WETLANDS, Vol. 27, No. 3, September 2007, pp. 610–619

CHANGE DETECTION OF WETLAND ECOSYSTEMS USING LANDSAT IMAGERY AND CHANGE VECTOR ANALYSIS

Corey Baker, Rick L. Lawrence, Clifford Montagne, and Duncan Patten
Department of Land Resources and Environmental Sciences
Montana State University
Bozeman, Montana, USA 59717-3490
E-mail: rickl@montana.edu

Abstract: Accurate, efficient, and repeatable mapping of changes in wetlands and riparian areas (referred to collectively as wetlands) is critical for monitoring human, climatic, and other effects on these important systems. We used Landsat-based satellite imagery from 1988 and 2001 to map changes in wetland ecosystems in the Gallatin Valley of southwest Montana. Stochastic gradient boosting (SGB) was used to classify the 2001 image, and change vector analysis (CVA) was used to identify locations where wetland areas might have changed between 1988 and 2001. These potentially changed locations again were classified for the 1988 Landsat image using SGB. Areas of change constituted 3.4% of the study area, thus only this small percentage of the image was reclassified for the 1988 image. Overall change detection accuracy was 76%, although changes along the periphery of wetland boundaries and in areas of smaller upland inclusions were not distinguished as well as other changes. Overall accuracies of the SGB wetland classification maps were 81% for 1988 and 86% for 2001. CVA significantly reduced the number of pixels involved in the historical image classification compared to conducting independent classifications, thus reducing the potential for compounding classification errors in unchanged areas.

Key Words: classification trees, riparian zones, satellite imagery, stochastic gradient boosting, wetland mapping

INTRODUCTION

Anthropogenic activities such as urban development and agricultural management have caused a significant loss of wetland and riparian areas (Syphard and Garcia 2001). The majority of lost wetlands historically were drained or filled to create agricultural land; more than 80% of all wetland conversions since 1980, however, have been non-agricultural (Brown and Lant 1999). The 1972 Clean Water Act drastically decreased the rate of wetland loss, although wetland and riparian alterations continue (Brown and Lant 1999). Although certain ecological differences exist between wetlands and riparian zones (Baker et al. 2006), the ecological importance and human interaction between these ecosystems are very similar, and we use term wetland to describe both wetland and riparian areas unless otherwise specified.

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

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

High temporal resolution, precise spectral bandwidths, repetitive flight paths, and accurate georeferencing procedures are factors that contribute to the increasing use of satellite image data for change detection analysis (Jensen 1996, Coppin et al. 2004). Landsat-based classification procedures can provide equal or greater overall accuracies than other comparable space-borne sensors, such as Satellite Probatoire d'Observation de la Terra (SPOT) or Indian Remote Sensing Satellite (IRS), because of

Landsat's greater spectral resolution (Civco 1989, Hewitt 1990, Bolstad and Lillesand 1992). Landsat data have produced accurate maps for a variety of wetlands in Australia, Canada, Botswana, and the United States (Sader et al. 1995, Narumalani et al. 1997, Kindscher et al. 1998, Harvey and Hill 2001, Townsend and Walsh 2001, Toyra et al. 2002, Ramsey et al. 2005, Ringrose et al. 2005). The broad dynamic range of multispectral sensors enables accurate classification of narrow riparian systems and isolated wetland patches, despite moderate spatial resolutions (Ramsey 1995, Hosking et al. 2001, Masek et al. 2001).

The variety of image data sources and classification techniques presently used has led to the development of numerous change detection techniques (Coppin et al. 2004). Post-classification comparison has been applied to wetland studies to determine the total area of wetland change and to identify specific locations of such changes (Choung and Ulliman 1992, Ramsey and Laine 1997, Munyati 2000). Conducting independent classifications on multiple years, however, results in independent errors for each year that, when combined in the change detection, results in compounding the error. This is especially unfortunate in studies where the vast majority of the study area is unchanged, as is often the case in wetland change studies, because these unchanged locations are classified twice with the associated independent errors. Methods such as landcover class stability weighting have been introduced to reduce compound errors and improve effectiveness of change detection analyses (Ramsey et al. 2001). The compound error of simple comparisons between individual classified images has resulted in unreliable change detection with notoriously low accuracy (Lu et al. 2003, Coppin et al. 2004).

