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COMPUTER ANALYSIS OF X-BAND RADAR DATA

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ABSTRACT

Dual polarized X-Band Synthetic Aperture Radar (SAR) data were obtained for a test site in South Carolina containing a variety of forest and agricultural cover types, as well as water and urban areas. The optically correlated images were digitized with a scanning microdensitometer using a 40 μm aperture. Digital registration of the two polarizations was more difficult than anticipated due to geometric variations in the imagery. However, a successful registration was obtained, and a "degraded" 30 m resolution data set was generated in addition to the original 15 m resolution data set.

Computer analysis indicated a statistically significant look-angle effect in the radiometric characteristics of the data. Three different classification algorithms were tested: (1) GML, or Gaussian Maximum Likelihood; (2) Per-Field; and (3) SECHO or Supervised Extraction and Classification of Homogeneous Objects. The GML is a per-point classifier, whereas the latter two are contextual classifiers, in that the classification decision is based on both the mean and the variance of the spectral response over an area. Evaluation of the classification results, based on test data for the seven major cover types present in the study site, indicated a significant improvement in accuracy for the contextual algorithms as compared to the GML per-point algorithm, but overall performance was only 65% for even the contextual algorithms. The effects of spatial resolution and polarization of the radar signal, as well as the classification algorithm, are discussed in this paper.

The results indicate the need for: (1) completely digital data processing of SAR data (as compared to optical correlation techniques for producing the SAR imagery); (2) evaluation of longer wavelength SAR data for differentiating forest and other cover types and condition classes; and (3) improvements in contextual algorithms and analysis techniques.

I. INTRODUCTION

Dual-polarized, X-band Synthetic Aperture Radar (SAR) imagery obtained over a test area near Camden, South Carolina had been used for an earlier study by Knowlton and Hoffer (1981). The objective of that study involved the determination, qualitatively, of the value of SAR imagery for identifying various forest cover types. During the analysis of the HH (Horizontal-Horizontal) and HV (Horizontal-Vertical) polarized images, particular attention was given to the tonal and textural characteristics of the cover types involved. In general, the results of the study showed that: (1) certain forest cover features (e.g., deciduous versus coniferous) are more easily identified in one polarization than the other, but some features (e.g., mixed deciduous and tupelo) looked very similar in both polarizations; (2) overall tonal contrast between features was greater on the HH image; and (3) neither polarization was consistently better for identifying the various forest cover types being examined.

Following the qualitative analysis of the SAR data, the current work was undertaken to determine whether "standard" remote sensing computer classification procedures, developed primarily for multispectral scanner (MSS) data, could be effectively applied to digitized SAR data, even though the energy-matter interactions are quite different for data obtained in

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the microwave portion of the electromagnetic spectrum. The results of this quantitative analysis, which include the digitization, rectification, and classification of the SAR data, are the subject of this paper.

II. OBJECTIVES

The overall objective of this investigation was to determine, quantitatively, the value of dual-polarized, X-band SAR imagery for identifying various forest cover types. Specific sub-objectives identified were to:

(1) Define effective techniques to digitally register the two polarizations;

(2) Determine if a statistically significant look-angle effect is present in the radiometric characteristics of the data; and

(3) Examine the results of three different classification algorithms for identifying various forest and other cover types.

III. MATERIALS AND METHODS

A. RADAR DATA

The radar data was obtained using NASA's APQ-102 side-looking radar, which is a fully focused synthetic aperture radar imaging system. The system was mounted on NASA's RB-57 aircraft, and the data were collected on June 30, 1980 from an altitude of 60,000 feet (18 km) mean sea level (MSL).

A horizontally polarized pulse of energy of 9600 MHz ± MHz (commonly known as X-band) was transmitted by the radar system, and the returning energy was recorded on separate holograms as horizontally (HH) and vertically (HV) polarized responses. These holograms were then processed through an optical correlator by Goodyear Aerospace Corporation in Arizona (under contract to NASA, JSC), and the resulting images recorded on high resolution positive film (see Figure 1).

B. DIGITIZATION PROCESS

To convert the radar imagery into a numerical format, the positive film imagery was digitized using a microdensitometer. Both the HH and HV polarization images were digitized by the Lockheed Corporation at JSC. Due to a distinct banding effect in the imagery, only a portion of the original imagery, as indicated in Figure 1, was digitized.

