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# DEVELOPMENT OF VISIBLE/INFRARED/ <br> MICROWAVE AGRICULTURE CLASSIFICATION AND BIOMASS ESTIMATION ALGORITHMS 

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February 1882

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BEVELOPMENT OF VISIBLE/IBFRARED/MICROWAVE AGRICULTURE: CLASSIFICATION AND BIOMASS ESTIMATION ALGORITHMS
}

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TABLE OF CONTENTS
Page
LIST OF FIGURES ..... iv
LIST UF TABLES ..... \(x i\)
PREFACE ..... xit
ABSTRACT. ..... xili
INTRODUCTION. ..... 1
Objectives and Research ..... 7
REVIEN OF LITERATURE ..... 9
Spectral Theory. ..... 9
Classification Models ..... 22
Biomass Models ..... 24
Literature Overview. ..... 28
UATA COLLECTION ..... 29
Guymon Aircraft and Ground Data. ..... 29
Dalhart Aircraft and Ground Data ..... 40
Scatterometer Processing ..... 51
NSOOL/M²S Processing ..... 53
Passive Microwave Processing ..... 54
ANALYSIS. ..... 55
Techniques ..... 55
RESULTS ..... 58
Guymon Crop Condition. ..... 58
Ualhart Biomass and Crop Yield ..... 58
Problemi 1 ..... 60
Problem 2 ..... 81
Probleill 3 ..... 86
Problem 4 ..... 125
SUMMARY AND CONCLUSIONS ..... 140
Problem ..... 140
Problem 2 ..... 141
Problenl 3 ..... 141
Problem 4 ..... 143
Overview ..... 144
REFERENCES ..... 147
appenili a data quality, calibration anio omissions. ..... 152
APPENDIX B IJALHART DATA SET ..... 172
APPENDIX C GUYMON DATA SE'T ..... 183

\section*{LIST OF FIGURES}
Figure Pağe
1 Reflectance of 2 and 8 stacked mature cotton leaves. Standard deviation between observed and calculated points is about 1\%. From Allen et al., 1970 . ..... 16
2 Averaged normalized differences (IR-red/IR+red)values plotited against soybean wet biomass. Fromrucker et al., 197911
3 Diagram illustrating the principle of the perpen-dicular vegetation index (PVI) model. A perpen-dicuar from candidate plant coordinates (Rp5, Rp7)interserts the soil background line at coordinates(Rg5, Kg7). A PVI=0 indicates soll, and a PVI>0indicates vegetation. From Richardson and Wiegand,197727
Ha Area map of Guymon showing the relative locations of each field map ..... 30
4b Legend for the Guymon, ok lahoma fields maps ..... 31
\(4 c\) Locations of the sample fields at Gummon, East end, lines 1 and 2. ..... 32
4d Locations of the sample fields at Guynon, South end, Lines 3 and 4 . ..... 33
4e Locations of the sample fields at Guymon, West end, Lines 1 and 2 ..... 34
If Area map of Clayton showing the relative location of the field map ..... 35
49 Legend for the Clayton, New Mexico field maps ..... 36
4 Location of the sample fields at Clayton. ..... 37
Sampling pattern for fields at Guymon andDalhart. Points \(1,2,7\) and 8 were movedoutside the circle for rectangular fields41
Soil moisture samplipy depths at Dalhartand Guymon. The \(15-30\) and \(30-45\) cm coresamples were also taken in addition to theabove. Samples were collected from \(5-9 \mathrm{~cm}\)and \(9-15 \mathrm{~cm}\) at Gumon and \(5-15 \mathrm{~cm}\) at Dalhart. . . . . . . 427a Area map of Dalhart showing the relativelocations of each field map43
7b Legend for the Dalhart, Texas field maps ..... 44
7c Locations of the sample fields at Dalhart,
East end, Lines 1 and 2 ..... 45
7d Locations of the sample fields at Dalhart,Lines 1 and 246
'e Locations of the sample fields at Dalhart,West end, Lines 1 and 247
8 Scatterometer data processing procedure ..... 52
9 Spectra for millet and corn fields at Dalhart.[ \(\mathrm{H}=\mathrm{C}\) band horizontal (MFMR), \(\mathrm{V}=\mathrm{C}\) band verticalpole (MFMR), \(L=L\) band horizontal (MFMR), \(H=\) likepole \(40^{\circ}\) look angle (SCATTS), \(V=\) cross pole \(40^{\circ}\)look angle (SCATTS), \(A=0-2 \mathrm{~cm}\) soil moisture (SM),\(B=2-5 \mathrm{cIII}\) soil hioisture (SM)].61
10 Spectra for bare soll, pasture and wheat stubble atDalhart. [ \(H=C\) band horizontal (MFMR), \(V=C\) bandvertical pole (MFMR), \(\mathrm{I}=\mathrm{L}\) band horizontal (MFMR),\(H=\) like pole \(40^{\circ}\) look angle (SCATTS), \(V=\) crosspole \(40^{\circ}\) look angle (SCATTS), \(A=0-2 \mathrm{~cm}\) soilmoisture (SM), B = 2-5 cm soil moisture (SM) ] . . . . . . 62

11 Spectra comparing vegetated and non-vegetated fields at Jalhart. \([\mathrm{H}=\mathrm{C}\), band horizontal (MFMR), \(\mathrm{V}=\mathrm{C}\) band vertical pole (MFMR), \(L=L\) band horizontal (MFMR), \(H=\) like pole \(40^{\circ}\) look angle (SCATTS), \(V=\) cross pole \(40^{\circ}\) look angle (SCATTS), \(A=0-2 \mathrm{~cm}\) soil moisture (SM), \(B=2-5 \mathrm{clil}\) soil moisture (SM)]. . . . . . . . . . . . . . 63

12 An infrared aerial photo (scale \(1: 45,000\) ) of stressed corn fields (fields 1 and 2) at, Dalhart. The healthy areas are dark shaded and the stressed areas are light shaded.60

13 Spectra comparing healthy and stressed corn at Dalhart. No microwave comparisons could be made.67

14 Spectra comparing alfalfa, sorghum, and bare soil fields at Guymon. [ \(\mathrm{H}=\mathrm{C}\) band horizontal (MF:iR), V \(=\mathrm{C}\) band vertical pole (MFMR), \(\mathrm{L}=\mathrm{L}\) band horizontal (MFMR), \(H=\) like pole \(40^{\circ}\) look angle (SCATTS), \(V=\) cross pole \(40^{\circ}\) look angle (SCATTS), \(A=(0-2 \mathrm{~cm}\) soil moisture \((S M), B=2-5\) cill soil moisture (SM)] . . . . . 68

15 Spectra comparing sorghum fields with rows perpendicular and parallel to the flight line. [ \(H=C\) band horizontal (MFMR), \(V=G\) band vertical pole (MFMR), \(L=\) L band horizontal (MFMR), \(H x_{i}\) like pole \(40^{\circ}\) look angle (SCATTS), \(V \times\) cross pole \(40^{\circ}\) look angle (SCATTS), \(A=\) \(0-2 \mathrm{~cm}\) soll moisture (SM), B \(=2-5 \mathrm{~cm}\) soil moisture (SM)]

16 Spectra comparing wet bare soil, and a dry sorghum field at Guymon. [ \(H=C\) band horizontal (MFMR), \(V=\) C band vertical pole (MFMR), \(L=L\) band horizontal (MFMR), \(H=\) like pole \(40^{\circ}\) look angle (SCATTS), \(V=\) cross pole \(40^{\circ}\) look angle (SCATTS), \(A=0-2 \mathrm{~cm}\) soil moisture \((S M), B=2-5 \mathrm{~cm}\) soll moisture \((S M)] \ldots . . .1\)

17 Spectra comparing corn and sorghum at Clayton. No passive microwave or visible/infrared data was available. \(\left[H=\right.\) like pole \(40^{\circ}\) look angle (SCATTS), \(V=\) cross pole \(40^{\circ}\) luok angle (SCATTS)] . . . . . . . . . . 72

18 Spectrá comparing corn and sorghum at Clayton. No passive microwave or visible/infrared data was available. \(\left[H=\right.\) like pole \(40^{\circ}\) look angle (SCATTS), \(V=\) cross pole \(40^{\circ}\) look angle (SCATTS)] . . . . . . . . . . 73
19 Line plots ( \(\sigma^{0}\) vs time) for all like polarized scat. terometer data at \(10^{\circ}\) and \(40^{\circ}\) off nadir . . . . . . . 79

20 Line plots ( \(\sigma^{0}\) vs time) for all cross polarized scatterometer data at \(10^{\circ}\) and \(40^{\circ}\) off nadir ...... . . 80

21 Dendrogram (tree-classification) model using NSOO1 bands 2, 3, and 4, C, L and P band cross pole Dalhart data (accuracy 78\%)83

22 Pendrogram (tree-classification) model using NSOO1 bands C, L and P band cross pole Dalhart data (accuracy 80) . . . . . . . . . . . . . . . . 84

23 Dendrogram (tree-classification) modeling using \(M^{2} S\) bands \(4,7,8\) and \(9, C\) and \(L\) band cross pole Guymon data (accuracy 70\%). ............... 85
24 Dendrogram (tree-classification) model using all NSOO1 bands Dalhart (accuracy 78\%). . . . . . . . . . 87

25 Dendrogram (tree-classification) model using \(M^{2} S\) bands \(4,7,8\) and 9 data at Guymon ( \(65 \%\) accuracy) . . 88

26 The relationship between total biomass \(\left(9 / \mathrm{m}^{2}\right)\), . . . . 96
27 The relationship between final crop yield ( \(\mathrm{Kg} / \mathrm{Ha}\) ),
and TVI and PVI at Ualhart
28 Field radiance reflectance values of NSOO1 bands 1 and 2 versus band 3 at Dalhart in \(10^{-4}\) watts \(\mathrm{cm}^{-2}\) ster \(^{-1}\)

29 Field radiance reflectance values of NSOO1 bands 4 and 5 versus band 3 at Dalhart in \(10^{-4}\) watts \(\mathrm{cIII}^{-2}\) ster- \({ }^{-1}\) .100

30 Field radiance reflectance values of NSOOL bands 6 and 7 versus band 3 at Dalhart in \(10^{-4}\) watts \(\mathrm{cill}^{-2}\) ster\({ }^{-1}\). . . . . . . . . . . . . . . . . . .101

31 Field radiance reflectance values of NSOO1 bands 1 and 2 versus band 4 at Dalhart in \(10^{-4}\) watts \(\mathrm{cm}^{-2}\) ster- . .102

32 Field radiance reflectance values of NS001 bands 3 and 5 versus band 4 at Dalhart in \(10^{-4}\) watts \(\mathrm{cmin}^{-2}\) ster- \({ }^{-1}\)103

33 Field radiance reflectance values of NSOO1 bands 6 and 7 versus band 4 at Dalhart in \(10^{-4}\) watts \(\mathrm{cIII}^{-2}\) ster \(^{-1}\)104

34 Field radiance reflectance values of NSOO1 bands 1 and 2 versus band 5 at Dalhart in \(10^{-4}\) watts \(\mathrm{cm}^{-2}\) ster \(^{-1}\)105
35 Field radiance reflectance values of NSOO1 bands3 and 4 versus band 5 at Dalhart in \(10^{-4}\) watts\(\mathrm{cm}^{-2}\) ster \({ }^{-1}\).106

Field radiance reflectance values of NSOO1 bands 6 and 7 versus band 5 at Dalhart in \(10^{-4}\) watts \(\mathrm{cm}^{-2}\) ster- \({ }^{-1}\)107
37 The relationship between total (wet) biomass ( \(\mathrm{g} / \mathrm{m}^{2}\) )
and PVI64 at Dalhart ..... 108
33 The relationship between PVI64, and PVI and TVI at Dalhart. . . . . . . . . . . . . . . . . . . . . . . . 110

39 A photo indicating different PVI64 levels within a stressed corn field (1 and 2) at Dalhart . . . . 111

40 A photo indicating different PVI64 levels within a sorghum field (V2) at Dalhart. .112

41 A photo indicating different PVI64 levels within alfalfa fields (V11, V12, V13) at Dalhart. . . . . 113

42 The relationship between \(L\) band cross pole \(0^{0}\) and look angle for a corn field (field 9) and bare field (field 15)

43 The relationship between \(L\) band cross pole \(\sigma^{0}\) and look angle for a millet field (field 3) under different soil moisture conditions. .115

44 The L band cross pole \(\sigma^{0}\) response as a function of look angle for the same sorghum field (field \(1 X\) ) from two different directions, the flight line parallel and perpendicular to the tillage direction. . . . . . 117

45 The relationship between total biomass and the scatterometer vegetation index, SVI. (4.75 HV \(40^{\circ}\) look angle - \(4.75 \mathrm{HV} 5^{\mathrm{u}}\) look angle) \(\left(\mathrm{R}^{2}=0.88\right)\). . . . 119

