Radar and Optical Data Integration for Land-Use/Land-Cover Mapping

Barry N. Haack, Nathaniel D. Herold, and Matthew A. Bechdol

Abstract

This study evaluated the advantages of combining traditional spaceborne optical data from the visible and infrared wavelengths with the longer wavelengths of radar. East African landscapes, including areas of settlements, natural vegetation, and agriculture, were examined. For three study sites, multisensor data sets were digitally integrated with training data and ground-truth information derived from field visits. The primary methodology was standard image processing, including spectral signature extraction and the application of a statistical decision rule to classify the surface features. The relative accuracy of the classifications was established by comparison to ground-truth information. In all sites, the merger of optical and radar sensors improved the ability to map surface features over either sensor independently, although different manipulations of the radar data were necessary to obtain the most useful results. Those manipulations included measures of texture, spatial filtering, and despeckling prior to texture extraction.

Introduction

A basic problem in economic planning, environmental studies, or resource management is obtaining and maintaining current, accurate information. The need for basic surface characteristic information, such as land use and land cover, is critical to both scientific analysis and decision making activities. Without accurate information, scientists cannot complete valid studies and decision-makers often fail to make correct decisions. One significant method for providing current, reliable surface information is satellite remote sensing. Spaceborne remotely sensed data may be particularly useful in developing countries such as in Africa (Morain, 1991).

The use of remote sensing for resource assessment and basic mapping has a considerable history and increasing use in Africa. There have been regional and national centers for remote sensing established in many countries. Some of these have existed for over 20 years, even prior to the availability of spaceborne imagery with the launch of Landsat in 1972. A number of these centers were established under international assistance programs directed at remote sensing technology transfer. The United States Agency for International Development was quite active with these centers, including the establishment of regional centers in Nairobi, Kenya and Ouagadougou, Bukina Faso (Paul and Mascarenhas, 1981).

One of the more promising recent achievements in remote sensing has been the operational capability to collect radar data from space, such as has been established by the United States Shuttle Imaging Radar (SIR) missions, the European Space Agency ERS, the Japanese JERS, and the Canadian RADARSAT satellites. The research and applications remote sensing communities are still in the early stages of understanding the characteristics and uses of spaceborne radar. Some applications, including tropical deforestation and sea ice monitoring, are routinely being used.

The purpose of this study was to evaluate multisensor data sets of spaceborne multispectral optical data and spaceborne radar for the delineation of land use/land cover for sites in East Africa. The primary intentions were to ascertain what improvements may be obtained using a multisensor data set and how to improve the utility of radar data. East Africa provides a range of surface characteristics that are representative of many regions of the Earth. Mapping procedures established there should be spatially extendible.

Radar Background

Radar has special properties that make it a viable alternative and/or partner to traditional optical remote sensing techniques (Foody, 1988). For instance, microwave energy is capable of penetrating atmospheric conditions that render traditional spaceborne optical and multispectral systems useless (Elachi, 1988). Radar therefore has the ability to image through rain, fog, hail, smoke, and, most importantly, clouds. These characteristics hold enormous data-collection potential in many countries around the world, especially those areas such as Central Africa that experience persistent cloud cover. An additional advantage of radar is that the feature interaction is a function of geometry, texture, and dielectric constant which is different from the reflectance interactions of optical systems (Forster, 1996). These different interactions have the potential to provide information beyond that of optical data.

Remote sensing research on radar exists in two primary categories. The first includes methods to improve the capability of radar as an independent sensor. A difficulty with analysis of radar data as an independent sensor, particularly in automated classification, is that most spaceborne systems only collect data at a single wavelength with a fixed polarization. This prohibits many classifications. There are several options to provide more bands for digital classification from single-band radar. Those options typically include the use of multitemporal data sets or the extraction of texture as unique bands (Luckman *et al.*, 1997; Prasad and Gupta, 1998). Other manipulations of radar to improve information extraction include spatial filtering such as pre- or post-classification smoothing and despeckling (Durand *et al.*, 1987).

