USING REMOTELY SENSED DATA AND GIS to Assess Development in Essex County, Massachusetts

Peter S. Tardie
University of New Hampshire

ABSTRACT

Population and development of land in Essex County, Massachusetts have increased. As surrounding urban centers expand, proliferation into neighboring communities has become apparent. New residents create need for the development of land for housing, businesses, schools, ball-fields, and parks, and place significant strains on the existing land cover and available natural resources. To monitor development in the county, a change detection analysis was performed using remotely sensed data to determine the extent of land cover change over time. Change detection is a technique used in remote sensing to determine the changes in land cover or vegetation between two or more time periods. Change detection is an important process for monitoring and managing natural resources because it provides a means to quantify the areal extent and nature of the change. In this study, three change detection methods were applied to Landsat Thematic Mapper (TM) satellite data to detect land cover changes that occurred in Essex County, Massachusetts from 1990 to 2001: (1) Multi-date visual composite, (2) Image differencing and (3) Post-classification. The results from each change detection technique were compared to determine which method provided the most informative results. The post-classification method out-performed the multi-date visual composite and image differencing techniques as it provided the capability to qualitatively and quantitatively assess the type, nature, and extent of land cover change that occurred.
Keywords: change detection, land cover change, GIS, land development, remote sensing

Introduction

Since the 1970s, population and development of land in both Essex and Middlesex Counties in Massachusetts have increased, and as neighboring urban centers expand, both have proliferated into adjacent communities. This expansion has led to the conversion of land for housing, businesses, schools, recreation, and parks, placing significant strain on existing land cover and land use as well as available natural resources. In addition, mounting growth pressures and a reduction of undeveloped land have raised serious concerns as cropland and forest fragmentation, wetland destruction, protected open-space infringement, pollution, and systematic losses of rural conditions have become obvious. Without focused land cover and land use change research and community-wide environmental education, the continued loss of land may be accepted as "just" the results of progress.

Changes to the environment can provide insight into how land is or has been managed, and the use of established change detection research methodologies can serve to monitor these changes and evaluate management practices (Brothers and Fish 1978; Im et al. 2008). Change detection identifies the differences in the state of an object or phenomenon by observing it at different times and its methodology can provide the capability to: (1) detect occurrences of land cover change, (2) identify the types or nature of change, and (3) quantify its spatial extent (Brothers and Fish 1978; Singh 1989; Macleod and Congalton 1998). Change detection also can provide valuable insight into environmental and socio-economic conditions resulting from local, national, or international regulatory and/or land use policy changes over time (Lunetta and Elvidge 1998; Bontemps et al. 2008).

Traditionally, aerial photography had been utilized to detect changes in land cover in many areas (Richter 1969; Adeniyi 1980; Lo and Wu 1984). However, identifying land cover change through the use of aerial photography can be difficult because it requires a large data collection effort, time, manual interpretation (which can be subjective), and sophisticated mathematical computation to determine the distribution of the land cover type of specific interest (Weismiller et al. 1977; Lo and Shipman 1990). In addition, traditional or non-digital aerial photography cannot readily reveal the processes of land cover change without an extensive investigation or validation of the specific land cover classes of change within the field (Lo and Shipman 1990).

Beginning in 1972, the Landsat remote sensing satellite program has provided a more efficient and cost-effective method for monitoring land cover from space (Fung and LeDrew 1988; Lunetta and Elvidge 1998). Landsat has been utilized as an exclusive source of multi-spectral data for many studies because of its advantages over more traditional data capture methods like aerial photography (Gordon 1978; Martin 1989; DeFries and Chan 2000; Teillet et al. 2001). To detect changes in land cover, a comparison of two or more satellite images acquired at different times can be used to evaluate the temporal or spectral reflectance differences that have occurred between them (Masry et al. 1975; Yuan and Elvidge 1998). With its repetitive data acquisition (every 16 days), and seamless integration with advancing technologies such as geographic information systems (GIS), Landsat satellite data has made environmental monitoring applications such as change detection ubiquitous (Wickware and Howarth 1981; Rynzar and Wagner 2001; Thome 2001, Yuan et al. 2005; Wulder et al. 2008).

The primary objective of this research was to detect new development in Essex County, Massachusetts from 1990 to 2001. The specific objectives were to: (1) determine the appropriate methods to detect new development, (2) evaluate three change detection techniques and determine which provided the most informative results for Essex County, (3) quantify the nature and spatial extent of "from-to" land cover change that occurred, and (4) lay the groundwork for future land cover change research in Massachusetts.

Materials and Methods

Essex County is located in the northeast corner of the Commonwealth of Massachusetts. The county borders the Atlantic Ocean to its east, New Hampshire to its north, and Suffolk and Middlesex counties to its south and west, respectively. The county comprises a land area of approximately 501 square miles (320,640 acres) and contains thirty-four municipalities, most of which are bucolic in character. Essex County also has five major interstate highways passing through it: Routes US-1, I-95, I-93, SR-128, and I-495, and contains three predominant urban centers: Lawrence, Lynn, and Peabody.

To ensure the accurate detection of land cover change and reduce the effects of seasonal phenological differences of vegetation, two near-anniversary Landsat TM images collected on 8 September 1990 and 29 August 2001 covering Essex County and the surrounding area were used.[1]

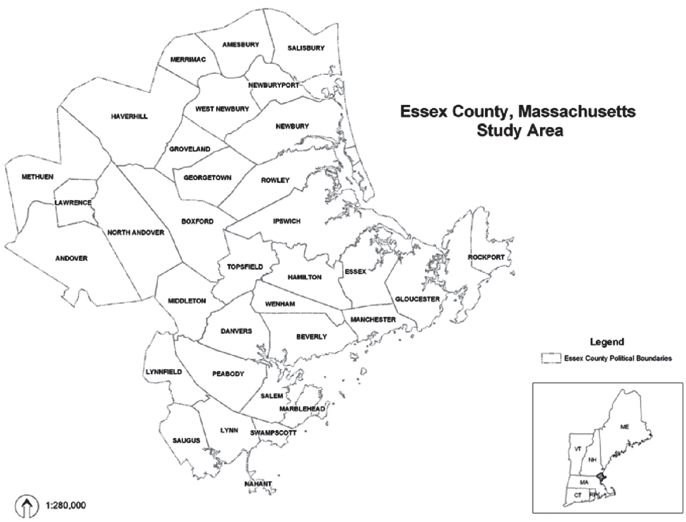

Figure 1. The study area of Essex County, Massachusetts is located in the northeast corner of the Commonwealth of Massachusetts in central coastal New England. The county comprises a land area of approximately 501 square miles and contains thirty-four cities or towns.

