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Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing

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Abstract

The importance of accurate and timely information describing the nature and extent of land resources and changes over time is increasing, especially in rapidly growing metropolitan areas. We have developed a methodology to map and monitor land cover change using multitemporal Landsat Thematic Mapper (TM) data in the seven-county Twin Cities Metropolitan Area of Minnesota for 1986, 1991, 1998, and 2002. The overall seven-class classification accuracies averaged 94% for the four years. The overall accuracy of land cover change maps, generated from post-classification change detection methods and evaluated using several approaches, ranged from 80% to 90%. The maps showed that between 1986 and 2002 the amount of urban or developed land increased from 23.7% to 32.8% of the total area, while rural cover types of agriculture, forest and wetland decreased from 69.6% to 60.5%. The results quantify the land cover change patterns in the metropolitan area and demonstrate the potential of multitemporal Landsat data to provide an accurate, economical means to map and analyze changes in land cover over time that can be used as inputs to land management and policy decisions.

Keywords: Land cover classification; Multitemporal; Change detection; Landsat

1. Introduction

Urban growth, particularly the movement of residential and commercial land use to rural areas at the periphery of metropolitan areas, has long been considered a sign of regional economic vitality. But, its benefits are increasingly balanced against ecosystem impacts, including degradation of air and water quality and loss of farmland and forests, and socioeconomic effects of economic disparities, social fragmentation and infrastructure costs (Squires, 2002). The land changes, commonly referred to as urban sprawl, associated with rapid expansion of low-density suburbs into formerly rural areas and creation of exurbs, urban or suburban areas buffered from others by undeveloped land, have ramifications for the environmental and socioeconomic sustainability of communities. Metropolitan areas across the U.S. have seen marked increases in urban growth and associated impacts of environmental degradation and traffic congestion (Center for Energy and Environment, 1999; Schrank & Lomax, 2004). These changes and their repercussions require careful consideration by local and regional land managers and policy makers in order to make informed decisions that effectively balance the positive aspects of development and its negative impacts in order to preserve environmental resources and increase socioeconomic welfare.

While metropolitan area decision makers are in constant need of current geospatial information on patterns and trends in land cover and land use, relatively little research has investigated the potential of satellite data for monitoring land cover in urban areas. However, the recent work, for example, of Alberti et al. (2004), Goetz et al. (2004), and Yang (2002) has shown that satellite remote sensing has the potential to provide accurate and timely geospatial information describing changes in land cover and land use of metropolitan regions. Although land use and land cover changes can be monitored by traditional inventories and

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surveys, satellite remote sensing provides greater amounts of information on the geographic distribution of land use and changes, along with advantages of cost and time savings for regional size areas. Importantly, remotely sensed imagery provides an efficient means of obtaining information on temporal trends and spatial distribution of urban areas needed for understanding, modeling, and projecting land change (Elvidge et al., 2004).

There are various ways of approaching the use of satellite imagery for determining land use change in urban environments. Yuan et al. (1998) divide the methods for change detection and classification into pre-classification and post-classification techniques. The pre-classification techniques apply various algorithms, including image differencing and image ratioing, to single or multiple spectral bands, vegetation indices or principal components, directly to multiple dates of satellite imagery to generate "change" vs. "no-change" maps. These techniques locate changes but do not provide information on the nature of change (Ridd & Liu, 1998; Singh, 1989; Yuan et al., 1998). On the other hand, post-classification comparison methods use separate classifications of images acquired at different times to produce difference maps from which "from–to" change information can be generated (Jensen, 2004). Although the accuracy of the change maps is dependent on the accuracy of the individual classifications and is subject to error propagation, the classification of each date of imagery builds a historical series that can be more easily updated and used for applications other than change detection. The post-classification comparison approach also compensates for variation in atmospheric conditions and vegetation phenology between dates since each classification is independently produced and mapped (Coppin et al., 2004; Yuan et al., 1998).

This paper describes the methods and results of classifications and post-classification change detection of multitemporal Landsat TM data of the seven-county Twin Cities Metropolitan Area (TCMA) for 1986, 1991, 1998, and 2002, extending the preliminary results for 1991 and 1998 reported by Bauer et al. (2004a,b) to additional years. The objectives were to: (1) develop a methodology to map and monitor land cover changes through post-classification change detection; (2) assess the accuracy of multitemporal Landsat classifications and change detection; and (3) analyze urban growth patterns and relate them to major factors thought to influence land cover conversion. The diversity of land cover types and uses, combined with the growing urbanization of the TCMA makes it a near ideal area to develop and evaluate the potential of satellite remote sensing for monitoring land change dynamics in a metropolitan area.

2. Study area

The study area (Fig. 1) is the seven-county Twin Cities Metropolitan Area of Minnesota, an area of approximately 7700 km^2. It includes a diversity of land cover classes interspersed with over 900 lakes, large areas of wetlands, and is transected by the Minnesota, Mississippi and St. Croix Rivers. Both high and low density urban development are found in the central portion while several rural land cover types of agricultural croplands, wetlands and forests characterize the surrounding landscape. The Minneapolis–St. Paul metropolitan area is the fifteenth largest metropolitan statistical area (MSA) in the U.S. The 2000 federal census reported that the core seven counties – Anoka, Carver, Dakota, Hennepin, Ramsey, Scott, and Washington – had a population of 2,642,062, an increase of 15.3% from 1990, and 1,021,459 households, an increase of 16.7%. The Metropolitan Council, the regional planning agency for the Twin Cities area, forecasts the metropolitan area population will increase by 500,000 and will add 270,000 additional households by 2020. The U.S. Environmental Protection Agency (2003) has reported that from 1974 to 2000 the population of the seven-county TCMA increased by 38% while the urban land area increased by 59%.

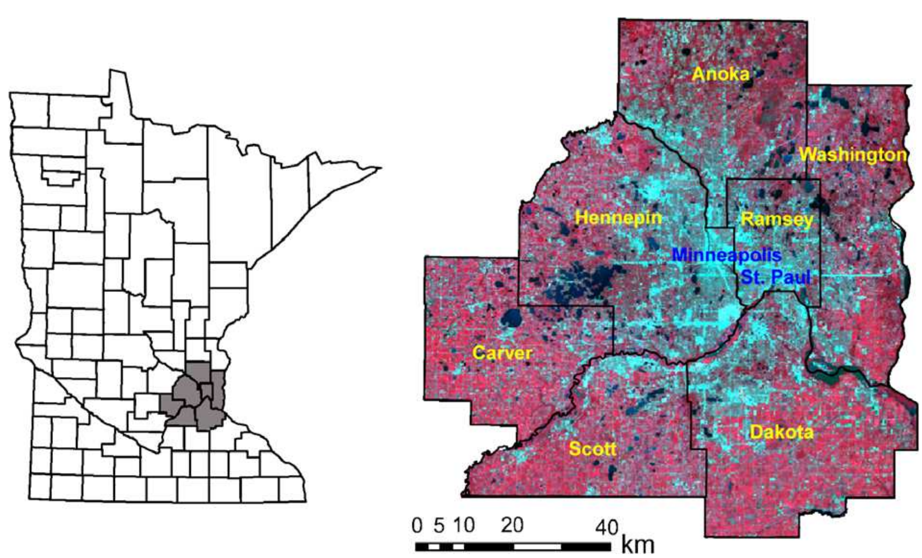

Fig. 1. Seven-county Twin Cities Metropolitan Area of Minnesota.

