Seasonal Sensitivity Analysis of Impervious Surface Estimation with Satellite Imagery

Changshan Wu and Fei Yuan

Abstract
Numerous approaches have been developed to quantify the distribution of impervious surfaces using remote sensing technologies. Most of these approaches have been applied to data from a single time period, typically in the summer season (June to September). Presently, it is not clear whether there is an optimal time for impervious surface estimation with these methods. In this paper, the seasonal sensitivity of impervious surface estimation is examined. In particular, Landsat TM/ETM+ imagery for four different seasons has been acquired for the environs of Franklin County, Ohio. Two impervious surface estimation methods, spectral mixture analysis and regression modeling, are used to test for seasonal variations. Results indicate that the summer image provides better accuracy with the spectral mixture analysis method, while consistent accuracies are obtained for all four seasons with regression modeling.

Introduction
Impervious surface refers to any material that water cannot infiltrate. Typical impervious surfaces include building rooftops, streets, highways, parking lots, and sidewalks, all of which are major components of urban infrastructure. Therefore, impervious surfaces have been found to reveal essential information about built-up areas, and can be utilized to quantify urban development and land-use intensity. Ridd (1995) proposed the vegetation-impervious surface-soil (V-I-S) model to parameterize the biophysical composition of urban environments, and illustrated the relationship between impervious surface distribution and urban land-use types. Applying the V-I-S model, Rashed et al. (2001) and Lu and Weng (2004) quantified the extent of urban and suburban development and indicated that urban land-use classification accuracy can be significantly improved with impervious surface information. Yang et al. (2003b), Rashed et al. (2005), and Xian and Crane (2005) analyzed urban growth rates and patterns, and suggested that impervious surface information serves as a better alternative than traditional measurements of urban growth. Besides quantifying urban extent and land-use, imperviousness has been utilized to assess adverse influences of urbanization on water quality, urban climate, air quality, and natural habitat (Dougherty et al., 2004; Schueler, 1994; Weng et al., 2004), and it has been listed as a key indicator for the health of water and terrestrial ecosystems by U.S. Environmental Protection Agency (USEPA, 2003).

In addition to its role in evaluating the effects of urbanization on natural environments, impervious surface information also serves as an important factor in urban socio-economic studies. With the help of impervious surface information, Wu and Murray (2005) estimated detailed population distribution in Columbus, Ohio; Yu and Wu (2004) incorporated impervious surface fraction in understanding population segregation patterns in Milwaukee, Wisconsin. Alse, Yu and Wu (2006) evaluated the influences of impervious surface distribution on housing prices in Milwaukee, Wisconsin. Because of the influential role that impervious surface plays, the generation of impervious surface data has become an emerging area of interest to both scientists and decision makers.

Traditionally, impervious surface areas have been quantified based on photographic or survey methods, in which impervious surfaces are digitized manually from high-resolution air photographs or survey maps. Although relatively accurate, these methods are labor intensive and time consuming. Consequently, various techniques have been developed in recent years for the automatic estimation of impervious surface fraction from medium-resolution remote sensing imagery such as Landsat Thematic Mapper (TM) and SPOT satellite data. In summary, major methods include spectral mixture analysis (SMA), regression modeling, regression trees, artificial neural networks (ANN), and subpixel classification. Spectral mixture analysis involves modeling a mixed spectrum as a combination of spectra for pure land-cover types, also called endmembers, such as vegetation, impervious surface, and soil. Applying the spectral mixture analysis method, Phinn et al. (2002) estimated impervious surface distribution with endmembers chosen from aerial photos. Wu and Murray (2003) implemented a constrained linear SMA to generate an impervious surface distribution for Columbus, Ohio, and found that the impervious surface fraction can be estimated by a linear model of low and high albedo endmembers. Further, Wu (2004) proposed a normalized spectral mixture analysis (NSMA) to achieve a better estimation accuracy of impervious surface distribution. Instead of utilizing a single set of endmembers, Rashed et al. (2003) developed a multiple endmember spectral mixture model to quantify impervious surfaces. Regression modeling involves estimating impervious surface distribution using the greenness component generated from a Tasseled Cap transformation applied to

Changshan Wu is with the Department of Geography, University of Wisconsin-Milwaukee, Bolton Hall 462, P.O. Box 413, Milwaukee, WI 53201 (cswu@uwm.edu).