B.N. Haack and N.D. Herold are with the Department of Geography and Earth Sciences, MSN 1E2, George Mason University, Fairfax, VA 22030 (bhaack@gmu.edu.).

M.A. Bechdol is with Global Science and Technology, 6411 Ivy Lane, Greenbelt, MD 20770.

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The second area for research with spaceborne radar is to evaluate its relative value and complementarity with more traditional visible and infrared wavelength sensors. In some situations it is clear that one system has advantages over the other. In other situations, the integrated use of data from these discrete portions of the electromagnetic spectrum may be advantageous (Welch and Ehlers, 1988; Harris *et al.*, 1990; Raghavawamy *et al.*, 1996; Pohl and Van Genderen, 1997). Sensor integration may provide a clearer image, may reduce redundancy of optical bands, and may improve classification accuracies.

Paris and Kwong (1988) used a combination of SIR-B and Landsat Thematic Mapper (TM) data to provide quantitative information on the amounts of herbaceous and woody vegetation. They found these data types to be complementary, with the optical TM providing information on green biomass and the radar on woody biomass. The synergism of airborne radar and Landsat Thematic Mapper (TM) was examined by Brisco and Brown (1995) for agricultural fields using both single-date and multi-date data. They obtained the best classification accuracy, 92 percent, by a multitemporal combination of the two data types.

In automated classification with multispectral data, often the best band combinations are those with at least one band from each available portion of the electromagnetic spectrum. By merging optical and radar data, an additional portion of the spectrum is available that may improve classification. Radar, because it responds more to the structure of surface features rather than to their internal characteristics and reflectivity, is potentially an interesting and useful addition to optical data.

Study Sites and Data

A number of sites in East Africa were selected in order to examine different climatic areas and surface features. These sites include a very dry landscape with settlements and irrigated agriculture in central Sudan (Wad Medani); a very wet location of natural forest, plantation agriculture, and intense small scale agriculture in western Kenya (Kericho); and a site of refugee camps in an arid region in eastern Kenya (Dadaab). There is a temporal difference in the analysis of these sites. The original work was in Sudan and, based on its success, the methods have been extended to Kenya.

Wad Medani, Sudan

This analysis was limited to an area along the Blue Nile River, in central Sudan, where coincident radar and optical data had been acquired. Specifically, the study area was approximately 25 km by 40 km, and included the second largest city in Sudan, Wad Medani. The site extended northwest from Wad Medani along the Blue Nile. Wed Medani is about 160 km southeast of Khartoum and has a population near 100,000. It is a service city for the large Geneid Gezira irrigated agricultural schemes along the Blue Nile that extends west to the White Nile. This is an extremely productive area for cotton and sugar cane.

Two primary data sets were obtained for this analysis. The first was digital radar data from the SIR-B mission. The SIR-B mission was flown in October 1984 and collected L-band (23.5-cm) synthetic aperture data at a pixel size of 12.5 m. The second data set came from a standard, seven-band digital Landsat TM image, acquired on 18 November 1984. The TM sensor collects data in six visible and infrared wavelengths at a 30-m spatial resolution, and a thermal wavelength at a 120-m resolution. The two data sets were geometrically registered and merged to the 12.5-m pixel size of the original SIR-B using a nearest-neighbor intensity resampling.

Ground information was obtained during a field visit in 1988. Using enlarged SIR-B and Landsat TM prints with limited available maps, samples of the various land use/land covers were documented on overlays to the hardcopy imagery. This information was then converted to a raster-based GIS format and registered to the TM/SIR-B data set. There were four categories of basic land use/land cover incorporated into the GIS layer. Those categories were urban, agricultural, natural vegetation, and background/other. The background/other category was primarily the extensive, flat areas of bare soil, which produced a low radar backscatter return. Housing in the area is made of indigenous materials, primarily clay, which is spectrally similar to the surrounding bare soil.

