thematic Mapper Plus (ETM+)) are still in orbit. This provides over 30 years of data that can be utilized for change detection and landscape studies. Landsat scenes cover a swath of 185 km (YNP is in the center of one of these scenes) and collect data every eight days (TM and ETM+ are in relatively opposite orbits and have a repeat coverage of 16 days). A final advantage of Landsat data is that it is relatively inexpensive compared with many of the other datasets available today.

The development of an inexpensive, accurate, reproducible, and automated procedure for mapping non-forest vegetation across political boundaries and at a scale useful for specific studies would open the doors for many more important ecological studies in the NR. Scientists and managers would be able to monitor the landscape, observe spatial and temporal changes, and make scientifically sound management decisions appropriate for species of concern.

The purpose of this research was to: (1) provide YNP with an accurate base map of rangeland vegetation in the NR, examined in Chapter 3 and (2) conduct a change detection analysis of rangeland vegetation in the NR, ultimately providing YNP with a method to update the base map as needed, examined in Chapter 4. Chapter 2 reviews current literature and Chapter 5 summarizes this thesis.

CHAPTER 2

LITERATURE REVIEW

Ecological Role and Importance of Rangelands

Rangelands are "open regions over which animals may roam and feed" (Merriam-Webster, Inc., 2005), often composed of grassland and shrubland and existing in areas of relatively low elevation (Despain, 1990; Kershaw et al., 1998). Rangelands are widespread throughout the western United States and are utilized by wild ungulates along with domesticated stock. The health of rangelands often will determine the health of herds and thus the livelihood of western ranchers and the success of hunting season.

Fire and climate can affect ecosystems and the animals (or people) that rely on the landscape. The importance of rangelands has become more apparent in recent times as fires rage throughout the west during the summers and continuing drought increases fire potential (National Oceanic and Atmospheric Administration, 2005; Yellowstone National Park, 2005). Rangelands are essential for the survival of ungulates (ecologically) and provide the means of survival for many people (economically).

Rangelands are managed for domestic livestock and for wildlife. Scientists and managers in YNP are tasked with protecting wildlife (Yellowstone Park Act, 1872), and livestock are not permitted within the boundaries of YNP (aside from horses on some backcountry trails). The NR includes areas within YNP where only wild ungulates range, but also extends beyond the northern border of YNP where domestic livestock utilize rangelands alongside wild ungulates. YNP provides the perfect laboratory to study wild ungulates in their natural environment. Not only do the animals move in and out of YNP at will, they must endure whatever nature throws at them: harsh weather, harsh landscapes, natural predators, and human predators outside of the park. Knowledge of rangeland vegetation in the NR is imperative for research and management of wild ungulates in the area.

Vegetation Mapping

Land managers must make decisions about resources, ecological potential, and trends that affect every aspect of an ecosystem, such as plant ecology, small mammals, birds, and large herbivores (and in turn large predators) within areas they manage (Jensen et al., 2001). Informed decisions by these land managers are facilitated by understanding current and potential vegetation (Stalmans et al., 2002). Potential vegetation represents what a vegetation community will become if it progresses through successional stages without interruption. Accurate vegetation maps help land managers understand the vegetation in their management areas.

Several vegetation mapping procedures are commonly used with varying results. Three approaches are on-site analysis, aerial photo interpretation, and satellite remote imaging. The utility of each of these methods depends on the size of the study area (spatial extent), the minimum mapping unit (spatial resolution), available time, and available funding. A wide range of data exists that have pixel resolutions from less than 1-m to over 1-km. The resolution of the source data determines whether a classification will be general or specific.

On-Site Analysis

Mapping projects that utilize on-site analysis can create exceptionally detailed data sets. Plant and animal species, canopy structure, biomass, soil characteristics, hydrology, and landscape characteristics can be measured while on-site. Analog photographs can be taken along with GPS locations. This will enhance the researchers' ability to recall and revisit sites at a later date.

On-site analyses are cost- and time-prohibitive unless the study has unlimited time and funding. Mapping and cataloging an entire study area would require additional personnel and equipment, along with a large increase in the amount of time to perform the study. The resulting highly detailed data set does not always justify the means of obtaining it (Harvey and Hill, 2001).

Research that covers areas over political boundaries might have difficulties in gaining access to portions of the study area. Private landholders may not be amenable to researchers accessing their land, or it might simply be unsafe to spend time in the backcountry (i.e., several areas within YNP are closed to human access due to grizzly bear activity during spring).

A random sample of the study area can be taken utilizing on-site analysis instead of collecting data for the entire study area. The information collected can be used to characterize the rest of the area. This method has its merits in that it is less expensive and time-consuming, but it might not provide an accurate picture of the study area since the majority of the resulting data are estimated rather than collected.

Aerial Photo Interpretation

Aerial photographs were used to map the cover and habitat types of YNP (Despain, 1990). This method involves the interpretation of stereo pairs of photographs by a trained photo interpreter. Different species of trees are often easily identifiable on aerial photographs by their shape, texture and color. Entire landscapes can be mapped with high accuracies in this manner more rapidly and less costly than on-site analysis of the same area (Stone, 1998).

Archives of aerial photographs exist for much of the United States and in particular the GYE. The availability of these photos allows researchers to view the historic landscape and monitor changes over time. Hardcopy photos also can be scanned into digital format and utilized within Geographic Information Systems (GIS).

Difficulties with aerial photo interpretation arise when trying to delineate gradual changes within types. How can the interpreter differentiate between bluebunch wheatgrass (*Agropyron spicatum*) and bearded wheatgrass (*A. caninum*) for instance, unless at the site? Spectral differences between species can aid the interpreter in making these distinctions (Ramsey and Laine, 1997; Clark et al., 2001), especially when using color infrared (CIR) photos, however, the line between species is not always distinct.

Finally, the detail of the resulting delineated maps relies heavily on the scale of the aerial photograph. At small scales only general classifications can be made (Anderson et al., 1976). Small-scale photographs are more readily available (more of these photos exist in archive), less expensive, and less time-consuming to collect. Large-scale photographs on the other hand can provide very detailed information over a landscape, but are more expensive and time-consuming to collect.

Satellite Remote Imaging

A less expensive and less time consuming method for mapping vegetation is the use of satellite remote sensing. This method incorporates automated algorithms, allows for more frequent updates (Wynne et al., 2000), and efficiently determines vegetation cover of large areas (Innes and Koch, 1998; Clarke et al., 2001; Jensen et al., 2001; Vogelmann et al., 2001).

Satellite imagery has another advantage over aerial photographs in that the data collected are multi-spectral. Landsat in particular collects data from the visible portion of the electromagnetic spectrum along with several wavelengths from the infrared portion of the spectrum (near infrared, middle infrared, and thermal infrared). A panchromatic band is also collected by the ETM+ sensor. Most aerial photographs, on the other hand, are collected with fewer bands: CIR and true color utilize three bands, while black and white or panchromatic utilizes only 1. The combination of different bands in various ratios or transformations allows a researcher to narrow in on specific features on the landscape. The Normalized Difference Vegetation Index (NDVI), for instance, utilizes the red and near infrared bands to predict plant canopy or biomass (Rouse et al., 1973; Labus et al., 2002).

Landsat TM and ETM+ data have a spatial resolution of 28.5 m (typically resampled or simplified to 30 m on a side or 900 m^2), which can provide relatively detailed information of landscape-scale vegetation, whereas the minimum mapping unit of the current vegetation data at YNP is 2.02 ha or 20,234.28 m^2. Landsat data also have the distinct advantage of temporal continuity, including a fully archived data set dating from 1984 and a Congressional and NASA commitment to continue into the foreseeable future (NASA, 2004; USGS, 2005). This allows the development of comparable cover data over multi-decade periods. Previous Landsat data at somewhat coarser resolutions extend the archive back to the early 1970s, providing opportunities for change detection studies covering over a quarter of a century. The multitude of spatial and temporal data provided by the Landsat project continue to aid scientists in understanding the Earth system (Goward et al., 2001).

The addition of GIS data to remotely sensed data can increase the accuracy and detail of vegetation maps, in many cases allowing distinctions between communities or species (Clark et al., 2001; Everitt et al., 2001; Jensen et al., 2001; Lawrence and Wright, 2001; Saveraid et al., 2001; Stalmans et al., 2002). Ancillary data such as bedrock or surficial geology, soils, elevation, slope, or aspect can improve the accuracy of maps. Utilizing ancillary information can help distinguish between items with spectral similarities such as many rangeland and riparian vegetation types (Houhoulis and Michener, 2000).

Forested areas versus non-forested areas are easily delineated from satellite images. One study (Bauer et al., 1994) utilized Landsat TM data in northeastern Minnesota to classify forest community types and perform change detection. Overall classification accuracies of up to 75% were observed and changes were identified at greater than 90% accuracy. A study utilizing TM data to map age and development characteristics of lodgepole pine (*Pinus contorta*) in YNP resulted in correlations between understory factors such as live vegetation or litter and TM spectral bands with an overall accuracy of 84% (Jakubauskas, 1996; Jakubauskas and Price, 1997). GIS data were also incorporated in the study to allow the process to focus on areas of similar slope, elevation, and surficial geology.

Canopy structure, leaf area index (LAI), vegetation biomass, and landscape characteristics are common items mapped with remote sensing methods. A study conducted in YNP found that TM bands from the visible and middle infrared portion of the spectrum worked well for predicting height, basal area, biomass, and LAI of lodgepole pine, resulting in R^2 values of 0.80, 0.63, 0.58, and 0.62 respectively (Jakubauskas and Price, 1997). Another study in southwestern Idaho discovered fragmentation in semiarid shrubsteppe ecosystems using Landsat TM data for habitat research on breeding passerine birds (Knick and Rotenberry, 1995).

Non-forested areas, however, are more difficult to delineate because of similar spectral signatures found in grassland and shrubland vegetation. The distinction between different community types is not always obvious. Grass species might have stronger spectral signatures that could interfere with the spectral signatures of shrub species.

Many studies, however, have successfully mapped shrublands and grasslands. Using GIS and Landsat TM data, three forest types and six meadow types were classified in the GYE to model habitats and examine plant, butterfly, and bird species biodiversity, although classification accuracies were not reported (Debinski et al., 1999). Six native and two non-native intermountain plant communities in southwestern Idaho were successfully classified utilizing Landsat TM and SPOT 3 HRV data (Clark et al., 2001).

Overall accuracies ranged from 54.4% to 70.5% depending on data acquisition dates (data acquired in early August had higher accuracy than data acquired in early June because separability of spectral signatures was poor during peak growth). Landsat TM data along with climatic and topographic variables were used to map four grassland, five shrubland, and six woodland types in Little Missouri National Grasslands, North Dakota (Jensen et al., 2001). Accuracies were as high as 77% in grasslands, 100% in shrublands and 100% in woodlands. Montane meadows were classified using SPOT satellite imagery in an unsupervised classification to predict bird species occurrences in the GYE (Saveraid et al., 2001). Statistical analyses were conducted to determine correlations between bird species and habitat types. A 1993 Landsat TM image was utilized to map the distribution of grasslands in the Songiemvelo Game Reserve, Mpumalanga in South Africa (Maselli and Rembold, 2001). Overall accuracies ranged from 76.9% to 84.8%. A GIS aided in the quantification and mapping of the habitat types. IKONOS imagery along with classification tree analyses were utilized to classify prairie pothole community types in North Dakota (Lawrence et al., In Press). Three levels of detail were mapped with overall accuracies ranging from 71% to 92%.

Image Classification Procedures

Satellite images must be classified to create a vegetation map. Various methods exist for classifying images. Unsupervised and supervised classification techniques have been used commonly throughout different studies. The use of decision tree classifications, a form of supervised classifications, has increased in image processing more recently (Lawrence and Wright, 2001; Rogan et al., 2003).

Unsupervised Techniques

Unsupervised clustering algorithms do not use training data, but rather sift through unknown pixels and aggregate those pixels into statistical clusters (Kindscher, et al., 1998). Algorithms such as ISODATA and K-means statistically cluster pixels by reducing the spectral variation within each cluster (Evans, 2004). The analyst chooses how many clusters with which to begin and then must assign vegetation classes to each cluster (Kindscher, et al., 1998). In Texas, for example, an unsupervised classification utilizing the ISODATA algorithm was used to map redberry juniper and associated rangeland species with CIR photography (Everitt et al., 2001). This study yielded an overall accuracy of 89%. An unsupervised classification was used with Landsat TM data to map semi-arid grassland vegetation in the Jornada Experimental Range, Las Cruces, New Mexico, resulting in overall accuracies ranging from 83% to 94% (Langley et al., 2001). Six montane meadow community types were mapped with 70% overall accuracy in Grand Teton National Park using the ISODATA clustering algorithm (Kindscher et al., 1998).

Unsupervised classification techniques are a proven method for highly accurate vegetation mapping when fieldwork is difficult to execute and when the landscape is complex (Harvey and Hill, 2001). An unsupervised classification can be performed, followed by a stratified random sample taken for ground-truthing and accuracy assessment, allowing for less personnel and equipment expenses than aerial photo interpretation.

Many clusters (50 or more) often are created to be able to identify a few classes (McGwire, 1992; Kindscher et al., 1998; Debinski et al., 1999). The time it takes to label each of these clusters based on inter-cluster spectral confusion can be extensive and tedious (Kershaw and Fuller, 1992). Finally, variability among analysts in labeling clusters from unsupervised classifications is statistically significant, resulting in subjectivity in vegetation mapping (McGwire, 1992; Stalmans et al., 2002).

Supervised Techniques

A supervised classification involves three basic steps: (1) the training stage, (2) the classification stage, and (3) the output stage (Chen and Stow, 2002). The analyst must collect training data either in the field, from photo interpretation, or from *a priori* knowledge, then software can be used to categorize each pixel in an image according to the class it is most similar to based on those training data. Finally, thematic maps, tables of statistics, and digital data files are produced. Accurate designation of training data is essential within supervised classification to represent each class appropriately (Bolstad and Lillesand, 1991; Reese et al., 2002).

Different classification algorithms such as maximum likelihood, minimum distance, and parallelepiped are common methods used to map vegetation. Semi-automated training approaches were compared with traditional training in a maximum likelihood supervised classification using Landsat TM data in Northern Wisconsin (Bolstad and Lillesand, 1991). Forest, shrub/brush, and herbaceous vegetation were classified with overall accuracies ranging from 40% to 72% with traditional training techniques and 54% to 83% with the semi-automated approach. Agricultural areas, pastures, and natural vegetation were mapped in the Willamette River Basin of western Oregon using a maximum likelihood supervised classification with Landsat TM data with an overall accuracy of 73.8% (Oetter et al., 2000). A supervised maximum likelihood classification utilizing Landsat TM data resulted in an overall accuracy of 77% for 11 land cover classes in the Front Ranges, St. Elias Mountains, Yukon Territory, Canada (Wilson and Franklin, 1992).

Maximum likelihood algorithms assume normally distributed data for each class (Ghedira et al., 2000), however, most landscapes are highly variable and do not fit a normal distribution. Homogenous training sites can also be difficult to locate for some or all of the vegetation classes in a particular study, consequently this technique can be successful, but not always.

In a parallelepiped classification the range of values for each class in a training set are identified, a parallelepiped is formed, and classes are specified based on where the parallelepiped is located in feature space (Kartikeyan et al., 1995). A parallelepiped classification was used with IKONOS and Landsat ETM+ data to aid in malaria control in the Republic of Korea by mapping mosquito breeding habitats (Masuoka et al., 2003). Rice paddy fields were mapped with overall accuracies of 65% for the Landsat data and 92% for the IKONOS data. Agricultural lands were mapped using a parallelepiped classifier with Landsat ETM+ data in the Flevoland polder, the Netherlands (Smits, 2002). Overall accuracies in this study ranged from 30.8% to 95.7%.

The minimum distance classifier is a linear classifier that first finds the average value of each category based on training data, then assigns the unknown pixels to the category with the minimum distance (Shahshahani and Landgrebe, 1994; Fukuda and Hirosawa, 1999). This classifier was used to map landcover in the Flevoland site in the Netherlands with an overall accuracy of 91.09% (Fukuda and Hirosawa, 1999). The primary shortcoming of the minimum distance classifier is that it utilizes only first order statistics (Lee and Landgrebe, 1993). Without using second order statistics the classifier defines an error prone decision boundary.

Decision Tree Classifications

Decision tree classification methods in image processing such as classification tree analysis (CTA, sometimes referred to as classification and regression trees, CART, or binary recursive partitioning) allow an analyst to utilize ancillary data without requiring expert knowledge to conduct highly accurate image classification (Lawrence and Wright, 2001; Lawrence et al., 2004). Many different types of data can be incorporated in this process, including continuous and thematic data such as the original raw imagery, GIS data, digital elevation model (DEM) information, and derived spectral information (e.g., principal components or tasseled cap components) (Lawrence et al., 2004). CTA automatically chooses which of these predictors to use in the classification and then creates easily interpreted dichotomous trees that have multiple branches defining the different categories within the classification. CTA methods have increased in popularity and use in recent years because of higher accuracy outputs than traditional supervised classifications such as those mentioned above (Lawrence and Wright, 2001; Rogan et al., 2003). CTA was successfully used to map landcover in the northwest portion of the GYE (Lawrence and Wright, 2001). Overall accuracies ranged from 65% for the map with eleven landcover categories to 96% for the map with three landcover categories. Land cover change was mapped to high accuracies (72% to 92%) using Landsat TM data and CTA in San Diego County (Rogan et al., 2003).

Substantial concerns with CTA are that it is highly affected by outliers and inaccuracies in the training data, and unbalanced data sets (Rogan et al., 2003; Lawrence et al., 2004). Training data might contain outliers and/or inaccuracies that could potentially account for much of the variability in the data. The CTA process is a non-parametric technique that does not make any assumptions about the data distribution, therefore, it might concentrate on the variability of the training data rather than on the accurate training data, resulting in errors in the classification. It is also common when mapping vegetation classes to have a number of categories that represent only a fraction of the entire study area. These categories might be ignored in the decision tree because CTA sometimes splits out classes that are well represented rather than those that are minimally represented, adversely affecting the outcome of the process (Lawrence et al., 2004). Also, CTA trees are formed with a one-step-look-ahead algorithm, thus the initial splits largely determine the ability of the tree to discern more detailed separations further down the tree (Lawrence et al., 2004).

Boosting is a data mining technique that can improve upon CTA (McIver and Friedl, 2002). It improves predictive ability and reduces error by using the results of earlier classifications to influence subsequent classification tree development (Drucker, 1997;

Schapire, 1999). Boosting is an iterative process where a standard classification tree is produced first, then training data are weighted with misclassified data assigned greater weight. Subsequent trees focus on the most difficult classification problems in the training data. The process is repeated a user-specified number of times, then a majority vote on the resulting trees determines the correct classification (Freund and Schapire, 1999). Boosting with decision tree analysis was used on AVHRR data to map North American and global land cover (Friedl et al., 1999). Compared to unboosted classifications, the boosted classification accuracies were higher in all but one instance. Overall boosted accuracies ranged from 74.9% to 96.6% for the global classification and 54.9% to 79.5% for the continental classification. Landsat TM data in a boosted CTA mapped 23 landcover classes in Guondong Province, China with an overall accuracy of 98% (McIver and Friedl, 2001).

Boosting techniques are adversely affected by inaccuracies and outliers in the training data. Because outliers will be poorly classified and given the greatest weight, the algorithm will focus on the outliers and place less emphasis on more accurate observations (Lawrence et al., 2004).

Addressing Landscape Change

Habitats are not static. Disturbances are constantly changing landscapes (Knick and Rotenberry, 2000). Many factors of ecological (including vegetation) change are seen on a landscape scale. Sudden changes might stem from management practices such as clear cuts or prescribed fires, as well as natural phenomena such as lightning caused fires or massive flooding (Carpenter, 1990). More gradual changes, such as shifts in vegetation community structure, might be more extensive and result from factors such as management practices (e.g., grazing intensity) and moderate to long-term climate variation. Changes in rangeland vegetation can be subtle, however, detecting that change can be simplified with the use of integrated remote sensing and GIS techniques (Yool et al, 1997). Change detection ideally would be automated and simple (Muchoney and Haack, 1994; Michener and Houhoulis, 1997; Knudsen and Olsen, 2003).

Change Detection Procedures

Change detection is the process of comparing two or more dates of remotely sensed imagery to find differences in land surface features between or among those dates (Singh, 1989; Collins and Woodcock, 1996;). Remote sensing can be used to perform these change analyses with multi-temporal data. Change detection can be divided into two basic techniques: pre-classification and post-classification (Yuan et al., 2005). Pre-classification techniques utilize spectral bands, ratios, differencing, indices, or principal components to create maps of change and no-change, and by its very nature must be used with digital data. The process can identify where change occurs, but does not identify the nature of the change. Post-classification comparison is a basic method of determining changes between multiple classified images, the results of which can be easily interpreted and quantified.

Two commonly utilized techniques for change detection are aerial photo interpretation and satellite image classification. Aerial photographs have been used for over 100 years. With over a century of historical images available, land cover changes can be tracked over time by trained photo interpreters. CIR and true-color photos have enabled interpreters to identify vegetation on the ground. Fourteen cover types were manually delineated using aerial photographs along with extensive ground truth data with an overall accuracy of 89% in Northern Territory, Australia (Harvey and Hill, 2001). Using digital orthophotography as a means to map vegetation, however, is a more modern and accurate technique than analog aerial photo interpretation (Barrette et al., 2000). The accuracy of wetland boundaries delineated using digital orthophotos was higher than those boundaries delineated using manual aerial photo interpretation in a study in Rhode Island (Barrette et al., 2000). The mean distance from “true” was 3.43 +/- 3.45 m for the orthophoto-derived boundaries, and 4.53 +/- 4.05 m for the aerial photo-derived boundaries.

The use of satellite remote sensing for change detection has advantages over photo interpretation in that images have high temporal and spatial resolution, can provide greater amounts of landscape information based on multiple bands, and cost less over large areas. Landsat data in particular have the distinct advantage of temporal continuity, identical spatial and spectral resolution, and consistent geometric rectification, including a fully archived data set dating from 1984 and a Congressional and NASA commitment to continue into the foreseeable future (NASA, 2004; USGS, 2005). This allows the development of comparable cover data over multi-decade periods to help scientists understand the Earth system (Goward et al., 2001). Previous Landsat data at somewhat coarser spatial resolutions and slightly different spectral resolutions extend the archive back to the early 1970s, providing opportunities for change detection studies covering over a quarter of a century.

Transformations and Standardizations for Image Data

Landsat data contain noise from changes in sun angle, atmospheric interferences with electromagnetic energy, and instrument noise (Huang et al., 2001). These factors would be corrected before delivery to user in an ideal situation, however, the task to do so would require collecting more data during each overpass by the sensor.

Landsat data can be converted to at-sensor reflectance values that adjust for sun angle, earth-sun distance, solar irradiance, and instrument noise (Huang et al., 2001; Huang et al., 2002b). An equation to perform this conversion was developed by the United States Geological Survey (USGS). Up to one hundred pseudo-invariant targets were collected from each of 10 Landsat scenes across a variety of landscapes and seasons and then used to test the accuracy and stability of the conversion equation (Huang et al., 2001). These converted at-sensor reflectance values contain less than half the noise of raw digital number data and no extraneous noise was introduced. Radiometric and solar illumination differences have been normalized by the conversion. Conversion factors developed for both ETM+ and TM sensors are reliable and accurate (Huang et al., 2001; Masek et al., 2001; Huang et al., 2002b; Chander and Markham, 2003).

Crop development studies were the original drive behind developing the Tasseled Cap (TC) transformation (Kauth and Thomas, 1976). The use of TC transformations has increased in recent years because it is highly effective, and consistently and predictably compresses data characteristics into three definable spectral bands (Huang et al., 2002a).

These bands can be directly associated to physical characteristics within a scene, specifically as measures of brightness (component 1), greenness (component 2), and wetness (component 3), and can generally account for up to 97% of spectral variability within a scene (Crist and Cicone, 1984; Collins and Woodcock, 1994; Huang et al., 2002a). The invariant nature of TC transformations allows a user to directly compare TC components across multiple Landsat scenes and utilize data to quantify spectral change over time (Crist and Cicone, 1984; Lawrence and Wright, 2001).

Change Detection Techniques

Individual spectral bands or transformations of spectral bands can be differenced (i.e., one date subtracted from another) and a threshold can be established to detect where changes occurred. This method is more mathematically dependent but is susceptible to data noise and spectral sensitivity of individual sensors (Nielsen et al., 1998), and the process often results in incorrect output. Differencing of indices, such as the Normalized Difference Vegetation Index (NDVI), is less sensitive to noise, however, it depends on very few image bands and thus provides inaccurate results (Hayes and Sader, 2001; Stefanov et al., 2001).

