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An evaluation of radar texture for land use/cover extraction in varied landscapes

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Abstract

One of the more recent developments in operational spaceborne remote sensing is the availability of radar. This sensor has the ability to penetrate through clouds making it a more easily available data set for some locations. In addition, radar interacts very differently with surface features than optical data providing information more related to shape and structure than composition. A disadvantage of currently available spaceborne radar is that the data are almost entirely single wavelength and single polarization limiting the ability to do traditional digital classification. This study examined the usefulness of radar-derived texture measures for feature identification. Texture measures were compared independently and in combination with the original radar for digital land cover delineation. The primary methodology was standard image processing spectral signature extraction and the application of a statistical decision rule to classify the surface features for several sites in East Africa and one in Nepal. Relative accuracy of the resultant classifications was established by digital integration and comparison to validation information derived from field visitations. Variance texture measures were found to be generally very advantageous over original radar values but quite variable in their delineation accuracies from one cover type to another.

Keywords: Kenya; Land cover; Nepal; Radar; Sudan; Texture; Remote sensing

1. Introduction

In a world with increasing population and the misuse of limited land resources, there is a greater demand for current, accurate spatial information. This issue of reliable information has taken on global dimensions as the world community has recognized the need to assess problems and tasks such as environmental studies, economic planning and resource management in many diverse and separate geographical regions. Basic information concerning land use/cover is, therefore, critical to both scientific analysis and decision-making activities. Without this information scientists cannot complete valid studies and decision makers will often fail to make the correct choices (Haack and English, 1996).

One significant method for providing current, reliable land surface information is spaceborne remote sensing. Traditionally, this has taken the form of multispectral systems, such as the Landsat Thematic Mapper (TM), which collect data at several discrete bandwidths within the visible and infrared regions of the electromagnetic spectrum (EMS). These systems

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have the advantage of being a mature technology, with a broad knowledge base achieved through several decades of experimentation and use (Gerstl, 1990). More recently Earth observation research has grown with the launch of several satellite systems capable of operationally collecting radar data. These all weather sensors hold significant data-collecting potential for many geographic areas around the world, especially those often obscured by adverse weather conditions.

A radar system is an active sensor, illuminating a ground target area with its own energy signal. Radar surface feature interaction, or scattering, and the characteristics of this scattered energy, or backscatter, are dependent upon the geometric and electrical factors of the ground target area. Such factors include target material, orientation, moisture content and the degree of surface roughness. Radar image backscatter is often a direct result of the ground surface texture (Dobson et al., 1995, 1997).

A difficulty with the analysis of radar as an independent sensor is that current radar spaceborne systems only collect data at a single wavelength with a fixed polarization. Only one component of the total surface scattering is thereby being measured, while any additional information contained within the reflected radar signal is lost (Zebker and Van Zyl, 1991). Future systems will include an increased number of wavelengths and polarizations, but until then the goal of increased informational content may possibly be reached through simpler methods, such as the extraction of textural measures. Textural information may be used in addition to the spectral measurements of a single wavelength for analysis (Mauer, 1974).

Textural information may be as important as spectral information in radar images as the content of an image resides in both the intensity (spectral) of individual pixels and the spatial arrangement of those pixels (Anys and He, 1995). Standard image classification procedures, used to extract information from remotely sensed images, usually ignore this spatial information and are based on purely spectral characteristics. Such classifiers will be ineffective when applied to land use/cover classes such as residential and urban areas that are largely distinguished by their spatial, rather than their spectral, characteristics (Lee and Philpot, 1991).

The purpose of this study was to examine and improve upon the classification accuracy of specific land use/cover categories by radar-derived measures of texture in comparison to and in combination with the original radar for several study sites in East Africa and one in Nepal. By increasing the information content by specific radar manipulations, the accuracy of land use/cover classification may be improved, providing a more useful source of spatial information to scientists and planners. A cautionary note is that radar texture measures, the focus of this study, may vary with depression and incidence angle, look direction and acquisition date. It was not the intent of this study to evaluate these additional parameters but a more basic, initial evaluation of image texture.

2. Study sites and data

Several different study sites were included representing different surface conditions. These include two sites in East Africa and one in Nepal. These multiple sites allow for comparison of results in varied landscapes.

2.1. Kericho, Kenya

The Kericho site is a complex geographic region, about 80 km to the east of Lake Victoria and the port city of Kisumu, in western Kenya. The site covers an area approximately 20 km × 20 km that has an average elevation of 1500 m and a highly variable topography. Various spaceborne dates of RADARSAT were acquired for this area but with little apparent differences between them. The scene from 27 February 1997 (Fig. 1) was used for this study. RADARSAT is C-band, 5.6 cm data, with a single horizontal–horizontal (HH) polarization. It can collect data in various incident angles, spatial resolutions and swath widths. The RADARSAT data acquired for this study were with an approximate 50° depression angle and a spatial resolution of about 25 m × 28 m. The primary cover types investigated as part of this study include small, intense agricultural areas which are fallow during this date, tea plantations, natural forest and settlements.