Radar data have been effectively used in locating cultural targets, because man-made features provide a large return due to the high dielectric properties of some construction materials (such as metal) and the geometric shape of many cultural surfaces. Buildings often act as corner reflectors to the radar signal and thus have a high return, but radar can also produce a high backscatter from vegetation. This is due to the texture of the vegetative canopy and the dielectric properties of leaf moisture (Richards, 1990; Dobson *et al.*, 1992; Ranson *et al.*, 1995). This similarly high radar backscatter between villages and vegetation can be observed in the SIR-B image of the Wad Medani area (Figure 1). This image is oriented such that north is to the upper left and the Blue Nile is very apparent. The city of Wad Medani is the large, very high return area at the extreme right within a major bend of the Blue Nile.

The agricultural areas are obvious along the lower left portion of the scene, due to their rectilinear patterns. These areas include both high and low returns. The high-return agricultural features are active fields, generally cotton or sugarcane, while the low-return fields are fallow. These fallow fields act as specular features and reflect the radar energy away from the sensor.

The villages and urban areas are not identifiable on the TM image because much of the construction material (vegetation, bricks, and adobe) spectrally blends into the surrounding landscapes. Both the bare soil and villages provide similar blue-grey returns on a standard false color composite image. Visually, neither the TM nor SIR-B imagery can independently differentiate between the primary surface features in this area of Sudan (Haack and Slonecker, 1994).

Kericho, Kenya

This is a complex site in western Kenya, about 80 km to the east of Lake Victoria and the port city of Kisumu. This area has a

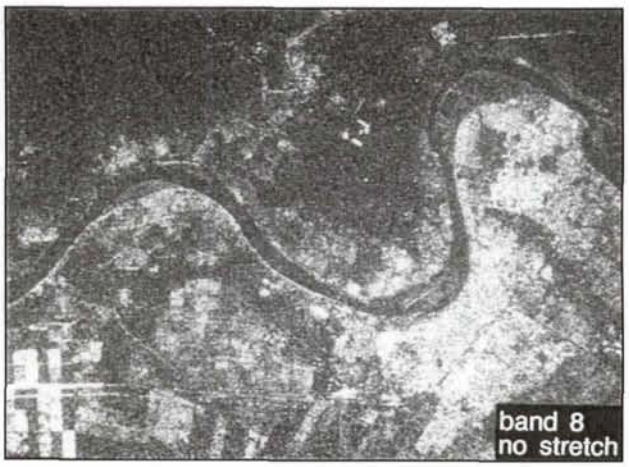

Figure 1. SIR-B Image along the Blue Nile in Sudan. Approximate original scale 1:40,000, reduced to approximately 1:110,000. North is to the upper left.

high average elevation (1500 m) with considerable local variations and several steeply sloping features. The area has excellent volcanic soils and suitable climatic conditions for agriculture, and also one of the highest population densities in East Africa.

Small, family owned and operated farms of mixed crops cover much of the region. This is very intense agriculture, as field sizes are small and the cropping patterns are complex. The crops include corn, legumes of various types, mixed vegetables, fruit including bananas and papaya, and small plots of tea and coffee, most of which are for family consumption. This crop complexity and the small field sizes make it nearly impossible to map individual crops.

Large-scale plantations of tea are present in the more elevated areas. These fields are quite extensive and provide a high green vegetation response thoughout the year as tea does not have an annual dormant season. Each year a small number of fields are cut back to a minimum stem and primary branches to promote better growth on about a seven-year rotation. For several months following this cut back, there is no green vegetation in these fields, and optically the fields are spectrally similar to bare soil. Another cover type in this region is mature, evergreen forest which occupies the highest elevations.

Plate 1 is a Landsat TM image of this study site. Three of the primary cover types (urban areas excluded) are easily seen in this image based on their tone, texture, and continuity. This is a dry season image and the small, fallow fields are distinctly visible in the northwestern part of the image as blue-grey spectral tones. Small areas of green trees, tea, and coffee are the interspersed red features among the fields. Moving east the large, pink toned and flat textured tea plantations are distinctly visible, while at higher elevations on the southeast edge of the subscene is the natural forest in dark red.

