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Change detection with heterogeneous data using ecoregional stratification, statistical summaries and a land allocation algorithm

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Abstract

A ca. 1980 national-scale land-cover classification based on aerial photo interpretation was combined with 2000 AVHRR satellite imagery to derive land cover and land-cover change information for forest, urban, and agriculture categories over a seven-state region in the U.S. To derive useful land-cover change data using a heterogeneous dataset and to validate our results, we a) stratified the classification using predefined ecoregions, b) developed statistical relationships by ecoregion between land-cover proportions derived from the 1980 national-level classification and aggregate statistical data that were available in time series for all regions in the U.S., c) classified multi-temporal AVHRR data using a process that constrained the results to the estimated proportions of land covers in ecoregions within a multi-objective land allocation (MOLA) procedure, d) interpreted land cover from a sample of aerial photographs from 2000, following the protocols used to produce the 1980 classification for use in accuracy assessment of land cover and land-cover change data, and e) compared land cover and land-cover change results for the MOLA method with an unsupervised classification alone. Overall accuracies for the 2000 MOLA and unsupervised land-cover classifications were 85% and 82%, respectively. On average, the 1980–2000 land-cover change RMSEs were one order of magnitude lower using the MOLA method compared with those based on the unsupervised data.

Keywords: Land cover change; Midwest USA; Change detection

1. Introduction

Remote sensing provides important data for monitoring land-cover changes on regional and global scales (Skole et al., 1997; Hansen et al., 2000). While methods for detecting, mapping and analyzing land-cover changes are diverse and well established in the remote sensing literature (e.g., Collins & Woodcock, 1996; Song et al., 2001; Rogan et al., 2002), the vast majority of applications are based on data derived from the same sensor platform at different dates. In order, however, to take advantage of the historical record of land-cover changes represented in archival aerial photographs and data sets derived from them, longer-term land-cover change detection may require use of heterogeneous data sources. Innovative methods are needed that can account for the differences in spatial and thematic characteristics that result from extraction of land-cover information using different data sources (Petit & Lambin, 2001).

In this paper we describe and demonstrate a methodology for combining a photo-digitized historical land-cover map with contemporary satellite imagery to identify land-cover changes. The research described in this paper contributes to the Changing Midwest Assessment carried out by the United States Forest Service (USFS) North Central Research Station. The purpose of the Assessment was to describe the spatial distribution, direction and intensity of the changes that have occurred on the biophysical and social landscapes of the region over the past two decades (1980 to 2000), including change in land cover, forest characteristics, plants and animals, and human demographics (Potts et al., 2004; http://ncrs.fs.fed.us/4153/deltawest/). Our specific goal in contributing to the project was to generate land-cover change data at a 1-km spatial

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resolution and to map hotspots of land-cover change between agriculture, forest, and urban cover. This posed a challenge, as no identical remote sensing or land-cover datasets exist at that resolution for both dates. However, existing national land-cover classifications combined with current satellite imagery could be useful for our purposes, if we could assure their comparability.

The specific objectives and methodologies we developed are based on the premise that, by imposing constraints on the classification process that are based on other data for which a consistent time series exists, we can improve the consistency of the resulting land-cover products. We achieve this improvement using existing statistical summaries of land cover that are collected in regular intervals by ecological sub-regions within our study area. These statistical summaries for the year closest to 2000 were used to constrain the classification of remotely sensed data from the year 2000 using a multi-objective land allocation algorithm. The existing national land-cover dataset (1980) was then combined with the remote sensing classification (2000) developed in this project, and used to determine the spatial distribution of land-cover change over the 20-year time period in the seven-state region. We focus our analysis on changes in forest, agriculture, and urban areas, and especially areas that have experienced urban growth and forest growth.

To demonstrate the methodological improvement of using remote sensing satellite data constrained by statistical data and modeling, we compared the resulting data with results based on an unsupervised classification. The accuracies of the land-cover and land-cover-change products resulting from both constrained and unconstrained classifications were evaluated in two ways. First, land cover was mapped at 86 sites using a sample of aerial photos taken in 2000 and interpreted according to the same protocols developed for an aerial-photo derived national land-cover dataset created for ca. 1980. Land-cover and land-cover-change results from the two classifications were evaluated and compared at sample sites. Second, we compared estimates of percentages of land-cover change obtained over two sets of regional area aggregations (i.e., ecoregions and states) with those observed in the statistical data set for these same areas.

For the two dates of interest the most suitable datasets by which to achieve the above objectives included an aerial photo-derived national land-cover classification from ca. 1980, i.e., the USGS (United States Geological Survey) LUDA (Land-Use and Land-Cover Dataset); 1-km AVHRR (Advanced Very High Resolution Radiometer) satellite imagery from 2000; and the United States Department of Agriculture (USDA) Natural Resources Inventory (NRI) statistical land cover survey, collected every five years since 1982.

2. Study region

The research in this paper addresses the North Central Region of the United States, as defined by the USFS and comprising the states of Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri and Wisconsin (Fig. 1). In the past century, the region has been and continues to be dominated by agriculture; it includes the majority of the productive

Fig. 1. Location of the study region in the United States.

Table 1
State-wide land-cover statistics from the Natural Resources Inventory (NRI) statistical surveys (1982 and 1997)

State	Land area	Agriculture			Forest			Urban		
		1982	1997	Change (%)	1982	1997	Change (%)	1982	1997	Change (%)
Illinois	56,342	115,688	112,872	−2.4	14,509	15,312	+5.5	10,881	12,872	+18.3
Indiana	36,185	67,679	65,916	−2.6	15,294	15,299	0.0	7426	9148	+23.2
Iowa	56,276	129,404	127,444	−1.5	7527	8829	+17.3	6402	6889	+7.6
Michigan	58,358	58,733	52,901	−9.9	64,007	66,182	+3.4	11,028	14,349	+30.1
Minnesota	84,390	120,836	117,796	−2.5	64,670	65,755	+1.7	6959	8845	+27.1
Missouri	69,709	114,895	108,972	−5.2	46,364	50,306	+8.5	8433	10,186	+20.8
Wisconsin	56,125	67,208	64,450	−4.1	57,526	58,469	+1.6	8050	9785	+21.6
Total	417,385	674,446	650,352	−3.6	269,894	280,155	+3.8	59,182	72,075	+21.8

Data include land area in square kilometers, percent of non-federal land occupied by agriculture, forest, and urban land-covers in 1982 and in 1997, and percent change of each land cover with respect to its original 1982 area.