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

Change vector analysis (CVA), similar to pixel vector modulus and cross correlation analysis, is a change detection technique that can determine the direction and magnitude of changes in multidimensional spectral space (Collins and Woodcock 1994, Johnson and Kasischke 1998, Allen and Kupfer 2000, Houhoulis and Michener 2000, Civco et al. 2002). CVA concurrently analyzes change in all data layers, instead of a few selected spectral bands (Coppin et al. 2004). CVA was first used to identify changes in forest vegetation through measures of change magnitude (Malila 1980, Coppin et al. 2004). The CVA method identifies a change magnitude threshold that is used to separate actual land cover changes from subtle changes that do not result in actual class changes and variability within landcover classes, as well as radiometric changes associated with instrument and atmospheric variations (Hame et al. 1998, Johnson and Kasischke 1998). Defining spectral threshold values to separate true landscape changes from inherent spectral variation is particularly beneficial for studies of broadly diverse ecosystems, such as wetlands (Houhoulis and Michener 2000). These thresholds are commonly defined using the expert knowledge of the remote sensing analyst with reference to known locations of change and no change. Since only highly changed pixels are reclassified with CVA, problems associated with within-class sensitivity to phenologic or hydrologic differences between image dates are reduced (Civco et al. 2002). Classifying only the changed pixels on historical imagery reduces compound error in this classification, although compound error will exist for the pixels that are identified as potentially changed and are reclassified. CVA also minimizes the difficult task of collecting training and reference data for historical images, since unchanged locations can be used as reference data (Hame et al. 1998, Mas 1999, Lu et al. 2003).

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

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

We demonstrated in a previously reported study (Baker et al. 2006) that stochastic gradient boosting (SGB) could be an effective classification algorithm for identifying wetland and riparian areas using a 2001 Enhanced Thematic Mapper Plus (ETM+) image of the Gallatin Valley of southwestern Montana. We sought to examine in this study whether the use of CVA would be effective in this landscape with the advantages of 1) only needing to reclassify potential locations of wetland area changes and 2) not needing to collect separate reference data for the earlier date. We used CVA with the previously reported results from 2001 ETM+ imagery and a 1988 Landsat Thematic Mapper (TM) image. CVA was performed for wetlands and non-wetland areas using the first three TC components derived from the Landsat images. Locations identified by CVA as being potentially changed were classified for 1988 using SGB, while those locations identified as unchanged remained the same as in the 2001 classification.

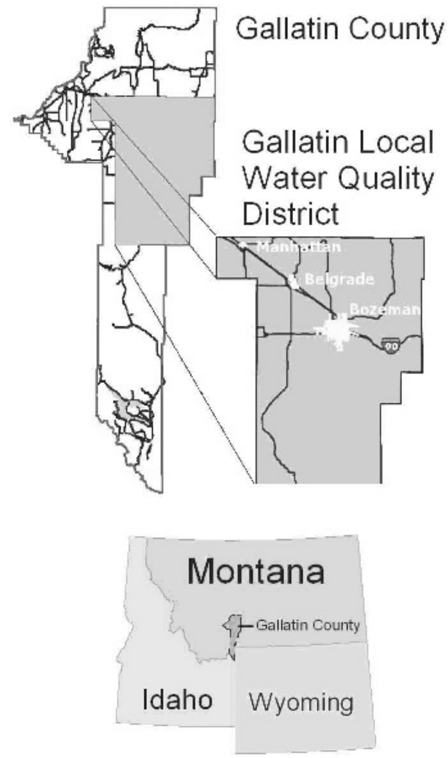

Figure 1. Location map for the Gallatin Local Water Quality District.

METHODS

Study Area

The 135,570-ha study site was the lower basin of the Gallatin River watershed, located in the Gallatin Valley of southwestern Montana, USA (Figure 1). The project area boundary generally follows the boundary of the Gallatin Local Water Quality District. The Gallatin and East Gallatin rivers have shaped the majority of landscape formations on the valley floor (Willard 1935). The population of Gallatin County increased from 50,000 in 1985 to nearly 64,000 in 1999 (Census and Economic Information Center 2004). Agricultural land across the state of Montana is increasingly being converted into residential and commercial development as a result of population growth (Kendy 2001, Census and Economic Information Center 2004). In contrast to wetland losses from agriculture, increasing construction of private ponds across the Gallatin Valley could result in increased wetland habitat.