46 The relationship between SVI (db), and TVI and PVI at Dalhart .120

47 The relationship between SVI (db), and TVI and PVI at Guymon .121

48 The relationship between SVI (db), and \(0-2 \mathrm{~cm}\) soil moisture (\%) for selected fields at Guymon and Dalhart .122

49 The relationship between soil moisture corrected SVI (db) and TVI and PVI at Dalhart . . . . . . . . . 123

50 The relationship between the soil moisture corrected SVI (db), and TVI and PVI at Guymon. . . . . . . . 124

51 The red/near-infrared relationship for fields at Guymon and Dalhart127

52 The \(K\) band like pole \(\sigma^{0}\) response as a function of look angle for bare soil (field 22), sorghum (field V2 and V6), and corn (field 2) at Dalhart . . . . . . . 128

53 The C band cross pole \(\mathrm{o}^{0}\) response as a function of look angle for bare soil (field 22), sorghum (field V2 and V6), and corn (field 2) at Dalhart . . . . . . . . 129

54 The L band cross pole \(0^{0}\) response as a function of look angle for bare soil (field 22), sorghum (field V2 and V6), and corn (field 2) at Dalhart ...... . . . 131

55 The P band cross pole \(0^{0}\) response as a function of look angle for bare soll (field 22), sorghum (field V'2 and V6), and corn (field 2) at Dalhart132

56 The \(K\) band like pole \(\sigma^{0}\) response as a function of look angle for bare soll (field 14), alfalfa (field 4), emerging sorghum (field 15) and headed sorghum (field 1 X ).133

57 The \(C\) band cross pole \(\sigma^{0}\) response as a function of look angle for bare soil (field 14), alfalfa (field 4), emerging sorghum (field 15) and headed sorghum (field 1 X ).134

58 The \(L\) band cross pole \(o^{0}\) response as a function of look angle for bare soil (field 14), alfalfa (field 4), energing sorghum (field 15) and headed sorghum (field 1 X).. . . . . . . . . . . . . . . . . . . . . . . 135 The \(P\) band cross pole \(\sigma^{0}\) response as a function of look angle for bare soil (field 14), alfalfa (field 4), emerging sorghum (field 15) and headed sorghum (field 1 X ).136

60 The relationship between total biomass at Dalhart and the modified scatterometer vegetation index, SVIM [ (C band cross pole \(40^{\circ}-\mathrm{C}\) band cross pole \(5^{\circ}\) ) \(+\left(\mathrm{P}\right.\) band cross pole \(40^{\circ}-\mathrm{P}\) band cross pole \(\left.\left.5^{\circ}\right)\right]\). . 138

61 The relationship between the modified SVI (SIVM) and TVI and PVI at Guynon . . . . . . . . . . . . . . . . 139

A1 Field \(1 X\) (sorghum) \(P\) band like and cross pole response with rows perpendicular to the flight line . . . 160

A2a Scatterometer response from the \(P\) band like pole system over field 25 (sorghuin) with rows perpendicular to the flight line.

A2b Scatterometer response from the \(P\) band cross pole system over field 25 (sorghum) with rows perpendicular to the flight line. 162

A3 Scatterometer response ( \(C\) and \(L\) like and cross pole) from field 25 at Dalhart on 8/16/80 . . . . . . . . . . . 164

A4 Scatterometer response ( \(K\) band like pole) from field 19 at Dalhart on 8/16/80 and field 14 at Guyrion on 8/5/78. Soil moisture conditions were approximately \(90 \%\) of field capacity . . . . . . . . . . . . . . . . . . 165

A5 Scatterometer response (C band like and cross pole) from field 19 at Dalhart on 8/16/80 and field 14 at Guymon on \(8 / 5 / 78\). Soil moisture conditions were approximately \(90 \%\) of field capacity . . . . . . . . . . . 166

A6 Scatterometer response (L. band like and cross pole) from field 19 at Dal hart on 8/16/80 and field 14 at Guymon on 8/5/78. Soil moisture conditions were approximately \(90 \%\) of field capacity . . . . . . . . . . . 167

A7 Scatterometer response ( \(P\) band like and cross pole) from field 19 at Dalhart on \(8 / 16 / 80\) and field 14 at Guymon on \(8 / 5 / 78\). Soll meistura conditions were approximately \(90 \%\) of fie!d capacity . . . . . . . . . . . 168

\section*{LIST OF TAbles}
Table ..... Page
1 Operating sensors for the Guymon, Oklahoma study. ..... 39
2 Operating sensors for the Dalhart, Texas study. ..... 50
3 Dalhart bicmass and crop yield. ..... 59
4 Results of Duncan's Multiple Range Test forDalhart active microwave data75
5 Results of Duncan's Multiple Range Test forGuymon active microwave data77
6 Dalhart discriminant analysis results using (a)all NSOO1 channels and (b) all NSOOL channelsplus \(K\) band like pole and \(L\) band cross pole ( \(40^{\circ}\)look angle) data from August 14 and 18 as a train-ing classifier. The resuits are from August 16testing of the model.
7 Dalhā̃t dísçíminant anaiysis using (a) NSOOLchannels 2, 3 and 4 and (b) NSOO1 channels 2, 3, and4 and \(K\) band like pole and \(L\) band cross pole data.Contingency table resuits from the model tested on
August 16 spectral data . ...... . . . . . ..... 91
8 Discriminant analysis of Gummon visible/infrareddata using August 2 and 17 data as the trainingclassifier. Results from classification of August\(5,8,11\), and 14 data92
9 Dalhart stepwise classification regression equationsusing (a) all NSOO1 band (Ch) data and (b) all NSOO1data plus scatterometer data ( \(40^{\circ}\) look angle) [CropType: \(10=\) corn, \(8=\) sorghum, \(6=\) weeds, \(4=\) bare soiland weeds, \(3=\) pasture, \(2=\) wheat stubble, \(1=\) bare
soil] ... 1 soil] ..... 94
10 Guymon stepwise classification regression equationsusing (a) only visible/infrared data and (b) scat-terometer ( \(40^{\circ}\) look angle) and visible/infrared data[Crop Type: \(8=\) sorghum, \(4=\) alfalfa, \(0=\) bare soil].95
Al Equations used to convert raw NSOOL/M2S digitalcounts (DC) to radiance values, \(R\), \(\left(10^{-4}\right.\) watts \(\mathrm{cm}^{-2}\)ster \({ }^{-1}\) ) for Guymon (a) and Dalhart (b)......... . 153

A2 Questionable scatteroneter data for Dalhart . . . . . . . 155
A3 Questionable scotterometer data for Guymon. . . . . . . .15)
A Guymon and Dalhart questionable MFMR data . . . . . . . . 170

\section*{PREFACE}

The final report of Project RSC-3458, "Measurement of Soil Mois" ture Trends with Airborne Scatterometers" is divided into three volumes. The first volume deals primarily with the work completed by Dr. Sidney Theis relating multispectral (visible through microwave) information to soil moisture trends in bare and vegetated fields. The second volume deals primarily with the work of Dr. Wesley Rosenthal in relating the same multispectral data sets to agricultural crop classification and biomass estimation. The third volume by Ms. Cheryl Jones, details field work, aircraft schedules, data processing and calibrations, and the final data sets.

\section*{ABSTRACT}

Due to inadequate crop acreage and bionass estimates using satellite and aircraft visible and infrared data, a study was conducted to (1) develop and test agricultural crop classification models using two or more spectral regions (visible through microwave), and (2) estimate biomass by including microwave with visible and infrared data. The study was conducted at two locations; Guymon, Oklahoma in 1978, and Ualhart, Texas in 1980. Aircraft multispectral data collected during the study included visible and infrared data (multiband data from 0.5 \(\mu \mathrm{m}\) - \(12 \mu \mathrm{~m})\), passive microwave data \([\mathrm{C}\) band ( 6 cm ) vertical and horizontal polarizations, and \(L\) band ( 20 cm ) horizontal polarization] and active microwave data \([\mathrm{K}\) band ( 2 cm ), C band ( 6 cm ): L band ( 20 cm ), and P band ( 75 cm ) like and cross polarizations]. Ground truth data from each field consisted of soil moisture at both sites and biomass at Dalhart. The study was divided into four problems: (1) are differences in individual band responses related to crop type differences? (2) what is the most accurate multifrequency crop classifying dendrogram (tree classifier) at both locations? (3) what is the utility of microwave data alone or in combination with other spectral bands for classifying crops and estimating total biomass? and (4) is the multifrequency tree-classification model variability dependent on phenological or biomass differences? Results indicated that inclusion of \(C, L\), and \(P\) band active microwave data from look angles greater than \(35^{\circ}\) from nadir with visible and infrared data improved crop discrimination and biomass estimates compared to results using only visible and infrared data. The active microwave frequencies were
sensitive to different biomass levels. \(K\) and \(C\) band were sensitive to differences at low biomass levels, while \(P\) band was sensitive to differences at high biomass levels. In addition, two indices, one using only active microwave data and the other using data from the middle and near infrared bands, were well correlated to total biomass. Results from the study implied that inclusion of active microwave sensors with visible and infrared sensors on future satellites could aid in crop discrimination and biomass estimation.

\section*{INTROOUCTIOM}

With world population increasing to a point where food supplies will becone scarce, the need to improve global agricultural information systems becomes critically important. Such emphasis is needed to avert potential world disasters of starvation and malnutrition due to inadequate food supplies. The delicate imbalance is denonstrated by the fact that since 1948 the amount of exported grain from developed countries to developing countries has risen dramatically. As a result, the less developed countries are more dependent on surplus production in a few developed countries (Wortman, 1976). A recent World Food and Nutrition Study (National Academy of Sciences, 1977) emphasized the need for improved systems by recommending high priority research on
1. information needs of producers,
2. crop monitoring systems,
3. international data bases for land and nutrition, and
4. a total information system,

Perhaps the major priority is developing crop monitoring systems. This ivorld-wide need was emphasized when the United States lost millions of dellars by selling wheat to the Soviet Union, who later sold the wheat at much higher prices. An adequate crop monitoring system would possibly have averted the deal. The benefits of improved agricultural monitoring systems used for predicting food production would include
1. comnodity prices would be more stable,
2. governments will be able to plan foreign policy, and
3. storage, transportation and processing facilities will be more efficiently used.

The first benefit would prevent rapid and drastic seasonal commodity price fluctuations due to large and small supplies. Second, the United States government, with an estimate of foreign production, would be able to deal according to the foreign government's true needs. This would prevent events such as the U. S./Soviet Union wheat deal of 1974. Third, more efficient use of transport and storage facilities would help achieve the first two benefits.

The major problem of monitoring production systems within foreign countries is the inadequate source of data on acreages and climate variables. Several countries do not presently have any means for estimating acreage or production within the country. Other countries have production monitoring systems which are highly inaccurate. Acreage and yield estimates by the government are often inaccurate. In addition, several countries do not permit other countries to use the production information. Consequently, ä universal uechnique is needed soon.

One technique developed within the past twenty years uses remotely sensed data--sensors aboard satellites or aircraft--to estimate production. From remotely-sensed data much information can be obtained with a minimum of ground sampling (Bauer, 1975). Such information would drastically reduce the cost of monitoring agricultural systems. The technique is based primarily on the relationship of reflectance in the visible and infrared region of the electromagnetic spectrum to vegetation type, cover, and crop condition. Idealistically, each healthy species has a characteristic electromagnetic signa-
ture at a given growth stage. Any departure from the signature indicates physiological stress which could impact crop yield. However, the actual spectrum varies to an extent that crop and stress identification is impossible using available data. The variability of a crop spectrulir due to stress is much larger than variability due to differences between crops. The vegetation spectrum also differs significantly from the non-vegetated spectrum. Consequently, based upon the difference within the spectrum, crop types have been discriminated to a good degree of accuracy. Also, based on the spectra, models have been developed which estimate biomass, leaf area index, or percent cover (Richardson and Wiegand, 1977; Rouse et al., 1973). Biomass estimates can then be correlated to final economic yield (Holliday, 1960a, b; Donald, 1963). As a result, visible/ infrared satellite and aircraft data have been used in (1) estimating the percentage of area planted in a given crop, and (2) evaluating crop condition and biomass. The combination of the two gives a production estimate for the area (MacDonald, 1979). Consequently, through the use of satellite and aircraft data, agricultural classification and biomass estimation became important as a means of obtaining reasonable estimates of planted acreage and ultimately, yield. In addition, agricultural data can be collected by satellites and aircraft from isolated areas of the world where agricultural information had been difficult to obtain.