United States corn and soybean belt that cuts diagonally through the seven-state region. In the northwest and west, the region borders the wheat-growing region of the Great Plains. Forests dominate the glacial landscapes in the north, which are also characterized by wetlands and lakes, and in areas of topographic relief (e.g. Ozarks and Shawnee Hills) in the south. Urban centers developed near water and rail transportation routes. The largest urban centers in the region include Chicago, Illinois; Detroit, Michigan; Indianapolis, Indiana; St. Louis, Missouri; and Minneapolis, Minnesota.

Investigation of NRI statistical data indicated that agriculture was being lost while urban and forest land covers were increasing in the region between 1982–1997 (Table 1) (U.S. Department of Agriculture, 2001). More specifically, agriculture has decreased in all seven of the study states relative to its percent presence in 1982, ranging from −1.5% (Iowa) to −9.9% (Michigan). Urban land-cover has increased in all seven states relative to its percent presence in 1982, ranging from +7.6% (Iowa) to +30.1% (Michigan). Forest has remained stable in one state (Indiana) and increased in six of the seven states relative to its percent presence in 1982, ranging from +1.6% (Wisconsin) to +17.3% (Iowa). The major trajectories and locations of rapid change within the region were hypothesized to be: 1) the conversion of agriculture and forest to high and low-density urban land-use near urban centers, and 2) the conversion of agriculture to forest in marginally productive areas, often near transition zones between predominantly agricultural and predominantly forested ecological regions (Brown et al., 2000; Theobald, 2001).

Geographical units of interest for summarizing and analyzing land-cover change information were states, counties, and ecological regions. The North Central Region includes seven states and 650 counties. Given the large geographical extent in both the N–S and E–W directions, and the significant range of ecosystem types, the amount of variability in a single remote sensing dataset for the region is quite high. Therefore, we managed this variability by stratifying the region prior to the remote sensing classification and all other analytical procedures. We chose to stratify the region into ecological sub-regions (hereafter referred to as sub-regions) defined by the Major Land Resource Area (MLRA) units used by the NRI, because they were appropriate in terms of number (there are 35 in the region) and size (average size is just over 29,000 km^2, or 7 million acres), and because we were incorporating NRI statistical data into our methodology. A MLRA is a geographic area that is characterized by a particular pattern of soils, climate, water resources, land uses, and types of farming. As such MLRA spatial configurations are independent of state or other jurisdictional boundaries; for example 22 of the 35 MLRAs in the region span two or more states. Examination of these units with respect to the remote sensing data revealed that they captured very well much of the spatial variability on the actual landscape and also in the NDVI time series, and to a much greater extent than political strata, such as states (Fig. 2).

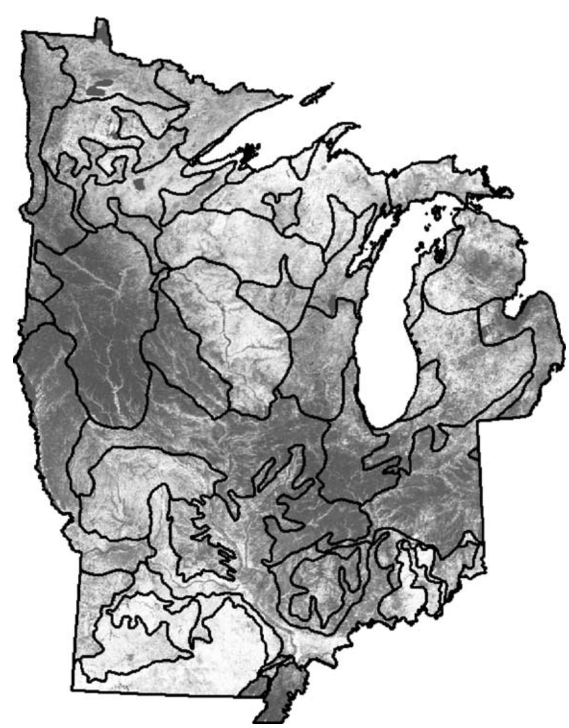

Fig. 2. AVHRR NDVI composite from May 18 to June 1, 2000. Boundaries shown and used for ecoregional stratification of the remote sensing classification are NRI MLRAs.

3. Data

AVHRR records radiance in a visible (green-red 0.58–0.68 μm) and a near-infrared (0.725–1.1 μm) band and these are routinely processed to produce the Normalized Difference Vegetation Index (NDVI) (Loveland et al., 1991). The USGS EROS Data Center has consistently processed the AVHRR 1-km resolution daily observations to produce standard bi-weekly maximum NDVI composites for the conterminous United States beginning in 1989. Over a growing season, these bi-weekly NDVI composites capture differences in the phenological trajectories of different land-cover types (Loveland et al., 1991; Reed et al., 1994) and these different spectral-temporal trajectories form the basis for discriminating between different land-cover types using image classification techniques. We acquired these NDVI composites for the months of May through October 2000 (U.S.G.S., 2001).

We acquired the ca. 1980 digital Land-Use and Land-Cover Dataset (LUDA) from the USGS. Interpretation of land cover for LUDA had been carried out using National High Altitude Aerial Photography Program (NHAP) or National Aeronautics and Space Administration (NASA) aerial photos at scales of 1:58,000 or smaller (U.S.G.S., 1990). Dates of the photos ranged from 1978 to 1983. The minimum mapping unit was 10 acres for urban and water features and 40 acres for all other cover types. In some cases, pre-existing land-cover and survey maps were used in addition to aerial photographs. Land-use and land-cover polygons were interpreted by USGS from the photographs to create analog maps that were later digitized as land-cover polygons forming the vector LUDA dataset. We rasterized this product by assigning all 1-km cells to the dominant land-cover category found within them.