CVA Change Detection Overview

The 2001 ETM+ images and ancillary data were used with a stochastic gradient boosting (SGB) decision tree classification algorithm (Lawrence et al. 2004) to develop a 2001 image classification of wetland and non-wetland landcover types (this classification is described in detail in Baker et al. 2006). The CVA equation was then used to calculate the magnitude of spectral change among the three TC components between September 1988 and September 2001. The objective of this CVA analysis was to identify areas of substantial change with respect to TC response regardless of what wetland areas changed from or to; therefore, we considered only the magnitude of the change vector and not its direction. A change threshold value was established using areas of known wetland change as a guide. Only the potentially changed locations (i.e., high change threshold values) were classified with the SGB algorithm utilizing 1988 spectral and ancillary data. The potentially changed pixels that were classified differently in 1988 than in 2001 were then merged with the unchanged pixels from the 2001 classification. Each procedural step is described in more detail below.

Image Pre-Processing

Landsat images acquired May 22, 2001 and September 11, 2001 were used to create the wetland classification for 2001 (for details see Baker et al. 2006). A Landsat TM image from September 15, 1988 was selected as the historical image and used for change detection against the September 2001 image. The 1988 image was selected to closely match the 2001 image based on seasonal and daily weather station data for the years 1988 and 2001, and each was compared to 100-year average data to avoid false changes due to anomalous precipitation patterns. This climate analysis was designed to minimize false change results from differences between the dates due to soil moisture, temporary surface water from recent rainfall events, or leaf water content. The Landsat image from 1988 was selected based on these identified similarities in hydrologic and temperature regimes from 1988–2001 as well as the availability of a cloud-free, anniversary date image.

Color infrared aerial photos acquired July 1985 and September 2001 were used as the reference data to evaluate the accuracy of the classifications. Geometric errors were reduced through geo-registering the 1988 Landsat image to the 2001 Landsat image (Root Mean Square Error (RMSE) = 8.2 m). The 2001 Landsat image had previously been georeferenced to the 2001 aerial photos (RMSE = 5.2 m). In all image processing steps, nearest neighbor resampling was used to preserve radiometric integrity.

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

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

Change Detection Procedure

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

$$\begin{aligned} Cm = {} & ((\text{Brightness}_1 - \text{Brightness}_2)^2 \\ & + (\text{Greenness}_1 - \text{Greenness}_2)^2 \\ & + (\text{Wetness}_1 - \text{Wetness}_2)^2)^{0.5} \end{aligned}$$

where C_m = Change magnitude (Euclidean TC component distance)

^{1,2} refer to respective TC component value for separate imagery dates

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

The change threshold value was established in an iterative process using documented sites of wetland increase and decrease from 1988–2001. The change detection threshold, therefore, was determined using the remote sensing analyst's expert knowledge of the study area, similarly to many remote sensing techniques such as an unsupervised classification where expert knowledge of landcover classes within the study area is required to relate spectral clusters to landcover types (Jano et al. 1998). During research planning, we selected a variety of known wetland change sites as detection goals for the CVA procedure. Change magnitude training sites included subtle natural wetland changes occurring on agricultural land and more obvious wetland destruction and mitigation sites resulting from land development. A more sensitive (i.e., lower value) change magnitude was selected for this project to improve detection of relatively minor wetland changes.

The potentially changed pixels (pixels with a change magnitude greater than 0.130) were used to identify sites of possible landcover change. At this point, the sites were only considered potential change sites, since changes in magnitude greater than 0.130 could result from areas with changes in spectral response that were not related to wetland changes (i.e., agricultural land that had been fallow in 1988 but not in 2001). The potentially changed sites were used to create a mask for the 1988 Landsat image that removed all areas except the highly changed areas. Extracting the 1988 spectral data for only the changed pixels reduced the number of pixels classified for the historical wetland image. Only 22.0% (331,038 pixels) of the study area was classified for 1988 using the CVA threshold mask, thus theoretically reducing compound errors resulting from two independent full-image classifications. The remaining 78.0% of the study area was considered "unchanged," and thus these pixels were inserted into the 1988 wetland classification using the 2001 classified results.

Table 1. Designations for land cover change classes.