Reference data of Essex County were obtained from the: (1) Massachusetts Office of Geographic Information Systems (MassGIS); (2) Department of Natural Resources Conservation Resource Mapping Land Information Systems Laboratory at the University of Massachusetts (Amherst campus); (3) global positioning system (GPS) field assessments, and (4) aerial photography and imagery interpretations. These data consisted of primarily 1:12,000 scale CIR analog ortho-photographs produced in 1991, 0.5-meter resolution 1:5,000 scale color digital ortho-images produced in 2001, and scanned 1:24,000 scale USGS topographic quadrangles produced from 1982 to 1987. In addition, 1:5,000 scale GIS vector shapefiles produced from 1971 to 1999 comprising local, state, county, and township political boundaries were also acquired and used for image masking and community landmark identification.

Reference data used exclusively for image classification accuracy assessment were acquired through field surveys using GPS and aerial photography/imagery interpretations. These data were consolidated and transformed into six GIS vector (point) shapefiles each containing fifty-one land cover class-specific reference data samples. Descriptive attributes embedded within these shapefiles (e.g., identification, land cover type, field position, etc.) were standardized using alphanumeric coding and condensed to form one conglomerate shapefile which housed all reference data samples (306 in total). All digital reference data utilized for comparison with the Landsat TM image classifications were projected into Massachusetts State Plane Coordinate System, North American Datum 1983 (NAD83) meters and were used in the ESRI ArcGIS version 9.0 geographic information system and ERDAS Imagine version 8.6 image processing platforms (ESRI 2004; ERDAS 2004).

Image Rectification, Masking, and Normalization

To prepare the satellite images for an accurate change detection comparison, it was imperative to geometrically rectify the imagery (Townshend et al. 1992; Kwarteng and Chavez 1998). Lunetta and Elvidge (1998) indicate that if any mis-registration greater than one pixel occurs, erroneous land cover change results will occur. Therefore, to lessen the impact of mis-registration on the change detection results, geometric registration was performed on a pixel-by-pixel basis using GPS-acquired ground control points. The accuracy of image registration is usually conveyed in terms of root-mean-square (RMS) error and for Landsat TM imagery, the acceptable RMS error is approximately 0.5 pixels (Townshend et al. 1992; Yuan and Elvidge 1998; Lunetta and Elvidge 1998). The research area was then extracted from each of the rectified images using the Essex County political boundary GIS shapefile (excluding offshore islands), and was re-projected into Massachusetts State Plane Coordinate System (NAD83) meters.

To improve the results of the change detection analyses and allow the differences of pixel brightness values between 1990 and 2001 imagery to be maintained as the actual changes in surface conditions (Mas 1999; Dobson et al. 1995; Yuan and Elvidge 1998), pixel reflectance values from clear and deep water bodies were assessed (Song et al. 2001; Gordon 1978). The spectral bands within each image were then extracted individually and evaluated, and the minimum digital number value (often attributed to the effects of the atmosphere) was subtracted from all of the pixels to shift the image histogram to the left so that zero values appear within the data (Chavez 1989; Jensen 1996; Pax-Lenney et al. 2001; Song et al. 2001). The spectral bands were then re-assembled into their appropriate origin and all histograms (adjusted and unadjusted) were reviewed to confirm the reliability of the corrections prior to performing the selected change detection analyses.

Data Exploration and Image Classification

Prior to image classification, a variety of false color composites were generated for each of the normalized images by loading the spectral bands in the imagery. These composites were used qualitatively to enhance the visual discrimination of land cover class types using the specific responsiveness characteristics of each spectral band. In addition, spectral pattern analyses and bi-spectral plots were developed and spectral/spatial enhancement filters (e.g., texture and smoothing filters) were incorporated to qualitatively distinguish land cover types and to assist with image classification.

To perform the post-classification change detection technique, classification of the 1990 and 2001 images was required. In addition, the development of a classification scheme was essential in order to organize and characterize the spatial information contained within the imagery into logical map categories for the change detection analyses (Congalton and Green 1999). The National Ocean Service's C-CAP Coastal Land-Cover Classification System (Dobson et al. 1995) served as the primary reference guide to develop seven distinct class categories: (1) Developed, (2) Bareland, (3) Forest, (4) Grassland, (5) Water, (6) Wetland, and (7) Unclassified.

The 1990 and 2001 images were classified independently using the unsupervised ISODATA (Iterative Self-Organizing Data Analysis Technique) algorithm (ERDAS 2004), to produce an output layer and signature to identify the spectrally unique clusters contained within the imagery. The pixels represented by these clusters were layered upon the rectified and normalized imagery for labeling. Clusters which could not be readily classified were subjected to an iterative "cluster-busting" algorithm technique for further ISODATA processing to identify additional clusters (Jensen et al. 1993). This procedure was iterated to achieve the desired level of classification for each image.

Upon completion, the final clusters were recompiled, mosaicked, and recoded into the appropriate categories of the classification scheme and smoothed using a 3x3 majority filter to remove or reduce speckling. An independent and quantitative accuracy assessment was then performed on the resulting 1990 and 2001 image classifications using the reference data and individual 6-class single date error matrices (Congalton 1988). In consideration of possible GPS positional errors often introduced during the field data acquisition process (e.g., from GPS unit limitations, satellite constellation configuration, atmospheric or ground surface disturbances, or forest canopy obstructions), 3x3, 6x6, and 9x9 window majority sizes (using a variety of clear majority thresholds) were tested in order to determine class value. Accuracy assessment measures (error matrix, class accuracy totals, and Kappa statistics) were generated for the 1990 and 2001 image classifications, and a Visual Basic program, KAPPA (Congalton 2004), was used to test and confirm the accuracy assessment statistics.

Change Detection

Three change detection techniques: multi-date visual composite, image differencing, and post-classification were selected and compared in this study. In addition, reduction in vegetation was viewed as an indicator of development. Therefore, the multi-date visual composite image change detection technique was performed by inserting band 4 (Landsat TM near infrared) of the 2001 image into the green image plane and band 4 of the 1990 image into the red and blue image planes of the specific write function memory banks (e.g., red, green, and blue portions) of the computer monitor. The images were then overlaid to produce a visual composite to highlight the changes (growth and reduction) in vegetation and therefore development using additive color theory (i.e., the mixing of equal intensities of primary colors to make secondary colors) (Jensen 1996).

