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Active Microwave Responses: An Aid in Improved Crop Classification

Inclusion of active microwave responses from 4.75 GHz, 1.6 GHz, and 0.4 GHz with visible and infrared data helped improve crop classification compared to only visible and infrared classification models.

Abstract: *Due to the dependence of visible and infrared spectral data collection upon clear weather, agricultural crop classification has been limited. Active microwave responses are generally independent of clouds. Consequently, a study determined the feasibility of using visible, infrared, and active microwave data to classify agricultural crops such as corn, sorghum, alfalfa, wheat stubble, millet, shortgrass pasture and bare soil. Visible through microwave data were collected by instruments on board the* NASA *C-130 aircraft over 40 agricultural fields near Guymon, Oklahoma in 1978 and Dalhart, Texas in 1980. Results from stepwise and discriminant analysis techniques indicated 4.75 GHz, 1.6 GHz, and 0.4 GHz cross-polarized microwave frequencies were the microwave frequencies most sensitive to crop type differences. Inclusion of mirowave data in visible and infrared classification models improved classification accuracy from 73 percent to 92 percent. Despite the results, further studies are needed during different growth stages to validate the visible, infrared, and active microwave responses to vegetation.*

Introduction

Given visible and infrared response differences between vegetative species, visible and infrared models have been developed to classify vegetation and assess crop acreage (Gausman, 1977; Thomas and Gausman, 1977). With minimal ancillary data, classification accuracies have been as high as 80 percent in some areas. Techniques were developed to inventory foreign agriculture with satellite-collected data. The National Aeronautics and Space Administration (NASA) through the Large Area Crop Inventory Experiment was successful is using Landsat visible and infrared data to estimate U.S. and foreign wheat acreage to greater than 90 percent accuracy (Heydorn *et al.*, 1979).

In spite of the widespread use of visible and infrared spectral data to classify vegetation, several factors, such as variable atmospheric effects, soil background reflectance and large variations within crop types, influence the accuracy and utility of spectral data (Bauer *et al.*, 1979). Large spectral diversity within crop types made vegetation classification for Wigton and VonSteen (1973) difficult. In addition, the soil background reflectance also increased the spectral diversity within a crop and influenced the composite reflectance (Westin and Lemme, 1978). With the increased diversity, crops growing during the same time of year will often be difficult to discriminate.

Several studies have successfully used active microwave data alone to classify agricultural crops. Bush and Ulaby (1978) found horizontal like- and cross-polarized K-band (14.0 GHz) active microwave

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TABLE 1. TOTAL PHYTOMASS OF VEGETATED FIELDS AT DALHART.

Field	Crop Type	Wet Phytomass $(Kg/m)^3$	Dry Phytomass $(Kg/m)^3$	Yield (Kg/Ha)	Height (m)	Corn population (plants/m)
1/2 (Healthy)	Corn	6.9151	1.2598	4287	2.1-2.4	6
1/2 (Stressed)	Corn	2.0057	0.4111	0	1.8	6
3/4	Millet	0.7975	0.1206	1500	0.3	
5/6	Pasture	0.1253	0.0162	—	0.05	
7/8	Corn	7.8911	1.3406	5676	2.1-2.4	10
9/10	Corn	7.6653	1.2804	5499	2.1-2.4	7
11/12	Corn	5.8927	1.1486	9245	2.1-2.4	7
13/14	Weeds and bare soil	—	—	—	—	
17/18 (Wheat)	Stubble	0.3652	0.3405	—	0.3	
V2	Sorghum	1.2682	0.3050	3500	0.9-1.2	
V6	Sorghum	0.8016	0.1739	—	0.6-0.9	

systems viewing fields at a 40° to 60° angle off nadir classify sorghum, corn, alfalfa, soybeans, and wheat most accurately. Additional information can be obtained at other frequencies and polarizations. In another study, Ulaby *et al.* (1980) found by including L-band cross-polarized (HV) data with like-polarized (HH) data, the linear discriminant classification accuracy improved from 67 percent to 71 percent. The improvement was in being able to discriminate trees from corn.