The small, family owned and operated farms of mixed crops cover much of the northwest portion of Fig. 1. This is very productive agriculture with small

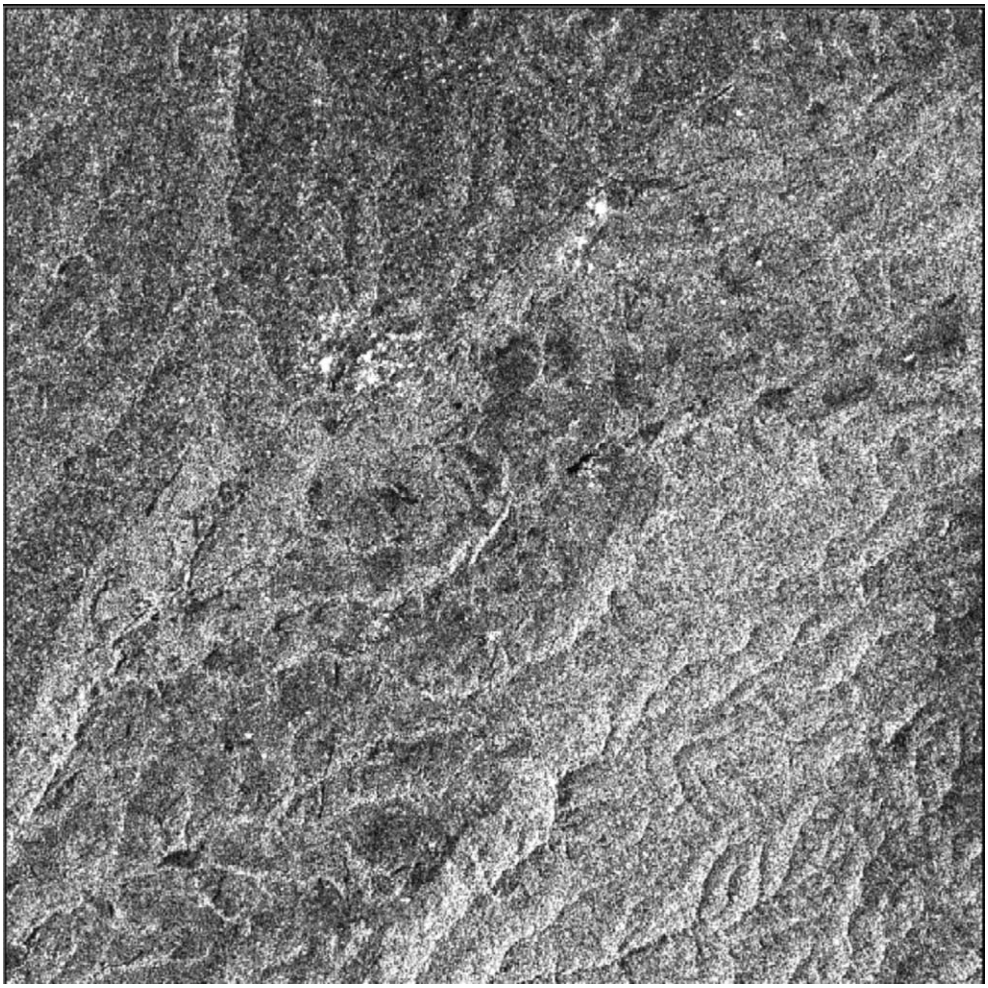

Fig. 1. RADARSAT scene of Kericho, Kenya (27 February 1997). Scene width is approximately 20 km. Visually the backscatter variations via cover type are not clearly delineated. The closed canopy forest in the southeast has a higher overall backscatter. The small, primarily fallow, agricultural fields in the northwest have a lower response. The city of Kericho in the center, while small, has some very high backscatter features. Copyright RADARSAT International.

field sizes and complex cropping patterns. Most crops grown are for family consumption and include corn, various legumes, mixed vegetables, bananas, papaya and small plots of tea or coffee. These areas include some isolated large trees and structures. These inclusions further add to the complexity of this already diverse agricultural area. Such complexity in crop type, field size and structures make it nearly impossible to map individual crops in this region. The radar image was acquired during the dry season when most fields lay fallow. The fallow fields are expected to provide little radar backscatter as they will act specularly to the incoming radar.

Large-scale tea plantations are located in the more elevated areas of the region, transecting Fig. 1 from northeast to southwest. These fields are quite extensive and provide a healthy green vegetation response throughout the year, as tea does not have an annual dormant season. A small portion of these fields are cut back to a minimum stem and primary branches each year to promote better growth. During this period and for several months following, there is no

Fig. 2. Ground photograph of the high-density settlements within the tea plantations near Kericho, Kenya.

green vegetation in these fields and they are spectrally similar to bare soil in optical sensors such as Landsat. At the highest elevations in the southeast, an area of greater topography, is a third cover type of natural, broadleaf evergreen forests. These forests are quite mature providing a high radar backscatter (light tones).

Limited areas of settlement constitute the final cover type located within this study site. Most housing in this region is associated with the small farms, and scattered throughout the mixed agricultural landscape. Though these interspersed houses make up a majority of the dwellings, they are too small and isolated to be mapped. Kericho City is located near the center of Fig. 1, between the small-scale agriculture to the northwest and tea plantations transecting the middle of the scene. The housing for the employees of the large-scale tea estates is quite concentrated, interspersed among the tea plantations. Fig. 2 is a view of one of the plantation employee settlement units. Both the city of Kericho and the plantation employee housing provide high backscatter.

