THE EFFECTIVENESS OF TEXTURE ANALYSIS FOR MAPPING FOREST LAND USING THE PANCHROMATIC BANDS OF LANDSAT 7, SPOT, AND IRS IMAGERY

Michael L. Hoppus, Research Forester; Rachel I. Riemann, Research Forester; Andrew J. Lister, Forester
USDA Forest Service, Northeastern Research Station
11 Campus Blvd., Suite 200
Newtown Square, PA 19073

Mark V. Finco
USDA Forest Service, Remote Sensing Applications Center
2222 West 2300 South
Salt Lake City, UT 84119

ABSTRACT

The panchromatic bands of Landsat 7, SPOT, and IRS satellite imagery provide an opportunity to evaluate the effectiveness of texture analysis of satellite imagery for mapping of land use/cover, especially forest cover. A variety of texture algorithms, including standard deviation, Ryherd-Woodcock minimum variance adaptive window, low pass etc., were applied to moving 3x3 and 7x7 pixel windows. These windows provide quantitative information over local spatial regions that may be correlated with land cover. The three spatial resolutions of Landsat 7, SPOT and IRS panchromatic imagery, 15m, 10m and 5m respectively, provide for an analysis of pixel size when constructing cover maps. Comparison of technique effectiveness and Pan image type for providing forest cover maps was accomplished by qualitative assessment using aerial photo interpretation.

INTRODUCTION

Relatively high-resolution digital panchromatic satellite images have been commercially available since 1986 when the French satellite SPOT 1 was launched. SPOT 1 imagery offered a panchromatic image with a spectral bandwidth of 510-730 nm (the green, red, and small portion of near infrared part of the spectrum) and pixel size of 10x10 m. Urban and suburban features, such as roads and buildings, are more clearly defined on this imagery as are edges and boundaries between cover types. Subsequently, six more satellites were launched that provide commercial panchromatic digital imagery, including the Indian Remote Sensing Satellite (IRS), launched in 1997 and the U.S. satellite Landsat 7 launched in 1999. Table 1 compares the spectral and spatial resolution and the scene area coverage of these satellites. Cost per scene is provided only for those scenes we used in this study since the costs vary over time and there are different costs for large area purchases and older versus newer imagery. However, there is value in providing some cost information because SPOT and IRS panchromatic imagery costs are much higher per unit area than the Landsat panchromatic imagery. Also, for the price of $850 for Landsat 7 imagery, the other seven bands of multispectral layers are included; not so with SPOT and IRS pan bands.

Table 1. Characteristics of SPOT, IRS, and Landsat TM panchromatic imagery

Satellite	Launch Date	Bandwidth (nm)	Pixel size (m)	Scene size (km)	Cost Per scene ($)	Cost per unit area ($/km)
SPOT 1	1986	510-730	10x10	60x60		
SPOT 2	1990	510-730	10x10	60x60		
SPOT 3	1993	510-730	10x10	60x60		
SPOT 4	1998	610-680	10x10	60x60	1,250	0.34
SPOT 5	2002	510-730	5x5 & 2.5x2.5	?		
IRS-1D	1997	500-750	5x5	70x70	1,500	0.31
Landsat 7	1999	520-900	15x15	180x180	850	0.03

Higher spatial resolution is the primary value of these panchromatic layers. Detailed features, such as roads, houses and buildings, streams, forest edges, etc., are easier to differentiate. These are the same features that that are often the distinguishing characteristics of some land-use types. This greater resolving power, plus the fact that they are not multispectral, lends these layers to visual interpretation rather than classification through digital image processing. In fact, the smaller the pixel size the more likely an image is to be visually interpreted and used as a visual base map in GIS projects (Jensen, 1996). Commonly employed digital processing techniques use the pixel brightness values of each of the spectral bands almost exclusively, leaving out of the automated process other basic elements of image interpretation. The value of all the elements of image analysis, including size, shape, shadow, color (tone), pattern, texture, site, and association (Lillesand and Kiefer, 1994), is evident when you observe satellite image analysts looking at a raw color composite image to "see" where their automated spectral classification is inaccurate. The human eye-brain system is unsurpassed in using all the elements of image interpretation. Can we hope to add more of these elements to automated classification of digital images?

Can the smaller pixel sizes of the panchromatic bands of Landsat 7, SPOT, and IRS be exploited to provide texture information to automated image classification techniques? Texture, defined as the degree of coarseness or smoothness exhibited by images (Avery, 1968), plays a major role in the interpretation of panchromatic images. After color and tone, texture is most amenable to automated quantification. Hsu (1978) defines texture as the spatial distribution of tones of the pixels in digital images. This spatial frequency and distribution of pixel brightness values can be quantified by measuring changes in brightness values over a defined spatial region. This can be accomplished in a straightforward manner by employing a spatial filter window, e.g., a 3x3 pixel box, on the input image that calculates for each pixel an output value, such as the "maximum" of pixel values in the 9 pixels surrounding the input pixel (Jensen, 1996).

