Multidate SAR/TM Synergism for Crop Classification in Western Canada

B. Brisco and R. J. Brown

Abstract

Multidate synthetic aperture radar (SAR) and Thematic Mapper (TM) visible and near-infrared (VNIR) data were evaluated for classifying crops frequently grown in western Canada. The VNIR data were superior to the SAR data for single date classifications due to the multispectral information content. Multidate classifications with SAR data improved classification accuracy from 30 to 74 percent although multidate VNIR produced the highest single sensor result of 90 percent correct classification. This was slightly improved to 92 percent by including the SAR data with the VNIR data. However, transformed divergence statistics show that the SAR and VNIR channels are both found in the top eight channels, and, indeed, the best two SAR channels and the best two VNIR channels, based on their transformed divergence statistics, produced an overall classification accuracy of 85 percent. Furthermore, the May TM data combined with the SAR data yielded an 87 percent correct classification because the grain and alfalfa classes were much better separated when VNIR data was combined with SAR data. These results demonstrate significant synergism between the two sensors and suggest the need for a feature selection approach, or at least a knowledge based system incorporating the synergism effect, once multidate, multisensor data become available on a regular basis. The substitution of SAR data beneath cloud covered terrain in TM data is used to demonstrate another aspect of SAR/VNIR synergism.

Introduction

Remote sensing techniques have become an important tool for resource management, with successful mapping and monitoring projects demonstrated for a wide variety of applications. One such application is crop identification and monitoring (Ryerson *et al.*, 1985; Boatwright and Whitehead, 1986; Sharman, 1990). One of the limitations of using remote sensing data for this application is data availability due to cloud cover and the relatively long repeat cycle of the high spatial resolution optical sensors. This has led to the implementation of a Crop Information System (CIS) within Canada which utilizes a compositing procedure using low resolution, high temporal coverage data, provided by the Advanced Very High Resolution Radiometer (AVHRR), into weekly images (Brown *et al.*, 1990). These weekly images are used to generate normalized difference vegetation indices (NDVI) which are the basis for the crop condition assessment. The increased information content in the finer spatial resolution Thematic Mapper (TM) and SPOT HRV imagery is offset by the uncertainty of data availability.

The impending launch of RADARSAT and other existing spaceborne synthetic aperture radar (SAR) sensors, such as the European Remote Sensing Satellite (ERS-1) and the Japanese Earth Resource Satellite (JERS-1), is changing this situation. Due to the all-weather, day or night capabilities of SAR, imagery will be available on a regular and timely basis. The synergism of SAR and visible and near-infrared (VNIR) data has been previously demonstrated for some applications (Ahern *et al.*, 1978; Ulaby *et al.*, 1982; Brisco, 1985) and will be expanded upon within this paper. SAR has the potential to provide unique information on a timely basis due to it's all weather day/night capabilities. Because of these implications, the Canada Centre for Remote Sensing (CCRS) is undertaking research to develop the procedures to integrate SAR data into the CIS. The research program is using microwave data from ground-based and airborne platforms to achieve this objective (Brown, 1987).

During the summer of 1988, an extensive multidate airborne SAR data set was acquired of a site near Saskatoon, Saskatchewan. Early and mid-season cloud-free TM imagery were also available. This data set provided an excellent opportunity to investigate the synergism of SAR and VNIR data for crop classification in western Canada. Specifically the objectives of the study presented in this paper were

- To evaluate the crop classification accuracy achieved using C-HH SAR and TM data alone and in combination for crops commonly grown in western Canada,
- To demonstrate the impact on crop classification accuracy of replacing cloud covered TM data with SAR data, and
- To evaluate the improvement in crop classification accuracy using multidate TM and SAR data.

Study Area, Data Set, and Approach

The test site is located east of Saskatoon, Saskatchewan in a predominately agricultural area where there are fields of canola, barley, wheat, summerfallow, and alfalfa (Figure 1). This area is characterized as a glaciolacustrine plain with minor areas of hummocky topography. The surficial geological deposits are predominantly glaciolacustrine clays and silts which have developed into Dark Brown soils. Annual precipitation is approximately 350 mm per year.

Geocoded cloud-free TM scenes from 28 May and 16 July 1988 were obtained, but only TM channels 2 through 5 were

B. Brisco is with Intera Information Technologies, 2 Gurdwara Road, Suite 200, Nepean, Ontario K2E 1A2, Canada.

R.J. Brown is with the Canada Centre for Remote Sensing, 588 Booth Street, Ottawa, Ontario K1A 0Y7, Canada.

