The Use of Structural Information for Improving Land-Cover Classification Accuracies at the Rural-Urban Fringe

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ABSTRACT: A methodology for incorporating structural information into conventional classification procedures is described. The technique is based on the use of an edge-density image which is generated using a Laplacian operator. This image is included in a Mahalanobis classifier as an additional band of data. The method is particularly designed for higher spatial resolution data in which plenty of spatial information is available. It has been tested using SPOT HRV multispectral data obtained over part of the rural-urban fringe of Metropolitan Toronto, Canada. Twelve land-cover types have been used to evaluate the approach and the classification results have been compared with those obtained by conventional maximum-likelihood classification. An overall accuracy of 86.1 percent was achieved by incorporating structural information into the classification compared with an accuracy of only 76.6 percent obtained without the structural information.

INTRODUCTION

RECENT STUDIES of multispectral classification using higher spatial resolution satellite data, such as Landsat Thematic Mapper (TM) and SPOT High Resolution Visible (HRV) data, have shown that, when conventional per-pixel classifiers are employed, better accuracies may not necessarily be obtained over lower spatial resolution data such as Landsat Multispectral Scanner (MSS) data (Clark and Bryant, 1977; Townshend and Justice, 1981; Williams *et al.*, 1983; Toll, 1984; Shimoda and Sakata, 1987; Howarth *et al.*, 1988; Martin *et al.*, 1988). Two factors in particular have been recognized as influencing the classification results obtained with higher spatial resolution images. First, the improved resolution has increased the spatial variation in such images which in turn makes the training process more complex. Second, commonly-used classifiers, such as the minimum-distance (MD) classifier and the maximum-likelihood (ML) classifier, are per-pixel classifiers which make decisions based solely on the spectral information of each individual pixel. A large amount of spatial information that might be obtained from surrounding pixels is thus ignored.

Several approaches have been tried to overcome these problems. They include improving the quality of the training statistics by refining the supervised training samples (Badhwar *et al.*, 1984; Irons *et al.*, 1985; Toll, 1985a; Buchheim and Lillesand, 1987; Khorram *et al.*, 1987), testing unsupervised training strategies (Wang, 1984; Kiyonari *et al.*, 1988), preclassification filtering (Cushnie and Atkinson, 1985; Toll, 1985b; Cushnie, 1987), the use of advanced classification procedures such as the ECHO (Extraction and Classification of Homogeneous Objects) per-field classifier (Latty *et al.*, 1985), and the probabilistic relaxation classification method (Gong and Howarth, 1989). Among these procedures, the majority have shown no significant improvement in classification results. However, the preclassification filtering methods, using median, mean and other low-pass filters, have resulted in accuracy improvements approaching 20 percent (Cushnie, 1987). This was achieved using 5-m by 5-m spatial resolution airborne MSS data to simulate 10-m by 10-m and 20-m by 20-m SPOT HRV data for classifying general land-use categories, such as residential. However, such data-smoothing strategies may discard too much information when attempts are made to map detailed land covers using SPOT HRV data.

In this paper, a procedure to improve land-cover classification accuracies obtained with SPOT multispectral (XS) data is presented. First, a "structural information" (SI) image is generated and used as an additional band of data in the classification. In this study, an edge-extraction algorithm was applied to the SPOT XS Band 1 data to produce an edge-density image as the SI band. The SI band is then combined with two bands created by principal component analysis (PCA) from the original three SPOT XS bands. An MD classifier is applied to the two PCA bands and the SI band to produce the classification. A comparison of the results obtained with this method and the results obtained using the two PCA bands and the standard ML classifier is reported.

