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Land-cover change detection using multi-temporal MODIS NDVI data

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Abstract

Monitoring the locations and distributions of land-cover changes is important for establishing links between policy decisions, regulatory actions and subsequent land-use activities. Past studies incorporating two-date change detection using Landsat data have tended to be performance limited for applications in biologically complex systems. This study explored the use of 250 m multi-temporal MODIS NDVI 16-day composite data to provide an automated change detection and alarm capability on a 1 year time-step for the Albemarle–Pamlico Estuary System (APES) region of the US. Detection accuracy was assessed for 2002 at 88%, with a reasonable balance between change commission errors (21.9%), change omission errors (27.5%), and Kappa coefficient of 0.67. Annual change detection rates across the APES over the study period (2002–2005) were estimated at 0.7% per annum and varied from 0.4% (2003) to 0.9% (2004). Regional variations were also readily apparent ranging from 1.6% to 0.1% per annum for the tidal water and mountain ecological zones, respectfully. This research included the application of an automated protocol to first filter the MODIS NDVI data to remove poor (corrupted) data values and then estimate the missing data values using a discrete Fourier transformation technique to provide high-quality uninterrupted data to support the change detection analysis. The methods and results detailed in this article apply only to non-agricultural areas. Additional limitations attributed to the coarse resolution of the NDVI data included the overestimation of change area that necessitated the application of a change area correction factor.

Keywords: Land cover; Change detection; Multi-temporal imagery; Accuracy assessment

1. Introduction

Land-cover (LC) composition and change are important factors that affect ecosystem condition and function. These data are frequently used to generate landscape-based metrics and to assess landscape condition and monitor status and trends over a specified time interval (Jones et al., 1997). The use of satellite-based remote sensor data has been widely applied to provide a cost-effective means to develop LC coverages over large geographic regions. Past and ongoing efforts for generating LC data for the United States have been implemented using an inter-agency consortium to share the substantial costs associated with satellite data acquisition, processing and analysis. The first fine-resolution National Land-Cover Data (NLCD) set was developed for the conterminous United States using Landsat Thematic Mapper (TM) imagery collected between 1991 and 1992 (Vogelmann et al., 1998). Currently, the NLCD-2001 is under development for all 50 states and the Commonwealth of Puerto Rico (Homer et al., 2004).

Although the NLCD-2001 is expected to provide the most timely national LC database currently available, the required development time will result in approximately a 6-year delay between data collection and product availability (Homer et al., 2004). Ideally, a more current NLCD product would be available to support on-going environmental assessment and policy decisions. To achieve this goal in a cost-effective manner, one possible approach would be to identify areas of LC change occurring subsequent to 2001 and append the NLCD-2001 for only those areas that have undergone change. The updated NLCD would not only provide the user with current LC data, but could also be used to identify both the pattern and nature of changes that

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had occurred between dates of interest. Other advantages associated with the updated editing change images would include (a) potentially substantial cost savings, (b) no introduction of new classification errors for non-change areas, and (c) minimization of registration errors that typically limit the overlay of multiple date coverages (post-classification) to support change detection analysis. Major impediments that need to be overcome for the development of practical methods for large-area change detection monitoring using remote sensor data include both the elimination or significant reduction of inter- and intra-annual vegetation phenology mediated errors and robust methods for error assessment.

There is also an expanding need for continuous data streams to support the development of the next generation of spatially distributed landscape process models that would incorporate both greater spatial resolution and higher frequency simulations (time steps). Specifically, remote sensing can provide estimates of standing Photosynthetically Active Biomass (PAB) that can serve as a nearly continuous measurement surrogate of primary productivity distributions and provide accurate measurement metrics of the timing and duration of important physiological events (i.e., green-up, duration of growing season, and senescence). Desirable diagnostic data include numerous Vegetation Indices (VIs) such as the Normalized Difference Vegetation Index (NDVI), fraction of Photosynthetically Active Radiation (fPAR), and Leaf Area Index (LAI). To maximize both performance and utility, future LC change detection methods that incorporate PAB data streams could provide a robust approach for the near real-time monitoring of LC change events while simultaneously supporting the development of landscape indicators, modeling of important to landscape processes, and the forecasting of future LC change distributions.

2. Background

Past spectral-based change detection techniques have tended to be performance limited in biologically complex ecosystems due, in larger part, to phenology-induced errors (Lunetta et al., 2002a,b). An important consideration for LC change detection is the nominal temporal frequency of remote sensor data acquisitions required to adequately characterize change events (Lunetta et al., 2004). Ecosystem-specific regeneration rates are an important consideration for determining the required frequency of data collections to minimize errors. As part of the natural processes associated with vegetation dynamics, plants undergo intra-annual cycles (phenology). During different stages of vegetation growth, plant structures and associated pigment assemblages can vary significantly. Our ability to identify vegetation classes using remote sensor systems is a result of wavelength-specific foliar reflectance (0.76–0.90 μm), pigment absorptions (0.45–0.69 μm), and foliar moisture content (1.55–1.75 μm). The same vegetation type can appear significantly different and different types similar, at various stages during intra-annual growth cycles.

Also, significant difficulties in evaluating the performance of change detection methods result from the inability to adequately