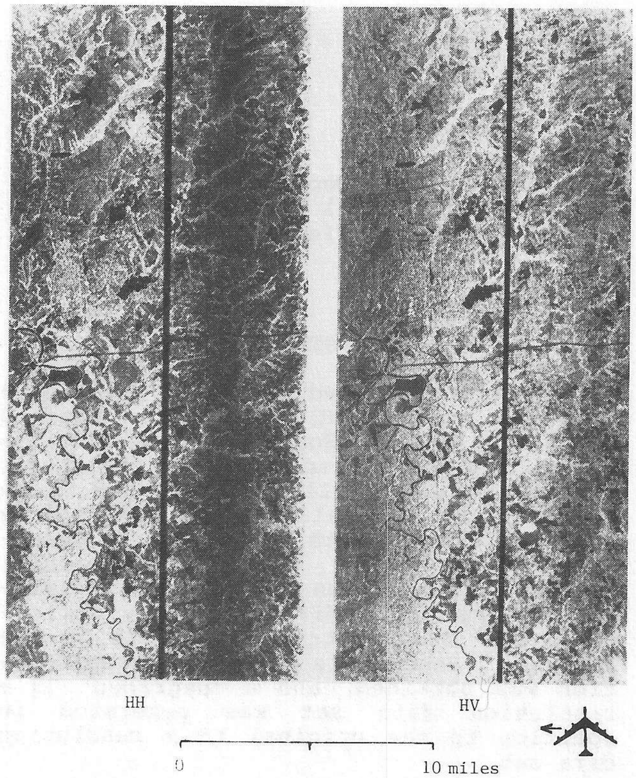

Figure 1. HH and HV polarizations of the X-band SAR imagery showing both the banding effects and tonal variations. Only the portion of the data left of the vertical black line was digitized.

The parameters for digitizing the imagery were calculated using the specifications of the radar system and an approximate scale of the imagery. Based on the system characteristics, the ground resolution for both the across track and along track resolutions was slightly less than 15 m. This resolution performance was defined as the minimum allowable dimension for a ground resolution element. Using the positive film image scale of 1:376,000, it was determined that an aperture setting of 40 μm on the microdensitometer would provide a digitized pixel with a ground spatial resolution of 15 m, thereby approximating the ground resolution of the SAR system.

The sampling interval and scan line spacing were also set at 40 μm to prevent any sidelap and overlap of adjacent pixels, thus providing independence between pixels. If there was any sidelap and/or overlap of the pixels, the variance between adjacent pixels would have been reduced. This would not have allowed as effective a comparison among various classification algorithms, since the design of some algorithms are more sensitive to a change in variance than others.

C. DIGITAL REGISTRATION

Since the HH and HV images were digitized independently, the data had to be overlaid or digitally registered (i.e., share the same line and column coordinates) before being combined onto a single LARSYS (1) data tape. Initial attempts to overlay the two data sets did not produce satisfactory results. Examination of the data indicated that a curvilinear orientation with more than one inflection point existed in the along track direction between the data sets. This type of orientation may have developed through a combination of variables such as radar-platform velocity deviations, electromagnetic path length fluctuations, and electronic equipment instabilities (Anuta et al., 1978; Tomiyasu, 1978; and Mauer et al., 1979). In addition, two separate antennas were used in the collection of the data which could have influenced the orientation between the polarizations.

To compensate for the orientation differences, the data along the flight line were divided into discrete blocks. The data were initially divided into approximately two equal blocks. Over 30 potential control points were located in each block, a second order biquadratic transformation was applied to each block, and RMS errors were calculated (see Anuta, 1977, and Steel and Torrie, 1980). RMS errors of less than 0.5 for both line and column coordinates were considered to give the accuracy needed for the image registration process (Smith, 1980).

The RMS error values indicated that the overlay was still not sufficiently accurate, so each block was again divided in half, forming a total of four blocks. At least 30 control points were located in each of the four blocks. The biquadratic transformation was applied to each of the blocks and RMS errors were calculated. The results for the three northern blocks showed RMS errors of less than 0.5, thereby indicating that each of these blocks could be overlayed using their associated transformations. Although the fourth block had RMS errors of 0.64 to 0.86, rather than less than 0.5, it was decided to attempt to overlay the data using the derived transformation rather than to divide the block into smaller units. However, after the data was overlaid, it was determined through visual examination that the registration of the fourth block was extremely poor, so this area had to be deleted from further analysis.

