LANDSAT ETM^{+} SUB-PIXEL ANALYSIS OF URBAN LANDSCAPE USING FUZZY C-MEANS CLUSTERING AND DIFFERENTIATED IMPERVIOUS SURFACE CLASSES

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ABSTRACT

Fuzzy c-means clustering (FCM) algorithm has been used to analyze the sub-pixel composition of medium spatial-resolution satellite image (i.e., Landsat ETM^{+}). As urban landscape shows complex patterns of land cover composition and setting, it is difficult to have high accuracy in estimating urban land cover composition from Landsat image because of the mixed pixel problem. This study evaluates the utility of FCM algorithm in the sub-pixel analysis of Landsat image with simplified urban land cover classes: impervious surface, lawn, and woody tree. The training pixels of impervious surface are further divided into three sub-classes. The cluster center number and value of FCM is given as the number and the pure pixel spectral value of the three land cover classes. The cluster center value of FCM is defined as the median spectral value of the training pixels of each land cover class and the training pixels of impervious surface is further classified into three subclasses. The accuracy assessment is based on NJDEP LU/LC map that contains DOQQ-based impervious surface estimate value. This study shows how the FCM-based sub-pixel analysis with simplified spectral values of the training pixels estimates accurately the land cover composition of medium spatial resolution satellite image.

INTRODUCTION

Urbanization inevitably changes land cover from forest, grassland or agricultural to impervious surfaces (i.e. buildings and roads) as well as artificial vegetated spaces (i.e. planted trees and lawn). Impervious surface can be defined as any material that prevents the infiltration of water into the soil. Impervious surface is a major contributor to the environmental impacts of urbanization (Arnold and Gibbons, 1996), such as increased surface runoff, erosion, and reduced groundwater recharge. Urban runoff, mainly from impervious surfaces, is the leading source of pollution in estuaries and is the third and fourth leading source of pollution in lakes and rivers (Civco and Hurd, 1997).

Estimating the percentage of impervious surface in urban landscape is the essential information for environmental monitoring. Due to the vast area extent and the necessity of frequent update, medium spatial resolution satellite image is widely used, but, at the same time, the spatial resolution of the most-widely used Landsat ETM is still coarse to monitor urban landscape change accurately. To minimize the mixed pixel problem of Landsat ETM, different algorithms of sub-pixel analysis are developed and evaluated, e.g., spectral mixture analysis (Settle and Drake, 1993; Small 2001), fuzzy c-means clustering (Key *et al*. 1989; Foody and Cox, 1994; Bastin 1997), artificial neural networks (Foody *et al*, 1997; Zhang and Foody, 2001), and regression tree (Huang and Townshend, 2003).

Fuzzy c-means clustering (FCM) is the best known and the most popular fuzzy clustering method. The FCM clustering method is a modification of the common hard c-means clustering approach and showed a good accuracy in the sub-pixel analysis of Landsat image. FCM-based sub-pixel analysis is done by measuring fuzzy partition value to each cluster center.

This study examines the performance of the FCM-based Landsat ETM^{+} sub-pixel analysis as compared to the impervious surface estimates of the NJDEP LU/LC map.

DATA

The study area is the Mullica River basin in NJ, which is the largest watershed inside the Pinelands National Reserve. This study area was chosen as it contained a sufficient range of urban densities and was the site of a companion study examining the influence of land use intensity on the water quality of coastal watersheds.

The test data set is the leaf-on (23 September 1999) scene of Landsat 7 ETM$^+$ (Path 14, Row 32). This image was processed by the USDA Forest Service and rectified to Albers Equal Area projection, North American Datum (NAD) 1983 using cubic convolution resampling. The image was re-projected to Universal Transverse Mercator (UTM), NAD 1983. The root mean square error (RMSE) of the rectification is sufficiently less than 1/2nd of a pixel. The imagery was not atmospherically and topographically corrected. A New Jersey Department of Environmental Protection (NJDEP) land use/land cover (LU/LC) GIS map of the study area was used to mask non-urbanized areas in the Landsat ETM$^+$ image. This masking was undertaken due to the difficulty in spectrally differentiating between impervious surface and bare soil/fallow areas as well between urban/suburban grass cover and cropped fields within agricultural landscapes.

The reference data set, the NJDEP LU/LC map, was developed from digital color infrared orthophoto quarter quads (DOQQ) with 1 m spatial resolution acquired in March 1995 and visually interpreted using a 0.4ha minimum mapping unit. The NJDEP LU/LC map provides the mean impervious surface percentage of each LU/LC polygon. This mean impervious surface percentage is used as reference data to assess the accuracy of the impervious surface estimates of FCM-based sub-pixel analyzed Landsat image.

