Comparison of Spectral Analysis Techniques for Impervious Surface Estimation Using Landsat Imagery

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Abstract
Various methodologies have been used to estimate and map percent impervious surface area (%ISA) using moderate resolution remote sensing imagery (e.g., Landsat Thematic Mapper). There is, however, a lack of comparative analyses among these methods. This study compares three major spectral analysis techniques (regression modeling, regression tree, and normalized spectral mixture analysis (NSMA)) for continuous %ISA estimation using Landsat imagery for 1986 and 2002 for the seven-county Twin Cities Metropolitan Area of Minnesota. Our study showed that all three techniques demonstrate the capability for estimating %ISA accurately, with RMSE ranging from 7.3 percent to 11 percent and $R^2$ of 0.90 to 0.96 for both years. Comparatively, regression modeling and regression tree methods produced similar results; however, both of them are highly dependent on accurate masks to differentiate urban impervious surfaces from bare soil. Within the urban mask, the regression tree-based estimates were the most accurate. In terms of time and cost, the NSMA approach is most efficient, but it tends to underestimate the percent imperviousness for highly developed areas. Findings from the study provide guidance for the selection of %ISA estimation techniques using moderate resolution remote sensing data, along with information for further methodological improvements.

Introduction
Impervious surfaces represent those materials that do not absorb water or moisture, and most urban infrastructures, such as rooftops, streets, highways, parking lots, and sidewalks, are impervious. Accurate measurement of impervious surface area (ISA) provides an essential indicator of environmental quality and valuable inputs to urban and environmental planning and management (Schueler, 1994; USEPA, 2003). Urban imperviousness has been utilized to quantify urban development and land-use intensity (Lu and Weng, 2004; Rashed et al., 2001; Rashed et al., 2005; Xian and Crane, 2005; Yang et al., 2003b), as well as to assess adverse impacts of urbanization on water and terrestrial ecosystems (Civco et al., 2002; Gillies et al., 2003; Schueler, 1994; Weng, 2001; Yuan and Bauer, 2007).

Traditional ground surveys and aerial photographic interpretation and digitizing are the most accurate methods for impervious mapping, but these methods are time consuming and labor intensive. Automatic extraction of impervious surface information, therefore, has been a focus of recent studies. Moderate resolution satellite remote sensing images, with a synoptic view of relatively large areas, multiple spectral bands, and repetitive coverage, have been utilized as major data sources for impervious surface information extraction (Bauer et al., 2004 and 2007; Lu and Weng, 2004; Wu, 2004; Wu and Murray, 2003; Yang et al., 2003a). However, moderate resolution remote sensing images, such as Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data with a spatial resolution of 30 meters have issues associated with mixed pixels as most urban features have a dimension smaller than 30 meters (Small, 2003). Because traditional hard classifications of mixed pixels in moderate resolution imagery usually lead to information loss, decreased accuracy, and degradation of modeling results (Foody and Cox, 1994), various methodologies have been developed to address the mixed pixel issue and quantify impervious surfaces at the subpixel level as percent impervious area (%ISA) (Bauer et al., 2004 and 2007; Civco and Hurd, 1997; Civco et al., 2006; Chabaeva et al., 2004; Dougherty et al., 2004; Flanagan and Civco, 2001; Lee and Lathrop, 2006; Liu and Wu, 2005; Lu and Weng, 2004; Phinn et al., 2002; Wu, 2004; Wu and Murray, 2003; Wu and Yuan, 2007; Yang et al., 2003a; Yuan et al., 2005a).