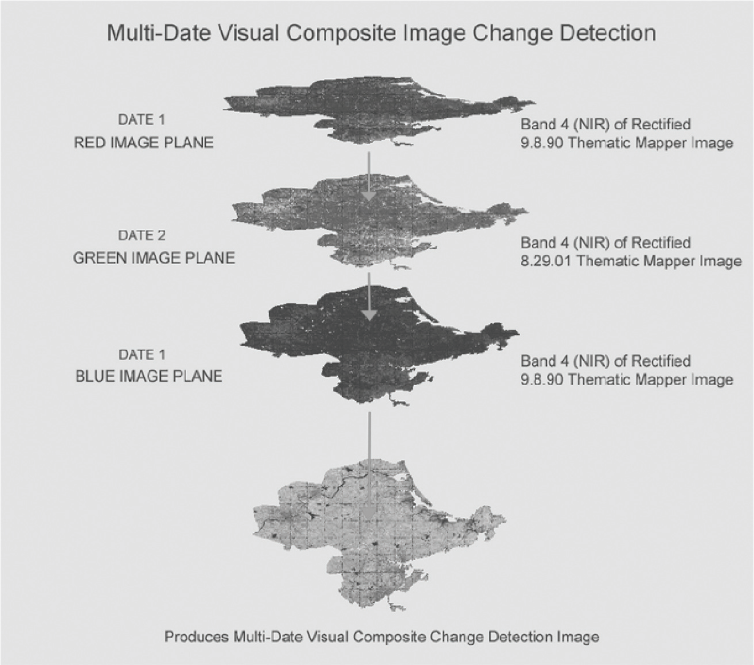

Figure 2. Procedural steps in performance of the Multi-Date Visual Composite Image Change Detection technique.

Image differencing was performed by subtracting the normalized digital number (DN) value of band 4 (Landsat TM near infrared) within the 1990 image from the DN value of the same pixel and band within the 2001 image. Standard deviation thresholds were then tested to separate these pixels within the image mask into the appropriate changed and unchanged categories to reflect the areas where "likely" or "realistic" change took place (e.g., where vegetation had been cleared to form new development).

In the post-classification technique, the 1990 and 2001 images were classified independently following the procedures outlined in the data exploration and image classification section and then compared within ERDAS Imagine and combined using the GIS MATRIX technique.

The matrix change image classification was then compared within ArcGIS with the reference data and image results from the previous techniques. A GIS analysis was conducted to refine the change image classification and "select-out" the areas where the land cover changed to form

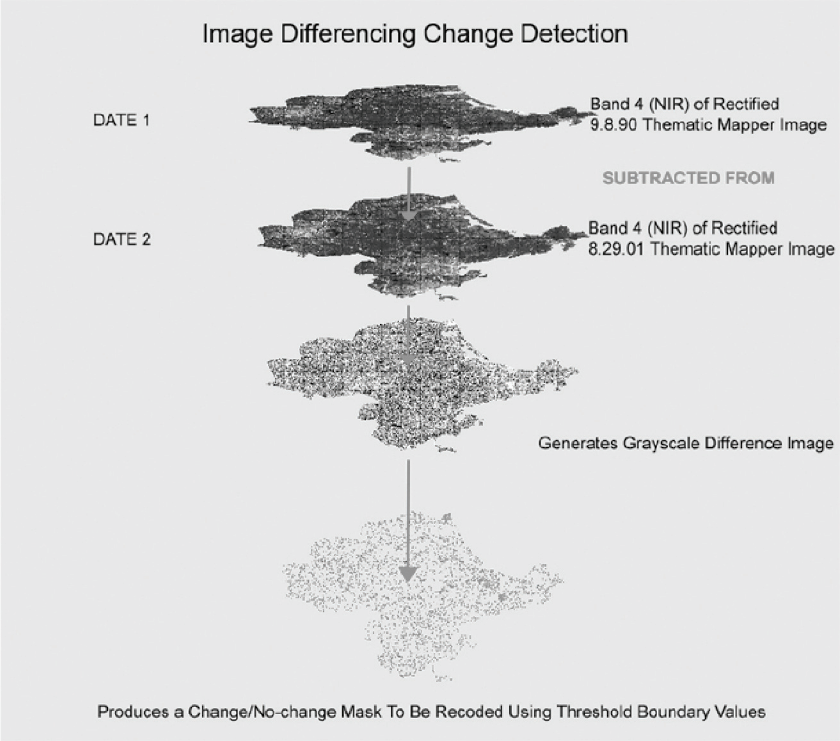

Figure 3. Procedural steps in performance of the Image Differencing Change Detection technique.

newly developed land. These areas were then assigned a distinctive thematic color value to differentiate the "from-to" or type and nature of land cover change which took place, and the corresponding pixel count information for each land cover class was then converted into ground area measurement units (or 0.162 acres which is the land area value of one 28.0-meter Landsat TM pixel), to quantify its areal extent. To determine how effective each method was in detecting change, the results from the image differencing and post-classification methods were qualitatively assessed using the reference data. In addition, the results of each change detection method were assessed for its capability to provide descriptive information on the land cover change that occurred.

Change Detection Technique Comparison

To provide a meaningful assessment of the agreement or disagreement present within the results generated from both the image differencing and post-classification techniques, a quantitative analysis was performed using the statistical analysis software package, SAS-Version 8.0 (SAS Institute, Inc. 2005). The pixel area results of the image differencing and post-classification techniques were recoded separately into three distinct values or groupings: 0 = background, 1 = no change, 2 = change, and were exported into ASCII format. Each image was then imported independently into SAS and the background was removed from each of the image data sets and a cross tabulation of the coded values (1 = no change, 2 = change) was then performed using the PROC FREQ option for statistical analysis.

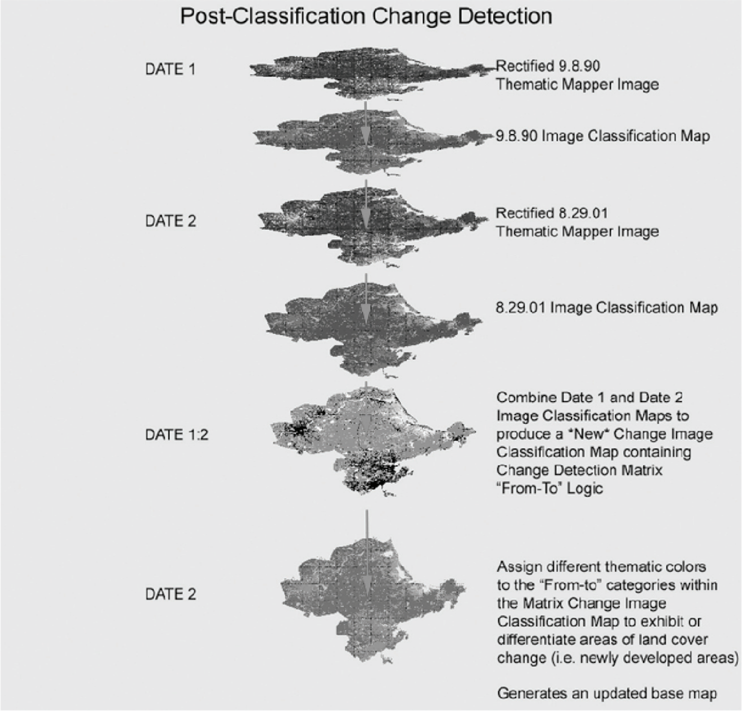

Figure 4. Procedural steps in performance of the Post-Classification Change Detection technique.