Fei Yuan is with the Department of Geography, Minnesota State University-Mankato, 7F Armstrong Hall, Mankato, MN 56001.
remote sensing imagery. This method has been tested in the Minneapolis-St. Paul, Minnesota with Landsat TM/ETM+ data (Bauer et al. 2004; Yuan et al. 2005) and IKONOS imagery (Sawaya et al., 2003). Similar to, but more sophisticated than regression modeling, the regression tree approach was proposed by Yang et al. (2003a and 2003b) to quantify impervious surface fraction from Landsat ETM+ imagery. This method has been adopted by the United States Geological Survey (USGS) to produce a 30 × 30 meter national impervious surface dataset as a component of the National Land Cover Dataset (NLCD). Other methods have also been applied to estimate impervious surface fraction with some success. Specifically, Ji and Jensen (1999) estimated impervious surface fraction based on ERDAS IMAGINE subpixel analysis and layered classification. However, their results are represented as eight discrete classes (10 percent intervals) due to the limitations of the subpixel classifier. Planagan and Civco (2001) applied an artificial neural network (ANN) to estimate impervious surface distribution for Connecticut using Landsat ETM+ images.

Although many methods have been developed, most were tested during one time period only, typically in the summer season. One exception is the regression tree method, which utilizes both summer and fall images for training and testing. This method, however, does not provide seasonal sensitivity analysis. Consequently, it is not clear whether there is an optimal time for estimating impervious surface fraction using satellite remote sensing techniques. For example, some researchers may favor the winter season when impervious surface estimations are less likely to be influenced by vegetation canopy. The main purpose of the present research is to explore the seasonal sensitivity of impervious surface estimating techniques. In particular, two methods, spectral mixture analysis and regression modeling, were chosen because they are more likely to be affected by seasonal changes of vegetation. In particular, vegetation phenology may have significant influence on endmember selection in the SMA method and the Tasseled Cap greenness value in regression modeling. The remaining sections of this paper are organized as follows. The following section describes the study area and data. Next, the selected impervious surface estimation methods and accuracy assessment procedures are detailed. Finally, analytical results, conclusions and discussion are given.

### Study Area and Data
Franklin County, Ohio was chosen as the study area for this research (Figure 1). Franklin County encompasses an area of approximately 1,400 km² and has a population of just over one million. The region includes both urban (commercial, residential, industrial) and rural land-use (cropland and forestland). The county has encountered fast population growth and urban expansion in recent years. According to the 2000 Census, the total population in Franklin County increased 11.2 percent from 1990 to 2000. Therefore, developing accurate estimates of impervious surface area and managing impervious surface ratios have been major concerns for local agencies in this area.

Three Landsat-7 ETM+ images (path 19, row 32) for spring (05 April 2000), summer (08 July 1999), and fall (30 October 2000), and one Landsat-5 TM image for winter (02 December 2003) were acquired for the study area. Preprocessing was conducted using 50 to 60 ground control points, and the geometric errors are corrected within 15 meters. Normalized exo-atmospheric reflectance was calculated from the original digital numbers (DNs) of the TM/ETM+ images based on the conversion formula provided in the Landsat-5 and -7 handbooks (Chander and Markham, 2003; Landsat-7 Science Data.

**Impervious Surface Estimation Methods**

**Spectral Mixture Analysis**
Spectral mixture analysis assumes several land-cover types exist within a single pixel of remote sensing imagery, and the area fraction of each land-cover type within that pixel can be estimated through analysis of the spectra of the mixed and pure land-cover types (endmembers). Depending on the complexity of scattering, spectral mixture analysis is divided into two classes: linear spectral mixture analysis and non-linear spectral mixture analysis. In most urban applications, non-linear effects are assumed to be negligible, and therefore linear spectral mixture analysis has been widely utilized (Phinn et al., 2002; Rashed et al., 2001; Small, 2001; Wu and Murray, 2003; Wu, 2004). In this study, the normalized spectral mixture analysis (NSMA) model developed by Wu (2004) has been utilized for generating the fraction of impervious surface. The NSMA model includes two steps: spectral normalization and spectral mixture analysis. Spectral normalization (see Equation 1) reduces spectral variation associated with absolute brightness, while maintaining useful information to separate major land-cover types.