The accuracy of change detection has increased through the use of techniques that measure the magnitude of spectral changes observed, thus also increasing the applicability of change detection methods (Parmenter et al., 2003). Values that define the threshold of spectral change determine true landscape changes from inherent spectral variation (Houhoulis and Michener, 2000).

Change vector analysis (CVA) is a rule-based change detection method that examines the angle and magnitude of change between dates in spectral space (Chen et al., 2003; Parmenter et al., 2003). CVA measures spectral change based on the Pythagorean theorem in the three components, often the TC components, brightness, greenness, and wetness (Malila, 1980; Allen and Kupfer, 2000). By combining these three TC bands with CVA procedures, definitive biophysical differences can be detected rather than being confused with inherent spectral variations, thus reducing much of the uncertainty of previous methods and making the results easier to interpret (Allen and Kupfer, 2000; Parmenter et al., 2003).

CVA was used to examine spruce-fir ecosystems in the Great Smoky Mountains with two Landsat TM scenes from 1988 and 1998 resulting in overall accuracies of 57% with six classes and 72% for three classes (Allen and Kupfer, 2000). Pixel vector modulus, which is a method similar to CVA, aided in detecting wetland change between 1994 and 1995 at the Flint River Basin in Georgia with an overall change detection accuracy of 97% (Houhoulis and Michener, 2000). A form of CVA, called cross-correlation analysis (CCA), was utilized in the Stony Brook Millstone River Watershed in New Jersey to conduct a change detection analysis on Landsat TM and ETM+ data from 1989 and 1999, respectively, although classification accuracies were not reported (Civco et al., 2002). Finally, CVA was used successfully to detect change in land cover classes in the Greater Yellowstone Ecosystem from 1975 to 1995, by only reclassifying areas of potential change based on the established change threshold (Parmenter et al., 2003). This study yielded overall accuracies ranging from 74% at the finest level of detail and 94% at the coarsest.

A great benefit of only reclassifying areas that have changed is that training data can be provided from the areas of no change between the images (Podger and Scarpace, 2002). Not only does this provide a large amount of training data (that is assumed to be accurate), it makes each consecutive year of change detection less time-consuming and difficult (i.e., no long and costly forays into the field to collect training data). It also potentially reduces compound error from multiple classifications for much of the imagery.

Accurate rangeland vegetation maps can be produced by utilizing Landsat satellite imagery, decision trees, and boosting with Landsat imagery. These methods have the potential of being accurate, inexpensive, and easily reproducible for mapping rangelands over the NR and detecting change over time.

CHAPTER 3

MAPPING RANGELAND VEGETATION OF YELLOWSTONE'S NORTHERN RANGE

Introduction

Rangeland managers must make decisions about resources, ecological potential, and trends that affect every aspect of the ecosystem, such as plant ecology, small mammals, birds, and large herbivores (and in turn large predators) within areas they manage (Jensen et al., 2001). Informed decisions by these land managers are facilitated by understanding current and potential vegetation (Stalmans et al., 2002). Accurate vegetation maps support this understanding.

Rangelands are "open regions over which animals may roam and feed" (Merriam-Webster, Inc., 2005), often composed of grassland and shrubland and existing in areas of relatively low elevation (Despain, 1990; Kershaw et al., 1998). Rangelands are widespread throughout the western United States and are utilized by wild ungulates along with domesticated stock. The health of rangelands often will determine the health of herds and thus the livelihood of western ranchers and the success of hunting season. Fire and climate are significant factors that can affect ecosystems and the animals (or people) that rely on the landscape. The importance of rangelands has become more apparent in recent times as fires rage throughout the west during summer, and continuing drought increases fire potential (National Oceanic and Atmospheric Administration, 2005; Yellowstone National Park, 2005). Not only are rangelands essential for the survival of ungulates (ecologically), they provide the means of survival for many people (economically).

Satellite remote sensing was chosen as the best method for vegetation mapping of rangelands in the NR. Remote sensing incorporates automated algorithms, allows for more frequent updates (Wynne et al., 2000), and can be used to efficiently determine vegetation cover for large areas (Innes and Koch, 1998; Clark et al., 2001; Jensen et al., 2001; Vogelmann et al., 2001).

Forested areas versus non-forested areas are easily delineated from Landsat satellite images. Canopy structure, leaf area index (LAI), vegetation biomass, and landscape characteristics are also commonly mapped with remote sensing methods utilizing Landsat data (Knick and Rotenberry, 1995; Jakubauskas and Price, 1997). Non-forested areas, however, are more difficult to delineate because of similar spectral signatures of grassland and shrubland vegetation. Grass species might have stronger spectral signatures that could interfere with the spectral signatures of shrub species. The distinction between different community types is not always obvious. Many studies, however, have successfully mapped shrubland and grassland species. Landsat TM data have been used to map rangelands in the GYE, Idaho, North Dakota, and Africa (Debinski et al., 1999; Clark et al., 2001; Jensen et al., 2001; Maselli and Rembold, 2001).

Landsat sensors collect data from the visible portion of the electromagnetic spectrum along with several wavelengths from the infrared portion of the spectrum (near infrared, middle infrared, and thermal infrared). A panchromatic band is also collected by the

ETM+ sensor. The combination of different bands in various ratios or transformations allows a researcher to narrow in on specific features on the landscape. The Normalized Difference Vegetation Index (NDVI) for instance utilizes the red and near infrared bands to predict plant canopy or biomass (Rouse et al., 1973; Labus et al., 2002).

Landsat TM and ETM+ data have a spatial resolution of 28.5 m (typically resampled to 30 m on a side or 900 m^2), which can provide relatively detailed information of landscape-scale vegetation, whereas the minimum mapping unit of the current vegetation data at YNP is 2.02 ha or 20,234.28 m^2. Landsat data also have the distinct advantage of temporal continuity, including a fully archived data set dating from 1984 and a Congressional and NASA commitment to continue into the foreseeable future (NASA, 2004; USGS, 2005). This allows the development of comparable cover data over multi-decade periods. Previous Landsat data at somewhat coarser resolutions extend the archive back to the early 1970s, providing opportunities for change detection studies covering over a quarter of a century. The multitude of spatial and temporal data provided by the Landsat project continues to help scientists understand the Earth system (Goward et al., 2001).

Decision tree classification methods in image processing such as CTA allow an analyst to utilize ancillary data without requiring expert knowledge to perform highly accurate image classification (Lawrence and Wright, 2001; Lawrence et al., 2004). Many different types of data can be incorporated in this process, including continuous and thematic data such as the original raw imagery, GIS data, digital elevation model (DEM) information, and derived spectral information (e.g., principal components or tasseled cap components) (Lawrence et al., 2004). CTA automatically chooses which of these predictors to use in the classification and then creates easily interpreted dichotomous trees that have multiple branches defining the different categories within the classification.

Substantial concerns with CTA are that it is highly affected by outliers and inaccuracies in the training data and unbalanced data sets (Rogan et al., 2003; Lawrence et al, 2004). A possibility exists that training data might contain outliers and/or inaccuracies that could potentially account for much of the variability in the data. The CTA process is a non-parametric technique that does not make any assumptions about the data distribution, therefore, it might concentrate on the variability of the training data rather than on the accurate training data, resulting in errors in the classification. It is also common when mapping vegetation classes to have a number of categories that represent only a fraction of the entire study area. These categories might be ignored in the decision tree because CTA sometimes splits out classes that are well represented rather than those that are minimally represented, adversely affecting the outcome of the process (Lawrence et al., 2004). Also, CTA trees are formed with a one-step-look-ahead algorithm, thus the initial splits largely determine the ability of the tree to discern more detailed separations further down the tree (Lawrence et al., 2004).

Boosting is a data mining technique that can improve upon CTA (McIver and Friedl, 2002). It is a means to improve predictive ability and reduce error by using the results of earlier classifications to influence subsequent classification tree development (Drucker, 1997; Schapire, 1999). Boosting is an iterative process where a standard classification tree is produced first, after which training data are weighted with misclassified data assigned greater weight. Subsequent trees are created that focus on the most difficult classification problems in the training data. The process is repeated a user-specified number of times, and a majority vote on the resulting trees determines the correct classification (Freund and Schapire, 1999). Boosting techniques are adversely affected by outliers in the training data. Since the outliers will be the worst classified and given the greatest weight, the algorithm will focus on the outliers and place less emphasis on the more accurate observations (Lawrence et al., 2004).

See 5 is a “data mining tool for discovering patterns that delineate categories, assembling them into classifiers, and using them to make predictions,” (RuleQuest Research, 2004) that utilizes boosting in its calculations. CART, an extension for IMAGINE created for the U.S. Geological Survey (Earth Satellite Corporation, 2003), uses the See 5 decision tree output to create thematic maps.

The purpose of this project was to develop an accurate, inexpensive, and easily reproducible method for mapping rangelands over the NR utilizing Landsat satellite imagery. The value in this study lies mostly in the previous difficulty in mapping at species/near species level over large areas in an efficient manner. Supervised classifications, binary splits of two different classes, and CTA and boosting were used for classification within the programs IMAGINE, See 5, and the CART extension for IMAGINE.

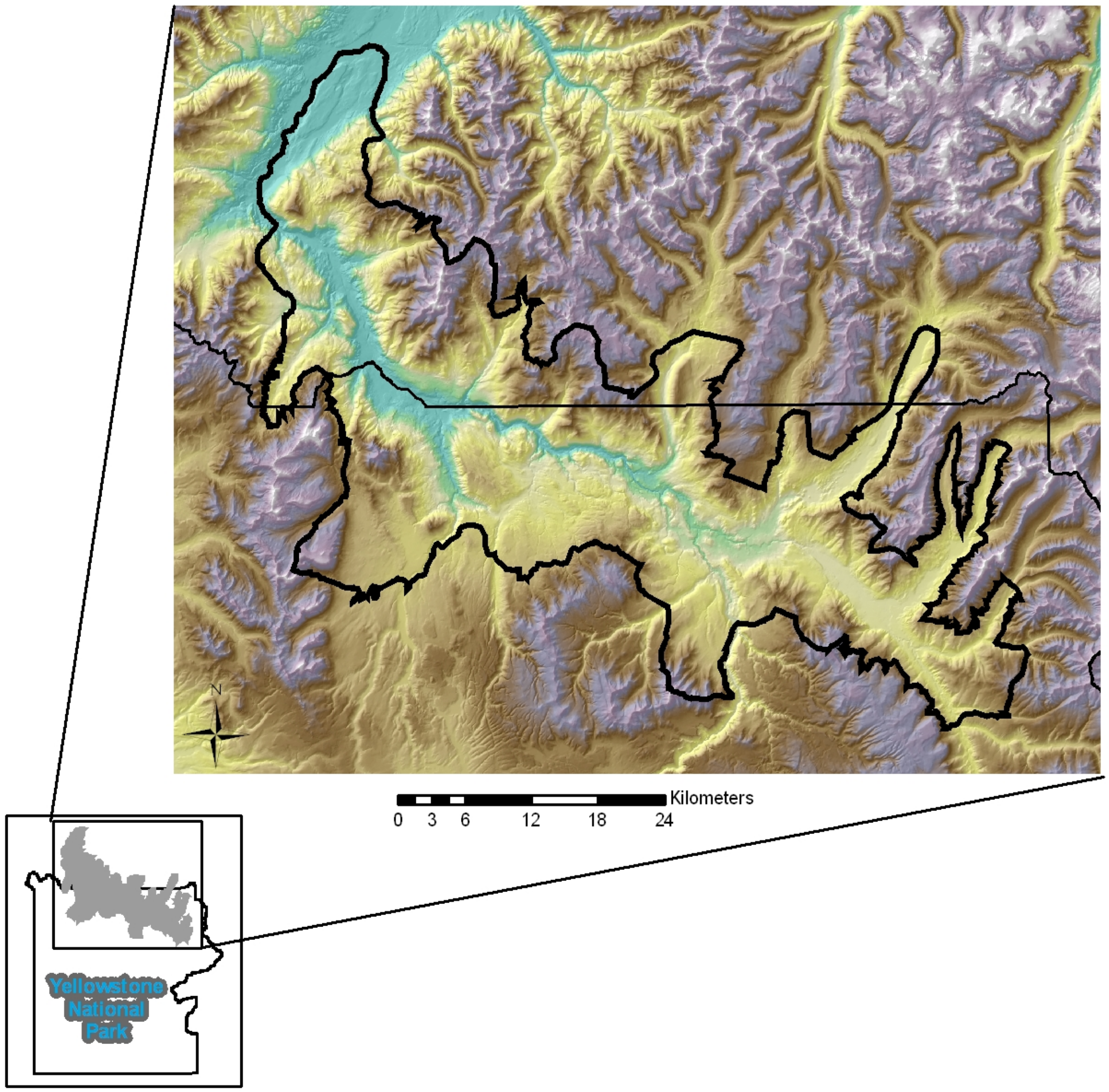
Methods

Study Area

The NR encompasses the area of the Yellowstone and Lamar River basins that is utilized by wintering ungulates. At 152,665 ha, the NR covers an area just south of Emigrant, Montana, through Gardiner, Montana, then Mammoth Hot Springs, Wyoming, and out to Cooke City, Montana (Figure 3.1). Elevation ranges from 1500 to 3209 m (Spatial Analysis Center, 1998). Habitats range from grassland and shrubland to forest community types (Despain, 1990). Average precipitation over the last 30 years has been 25 –30 cm in the lower elevations and up to 152 cm in the higher elevations (Spatial Analysis Center, 2000). One third of the Northern Range (approximately 53,200 ha, or 532,000,000 m^2) is located on public and private land outside of YNP (Spatial Analysis Center, 2005).

Mapping the rangeland vegetation of the NR required 51 data layers and several different classification methods. The general steps were: (1) acquire Landsat imagery, (2) derive additional data from the Landsat data, (3) collect additional ancillary data, (4) clip out the NR from all the data layers, (5) mask out forest, water, snow, thermal areas, and developed areas, (6) classify the data, and (7) perform an accuracy assessment on the

Figure 3.1: Location map for the Northern Range



resulting map (Figure 3.2). Additional classifications were necessary to identify difficult classes. A final map of five levels of vegetation information was created.

Figure 3.2: General steps in classification process

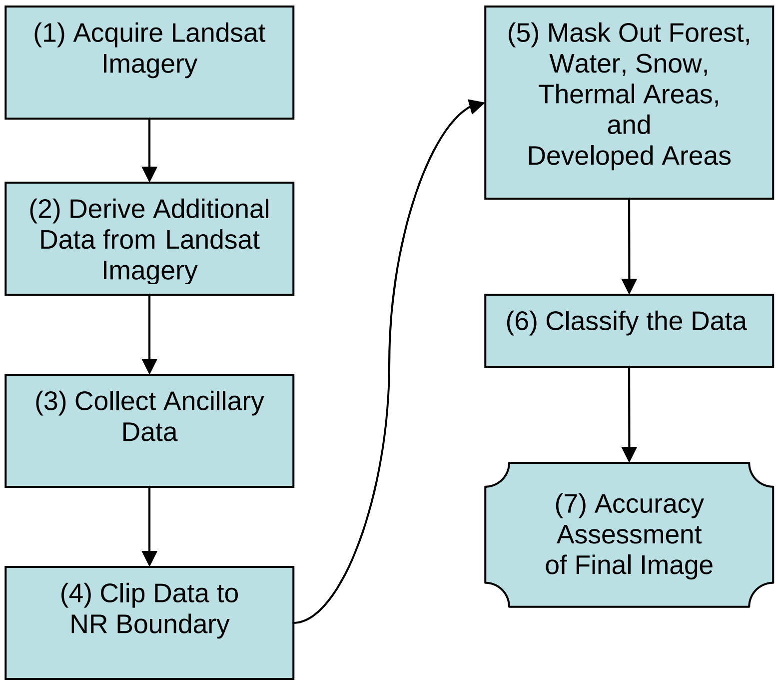


Image Pre-Processing

Landsat ETM+ satellite images of the study area from July 18, 1999 and September 15, 1999 were acquired to include wet and dry season conditions. The images have 30-m spatial resolution and include seven bands of spectral data: blue, green, red, near infrared, two middle infrared, and thermal infrared. These images were rectified by the USGS EROS Data Center in UTM, Zone 12, NAD83 projection (the standard projection used for data at the YNP Spatial Analysis Center).

By deriving supplementary data from the original data, specific qualities in the data can be singled out to aid in the classification process. Therefore, in addition to the original 14 bands, the two images were converted in several ways to produce 33 more unique components of data, as follows.

Using the 14 original bands, a standardized principal components analysis (PCA) was performed resulting in 14 new components. PCA reduces the amount of data to be analyzed and accounts for the most variance in the original images (Singh, 1989). The components generated from a multidate PCA often represent changes in brightness and greenness (Ingebritsen and Lyon, 1985; Collins and Woodcock, 1996). The change in greenness provides information regarding vegetative cover (Ingebritsen and Lyon, 1985).

A single band of Normalized Difference Vegetation Index (NDVI) (Rouse et al, 1973) was produced for each date (2 new bands). This process used the near infrared and red bands of Landsat imagery to create an index with values from -1 to 1 ([near infrared – red]/[near infrared + red]). Vegetation has high reflectance values in the near infrared portion of the spectrum, and lower values in the visible portion. When NDVI values are closer to 1 there are higher amounts of vegetation in the pixel. When the value is closer to 0 there is more bare ground in the pixel. NDVI has been shown to be effective in extracting vegetation data from imagery (Rouse et al., 1973; Labus et al., 2002).

A Tasseled Cap (TC) transformation was performed on each date of imagery (6 new bands). This process is similar to PC in that it reduces the amount of information to be analyzed into the first three components. The first three components from the TC transformation represent brightness (soil brightness or total reflectance), greenness (relative amounts of leafy green vegetation), and wetness (soil moisture status) (Crist and Cicone, 1984). The original six bands (minus the thermal band) had to be converted from digital numbers (DNs) to reflectance values to create these three components for each image. This reduces the amount of relative noise and between-scene variability (Huang et al., 2001; NASA, 2004).

Additional information can be gleaned from the data, especially information about changes between seasons, by subtracting the values from one image to another (Image Differencing) (Mas, 1999; Melgani et al., 2002). The previously mentioned bands and new components were image differenced to produce seven components of image difference (the original seven July bands subtracted from the original seven September bands), one component of NDVI difference (the July NDVI component subtracted from the September NDVI component), and three components of TC difference (the three July TC components subtracted from the three September TC components) to generate as much useful data from the original 14 bands as possible. The total number of components prepared for use in the classification based on the two dates of imagery was 47.

Ancillary data used in the study were 30-m elevation data (from a Digital Elevation Model (DEM)), slope in degrees and aspect (N, S, E, W, NE, SE, SW, NW, and flat) derived from the 30-m DEM, and a layer depicting distance from streams utilizing stream data from the USGS National Hydrography Dataset (NHD). The final image used in the classification process was comprised of 51 components (Table 3.1).

Table 3.1: Components used in the classification process

Number	Component Name	Number	Component Name
1	July 1999 Band 1 - Blue	31	July TC - Brightness
2	July 1999 Band 2 - Green	32	July TC - Greenness
3	July 1999 Band 3 - Red	33	July TC - Wetness
4	July 1999 Band 4 - NIR	34	Sept TC - Brightness
5	July 1999 Band 5 - MIR	35	Sept TC - Greenness
6	July 1999 Band 7 - MIR	36	Sept TC - Wetness
7	July 1999 Band 6 - Thermal	37	Image Difference Band 1 - Blue
8	Sept 1999 Band 1 - Blue	38	Image Difference Band 2 - Green
9	Sept 1999 Band 2 - Green	39	Image Difference Band 3 - Red
10	Sept 1999 Band 3 - Red	40	Image Difference Band 4 - NIR
11	Sept 1999 Band 4 - NIR	41	Image Difference Band 5 - MIR
12	Sept 1999 Band 5 - MIR	42	Image Difference Band 7 - MIR
13	Sept 1999 Band 7 - MIR	43	Image Difference Band 6 - Thermal
14	Sept 1999 Band 6 - Thermal	44	Image Difference NDVI
15	PCA Component 1	45	Image Difference TC - Brightness
16	PCA Component 2	46	Image Difference TC - Greenness
17	PCA Component 3	47	Image Difference TC - Wetness
18	PCA Component 4	48	Elevation
19	PCA Component 5	49	Slope in degrees
20	PCA Component 6	50	Aspect
21	PCA Component 7	51	Distance from streams
22	PCA Component 8		
23	PCA Component 9		
24	PCA Component 10		
25	PCA Component 11		
26	PCA Component 12		
27	PCA Component 13		
28	PCA Component 14		
29	July NDVI		
30	Sept NDVI		

Classification Procedures

1999 was selected as the year for the base map because of the high quality of the imagery (i.e., no clouds or smoke) and the availability of aerial photographs over the study area to refer to as training data. A hierarchical classification scheme was developed for this study. This multi-level classification was designed to meet the needs of diverse researchers and managers. The hierarchy has five levels, ranging from very broad vegetation types such as woodland, shrubland, or herbaceous vegetation (Level 1) to specific vegetation types such as aspen (*Populus tremuloides*), tufted hairgrass/sedge (*Deschampsia cespitosa*/*Carex spp.*), or big sagebrush/Idaho fescue (*Artemisia tridentata*/*Festuca idahoensis*) (Level 5). This multi-level classification scheme is flexible and can be used in many different studies, including studies on pronghorn habitat use (Level 5) or studies on successional changes in edge habitat (i.e., grassland to shrubland, Level 1). A needs analysis was conducted to determine the most appropriate classification hierarchy for cross-discipline studies in the NR. The classification hierarchy originally was based on habitat community types used by Don Despain to map YNP in the late 1980s (Despain, 1990). The initial classification scheme was presented to several specialists at YNP and Montana State University. The results of this survey were compiled after the comment period and used to create a draft classification scheme. The draft classification scheme was presented to the same group and approved with a few minor adjustments (Table 3.2). Several classes were extracted from previously derived data because they had already been mapped relatively well in other studies. These classes were forest, water, thermal, developed, snow, and agriculture. The number of classes in Level 5 run through the classification procedures in this portion of the project consequently was 21, but the final output map has 27 classes. Levels 1 through 4 of the classification hierarchy are based on the FGDC National Vegetation Classification Standard and Level 5 is based on the Despain habitat types (Despain, 1990; FGDC, 1997).

Table 3.2: 21-class five level classification hierarchy

Level 1	Level 2	Level 3	Level 4	Level 5 Full Name
Woodland	Deciduous woodland	Deciduous woodland - Dry	Cold-deciduous woodland	Aspen
		Deciduous woodland - Wet	Temporarily flooded cold-deciduous woodland	Cottonwood
Shrubland	Evergreen shrubland	Evergreen shrubland - Dry	Lowland microphyllous evergreen shrubland	Big sagebrush/bluebunch wheatgrass
				Big sagebrush/Idaho fescue
				Big sagebrush/Idaho fescue-sticky geranium phase
	Deciduous shrubland	Deciduous shrubland - Wet	Temporarily flooded cold-deciduous shrubland	Shrubby cinquefoil-silver sage/tufted hairgrass
			Seasonally flooded cold-deciduous shrubland	Willow/sedge
Herbaceous vegetation	Perennial graminoid vegetation	Perennial graminoid vegetation - Dry	Perennial grass crops (hayland, pastureland)	Crested wheatgrass (Exotic)
				Mustard (Exotic)
				Russian thistle (Exotic)
			Medium-tall bunch temperate or subpolar grassland	Smooth brome (Exotic)
				Bluebunch wheatgrass/Sandberg's bluegrass-needle-and-thread phase

Herbaceous vegetation (continued)	Perennial graminoid vegetation (continued)	Perennial graminoid vegetation – Dry (continued)	Medium-tall bunch temperate or subpolar grassland (continued)	Idaho fescue/bearded wheatgrass
				Idaho fescue/bearded wheatgrass-sticky geranium phase
				Idaho fescue/bluebunch wheatgrass
				Idaho fescue/Richardson's needlegrass
				Mudflow mosaic
		Perennial graminoid vegetation - Wet	Temporarily flooded temperate or subpolar grassland	Silver sage/Idaho fescue, Idaho fescue/tufted hairgrass
				Tufted hairgrass/Sedge
			Seasonally flooded temperate or subpolar grassland	Sedge bogs
Sparse vegetation	Boulder, gravel, cobble, or talus sparse vegetation	Boulder, gravel, cobble, or talus sparse vegetation - Dry	Lowland or submontane talus/scree	Talus

Training and validation data were collected in three different ways: (1) in the field by drawing polygons on high resolution color infrared aerial photographs flown in August of 1998 – Roy Renkin, a highly respected YNP vegetation specialist who has worked in YNP for more than 20 years helped with the photo interpretation, (2) in office photo interpretation, and (3) in the field by collecting GPS coordinates along field transects of different habitat types for a noxious weeds study in YNP.