The major experiment during the 1970 s which classified wheat and estimated wheat acreage using only visible and near infrared data from Landsat was the Large Area Crop Inventory Experiment (LACIE) (MacDonald, 1979). LACIE was developed primarily at the request of the
U. S. government to help monitor foreigin production. The objective was to estimate foreign wheat production in several key countries, such as the Soviet Union and Argentina. Success of the program would prevent another U. S./Soviet Union grain trade incident. Results were well documented and the experiment was successful in some geographical areas (Heydorn et al., 1979a; Potter et al., 1979). From that experiment and other studies, many crops were discriminated from bare soil and water, but acreage estimates were still inaccurate as a result of simflar spectral responses from other crops grown during the same time of year (Heydorn et al., 1979a). To improve estimates, ground ancillary data, such as crop growth stage or spectral data from different wavelength regions, are needed. With the proposed launch of the Thematic Mapper, with finer spatial resolution and different spectral bands than Landsat, land-use and vegetation classification will again be the primary objective of further research (National Research Council, 1976). The Thematic Mapper will have spatial resolution of 30 m \(\times 30 \mathrm{~m}\) while Landsat has a resolution of 80 mx 80 m . The Thematic mapper will have spectral bands of (1) 0.45 to \(0.52 \mu \mathrm{~m}\), (2) 0.52 to \(0.60 \mu \mathrm{~m}\), (3) 0.63 to \(0.69 \mu \mathrm{~m}\), (4) 0.76 to \(0.90 \mu \mathrm{~m}\), (5) 1.00 to 1.30 \(\mathrm{m}_{\mathrm{m}}\); (5) 1.55 to 1.75 mm and (7) 2.08 to \(2.35 \mu \mathrm{~m}\). Landsat has spectral bands of (1) 0.50 to 0.60 mm (2) 0.60 to 0.70 mm (3) 0.70 to 0.80 and (4) 0.80 to \(1.1 \mu \mathrm{~m}\).

Different supervised and unsupervised classification techniques emerged from LACIE. In the first method, "samples" of spectral data were compared to a "training" sample of known land use. If the two samples were similar, the sample was classified as the same land use or vegetation cover that was present in the training area. In this
technique, the analyst input the training information in a classifier algorithnn (Bauer et al., 1977). In the unsupervised method, similar responses are grouped together into clusters and these clusters are then compared to actual species clusters (Cooley and Lohnes, 1971). From this technique a tree-classification diagram can be developed based on spectral differences between the clusters. Both techniques are widely used in analyzing visible/near infrared spectral data with supervised techniques being more widely used with satellite data.

The major problems in classifying agricultural crops with visible/infrared data have been the dependence for reliable data on clear weather and the variability of the classification estimate due to phenological or biomass differences. Billingsley et al. (1976) proposed to eliminate these problems by including data from additional bands, such as microwave data, which are independent of cloud cover. Spectral data from many countries are predominantly influenced by excessive cloud cover. In many countries, agricultural Landsat data were obtained only once during the growing season. Consequently, more frequent passes or additional bands were needed to improve satellite coverage. Also, with additional bands more accurate biomass estimates may be possible. During the LACIE experiment it was also found that cl illate data, primarily precipitation, was necessary before good estimates of yield could be obtained. In the LACIE stidy, precipitation was used to estimate the soil moisture avallable to the crop. The inicrowave sensors have been recognized as a possible source of moisture estimates. In addition to this purpose they could also be used to aid in discriminating crops.

Sensors can detect from two modes of radiation-active and passive. Active sensors refer to sensing reflected surface radiation which originated from a known man-made energy source. Passive sensors refer to detection of natural surface emitted and reflected radiation. In this case, the surface is the source of radiation. Considerable effort has been made to take advantage of polarization effects in active sensors while little has been done in polarization effects in passive systems. Both have significant polarization differences; however, passive microwave systems have too coarse spatial resolution to be used effectively in crop discrimination. Microwave data can be either active or passive. Active microwave responses are expressed as \(\sigma^{\circ}\), the scattering coefficient, while passive microwave responses are expressed as brightness temperature. In contrast to the microwave data, visible studies are primarily passive systems. Active visible/infrẵed data have been analyzed, but are too complicated to be widely used.

Active microwave responses are primarily dependent on two surface characteristics--surface roughness and soil moisture. Consequently, crops having different roughnesses or morphologies would respond differently in different radar bands (Simonett et al., 1967). Higher frequencies and the consequent shorter wavelength should be more sensitive than lower frequencies to the roughness characteristics of vegetation. Different microwave frequencies should also have different capabilities of penetrating crop canopies and different sensitivity to soil moisture. Active microwave responses in the \(8-18 \mathrm{GHz}\) range at high incidence angles of \(H H\) (horizontally polarized transmit and received) and VV (vertically polarized transinit and received) have
been related to vegetative characteristics (Ulaby et al., 1975). High emissivity in the passive microwave have also been related to vegetative biomass (Sibley, 1973; Peake et al., 1966; Newton, 1977).

In spite of the extensive research in the active microwave region, few studies have related combinations of visible, infrared, and microwave data to vegetation characteristics (Brakke et al., 1981; Ulaby et al., 1981). Consequently, it is felt that a classification and biomass estimation study using visible, near infrared, far or thermal infrared, and microwave data collected over an agricultural area may produce a multifrequency system that will provide improved estimates of crop acreage and crop conditions.

\section*{Objectives and Research}

The purpose of this study was to (1) develop and test an agricultural classification model using two or more spectral regions (visible through microwave), and (2) estimate biomass by including microwave with visible end infrared data. The hypothesis was that microwave data can improve classification and biomass estimation accuracy over present classification and estimation techniques that use visible and infrared data.

The study was divided into four problems which were intended to answer the previously mentioned goals. The first two deal primarily with crop classification and the last two with biomass and crop classification:
1. Are differences in individual spectral band responses related to crop type differences and what is the relationship of each individual multispectral band response to crop type?
2. What is the most accurate multifrequency dendrogram (tree-classification diagram) of agricultural crops in the Dalhart, Texas and Guymon, Oklahoma areas?
3. What is the utility of microwave data alone or in combination with other spectral bands for classifying agricultural crops and estimating biomass?
4. Is the multifrequency crop tree-classification model influenced by phenological or biomass differences and can the model be adjusted to apply for all biophases?

Data used in this study were collected from the Guymon, Oklahoma area in 1978 and the Dalhart, Texas area in 1980. Alrcraft data were collected using the NASA C-130 aircraft with its full complement of sensors and crew from the Johnson Space Center in Houston, Texas. Ground measurements were collected and processed with extensive support from graduate students and technical personnel from both Texas A8M University and the University of Californid at Santa Barbara. Further discussion of the collection and processing of these data will be found in a following section.

A valid hypothesis implies that more accurate production estimates are possible by including microwave with visible and infrared data. Microwave data could add another dimension--vegetative roughness--to the analysis of visible and infrared data which are highly chrrelated to the amount of biomass. In addition, the independence of microwave data to weather conditions allows analysis of many other areas of the world which were difficult to monitor using visible and infrared data.

\section*{REVIEM OF LITERATURE}

Classification and biomass models are based on spectial response differences between and within crop types in given wavelength regions. Consequently, to better understand classification models, an understanding of the spectral response at all wavelengths is required.

\section*{Spectral Theory}

The reflection of elestromagnetic radiation from a given surface as given by equations 1 and 2 is described by Janza (1975):
\[
R_{v}=\frac{-\left(\varepsilon_{2} \cos \theta_{i}\right)+\sqrt{\varepsilon_{2}-\sin ^{2} \theta_{1}}}{\left(\varepsilon_{2} \cos \theta_{i}\right)+\sqrt{\varepsilon_{2}-\sin ^{2} \theta_{1}}}
\]
and
\[
\begin{equation*}
R_{h}=\frac{\left(\cos \theta_{i}\right)-\sqrt{\varepsilon_{2^{-}} \sin ^{2} \theta}}{\left(\cos \theta_{i}\right)+\sqrt{\varepsilon_{2}-} \sin ^{2} \theta} \tag{2}
\end{equation*}
\]
where \(R_{v}\) and \(R_{h}\) are the reflection coefficients for vertical and horizuntal polarizations, respectively; \(\varepsilon_{2}\) is the dielectric constant of the reflecting medium, and \(\theta_{j}\) is the incidence angle of the plane wave source. Consequently, the dielectric constant plays an important role in letermining reflectance at all wavelengths. The dielectric constant varies with wavelength, moisture content, and temperature. For example, veriations of the dielectric with wavelength are demonstrated by water--tine dielectric at high microwave frequencies is 81 ,
and in the visible, 1.77 (Janza, 1975). Also, the relationship between wavelength and roughness affects reflectance. If surface roughness is greater than one-eighth of the wavelength, the reflectance is diffuse; otherwise, reflectance is primarily specular. This explains why some surfaces look rough at one frequency and sinooth in another. Equations 1 and 2 apply for conditions involving an external source.

In the visible and near-infrared spectral regions, solar radiation is the primary source for reflected radiation at the earth surface. In this spectral region, different materials possess different reflective properties. These spectral differences can be analyzed and used in discriminating many materials on earth. Given that solar radiation is relatively constant at a given zenth angle--assuming constant atmospheric absorption and transmission--reflectance is analyzed through radiance. Radiance ( \(L\) ) can be defined as radiant flux per unit of projected source ared in a specified direction (Janza, 1975). Radiance is calculated for a wavelength channel, \(\lambda_{2}-\lambda_{1}\), by
\[
\begin{equation*}
L=\frac{1}{\pi} \int_{\lambda_{1}}^{\lambda_{2}}\left[E(\lambda) R(\lambda)\left(T_{B}(\lambda) T_{z}(\lambda) p(T) \sin B+p_{B}^{\prime}(\lambda)\right] d \lambda\right. \tag{3}
\end{equation*}
\]
where \(E(\lambda)\) is the specular solar irradiance at the top of the atmosphere at normal incidence, \(R(\lambda)\) the spectral response function of the wavelength channel, \(T_{B}(\lambda)\) the monochromatic one-way tranmissivity of the atmosphere at elevation angle \(\mathrm{B}, \mathrm{T}_{\mathrm{Z}}(\lambda)\) the monochromatic transmissivity of the atmosphere in the zenith direction for solar radia-
tion roflected by the surface to the nadir-viewing sensor, \(p(\lambda)\) the reflectance of the surface, and \(P^{\prime} B(\lambda)\) the atmospheric reflectances as dependent on solar elevation, B.

Microwave emissions can be measured in two modes-active (surface reflection of energy from a source) or passive (emitted from the surface). This is in contrast with visible and infrared data vich is generally sensed in a passive mode. Active visible research has been conducted using lidar, but measurements are quite complicated. The active microwave (radar) responses from many surfaces have been extensively analyzed primarily due to the application of active systems by the military; however, passive microwave research has been less developed due to limitations in spectral resolution or antenna size. Since active and passive microwave data are two different sensing modes, the responses are expressed differently--radar returns are expressed in \(\sigma^{\circ}\) and passive microwave returns are expressed as brightness temperature.

The microwave region has more complex relationships which define reflected radiation. With active microwave systems, surface characteristics have been analyzed by ramparing the power returned to a radar receiver with the transmitted power as calsulated from the radar equation
\[
\begin{equation*}
W_{r}=\frac{W_{t} G_{t}}{4 \pi R^{2}} \quad \sigma \quad \frac{1}{4 \pi R^{2}} A_{r} \tag{4}
\end{equation*}
\]
where \(W_{r}\) is the received power, \(H_{t}\) the transmitted power, \(G_{t}\) the gain of the transmitting antenna in the direction of the target, \(R\) the distance between the antenna and target, o the radar cross section,
and \(A_{r}\) the effective area of the receiving antenno aperture (lanza, 1975). Most applications involve targets which are larger than a resolution cell of radar. Consequently, it is more convenient to consider the average return power over an irradiated area. The average difierential cross-section is known as the scattering coefficient, \(\sigma^{0}\). The above equation implies that radar returns from a target depend upon the strength of the transmitted energy and the reflecting capability of the target. The target roughness and dielectric characteristics produce varying proportions of the return described by the backscatter. In addition to determining the return power, scattering properties of targets can also depolarize the return causing crosspolarized (HV or \(V H\) ) radar data to be useful in geological and agricultural applications. Such depolarization leaves the cross-polarized data sensitive to dielectric properties.

The effect of roughness and the dielectric constant on active and passive microwave returns differ. The roughness effect dominates the active microwave returns, while the dieleciric influence dominates the passive microwave return. The effects also depend on look angle. At high look angles, roughness becomes even more predominant.

According to Planck's equation, emitted radiation from the earth surface peaks in the thermal infrared region. Total emitted surface radiation is described by the Stephan-Boltzmann Law (Planck's Equation applied over all wavelengths):
\[
\begin{equation*}
R=\varepsilon_{S} \sigma T^{4} \tag{5}
\end{equation*}
\]
where \(R\) is emitted radiation, \(\varepsilon_{s}\) is the emissivity of the surface, \(\sigma\) is the Stephan-Boltzmann constant \(\left(5.7 \times 10^{-8} \mathrm{Wm}^{-2}{ }^{\circ} \mathrm{K}^{-4}\right)\), and
\(T\) is the absolute temperature. Most natural objects have emissivities between 0.8 and 1.0 in the thermal region. This will be different in the mitcrowave region. Several factors, such as topography and weather, have made it difficult to classify crops using thermal infrared data. Thermal data, however, have often been used to evaluate soil moisture conditions.