(1) LARSYS is a remote sensing data-processing system developed at Purdue University's Laboratory for Applications of Remote Sensing (LARS). For complete documentation of LARSYS see Phillips (1973).

D. SPATIAL RESOLUTION DEGRADATION

After the registration process, a second SAR data set was produced having a reduced spatial resolution of 30 m. The purpose of this was two-fold: (1) to simulate the spatial resolution of the Thematic Mapper, and (2) to reduce the amount of speckle associated with the SAR data. The spatial resolution was degraded by averaging pairs of neighboring pixels together. Since the original data set had a spatial resolution of approximately 15 m, by averaging cells of four pixels, a degraded data set having a spatial resolution of 30 m was produced. The steps and considerations used to degrade the spatial resolution were similar to those described by Latty (1981).

E. CLASSIFICATION ALGORITHMS

Three classification algorithms were used in the investigation, one being a "pixel-by-pixel" classifier and the other two classifiers being "textural" classifiers. The purpose of all three classifiers is the same: to assign each resolution element, or pixel, to a given class, based on the statistical characterization of that pixel. The major difference between these two groups of classifiers is that the pixel-by-pixel classifier assigns the pixel to a given class based on the spectral information of that pixel alone, whereas textural classifiers use the data from spatially adjacent pixels to aid in the classification of each pixel.

The pixel-by-pixel classifier used was the Gaussian Maximum Likelihood (GML) classifier. This particular classifier is widely used in remote sensing applications. Rather than go into detail about this particular classifier, the authors suggest the following references: Swain (1973), and Swain and Davis (1978).

The two textural classifiers used in this study were the Minimum Distance (PER-FIELD) classifier and the Supervised Extraction of Homogeneous Objects (SECHO) classifier. These two classifiers are similar in that they classify groups of pixels into the various spectral classes based on both their spectral and spatial information. However, they are distinctly different in their approach to classifying the data, and especially in partioning the area to be classified. In using the per-field classifier, the analyst must define each specific block or area to be classified, whereas with the SECHO classifier, the analyst simply defines the entire segment of the Landsat data to be classified, and the algorithm defines the boundaries of the various forest stands or agricultural fields (i.e., "homogeneous objects") to be classified. The following references are suggested for more information concerning the two textural classifiers: PER-FIELD - Duda and Hart (1973), Phillips (1973), and Wacker and Landgrebe (1971); SECHO - Kettig (1975), Kettig and Landgrebe (1976), and Scholz et al. (1977).

F. STATISTICAL ANALYSIS

To fully examine and to make inferences about the classification results, a statistical analysis was performed to determine if significant differences existed between the classifiers for a given data set and between data sets for a given classifier. The results of the classifications were given in terms of overall percent correct classification (PCC) performance and individual class PCC performance, based on test pixels.

The PCC performances for individual cover types were computed by the following equation:

$$PCC_i = P_i/P_i'$$

where,

P_i = the total number of test pixels correctly classified for the ith cover class,

P_i' = the total number of test pixels for the ith cover class.

The overall PCC performances are computed by the following relationship:

$$PCC = \sum_{i=1}^{n} \frac{P_i}{P_i'}$$

where,

n = number of cover classes.

The PER-FIELD classifier also allows the class PCC and overall PCC performances to be calculated in terms of the number of fields correctly classified. The PCC's are calculated in a fashion similar to that described above, except that the test fields are used in the calculations rather than the individual test pixels. The two performances allow the analyst to compare pixel versus field performances and determine the influence of field size (i.e., the number of pixels per field) on the classification results. However, the following discussion of the classification results is given only in terms of the number of test pixels, rather than test fields, correctly classified. This is done to allow for clarity in the discussion between classifiers.

Statistically significant differences for the various combinations of data sets and classifiers were determined using the Newman-Keuls multiple range test. An alpha (α) level of 0.05 was used for all possible combinations of tests.

IV. RESULTS AND DISCUSSION

A. LOOK-ANGLE EFFECT

Even though only a portion of the entire swath width of the SAR data had been digitized, there still appeared to be a distinct tonal variation across even this portion of the flight line. This was particularly evident on the HV image. A statistical evaluation was conducted to determine if the SAR training data should be separated into spectral classes according to the location of the individual fields across the flight line. The flight line was first divided into six discrete strips. Fields of the dominant forest cover class, which was the hardwood class, were identified within each strip and their means and standard deviations calculated. Figure 2 illustrates the mean $\pm$ 1 standard deviation for each of the six strips, for both the HH and HV channels. From this figure it can be seen that on the HH polarization, although the means are somewhat different from one strip to the next, there doesn't seem to be an obvious trend across the data set; however, on the HV polarized data, except for strip No. 6, the means show a definite increase from left to right across the imagery.

data sets, and for the left and right sides of the flight lines.