The 1998 CIR aerial photos were flown of YNP and funded partially by Monica Turner at the University of Wisconsin – Madison for a soil study within YNP. None of the available scenes in the available 1998 imagery were cloud-free, and in most cases were greater than 70% cloud covered, making classification with those scenes impossible. There were no catastrophic weather or fire events from 1998 to 1999, so training data from the 1998 photos could be used on cloud-free imagery from 1999.

The majority of the training data used were from the field drawings on the 1998 photos. Time and workforce constraints made field GPS collection for all of the training and validation data impractical. The data from the three different collection methods were combined to produce a layer from which validation data could be extracted randomly. 5,206 sites were initially collected and 3,604 of those sites were used for training data.

The classification processes were run through See 5 and IMAGINE. The training data were run through See 5 to produce classification/decision trees of 21 classes. When two classes were confused with one another, those classes were extracted from the image and binary splits (e.g., cottonwood vs. willow) were run through See 5 to create additional decision trees of 21 classes. Results from these trees were run through CART to create thematic maps. A final classified image was produced from these thematic maps.

Validation sites were chosen at random (stratified by class). 1,602 sites were used for validation data. The vegetation information from these validation sites was used as reference data to compare to the output of the classification. Error matrices were created for Level 5 to determine the overall map accuracies at the most detailed level. The error matrices for Levels 1 through 4 were created by combining classes from the Level 5 error matrix (i.e., the Level 1 class, Woodland, is made up of Level 5 classes, Aspen and

Cottonwood). A Kappa statistic was calculated for each level of the hierarchy in each of the iterations. The Kappa statistic measures how far the classification is from a random classification and is more conservative than the overall accuracy. A Kappa value of 1 means the classification is 100% correct.

Results

Level 1

Classes from Level 5 of the hierarchy (the most specific) were combined to produce the remaining four levels of the hierarchy (the broadest). Level 1 of the classification hierarchy had four classes. The overall accuracy of the final map produced at Level 1 was 83.65% (Table 3.3).

Error matrices also show errors of commission and errors of omission by looking at the accuracies of the individual classes. Errors of commission can be determined with user's accuracy, which indicates how well a classified pixel actually represents the truth on the ground. User's accuracy compares the number of correctly classified pixels with the row totals, which represent the total number of classified pixels in each class (Congalton, 2001). User's accuracies for Level 1 ranged from 78.18% for shrubland to 85.22% for herbaceous vegetation (Table 3.4).

Errors of omission can be determined with producer's accuracy, which indicates the probability of the reference or validation data being classified correctly. Producer's accuracy compares the number of correctly classified pixels with the column totals, which represent the reference data (Congalton, 2001). Producer's accuracies for Level 1 ranged from 56.43% for shrubland to 100% for sparse vegetation (Table 3.4).

Table 3.3: Error matrix for Level 1

Reference Data

	Class Name	Sparse Veg	Herbaceous Veg	Shrubland	Woodland	Row Total
Classified Data	Sparse Veg	73	7	8	0	88
	Herbaceous Veg	0	928	141	20	1089
	Shrubland	0	51	215	9	275
	Woodland	0	9	17	124	150
	Column Total	73	995	381	153	1340

Overall Accuracy = 83.65%
Kappa = 0.689

Table 3.4: User's and producer's accuracies for Level 1

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Sparse Veg	73	88	73	100.00%	82.95%
Herbaceous Veg	995	1089	928	93.27%	85.22%
Shrubland	381	275	215	56.43%	78.18%
Woodland	153	150	124	81.05%	82.67%
Totals	1602	1602	1340		

The major areas of confusion for the Level 1 classification were the areas classified as shrubland but found to be herbaceous vegetation on the ground, explaining the user's accuracy of just over 75% and the low producer's accuracy. Sparse vegetation, herbaceous vegetation, and woodland classes had fewer areas of confusion.

Level 2

Level 2 of the classification hierarchy had five classes. The overall accuracy for the final map produced at this level was 82.27% (Table 3.5). User's accuracies ranged from 60.32% for evergreen shrubland to 91.86% for deciduous shrubland. Producer's accuracies ranged from 47.90% for evergreen shrubland to 100% for boulder, gravel, cobble, or talus sparse vegetation (Table 3.6).

Table 3.5: Error matrix for Level 2

Reference Data

	Class Name	Boulder, gravel, cobble, or talus sparse veg	Herbaceous veg	Evergreen shrubland	Deciduous shrubland	Deciduous Woodland	Row Total
Classified Data	Boulder, gravel, cobble, or talus sparse veg	73	7	1	7	0	88
	Herbaceous veg	0	928	123	18	20	1089
	Evergreen shrubland	0	51	114	22	2	189
	Deciduous shrubland	0	0	0	79	7	86
	Deciduous woodland	0	9	0	17	124	150
	Column Total	73	995	238	143	153	1318

Overall Accuracy = 82.27%

Kappa = 0.674

Table 3.6: User's and producer's accuracies for Level 2

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Boulder, gravel, cobble, or talus sparse veg	73	88	73	100.00%	82.95%
Herbaceous veg	995	1089	928	93.27%	85.22%
Evergreen shrubland	238	189	114	47.90%	60.32%
Deciduous shrubland	143	86	79	55.24%	91.86%
Deciduous woodland	153	150	124	81.05%	82.67%
Totals	1602	1602	1318		

Similar to Level 1, the major areas of confusion in Level 2 were in areas mapped as evergreen shrubland, but actually were herbaceous vegetation. Both user's and producer's accuracies were quite low for this class indicating confusion both on the ground and in the classified map. Many areas of herbaceous vegetation, evergreen shrubland, and deciduous woodland also were confused with deciduous shrubland, which is evident in the producer's accuracy for deciduous shrubland of just over 50%.

Level 3

Level 3 of the classification hierarchy had seven classes. The overall accuracy for the final map produced at this level was 78.53% (Table 3.7). User's accuracies ranged from 60.32% for evergreen shrubland – dry to 96.08% for deciduous woodland – dry. Producer's accuracies ranged from 47.90% for evergreen shrubland – dry to 100% for boulder, gravel, cobble, or talus sparse vegetation (Table 3.8).

Table 3.7: Error matrix for Level 3

Reference Data

	Class Name	Deciduous Woodland - Dry	Deciduous Woodland - Wet	Evergreen Shrubland - Dry	Deciduous Shrubland - Wet	Perennial Graminoid Veg - Dry	Perennial Graminoid Veg - Wet	Boulder, Gravel, Cobble, or Talus Sparse Veg	Row Total
Classified Data	Deciduous Woodland - Dry	49	0	0	2	0	0	0	51
	Deciduous Woodland - Wet	0	75	0	15	0	9	0	99
	Evergreen Shrubland - Dry	0	2	114	22	22	29	0	189
	Deciduous Shrubland - Wet	0	7	0	79	0	0	0	86
	Perennial Graminoid Veg - Dry	12	4	98	18	771	53	0	956
	Perennial Graminoid Veg - Wet	4	0	25	0	7	97	0	133
	Boulder, Gravel, Cobble, or Talus Sparse Veg	0	0	1	7	6	1	73	88
	Column Total	65	88	238	143	806	189	73	1258

Overall Accuracy = 78.53%

Kappa = 0.675

Table 3.8: User's and producer's accuracies for Level 3

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Deciduous Woodland - Dry	65	51	49	75.38%	96.08%
Deciduous Woodland - Wet	88	99	75	85.23%	75.76%
Evergreen Shrubland - Dry	238	189	114	47.90%	60.32%
Deciduous Shrubland - Wet	143	86	79	55.24%	91.86%
Perennial Graminoid Veg - Dry	806	956	771	95.66%	80.65%
Perennial Graminoid Veg - Wet	189	133	97	51.32%	72.93%
Boulder, Gravel, Cobble, or Talus Sparse Veg	73	88	73	100.00%	82.95%
Totals	1602	1602	1258		

The overall accuracy for this level was fairly high. Confusion was observed between perennial graminoid vegetation – dry, evergreen shrubland – dry, and perennial graminoid vegetation – wet.

Level 4

Level 4 of the classification hierarchy had 10 classes. The overall accuracy for the final map produced at this level was 73.66% (Table 3.9). User's accuracies ranged from 60.32% for lowland microphyllous evergreen shrubland to 100% for seasonally flooded temperate or subpolar grassland. Producer's accuracies ranged from 43.14% for seasonally flooded temperate or subpolar grassland to 100% for sparse vegetation (Table 3.10).

Table 3.9: Error matrix for Level 4

Reference Data

Classified Data

Class Name	Lowland or submontane talus/scree	Pernnial grass crops (hayland, pastureland	Medium-tall bunch temperate or subpolar grassland	Temporarily flooded temperate or subpolar grassland	Seasonally flooded temperate or subpolar grassland	Lowland microphyllous evergreen shrubland	Temporarily flooded cold-deciduous shrubland	Seasonally flooded cold-deciduous shrubland	Cold-deciduous woodland	Temporarily flooded cold-deciduous woodland	Row Total
Lowland or submontane talus/scree	73	6	0	1	0	1	7	0	0	0	88
Pernnial grass crops (hayland, pastureland)	0	207	0	2	0	9	15	0	0	0	233
Medium-tall bunch temperate or subpolar grassland	0	2	562	51	0	89	1	2	12	4	723
Temporarily flooded temperate or subpolar grassland	0	0	7	75	0	25	0	0	4	0	111
Seasonally flooded temperate or subpolar grassland	0	0	0	0	22	0	0	0	0	0	22
Lowland microphyllous evergreen shrubland	0	1	21	0	29	114	22	0	0	2	189
Temporarily flooded cold-deciduous shrubland	0	0	0	0	0	0	12	0	0	0	12
Seasonally flooded cold-deciduous shrubland	0	0	0	0	0	0	1	66	0	7	74
Cold-deciduous woodland	0	0	0	0	0	0	2	0	49	0	51
Temporarily flooded cold-deciduous woodland	0	0	0	9	0	0	0	15	0	75	99
Column Total	73	216	590	138	51	238	60	83	65	88	1255

Overall Accuracy = 73.66% Kappa = 0.722

Table 3.10: User's and producer's accuracies for Level 4

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Lowland or submontane talus/scree	73	88	73	100.00%	82.95%
Perennial grass crops (hayland, pastureland)	216	233	207	95.83%	88.84%
Medium-tall bunch temperate or subpolar grassland	590	723	562	95.25%	77.73%
Temporarily flooded temperate or subpolar grassland	138	111	75	54.35%	67.57%
Seasonally flooded temperate or subpolar grassland	51	22	22	43.14%	100.00%
Lowland microphyllous evergreen shrubland	238	189	114	47.90%	60.32%
Temporarily flooded cold-deciduous shrubland	60	12	12	20.00%	100.00%
Seasonally flooded cold-deciduous shrubland	83	74	66	79.52%	89.19%
Cold-deciduous woodland	65	51	49	75.38%	96.08%
Temporarily flooded cold-deciduous woodland	88	99	75	85.23%	75.76%
Totals	1602	1602	1180		

The biggest discrepancies at this level of the classification were as follows: temporarily flooded cold-deciduous shrubland was confused with lowland microphyllous evergreen shrubland and perennial grass crops (hayland, pastureland), lowland microphyllous evergreen shrubland and temporarily flooded temperate or subpolar grassland were confused with medium-tall bunch temperate or subpolar grassland, and seasonally flooded temperate or subpolar grassland was confused with lowland microphyllous evergreen shrubland .

Level 5

The final classified map included 27 classes (Figure 3.3), however, Level 5 of the classification hierarchy had only 21 classes (see Appendix A for class definitions). The overall accuracy for the final map produced at this level was 72.30% (Table 3.11). User's accuracies ranged from 40.91% for big sagebrush/Idaho fescue – sticky geranium phase (*Artemisia tridentata/Festuca idahoensis –Geranium viscosissimum* phase) to 100% for Russian thistle (*Salsola australis*), sedge bogs (*Carex spp.*), shrubby cinquefoil-silver sage (*Potentilla fruticosa-Artemisia cana*)/tufted hairgrass, and silver sage /Idaho fescue, Idaho fescue/tufted hairgrass. Producer's accuracies ranged from 18.00% for silver sage/Idaho fescue, Idaho fescue/tufted hairgrass to 100% for crested wheatgrass (*Agropyron cristatum*), mudflow mosaic, and talus (Table 3.12).

The biggest discrepancies at this level of the classification were as follows: big sagebrush/Idaho fescue was confused with bluebunch wheatgrass/Sandberg's bluegrass – needle-and-thread phase (*Poa secunda*, *Stipa comata* phase) and Idaho fescue/bluebunch wheatgrass, big sagebrush/Idaho fescue – sticky geranium phase was confused with tufted hairgrass, and silver sage/Idaho fescue, Idaho fescue/tufted hairgrass was confused with Idaho fescue/bluebunch wheatgrass.

Figure 3.3: Classified map of NR from 1999

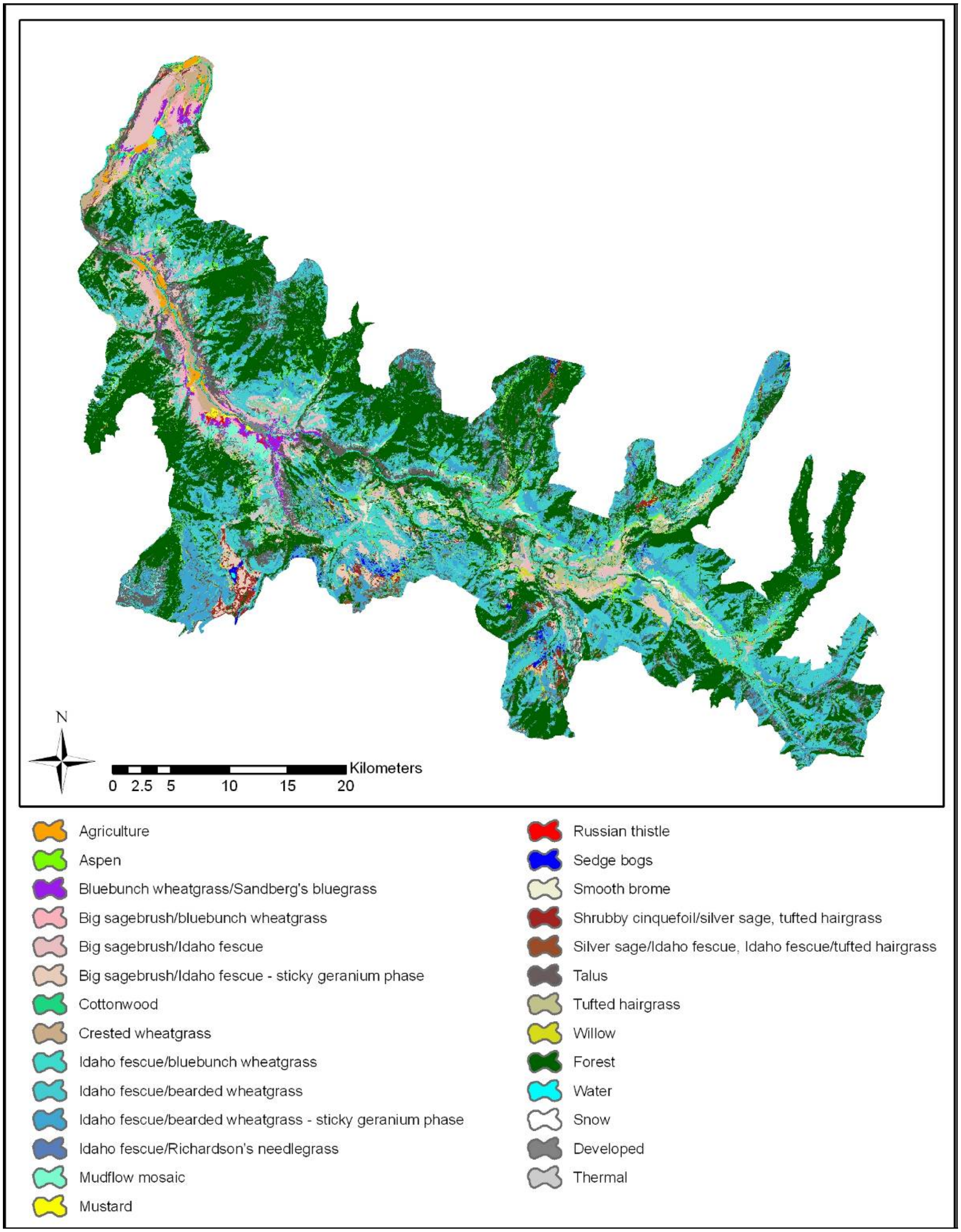


Table 3.11: Error matrix for Level 5

Class Name	asp	bbwgsbg	bsbbbw	bsbif	bsbifst	ctnwd	cw	ifbbwg	ifbwg	ifbwgst	ifrng	mud	must	rt	sbog	sbrm	scssth	ssifth	tal	thg	wil	Row Total
Aspen	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	51
Bluebunch wheatgrass/Sandberg's bluegrass – needle-and-thread phase	0	62	0	24	0	0	0	0	0	0	0	0	0	1	0	4	0	5	0	0	0	96
Big sagebrush/bluebunch wheatgrass	0	0	40	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	42
Big sagebrush/Idaho fescue	0	20	10	28	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	59
Big sagebrush/Idaho fescue – sticky geranium phase	0	0	0	0	36	0	0	0	0	1	0	0	0	0	29	0	22	0	0	0	0	88
Cottonwood	0	0	0	0	0	75	0	0	0	0	0	0	0	0	0	0	0	0	0	9	15	99
Crested wheatgrass	0	0	9	0	0	0	81	0	0	0	0	0	12	6	0	0	15	0	0	0	0	123
Idaho fescue/bluebunch wheatgrass	0	5	3	39	0	4	0	101	0	2	10	0	1	0	0	2	1	27	0	11	2	208
Idaho fescue/bearded wheatgrass	4	0	0	0	0	0	0	3	64	0	3	0	0	0	0	0	0	0	0	0	0	74
Idaho fescue/bearded wheatgrass – sticky geranium phase	0	0	0	0	0	0	0	0	4	67	0	0	0	0	0	0	0	7	0	0	0	78
Idaho fescue/Richardson's needlegrass	8	0	0	0	9	0	0	0	0	0	73	0	0	0	0	0	0	0	0	0	0	90
Mudflow mosaic	0	0	14	0	0	0	0	0	0	0	0	92	0	0	0	0	0	0	0	1	0	107
Mustard	0	0	0	0	0	0	0	0	0	0	0	0	49	6	0	0	0	2	0	0	0	57
Russian thistle	0	0	0	0	0	0	0	0	0	0	0	0	0	53	0	0	0	0	0	0	0	53
Sedge bogs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	22
Smooth brome	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	61	0	0	0	0	0	70
Shrubby cinquefoil-silver sage/tufted hairgrass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	12
Silver sage/Idaho fescue, Idaho fescue/tufted hairgrass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	9
Talus	0	0	1	0	0	0	0	0	0	0	0	0	6	0	0	0	7	0	73	1	0	88
Tufted hairgrass/sedge	4	0	0	0	25	0	0	0	0	0	2	0	0	0	0	5	0	0	0	66	0	102
Willow/sedge	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	1	0	0	0	66	74
Totals	65	87	77	91	70	88	81	113	68	70	88	92	68	67	51	72	60	50	73	88	83	1602

Overall Accuracy = 72.30% Kappa = 0.722

Table 3.12: User's and producer's accuracies for Level 5

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Aspen	90	51	49	54.44%	96.08%
Bluebunch wheatgrass/Sandberg's bluegrass – needle-and-thread phase	87	96	62	71.26%	64.58%
Big sagebrush/bluebunch wheatgrass	77	42	40	51.95%	95.24%
Big sagebrush/Idaho fescue	91	59	28	30.77%	47.46%
Big sagebrush/Idaho fescue – sticky geranium phase	70	88	36	51.43%	40.91%
Cottonwood	89	99	75	84.27%	75.76%
Crested wheatgrass	81	123	81	100.00%	65.85%
Idaho fescue/bluebunch wheatgrass	113	208	101	89.38%	48.56%
Idaho fescue/bearded wheatgrass	68	74	64	94.12%	86.49%
Idaho fescue/bearded wheatgrass – sticky geranium phase	70	78	67	95.71%	85.90%
Idaho fescue/Richardson's needlegrass	88	90	73	82.95%	81.11%
Mudflow mosaic	92	107	92	100.00%	85.98%
Mustard	68	57	49	72.06%	85.96%
Russian thistle	67	53	53	79.10%	100.00%
Sedge bogs	51	22	22	43.14%	100.00%
Smooth brome	72	70	61	84.72%	87.14%
Shrubby cinquefoil-silver sage/tufted hairgrass	60	12	12	20.00%	100.00%
Silver sage/Idaho fescue, Idaho fescue/tufted hairgrass	50	9	9	18.00%	100.00%

Talus	73	88	73	100.00%	82.95%
Tufted hairgrass/sedge	91	102	66	72.53%	64.71%
Willow/sedge	83	74	66	79.52%	89.19%
Totals	1602	1602	1180		

Shrubby cinquefoil – silver sage/tufted hairgrass and silver sage/Idaho fescue, Idaho fescue/tufted hairgrass had extremely low producer's accuracies and 100% user's accuracies. This indicated that very few of the pixels were classified as these classes when they should have been. Shrubby cinquefoil – silver sage/tufted hairgrass was confused with big sagebrush/Idaho fescue – sticky geranium phase and crested wheatgrass, while silver sage/Idaho fescue, Idaho fescue/tufted hairgrass was confused with Idaho fescue/bluebunch wheatgrass. Finally, Idaho fescue/bluebunch wheatgrass was confused with big sagebrush/Idaho fescue and silver sage/Idaho fescue, Idaho fescue/tufted hairgrass, resulting in a fairly low user's accuracy.

Despain Habitat Types

An accuracy assessment of the existing map created by Despain was also completed to demonstrate how well the classification performed in this study compared to the existing map created by air photo interpretation. The same 21 classes and the same 1,602 validation sites were utilized for the error matrix (Table 3.13). The overall accuracy at Level 5 was 31.28%. User's accuracies ranged from 0% for big sagebrush/Idaho fescue – sticky geranium phase, Idaho fescue/bearded wheatgrass – sticky geranium phase, and tufted hairgrass/sedge to 15.27% for big sagebrush/Idaho fescue to 100% for talus.

Producer's accuracies ranged from 0% for aspen, cottonwood, crested wheatgrass, Idaho fescue/bluebunch wheatgrass, mustard, Russian thistle, smooth brome, tufted hairgrass/sedge, and willow/sedge to 23.19% for Idaho fescue/bearded wheatgrass to 98.91% for mudflow mosaic (Table 3.14).

The overall accuracy was extremely low compared with the classification from this study. User's and producer's accuracies were very high for the mudflow mosaic class, and very low for many of the other classes. Talus had a high user's accuracy, but a very low producer's accuracy, whereas sedge bogs had a high producer's accuracy, but a low user's accuracy. Confusion was observed between big sagebrush/Idaho fescue and big sagebrush/Idaho fescue – sticky geranium phase and between Idaho fescue/bearded wheatgrass and Idaho fescue/bearded wheatgrass – sticky geranium phase.

Discussion

The overall accuracies that resulted from this study were relatively high compared to the current vegetation map used at YNP. The accuracies ranged from 72.30% for the finest classification level to 83.65% for the coarsest classification level. There was a trade-off between the different levels and how specific they were and the accuracies of those levels. As the levels of the classification became more specific, the overall accuracies decreased, as expected.