Figure 1 describes how a spatial filter window works. The size and shape of the window can be selected. Many of the commonly available image processing software programs have a moving filter feature that lets the user select a square window of certain size. The algorithm can either be selected from a menu or applied manually.

In a previous study, the USDA Forest Service's Northeastern Research Station's Forest Inventory and Analysis group and the Remote Sensing Application Center added texture images derived from the Landsat 7 pan layer to the multispectral layers of the same scene. Researchers wanted to determine if the higher spatial resolution of the pan layer could be exploited to yield a more accurate land-cover classification. The hypothesis was that the texture information provided by the more spatially resolute pan layer would increase the accuracy of an unsupervised classification of land cover, especially the forest-land class. Water, farmland, and some portions of urban areas can be seen to have smoother (less local spatial diversity) texture, and most urban and suburban areas have coarser (more local spatial diversity) texture than forest land on the Landsat 7 pan image. Forest land is perceived to have a medium texture compared to other types – e.g. water and agricultural fields have a smoother texture (less local spatial diversity), and most urban and suburban areas have a coarser texture (more local spatial diversity).

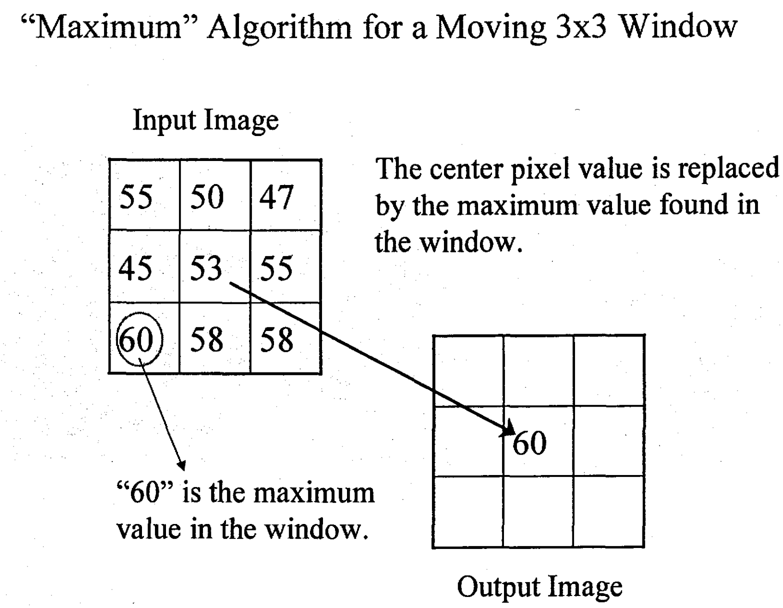
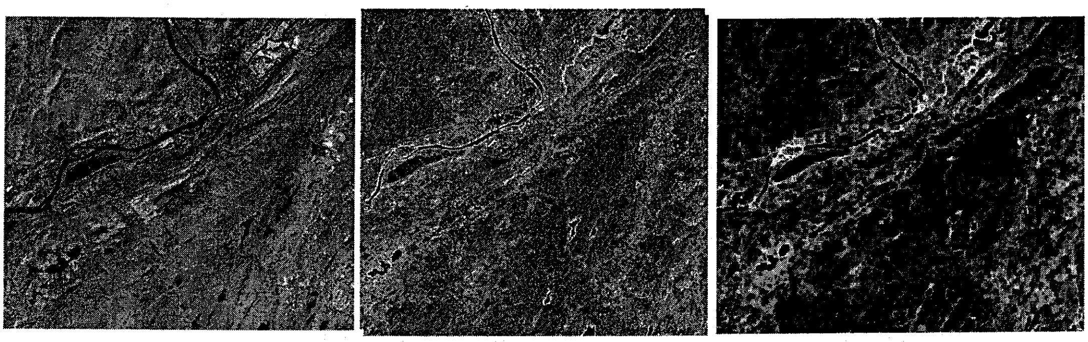


Figure 1. This 3x3 spatial filter window calculates the algorithm specified for the filter, such as maximum, minimum, standard deviation, etc., for the 9 pixels in the input window. It places the value in the output image at the location of the central pixel and then moves to the next pixel in the input image. The output image represents a type of neighborhood diversity, or texture, of the input image.