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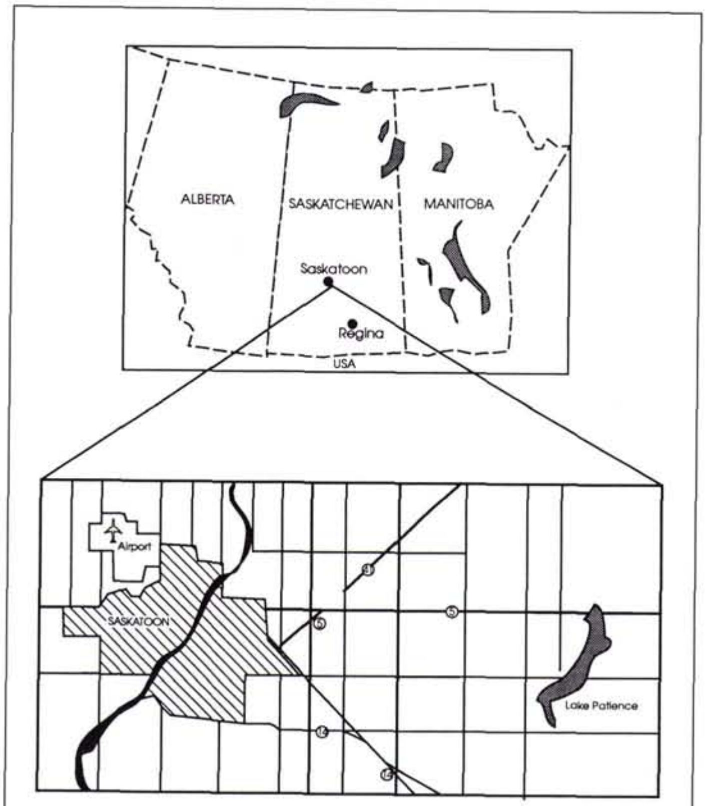

Figure 1. The location of the study site near Saskatoon, Saskatchewan.

considered in this analysis. TM channel 1 is susceptible to atmospheric effects, channel 6 is the low resolution thermal band, and channel 7 is very highly correlated to channel 5 (Crist and Cicone, 1984). C-HH SAR data were acquired on 25 May, 24 June, 21 July, and 10 August 1988 using the CCRS SAR (Livingstone *et al.*, 1987) in narrow swath mode (45 to 76 degrees incidence angle) with a 6-metre resolution. The SAR imagery used in this analysis was the output from the real-time processor on board the aircraft (seven-look amplitude data) which was resampled to 25-metre pixel spacings using the nearest-neighbor algorithm and then registered to the TM data. A 3 by 3 median filter was then applied to each SAR channel to further reduce the effects of fading.

The maximum-likelihood algorithm was used to classify all single channels (both VNIR and SAR) and various multichannel combinations. Due to the difficulty in separating barley from wheat, these two crops were combined into a grain class. The training areas for grain, canola, alfalfa, and summerfallow crops were outlined on a per-field basis. Sloughs, wooded areas, buildings, field edges, and other non-cultivated areas were excluded from the training area. This training area mask was registered to the TM data. Approximately a 30 percent training sub-sample of each field was used from the crop mask for generating class statistics, with the remaining 70 percent used for testing the classification accuracy. All classifications were done on a per-pixel basis with equal *a priori* probabilities for each class. Unless otherwise stated, total classification accuracy is the criteria used to evaluate the classifications throughout the paper.

The approach of training and testing on pixels taken from the same field (but not the same pixels) was followed because of our concern that the variations in reflectances/backscatter between fields would not be the same in the optical and microwave portions of the spectrum. If this were the case, we would not be able to adequately address the objective of assessing the synergy between the VNIR and SAR bands. Although the classifications were done on a per-pixel basis, it would have been preferable to use a segmentation and field classifier approach for the analysis in order to reflect operational approaches. Unfortunately, the crop map available for this study did not cover enough fields to support this approach. However, the results of this analysis can still be used to meet the stated objectives of comparing SAR and VNIR data for crop separability information. A summary of the number of fields and pixels per class are given in Table 1.