The factors which are important in microwave agricultural classification are different from the factors which are important in visible and infrared classification. Microwave responses are sensitive to surface roughness, geometry, and dielectric constant, while the visible and infrared responses are sensitive to chlorophyll content, surface moisture changes, and soil background color. Consequently, additional classification information can be obtained by analyzing combinations of visible, infrared, and microwave data.

Therefore, our objective was to use aircraft mul-

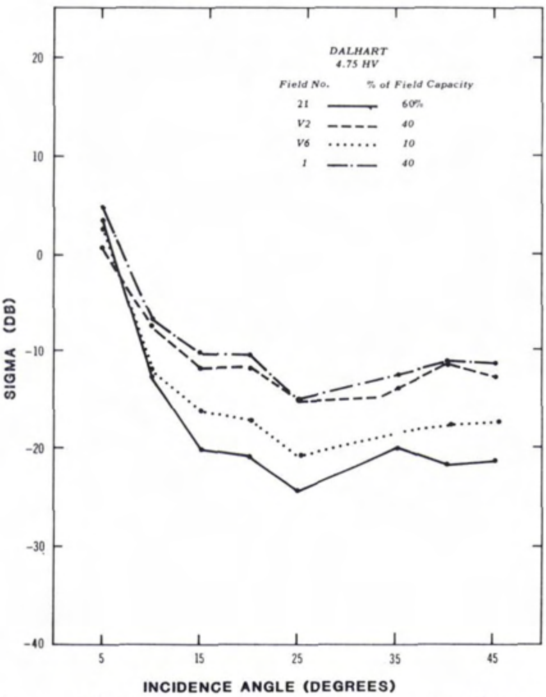


FIG. 1. The scatterometer response from corn (field 1), sorghum (fields V2 and V6), and bare soil (field 21) as a function of look angle.