In this previous study, images derived from three different spatial filter windows were evaluated: a 3x3 standard deviation window, a 3x3 Woodcock-Ryherd standard deviation window, and a 7x7 Woodcock-Ryherd standard deviation filter window. The Woodcock-Ryherd standard deviation window functions the same as the standard standard deviation filter window, except that after the standard deviation is calculated for the original 9 (or 49) pixels, the window "moves around" the central pixel and calculates the standard deviation of the 3x3 (or 7x7) pixel box around each of the original 9 (or 49) pixels. The lowest standard deviation of the 9 (or 49) calculations is placed in the output image at the location of the center pixel of the original 3x3 (or 7x7) window. The Woodcock-Ryherd technique is designed to produce an image that represents the local variance of pixel brightness values without the edge-enhancing effects of the simple standard deviation filter window (Woodcock and Ryherd, 1989). However, in this study we found that the Woodcock-Ryherd filter produced images consisting of blocks of uniform brightness, which obliterated the fine detail of streams and roads and other linear features desired.

The resulting unsupervised classifications using TM bands 1-5 and 7 plus the texture layers yielded less accurate results than when the pan layer wasn't used. Many of the 60 classes created by the classifications using texture were highly fragmented and were more correlated with the edges of land cover than any single land-cover type. Accuracy assessment was accomplished with 174 FIA ground plots located with GPS. The accuracies for the classifications using the standard deviation 3x3, Woodcock-Ryherd 3x3, and Woodcock-Ryherd 7x7 filter windows were 78% (Kappa 0.55), 77% (Kappa 0.53), and 74% (Kappa 0.48), respectively. An unsupervised classification of the same scene without using the texture layer had an accuracy of 81% (Kappa 0.59). Ferro and Warner (2002) found that classification errors using texture were most likely associated with class edges and the tendency of texture algorithms to introduce more edge area may contribute to the low accuracy values observed here.

The hypothesis of this previous study was proven false, at least for the imagery and methods used. In spite of these results, visual inspection of the individual texture images indicated that they were enhancing the contrast between the basic land-cover types observed in the panchromatic image (Fig. 2). Furthermore, the original pan image can be interpreted visually with confidence. Consequently a new study was designed to concentrate only on the pan image and its derivative texture images. Texture is a way to incorporate contextual information around pixels into a classification, and a way to incorporate within-class variability into class definitions. Can these scenes be combined and classified using standard image processing techniques? The results of this new study are described in the rest of the paper.



Original Panchromatic   Standard Deviation 3x3   Woodcock-Ryherd 7x7

Figure 2. A portion of a Landsat 7 panchromatic image along with two corresponding texture images are shown here. Notice the forest land in the upper left and lower right of the two texture images has a darker tone than other cover types except for water. The unaltered original panchromatic scene has much less contrast between types. Can these scenes be combined and classified using standard image processing techniques?

OBJECTIVE

The primary objective was to determine if several different types of texture images, derived from a single panchromatic image, could be combined and classified using an unsupervised image processing method. The hypothesis was that each of the texture algorithms would provide a different type of image intelligence, manifested by pixel brightness levels based on the variance and brightness values of small neighborhoods of pixels surrounding each pixel in the original image. Secondarily, we wanted to determine if either the different pixel sizes, e.g., 15m, 10m, and 5m, or the different bandwidths, had any affect on the information provided by the texture images. The null hypothesis: Texture images derived from Landsat 7, SPOT, or IRS satellite panchromatic images do not provide information sufficient for producing usable maps using an unsupervised image classification method. The classification key was kept simple and the final image classifications could be verified by simple visual inspection of the original image. All that was asked of the classification was that it duplicates what an interpreter could accomplish visually. Forests, roads, crops, pasture, and water can be identified on the original pan images. Successful recognition and delineation of these cover types using image processing techniques and the pan images and their corresponding texture image derivatives was to determine whether the objective was met.

METHODS

Panchromatic Imagery

Panchromatic images from three different satellites, Landsat 7, SPOT 4, and IRS, were acquired of the Delaware Gap area of northeastern Pennsylvania during the summer of 2000. The images vary in spatial and spectral resolution as noted in Table 1. Each of the images can be visually interpreted without much difficulty. Naturally, the 5m IRS pan image shows the most detail. The SPOT 4 pan image has very low contrast. This is probably due to its narrow bandwidth, only a portion of the green part of the spectrum. The bandwidth of Landsat 7 pan imagery, which covers green, red, and a large portion of the near infrared causes some problems with manual interpretation since certain cover types, such as rock or bare ground, may have nearly the same brightness level as green vegetation. This lack of discrimination between types was expected to adversely affect the texture images.

The Landscape

Most of the area imaged in the Delaware Gap is forested. Forest land is predominately deciduous with scattered coniferous stands. There are numerous lakes and ponds, as well as wooded wetland areas. Pastures and cropland also are scattered throughout the area. Another land-cover feature of great interest are large areas of low-density residential housing.