The major subpixel level approaches to estimate and map %ISA include: spectral mixture analysis (SMA), regression modeling, regression tree, artificial neural networks (ANN), expert systems, and subpixel classification. In particular, spectral mixture analysis (SMA) estimates %ISA by analyzing the fractions of vegetation-impervious-soil (V-I-S) end-members (pure land covers) in a mixed spectrum (Adams et al., 1995; Lu and Weng, 2004; Wu, 2004; Wu and Murray, 2003). Regression modeling and estimation of %ISA has several variants. For example, per-pixel %ISA maps generated by regressing the greenness index generated from a tasseled...
cap (TC) transformation (Bauer et al., 2004 and 2007; Yuan et al., 2005a) or the normalized difference vegetation index (Ridd, 1995; Sawaya et al., 2003). Coupled with interpolated population density and NLCD data, another linear regression model proposed by Chabaeva et al. (2004) successfully classified percent imperviousness for each census tract in Connecticut. The more sophisticated regression tree approach quantifies impervious surface fraction using a hierarchical decision scheme. Specifically, it recursively partitions an image into smaller subdivisions in a binary fashion until the final subdivisions can no longer be partitioned or user-defined criteria are satisfied (Dougherty et al., 2004; Yang et al., 2003a; Xu et al., 2005). The regression tree has been found to be more robust than regression modeling due to its capability of approximating complex non-linear relationships using a set of linear equations (Huang et al., 2001). Artificial neural networks (ANN) techniques are also increasingly used for mapping %ISA (Civco et al., 1997; Flanagan and Civco, 2001; Foody, 2002; Lee and Lathrop, 2006; Liu et al., 2000; Liu and Wu, 2005). ANN are computational systems inspired by the structure, processing method, and learning ability of a biological brain which are frequently applied in situations where good analytic models are either unknown or extremely complex (Cybenko, 1996). Expert systems that apply expert knowledge for land cover classification have been utilized to quantify %ISA by Moller-Jensen (1990) and Stefanov et al. (2001). Subpixel classifiers, as exemplified by ERSAS Imagine®, which uses an intelligent background estimation process to calculate the amount of impervious surfaces of four to eight discrete classes at 10 to 20 percent ISA intervals, have been investigated by Ji and Jensen (1999) and Civco et al. (2002).

Among the diverse methods, regression modeling, regression tree, and SMA models are conceptually and computationally simpler, and therefore have been widely used to map per-pixel %ISA (0 to 100 percent) in moderate resolution imagery, typically Landsat data. (Dougherty et al., 2004; Bauer et al. 2004, 2007; Lu and Weng, 2004; Lu and Weng, 2006; Rashed et al., 2003; Wu, 2004; Wu and Murray, 2003; Xu et al., 2005; Yang et al., 2003a; Yang et al., 2003b; Yuan et al. 2005a). In particular, the regression modeling method developed by Bauer et al. (2004 and 2007) has been used to map %ISA for the entire state of Florida, covered by 41 Landsat TM/ETM+ images, for 1990 and 2000. They reported that the statistics for all of the images for both the 1990 and 2000 classifications were consistent with R² coefficient values ranging from 0.80 to 0.94 for measured versus Landsat estimates of %ISA and root mean squared errors (RMSE) of 7.7 to 15.9 percent. The seasonal sensitivity of this approach was examined by Wu and Yuan (2007) using Landsat TM/ETM+ images for four different seasons in Franklin County, Ohio. They found that although the best performance was achieved in the summer season, no significant seasonal variations were identified for the resulting impervious estimates, with all of the seasons having an RMSE of approximately 11 to 12 percent. The second technique, regression tree modeling proposed by Yang et al. (2003a), was adopted by the U.S. Geological Survey (USGS) for characterizing %ISA at both the national and local land cover data (NLCD) (Homer et al., 2007). Yang et al. (2003a) reported the average error of predicted versus actual %ISA ranged from 8.8 to 11.4 percent, with R² from 0.82 to 0.91. The third technique, spectral mixture analysis, has been utilized frequently in urban impervious mapping after Ridd (1995) established the fundamental applicability of the V-S model for deriving biophysical information from remotely sensed data. For example, Rashed et al. (2003) developed a multiple end-member spectral mixture model (MESMA) to quantify impervious surfaces for Los Angeles County. He obtained an average 8.2 percent absolute difference between estimates of MESMA and aerial photo-derived estimates. Wu (2004) examined a normalized spectral mixture method (NSMA) for the metropolitan region of Columbus, Ohio and obtained an overall RMSE of 10.1 percent. Lu and Weng (2006) integrated a linear SMA method with surface temperature information for %ISA mapping with a RMSE of 9.22 percent for their study area: Indianapolis, Indiana.

However, so far, no comparison of these three widely used spectral analytical techniques for continuous %ISA estimation using medium resolution imagery has been conducted. Consequently, answers for questions, such as: Which approach provides higher classification accuracy?, What factors influence the model performances?, and What are the costs (e.g., time, labor, etc.) of image processing? are still unclear. This study evaluates and compares three major approaches, regression modeling, regression tree, and normalized SMA, of %ISA estimation using Landsat-5 TM images. Results from this study may provide information for further methodological improvement and guidance for the selection of %ISA estimation techniques.