Areas of settlement are limited within this region. Most housing is associated with the small, dispersed farms or the large-scale agricultural landscapes. The housing for the employees of the tea estates is quite concentrated. These areas are small blue-grey tones among the tea. They are, however, spectrally and spatially very similar to the cut-back tea fields on the TM subscene. The larger city of Kericho, located near the center of the subscene between the small-scale agriculture and tea, is difficult to delineate due to the similarity in tone (blue-grey) to the bare soil.

Figure 2 is a RADARSAT, C band (5.6 cm) HH polarization, image collected on 27 February 1997. There is surprisingly little differentiation between the primary land covers in this scene. The city of Kericho is a bit more evident, as an area of very high returns. The limited variation in the scene was consistent over a variety of dates and is apparently a result of frequent rainfall and surfaces being quite moist, providing similar backscatter.

Dadaab, Kenya

This is a refugee area located in the very arid region of eastern Kenya just north of the equator, about 100 km northeast of the larger city of Garissa and 70 km west of the Somali border. This is a historic area of low population density, based on nomadic herding with virtually no agricultural cropping. There are three large refugee camps, each with about 30,000 individuals, mostly from Somalia. These three camps are under the supervision of

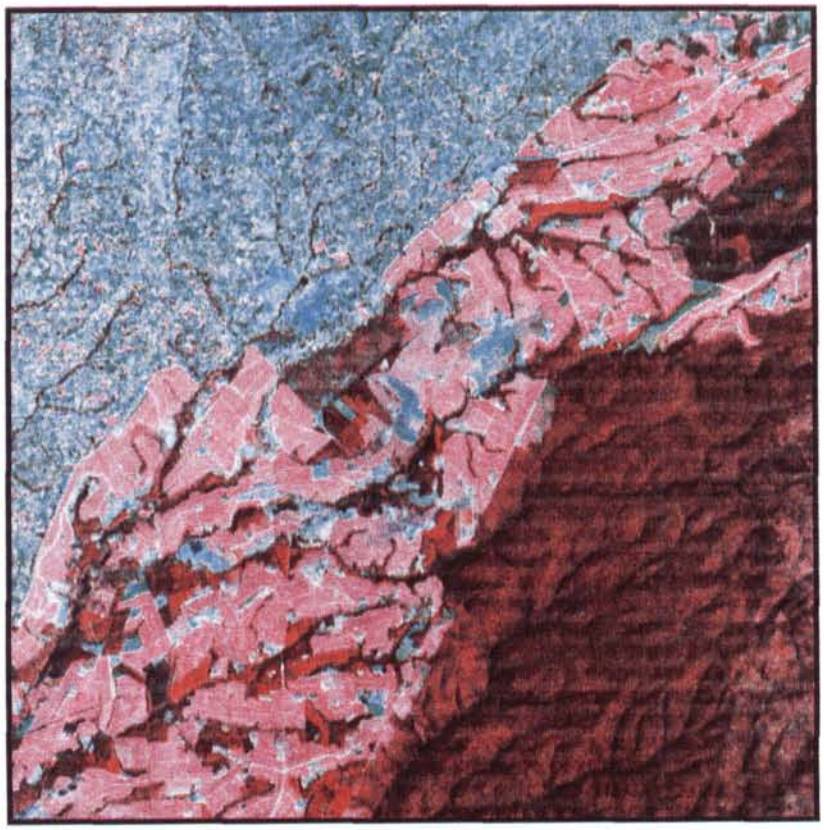

Plate 1. Landsat TM scene of Kericho collected on 21 January 1995. Bands 3, 5, 4, are displayed in BGR. Approximate original scale of 1:140,000, reduced to approximately 1:185,000. North is at the top. © Space Imaging/Landsat 1995.