The RADARSAT scene shows remarkably little difference in backscatter between the primary surface features. The natural forest has a higher tone, backscatter, as do the settlements but in general, there is little clear tonal separability in the primary land covers. Calibration (training) and validation (truth) information obtained during field visitation were converted to a raster-based geographic information system (GIS) layer and spatially fused to the imagery for signature extraction and comparison to the classification results.

2.2. *Wad Medani, Sudan*

The Wad Medani study site is situated along the Blue Nile River in central Sudan. It includes the second largest city in Sudan, which is 160 km southeast of Khartoum. Wad Medani has a population near 100,000 and is an extremely successful agricultural production area for cotton and sugar cane.

This region of Sudan is extremely flat and dry, and, with the exception of irrigated agricultural fields, contains very little vegetation. The natural vegetation is

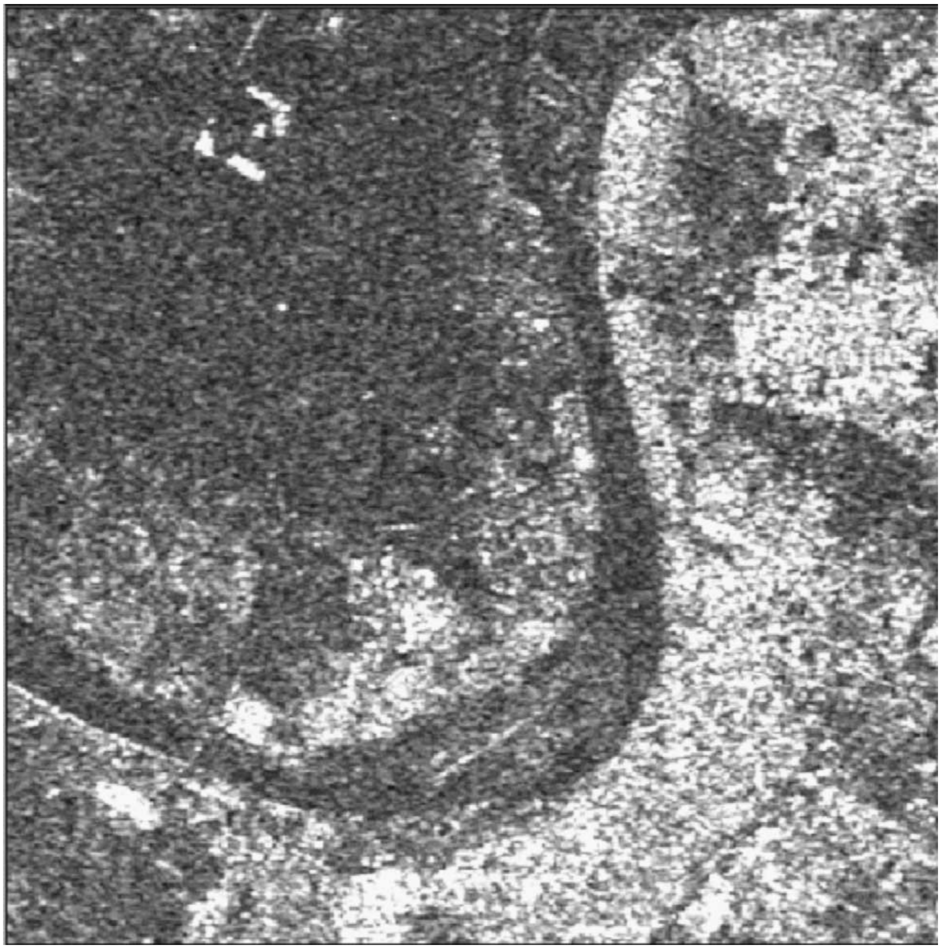

Fig. 3. SIR-B scene for Wad Medani, Sudan, collected in November 1984. Scene width is approximately 10 km. The river can be seen as a meandering low backscatter feature across the frame. Along the river and to the east and south are high backscatters from the urban and vegetative features. The low backscatter to the northwest is flat, bare soil acting as a specular feature.

mostly riparian. Areas of both agriculture and vegetation can be seen in Fig. 3 as high backscatter regions. Due to the limited extent of the natural vegetation and its similarity of response to the crops within this scene, both of these features were included under the general cover classification of agricultural. Fig. 4 is a ground photograph at the edge of the agricultural areas. In this photograph, fast-growing eucalyptus trees are under irrigation.

Other cover types include: water of the Blue Nile River, which transects the scene from the northeast to the southwest; urban areas, including villages and the city of Wad Medani; and areas of dry, bare soil, seen as the dark, low backscatter tones, in the northwestern portion of the image. Wad Medani is located in the southeastern portion of the scene below the Blue Nile. It is not clearly identifiable because it has similarly high backscatter to the vegetation.

Radar data from the Shuttle Imaging Radar mission B (SIR-B) were used in this analysis. The SIR-B mission was flown in October 1984 and collected L-band (23.5 cm) horizontal–horizontal polarization synthetic aperture data. The digitally correlated data were obtained at a 12.5 m spatial resolution and fused with raster-based calibration and validation information from field visits.

Fig. 4. Ground photograph of an irrigated agricultural area near Wad Medani, Sudan.

