A Comparison of Fuzzy vs. Augmented-ISODATA Classification Algorithms for Cloud-Shadow Discrimination from Landsat Images

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Abstract

Satellite images are the most important source of land-cover data over a large range of temporal and spatial scales. However, the complete realization of satellite imagery as a source of land-cover information is limited by the presence of contaminants such as cloud and associated shadows in the image. These contaminants are not adequately handled with conventional image classification techniques such as the unsupervised maximum-likelihood technique. This study comprises a comparison of two classification algorithms, the fuzzy technique and an augmented form of the Iterative Self-Organizing Data Analysis (ISODATA) technique, which were used to discriminate low-altitude clouds and their shadows on a Landsat Thematic Mapper (TM) image of the Econlockhatchee River basin (Econ), in central Florida. Preliminary conventional unsupervised maximum-likelihood classification of the image resulted in clouds being mixed with built-ups and shadows being mixed with water bodies. Regions containing these two kinds of mixed categories were first masked, then fuzzy and augmented-ISODATA classifications were performed on them. The ISODATA classification algorithm was run on the TM visible/shortwave bands and augmented with scatter diagrams of surface temperature versus several vegetation indices; the fuzzy algorithm was run on TM bands 1 through 5 and band 7. An accuracy assessment of the techniques was carried out using 40 randomly selected points within the image. Results of the classifications showed that both algorithms successfully discriminated clouds from other bright features, and shadows from other dark features, with an overall accuracy of greater than 80 percent.

Introduction

Satellite images are the most important source of land-cover data over a large range of temporal and spatial scales. The complete realization of satellite imagery as a source of land-cover information is, however, limited by many factors. One of the most commonly encountered problems is the presence of cloud shadows, and mixed pixels containing these in the image, which are not adequately handled using conventional image classification techniques. Conventional, hard-classification algorithms that assign one class per pixel ignore the fact that many pixels in a remote sensing image may represent a spatial average of spectral signatures from two or more surface categories.

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Conventional methods for classifying remotely sensed data generally produce discrete information categories. It is implicitly assumed that spectral class memberships are precisely defined, so that the attribution of a pixel to a land-cover category is always feasible (Curran *et al.*, 1985). Implicit in the traditional classification process is the concept that each feature vector should be mapped into one of the classes of interest. In remote sensing, however, this is unrealistic, because the classes represented by a pixel's spectral features depend on the sensor's instantaneous field of view. Therefore, within each pixel multiple classes can occur and, only if every pixel is completely covered by a single class (i.e., a pure pixel) is conventional classification appropriate.

Of the many conventional classification techniques available, the most widely used are statistical algorithms such as discriminant analysis and maximum-likelihood classification. Problems with this type of classification, particularly in relation to distribution assumptions and the integration of ancillary data, especially if the latter is incomplete or acquired at a low level of measurement precision (Moon, 1993; Peddle, 1993), prompted the development of alternative classification approaches.

ISODATA Classification

The Iterative Self-Organizing Data Analysis (ISODATA) technique (Tou and Gonzalez, 1974) method of unsupervised classification uses a maximum-likelihood decision rule to calculate class means that are evenly distributed in the data space and then iteratively clusters the remaining pixels, using minimum-distance techniques. Each iteration recalculates means and reclassifies pixels with respect to the new means. This process continues until the number of pixels in each class changes by less than a selected pixel change threshold or until a specified maximum number of iterations is reached.