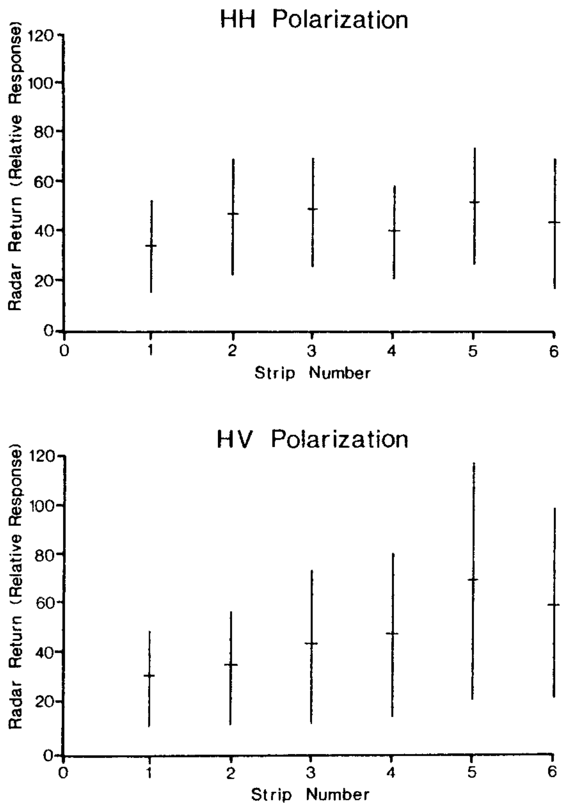

Figure 2. Plots of the mean ± 1 standard deviation of each strip across the flight swath, for both the HH and HV polarizations of the 15 meter SAR data.

To determine the significance of the tonal variation an analysis of variance was performed on the data. The strip means of the HV image were found to be significantly different but those of the HH image were not. It was therefore decided that the training and test data sets would need to be stratified as a function of location across the flight line. However, several cover types had relatively limited numbers of training or test fields, so some of the six strips would not have had sufficient training and/or test data for the various cover types. Therefore, the data was sub-divided only into column coordinates that represented either the left or right portion of the flight line. Table 1 lists the cover classes and number of pixels for both the training and test data sets used in the computer-aided classification of both the 15 m and 30 m data sets. Table 2 shows the means and standard deviations, by cover type, for both the 15 m and 30 m data sets, and for the left and right sides of the flight lines.

Table 1. The number of training pixels and test pixels associated with each cover class for the quantitative analysis of the SAR data.

	No. of Training Pixels		No. of Test Pixels	
Cover Class	SAR 15	SAR 30	SAR 15	SAR 30
PINE	845	251	840	249
HDWD	3332	935	3131	840
RGHD	3027	849	1490	442
PAST	714	218	1239	360
CROP	2001	594	2250	690
SOIL	1704	466	1398	414
WATR	547	166	552	161
TOTAL	12170	3479	10900	3156

Table 2. Means and Standard Deviations for each cover class for both the left and right portions (i.e., spectral classes) of the 1980 SAR data sets.

		15 m				30 m			
		HH		HV		HH		HV	
Cover Class		Left	Right	Left	Right	Left	Right	Left	Right
SOIL	$\bar{X}$	6.4	13.8	6.8	16.6	6.7	13.4	6.7	17.0
	S	2.7	6.2	3.3	10.7	1.9	4.4	1.7	8.7
CROP	$\bar{X}$	22.1	14.6	26.9	18.1	21.9	15.4	26.3	19.0
	S	11.4	8.4	17.3	14.4	7.6	6.6	12.3	11.1
HDWD	$\bar{X}$	42.4	40.7	44.0	52.5	43.4	41.1	44.0	53.2
	S	21.7	21.6	32.6	38.1	15.0	14.1	21.5	25.1
RGHD	$\bar{X}$	33.4	34.9	37.2	56.3	33.4	34.4	36.9	56.3
	S	16.6	16.6	22.9	33.2	11.0	11.0	14.5	19.5
PINE	$\bar{X}$	10.4	14.4	19.4	39.1	10.8	14.6	20.0	39.2
	S	5.3	6.9	11.8	23.1	4.2	4.7	8.2	14.1
PAST*	$\bar{X}$		13.4		42.2		14.0		43.1
	S		6.8		24.6		5.5		16.7
WATR	$\bar{X}$	3.8	4.3	6.2	6.9	4.6	5.0	6.4	7.5
	S	1.3	2.0	3.8	2.4	2.6	3.0	3.0	1.9

*The pasture class only had representative fields on the right portion of the flight swath.