2.3. Kathmandu, Nepal

The Kathmandu Valley is in the central region of Nepal and encompasses an area of approximately 30 km × 35 km. The valley has very rapid urbanization resulting in the loss of valuable agricultural lands and also increasing environmental and infrastructure problems. The generally flat floor of the valley is at an average elevation of 1300 m and the sides of the valley are very steeply sloping to elevations of over 2000 m. The floor of the valley consists of two primary landforms, broad river floodplains and elevated ancient lake and river terraces, locally called tars. Major crops include rice, wheat, maize, potatoes, mustard and a number of other seeds used for oil production. A large variety of vegetables are grown throughout the year, providing fresh produce to the local population. The flat floodplains are multi-cropped, often with rice grown during the wet season followed by wheat, oil seeds or vegetables. These areas are usually irrigated and out of production only long enough for the ground to be readied for the next crop. The upland tars are typically maize during the wet season and fallow during the dry. Fig. 5 is a ground photo of the outer regions of the valley.

For this study, four land uses/covers were examined. These include the dense, older urban core; the more recent expansions of the urban areas on the margins, suburban or new urban; agriculture which is primarily fallow at the time of year of the imagery examined; and a few areas of open grass. For the purposes of urban growth mapping, it may not be necessary to separate the old urban and new urban. The grass and agriculture are also not significantly different from a land use/cover perspective for urban delineations. In examining the results from this study, the new and old urban could be combined to urban and the grass and agriculture to a non-urban class.

The old and new urban areas differ significantly, particularly from a remote sensing perspective, and thus it was necessary to separate them initially. The old urban areas are very compact with smaller but taller buildings with sloping roofs. The newer urban buildings are less dense and have flat concrete or metal roofs.

Fig. 5. Typical Kathmandu Valley view of agricultural fields on the flat valley floor and terraced slopes during the dry season.

Structures act as corner reflectors to radar and will provide high backscatter values particularly relative to the almost specular nature of fallow fields or grass surfaces. The denser, old urban areas will have higher radar backscatter than the less dense new urban locations. The new urban are mixed areas of interspersed crop fields and structures. These areas should have a high radar texture. The old urban should have a lower radar texture because of the more compact land use but there will still be some open areas with low backscatter and thus higher texture than the agriculture and grasses that should have very low radar backscatter and texture.

RADARSAT was acquired for this study (Fig. 6). In this scene, the vast majority of high backscatter, light tones, are the urban features on the valley floor. There are also areas of high return from the greater topography along the valley edges. There are virtually no remaining forest areas within the valley that would be expected to provide high backscatter and would likely be confused with the urban features. That lack of forest also limits the classification scheme. Similarly, there are insufficient areas of water for a separate classification although the river patterns are evident in the scene. The primarily fallow agriculture and grass features are both low in backscatter on this image and not easily separable.

3. Methodology

The basic procedure for this study was to conduct a digital classification of selected surface classes using standard processing techniques. Spectral signatures were extracted for the various cover types using supervised training sites identified through fieldwork. After signature extraction, a maximum likelihood decision rule was employed to classify the data sets. Accuracy assessment was calculated from a comparison of the classifications obtained to a set of validation sites, separated from the calibration areas, also derived from field efforts. An issue with window-based mea-