3. Methods

3.1. Landsat data

Four pairs of bitemporal clear, cloud-free Landsat images were selected to classify the study area: June 2 and August 23, 1986; June 16 and September 4, 1991; May 18 and September 7, 1998; and May 21 and July 16, 2002. The seven-county TCMA is entirely contained within Landsat path 27, rows 28–29. The images were Landsat-5 TM, except for a Landsat-7 ETM+image for May 2002. All images were rectified to UTM zone 15, GRS1980, NAD83 using at least 35 well distributed ground control points and nearest neighbor resampling. The root mean square errors were less than 0.25 pixel (7.5 m) for each of the eight images. Image processing was performed using ERDAS Imagine, version 8.5.

Numerous researchers, including Lillesand et al. (1998), Lunetta and Balogh (1999), Oettera et al. (2000), Wolter et al. (1995), and Yuan et al. (2005) have demonstrated the value of multitemporal imagery for classification of land cover. Our approach combined late spring and summer images. In the spring images fields planted with annual crops (e.g., corn and soybean) respond as bare soil and are distinguishable from forests that are already fully leafed out. When only a summer image is used, forests and some crops are spectrally similar. However, the late summer image is needed to separate those same crop fields from urban areas with significant amounts of asphalt and concrete and other impervious surfaces that are spectrally similar to bare soil in a spring image. The importance of multitemporal imagery was confirmed by determining the transformed divergences for the 1998 data set. Compared to the single dates, both the average and the minimum separability of classes were increased by the combination of spring and summer images.

3.2. Reference data

Reference data were developed for each of the four years and then randomly divided for classifier training and accuracy assessment. Due to the retrospective nature of our study, it was necessary to employ a variety of methods to develop reference data sets for training and accuracy assessment.

Large scale (1 : 9600) black and white aerial photos acquired in 1987 were used as reference data for the 1986 classification. Stratified random sampling was used for selecting samples. More specifically, the TCMA was divided into 19 columns and 18 rows resulting in 342 cells, and a 600×600 m site was randomly sampled from each cell. The aerial photos corresponding with the sample sites were then interpreted and 1044 polygons of cover types were delineated. These polygons included approximately 1.66 % of the total TCMA pixels; 63% were used for training and the remainder for accuracy assessment.

Reference data for the 1991 training and accuracy assessment were obtained from previous studies by Bauer et al. (1996) and Özesmi (2000). In those studies, the agricultural classes were obtained from 35-mm color aerial photography acquired in July–August 1991 combined with USDA Agricultural Stabilization and Conservation records of crops. A systematic, stratified sample of 72 sections was used as the reference data for training and accuracy assessment. Reference data for other cover types were not limited to these sections and were obtained from random sampling of a combination of aerial photography, a 1990 Metropolitan Council land use map, and National Wetland Inventory (NWI) data for the wetland classes. The classes of all training and accuracy assessment data were also checked against digital orthophoto quadrangles (DOQs). The polygon was deleted if the cover type identification was questionable. For example, some areas that were wetlands according to the NWI, looked like farm fields on the 1990 DOQs and these were not used as reference data for the wetland class. The reference data included 931 polygons with 1.91 % of the total pixels; 67% were used for training and 33% for accuracy assessment.

The reference data for 1991 were used to examine the field and spectral response patterns of the corresponding 1998 TM imagery to derive reference data for 1998 land cover classes. Each area used for training signatures and accuracy assessment for 1991 was checked against the 1998 TM imagery sets and 1997 DOQs to be certain that the general land cover class was the same. Areas that had changed between the years were discarded from the reference data if the 1998 cover type could not be identified with certainty. Approximately 1.73% of the total pixels, in 929 polygons, was available for training and accuracy assessment with 76% used for training and 24% for accuracy assessment.

The reference data for the 2002 classification were acquired from three sources. The primary data was a field verified set of reference sites collected in the fall of 2002. This data set was created by collecting cover type information for a stratified random sample of 300 points with 60 points per level 1 class (excluding extraction and water). The strata were from a previous classification of 2000 Landsat TM imagery (Yuan et al., 2005). At each sample point a field computer with ArcPad GIS and GPS was used to digitize a polygon of the area of the 2002 cover type identified, along with other cover types in the vicinity of the randomly generated point. This procedure resulted in 646 reference sites. The second source of data was a randomly selected forest cover type data set with 425 additional polygons, created and field verified during the summer of 2002 by Loeffelholz (2004). The third source was 30 small grain fields derived from interpretation of high-resolution color DOQs acquired in the summer of 2002. The 1101 potential reference sites were buffered by 30 m to avoid boundary pixels, leaving 672 polygons (0.75% of the total pixels) from which 354 sites were selected for training and 318 for testing.

3.3. Image classification

Our classification scheme, with seven level 1 classes (Table 1), was based on the land cover and land use classification system developed by Anderson et al. (1976) for interpretation of remote sensor data at various scales and resolutions. A combination of the reflective spectral bands from both the

Table 1
Land cover classification scheme

Land cover class	Description
Agriculture	Crop fields, pasture, and bare fields
Grass	Golf courses, lawns, and sod fields
Extraction	Quarries, sand and gravel pits
Forest	Deciduous forest land, evergreen forest land, mixed forest land, orchards, groves, vineyards, and nurseries
Urban	Residential, commercial services, industrial, transportation, communications, industrial and commercial, mixed urban or build-up land, other urban or built-up land
Water	Permanent open water, lakes, reservoirs, streams, bays and estuaries
Wetland	Non-forested wetland

spring and summer images (i.e., stacked vector) was used for classification of the 1986, 1991 and 1998 images. The 2002 classification used the brightness, greenness and wetness components from the tasseled cap transformation. A hybrid supervised–unsupervised training approach referred to as "guided clustering" in which the level 1 classes are clustered into subclasses for classifier training was used with maximum likelihood classification (Bauer et al., 1994). Except for the extraction class, training samples of each level 1 class were clustered into 5–20 subclasses. Class histograms were checked for normality and small classes were deleted. Following classification the subclasses were recoded to their respective level 1 classes.