METHOD

The FCM clustering method is a modification of the common hard c-means clustering approach. Instead of assigning each pixel to only one cluster, fuzzy membership values for each cluster are assigned to each image pixel. FCM makes no assumption of data distribution and fuzzy membership values are not based on a probability density function (Key *et al.*, 1989). Fuzzy membership values are calculated based on the weighted distance, i.e., Euclidean distance, between an input sample and cluster center in the feature space (equation [3], [4]). The cluster centers and fuzzy memberships are updated iteratively from the initial random cluster center. The original purpose of FCM was data reduction for pattern recognition (Bezdek, 1981). In image analysis, FCM is widely used as an unsupervised classification approach to segment remotely sensed image (Trivedi and Bezdek, 1986; Cannon *et al*, 1986). FCM has also been applied in a supervised classification approach (Key *et al*, 1989; Zhang and Foody, 1998).

The FCM is derived by:

$$M = \{U : u_{ik} \in [0,1]; \sum_{k=1}^{n} u_{ik} > 0, I = 1...c; \sum_{i=1}^{c} u_{ik} = 1, k = 1...n\} \quad (1)$$

where U is a fuzzy c-partition of a sample of n observations and c clusters; u_{ik} is an element of U and represents the membership of an observation, x_k, to the ith fuzzy group (Bezdek 1981). Each x_k is a vector of length p where p is the number of attributes used. This algorithm is based on an iterative minimization of the criterion function (Bezdek 1981; Zimmermann 1991; Bezdek and Pal 1992):

$$J(U,V) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} \left| X_k - V_i \right|^2 \quad (2)$$

where X_k is data sample vectors; V_i is cluster centers; m is and exponent weight factor. The iterative process updates the membership value of the input data, u_{ik}, and the cluster center, V_i, until the criteria, max $|u^{()}_{ik} - u^{(-1)}_{ik}|$, is met, where is the pre-specified threshold value. The update is based on these equations:

$$V_i = \frac{1}{\sum_{k=1}^{n} u_{ik}^{m}} \sum_{k=1}^{n} u_{ik}^{m} x_{ik} \quad i = 1,2,\ldots,c. \quad (3)$$

$$u_{ik} = \frac{[1/|x_k - v_i|^2]^{1/(m-1)}}{\sum_{j=1}^{c}[1/|x_k - v_j|^2]^{1/(m-1)}} \quad i = 1,2,\ldots,\mathrm{c};\ k = 1,2,\ldots,\mathrm{n}. \tag{4}$$

The FCM-based sub-pixel analysis is an one-step calculation algorithm where a single pixel value of each land cover class (the pure spectra) is given as the cluster center of the FCM (Key *et al*. 1989; Foody and Cox 1994; and Bastin 1997). As the cluster center values are given as the pure pixel of each target land cover class, the iterative process of FCM to find cluster center, equation [3], is not necessary. With the pure spectral value of each land cover class as the cluster center, the fuzzy membership values of each pixel to each land cover class are estimated based on equation [4]. This study used Euclidean distance to measure the fuzzy membership.

The impervious surface training pixels were classified into three sub-classes (bright, medium-bright, and dark impervious surface) by using FCM. The pure pixel values for the cluster center of the FCM were defined as the median value of the training pixels in the feature space. Based on the pure pixel value defined by this way, five median pixel values (bright, medium-bright, dark impervious surface, grass, and woody/shrub) were used as FCM cluster centers. The accuracy of the impervious surface estimates of the FCM-analyzed Landsat image was assessed by comparing to NJDEP impervious surface estimates based on DOQQ image. To minimize the effect of the outlier pixels on the zonal mean value of each polygon, I subset the polygons larger than 16200m^2 that is equivalent to the size of 20 Landsat pixels.

RESULTS

This study evaluates the performance of the FCM-based Landsat sub-pixel analysis as compared to the NJDEP reference data in estimating impervious surface proportion of NJDEP LU/LC polygons. An accuracy assessment is done by comparing mean impervious surface %, total impervious surface area, scatter plot, correlation coefficient, and Root Mean Square Error. Among these three assessments, the scatter plot of the % estimate (Figure 1) clearly shows the overall accuracy of the FCM-based Landsat sub-pixel analysis.

The mean impervious surface % and the total area estimate show consistent results, the overestimated impervious surface proportion of the Landsat-FCM as compared to that of the NJDEP (Table 1). These results are confirmed by the scatter plots (Figure 1 and 2): more polygons in the upper part of the 1:to:1 line.