Table 3.13: Error matrix for Level 5 of the Despain habitat types

Class Name	asp	bbwgsbg	bsbbbw	bsbif	bsbifst	ctnwd	cw	ifbbwg	ifbwg	ifbwgst	ifrng	mud	must	rt	sbog	sbrm	scssth	ssifth	tal	thg	wil	Row Total
Aspen	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bluebunch wheatgrass/Sandberg’s bluegrass – needle-and-thread phase	0	56	0	0	0	0	56	1	0	0	0	0	48	67	1	26	0	33	0	0	0	288
Big sagebrush/bluebunch wheatgrass	0	0	36	0	0	4	25	11	1	0	0	0	7	0	0	0	0	0	0	0	0	84
Big sagebrush/Idaho fescue	26	30	21	40	0	0	0	45	16	0	13	0	0	0	0	1	0	12	26	26	6	262
Big sagebrush/Idaho fescue – sticky geranium phase	15	0	0	119	0	0	0	5	6	0	5	0	0	0	0	0	12	0	0	0	0	162
Cottonwood	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Crested wheatgrass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Idaho fescue/bluebunch wheatgrass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Idaho fescue/bearded wheatgrass	0	0	0	0	0	0	0	0	32	0	0	0	0	0	0	0	0	0	0	0	0	32
Idaho fescue/bearded wheatgrass – sticky geranium phase	0	0	0	0	0	0	0	32	83	0	1	0	0	0	11	1	0	0	0	0	0	128
Idaho fescue/Richardson’s needlegrass	0	0	0	2	0	1	0	0	0	0	69	1	0	0	0	0	0	0	0	0	0	73
Mudflow mosaic	0	0	20	0	0	0	0	0	0	0	0	91	1	0	0	0	0	0	0	0	0	112
Mustard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Russian thistle	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sedge bogs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	53	0	0	0	0	65	1	119
Smooth brome	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shrubby cinquefoil-silver sage/tufted hairgrass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	1	0	0	0	32
Silver sage/Idaho fescue, Idaho fescue/tufted hairgrass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	1	0	0	18
Talus	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	12
Tufted hairgrass/sedge	10	1	0	0	0	0	0	19	0	0	0	0	0	0	0	44	1	0	0	0	0	75
Willow/sedge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Totals	51	87	77	161	0	5	81	113	138	0	88	92	56	67	65	72	44	63	39	91	7	1397

Overall Accuracy = 31.28% Kappa = -0.061

Table 3.14: User's and producer's accuracies for Level 5 of the Despain habitats

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Aspen	51	0	0	0.00%	-------
Bluebunch wheatgrass/Sandberg's bluegrass – needle-and-thread phase	87	288	56	64.37%	19.44%
Big sagebrush/bluebunch wheatgrass	77	84	36	46.75%	42.86%
Big sagebrush/Idaho fescue	161	262	40	24.84%	15.27%
Big sagebrush/Idaho fescue – sticky geranium phase	0	162	0	-------	0.00%
Cottonwood	5	0	0	0.00%	-------
Crested wheatgrass	81	0	0	0.00%	-------
Idaho fescue/bluebunch wheatgrass	113	0	0	0.00%	-------
Idaho fescue/bearded wheatgrass	138	32	32	23.19%	100.00%
Idaho fescue/bearded wheatgrass – sticky geranium phase	0	128	0	-------	0.00%
Idaho fescue/Richardson's needlegrass	88	73	69	78.41%	94.52%
Mudflow mosaic	92	112	91	98.91%	81.25%
Mustard	56	0	0	0.00%	-------
Russian thistle	67	0	0	0.00%	-------
Sedge bogs	65	119	53	81.54%	44.54%
Smooth brome	72	0	0	0.00%	-------
Shrubby cinquefoil-silver sage/tufted hairgrass	44	32	31	70.45%	96.88%
Silver sage/Idaho fescue, Idaho fescue/tufted hairgrass	63	18	17	26.98%	94.44%
Talus	39	12	12	30.77%	100.00%
Tufted hairgrass/sedge	91	75	0	0.00%	0.00%
Willow/sedge	7	0	0	0.00%	-------
Totals	1397	1397	437		

The overall accuracy of 72.30% for Level 5, although not as high as the USGS standard of 85% (Anderson, 1976), was acceptable for this project. Landsat has typically been used to map broad land cover classes with coarse resolution over large land masses and consequently was thought unable to distinguish between different non-forest species due to small patch size and heterogeneity of classes over the landscape (Clark et al., 2001; Smith et al., 2002).

Despain habitat classification resulted in an overall accuracy of 31.28%. The much greater minimum mapping unit for the Despain classification helped to explain the very low accuracy. Since imagery with 30-m resolution was successful in mapping some specific classes in this study, it follows that utilizing imagery with higher spatial resolution could allow for higher accuracies with very specific classes.

The results from this project were promising. Overall accuracies were comparable to several previous rangeland studies (Wilson and Franklin, 1992; Kindscher et al., 1998; Oetter et al., 2000; Maselli and Rembold, 2001). The accuracies from this study were much higher in a few cases (Bolstad and Lillesand, 1991; Clarke et al., 2001; Masuoka et al., 2003).

Boosting can improve classification accuracy, but not always. These results indicated that the See 5 boosting process was able to differentiate between similar spectral signatures and thus differentiate between similar habitat types (i.e., big sagebrush/Idaho fescue versus big sagebrush/bluebunch wheatgrass), which improved the overall classification accuracy at Level 5 beyond what a simple unsupervised classification did. These are positive results for rangeland and riparian biologists, because an inexpensive and easy to perform method for mapping rangeland and riparian habitats will be highly utilized, especially at YNP.

Variability in a landscape can affect classification accuracy. A landscape that is homogenous will most likely be mapped at a very high overall accuracy, whereas a landscape that is highly heterogeneous might be harder to map at high accuracies. Some vegetation, such as in riparian areas, is inherently linear and might be more difficult to classify with high accuracy. Also, mixed vegetation can be difficult to classify accurately unless subpixel classification procedures are used. Rangelands can be highly variable as is seen in the 21 classes used in this project.

For Level 5, cottonwood, mudflow mosaic, smooth brome, talus, and willow were mapped especially well. The high accuracy of talus is easily explained because it is the only non-vegetative category in the classification. Its spectral signature is different from vegetation, and certainly would be extracted by the TC brightness component.

The relative high accuracies of cottonwood and willow were somewhat surprising. These species are broad-leaved and turn gold to red in the fall. Utilizing a fall image (the September image) probably aided in identifying these species as they would have reflected stronger in different components of the 51-layer image than the grassland and shrubland species that either turn light yellow to brown or stay green.

Mudflow mosaic and smooth brome are both in the Level 4 class, medium-tall bunch temperate or subpolar grassland. The remaining habitat types in this class included Idaho fescue, discussed below. The spectral signatures of these two habitat types were different enough from Idaho fescue to allow the types to be distinguished from the remaining classes in the Level 4 class and also from the other wet classes.

In the Level 5 error matrix, most of the errors in the classification are found in the confusion between classes that contain Idaho fescue. Idaho fescue is a very common plant in the NR and is part of seven of the 12 naturally occurring shrubland and herbaceous vegetation classes in this study. The confusion might reflect that these seven classes are a mixture of different species including Idaho fescue, and mixed classes are often difficult to differentiate. Rangelands are highly diverse landscapes that have a large variety of physical and chemical properties that can be detected from satellite imagery. The results of this study indicate that highly accurate detection of diverse landcover is achievable using automated classification methods. Combining automated classification procedures with the acquisition of recent remote sensing data is an efficient and effective method to accurately map highly variable ecosystems, thus providing a monitoring tool for land managers.

The accuracy of classifications in the future can be improved in several ways. First, if possible, training and validation data should be collected at the same time the image is flown or near the same time. Second, if cost is not a factor, higher resolution data could be purchased for the classification procedure. Finally, collecting larger amounts of unbiased training and validation data would improve classifications conducted in the manner of this project.

CHAPTER 4

CHANGE DETECTION OF RANGELAND VEGETATION

Introduction

Rangelands are widespread throughout the western United States and are utilized by wild ungulates along with domesticated livestock. Often the health of rangelands determines the health of herds, and thus the livelihood of western ranchers and the success of hunting season. Fire and climate are significant factors that can affect ecosystems and the animals (or people) that rely on the landscape. The importance of rangelands has become more apparent in recent times as fires rage throughout the west during the summers and continuing drought gives rise to higher fire potential (National Oceanic and Atmospheric Administration, 2005; Yellowstone National Park, 2005). Not only are rangelands essential for the survival of ungulates (ecologically), they provide the means of survival for many people (economically).

Land managers must make decisions about resources, ecological potential and trends that affect every aspect of an ecosystem, such as plant ecology, small mammals, birds, and large herbivores (and in turn large predators) within areas they manage (Jensen et al., 2001). Informed decisions by these land managers are facilitated by understanding current and potential vegetation (Stalmans et al, 2002), along with changes to the vegetation over time. By exploring changes in rangeland vegetation from the past to the present, land managers might discover answers to why vegetation changes.

The NR is undergoing change at many levels. These changes are difficult to track with the maps currently available. These data are mapped at too low of a resolution (20,234.28 m^2), are not accurate enough (31.28% overall accuracy), and are only available for vegetation in the 1980s. Remote sensing enables mapping of large areas with high resolution, relatively high accuracies, and many years of coverage.

Aerial photograph interpretation has been utilized in the past to monitor changes in vegetation, however, identifying individual species on multiple years of photos can be time consuming and costly (Ramsey and Laine, 1997). In many cases aerial photographs have very high spatial resolution, thus allowing the interpreter to delineate specific types of vegetation. When multiple interpreters are used, or even when one individual is doing the work, but at different times of day, an undesired result might be inconsistent interpretations, thus decreasing the accuracy of the method (Coppin et al., 2004).

The use of satellite remote sensing for change detection has advantages over photo interpretation in that images have high temporal and spatial resolution, can provide greater amounts of landscape information based on multiple bands, and are less costly over large areas. Landsat TM data in particular have the distinct advantage of temporal continuity, identical spatial and spectral resolution, and consistent geometric rectification, including a fully archived data set dating from 1984 and a Congressional and NASA commitment to continue into the foreseeable future (NASA, 2004; USGS, 2005). This allows the development of comparable cover data over multi-decade periods. Landsat data have been used successfully to map rangeland in the United States and South Africa (Debinski et al., 1999; Jensen et al., 2001; Maselli and Rembold, 2001).

Change detection is the process of comparing two or more dates of remotely sensed imagery to find differences in land surface features between or among those dates (Singh, 1989; Collins and Woodcock, 1996). Satellite remote sensing can be used to perform these change analyses with a variety of image sources and dates. Change detection techniques range from simple image comparisons to spectral change measurements and can be divided into two basic techniques: pre-classification and post-classification (Yuan et al., 2005).

Pre-classification techniques utilize spectral bands, ratios, differencing, indices, or principal components to create maps of change and no-change. The process can identify where change occurs, but does not aid in identifying the nature of the change. Post-classification image comparison is a basic method of determining changes between multiple classified images, the results of which can be easily interpreted and quantified. Individual spectral bands or transformations of spectral bands can be differenced (i.e., one date subtracted from another) and a threshold can be established to detect where changes occurred. This method is more mathematically dependent but is susceptible to data noise and spectral sensitivity of individual sensors (Nielsen et al., 1998). Subsequently the process often results in incorrect output. Differencing of indices, such as the Normalized Difference Vegetation Index (NDVI), is less sensitive to noise, however, it depends on very few image bands and thus also provides inaccurate results(Hayes and Sader, 2001; Stefanov et al., 2001).

The accuracy of change detection has increased through the use of techniques that measure the magnitude of spectral changes observed, thus also increasing the applicability of change detection methods (Parmenter et al., 2003). Values that define the threshold of spectral change determine true landscape changes from inherent spectral variation (Houhoulis and Michener, 2000).

Change vector analysis (CVA) is a rule-based change detection method that looks at the angle and magnitude of change between dates in spectral space (Chen et al., 2003; Parmenter et al., 2003). Rule-based systems use expert systems or machine learning (artificial intelligence) to analyze information and predict outcomes (Lawrence and Wright, 2001). CVA measures spectral change based on the Pythagorean theorem in the three components, often the TC components, brightness, greenness, and wetness (Malila, 1980; Allen and Kupfer, 2000). By combining these three TC bands with CVA procedures, definitive biophysical differences can be detected rather than being confused with inherent spectral variations, thus reducing much of the uncertainty of previous methods and making the results easier to interpret (Allen and Kupfer, 2000; Parmenter et al., 2003;).

Orthogonal spectral data transformations condense large amounts of spectral data into a small number of spectral components that can detect diverse features accurately (Nielsen et al., 1998; Dymond et al., 2002; Parmenter et al., 2003). Principal components analysis (PCA) and tasseled cap (TC) are two orthogonal data transformations that are commonly applied in remote sensing (Crist and Cicone, 1984; Ingebritsen and Lyon, 1985; Conese et al., 1993; Dymond et al., 2002; Hall-Beyer, 2003). PCA decreases the redundancy of information in multiple spectral bands (Armenakis, 2003), however, it can be difficult to interpret and often varies between different landscapes (Collins and Woodcock, 1994).

The TC transformation is a physically based identification process and therefore the resulting components can be interpreted ecologically (Collins and Woodcock, 1994). Landsat spectral data are rotated onto three axes during a TC transformation: brightness, greenness, and wetness, resulting in components that correspond directly to those physical characteristics of the vegetation, while accounting for as much as 97% of spectral variability within a scene (Crist and Cicone, 1984; Collins and Woodcock, 1994; Huang et al., 2002a; Parmenter et al., 2003). The brightness, greenness, and wetness components can be used to quantify spectral changes. They have been proven effective in isolating wet sites (Dymond et al, 2002), and have been used to improve detection of moist versus senescent vegetation (Crist and Cicone, 1984).

The objective of this study were to use Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data along with CVA to identify and locate areas of vegetation change between 1985 and 1999 in the NR of YNP. CVA was conducted using the first three TC components derived from the Landsat images. NR rangeland vegetation maps were developed for the years 1985 and 1999, and a map of changed vegetation areas was produced based on the differences between the 1985 and 1999 maps.

Methods

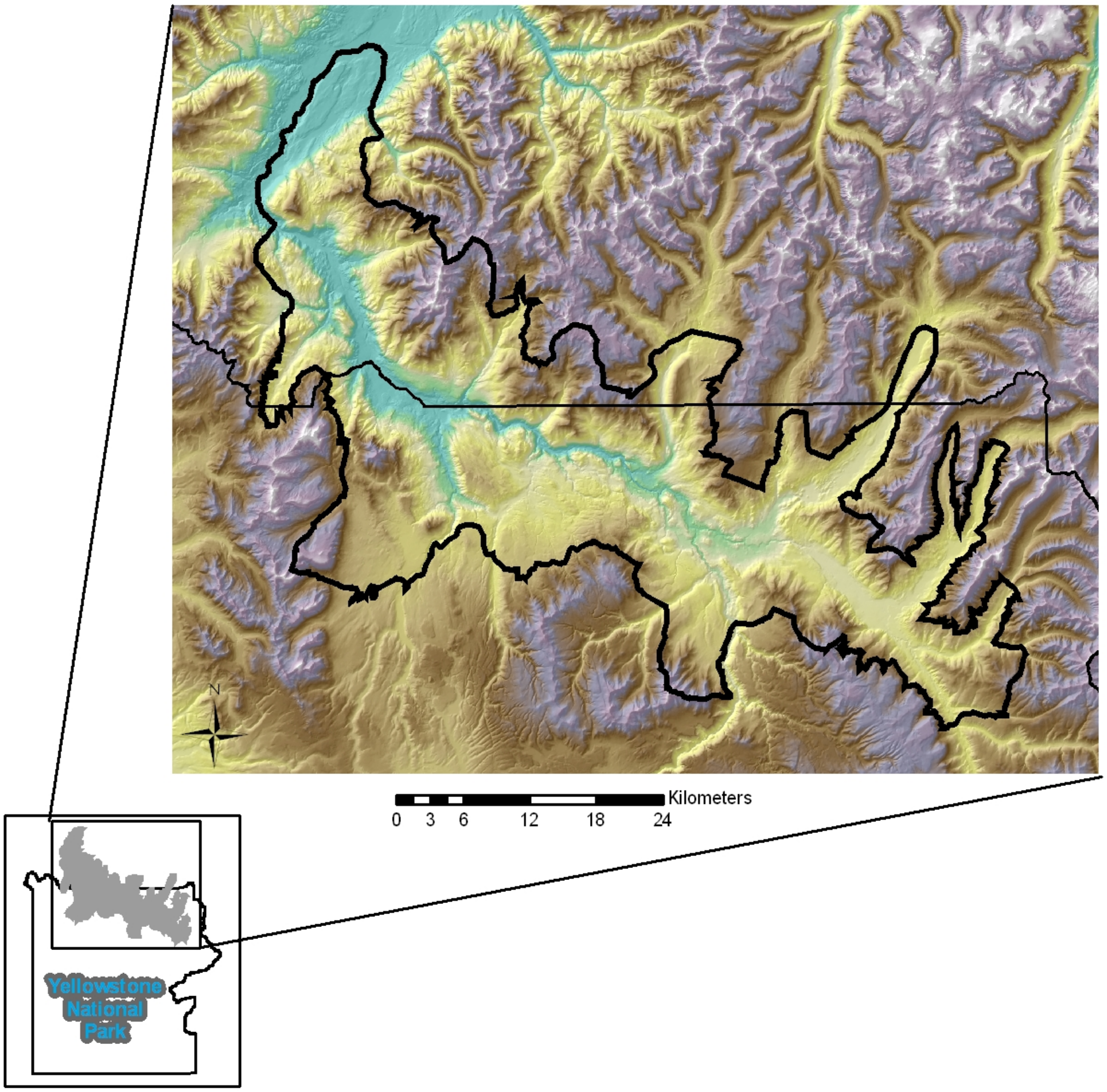
Study Area

The NR of YNP encompasses the area of the Yellowstone and Lamar River basins that is utilized by wintering ungulates. At 152,665 ha, the NR covers an area just south of Emigrant, Montana, through Gardiner, Montana, then Mammoth Hot Springs, Wyoming, and out to Cooke City, Montana (Figure 4.1). Elevation ranges from 1500 to 3209 m (Spatial Analysis Center, 1998). Habitat types range from grassland and shrubland to forest community types (Despain, 1990). Average precipitation over the last 30 years has been 25 –30 cm in the lower elevations and up to 152 cm in the higher elevations (Spatial Analysis Center, 2000). One third of the Northern Range (approximately 53,200 ha) is located on public and private land outside of YNP (Spatial Analysis Center, 2005).

CVA Change Detection Overview

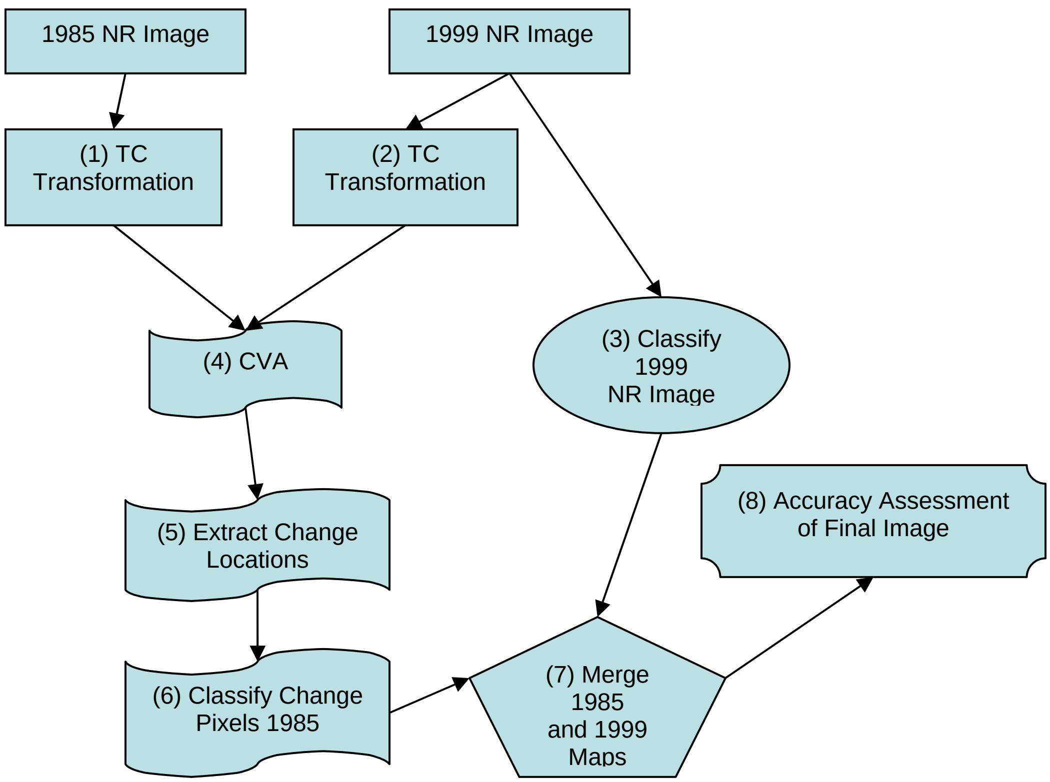
A 1999 base map of rangeland vegetation in the NR was created using 1999 Landsat ETM+ images and ancillary data within the See 5 boosting decision tree classification algorithm as described in Chapter 3. The TC components from the 1999 ETM+ images and the 1985 TM images were used along with CVA (Equation 4.1) to calculate the magnitude of spectral change between the two dates. The change magnitude value allowed a change threshold to be established and utilized to reclassify potentially changed areas on the 1985 image with the decision tree algorithm. The areas of potential change that were classified differently in 1985 than in 1999 were merged together with the unchanged 1999 data to produce a complete map for 1985.

Figure 4.1: Location map for the Northern Range



CVA change detection incorporates the following steps (based on the 1985 and 1999 images above): (1) perform a TC transformation on the 1985 image, (2) perform a TC transformation on the 1999 images, (3) classify the entire 1999 image,(4) conduct a CVA on the TC components of the 1985 and 1999 images, (5) extract potentially changed areas from the 1985 image, (6) reclassify the potentially changed areas on the 1985 image utilizing data from the potentially unchanged pixels as training data, (7) merge the reclassified 1985 image with unchanged pixels in the 1999 image to create the final map, and (8) perform an accuracy assessment on the final map (Figure 4.2).

Figure 4.2: General steps in CVA Process



<u>Image Pre-Processing</u>

The 1999 base map classification was performed using ETM+ imagery. The ETM+ sensor went into operation in 1999. In 1985 the TM sensor was in use. These sensors collect essentially the same information with minor differences in wavelengths and different spatial resolutions for the thermal band (120m for TM and 60m for ETM+). These differences are small enough that comparing differences between images from each sensor is reasonable.

One of the two 1985 images at the Spatial Analysis Center was too cloudy to use in analysis, so one Landsat TM satellite image from September 16, 1985 was utilized in the project. The image has 30-m spatial resolution and includes seven bands of spectral data: blue, green, red, near infrared, two middle infrared, and thermal infrared.

The image provided was unrectified so geometric correction was necessary. The image was georectified to match the September 1999 image using the Geometric Correction Tool in IMAGINE and the nearest neighbor resampling method. The resulting RMS error was 0.1959 or less than half a pixel, which is acceptable for image registration. The output image was in UTM, Zone 12, NAD83 projection.

The scene was masked to the NR boundary to reduce processing time. The image was also transformed in several different ways to produce 11 more unique components of data, as follows.

Using the seven original bands, a standardized principal components analysis (PCA) was performed resulting in seven new components. PCA reduces the amount of data to be analyzed and accounts for the most variance in the original images (Singh, 1989). The components generated from a multidate PCA often represent changes in brightness and greenness (Ingebritsen and Lyon, 1985; Collins and Woodcock, 1996). The change in greenness provides information regarding vegetative cover (Ingebritsen and Lyon, 1985).

A single band of Normalized Difference Vegetation Index (NDVI) (Rouse et al, 1973) was produced. This process used the near infrared and red bands of Landsat imagery to create an index with values from -1 to 1 ([near infrared – red]/[near infrared + red]). Vegetation has high reflectance values in the near infrared portion of the spectrum, and lower values in the visible portion. When NDVI values are closer to 1 there are higher amounts of vegetation in the pixel. The closer the value is to 0, the more bare ground in the pixel. NDVI is effective in extracting vegetation data from imagery.

A Tasseled Cap (TC) transformation was performed to produce three new bands. This process is similar to PC in that it reduces the amount of information to be analyzed into the first three components. The first three components from the TC transformation represent brightness (soil brightness or total reflectance), greenness (relative amounts of leafy green vegetation), and wetness (soil moisture status) (Crist and Cicone, 1984). The original six bands (minus the thermal band) had to be converted from digital numbers (DNs) to reflectance values to create these three bands for the image. This reduces the amount of relative noise and between-scene variability (Huang et al., 2001; NASA, 2004). The total number of components prepared for use in the classification was 18.

Ancillary data used in the study were 30-m elevation data (from a Digital Elevation Model (DEM)), slope in degrees and aspect (N, S, E, W, NE, SE, SW, NW, and flat) derived from the 30-m DEM, and a layer depicting distance from streams utilizing stream data from the USGS National Hydrography Dataset (NHD). The final image used in the change detection and classification process was comprised of 22 components (Table 4.1).

Table 4.1: Components used in the classification process

Number	Component Name	Number	Component Name
1	Sept 1985 Band 1 - Blue	12	PCA Component 5
2	Sept 1985 Band 2 - Green	13	PCA Component 6
3	Sept 1985 Band 3 - Red	14	PCA Component 7
4	Sept 1985 Band 4 - NIR	15	NDVI
5	Sept 1985 Band 5 - MIR	16	TC - Brightness
6	Sept 1985 Band 7 - MIR	17	TC - Greenness
7	Sept 1985 Band 6 - Thermal	18	TC - Wetness
8	PCA Component 1	19	Elevation
9	PCA Component 2	20	Slope in degrees
10	PCA Component 3	21	Aspect
11	PCA Component 4	22	Distance from streams

Change Detection Procedure

The CVA equation utilized in the project applied an adaptation of the Pythagorean Theorem to calculate the change in magnitude between dates in the three main components of TC space: brightness, greenness, and wetness (Equation 4.1) (Parmenter et al., 2003).