B. CLASSIFICATION

As previously indicated, both the 15 m and 30 m SAR data sets were classified using three different classifiers -- one pixel-by-pixel (the Gaussian Maximum Likelihood) classifier, and two textural (Per-Field and SECHO) classifiers. The overall PCC performances for both data sets and all three classifiers are compared in Figure 3, and the results of the statistical comparisons between the results are shown in Table 3. The overall PCC performances between the two data sets were found to be significantly different for the GML and PER-FIELD classifiers, and were not significantly different for the SECHO classifier.

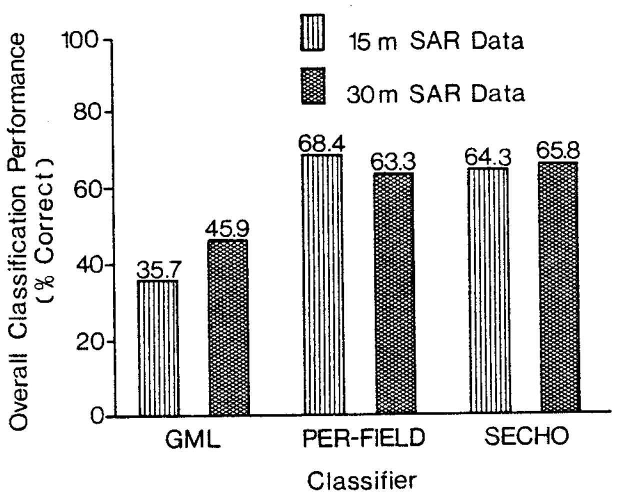

Figure 3. The overall classification performances for three classifiers using the SAR 15 m and 30 m data.

Table 3. Statistical comparison between the overall classifications of the SAR 15 m and 30 m data sets, for each classification algorithm.*

Classifier	Data Set SAR 15 m	SAR 30 m
GML	35.7[a]	45.9[b]
PER-FIELD	68.4[b]	63.3[a]
SECHO	64.3[a]	65.8[a]

*Different superscripts indicate significantly different classification performances between the data sets, based on a Newman-Keuls comparison with $\alpha = 0.05$.

For the GML classifier, these results show that overall PCC performance tends to increase by degrading the spatial resolution. This is because the spectral variability associated with each cover class is reduced. Table 2, introduced earlier, shows the means and standard deviations for each cover class for both the SAR 15 m and SAR 30 m data sets. The means of the various cover classes do not change very much between the two data sets. However, the standard deviations for each class are significantly reduced on the SAR 30 m data set, except for the WATR (water) class. The WATR class has a very low standard deviation on the SAR 15 m, but by averaging small blocks of 4 pixels to create the 30 m spatial resolution data set, an amount of variation was introduced by the non-water border pixels. This variation caused the standard deviation to increase for the WATR class in the 30 m data set. Except for the water class, however, the smaller standard deviations found in the other cover type classes in the 30 m data resulted in a reduction in the amount of overlap between the spectral distributions, thereby reducing the probability of misclassification.

Again referring to Table 3, comparison of the results of the two data sets for both the PER-FIELD and SECHO classifiers shows that the overall results are very similar, with the PCC performance of the SAR 15 m data set being slightly higher than the SAR 30 m data set for the PER-FIELD classifier. These two textural classifiers performed much better than the GML classifier given either data set. This suggests that the <u>incorporation of both spectral and spatial information will significantly increase the overall PCC performance for the SAR data sets</u>. These results also indicate that if spatial resolution has been degraded, the overall PCC performances may not increase when using textural classifiers. This is attributed to the fact that the PER-FIELD and SECHO classifiers were designed to incorporate texture into the classification process, and by removing the texture within the scene (e.g., spatial degradation), the major advantage of the textural classifiers is eliminated resulting in the lack of improvement in classification performance for the higher spatial resolution data.