The 1990 image exhibited a north-westerly ground coordinate position shift of 1,026.25 meters from the 2001 image. A geometric correction was performed using ninety-three ground control points (GCPs) to register the 1990 image to the 2001 image with a first order polynomial transformation and nearest neighbor re-sampling algorithm. Geometric registration of

1990 Image Classification

		REFERENCE DATA						
		D	B	F	G	W	WT	Row Total
CLASSIFIED DATA	D	**50**	12	0	0	2	0	64
	B	1	**27**	0	2	0	0	30
	F	0	7	**51**	2	0	35	95
	G	0	3	0	**47**	0	9	59
	W	0	2	0	0	**49**	2	53
	WT	0	0	0	0	0	**5**	5
	Col. Total	51	51	51	51	51	51	**229**

PRODUCER'S ACCURACY			USER'S ACCURACY		
Developed (D)	= 50/51	98.0%	**Developed (D)**	= 50/64	78.1%
Bareland (B)	= 27/51	52.9%	**Bareland (B)**	= 27/30	90.0%
Forest (F)	= 51/51	100.0%	**Forest (F)**	= 51/95	53.7%
Grassland (G)	= 47/51	92.2%	**Grassland (G)**	= 47/59	79.7%
Water (W)	= 49/51	96.1%	**Water (W)**	= 49/53	92.5%
Wetland (WT)	= 05/51	9.8%	**Wetland (WT)**	= 05/51	100.0%

OVERALL ACCURACY

= 299/306	74.8%

KAPPA ANALYSIS RESULTS

KHAT	Variance	Z Statistic
0.698	0.0008259	24.288858

Table 1. Accuracy assessment of the 1990 image classification.

the 1990 image to the 2001 image resulted in an overall root-mean-square (RMS) error of 11.8 meters, which was well within the documented acceptable limits (Lunetta and Elvidge 1998).

A noticeable upward shift in the pixel values from 1990 to 2001 was present within the visible bands (Landsat TM bands 1-3), likely a result of effects of atmospheric conditions at the time of satellite acquisition (Jensen 1996). In addition, the National Oceanic and Atmospheric Administration (NOAA) recorded differences in the temperature and precipitation values (in several climate monitoring stations county-wide) for each image acquisition date. Therefore, the high minimum values were subtracted with the appropriate bias values to adjust and shift the affected histograms in each image to the left to within one positive brightness value of a zero reflectance value, thus ensuring the 1990 and 2001 satellite data were valid for comparison.

The "cluster-busting" classification technique (Jensen 1996) produced 271 clusters for the 1990 image and 284 clusters for the 2001 image. For the accuracy assessment, the results produced for the 3x3, 6x6, and 9x9 window majority sizes and thresholds were similar for all sizes of clusters. Therefore, the 6x6 window majority size with a 36 out of 36 clear majority threshold rule was selected and used for the assessment. Tables 1 and 2 display the assessment results from the error matrices derived for each image classification. The overall accuracy achieved for the

2001 Image Classification

		REFERENCE DATA						
		D	B	F	G	W	WT	Row Total
CLASSIFIED DATA	D	**51**	10	0	0	2	0	63
	B	0	**38**	0	0	0	0	38
	F	0	1	**51**	2	0	20	74
	G	0	2	0	**49**	0	3	54
	W	0	0	0	0	**49**	2	51
	WT	0	0	0	0	0	**26**	26
	Col. Total	51	51	51	51	51	51	**264**

PRODUCER'S ACCURACY

Developed (D)	= 51/51	100.0%
Bareland (B)	= 38/51	74.5%
Forest (F)	= 51/51	100.0%
Grassland (G)	= 49/51	96.1%
Water (W)	= 49/51	96.1%
Wetland (WT)	= 26/51	51.0%

USER'S ACCURACY

Developed (D)	= 51/63	81.0%
Bareland (B)	= 38/38	100.0%
Forest (F)	= 51/74	68.9%
Grassland (G)	= 49/54	90.7%
Water (W)	= 49/51	96.1%
Wetland (WT)	= 26/26	100.0%

OVERALL ACCURACY

= 264/306 86.3%

KAPPA ANALYSIS RESULTS

KHAT	Variance	Z Statistic
0.831	0.0005469	35.752

Table 2. Accuracy assessment of the 2001 image classification.

1990 classification was 74.8% with a KHAT value of 0.698, and the overall accuracy for the 2001 classification was 86.3% with a KHAT value of 0.831.

Change Detection - Multi-date Visual Composite

The multi-date visual composite image change detection technique performed using the 1990 and 2001 images resulted in the generation of a new "virtual" composite. Figure 5 illustrates these results in a larger scale image subset comprising the Merrimack Valley portion of the county. An interpretation (of Figure 5) suggests that the magenta regions (or dark grayscale areas if in b/w) within the image composite represent vegetation which has been cleared for new urban development. The green regions (or lighter gray areas) represent higher response in the near infrared wavelength due to the re-growth of vegetation, and the mid-range gray regions represent areas where no change in land cover occurred.