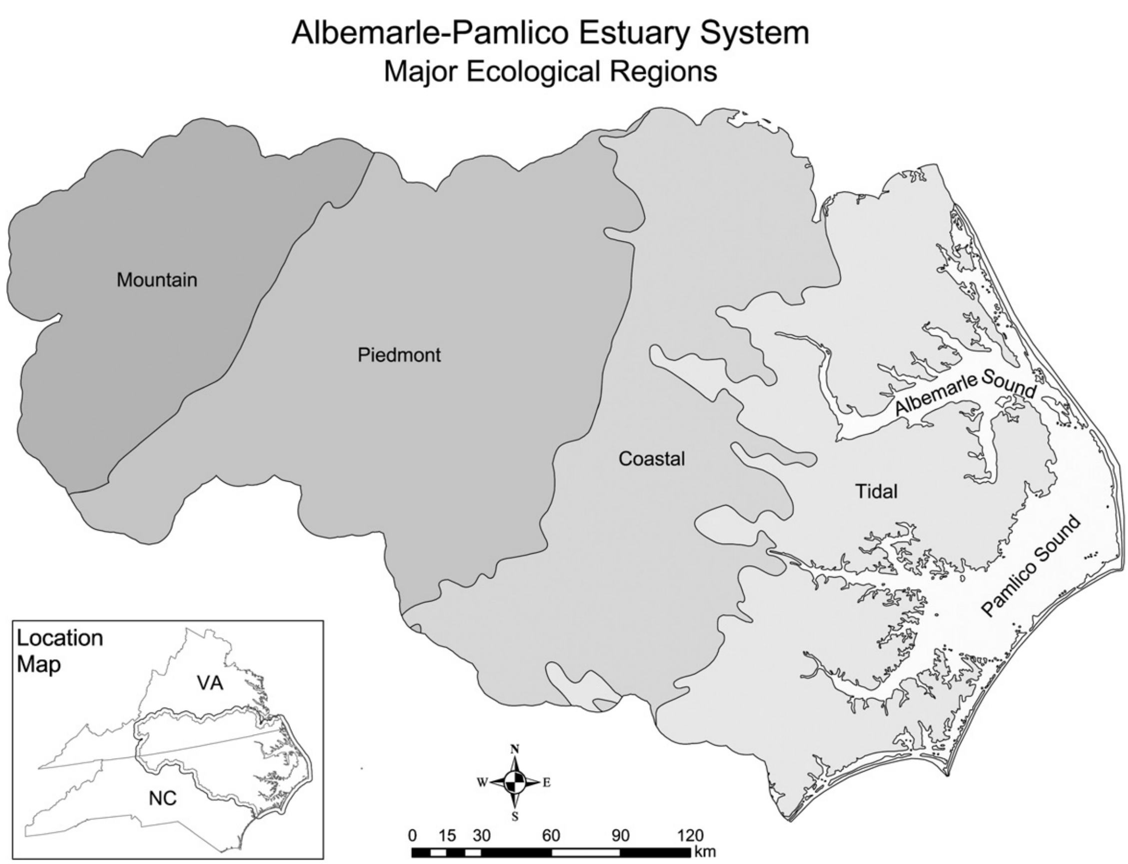

Fig. 1. Study area location map including major ecological regions.

characterize outcome accuracies (Khorram et al., 1999). Unlike typical LC classification assessment that requires only single date validation data, change detection validation data must be available for multiple dates to provide sufficient change event documentation (i.e., before and after). In particular, the characterization of change omission errors represents an especially difficult challenge (Lunetta et al., 2002b, 2004). Because LC change (conversion) is a relatively rare occurrence over a large area, it is problematic to derive a robust estimate of change omission errors. Consequently, standard LC accuracy assessment methods tend to overestimate the actual performance. Rather than relying on the traditional percent accuracy statistic, a more useful representation of performance is the Kappa coefficient (Cohen, 1960) and characterization of the percentage of both change and no-change omission and commission errors (Lunetta et al., 2002b, 2004).

Remote sensing change detection techniques can be broadly classified as either pre- or post-classification change methods. Pre-classification methods can further be characterized as being spectral or phenology based. Originally, the post-classification approach was considered to be the most reliable approach and was used to evaluate emerging methods (Weismiller et al., 1977). Factors that limit the application of post-classification change detection techniques can include cost, consistency, and error propagation (Singh, 1989). Numerous pre-classification change detection approaches have been developed and refined to provide optimal performance over the greatest possible range of ecosystem conditions. These semi-automated digital data processing approaches include image-based composite analysis (Weismiller et al., 1977) and principal components analysis (PCA) (Lillesand & Keifer, 1972; Byrne et al., 1980; Richards, 1984). The most commonly applied data transformations applied include band ratioing, NDVI, and the tasseled-cap transformation (Crist, 1985; Jensen, 2005). Recent techniques have been applied that can interpret data transformation results using change vector analysis (CVA) to indicate the magnitude and nature of change (Lambin & Strahler, 1994).

Research evaluating the comparative performance of various LC change detection methods has indicated that no uniform combination of data types and methods can be applied with equal

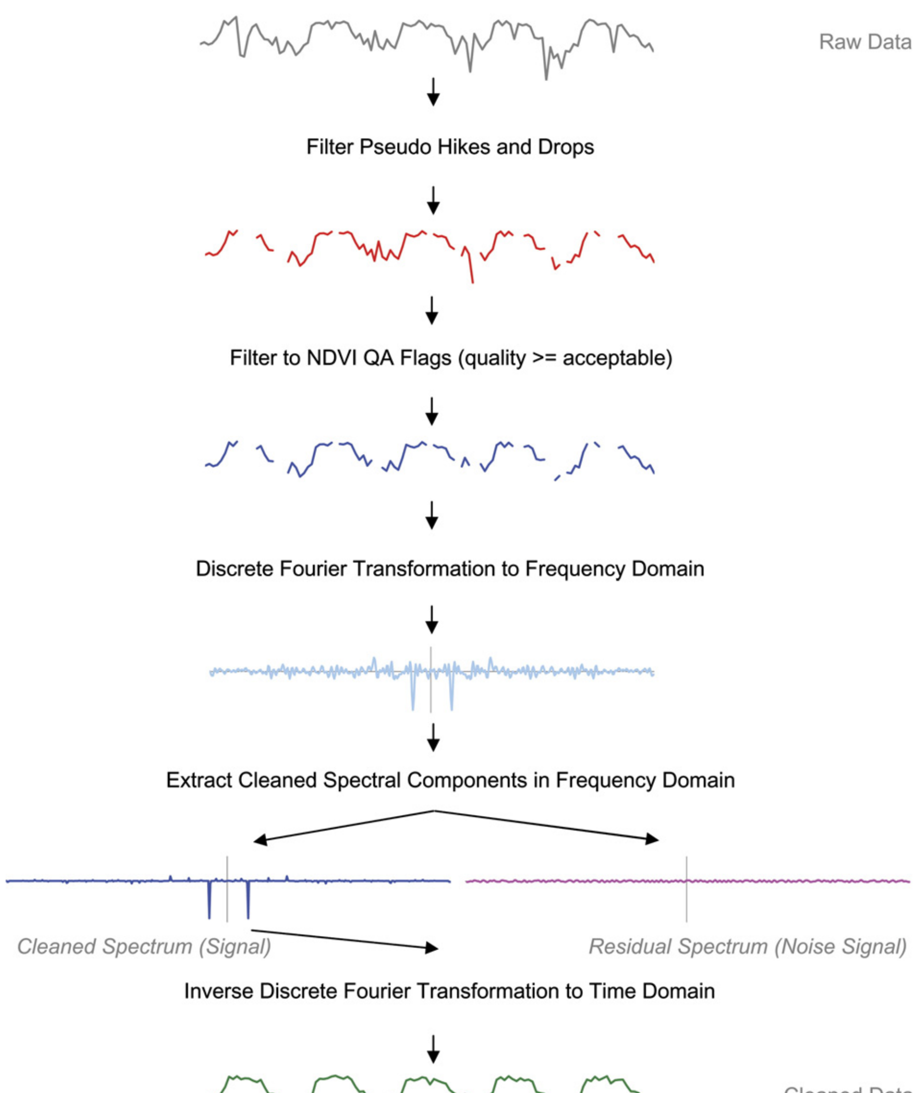

Fig. 2. Automated data processing steps for filtering and cleaning the MODIS NDVI (MOD13Q1) product to support automated change detection analysis.

success across different ecosystems (Lu et al., 2004). Cohen and Fiorella (1998) found that composite analysis out-performed both image differencing and CVA in a two-date experiment for detecting conifer forest change using Landsat Thematic Mapper (TM) imagery in the Oregon Cascades. Lyon et al. (1998) reported that the NDVI was the best performing Vegetation Index (VI) for detecting LC changes in the biologically complex vegetation communities in Chiapas, Mexico. Subsequently, Lunetta et al. (2002a,b) determined that two-date NDVI differencing and Multiband Image Differencing (MID) both performed poorly in a biologically complex vegetation community in North Carolina. Analysis of LC data for the country of Mexico using three dates of Landsat Multi-Spectral Scanner (MSS) imagery over a two-decade (1972–1992) study period demonstrated that ecosystem variability combined with classification errors precluded scene-wise or pixel-wise change detection (Lunetta et al., 2002a,b).