LUDA data have not undergone a comprehensive independent accuracy assessment on a national scale. However,

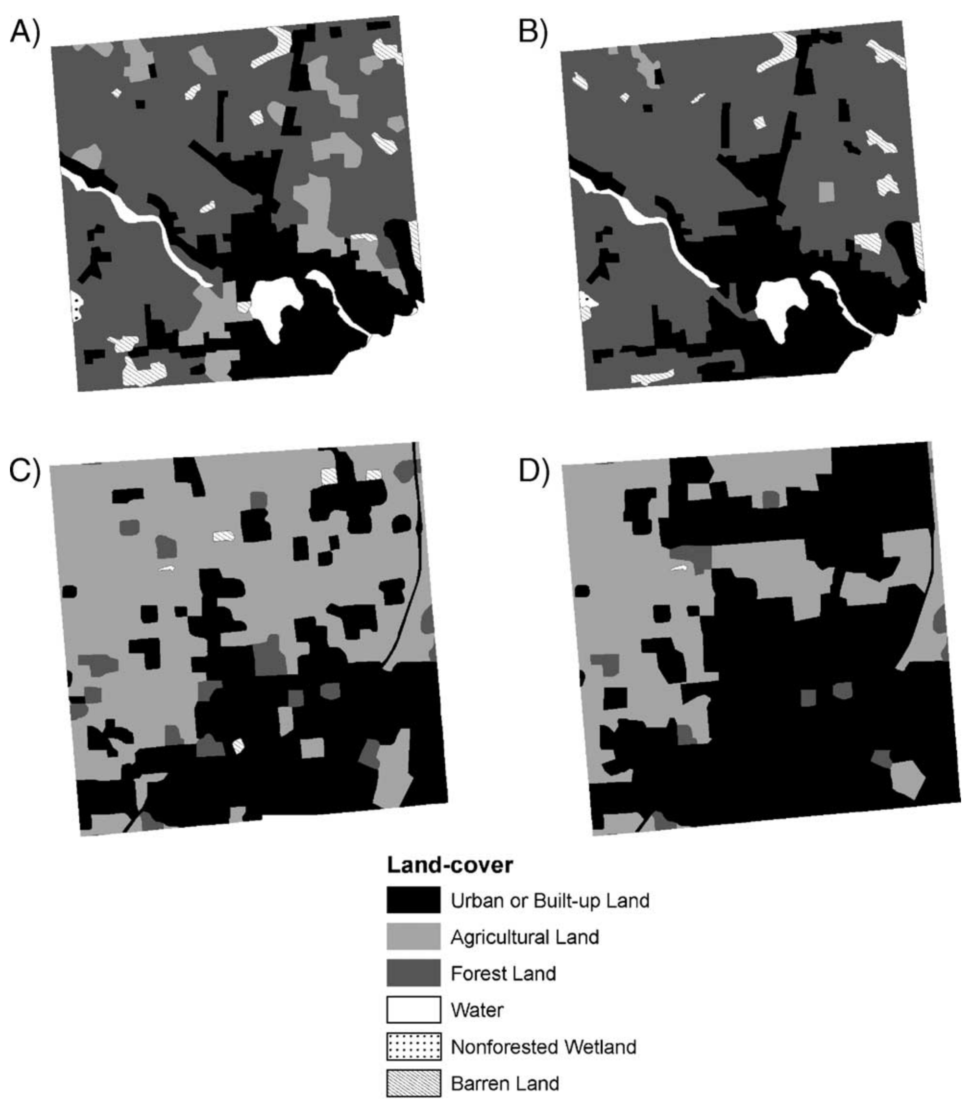

Fig. 3. Land-use change from NAPP photo interpretation for photos near Alpena, Michigan (top), and Fort Wayne, Indiana (bottom) where A) and C) show land-use in 1980 (LUDA), and B) and D) show land-use in 2000 ("simulated LUDA").

LUDA was manually interpreted with USGS quality control requirements and procedures (U.S.G.S., 1990). Our experience was that it is a reliable dataset—we found almost no errors (e.g.,< 10) in 1980 polygon labeling in the 2328 polygons that we examined for our validation dataset (described below). Therefore, we are confident in making the (necessary) assumption that these data can be considered accurate for the purposes of this project. Our focus is, instead, on the accuracy of our remotely sensed classification of 2000 land cover and of land-cover change.

Statistical data on land cover have been summarized as part of the Natural Resources Inventory (NRI) and are available by state and Major Land Resource Area (MLRA) every 5 years starting in 1982 (Nusser & Goebel, 1997). The 1982 and 1997 surveys were the closest to our two target years of 1980 and 2000. Our study area contained 35 ecoregions of variable size. Federal lands, which make up ~4% of the study region, were excluded in our analysis because they were not represented in the associated NRI data. All other lands (96%) are included in the NRI survey and data, including privately owned land, tribal and trust land, and lands controlled by state and local governments.

All NRI estimates have a documented uncertainty associated with them, and this uncertainty ranges from quite large at small spatial units such as counties, to small uncertainty at the larger spatial units of MLRAs and states. The sampling is designed so that the standard error was less than 20 percent for any estimate of a resource condition (e.g., land cover) that comprised at least 10 percent of an MLRA; in actual implementation most were estimated more precisely (U.S. Department of Agriculture, 2000, 2001).

In order to classify land cover in 2000 and validate the analysis of change from 1980–2000, we used a sample of non-stereo National Aerial Photography Program (NAPP) aerial photos (color infrared or black and white panchromatic at 1 : 40,000) for 2000. Like the photos used by USGS to create the 1980 LUDA dataset, the photos in our validation set were from a small range of years (1997–2000) because the NAPP program does not fly the entire United States, or even entire states, in the same year. The total number of sample photos chosen (86) resulted in about 0.5% coverage of the land area of the seven states. The number of photos chosen per MLRA was selected in proportion to the size of the MLRA and ranged from one in the smallest sub-regions to five in the largest. We selected photos in a way that considered (a) the consistency of the resulting validation dataset, because the NAPP photos were inconsistent in terms of available photo dates and types, and (b) locations in which land covers actually changed. Therefore, photos were not chosen completely randomly; there was a bias towards selecting photos closest in time to 1997–2000 and in transition zones between land-cover types, i.e., the areas undergoing most rapid change. Fig. 3 is an example of the type of land-cover and land-cover change data captured through a combination of 1980 LUDA and 2000 NAPP-classified aerial photographs.

4. Methods

In summary our methods involved the following. The innovative classification process we developed to produce a ca. 2000 land-cover dataset that was comparable to the available 1980 land-cover data involved (1) estimating the proportions of each land cover that should be expected within each of a set of sub-regions (defined by MLRAs); (2) performing unsupervised classification on multi-temporal AVHRR data within sub-regions and labeling the resulting clusters to land-cover classes; (3) extracting spectral–temporal signatures for each class within each sub-region and assigning all pixels a probability of belonging to each class based on its Mahalanobis (Jensen, 1996) distance to each class; (4) ranking all pixels in the resulting probability maps from most to least probable for each class; and, finally, (5) assigning all pixels to a class using a multi-objective land allocation (MOLA) procedure that seeks to classify a predetermined number of pixels (based on step 1) to each class based on the set of pixels with high probability of belonging to that class (Fig. 4). We used the resulting 2000 classified land-cover maps with the USGS c. 1980 LUDA to create land-cover change maps for the entire region. We used our sampled aerial photos and aggregate statistical data to calculate and compare the accuracies of both the land-cover and land-cover change maps resulting from processes with and without the land-allocation procedure.