Class in 1988	Class in 2001	Change Class Designation
Non-wetland	Non-wetland	No change – non-wetland
Non-wetland	Wetland	Wetland Increase
Wetland	Non-wetland	Wetland Decrease
Wetland	Wetland	No change – wetland

Training locations for wetland and non-wetland classes were identified using the unchanged locations from the 2001 classification and verified using 1985 color infrared (CIR) photographs. The data sources for the historical wetland classification were 1988 Landsat spectral data combined with topographic and hydric soils ancillary data. The potentially changed pixels in the 1988 image were classified using SGB to identify wetland and non-wetland landcover classes. These classes were then compared to the same classes identified in the 2001 wetland classification to determine if landcover had changed in regards to wetland areas between the two image dates (Table 1).

Accuracy Assessment

Accuracy assessment locations were randomly generated in a stratified random format to define a minimum of 75 points for both wetland increase and wetland decrease classes. For the 1988 and 2001 classifications, approximately 100 points for the wetland class and 150 points for the more predominate non-wetland class were generated in a stratified random format. On-site evaluations and CIR photographs from 1985 and 2001 were used as reference data for classification accuracy assessments.

Land cover determinations, which were based on vegetation and hydrology characteristics, used a variation of the 50% rule (Tiner 1999). In this study, 20% was the confidence level above which wetland areas could reliably be detected (i.e., a pixel was classified as wetland only if at least 20% of the location was wetland), based on comparisons of classified images and reference data. This level of sensitivity to wetland features was established during project design to match on-going water quality mapping and monitoring projects associated with this research.

The change detection error matrix for this analysis was comprised of two change classes and two non-change classes (Table 2). Error matrices were also compiled for the 1988 and 2001 SGB wetland

Table 2. Error matrix for 1988 –2001 change detection analysis.

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

classifications for accuracy comparisons between image classifications resulting from this change detection and classification procedure (Table 3). Wetland and riparian classes were segregated for this purpose.

RESULTS

Overall accuracy of the change detection analysis was 75.8% (Table 2). The high user (97.2%) and producer (88.3%) accuracies for the unchanged wetland class showed that we were able to effectively distinguish stable wetland sites on both image dates. The unchanged non-wetland class had markedly lower user (50.0%) and producer (76.0%) accuracies. The low user accuracy for this unchanged non-wetland class provides evidence that the CVA threshold value was too high, thus excluding a variety of wetland changes from the analysis (Table 2). Compound errors in the wetland class for the 1988 and 2001 classifications (Table 3) were inherent in the post-classification comparison of the classified images and likely contributed to change detection errors.

Using the change threshold mask, we determined a total of 331,038 pixels (22.0% of the study area) had change magnitude values greater than the 0.130 change threshold and were considered potentially changed sites (Table 4). Only 50,651 pixels (3.4% of the study area) of these potential change pixels were classified differently in 1988 than in 2001 and thus represented estimated ecological change. The landscape area classified as wetland was somewhat inflated since each pixel could be comprised of as little as 20% wetland vegetation. As a result, the size of most wetlands was notably larger in these classifications than previous ecosystem inventories of this region.

The results of this change detection analysis (Table 4) showed that wetlands have generally

Table 3. Error matrices of 1988 and 2001 wetland/riparian classifications.

1988 Classification	Overall Accuracy 81.0% — Reference Data			
Classified Data	Non-wetland	Wetland	Riparian	Users Accuracy
Non-wetland	119	6	8	89.5%
Wetland	19	71	8	98.0%
Riparian	8	8	53	76.8%
Producers Accuracy	81.5%	83.5%	76.8%	

2001 Classification	Overall Accuracy 86.0% — Reference Data			
Classified Data	Non-wet	Wetland	Riparian	Users Accuracy
Non-wetland	122	3	4	94.5%
Wetland	23	96	7	76.2%
Riparian	8	4	83	87.4%
Producers Accuracy	79.7%	93.2%	88.3%	

Table 4. Histogram values of change classes and quantity of pixels included in study area.