Past studies have demonstrated the potential of using NDVI to study vegetation dynamics (Townshend & Justice, 1986; Verhoef et al., 1996), illustrate the value of using high temporal resolution MSS imagery to monitor changes in wetland vegetation (Elvidge et al., 1998) and document the importance of image temporal frequency for accurately detecting forest changes in the southeastern United States (Lunetta et al., 2004). Time series data analyses using remote sensor data have largely focused on the use of coarse-resolution (≥ 1.0 km^2) AVHRR data to document land cover and analyze vegetation phenology and dynamics (Justice et al., 1985; Townshend & Justice, 1986; Justice et al., 1991; Loveland et al., 1991). With the advent of MODIS NDVI 250 m data, time series data analysis can be adapted for higher (moderate) resolution applications. However, the utility of the MODIS NDVI data products are limited by the availability of high-quality (e.g., cloud-free) data (Jin and Sader, 2005). The availability of high-quality data is a critical factor in determining application utility. To best deal with the data quality issues, researchers have incorporated a number of processing techniques including weighted regression smoothing (Li & Kafatos, 2000), Fourier and wavelet transformation filtering (Sakamoto et al., 2005), weighted least squares (Reed, 2006) and wavelet feature extraction (Bruce et al., 2006).

2.1. Study objectives

The purpose of the research described here was to investigate the feasibility of using Moderate-Resolution Image Spectroradiometer (MODIS) derived NDVI data to identify change areas on an annual time step. The goal was to develop an automated change detection alarm capability for regional-scale applications using a nearly continuous high-quality data stream that could also be used to support phenology-based cover type classification and further the study agricultural land-use dynamics. This research effort focused only on non-agriculture cover types. Because of the unique issues associated with differentiating between agricultural land-use and land-cover conversions, methods for agricultural conversions to non-

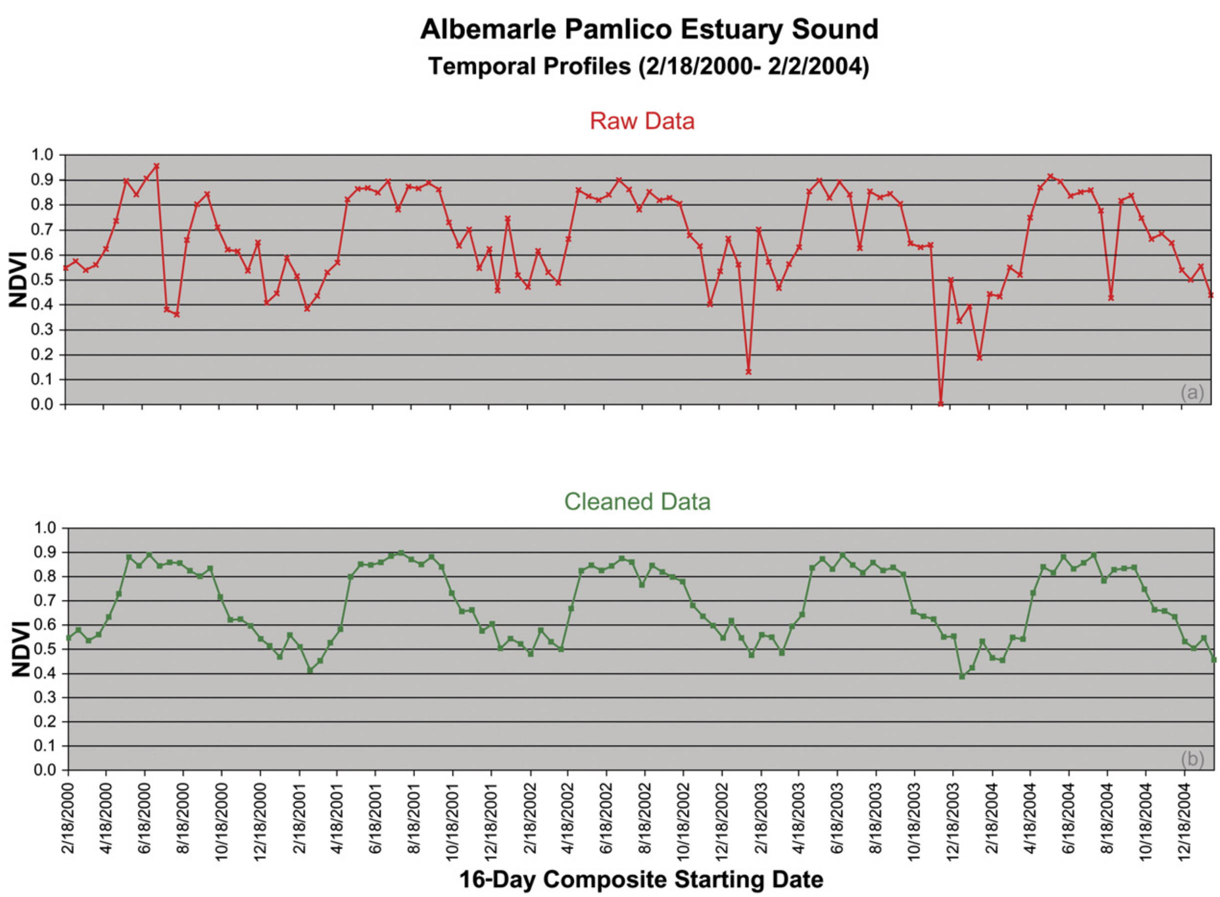

Fig. 3. Temporal profiles of raw and cleaned MODIS NDVI data over a 5-year period (2000–2004).

agricultural cover types (e.g., urban and forest) are being developed separately from the effort described in this article.

2.2. Study area

This research was conducted across the 52,000-km^2 Albemarle–Pamlico estuary system (APES) located in North Carolina and Virginia (Fig. 1). The study area includes diverse ecoregion types ranging from tidal plain (east) to the Blue Ridge Mountains (west). Landscape "patch" sizes are relatively small, with approximately 95% of the study area exhibiting heterogeneous cover within an individual MODIS NDVI (250 m) pixel. Additionally, biological diversity and vegetation regrowth rates are at the high end of the spectrum for locations within the conterminous United States (Currie & Paquin, 1987). The composition of the major upland-cover types throughout the area as of 2001 were approximately 51% forest, 23% agriculture, 14% water, 7% urban and barren, 4% grassland, and 1% herbaceous wetland (NASS, 2002; Homer et al., 2004). The predominant LC conversions that occur in the APES are associated with deforestation for both urban development and forest harvesting (clear cutting).

3. Methods

Methods incorporated in this study included the application of an automated MODIS NDVI time series and reference databases for the APES study area to support multi-temporal imagery analysis and accuracy assessment. MODIS NDVI data preprocessing was conducted to provide a filtered (anomalous data removed) and cleaned (excluded data values estimated) uninterrupted data stream to support multi-temporal (phenological) analysis. Fig. 2 illustrates the complete data pre-processing flow that is detailed below. Total annual NDVI values for each 250 m grid cell within the study area (2001–2005) were compared on an annual basis to identify those cells exhibiting greater than specified threshold values (decrease in NDVI) and were labeled as LC conversion areas. An accuracy assessment was conducted using historical aerial photographs to document the occurrence or non-occurrence of conversion events to generate an overall accuracy and quantify both commission and omission errors.