Figure 4 shows the PCC performances, by cover class, for the three classifiers being tested using both the SAR 15 m and SAR 30 m data. Both the PER-FIELD and SECHO classifiers have relatively high PCC performances for the HDWD (hardwood) class for both spatial resolution data sets. The CROP and RGHD (regenerating hardwood) cover classes show similar, but not as dramatic, differences between the textural and the GML per-pixel classifiers. Since both the PER-FIELD and SECHO classifiers utilize the spectral variances of the different cover types in the classification, and all three of these cover types have relatively high spectral variances, the textural classifiers are more effective than the GML classifier. However, the RGHD and CROP cover classes generally have relatively low PCC performances with all three classifiers because of the confusion with other vegetation classes having similar spectral distributions.

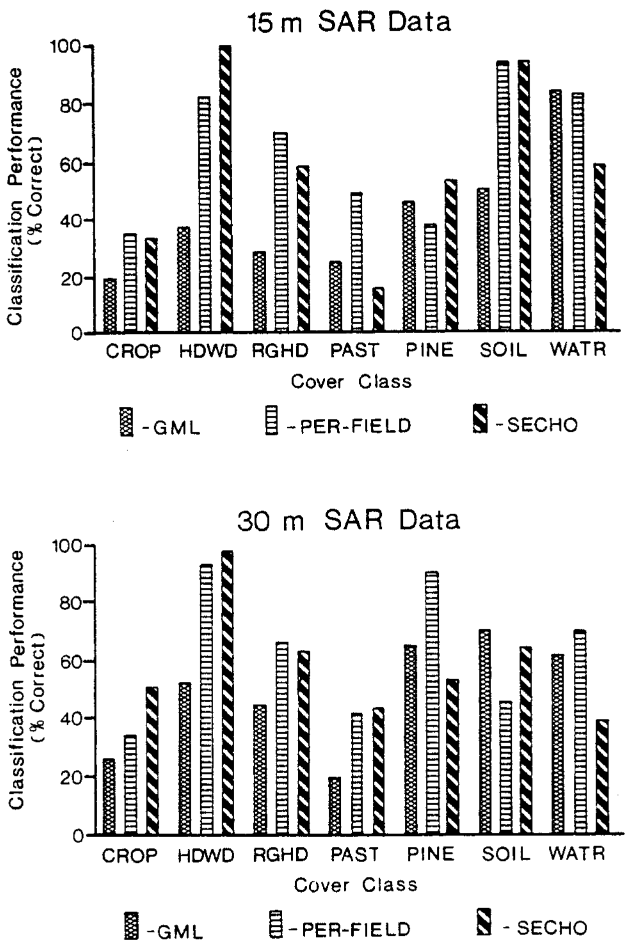

Figure 4. Classification performances by cover class for the three classifiers, and for both the SAR 15 m and 30 m data sets.

The cover classes PINE, PAST, SOIL, and WATR have an irregular pattern of PCC performances. PAST and PINE have very poor PCC performances at the 15 m spatial resolution for all three classifiers. This is due to the fact that on this particular data set, these two cover types have very similar spectral distributions, thus causing considerable confusion. By spatially degrading the 15 m data set, the PCC performance for PINE increased significantly for all three classifiers, whereas the PCC performance for the PAST class decreased for both the GML and PER-FIELD classifiers and increased for the SECHO classifier.

Using the GML classifier, SOIL has a much higher PCC performance with the 30 m data. However, SOIL has a much higher PCC performance for the PER-FIELD and SECHO classifiers using the 15 m data. By degrading the resolution the amount of pixel-to-pixel variation was reduced within the bare soil fields. This enabled the GML classifier to discriminate the SOIL class from the WATR class. However, by reducing the amount of variance associated with the spectral classes for SOIL, the PER-FIELD and SECHO classifiers did not perform as well as with the 15 m data set because the spectral response and the pixel-to-pixel variation between the SOIL and WATR classes were very similar, and therefore the classifiers could not discriminate between the spectral distributions. The WATR class had high PCC performances for both the GML and PER-FIELD classifiers using the 15 m data set. This was primarily due to the low probability of error associated with the SOIL class as compared to the distributions of the SOIL and WATR classes using the 30 m data, which had a higher probability of error.