	# of pixels	% of study area	hectares
Change Classes			
No-change (non-wet)	1,194,843	79.3%	107,536
Wet/Rip Increase	13,395	0.9%	1,206
Wet/Rip Decrease	37,256	2.5%	3.353
No-change (wet)	261,935	17.4%	23.574
Total # of pixels =	1,507,429		135.669
potential change pixels =	331,038	22.0%	29.793

decreased within the Gallatin Valley. Wetland change locations occurred in the interior of existing wetland clusters and around the peripheral areas of unchanged wetland sites (Figure 2). Many relatively large, contiguous change clusters were visible for both positive and negative change classes. CVA accurately detected shifts of large areas, such as sub-irrigated wet meadows converted to residential development.

The majority of land cover changes occurred in the northern and the southeastern sections of the study area. The East Gallatin and West Gallatin rivers converge in the northern end of the valley and produce a matrix of surface and sub-irrigated wetland ecosystems. Decreasing wetland area accounted for the majority of landcover change in this region. The southeastern portion of the valley contained the rapidly growing urban and suburban communities that surround the city of Bozeman. This section of the Gallatin Valley was also dominated by decreasing wetland area, although some new wetland areas were detected in this increasingly fragmented landscape.

The 2001 classified image had 86.0% overall accuracy, and the 1988 classified image had 81% overall accuracy (Table 3). The decrease in the 1988 classification accuracy was partially the result of intensive sampling of underrepresented land cover types (wetland) during the accuracy assessment. Both of these accuracy values showed that the classification algorithm distinguished the majority of wetland sites from other land cover. In both the 1988 and 2001 classifications, the majority of error resulted from non-wetland locations being incorrectly classified as wetlands. The majority of these inclusion errors occurred along the periphery of wetland boundaries and in areas of smaller upland inclusions. Similar errors have been observed in other wetland classifications and are likely the result of the coarse spatial resolution of the Landsat sensor (Ramsey 1995). This over-classification of wetlands,

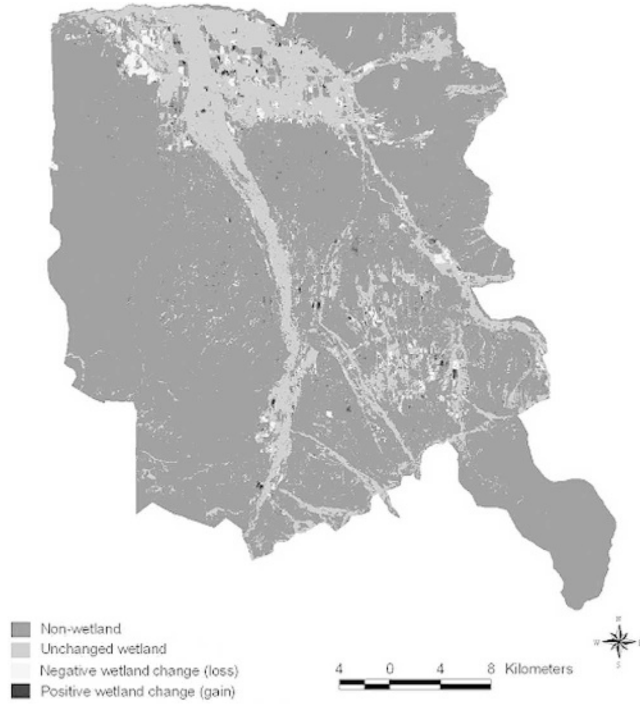

Figure 2. Map of wetland/riparian change sites (1988–2001) in the Gallatin Valley, as identified by CVA.

as opposed to under-classification, is advantageous for inventories designed to locate all possible wetlands. These errors, however, also likely contributed to errors in the change detection analysis.

DISCUSSION

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

The individual 2001 and 1998 image classification accuracies (86.0% and 81.0%, respectively) indicated that we effectively distinguished wetland sites from other land cover types. Analysis of the change detection error matrix also showed a lack of confusion between the unchanged classes. These results supported the theory that reducing the number of reclassified pixels using CVA thresholding helps to maintain the integrity of classification accuracies between multiple images, one of our primary objectives for this study. This approach achieved our goal of maintaining accuracies without the need for separate reference data for the second classification and was, therefore, an efficient method for locating historical wetland communities.