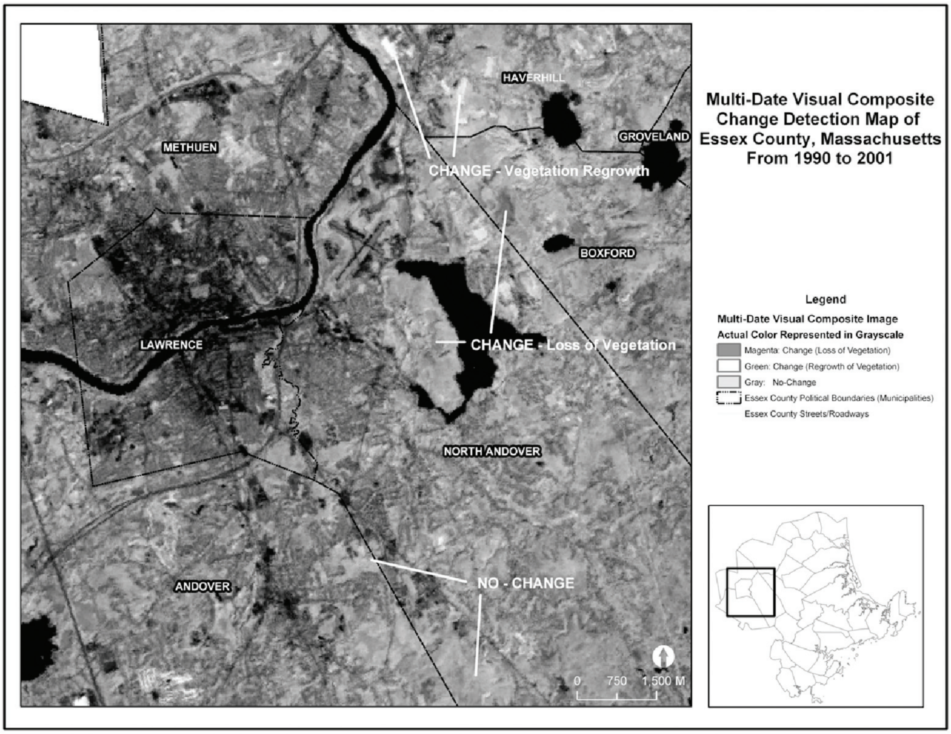

Figure 5. Multi-date visual composite change detection map of Essex County. The magenta regions (or dark grayscale areas if in b/w) within the image composite represent vegetation which has been cleared for new urban development. The green regions (or lighter gray areas) represent higher response in the near infrared wavelength due to the re-growth of vegetation, and the mid-range gray regions represent areas where no change in land cover occurred.

Change Detection - Image Differencing

The image differencing change detection technique produced a grayscale difference image which reflected the changes or differences in the individual pixel values between the two image dates. A comparative assessment of the histogram values within the change/no-change mask and multi-date visual composite image revealed that the pixels which did not change in brightness value between the two image dates were distributed around the mean, and the pixels that changed between the two image dates were found within the tails of the histogram (Khorram et al. 1999). Therefore, twelve standard deviation thresholds were tested in order to separate these pixels within the mask into the appropriate changed and unchanged categories to reflect the areas where "likely" or "realistic" change took place within the county (e.g., where vegetation had been cleared to form new development). At the lowest threshold level (1.0) too many pixels were classified as changed. As the threshold level increased, a reduction in amount of change pixels displayed occurred, and at the highest threshold level (6.0) there were not enough pixels classified as 'changed'.

The best threshold boundary for use in the change detection analysis technique maximizes the appropriate amount of changed pixels displayed by reducing or removing those pixels which are the products of slight pixel-radiance change introduced from active land cover changes (at various phenological stages), geometric alignment errors, radiometric normalization errors, and/or surface moisture differences. Therefore, after several iterations, using the field reference data and multi-date visual composite change image for a comparative assessment, the (3.0) standard deviation from the mean was found to be the most suitable threshold boundary to achieve the desired extraction result (i.e., separation of changed from unchanged pixels).

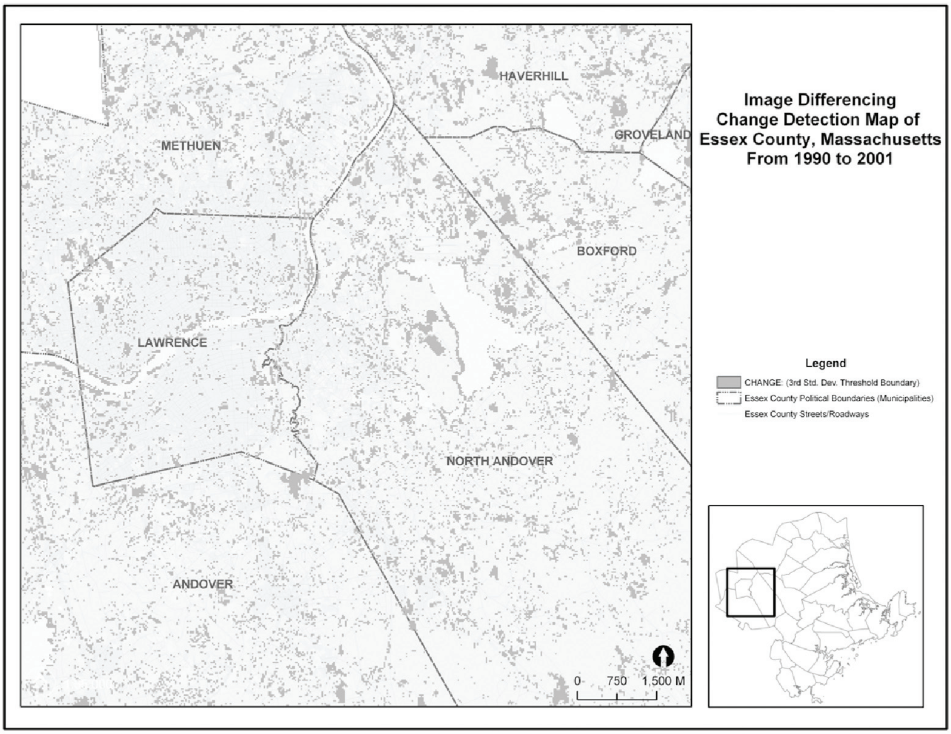

Figure 6. Image Differencing change detection map of Essex County. The grayscale difference image reflects the changes or differences in the individual pixel values between the two image dates. This image was derived by testing several standard deviation thresholds to separate these pixels within the image into the appropriate changed and unchanged categories to reflect the areas where "likely" or "realistic" land cover change took place within the county.

Change Detection - Post Classification

The GIS MATRIX procedure produced a grayscale matrix change image classification (raster) with an associated database attribute table depicting the land cover class changes that occurred between the 1990 and 2001 image classifications using thirty-six "from-to" land cover class identifier categories with corresponding classified pixel counts. This study's primary focus was to detect and quantify areas within Essex County that changed to form new development. Therefore, as can be seen in Figure 7, the appropriate "from-to" class identifier categories and/or pixel regions within the matrix change image classification (i.e., from Bareland to Developed, From Forest to Developed, From Grassland to Developed, etc.), were selected.