STUDY AREA

The study area covers the Town of Markham (43° 52′ N; 79° 15′ W), which is situated at the rural-urban fringe of northeastern Toronto. This site has been used for a variety of remote sensing studies of rural-to-urban land conversion over a period of several years (Martin, 1975; Johnson and Howarth, 1987; Howarth *et al.*, 1988; Martin *et al.*, 1988; Martin, 1989). It provides a good study site for this analysis as large tracts of natural and agricultural land are being rapidly converted to urban uses. As a result, the spatial structure within the study area presents a variety of patterns. These structural patterns are considered to be useful signatures for discriminating some of the rural and urban land-cover types whose spectral signatures are often difficult to differentiate.

SPOT XS data used for this study were obtained on 4 June 1987. For the analysis, a subscene of 512 by 512 pixels (approximately 10 km by 10 km) was selected. A portion of the area covering approximately 300 by 400 pixels (6 km by 8 km) is shown in Plate 1. This color composite displays the three XS bands after geometric correction with Bands 1, 2, and 3 being assigned to the blue, green, and red color guns, respectively.

Land-cover types which exist in the study area are shown in Table 1. Most of them are self-explanatory. It should be noted, however, that the lawn and tree complex occurs within urban areas, while the cultivated grass primarily forms the fairways on golf courses. The distinction between crop cover, and new crops and pasture, is easily made on the basis of high and low reflectances, respectively, in the infrared band.

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TABLE 1. LAND-COVER TYPES USED IN THE CLASSIFICATION

Type	Abbreviation	Color
Residential Roof	RR	Red
Paved Surface	PS	Light Green
Industrial and Commercial Roof	ICR	Mid Blue
Cleared Land	CL	Yellow
Lawn and Tree Complex	LTC	Pink
Cultivated Grass	CG	Turquoise
Deciduous Trees	DT	Tan
Coniferous Trees	CT	Gray
Crop Cover	CC	Dark Green
New Crops and Pasture	NCP	Dark Blue
Bare Field	BF	Purple
Water Surface	WS	Light Blue

TABLE 2. CORRELATION MATRIX AND EFFECTIVE DIGITAL DATA RANGES FOR THE SPOT HRV MULTISPECTRAL DATA

	Band 2	Band 3	Digital Range
Band 1	0.98	−0.34	34 - 116
Band 2		−0.42	22 - 116
Band 3			22 - 153

DATA PREPARATION

No radiometric correction was applied to the image because the selected test site is small and relatively flat and the topographic and atmospheric conditions were assumed to be homogeneous throughout the image. However, a geometric correction was performed to make it easier for the analyst to locate the reference data on a map of the area and on the image. The original data were spatially transformed to the UTM map projection using a third-order polynomial and were resampled to 20-m by 20-m pixels using a cubic-convolution interpolation. These procedures were undertaken using the standard software on a Dipix ARIES III image analysis system.

The original SPOT XS data were quantified in 8 bits, but an examination of the histograms for each of the three bands showed the effective ranges of the digital data to be far less. In addition, a correlation analysis indicated that the Band 1 and Band 2 data are highly correlated (Table 2). This seems to be a deficiency of the gain setting of the sensor because other researchers (Quarmby and Townshend, 1987; Chavez, 1989) have encountered similar problems. In order to minimize the redundancy and reduce the amount of computation, the original three bands of multispectral data were transformed into two bands through principal component analysis. The two new bands of data contain over 99.6 percent of the variance of the original data.

METHODOLOGY

The procedures used in this study were implemented on a VAX 11/785 computer using FORTRAN 77 as the programming language.

STRUCTURAL INFORMATION EXTRACTION

The procedure for generating the SI band involves three steps:

(1) A high-pass filter is applied to the image.
(2) Edge extraction is performed.
(3) An edge-density image is generated.

In Step 1, a Laplacian high-pass filter (Pratt, 1978), which enhances the high-frequency components of an image in all directions, is applied to the Band 1 image of the SPOT XS data. The Band 1 image was selected because visually it shows the largest contrast in spatial structure between the rural and the urban areas. Road networks and residential structures in particular are easily identified on the Band 1 image.