Equation 4.1. CVA equation to determine the magnitude of spectral change

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Change Magnitude =

$$((Brightness_1 – Brightness_2)^2 + (Greenness_1 – Greenness_2)^2 + (Wetness_1 – Wetness_2)^2)^{0.5}$$

$*_{1,2}$ refer to the 1999 and the 1985 images respectively

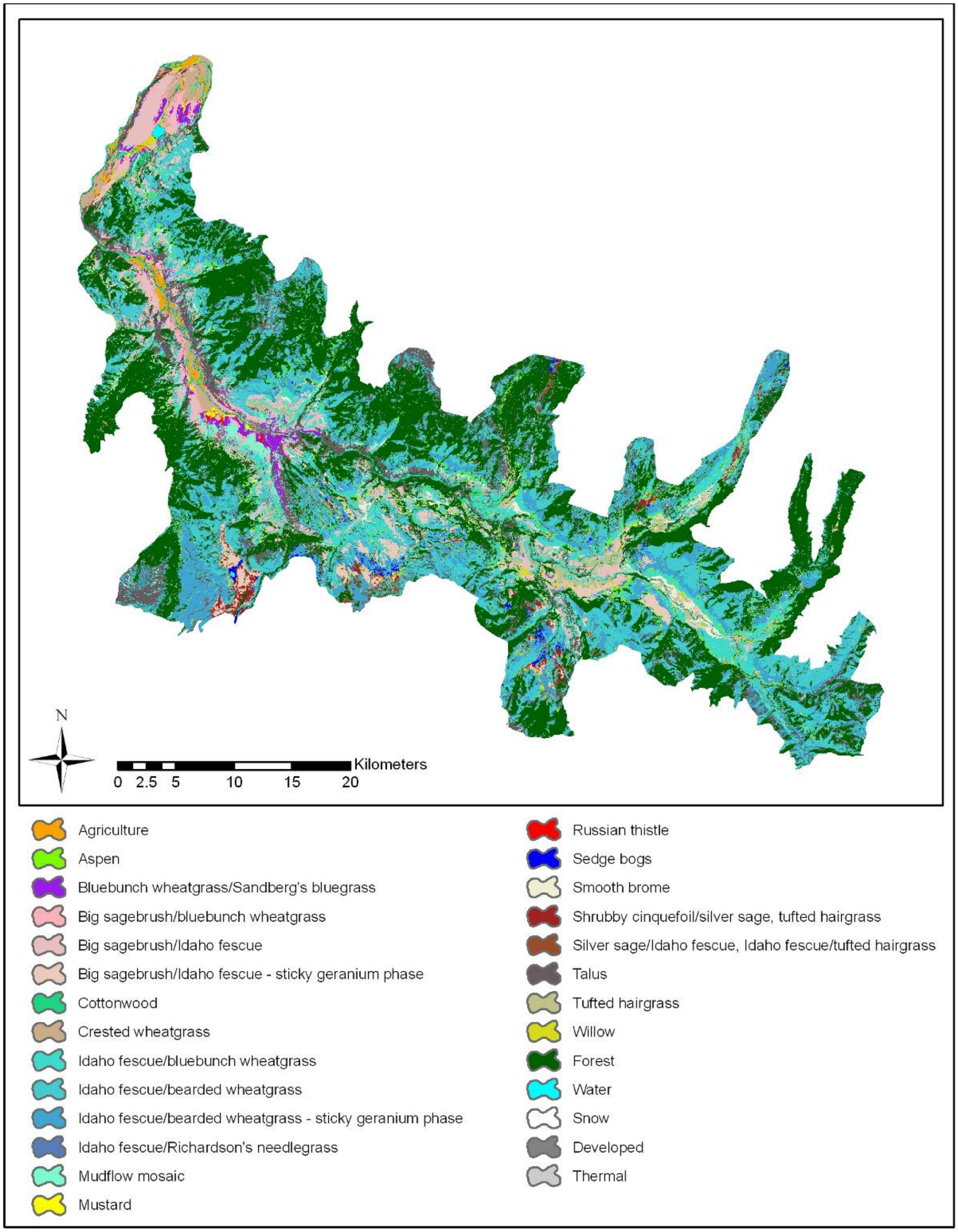
Determining the threshold of change was fairly simple, but somewhat arbitrary. It was important to choose the threshold value so all changes would be detected, but not so high that too many unchanged pixels were included. A value for the threshold was determined interactively on-screen and this threshold delineated where pixels were assumed to have remained the same within the image.

Only the potentially changed pixels were reclassified in the 1985 image. It was necessary to reclassify 10.5% of the image to ensure that all changes were detected. The potentially changed pixels were used to mask out the potentially changed areas from the 22-component 1985 image and the potentially unchanged pixels were used to extract training data from the same image. These training data were input into See 5 along with the 1985 potentially changed data to produce classification trees that were run through the CART extension in IMAGINE, creating a 27-class map for 1985 (Figure 4.3). This process simplified the steps for classifying an image by reducing the area to be classified and increasing the amount of training data.

Accuracy Assessment

High resolution (1:9600-scale) aerial photos from 1986 were provided by the Planning, Compliance and Landscape Architecture Division (PCLA) of YNP. The photos cover a small portion of the NR and were used for accuracy assessment. Cost constraints prohibited the purchase of 1986 images. Since the Spatial Analysis Center at YNP already had images from 1985 and there had been no drastic or catastrophic weather or fire events between years, it was acceptable to use validation data from the 1986 photos to test the accuracy of the classification of the 1985 image.

Figure 4.3: Classified map of the NR from 1985



CIR aerial photos were flown of the entire park in 1998 and funded partially by Monica Turner at the University of Wisconsin – Madison for a soil study within the park. There were no drastic or catastrophic weather or fire events from 1998 to 1999, so it was acceptable to use these 1998 photos for comparison between 1985 and 1999.

A cursory accuracy assessment with the 1986 aerial photos was necessary. An assumption was made that the potentially unchanged pixels were, in fact, unchanged, and that errors of omission did not occur. A total of 269 stratified random validation sites on 38 photos were used to determine the accuracies of the 1985 classification. The high resolution of the photos allowed interpretation of specific vegetation details.

The vegetation information from these validation sites was used as reference data to compare to the output of the 1985 classification. An error matrix was created for Level 5 to demonstrate the overall accuracies at the most detailed level. The error matrices for Levels 1 through 4 were created by combining classes from the Level 5 error matrix. A Kappa statistic was also calculated for each level of the hierarchy. The Kappa statistic measures how far the classification is from a random classification and is more conservative than the overall accuracy. A Kappa value of 1 means the classification is 100% correct.

Two sets of aerial photos from 1986 and 1998 were visually compared in addition to the accuracy assessment, specifically in areas where change was known to have occurred and areas where the change threshold indicated changes did not happen. One hundred random sites were examined on both sets of photos.

A full accuracy assessment on the change detection of 27 classes was impractical as the error matrix would have 729 classes (each of the 27 classes could either stay the same or, theoretically, change to any of the other 26 classes). To test the accuracy of the change detection analysis in a simple manner, four change classes were designated for the error matrix (Table 4.2). 30 random sites were identified on the 1998 photos for each of the four change classes.

Table 4.2: Designations for land cover change classes

Class in 1985	Class in 1999	Change Class Designation	Ecological Interpretation
Shrubland	Shrubland	NC - Shrub	No Change - Shrubland
Herbaceous	Shrubland	Shrub Increase	Shrubland Increase
Shrubland	Herbaceous	Shrub Decrease	Shrubland Decrease
Herbaceous	Herbaceous	NC - Herb	No Change - Herbaceous

Results

Overall accuracy of the change detection analysis was 73.33% (Table 4.3). The change detection process was fairly successful at distinguishing areas of change from areas of no change within the shrubland and herbaceous vegetation classes of Level 1. The presence of no markedly low accuracies shows that the CVA threshold value was not too high. Compound errors within the many different classes for the 1985 and 1999 classifications might have contributed to misclassifications within the change detection.

Table 4.3: Error matrix for 1985-1999 change detection analysis

	Reference Data					
	Class Designation	NC - Shrub	Shrub Increase	Shrub Decrease	NC - Herb	User's accuracy
Classified Data	NC - Shrub	22	4	2	2	73.33%
	Shrub Increase	2	24	3	1	80.00%
	Shrub Decrease	2	5	21	2	70.00%
	NC - Herb	1	3	5	21	70.00%
	Producer's accuracy	81.48%	66.67%	67.74%	80.77%	

Overall Accuracy = 73.33%
Kappa = 0.644

<u>Level 1</u>

Level 1 of the classification had four classes. The overall accuracy of the final map produced at this level was 88.73% (Table 4.4). Error matrices also showed errors of commission and errors of omission by looking at the accuracies of the individual classes. Errors of commission can be determined with user's accuracy, which indicates how well a classified pixel actually represents the truth on the ground. User's accuracy compares the number of correctly classified pixels with the row totals, which represent the total number of classified pixels in each class (Congalton, 2001). User's accuracies for Level 1 ranged from 80.70% for shrubland to 93.39% for herbaceous vegetation (Table 4.5).

Errors of omission can be determined with producer's accuracy, which indicates the probability of the reference or validation data being classified correctly. Producer's accuracy compares the number of correctly classified pixels with the column totals, which represent the reference data (Congalton, 2001). Producer's accuracies for Level 1 ranged from 83.33% for woodland to 91.13% for herbaceous vegetation (Table 4.4).

Table 4.4: Error matrix for Level 1

Reference Data

	Class Name	Sparse veg	Herbaceous veg	Shrubland	Woodland	Row Total
Classified Data	Sparse veg	12	1	1	0	14
	Herbaceous veg	1	113	5	2	121
	Shrubland	1	10	46	0	57
	Woodland	0	0	2	10	12
	Column Total	14	124	54	12	181

Overall Accuracy = 88.73%
Kappa = 0.798

Table 4.5: User's and producer's accuracies for Level 1

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Sparse veg	14	14	12	85.71%	85.71%
Herbaceous veg	124	121	113	91.13%	93.39%
Shrubland	54	57	46	85.19%	80.70%
Woodland	12	12	10	83.33%	83.33%
Totals	204	204	181		

Level 2

Level 2 of the classification hierarchy had five classes. The overall accuracy for the final map produced at this level was 88.73% (Table 4.6). User's accuracies ranged from 73.68% for deciduous shrubland to 93.39% for herbaceous vegetation. Producer's accuracies ranged from 82.05% for evergreen shrubland to 93.33% for deciduous shrubland (Table 4.7).

Table 4.6: Error matrix for Level 2

Reference Data

Classified Data

Class Name	Boulder, gravel, cobble, or talus sparse veg	Herbaceous veg	Evergreen shrubland	Deciduous shrubland	Deciduous Woodland	Row total
Boulder, gravel, cobble, or talus sparse veg	12	1	1	0	0	14
Herbaceous veg	1	113	5	0	2	121
Evergreen shrubland	0	6	32	0	0	38
Deciduous shrubland	1	4	0	14	0	19
Deciduous woodland	0	0	1	1	10	12
Column total	14	124	39	15	12	181

Overall Accuracy = 88.73%

Kappa = 0.809

Table 4.7: User's and producer's accuracies for Level 2

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Boulder, gravel, cobble, or talus sparse veg	14	14	12	85.71%	85.71%
Herbaceous veg	124	121	113	91.13%	93.39%
Evergreen shrubland	39	38	32	82.05%	84.21%
Deciduous shrubland	15	19	14	93.33%	73.68%
Deciduous woodland	12	12	10	83.33%	83.33%
Totals	204	204	181		

Level 3

Level 3 of the classification hierarchy had seven classes. The overall accuracy for the final map produced at this level was 84.31% (Table 4.8). User's accuracies ranged from 68.18% for perennial graminoid vegetation – wet to 100% for deciduous woodland - dry. Producer's accuracies were 75% for perennial graminoid vegetation – wet to 93.33% for deciduous shrubland – wet (Table 4.9).

Table 4.8: Error matrix for Level 3

Reference Data

		Deciduous Woodland - Dry	Deciduous Woodland - Wet	Evergreen Shrubland - Dry	Deciduous Shrubland - Wet	Perennial Graminoid Veg - Dry	Perennial Graminoid Veg - Wet	Boulder, Gravel, Cobble, or Talus Sparse Veg	row total
Classified Data	Deciduous Woodland - Dry	4	0	0	0	0	0	0	4
	Deciduous Woodland - Wet	0	6	1	1	0	0	0	8
	Evergreen Shrubland - Dry	0	0	32	0	5	1	0	38
	Deciduous Shrubland - Wet	0	0	0	14	2	2	1	19
	Perennial Graminoid Veg - Dry	1	1	5	0	89	2	1	99
	Perennial Graminoid Veg - Wet	0	0	0	0	7	15	0	22
	Boulder, Gravel, Cobble, or Talus Sparse Veg	0	0	1	0	1	0	12	14
	column total	5	7	39	15	104	20	14	172

Overall Accuracy = 84.31%
Kappa = 0.774

Table 4.9: User’s and producer’s accuracies for Level 3

Class Name	Reference Totals	Classified Totals	Number Correct	Producer’s Accuracy	User’s Accuracy
Deciduous Woodland - Dry	5	4	4	80.00%	100.00%
Deciduous Woodland - Wet	7	8	6	85.71%	75.00%
Evergreen Shrubland - Dry	39	38	32	82.05%	84.21%
Deciduous Shrubland - Wet	15	19	14	93.33%	73.68%
Perennial Graminoid Veg - Dry	104	99	89	85.58%	89.90%
Perennial Graminoid Veg - Wet	20	22	15	75.00%	68.18%
Boulder, Gravel, Cobble, or Talus Sparse Veg	14	14	12	85.71%	85.71%
Totals	204	204	172		

The overall accuracy was fairly high and none of the user’s or producer’s accuracies were substantially low. Confusion was observed between perennial graminoid vegetation – wet and perennial graminoid vegetation – dry.

Level 4

Level 4 of the classification hierarchy had 10 classes. The overall accuracy for the final map produced at this level was 79.90% (Table 4.10). User’s accuracies ranged from 61.54% for temporarily flooded temperate or subpolar grassland to 100% for perennial grass crops (hayland, pastureland) and cold-deciduous woodland. Producer’s accuracies ranged from 72.73% for temporarily flooded temperate or subpolar grassland to 86.25% for medium-tall bunch temperate or subpolar grassland (Table 4.11).

Table 4.10: Error matrix for Level 4

Reference Data

Classified Data: Class Name	Lowland or submontane talus/scree	Pernnial grass crops (hayland, pastureland	Medium-tall bunch temperate or subpolar grassland	Temporarily flooded temperate or subpolar grassland	Seasonally flooded temperate or subpolar grassland	Lowland microphyllous evergreen shrubland	Temporarily flooded cold-deciduous shrubland	Seasonally flooded cold-deciduous shrubland	Cold-deciduous woodland	Temporarily flooded cold-deciduous woodland	Row Total
Lowland or submontane talus/scree	12	1	0	0	0	1	0	0	0	0	14
Pernnial grass crops (hayland, pastureland)	0	18	0	0	0	0	0	0	0	0	18
Medium-tall bunch temperate or subpolar grassland	1	2	69	1	1	5	0	0	1	1	81
Temporarily flooded temperate or subpolar grassland	0	0	5	8	0	0	0	0	0	0	13
Seasonally flooded temperate or subpolar grassland	0	1	1	0	7	0	0	0	0	0	9
Lowland microphyllous evergreen shrubland	0	2	3	1	0	32	0	0	0	0	38
Temporarily flooded cold-deciduous shrubland	0	0	1	1	1	0	7	0	0	0	10
Seasonally flooded cold-deciduous shrubland	1	0	1	0	0	0	1	6	0	0	9
Cold-deciduous woodland	0	0	0	0	0	0	0	0	4	0	4
Temporarily flooded cold-deciduous woodland	0	0	0	0	0	1	0	1	0	6	8
Column Total	14	24	80	11	9	39	8	7	5	7	169

Overall Accuracy = 79.90% Kappa = 0.781

Table 4.11: User's and producer's accuracies for Level 4

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Lowland or submontane talus/scree	14	14	12	85.71%	85.71%
Perennial grass crops (hayland, pastureland)	24	18	18	75.00%	100.00%
Medium-tall bunch temperate or subpolar grassland	80	81	69	86.25%	85.19%
Temporarily flooded temperate or subpolar grassland	11	13	8	72.73%	61.54%
Seasonally flooded temperate or subpolar grassland	9	9	7	77.78%	77.78%
Lowland microphyllous evergreen shrubland	39	38	32	82.05%	84.21%
Temporarily flooded cold-deciduous shrubland	8	10	7	87.50%	70.00%
Seasonally flooded cold-deciduous shrubland	7	9	6	85.71%	66.67%
Cold-deciduous woodland	5	4	4	80.00%	100.00%
Temporarily flooded cold-deciduous woodland	7	8	6	85.71%	75.00%
Totals	204	204	163		

Level 5

Level 5 of the classification hierarchy had 27 classes (see Appendix A for class definitions). The overall accuracy for the final map produced at this level was 72.60% (Table 4.12). User's accuracies ranged from 53.85% for thermal areas to 100% for agriculture, aspen, crested wheatgrass, and water. Producer's accuracies ranged from 16.67% for crested wheatgrass to 100% for mudflow mosaic, Russian thistle, and developed areas (Table 4.13).

Table 4.12: Error matrix for Level 5 (with abbreviations – see Appendix A)

Classified Data	ag	asp	bbwgsb	bsbbbw	bsbif	bsbifst	ctnwd	cw	ifbbwg	ifbwg	ifbwgst	ifrng	mud	must	rt	sbog	sbrm	scssth	ssifth	tal	thg	wil	forest	water	snow	dev	therm	Row Total
ag	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
asp	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
bbwgsb	2	0	9	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14
bsbbbw	0	0	0	8	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11
bsbif	0	0	1	0	9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	13
bsbifst	0	0	0	0	0	13	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	16
ctnwd	0	0	0	0	1	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	8
cw	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
ifbbwg	0	0	0	0	0	1	1	0	12	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16
ifbwg	0	0	0	0	0	1	0	0	1	11	2	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	2	19
ifbwgst	0	0	0	0	0	0	0	0	0	1	8	0	0	0	0	1	0	0	1	1	0	0	2	0	0	0	0	14
ifrng	0	0	0	0	0	1	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
mud	0	0	0	1	0	0	0	0	0	1	0	0	7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	10
must	0	0	0	0	0	0	0	1	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	9
rt	0	0	0	0	0	0	0	0	0	0	0	0	0	1	7	0	0	0	0	0	0	0	0	0	0	0	0	8
sbog	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	7	0	0	0	0	0	0	0	0	0	0	0	9
sbrm	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	8
scssth	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	7	0	0	1	0	0	0	0	0	0	10
ssifth	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	4
tal	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	12	0	0	0	1	0	0	0	15
thg	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	5	0	0	0	0	0	0	9
wil	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	6	0	0	0	0	0	9
forest	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	2	0	0	10	1	0	0	0	16
water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	6
snow	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dev	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	13	0	18
therm	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	3	0	7	13
Column Total	4	5	13	9	14	17	8	6	15	19	15	7	7	13	7	10	8	8	5	17	7	7	14	8	4	13	9	269

Overall Accuracy = 72.60% Kappa = 0.714

Table 4.13: User’s and producer’s accuracies for Level 5

Class Name	Reference Totals	Classified Totals	Number Correct	Producer’s Accuracy	User’s Accuracy
Agriculture	4	2	2	50.00%	100.00%
Aspen	5	4	4	80.00%	100.00%
Bluebunch wheatgrass/Sandberg’s bluegrass – needle-and-thread phase	13	14	9	69.23%	64.29%
Big sagebrush/bluebunch wheatgrass	9	11	8	88.89%	72.73%
Big sagebrush/Idaho fescue	14	13	9	64.29%	69.23%
Big sagebrush/Idaho fescue – sticky geranium phase	17	16	13	76.47%	81.25%
Cottonwood	8	8	6	75.00%	75.00%
Crested Wheatgrass	6	1	1	16.67%	100.00%
Idaho fescue/bluebunch wheatgrass	15	16	12	80.00%	75.00%
Idaho fescue/bearded wheatgrass	19	19	11	57.89%	57.89%
Idaho fescue/bearded wheatgrass – sticky geranium phase	15	14	8	53.33%	57.14%
Idaho fescue/Richardson’s needlegrass	7	7	6	85.71%	85.71%
Mudflow mosaic	7	10	7	100.00%	70.00%
Mustard	13	9	8	61.54%	88.89%
Russian thistle	7	8	7	100.00%	87.50%
Sedge bogs	10	9	7	70.00%	77.78%
Smooth brome	8	8	5	62.50%	62.50%
Shrubby cinquefoil-silver sage/tufted hairgrass	8	10	7	87.50%	70.00%
Silver sage/Idaho fescue, Idaho fescue/tufted hairgrass	5	4	3	60.00%	75.00%
Talus	17	15	12	70.59%	80.00%

Tufted hairgrass/sedge	7	9	5	71.43%	55.56%
Willow/sedge	7	9	6	85.71%	66.67%
Forest	14	16	10	71.43%	62.50%
Water	8	6	6	75.00%	100.00%
Snow	4	0	4	---	---
Developed	13	18	13	100.00%	72.22%
Thermal	9	13	7	77.78%	53.85%
Totals	281	281	204		

The overall accuracies for the 1985 and 1999 classifications were quite similar (Table 4.14), which is not surprising since the 1999 data were used to train the 1985 data. Both classifications experienced some confusion among the classes with Idaho fescue and between cottonwood and willow. There appeared to be higher error within the talus class and a couple of the classes of exotic species (crested wheatgrass and mustard (*Chorispora tenella*)) in the 1985 map.

Table 4.14: Overall accuracies of the 1985 and 1999 classifications

Level	1985 Accuracy	1999 Accuracy
1	88.73%	83.65%
2	88.73%	82.27%
3	84.31%	78.53%
4	79.90%	73.66%
5	72.60%	72.30%

The values of the change in magnitude between the 1985 and 1999 images ranged from 0.004 to 1.079 and the threshold was chosen at 0.173. Pixels with change values less than 0.173 were assumed to have remained the same and were utilized as a mask for training data. This value appears to have caught most of the changes, but not all of them.

Although 10.5% of the image was reclassified, around 95% of the NR remained unchanged from 1985 to 1999, thus just over 5% of the potentially changed pixels in the 1985 image were reclassified to the same categories as the 1999 classification and around 5% were classified as changed. Changes were detected between the two images (Table 4.15). Level 5 classes of note that increased were aspen and forest. Level 5 classes of note that decreased were crested wheatgrass, Russian thistle, and Idaho fescue/bearded wheatgrass (including the sticky geranium phase). The largest changes within the entire NR were in the forest and Idaho fescue/bearded wheatgrass classes, although only the forest class changed by more than 1%. The largest changes within classes were increases in aspen, water, snow, developed, and thermal areas, and decreases in crested wheatgrass and Russian thistle.