Fuzzy Classification

Fuzzy set theory has been applied to a range of issues related to the classification of multispectral imagery (Fisher and Pathirana, 1990; Key and Barry, 1989; Pedcryz, 1990; Wang, 1992; Robinson and Throngs, 1986). The spectral response of each

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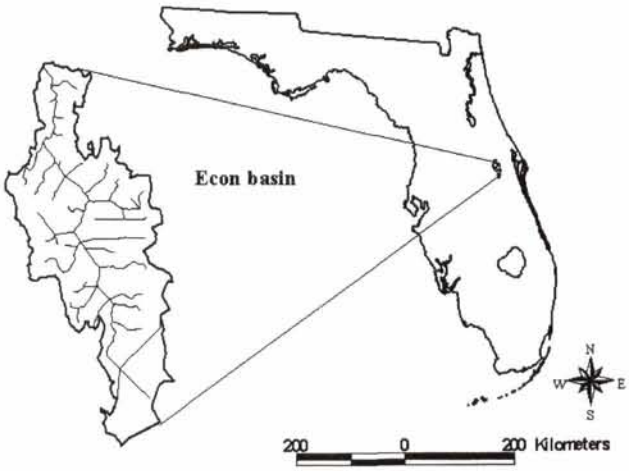

Figure 1. Econlockhatchee River sub-basin (Econ) on the map of Florida.

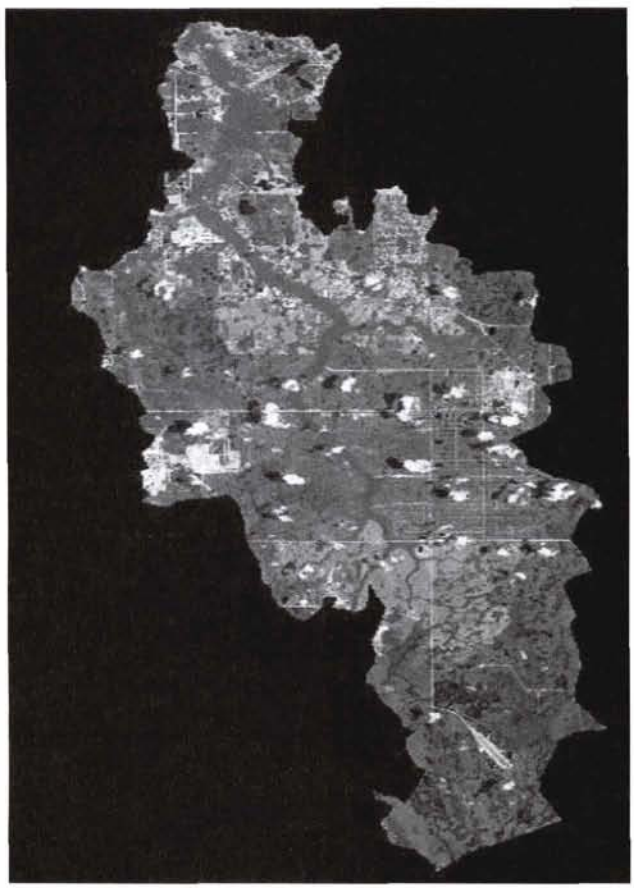

Figure 2. Landsat TM image (with clouds and associated shadows) covering Econ basin on 14 May 1984.

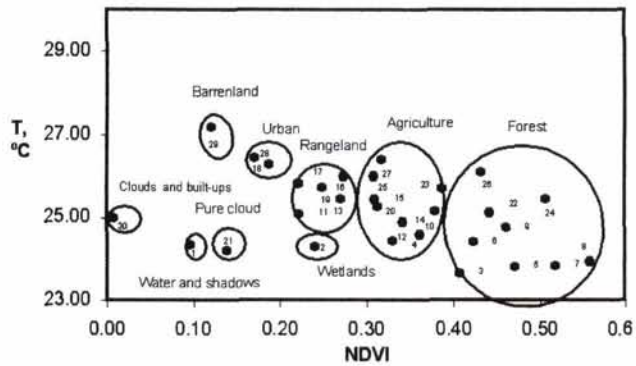

Figure 3. Scatter diagram of temperature (T) vs NDVI of the 30 land-cover classes of the studied image.

pixel is the result of the contribution of all sub-pixel components, so that the attribution of the pixel to a unique category becomes problematic (Gopal and Woodcock, 1994).