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

where \( m = \frac{1}{n} \sum_{b=1}^{n} R_b \), where \( \bar{R}_b \) 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 (six for TM and ETM+ imagery). With the normalized spectra, the next step is to apply the spectral mixture analysis (SMA) method to calculate the fraction of each endmember, including vegetation, impervious surface, and soil:

\[
\bar{R}_b = \sum_{i=1}^{n} f_i \bar{R}_{i,b} + e_b
\]  

where \( \sum_{i=1}^{n} f_i = 1 \), and \( f_i \geq 0 \), where \( \bar{R}_b \) is the normalized reflectance for band \( b \) obtained from Equation 1, \( \bar{R}_{i,b} \) 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. The fraction of each land-cover type, including vegetation, impervious surface, and soil, in a pixel can be derived with a least squares method in which the residual \( e_b \) is minimized. Details of this normalized spectral mixture analysis method can be found in Wu (2004).

**Regression Modeling**
Regression modeling quantifies relationships between impervious surface distribution and information derived from remotely sensed images, and applies these relationships for estimating impervious surface information. Recently, Tasseled Cap greenness has been identified as a valuable parameter for impervious surface estimation (Sawaya et al., 2003; Bauer et al., 2004). The Tasseled Cap transformation converts a multi-band remotely sensed image such as Landsat TM/ETM+ to a set of mutually orthogonal components (Crist and Cicone, 1984). The first component, brightness, is closely associated with pixel reflective values with bare soil and bright impervious surfaces (e.g., concrete, glass) having high values. The second component, greenness, illustrating a contrast between the red and near-infrared bands, is strongly related to the amount of green vegetation. In developed areas where the amount of bare soil is limited, greenness is generally inversely related to the amount of impervious surface. The regression model utilized in this research involves three steps: (a) developing relationships between Tasseled Cap greenness and impervious surface distribution through regression analysis, (b) masking out non-urban areas, and (c) performing inverse calibration on the estimated percent impervious surface area.

Based on the relationship between Tasseled Cap greenness and DOQ-measured percent impervious surface area of the Franklin County, a second-order polynomial relationship was constructed as follows (Equation 3):

\[
I = a_I G^2 + a_2 G + a_3 + e
\]  

where \( I \) is the impervious surface fraction of a pixel, \( G \) is the Tasseled Cap greenness for that pixel, \( a_I, a_2, \) and \( a_3 \) are the regression coefficients, and \( e \) is the regression error. Subsequently, polynomial Equation 3 was entered into the spatial modeler in ERDAS IMAGINE in which the Tasseled Cap greenness image was utilized as the input to estimate the distribution of impervious surface. Next, an urban mask generated by a combined unsupervised and supervised classification method was applied to separate urban from non-urban areas. The major reason for masking out non-urban areas is to reduce the influence of bare soil on impervious surface estimation since the inverse relationship between impervious surfaces and Tasseled Cap greenness holds only in the areas where bare soil is restricted. The final step of this approach is applying the inverse calibration proposed by Walsh and Burk (1993) as a post-calibration method. In this step, the proportion of impervious surface area within a pixel is regressed to ground measurements digitized from aerial photos and adjusted accordingly. More details about this technique can be found in Walsh and Burk (1993) and Bauer et al. (2004). With this inverse calibration approach, the regression \( I \) normally increase 1 to 2 percent, and the standard error of impervious surface estimation may decrease by several percent (Bauer et al., 2004).

**Accuracy Assessment**
The performance of both spectral mixture analysis and regression modeling and their sensitivity to seasonal change were evaluated using test samples generated from the 1 m DOQs. Initially, 256 random samples were created, from which a subset of 200 samples were utilized in the assessment by eliminating those falling outside the study area or inside water bodies. A 3 pixel by 3 pixel sampling unit was chosen in order to reduce estimation errors due to geometric misregistration of the Landsat data and aerial photos. For each sample, a 90 m × 90 m sampling area was identified, and impervious surfaces within it were manually digitized using ERDAS IMAGINE (Area of Interest) tools. The fraction of impervious surface within the sample was calculated by dividing the impervious surface area by the total sample area. Three parameters were utilized to quantify the accuracy of the impervious surface estimation. In particular, the root mean square error (RMSE) (Equation 4), the systematic error (SE) (Equation 5), and the correlation coefficient (R²) (Equation 6) between estimated and measured impervious surface fraction, were utilized:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N}(I_i - \bar{I})^2}{N}}
\]  

where \( I_i \) is the estimated fraction, \( \bar{I} \) is the measured fraction, and \( N \) is the number of samples.
Analytical Results