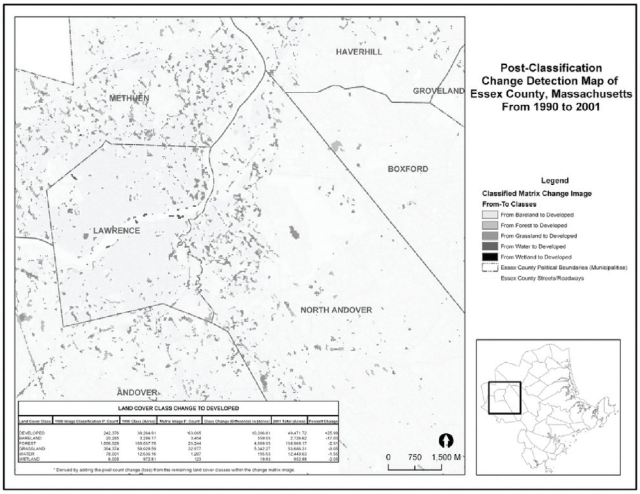

Figure 7. The post-classification change detection map of Essex County. This technique provided the capability to illustrate the land cover class changes that occurred between the 1990 and 2001 image classifications (as shown here in grayscale format) in thirty-six "from-to" land cover class identifier categories with corresponding classified pixel counts. The "from-to" class identifier categories and/or pixel regions (e.g., from Bareland to Developed, from Forest to Developed, from Grassland to Developed, etc.) within the matrix change image classification were originally assigned thematic colors (shown here in grayscale format) to highlight land cover change to developed land.

Essex County gained approximately 10,200 "new" acres of development from 1990 to 2001 through a combined loss in acreage from the Bareland, Forest, Grassland, Water, and Wetland land cover class categories. This indicates that there was an approximate 26.0% overall increase in newly developed land areas within the 1990 and 2001 image classifications from approximately 39,000 to 49,000 acres or 60.93 to 76.56 square miles.

The resulting matrix (Figure 8) shows the pixel count and percentage agreement between the post-classification and the image differencing technique.

The two techniques agreed with each other in the detection of change and no change 77.3%

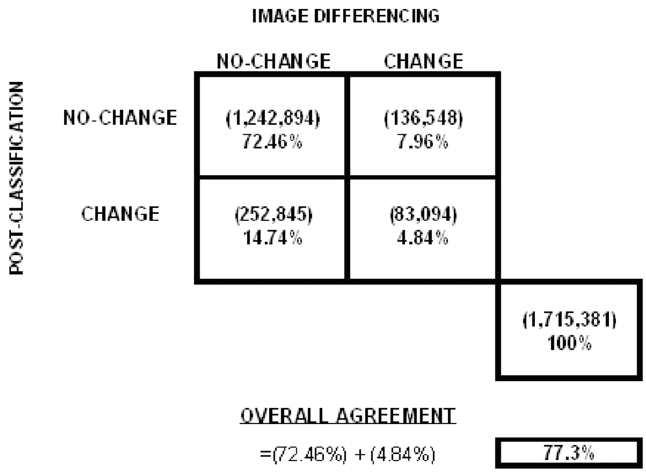

Figure 8. Percentage agreement matrix for the image differencing and post-classification change detection techniques.

of the time. For approximately 15.0% of the pixels, the post-classification technique detected a change while image differencing did not. Conversely, for approximately 8.0% of the pixels, image differencing detected a change while post-classification did not. Therefore, in all, the two techniques were in disagreement for 23.0% of the pixels.

Discussion and Conclusions

The multi-date visual composite image change detection technique proved to be efficient to produce a rapid "on-screen" visualization of the changes in both vegetation and development that occurred within the county. As the results from this technique are generated and stored within the computer workstation's virtual memory, statistical image classification is not feasible. Therefore, the unique spectral clusters contained within the composite of satellite data of Essex County could not be effectively labeled or classified with the distinct land cover class information required to perform further, more robust, land cover change analyses.[2] Although this technique was unable to provide a quantitative assessment through the use of classified "from-to" land cover change identifiers, the resulting image composite was useful to qualitatively assess and explore the overall amount and location of land cover change which took place within the county from 1990 to 2001. Furthermore, the results derived from this technique proved to be a valuable asset as they were used extensively within the GIS to: (1) test and develop the optimum threshold boundary to separate the change/no-change pixels within the change/no-change mask produced by the image differencing technique, (2) interpret the results from the post-classification technique, and (3) compare and contrast the correspondence of the change pixels derived from each of the selected change detection techniques. Therefore, this technique was effective in providing the capability to rapidly look at the changes that occurred in Essex County using two dates of remotely sensed imagery at one time.

Image differencing, like the multi-date visual composite technique, also provided an efficient means to illustrate the individual pixels within the imagery that have changed between the two time periods. The results generated from this technique simply identified the areas that may have changed or were in the process of change, and did not provide definitive information on the nature of the change (i.e. from-to information) which occurred within the county within the given study period (Jensen 1996). However, image differencing is extremely valuable when used in combination with other change detection techniques (Khorram et al. 1999). The results from the image differencing technique indicate a 15.37% (47,469.62 acres or 74.17 square miles) overall change in land cover took place within the county from 1990 to 2001. As compared to the post-classification's 19.58% (62,484.65 acres or 97.63 square miles) change results, clearly, the success of this technique relies heavily upon the highly subjective and empirical testing and placement of pixel value thresholds to discriminate and extract the changed from unchanged pixels from within the change/no-change mask. Furthermore, additional data exploration and more extensive field research may prove useful in the development of "optimum" or appropriate threshold boundaries to more accurately depict the land cover changes that took place.

Though the operation of image differencing is straightforward, careful consideration of its limitations or sensitivities also must be taken. The results from this technique can often be misinterpreted, because some of the pixels reflecting change between the two time periods can be the products of slight, subtle, or variable pixel value changes caused by image rectification or radiometric correction (normalization) differences, and/or environmental moisture conditions. These effects can increase the difficulty of distinguishing areas where land cover classes definitively changed. Therefore, a strong understanding of the sources of errors which can be introduced to the remotely sensed data, coupled with the procedures to correct or reduce their effects prior to performing the analysis, can greatly enhance or improve the overall reliability of the results of this (and other) change detection techniques.

Prior to performing the post-classification technique, a good overall agreement was found between the interpretations of the reference data and the land cover classifications for the image data sets used. The accuracy measures (producer's, user's, Kappa, and Z significance statistics) calculated in the error matrices imply that the classification of the Landsat TM data were appropriate for the purposes of the study, and they justified the use of the derived image classifications for this technique. This technique supplied the most informative results of the three change detection techniques performed, as it provided the capability for both qualitative and quantitative assessment of the land cover changes that occurred to form new developed areas within Essex County from 1990 to 2001.