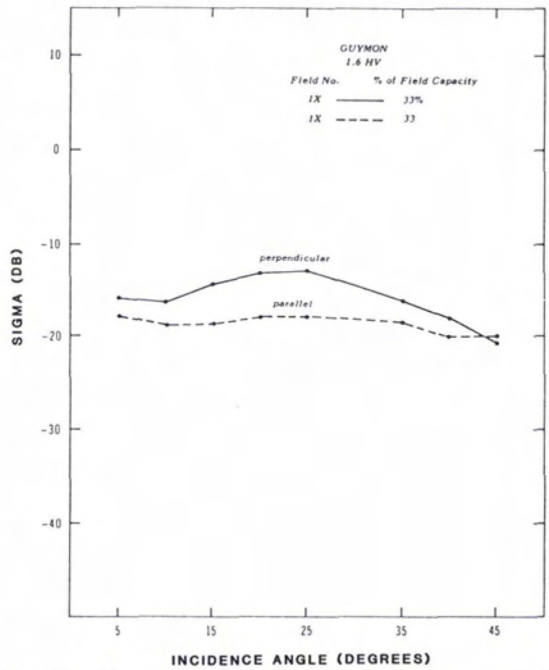
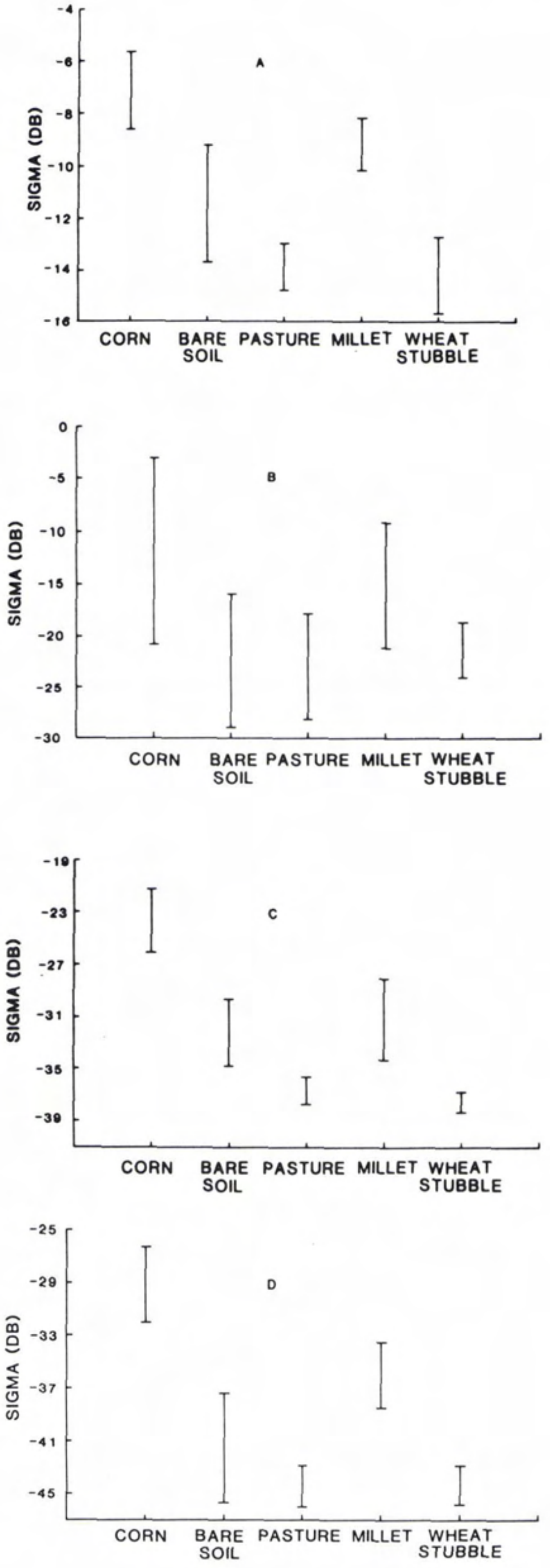


FIG. 2. The scatterometer response from a bare field where the response was (a) parallel and (b) perpendicular to row direction.



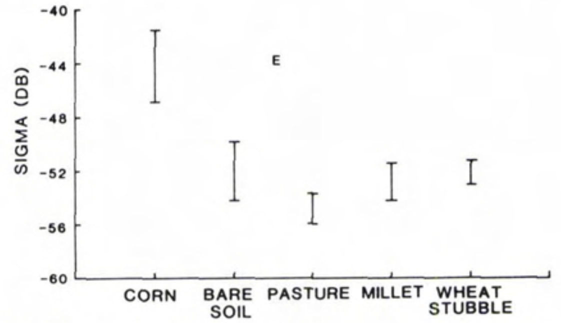


FIG. 3. Forty degree incidence angle scatterometer ranges from each crop type at Dalhart for (a) K-band like-polarized (13.3 GHz VV), (b) C-band cross-polarized (4.75 GHz HV), (c) L-band like-polarized (1.6 GHz HH), (d) L-band cross-polarized (1.6 GHz HV), and (e) P-band cross-polarized (0.4 GHz HV) frequencies and polarizations.

tispectral data (visible through microwave frequencies) to determine (1) if differences in crops are apparent in multifrequency microwave data, and (2) if active microwave information included with visible and infrared data can improve classification accuracy.