Figure 2. RADARSAT scene of Kericho collected on 27 February 1997. Approximate original scale of 1:140,000 reduced to approximately 1:185000. North is to the top. ©RADARSAT (1997).

the United Nation's High Commission for Refugees (UNHCR) and are very compact and densely populated. The areas around the camps are medium height desert shrubs (1 to 3 m) with little grass cover. Much of the vegetation within the immediate proximity of the camps has been removed by grazing or for fuel and building materials.

Various spaceborne data were received for this site, including a Landsat TM scene from 17 February 1995. A RADARSAT image from 15 August 1996 (Figure 3), having a spatial resolution of 25 by 28 m, was also acquired and co-registered to the optical bands. The camps are very distinct visually due to their high backscatter and geometric shape. Areas around the camps are dark tones of low backscatter from bare soil, because much of the vegetation has been removed for fuel or by grazing. The vegetation provides a range of backscatter that is generally quite high and similar to the camps in intensity. The classes selected for this scene included these camps, the bare soil, and various types of vegetation.

Methodology and Results

The basic procedure was to conduct a digital classification using standard processing techniques applied to the spatially coregistered set of spaceborne radar and optical bands, all resampled to the same pixel size. Spectral signatures were extracted for the various land uses/covers using supervised training site procedures. Field visits were used to identify valid training sites. After signature extraction, a decision rule was employed to classify the data set and a contingency table compiled for accuracy assessment. The contingency tables were created from comparison of classifications to a set of truth sites, separate from the training areas, which were also derived from the field efforts. For all accuracy assessments, polygons of the primary cover types were used as truth areas and not individual pixels.

The results from this study compare the accuracy from various classifications for individual land-use/land-cover types and for all of these classes combined. A number of data combinations and geospatial manipulations of the data were examined, including comparisons of the original sensor data independently and in combination, incorporation of texture measures, and speckle reduction procedures.

Wad Medani, Sudan — Original Values

Spectral signatures for the primary surface features (Table 1) were extracted from training data, obtained during field visitation. Two training sites were included for each of these features to provide information on the within-class variations. An examination of this table correlates well with what can be observed in the imagery. Reflectance values for the urban and other (bare soil) classes are not significantly different in any of the TM bands, but can be differentiated in the SIR-B data. By contrast, the spectral signatures for the agriculture and urban classes are similar in the radar data, but are separable in several of the TM bands, particularly bands 5 and 7. Neither sensor can independently delineate the primary cover types, either visually or digitally.

The classification strategy was to first separate the urban and other (bare soil) sites from the agricultural sites using the TM bands; then, the urban areas could be delineated from the other (bare soil) areas using the SIR-B data. This process was

Figure 3. RADARSAT scene of Dadaab from 15 August 1996. Approximate original scale of 1:180,000 reduced to approximately 1:240,000. North is to the top. ©RADARSAT (1996).

TABLE 1. SPECTRAL SIGNATURES FOR WAD MEDANI, SUDAN

Cover		TM1	TM2	TM3	TM4	TM5	TM6	TM7	SIR-B
Agriculture 1	Mean	87	40	47	86	82	162	35	168
	SD	10	7	15	22	17	7	12	42
Agriculture 2	Mean	89	41	51	75	82	165	38	161
	SD	10	8	15	14	23	9	14	38
Urban 1	Mean	106	56	82	74	129	183	80	151
	SD	5	4	7	4	12	2	9	60
Urban 2	Mean	116	60	85	75	118	182	74	153
	SD	7	6	8	6	10	2	8	46
Other 1	Mean	103	56	85	72	129	191	79	77
	SD	3	2	4	3	6	1	3	17
Other 2	Mean	100	55	87	72	132	189	79	78
	SD	4	4	8	6	14	2	8	17

implemented using a parallelepiped classification procedure. This is a simple classification logic that draws upon the basic complimentary nature of the fused TM and SIR-B data set.

The confusion matrix showing the classification results for these categories can be seen in Table 2. An overall classification accuracy of 94 percent was achieved, demonstrating the value of sensor integration (Haack and Slonecker, 1994).