Utility of the TM Thermal Band

Spectrally, clouds are often grouped with brighter surfaces such as rooftops of buildings. Shadows are often grouped with darker surfaces such as water bodies, coal piles, and fresh asphalt. It is difficult to distinguish among these features in the visible and near-infrared spectra. The thermal-infrared (TIR) TM band 6 has the ability to discriminate low-altitude cloud pixels from the rest of the scene, because clouds are generally colder than the surrounding ground-level features (Melesse *et al.*, 2000); likewise, there are often temperature differences between shadows, water bodies, and coal piles/asphalt. For this reason, TM band 6 was used in addition to the visible/shortwave TM bands (1, 2, 3, 4, 5, and 7) in both the fuzzy and augmented-ISODATA techniques.

Utility of Vegetation Index

The Normalized Difference Vegetation Index (NDVI) (Rouse *et al.*, 1974) is a measure of the amount of greenness in the vegetation cover. It is the ratio of the difference to the sum of the reflectance values in the near-infrared (NIR) (0.76- to 0.91-μm) and red (0.62- to 0.7-μm) bands: i.e.,

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{red}}{\mathrm{NIR} + \mathrm{red}}. \tag{1}$$

In highly-vegetated scene areas, the NDVI typically ranges from 0.1 to 0.6, in proportion to the density and greenness of the plant canopy. Clouds, water, and snow, which have larger visible reflectances than NIR reflectances, can yield very low or negative index values. Rock, pavement, and bare soil areas have similar reflectance in the two bands and yield near-zero NDVI values. For this reason, vegetation indices were used in the form of scatter-diagrams (versus temperature) in addition to the visible/shortwave TM bands (1, 2, 3, 4, 5, and 7) to augment the ISODATA technique.

The purpose of this study was to assess and compare the ability of the fuzzy and augmented-ISODATA classification techniques to discriminate low-altitude clouds and shadows from other features on a satellite image. Objectives included separating clouds from other bright features, and shadows from other dark features.