MODIS NDVI 16-day composite grid data (MOD13Q1) in HDF format were acquired between February 2000 and December 2005 from the NASA Earth Observing System (EOS) data gateway. Details documenting the MODIS NDVI compositing process and Quality Assessment Science Data Sets (QASDS) can be found at NASA's MODIS web site (MODIS, 1999). NDVI data were subset to the APES study boundary plus a 10 km buffer, re-projected from a sinusoidal to an Albers Equal-Area Conic projection, using a nearest neighbor resampling routine, and entered into a 250 m × 250 m grid cell multilayer image stack. Separate data stacks were developed for both the original NDVI data and QASDS.

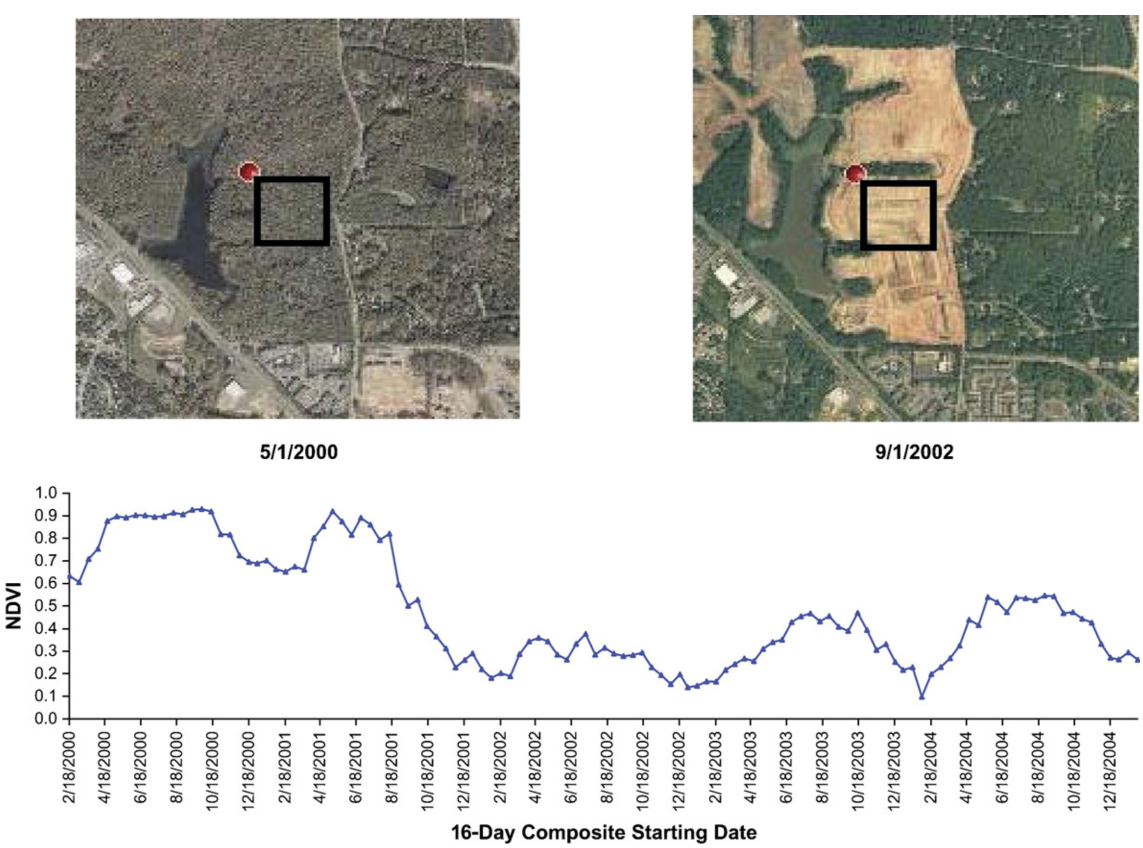

Fig. 4. Example illustrating the use of multiple date aerial photography in conjunction with 5-year MODIS NDVI profiles to validate predicted land-cover change events.

Table 1
The raw error matrix numbers for individual change detection thresholds by standard deviation levels evaluated

Reference	Change 3.5	No change 3.5	Change 3.0	No change 3.0	Change 2.5	No change 2.5	Change 2.0	No change 2.0	Total	Correct (%)	Commission (%)
Change 3.5	51	7							58	87.9	12.1
No change 3.5	36	155							191	18.8	81.2
Change 3.0			50	12					62	80.6	19.4
No change 3.0			26	216					242	89.3	10.7
Change 2.5					50	14			64	78.1	21.9
No change 2.5					19	189			208	90.9	9.1
Change 2.0							59	34	93	63.4	36.6
No change 2.0							27	192	219	87.7	12.3
Total	87	162	76	228	69	203	86	226	1137		
Correct (%)	58.6	4.3	65.8	94.7	72.5	93.1	68.6	85.0			
Omission (%)	41.4	95.7	34.2	5.3	27.5	6.9	31.4	15.0			

The NDVI data stack was first filtered to eliminate anomalous high (hikes) and low (drops) values and then filtered for a second time using the QASDS ratings to remove poor-quality data values from the NDVI data stack. Hikes and drops were effectively eliminated by removing data values that suddenly decreased or increased and then immediately returned to near the previous NDVI value. The threshold for the removal of pseudo-hikes and drops was set at ±0.15% to achieve the best setting (determined qualitatively) to eliminate most all anomalous points, while not inadvertently removing good data points, thus producing a smoother temporal profile. The MODIS QASDS data quality ratings were then applied to retain only those pixels rated as "acceptable" or higher. The filtered data were then transformed into frequency domain using a discrete Fourier transformation and the signal and noise spectrum separated (Roberts et al., 1987; Assali & Menenti, 2000; Roerink & Menenti, 2000). The removed (corrupted) NDVI data points were estimated from the frequency domain signal spectrum using a nonlinear deconvolution approach described by Roberts et al. (1987) to estimate complete "filtered and cleaned" NDVI temporal profiles for each pixel within the APES (Fig. 3).