The multichannel combinations were chosen to assess SAR versus TM information content and synergism from a multisensor and multidate perspective. Thus, all various combinations of the four dates of SAR were classified (i.e., all one-, two-, three-, and four-channel combinations) as well as each four-channel TM data set (i.e., each date). The two dates of TM were also combined for an eight-channel classification. Each date of TM imagery was also combined with various multidate combinations of SAR data (i.e., into five-, six-, seven-, and eight-channel combinations) and classified. Finally, all 12 channels (i.e., four dates of SAR and two dates of TM) were also classified to evaluate the maximum classification accuracy achievable with this data set.

To further evaluate which channel(s) provided the best information for crop separability, the total average transformed divergence was calculated for each of the 12 channels. Average transformed divergence was used as the evaluation criteria because very high correlations with classification results have been demonstrated (Kramber *et al.*, 1988) and it provides a useful measure of separability (Swain and Davis, 1978; Goodenough *et al.*, 1978). The best two SAR channels and the best two VNIR channels, as identified by the value of their transformed divergence statistic, were then classified using the maximum-likelihood classifier in the same manner as described above.

As a simulation of the effect of cloud cover on crop classification using TM data, a cloud mask was generated (i.e., saturate the DN values) and imposed on the 16 July TM scene. Approximately 30 to 40 percent of the study area was "cloud covered" using this technique. A maximum-likelihood classification was then performed on these data using the class statistics generated previously. The area beneath this mask was then replaced with the 21 July SAR classification and the crop classification accuracy was recalculated. This allowed us to evaluate the effect of replacing the cloud covered TM data with SAR data for crop classification purposes.

TABLE 1. THE NUMBER OF FIELDS AND PIXELS FOR THE CROP CLASSES GRAIN, CANOLA, ALFALFA, AND SUMMERFALLOW.

Crop Type	Number of Fields	Number of Pixels
Summerfallow	38	52,618
Grain	40	48,680
Alfalfa	5	8,924
Canola	4	7,116

Results and Discussion

The classes exhibited Guassian or near Guassian distributions. Equal *a priori* probabilities were used because unequal *a priori* probabilities were inappropriate for our objectives. Unequal *a priori* probabilities are useful when attempting to minimize risk or ensure that all of a particularly large class be correctly identified. For example, if 80 percent of a region were wheat, then one could force a high classification accuracy of wheat by using a proportionatley high *a priori* probability. However, this would give no insight into how well one could distinguish between wheat and the minority clases. In this study, the objective was to evaluate separability between the various classes.

The single channel classification accuracies for the TM and SAR data can be found in Table 2. In general, the July data are superior to the other dates in correctly classifying the crop types in both the VNIR and microwave regions. This time period has been found to be superior for crop classification purposes in other multitemporal studies (Brisco *et al.*, 1992; Foody *et al.*, 1989; Brown *et al.*, 1984, Brown *et al.*, 1980) and has been attributed to the crops being at maximum phenological development during this time.

There are some other interesting observations in Table 2. For example, the alfalfa crop is most accurately identified in the May TM channels 2 and 3 and the June SAR data. Alfalfa is the first crop to green up after the winter and thus becomes separable from the other cultivated areas in the visible channels of the TM sensor. The repeated harvest of the alfalfa crop throughout the growing season influences the radar backscatter because uncut and cut alfalfa have different signatures. The importance of the crop calendar on class separability for alfalfa and other hay crops using SAR data has been previously reported (Brisco *et al.*, 1984). For example, the alfalfa is poorly classified in the August C-HH image, perhaps because of recent harvest operations.

Also note that, although canola is most accurately identified in July and then August, it becomes separable (72 percent correct classification) as early as June in the SAR data. Canola is a broadleaf crop with high moisture content, and thus only a little plant growth is required before significant backscatter occurs in the microwave region (Brown *et al.*, 1984). The crop must be in flower before accurate identification in the VNIR region (Brown *et al.*, 1980). Summerfallow can be identified with greater than 80 percent accuracy on TM channels 2 and 3 in July and on the C-HH SAR channel by August. However, a single SAR image alone may give deceiving results when identifying summerfallow fields. The radar backscatter value will be strongly dependant upon whether the field has been cultivated to reduce weed growth and on the soil moisture content.