Emissions in the passive microwave region are much smaller than thermal infrared emission. Emitted responses are based upon Rayleigh-Jean's approxtmation to Plank's equation (Wolfe and Zissis, 1978)
\[
\begin{equation*}
R_{b}=\frac{2 k T}{\lambda^{2}} \tag{6}
\end{equation*}
\]

Where \(R_{b}\) is radiation (brightness) from a blackbody, \(T\) the absolute temperature, \(k\) Plank's constant and \(\lambda\) the wavelength. The emitted radiation in the microwave region is often expressed as brightness temperature. It can be expressed as a function of ground and atmospheric emissivity ( \(\varepsilon_{g}\) and \(\varepsilon_{a}\) ), ground reflectance ( \(\mathrm{pg}_{\mathrm{g}}\) ), and sky , groünd, and atmospheric (clouds, water vapor, pariticulates) temperatures ( \(T_{s}, T_{g}, T_{a}\) ):
\[
\begin{equation*}
T_{b}=p_{g} T_{s}+\varepsilon_{g} T_{g}+\varepsilon_{a} T_{a}+p_{g} T_{a} \tag{7}
\end{equation*}
\]

Effects of the atmosphere are often negligible, especially with cloudless skj. Consequently, \(\mathrm{T}_{\mathrm{a}}\) is often neglected giving
\[
\begin{equation*}
T_{b}=\varepsilon_{g} T_{g}+\left(1-\varepsilon_{g}\right) T_{s} \tag{8}
\end{equation*}
\]

Since \(T_{s}\) and \(\left(1-\varepsilon_{g}\right)\) are both small, the reflection term, (1\(\varepsilon_{g}\) ) \(T_{s}\), is often onitted leaving only
\[
\begin{equation*}
T_{b}=\varepsilon_{g} T_{g} \tag{9}
\end{equation*}
\]

The variation in ground emissivity, \(\mathrm{eg}_{\mathrm{g}}\) provides much information on dielectric constant and roughness. Since healthy crops contain over 50\% water and appear rough in certain microwave wavelengths, ground emissivity will vary under different vegetation conditions (Peake, 1966; Sibley, 1973).

Given the spectral theory, which is applicable at all wavelengths, one must turn to the factors which primarily influence spectral responses of agricultural crops. To slimplify the description, the electromagnetic spectrum will be divided into the visible/infrared and the microwave regions.

Visible/Infrared Responses

Water and chlorophyll are the most important substances which influence vegetation and soil reflectance in the visible/infrared. At high solar elevation angles, water strongly absorbs solar radiation in both the visible and infrared. Consequently, visible and infrared reflectance from a soil would often decrease under high moisture conditions. The moisture effect is highly dependent on conditions within the top thin layer of the surface being observed. No subsurface moisture can be directly determined using wavelengths shorter than one centimeter (Davis et al., 1965).

Leaves, however, have a completely different spectrum. Due to Fresnel reflectance at air/water interfaces within the leaves, near
and middle infrared radiation is strongly reflected (Figure 1) (Gates, 1980). Figures 2 demonstrates that the relationship between biomass and reflectance is dependent upon crop type and maturity (Tucker et al., 1979, Park and Drering, 1981). Reflectance increases rapidly with toial biomass in the near- and middle-infrared region until a saturated reflectance is reached. At that point reilectance becomes inserisitive to increases in biomass. Then at a point near maturity, the reflectance in this region begins to decrease with biomass. Consequently for corn and soybeans, crops with a near-complete canopy cover, reflectance is insensitive to total biomass increases for a given period of time. Other techniques are needed to quantify biomass estimates in this region. Reflectance is also a function of the chlorophyll content. Chlorophyll absorbs radiation in the red and blue regions, and has a slight reflectance in the green and high reflectance in the near infrared. Studies by Hoffer and Johannsen (1969) indicated changes in chlorophyll content allowed other carotenes and xanthopiylls to become evident, thus affecting primarily the visible/infrared reflectance. Since infrared reflectance is strongly dependent on the air/water interface and chlorophyll content, any environmental effect which changes the area of air/water interface or the number of leaves will influence the reflectance. Consequently, disease and stress (moisture, nutrient, etc.) drastically decrease infrared reflectance. In spite of these effects, differences between the visible and near infrared data have been the basis for classifying vegetation and estimating biomass. The main premise is that at a given phenological period for a crop, spectral characteristics in the

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FIG. 1 Reflectance of 2 and 8 stacked mature cotton leaves. Standard deviation between


FIG. 2. Averaged normalized difference (IR-red/IR + red) values plotted against soybean west biomass. from Tucker et al., 1979.
crop allow for crop discrimination-assuming that spectral differences within the crop attributed to stress or disease are less than the differences between crops. Also, if two crops have the same phenology and spectral characteristics, they will not be spectrally separable. Given difference in chlorophyll content and leaf succulence between plant species, classification and biomass estimation models have beefi developed. The detection is consequently based on visiole/infrared differences between crop types. Different biomass models will be discussed later.

Integrating the soil and vegetation reflectance has been a problem. Many have tried to model canopy (integrated) reflectance (Kubelka and Munk, 1931; Chance and LeMaster, 1977; Richardson et al., 1975). Chance and LeMaster (1977) used the Suits model to estimate reflected and non-reflected radiation from a boundary layer. However, the model showed littile agreement with wheat reflectance data as a function of solar angle. Richardson et al. (1975) used the Kubelka-Munk and a regression model, using biophysical parameters for extracting plant, soil, and shadow reflectance compone s of cropped fields. The model did correlate well to actual scene reflectance. Microwave Responses

Three factors primarily affect reflectance and emission from agricultural surfaces in the microwave region--surface roughness, soil moisture, and vegetation. To fully understand the return from an agricultural scene, one must account for each factor. Each factor will be discussed in greater detail.

Roughness - As mentioned before, for active microwave systems \(\sigma^{0}\) is governed by the geometric properties of the surface. Beckman (1966) found the backscatter to be related to the variance and mean slope of the surface. Ulaby et al. (1978) found \(\sigma^{0}\) variations attribUtable to soll roughness decrease with look angle out to \(10^{\circ}\) from nadir, which is the least sensitive to roughness. Fenner et al. (1981) and Ulaby and Bare (1979) found row direction was very important in the radar return. Rows perpendicular to the emitted beam have much higher returns compared to rows parallel to the emitted beam. At certain look angles and frequencies the surface roughness effect may dominate the terims that are due to changes in the dielectric constant brought about by changes in soil moisture.

Wang et al. (1980) noted that tilled row direction is also a major factor in passive inicrowave emission, especially when the antenna is directed off nadir to the ground. The difference between vertical and horizontal polarized returns in passive microwave returns can be related to the soil surface roughness (Newton 1977, Choudhury et al., 1979). The effect appears to decrease at look angles larger than 35 degrees off nadir. The roughness effect is also dependent on the relative height of the roughness in relation to the wavelength of the sensor.

Soil moisture - The effect of the dielectric constant on the active microwave response is demonstrated by changes in soil moisture. In the high frequency microwave regions, soil has a dielectric constant of 3 , and water, 81. Consequently, any significant change in soil moisture should be detectable. The relationship has been studied
in great detail using active systems. Laboratory experiments by Lundien (1971) showed L band ( 21 cm wavelength) data should be more sensitive to soll moisture differences thaf \(K\) band \((1.55 \mathrm{~cm}\) wavelengith) due to differences in the dielectric constant of water at the two frequencies. However, Haby et al. (1978) found C band active microwave data to be most sensitive to soil moisture differences in the surface two centimeters. The severe effect of roughness that is inherent in active microwave returns was minimum in Ulaby's experiment which was carried out over tillage common to Kansas using \(C\) band at \(10^{\circ}\) off nadir.

Field experiments by Newton (1977) and analysis of satellite data by McFarland (1976) had shown L. band passive microwave data was sensitive to soil moisture changes within approximately the surface 5 cm layer. Other similar work had been done in using active and passive microwave data. An excellent review of studies concerning soll moisture estimates using microwave systems was given by Schmugge (1978).

Vegetation - The effect of vegetation on the active microwave return has been studied since the mid-1960s. Early work concentrated on analyzing effects in the \(K\) band ( \(1-2 \mathrm{cin}\) ) region (Simonett at al., 1967, Ellermeier et al., 1969). The studies indicated radar was a potential tool for discriminating crops. The response is based on both moisture and roughness. As a crop matures, the crop moisture increases to the time that the crop begins to senesce and then decreases. At look angles of greater than \(40^{\circ}\) from nadir, \(\sigma^{0}\) is strongly correlated to plant water content in com and wheat (Ulaby and Bush, 1976a and 1976b). Consequently, biomass could be estimated
for the growing period. Also crops have different morphologies which can be applied to crop discrimination. However, other factors may influence the scatterometer return. De Loor et al. (1974) found \(\sigma^{0}\) to vary as much as 4 to 5 db under different wind speeds. Brakke et al. (1981), however, found no influence of wind speed on \(\sigma^{0}\) over wheat and sorghum in the \(K\) band region. Ulaby et al. (1975) found that crops can be discriminated with multifrequency vertically polarized data (beiween 8 to \(18 \mathrm{GHz}(2.5-3.5 \mathrm{~cm})\) ). Look angles at \(30^{\circ}\) to \(65^{\circ}\) from nadir removed the soil moisture effects leaving only the vegetative effects. Comparisons between like- and cross-polarized active
 vegetation. Classification accuracies improved from 65\% to 71\% by including cross with like-polarized data (Ulaby et ales 1980).

Comparisons of different polarizations of passive microwave data also indicated crop morphological differences (Kirdyashev et al., 1979). Relationships between biomass, height, plant nioisture content and brightness temperature at multiple frequencies were found. Such parameters can be related to crop type differences. The passive microwave data, however, are less practical for crop discrimination due to the poor resolution associated with aircraft and spacecraft passive systems.

To sumarize, active microwave data at look angles greater than \(30^{\circ}\) from nadir appear to be related to vegetative characteristics Which can imply crop type differences. Active microwave systems are more sensitive to roughness, while passive systems are more sensitive to soil moisture. Multifrequency passive microwave data also have been related to similar vegetative characteristics but are less
sensitive to roughness and vegetation, and have less acceptable resolution capabilities than the active systems. The sensitivity to all three factors is dependent on wavelength (frequency) as well as polarization and look angle for both active and passive systems.

\section*{Classification Models}

\section*{Supervised Models}

From the previously mentioned visible and near-infrared relationships of vegetation, several classification models have been developed. Heydorn et al. (1979b) gave a general description of several supervised and unsupervised techniques which emerged from studies with LACIE.

Supervised classification techniques became one of the key classification techniques. T'ne methods required information on the classes--means, standard deviations, or vectors of data. This information was termed the training classifier. Using various comparison techniques, sampled data were compared to the training classifier and placed into the proper class. To separate classes, discrimiñant functions as determined from class statistics were calculated. Any sample which fell on either side of the function was placed into one of the classes (Swain and Davis, 1979). Several of the widely used supervised techniques were maximum likelihood per point, maximum likelihood per homogeneous group, ECHO--Extraction and Classification of Homogeneous Objects--minimum distance to the class means, and standard deviations to calculate the probability of including the sample in a given class. The only difference between the ECHO classifier and the maxi-
mam likelihood classifier was the sample; ECHO uses a homogeneous group of sample points, while the maximum likelihood per point method analyzes only one sample point at a time. In the minimum distance classifier, a Euclidean distance was caiculated between the data vec. tor at one point and the mean vector. If the distance was less than a given threshold, the point was placed into the given class. The layered classifier differed from the maximum likelihood per point classifier in that multiple decisions, rather than one decision were made at each point. This allowed for different subsets of channels to be used. Bauer et al. (1977) found no significant difference in accuracy using each of these techniques. However, the minimum distance classifier had the lowest computer cost.

\section*{Unsupervised Models}

Unsupervised classification, or clustering, models require no information on classes. The techniques grouped similar spectral averzges. The most widely used technique involved the minimum distance between observations (Johnson, 1967). Another similarity criterion technique involved minimizing variance or the sum of squares. Other techniques were described by Orloci (1978) and Hartigan (1974). Such techniques had been used in combination with other supervised techniques to classify agricultural scenes and estimate areal coverage from Landsat data (Heydorn et al., 1979a). A major part of the classifier was the "tree structure" which defined decision points as determined by variable differences between spectral classes involved.

Classification accuracies using these techniques had varied from one location to another. The areas having the lowest accuracy had
"confusion" crops growing in the same area--crops which have the same spectra at a given period. Accuracies ranged from 60\% to over \(90 \%\) in some areas.