The variable nature of water bodies (i.e., turbidity and water level fluctuations) tended to confound change analyses and, thus, they were excluded to reduce commission errors (false positives). A water mask developed using Landsat Enhanced Thematic Mapper plus (ETM+) images (year 2000) was used to delineate open-water areas for exclusion from further change analysis. ETM+ pixels with negative NDVI values were identified as open water and an overlay of water pixels (30 m^2) was applied to the

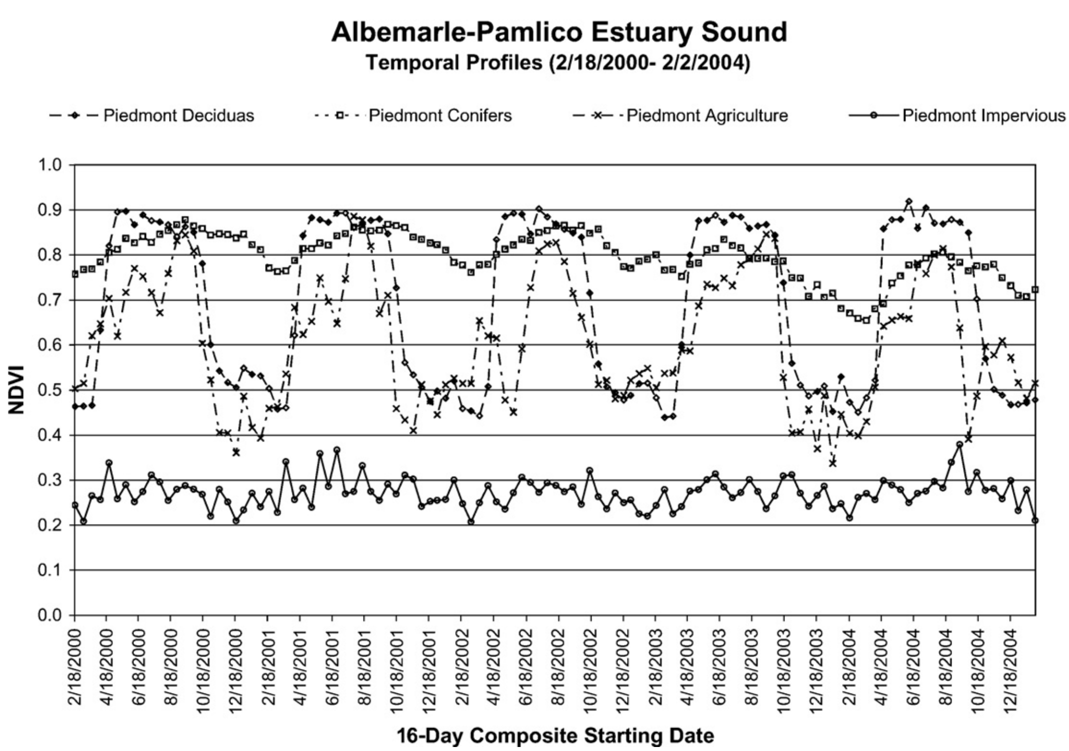

Fig. 5. MODIS NDVI temporal profiles for the major phenological endmembers corresponding to the Piedmont ecological region.

Table 2
Normalized error matrices for each threshold level including kappa coefficients and significance probabilities

Reference	Change (%)	No change (%)	Total (%)	Correct (%)	Commission (%)
TH factor = 3.5					
Change (%)	20.5	2.8	23.3	87.9	12.1
No change (%)	14.5	62.2	76.7	81.2	18.8
Total (%)	34.9	65.1	100.0		
Correct (%)	58.6	95.7		82.7	
Omission (%)	41.4	4.3			
					$\kappa = 0.59$
TH factor = 3.0					
Change (%)	16.4	3.9	20.4	80.6	19.4
No change (%)	8.6	71.1	79.6	89.3	10.7
Total (%)	25.0	75.0	100.0		
Correct (%)	65.8	94.7		87.5	
Omission (%)	34.2	5.3			
					$\kappa = 0.64$
TH factor = 2.5					
Change (%)	18.4	5.1	23.5	78.1	21.9
No change (%)	7.0	69.5	76.5	90.9	9.1
Total (%)	25.4	74.6	100.0		
Correct (%)	72.5	93.1		87.9	
Omission (%)	27.5	6.9			
					$\kappa = 0.67$ [a]
TH factor = 2.0					
Change (%)	18.9	10.9	29.8	63.4	36.6
No change (%)	8.7	61.5	70.2	87.7	12.3
Total (%)	27.6	72.4	100.0		
Correct (%)	68.6	85.0		80.4	
Omission (%)	31.4	15.0			
					$\kappa = 0.52$

[a] Statistical significance compared to TH factors 2.0 ($p = 0.05$), 3.5 ($p = 0.27$), and 3.0 ($p = 0.72$).

250 m^2 APES grid cells was performed and the percent open-water area within each cell was calculated for the entire APES. Grid cells containing ≥30% open water were included in the APES water mask and those containing between <30% open water were used to create the APES transitional water mask. Approximately 14% of the APES study area was included in the open water mask and 5.1% in the transitional water mask, leaving 80.8% (approximately 42,016 km^2) of the APES defined as upland (non-water).

Intensive land-use activities associated with agricultural crop rotations often confound LC conversion determinations and can frequently result in unacceptable levels of false positives (change commission errors). Accordingly, an initial stratification step was implemented to subset the agricultural versus non-agricultural pixels for independent analysis to effectively minimize the potential for omission change errors in non-agricultural areas and commission change errors for agricultural areas. The identification of agricultural cells was accomplished by manually interpreting agricultural cover using the same ETM+ data used to create the above-described water mask. All APES 250-m^2 grid cells containing >20% agricultural cover were included in the agricultural subset for the upland areas (Knight et al., 2006). Change analysis methods for the agricultural areas are being developed will independent of this effort for agriculture cells throughout the APES study area.

Total annual NDVI values were computed for all upland grid cells using the filtered and cleaned data stack. NDVI difference values for non-agricultural areas were calculated corresponding to each individual upland cell for all consecutive study years (i.e., 2001–2002, 2002–2003, 2003–2004, 2004–2005). The total NDVI difference output data for the four change periods beginning with 2001–2002 exhibited an approximately normal distribution about the mean ($\mu = 0$), which, for this application, represented no change in NDVI between T_1 and T_2. Standard normal distribution statistical analysis was performed to identify those cells that had the greatest reduction in cumulative NDVI for each change period. Four negative (decrease) change thresholds were selected corresponding to a range of z-value probabilities (i.e., 2.0, 2.5, 3.0, 3.5). This range of values were selected because they produced appropriate estimates of annual change values based on previous change rate studies for the area (Loveland et al., 2002; Lunetta et al., 2004).

3.1. Accuracy assessment

Reference data to support the accuracy assessment consisted of available historic aerial photography over a two-county area (Durham and Wake) in the Piedmont region of the study area. The accuracy assessment was limited to these two counties because they were the only counties within the APES with sufficient historical aerial photography to support an assessment. Contained within these two counties are the metropolitan areas of Raleigh and Durham. All major cover types found throughout the APES study area were represented within the two counties. For each validation point, a coordinate-based search was performed to identify all available historical photographs. Those sampling points with available photographs that both predated and postdated the change or no-change event were identified for further processing. Using the two dates of photographs and NDVI temporal profile, the interpreter determined the usability of the photographs as a reference source for the assessment. If the photographs spanned the pre- and post-time of change event as indicated by the temporal

Table 3
Percent adjusted change detection area results for each threshold level evaluated corresponding to 2002

Study area	Threshold factor (SD)	Number of changed pixels	Changed area (km^2)	Change percent	Adjusted change percent [a]
Wake and Durham Counties (2002)	3.5	412	26	1.0	0.4
	3.0	572	36	1.4	0.6
	2.5	847	53	2.1	0.8
	2.0	1347	84	3.3	1.3
Albemarle–Pamlico Estuary System (2002)	3.5	7763	485	0.7	0.3
	3.0	11,194	700	1.0	0.4
	2.5	16,858	1054	1.5	0.6
	2.0	26,975	1686	2.4	1.0

[a] Adjusted change factor = 0.404.