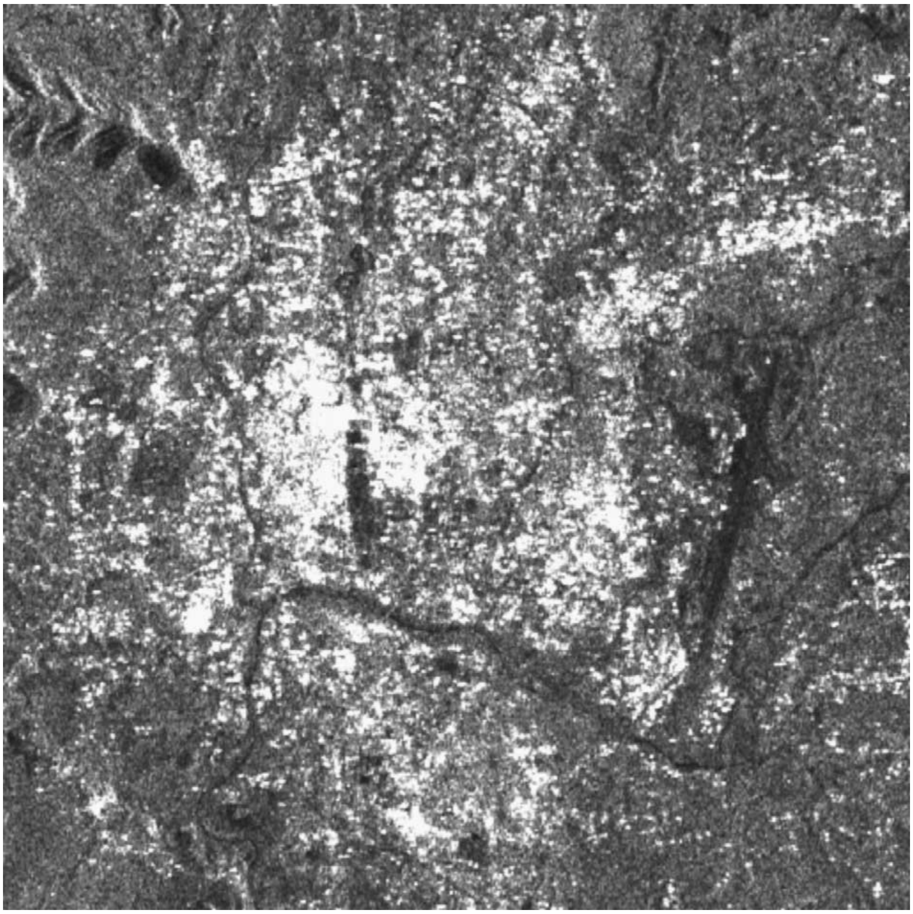

Fig. 6. RADARSAT scene of Kathmandu, Nepal (19 November 1998). Approximate image width is 10 km. The urban features are high backscatter. The dark, linear feature to the east is the airport. Some river patterns meander across the frame and some topographic shadow is apparent in the northwest. Copyright RADARSAT International.

sures, such as texture, is the boundary or edge feature delineations. Since this study was a relative comparison of classification accuracies between data and processing strategies, those boundary issues are not considered but an applied implementation of these procedures may require additional evaluations.

The results from this study consist of comparisons between the accuracy assessments from various classifications for the individual cover types, and for all of the cover types combined in an overall classification accuracy for each site. A number of data comparisons were examined. These included the original radar data independently, textural manipulations of the radar data and combinations of original radar and texture measures.

Texture is often one of the factors used to delineate or identify features by visual interpretation of remotely sensed images or photographs. Increasingly digital measures of texture are incorporated in automated classifications. Digital texture is the spatial variation of pixel values (Haralick, 1973; Nuesch, 1982). Many attempts have been made to define, characterize and construct quantitative texture measures in remote sensing with both optical or radar data (Durand et al., 1987; Irons and Peterson, 1981; Prasad and Gupta, 1988; Schistad and Jain, 1992).

Previous studies with similar radar data and landscapes evaluated texture measures to ascertain their relative value in mapping land cover in Tanzania (Haack and Bechdol, 2000). Three texture algorithms were examined: mean Euclidean distance, variance and kurtosis. In that study, the variance (second order) extraction method achieved 5–15% higher overall classification accuracies than the other texture measures. Based on those results, the variance measure of texture was examined in this study.

Most texture measures utilize a moving array of cells with a variety of mathematical measures to derive texture values for the center cell of the moving array. It is unclear how the size of the moving window influences classification accuracies. Haralick (1973) used windows of 64×64 and achieved Level 1 USGS classification levels. Mauer (1974) conducted texture measures with 50×50 windows on 1:7800 scale aerial photographs and recorded promising results. Different window sizes can have a positive or negative effect depending on the intended application. Hsu (1978) stated that even relatively small moving arrays (5×5) can cause extensive misclassification at the boundaries between classes. However, Blom (1982) found that window sizes of 15×15, 31×31 and 61×61 provided constructive results for larger-scale applications. The influence of various window sizes is a function of surface characteristics, sensor type and spatial resolutions.

Texture measures were examined by Haack and Bechdol (2000) with varied window sizes using the variance (second order) measure of texture. Although an increase in overall classification accuracy was steady as window sizes became larger, the increase was very slight and the point of diminishing returns for overall classification accuracies due to window size was at the 13×13 window size. This study also evaluated several different window sizes. Texture will vary as a function of a variety of factors but particularly sensor spatial resolution and surface feature sizes. By evaluating a range of window sizes, the impact of texture window size may be better evaluated. For the Kathmandu site, there are many smaller features, structures, and thus smaller window sizes were evaluated.

4. Results

4.1. Kericho

Evaluation of the Kericho study site was accomplished by comparing classifications to validation information. For Kericho there were 16,780 validation pixels, which included four forest sites (8848 pixels), five tea plantation sites (2761 pixels), one urban site (114 pixels) and four sites of mixed agriculture (5057 pixels). The low number of urban pixels was due to the lack of large urban areas within the scene. The city of Kericho was the only urban area available for the purposes of accuracy assessment. The differences in the size and number of the validation information was of particular importance, as larger classes, such as the forest class, would contribute more substantially to an overall classification percentage, while a small class, such as urban, will have little influence. This could result in misleading overall classification accuracies. For this reason, individual class accuracies were evaluated in addition to the overall percentage of correctly identified pixels.

4.1.1. Original radar

Initial examination of the RADARSAT image for Kericho provided poor classification results. As can be seen in Table 1, the overall classification, as well as most of the individual class accuracies, were quite low. The more unique, higher backscatter areas of the urban/settlement class had the best producer's classification accuracy at approximately 67%, but provided a very low user's accuracy.

A larger number of pixels from each of the forest, tea and mixed agricultural classes were incorrectly included as part of the urban category (1948 out of 2024 pixels) than were correctly classified as urban pixels. Though this misclassification did not affect the proportion of correctly identified urban pixels (76 out of 114 pixels), it did decrease the reliability of the urban class. The reliability was decreased because as the total number of pixels classified as urban features increased, the correctly identified urban pixels occupied an increasingly lower proportion of that total (76 out of 2024 pixels). This resulted in a much larger urban area than should have been present within the classification. The accuracy of the other classes decreased as well, as a number of pixels that should have been included within each of these classes were removed and instead classified as urban.