Kericho, Kenya — Variance Texture Measures

Multiple-spectral signatures were extracted using training sites for the surface features in Kericho. Representative spectral signatures for the different land uses/covers can be seen in Table 3. These signatures were extracted from training data obtained during field visitation. There was little spectral variation within surface features, so only one signature per class is presented.

TABLE 2. CONTINGENCY TABLE FOR WAD MEDANI, SUDAN. THE TRUTH INFORMATION CONSISTED OF SEVERAL POLYGON AREAS, NOT INDIVIDUAL PIXELS

Classified/Truth	Urban	Vegetation	Other	Totals
Urban	16,248	135	502	16,885
Vegetation	1,612	3,415	159	5,187
Other	334	0	23,961	24,295
Totals	18,194	3,551	24,622	46,367
Correct %	89.3%	96.2%	97.3%	
Correctly Identified Pixels	43,625/=46,367	94.1%		

TABLE 3. SPECTRAL SIGNATURES FOR THE KERICHO, KENYA

Cover		TM3	TM4	TM5	RSAT	RSAT Texture
Forested	Mean	17	74	46	132	39
	SD	1	6	4	45	3
Tea	Mean	23	114	71	109	30
	SD	1	7	4	30	2
Urban	Mean	49	46	76	193	59
	SD	7	8	8	59	4
Mixed Agriculture	Mean	35	66	94	95	30
	SD	4	14	10	31	4

For the Landsat data, three bands were selected for initial examination. Those were bands 3, 4, and 5 from the visible red, near-infrared, and mid-infrared regions of the electromagnetic spectrum. These three spectral regions, as recorded in TM, generally provide good analysis results. A more traditional maximum-likelihood decision rule was employed over a parallelepiped decision as in Wad Medani. There was, therefore, a preference to use a smaller number of optical bands in the merger, so that the radar data would maintain a sufficient influence in the integration. Maximum likelihood also has the advantage of being a simpler decision rule to use.

The TM bands 3, 4, 5 analysis provides a very good overall classification, but poor discrimination of settlements. The extremely poor resultant accuracy for the settlement class can be seen in Table 4, along with a summary of all the classification accuracies. A classification based on all seven TM bands increased the settlement accuracy to 31 percent, which was still not useful. The potential for TM spectral confusion between urban and mixed agriculture, primarily bare soil at this date, can be recognized in Table 3. Both have very similar spectral responses and relatively high standard deviations, making their separability difficult.

The overall classification results for the original RADARSAT data are quite low. The more unique, higher backscatter areas of settlements have the best classification accuracy at 67 percent. The RADARSAT spectral signatures, seen in Table 3, for the three primary covers are not greatly different. Their average values are 95, 109, and 132 and all have high standard deviations, resulting in spectral confusion.

As both a function of the radar signal and the complexity of the radar interaction with surface features, radar generally has a high texture in comparison to optical data. 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, construct, and incorporate quantitative texture measures in remote sensing with varied results (Fasler, 1980; Irons and Peterson, 1981; Wang and He, 1990).

A previous study has compared different texture measures and window sizes for East Africa (Haack and Bechdol, 2000). Four texture algorithms were examined: mean Euclidean distance, variance, skewness, and kurtosis. Results indicated that the second-order measure of texture, variance, was the most useful for feature delineations in East Africa.

Most texture measures use a moving array of cells with a variety of mathematical measures to derive texture values for the center cell of the moving array. The size of the moving window may influence classification accuracies. Hsu (1978) stated that relatively small moving arrays can cause extensive misclassification at the boundaries between classes. Blom and Daily (1982) found that window sizes of 15 by 15, 31 by 31, and 61 by 61 provided constructive results for larger scale applications.

Texture measures were examined for East African sites with many window sizes. Although an increase in overall classification accuracy was steady as window sizes became larger, the increase was very slight. The point of diminishing returns for overall classification accuracies due to window size was generally at the 13 by 13 window size (Haack and Bechdol, 2000).