4.1. Estimating land-cover proportions

In order to allocate pixels to classes, we first required estimates of land-cover proportions in 2000. We extracted land-cover statistics for 1982 and 1997 from the 1997 NRI CD at the finest available level of spatial detail and aggregated them to sub-regions following published guidelines for doing so (Nusser & Goebel, 1997). Land-cover classes used by the NRI were recoded to match the classes in the existing 1980 land-cover dataset (Table 2). We then calculated the percentages of each land cover in each sub-region.

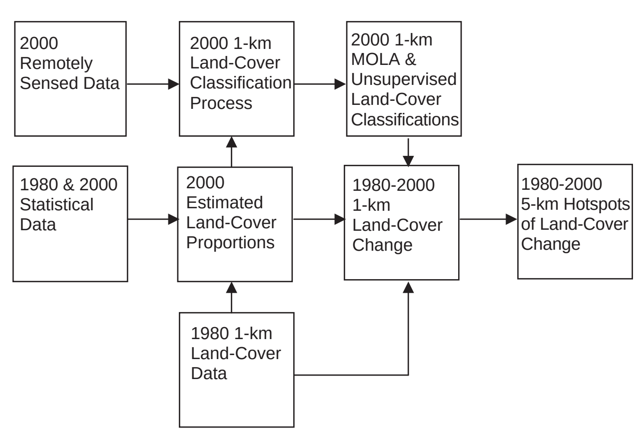

Fig. 4. Overview of the land-cover and land-cover change classification and validation process.

Table 2
Relationships between level I land-cover classes as defined in this project and in the LUDA and NRI datasets

	Project classes	LUDA (Level 2)	NRI (Specific land cover/use)
1	Urban	Urban (11–17)	Urban, transportation (700–870)
2	Agriculture (includes rangelands)	Agricultural land, rangeland (21, 23, 24, 31, 32, 33)	Cropland, pastureland, rangeland (1–213, 250, 400–410, 650)
3	Forest (includes forested wetlands and orchards)	Forestland, forested wetland, orchards (22,41,42,43,61)	Forestland (341, 342)
5	Nonforested wetlands	Nonforested wetlands (62)	Marshland (640)
6	Barren	Barren (72–76)	Barren (611–620)
7	Water	Water (51–54)	Water (901–924)

Because of definitional and methodological differences between the statistical survey and a remote sensing based analysis, we needed to determine the quantitative relationship between land-cover proportions calculated from the 1982 NRI statistical dataset and the 1980 air-photo-based LUDA dataset for each sub-region and for each land-cover type. We initially tested region-wide regression relationships between land-cover proportions of each type; however, the relationships were too weak, given the ecological variability among sub-regions, to make a single regression model useful across the entire study area. Instead we employed another approach, which was to calculate the ratios between the sub-region proportions of each type of land-cover estimated from the two datasets. These ratios were then applied to the sub-regional land-cover proportions from the 1997 NRI dataset to estimate the proportions of each land-cover class in each sub-region that should result from the 2000 AVHRR classification for it to be comparable with the 1980 land-cover map. The process is illustrated for one of our sub-regions in Table 3. We considered extending any trends in land-cover proportions observed in the NRI dataset between 1982 and 1997, to produce estimates for 2000. Because we could not absolutely know that a trend would continue in the same form, we chose to not do so, and instead used the 1997 proportions to guide our classification of 2000 AVHRR data. However trend extrapolation might be a useful extension of the methods presented here for similar projects.

4.2. Unsupervised classification

Bi-weekly composites of NDVI calculated from AVHRR images were chosen from among the 12 composites available from the 2000 growing season to minimize the effects of clouds and image defects. In most cases, some of the bi-weekly composites had visible anomalies over a given sub-region, and the selection process netted 7–10 NDVI composites for use in the classifications.

The ISODATA classification method (Tou & Gonzalez, 1974), as implemented in the ISOCLUS program in PCI (PCI Geomatics, Richmond Hill, Ontario, Canada), was used to identify clusters of pixels with similar spectral–temporal sequences. The classification process was run separately for each of the 35 sub-regions in the study region. All water areas, identified using the 1980 land-cover data set, were excluded from the clustering process. The resulting classifications contained 14–40 clusters (depending on size and complexity of the sub-regions), that we labeled as urban, agriculture, forest, non-forested wetland or barren. While we were ultimately interested in the change between the three dominant land-cover classes (i.e., agriculture, forest and urban), non-forested wetland and barren were included because they also existed on the landscape. Because these non-forested wetland and barren categories were often confused with other classes, they were further refined in a later step.

As references, and to evaluate change trajectories as logical or illogical, the 1992 National Land Cover Data (NLCD) (Vogelmann et al., 1998) and the LUDA 1980 data sets were consulted during cluster labeling. Clusters generated for all 35 sub-regions were labeled by two of the authors, and both analysts reviewed all classifications.

4.3. Spectral signature identification

In order to implement the land-cover allocation process, we required spectral–temporal signatures for our target classes. These were derived on the basis of a version of the unsupervised classification described above, modified to account for the spectral limitations of AVHRR data. Because urban development is not generally replaced by agricultural or forest land over time, we reclassified as urban all pixels that were labeled urban in the rasterized 1980 land-cover dataset, but not classified as urban in the 2000 unsupervised classification. We also found that AVHRR data could not consistently distinguish non-forested wetlands from other classes due to their small size, patchiness, or confusion with other classes (Gaston et

Table 3
Example land-cover proportions in one sub-region (MLRA 99)

	Urban	Agriculture	Forest	Non-forested wetland	Barren	Total
1980 LUDA	0.1021	0.7572	0.1350	0.0042	0.0015	1.0
1982 NRI	0.1594	0.6658	0.1617	0.0088	0.0043	1.0
Ratio = 1980 LUDA/1982 NRI	0.6405	1.1373	0.8349	0.4773	0.3488	NA
1997 NRI	0.1910	0.6140	0.1810	0.0078	0.0062	1.0
Predicted ~2000 AVHRR	0.1252	0.7143	0.1546	0.0038	0.0021	1.0