In the microwave region, success in classifying vegetation has been equally as accurate. Simonett et al. (1967) was one of the first to classify an agricultural scene using like- and cross-polarized data. Ulabs et al. (1980) also classified correctly 71\% of an area using like- and cross-polarized microwave data. Other work was done by Morain and Simonett (1967), Schwarz and Caspell (1968), Waite and MacDonald (1971), and Ulaby et al. (1975). Blanchard et al. (1979) classified pasture, timber and bare soll with reasonable accuracy using airborne scatterometer data. Land use was correctly deterinined in greater than \(80 \%\) of the cases by anaiyzing the differences in the \(10^{\circ}\) and \(35^{\circ}\) look angle \(0^{\circ}\) values for like-polarized data, differences in the like- and cross-polarized data at \(10^{\circ}\) look angle, and the cross polarized data at \(10^{\circ}\) look angle. Few studies, however, have combined active and passive microwave data with visible and near-infrared data. Ulaby et al. (1981) analyzed scatterometer and Landsat data collected over an agricultural area in 1978. Classification accuracy increased \(10 \%\) by including scatterometer data with Landsat data. Further work needs to be done relating vegetation type to visible, infrared, and passive and active microwave data.

\section*{Biomass Models}

\section*{Visible/Infrared Region}

Because infrared leaf reflectance is strongly influenced by the number of leaves, which in turn is related to plant hiomass, many
models have been developed using a combination of visible/infrared reflectance data. Only a few significant models are mentioned here.

The transformed vegetation index (TVI) has been used primarily as an estimater of rangeland biomass (Rouse et al., 1973; Deering et al., 1975). The model was expressed as
\[
\begin{equation*}
T V I=\sqrt{\left(\frac{M S S 7-M S S 5)}{(M S S T+M S S 5)}+0.5\right.} \tag{10}
\end{equation*}
\]

Where MSS7 and 5 are radiances from Landsat bands 7 (0.8-1.1 \(\mu \mathrm{m}\) ) and 5 ( \(0.6-0.7 \mathrm{~mm}\) ), respectively. The ratio was used as a normalizing term to remove temporal index variations, such as illumination differences due to aerosols and solar angle, and 0.5 was added to keep the term under the square root from going negative. A modification of the index involved replacing band \(6(0.7-0.8 \mathrm{pm})\) data for bayd 7. The modified index was TVI6. Both were well correlated to green biomass.

Kauth and Thomas (1976) developed transformation matrices which converted Landsat data for cultivated agricultural areas to data which enhanced greenness, brightness, and yellowness. By comparing transformed data from temporal scenes, the progression of phenology followed the shape of a "tasseled cap." Converting the matrices to index GVI \(=-0.290\) MSSA -0.562 MSS5 + 0.600 MSS6 + 0.491 MSS7 and the brightness index was

SBI \(=0.433\) MSS4 +0.632 MSS5 +0.586 MSS6 +0.264 MSS7
where MSS4, 5, 6 and 7 refer to Landsat bands 4, 5, 6 and 7 digita? counts. GVI had been found to be highly correlated to leaf area index (Richardson and Wiegand, 1977).

Another vegetation index model used to estimate bionases is the perpendicular vegetation index (PVI), developed by Richardson and Wiegand (1977). PVI was calculated by the equation
\[
\begin{equation*}
P V I=\sqrt{(R g g 5-R p 5)^{2}+(R g g 7-R p 7)^{2}} \tag{13}
\end{equation*}
\]
where \(R p\) is the reflectance for a candidate vegetation point for Landsat bands MSS5 and MSS7 and Rgg is the reflectance of soil background corresponding to the same candidate vegetation point. Figure 3 describes the principle of the perpendicular vegetation index. Simply, PVI is the perpendicular distance from a given radiance in bands 5 and 7 to the soil background line. It was demonstrated by Richardson and Wiegand (1977) that PVI6 and TVI6 (where Landsat band 6 is used instead of band 7) are both highly correlated to leaf area index. Picrowave Models

Work is just beginning in relating microwave data to vegetation characteristics. Brakke et al. (1981) related corn, wheat, and sorghum characteristics, such as plant moisture content, crop height, and leaf area index, to microwave, visible and near-infrared data. The authors determined dry matter was highly correlated with \(\sigma^{0}\) at look angles of \(70^{\circ}\) off nadir. Jackson et al. (1981) compared biomass estimates to changes in the slope of regression lines relating soil moisture and normalized passive microwave brightness temperature. As biomass increased, the sensitivity of normalized brightness temperature related to soil moisture decreased.


FIG. 3. Diagram illustrating the principle of the perpendicular vegetation index (PVI) model. A perpendicular from candidate plant coordinates (RP5, P.07) intersects the soil background line at coordinates (Rg5, Rg7). A PVI 0 indicates soil, and a PVI>0 indicates vegetation. From Richardson and Wiegand (1977).

\section*{Literature Overview}

From the research reported, it is evident that simultaneous data using visible, infrared, and microwave bands have rarely been collected. More data sets of visible, infrared, and microwave data are needed to compare against vegetation type and characteristics, such as biollass. According to theory, microwave frequencies should be sensitive to different vegetation characteristics (primarily geometric and dielectric properties) than characteristics seen by visible and infrared data. As a result, classification accuracies and biomass estimates should improve by including microwave (active or passive) bands with visible and infrared.

\section*{DATA COLLECTION}

Aircraft data were collected near Guymon, Oklahoma in August, 1978, and near Dalhapt, Texas in August 1980. Data collection and processing will be described for each site.

\section*{Guymon Aircraft and Ground lata}

In August, 1978, aircraft and ground data were collected in commercial agricultural fields located from 3 to 20 km southwest of Guymon, Oklahoma and near Clayton, New Mexico (Figures 4a through 4h). vegetative cover in the area included bare soil, corn, sorghum, and alfalfa. Soil type was generally a silty clay (averaging \(35 \%\) clay, \(35 \%\) silt, and \(30 \%\) sand) with many areas having a caliche ( \(\mathrm{CaCO}_{3}\) ) layer near the surface. Different tillage practices allowed spectral data from sorghum and bare fields having rows perpendicular and parallel to the flight line to be analyzed. Aircraft and ground data were collected in fields along four flight lines covering \(38.4 \mathrm{~km}^{2}\) area ( 1.6 x 24 km ).

Aircraft data collected by the NASA C-130 on August 2, 5, 8, 11, 14, and 17 consisted of (1) sevell scatterometer frequencies and polarizations, (2) three passive inicrowave frequencies and polarizations, (3) five visible/near-infrared/thermal channels, (4) Barnes PRT-5 radiometer thermal data, and (5) black and white aerial photograpioy. The aircraft flew at least twice at 500 m over each flight line on each flight day. Also, on August 5 , the \(\mathrm{C}-130\) collected only scatterometer data over fields near Cl ayton, New Mexico.

\section*{\(101^{\prime \prime} 30^{\prime}\)}

GUYMON AREA MAP
INDEX TO FIELD MAPS
Approximote scale is \(1: 250,000\)
FIG. 4 a Area map of Guymon showing the relative locations of each field map.

FIG. 4b Legend for the Guymon, Oklahoma field maps.


FIG. 4c Locations of sample fields at Guymon, East end, Lines 1 and 2.


FIG. 4d Löcations of sample fields at Guymon, West end, Lines 1 and 2.

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FIG. 4e Locations of sample fields at Guymen, South end, Lines 3 and 4.


CLAYTON AREA MAP
Approximate scole is \(1: 250,000\)


FIG. \(4 f\) Area map of Clayton showing the relative location of the field map.

FIG. 4 g Legend for the Clayton, New Mexico field maps.

FIG. 4h Locations of the sample fields at Clayton.

The scatterometer frequenctes and polarizations included (1) 13.3 GHz VV (K band) vertically polarized transinitted and received), (2) 4.75 GHz HH (C band horizonially polarized transmitted and received), (3) 4.75 GHz HV (horizontally polarized transmitted and vertically polarized received), (4) \(1,6 \mathrm{GHz} \mathrm{HH}\) (L band), (5) 1.6 GHz HV , (6) 0.4 GHz HH ( P band), and (7) 0.4 GHz HV . These frequencies will be referred to as \(K\) band, \(C\) band, \(\mathbb{L}\) band or \(P\) band throughout the remainder of this report. The polarizations will be referred to as like pole or cross pole instead of HH or HV , respectively. Data froin eight look angles from nadir were processed for each frequency: \(5^{\circ}\), \(10^{\circ}, 15^{\circ}, 20^{\circ}, 25^{\circ}, 35^{\circ}, 40^{\circ}, 45^{\circ}\).

Passive microwave data were collected in 1.6 GHz (L band) horizontal polarization, and 4.75 GHz ( \(c\) band) vertical añ horizōntal polarizations. These data will be referred to as \(L\) band horizontal, \(C\) band vertical and C band horizontal, respectively.

Five channels from the modular multispectral scanner ( \(M^{2} S\) ) were available: (1) channel 4: 0.548-0.583 \(\mu \mathrm{m}\), (2) channel 7: 0.662-0.701 \(\mu \mathrm{m}\), (3) channel 8: 0.703-0.747 \(\mu \mathrm{m}\), (4) channel 9: \(0.770-0.863 \mu \mathrm{~m}\), and (5) channel 11: 8.000-12.080 \(\mu \mathrm{m}\).

Barnes PRT-5 measurements were also included to calibrate the \(M^{2} S\) thermal band (channel 8) and normalize the passive microwave brightness temperature.

The sensors were operating at different times throughout the study because the active microwave data would interfere with the passive microwave data. Windy conditions on August 14 also forced a third run over each flight line. Table 1 lists the operating sensors

TABLE 1. Operating Sensors for the Guymon, Oklahoma Study
\begin{tabular}{|c|c|c|c|}
\hline Date & Line & Run & Operating Sensors \\
\hline \(\left[\begin{array}{c}8 / 2 / 78 \\ 8 / 5 / 78 \\ 8 / 8 / 78\end{array}\right]\) & 1-4 & 1 & all scatterometer; M \({ }^{2}\) S; PRT-5; C-band passive microwave; photos; \\
\hline \(8 / 11 / 78\)
\(8 / 11 / 78\) & 1-4 & 2 & \begin{tabular}{l}
K-band, C-band, P-band scatterometer; and \\
L-band passive microwave; PRT-5; photos
\end{tabular} \\
\hline \([8 / 14 / 78]\) & \[
\begin{aligned}
& 1-4 \\
& 1-4 \\
& 1-4
\end{aligned}
\] & 1

2 & \begin{tabular}{l}
all scatteroneter; \(M^{2} S\); C-band passive microwave; PRT-5; photos \\
K-band, C-band, P-band scatterometer; and L-band passive microwave; PRT-5; photos all scatterometer; \(M^{2} S\); C-band passive microwave; PRT-5, photos
\end{tabular} \\
\hline
\end{tabular}
for each flight line and run. Field averages were determined for each sensor. Because of the uncertainty of the target and look angle, field averages were deleted from the data set when the NASA C-130 had excessive roll (greater than \(3.5^{\circ}\) ) and/or drift (greater than \(9^{\circ}\) ).

Soil moisture samples were collerted at eight points approximately 200 m apart within each 32 hectare field (Figure 5). Samples collected at each site were \(0-2 \mathrm{~cm}, 2-5 \mathrm{~cm}, 5-9 \mathrm{~cm}, 9-15 \mathrm{~cm}, 0-15 \mathrm{~cm}\), \(15-30 \mathrm{~cm}\), and \(30-45 \mathrm{~cm}\) (Figure 6). Field averages were calculated for each depth. Data included in calculating the average were from sites within the maximum sensor swath width. In the majority of the cases, data from all eight sample points were included. Approximately onethird of the fields were sampled on flight days. As a result, moisture averages for fields not sampled on flight days were interpolated from time series plots of measurements taken the day before or the day after flights. Field notes of tillage, center pivot location and wet/dry areas were also tabulated. No biomass information was cullected at Guymon; however, photographs of crops at the time of the experiment were collected which provided a rough estimate of crop cover.

\section*{Dalhart Aircraft and Ground Data}

During August, 1980, aircraft and ground data were collected in commercial agricultural fields 20 km northwest of Dalhart, Texas (Figures 7a through 7e). Figure 7a represents the general view of the area showing the relative locations of \(7 b, c\) and \(d\). Figure 7 b is the legend which describes the crop types. Crop types within the area included bare soil, pasture, corn, alfalfa and sorghum. The soil type

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These points were moved outside the pivot boundary for fields \(5 \$ 6\).

FIG. 5 Sampling pattern for fields at Guymon and Dalhart. Points 1, 2, 7 and 8 were moved outside the circle for rectangular fields.