Post-classification refinements were applied to reduce classification errors caused by the similarities in spectral responses of certain classes such as bare fields and urban and some crop fields and wetlands. Parcels classified as agriculture within the boundaries of a residential and commercial mask generated from the Metropolitan Council land use maps were changed to grass using a rule-based spatial model in ERDAS Imagine. The eight National Wetland Inventory (NWI) Circular 39 classes (Shaw & Fredine, 1956; Özemi, 2000) that exist in the TCMA (bogs, deep marsh, seasonally flooded basin, shallow marsh, shallow open water, shrub swamp, wet meadow, and wooded swamp) were extracted and used as a wetland mask. Wetlands were separated from the crops by applying the following rule in the ERDAS Imagine spatial modeler: pixels in an agriculture class were reclassified to wetland if they fell within the NWI lowland mask. In addition, areas identified as extraction were delineated manually using 1987 aerial photos, 1990, 1997, and 2002 digital orthophoto quads (DOQs), and Metropolitan Council land use maps for 1984, 1990, 1997, and 2000. An additional rule-based procedure was used to differentiate urban from bare agriculture land in Anoka County in the 2002 classification. The 2002 summer Landsat image was earlier in the season than those for the other years and in Anoka County some relatively bare crop fields were misclassified as urban. Specifically, an agriculture mask of Anoka County was created using the 2000 Metropolitan Council land use map and 2003 color DOQ imagery and pixels classified as urban were reclassified as agriculture if they were located in the agriculture mask. Finally, a 3×3 majority filter was applied to each classification to recode isolated pixels classified differently than the majority class of the window.

3.4. Classification accuracy assessment

An independent sample of an average of 363 polygons, with about 100 pixels for each selected polygon, was randomly selected from each classification to assess classification accuracies. Error matrices as cross-tabulations of the mapped class vs. the reference class were used to assess classification accuracy (Congalton & Green, 1999). Overall accuracy, user's and producer's accuracies, and the Kappa statistic were then derived from the error matrices. The Kappa statistic incorporates the off-diagonal elements of the error matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance.

In addition, to assess how well the Landsat classifications compared with other land cover inventories, the results of Landsat classifications for 1986, 1991 and 1998 were compared to the USDA Natural Resources Inventory (NRI). County estimates for the 2002 NRI are not available for comparison. Since NRI data have different classes than those of our Landsat classification, data from both sources were aggregated into four categories: agriculture, rural, water, and developed. For the NRI, cropland-cultivated, cropland-non-cultivated, pastureland and conservation reserve program were combined to form the agriculture category; forest land and minor land covers, including wetland, were combined to form the rural category; urban small and large built-up, rural non-agriculture, transportation (roads and railroads) were joined to create the developed

Table 2
Summary of Landsat classification accuracies (%) for 1986, 1991, 1998, and 2002

Land cover class	1986		1991		1998		2002	
	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
Agriculture	89.9	98.8	92.3	98.1	93.8	95.6	95.8	96.4
Forest	97.1	94.2	96.9	95.3	94.5	89.9	97.3	88.8
Grass	99.7	86.6	99.9	85.7	99.6	90.6	98.1	78.9
Urban	97.8	95.7	96.0	98.2	90.4	99.8	89.6	99.8
Water	98.1	97.8	97.0	89.3	91.7	97.5	95.9	96.7
Wetland	94.4	91.4	86.7	87.8	89.7	78.5	81.9	84.3
Overall accuracy	95.5		94.6		92.6		93.2	
Kappa statistic	94.4		93.2		90.9		91.6	

category. For the Landsat classification, forest and wetland were combined to create the rural (non-agriculture) class, while urban, grass, and extraction were grouped into the developed class. A Chi-square analysis was performed to test the hypothesis that there was no significant difference between the Landsat classification and NRI land cover area estimates.

3.5. Change detection

Following the classification of imagery from the individual years, a multi-date post-classification comparison change detection algorithm was used to determine changes in land cover in four intervals, 1986–1991, 1991–1998, 1998–2002, and 1986–2002. This is perhaps the most common approach to change detection (Jensen, 2004) and has been successfully used by Yang (2002) to monitor land use changes in the Atlanta, Georgia area. The post-classification approach provides "from–to" change information and the kind of landscape transformations that have occurred can be easily calculated and mapped. A change detection map with 49 combinations of "from–to" change information was derived for each of the four seven-class maps.

3.6. Change detection accuracy assessment

Change detection presents unique problems for accuracy assessment since it is difficult to sample areas that will change in the future before they change (Congalton & Green, 1999). A concern in change detection analysis is that both position and attribute errors can propagate through the multiple dates. This is especially true when more than two dates are used in the analysis. The simplest method of accuracy assessment of change maps is to multiply the individual classification map accuracies to estimate the expected accuracy of the change map (Yuan et al., 1998).

A more rigorous approach is to randomly sample areas classified as change and no-change and determine whether they were correctly classified (Fuller et al., 2003). We took this approach to evaluate the change maps for the 1986 to 2002 interval. Sample size was determined using the standard formula, $N = Z^2 \times P \times (1-P)/E^2$, where Z= Z value (e.g., 1.96 for 95% confidence level), P= expected accuracy, and E=allowable error. For 50% accuracy, 95% confidence level, and 5% margin of error, a sample of 384 pixels was randomly selected from each class. Pixels on the boundaries of change areas (i.e., mixed pixels) were excluded, leaving 318 samples of change and 352 of no-change. Each sample point was compared to the reference data from 1-m DOQs, Metropolitan Council land use maps, and the NWI to determine whether the Landsat-classified change had actually occurred. This method

Table 3
Change detection error matrix for 1986–2002

Reference class	Classification		Producer's accuracy (%)
	Change	No-change	
Change	211	18	92.1
No-change	107	334	75.7
User's accuracy (%)	66.4	94.9	
Overall accuracy: 81.3% Kappa statistic: 62.1%			

Table 4
Comparison of cover type area estimates from Landsat classifications and the USDA Natural Resources Inventory

Source - year	Agriculture (%)	Rural (%)	Water (%)	Developed (%)
Landsat - 1986	47.4	22.2	5.5	24.9
NRI - 1987	46.7	22.3	6.1	24.8
Landsat - 1991	44.1	22.7	6.0	27.3
NRI - 1992	44.4	21.7	6.1	27.7
Landsat - 1998	41.1	20.9	5.9	32.2
NRI - 1997	40.6	19.2	6.2	34.0