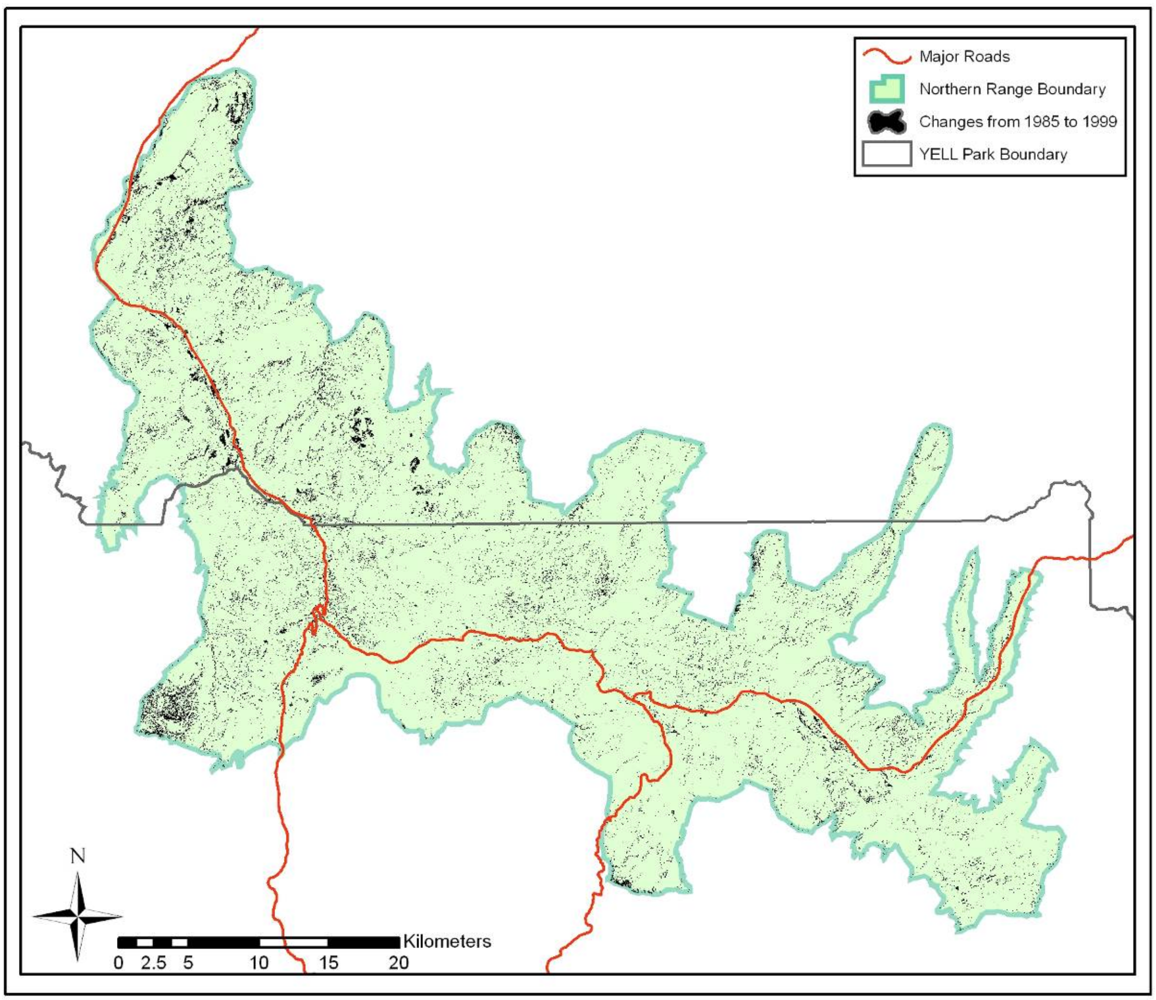
The increase of aspen is positive in the realm of habitat management in YNP, as this species is thought to be slowly going extinct (Renkin, 2002). As crested wheatgrass and Russian thistle are non-native to the NR, the large decrease in their numbers is positive for the ecosystem. Crested wheatgrass was introduced in northern YNP and Paradise Valley between 1930 and 1950 as a reclamation species on disturbed sites because it was thought that after five years or so it would give way to native vegetation. On the contrary, it has proven to be a very hardy and aggressive exotic species. Russian thistle, commonly known as tumbleweed, is an exotic annual that was most likely introduced into the area with contaminated seed.

Table 4.15: Increases and decreases in classes between 1985 and 1999

Class	1985	1999	Difference	NR % change	Class % change
Forest	570351	588208	17857	1.05%	3.13%
Aspen	38072	41583	3511	0.21%	9.22%
Talus	155055	156938	1883	0.11%	1.21%
Water	9418	11221	1803	0.11%	19.14%
Big sagebrush/bluebunch wheatgrass	24324	25012	688	0.04%	2.83%
Silver sage/Idaho fescue, Idaho fescue/tufted hairgrass	8243	8838	595	0.04%	7.22%
Shrubby cinquefoil – silver sage/tufted hairgrass	18710	19177	467	0.03%	2.50%
Thermal	1493	1827	334	0.02%	22.37%
Developed	1706	2011	305	0.02%	17.88%
Cottonwood	13111	13357	246	0.01%	1.88%
Idaho fescue/Richardson’s needlegrass	5128	5333	205	0.01%	4.00%
Snow	529	629	100	0.01%	18.90%
Mustard	2683	2722	39	0.00%	1.45%
Sedge bogs	5973	6012	39	0.00%	0.65%
Russian thistle	1454	1273	-181	-0.01%	-12.45%
Smooth Brome	15472	15228	-244	-0.01%	-1.58%
Mudflow mosaic	8925	8671	-254	-0.01%	-2.85%
Willow	16015	15738	-277	-0.02%	-1.73%
Agriculture	7287	6849	-438	-0.03%	-6.01%
Big sagebrush/Idaho fescue	63300	62356	-944	-0.06%	-1.49%
Bluebunch wheatgrass/ Sandberg’s bluegrass – needle-and-thread phase	15302	14324	-978	-0.06%	-6.39%
Tufted hairgrass	25939	24672	-1267	-0.07%	-4.88%
Big sagebrush/Idaho fescue – sticky geranium phase	60297	58706	-1591	-0.09%	-2.64%
Crested wheatgrass	20611	18789	-1822	-0.11%	-8.84%
Idaho fescue/bluebunch wheatgrass	131923	129186	-2737	-0.16%	-2.07%
Idaho fescue/bluebunch wheatgrass – sticky geranium phase	170072	163367	-6705	-0.40%	-3.94%
Idaho fescue/bearded wheatgrass	304949	294315	-10634	-0.63%	-3.49%
Total number of pixels classified	1696342				

Changes were observed throughout the NR (Figure 4.4). Many of the changes were located along road corridors, especially outside of YNP. This is to be expected as this is where human impacts are most prominent. Much of the change within and to some extent outside of YNP was in the flat lowlands of valleys. Other compact groups of change were observed in higher elevations where snow in 1985 was covering vegetation that was exposed in 1999.

Figure 4.4: Map of changes from 1985 to 1999



Discussion

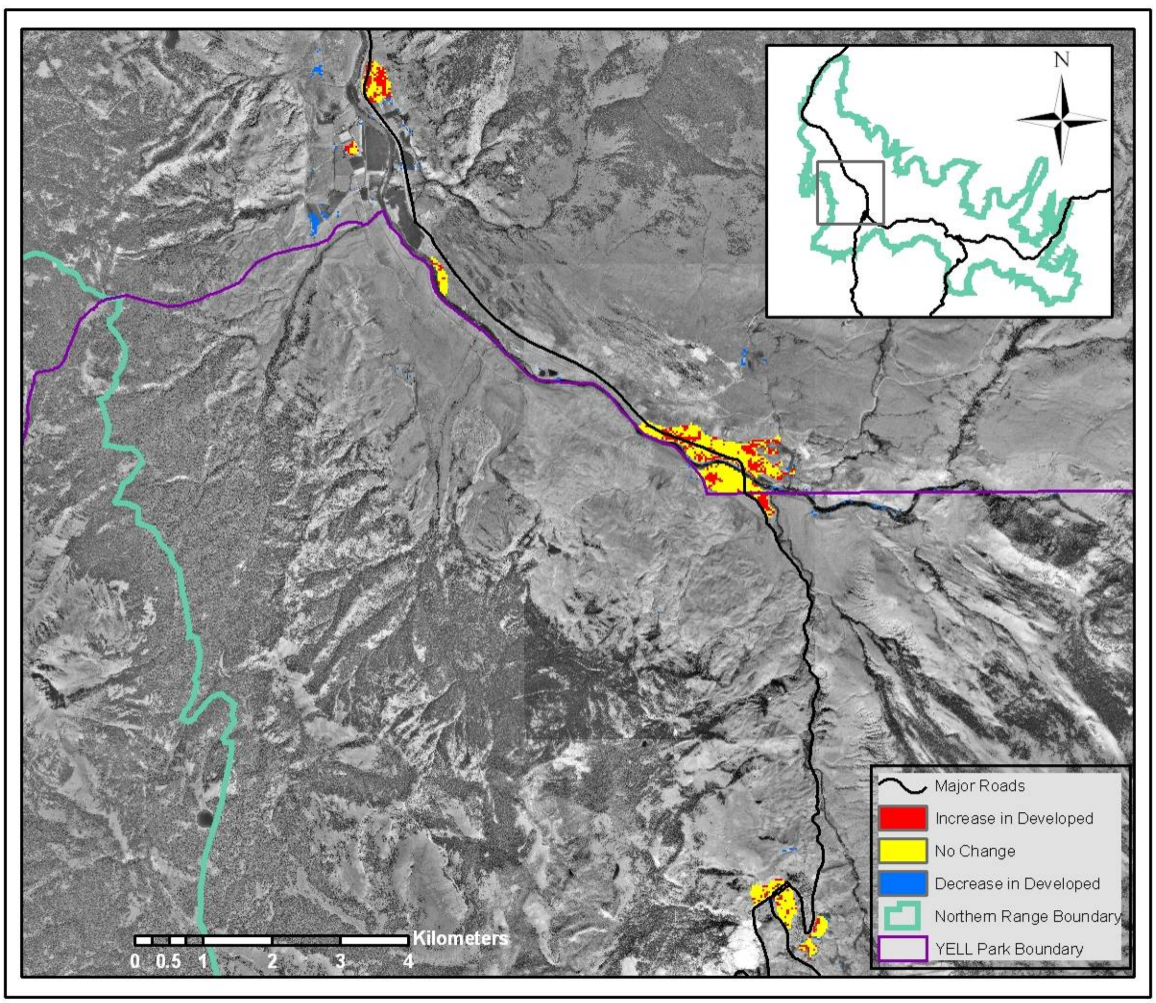
Why did certain classes change in the manner they did? One possible explanation is to attribute the majority of the changes to fire, since it is a natural successional event. Even with the catastrophic fire events of 1988, however, 37.6% of the NR was burned between 1985 and 1999 and the majority of the areas burned were forested areas. Fire can account for some of the changes, but definitely not all. A study in YNP indicated that human-induced suppression of fire might be a contributing factor to vegetation change (Ripple and Larsen, 2001).

Another possible explanation for the changes could be climate. The climate of a particular area depends on temperature and moisture (Gurevitch et al., 2002). The Spatial Analysis Center provided weather data from 1985 through 1999 (Spatial Analysis Center, 1999). The average temperature ranges between years in the weather data do not signify a drastic change in trends during that period. The precipitation data provided, however, indicate that there was 1/3 less precipitation in 1985 than in 1999. The increased precipitation levels in September of 1999, as well as the remains of snow in the high country, might have lengthened the growing season and increased the water levels in rivers and lakes, explaining the increase in some wet vegetation classes, and the decrease in many of the dry vegetation classes in the study (Table 4.15). This represents only the vegetation during that growing season, and does not provide proof that the climate has drastically changed.

Studies are currently under way on the return of beaver to YNP and their influence on willow (Singer et al., 2004). A very slight decrease of willow was indicated in the change detection, hardly enough to warrant concern (Table 4.15). Nevertheless, the small amount of change might be attributable to beaver populations thriving in recent years because beaver utilize willow for food and shelter.

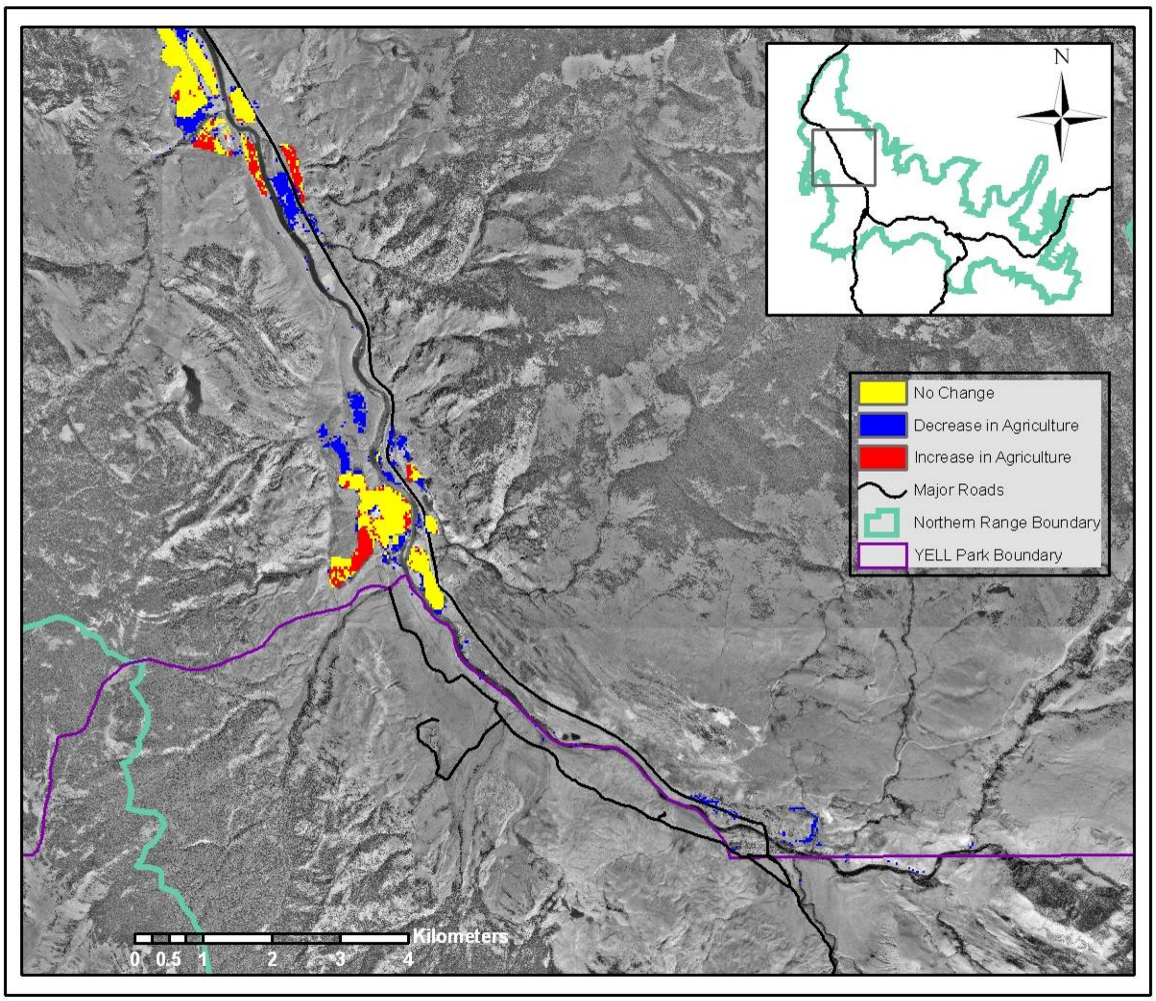
The increase in developed areas (Figure 4.5) is easily explained by the apparently exponential increase in rural sprawl outside YNP in the Paradise Valley (Greater Yellowstone Coalition, 2000). New homes are added to the landscape every year, decreasing the amount of uninterrupted rangeland in the NR.

Figure 4.5: Changes in developed areas from 1985 to 1999



Agricultural land use has decreased significantly in Paradise Valley (Parmenter et al., 2003). This decrease likely corresponds to the increase in development in the area. Many ranches have been sold and subdivided for new housing communities. Several exotic species that have been used in agriculture (crested wheatgrass and mustard) also have decreased within YNP. This can be attributed to the intensive exotic plant removal program YNP has instigated, especially along road and trail corridors near the north entrance (Figure 4.6).

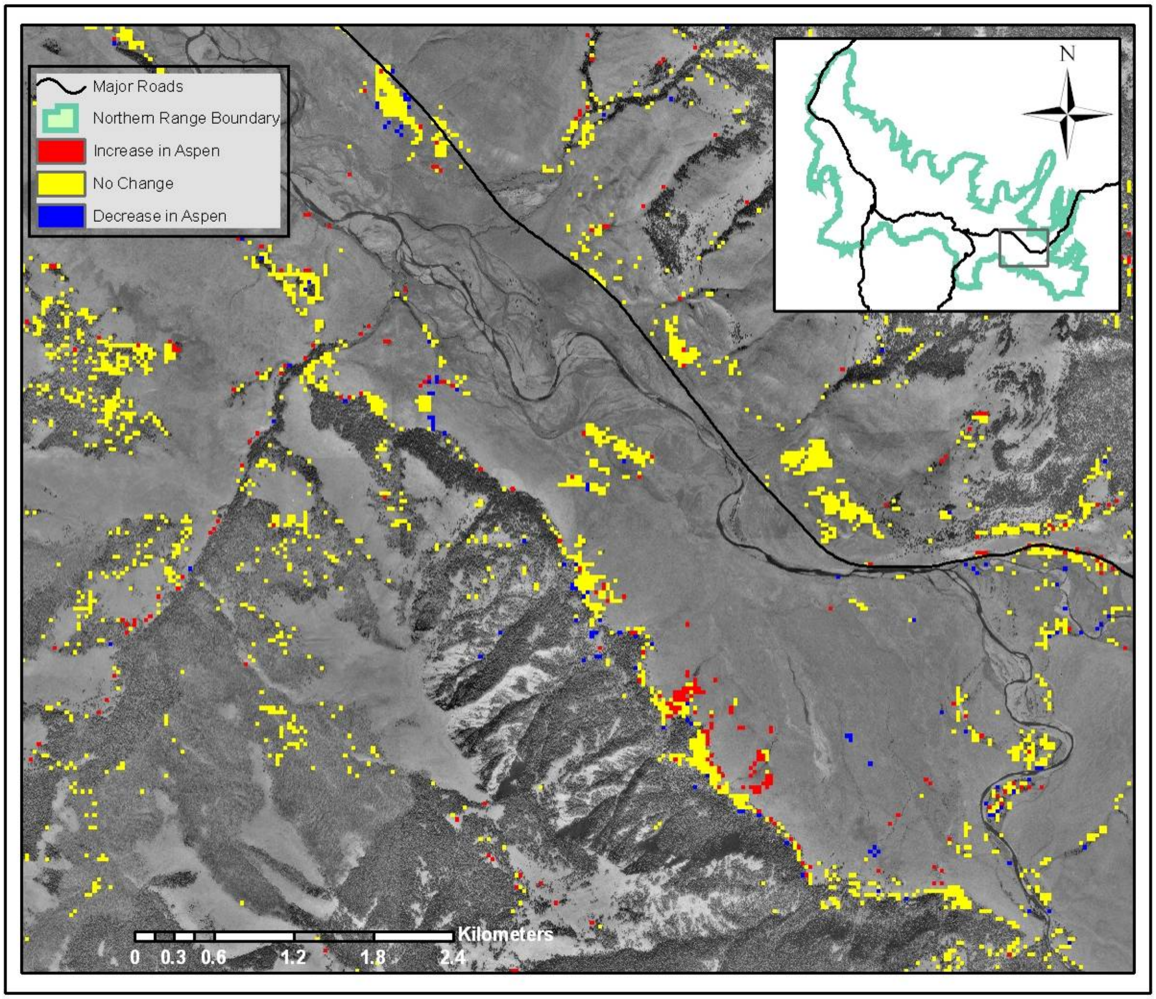
Figure 4.6: Changes in agriculture from 1985 to 1999



Another possible explanation for why certain changes occurred has been proposed by several researchers at YNP (Ripple and Larsen, 2000; Renkin, 2002; Smith, 2004). They hypothesize that the reintroduction of wolves to YNP in 1995 and 1996 has affected the movement of elk in their habitats and thus their use of certain species for food. This specifically relates to edge and riparian species. The idea is that the elk can no longer browse at their leisure and must stay out of open areas for fear of being trapped by wolves. Aspen overstory has declined greatly in the last century (Houston, 1982; Despain, 1990; Kay, 1990; Meagher and Houston, 1990). Scientists in YNP believe that species such as willow and aspen will be utilized less by the elk, therefore will grow at greater rates than in previous years. As the wolves were reintroduced in 1995, these changes might not yet be highly evident in the 1999 classification, although aspen might already be confirming this hypothesis. We would expect to observe an increase in the aspen class if this hypothesis is true (Figure 4.7). The increase in aspen in the NR was second only to forest types (Table 4.15).

Combining CVA and boosting algorithms was an accurate and efficient method for mapping historical rangelands as well as for performing change detection analyses. Determining the magnitude of change value is key in this process. It is important to choose the threshold value so all changes would be detected, but not so high that too many unchanged pixels would be included.

Figure 4.7: Changes in aspen from 1985 to 1999



The individual 1985 and 1999 classification accuracies (88.73% and 83.65% respectively at Level 1, and 72.60% and 72.30% respectively at Level 5) indicate that the boosting algorithm utilized in the classification procedure was effective in distinguishing broad to specific types of rangeland vegetation, however, several classes were mapped poorly at Level 5 in both maps. The accuracy of classifications in the future can be improved in several ways. First, if possible, training and validation data should be collected at the same time the image is flown or near the same time. Second, if cost is not a factor, higher resolution data could be purchased for the classification procedure. Finally, collecting more training and validation data could improve classifications conducted in the manner of this project.

Rangelands by their very nature do not change rapidly (unless through catastrophic events). Monitoring rangelands for change would require updating vegetation maps every five years or so. Using the CVA technique described in this paper, a standard procedure can be established to allow land managers in the NR to study changes over time in this very important ecosystem by comparing current maps with those created for this study.

CHAPTER 5

CONCLUSIONS

The results of this study supported the hypothesis that an accurate, inexpensive, and easily reproducible method for mapping rangelands over the NR and detecting change over time could be developed. Utilizing Landsat satellite imagery, decision trees, and boosting can produce accurate rangeland vegetation maps, even at very specific levels. Good training and validation data are needed for this process to work well. Time spent in the field is imperative for collecting good data. Utilizing the boosting algorithm from See 5 to map the rangeland vegetation for the 1999 base map was an efficient and effective method to classify Landsat imagery and predict the output accuracy. It was an inexpensive method relative to other commercially available software packages (Homer et al., 2004).

CTA performed well overall for mapping the NR. The overall accuracy of this classification on all levels of the hierarchy, although slightly less than the established USGS standard of 85% (Anderson, 1976), was much higher than the current vegetation map used at YNP. The Level 5 classification was particularly exciting because it indicated that specific vegetation types can be distinguished using Landsat data, although some types were harder to distinguish than others. It was previously thought that the relatively low spatial resolution of Landsat data would preclude it from making specific distinctions since the similarity of spectral signatures between species suggested that they would be difficult to discern from one another.

An effective vegetation mapping procedure is important for monitoring ecosystem change at multiple levels, from the broadest vegetation types (forest, woodland or shrubland) to the most specific types (aspen, tufted hairgrass/sedge, or big sagebrush/Idaho fescue). Changes within the NR can be monitored as often as needed by the establishment of the 1999 base map. With Landsat imagery available as far back as 1972, ecosystem-wide changes can be investigated for more than a quarter century. Providing a highly accurate base map is the first step in giving resource managers and scientists tools to study the ecosystem and factors that induce change.

Monitoring techniques such as combining TC and CVA with CTA can be effective methods for change detection at a landscape scale. This method allows the land manager to specify a level of ecological change to be included in the analysis, thus reducing confusion between actual physical changes and image variability.

Utilizing the 1999 rangeland vegetation base map and the CVA method on the 1985 image was an efficient and effective method to detect change over time in rangeland vegetation. The process detected change between the two dates with reasonable accuracy and also produced acceptable accuracy for the 1985 rangeland vegetation classification. The CVA process was an intuitive process once the TC transformations had been completed, and the TC transformation process can be conducted rapidly with the proper instructions. Choosing a threshold of change is an important aspect of this procedure. The threshold must be high enough to detect all changes, yet low enough that it does not include too many no-change pixels. Choosing the threshold is somewhat arbitrary. The threshold used in this study proved to be a bit too low given that some areas of change were missed in the classification.

Creating a base map of rangeland vegetation for 1999 allows the NR to be monitored as often as needed. This base map will be a useful tool for land managers since the NR and the animals that inhabit the area are currently important subjects for research. The 1985 map and the results of the change detection analysis will also be tools for land managers. The classes of greatest change will provide starting points for managers to monitor, while the change detection method will allow for the same sort of analysis for future images of the area.

Landsat TM data continue to be collected every 16 days and should continue through 2009 (USGS, 2005). Landsat data are inexpensive relative to many other available satellite imagery, although they do not have high spatial resolution as compared with IKONOS for example. Along with being inexpensive, thousands of Landsat images are available over a 33-year period, making Landsat a reasonable choice for continuing change detection studies in the NR until a comparable sensor is in orbit.