The enhanced image contains both edge and non-edge components. At Step 2, a threshold is set from the histogram of the enhanced image. This threshold is selected interactively so that on the resultant image only the road networks and some other high frequency components are displayed (Figure 1).

At Step 3, the thresholded image or edge image is further processed to create the edge-density image. This involves moving a window pixel by pixel over the edge image. At each position of the window, the edge points are counted and the number of edge points is divided by the window size. This process results in the generation of an edge-density image which is then used as an additional feature in the classification. The size of the window is determined by visual examination of the edge-density images. The procedure is repeated using a range of window sizes. The window size which visually gives the best discrimination between urban and rural areas is then chosen. In this study, 13 edge-density images were generated in which the window sizes varied from 7 by 7 to 31 by 31. The window size of 25 by 25 was selected and the resultant edge-density image (Figure 2) was used as the SI band.

CLASSIFICATION

Two methods were used to classify the SPOT XS data. First, the standard ML classification was applied to the two PCA bands. The second classification method combined the edge-density image or SI band with the two PCA bands. The conventional per-pixel MD classifier with the Mahalanobis distance measure was then applied as the classification algorithm. A detailed description of the classifier is given in Richards (1986). Two factors were considered in this choice. First, the MD classifier was chosen rather than the ML classifier for this second classification because the normal distribution required by the ML classifier may be violated by the newly created SI band. Second, the Mahalanobis distance measure was selected rather than the Euclidean distance measure as it has the advantage of directional insensitivities and experience shows that it performs almost as accurately as the ML classifier. In other words, by using the Mahalanobis classifier, the classification results will not be biased by the data variations that exist in the different digital bands.

Supervised training was adopted in this study for both

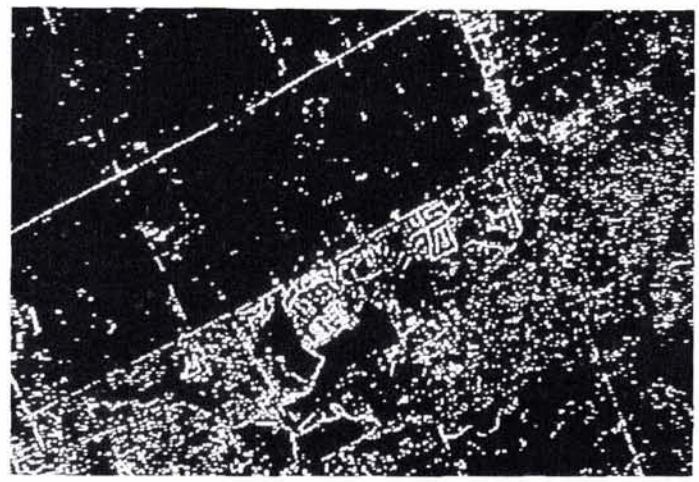

FIG. 1. An edge image produced by applying the Laplacian filter to the SPOT XS Band 1 image. The area shown is the same as in Plate 1. Note that urban features are emphasized rather than the rural components of the image.

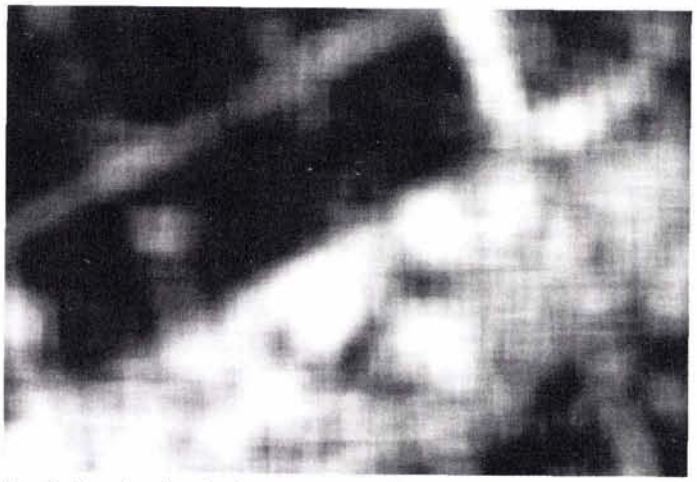

FIG. 2. An edge-density image generated by passing a 25 by 25 window across the image shown in Figure 1. The lighter tones indicate areas of higher edge densities which are primarily urban features.