This was a particular problem within the forest class, which had the largest number of pixels incorrectly assigned as urban, though the incorrect classification of forest areas was not limited to this

Table 1
Contingency table for Kericho RADARSAT

	Forest	Tea	Urban	Mixed agriculture	Total	User's accuracy (%)
Forest	2750	541	19	525	3835	71.71
Tea	2696	1094	10	1530	5330	20.53
Urban	1756	108	76	84	2024	37.55
Mixed agriculture	1646	1018	9	2918	5591	52.19
Total	8848	2761	114	5057	16780	
Producer's accuracy (%)	31.08	39.62	66.67	57.70		
Overall accuracy (%)						40.75

urban misclassification. The urban class occupied 20% (1756) of the forest truth pixels, but nearly 30% of the forest class was misidentified as tea plantations (2696) and 19% (1646) as mixed agriculture. These errors of omission decreased the producer's accuracy of the forest class and increased the total number of pixels assigned to the other classes, which in turn decreased their user's accuracy or reliability.

Errors of omission and commission are directly related and overlap in effect. An individual class may possess one or the other, or it may possess both types of errors. The urban class had a fairly high producer's, or classification, accuracy with a very low user's accuracy, while the forest class had a fairly high user's, but a low producer's accuracy. The tea and mixed agricultural classes added to the errors associated with both the urban and the forest classes, but also had a more general confusion between themselves. Both the user's and producer's accuracies for these classes were low, as they had nearly the same number of pixels confused with the other classes as they have correctly classified.

These results are consistent with examination of the RADARSAT imagery (Fig. 1). The RADARSAT spectral signatures for the forest, tea and mixed agriculture covers do not greatly differ, returning visually and spectrally similar responses. They have average digital number (DN) values of 139, 113 and 103 (respectively) and all possess high standard deviations. This creates areas of overlap in their spectral signatures, which creates confusion, and limits their spectral separability. The urban class has a much higher average DN value at 206, which improves its spectral discrimination, but also has a much higher standard deviation. This high standard deviation indicates that both high and low DN values may be included in the urban class, which accounts for the overclassification of urban as many pixel values fall within this signature range.

4.1.2. Texture

The high standard deviation associated with the RADARSAT's urban class suggested that measures of image texture could possibly increase the discriminatory ability of radar. Measures of variance texture were applied to the original RADARSAT data over 13×13, 21×21 and 29×29 moving window sizes. The results indicate that texture does improve discrimination. Overall classification accuracies of 67, 72 and 71% (respectively) were achieved, improving over those of the original radar data by about 30%.

Results achieved with use of the 21×21 texture window size were best. The effectiveness of this texture window size is closely related to the spacing and size of the ground features being observed. Table 2 contains the contingency matrix for these results. This texture-based classification greatly increased the overall accuracy and especially increased the accuracy and reliability of the forest and urban classes. The urban features were discriminated perfectly by the 21×21 texture image, eliminating all of the confusion and errors previously seen with that class. The confusion associated with the forest class (both errors of omission and commission) was also all eliminated, but with only minor confusion between it and the mixed agriculture and tea classes. The only remaining area of major confusion was isolated between the mixed agricultural class and the tea plantations. These two land covers seemed to be very similar in terms of radar backscatter value and spatial variability or texture.

The impressive improvements obtained with the use of texture can be explained through examination of the 21×21 variance texture image's spectral signatures,

Table 2
Contingency table for Kericho 21 × 21 variance texture RADARSAT

	Forest	Tea	Urban	Mixed agriculture	Total	User's accuracy (%)
Forest	8672	410	0	99	9181	94.46
Tea	0	1205	0	2949	4154	29.01
Urban	0	0	114	0	114	100
Mixed agriculture	176	1146	0	2009	3331	60.31
Total	8848	2761	114	5057	16780	
Producer's accuracy (%)	98.01	43.64	100	39.73		
Overall accuracy (%)						71.51

and the comparison of these signatures to those of the original RADARSAT data. Both of these spectral signatures are contained in Table 3. Signatures from the 21×21 variance texture image were much more unique and separable than those of the original RADARSAT, which had several similar values and large overlapping responses. The most unique of the textural signatures belonged to the urban class. It had the highest mean value (60), indicating a high degree of texture and a low standard deviation. This made the urban class easily separable from the other land covers. The forest class was similar, in that it was also highly textured (40) and substantially isolated from the other class signatures, explaining its high degree of accuracy. These signatures also explain the mutual misclassification of the tea and mixed agricultural classes, as backscatter and textural confusion between these two classes created a large degree of spectral overlap, leaving the statistical decision rule little information on which to base its pixel assignment.

4.1.3. Radar fusion

Several combinations of the original radar data and texture were examined to assess the utility associated with an increased number of radar bands. The producer's accuracies for the best of these can be seen in Table 4 in comparison to the original radar and texture. Results demonstrate that the addition of texture measures to the original radar data provided no improvement over the classification accuracies of the radar texture alone. This could have been expected, as a high degree of confusion was associated with the original RADARSAT data. As the original data were of little use on their own, they provided little additional information content when merged with a texture image.