DATA COLLECTION

The study was conducted over agricultural fields near Guymon, Oklahoma in 1978 and Dalhart, Texas in 1980. Fields included in the study were eight corn, eight bare soil, four sorghum, two short grass pasture, two wheat stubble, and two weed and bare soil fields at Dalhart, and ten sorghum, four alfalfa, and eight bare soil fields at Guymon. The time frame for the study was during August, a period when most crops were nearing maturity. Spectral information was collected continuously by a visible/infrared scanner and active microwave scatterometers on board a NASA C-130 aircraft which flew at approximately 500-m above the ground. Visible and infrared data collected at Dalhart were from the following spectral regions:

TM1 0.45 – 0.52 μm
TM2 0.52 – 0.60 μm
TM3 0.63 – 0.69 μm
TM4 0.76 – 0.90 μm
TM5 1.00 – 1.30 μm
TM6 1.55 – 1.75 μm
TM7 2.08 – 2.35 μm

The visible and infrared data collected at Guymon were from the following spectral regions:

MSS1 0.54 – 0.58 μm
MSS2 0.66 – 0.70 μm
MSS3 0.70 – 0.75 μm
MSS4 0.77 – 0.86 μm

At both locations the spatial resolution was approximately 11 m. The visible and infrared data were

TABLE 2. STEPWISE LINEAR REGRESSION RESULTS IN CLASSIFYING CROPS AT DALHART USING (a) ALL VISIBLE/INFRARED DATA AND (b) ALL VISIBLE INFRARED AND ACTIVE MICROWAVE DATA (40° LOOK ANGLE) [CROP TYPE: 10 = CORN, 8 = SORGHUM, 6 = WEEDS, 4 = BARE SOIL AND WEEDS, 3 = PASTURE, 2 = WHEAT STUBBLE, 1 = BARE SOIL]. (N = 44)

		R^2
(a)	Crop Type Response = −(Tm3*1.99) + (Tm4*0.71) + 3.03	0.94
	Crop Type Response = (Tm2*1.78) − (Tm3*3.60) + (Tm4*0.60) + 3.26	0.95
	Crop Type Response = (Tm2*1.90) − (Tm3*3.66) + (Tm4*0.63) − (Tm5*0.07) + 3.26	0.95
	Crop Type Response = (Tm2*1.87) − (Tm3*3.69) + (Tm4*0.60) − (Tm6*0.05) + (Tm7*0.11) + 3.31	0.95
	Crop Type Response = −(Tm1*0.04) + (Tm2*1.87) − (Tm3*3.67) + (Tm4*0.60) − (Tm6*0.05) + (Tm7*0.12) + 3.35	0.95
(b)	Crop Type Response = −(Tm7*1.08) + (Tm5*1.44) + 3.38	0.96
	Crop Type Response = −(Tm3*1.25) + (Tm5*1.39) − (Tm7*0.60) + 3.06	0.97
	Crop Type Response = (Tm2*1.84) − (Tm3*2.33) + (Tm5*1.09) − (Tm7*0.77) + 3.33	0.97
	Crop Type Response = −(Tm3*0.73) − (Tm4*0.56) + (Tm5*2.33) − (Tm7*0.96) + (C-band like pole * 0.13)	0.98
	Crop Type Response = (Tm4*4.20) − (Tm3*0.91) − (Tm4*1.13) + (Tm5*3.82) − (Tm6*0.58) − (Tm7*0.92) + 2.71	0.98

calibrated using a calibration lamp and black body aboard the aircraft. The data were normalized to a given solar angle using a solar correction factor as given by the equation

$$I_o = \frac{\cos \Theta_o}{\cos \Theta_e} I_e$$

where I_0 and I_e are the normalized and actual radiances from a given target, and θ_0 and θ_e are solar zenith angles on day 0 (calibration date) and e (flight date).

The active microwave frequencies and polarizations analyzed at both sites included

13.3 GHz vertical like polarization (K-band):K_{vv}
4.75 GHz horizontal like and cross polarization (C-band):C_{HH}, C_{Hv}
1.6 GHz horizontal like and cross polarization (L-band):L_{HH}, L_{Hv}
0.4 GHz horizontal like and cross polarization (P-band):P_{HH}, P_{Hv}

The line microwave data were processed at every 5° angle from 5° through 45° off nadir with the response being defined as σ. The processing is described in detail by Classen *et al.* (1979) and Clark and Newton (1979). The spatial resolution varied with frequency—25 m for 13.3 GHz to 75 m for 0.4 GHz. No means were available for calibrating and normalizing the active microwave data directly. Times when the plane flew over field boundaries were determined from the microwave amplitude and flight line plots (σ versus time) and aerial photography. These times were then used in calculating the field spectral data averages.