Methods

Study Area

The study area (Figure 1) covers the seven-county Twin Cities Metropolitan Area (TCMA) of Minnesota, an area of approximately 7,700 km². With a population of 2.28 and 2.64 million in 1990 and 2000, it includes a diversity of land-cover classes with urban development characterizing the central portion, and rural land covers of agricultural cropland, grasslands, wetlands, and forests dominating the surrounding area. A previous study (Yuan et al., 2005b) found that from 1986 to 2002, the amount of urban land-cover, defined as urban developed areas that have per-pixel imperviousness of 1 to 100 percent, increased from 23.7 to 32.8 percent of the total area, while rural cover types decreased from 69.6 to 60.5 percent.

Landsat Data and Preprocessing

Two cloud-free Landsat-5 TM images acquired on 21 August 1986 and 16 July 2002 were used to estimate %ISA for the study area. The seven-county TCMA is entirely within two consecutive Landsat scenes (path 27, rows 28 and 29). All images were rectified to UTM Zone 15, GRS1980, NAD83 using at least 35 well-distributed ground control points and nearest neighbor resampling. The geometric errors were less than 7.5 meters for both images. Normalized, topo-atmospheric reflectance was calculated from the original digital numbers (DNs) of the Landsat-5 TM images based on the conversion formula provided by Chander and Markham (2003).

Reference Data

Two-meter black and white 1986 National High Altitude Photography (NHAP) imagery and 1 m color 2003 National Agriculture Imagery Program (NAIP) digital orthoimagery were utilized for model calibration and accuracy assessment of impervious surface classifications. Samples representing the range of vegetation types (e.g., grass and trees) and impervious types (e.g., streets, parking lots and rooftops) and levels from 0 to 100 percent were selected from the high-resolution aerial imagery. The percent imperviousness for each sample was determined by digitizing the impervious area in the images. The mean sample size was about 30 pixels per AOI to incorporate the desired mix of impervious surface and vegetation cover types.

Part of the samples for both years came from the previous study conducted by Bauer et al. (2004) in which the areas of
interest (AOI) samples with varying kinds and amounts of impervious areas were selected and digitized. Bauer et al. (2004) had 40 training and 20 test samples for 1986 and 62 training and 26 test samples for 2002. To better evaluate the accuracy of each of the classification approaches, we added 90 more test samples for each year and combined them with samples from the previous study.

Regression Modeling
The essence of the regression approach to %ISA estimation used by Bauer et al. (2004 and 2007) is to develop a regression model that relates %ISA to Landsat TM tasseled cap greenness for a set of training areas. Greenness is the second component of the orthogonal tasseled cap transformation of the reflective bands of the TM data (Crist and Cicone, 1984; Crist and Kauth, 1986). In urbanized areas where the amount of bare soil is limited, greenness is strongly related to the amount of green vegetation and inversely related to the amount of impervious area (Bauer et al., 2004 and 2007). In general, the major steps of this method are: (a) classification of the imagery into general land covers of urban and non-urban (cropland, forest, wetland, and water) classes, (b) development of a regression model relating percent impervious to Landsat TM tasseled cap greenness for the training sites, (c) applying the model to estimate %ISA of all pixels in the tasseled cap greenness image, (d) conducting an inverse calibration in which the errors of the estimation determined from test samples are used to adjust for biases in the initial impervious estimation, (e) generating the final %ISA image by incorporating an urban mask derived from the independent land-cover classification of Step (a), and (f) accuracy assessment by comparison to independent test samples.

Figure 1. The seven-county Twin Cities Metropolitan Area of Minnesota, U.S.A. and Landsat TM, 16 July 2002 composite image of bands 4, 3, and 2 (in gray scale).
For model training and calibration, a second order polynomial equation (Equation 1) was utilized:

\[ I = a_1 + a_2 G + a_3 G^2 \]  

(1)

where \( I \) is the impervious surface fraction of a pixel (from 0 to 1), \( G \) is the tasseled cap greenness for that pixel, and \( a_1, a_2, a_3 \) are regression coefficients. The values for percent impervious and mean greenness for each training AOI were calculated and the regression equation was computed for both years. Based on the regression equations, models were developed in ERDAS Imagine® Spatial Modeler to convert the greenness images to %ISA images. Next, a post-classification correction technique, called inverse calibration (Walsh and Burk, 1993), was applied to the initial %ISA estimate based on the classification of the test samples to reduce bias in the impervious surface estimation. More specifically, similar to the method used to produce the initial ISA estimate from the greenness image, a linear equation was determined by regressing samples from the initial impervious estimation (dependent variable) against an independent set of high resolution image measurements (independent variable). Equation 2 was then inverted to Equation 3 and applied to the initial %ISA estimate in ERDAS Imagine® Spatial Modeler:

\[ I_{\text{imp}} = a I_{\text{DOY}} + b \]  