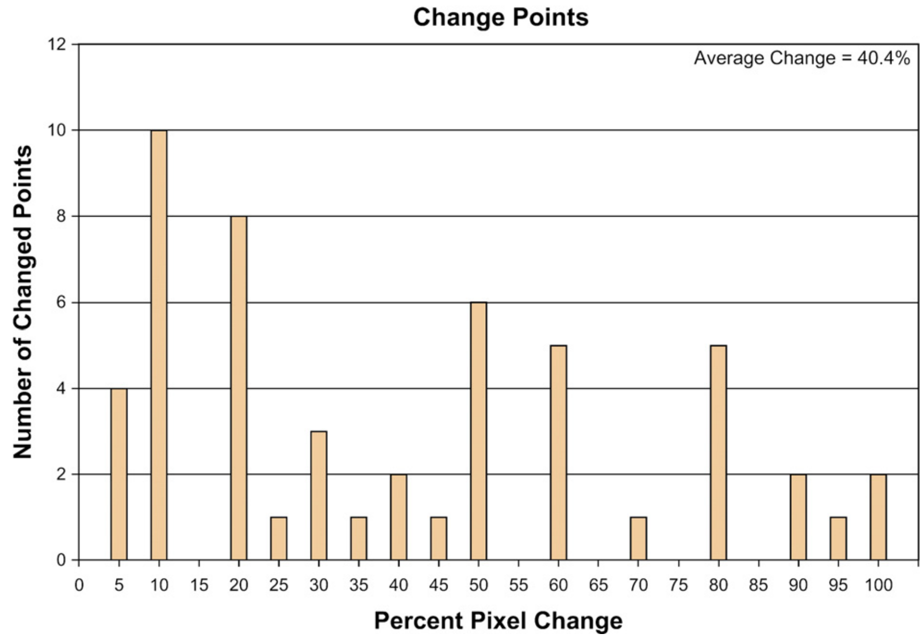

Fig. 6. Histogram of percent sub-pixel change area for a subset ($n=52$) of correctly predicted change pixels.

profile, then the photographs were deemed appropriate for assessment purposes. However, if the timing of the change indicated by the temporal profile was not within the dates of photograph collection, the validation point was eliminated.

For each assessment point with acceptable photographs, interpretations were conducted by first delineating the cell boundary on the digital images for both dates. The cover type(s) and percent coverage within the cell were interpreted for both dates and recorded. Interpretations were conducted by two interpreters. As part of the quality control (QC) process, the lead interpreter reviewed all interpretations for consistency and data recording completeness. Also, for quality assurance (QA) purposes, all reference image pairs were electronically filed to support subsequent analyses (Fig. 4). Additionally, for a subset of the change points ($n=52$) and no-change points ($n=44$) sufficient image data were available to document with a high level of certainty the percentage of change that occurred within the cells (Figs. 6 and 7).

Reference data were developed using a stratified random sampling approach that included both the change and no-change areas. Change areas were weighted with a higher proportion of samples because the vast majority of the study area was no-

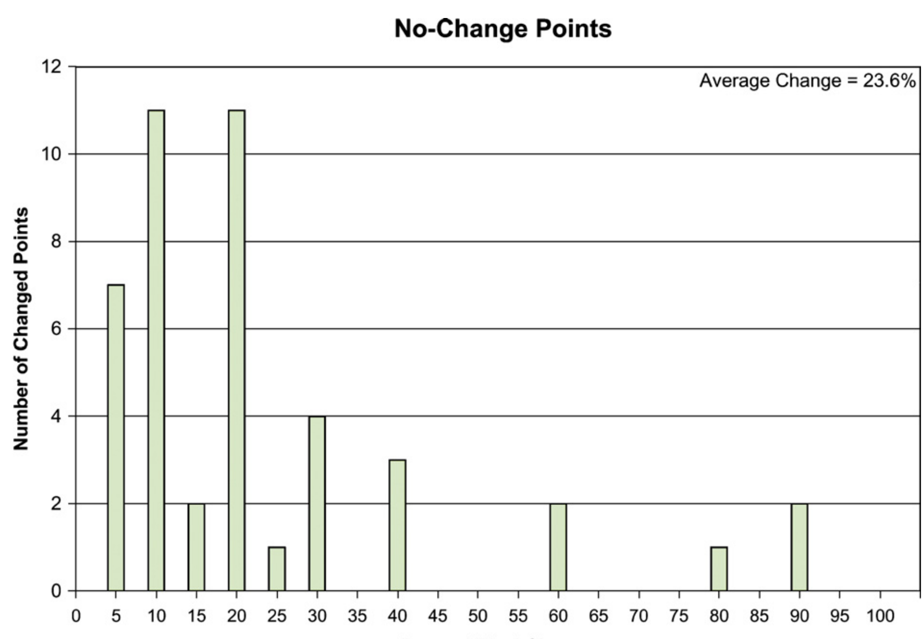

Fig. 7. Histogram of percent sub-pixel change area for a subset ($n=44$) of no-change pixels (change omission pixels).

change for the reference study period. A validation was performed only for change that occurred during 2002 due to the lack of available photographs for later time periods. A total of 1137 samples were successfully validated corresponding to change ($n=318$) and no-change ($n=819$) pixels. Note that the no-change pixels were over-sampled to provide a sufficient sample size to assess no-change omission errors (Table 1).

4. Results

4.1. NDVI Profiles

A qualitative analysis of the temporal profiles corresponding to phenological endmembers was performed to provide an initial performance assessment of the automated MODIS NDVI protocol described above for producing high-quality time series data to support subsequent change detection analysis. Fig. 5 illustrates the four principal endmembers for the Piedmont region of the study area. The patterns and time sequencing of phenological events for both the deciduous and coniferous forest types demonstrate the robust nature of the profiles derived from the automated data processing procedures. Also, the substantially lower NDVI for the impervious compared to chlorophyll-bearing endmembers is what would be expected, and the sawtooth pattern provided some indication of the inherent noise level in the NDVI product. The agricultural endmember serves to demonstrate the conflict between agricultural land-use activities and land-cover conversions. For example, over the first 2-year period (2000 and 2001), it appeared that the same (or similar) crop type was grown that exhibited a multiple maturation growth pattern. During year 3 (2002), the field appeared to be planted later in the season with an alternative crop type, then was apparently replanted in 2003 and 2004 with a new crop type possibly as part of a crop rotation cycle. This change in phenological cycle demonstrated the potential for land-cover change false positives in agricultural areas.

A unique approach to supplement the validation process is illustrated in Fig. 4, which shows an example of aerial photographs in combination with the 5-year NDVI temporal profile for an accuracy assessment sampling site (reference pixel) before and after a conversion event. Much of the forest that was present in the May 1, 2000, image had been subsequently cleared by the date of the companion image on September 1, 2002. By visually interpreting the NDVI temporal profile, it is apparent that the forest clearing began approximately mid-August 2001 and was completed by early December 2001. The area was in a transitional state throughout calendar year 2002 and appears to have reached a new steady state beginning in 2003 and throughout 2004. With the subsequent addition of the calendar year 2005 temporal profile the achievement of a new steady-state condition should be confirmed. (Subsequent 2005 field reconnaissance has revealed that the site was converted to a condominium complex.)