Based on these previous studies, classification for Kericho used the variance measure of texture at a 13 by 13 moving window to determine if results could be improved over those of the original RADARSAT data. Overall classification accuracy was improved from 41 to 67 percent. Despite the fact that this is still far below the results achieved with the use of the three TM bands, texture provided an excellent ability to discriminate the settlement/urban areas (99 percent correct). The spectral signatures for texture (Table 3) indicate this potential. The high texture of the urban areas seems reasonable because the city of Kericho and the tea estate settlements are structurally complex areas with buildings of high backscatter separated by open areas of low backscatter and, thus, high texture. In contrast, the forest, tea, and agriculture have much lower texture values.

As was the case in Wad Medani, there is an advantage to sensor fusion. In Wad Medani, neither sensor could independently delineate the primary cover types. In Kericho, each sensor could independently classify one or more covers, but not all covers, and an added textural variable was needed. The combined classification, seen in Plate 2, delineates all covers. This plate as well as the classification results (Table 4) clearly indicate the advantage of the TM and radar texture fusion.

TABLE 4. CLASSIFICATION ACCURACIES COMPARING SENSORS AND SENSOR COMBINATIONS FOR KERICHO

	Forested	Tea	Urban	Mixed Agriculture	Overall
Landsat TM bands 345 - 21 Jan, 1995	99.44	99.93	00.88	98.68	98.62
Radarsat - 27 Feb, 1997	30.96	39.62	66.67	57.70	40.67
Radarsat Variance Texture - 13 × 13 Window	91.72	55.41	99.12	28.46	66.78
TM 345 and RSAT Variance Texture	99.95	99.46	98.25	99.96	99.65

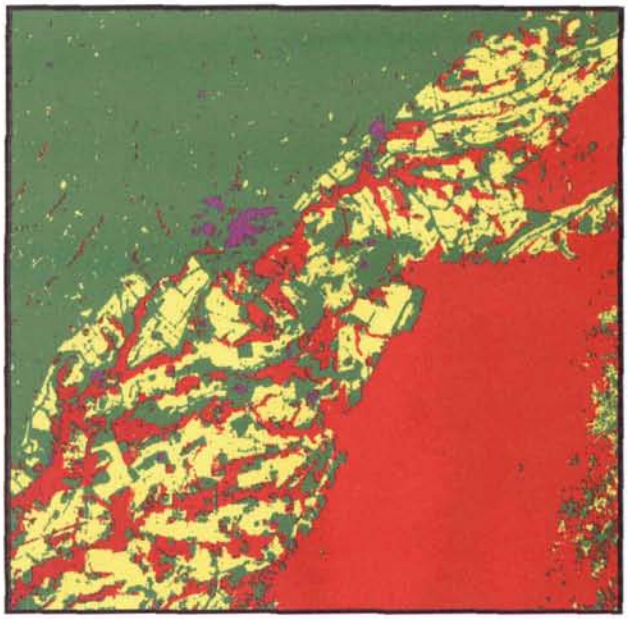

Plate 2. Sensor integration classification of Kericho for small-scale agriculture, tea, settlements, and forest. Approximate original scale of 1:140,000 reduced to approximately 1:250,000. Forest in red, tea in yellow, small scale agriculture in green, and settlements in purple.

Dadaab, Kenya — Speckle Reduction and Texture

The problem of mapping settlements also occurs in Dadaab, as a significant spectral confusion exists between the refugee camps and the areas of bare soil and dry vegetation. From visual inspection of either the optical TM or radar data, the settlements are quite apparent based on their geometry. However, spectrally the discrimination is not easy. Many of the housing units are constructed of natural brush, thus creating confusion with dry vegetation. In addition, some of the housing uses metal or plastic roofs that are spectrally similar to bare soil in these wavelengths.

Classification accuracies (Table 5) for the TM bands 3,4,5 combination is limited, at 73 percent overall. The results for the camps are reasonable, at 65 percent, but there are many errors of commission where the scattered vegetation and bare soil are incorrectly delineated as urban.