(2)

\[ I_{\text{imp}} = \frac{I_{\text{imp}} - b}{a} \]  

(3)

where \( I_{\text{imp}} \) is the percent impervious surface estimate from Landsat greenness images, \( I_{\text{DOY}} \) is the digital imagery-measured %ISA, \( I_{\text{im}} \) is the percent impervious surface estimate after the inverse calibration, and \( a, b \) are the regression coefficients. The inverse calibration improves the regression results by reducing the biases of underestimating the values for pixels of high percent imperviousness and overestimating the values of low percent imperviousness. Finally, an urban mask from an independent land-cover classification was applied to remove the classes of agriculture, bare fields, forest, wetland, and water. The urban masks for both years were generated based on the general land-cover classification maps from another study Yuan et al. (2005b). In that study, urban was defined as developed area with percent impervious surface ranges from 1 percent to 100 percent. Landsat TM/ETM+ data acquired from both spring and summer seasons for each year was used for the land-cover classifications. A hybrid supervised-unsupervised training approach referred to as “guided clustering” along with the maximum likelihood classifier was utilized. The mean overall accuracy for the seven land cover classes was 94 percent.

Regression Tree Modeling
Regression tree modeling is another popular method for generating %ISA information in an urban area. Like regression analysis, a regression tree constructs the relationships between a dependent variable (e.g., %ISA) and predictive variables (e.g., spectral reflectances). The regression tree model is more complicated than regression analysis, but has the advantages of examining and accounting for non-linear relationships between the dependent variable and predictive variables. In particular, it grows a categorical and binary tree by repeatedly splitting the data into two subsets according to specific rules, depending on how the dependent variable and the independent variables interact. The goal of the algorithm is to categorize the data into more homogeneous subsets by uncovering the predictive structure of the problem under consideration (Breiman et al., 1984). For each subset, a multivariate linear regression model is constructed, and the splitting rules are specified such that the combined regression model residual error of each subset is substantially lower than that of the single best model before partition (Huang and Townshend, 2003). Yang et al. (2003a and 2003b) have applied the regression tree model approach to Landsat ETM+ images to quantify impervious surface fraction, and the USGS has adopted this model for generating moderate resolution (30 m) impervious surface information as part of the National Land Cover Data (NLCD) classifications (Homer et al., 2007). Therefore, it is useful to compare this method to other commonly applied methods.

For this study, a regression tree program, Cubist, developed by Quinlan (1993), was used. The six tasseled cap components were utilized as independent variables for estimating %ISA. The first three components (TC1, TC2, and TC3) referred to as brightness, greenness, and wetness have clear physical meanings. The other three components (TC4, TC5, and TC6), though lacking exact interpretations, may also be helpful in establishing splitting rules. Moreover, the selections of these independent variables are consistent with the method utilized by the researchers in the USGS (Yang et al., 2003a) for producing the 30 m NLCD. For regression tree model development and assessment, the same training and test samples as used in regression modeling were utilized. With these training and test samples, regression tree models were developed for the 1986 and 2002 data using the Cubist program. To be consistent with the regression modeling approach, the inverse calibration procedure was used to adjust the initial estimates for biases and the same urban mask was used to mask rural areas.

Normalized Spectral Mixture Analysis
The normalized spectral mixture analysis (NSMA) model was originally developed by Wu (2004) and successfully applied by Yuan and Bauer (2007) and Wu and Yuan (2007) in different studies. The NSMA estimates the percent impervious surfaces by modeling a mixed spectrum as a linear combination of three end-members, vegetation-impervious surface-soil, rather than the typical four end-members of vegetation-soil-high albedo-low albedo (Wu, 2004; Wu and Murray, 2003). According to Wu (2004), the normalization process of NSMA reduces the within-class radiometric variations, and therefore facilitates separating the land-cover types. By masking out water from the imagery, the three end-member NSMA can produce %ISA estimates with higher accuracy than the typical four-end-member models. Further detailed information about the NSMA can be found in Wu (2004).