The combined image classifications allowed for the production of a change image classification from which matrix logic could be used to thematically represent and highlight the "from-to" land cover class changes that took place. In addition, this technique provides valuable change/no-change pixel count information which could be stored within a GIS and converted to the actual ground area to assess the overall gain or loss of a particular land cover class of interest within a given area. However, the results of this technique are directly influenced by the image classifications produced prior. As can be seen from the differences reported in the overall land cover percentage change results, careful consideration of the procedural complexities of image classification and a quantitative accuracy assessment of the change detection results are recommended.

The comparison of results from the image differencing and post-classification change detection analyses provided the capability to explore and gather further insight into the land cover changes using the specific capabilities of more than one technique at one time. After an extensive evaluation of the results from the quantitative analyses, the majority of the disagreements were found to be in pixel regions where the land cover was in the process of change or where the land cover did not change, but differences in moisture content were likely present (e.g., grasslands). In addition, slight pixel reflectance value changes were detected and may have been introduced during the data preprocessing phase from errors in geometric registration, radiometric normalization, and/or image classification errors.

However, the overall percentage of land cover change statistics generated by the image differencing and post-classification techniques (image differencing 15.37% and post-classification 19.58%), indicate that these techniques produced similar results and that the actual amount of change may fall somewhere between these two values, given the constraints of the image data sets used and the image processing methodologies employed within this study. Furthermore, this comparison can provide an image analyst with a powerful diagnostic tool to explore and evaluate the results of numerous change detection analysis techniques, gain further insight into the nature of land cover changes (e.g., stages of surface changes or disturbances) which can occur within a given region at a given time, and/or expose image data processing errors which can reappear as inaccurate change detection analysis results.

This study compared three change-detection techniques to detect new development using Landsat TM imagery. Assessing land cover change through the use of remotely sensed data can often be challenging and the results uncertain. Extensive processing of the satellite imagery is required in order to produce accurate change detection results. Performing this change-detection analysis allowed for the monitoring of a landscape over time and has shown that the integrated use of satellite remote sensing and geographic information systems (GIS) technology is suitable for the detection and quantification of the nature and extent of land cover change of newly developed areas within Essex County from 1990 to 2001. This research also lays the foundation for further research to be conducted in a variety of disciplines within this region, and the methods employed here may serve as a valuable reference guide for land managers to not only provide a basic awareness of the capabilities of the readily available technology to perform land change analyses, but also foster learning about the environment, and assist in advancing sound and sustainable land-use practices.

PETER S. TARDIE is a doctoral student in the Natural Resources and Earth Systems Science Ph.D. Program of the Department of Natural Resources and the Environment, University of New Hampshire Durham, NH 03824. Email: *ptardie@unh.edu*. His research interests include land cover change detection using remote sensing and GIS, and monitoring land development and its effects on the environment.

Acknowledgments

I would like to thank the following:
NASA (National Aeronautics and Space Administration); New Hampshire Space Grant Consortium; Dr. Russell G. Congalton, Dr. Barrett N. Rock, and Lucy Plourde, UNH Department of Natural Resources and the Environment; the anonymous reviewers of my manuscript; and the editors of *The Northeastern Geographer*.

Notes

1. Two near-anniversary Landsat TM images were collected on 8 September 1990 (Landsat 5: ID# 5012030009025110) and 29 August 2001 (Landsat 7 ETM+: ID# 7012030000124150), covering Essex County and the surrounding area (WRS 12/30).

2. For instance, using TM bands(B,G,R, NIR or 1,2,3,4) an image analyst can select and place TM band 4 into the (RGB) color guns of the computer monitor display to compare vegetation and/or water differences between the two time periods. This technique only provides a virtual "layering" of image data within an image viewer within ERDAS Imagine. This technique does not generate or store statistical attributes (or brightness value data behind the raster pixels in tabular format), and therefore, image classification algorithms cannot be performed. Its results are only "visual". These data can be exported in "image" format but not analyzed statistically.

References

Adeniyi, P.O. 1980. Land use change analysis using sequential aerial photography and computer techniques. *Photogrammetric Engineering and Remote Sensing* 46(11): 1447-1464.

Bontemps, S., P. Bogaert, N. Titeux, and P. Defourny. 2008. An object-based change detection method accounting for temporal dependences in time series with medium to coarse spatial resolution. *Remote Sensing of Environment* 112: 3181-3191.

Brothers, G. L. and E. B. Fish. 1978. Image Enhancement for vegetation pattern change analysis. *Photogrammetric Engineering and Remote Sensing* 44(5): 607-616.

Congalton, R.G. (1988). A Comparison of Sampling Schemes Used in Generating Error Matrices for Assessing the Accuracy of Maps Generated from Remotely Sensed Data. *Photogrammetric Engineering and Remote Sensing* 54(5): 593-600.

Congalton, R.G. 2004. *The VB Version of Margfit and Kappa Analysis Software*. Unpublished report, University of New Hampshire, Durham.

Congalton, R.G. and K. Green. 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Boca Raton, FL: CRC/Lewis Press.

Chavez, P. S. 1989. Radiometric Calibration of Landsat Thematic Mapper Multispectral Images. *Photogrammetric Engineering and Remote Sensing* 55(9): 1285-1294.

DeFries, R.S. and J. Cheung-Wai Chan. (2000). Multiple Criteria for Evaluating Machine Learning Algorithms for Land Cover Classification from Satellite Data. *Remote Sensing of Environment* 74(3): 503-515.

Dobson, J. E., E. A. Bright, R. L. Ferguson, D. W. Field, L. L. Wood, K. K. Haddad, H. Iredale III, J. R. Jensen, V. V. Klemas, R. J. Orth, and J. P. Thomas. 1995. *NOAA Coastal Change Analysis Program (C-CAP): Guidance for Regional Implementation*. National Ocean Service, National Marine Fisheries Service. Seattle, WA: Scientific Publications Office, NOAA.

ERDAS. 2004. *ERDAS Imagine v 8.6 Online Manuals*. Atlanta, GA: Leica Geosystems GIS & Mapping, LLC.

ESRI. 2004. *ArcGIS Desktop 9.0 Help* (online). Redlands, CA: Environmental Systems Research Institute, Inc..

Fenstermaker, L. K. 1991. A Proposed Approach for National to Global Scale Error Assessments. *Proceedings of GIS/LIS '91* 1: 293-300.