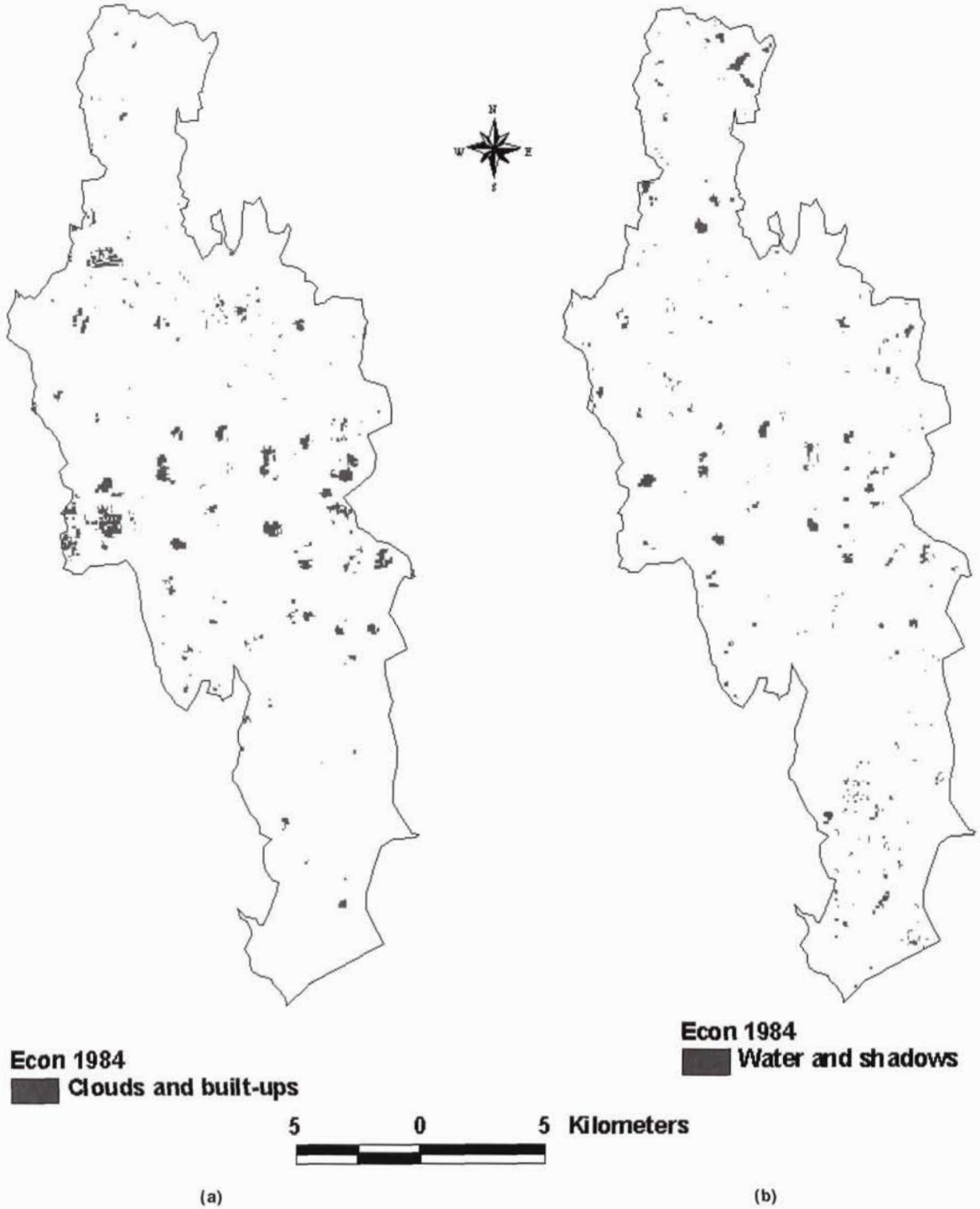

Figure 4. Masked clouds and built-ups class (a) and masked shadows and water class (b) from the 14 May 1984 Landsat TM image.

Methodology

A Landsat image was obtained for this study. The commercial image-processing software ERDAS Imagine (ERDAS, 1999) provided the two image classification algorithms, ISODATA and fuzzy.

Image Dataset

The image used here, which was part of a land-cover-change study, covered the Econlockhatchee River (Econ) basin in central Florida (Figure 1). A Landsat-5 Thematic Mapper (TM) image was obtained from USGS with a processing level of 1B.