Two key steps are included in NSMA. First, the original TM data are normalized using the following equation to reduce within-class radiometric variations while maintaining necessary information to separate major end-members (Wu, 2004):

\[ \overline{R}_b = \frac{R_b}{m} \times 100 \]  

(4)

where \( m = \frac{1}{n} \sum_{b=1}^{n} R_b \) and \( \overline{R}_b \) is the normalized reflectance for band \( b \) in a pixel, \( R_b \) is the original reflectance for band \( b \), \( m \) is the average reflectance for that pixel, and \( n \) is the total number of bands.

Second, a linear spectral mixture analysis (LSMA) is applied to calculate the fractions of the three end-members within the normalized spectra. The LSMA describes the surface composition in each pixel of an image using end-members, and assumes a linear combination of these end-members (Equation 5). Clusters of each of the end-members were identified by visual interpretation of the Landsat images and the feature space images of a principal component transformation. The fraction of V-I-S end-members in
a pixel was derived with a least squares method in which the residual $e_b$ is minimized:

$$\bar{R}_b = \sum_{i=1}^{n} f_i R_{i,b} + e_b$$  \hspace{1cm} (5)$$

where $\sum f_i = 1$ and $f_i \geq 0$, $\bar{R}_b$ is the normalized reflectance for band $b$ obtained from Equation 4, $R_{i,b}$ is the normalized reflectance of endmember $i$ in band $b$, $f_i$ is the fraction of endmember $i$, $n'$ is the number of endmembers, and $e_b$ is the residual. Spectral mixture analysis is more time and cost efficient by saving the time for digitizing the training samples of various percent imperviousness that are required by the regression-based methods.

The NSMA was applied to the whole image. It is not necessary to mask out urban from rural for this method since spectral mixture analysis can differentiate soil from impervious surface directly. Nevertheless, to facilitate comparison to the results from the other two methods, the inverse calibration and urban mask were still applied at the completion of the NSMA.

Results

Scatter plots of tasseled cap greenness versus $\%ISA$ of the training samples for both years are plotted in Figure 2. Two parameters, $R^2$ and root mean square error (RMSE), were utilized to evaluate the strength of the relationship of greenness to ISA and quantify the goodness of fit of the regression models. High $R^2 (>0.90)$ and low RMSE (<12%) values were obtained for both years.

The rule definitions and model formulations of the regression tree models for 1986 and 2002 are listed in Table 1. Like regression analysis, the regression tree models also illustrate a high degree of goodness-of-fit for the training samples of 1986 ($R^2 = 0.94$, and RMSE = 9.1 percent) and 2002 ($R^2 = 0.93$, and RMSE = 9.3 percent). Table 1 also shows that tasseled cap greenness (TC2) is the most important variable for $\%ISA$ estimation. To find out if other components, especially TC4 to TC6, contribute to the regression models or not, we did a comparison analysis for 2002 data without utilizing TC4 to TC6. We found out that the RMSE increased from 7.3 percent to 11.1 percent with the $R^2$ decreased from 0.96 to 0.83. Moreover, an analysis of variance (ANOVA) further confirmed that the regression tree model with six TC components is significantly better than that with only the first three components. These tests indicated that although lacking clear physical meanings, the last three TC components play certain roles in regression tree analysis of $\%ISA$. For the 1986 TM image, TC2 and TC4 served as the variables for splitting the image into four different groups; and for each group, an independent regression analysis was performed. Comparatively, the regression tree model for the 2002 image was degraded to
a simple regression model, indicating a linear relationship between %ISA and multiple tasseled cap components. In addition, we can see from Table 1 that there is a consistently inverse relationship between %ISA and TC2 (greenness) for both years; however, other TC components show different directions of associations to the %ISA for 1986 and 2002.

On the other hand, %ISA training samples are not needed for the NSMA method. But the three V-I-S end-members were located and digitized on the normalized TM images for both years. The normalization process of NSMA reduced spectral variation within each land cover type while maintaining useful information for separating vegetation, impervious surface, and soil. For example, Figure 3 shows the mean normalized spectra of the selected three end-members for both years. From Figure 3, we can see that the three end-members exhibit disparate spectral signatures, based on which the fraction maps of V-I-S can be generated effectively by a spectral unmixing analysis.

The linear inverse calibration models that were applied to the initial estimations are shown in Table 2. For regression modeling, the inverse calibration increased the regression $R^2$ by 2 to 4 percent and decreased the RMSE by 1 to 2 percent. No obvious improvements were achieved by the inverse calibration process for regression tree and NSMA approaches.