Both the classifications of the original RADARSAT values and variance texture provide low overall results. Texture measures failed to delineate camp areas even though, intuitively, it would seem as if the camps should have a texture different from the surrounding landscapes. The housing units are so dense that there may be little texture at the spatial resolution of the sensor.

One of the problems associated with radar is speckle and the relationship between speckle reduction, measures of texture, and smoothing methods. Speckle is an unavoidable result of using coherent monochromatic light/energy such as in radar, and appears as a noisy, high textured image. Speckle is perhaps the most difficult problem to address when employing radar imagery because even homogeneous surfaces may have a grainy appearance and high backscatter standard deviations (Durand *et al.*, 1987).

It is difficult to separate which radar tonal variations are due to coherent speckle and which are due to actual ground variations. Because an automatic classifier expects a given surface to be represented by a certain image tone or brightness, the incorrect values caused by speckle make automated classifications difficult. As a result, the presence of speckle often precludes a pixel-by-pixel classification unless the data are smoothed (Nüesch, 1982).

While speckle cannot be removed from data, its impact can be significantly suppressed through speckle reduction algorithms. The application of a window that averages pixels will reduce the effect of speckle (Blom and Daily, 1982), but will also visibly degrade edges. This is especially important when dealing with smaller agricultural fields or urban studies where boundaries play a critical role (Jensen, 1979; Nüesch, 1982).

Generally, there is no value in using a speckle reduction algorithm and extracting texture measures from the same data, because the speckle reduction will remove most of the texture. The exception to this is if the speckle reduction and texture measures are at different window sizes. For Dadaab, a median speckle reduction method was applied using a 5- by 5-pixel window. This was a compromise between limiting the speckle and still retaining image detail including texture. A variance texture extraction and classification was then applied using a much larger 21- by 21-pixel window. The results are an improvement for overall classification, and especially for camps, in comparison to the two other radar classifications.

The TM bands 3,4,5 and despeckled variance texture combination results are a considerable improvement in overall classification (84 percent) and in individual class discrimination. Further refinement of the manipulations of the radar and inclusion of different dates of the optical data such as a green season image (similar to the strategy used in Wad Medani), may further improve upon these results.

Summary and Future Directions

These results show the potential of optical/radar merger for mapping basic land-use/land-cover patterns in different environments in East Africa. Given the range of landscapes examined, the results of this study should have applicability beyond East Africa. The results support the value of integrating optical and radar data. In all sites examined in this study, sensor fusion improves the classification accuracies, particularly for settlements.

The radar results can be improved by various manipulations, such as derived texture measures and filtering. The strategies for using radar that provided the best results were not consistent. As with optical data, the most productive processing strategies may be site and data specific. More case stud-

TABLE 5. CLASSIFICATION ACCURACIES COMPARING SENSORS AND SENSOR COMBINATIONS FOR DADAAD, KENYA

	Thicket	Bare Soil	Urban/ Camps	Scattered Vegetation	Natural Agriculture	Overall
Landsat TM bands 345	96.42	69.05	64.57	51.94	99.04	72.77
Radarsat- 15 Aug. 1996	26.00	14.62	00.00	31.02	54.71	26.49
Radarsat Variance Texture - 21 × 21 Window	14.52	23.88	54.91	39.26	14.41	24.49
Despeckled Radarsat Variance Texture - 21 × 21 Window	36.67	00.00	64.40	56.01	17.72	39.57
TM 345 and Despeckled RSAT Variance Texture	95.60	67.71	72.29	78.45	98.96	83.78

ies will contribute to an improved understanding of useful analysis techniques.

Future applications of this project will include a comparison of the parallelepiped accuracy with that of a maximum-likelihood and other classifiers, including a hierarchical approach, and an extension of basic land use/cover to more complex land use/cover classification schemes. Most importantly, further evaluation of the contribution of the individual bands and selection of band subsets for classification will be undertaken. Another extension of this study will be a more complete evaluation and comparison of texture and spatial filters to improve accuracy.

Acknowledgments

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