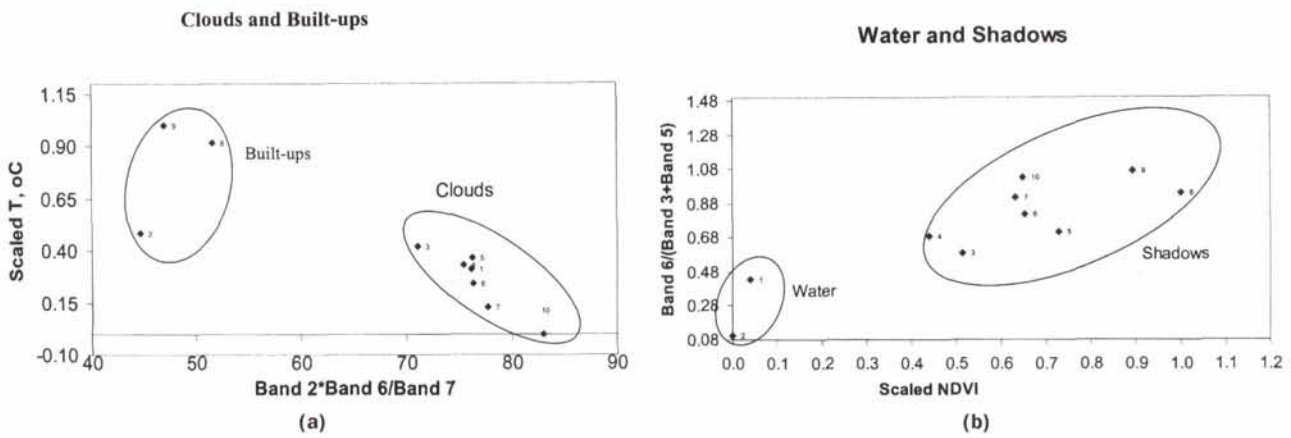

Figure 5. Scatter diagrams of scaled temperature vs (Band 2*Band 6/Band 7) of the ten clusters of clouds and built-ups (a) and scatter diagrams of Band 6/(Band 3 + band 5) vs scaled NDVI of the ten clusters of shadows and water (b) on the 14 May 1984 Landsat TM image.

The Level 1B product is radiometrically and geometrically corrected (systematically) to the user-specified parameters, including output map projection, image orientation, and pixel size.

The 14 May 1984 TM image (WRS2 row 16, path 40) contains clouds and shadows within the areas of the Econ basin (Figure 2).

Augmented-ISODATA Method

ISODATA is an unsupervised classification method that uses an iterative approach incorporating a number of heuristic procedures to compute classes. The ISODATA utility repeats the clustering of the image into classes until either a specified maximum number of iterations has been performed, or a maximum percentage of unchanged pixels has been reached between two successive iterations. The algorithm starts by randomly selecting cluster centers in the multidimensional input data space. Each pixel is then grouped into a candidate cluster based on the minimization of a distance function between that pixel and the cluster centers. After each iteration, the cluster means are updated, and clusters may be split or merged further, depending on the size and spread of the data points in the clusters.

The ISODATA clustering method uses the minimum spectral distance formula to form clusters. The equation for classifying by spectral distance is based on the equation for Euclidean distance (Swain and Davis, 1978): i.e.,

$$SD_{xyc} = \sqrt{\sum_{i=1}^{n} (\mu_{ci} - X_{xyi})^2} \tag{2}$$

where n is the number of bands; i is the band number; c is a particular class; X_{xyi} is the data file value of pixel x, y in band i; μ_{ci} is the mean of data file values (digital numbers) in band i for the sample for class c; and SD_{xyc} is the spectral distance from pixels x, y to the mean of class c.

A preliminary ISODATA classification of the image based on the TM visible/shortwave bands was set to yield a maximum of 30 spectral classes. The resulting 30-class image was then recoded into nine classes using the augmentation information of temperature and NDVI (Figure 3).

The surface temperature was obtained from Landsat TIR band 6 using the simplified Planck function (Markham and Barker, 1986): i.e.,

$$T = \frac{k_2}{\ln\left(\frac{k_1}{R} + 1\right)} \tag{3}$$

where T is the effective at-satellite temperature (K), R is the band 6 spectral radiance (mW.cm^{-2}.ster^{-1}.μm^{-1}), k_1 is the calibration constant 1 (mW.cm^{-2}.ster^{-1}.μm^{-1}); and k_2 is the calibration constant 2 (K). For Landsat 5 TM, k_1 and k_2 are 60.7776 mW.cm^{-2}.ster^{-1}.μm^{-1} and 1260.56 K, respectively.

For Landsat 5 TM band 6, R is a linear function of the Landsat TM digital numbers (DNs) and is related to DN according to

$$R = c\mathrm{DN} + d \tag{4}$$

where $c = 0.0056322$ mW.cm^{-2}.ster^{-1}.μm^{-1} and $d = 0.1238$ mW.cm^{-2}.ster^{-1}.μm^{-1}.