Texture Algorithms

First, the texture algorithms were chosen. From the literature it had been observed that second-order statistical measures, such as grey-level co-occurrence matrix, "diversity index" moran's I, log index, etc., did not necessarily result in improved classifications of multispectral images (Marceau et al. 1990). Similarly, Ferro and Warner (2002) observed that the specific texture algorithm used is usually much less important than the scale (window size) used. Thus, since we also wanted to interpret the texture images with some understanding of each texture algorithm's effect on the original pan image, the simple first-order measures of standard deviation, maximum, minimum, and average were chosen.

Next, several tests were applied to determine the appropriate window size for each image. Typically, a compromise has to be made between large window sizes that produce a stable texture but can have substantial edge effects and small window sizes that minimize edge effects but often do not provide stable texture measures (Ferro and Warner 2002). To chose window size(s) in this study, the four simple first-order texture algorithms (standard deviation, maximum, minimum, and average) were applied to 3x3 and 7x7 moving filter windows to produce texture images of the three pan scenes. After the eight texture images were produced for each pan scene, they were visually evaluated for their ability to highlight land cover features such as forest land, wetlands, water, residential, roads, powerline cuts, etc. They also were evaluated for excessive edge effects and blockiness. Finally, they were compared with one another to select those images that would work together best for separating image features. For example, two texture images, one produced by a "minimum" algorithm and the other produced by a "maximum" algorithm, should have greater separation between pixel brightness values in urban areas than in forested or water areas. There is greater variance in brightness levels between houses, streets, yards, and wooded lots of the urban landscape than there is in forest or water cover. An unsupervised classifier would cluster these pixels differently, and the classes could be labeled correctly. Except for the IRS 5m pan image, all of the 7x7 filter windows were rejected as too coarse. However, in the IRS 5m image the 3x3 standard deviation and maximum windows applied to the IRS 5m pan image created too many difficult-to-interpret edges, and the 7x7 windows appeared more usable for the IRS pan image (Fig. 3). This is a function of the general size of the objects causing variability vs. the size of the window used (Ferro and Warner, 2002).

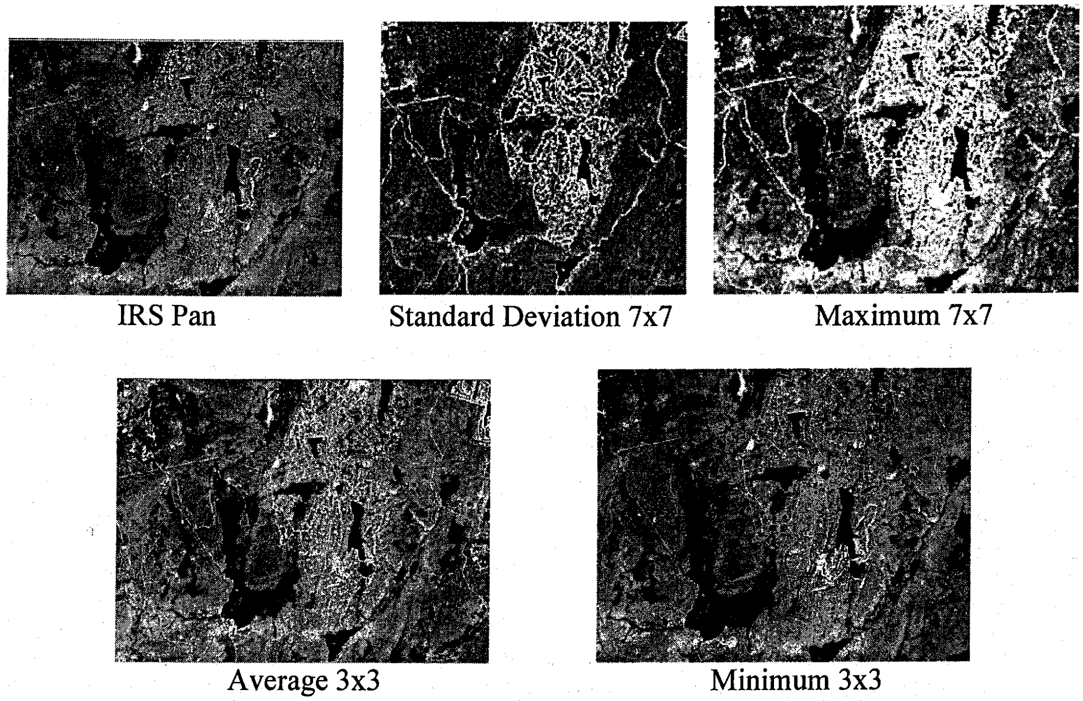


Figure 3. A small portion of the original IRS 5m panchromatic image and corresponding texture images derived by filter windows with the window size and algorithm indicated. Notice that the suburban residential area has more contrast against the surrounding forest area in images created by the standard deviation and maximum algorithms.