classifications. However, rather than training on blocks of pixels, single pixel sampling of a large number of individual pixels was used. According to Campbell (1981) and Labovitz and Masuoka (1984), this type of training prevents violation of the statistical independence assumption. Each pixel selected as part of the training sample was obtained at least 5 pixels away from any adjacent training pixel. Selection of the training pixels was aided by the use of aerial photographs at 1:8,000 scale recorded over the study area in April 1987, less than two months prior to the acquisition of the imagery. As a result, about 60 pixels were selected for each class to obtain training statistics.

ACCURACY ANALYSIS

In order to determine the accuracy of each classification, approximately 30 individual test pixels per class were selected as reference data for comparison of ground information with the classification results. These pixels had to be pure rather than mixed pixels to ensure that the correct land cover was identified for each pixel. As with the training pixels, they were chosen with the aid of the 1:8,000-scale aerial photographs of the study site. For each pixel, the ground information determined from the aerial photographs (and field checking when necessary) was compared with the classification results by means of confusion matrices.

RESULTS AND DISCUSSION

In order to assess the contribution of the SI image to the classification transformed divergence (TD) matrices (Jensen, 1986), which indicate the separabilities of the training signatures, were calculated. In Table 3, the TD matrix calculated from the PCA bands only is presented. As suggested by Jensen (1986), the underlined values (less than 1900) indicate that the separabilities of those corresponding pairs are relatively poor. This occurs in 14 out of 66 pairs. The overall average (1881) is also lower than expected. It indicates that considerable confusion will occur in the final classification. In Table 4, the TD matrix generated from the two PCA bands in combination with the SI band is shown. Improved separabilities can be observed from the reduced number of underlined TD values (nine pairs) and from the higher value of 1953 for the average.

Tables 5 and 6 show the confusion matrices for the two classifications. The overall accuracies are 76.6 percent and 86.1 percent, respectively. A simple comparison of Tables 5 and 6 shows that inclusion of the SI band increased the accuracies of seven cover classes. Among the remaining five classes, one of them displays no change, while the other four are only slightly reduced in accuracy. This may be attributed to the use of different classifiers in the study.

In order to determine the significance of the difference between the two classifications, the Kappa coefficient and its variance (Cohen, 1960) were calculated for each confusion matrix. The Kappa value for Table 5 is 0.744 and 0.848 in Table 6 due to the inclusion of the SI band. A test shows that the improvement in the classification is significant at the 99.9 percent confidence level.

An examination of Table 5 shows that the classes obtained using the ML classification of the two PCA bands displays considerable confusion. Pairs of classes where obvious omission and commission errors occur are residential roof versus bare field, paved surface versus industrial and commercial roof, paved surface versus bare field, new crop and pasture versus lawn and tree complex, and deciduous trees versus crop cover. It can be seen that much of the confusion is between rural and urban land covers. The situation is very different for the MD classification of the two PCA bands combined with the SI band (Table 6). Most of the confusion between urban and rural areas has been removed or has been greatly reduced. Within urban areas, however, there is still some confusion between paved surface and industrial and commercial roof. In rural areas, the cultivated grass and the crop cover display slight confusion.