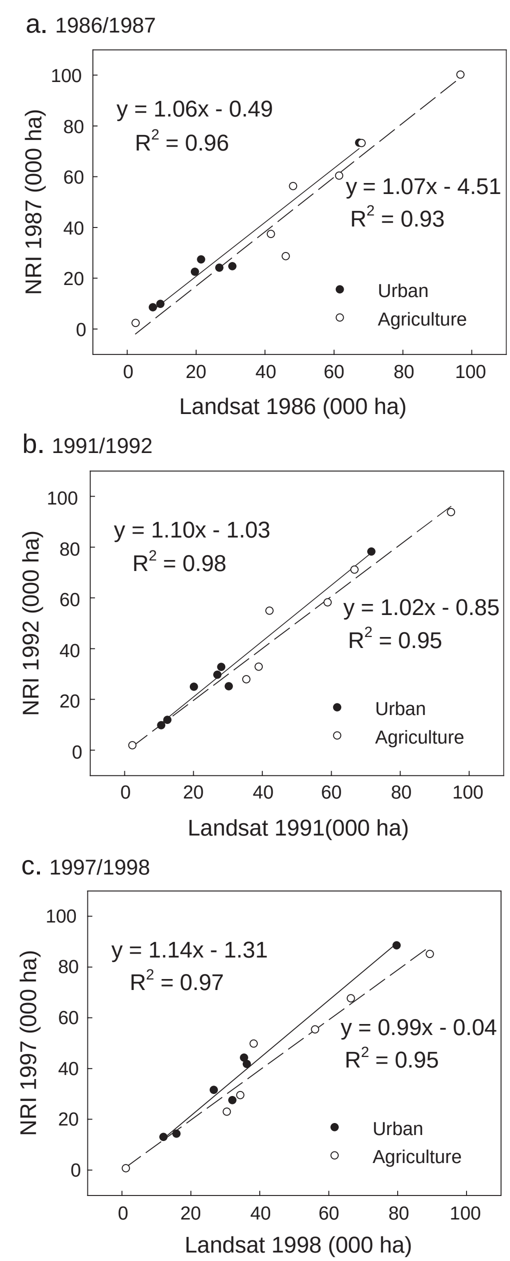

Fig. 2. Comparisons for three time periods of Natural Resources Inventory and Landsat cover type area estimates for agriculture and urban classes. Data are county totals.

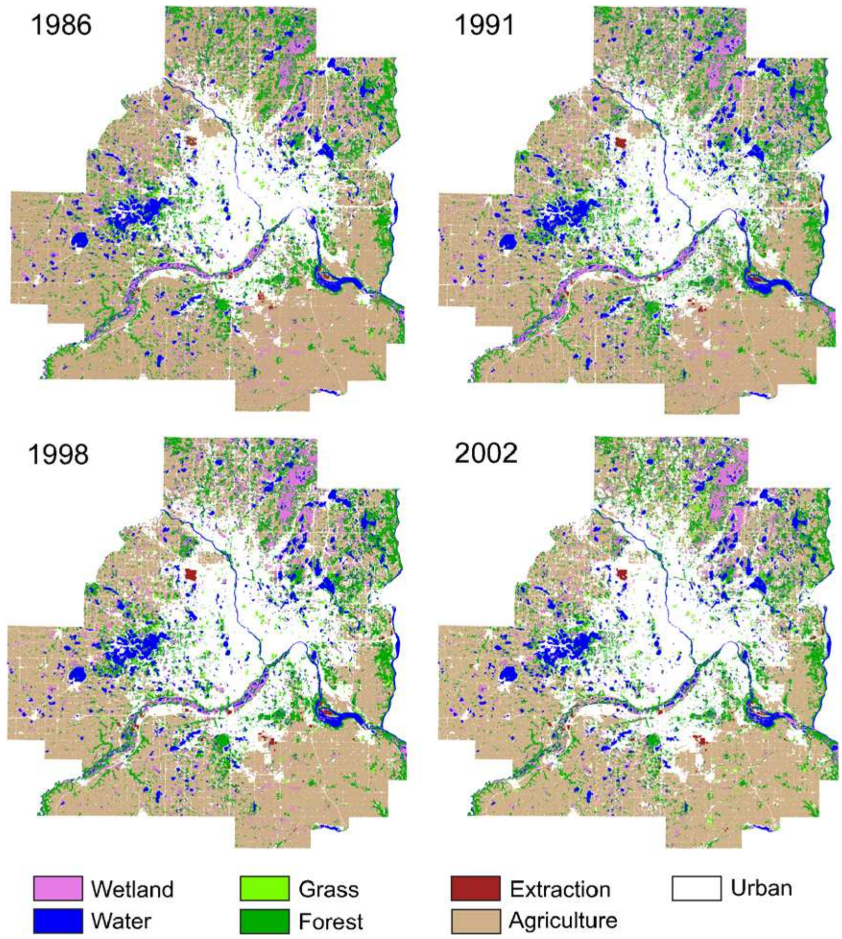

Fig. 3. Landsat land cover classifications from 1986 to 2002 for the TCMA.

required intensive visual analysis because of the different formats and spatial characteristics of the several sources of reference maps. Nevertheless, it provided additional information to evaluate the accuracy of the Landsat change detection.

4. Results and discussion

4.1. Classification and change detection accuracy

Error matrices were used to assess classification accuracy and are summarized for all four years in Table 2. The overall accuracies for 1986, 1991, 1998, and 2002 were, respectively, 95.5%, 94.6%, 92.6%, and 93.2%, with Kappa statistics of 94.4%, 93.2%, 90.9%, and 91.6%. User's and producer's accuracies of individual classes were consistently high, ranging from 78% to 99%. Compared to the preliminary five-class classifications in the previous study (Bauer et al., 2004a,b), the overall accuracies for six classes increased 6.0% and 0.3% for 1991 and 1998, respectively, using the guided clustering procedure rather than supervised training. Further, the post-classification processing increased the overall accuracy 4%–5%, with increases in the accuracies of wetland of more than 10% for both 1986 and 1991.

Multiplying the individual classification accuracies from Table 2 gives expected overall change detection accuracies of 90.3% for 1986–1991, 87.6% for 1991–1998, 86.3% for

Table 5
Summary of Landsat classification area statistics for 1986, 1991, 1998, and 2002

Land cover class	1986		1991		1998		2002		Relative change, 1986–2002 (%)
	Area (000 ha)	%	Area (000 ha)	%	Area (000 ha)	%	Area (000 ha)	%	
Agriculture	365	47.4	339	44.1	316	41.1	310	40.3	−15.0
Urban	183	23.7	200	26.0	238	30.9	253	32.8	38.5
Forest	113	14.6	111	14.4	106	13.7	104	13.5	−7.9
Wetland	58	7.6	64	8.3	55	7.1	51	6.6	−12.4
Water	42	5.5	46	6.0	45	5.9	43	5.6	3.5
Grass	7.4	1.0	7.6	1.0	7.0	0.9	6.6	0.9	−9.7
Extraction	1.8	0.2	2.4	0.3	2.7	0.4	2.6	0.3	42.6

1998–2002, and 89.0% for 1986–2002. The change detection accuracy was also evaluated by the method described in Section 3.6 in which 670 random samples classified as no-change or changed between 1986 and 2002 were evaluated and a change detection error matrix was derived (Table 3). The overall accuracy of change detection was 81.3%, with Kappa of 62.1%. Of the 18.7% error in change detection, 16.0% was false detection or commission errors and 2.7% was omission errors.