4.2. Change detection

The change detection results for non-agricultural areas are presented in Table 2. A standard deviation (S.D.) threshold (TH) of 2.5 provided the best accuracy at 87.5% and a kappa coefficient of 0.67. This result was statistically significant compared to the TH factors of 2.0 ($p=0.05$) and 3.5 ($p=0.27$); however, it was not significantly different from 3.0 ($p=0.72$). Most importantly, the TH of 2.5 provided the best balance between change commission errors (21.9%) and omission errors (27.5%). Alternatively, the TH of 3.0 could be applied if the goal was to bias for lower change commission errors (19.4%) at the expense of higher omission errors (34.2%). Estimates of the area extent of change for the APES varied by a factor of 3.3× across the entire TH factor range; however, the TH 2.5–3.0 range varies only by 0.3× (Table 3).

An important consideration for the application of the change detection procedures presented here is the sub-pixel sensitivity or the minimal detection limit associated with the approach. The sub-pixel sensitivity is also important to accurately determine the area extent of land-cover conversions. For example, because the majority of identified changes are sub-pixel in extent, a correction factor must be applied to capture a true area estimate of change. Fig. 6 illustrates the distribution of sub-pixel sensitivity for Wake County, NC. Approximately 96% of the identified change was at the sub-pixel level, averaging 40.4%. To best estimate the

Table 4
Change detection results by APES major ecological regions corresponding to a threshold level of 2.5 standard deviations for four change year increments

Study area (date)	Changed area (km^2)	Changed percent	Adjusted changed area (km^2) [a]	Adjusted changed percent [a]
Mountain ecological region				
2002	58	0.4	23	0.2
2003	30	0.2	12	0.1
2004	64	0.5	26	0.2
2005	51	0.4	20	0.2
Piedmont ecological region				
2002	356	1.5	144	0.6
2003	192	0.8	77	0.3
2004	342	1.5	138	0.6
2005	273	1.2	110	0.5
Coastal plain ecological region				
2002	293	1.8	118	0.7
2003	154	1.0	62	0.4
2004	379	2.4	153	1.0
2005	478	3.0	193	1.2
Tidal ecological region				
2002	342	2.0	138	0.8
2003	302	1.8	122	0.7
2004	677	4.0	273	1.6
2005	445	2.6	180	1.1
Albemarle–Pamlico estuary system				
2002	1054	1.5	426	0.6
2003	678	1.0	274	0.4
2004	1467	2.1	593	0.9
2005	1252	1.8	506	0.7
Raleigh metropolitan area				
2002	40	2.6	16	1.0
2003	16	1.1	7	0.4
2004	38	2.4	15	1.0
2005	43	2.8	17	1.1

[a] Adjusted change factor=0.404.

Table 5
APES cover type composition, change distributions and accuracies by cover type for Wake and Durham Counties, NC

Cover type	Composition (%) (2001)	Change (%) (2002–2005)	Change accuracy (%) (2002)
Urban and barren	7	7	83 (n=89)
Forest (deciduous)	32	35	91 (n=75)
Forest (coniferous)	14	44	93 (n=41)
Forest (mixed)	5	6	90 (n=10)
Herbaceous/grassland	4	6	91 (n=22)
Wetland (herbaceous)	1	2	(n=1)
Agriculture	23	NA	NA
Water	14	0	NA

minimum detection limit, the distribution of percent change associated with change omission pixels can be used (Fig. 7). The distribution shows that approximately 71% of the change omission pixels had ≤20% change. This equates to an effective minimum detection limit of approximately 1.5 ha. Although pixels with ≤20% change are detected, the detection accuracy drops substantially (increased omission errors) below 1.5 ha (Fig. 6).

The impact of using non-adjusted change detection area extent values is clearly apparent between the raw versus adjusted values (Table 3). Comparing the adjusted values across the study area reveals a large (5.0×) variation in land-cover change by APES major ecological regions (Table 4). The tidal ecological region had the greatest adjusted average annual change over the 4-year change period (1.1%), followed by the coastal plain (0.8%), Piedmont (0.5%) and mountain (0.2%). Although the change rate for the Piedmont was (0.5%), the adjusted average change rate in the Raleigh metropolitan area (a subset of the Piedmont) was substantially higher at 0.9%. These results indicate that the tidal and coastal ecological regions, along with major metropolitan areas, would probably require more frequent change updates than the mountain region to provide relevant change patterns and current land-cover data sets. Additionally, the tidal ecoregion had undergone the greatest change during 2004 (1.6%).

An additional analysis was conducted to better understand the relationship between cover composition, change distributions, and detection accuracies (Table 5). Although coniferous forest cover represented only 14% of the APES, 44% of all changes were associated with this cover type and were a result of the intensive silviculture operations located primarily in the tidal and coastal ecoregions. This change rate was approximately 3× that of the deciduous and mixed forest and urban and barren areas. Accuracies were consistently in the low nineties for all reported cover types with the exception of the urban and associated barren cover types, which were substantially lower at 83%.

A high-resolution graphic of the Raleigh metropolitan area was developed to further evaluate both the utility and performance of the annual change products (Fig. 8). The graphic uses Landsat ETM+ panchromatic images (15 m) as the backdrop to aid in the interpretation of the MODIS NDVI derived annual change product. Qualitatively, the change patterns appear to match very well with known development patterns over the 4-year period (2002–2005). Individual residential communities, shopping centers and