TABLE 3. STEPWISE LINEAR REGRESSION RESULTS IN CLASSIFYING CROPS AT GUYMON USING (a) ONLY VISIBLE AND INFRARED DATA AND (b) VISIBLE, INFRARED AND ACTIVE MICROWAVE DATA [CROP TYPE: 8 = SORGHUM, 4 = ALFALFA, 0 = BARE SOIL]. (N = 74)

		R^2
(a)	Crop Type Response = (MMS 1*17.350) − (MMS 2*14.76) − (MMS 3*1.30) + 2.85	0.59
(b)	Crop Type Response = (P_{Hv}*0.26) + (C_{Hv}*0.49) + 26.147	0.67
	Crop Type Response = (P_{Hv}*0.27) − (C_{Hv}*0.57) + (C_{HH}*0.88) + 28.07	0.73
	Crop Type Response = (P_{Hv}*0.25) + (L_{Hv}*0.23) − (C_{HH}*0.76) + (C_{Hv}*0.80) + 28.22	0.74
	Crop Type Response = (K_{HH}*0.30) + (L_{Hv}*0.29) + (P_{Hv}*0.18) − (C_{HH}*0.89) + (C_{Hv}*0.74) + 27.39	0.75
	Crop Type Response = (MMS 1*0.27) + (K_{HH}*0.32) + (L_{Hv}*0.32) + (P_{Hv}*0.17) − (C_{HH}*0.81) + (C_{Hv}*0.60) + 24.2	0.76

TABLE 4. DISCRIMINATION RESULTS USING (a) VISIBLE AND INFRARED (VIR) AND (b) VIR AND ACTIVE MICROWAVE (40° LOOK ANGLE) DATA AT DALHART.

(a) Visible and infrared (VIR) data (N = 52).

	Number of Observations Classified into Crop Types:						
From Crop Types:	Corn	Bare soil	Wheat stubble	Weeds and bare soil	Pasture	Millet	Weeds
Corn	16	0	0	0	0	0	0
Bare soil	0	16	0	0	0	0	0
Wheat stubble	0	4	0	0	0	0	0
Weeds and bare soil	0	3	0	0	0	0	0
Pasture	0	4	0	0	0	0	0
Millet	0	0	0	0	0	4	0
Weeds	0	0	0	0	2	2	0

* Combined classification accuracy of 73%

(b) VIR and microwave data (N = 44).

	Number of Observations Classified into Crop Types:						
From Crop Types:	Corn	Bare soil	Wheat stubble	Weeds and bare soil	Pasture	Millet	Weeds
Corn	16	0	0	0	0	0	0
Bare soil	0	11	0	0	0	0	0
Wheat stubble	0	4	0	0	0	0	0
Weeds and bare soil	0	0	0	4	0	0	0
Pasture	0	0	0	0	4	0	0
Millet	0	0	0	0	0	4	0
Weeds	0	0	0	0	1	0	0

* Combined classification accuracy of 92%

TECHNIQUE

To determine which microwave frequency was sensitive to crop type differences and unresponsive to dielectric and surface roughness effects, line plots (σ versus time) and graphs showing the maximum and minimum received signal ranges of each crop were plotted and analyzed. Using field spectral average data from frequencies at incidence angles which were sensitive to crop type differences, stepwise regression equations were developed to predict crop types. Discriminant analysis, available in the Statistical Analysis System, aided in evaluating if classification accuracies improved by including microwave data with visible and infrared data. The field spectral average data from flights on 16 August 1980 (N = 52) and 2 August and 17 August 1978 (N = 96) were used as inputs to develop discriminant functions in the method described by Swain and Davis (1979). Field spectral averages from the other sample dates—14 and 18 August 1980 (N = 44) and 5 August, 8 August, and 14 August 1978 (N = 74)—were input into the functions and the classification accuracy was determined from the contingency table.