While it is a non-site specific comparison, it is also useful to compare the Landsat classification estimates to another, independent inventory such as the Natural Resources Inventory (Table 4). Although there is a one-year difference between each pair of NRI and Landsat estimates, the two surveys concur on the trends of increasing urbanization in the Twin Cities Metro Area with similar estimates. Perfect agreement would not be expected due to the differences in the dates of data collection, as well as differences in classes

Table 6
Matrices of land cover and changes (000 ha) from 1986 to 2002

a. 1986–1991

1991	1986							1991 Total
	Agriculture	Urban	Forest	Wetland	Water	Grass	Extraction	
Agriculture	307.4	10.3	12.6	7.7	0.5	0.2	0.1	338.8
Urban	26.3	158.4	7.8	3.8	0.9	2.2	0.3	199.6
Forest	15.4	7.4	79.7	6.6	0.8	0.8	0.0	110.6
Wetland	13.3	2.6	11.0	33.7	2.7	0.2	0.0	63.5
Water	0.4	1.5	0.9	6.0	36.9	0.0	0.1	45.8
Grass	1.3	2.0	0.3	0.1	0.0	3.9	0.0	7.7
Extraction	0.5	0.2	0.2	0.1	0.0	0.0	1.4	2.4
1986 Total	364.7	182.4	112.4	58.0	41.8	7.4	1.8	768.5

b. 1991–1998

1998	1991							1998 Total
	Agriculture	Urban	Forest	Wetland	Water	Grass	Extraction	
Agriculture	295.9	5.9	5.0	8.5	0.2	0.4	0.0	315.9
Urban	31.7	184.8	12.2	4.6	1.4	2.6	0.2	237.4
Forest	3.9	6.0	86.1	8.0	0.8	0.6	0.0	105.5
Wetland	5.5	1.3	6.3	39.3	2.2	0.1	0.0	54.8
Water	0.2	0.3	0.5	2.8	41.2	0.0	0.0	45.0
Grass	1.2	1.2	0.5	0.3	0.0	3.9	0.0	7.1
Extraction	0.3	0.1	0.1	0.0	0.1	0.0	2.1	2.7
1991 Total	339.3	199.9	110.8	63.6	45.9	7.7	2.4	768.5

c. 1998 – 2002

2002	1998							2002 Total
	Agriculture	Urban	Forest	Wetland	Water	Grass	Extraction	
Agriculture	266.7	20.0	10.1	11.3	0.4	1.1	0.1	309.7
Urban	29.5	206.3	8.9	2.6	2.3	2.5	0.4	252.5
Forest	10.0	7.5	76.8	7.6	1.3	0.3	0.0	103.4
Wetland	6.4	2.4	8.6	31.0	2.2	0.1	0.0	50.7
Water	0.3	0.7	0.8	2.2	38.8	0.0	0.0	42.8
Grass	2.7	0.4	0.3	0.1	0.0	3.1	0.0	6.7
Extraction	0.2	0.3	0.0	0.0	0.0	0.0	2.2	2.6
1998 Total	315.8	237.7	105.5	54.7	45.0	7.1	2.7	768.5

d. 1986–2002

2002	1986							2002 Total
	Agriculture	Urban	Forest	Wetland	Water	Grass	Extraction	
Agriculture	274.0	11.9	11.7	10.9	0.5	0.6	0.1	309.7
Urban	64.4	162.0	14.1	6.2	1.8	3.4	0.6	252.5
Forest	12.8	6.2	74.0	8.2	1.5	0.6	0.0	103.4
Wetland	8.8	1.3	11.4	26.9	2.1	0.2	0.0	50.8
Water	0.3	0.6	0.6	5.6	35.8	0.0	0.0	42.9
Grass	3.2	0.4	0.4	0.2	0.0	2.5	0.0	6.7
Extraction	1.0	0.2	0.2	0.1	0.0	0.0	1.1	2.6
1986 Total	364.5	182.6	112.4	58.0	41.8	7.4	1.8	768.5

between the two surveys. In addition, the NRI is subject to sampling errors and the Landsat estimates to classification errors. However, the Chi-square tests indicated that differences between the Landsat and NRI estimates are not significant. Fig. 2 further supports this conclusion with comparisons of NRI and Landsat area estimates for agriculture and urban uses by county.

4.2. Classification and change maps and statistics

Classification maps were generated for all four years (Fig. 3) and the individual class area and change statistics for the four years are summarized in Table 5. From 1986 to 2002, urban area increased approximately 70,000 ha (9.1%) while agriculture decreased 55,000 ha (7.1%), forest decreased 9000 ha (1.1%), and wetland decreased 7000 ha (1.0%). Relatively, urban and developed areas increased 38.5% from 1986 to 2002, with the greatest increase occurring from 1991 to 1998, while agriculture, forest, and wetland decreased, respectively, 15.0%, 7.9% and 12.4%. Although the extent of wetlands may change from year to year due to varying precipitation and temperature, the variation in wetland area is also likely due to classification errors (Table 2). However, the small fluctuations in water are believed to be related to varying lake levels given the high classification accuracy for water.

To further evaluate the results of land cover conversions, matrices of land cover changes from 1986 to 1991, 1991 to 1998, 1998 to 2002, and 1986 to 2002 were created (Table 6). In the table, unchanged pixels are located along the major diagonal of the matrix. Conversion values were sorted by area and listed in descending order. These results indicate that increases in urban areas mainly came from conversion of agricultural land to urban uses during the sixteen-year period, 1986–2002 (Table 6d). Of the 70,000 ha of total growth in urban land use from 1986 to 2002, 75.1% was converted from agricultural land and 11.3% from forest.

Table 6d shows that 14,093 ha of forest was converted to urban between 1986 and 2002, while at the same time, 6201 ha of urban was converted to forest. These changes may seem to be classification errors, but forested areas are among some of the most sought after areas for developing new housing. Streets and highways were generally classified as urban, but when urban tree canopies along the streets grow and expand, the associated pixels may be classified as forest. We note that the changes from urban to forest occurred almost entirely near highways and streets. Classification errors may also cause other unusual changes. For example, between 1986 and 2002, 11,900 ha of urban changed to agriculture and 1300 ha of urban and 8800 ha of agriculture changed to wetland. These changes are most likely associated with omission and commission errors in the Landsat classifications change map. Registration errors and edge effects can also cause apparent errors in the determination of change vs. no-change.