Classification

Each of the original pan images was combined with its four texture images to create a five-band dataset in the same fashion that the different bands of a multispectral scene are combined. When applied directly, an unsupervised classification of these data layers resulted in classes that were highly fragmented and sometimes scattered apparently randomly across all cover types, creating a land-cover map with a lot of ambiuity and obviously misclassified pixels. Observing a high degree of correlation between the five bands and large amount of noise, principal components analysis (PCA) was applied to the five-band dataset prior to classification, since it was known to reduce noise and create new bands that have less correlation with each other and can provide more information for classification than the original data (Singh and Harrison, 1985). The first three principal components typically capture much of the variation in the original data (Fig. 4).

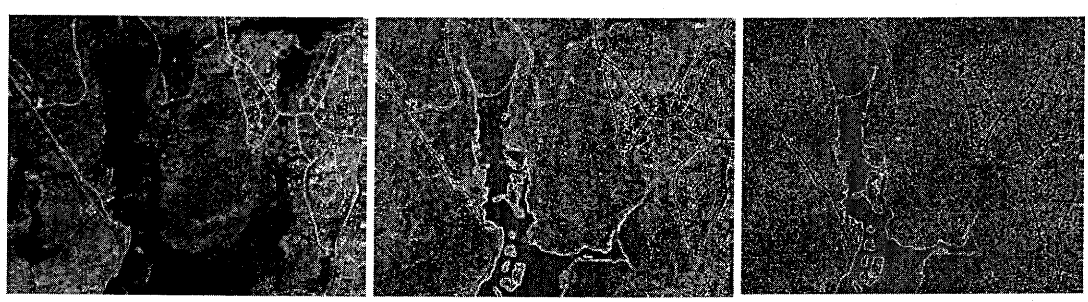


Figure 4. The first, second,and third principal components (from left, respectively) derived from the IRS 5m data and its four derived texture images.

The first three components of PCA were classified using the unsupervised method (Fig. 5). The 30 classes were labeled as either forest, road, crop, pasture, or water with the assistance of 1:40000 and 1:24000 scale aerial photography. The supervised method was not used in this evaluation because we wanted the pixel clustering to be based on an objective mathematical analysis of the input layers. In addition, it would take time to determine whether good or poor cover maps resulting from a supervised classification were the result of flawed selection of the training sites rather than lack of information in the images.

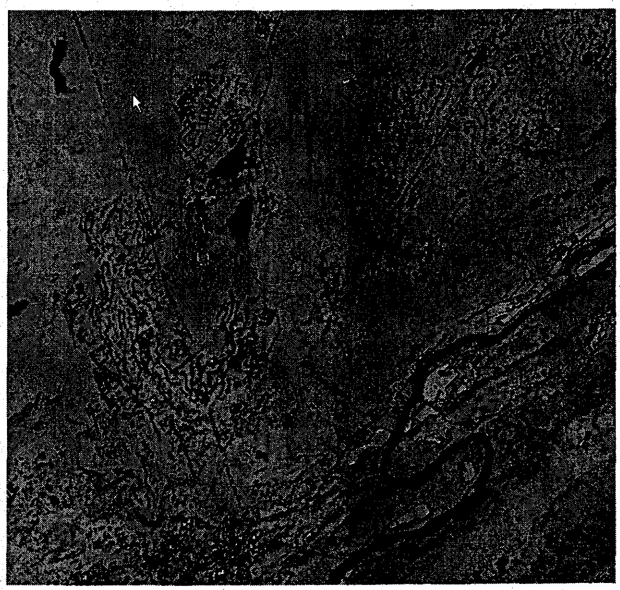


Figure 5. Land-cover map produced from the unsupervised classification of the first three principal components calculated from 5 bands: a SPOT 4 pan image and four texture images. Each of the four texture images was created using a 3x3 window and the algorithms: standard deviation, minimum, maximum, and average, respectively. Clusters of roads can be interpreted as suburban areas.

RESULTS

The land-cover maps produced by the unsupervised classification of the Landsat 7, SPOT 4, and IRS panchromatic images and their derived texture images are reasonably accurate based on a qualitative comparison with aerial photos. Creating principal components from these images prior to creating the 30 unsupervised classes helped reduce noise and ambiguous classes. Nevertheless, 30 % of the classes in each case were edges between two land-cover types. These were forced into one type or another rather than maintaining a separate "edge" class, and the default was to put the edge class into its more developed component – e.g., the forest-road edge class was added to the road class. Edge classes should be expected due to the higher resolution of the images and the nature of the texture images, which enhance edges.