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APPENDICES

APPENDIX A

HIERARCHICAL CLASSIFICATION

Level 5	Level 4	Level 3	Level 2	Level 1
Agriculture (ag)	Perennial grass crops (hayland, pastureland)	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Aspen (asp) (*Populus tremuloides*)	Cold-deciduous woodland	Deciduous woodland - Dry	Deciduous woodland	Woodland
Bluebunch wheatgrass/Sandberg's bluegrass-needle-and-thread phase (bbwgsbg) (*Agropyron spicatum/Poa secunda -Stipa comata* phase)	Medium-tall bunch temperate or subpolar grassland	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Big sagebrush/bluebunch wheatgrass (bsbbbwg) (*Artemisia tridentata/Agropyron spicatum*)	Lowland microphyllous evergreen shrubland	Evergreen shrubland - Dry	Evergreen shrubland	Shrubland
Big sagebrush/Idaho fescue (bsbif) (*Artemisia tridentata/Festuca idahoensis*)	Lowland microphyllous evergreen shrubland	Evergreen shrubland - Dry	Evergreen shrubland	Shrubland
Big sagebrush/Idaho fescue-sticky geranium phase (bsbifst) (*Artemisia tridentata/Festuca idahoensis - Geranium viscosissimum* phase)	Lowland microphyllous evergreen shrubland	Evergreen shrubland - Dry	Evergreen shrubland	Shrubland
Cottonwood (ctnwd) (*Populus spp.*)	Temporarily flooded cold-deciduous woodland	Deciduous woodland - Wet	Deciduous woodland	Woodland
Crested wheatgrass (Exotic) (cw) (*Agropyron cristatum*)	Perennial grass crops (hayland, pastureland)	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation

Level 5	Level 4	Level 3	Level 2	Level 1
Idaho fescue/bluebunch wheatgrass (ifbbwg) (*Festuca idahoensis/Agropyron spicatum*)	Medium-tall bunch temperate or subpolar grassland	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Idaho fescue/bearded wheatgrass (ifbwg) (*Festuca idahoensis/Agropyron caninum*)	Medium-tall bunch temperate or subpolar grassland	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Idaho fescue/bearded wheatgrass-sticky geranium phase (ifbwgst) (*Festuca idahoensis/Agropyron caninum - Geranium viscosissimum* phase)	Medium-tall bunch temperate or subpolar grassland	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Idaho fescue/Richardson's needlegrass (ifrng) (*Festuca idahoensis/Stipa richardsonii*)	Medium-tall bunch temperate or subpolar grassland	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Mudflow mosaic (mud)	Medium-tall bunch temperate or subpolar grassland	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Mustard (Exotic) (must) (*Chorispora tenella*)	Perennial grass crops (hayland, pastureland)	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Russian thistle (Exotic) (rt) (*Salsola australis*)	Perennial grass crops (hayland, pastureland)	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Sedge bogs (sbog) (*Carex spp.*)	Seasonally flooded temperate or subpolar grassland	Perennial graminoid vegetation - Wet	Perennial graminoid vegetation	Herbaceous vegetation

Level 5	Level 4	Level 3	Level 2	Level 1
Smooth brome (Exotic) (sbrm) (*Bromus inermis*)	Medium-tall bunch temperate or subpolar grassland	Perennial graminoid vegetation - Dry	Perennial graminoid vegetation	Herbaceous vegetation
Shrubby cinquefoil-silver sage/tufted hairgrass (scssth) (*Potentilla fruticosa-Artemisia cana/Deschampsia cespitosa*)	Temporarily flooded cold-deciduous shrubland	Deciduous shrubland - Wet	Deciduous shrubland	Shrubland
Silver sage/Idaho fescue, Idaho fescue/tufted hairgrass (ssifth) (*Artemisia cana/Festuca idahoensis, Festuca idahoensis/Deschampsia cespitosa*)	Temporarily flooded temperate or subpolar grassland	Perennial graminoid vegetation - Wet	Perennial graminoid vegetation	Herbaceous vegetation
Talus (tal)	Lowland or submontane talus/scree	Boulder, gravel, cobble, or talus sparse vegetation - Dry	Boulder, gravel, cobble, or talus sparse vegetation	Sparse vegetation
Tufted hairgrass/sedge (thg) (*Deschampsia cespitosa/Carex spp.*)	Temporarily flooded temperate or subpolar grassland	Perennial graminoid vegetation - Wet	Perennial graminoid vegetation	Herbaceous vegetation
Willow/sedge (wil) (*Salix spp./Carex spp.*)	Seasonally flooded cold-deciduous shrubland	Deciduous shrubland - Wet	Deciduous shrubland	Shrubland
Forest (forest)				
Water (water)				
Snow (snow)				
Developed (dev)				
Thermal (therm)				

APPENDIX B

FGDC COMPLIANT METADATA FOR 1999 CLASSIFICATION

Identification_Information:
 Citation:
  Citation_Information:
   Originator: Spatial Analysis Center - Yellowstone National Park
   Originator: Montana State University - Remote Sensing Lab
   Originator: Shannon Savage
   Publication_Date: 20051103
   Title: 1999 Five-Level Non-Forest Vegetation Map of the Northern Range, Yellowstone National Park, Montana, Wyoming
   Geospatial_Data_Presentation_Form: remote-sensing image
 Description:
  Abstract: This is an image file showing the non-forest vegetation in the Northern Range (NR) of Yellowstone National Park (YNP) in 1999. The data were extracted from two Landsat ETM+ images from July 13, 1999 and September 15, 1999 utilizing boosting and classification tree analysis in the program, See 5. The minimum mapping unit is 30-m pixels. The data were created with a hierarchical classification scheme that ranges from very broad vegetation in Level 1 to specific habitat types in Level 5.
  Purpose: To create a base map of non-forest vegetation in the NR of YNP to be used in change detection analyses. The intended use of all data in the park's GIS library is to support diverse park activities including planning, management, maintenance, research, and interpretation.
 Time_Period_of_Content:
  Time_Period_Information:
   Range_of_Dates/Times:
    Beginning_Date: 19990713
    Ending_Date: 19990915
  Currentness_Reference: ground condition
 Status:
  Progress: Complete
  Maintenance_and_Update_Frequency: None planned
 Spatial_Domain:
  Bounding_Coordinates:
   West_Bounding_Coordinate: -110.905418
   East_Bounding_Coordinate: -110.018798
   North_Bounding_Coordinate: 45.322369
   South_Bounding_Coordinate: 44.764661
 Keywords:
  Theme:
   Theme_Keyword_Thesaurus: none
   Theme_Keyword: Vegetation, Landsat, Rangelands, Non-forest, Classification, Satellite Remote Sensing
  Place:
   Place_Keyword_Thesaurus: none

Place_Keyword: National Park Service, NPS, Department of the Interior, DOI, US Government
Place_Keyword: United States of America, US, USA, North America
Place_Keyword: Northern Range, Yellowstone National Park, YNP, YELL, Greater Yellowstone Area, GYA, Greater Yellowstone Ecosystem, GYE, Park County, Montana, Wyoming, Northern Rocky Mountains
Access_Constraints: none
Use_Constraints: none
Point_of_Contact:
Contact_Information:
Contact_Organization_Primary:
Contact_Organization: Spatial Analysis Center - Yellowstone National Park
Contact_Position: GIS Specialist
Contact_Address:
Address_Type: mailing address
Address: Yellowstone Center for Resources
Address: Spatial Analysis Center
Address: P.O. Box 168
City: Yellowstone National Park
State_or_Province: Wyoming
Postal_Code: 82190
Country: USA
Contact_Voice_Telephone: 307-344-2246
Contact_Facsimile_Telephone: 307-344-2211
Contact_Electronic_Mail_Address: yell_gis@nps.gov
Hours_of_Service: 8:00 a.m. to 4:00 p.m. (Mountain Time) Monday through Friday
Contact_Instructions: Please check website first: http://www.nps.gov/yell/technical/gis
Data_Set_Credit:
National Park Service, Yellowstone National Park, Intermountain Region
Montana State University, Remote Sensing Lab
Shannon Savage, GIS Specialist and Masters Candidate
Security_Information:
Security_Classification_System: None
Security_Classification: None
Security_Handling_Description: None
Native_Data_Set_Environment: Microsoft Windows XP Version 5.1 (Build 2600) Service Pack 2; ESRI ArcCatalog 9.0.0.535
Cross_Reference:
Citation_Information:
Originator: Shannon Savage
Publication_Date: 20051128
Title: Vegetation Dynamics in Yellowstone's Northern Range: 1985-1999

Other_Citation_Details: Master's thesis, Montana State University, Department of Land Resources and Environmental Sciences. 153 pp.
Data_Quality_Information:
Attribute_Accuracy:
Attribute_Accuracy_Report: Data were developed from Landsat ETM+ images for Path 38 Row 29 (July 13, 1999 and September 15, 1999). Park staff have ground checked and verified all features to the best of their knowledge. GIS personnel verified all features and attributes.
Logical_Consistency_Report: There are no duplicate features present.
Completeness_Report: The data only include features shown in the Landsat image. Additional features may exist.
Positional_Accuracy:
Horizontal_Positional_Accuracy:
Horizontal_Positional_Accuracy_Report:
Overall accuracies of these data were calculated by error matrices. A Kappa statistic was calculated for each level as well.

Level 1 Accuracy = 83.65% Kappa = 0.689
Level 2 Accuracy = 82.27% Kappa = 0.674
Level 3 Accuracy = 78.53% Kappa = 0.675
Level 4 Accuracy = 73.66% Kappa = 0.722
Level 5 Accuracy = 73.30% Kappa = 0.722
Lineage:
Source_Information:
Source_Citation:
Citation_Information:
Originator: United State Geological Survey
Originator: EROS Data Center - Sioux Falls
Publication_Date: 19990713
Title: Landsat ETM+ 7-band Image from July 13, 1999
Geospatial_Data_Presentation_Form: remote-sensing image
Source_Scale_Denominator: 30-m
Type_of_Source_Media: Landsat ETM+ 7-band Image
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 19990713
Source_Currentness_Reference: ground condition
Source_Citation_Abbreviation: JulyETM
Source_Contribution: Provided original data from which to derive vegetation information.
Source_Information:
Source_Citation:
Citation_Information:

Originator: United State Geological Survey
Originator: EROS Data Center - Sioux Falls
Publication_Date: 19990915
Title: Landsat ETM+ 7-band Image from September 15, 1999
Geospatial_Data_Presentation_Form: remote-sensing image
Source_Scale_Denominator: 30-m
Type_of_Source_Media: Landsat ETM+ 7-band Image
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 19990915
Source_Currentness_Reference: ground condition
Source_Citation_Abbreviation: SeptETM
Source_Contribution: Provided original data from which to derive vegetation information.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Publication_Date: 1999
Title: 30-Meter Digital Elevation Model of the Greater Yellowstone Area
Geospatial_Data_Presentation_Form: raster digital data
Source_Scale_Denominator: 30-m
Type_of_Source_Media: raster digital data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 1999
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: DEM
Source_Contribution: Ancillary elevation data for classification tree analysis.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Publication_Date: 1999
Title: 30-Meter Thematic Aspect of the Greater Yellowstone Area
Geospatial_Data_Presentation_Form: raster digital data
Source_Scale_Denominator: 30-m
Type_of_Source_Media: raster digital data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 1999

Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: ASPECT
Source_Contribution: Thematic aspect information derived from DEM and used in the classification tree analysis.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Publication_Date: 1999
Title: 30-Meter Slope in Degrees of the Greater Yellowstone Area
Geospatial_Data_Presentation_Form: raster digital data
Source_Scale_Denominator: 30-m
Type_of_Source_Media: digital raster data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 1999
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: SLOPE
Source_Contribution: Slope in degrees derived from the DEM and used in the classificaiton tree analysis.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Publication_Date: Unknown
Title: Rivers of the Greater Yellowstone Area
Geospatial_Data_Presentation_Form: vector digital data
Other_Citation_Details: From the National Hydrography Dataset.
Source_Scale_Denominator: 1:24,000
Type_of_Source_Media: vector digital data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: unknown
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: NHD
Source_Contribution: Streams information for use in the classification tree analysis.
Source_Information:
Source_Citation:
Citation_Information:
Originator: Yellowstone National Park - Spatial Analysis Center
Publication_Date: Unknown
Title: Northern Range of Yellowstone National Park, Wyoming, Montana

Geospatial_Data_Presentation_Form: vector digital data
Source_Scale_Denominator: 1:24,000
Type_of_Source_Media: vector digital data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: unknown
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: NR
Source_Contribution: Boundary of the Northern Range used to clip image data for study area.
Process_Step:
Process_Description:
The Landsat images were clipped to the NR boundary and several additional processes were run to create a total of 51 components for the classification tree analysis.

Using the 14 original bands, a standardized principal components analysis (PCA) was performed resulting in 14 new components. PCA reduces the amount of data to be analyzed and accounts for the most variance in the original images. The components generated from a multidate PCA often represent changes in brightness and greenness. The change in greenness provides information regarding vegetative cover

.

A single band of Normalized Difference Vegetation Index (NDVI) was produced for each date (2 new bands). This process used the near infrared and red bands of Landsat imagery to create an index with values from -1 to 1 ([near infrared - red]/[near infrared + red]). Vegetation has high reflectance values in the near infrared portion of the spectrum, and lower values in the visible portion. When NDVI values are closer to 1 there are higher amounts of vegetation in the pixel. When the value is closer to 0 there is more bare ground in the pixel. NDVI has been shown to be effective in extracting vegetation data from imagery

.

A Tasseled Cap (TC) transformation was performed on each date of imagery (6 new bands). This process is similar to PC in that it reduces the amount of information to be analyzed into the first three components. The first three components from the TC transformation represent brightness (soil brightness or total reflectance), greenness (relative amounts of leafy green vegetation), and wetness (soil moisture status). The original six bands (minus the thermal band) had to be converted from digital numbers (DNs) to reflectance values to create these three components for each image. This reduces the amount of relative noise and between-scene variability

.

Additional information can be gleaned from the data, especially information about changes between seasons, by subtracting the values from one image to another. The previously mentioned new components were image differenced to produce seven components of image difference (the original seven July bands subtracted from the original seven September bands), one component of NDVI difference (the July NDVI component subtracted from the September NDVI component), and three components of TC difference (the three July TC components subtracted from the three September TC components) to generate as much useful data from the original 14 bands as possible.

Ancillary data used in the study were 30-m elevation data (from a Digital Elevation Model (DEM)), slope in degrees and aspect (N, S, E, W, NE, SE, SW, NW, and flat) derived from the 30-m DEM, and a layer depicting distance from streams utilizing stream data from the USGS National Hydrography Dataset (NHD).
Source_Used_Citation_Abbreviation: JulyETM
Source_Used_Citation_Abbreviation: SeptETM
Source_Used_Citation_Abbreviation: DEM
Source_Used_Citation_Abbreviation: ASPECT
Source_Used_Citation_Abbreviation: SLOPE
Source_Used_Citation_Abbreviation: NHD
Process_Date: 20041006
Source_Produced_Citation_Abbreviation: 1999Stack
Process_Contact:
Contact_Information:
Contact_Organization_Primary:
Contact_Organization: Spatial Analysis Center - Yellowstone National Park
Contact_Position: GIS Specialist
Contact_Address:
Address_Type: mailing address
Address: Yellowstone Center for Resources
Address: Spatial Analysis Center
Address: P.O. Box 168
City: Yellowstone National Park
State_or_Province: Wyoming
Postal_Code: 82190
Country: USA
Contact_Voice_Telephone: 307-344-2246
Contact_Facsimile_Telephone: 307-344-2211
Contact_Electronic_Mail_Address: yell_gis@nps.gov
Hours_of_Service: 8:00 a.m. to 4:00 p.m. (Mountain Time) Monday through Friday
Contact_Instructions: Please check website first: http://www.nps.gov/yell/technical/gis
Process_Step:
Process_Description: The general steps were: (1) acquire Landsat imagery, (2) derive additional data from the Landsat data, (3) collect additional ancillary data, (4) clipp out the NR from all the data layers, (5) mask out forest, water, snow, thermal areas, and developed areas, (6) classify the data, and (7) perform an accuracy assessment on the resulting map.

A classification tree analysis was run on the final stacked image through See 5 using training and validation data collected over the previous couple of years.
      Source_Used_Citation_Abbreviation: 1999Stack
      Process_Date: 20041022
      Source_Produced_Citation_Abbreviation: allclassesmap
    Process_Step:
      Process_Description: A confusion matrix was created with the validation data to determine accuracies of the classification. Where confusion was seen, additional classification tree analyses were run as binary splits (the two classes that were confused). After several iterations, all of the final "good" data were combined with the new individual classifcations to create the final 27 class map.
      Source_Used_Citation_Abbreviation: allclassesmap
      Process_Date: 20041120
      Source_Produced_Citation_Abbreviation: 1999classification.img
Spatial_Data_Organization_Information:
  Direct_Spatial_Reference_Method: Raster
  Raster_Object_Information:
    Raster_Object_Type: Pixel
    Row_Count: 2050
    Column_Count: 2314
    Vertical_Count: 1
Spatial_Reference_Information:
  Horizontal_Coordinate_System_Definition:
    Planar:
      Grid_Coordinate_System:
        Grid_Coordinate_System_Name: Universal Transverse Mercator
        Universal_Transverse_Mercator:
          UTM_Zone_Number: 12
          Transverse_Mercator:
            Scale_Factor_at_Central_Meridian: 0.999600
            Longitude_of_Central_Meridian: -111.000000
            Latitude_of_Projection_Origin: 0.000000
            False_Easting: 500000.000000
            False_Northing: 0.000000
      Planar_Coordinate_Information:
        Planar_Coordinate_Encoding_Method: row and column
        Coordinate_Representation:
          Abscissa_Resolution: 30.000000
          Ordinate_Resolution: 30.000000
        Planar_Distance_Units: meters
    Geodetic_Model:
      Horizontal_Datum_Name: North American Datum of 1983
      Ellipsoid_Name: Geodetic Reference System 80
      Semi-major_Axis: 6378137.000000

Denominator_of_Flattening_Ratio: 298.257222
Entity_and_Attribute_Information:
Detailed_Description:
Entity_Type:
Entity_Type_Label: Layer_1
Attribute:
Attribute_Label: ObjectID
Attribute_Definition: Internal feature number.
Attribute_Definition_Source: ESRI
Attribute_Domain_Values:
Unrepresentable_Domain: Sequential unique whole numbers that are automatically generated.
Attribute:
Attribute_Label: Value
Attribute:
Attribute_Label: Count
Attribute:
Attribute_Label: Red
Attribute:
Attribute_Label: Green
Attribute:
Attribute_Label: Blue
Attribute:
Attribute_Label: Opacity
Overview_Description:
Entity_and_Attribute_Overview:
Aside from the standard attributes for Imagine images (IMG), there are six additional attributes covering the five-level hierarchy as follows: Level 1 Class, Level 2 Class, Level 3 Class, Level 4 Class, Level 5 Class, Scientific Name.

Defined values for each attribute are as follows:

Level 1 Class:
Herbaceous vegetation
Shrubland
Sparse vegetation
Woodland

Level 2 Class:
Boulder, gravel, cobble, or talus sparse vegetation
Deciduous shrubland
Deciduous woodland
Evergreen shrubland
Perennial graminoid vegetation

Level 3 Class:
Boulder, gravel, cobble, or talus sparse vegetation - Dry
Deciduous shrubland - Wet
Deciduous woodland - Dry
Deciduous woodland - Wet
Evergreen shrubland - Dry
Perennial graminoid vegetation - Dry
Perennial graminoid vegetation - Wet

Level 4 Class:
Cold-deciduous woodland
Lowland microphyllous evergreen shrubland
Lowland or submontane talus/scree
Medium-tall bunch temperate or subpolar grassland
Perennial grass crops (hayland, pastureland)
Seasonall flooded cold-deciduous shrubland
Seasonally flooded temperate or subpolar grassland
Temporarily flooded cold-deciduous shrubland
Temporarily flooded cold-deciduous woodland
Temporarily flooded temperate or subpolar grassland

Level 5 Class (Scientific Name):
Agriculture (Agriculture)
Aspen (Populus tremuloides)
Bluebunch wheatgrass/Sandberg's bluegrass - needle-and-thread phase
(Agropyron spicatum/Poa secunda -Stipa comata phase)
Big sagebrush bluebunch wheatgrass (Artemisia tridentata/Agropyron spicatum)
Big sagebrush/Idaho fescue (Artemisia tridentata/Festuca idahoensis)
Big sagebrush/Idaho fescue - sticky geranium phase
(Artemisia tridentata/Festuca idahoensis - Geranium viscosissimum phase)
Cottonwood (Populus spp.)
Crested wheatgrass (Exotic) (Agropyron cristatum)
Idaho fescue/bluebunch wheatgrass (Festuca idahoensis/Agropyron spicatum)
Idaho fescue/bearded wheatgrass (Festuca idahoensis/Agropyron caninum)
Idaho fescue/bearded wheatgrass - sticky geranium phase
(Festuca idahoensis/Agropyron caninum - Geranium viscosissimum phase)
Idaho fescue/Richardson's needlegrass (Festuca idahoensis/Stipa richardsonii)
Mudflow mosaic (Mudflow mosaic)
Mustard (Exotic) (Chorispora tenella)
Russian thistle (Exotic) (Salsola australis)
Sedge bogs (Carex spp.)
Smooth brome (Exotic) (Bromus inermis)
Shrubby cinquefoil - silver sage/tufted hairgrass

(Potentilla fruticosa-Artemisia cana/Deschampsia cespitosa)
Silver sage/Idahoe fescue, Idaho fescue/tufted hairgrass
(Artemisia cana/Festuca idahoensis, Festuca idahoensis/Deschampsia cespitosa)
Talus (Talus)
Tufted hairgrass/sedge (Deschampsia cespitosa/Carex spp.)
Willow/sedge (Salix spp./Carex spp.)
Forest (Forest)
Water (Water)
Snow (Snow)
Developed (Developed)
Thermal (Thermal)
Entity_and_Attribute_Detail_Citation: Savage, S.L., 2005. Vegetation Dynamics in Yellowstone's Northern Range: 1985-1999. Master's Thesis. Montana State University, Department of Land Resources and Environmental Sciences. 153 pp.
Distribution_Information:
Distributor:
Contact_Information:
Contact_Organization_Primary:
Contact_Organization: NPS, Denver Service Center, Reprographic Imaging Center and Technical Information Center
Contact_Position: DSC Records Manager
Contact_Address:
Address_Type: mailing address
Address: P.O. Box 25287
City: Denver
State_or_Province: Colorado
Postal_Code: 80225
Country: USA
Contact_Voice_Telephone: 303-969-2130
Contact_Facsimile_Telephone: 303-969-2557
Contact_Electronic_Mail_Address: TIC-requests@nps.gov
Hours_of_Service: 9:00 a.m. to 5:00 p.m. Monday through Friday (Mountain time)
Resource_Description: IMR-YELL-NR-VegClassification.zip
Distribution_Liability: The National Park Service shall not be held liable for improper or incorrect use of the data described and/or contained herein. These data and related graphics, (if available), are not legal documents and are not intended to be used as such. The information contained in these data is dynamic and may change over time. The data are not better than the original sources from which they were derived. It is the responsibility of the data user to use the data appropriately and consistent within the limitations of geospatial data in general and these data in particular. The related graphics are intended to aid the data user in acquiring relevant data; it is not appropriate to use the related graphics as data. The National Park Service gives no warranty, expressed or implied, as to the accuracy, reliability, or completeness of these data. It is strongly recommended that these data be directly acquired from an NPS server and not indirectly

through other sources, which may have changed the data in some way. Although these data have been processed successfully on a computer system at the National Park Service, no warranty expressed or implied is made regarding the utility of the data on another system or for general or scientific purposes, nor shall the act of distribution constitute any such warranty. This disclaimer applies both to individual use of the data and aggregate use with other data.
  Standard_Order_Process:
    Digital_Form:
      Digital_Transfer_Information:
        Format_Name: IMG
        Format_Version_Number: Version 8.7
        Format_Specification: .zip
        File_Decompression_Technique: WinZip
        Transfer_Size: 0.000
      Digital_Transfer_Option:
        Offline_Option:
          Offline_Media: CD-ROM
          Recording_Format: ISO 9660
    Fees: Contact NPS, Denver Service Center, Reprographic Imaging Center and Technical Information Center for a price quote.
    Ordering_Instructions: Complete, print, and submit the CD-ROM Order Form found at http://nps.gov/gis/TIC-requests.html to the NPS Denver Service Center Reprographic Imaging Center and Technical Information Center. Use the "Resource_Description" above for the Item No.
    Turnaround: Contact NPS, Denver Service Center, Reprographic Imaging Center and Technical Information Center for a quote.
Metadata_Reference_Information:
  Metadata_Date: 20051103
  Metadata_Contact:
    Contact_Information:
      Contact_Organization_Primary:
        Contact_Organization: Spatial Analysis Center - Yellowstone National Park
      Contact_Position: GIS Specialist
      Contact_Address:
        Address_Type: mailing address
        Address: Yellowstone Center for Resources
        Address: Spatial Analysis Center
        Address: P.O. Box 168
        City: Yellowstone National Park
        State_or_Province: Wyoming
        Postal_Code: 82190
        Country: USA
      Contact_Voice_Telephone: 307-344-2246
      Contact_Facsimile_Telephone: 307-344-2211

Contact_Electronic_Mail_Address: yell_gis@nps.gov
Hours_of_Service: 8:00 a.m. to 4:00 p.m. (Mountain Time) Monday through Friday
Contact_Instructions: Please check website first: http://www.nps.gov/yell/technical/gis
Metadata_Standard_Name: FGDC Content Standards for Digital Geospatial Metadata
Metadata_Standard_Version: FGDC-STD-001-1998
Metadata_Time_Convention: local time
Metadata_Access_Constraints: none
Metadata_Use_Constraints: none
Metadata_Security_Information:
Metadata_Security_Classification_System: none
Metadata_Security_Classification: none
Metadata_Security_Handling_Description: none
Metadata_Extensions:
Online_Linkage: http://www.esri.com/metadata/esriprof80.html
Profile_Name: ESRI Metadata Profile