Table 3
Spectral signatures for Kericho RADARSAT and 21 × 21 variance texture RADARSAT

	Forest	Tea	Urban	Mixed agriculture
RADARSAT				
Mean	103	113	206	139
S.D.	31	32	60	43
21 × 21 variance texture				
Mean	40	30	60	30
S.D.	2	1	2	3

4.2. Wad Medani

Evaluation of the Wad Medani, Sudan, study site analysis was accomplished by comparing the classifications to areas of known features obtained during ground visitation. For Wad Medani, there were 9625 validation pixels. These pixels included four areas of water (970 total pixels), three agricultural and natural vegetation sites (1621 pixels), three urban areas (3435 pixels) and three areas of other ground cover or bare soil (3599 pixels). The lower number of water and agricultural pixels is primarily due to the dry climate of this area and the resulting lack of moisture for these features. The only body of water within the study region was that of the Blue Nile River, which meanders across a thin section of the scene. Agricultural areas, too, were limited in this subscene as irrigation is needed to sustain crops. The riparian vegetation exists only at very close proximity to the Blue Nile.

4.2.1. Original radar

The SIR-B image of Wad Medani provided poor overall classification results (∼51% accuracy). Con-

Table 4
Producer's accuracies for Kericho radar manipulations

	Forest	Tea	Urban	Agriculture	Total
Radar	31	40	67	58	41
Variance texture 21 × 21	98	44	100	40	72
Two-band radar and 21 × 21 texture	97	50	100	41	72

fusion was caused by similarities in the radar spectral responses between the urban and agricultural areas, as well as between the water and other/bare soil classes. These areas of confusion are clearly demonstrated in Table 5 which contains the distribution of pixels and resulting classification accuracies for each of these individual classes.

The water class is most representative of the confusion associated within the scene as it has both the poorest producer's (∼33%) and user's accuracies (∼20%), indicating a high degree of both errors of omission and commission. More water areas were incorrectly classified as other/bare than were classified as water (602 versus 326 pixels). These incorrect pixels accounted for approximately 62% of the actual water areas. More pixels were also identified as water (errors of commission), than were correctly identified as water (1398 pixels). The majority of these pixels should have been assigned to the other/bare cover class (1200 pixels).

Conversely, the pixels incorrectly included as part of the other/bare cover class should almost entirely have been assigned as water pixels (2313 pixels), and though this class has the highest producer's (∼64%) and user's (∼68%) classification accuracies, these incorrectly included water pixels make up over 60% of the area identified as other/bare. Confusion similar to that between the water and other/bare classes was found between the agriculture and urban areas. Agricultural areas were commonly classified as urban features (∼47% of the time) and the urban features were often misclassified as agricultural areas (∼40% of the time).

Such confusion can be expected from the examination of the SIR-B radar image in Fig. 3. Both the agriculture and urban areas are represented by similarly high backscatter values with high texture or standard deviations, while the water and other/bare classes are both represented with similarly low backscatter values and relatively low texture and standard deviations. As such, radar backscatter values alone were not enough to discriminate between these land cover classes.

4.2.2. Texture

Variance texture measures were extracted to increase the discrimination between land use/cover classes. The results for 13 × 13, 21 × 21 and 29 × 29 textural window sizes indicate that texture did improve the overall class discrimination within this scene. Overall classification accuracies of 67, 71 and 68% were achieved with each of these moving window sizes (respectively). Table 6 lists the producer's accuracies for the 21 × 21 texture image. An interesting aspect of Table 6 is the significant improvement

Table 5
Contingency table for Wad Medani SIR-B radar

	Water	Agriculture	Other/bare	Urban	Total	User's accuracy (%)
Water	326	84	1200	114	1724	19.91
Agriculture	0	594	0	1366	1960	30.31
Other/bare	602	185	2313	285	3385	68.33
Urban	42	758	86	1670	2556	65.34
Total	970	1621	3599	3435	9625	
Producer's accuracy (%)	33.61	36.64	64.27	48.62		
Overall accuracy (%)						50.94

Table 6
Producer's accuracies for Wad Medani radar manipulations

	Water	Agriculture	Bare soil	Urban	Total
Radar	34	37	64	49	51
Variance texture 21 × 21	41	87	99	42	71
Two-band radar and 29 × 29 texture	69	70	99	45	72

for some classes, agriculture and bare soil, and not similar improvement for all classes.

4.2.3. Radar fusion

Combinations of radar and texture were examined to assess the utility of an increased number of bands. The result of one of these mergers and their resulting classification accuracies are also included in Table 6. There is no significant improvement in total classification over texture. However, there are significant individual class differences such as the increase in water and decrease in agriculture and urban accuracies. The increase in water classification may be due to the small size of the water that was lost in the large window size of the texture. By including the original radar without filtering, it may have been able to more accurately identify the water. The decrease in urban and agriculture may be because of their similarity in the original SIR-B backscatter.

4.3. Kathmandu

4.3.1. Original radar

Initial examination of the RADARSAT image for Kathmandu provided poor classification results. As can be seen in Table 7, the overall classification, as well as most of the individual class accuracies, were quite low. The more unique, higher backscatter areas of the old urban class had the best producer's classification accuracy at approximately 77%, but provided a very low user's accuracy (42%). The primary confusion was between old and new urban. If these classes were combined, the results would be much better. There was, however, also considerable confusion between agriculture and new urban (1081 erroneously classified truth pixels) and thus poor results for new urban.