The accuracy assessment shows not a good result of urban impervious surface estimation of the Landsat-FCM (Figure 1 and Table 2). While the area estimates of impervious surface show good correlation coefficient (Table 2) and linear spread pattern (Figure 2), the inaccuracies of the area estimates are masked out by the few large polygons.

Unlike the linear spread pattern of the area estimate, the scatter plot of the percentage estimate shows very wide spread patter. The wide spread of the scatter plot (Figure 1) is an indicator of poor performance of the FCM-based sub-pixel analysis. Both the R.M.S.E and the correlation coefficient of the % estimates also show poor accuracy (0.229 and 0.515, respectively). The scatter plot of the % estimates clearly shows that mixed pixels with low and high impervious surface proportion are overestimated and underestimated, respectively.

This inverse sigmoid spread pattern of the % estimates suggests a serious problem of the FCM-based sub-pixel analysis. This problem is confirmed by the land use types of the polygons that are over-/underestimated. Over half of the overestimated polygons are residential area with low density (Table 3) and over 80% of the underestimated polygons are commercial/industrial area (Table 4).

Table 1. Mean impervious surface % and total area estimates of NJDEP and Landsat-FCM

	NJDEP	Landsat-FCM
Mean Impervious Surface %	0.240	0.393
Total Area	1301.8 ha	1974.8 ha

Table 2. Correlation Coefficient and Root Mean Square Error of impervious surface % and area estimates of NJDEP and Landsat-FCM

	Correlation Coefficient	R.M.S.E
% estimates	0.515	0.229
Area estimates	0.894	14168

Table 3. Land use types of the overestimated polygons of which impervious surface percentage is estimated lower than 0.4 by NJDEP and higher than 0.4 by the FCM model

LABEL95	COUNT
ATHLETIC FIELDS (SCHOOLS)	25
COMMERCIAL/SERVICES	143
INDUSTRIAL	84
MILITARY RESERVATIONS	18
MIXED URBAN OR BUILT-UP LAND	6
OTHER URBAN OR BUILT-UP LAND	355
RECREATIONAL LAND	89
RESIDENTIAL, HIGH DENSITY, MULTIPLE DWELLING	5
RESIDENTIAL, RURAL, SINGLE UNIT	936
RESIDENTIAL, SINGLE UNIT, LOW DENSITY	370
RESIDENTIAL, SINGLE UNIT, MEDIUM DENSITY	162
TRANSPORTATION/COMMUNICATIONS/UTILITIES	101

Table 4. Land use types of the underestimated polygons of which impervious surface percentage is estimated higher than 0.7 by NJDEP and lower than 0.7 by the FCM model

Land Use Type	COUNT
ATHLETIC FIELDS (SCHOOLS)	1
COMMERCIAL/SERVICES	185
INDUSTRIAL	42
MIXED URBAN OR BUILT-UP LAND	1
OTHER URBAN OR BUILT-UP LAND	1
RECREATIONAL LAND	5
RESIDENTIAL, HIGH DENSITY, MULTIPLE DWELLING	12
TRANSPORTATION/COMMUNICATIONS/UTILITIES	29

DISCUSSION

The performance of the FCM-based Landsat sub-pixel analysis in estimating the impervious surface proportion of mixed pixels of urban landscape is evaluated in this study. The results show the overestimation problem of the FCM-based Landsat sub-pixel analysis. This poor performance of the FCM-based Landsat sub-pixel analysis is quite contrary to the results of the previous FCM-based sub-pixel studies. Previous studies showed a good accuracy of the FCM-based sub-pixel analysis in urban landscape.

As the spectral mixture of remotely sensed image is extremely complex, it is expected to have some extent of errors. Besides the overestimation problem of the FCM-based Landsat sub-pixel analysis, the spread pattern of the % estimates (Figure 1) shows a serious problem of the FCM-based Landsat sub-pixel analysis. Initially a sigmoid spread pattern is expected because of the point-spread-function (PSF) of Landsat sensor. Due to the PSF, the spectral reflectance of the smaller land cover class within a pixel is diminished and that of the larger land cover class is emphasized, so it is expected that the sub-pixel analysis tends to overestimate the land cover proportion in a pixel dominated by that land cover and to underestimate the land cover proportion in a pixel dominated by other land cover types. The scatter plot of the % estimates is completely contrary to this expectation. The estimated I.S % of almost all pixels with little and high impervious surface proportions are overestimated and underestimated, respectively. The inverse sigmoid spread pattern (Figure 1) suggests that the false over-/underestimations of the impervious surface proportion in the Landsat pixels of urban landscape are occurred systematically. It means that the FCM-based sub-pixel analysis algorithm used in this study has a systematic problem to unmix the spectral mixture of a mixed pixel.