Thresholding can also be a source of change detection error that must be considered against the benefits this technique provides. The use of thresholding has been debated in regards to statistical analysis, although many studies have opted for the higher accuracies thresholding can provide (Allen and Kupfer 2000, Coppin et al. 2004). It was difficult in this complex landscape to establish a threshold value that was sensitive to the ecological change of interest without including extraneous land use changes, such as differences in agricultural practices. This method is also subject to variable results based on the ability of the analyst to set an accurate threshold, as are all methods dependent on expert knowledge. The thresholding sensitivity might be more readily identified if a specific type of landcover change (e.g., conifer mortality) was the subject of analysis. More recent studies suggest that statistically based determinations of threshold values might improve change detection accuracy and reproducibility (Warner 2005).

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

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

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

LITERATURE CITED

Allen, T. R. and J. A. Kupfer. 2000. Application of spherical statistics to change vector analysis of Landsat data: Southern Appalachian spruce-fir forests. Remote Sensing of Environment 74:482–93.

Armenakis, C., F. Leduc, I. Cyr, F. Savopol, and F. Cavayas. 2003. A comparative analysis of scanned maps and imagery for mapping applications. ISPRS Journal of Photogrammetry and Remote Sensing 57:304–14.

Baker, C., R. Lawrence, C. Montagne, and D. Patten. 2006. Mapping wetlands and riparian areas using Landsat ETM+ imagery and decision-tree-based models. Wetlands 26:465–74.

Bolstad, P. V. and T. M. Lillesand. 1992. Rule-based classification models: flexible integration of satellite imagery and thematic spatial data. Photogrammetric Engineering and Remote Sensing 58:965–71.

Brown, P. H. and C. L. Lant. 1999. The effect of wetland mitigation banking on the achievement of no-net-loss. Environmental Management 23:333–45.

Census Economic Information Center. 2004. Census of Agriculture – county data – Montana. http://ceic.commerce.state.mt.us. Last accessed 15 May 2004.

Chander, G. and B. Markham. 2003. Revised Landsat 5TM radiometric calibration procedures and post-calibration dynamic ranges. http://landsat7.usgs.gov/documents/L5TMCal2003.pdf

Choung, S. H. and J. J. Ulliman. 1992. A comparative study of wetland change detection techniques using post-classification comparison and image differencing on Landsat-5 TM data. Journal of Korean Forestry Society 81:346–56.

Civco, D. L. 1989. Knowledge-based land use and land cover mapping. Technical Papers. 1989 Annual Meeting of the American Society for Photogrammetry and Remote Sensing, Baltimore, MD, p. 276–91.

Civco, D. L., J. D. Hurd, E. H. Wilson, M. Song, and Z. Zhang. 2002. A comparison of land use and land cover change detection methods. American Congress on Surveying & Mapping – American Society for Photogrammetry and Remote Sensing 2002 Annual Conference Proceedings.

Collins, J. B. and C. E. Woodcock. 1994. Change detection using the Gramm-Schmidt transformation applied to mapping forest mortality. Remote Sensing of Environment 50:267–79.

Coppin, P., I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin. 2004. Digital change detection methods in ecosystem monitoring; a review. International Journal of Remote Sensing 25:1565–96.

Crist, E. P. and R. C. Cicone. 1984. A physically-based transformation of Thematic Mapper data – The TM Tasseled Cap. IEEE Transactions on Geoscience and Remote Sensing 22:256–63.

Crist, E. P., R. Laurin, and R. C. Cicone. 1986. Vegetation and soils information contained in transformed Thematic Mapper data. Proceedings of the IGARSS 1986 Symposium, Zurich Switzerland (p. 1465–70). Paris, France.

Dymond, C. C., D. J. Mladenoff, and V. C. Radeloff. 2002. Phenological differences in Tasseled Cap indices improve deciduous forest classification. Remote Sensing of Environment 80:460–72.

Ehrenfeld, J. G. 2000. Evaluating wetlands within an urban context. Ecological Engineering 15:253–65.

Ghermay, L., H. S. Rochon, B. West, and S. Abdullah. 2000. Utilizing archival remotely sensed data in support of wetland resource management. IGARSS 2000: 2000 International Geoscience and Remote Sensing Symposium, p. 1921–24.

Hame, T., I. Heiler, and J. S. Miguel-Ayanz. 1998. An unsupervised change detection and recognition system for forestry. International Journal of Remote Sensing 19:1079–99.