In Table 7 we examine more specifically the changes in cover type between 1986 and 2002 for the random sample of the correctly classified 211 change samples from the 318 change sites evaluated. In 72.5% of the cases the change was “agriculture to urban” and 21.3% was “forest to urban” change. These percentages of change are similar to the results of the change detection from the Landsat classifications of the entire area. Table 7 also reveals that residential uses comprise over half the cases that changed to urban. Relatively rare and

Table 7
Change types determined from random sampling of correctly classified change areas

Change type from Landsat classifications	No. of pixels	Specific change types	No.	Percent
Agriculture to urban	153	Agriculture to single family residential	86	40.8
		Agriculture to multifamily residential	9	4.3
		Agriculture to farmstead	6	2.8
		Agriculture to park and recreation	9	4.3
		Agriculture to public semi public	19	9.0
		Agriculture to road	2	0.9
		Agriculture to airport	1	0.5
		Agriculture to commercial	7	3.3
		Agriculture to industrial	14	6.6
Forest to urban	45	Forest to single family residential	30	14.2
		Forest to multifamily residential	3	1.4
		Forest to park	4	1.9
		Forest to commercial	3	1.4
		Forest to industrial	5	2.4
Wetland to urban	3	Wetland to single family residential	1	0.5
		Wetland to park	2	0.9
Other changes	9	Agriculture to forest, then to industrial	2	0.9
		Agriculture to forest, then to single family residential	2	0.9
		Forest to wetland, then to single-family residential	1	0.5
		Forest to agriculture, then to single-family residential	1	0.5
		Forest to agriculture, then to commercial	1	0.5
		Forest to agriculture	1	0.5
		Single family residential to commercial	1	0.5

The specific change types are from Metropolitan Council land use maps.

unlikely types of conversions, such as agriculture to forest, and then to urban uses and forest to agriculture, and then to urban, totaling 5%, are assumed to largely be classification errors.

4.3. Analysis of change patterns

Although similar statistics could be generated for other units such as county, township, or census tract, etc., the above change statistics shed little light on the question of where land use changes are occurring. However, by constructing a change detection map (Fig. 4), the advantages of satellite remote sensing in spatially disaggregating the change statistics can be more fully appreciated. Fig. 4 shows a map of the major land cover types and the conversion from rural to urban uses. Agriculture, urban, and forest, representing 85% of the total area, are the three major land cover types in the TCMA.

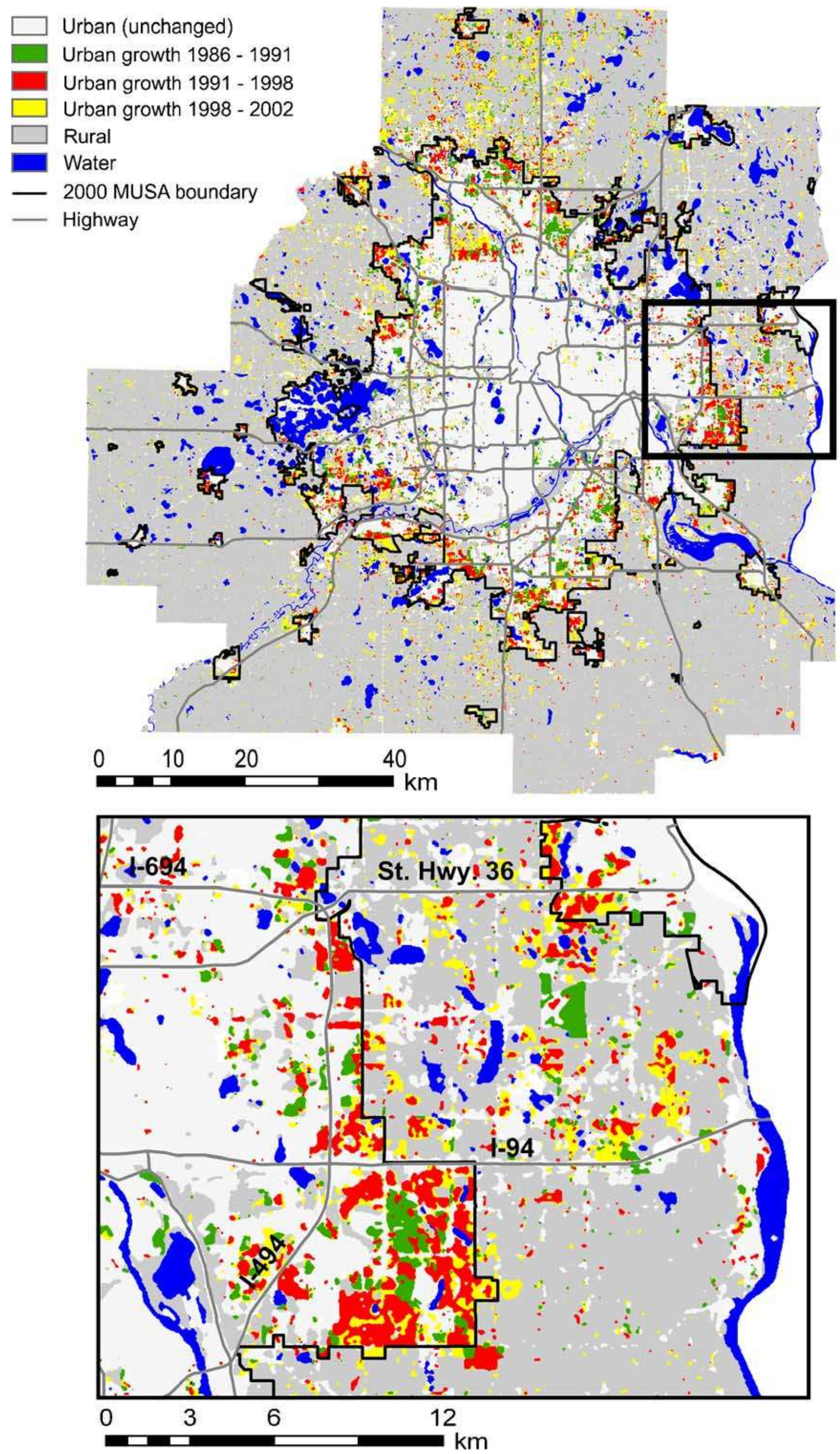

Fig. 4. Twin Cities Metropolitan Area urban growth from 1986 to 2002 with 2000 MUSA boundary. Rural land cover (agriculture, forest and wetland) that was converted to urban from 1986 to 1991, from 1991 to 1998, and from 1998 to 2002 are highlighted in green, red and yellow, respectively.