The classification results using the two PCA bands and the ML classifier are shown in Plate 2, while the results obtained by including the SI band in the classification are shown in Plate 3. These results parallel the figures reported in the matrices (Ta-

TABLE 3. THE TRANSFORMED DIVERGENCE MATRIX CALCULATED USING THE TWO PCA-BAND IMAGES*

	RR	PS	ICR	CL	LTC	CG	DT	CT	CC	NCP	BF
PS	1642										
ICR	1997	1804									
CL	2000	1984	1903								
LTC	1954	1951	2000	2000							
CG	2000	2000	2000	2000	1996						
DT	2000	2000	2000	2000	1995	1998					
CT	1911	2000	2000	2000	1668	2000	1988				
CC	2000	2000	2000	2000	1554	1845	1343	1964			
NCP	1832	1938	2000	2000	459	2000	1978	1358	1681		
BF	1745	562	1719	1492	1999	2000	2000	2000	2000	1999	
WS	1983	1986	1952	2000	2000	2000	2000	1998	2000	2000	1967
AVERAGE				1881							

*The abbreviated classes are listed in Table 1.

TABLE 4. THE TRANSFORMED DIVERGENCE MATRIX CALCULATED USING THE TWO PCA-BAND IMAGES AND THE SI-BAND IMAGE*

	RR	PS	ICR	CL	LTC	CG	DT	CT	CC	NCP	BF
PS	1787										
ICR	1999	1846									
CL	2000	1988	1920								
LTC	1961	1961	2000	2000							
CG	2000	2000	2000	2000	2000						
DT	2000	2000	2000	2000	1995	2000					
CT	1928	2000	2000	2000	1827	2000	1992				
CC	2000	2000	2000	2000	1787	1900	1578	1976			
NCP	1990	1987	2000	2000	1757	2000	1988	1563	1732		
BF	1982	1607	1944	1971	2000	2000	2000	2000	2000	1999	
WS	1991	1988	1964	2000	2000	2000	2000	1999	2000	2000	1977
AVERAGE				1953							

*The abbreviated classes are listed in Table 1.

TABLE 5. THE CONFUSION MATRIX CALCULATED FROM THE CONVENTIONAL CLASSIFICATION*

		Classified Results													Omission
		RR	PS	ICR	CL	LTC	CG	DT	CT	CC	NCP	BF	WS	Total	errors(%)
Reference Data	RR	30		2								6		38	21.1
	PS		15	12								5		32	53.1
	ICR			28								4		32	14.2
	CL				33									33	0.0
	LTC					27		1			9			37	27.0
	CG					1	27			5				33	18.2
	DT							27		5				32	15.6
	CT	1							22		2			25	12.0
	CC						1	7		18				26	30.8
	NCP		1			8			2		20			31	35.5
	BF	1	9	1	1							23	1	36	36.1
	WS	1							1			2	21	25	16.0
	Total	33	25	43	34	36	28	35	25	28	31	40	22	380	
	Commission errors (%)	9.1	40.0	34.9	2.9	25.0	3.6	22.9	12.0	35.7	35.5	42.5	4.5		

*The abbreviated classes are listed in Table 1

TABLE 6. THE CONFUSION MATRIX CALCULATED FROM THE CLASSIFICATION PRESENTED IN THIS PAPER*

		Classified Results													Omission
		RR	PS	ICR	CL	LTC	CG	DT	CT	CC	NCP	BF	WS	Total	errors(%)
Reference Data	RR	35		1								2		38	7.9
	PS		21	10							1			32	34.4
	ICR	1		27	1							3		32	15.6
	CL				33									33	0.0
	LTC					35		1			1			37	5.4
	CG					2	26			5				33	21.2
	DT							29		3				32	9.4
	CT	1				2			21		1			25	16.0
	CC						2	4		20				26	23.1
	NCP					4			1		26			31	16.1
	BF											35	1	36	2.8
	WS		3						1			2	19	25	24.0
	Total	37	24	38	34	43	28	34	23	28	29	42	20	380	
	Commission errors (%)	5.4	12.5	28.9	2.9	18.6	7.1	14.7	8.7	28.6	10.3	19.0	5.0		

*The abbreviated classes are listed in Table 1.

bles 5 and 6). In Plate 2 the classes are fragmented, even in the rural areas where the fields are large and relatively homogeneous. Many of the fields show several land covers and the paved surface class is frequently displayed with the bare fields. In addition, the tree and lawn complex, which should be restricted to urban areas, is also displayed in the rural areas. In Plate 3, where the SI Band is introduced into the classification, the classified pixels are much more concentrated in homogeneous groups. Most fields display only one land cover and the paved surface misclassification in rural areas has been largely removed. In turn, the class of new crops and pasture is no longer displayed in urban areas.