Harvey, K. R. and G. J. E. Hill. 2001. Vegetation mapping of a tropical freshwater swamp in the Northern Territory, Australia: a comparison of aerial photography, Landsat TM and SPOT satellite imagery. International Journal of Remote Sensing 22:2911–25.

Hayes, D. J. and S. A. Sader. 2001. Comparison of change-detection techniques for monitoring tropical forest clearing and vegetation regrowth in a time series. Photogrammetric Engineering and Remote Sensing 67:1067–75.

Hewitt, M. J. 1990. Synoptic inventory of riparian ecoystems: The utility of Landsat Thematic Mapper data. Forest Ecology and Management 33/34:605–20.

Hosking, E. J., C. S. Bach, R. J. Applegate, R. A. Karfs, and J. F. Wallace. 2001. Mangrove monitoring using sequences of Landsat imagery in the Mary River wetlands. IGARSS 2001; 2001 IEEE International Geoscience and Remote Sensing Symposium, p. 2241–43.

Houhoulis, P. F. and W. K. Michener. 2000. Detecting wetland change: a rule-based approach using NWI and SPOT-XS data. Photogrammetric Engineering and Remote Sensing 66:205–11.

Huang, C., B. Wylie, L. Yang, C. Homer, and G. Zylstra. 2002a. Derivation of a Tasseled Cap transformation based on Landsat and at-satellite reflectance. International Journal of Remote Sensing 23:1741–48.

Huang, C., L. Yang, C. Homer, B. Wylie, J. Vogelman, and T. DeFelice. 2001. At-satellite reflectance: a first order normalization of Landsat and ETM+ images. USGS White Papers. http://landcover.usgs.gov/pdf/huang2.pdf.

Huang, C., Z. Zhang, L. Yang, B. Wylie, and C. Homer, C. 2002b. MRLC 2000 image preprocessing procedure, USGS White Paper. http://landcover.usgs.gov/pdf/image_preprocessing.pdf

Jano, A. P., R. L. Jeffries, and R. F. Rockwell. 1998. The detection of vegetational change by multitemporal analyis of Landsat data: the effects of goose foraging. Journal of Ecology 86:93–99.

Jensen, J. R. 1996. Introductory Digital Image Processing, third edition. Prentice Hall, Upper Saddle River, NJ, USA.

Johnson, R. D. and E. S. Kasischke. 1998. Change vector analysis: a technique for the multispectral monitoring of landcover and condition. International Journal of Remote Sensing 19:411–26.

Kendy, E. 2001. Ground-water resources of the Gallatin Local Water Quality District, southwestern Montana. U.S. Geologic Survey: Fact Sheet 007–01.

Kindscher, K., A. Fraser, M. E. Jakubauskas, and D. M. Debinski. 1998. Identifying wetland meadows in Grand Teton National Park using remote sensing and average wetland values. Wetlands Ecology and Management 5:265–73.

Lawrence, R., A. Bunn, S. Powell, and M. Zambon. 2004. Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. Remote Sensing of Environment 90:331–36.

Lawrence, R. L. and A. Wright. 2001. Rule-based classification systems using classification and regression tree (CART) analysis. Photogrammetric Engineering and Remote Sensing 67:1137–42.

Lu, D., P. Mausel, E. Brondizio, and E. Moran. 2003. Change detection techniques. International Journal of Remote Sensing 25:2365–2407.

Malila, W. A. 1980. Change vector analysis: an approach to detecting forest change with Landsat. Proceedings of the 6th International Symposium on Machine Processing of Remotely Sensed Data. Purdue University, West LaFayette, IN, USA, (West LaFayette, IN: Purdue University), p. 326–35.

Mas, J. F. 1999. Monitoring land-cover changes: a comparison of change detection techniques. International Journal of Remote Sensing 20:139–52.

Masek, J. G., M. Honzak, S. N. Goward, P. Liu, and E. Pak. 2001. Landsat-7 ETM+ as an observatory for land cover: initial radiometric and geometric comparisons with Landsat-5 Thematic Mapper. Remote Sensing of Environment 78:118–30.

Mitsch, W. J. and J. G. Gosselink. 2000. The value of wetlands: importance of scale and landscape setting. Ecological Economics 35:25–33.

Munyati, C. 2000. Wetland change detection on the Kafue Flats, Zambia, by classification of a multitemporal remote sensing image dataset. International Journal of Remote Sensing 21:1787–1806.