Comparisons between the three satellite images reveal differences related to their pixel size and bandwidth (Fig. 6). The IRS 5m pan image produced a more detailed map with more roads and streams depicted. Boundaries seemed to be better defined. It also had a considerable number of forested pixels misclassified as roads and urban. The smaller pixel size may allow the texture algorithms to create edges between forest conditions similar to the edge of roads. The SPOT 4 image produced the least detailed map even though the pixel size is one quarter the area of a Landsat 7 pixel. The narrow bandwidth centered on green light probably caused the pan image to lack contrast between features. (Note: This is actually only a feature of SPOT 4 and SPOT 5 will have the larger pan bandwidth.) The land-cover map produced from the Landsat 7 15m pan image compared favorably with the other pan-derived maps. It does not have the fine spatial detail of the IRS image, and its rather broad bandwidth, covering, as it does, all the green and red plus most of the near infrared, created ambiguities between roads and streams (Fig. 7). However, it does seem to pick up detail in the forest that the other pan images don't, such as forested wetland and some forest structure. This deserves further investigation.

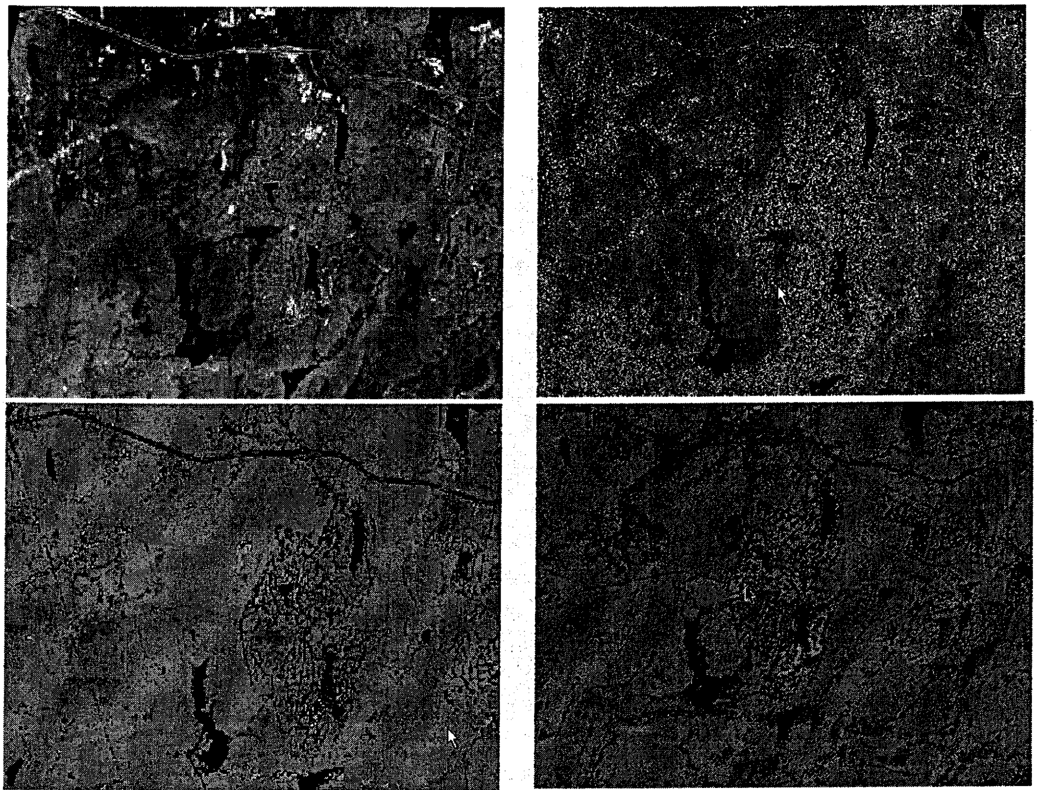


Figure 6. Clockwise from the upper left: the IRS pan image, the IRS classified map, the Landsat 7 classified map, and the SPOT 4 classified map. The key is the same as in Figure 5 except that the red and yellow of the IRS map are roads.

Figure 7. Labeling the classes for the land-cover map based on the Landsat 15 m imagery. The classes depicted by red and olive-green are covering roads and streams simultaneously. Unlike the IRS and SPOT pan images, the roads are dark on the Landsat images due to the bandwidth that reaches far into the near infrared.

Aerial photographs taken the same summer as the satellite images were acquired and interpreted for basic land-cover type. The resulting digitized and rectified polygons fit reasonably well over the land-cover classes of the pan image based maps (Fig. 8). In addition, it was interesting to observe that even those residential areas that were photointerpreted to have between 75% and 90% forest cover were quite visible in the classified image.