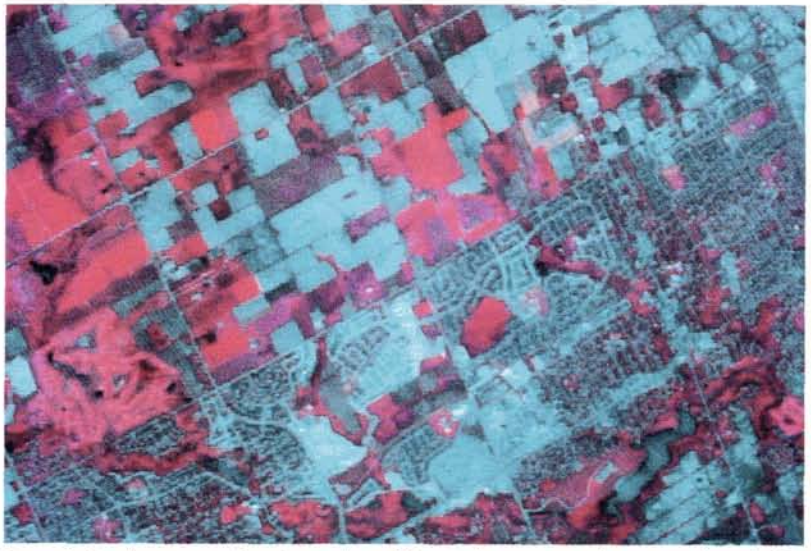

PLATE 1. A color composite of a portion of the study area covering approximately 300 by 400 pixels (6 km by 8 km). This color composite displays the original three SPOT HRV multispectral bands, after geometric correction. Bands 1, 2, and 3 of the image have been assigned to the blue, green, and red color guns, respectively. Fields predominate in the upper and left portions of the image, while residential and commercial areas cover much of the lower and right sections of this scene.

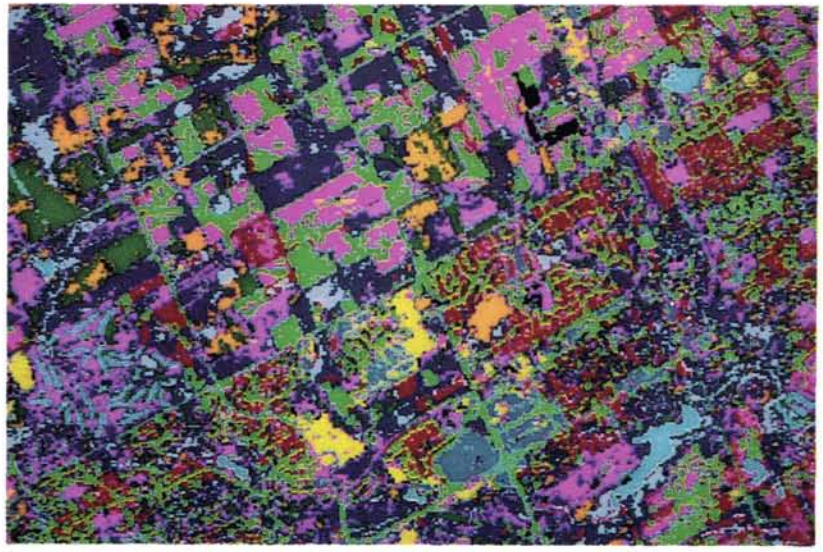

PLATE 2. Results of a maximum-likelihood classification applied to the two bands of data generated by the principal component analysis. (The 12 land covers shown by the different colors in the image are listed in Table 1.) Note that there is considerable fragmentation and confusion between classes in the image. In particular, many of the fields show more than one class. Often this is the paved surface class which should only be in the urban sections of the image and along the roads. Tree and lawn complex is also incorrectly encountered in the rural areas.