Conversions involving these three classes also represent the most significant changes. Urban growth and the loss of agricultural land are the most important conversions in this area. Although Fig. 4 only displays the changes from rural (agriculture, forest, or wetland) to urban, other changes can also be mapped.

The majority of the changes occurred within the second and third rings of suburbs surrounding Minneapolis and St. Paul. Clear patterns emerge that highlight the urbanization activity that has occurred east of St. Paul along the I-94 corridor (completed in the mid-1980s) that connects the metropolitan area to western Wisconsin. Growth also was concentrated in a strip along the southwestern perimeter following the Minnesota River and Highway 169, and in intermittent patches throughout the northwestern perimeter along I-94, U.S. Highway 10 and Highway 65. Further GIS analysis revealed a strong relationship between new development and proximity to highways. Almost half (47%) of the development detected in our classifications occurred within 2 km of highways, and 25% was between 2 and 4 km.

The 2000 Metropolitan Urban Service Area (MUSA) boundary in Fig. 4 delineates the outer reaches of the regional sewer services during the time period of our study. The boundary is determined through reviews of local comprehensive plans performed by the Metropolitan Council in collaboration with local governments (Kotz, 2000). Slightly more than half of the increase in developed area occurred inside of the MUSA, in accordance with the land use policies developed for the region. Regional policy also encourages development in centers along transportation corridors in order to protect natural areas and agricultural lands (Metropolitan Council, 1996).

The relationship between population growth and growth in urban land area as determined from the Landsat-derived change maps was also examined. Development patterns of the metropolitan area reflect the distribution of population and households because residential land uses take over half the land that is developed (Metropolitan Council, 1996). The average annual growth in urban area determined from the Landsat change detection was 1.9% from 1986 to 1991, 2.7% from 1991 to 1998, 1.6% from 1998 to 2002, and 2.4% for the entire period, 1986 to 2002. This compares to an annual population growth rate of approximately 1.5% from 1986 to 2002. Although the growth in urban area is greater than the population growth rate, it is less than in many metropolitan areas where urban area growth rates are more than two times the rate of population increase (Dept. Housing and Urban Development, 2000). In other words, there is relatively less urban "sprawl" in the TCMA as measured in terms of the ratio between population growth and growth in urban and developed areas, although it is important to note this is just one measure of sprawl (Hasse & Lathrop, 2003).

Population and urban expansion data were also tabulated at the county level (Table 8). All the counties with significant population growth also had increases in urban area. An "urban sprawl index" was calculated as the ratio of urban expansion to population increase. This index provides a way to assess the degree of sprawl for each county. Anoka County has the highest sprawl index of 0.21, which indicates that it has the sparsest development pattern. Scott County also has a high index, and a similar sprawl rate is expected in the future since this county has the largest amount of urban reserve land for further development. Hennepin County, a much more urbanized county than Anoka and Scott Counties, had a large absolute amount of urban expansion and the largest population growth from 1986 to 2002 with a sprawl index of 0.13, suggesting relatively condensed development patterns. Dakota and Washington also had considerable population growth, but with lower than average urban sprawl indexes, indicating more condensed development patterns. Ramsey, the most urbanized county of the TCMA, has the lowest index, suggesting that its growth is mainly in the form of increased development intensity in the built-up areas. On the other hand, Carver County, a largely rural county with the highest proportion of land reserved for agriculture, had the lowest population growth but a relatively high degree of sprawl.

Once the initial classifications have been performed additional information can be developed. For example, Ewijk (2002) derived landscape metrics from the classifications to investigate changes in diversity and fragmentation of the TCMA landscape. Mapping percent impervious surface area, an alternative way of monitoring urban growth, was performed using urban masks generated from the land cover classification maps (Bauer et al., 2004a,b). In addition, the classifications have been used as inputs to an environmental impact analysis project by the U.S. Environmental Protection Agency (2003) and in a land use transformation model to project future land use change in the TCMA (Pijanowsky et al., 2001). In summary, information

Table 8
Seven-county population (000) change and urban growth (000 ha) from 1986 to 2002

County	Total area	1986 Population	2002 Population	Population growth	1986 Urban area	2002 Urban area	Urban expansion	Urban sprawl index*
Anoka	115.4	225	308	84	21.4	38.8	17.4	0.21
Carver	97.1	44	75	31	7.4	12.7	5.3	0.17
Dakota	151.5	243	370	127	26.7	40.0	13.3	0.10
Hennepin	156.6	996	1131	135	67.3	84.3	17.0	0.13
Ramsey	43.9	475	515	40	30.5	32.0	1.5	0.04
Scott	95.2	52	100	48	9.6	18.7	9.1	0.19
Washington	109.2	133	211	78	19.6	26.4	6.8	0.09
TCMA total	768.5	2168	2709	541	182.6	252.8	70.2	0.13

* Urban Sprawl Index=Urban Expansion / Population Growth.

from satellite remote sensing can play a significant role in quantifying and understanding the nature of changes in land cover and where they are occurring. Such information is essential to planning for urban growth and development.

5. Conclusions

The results demonstrate that Landsat classifications can be used to produce accurate landscape change maps and statistics. General patterns and trends of land use change in the Twin Cities Metropolitan Area were evaluated by: (1) classifying the amount of land in the seven-county metropolitan area that was converted from agricultural, forest and wetland use to urban use during three periods from 1986 to 2002; (2) comparing the results of Landsat-derived statistics to estimates from other inventories; (3) quantitatively assessing the accuracy of change detection maps; and (4) analyzing the major urban land use change patterns in relation to policy, transportation and population growth. In addition to the generation of information tied to geographic coordinates (i.e., maps), statistics quantifying the magnitude of change, and "from–to" information can be readily derived from the classifications. The results quantify the land cover change patterns in the metropolitan area and demonstrate the potential of multitemporal Landsat data to provide an accurate, economical means to map and analyze changes in land cover over time that can be used as inputs to land management and policy decisions.

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References

Alberti, M., Weeks, R., & Coe, S. (2004). Urban land cover change analysis in Central Puget Sound. *Photogrammetric Engineering and Remote Sensing*, *70*(9), 1043–1052.

Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, W. E. (1976). A land use and land cover classification system for use with remote sensing data. *USGS professional paper 964* (pp. 138–145). Reston, Virginia: U.S. Geological Survey.

Bauer, M. E., Burk, T. E., Ek, A. R., Coppin, P. R., Lime, S. D., Walters, D. K., et al. (1994). Satellite inventory of Minnesota forests. *Photogrammetric Engineering and Remote Sensing*, *60*(3), 287–298.

Bauer, M. E., Heinert, N. J., Doyle, J. K., & Yuan, F. (2004). Impervious surface mapping and change monitoring using satellite remote sensing. *Proceedings, American society of photogrammetry and remote sensing annual conference. May 24–28, Denver, Colorado,* unpaginated CD ROM, 10 pp.