Clouds and shadows, respectively mixed with other bright features (built-ups) and other dark features (water bodies), were masked on the preliminary 30-class output (Figures 4a and 4b). A second ISODATA classification (set to produce a maximum of 30 classes) was conducted for just the two masked mixed-class areas (cloud/built-ups and shadows/water), which resulted in an output of ten spectral classes. Scatter diagrams using scaled temperature (scaled between low and high temperatures of the image) and derived NDVI were used to identify the ten spectral classes as cloud, urban, cloud-shadow, or water. The results of this augmented-ISODATA technique are shown in Figures 5a and 5b. Figure 5a shows that a plot of scaled surface temperature against the product of Bands 2 and 6 divided by Band 7 discriminates clouds well from built-ups. Similarly, Figure 5b shows that a plot of Band 6/(Band 3 + Band 5) against scaled NDVI discriminates water well from shadows.

Fuzzy Method

To address the possibility of encountering mixed pixels in land-cover mapping, it is appropriate to use a fuzzy classification rather than a hard classification. Satellite images with resolutions that are coarse relative to features of interest, and with clouds and cloud-shadow spots, may contain many mixed pixels. Therefore, fuzzy classification, which allows multiple and partial membership for each pixel, may be more applicable than hard classification.

The ERDAS Imagine program (ERDAS, 1999) contains a fuzzy classification tool that can perform supervised fuzzy