Through comparison of the %ISA results before and after applying urban masks, we found that the regression modeling and regression tree approaches are much more sensitive to bare soil in rural areas than the NSMA method. In other words, for the two regression-based methods, highly accurate urban masks are critical for their success. On the other hand, NSMA un-mixes the spectrum of a pixel as a linear combination of V-I-S components. Therefore, the problems associated with soils can be addressed efficiently. The %ISA maps generated after applying urban masks for the three methods for both years are displayed in Figure 4.

To better visualize and compare the results, more detailed subsets of the 2002 %ISA classifications for the three methods are shown in Figure 5 for Woodbury and Minneapolis. Woodbury is a fast growing suburb of St. Paul over the past two decades. Single family residential land use dominates this area with some wetland, water, forest, and agricultural land. Minneapolis, the largest city in Minnesota, is dominated by high density commercial, industrial, and institutional land uses in its center; this high density area is surrounded by medium and high density residential areas intersected by a dense network of streets. By examining Figure 5, we can see that the %ISA maps for all three methods have similar general patterns. However, the regression tree approach has slightly higher %ISA estimates for residential areas while the NSMA shows slightly lower values for the highest density regions.

To assess the results quantitatively, the estimated %ISA values were compared to independent test samples representing varying percentages of impervious surfaces that were derived from the aerial imagery measurements. $R^2$ and RMSE were used again to quantify the accuracy of impervious surface estimation. For rural areas (agriculture, forest, wetland,) where the percent imperviousness was 0, regression-based per-pixel %ISA estimates can have overestimates due to confusion between bare soil and impervious surfaces. However, most of these were resolved by applying the urban masks created from general land use land cover classifications.

We found the accuracy of all %ISA maps increased after applying urban masks. The regression tree based estimates have the largest accuracy improvements. Its RMSE decreased 6.8 and 5.1 percent for 1986 and 2002, respectively, which was followed by 1.2 and 3.6 percent decreases for the regression modeling method. Small RMSE decreases of 1.2 percent and 0.7 percent were obtained for the NSMA. For both years, the regression tree based estimates have the lowest accuracy before applying the urban mask, but the opposite is true after applying the urban mask, with $R^2$ = 0.94 and RMSE = 7.9 percent for 1986, and $R^2$ = 0.96 and RMSE = 7.3 percent for 2002.

### Table 2. Linear Inverse Calibration Models After the Initial Estimation by Regression, Tree, and Regression NSMA Methods

<table>
<thead>
<tr>
<th>Year</th>
<th>Regression</th>
<th>Regression Tree</th>
<th>NSMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986</td>
<td>$I' = (I - 8.5152)/0.7783$</td>
<td>$I' = (I - 3.7255)/0.9265$</td>
<td>$I' = (I - 1.2749)/0.9078$</td>
</tr>
<tr>
<td>2002</td>
<td>$I' = (I - 11.997)/0.7478$</td>
<td>$I' = (I - 2.5861)/0.957$</td>
<td>$I' = (I - 2.3552)/0.8969$</td>
</tr>
</tbody>
</table>

Figure 3. Mean normalized spectra of the three V-I-S end-members: (a) 21 August 1986, and (b) 16 July 2002.
The agreements between the TM-estimated %ISA within the urban mask and the measurements from the aerial imagery are shown in Figure 6. In general, strong agreements were obtained for both dates for all three methods. By comparing the regression line to the 1:1 line ($y = x$) in Figure 6, we can see that the regression-based methods demonstrate slightly better performance while the NSMA-based results show a higher degree of underestimation for high density urban areas. Moreover, the NSMA method seems to underestimate %ISA proportions more in 1986 than in 2002. This may be attributed to the fact that the 1986 TM image was acquired in late summer (21 August) while the 2002 image was obtained in mid summer (16 July). There is more bare soil which has similar spectral response as impervious surfaces in the 1986 imagery. As a result, more of the impervious fraction was misclassified as soil fraction.
in the 1986 image for the NSMA method. The purity of selected end-members may also affect the results because the V-I-S model is constrained by the assumption that an exhaustive set of end-members has been defined at each pixel, which may not hold true in practice, since the pure end-members only exist as a conceptual convenience in real images because of sensor noise and within-class signature variability (Schowengerdt, 2007).