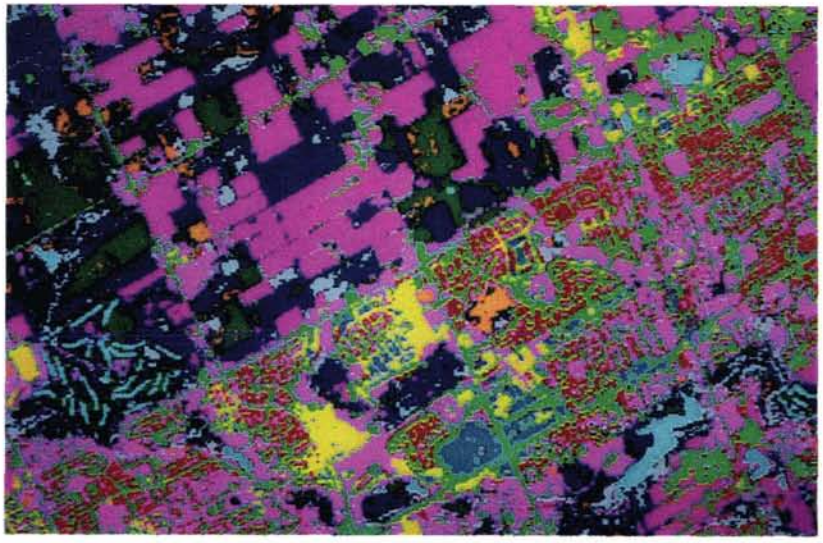

PLATE 3. Results of applying a minimum-distance classifier, with the Mahalanobis distance measure, to the two bands of data generated by the principal component analysis and the "Structural Information" (SI) band. In this case the SI band consisted of an edge-density image. Note that the confusion observed in Plate 2 has been largely eliminated. Both within the rural and the urban areas the land covers are more homogeneous.

The changes observed in the matrices and the classifications can readily be explained by reference to Figures 1 and 2. In Figure 1, it can be observed that the edges are primarily associated with roads and other structures in the urban area. When converted to an edge-density image (Figure 2), the bright areas represent urban development while the dark areas of the image are rural components, in particular the fields. For many of the classes, this differentiation in the edge-density image eliminates the confusion between the rural and urban land covers which have similar spectral characteristics. They include paved surface versus bare field, new crop and pasture versus lawn and tree complex, and deciduous trees versus crop cover.

It should be noted, however, that the edge-density image does not entirely eliminate the spectral confusion that is encountered. For example, in the urban area both the paved surface and the industrial and commercial roof display a relatively high density of edges. In the rural area, it is the cultivated grass and the crop cover that both display a relatively low density of edges. In other words, for these pairs of classes there is still some spectral and spatial confusion between them, which makes accurate classification difficult. It is suggested, however, that if other measures, such as textural or contextual measures were to be employed as the SI band or as an additional SI band, the confusion might be further reduced.

CONCLUSIONS

It has been demonstrated that a structural information (SI) band generated from using high spatial resolution data, such as SPOT XS data, can be readily combined with spectral data for image classification. For this study, an edge-density image generated using a Laplacian filter was used as the SI band. High edge densities were encountered in urban areas due to the presence of roads and buildings, while the field patterns in rural areas led to low edge densities. Thus, the edge-density image provided a distinction between rural and urban environments. As a result, it improved differentiation of land covers with similar spectral signatures that are encountered in both environments. Classification accuracies increased from 76.6 percent to 86.1 percent overall with the use of the SI band. In other multispectral classification studies where spectral confusion is encounted, it is suggested that an edge-density image or other spatial measure used for the SI band may help to improve the classification accuracy.