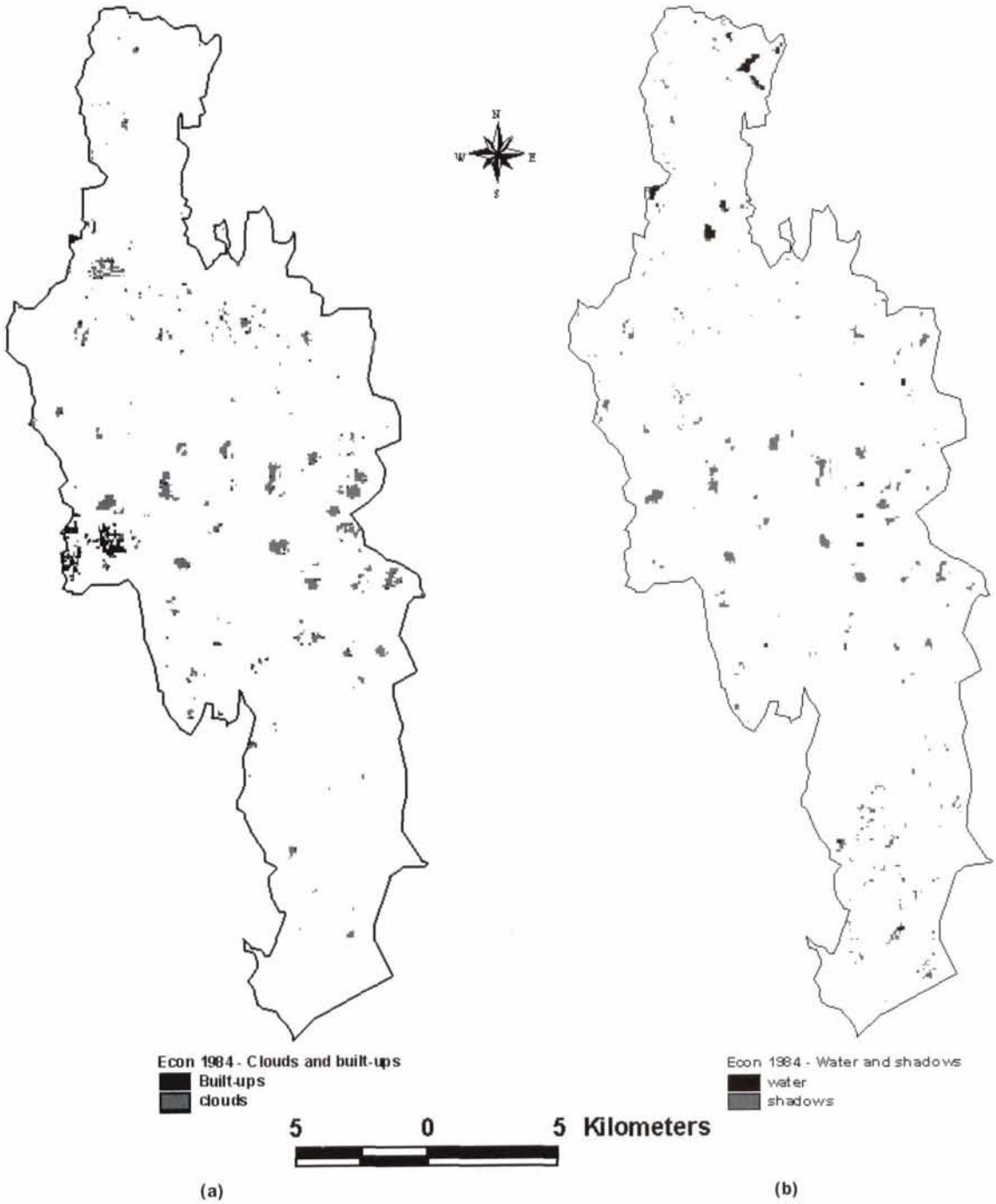

Figure 6. Results of augmented-ISODATA classification of the masked bright areas (clouds and built-ups) (a) and of the masked dark areas (shadows and water) (b).

classification using training areas or signature files provided by the user. Once the fuzzy classification is carried out, the fuzzy convolution utility creates a single-class output from the multi-layer classification and distance file by computing a total weighted distance for all the classes in the window, using the equation

$$S[k] = \sum_{i=0}^{s} \sum_{j=0}^{s} \sum_{i=0}^{n} \frac{W_{ij}}{D_{ijl[k]}} \tag{5}$$

where i is the row index of the window, j is the column index of the window, s is the size of the window; l is the layer index of the fuzzy set, n is the number of fuzzy layers used; w is the weight table for the window, k is the class value; $D[k]$ is the distance file value for class k, and $S[k]$ is the total weighted distance of the window for class k.

The masked image of bright areas (mixed built-ups and cloud) and dark areas (mixed shadows and water) was classified from TM bands 1 through 5 and band 7 using the fuzzy technique using an assumption of two classes per pixel. The

Figure 7. Results of fuzzy classification of the masked bright areas (clouds and built-ups) (a) and of the masked dark areas (shadows and water) (b).

resulting image from fuzzy convolution using a moving window size of 5 was then produced. The fuzzy classification did not use the scaled temperature versus NDVI scatter diagrams.

A classification accuracy assessment was carried out. Results from both the augmented-ISODATA and fuzzy techniques were compared to assess their accuracy in discriminating clouds and shadows from other features in the image. Truth was provided in the form of a set of 40 randomly chosen points from aerial photos.

Results and Discussion

Based on the scatter diagram clusterings in Figures 5a and 5b, land-cover maps were produced of clouds separated from built-ups and shadows separated from water bodies (Figures 6a

and 6b, respectively). Results show that the overall accuracy of these classifications was over 85 percent.

Similarly, results of the fuzzy classification (Figures 7a and 7b) were checked for accuracy using the same random sampling points. The overall accuracy of the classification was found to be over 82.5 percent. Thus, almost the same overall accuracy was obtained with the fuzzy as with the augmented-ISODATA classification.

Conclusion

This study evaluated two clouds/shadows discrimination techniques on a Landsat TM image. Augmented-ISODATA and fuzzy classification techniques were employed and results of the corresponding techniques were presented. ISODATA clustering augmented by scatter diagrams of temperature and derived NDVI was found to be successful for discriminating clouds and shadows, respectively, from built-ups and water bodies. The overall accuracy assessment of the augmented-ISODATA clustering was over 85 percent. The overall accuracy assessment of the fuzzy classification was 82 percent. Thus, the results of both techniques are found to be comparable. However, the fuzzy technique did not require the added complexity of using temperature and vegetation index scatter diagrams, and so in this case may be considered the optimal of the two techniques.

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