Finally, note the poor separability of grains throughout the growing season if only one channel is being considered. The poor separability of the wheat and barley crops in both the microwave and VNIR regions of the electromagnetic spectrum has been previously reported as well (Brown *et al.*, 1984; Brisco *et al.*, 1989). This is due to the very similar structure and color of the grain crops. This problem may be overcome by using crop rotation information, historical averages, crop calendar differences, and/or other ancillary information. CCRS is pursuing these approaches to solving the small grain classification problem and will report on the progress in the future.

An increase in the number of dates of SAR used in the analysis results in increased total classification accuracy until a maximum of 74 percent is achieved with four dates (Table 3). Bush and Ulaby (1978) predicted reaching 90 percent accuracy with four dates of microwave data in a simulation study but the revisits were ten days apart. The SAR data used in this study were acquired approximately a month apart, which may be too long a time period to maximize changes in target properties (dielectric and geometric) as a function of the crop calendars. Multitemporal observation certainly does increase classification accuracy, as many other studies have observed (Brisco *et al.*, 1992; Le Toan *et al.*, 1989; Foody *et al.*, 1989; Brisco *et al.*, 1984; Hoogeboom, 1983). The successful launch of ERS-1 and JERS-1 and the upcoming RADARSAT and ERS-2 spaceborne SARs means that more and more SAR data will be available in future years. As SAR calibration techniques have recently improved (Freeman, 1992), it is feasible to expect calibrated products to become more routinely available from these platforms. This will make it possible to effectively use data from different sensors which will enhance using multidimensional approaches, including multitemporal, for crop classification.

This same effect is seen in the TM data (Table 4). For this analysis, all four channels of the TM data (i.e., TM 2 to 5) were used in the classification algorithm for each date and

Table 2. Single-Channel Crop Classification Results Using 1988 TM and C-HH SAR Data.

Channel		% Correctly Classified				Overall
		Summer-fallow	Grains	Alfalfa	Canola	Accuracy % ± Std. Dev.
25 May	C-HH	23	18	21	51	28 ± 15
28 May	TM 2	67	0	73	41	45 ± 33
	TM 3	69	0	71	55	49 ± 33
	TM 4	55	33	43	54	46 ± 10
	TM 5	63	44	46	22	44 ± 17
24 June	C-HH	56	0	65	72	48 ± 33
16 July	TM-2	85	22	17	77	50 ± 36
	TM-3	88	4	55	79	57 ± 38
	TM-4	78	54	0	84	54 ± 38
	TM-5	78	38	56	84	64 ± 21
21 July	C-HH	78	54	19	91	61 ± 32
10 Aug	C-HH	82	55	4	81	56 ± 37

Table 3. Multidate Crop Classification Accuracy Using C-HH SAR Data (25 May, 24 June, 21 July, and 10 August 1988).

Channel Combination	% Correctly Classified				Overall
	Summer-fallow	Grains	Alfalfa	Canola	Accuracy % ± Std. Dev.
2 Channel					
May/June	50	1	72	75	50 ± 34
May/July	67	54	40	92	63 ± 22
May/August	76	53	22	81	38 ± 35
June/July	68	52	58	91	67 ± 17
June/August	71	45	61	82	65 ± 16
July/August	71	58	47	89	66 ± 18
3 Channel					
May/June/July	67	53	63	92	69 ± 17
May/June/Aug	72	46	66	84	67 ± 16
May/July/Aug	68	62	60	90	70 ± 14
June/July/Aug	73	59	68	89	72 ± 13
4 Channel					
May/Jun/Jul/Aug	75	62	69	91	74 ± 12

TABLE 4. SINGLE DATE AND TWO-DATE TM CROP CLASSIFICATION ACCURACIES (1988).

Channels	% Correctly Classified Summer-fallow	Grains	Alfalfa	Canola	Overall Accuracy % ± Std. Dev.
TM 2-5 (28 May)	63	58	82	53	64 ± 13
TM 2-5 (16 July)	89	73	63	90	79 ± 13
TM 2-5 (both dates)	91	91	88	90	90 ± 1

TABLE 5. SAR/TM MULTI SENSOR CROP CLASSIFICATION ACCURACIES (1988). THE C-HH SAR DATA WERE ACQUIRED ON 29 MAY, 24 JUNE, 21 JULY, AND 10 AUGUST.