Lines 1–5 in the table are: 1) the proportion of each land-cover type calculated from the LUDA data (ca. 1980); 2) the proportion of each land-cover type in 1982 calculated from the NRI data; 3) the ratio between the proportions from the LUDA and NRI data; 4) the proportion of each land-cover type in 1997 calculated from the NRI data; and 5) the estimated proportion of each land-cover type for use in the MOLA mapping process.

al., 1994; Muller et al., 1999), and that the barren class was very small and isolated (e.g., dunes occurred in narrow, non-continuous strips along the Great Lakes shorelines). Consequently, the few clusters that were clearly non-forested wetland or barren were labeled as such, and clusters that were mixed or confused were labeled as urban, agriculture, or forest, depending on the dominant class present in the mixture. The non-forested wetlands and barren pixels in the unsupervised classification were supplemented with all pixels labeled as these two classes in the 1980 LUDA data set to ensure enough pixels for signature generation. Temporal–spectral signatures for the five land-cover categories were extracted using the classification results supplemented by appropriate pixels from the 1980 land-cover data as described above (the combination of which is hereafter referred to as the unsupervised classification).

4.4. Spatial allocation of land covers

The spectral–temporal signatures were used to generate five raster probability maps, one for each land-cover and representing the probability that each pixel belonged to that class based on Mahalanobis distance (Eastman, 2001). Because the Idrisi classification program we used allowed only seven bands to be used, we used the best seven bi-weekly composite images for each sub-region that also formed a good time-series over the growing season. To ensure that areas identified as urban in 1980 remained urban through subsequent processing, these pixels were given an urban probability of 100% and a probability for other classes of 0%. The probability maps were converted to rank maps, in which all pixels were rank-ordered based on their calculated probability of belonging to the land-cover class (i.e., the pixel with the highest probability in a given class was ranked one, etc.).

The Multi-Objective Land Allocation (MOLA) algorithm seeks to assign a predetermined number of pixels to each class based on the set of pixels that maximizes the collective probability of pixels assigned to each class (Eastman et al., 1993; Eastman, 2001). The five land-cover classes were input as equally weighted objectives for the MOLA procedure. Each objective (e.g., a land cover) was defined using its corresponding ranked probability map and also was given the expected number of pixels, derived from the NRI statistical data in the process described above. MOLA is an iterative process that allocates the highest ranked available pixels to each land-cover until it reaches the expected number of pixels for that land-cover. When a pixel that is the next highest ranked available for more than one class, it is assigned to the class in which its rank is highest. The MOLA procedure was run for every sub-region separately and the results were combined to produce a raster map showing 2000 land-cover in the entire region (hereafter referred to as the MOLA classification).

4.5. Land-cover accuracy assessment

In order to assess the accuracy of the products resulting from both the unsupervised classification and MOLA processes, we first used our sampled set of aerial photographs. The photos we acquired were scanned at 800 dpi and georeferenced to the digital orthophotoquads from the various state agencies, with RMS errors of less than 5 m. The land-cover polygons from the 1980 dataset (i.e., LUDA) were overlaid on the georectified 2000 photos, the 2000 land-cover interpreted from the photos, and the 1980 polygons edited to reflect interpreted 2000 conditions. Our photo interpretation process followed the same protocol and class definitions used to create the 1980 LUDA data set (Anderson et al., 1976; U.S.G.S., 1990). As with the LUDA data set, each updated land-cover polygon had to meet the minimum area requirement of 40 acres for all classes except urban and barren lands, which had a minimum mapping unit of 10 acres. Minimum polygon widths of 200 m for urban and barren and 400 m for other classes were also enforced in accordance with the protocol. All 86 aerial photographs were interpreted by trained remote sensing analysts and verified by a second and lead interpreter to ensure that all change areas were detected. The output of this process was a set of new vector-digitized land-cover maps representing 2000 conditions in an identical manner to the LUDA data set, which represents 1980 conditions.

The vector land-cover polygons for both dates were rasterized to a 1-km grid, to match the resolution of the AVHRR data and the rasterized version of the LUDA data. These data were then compared with the unsupervised and MOLA classifications to extract accuracy statistics. Producer's, user's and overall accuracy, and the Kappa coefficient were calculated for each land cover.

We also analyzed patterns in each individual sub-region to determine if any were particularly problematic, in terms of containing too much heterogeneity to have achieved adequate classification accuracy. One test of this was to calculate land-cover percentages at the state level, i.e., to summarize results on these strata not used in the classification process. This analysis indicated that several very large sub-regions had low-levels of accuracy even though, in the case of the MOLA classification, their percentages for each land cover were accurate. To address this problem, we split five of the 35 sub-regions at state boundaries resulting in 42 sub-regions total (as two of the split MLRAs spanned more than two states). All other sub-regions remained unchanged. We then repeated all previous processes to recreate the unsupervised and MOLA classifications on these slightly revised sub-regions, including summarizing the NRI statistics by these units. Although NRI protocols caution against analyzing NRI data by very small units such as counties (U.S.D.A., 2001), the split sub-regions were still quite large (i.e., they included many counties). The final results and accuracy figures for the land-cover classifications include these improvements.

4.6. Land-cover change

For several reasons it may not be advisable to directly analyze change in land-cover data from heterogeneous sources on a pixel-by-pixel basis, even with the method we developed to improve comparability. First, the underlying spatial scales of the two datasets were different. The data representing land cover in 1980 were vector-digitized using a minimum mapping unit and then aggregated to 1 km, while the AVHRR data were collected for 1-km pixels. Second, the spectral characteristics of the two datasets were different; one was interpreted from the visible spectrum (0.4–0.7 μm) and the other was an index derived from a combination of the green-red (0.58–0.68 μm) and near-infrared (0.725–1.1 μm) band. Third, the signal in any given AVHRR pixel may actually include some "bleeding" or contamination from adjacent pixels (Goward et al., 1991; Huang et al., 2002). Fourth, some spatial mis-registration may occur between two datasets.

To reduce the effects of these problems, we suggest that it may be necessary to either (a) perform the change analysis using data aggregated to a slightly coarser resolution, which would require an analysis of change in land-cover percentages within each larger (and mixed) pixel, or (b) analyze change at the pixel level, but aggregate and present the results at larger pixel sizes. Choosing the former approach, we (1) aggregated 1-km classifications from each method for each date by calculating the percentage of each 5-km pixel in each land-cover class and (2) calculated the change in land-cover percentages within each 5-km pixel as our measure of change. Although small-scale changes (i.e., those occurring over a single pixel or pair of pixels) are obscured by aggregation, the results serve to identify the areas within the region of high rates of change relative to other areas.