The SECHO classifier performed poorly for the WATR class using either the SAR 15 m or 30 m data sets, with the 15 m data having the better PCC performance for the two data sets. This was attributed to the fact that the moving window, which was a three by three pixel cell, obliterated the major water feature - the Wateree River. Depending on where the window was located, adjacent border pixels would have been included in the window, and would then influence the calculated homogeneity value. Due to the speckling nature throughout both sets of SAR data, these mixed water and "other" cells apparently resembled other features and were classified accordingly by the SECHO classifier.

V. SUMMARY AND CONCLUSIONS

This investigation has provided some very valuable insights regarding the quantitative analysis of dual-polarized, X-band SAR data. Additional data sources such as SAR have considerable potential for a variety of applications, but it is important to recognize that SAR data also have some distinct limitations. The quantitative analysis of the digitized SAR data provided results which suggest that special preprocessing procedures and classification algorithms are required in order to effectively utilize computer-aided analysis techniques. The findings of this study can be summarized as follows:

1. The HH and HV polarized data sets had independent geometric distortions which required special preprocessing techniques to achieve satisfactory digital registration.

2. A distinct tonal variation related to range angle was quantitatively documented for the HV polarization, but not for the HH polarization.

3. Utilization by the classification algorithm of both the spectral and spatial information content of the SAR data resulted in a distinct and significant increase in overall classification performance. Both the PER-FIELD and SECHO textural classifiers had much higher classification performances than the GML pixel-by-pixel classifier. These improvements were approximately 20% for the 30 m SAR data and 30% for the 15 m data set.

4. Overall percent classification performance of the GML pixel-by-pixel classifier increased for the dual-polarized X-band SAR data by degrading the spatial resolution.

5. Degrading the spatial resolution may not necessarily result in an increase in overall percent classification performance for textural (e.g., the PER-FIELD and SECHO) classifiers.

6. Pine and hardwood cover classes could be reliably differentiated on the X-band SAR data sets.

7. Pine and pasture cover classes, and bare soil and water cover classes were consistently confused with each other on the SAR data.

8. The various threshold parameters utilized in the SECHO classifier (i.e., window size, homogeneity, and annexation) are data dependent and are strongly influenced by the size, shape, and textural characteristics of the cover types being classified.

VI. RECOMMENDATIONS

In addition to meeting the stated objectives, this investigation has also indicated several areas in which further research is needed. These include the following:

1. The banding effect and tonal variation related to range angle, which were inherent in the data, had a definite impact on our ability to fully assess the information content of the data in a quantitative fashion. Research is needed to determine the cause of these effects, whether it be due to the system itself or to interactions between the system, possible topographic effects, and/or the characteristics of the cover types involved.

2. Although the X-band SAR data could be used to separate some cover types with a relatively high degree of reliability, other cover types could not be adequately separated even those that are physically very different. It is recommended that the value of multiple frequencies (i.e., short and long wavelengths) as well as multiple polarizations and look angles be assessed to determine what forest classes and characteristics can be reliably separated. In addition, further research is needed to examine how the dielectric and physiognomic properties of forest vegetation influence the radar signal.

3. Classifiers which incorporate texture (e.g., SECHO) must be more fully examined to determine the effect of speckle on the classifier itself and how it can be effectively used to discriminate the cover classes of interest.

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Douglas J. Knowlton (B.S., University of Maine at Orono; M.S., Purdue University) is an Analyst/Programmer in the Photogrammetric Research Section of DBA's Imaging Systems Division. He is currently involved with the development of photogrammetric models for oblique photography. At the time this research was conducted, Mr. Knowlton was a Research Associate at LARS, Purdue University. His responsibilities included the evaluation of radar data using computer-aided analysis techniques. He was also responsible for the preprocessing of MSS data, which included geometric corrections, radiometric corrections, and spatial degradation of the data set.

Roger M. Hoffer is Professor of Forestry and Leader of the Ecosystems Research Programs, LARS, Purdue University. B.S. in Forestry, Michigan State University; M.S. and Ph.D. in Watershed Management, Colorado State University. Co-founder of LARS in 1966, Dr. Hoffer currently teaches three courses in Remote Sensing of Natural Resources. He has lectured, consulted, and participated in remote sensing activities in many countries throughout North and South America, Asia, and Europe; has served as a principal investigator on Landsat, Skylab, and other major remote sensing projects, and has authored over 130 scientific papers and publications on remote sensing. Professor Hoffer's research has focused on the use and refinement of computer-aided analysis techniques for forestry applications, and on the study of the spectral characteristics of earth surface features.