Bauer, M. E, Sersland, C. A., & Steinberg, S. J. (1996). Land cover classification of the Twin Cities metropolitan area with Landsat TM data. *Proceedings, Pecora 13 symposium. August 20–22, Sioux Falls, South Dakota* (pp. 138–145).

Bauer, M. E., Yuan, F., & Sawaya, K. E. (2004). Multi-temporal Landsat image classification and change analysis of land cover in the Twin Cities (Minnesota) metropolitan area. In P. C. Smits, & L. Bruzzone (Eds.), *Proceedings of the second international workshop on the analysis of multi-temporal remote sensing images* (pp. 368–375). Singapore: World Scientific Publishing Co.

Center for Energy and Environment. (1999). *Two roads diverge: analyzing growth scenarios for the Twin Cities region*. Minnesota: Minneapolis, 22 pp.

Congalton, R. G., & Green, K. (1999). *Assessing the accuracy of remotely sensed data: Principles and practices* (pp. 43–64). Boca Rotan, Florida: Lewis Publishers.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing*, *25*(9), 1565–1596.

Department of Housing and Urban Development. (2000). *The state of the cities*. Washington, D.C.: U.S. Department of Housing and Urban Development, 105 pp.

Elvidge, C. D., Sutton, P. C., Wagner, T. W., et al. (2004). Urbanization. In G. Gutman, A. Janetos, Justice C., et al., (Eds.), *Land change science: Observing, monitoring, and understanding trajectories of change on the earth's surface* (pp. 315–328). Dordrecht, Netherlands: Kluwer Academic Publishers.

Environmental Protection Agency. (2003). *The urban environment. Minneapolis–St. Paul indicators*. http://www.epa.gov/urban/msp/indicators.htm. (website last visited August 5, 2005).

Ewijk, K. (2002). Analysis of landscape changes in the Twin Cities metropolitan area from 1986 to 1998 using Landsat TM classifications and landscape metrics. *MGIS capstone paper*. Minneapolis, Minnesota: University of Minnesota, 150 pp.

Fuller, R. M., Smith, G. M., & Devereux, B. J. (2003). The characterization and measurement of land cover change through remote sensing: Problems in operational applications. *International Journal of Applied Earth Observation and Geoinformation*, *4*, 243–253.

Goetz, S. J., Varlyguin, D., Smith, A. J., Wright, R. K., Prince, S. D., Mazzacato, M. E., et al. (2004). Application of multitemporal Landsat data to map and monitor land cover and land use change in the Chesapeake Bay watershed. In P. C. Smits, & L. Bruzzone (Eds.), *Proceedings of the second international workshop on the analysis of multi-temporal remote sensing images* (pp. 223–232). Singapore: World Scientific Publishing Co.

Hasse, J. E., & Lathrop, R. G. (2003). Land resource impact indicators of urban sprawl. *Applied Geography*, *23*(2-3), 159–175.

Jensen, J. R. (2004). Digital change detection. *Introductory digital image processing: A remote sensing perspective* (pp. 467–494). New Jersey: Prentice-Hall.

Kotz, M. (2000). *MUSA boundary metadata*. St. Paul, Minnesota: Metropolitan Council.

Lillesand, T. M., Chipman, J. W., Nagel, D. E., Reese, H. M., Bobo, M. R., & Goldmann, R. A. (1998). Upper Midwest Gap Analysis Program Image Processing Protocol. U.S. Geological Survey, Environmental Management Technical Center, Onalaska, Wisconsin. EMTC 98-G001. 25 pp.+ Appendices.

Loeffelholz, B.C. (2004). Quantifying the effects of urbanization on oak forests. M.S. Thesis, University of Minnesota, St. Paul, Minnesota, 158 pp.

Lunetta, R. S., & Balogh, M. (1999). Application of multi-temporal Landsat 5 TM imagery for wetland identification. *Photogrammetric Engineering and Remote Sensing*, *65*, 1303–1310.

Metropolitan Council. (1996). *Regional blueprint forecast procedures, detailed methodology*. St. Paul, Minnesota: Metropolitan Council.

Oettera, D. R., Cohenb, W. B., Berterretchea, M., Maierspergera, T. K., & Kennedy, R. E. (2000). Land cover mapping in an agricultural setting using multiseasonal Thematic Mapper data. *Remote Sensing of Environment*, *76*, 139–155.

Özesmi, S. L. (2000). Satellite remote sensing of wetlands and a comparison of classification techniques. Ph.D. Thesis, University of Minnesota, St. Paul, Minnesota, 220 pp.

Pijanowsky, B. C., Shellito, B. A., Bauer, M. E., & Sawaya, K. E. (2001). Using GIS, artificial neural networks and remote sensing to model urban change in the Minneapolis–St. Paul and Detroit Metropolitan areas. *Proceedings, American Society of Photogrammetry and Remote Sensing annual conference, April 23–27, 2001, St. Louis, Missouri*, 13 pp.

Ridd, M. K., & Liu, J. (1998). A comparison of four algorithms for change detection in an urban environment. *Remote Sensing of Environment*, *63*, 95–100.

Schrank, D., & Lomax, T. (2004). The 2004 urban mobility report. *Texas transportation institute, Texas A & M University*. Texas: College Station, 27 pp.

Shaw, S. P., & Fredine, C. G. (1956). Wetlands of the United States – their extent and their value to waterfowl and other wildlife. *U.S. Department of the Interior, Washington, D.C. Circular 39,* 67 pp.

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

Squires, G. D. (2002). Urban Sprawl and the Uneven Development of Metropolitan America. In Gregory D. Squires (Ed.), *Urban sprawl: Causes, consequences, and policy responses* (pp. 1–22). Washington, D.C.: Urban Institute Press.

Wolter, P. T., Mladenoff, D. J., Host, G. E., G. E., & T.R. (1995). Improved forest classification in the Northern Lake States using multi-temporal Landsat imagery. *Photogrammetric Engineering and Remote Sensing*, *61*, 1129–1143.

Yang, X. (2002). Satellite monitoring of urban spatial growth in the Atlanta metropolitan area. *Photogrammetric Engineering and Remote Sensing*, *68*(7), 725–734.

Yuan, F., Bauer, M. E., Heinert, N. J., & Holden, G. (2005). Multi-level land cover mapping of the Twin Cities (Minnesota) metropolitan area with multi-seasonal Landsat TM/ETM+data. *Geocarto International*, *20*(2), 5–14.

Yuan, D., Elvidge, C. D., & Lunetta, R. S. (1998). Survey of multispectral methods for land cover change analysis. *Remote sensing change detection: Environmental monitoring methods and applications* (pp. 21–39). Michigan: Ann Arbor Press.