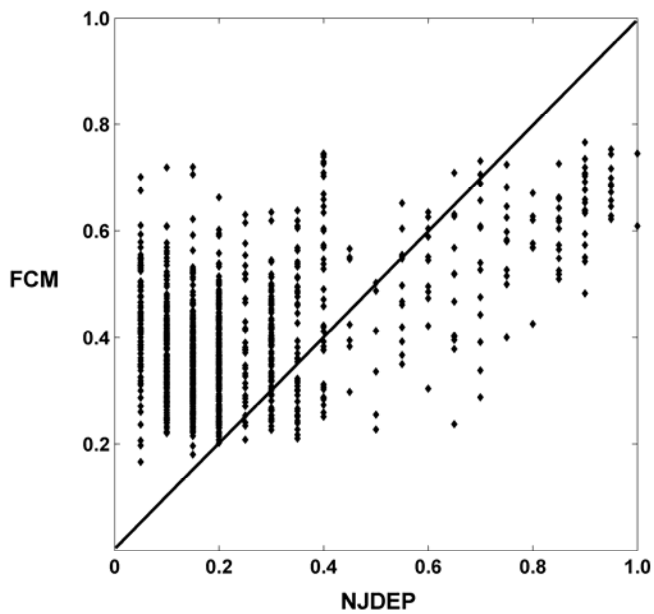
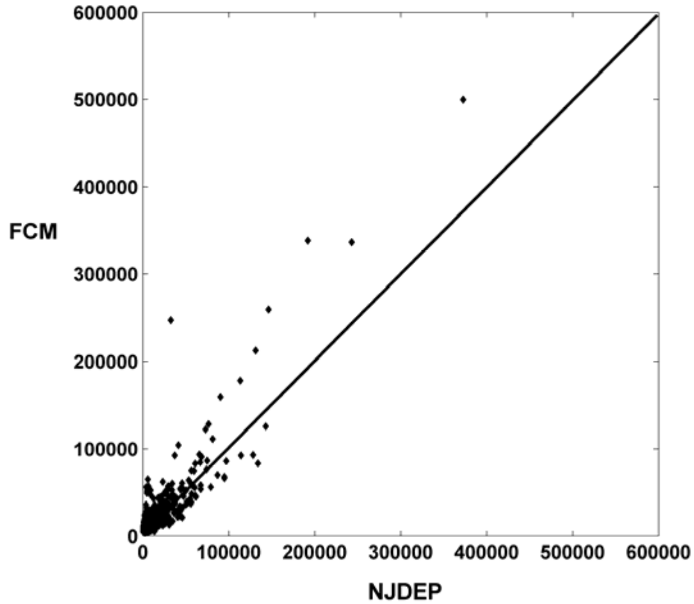


Figure 1. Scatter plot of impervious surface % estimates of NJDEP and Landsat-FCM.



Unit: m^2

Figure 2. Scatter plot of impervious surface area estimates of NJDEP and Landsat-FCM.

The overestimated polygons of residential land use with low density are expected to be underestimated by the FCM-based Landsat sub-pixel analysis because most impervious surface is overshadowed by urban tree canopy, but these polygons are overestimated. Unlike the polygons of residential area, the underestimated polygons of commercial/industrial land use are expected to be overestimated by the FCM-based Landsat sub-pixel analysis because the spectral reflectance of the scattered tree/lawn is obscured by the spectral reflectance of the bright impervious surface cover. Detailed study on this problem should be done to clarify the problem of the FCM model to estimate the impervious surface proportion of residential and commercial/industrial land use polygons.

As the accuracy assessment is done by the zonal mean value of Landsat pixels within NJDEP LU/LC polygon, it is uncertain whether this results show the real performance of the FCM-based Landsat sub-pixel analysis in the mixed pixel analysis of urban landscape. But, at least, this study confirms that the FCM-based Landsat sub-pixel analysis algorithm used in this study is not a practically applicable substitute of NJDEP aerial-photograph-based impervious surface estimates because of the systematically false under-/overestimation of impervious surface proportions of mixed pixels. To have a whole picture of the performance of the FCM-based Landsat sub-pixel analysis, further accuracy assessments should be done, such as a direct comparison of aerial-photograph-based impervious surface estimates and the FCM-based Landsat sub-pixel analysis at the scale of an individual Landsat pixel. Next study should focus on the accuracy of the FCM-based Landsat sub-pixel analysis as compared to the impervious surface estimates based on higher spatial resolution remotely sensed image at different scales

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