Narumalani, S., Y. Zhou, and J. R. Jensen. 1997. Application of remote sensing and geographic information systems to the delineation and analysis of buffer zones. Aquatic Botany 58:393–409.

Nielsen, A. A., K. Conradsen, and J. J. Simpson. 1998. Multivariate alteration detection (MAD) and MAF postprocessing in multispectral, bitemporal image data: new approaches to change detection studies. Remote Sensing of Environment 64:1–19.

Oetter, D. R., W. B. Cohen, M. Berterretche, T. K. Maiersperger, and R. E. Kennedy. 2001. Land cover mapping in an agricultural setting using multiseasonal Thematic Mapper data. Remote Sensing of Environment 76:139–55.

Parmenter, A. W., A. Hansen, R. Kennedy, W. Cohen, U. Langner, R. Lawrence, B. Maxwell, A. Gallant, and R. Aspinall. 2003. Land use and land cover change in the Greater Yellowstone Ecosystem: 1975–1995. Ecological Applications 13:687–703.

Ramsey, E. W. 1995. Wetlands, global climate change, and remote sensing. Elements of Change: Aspen Global Change Institute. http://www.agci.org/publications/eoc95/session1/Ramsey.html

Ramsey, E. W. and S. C. Laine. 1997. Comparison of Landsat Thematic Mapper and high resolution aerial photography to identify change in complex coastal wetlands. Journal of Coastal Research 13:281–92.

Ramsey, E. W., G. A. Nelson, and S. K. Sapkota. 2001. Coastal Change Analysis Program implemented in Louisiana. Journal of Coastal Research 17:53–71.

Ramsey, E. W., A. Rangoonwala, G. Nelson, and R. Ehrlich. 2005. Mapping the invasive species, Chinese tallow, with EO1 satellite Hyperion hyperspectral image data and relating tallow occurrences to a classified Landsat Thematic Mapper land cover map. International Journal of Remote Sensing 26:1637–57.

Ringrose, S., A. Jellema, P. Huntsman-Mapila, L. Barker, and K. Brubaker. 2005. Use of remotely sensed data in the analysis of soil-vegetation changes along a drying gradient peripheral to the Okavango Delta, Botswana. International Journal of Remote Sensing 26:4293–4319.

Sader, S. A., D. Ahl, and W. S. Liou. 1995. Accuracy of Landsat-TM and GIS rule-based methods for forest wetland classification in Maine. Remote Sensing of Environment 53:133–44.

Stefanov, W. L., M. S. Ramsey, and P. R. Christensen. 2001. Monitoring urban land cover change: an expert system approach to land cover classification of semiarid to arid urban centers. Remote Sensing of Environment 77:173–85.

Syphard, A. D. and M. W. Garcia. 2001. Human and beaver induced wetland changes in the Chickahominy River watershed from 1953 to 1994. Wetlands 21:342–53.

Tiner, R. W. 1999. Using plants as indicators of wetlands. Proceedings of the Academy of Natural Sciences of Philadelphia 144:240–53.

Townsend, P. A. and S. J. Walsh. 2001. Remote sensing of forested wetlands: application of multitemporal and multispectral satellite imagery to determine plant community composition and structure in southeastern USA. Plant Ecology 157:129–49.

Toyra, J., A. Pietroniro, L. W. Martz, and T. D. Prowse. 2002. A multisensor approach to wetland flood monitoring. Hydrological Processes 16:1569–81.

Wang, L., J. Lyons, and P. Kanehl. 2001. Impacts of urbanization on stream habitat and fish across multiple spatial scales. Environmental Management 28:255–66.

Warner, T. 2005. Hyperspherical direction cosine change vector analysis. International Journal of Remote Sensing 26: 1201–15.

Whigham, D. F. 1999. Ecological issues related to wetland preservation, restoration, creation and assessment. The Science of the Total Environment 240:31–40.

Willard, D. E. 1935. Montana: The Geological Story. The Science Press Printing Company, Lancaster, PA, USA.

Winter, T. C., D. O. Rosenberry, D. C. Buso, and D. A. Merk. 2001. Water source to four U.S. wetlands: implications for wetland management. Wetlands 21:462–73.

Manuscript received 16 June 2006; accepted 28 March 2007.