4.3.2. Texture

The high standard deviation associated with the RADARSAT's urban classes (Table 8) suggests that measures of image texture could possibly increase the discriminatory ability of radar. Measures of variance texture were applied to the original RADARSAT data over 5 × 5, 13 × 13 and 21 × 21 moving window sizes. The initial smaller window sizes reflect the knowledge of smaller features in the scene. The results indicate that texture does improve discrimination. Overall classification accuracies of 71, 75 and 69% by respective window size were achieved, improving over those of the original radar data by about 20%.

Results achieved with the 13 × 13 texture window size were best. The effectiveness of this window size is related to the variability and spacing of the ground

Table 7
RADARSAT original data results for Kathmandu

	Grass	Agriculture	Old urban	New urban	Total	User's accuracy (%)
Grass	337	1257	0	115	1709	19.72
Agriculture	112	2882	44	1081	4119	69.97
Old urban	0	6	1086	1499	2591	41.91
New urban	0	185	284	1594	2063	77.27
Total	449	4330	1414	4289	10482	
Producer's accuracy (%)	75.06	66.56	76.80	37.16		
Overall accuracy (%)						56.28

Table 8
Kathmandu sample spectral signatures (RADARSAT and RADARSAT 13 × 13 texture)

	RADARSAT	Texture
Grass		
χ	44.366	21.743
σ	11.005	10.674
Agriculture		
χ	71.537	20.721
σ	21.204	2.228
Old urban		
χ	238.677	45.338
σ	34.295	9.642
New urban		
χ	166.089	57.855
σ	59.224	3.642

features being observed such as field and building size, particularly in the new urban locations. Table 9 contains the contingency matrix for these results. The confusions are within the two non-urban and the two urban classes. Class combinations would improve results greatly. Table 8 contains selected class mean texture values for a 13×13 window. The almost identical mean texture values for grass and agriculture (22 and 21) explain their classification confusion. Similarly, Table 8 documents the large texture differences between the two urban and two non-urban classes that allow their easy discrimination with variance measures.

4.3.3. Radar fusion

Several two- and three-band combinations of the original radar data and the manipulations of those data were examined to assess the utility associated with an increased number of radar bands. Combinations examined included original radar and texture combinations as well as combinations of multiple textures. Table 10 contains the results from the original RADARSAT and 13 × 13 window variance texture. The overall results are similar to the independent texture but there are considerable changes from class to class. Almost all of the confusion, however, is between the grass and agriculture or new and old urban. Table 11 is a summary of all three Kathmandu radar classifications.

5. Discussion

The radar data have been shown to be incapable of accurately delineating the land use/cover types of these three study sites. Variance texture measures were found to be advantageous. The overall results were significant improvements over radar and several individual classes had excellent results with texture. The combination of original radar and texture measures generally did not provide significant improvements over the texture measures independently. An important observation is that the radar improvements with texture are not for all classes but some specific classes. To some degree, it would be expected that the texture measures will improve results simply because of the filtering procedure. However, filtering alone should have improved all covers similarly which is not the case. Clearly some covers do have more separability by use of texture where they do not have separability in the original radar.

RADARSAT data were used for two sites, Kericho and Kathmandu, while SIR-B was used for Wad Medani. This was simply a function of data availability. There was no intent to compare the sensors in this study and no conclusions can be drawn.

Table 9
Kathmandu RADARSAT 13 × 13 pixel variance texture

	Grass	Agriculture	Old urban	New urban	Total	User's accuracy (%)
Grass	62	624	88	46	820	7.56
Agriculture	213	3594	2	0	3809	94.36
Old urban	122	112	801	791	1826	43.87
New urban	52	0	523	3452	4027	85.72
Total	449	4330	1414	4289	10482	
Producer's accuracy (%)	13.81	83.00	56.65	80.48		
Overall accuracy (%)						75.45

Table 10
Kathmandu contingency table for RADARSAT and 13 × 13 variance texture

	Grass	Agriculture	Old urban	New urban	Total	User's accuracy (%)
Grass	302	552	3	267	1124	26.87
Agriculture	130	3755	0	5	3890	96.53
Old urban	0	6	973	1043	2022	48.12
New urban	17	17	438	2974	3446	86.30
Total	449	4330	1414	4289	10482	
Producer's accuracy (%)	67.26	86.72	68.81	69.34		
Overall accuracy (%)						76.36

Table 11
Producer's accuracies by class for Kathmandu radar processing

	Grass	Agriculture	Old urban	New urban	Total
Radar	75	67	77	37	56
Variance texture 13 × 13	14	83	57	80	75
Two-band radar and 13 × 13 texture	67	87	69	69	76

Interestingly perhaps is that the overall classification accuracy for the SIR-B site, Wad Medani, was 51%, between the two RADARSAT accuracies of 41 and 56%.

These results show the potential of radar texture for mapping some basic land use/cover patterns. More case studies will contribute to an improved understanding of useful radar analysis techniques. Future applications of this project will include a comparison with other classifiers, including a hierarchical and regression tree approaches; an extension of basic land use/cover to more complex land use/cover classification schemes; more radar manipulations such as speckle reduction or post-classification filtering; different depression angles, look directions or radar dates; and sensor merger with optical data.

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