All four SAR	% Correctly Classified Summer-fallow	Grains	Alfalfa	Canola	Overall Accuracy % ± Std. Dev.
+ TM 2-5 (28 May)	87	85	85	91	87 ± 3
+ TM 2-5 (16 July)	90	80	76	92	85 ± 8
+ TM 2-5 (both dates)	91	94	89	94	92 ± 2
May, June, July C-HH + TM 2-5 (16 July)	90	79	72	93	84 ± 10

then for both dates together. The TM sensor performs much better on a single date then the SAR because of the multispectral information content. Indeed, the two dates of TM yield an overall total classification accuracy of 90 percent. This is only slightly improved to 92 percent by adding all four dates of SAR to create a 12-channel data set (Table 5). This accuracy is sufficient for most crop identification applications.

To be of most use to present crop forecasting approaches, the timeliness and/or accuracy of the information must improve on the early August date already achievable with conventional approaches. In one example, we assumed only one date of TM data was available (from July), and it was combined with May, June, and July SAR data to evaluate classification accuracy achievable by mid-July. Although the results indicate only an 84 percent classification accuracy (Table 5), this is close to the operational goal of 90 percent correct classification and only improves to 85 percent by adding the August SAR channel. As another example, if only a May TM scene were available and it was combined with all four dates of SAR, then an overall accuracy of 87 percent correct classification was achieved. These results show that only one date of VNIR data combined with multitemporal SAR data will provide suitable classification accuracies.

The total average transformed divergence for each of the 12 channels is presented in Table 6. July TM channel 5 has the overall highest separability, followed very closely by the July and August SAR data. July TM channels 4, 3, and 2 are next, followed by May TM channels 2, 3, and 4 and the June SAR. Note that May TM channel 5 and, in particular, the May SAR provide the least separability. These results further demonstrate the synergism of both the TM and SAR sensors and the optimum date for data acquisition.

The synergism is related to both the different information on crop type as a function of wavelength and the change in information with time. Table 7 provides the transformed divergence statistic for each class pair and all 12 channels being considered. The July/August TM and SAR data provide the most separability at a given time because of maximum

TABLE 6. THE TOTAL AVERAGE TRANSFORMED DIVERGENCE STATISTICS FOR CROP TYPE FROM EACH SAR AND TM CHANNEL.

Channel	Total Transformed Divergence
28 May 1988 TM-2	2.2
28 May 1988 TM-3	2.6
28 May 1988 TM-4	2.0
28 May 1988 TM-5	1.4
16 July 1988 TM-2	3.2
16 July 1988 TM-3	4.5
16 July 1988 TM-4	5.2
16 July 1988 TM-5	5.6
25 May 1988 C-HH SAR	0.1
24 June 1988 C-HH SAR	2.0
21 July 1988 C-HH SAR	5.5
10 Aug 1988 C-HH SAR	5.5

TABLE 7. TRANSFORMED DIVERGENCE STATISTIC FOR ALL CLASS PAIRS AND EACH OF THE 12 CHANNELS BEING CONSIDERED. (FAL=SUMMERFALLOW, GRN=GRAIN, ALF=ALFALFA, AND CAN=CANOLA).

Channel	Fal/Grn	Fal/Alf	Fal/Can	Grn/Alf	Grn/Can	Alf/Grn
May C-HH	0.02	0.03	0.02	0.02	0.01	0.00
Jun. C-HH	0.07	0.12	0.58	0.18	0.28	0.81
Jul. C-HH	0.49	0.02	1.84	0.34	1.10	1.75
Aug. C-HH	0.43	0.15	1.95	0.09	1.37	1.51
TM-2 May	0.33	1.02	0.24	0.25	0.01	0.35
TM-3 May	0.35	1.12	0.29	0.35	0.01	0.45
TM-4 May	0.36	0.10	0.32	0.59	0.01	0.58
TM-5 May	0.25	0.61	0.10	0.14	0.04	0.24
TM-2 July	0.89	0.96	1.22	0.02	0.08	0.02
TM-3 July	1.05	1.11	1.62	0.10	0.18	0.41
TM-4 July	0.20	0.05	1.87	0.05	1.33	1.66
TM-5 July	1.04	0.62	1.81	0.29	0.53	1.30

differences in crop phenology. This is followed by the addition of May TM data, which incorporates the change due to the crop growth stages in the separability information. Note that the May TM data provide the best summerfallow/alfalfa and grain/alfalfa separability. As discussed earlier, this can be related to the physical interaction of the radiation with the crops. For example, TM is superior for separating summerfallow from grain classes due to the marked spectral difference (i.e., green versus brown/black). However, the SAR data are superior for separating canola, especially early in the growing season, due to the high backscatter from the broad-leafed crops as opposed to the lower backscatter from grains and summerfallow. Also note that the grain class separability benefits from the combined SAR and TM data largely because of reduced confusion with alfalfa and summerfallow on TM data and increased separability from canola on the SAR data.