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FIG. 6 Soll motsture sampling depths at Dalhart and Guymon. The \(15-30\) and \(30-45 \mathrm{~cm}\) core samples were also taken in addition to the above. Samples were collected from \(5-9 \mathrm{~cm}\) and \(9-15 \mathrm{~cm}\) at Guymon and \(5-15 \mathrm{~cm}\) at Dalhart.

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\section*{DALHART, TEXAS 1980 LEGEND FOR FIELD MAPS \(1,2 \& 3\)}


Bare: wheat stubble
disked wheat stubble
mutched wheat stubble
Millet
Milo

- Flight line markers

A Corner reflectors
* Rain gauges
- Vegetation sample sites

Row direction was east-west for all sample fields with row crops.


Prepored by the Texas A\&M University Ramote Sensing Center. Base dato compilod from USGS topogrophic meps, R.S.C. tamm fiold notes and NASA controcted aerial photography collected Augusi 14. 18, 1980.

FIG. 7b Legend for the Dalhart, Texas field maps.


FIG. 7c Locations of sample fields at Dalhart, East end, Lines 1 and 2.


FIG. 7d Locations of the sample fields at Dalhart, Lines 1 ard 2.

of the surface 30 cm was a sandy loam ( \(75 \%\) sand, \(10 \%\) silt and \(15 \%\) clay). The commercial fields were located along two flight lines covering a \(36 \mathrm{~km}^{2}\) area ( \(1.6 \times 22.5 \mathrm{~km}\) ).

Aircraft data, which were collected by the NASA C-130 on August 14, 16 , and 18 , consisted of (1) seven scatterometer frequencies and polarizations, (2) three passive microwave radioneter frequencies and polarizations, (3) eight visible, near- middle- and far-infrared bands, (4) Barnes PRT-5 radiometer thermal data, and (5) color infrared aerial photography. The aircraft flew twice at 500 m over each flight line and once at 1500 m over the general area.

The scatteroneter frequencies and polarizations are the same as the scatterometer sensors at Dalhart. For each scatterometer, data were processed at the samie look angles analyzed at Guymon: \(5^{\circ}, 10^{\circ}\), \(15^{\circ}, 20^{\circ}, 25^{\circ}, 35^{\circ}, 40^{\circ}, 45^{\circ}\).

The passive microwave radiometer frequencies and polarizations operating over Dalhart were the same channels operating over Guymon: \(L\) band horizontal and C-band horizontal and vertical polarizations. The \(L\) band passive microwave radiometer used at Dalhart was not the same instrument used at Guymon.

The eight channels of NSOO1 scanner data (simulated thematic mapper bands) included channel 1: \(0.45-0.52 \mu \mathrm{~m}\), channel 2: 0.52-0.60 \(\mu \mathrm{m}\), channel 3: \(0.63-0.69 \mu \mathrm{n}\), channel \(4: 0.76-0.90 \mu \mathrm{~m}\), channel 5 : 1.00-1.30 \(\mathrm{\mu}^{\prime \prime}\), channel 6: 1.55-1.75 \(\mu \mathrm{ml}\), channel 7: 2.08-2.35 \(\mathrm{\mu m}\), and channel 8: 10.40-12.50 \(\mu \mathrm{m}\). The channels are similar to the proposed data channels of the thematic mapper aboard Landsat D. Channel 7 \(\left(M^{2} S\right)\) matches well with channel 3 ( \(N S 001\) ); channel \(9\left(M^{2} S\right)\) matches
with channel 4 (NSOO1); and channel \(11\left(M^{2} S\right)\) matches with channel 8 (NSOO1).

The sensors were operating at different times compared to the Guymon study. For example, at Dalhart all scatterometers were on during the first run, while at Guymon selected scatterometer sensors operated at 111 times. Table 2 lists the operating sensors for each flight line and run. Field averages were determined for each field. Again, field averages of the sensor data were deleted from the data set when the aircraft had excessive roll (greater than \(3.5^{\circ}\) ) and/or drift (greater than \(9^{\circ}\) ).

The ground data consisted only of soil moisture samples, biomass data, and photographs of crops. The soil moisture sampling scheme was similar to Guymon exceept for minor modification of the depth intervals and time of sampling. First, the \(5-9\) and \(9-15 \mathrm{~cm}\) sampling depths were combined into a \(5-15\) sampling depth. Second, fields were sampled less intensively on each flight day. And finally, each field was sampled every other day, rather than every third day. Two flights were flown on the same day \((8 / 16 / 80)\). The rest of the soil moisture sampling scheme was similar to the Guymon study.

Biomass samples were collected within each soil moisture sampling field along the filight lines in addition to several alfalfa and sorghum fields just south of the flight lines. The sampling locations are shown in Figure 7c, d and e. Samples were collected from a \(1 \mathrm{~m}^{2}\) area representative of biomass conditions in the field.

TABLE 2. Operating Sensors for the Dalhart, Toxas Study
\begin{tabular}{|c|c|c|c|}
\hline Date & Line & Run & Operating Sensors \\
\hline \multirow[t]{5}{*}{8/14/80} & 11 & 1 & scatterometers, NS()01, PRT-5, color IR photos \\
\hline & 12 & 1 & scatterometers, NSOO1, PRT-5, color IR photos \\
\hline & 11 & 2 & passive microwave, NS001, PRT-5, color IR photos \\
\hline & 12 & 2 & passive microwave, NS001, PRT-5, color IR photos \\
\hline & 13 & 1 & NS001, PRT-5, and color IR photos \\
\hline \multirow[t]{5}{*}{\(8 / 16 / 80\)
\((2\)
f1ights \()\)
and
\(8 / 18 / 80\)} & 11 & 1 & passive microwave, NS001, PRT-5, color IR photos \\
\hline & 12 & 1 & passive microwave, NS001, PRT-5, color IR photos \\
\hline & 11 & 2 & scatterometers, NSOO1, PRT-5, color IR photos \\
\hline & 12 & 2 & scatterometers, NSO01, PRT-5, color IR photos \\
\hline & 13 & 1 & NSOO1, PRT-5, and color IR photos \\
\hline
\end{tabular}

\section*{Scatterometer Processing}

Scatterometer data were collected aboard the NASA C-130 in analog form on a 14 -track tape. Copies of the tape were later sent to Texas ARM University/Remote Sensing Center for processing, which consisted of two phases (Figure 8). The initial processing converted the ana\(10 g\) data to digital values and copied the digital data onto 9-track magnetic tapes. The second phase processed the digital data using software which calculated the scattering coefficient ( \(\sigma^{0}\) ) for each look angle at given time intervals. Data were processed so that a cell size roughly had a length of 25 m for K band, 38 m for C band, 50 m for L band, and 75 m for \(P\) band. The processing software was described by Classsen et al. (1979) and Clark and Newton (1979). Crossover effects from the like-polarized data to the cross-polarized \(L\) band data were removed using a technique described by Blanchard and Theis (1981).

The cross-over effect is due to the inability to construct receivers which detect microwave energy in a single polarization. In actuality, a single polarized transmitter emits energy in one polarization when upon interacting with the surface is further modified and is recelved in two polarizations, thus influencing the cross- as well as the like-polarized data. Elanchard and Theis (1981) modeled the effect of the signal impurity on the cross-poiarized data and effectively calculated a correction factor for the small look angles.

After processing scatterometer data, field start and stop times were determined for each frequency and polarization from line plots of

\section*{PHASE I}


FIG. 8 Scatterometer data processing procedure.
\(0^{0}\) versus time, and aerial photographs. Times were adjusted by shifting the start/stop times at least 0.5 seconds toward the field center to insure full scatterometer coverage within the field. The final start and stop times defined the field boundary and were used in determining figld averages for each frequency, polarization, and look angle. Time frames during excessive aircraft roll and drift (roll greater than \(3.5^{\circ}\); drift greater than \(9^{\circ}\) ) were noted and data from affected look angles were deleted from further analysis.

No known technique or mechanism was available to calibrate all of the scatterometers. Consequently, any temporal variation in \(0^{\circ}\) was assumed to indicate either sofl moisture, roughness, or vegetation changes.

\section*{NS001/i \({ }^{2}{ }^{2}\) Srocessing}

The data were processed onto 9-track tiapes at NASA/Johnson Space Center. Included with the surface data were calibration data consisting of digital counts from looks at constant radiance targets within the sensor. The calibration data were then used to convert digital counts to radiance. To minimize processing costs, only data from the first runs were processed.

Since radiance is a function of the solar angle, a corraction factor was needed before comparing crop radiance differences. All the Dalhart data were normalized to August 18--the day with the smallest solar zenith angle; Guymon data were adjusted to August 11 zenith angle conditions. The correction factor used was
\[
\begin{equation*}
R_{c}=\frac{R_{i}}{\cos \theta} \tag{14}
\end{equation*}
\]

Where \(R_{i}\) and \(R_{C}\) are the non-normalized and normalized radiance values, respectively, and \(\theta\) is the solar zenith angle.

\section*{Passive Microwave Processing}

The raw analog data collected aboard the aircarft were converted to digital uncorrected brightness temperatures at NASA/Goddard Space Fight Center (GSFC). Corrected brightness temperatures (TB) were calculated from an equation developed at NASA/JSC ( \(0^{\prime}\) Neill, 1981):
\[
\begin{equation*}
T_{B}=\frac{1}{t}\left[T_{U}\left(\frac{L}{1-r^{2}}\right)-\frac{r^{2}\left(T_{\sigma}\right)(L)}{1-r^{2}}-T_{L}(L-1)-e T_{R}\right] \tag{15}
\end{equation*}
\]
where \(t\) is the transmittance of the radome, \(e\) is the emissivity of the radome, \(T_{u}\) is the uncorrected brightness temperature based on raw digital counts, \(L\) is antenna cable loss factor, \(T_{L}\) is an antenna temperature factor, \(T_{R}\) is the radome temperature factor, \(r^{2}\) is an internal parameter for each frequency, and \(T_{\sigma}\) is the self-emission of the receiver. For the Dalhart \(L\) band horizontal data, the radome terms are omitted since the sensor used on these flights was operating in the open rear door of the aircraft. The various constants used in the \(t\). sion were deterinined from flights over homogeneous areas. Once brightness temperatures were calculated, line plots of \(T_{B}\) versus time were produced and field start and stop times were determined from the plots. The times defining field boundaries used for scatterometer data were also used in calculating fields averages for each frequency and polarization.

\section*{AMAL.YSIS}

\section*{Techniques}

Once field averages had been calculated for each sensor and soil moisture depth, the ground and aircraft data sets were merged. Each problem mentioned in the objectives and research subsection was analyzed.

In the first problem, the major task was to note sensur variables which responded well to differences in crop type. Analysis techniques included a Duncan's multiple range technique, and graphical analysis-spectrums and response changes as a function of time (Cooley and Lohnes, 1971). Both Dalhart and Guymon spectral data sets were analyzed. The results consisted of a list of sensor variables which are sensitive to crop type differences. From this set, linear combinations were developed which should enhance crop discrimination sensitivity.

The procedure to solve the second problem used unsupervised (based on a minimized distance criterion) classification techniques to discriminate crops. A hierarchical (tree) classification system was developed using separation criterion emerging from the unsupervised techniques. Individual spectral bands and combinations, such as TVI, PVI, and other visible/infrared and scatterometer combinations, were analyzed. The supervised classification technique was developed using August 2 and 17, 1978 and August 14 and 18, 1980, data. The model was then tested on August 5. 8, 11 and 14, 1978 and August 16, 1980 spectral data. The unsupervised classification technique used all

Guymon and Dalhart data sets. From the unsupervised technique, tree-classification models (dendrograms) were developed for the Guynon and Dalhart data sets. The dendrograms were constructed using the same separation criterion used in the unsupervisea zanique. For example, if the separation criterion between two clusters were \(\sigma^{0}\) differences in the \(L\) band cross pole data, then this variable was used in the dendrogram model to separate groups. The dendrograms at both locations were compared and similarities noted, which may be applicable in developing a multifrequency dendrogram classification model.

The third problem was solved by developing linear step-wise regression, supervised and unsupervised crop classification and biomass estimation models to see if microwave data could improve classification and biomass estimation accuracy. Models using only visible/ infrared data were compared to models which included visible/infrared and microwave data. Any microwave sensor or combination which was more strongly related to crop type differences or biomass estination than other visible/infrared variables or combinations suggested an improvement over present techniques using only visible and infrared data. The linear step-wise models used spectral data fram Gumon and Dalhart. The supervised and unsupervised classification models were developed and tested on the same spectral data set as mentioned for problem 2.

The fourth problem analyzed the variability of the classification and biomass estimation models developed in problems 2 and 3 , and associated the variability with biomass differences (phenological differences) or soil moisture differences. The basic analysis technique was graphical analysis of \(\sigma^{0}\) versus look angle and visible/
infrared responses due to different growth stages or different soil moisture regimes. The results gave an indication of the model utility under different phenological and moisture regimes. If the model output variability was too large, the model was adjusted to remove influencing effects. This physically involves reducing the component variances of soil moisture and roughness, leaving vegetation variance as the major component of the total variance. Care was taken not to remove variance created by different biophases of stress conditions.