Fung, T., and E. LeDrew. 1988. The determination of optimal threshold levels for change detection using various accuracy indices. *Photogrammetric Engineering and Remote Sensing* 54(10):1449-1454.

Gordon, H. R. 1978. Removal of atmospheric effects from satellite imagery of the ocean. *Applied Optics* 17(10):1631-1636.

Im, J., J. R. Jensen, and M. E. Hodgson. 2008. Optimizing the binary discriminant function in change detection applications. *Remote Sensing of Environment* 112: 2761-2776.

Jensen, J. R. 1996. *Introductory Digital Image Processing: A Remote Sensing Perspective*, 2nd Edition. Upper Saddle River, NJ: Prentice Hall, Inc.

Jensen, J. R., D. J. Cowen, J. D. Althausen, S. Narumalani, and O. Weatherbee. 1993. An Evaluation of the CoastWatch Change Detection Protocol in South Carolina. *Photogrammetric Engineering and Remote Sensing* 59(4): 519-525.

Khorram, S., G. Biging, N. Chrisman, D. Colby, R. Congalton, J. Dobson, R. Ferguson, M. Goodchild, J. Jensen, and T. Mace. 1999. *Accuracy Assessment of Remote Sensing-Derived Change Detection*. Bethesda, MD: American Society for Photogrammetry and Remote Sensing.

Kwarteng, A. Y., and P.S. Chavez, Jr. 1998. Change detection study of Kuwait City and environs using multitemporal Landsat Thematic Mapper data. *International Journal of Remote Sensing* 19(9):1651-1662.

Lo, C. P. and C. Y. M. Wu. 1984. New town monitoring from sequential aerial photographs. *Photogrammetric Engineering and Remote Sensing* 50(8): 1145-1158.

Lo, C.P. and R. L. Shipman. 1990. A GIS Approach to Land-Use Change Dynamics Detection. *Photogrammetric Engineering and Remote Sensing* 56(11): 1483-1491.

Lunetta, R.S. and C.D. Elvidge. 1998. *Remote Sensing Change Detection: Environmental Monitoring Methods and Applications.* Ann Arbor, MI: Ann Arbor Press.

Macleod, R. D., and R. G. Congalton. 1998. A Quantitative Comparison of Change-Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data. *Photogrammetric Engineering and Remote Sensing* 64(3): 207-216.

Macleod, R. D. 1994. *Using a Quantitative Accuracy Assessment to Compare Various Change Detection Techniques for Eelgrass Distributions in Great Bay, NH with Landsat Thematic Mapper Data*. Master's Thesis, University of New Hampshire, Durham.

Martin, L. R. G. 1989. Accuracy Assessment of Landsat-Based Change-Detection Methods Applied to the Rural-Urban Fringe. *Photogrammetric Engineering and Remote Sensing* 55(2): 209-215.

Mas, J. F. 1999. Monitoring land-cover changes: a comparison of change detection techniques. *International Journal of Remote Sensing* 20(1): 139-152.

Masry, S. E., B. G. Crawley, and W. H. Hilborn. 1975. Difference Detection. *Photogrammetric Engineering and Remote Sensing* 41(9): 1145-1148.

Pathirana, S. 1999. Distribution of Errors in a Classified Map of Satellite Data. *Geocarto International* 14(4): 69-80.

Pax-Lenney, M., C. E. Woodcock, S. A. Macomber, S. Gopal, and C. Song. 2001. Forest mapping with a generalized classifier and Landsat TM data. *Remote Sensing of Environment* 77(3): 241-250.

Richter, D.M. 1969. Sequential Urban Change. *Photogrammetric Engineering* 35(8): 764-770.

Ryznar, R. M. and T.W. Wagner. 2001. Using Remotely Sensed Imagery to Detect Urban Change: Viewing Detroit From Space. *Journal of the American Planning Association* 67 (3): 327-336.

SAS. 2005. *SAS Users Manual*. Cary, North Carolina: SAS Institute, Inc.

Schroeder, T. A., W. B. Cohen, C. Song, M. J. Canty, and Z. Yang. 2006. Radiometric correction of multi-temporal Landsat data for characterization of early successional forest patterns in western Oregon. *Remote Sensing of Environment* 103: 16-26.

Singh, A. 1989. Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing* 10(6): 989-1003.

Song, C., C. E. Woodcock, K. C. Seto, M. P. Lenney, and S. A Macomber. 2001. Classification and Change Detection Using Landsat TM Data: When and How to Correct Atmospheric Effects? *Remote Sensing of Environment* 75: 230-244.

Stehman, S. V. 1992. Comparison of Systematic and Random Sampling for Estimating the Accuracy of Maps Generated from Remotely Sensed Data. *Photogrammetric Engineering and Remote Sensing* 58(9): 1343-1350.

Thome, K. J. 2001. Absolute radiometric calibration of Landsat 7 ETM+ using the reflectance based method. *Remote Sensing of Environment* 78: 27-38.

Teillet, P. M., J. L. Barker, B. L. Markham, R. R. Irish, G. Fedosejevs, and J. C. Storey. 2001. Radiometric cross-calibration of the Landsat-7 ETM+ and Landsat-5 sensors based on tandem data sets. *Remote Sensing of Environment* 78(1 & 2): 39-54.

Townshend, J. R. G., C. O. Justice, C. Gurney, and J. McManus. 1992. The Impact of Misregistration on Change Detection. *IEEE Transactions on Geoscience and Remote Sensing* 30(5): 1054-1060.

Weismiller, R. A., S. J. Kristof, D. K. Sholz, P. E. Anuta, and S. A. Momin. 1977. Change Detection in Coastal Zone Environments. *Photogrammetric Engineering and Remote Sensing* 43(12): 1533-1539.

Wickware, G.M., and P. J. Howarth. 1981. Change Detection in the Peace Athabasca Delta Using Digital Landsat Data. *Remote Sensing of Environment* 11: 9-25.

Wulder, M. A., J. C. White, S. N. Goware, J. G. Masek, J. R. Irons, M. Herold, W. B. Cohen, T. R. Loveland, and C. E. Woodcock. 2008. Landsat continuity: Issues and opportunities for land cover monitoring. *Remote Sensing of Environment* 112: 955-969.

Yuan, D. and C. Elvidge. 1998. NALC Land Cover Change Detection Pilot Study: Washington D.C. Area Experiments. *Remote Sensing of Environment* 66(2): 166-178.

Yuan. F., K E. Sawaya, B .C. Loeffelholz, and M. E. Bauer. 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. *Remote Sensing of Environment* 98: 317-328.