For a further comparison, the mean percent impervious area for the TCMA and each of the seven counties was tabulated for both years (Table 3). All estimation methods indicate a clear trend: percent imperviousness of the TCMA during the 16-year span increased significantly with an absolute increase of more than 4 percent and relative increases of 43 to 66 percent, depending on the method of classification. It is also evident that among the three methods, the results from
the two regression-based approaches are more comparable whereas the NSMA estimations are comparatively lower than the regression based models for all the counties in both years. By comparing the regression lines to the $y=x$ line in Figures 6e and 6f, we make the conclusion that the NSMA tends to underestimate overall imperviousness in TCMA compared to the other two methods.

### Conclusions

This study compared three common techniques of percent impervious surface estimation, regression modeling, regression tree, and normalized spectral mixture analysis, using moderate resolution Landsat-5 TM images. We found that all methods have the capability for accurately estimating %ISA, with the RMSE ranging from 7.3 to 11 percent and $R^2$ values of 0.90 to

### Table 3. Mean Percent Imperviousness Estimated by Regression, Regression Tree, and NSMA for the Seven-County TCMA for 1986 and 2002

<table>
<thead>
<tr>
<th>County</th>
<th>1986 %ISA</th>
<th>2002 %ISA</th>
<th>%ISA Change (2002 to 1986)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Regr. Tree</td>
<td>NSMA</td>
<td>Regr. Tree</td>
</tr>
<tr>
<td>Anoka</td>
<td>6.8</td>
<td>6.8</td>
<td>4.6</td>
</tr>
<tr>
<td>Carver</td>
<td>2.2</td>
<td>2.1</td>
<td>1.2</td>
</tr>
<tr>
<td>Dakota</td>
<td>6.6</td>
<td>6.6</td>
<td>4.7</td>
</tr>
<tr>
<td>Hennepin</td>
<td>17.5</td>
<td>18.8</td>
<td>15.2</td>
</tr>
<tr>
<td>Ramsey</td>
<td>29.5</td>
<td>30.9</td>
<td>26.9</td>
</tr>
<tr>
<td>Scott</td>
<td>3.4</td>
<td>3.1</td>
<td>1.8</td>
</tr>
<tr>
<td>Washington</td>
<td>5.2</td>
<td>4.6</td>
<td>3.4</td>
</tr>
<tr>
<td>TCMA total</td>
<td>9.0</td>
<td>9.2</td>
<td>7.1</td>
</tr>
</tbody>
</table>
0.96 for the two years. Comparatively, the regression modeling and the regression tree methods produced similar results. For both methods, a well-defined urban mask must be applied to differentiate urban developed areas (1 to 100 percent ISA) from pure undeveloped rural pixels (0 percent ISA). Within the urban mask, the regression tree based estimates were the most accurate due to its capability of approximating more complex spectral-impervious relationships using a set of linear equations. Nevertheless, results of the mask-based techniques will suffer when the urban-rural boundary is not clear and hard to delineate. On the other hand, the NSMA generates fraction maps for the three end-members of V-I-S directly by a spectral unmixing analysis. Considering time and labor, the NSMA is much easier to implement since, except for pure end-members, %ISA training samples do not have to be located and digitized. By comparing its estimates to the high resolution validation data, we found the NSMA method tends to underestimate the percent imperviousness for highly developed (%ISA > 50 percent) areas by misclassifying more impervious portion as soil fraction.

Due to the way they are constructed, all three methods may be more or less affected by seasonal or phenological variations within the Landsat images. While Wu and Yuan (2007) found the best performance was achieved with a summer image for both regression modeling and NSMA methods, further research investigating the sensitivity within different stages of the summer season will be helpful. In addition, all previous studies that have successfully utilized the “greenness-based” regression modeling approach are concentrated in the Upper Midwest region of the United States (Bauer et al., 2004 and 2007; Yuan et al., 2005a; Wu and Yuan, 2007). Future research should examine whether this method is applicable for semi-arid and arid areas. In summary, the efficacy and overall accuracy of %ISA estimation is determined by the combined effects of sensor noise, within-class signature variability, spectral similarity of pervious and impervious land uses, building and tree shadows, seasonal variation, and type, size, and spatial distribution of impervious surfaces as well as knowledge and experience of the analyst for sample/end-member selection, model development, and assessment. Although we could not explore all the factors and compare all available techniques in one paper, this study clarifies the differences in %ISA classification approaches.

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