RESULTS AND DISCUSSION

Relative differences in phytomass were most notable at Guymon, as many sorghum fields were at different growth stages—from the vegetative stage to heading. The Dalhart variations within a given crop were not as large as Guymon (Table 1). No phytomass information was collected from Guymon.

Microwave data from Dalhart indicated microwave responses at high incidence angles were mainly sensitive to crop type differences (Figure 1). The frequency and polarization most sensitive to crop type differences was C-band cross-polarized data. Like-polarized data were more sensitive to row direction differences related to look direction compared to cross polarized (HV) data (Figures 1 and 2). As much as a 9 db difference in HH data can be attributed to differences between parallel and perpendicular rows to look direction at Guymon. Cross-polarized responses from parallel and perpendicular rows were significantly less (3-4dB).

The cross-polarized response differences were due to roughness differences which were directly attributable to morphological differences, plant-water content differences, or both. At high inci-

TABLE 5. DISCRIMINATION ANALYSIS RESULTS USING (a) VISIBLE AND INFRARED (VIR) AND (b) VIR AND ACTIVE MICROWAVE (40° LOOK ANGLE) DATA AT GUYMON.

(a) Visible and infrared (VIR) data (N = 96).

	Number of Observations Classified into Crop Types:			
From Crop Types:	Alfalfa	Bare	Sorghum viewed parallel to rows	Sorghum viewed perpendicular to rows
Alfalfa	12	0	3	1
Bare	0	32	4	1
Sorghum viewed parallel to rows	1	1	18	1
Sorghum viewed perpendicular to rows	1	0	2	21

* Combined classification accuracy is 85% (assuming sorghum viewed parallel and sorghum viewed perpendicular are one group).

(b) VIR and microwave dates (N = 74).

	Number of Observations Classified into Crop Types:			
From Crop Types:	Alfalfa	Bare	Sorghum viewed parallel to rows	Sorghum viewed perpendicular to rows
Alfalfa	9	0	2	1
Bare	0	23	2	2
Sorghum viewed parallel to rows	1	1	8	6
Sorghum viewed perpendicular to rows	0	0	0	19

* Combined classification accuracy is 88% (assuming sorghum viewed parallel and sorghum viewed perpendicular are one group).

dence angles at both locations, corn, sorghum, and millet had higher responses compared to bare and low phytomass fields. At low frequencies, the microwave/phytomass response at high incidence angles increased at higher phytomass levels, implying corn was discriminated from the other crops. At Guymon, the large phytomass variability within crops was related to increased spectral variability. Of the incidence angles between 35° and 50°, 40° and 45° were equally efficient in discriminating between crops at both sites (Figure 3). L- and C-band data were most sensitive to crop type variations. Corn had the highest response, followed by millet, bare soil, and pasture/wheat stubble. P-band responses were able to separate corn from the other crops. K-band responses were only able to distinguish vegetated and non-vegetated fields.

Results from the stepwise classification indicated that the most accurate classification used a combination of green, red, near infrared, P-, L-, and C-band cross-polarized data (Tables 2 and 3). The Guymon results (Table 3) indicated that microwave data alone had less variability in classifying compared to the visible and infrared data. This is indicated by the increase in R^2 from 0.59 to 0.73 with the three-variable visible and infrared model from the three-variable microwave model. Comparisons of the Dalhart data did not show a strong improvement. The two-variable visible and infrared model was adequate to discriminate crops at Dalhart, because the intercrop variation was low. Because visible and infrared models are sensitive to biomass differences, and crop differences were reflected through biomass differences at Dalhart, the visible and infrared model alone was accurate. At both sites, the responses from the C-band (4.75 GHz) 40° look angle active microwave, red, and near and middle infrared bands provided the most discriminating information related to crop type differences.