APPENDIX C

FGDC COMPLIANT METADATA FOR 1985 CLASSIFICATION

Identification_Information:
  Citation:
    Citation_Information:
      Originator: Spatial Analysis Center - Yellowstone National Park
      Originator: Montana State University - Remote Sensing Lab
      Originator: Shannon Savage
      Publication_Date: 20051103
      Title: 1985 Five-Level Non-Forest Vegetation Map of the Northern Range, Yellowstone National Park, Montana, Wyoming
      Geospatial_Data_Presentation_Form: remote-sensing image
  Description:
    Abstract: This is an image file showing the non-forest vegetation in the Northern Range (NR) of Yellowstone National Park (YNP) in 185. The data were extracted from the September 16, 1985 Landsat TM image utilizing boosting and classification tree analysis in the program, See 5. The minimum mapping unit is 30-m pixels. The data were created with a hierarchical classification scheme that ranges from very broad vegetation in Level 1 to specific habitat types in Level 5.
    Purpose: To create a method for change detection of vegetation on the NR of YNP. The intended use of all data in the park's GIS library is to support diverse park activities including planning, management, maintenance, research, and interpretation.
  Time_Period_of_Content:
    Time_Period_Information:
      Single_Date/Time:
        Calendar_Date: 19840916
    Currentness_Reference: ground condition
  Status:
    Progress: Complete
    Maintenance_and_Update_Frequency: None planned
  Spatial_Domain:
    Bounding_Coordinates:
      West_Bounding_Coordinate: -110.905418
      East_Bounding_Coordinate: -110.018798
      North_Bounding_Coordinate: 45.322369
      South_Bounding_Coordinate: 44.764661
  Keywords:
    Theme:
      Theme_Keyword_Thesaurus: none
      Theme_Keyword: Vegetation, Landsat, Rangelands, Non-forest, Classification, Satellite Remote Sensing, Change Detection, Change Vector Analysis
    Place:
      Place_Keyword_Thesaurus: none
      Place_Keyword: National Park Service, NPS, Department of the Interior, DOI, US Government
      Place_Keyword: United States of America, US, USA, North America

Place_Keyword: Northern Range, Yellowstone National Park, YNP, YELL, Greater Yellowstone Area, GYA, Greater Yellowstone Ecosystem, GYE, Park County, Montana, Wyoming, Northern Rocky Mountains
Access_Constraints: none
Use_Constraints: none
Point_of_Contact:
Contact_Information:
Contact_Organization_Primary:
Contact_Organization: Spatial Analysis Center - Yellowstone National Park
Contact_Position: GIS Specialist
Contact_Address:
Address_Type: mailing address
Address: Yellowstone Center for Resources
Address: Spatial Analysis Center
Address: P.O. Box 168
City: Yellowstone National Park
State_or_Province: Wyoming
Postal_Code: 82190
Country: USA
Contact_Voice_Telephone: 307-344-2246
Contact_Facsimile_Telephone: 307-344-2211
Contact_Electronic_Mail_Address: yell_gis@nps.gov
Hours_of_Service: 8:00 a.m. to 4:00 p.m. (Mountain Time) Monday through Friday
Contact_Instructions: Please check website first: http://www.nps.gov/yell/technical/gis
Data_Set_Credit:
National Park Service, Yellowstone National Park, Intermountain Region
Montana State University, Remote Sensing Lab
Shannon Savage, GIS Specialist and Masters Candidate
Security_Information:
Security_Classification_System: None
Security_Classification: None
Security_Handling_Description: None
Native_Data_Set_Environment: Microsoft Windows XP Version 5.1 (Build 2600) Service Pack 2; ESRI ArcCatalog 9.0.0.535
Cross_Reference:
Citation_Information:
Originator: Shannon Savage
Publication_Date: 20051128
Title: Vegetation Dynamics in Yellowstone's Northern Range: 1985-1999
Other_Citation_Details: Master's thesis, Montana State University, Department of Land Resources and Environmental Sciences. 152pp.
Data_Quality_Information:
Attribute_Accuracy:

Attribute_Accuracy_Report: Data were developed from Landsat ETM+ images for Path 38 Row 29 (July 13, 1999 and September 15, 1999). Park staff have ground checked and verified all features to the best of their knowledge. GIS personnel verified all features and attributes.
Logical_Consistency_Report: There are no duplicate features present.
Completeness_Report: The data only include features shown in the Landsat image. Additional features may exist.
Positional_Accuracy:
Horizontal_Positional_Accuracy:
Horizontal_Positional_Accuracy_Report:
Overall accuracies of these data were calculated by error matrices. A Kappa statistic was calculated for each level as well.

Level 1 Accuracy = 88.73% Kappa = 0.798
Level 2 Accuracy = 88.73% Kappa = 0.809
Level 3 Accuracy = 84.31% Kappa = 0.774
Level 4 Accuracy = 79.90% Kappa = 0.781
Level 5 Accuracy = 72.60% Kappa = 0.714
Lineage:
Source_Information:
Source_Citation:
Citation_Information:
Originator: United State Geological Survey
Originator: EROS Data Center - Sioux Falls
Publication_Date: 19990713
Title: Landsat ETM+ 7-band Image from July 13, 1999
Geospatial_Data_Presentation_Form: remote-sensing image
Source_Scale_Denominator: 30-m
Type_of_Source_Media: Landsat ETM+ 7-band Image
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 19990713
Source_Currentness_Reference: ground condition
Source_Citation_Abbreviation: JulyETM
Source_Contribution: Provided original data from which to derive vegetation information.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United State Geological Survey
Originator: EROS Data Center - Sioux Falls
Publication_Date: 19990915
Title: Landsat ETM+ 7-band Image from September 15, 1999

Geospatial_Data_Presentation_Form: remote-sensing image
Source_Scale_Denominator: 30-m
Type_of_Source_Media: Landsat ETM+ 7-band Image
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 19990915
Source_Currentness_Reference: ground condition
Source_Citation_Abbreviation: SeptETM
Source_Contribution: Provided original data from which to derive vegetation information.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Publication_Date: 1999
Title: 30-Meter Digital Elevation Model of the Greater Yellowstone Area
Geospatial_Data_Presentation_Form: raster digital data
Source_Scale_Denominator: 30-m
Type_of_Source_Media: raster digital data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 1999
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: DEM
Source_Contribution: Ancillary elevation data for classification tree analysis.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Publication_Date: 1999
Title: 30-Meter Thematic Aspect of the Greater Yellowstone Area
Geospatial_Data_Presentation_Form: raster digital data
Source_Scale_Denominator: 30-m
Type_of_Source_Media: raster digital data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 1999
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: ASPECT
Source_Contribution: Thematic aspect information derived from DEM and used in the classification tree analysis.

Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Publication_Date: 1999
Title: 30-Meter Slope in Degrees of the Greater Yellowstone Area
Geospatial_Data_Presentation_Form: raster digital data
Source_Scale_Denominator: 30-m
Type_of_Source_Media: digital raster data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 1999
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: SLOPE
Source_Contribution: Slope in degrees derived from the DEM and used in the classificaiton tree analysis.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Publication_Date: Unknown
Title: Rivers of the Greater Yellowstone Area
Geospatial_Data_Presentation_Form: vector digital data
Other_Citation_Details: From the National Hydrography Dataset.
Source_Scale_Denominator: 1:24,000
Type_of_Source_Media: vector digital data
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: unknown
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: NHD
Source_Contribution: Streams information for use in the classification tree analysis.
Source_Information:
Source_Citation:
Citation_Information:
Originator: Yellowstone National Park - Spatial Analysis Center
Publication_Date: Unknown
Title: Northern Range of Yellowstone National Park, Wyoming, Montana
Geospatial_Data_Presentation_Form: vector digital data
Source_Scale_Denominator: 1:24,000
Type_of_Source_Media: vector digital data
Source_Time_Period_of_Content:

Time_Period_Information:
Single_Date/Time:
Calendar_Date: unknown
Source_Currentness_Reference: publication date
Source_Citation_Abbreviation: NR
Source_Contribution: Boundary of the Northern Range used to clip image data for study area.
Source_Information:
Source_Citation:
Citation_Information:
Originator: Yellowstone National Park - Spatial Analysis Center
Publication_Date: 20051103
Title: 1999 Five-Level Non-Forest Vegetation Map of the Northern Range, Yellowstone National Park, Montana, Wyoming
Geospatial_Data_Presentation_Form: raster digital data
Source_Scale_Denominator: 30-m
Type_of_Source_Media: raster digital image
Source_Time_Period_of_Content:
Time_Period_Information:
Range_of_Dates/Times:
Beginning_Date: 19990713
Ending_Date: 19990915
Source_Currentness_Reference: ground condition
Source_Citation_Abbreviation: 1999Classifcation
Source_Contribution: Unchanged areas were used as training data in the classif cation of the 1985 image, and were kept in the final map for 1985.
Source_Information:
Source_Citation:
Citation_Information:
Originator: United States Geological Survey
Originator: EROS Data Center - Sioux Falls
Publication_Date: 19850916
Title: Landsat TM 7-band Image from September 16, 1999
Geospatial_Data_Presentation_Form: raster digital data
Source_Scale_Denominator: 30-m
Type_of_Source_Media: Landsat TM 7-band Image
Source_Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 19850916
Source_Currentness_Reference: ground condition
Source_Citation_Abbreviation: SeptTM
Source_Contribution: Provided original data from which to derive vegetation information.

Process_Step:
Process_Description:
The Landsat images were clipped to the NR boundary and several additional processes were run to create a total of 51 components for the classification tree analysis.

Using the 14 original bands, a standardized principal components analysis (PCA) was performed resulting in 14 new components. PCA reduces the amount of data to be analyzed and accounts for the most variance in the original images. The components generated from a multidate PCA often represent changes in brightness and greenness. The change in greenness provides information regarding vegetative cover
.
A single band of Normalized Difference Vegetation Index (NDVI) was produced for each date (2 new bands). This process used the near infrared and red bands of Landsat imagery to create an index with values from -1 to 1 ([near infrared - red]/[near infrared + red]). Vegetation has high reflectance values in the near infrared portion of the spectrum, and lower values in the visible portion. When NDVI values are closer to 1 there are higher amounts of vegetation in the pixel. When the value is closer to 0 there is more bare ground in the pixel. NDVI has been shown to be effective in extracting vegetation data from imagery
.
A Tasseled Cap (TC) transformation was performed on each date of imagery (6 new bands). This process is similar to PC in that it reduces the amount of information to be analyzed into the first three components. The first three components from the TC transformation represent brightness (soil brightness or total reflectance), greenness (relative amounts of leafy green vegetation), and wetness (soil moisture status). The original six bands (minus the thermal band) had to be converted from digital numbers (DNs) to reflectance values to create these three components for each image. This reduces the amount of relative noise and between-scene variability
.
Additional information can be gleaned from the data, especially information about changes between seasons, by subtracting the values from one image to another. The previously mentioned new components were image differenced to produce seven components of image difference (the original seven July bands subtracted from the original seven September bands), onecomponent of NDVI difference (the July NDVI component subtracted from the September NDVI component), and three components of TC difference (the three July TC components subtracted from the three September TC components) to generate as much useful data from the original 14 bands as possible.

Ancillary data used in the study were 30-m elevation data (from a Digital Elevation Model (DEM)), slope in degrees and aspect (N, S, E, W, NE, SE, SW, NW, and flat) derived from the 30-m DEM, and a layer depicting distance from streams utilizing stream data from the USGS National Hydrography Dataset (NHD).
Source_Used_Citation_Abbreviation: JulyETM
Source_Used_Citation_Abbreviation: SeptETM

Source_Used_Citation_Abbreviation: DEM
Source_Used_Citation_Abbreviation: ASPECT
Source_Used_Citation_Abbreviation: SLOPE
Source_Used_Citation_Abbreviation: NHD
Process_Date: 20041006
Source_Produced_Citation_Abbreviation: 1999Stack
Process_Contact:
Contact_Information:
Contact_Organization_Primary:
Contact_Organization: Spatial Analysis Center - Yellowstone National Park
Contact_Position: GIS Specialist
Contact_Address:
Address_Type: mailing address
Address: Yellowstone Center for Resources
Address: Spatial Analysis Center
Address: P.O. Box 168
City: Yellowstone National Park
State_or_Province: Wyoming
Postal_Code: 82190
Country: USA
Contact_Voice_Telephone: 307-344-2246
Contact_Facsimile_Telephone: 307-344-2211
Contact_Electronic_Mail_Address: yell_gis@nps.gov
Hours_of_Service: 8:00 a.m. to 4:00 p.m. (Mountain Time) Monday through Friday
Contact_Instructions: Please check website first: http://www.nps.gov/yell/technical/gis
Process_Step:
Process_Description:
The general steps were: (1) acquire Landsat imagery, (2) derive additional data from the Landsat data, (3) collect additional ancillary data, (4) clipp out the NR from all the data layers, (5) mask out forest, water, snow, thermal areas, and developed areas, (6) classify the data, and (7) perform an accuracy assessment on the resulting map.

A classification tree analysis was run on the final stacked image through See 5 using training and validation data collected over the previous couple of years.
Source_Used_Citation_Abbreviation: 1999Stack
Process_Date: 20041022
Source_Produced_Citation_Abbreviation: allclassesmap
Process_Step:
Process_Description: A confusion matrix was created with the validation data to determine accuracies of the classification. Where confusion was seen, additional classification tree analyses were run as binary splits (the two classes that were confused).

After several iterations, all of the final "good" data were combined with the new individual classifcations to create the final 27 class map.

Source_Used_Citation_Abbreviation: allclassesmap

Process_Date: 20041120

Source_Produced_Citation_Abbreviation: 1999Classification

Process_Step:

Process_Description:

The image provided was unrectified so geometric correction was necessary. The image was georectified to match the September 1999 image using the Geometric Correction Tool in IMAGINE and the nearest neighbor resampling method. The resulting RMS error was 0.1959 or less than half a pixel, which is acceptable for image registration. The output image was in UTM, Zone 12, NAD83 projection.

The scene was masked to the NR boundary to reduce processing time.

Using the seven original bands, a standardized principal components analysis (PCA) was performed resulting in seven new components. PCA reduces the amount of data to be analyzed and accounts for the most variance in the original images. The components generated from a multidate PCA often represent changes in brightness and greenness. The change in greenness provides information regarding vegetative cover.

A single band of Normalized Difference Vegetation Index (NDVI) was produced. This process used the near infrared and red bands of Landsat imagery to create an index with values from -1 to 1 ([near infrared - red]/[near infrared + red]). Vegetation has high reflectance values in the near infrared portion of the spectrum, and lower values in the visible portion. When NDVI values are closer to 1 there are higher amounts of vegetation in the pixel. The closer the value is to 0, the more bare ground in the pixel. NDVI is effective in extracting vegetation data from imagery.

A Tasseled Cap (TC) transformation was performed to produce three new bands. This process is similar to PC in that it reduces the amount of information to be analyzed into the first three components. The first three components from the TC transformation represent brightness (soil brightness or total reflectance), greenness (relative amounts of leafy green vegetation), and wetness (soil moisture status). The original six bands (minus the thermal band) had to be converted from digital numbers (DNs) to reflectance values to create these three bands for the image. This reduces the amount of relative noise and between-scene variability. The total number of components prepared for use in the classification was 18.

Ancillary data used in the study were 30-m elevation data (from a Digital Elevation Model (DEM)), slope in degrees and aspect (N, S, E, W, NE, SE, SW, NW, and flat) derived from the 30-m DEM, and a layer depicting distance from streams utilizing stream data from the USGS National Hydrography Dataset (NHD).

Source_Used_Citation_Abbreviation: Sept1985

Source_Used_Citation_Abbreviation: SeptTM

Source_Used_Citation_Abbreviation: NR
Process_Date: 20041204
Source_Produced_Citation_Abbreviation: 1985Stack
Process_Step:
Process_Description:
CVA change detection incorporates the following steps (based on the 1985 and 1999 images): (1) perform a TC transformation on the 1985 image, (2) perform a TC transformation on the 1999 images, (3) classify the entire 1999 image,(4) conduct a CVA on the TC components of the 1985 and 1999 images, (5) extract potentially changed areas from the 1985 image, (6) reclassify the potentially changed areas on the 1985 image utilizing data from the potentially unchanged pixels as training data, (7) merge the reclassified 1985 image with unchanged pixels in the 1999 image to create the final map, and (8) perform an accuracy assessment on the final map

A change threshold was derived utilizing Tasseled Cap space to determine where changes potentially occured between 1999 and 1985. The unchanged 1999 pixels were used as training data for the classification tree analysis of the 1985 image. The unchanged 1999 classification pixels were also kept in the final 1985 classification map.
Source_Used_Citation_Abbreviation: 1999Classification
Source_Used_Citation_Abbreviation: 1985Stack
Process_Date: 20041208
Source_Produced_Citation_Abbreviation: 1985Classification.img
Process_Step:
Process_Description: A confusion matrix was created with validation data from 1986 aerial photographs to determine accuracies of the classification.
Source_Used_Citation_Abbreviation: 1985Classification.img
Process_Date: 20041208
Spatial_Data_Organization_Information:
Direct_Spatial_Reference_Method: Raster
Raster_Object_Information:
Raster_Object_Type: Pixel
Row_Count: 2050
Column_Count: 2314
Vertical_Count: 1
Spatial_Reference_Information:
Horizontal_Coordinate_System_Definition:
Planar:
Grid_Coordinate_System:
Grid_Coordinate_System_Name: Universal Transverse Mercator
Universal_Transverse_Mercator:
UTM_Zone_Number: 12
Transverse_Mercator:
Scale_Factor_at_Central_Meridian: 0.999600
Longitude_of_Central_Meridian: -111.000000

Latitude_of_Projection_Origin: 0.000000
False_Easting: 500000.000000
False_Northing: 0.000000
Planar_Coordinate_Information:
Planar_Coordinate_Encoding_Method: row and column
Coordinate_Representation:
Abscissa_Resolution: 30.000000
Ordinate_Resolution: 30.000000
Planar_Distance_Units: meters
Geodetic_Model:
Horizontal_Datum_Name: North American Datum of 1983
Ellipsoid_Name: Geodetic Reference System 80
Semi-major_Axis: 6378137.000000
Denominator_of_Flattening_Ratio: 298.257222
Entity_and_Attribute_Information:
Detailed_Description:
Entity_Type:
Entity_Type_Label: Layer_1
Attribute:
Attribute_Label: ObjectID
Attribute_Definition: Internal feature number.
Attribute_Definition_Source: ESRI
Attribute_Domain_Values:
Unrepresentable_Domain: Sequential unique whole numbers that are automatically generated.
Attribute:
Attribute_Label: Value
Attribute:
Attribute_Label: Blue
Attribute:
Attribute_Label: Count
Attribute:
Attribute_Label: Red
Attribute:
Attribute_Label: Green
Attribute:
Attribute_Label: Class
Overview_Description:
Entity_and_Attribute_Overview:
Aside from the standard attributes for Imagine images (IMG), there are six additional attributes covering the five-level hierarchy as follows: Level 1 Class, Level 2 Class, Level 3 Class, Level 4 Class, Level 5 Class, Scientific Name.

Defined values for each attribute are as follows:

Level 1 Class:
Herbaceous vegetation
Shrubland
Sparse vegetation
Woodland

Level 2 Class:
Boulder, gravel, cobble, or talus sparse vegetation
Deciduous shrubland
Deciduous woodland
Evergreen shrubland
Perennial graminoid vegetation

Level 3 Class:
Boulder, gravel, cobble, or talus sparse vegetation - Dry
Deciduous shrubland - Wet
Deciduous woodland - Dry
Deciduous woodland - Wet
Evergreen shrubland - Dry
Perennial graminoid vegetation - Dry
Perennial graminoid vegetation - Wet

Level 4 Class:
Cold-deciduous woodland
Lowland microphyllous evergreen shrubland
Lowland or submontane talus/scree
Medium-tall bunch temperate or subpolar grassland
Perennial grass crops (hayland, pastureland)
Seasonall flooded cold-deciduous shrubland
Seasonally flooded temperate or subpolar grassland
Temporarily flooded cold-deciduous shrubland
Temporarily flooded cold-deciduous woodland
Temporarily flooded temperate or subpolar grassland

Level 5 Class (Scientific Name):
Agriculture (Agriculture)
Aspen (Populus tremuloides)
Bluebunch wheatgrass/Sandberg's bluegrass - needle-and-thread phase
(Agropyron spicatum/Poa secunda -Stipa comata phase)
Big sagebrush bluebunch wheatgrass (Artemisia tridentata/Agropyron spicatum)
Big sagebrush/Idaho fescue (Artemisia tridentata/Festuca idahoensis)
Big sagebrush/Idaho fescue - sticky geranium phase
(Artemisia tridentata/Festuca idahoensis - Geranium viscosissimum phase)

Cottonwood (Populus spp.)
Crested wheatgrass (Exotic) (Agropyron cristatum)
Idaho fescue/bluebunch wheatgrass (Festuca idahoensis/Agropyron spicatum)
Idaho fescue/bearded wheatgrass (Festuca idahoensis/Agropyron caninum)
Idaho fescue/bearded wheatgrass - sticky geranium phase
(Festuca idahoensis/Agropyron caninum - Geranium viscosissimum phase)
Idaho fescue/Richardson's needlegrass (Festuca idahoensis/Stipa richardsonii)
Mudflow mosaic (Mudflow mosaic)
Mustard (Exotic) (Chorispora tenella)
Russian thistle (Exotic) (Salsola australis)
Sedge bogs (Carex spp.)
Smooth brome (Exotic) (Bromus inermis)
Shrubby cinquefoil - silver sage/tufted hairgrass
(Potentilla fruticosa-Artemisia cana/Deschampsia cespitosa)
Silver sage/Idahoe fescue, Idaho fescue/tufted hairgrass
(Artemisia cana/Festuca idahoensis, Festuca idahoensis/Deschampsia cespitosa)
Talus (Talus)
Tufted hairgrass/sedge (Deschampsia cespitosa/Carex spp.)
Willow/sedge (Salix spp./Carex spp.)
Forest (Forest)
Water (Water)
Snow (Snow)
Developed (Developed)
Thermal (Thermal)

Entity_and_Attribute_Detail_Citation: Savage, S.L., 2005. Vegetation Dynamics in Yellowstone's Northern Range: 1985-1999. Master's Thesis. Montana State University, Department of Land Resources and Environmental Sciences. 153 pp.

Distribution_Information:
Distributor:
Contact_Information:
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City: Denver
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Contact_Electronic_Mail_Address: TIC-requests@nps.gov

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Standard_Order_Process:
Digital_Form:
Digital_Transfer_Information:
Format_Name: IMG
Format_Version_Number: Version 8.7
Format_Specification: .zip
File_Decompression_Technique: WinZip
Transfer_Size: 0.000
Digital_Transfer_Option:
Offline_Option:
Offline_Media: CD-ROM
Recording_Format: ISO 9660
Fees: Contact NPS, Denver Service Center, Reprographic Imaging Center and Technical Information Center for a price quote.
Ordering_Instructions: Complete, print, and submit the CD-ROM Order Form found at http://nps.gov/gis/TIC-requests.html to the NPS Denver Service Center Reprographic Imaging Center and Technical Information Center. Use the "Resource_Description" above for the Item No.
Turnaround: Contact NPS, Denver Service Center, Reprographic Imaging Center and Technical Information Center for a quote.
Metadata_Reference_Information:
Metadata_Date: 20051103
Metadata_Contact:
Contact_Information:
Contact_Organization_Primary:

Contact_Organization: Spatial Analysis Center - Yellowstone National Park
Contact_Position: GIS Specialist
Contact_Address:
Address_Type: mailing address
Address: Yellowstone Center for Resources
Address: Spatial Analysis Center
Address: P.O. Box 168
City: Yellowstone National Park
State_or_Province: Wyoming
Postal_Code: 82190
Country: USA
Contact_Voice_Telephone: 307-344-2246
Contact_Facsimile_Telephone: 307-344-2211
Contact_Electronic_Mail_Address: yell_gis@nps.gov
Hours_of_Service: 8:00 a.m. to 4:00 p.m. (Mountain Time) Monday through Friday
Contact_Instructions: Please check website first:
http://www.nps.gov/yell/technical/gis
Metadata_Standard_Name: FGDC Content Standards for Digital Geospatial Metadata
Metadata_Standard_Version: FGDC-STD-001-1998
Metadata_Time_Convention: local time
Metadata_Access_Constraints: none
Metadata_Use_Constraints: none
Metadata_Security_Information:
Metadata_Security_Classification_System: none
Metadata_Security_Classification: none
Metadata_Security_Handling_Description: none
Metadata_Extensions:
Online_Linkage: http://www.esri.com/metadata/esriprof80.html
Profile_Name: ESRI Metadata Profile