The results from each problem were merged to give an overall view of classification improvements that are possible with combinations of visible, infrared and microwave data, and similar improvements that can be made in biomass estimation.

\section*{RESULTS}

With the analysis divided into four problems, the results from each problem will be discussed separately. But preceding each problem, a discussion of biomass and final yield conditions is in order.

\section*{Guymon Crop Condition}

A wide range of growing conditions was evident at Guymon. Irrigated sorghum fields ranged in height from 20 cm to 1 m , and in growth stage from just emerging (fields 7 and 8) to anthesis (field \(1 X\) ). Two irrigated alfalfa fields (fields 22 and 27) were cut on August 17, the last measurement day. Alfalfa height ranged from 15 cm to 60 cm . One of the bare fields (field \(2 X\) ) was tilled extensively on the last filight day where furrows were as deep as 30 cm . Two Bare fierds were irrigated during the experiment (fields 6 and 14). Most of the other vegetated fields were also irrigated.

Since no biomass or yield data were collected from Guymon, all biomass data were inferred using present visible/infrared combinations, such as PVI and TVI.

\section*{Dalhart Biomass and Crop Yield}

The 1980 crop year proved to be a below normal year in crop biomass and yield due to extremely high temperatures and shortage of moisture during critical growth stages (Table 3). Corn fields were in the tasseling stage and the millet field was just beginning to enter the heading stage during the experiment period. With maximum air temperatures near \(40^{\circ} \mathrm{C}\), the yields were reduced as much as \(50 \%\) compared to 1979 yields.

TABLE 3. Dalhart biomass and crop yield
\begin{tabular}{|c|c|c|c|c|c|c|}
\hline Field & \[
\begin{aligned}
& \text { Crop } \\
& \text { Type }
\end{aligned}
\] & \[
\begin{aligned}
& \text { Wet } \\
& \text { Biomass } \\
& \left(\mathrm{g} / \mathrm{m}^{3}\right)
\end{aligned}
\] & \[
\begin{gathered}
\text { Dry } \\
\text { Biomass } \\
\left(\mathrm{g} / \mathrm{m}^{3}\right)
\end{gathered}
\] & \[
\begin{gathered}
\text { Yield } \\
\text { (Kg/Ha) } \\
\hline
\end{gathered}
\] & Height (m) & \[
\begin{gathered}
\text { Corn } \\
\text { Popul. } \\
\text { (plants } / \mathrm{m})
\end{gathered}
\] \\
\hline 1/2 (Healthy) & Corn & 6915.1 & 1259.8 & 4287 & 2.1-2.4 & 6 \\
\hline 1/2 (Stressed) & Corn & 2005.7 & 411.1 & 0 & 1.8 & 6 \\
\hline 3/4 & Millet & 797.5 & 120.6 & 1500 & 0.3 & \\
\hline 5/6 & Pasture & 125.3 & 16.2 & - & 0.05 & \\
\hline 7/8 & Corn & 7891.1 & 1340.6 & 5676 & 2.1-2.4 & 10 \\
\hline 9/10 & Corn & 7665.3 & 1280.4 & 5499 & 2.1-2.4 & 7 \\
\hline 11/12 & Corn & 5892.7 & 1148.6 & 9245 & 2.1-2.4 & 7 \\
\hline 17/18(Wheat, & Stubble & 365.2 & 340.5 & - & 0.3 & \\
\hline V1 & Sorghum & 642.0 & 139.8 & - & 0.9-1.2 & \\
\hline V2 & Sorghum & 1268.2 & 305.0 & 3500 & 0.9-1.2 & \\
\hline V3 & Sorghum & 2117.0 & 387.4 & - & 1.2 & \\
\hline V4 & Sorghum & 4804.3 & 844.2 & - & 2.1 & \\
\hline V5 & Alfalfa & 945.3 & 108.7 & - & 0.3-0.6 & \\
\hline V6 & Sorghum & 801.6 & 173.9 & - & 0.6-0.9 & \\
\hline V7 & Alfalfa & 218.2 & 62.8 & - & 0.15 & \\
\hline V8 & Alfalfa & 1202.7 & 128.3 & - & 0.9 & \\
\hline v9 & Alfalfa & 897.7 & 95.0 & - & 0.8 & \\
\hline V10 & Alfalfa & 524.7 & 54.1 & - & 0.6 & \\
\hline V11 & Alfalfa & 946.5 & 113.1 & - & 0.8 & \\
\hline V12 & Alfalfa & 556.0 & 66.7 & - & 0.6 & \\
\hline V13 & Alfalfa & 814.9 & 115.4 & - & 0.8 & \\
\hline
\end{tabular}

The biomass samples were generally related to final crop yields... higher bionass indicated higher yields. The exception was field \(11 / 12\) where corn yield was the highest, but biomass was third highest. The discrepancy is likely in the unrepresentative biomass sample.

\section*{Problew 1}

The easiest method of graphical analysis of crop type differences was through spectral analysis. Returns from each spectral channel for each field were compared and differences attributed to soil moisture, roughness or vegetation. Several examples of spectra are given in Figures 9 through 11. The range of radiance for the visible and infrared region (bands 1-7) is 0 to \(3.0 \mathrm{~mm} \mathrm{~cm}^{-2}\) steradian- \({ }^{-1}\); the temperature range for the thermal (band 8 or 5) and microwave brightness temperature (BT) is \(220^{\circ}\) to \(325^{\circ} \mathrm{K}\). The normalized brightness temperature ( \(E\) ) ranged from 0.70 to 1.0 and the scatterometer response ( \(K\) band to \(P\) band) for like ( \(H\) ) and cross (V) pole data ranges from -60 to 0 db . The soil moisture field averages (SM) ranged from 0 to \(25 \%\) by volume for each sampling depth ( \(0-2 \mathrm{~cm}=A, 2-5 \mathrm{~cm}=\mathrm{B}\) ). The scatterometer \(40^{\circ}\) look angle was arbitrarily selected because of the strong relationship with vegetation as determined through other studies reported in the literature.

Examples of mature corn (field 2) and millet fields (field 3) with similar surface soil moisture conditions (approximately \(9 \%\) by volume) are illustrated in Figure 9. The largest difference was in the \(C, L\), and \(P\) band active microwave data--as large as 6 db in the \(L\) band cross pole data. Band 4 data also showed a difference of 0.3 mw \(\mathrm{cm}^{-2}\) steradian- \({ }^{-1}\). No Ns001 data was collected in the corn in bands

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6 and 7. Under wetter conditions in the corn (Field 8) the difference was enhanced in several frequencies and the maximun difference in return was 15 db in the P band cross pole data. The difference in the L band cros; pole and bands 4 alld 5 (NSOO1) remained the same. Consequently, the major variation in \(\sigma^{\circ}\) at the \(40^{\circ}\) look angle in \(L\) band cross pole data appeared to be caused by vegetation. Responses from like-polarized microwave data were not very sensitive to the crop type differences.

Examples of bare soll, pasture, and wheat stubble having similar surface moisture are shown in Figure 10. Only minor differences occurred in the visible and infrared bands, especially in bands 4 and 6. Band 6 and 7 data were unavailable for field 15. Other bands which had differences were L band like and cross pole and C band cross pole scatterometer data. These differences are likely due to surface roughness differences between the fields. The wheat stubble and pasture fields were smoother than the other tilled bare fields. The smoother fields consequently acted as a spectral reflector giving a lower \(0^{\circ}\) at the \(40^{\circ}\) look angle.

Conparing the response differences between vegetated and nonvegetation fields, several spectral regions were significant (Figure 11). Obvious differences were in bands 4, 5, and 6 of the NSOO1 data. Possible combinations using these bands may prove to be helpful in discriminating vegetation from non-vegetation. In addition, all of the active microwave channels were able to distinguish vegetative differences to some degree of success. The most significant differences occurred in the \(C\) band and \(L\) band \(\sigma^{0}\) values--as much as 12 db in the \(L\) band cross pole data.

An interesting anomaly demonstrating stressed and non-stressed conditions was evident in corn fields 1 and 2. Parts of the field were stressed as a result of a faulty irrigation system which did not apply adequate amounts of water in several areas through the growing season. A black and white aepial photo of the field is shown in figure 12. Approximately \(30-50 \%\) of the field was undergoing moisture stress. The stressed areas essentially had no grain yield; thus the total yield represented yield of the healthy areas. The visible/ infrared spectra showed significant differences between healthy and unhealthy corn in several bands (Figure 13). The differences were especially significant ( \(0.3 \mathrm{mw} \mathrm{cm}{ }^{-2}\) ster-1) in NSOO1 channels 4,5 , and 7 , suggesting possible combinations using these bands may indicate biomass differences or stress conditions.

At Guymon, the crop types were different--alfalfa, sorghum, and bare soil. Examples of bare soil (field 10), mature sorghum (field 1X), and alfalfa (field 4) spectra having similar surface soil motsture conditions are shown in Figure 14. Reflectance in the visible and infrared differed significantly between vegetated and non-vegetated fields (as much as \(6-10 \mathrm{mw} \mathrm{cm}{ }^{-2}\) ster \({ }^{-1}\) ). Differences in the active microwave, especially \(L, C\) and \(P\) band were also indicative of crop types differences. For example, a difference of 9 db in the L and \(P\) band like pole data was commen between sorghum and bare soil or sorghum and alfalfa. Part of the difference may be due to roughness variability in the soil surface. Also some microwave frequencies may be penetrating through the canopy and detecting tillage direction. The sorghum responses in field 1 X figure 14 were from a field with rows perpendicular to the flight line. An example of a response from

\section*{ORIGINAL PAGE BLACK AND WHITE PHOTOGRAPH}


FIG. 12 An infrared aerial photo (scale 1:45,000) of stressed corn fields (fields 1 and 2) at Dalhart. The healthy are dark shaded and the stressed areas are light shaded.

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FIG. 13 Spectra comparing healthy and stressed corn at Dalhart. No microwave comparisons could be made.

a sorghum field with rows parallel to the flight line (field \(2 A\) ) is given in Figure 15. The most significant differences were in the \(C\) band like pole and \(L\) band data-a 5 db difference. The near infrared band indicated field \(2 A\) had less canopy cover. Wetter conditions also affected the return. For example, the spectra from a wet bare soil, field 14 (Figure 16 ) vias similar to gimsita for a dry sorghum field (field 2A), especially in the scatterometer like pole data. Consequently, responses which include roughness and soil moisture differences are masking the crop type differences.

Soil moisture differences were removed from ihe analysis of data from Cl ayton, New Mexicc since the entire area had been saturated with a uniform rainfall on a large area of uniform soils. As a result of the rains, every field had approximately the same high soil moisture content, thus leaving only roughness and vegetation to affect the active inicrowave return. Assuming tillage practices were similar between crop types (corn and sorghum), the roughness effect is also minimized, leaving only vegetation effacts. Analysis of the spectra from four corn (Cl through C4) and two sorghum fields, M1 and M2 (Figures 17 and 18 ) indicated that scatterometer \(L\) and \(P\) band like and cross pole data discriminated between corn and sorghum well. Corn tended to have higher returns in the \(L\) and \(P\) band data as compared to the returns from sorghum fields. Other frequencies had smaller or no response difference between corn and sorghum.

Statistical analysis of the Dalhart and Guymon data sets, using Duncan's Multiple Range Technique confirmed results noted in graphical analysis. The charnels which discriminated the crops at Dalhart best were the \(K, C\) and \(L\) band active microwave data at look angles from \(40^{\circ}\)


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3SNOdS3y O3ZITVINYON

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FIG. 17 Spectra comparing corn and sorghum at Clayton. No passive microwave or visible/infrared data was avallable. [H = like pole \(40^{\circ}\) look angle (SCATTS), \(V=\) cross pole \(40^{\circ}\) look angle (SCATTS)]


FIG. 18 Spectra comparing corn and sorghum at Clayton. No passive microwave or visible/infrared data was available. [H = like pole \(40^{\circ}\) look angle (SCATTS), \(V=\) cross pole \(40^{\circ}\) look angle (SCATTS)]
and \(45^{\circ}\) off nadir (Table 4). The visible and infrared bands were able to discriminate between vegetated and non-vegetated fields very well, but not differences within the vegetated fields. At Guymon, the same active microwave frequencies did the best job of discriminating crops (Table 5). Fields and crops with higher biomass had the higher response, while fields with little or no biomass had the lower response. However, roughness also played an important role as indicated by differences between sorghum fields having perpendicular and parallel rows. The roughness effect was reduced in the cross-polarized data, thus suggesting the \(L\) band cross pole and \(C\) band cross pole active microwave data as possibly the best microwave frequencies and polarizations to use.