4.7. Land-cover change accuracy assessment

We assessed accuracy of the change maps, and tested the potential improvement of the MOLA method over the (augmented) unsupervised method at three aggregate levels. First, we compared changes in the percentages of agriculture, urban, and forest land covers estimated using the LUDA data set for 1980 and the unsupervised and MOLA results for 2000 to the air-photo-interpreted land-cover maps. Second, we compared the changes in the percentages of agriculture, urban, and forest land covers estimated using the LUDA data set for 1980 and the unsupervised and MOLA results for 2000, to the changes calculated from the statistical NRI data, summarized at the level of sub-regions and also by state. In order to make the comparisons with the NRI data, however, the proportions calculated from the LUDA data and the unsupervised and MOLA classifications were multiplied by scaling factors calculated to relate the NRI statistical and LUDA classifications at both the sub-region and state levels (based on the comparison of 1982 statistical data and the c. 1980 LUDA classification, and described in the section on Estimating land-cover proportions). We calculated and report the root mean squared error (RMSE) in the estimated change in land-cover percentages within the 5-km pixels, sub-regions and states.

For the 5-km pixels that fell within our sampled photos, we estimated the actual changes in land-cover percentages by comparing the rasterized LUDA data with a rasterized version our land-cover maps interpreted following the LUDA protocols. These figures were used to assess the accuracy of the respective change maps derived by comparing the rasterized LUDA data to the unsupervised and MOLA classifications, as described above. To reduce edge effects due to the small size of our sampled photos, only those 5-km cells that had at least 66% coverage of 1-km cells within the photo areas were used.

The accuracy of change estimates from the MOLA and unsupervised methods was calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (actualchange - classifiedchange)^2}{n}} \tag{1}$$

where n is the total number of 5-km pixels (i.e., across all sites), *actualchange* was the difference between 2000 and 1980 land-cover percentages, calculated using the photo-interpreted land covers for 2000 and the 1980 land-cover data (i.e., LUDA), and *classifiedchange* difference in land-cover percentages calculated using one of the two classification methods in comparison with the 1980 data (i.e., LUDA).

Given the small areal coverage provided by our photo validation sites, we also sought to compare our classifications with statistical data collected from across the region, but aggregated to larger spatial units (i.e., sub-regions and states). In order to calculate and compare the accuracy of estimates of the change in land-cover percentages within sub-regions and states, we calculated the actual difference in the percentages of agriculture, urban and forest within these regions from the 1997 and 1982 NRI statistical data. Next, we calculated the comparable changes based on sub-regional and state-wide estimates of land-cover percentages in 2000 from the unsupervised and MOLA classifications, compared to percentages from the 1980 LUDA classification. The accuracies of sub-regional and state-wide changes based on these two classifications were then estimated using the RMSE (Eq. (1)).

The by-state stratification tests the robustness of the classifications to an alternative aggregation. This is important because, in the case of the MOLA results, comparing them to NRI data for the original units of classification achieves a nearly exact match, as the MOLA process was constrained by the land-cover proportions reported in the NRI data. Comparison of state-level estimates tests whether this improvement as compared with the unsupervised method is retained when the results are aggregated by units that were not used as absolute constraints in the MOLA-based classification process. Note that though we split five large sub-regions of the 35 sub-regions at a state boundary, sub-region boundaries did not otherwise follow and did not nest within state boundaries.

5. Results

5.1. Land-cover classifications

Visual (Fig. 5) and quantitative (Table 4) comparisons of MOLA and unsupervised classifications confirmed the effectiveness of the classification methods. Though many 1-km pixels were actually composed of a mixture of land-cover classes, we classified the dominant cover class and used accuracy and change assessment methods appropriate to these discrete categories. So, some misclassifications are inevitable. The overall accuracy of the 1-km MOLA classification (85%, with a kappa of 73) compared favorably with the value for the unsupervised classification (82% with a kappa of 71). Though the results were fairly similar, the MOLA approach resulted in a small improvement in overall classification accuracy over the unsupervised classification approach. Recall that the unsupervised classification was adjusted to include ancillary data for the urban, non-forested wetlands, and barren categories.

Evaluation of the user's and producer's accuracies provides some indication of the strengths and weaknesses of the results. The relatively low producer's accuracy for Urban (73%) was a result of confusion between the urban and agricultural classes that is consistent with the presence of mixed urban-agriculture pixels in developing urban fringe areas. More pixels should have been assigned to Urban, but those classed as Urban were very likely (94%) to be Urban in the air-photo classification.

Though Agriculture was classified at consistent and relatively high levels of accuracy (90% producer's, 86% user's), the relatively lower producer's and user's accuracies for Forest (i.e., at 79% and 79%) resulted from confusion with agricultural land covers. This is probably because of mixed pixels and areas of transitioning young–shrubby vegetation where agricultural lands are more recently abandoned, a significant land-cover change phenomenon in the region.

There are two types of non-forested wetlands in the region: (a) small scattered wetlands that may be subject to change but have little or no effect on the classification at the 1-km scale, and (b) more extensive wetlands (in particular in northern Minnesota, Wisconsin, and Michigan) that are not subject to significant rates of land-cover change. The high levels of accuracy of Non-Forested Wetlands (90% producer's, 91% user's) in the MOLA classification, compared with the unsupervised classification, where user's accuracy was only 67%, was the likely result of the MOLA method improving on the unsupervised classification in capturing the 2000 Non-Forested Wetland pixels (even though the unsupervised classification had been supplemented by known Non-Forested Wetland regions based on both the 1980 LUDA and 2000 AVHRR). MOLA was able to allocate the correct number of wetland pixels and to allocate them in the place where they had the highest probability of being correct.

The Barren class occupied very little area, but because these pixels could not be classified into one of the other classes it was necessary to retain the class. Though we report the user's and producer's accuracy for Barren in Table 4, the small sample size was not adequate for us to draw conclusions or compare the classification methods on the basis of them.

Because of the bias towards selecting validation photos in areas of change, our accuracy results (Table 4) should be interpreted as representing accuracy for areas undergoing significant change and is probably lower than the accuracy of the areas of little change. Many of our validation photos represented the most difficult cases to correctly classify. For this reason, we believe that the results in Table 4 are conservative estimates of the accuracies of the classifications of the entire region.