To demonstrate this, the best four channels, as identified by the transformed divergence statistics, were classified with the results given in Table 8. The overall accuracy of 85 percent obtained with two July TM channels, and the July and August SAR data are better then that obtained with the four-channel SAR (74 percent) or the four-channel July TM data (79 percent). It is also approximately the same accuracy as that obtained by using all four SAR images with either date of TM data.

A final example of the synergism of SAR and TM data is

TABLE 8. CROP CLASSIFICATION RESULTS USING 16 JULY TM3+4, 21 JULY C-HH SAR, AND 10 AUGUST C-HH SAR DATA. OVERALL CLASSIFICATION ACCURACY IS 85 ± 5 PERCENT.

Crop Type	% Correctly Classified			
	Summerfallow	Grains	Alfalfa	Canola
Summerfallow	87	17	3	1
Grain	10	77	11	10
Alfalfa	3	2	86	1
Canola	0	4	0	89

TABLE 9. THE SIMULATED EFFECT OF CLOUD COVER ON TM CROP CLASSIFICATION ACCURACY AND THE RESULT OF REPLACING THE TM DATA WITH C-HH SAR DATA.

Feature Description	% Correctly Classified				Overall Accuracy % ± Std. Dev.
	Summer-fallow	Grains	Alfalfa	Canola	
16 July TM 2-5	89	73	63	90	79 ± 13
16 July TM 2-5 with 30 - 40% "Cloud"	57	51	50	60	55 ± 5
Cloudy 16 July TM 2-5 with 21 July C-HH SAR	86	68	52	91	74 ± 18

the cloud simulation results presented in Table 9. By replacing cloud covered pixels in a TM scene by SAR data for the same area, similar overall accuracies can be obtained. Thus, if a July TM scene were available for crop classification, it would be preferred due to the multispectral information content. If small areas of the scene were cloud covered, they could be replaced with SAR data with little effect on the overall classification accuracy. Indeed, multidate SAR data could be used to maintain the high classification accuracies obtainable with the TM data. With such an approach of replacing cloud corrupted TM data with SAR data, the TM data can be used to aid the classification of the SAR only areas by correlating SAR imagery to the TM data within the areas of data overlap.

Summary

Multidate TM and C-HH SAR data were used to evaluate classification accuracy for canola, grain, alfalfa, and summerfallow crop types. The results of maximum-likelihood classification and transformed divergence statistics show that multidate acquisitions considerably improve classification accuracy for both VNIR and SAR data. The time between SAR acquisitions (one month) may be too long to effectively use phenological changes during the growing season for improving crop classification. Satellite SARs such as ERS-1 and RADARSAT will allow for more observations throughout the growing season to further study this question. Revisits on a weekly time scale may be more useful. Although July is the best time for single date classifications, there is additional information available in the other time periods. There is also considerable synergism between the two types of sensors, suggesting that both electromagnetic regions be used for operational crop information systems. This suggests the need to consider feature selection as a tool for picking appropriate channels for analysis and/or the use of knowledge based systems which take account of multisensor synergism. Environmental conditions and the regional crop calendars will also influence the channel selection process.

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Brian G. Brisco

Brian G. Brisco was born in Chatham, Ontario in 1954. He received the B.Sc. Honours degree in Ecology from the University of Guelph in 1977 and an M.Sc. degree in Soil Science/Land Resource Science, also from the University of Guelph, in 1980. In 1985 he received the Ph.D. degree in Physical Geography/Remote Sensing from the University of Kansas. While attending KU, he worked in the Remote Sensing Laboratory as an associate project engineer. In 1987 he returned to Canada and worked as a Post Doctoral Fellow at the Canada Centre for Remote Sensing (CCRS) through a National Research Council fellowship. Since 1989 he has been employed by Intera Information Technologies as a research scientist under contract to CCRS. His research interests focus on using radar data for monitoring and managing renewable resources with an emphasis on agronomic applications. Dr. Brisco is a member of the Canadian Remote Sensing Society of the Canadian Aeronautics and Space Institute and is an associate editor of the *Canadian Journal for Remote Sensing*.