Spectral Mixture Analysis

In applying the normalized spectral mixture analysis, three endmembers (vegetation, impervious surface, and soil) were selected to model the heterogeneous land-cover types in Franklin County. These three endmembers were selected based on scatterplots of the principal components of the normalized Landsat TM/ETM+ images, the details of which can be found in Wu (2004). The resulting impervious surface fraction images indicate that the estimated impervious surface distribution is generally consistent with urban land-uses. In particular, commercial land-uses have the highest fraction, and rural land-uses contain the lowest fraction of impervious surfaces (Figure 2). The results of a detailed

\[
SE = \frac{\sum_{i=1}^{N}(\hat{I}_i - I)_i}{N}
\]

(5)

\[
R^2 = \frac{\sum_{i=1}^{N}(\hat{I}_i - \bar{I})^2}{\sum_{i=1}^{N}(I_i - \bar{I})^2}
\]

(6)

where \(\hat{I}_i\) is the estimated impervious surface fraction for sample \(i\), \(I_i\) is the true impervious surface fraction digitized from aerial photos, \(\bar{I}\) is the mean impervious surface fraction of the samples, and \(N\) is the total number of samples.

Figure 2. Fraction images of impervious surface for SMA generated by the normalized spectral mixture analysis method for different seasons: (a) April 2000, (b) July 1999, (c) October 2000, and (d) December 2003. The impervious surface distributions for all seasons are consistent with the known land-use types. That is, commercial land-uses have the highest fraction, and rural land-uses contain the lowest fraction of impervious surfaces.
accuracy assessment are reported in Figure 3 together with the RMSE, SE, and $R^2$ values. Results suggest that the accuracy of impervious surface estimation does have seasonal variation. In particular, the impervious surface estimates for the summer season (08 July) are the most accurate, having the lowest RMSE (11.5 percent) and the highest $R^2$ (0.82). Moreover, there is no significant systematic error (SE = 1.65) with the summer estimates. In contrast, the impervious surface estimates from the winter image (02 December) are associated with the highest RMSE (18.4 percent) and lowest $R^2$ (0.56). Compared to the results from the winter image, the accuracies with spring and fall images are slightly better with RMSE approximate 16 to 17 percent, and $R^2$ about 0.64 to 0.74. These results indicate that summer is the optimal season for impervious surface estimation using the spectral mixture analysis method.

Figure 3 also indicates that for a few samples, although the actual impervious surface fraction is near zero, the model produces a high percentage of impervious surface. This may be caused by some bare soils that have been erroneously considered as impervious surface. To address this problem, a non-urban mask was generated from the individual land-cover types and was used to determine whether the stratification of urban and non-urban areas would improve the estimation. Accuracy assessments made after applying the non-urban mask are shown in Figure 4. Compared to the accuracy reported in Figure 3, utilization of the non-urban mask has generally improved impervious surface estimation, especially for the non-summer seasons. Taking the winter season as an example, the RMSE decreased from 18.4 percent to 13.1 percent, and the $R^2$ increased from 0.56 to 0.82. Similar improvements are found in the spring and fall seasons. For the summer season, the RMSE decreased slightly from 11.5 percent to 10.2 percent, and the $R^2$ increased from 0.82 to 0.88. It is apparent that utilization of the non-urban mask improves the accuracy of impervious surface estimation. However, this does not change the seasonal variations in accuracy. The estimates from the summer imagery still demonstrate the highest accuracy, and winter estimation shows the lowest.

**Regression Model**

In order to construct the regression model between impervious surface fraction and remote sensing information, approximately 50 random samples representing the entire range of imperviousness from 0 to 100 percent and various land-cover types were created for the study site. Similar to the random samples selected for accuracy assessment, the true percent imperviousness for each sample was determined by manually digitizing impervious area on DOQs and then calculating the percent impervious for that sample. The mean greenness value (stretched to 8-bit) for each sample was also calculated. The relationship between the impervious surface fraction and the mean greenness for these samples was then determined and modeled with regression analysis using a second order polynomial equation (see Figure 5). While seasonal variations are apparent, relatively strong agreements between impervious surface fraction and Tasseled Cap greenness were found for all seasons. The strongest relationship was identified for the summer imagery.

![Figure 3](image_url)

**Figure 3.** Accuracy assessment of the impervious surface estimation by the normalized spectral mixture analysis: (a) 05 April 2000, (b) 08 July 1999, (c) 30 October 2000, and (d) 02 December 2003.
Figure 4. Accuracy assessment of the impervious surface estimation by the normalized spectral mixture analysis with a non-urban mask: (a) 05 April 2000, (b) 08 July 1999, (c) 30 October 2000, and (d) 02 December 2003.