5.2. Regional change maps

Two maps illustrate the spatial patterns of the two dominant land-cover change trajectories in the North Central Region: 1) percent change to forest, and 2) percent change to urban (Fig. 6). The maps in Fig. 6 show several distinct patterns and highlight the locations of rapid land-cover change in the region. The urban-change map highlights areas around urban cores—e.g. Minneapolis, Detroit, Chicago, etc. Other smaller cities are also showing significant change. In the change to forest map, the primary agricultural belt shows only scattered change. Instead, most of the forest change is in the urban–rural fringe and near the transition zones between predominantly agricultural and predominantly forested areas in both the northern and southern parts of the region.

Table 4
Accuracies of the unsupervised and MOLA classifications created using 2000 AVHRR data

Procedure	Urban	Agriculture	Forest	Non-forested wetland	Barren	Overall accuracy	Kappa
Unsupervised	83/80	83/90	82/73	95/67	60/17	82	71
MOLA	73/94	90/86	79/79	90/91	20/7	85	73

Reported are producer's/user's and overall accuracies by land cover in percent, plus the Kappa coefficient, for both the unsupervised and MOLA 1-km classifications.

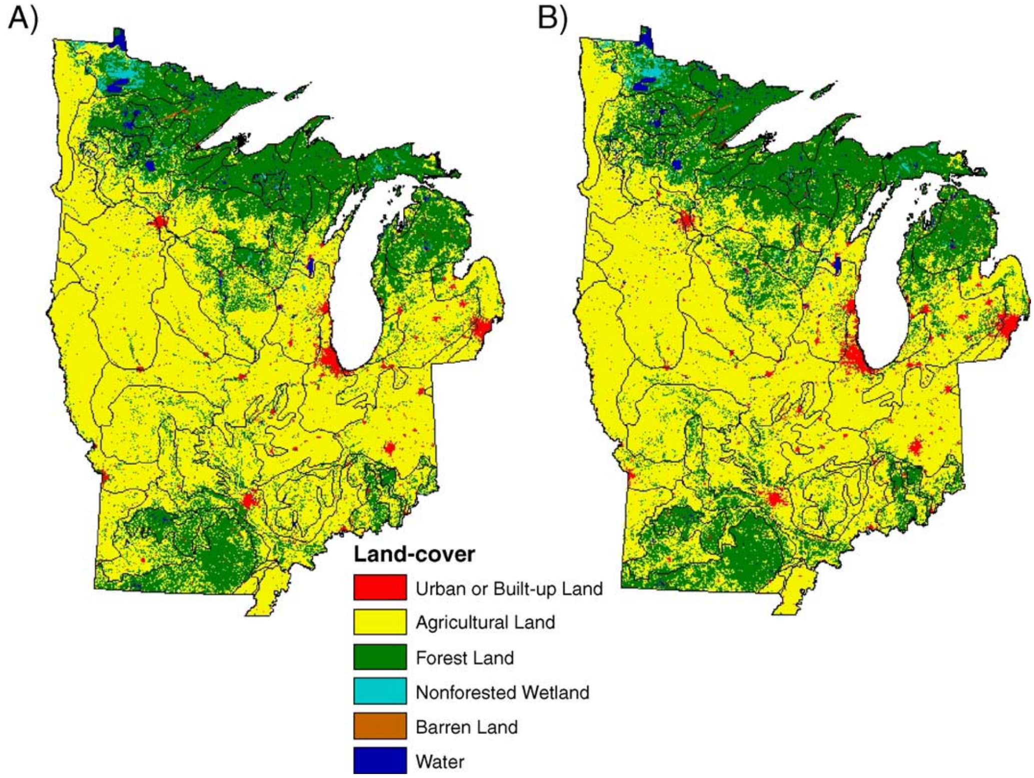

Fig. 5. Land cover in 1980 and 2000: A) 1980 land cover from LUDA, B) 2000 land cover from AVHRR.

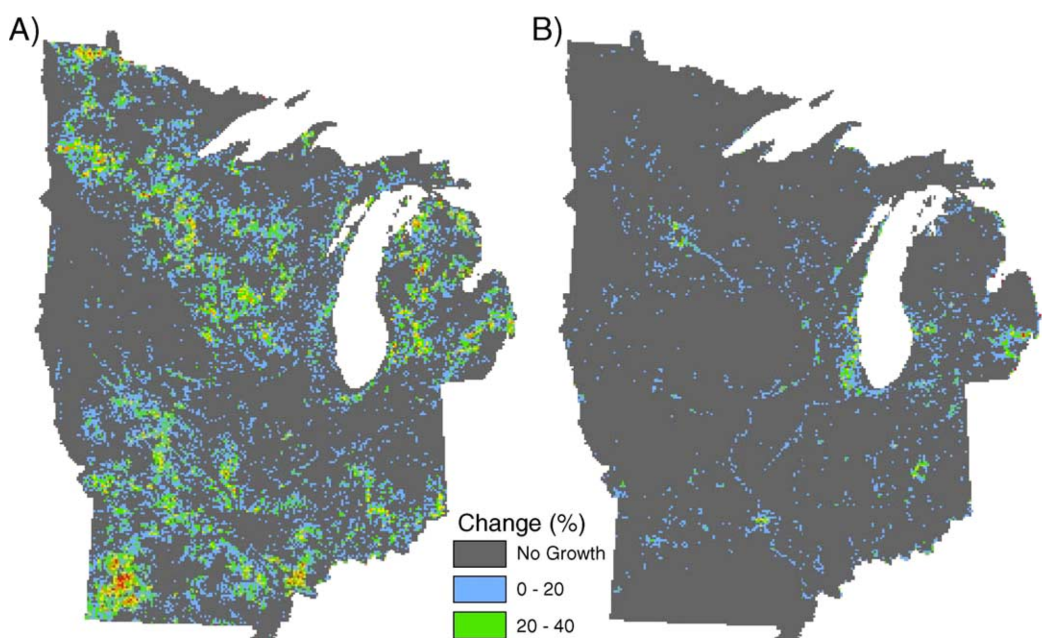

Fig. 6. Change maps showing A) percent change to forest, and B) percent change to urban. Pixel colors represent the change in percentage of pixels within the 5 km pixels that were in forest or urban. Gray represents no change, cool colors (blue) represent small increase, warm colors represent significant increase, and red represents 80% or greater increase.