Ronald J. Brown

Ron Brown is head of the Applications Development Section, Canada Centre for Remote Sensing (CCRS), coordinator within the Radar Data Development Program for applications development within agriculture, and overall coordinator for SAR applications development within CCRS Applications Division. He holds a PhD in Physics from the University of Manitoba but most of the research was carried out at St. Andrews University, Scotland and the Atomic Energy Establishment, Harwell, England. He is a former editor of the *Canadian Journal of Remote Sensing* and was a guest editor of a special issue of the *Canadian Journal of Remote Sensing* on the use of SAR in agricultural applications. He is also a principal investigator for SIR-C and ERS-1 for vegetation related investigations.

FORTHCOMING ARTICLES

The following list includes only those articles scheduled for publication in *PE&RS* through 1995 except for those in the November GIS Special Issue.

R. M. Batson and *E. M. Eliason*, Digital Maps of Mars.

Michael F. Baumgartner and *Albert Rango*, A Microcomputer-Based Alpine Snow Cover Analysis System (ASCAS).

Jorge Antonio Silva Centeno and *Victor Haertel*, Adaptive Low-Pass Fuzzy Filter for Noise Removal.

John L. Dwyer, Fred A. Kruse, and *Adam B. Lefkoff*, Effects of Empirical versus Model-Based Reflectance Calibration on Automated Analysis of Imaging Spectrometer Data: A Case Study from the Drum Mountains, Utah.

Sam Ekstrand, Landsat TM-Based Forest Damage Assessment: Correction for Topographic Effects.

Peng Gong, Ruiliang Pu, and *John R. Miller*, Coniferous Forest Leaf Area Index Estimation along the Oregon Transect Using Compact Airborne Spectrographic Imager Data.

Matthew Heric, Carroll Lucas, and *Christopher Devine*, The Open Skies Treaty: Qualitative Utility Evaluations of Aircraft Reconnaissance and Commercial Satellite Imagery.

Ronald Kwok and *Tom Baltzer*, The Geophysical Processor System at the Alaska SAR Facility.

Jussi Lammi and *Tapani Sarjakoski*, Image Compression by the JPEG Algorithm.

Donald L. Light, Film Cameras or Digital Sensors? The Challenge Ahead for Aerial Imaging.

Michel Massart, Marie Pétillon, and *Eléonore Wolff*, The Impact of an Agricultural Development Project on a Tropical Forest Environment: The Case of Shaba (Zaïre).

Janet E. Nichol, Monitoring Tropical Rain Forest Microclimate.

K. Olaf Niemann, Remote Sensing of Forest Stand Age Using Airborne Spectrometer Data.

Elijah W. Ramsey III and *John R. Jensen*, Remote Sensing of Mangrove Wetlands: Relating Canopy Spectra to Site-Specific Data.

Stephen A. Sader, Spatial Characteristics of Forest Clearing and Vegetation Regrowth as Detected by Landsat Thematic Mapper Imagery.

Tian-Yuan Shih, The Reversibility of Six Geometric Color Spaces.

Mohammed E. Shokr, Laurence J. Wilson, and *Dwayne L. Surdu-Miller*, Effect of Radar Parameters on Sea Ice Tonal and Textural Signatures Using Multi-Frequency Polarimetric SAR Data.

Patrick J. Starks, Frank R. Schiebe, and *John F. Schalles*, Characterization of the Accuracy and Precision of Spectral Measurements by a Portable, Silicon Diode Array Spectrometer.

Daniel R. Steinwand, John A. Hutchinson, and *John P. Snyder*, Map Projections for Global and Continental Data Sets and an Analysis of Pixel Distortion Caused by Reprojection.

Michael E. Wehde, Digital Image Comparison by Subtracting Contextual Transformations: Percentile Rank Order Differentiation.

Gary M. Wohl, Operational Sea Ice Classification from Synthetic Aperture Radar Imagery.

Peter T. Wolter, David J. Mladenoff, George E. Host, and *Thomas R. Crow*, Improved Forest Classification in the Northern Lake States Using Multi-Temporal Landsat Imagery.