$(R^2 = 0.79)$ followed by the spring imagery $(R^2 = 0.69)$, and the weakest relationship was found with the winter data $(R^2 = 0.53)$. This pattern of seasonal variation is not unexpected due to the high contrast between green vegetation and impervious surfaces, and the low confusion between impervious surfaces and soil in summer.

Utilizing the polynomial equations developed above, seasonal impervious surface fraction images were generated (see Figure 6). The accuracies of these impervious surface estimations were assessed and are reported in Figure 7. Generally, the results show no significant seasonal variation, with all of the seasons having an RMSE of approximately 11 percent to 12 percent, and $R^2$ equal to 0.82 to 0.85.

Conclusions and Discussion

Conclusions

This paper explores seasonal variations of impervious surface estimation using two remote sensing techniques: spectral mixture analysis and regression modeling. Analysis of the results suggests several conclusions.

First, seasonal variations are observed when impervious surfaces are estimated by spectral mixture analysis, and the best performance is achieved in the summer season. In particular, the RMSE equals 11.5 percent and the $R^2$ is 0.82 for the summer season image, noticeably better than the accuracies obtained in other seasons. In addition, application of the non-urban mask with the spectral mixture analysis method improves estimation accuracy for all seasons. As an example, with the summer images, the RMSE decreases from 11.5 percent to 10.2 percent. The largest improvements using a non-urban mask, however, are found in estimates for the leaf-off seasons. Specifically, the RMSE decreases from 18.4 percent to 13.1 percent for the winter estimation.

Although use of the non-urban mask reduces the seasonal differences of model performance, summer marginally remains the optimal season using this method.

For the regression analysis method, the relationship constructed between impervious surface fraction and Tasseled Cap greenness is strongest for the summer image. Nevertheless, no significant seasonal variations were identified for the resulting impervious estimations, with all of the seasons having an RMSE of approximately 11 percent to 12 percent, and $R^2$ equal to 0.82 to 0.85. Two major factors may account for this result. First, the regression modeling method can be considered a supervised approach in which the polynomial relationship is constructed independently for each image with the same set of training data. Second, most of the seasonal deviations can be eliminated by applying the non-urban mask and the inverse calibration.

Finally, it is noted that a systematic bias exists in the estimation of the impervious surface using the spectral mixture analysis method, whereby overestimates are made of imperviousness in less developed areas and underestimates for urbanized regions. The non-urban mask can mitigate the problem of overestimation in rural areas, but underestimation in urban areas still exists. In contrast, regression modeling procedures used in this study correct most of the underestimation by the inverse calibration process.
Discussion and Future Research

This study has investigated the seasonal sensitivity of impervious surface estimation using four seasons of Landsat TM/ETM+ data in spectral mixture analysis and regression modeling. Ideally, the Landsat TM/ETM+ data and corresponding DOQ images utilized for analysis should be derived from the same year. This was not possible for this study because of clouds and snow coverage. This necessitated the use of a summer ETM+ image acquired in 1999 and winter TM image acquired in 2003. The DOQs were acquired in April 2000. To minimize negative effects associated with the use of multi-year imagery, all training and testing samples were checked against the four dates of Landsat images, and only those samples without considerable land-use change from 1999 to 2003 were selected. Accuracy assessments (see Figure 3d and 7d) indicate the estimated impervious surface fraction determined from the 2003 TM image is not an over-estimate. This study has utilized only two methods to explore seasonal variations in impervious surface estimation. Although these two methods may be more sensitive to vegetation phenology compared to others, further analysis of other impervious surface estimation techniques is recommended.

Acknowledgments

The authors wish to thank the anonymous reviewers for their careful evaluation and insightful comments.

References


Figure 6. Fraction images of impervious surface generated by the regression modeling method for different seasons: (a) April 2000, (b) July 1999, (c) October 2000, and (d) December 2003. For all seasons, a spatial coherence between impervious surface distribution and urban land-use types can be recognized. For rural land-use types, impervious surface fractions are forced to be zero by applying a non-urban mask.


Figure 7. Accuracy assessment of the impervious surface estimation by regression modeling: (a) 05 April 2000, (b) 08 July 1999, (c) 30 October 2000, and (d) 02 December 2003.