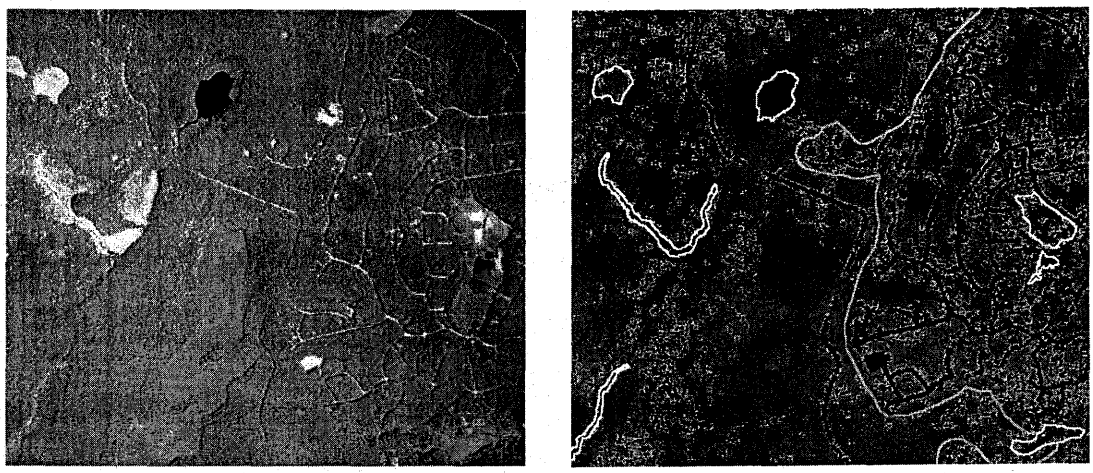


Figure 8. The color infrared aerial photo on the left was interpreted and the polygons digitized and rectified. The classified IRS pan image on the right agrees generally with the overlaid polygons.

One additional comparison was performed to better understand how much information was being added by just the brightness values of the more spatially resolute pan band without the addition of the texture information. To investigate this, the original unfiltered brightness values of the pixels in the pan image were used to produce a "density slice" map. All 256 brightness levels of the original pan image were divided into 51 groups of five values each, and each "slice" was labeled with a land cover type. Figure 9 shows a comparison. The density slice map has considerable detail and fine linear features are not made artificially thick. However, the density slice map also misses a fair number of roads and streams picked up by the texture images. Texture images noticeably enhance the urban areas.

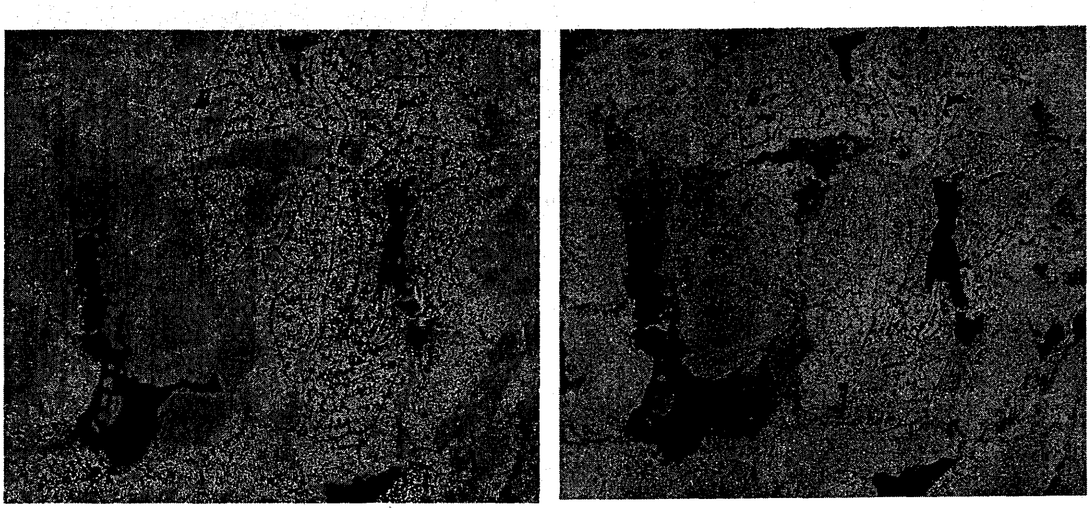


Figure 9. The unsupervised classification of the original IRS pan image plus the texture images (left) is compared with the IRS pan image pixel brightness "density slice" based map (right). The texture layers emphasize the urban residential cover type and allow for the identification of subtle linear features like roads and streams.