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BOOK REVIEW

D.H. Maling, *Measurements from Maps: Principles and Methods of Cartometry*. New York: Pergamon Press, 1989. 577 p. Hardcover: $80.00 [ISBN: 008 0302904]. Paper: $36.00 [ISBN: 008 0302890].

THIS VOLUME takes as its subject the use of maps for precise measurements. It consists of a survey of methods, problems, and ideas pertaining to measurements from maps. Its scope encompasses both conceptual and methodological issues; they are presented logically and clearly, with ample references. The volume is organized into 23 chapters, each addressing a topic such as data collection, sampling, projections, inherent inaccuracies in cartographic measurements, estimation of errors, errors in areal and linear measurements, spatial sampling, projections, fractals, stereology, deformation of paper, and map accuracy standards. I expect most readers will use this book as a reference work, but it could form a useful text for an upper level university course dedicated to examination of issues in cartographic accuracy or cartographic measurements.

Maling engages in a thorough pursuit of his topics; his work encompasses scientific literature from many nations, disciplines, and scientific traditions. In some instances the diversity of the material itself forms a statement to the unexpected complexity of ostensibly simple topics, and to the ingenuity of those who have attacked these issues. Who could have anticipated the remarkable diversity of the methods devised to evaluate errors in areal estimation? Certainly I was ignorant of many of the methods described here, and I expect that there are few among even the most expert and dedicated cartographers who have already mastered the book's content.

Some readers may question Maling's description of techniques that are antiquated in the context of digital cartography. For example, he describes in detail numerous manual methods for estimating distances along curved lines on maps, and for estimating areas depicted on maps. Some readers may regard his attention to such issues as misplaced enthusiasm for outmoded methodology. I defend Maling's approach on grounds of completeness, that he has documented methods that were not previously written out (at least in accessible documents) and that some of these methods can form conceptual models for more sophisticated methods. I do criticize this aspect of the book, however, to the extent that I wish he had provided comment, summary, and comparison, to provide the reader with more evaluation to accompany his excellent compilation of methods.

It is unfortunate perhaps that Maling presents this information through the vehicle of the paper map – a product that may be on the eve of its demise as the primary medium for cartographic innovation. Paper maps will be with us for many more years, but today most cartographic innovation is defined in the context of digital maps, so the shift to a new paradigm is already in progress. It is, however, a mistake to dismiss this volume as anachronistic on this basis. Its content is germane in both domains, and digital cartographers are well advised to master its content, as it records lessons that will be either learned from its pages, or repeated in practice. The errors Maling describes here do not disappear in the digital format, but are only systematized to be more deeply hidden.

The perfect illustration of the difficulty and the significance of Maling's topic is his concluding chapter on maritime boundaries. Here his description focuses on the truly Byzantine methodology required to implement the diplomatic concepts of international maritime boundary law – concepts intended no doubt to embody the essence of elegant simplicity, but which can be implemented only by the most intricate methodology and a detailed knowledge of maritime charts. Here is the ultimate illustration of the practical significance of the principles and methods presented in earlier chapters.

Maling develops and presents his mathematics and statistics with, I think, appropriate detail and rigor. For the most part, complete proofs are not presented, but the basic logic is given in sufficient detail to permit most readers to follow without difficulty. The reader who requires a more complete derivation will need to refer to other references, which are cited in ample number, and (as best I can determine) usually include the original or most authoritative work. Readers will appreciate the Index to Symbols, an essential aid, given the established use of so many multiple meanings for many of the symbols.

References encompass a diverse range of disciplines, perspectives, both theoretical, and applied topics. The references are mainly in English, but Maling has identified important works in other languages including Russian, German, and French. The subject index is adequate, but like many other scientific books, it seems to have been prepared in a mechanical manner by someone who is not really interested in the book's content. I found most items I searched for in the index, but many were listed in an awkward manner.

This book will soon become one of the modern cartographer's most valued references.

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