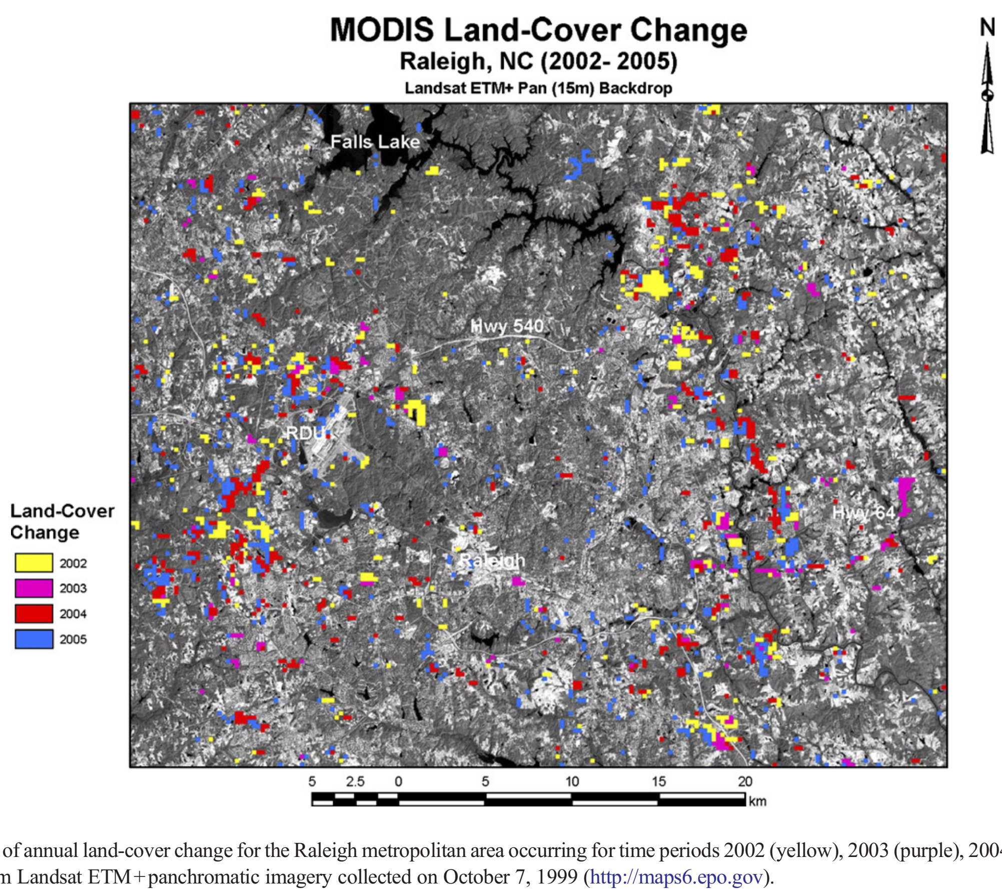

Fig. 8. The distribution of annual land-cover change for the Raleigh metropolitan area occurring for time periods 2002 (yellow), 2003 (purple), 2004 (red), and 2005 (blue). The background is 15 m Landsat ETM+panchromatic imagery collected on October 7, 1999 (http://maps6.epo.gov).

major road construction projects are discerned corresponding to expected time period (year). Also, the variability in change area for the study period was consistent with known economic development patterns. The drop in change area for 2003 to 0.4% (60% decrease) corresponded to the economic downturn in the technology sector, which resulted in a dramatic slowdown in new commercial construction permits (250% dollar value reduction) in 2002 (Wake County, 2005). Commercial construction permits began to rebound in 2003 and residential construction permits increased dramatically (35% increase) in 2004, resulting in a rebound back to a 1.0% change in 2004 (Table 4). It should be noted that change is graphically over-represented (Fig. 8) by approximately 2.5×, because the average pixel change area was only 40.4% (Fig. 6).

5. Discussion

Articulating a working definition of what constitutes LC change is an important first step for the implementation of change detection studies and applications involving the use of remote sensor data. In this study, we made the distinction between agricultural land-use activities and land-cover change to first provide a hierarchical segmentation of our change detection procedures. Here the segmentation has been applied to reduce land-use mediated false positives (change commission errors). Additionally, this segmentation approach will be applied to support the future development of specific analytical methods for monitoring agricultural land conversions to non-agricultural cover types and to determine the potential for providing useful information such as crop type and the monitoring of rotational cycles. The implementation of segregated agricultural and non-agricultural analytical protocols should become a practical approach for the automating change detection for many locations within the US that exhibit similar properties to the APES. Additionally, this approach may be optimized when applied in a hierarchical approach in combination with the ongoing development of agricultural maps by the US Department of Agriculture (USDA) National Agriculture Statistical Service (NASS) based on Landsat ETM+ imagery (NASS, 2002).

The importance of quantifying change omission errors is critical to the development of a robust assessment of change detection performance. Absent sufficient data documenting change omission errors, the tendency would be to bias the analysis to reduce change commission errors, while potentially increasing omission errors to unacceptable levels (Table 2). Because land-cover conversions typically represent only a small percentage of large geographic regions (e.g., 0.5–1.0%), the sampling of no-change areas at sufficient intensity to generate estimates of change commission errors represents a significant problem. This sampling problem is twofold: first a sample drawn from a no-change classified area has a very low probability of being a change omission pixel; and second, the probability of finding adequate reference data to determine the status of a sample site (i.e., change or no-change) is also low. In this study, we selected approximately 2.6× more samples from the no-change bin to support the determination of change omission errors.

With the anticipated release of the NLCD-2001 data scheduled for calendar year 2007, efforts can be initiated to create annual change alarm coverages beginning with 2002 using MODIS NDVI 250 m data for numerous regions of the US where this approach may be appropriate, providing supplemental information to support the interpretation and application of NLCD-2001 products. At the most basic level, a MODIS NDVI-derived annual change detection alarm product could be applied to identify those areas that have likely undergone land-cover change subsequent to 2001. Also, it may be possible to determine the likely outcome of the conversion, subsequent to the return to a new steady state based on the application of MODIS NDVI temporal profile match filtering techniques currently under development (Knight et al., 2006).

An additional advantage of the MODIS NDVI change detection procedures developed in this study is the capability for processing filtered and cleaned NDVI temporal profiles that track vegetation phenology on a nearly continuous basis to support the development of regional-scale landscape process models. For non-remote sensing scientists, the NDVI temporal profiles provide a particularly insightful data presentation that can readily be interpreted without any formal remote sensing training. Also, they provide a data presentation that can easily be exploited to extract data values of potential interest using widely available desktop software tools (i.e., phenological metrics). The potential ease of sharing these multi-temporal NDVI products with the general scientific community may hasten the future integration of these products by other disciplines and potentially lead to additional unanticipated applications.

6. Conclusions

The availability of no-cost MODIS NDVI data and new automated data processing techniques that provide high-quality continuous time series data represent a major advancement for the automated monitoring annual land-cover change and vegetation condition over large geographic regions. Major advantages of the NDVI-based change detection approach presented here include (a) robust results, (b) nominal computational requirements, (c)automated data processing protocols, (d) annual change alarm product capability, and (e) rapid product delivery. Additional advantages include the portability of intermediate data products and results to the non-remote sensing scientific community. This approach is particularly attractive due to the availability of no cost MODIS data and the very low cost associated with data processing. These advantages are in sharp contrast to the traditional Landsat data based approaches that are comparatively data and computationally expensive. The increased temporal resolution of the MODIS NDVI 250 m data has a significant advantage over traditional Landsat data for both capturing the actual timing of the change event and the subsequent monitoring of the recovery to the next steady state.

Disadvantages and limitations of the MODIS NDVI-based change detection approach are substantially associated with the moderate spatial data resolution (250 m). In particular, change events less than approximately 1.5 ha will have a low probability of being detected. One impact of this resolution limitation is potentially poorer accuracies for urban areas that tend to change at finer scales (Table 5). Also, because of the sub-pixel sensitivity of the technique, there is an inherent and significant overestimation (approximately 2.5×) of change area extent that must be corrected to provide reasonable change rate estimates. This issue is particularly problematic for the graphic representation of change extent, because there is no practical way to directly compensate for the overestimations. The spatial resolution of the MODIS NDVI data significantly limits their use for certain applications such as the monitoring of change in riparian buffers zones and urban areas and the monitoring of other relatively fine-scale conversion events that may be associated with high value ecological resources. Additionally, the method described in this article will not provide robust results for areas in intensively managed landscapes (e.g., agricultural land).

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