The accuracy assessment of the change information indicates that the MOLA classification improved on the unsupervised approach in every test (Table 5). The RMSEs can be interpreted as the error in the estimated change in percentages within the 5-km pixels. Comparing the change in land-cover percentages over the 5-km pixels that covered our photo validation sites, the RMSEs from the MOLA method were lower (better) than those of the unsupervised classification. The improvements were only slight, but the consistency of the improvement of the change estimates is a good sign. The small size of the photo sample, again, limits the power of our accuracy estimates. It should also be remembered that the raw unsupervised classification was augmented with ancillary data to improve its accuracy and it is the augmented unsupervised classification compared here.

Comparing the accuracy of estimates of percentage change in land-cover proportions at the sub-region and state levels produces much more striking evidence of the improvement that the MOLA approach provides, over the more traditional unsupervised approach. Starting with estimates of change at the sub-region level, the RMSEs on the MOLA estimates were an order of magnitude lower than the results from the unsupervised method for forest and agriculture. Note, however, that the error in the MOLA estimates should theoretically be 0.0, because the proportions used in the classifications by sub-region were derived from the same NRI data used to assess accuracy. That the estimates of change in percent were slightly non-zero is most likely due to minor effects introduced in the multiple steps of preparation and analysis of the spatial datasets.

The more useful test, perhaps, is the comparison of percentage change estimates made at the state level, because the states were not used or used only in a minimal way in the stratification of the classification process. Significantly, the RMSEs of percentage change in the percentages of each land-cover category at the state level were still significantly lower for the MOLA-based analysis versus that based on the unsupervised classification. These results demonstrate that the method developed here, using an independent statistical dataset to constrain a classification in a land-allocation algorithm (MOLA) for comparison with an earlier land-cover map, improved the accuracy of the land-cover change maps and estimates derived from it over a more standard classification technique, even one that was supplemented with ancillary data.

Table 5
Results and comparisons of change maps based on the unsupervised and MOLA classifications summarized in three ways: a) change in the percentage of 5-km pixels in each land-cover type, b) change in percentage of land-cover types over sub-regions, and c) change in land-cover percentages over states

Summarization	Method	Urban	Agriculture	Forest
a) 5-km pixels	Unsupervised	9.90	16.62	15.66
	MOLA	8.77	14.97	11.68
b) Sub-region	Unsupervised	5.75	6.53	8.51
	MOLA	0.21	0.90	0.43
c) State	Unsupervised	3.53	2.64	2.77
	MOLA	0.27	0.77	0.40

All numbers reported are Root Mean Squared Errors (RMSE) calculated for each change estimate, compared with aerial photo interpretation (for 5-km pixels) or NRI data (for sub-regions and states).

6. Discussion and conclusions

The overall goal of this research was to map land-cover change between agriculture, forest, and urban land-covers within the North Central Region of the U.S. at a coarse spatial resolution. We developed a method that allowed us to compare an automated classification of land cover in the year 2000, based on spectral–temporal signatures derived from bi-weekly composites of an AVHRR-derived vegetation index (i.e., NDVI), with an existing land-cover map derived from vector-digitized land-cover polygons that had been interpreted from aerial photographs taken in the period 1978–1982. Given the availability of a consistent multi-temporal statistical data set, we used a land allocation algorithm to classify land-cover classes in a way that constrained aggregate land-cover proportions to those reported in the statistical dataset.

The need for such an approach is that it facilitates combination of heterogeneous data for land-cover change studies. Such data integration is necessary, in that it allows for extension of land-cover change studies in time, forward through the use of satellite imagery and backward through the use of archival sources. Our analysis of the statistical output indicates that the refinement the AVHRR-based classification produced better results for mapping land-cover change, when compared to the 1980 Land Use Dataset (LUDA) from the USGS, than did an unconstrained unsupervised classification. The improvement was consistent at all levels of analysis, but especially notable, i.e., the refined land-cover classification was about an order of magnitude better than the unsupervised classification, when the analysis focused on estimating land-cover change over areas within the region (i.e., MLRAs and states). The data and methods limit the accuracy of an analysis of land-cover change at the level of 1-km pixels. Nonetheless, the accuracy of such an analysis, aggregated to 5-km pixels, was improved by the method presented here.

The scope of our project (i.e., seven states) created some challenges in implementation. Even after standard processing of the AVHRR data into bi-weekly composites, there were still anomalies in the AVHRR NDVI time series, such as mosaicing and cloud influences that caused problems in the classifications in isolated areas that could not be removed. An additional source of error comes from the size of the sub-regions of analysis (i.e., MLRAs), and the variability within them that was not removed using this stratification. Our analysis confirms that the pattern of variability in the AVHRR data accounts for spatial variations within the sub-regions and that, together, the pixel-level satellite data and the constraints on sub-regional land-cover proportions provides a better representation of region-wide land-cover patterns than the AVHRR data alone. Nonetheless, stratification of the region into more and smaller sub-regions would likely improve the classification accuracy. However, using much smaller sub-regions requires statistical data that accurately estimate the land-cover proportions for those sub-regions and finer-resolution satellite data. Although incorporating such finer-level data was beyond the scope and intent of this project, the methods presented here could theoretically be used in the same way with data at any level of detail.

Some refinements of the method may be of interest to improve and generalize its applicability. We have suggested that projection or interpolation of trends observed in the statistical data might be useful in cases where statistical and spatial data were not collected in exactly the same year. In addition, the MOLA procedure could be implemented to account for uncertainty in the sub-regional estimates of land-cover proportions by assigning ranges for the numbers of pixels assigned to each land-cover class instead of an exact number or percentage. The methodology developed here could also be used to combine data from other platforms, for example MODIS (Moderate Resolution Imaging Spectrometer), with archival data. Improved remote sensing data, such as BRDF nadir-corrected MODIS, may improve spectral consistency.

The 5-km change product for the region has been incorporated into a web site that highlights changes in several social and natural characteristics between 1980 and 2000 to identify those areas in which natural resources are undergoing particularly dynamic changes (www.ncrs.fs.fed.us/4153/deltawest). Together with demographic and forest inventory information, the regional patterns of change in land cover facilitate analysis and assessment at a regional level. Without the development of the new method presented here, which makes use of regional stratification, summary statistics, and a land allocation algorithm to ensure reasonable compatibility of heterogeneous remotely sensed data sets, the comparability of multi-disciplinary data in this assessment would have been undermined. The methods should be more broadly applicable where inconsistent remotely sensed data sets are available from multiple sensors, but where statistical summaries can be used to improve compatibility.

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