CONCLUSIONS

The panchromatic bands of Landsat, SPOT, and IRS satellites can be classified into usable land-cover maps. The verification of this conclusion was determined by simple visual inspection of the original pan images and corresponding aerial photographs. We have tried to provide the reader a similar opportunity to evaluate the classifications using the figures in this paper. Through use of simple first-order texture algorithms in moving filter windows, new images with added information can be created for use in an automated digital image processing method. The texture images are analogous to different bands in a multispectral image. Fig. 10 provides an illustration, via a transect across three cover types, of the added value of texture for identifying land-use/land-cover types.

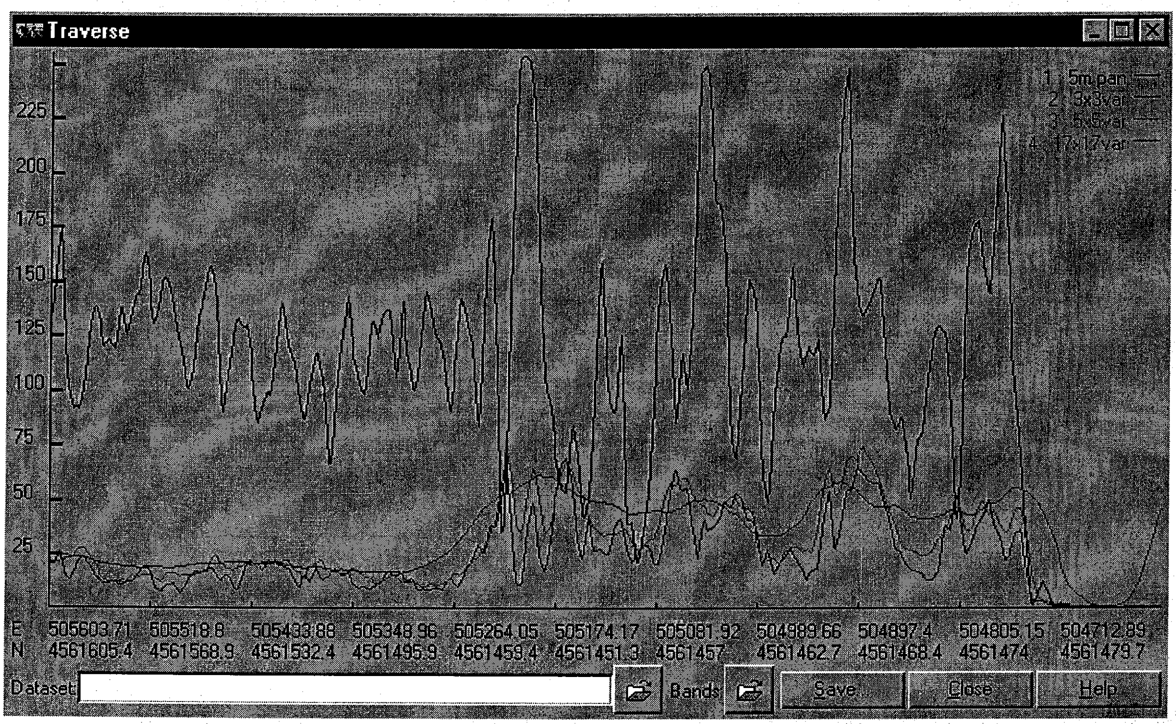


Figure 10. The added value of texture, and the effect of window size, is illustrated in this profile across 3 land use/land-cover types. Shown are the brightness values of the IRS pan images along with those of the three texture images: 3x3, 5x5, and 17x17 standard deviation. The profile starts in forest land on the left, moves into urban cover near the center, and moves into water on the right. The forest exists a medium texture (~ 25 in the 17x17 window), the urban a higher texture (~50), and the water a very low texture. Increasing window sizes smooth the variability within a class, while increasing the edge effect (area of edge) between the classes.

Maps of land cover types produced from 30m multispectral Landsat imagery incorrectly classify much of the extensive residential cover in the Delaware Gap area of Pennsylvania as forest land. Texture enhanced layers of the panchromatic bands can be automatically classified to capture this important class as well as other features requiring higher resolution images. Furthermore, this study shows that large areas covered by panchromatic images can be readily classified using simple keys at relatively high spatial detail.

SPOT and IRS panchromatic coverage are expensive compared to Landsat panchromatic images. The Landsat 7 panchromatic image is less than one-tenth the expense per unit area than IRS pan, plus it comes with an additional multispectral image (7 bands). Even though we have shown the IRS image to depict finer detail, Landsat 7 pan images are more cost effective for general mapping purposes. Perhaps the next study should look closely at ways to more quantitatively evaluate this apparent efficiency.

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