The discriminant analysis also evaluated the classification accuracies by including the L- and C-band cross-polarized active microwave data. Classification accuracies increased from 73 percent to 92 percent at Dalhart (Table 4) when active microwave data were included with all of the visible and infrared bands. The improvement was in differentiating pasture and weeds from bare soil. The Guymon results (Table 5) showed no significant improvement in classification accuracy using discrimination techniques. The lack of improvement may be due to the vari-

TABLE 6. DISCRIMINANT ANALYSIS RESULTS USING ONLY (a) AND (b) ALL VISIBLE AND INFRARED DATA AT DALHART.
(a) TM2, TM3, and TM4 (N = 58).

	Number of Observations Classified into Crop Types:						
From Crop Types:	Corn	Bare Soil	Weeds and bare soil	Pasture	Millet	Weeds	Wheat Stubble
Corn	16	0	0	0	0	0	0
Bare soil	0	12	0	0	0	0	0
Weeds and bare soil	0	0	3	0	0	1	0
Pasture	0	0	0	3	0	1	0
Millet	0	0	0	0	0	4	0
Weeds	0	0	0	0	0	4	0
Wheat stubble	0	4	0	0	0	0	0

* Combined classification accuracy of 81%

(b) All visible and infrared data (N = 51).

	Number of Observations Classified into Crop Types:						
From Crop Types:	Corn	Bare Soil	Weeds and bare soil	Pasture	Millet	Weeds	Wheat Stubble
Corn	16	0	0	0	0	0	0
Bare soil	0	16	0	0	0	0	0
Weeds and bare soil	0	3	0	0	0	0	0
Pasture	0	4	0	0	0	0	0
Millet	0	0	0	0	4	0	0
Weeds	0	0	0	2	2	0	0
Wheat stubble	0	4	0	0	0	0	0

* Combined classification accuracy of 73%

ability of surface roughness through the growing season.

To show the additional information gained using microwave, we compared the contingency tables from the discriminant analysis using all of the Dalhart visible and infrared data to the green, red, and infrared (TM2, TM3, and TM4) data, which were most sensitive to vegetation differences (Table 6). The classification accuracy decreased from 81 percent to 73 percent when all seven bands were used compared to using only the green, red, and infrared bands. This indicated that, by including extra visible and infrared bands, the classification accuracy may not improve.

SUMMARY

From the study results, visible, infrared, and active microwave information may be used in classifying different crops. However, the classification accuracy may be limited if certain crops are in different development stages, as indicated by results from Guymon. The lack of improvement in the discriminant analysis at Guymon is likely due to tillage differences. Bare soil, alfalfa, and sorghum were often misclassified. During the study, several bare fields were tilled leaving furrows 20-cm deep. Such furrows affected microwave responses as much as 9 db—a similar magnitude as the crop type differences. The classification accuracy was, however, equal to or better than when using visible/infrared information alone. The frequencies most sensitive to crop type differences were the L-, C-, and P-bands. Lower frequency data can discriminate high and low phytomass crops. The K-band data were only able to separate vegetated and non-vegetated fields only. Cross-polarized (HV) data were more sensitive to vegetation differences than the like-polarized (HH) data. Like-polarized (HH) data were more sensitive to surface roughness. Received responses viewed parallel and perpendicular to rows in the same field were 7-db higher in HH than HV data. Results from Guymon and Dalhart indicated P-band data differentiated between corn and sorghum—crops with high phytomass—compared to the high microwave frequencies. These results conflict with results found by Ulaby *et al.* (1975, 1980) which indicated high frequency microwave data greater than L-band data can discriminate crops more accurately than low frequency microwave data.

Results indicated satellite remote sensing systems, collecting visible, near infrared, middle infrared, and active microwave data simultaneously, could provide improved information for classifying vegetation. Such a system, if collecting data from as many as three or four microwave frequencies, could provide for vegetation classification in could-covered areas as well as improving classification in cloud-free areas. The cost-effectiveness of such a system needs to be determined.

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