Another means of demonstrating the effect of vegetation in the active microwave region was analyzing line plots of the data ( \(\sigma^{\circ}\) as a function of time). An example of three fields having roughly the same surface soil moisture is given in Figures 19 and 20. Data from a near \(\left(10^{\circ}\right)\) and far \(\left(40^{\circ}\right)\) look angle were plotted. The area covered fields V6, 1 and 19, on \(8 / 16 / 80\) at Dalhart, Texas. The crop types represented included sorghum (field V6), corn, (field 1) and bare soil (field 19). Crop type differences were enhanced at the far look angles, especially in the \(C, L\) and \(P\) band data. The responses from the near look angles tended tó be fairly stable along the flight line, especially at the lower frequencies.

Summarizing, in addition to several visible/infrared channels, active microwave frequencies ( \(C, L\) and \(P\) band) are sensitive to crop type differences between selected crop pairs. For instarice, \(L\) band and \(P\) band discriminated between sorghum and corn, while \(C\) band did

TABLE 4. Results of Duncan's Multiple Range Test for Dalhart active ilicrowave data
\begin{tabular}{|c|c|c|c|}
\hline \multicolumn{2}{|l|}{\(40^{\circ}\) look angle} & \multicolumn{2}{|l|}{\(45^{\circ}\) look angle} \\
\hline Crop K band like pole & Mean & Crop K band like pole & Mean \\
\hline Corn & -7.1 \({ }^{*}\) & Corn & -7.1 a \\
\hline Millet & -9.1 b & Millet & -8.8 b \\
\hline Weeds and Bare Soil & -10.9 c & Weeds and Bare Soil & -10.6 c \\
\hline Bare Soil & -11.3 c & Bare Soil & -10.9 c \\
\hline Pasture & -14.0 d & Pasture & -13.6 d \\
\hline Wheat Stubble & -14.6 d & Wheat Stubble & -14.3 d \\
\hline
\end{tabular}
\begin{tabular}{ll}
\multicolumn{2}{c}{ L. band like pole } \\
\hline Corn & -22.4 a \\
Weeds and Bare Soil & -29.8 a \\
Millet & -30.6 b \\
Bare Soil & -30.7 b \\
Pasture & -34.7 c \\
Wheat Stubble & -36.2 c
\end{tabular}
\(L\) band cross pole
\begin{tabular}{ll}
\hline Corn & -28.9 a \\
Millet & -37.1 b \\
Bare Soil & -39.5 c \\
Weeds and Bare Soil & -39.7 c \\
Wheat Stubble & -44.2 d \\
Pasture & -44.2 d
\end{tabular}

C band like pole
\begin{tabular}{lr}
\hline Corn & -2.6 a \\
Millet & -4.7 a \\
Weeds and Bare Soil & -7.5 b \\
Bare Soil & -8.0 c \\
Pasture & -11.6 c \\
Wheat Stubble & -12.9 \\
&
\end{tabular}
\begin{tabular}{ll}
\multicolumn{2}{c}{ L band like pole } \\
\hline & -23.1 \\
Corn & -30.9 \\
Weeds and Bare Soil & -31.9 b \\
Millet & -32.9 b \\
Bare Soil & -36.8 c \\
Pasture & -37.3 c
\end{tabular}
\begin{tabular}{ll}
\multicolumn{3}{c}{ L band cross pole } \\
\hline Corn & -28.6 a \\
Millet & -37.2 b \\
Weeds and Bare Soil & -39.3 bc \\
Bare Soil & -41.2 c \\
Pasture & -44.6 d \\
Wheat Stubble & -48.8 d
\end{tabular}
\begin{tabular}{ll}
\multicolumn{3}{c}{ C band like pole } \\
\hline Corn & -4.1 a \\
Millet & -5.8 a \(b\) \\
Weeds and Bare Soil & -8.7 a b c \\
Bare Soil & -10.1 b c \\
Pasture & -13.2 c d \\
Wheat Stubble & -15.4 d
\end{tabular}

TABLE 4. (Continued)
\begin{tabular}{|c|c|c|c|}
\hline \multicolumn{2}{|l|}{\(40^{\circ}\) Look Angle} & \multicolumn{2}{|l|}{45* Look Angle} \\
\hline \multicolumn{2}{|l|}{\(C\) band cross pole} & \multicolumn{2}{|l|}{C band cross pole} \\
\hline Corn & -5.6 a & Corn & -6.0 a \\
\hline Millet & -11.4 b & Millet & -11.5 b \\
\hline Weeds and Bare Soil & -14.4 b c & Weeds and Bare Soil & -14.0 b \\
\hline Wheat Stubble & -17.6 b c & Bare Soil & -17.4 b \\
\hline Bare Soll & -17.8 c & Wheat Stubble & -18.1 b \\
\hline Pasture & -19.5 c & Pasture & -19.2 b \\
\hline \(P\) band like pole & Mean & \(P\) band like pole & Mean \\
\hline Corn & -28.7 a & Corn & -28.9 a \\
\hline Weeds and Bare Soil & -35.1 b & Weeds and Bare Soil & -36.3 b \\
\hline Wheat Stubble & -35.3 b & Wheat Stubble & -37.3 b \\
\hline Millet & -36.2 b & Millet & -37.6 b \\
\hline Bare Soil & -37.3 b & Bare Soil & -38.0 b \\
\hline Pasture & -37.5 b & Pasture & -38.5 b \\
\hline \multicolumn{2}{|l|}{\(P\) band cross pole} & \multicolumn{2}{|l|}{\(P\) band cross pole} \\
\hline & & Corn & \\
\hline Weeds and Bare Soil & \[
-47.6
\] & Weeds and Bare Soil & -52.9 b \\
\hline Wheat Stubble & -52.7 & Bare Soil & -54.2 b \\
\hline Bare Soil & -52.8 & Millet & -54.2 b \\
\hline Millet & -52.9 & Wheat Stubble & -54.8b \\
\hline Pasture & -54.9 c & Pasture & -55.1 b \\
\hline
\end{tabular}

\footnotetext{
*The treatinent means followed by the same letter in each column are not significantly different at the 5\% probability level of Duncan's Multiple Range Test.
}

TABLE 5. Results of Duncan's Multiple Range Test for Guymon active microwave data
\begin{tabular}{lr} 
Crop \(\quad 40^{\circ}\) Look Angle & Mean \\
\multicolumn{3}{c}{ K band like pole } & \\
Sorghum(perp, rows) & -7.1 a \\
Sorghum(paral. rows) & -9.5 b \\
Bare Soil & -12.1 c \\
Alfalfa & -12.1 c
\end{tabular}
\(\underline{L}\) band like pole
\begin{tabular}{lr} 
Sorghum(perp. rows) & -9.3 a \\
Sorghum(paral. rows) & -18.1 b \\
Bare Soil & -18.2 b \\
Alfalfa & -20.5 b
\end{tabular}
\begin{tabular}{ll}
\multicolumn{3}{c}{ L band cross pole } & \\
Sorghum(perp. rows) & -19.1 a \\
Sorghum(paral. rows) & -21.5 a \\
Bare Soil & -27.1 b \\
Alfalfa & -27.7 b
\end{tabular}

C band like pole
Sorghum(perp. rows) Sorghum(paral. rows) Alfalfa Bare Soil

C band cross pole
Sorghum (perp, rows) Sorghum(paral. rows) Alfalfa Bare Soil
\(P\) band like pole
Sorghum (perp. rows) Bare Soil Sorghum (paral. rows) Alfalfa
-8.2 a \(-12.5 \mathrm{~b}\) \(-14.2 b\) \(-15.2 \mathrm{~b}\)
-17.2 a -19.6 a b -22.6 b -26.9 c
\[
\begin{aligned}
& -27.8 \mathrm{a} \\
& -31.4 \mathrm{~b} \\
& -31.5 \mathrm{~b} \\
& -35.6 \mathrm{c}
\end{aligned}
\]
Crop \(45^{\circ}\) Look Angle Mean
\(K\) band like pole
Sorghum (perp, rows) -7.7 a Sorghum (paral. rows) -9.7 b Bare Soil -12.3 c Alfalfa -12.5 c

\section*{\(L\) band like pole}

Sorghum (perp, rows) -11.9 a Sorghum (paral. rows) -19.2 b Bare Soil -21.1 b Alfalfa \(\quad-21.9\) b

\section*{\(L\) band cross pole}

Sorghum (perp. rows) -20.2 a Sorghum (paral. rows) -22.4 a Alfalfa \(\quad-27.9 \mathrm{~b}\) Bare Soil
\(-28.5 \mathrm{~b}\)

C band like pole
Sorghum (perp. rows) -10.3 a
Sorghum (paral. rows) -13.7 b Alfalfa -15.4 b Bare Soil \(-16.3 b\)

\section*{\(C\) band cross pole}

Sorghum (perp. rows) -19.5 a Sorghum (paral. rows) -22.0 a b Alfalfa \(-23.7 b\) Bare Soil
-28.7 c

P band like pole Sorghum (perp. rows) -23.7 a Bare Soil -30.3 b Sorghum (paral. rows) -32.0 b c Alfalfa -35.1 c

TABLE 5. (Continued)
\begin{tabular}{|c|c|c|c|}
\hline P band cross pole & & \multicolumn{2}{|l|}{P band cross pole} \\
\hline Sorghum (perp. rows) & -37.2 a & Sorghum (perp. rows) & -34.3 a \\
\hline Sorghum (paral. rows) & -38.5 a & Sorghum (paral. rows) & -37.4 a \\
\hline Alfalfa & -46.5 b & Bare Soil & -45.6 b \\
\hline Bare Soil & -47.4 b & Alfalfa & -46.9 b \\
\hline *The treatinent means f significantly different Multiple Range Test. & llowed by at the & letter in each co bility level of Dunc & \[
\begin{aligned}
& \text { mn are } \\
& \text { s }
\end{aligned}
\] \\
\hline
\end{tabular}



FIG. 20 Line plots ( \(\sigma^{0}\) vs time) for all cross polarized scatterometer data at \(10^{\circ}\) and \(40^{\circ}\) off nadir.
not. \(C\) band discriminated between bare soll and alfalfa while \(K, L\) and P bands did not discriminate batween this pair. All bands discriminated between corn and bare soll. Soll moisture and roughness had an effect on the active microwave responses, but the vegetation effect generally predominated at the far look angles (greater than \(35^{\circ}\) ).

\section*{Problem 2}

To develop the proper combination for analyzing crop type differ. ences in a tree-classification model, a hierarchical (unsunervised) clustering routine was used. The routine was based on a cluster criterion of a minimum Euclidean distance from the mean of the cluster. By gotng through the same classifying criteria used within the routine, individual channels or combinations which separated individual clusters were detected. By following this technique through several iterations, a dendrogram (tree-classification system) using visible, infrared, and microwave data was developed. Data from crop discriminating scatterometer frequencies and polarizations at \(40^{\circ}\) look angles were included with the visible/infrared data (omitting thermal) at Guymon and Dalhart. In addition, a dendrogram was deve1oped from the Dalhart spectral data set using the scatterometer \(40^{\circ}\) look angle and only bands 2, 3, and 4 from the NSOOL data. This analysis was done to allow unbiased comparisons of classification accuracy between the Dalhart and Guymon data sets. Active microwave data from the \(40^{\circ}\) look angle was used because the data from this look angle was most sensitive to crop type differences (results from the previous problem).

Results from the Dalhart dendrogram using the active microwave bands and NSOO1 bands 2, 3 and 4 indicated that \(C\) and \(L\) band cross pole data can classify reasonably well without visible and near infrared information (Figure 21). The largest error was separating wheat stuate and pasture from bare soll. Allowing these three groups to be ©!assified the same, the overall accuracy was 78\%. The first separation criterion used differences in the \(L\) band cross pole \(40^{\circ}\) look angle data to separate corn and sorghum, (class 1) from weeds, pasture, bare soil, and wheat stubble. The second criterion again used differences in the suln of \(L\) band and \(C\) band cross pole \(40^{\circ}\) look angle data to separate millet, corn and sorghum (class 2) from millet, pasture, wheat stubble and weeds. The thipd criterion used the same sum to separate pasture, wheat stuttele and bare soll (class 3) from other weeds, pasture and bare soil. Then the last criterion used was \(\overline{\mathrm{C}}\) band cross pole data to separate pasture, wheat stubble and bare soil (class 5) from weeds and bare soil (class 4). The difference between the bare fields in class 4 and 5 was the class 4 bare fields included some weeds while class 5 bare fields did not. Consequently, responses in class 4 appear to be sensitive to low bionass levels.

Using all of the NSOO1 with active microwave data, the accuracy improved to \(80 \%\) as more information was gathered in NSOO1 bands 3, 4, 5 and 6. The dendrogram was different in that most of the criterion used \(L\) and \(C\) band cross pole data (Figure 22).

In spite of the different crop types and visible/infrared bands, a similar dendrogram to the one using all NSOO1 data was developed at Guymon (Figure 23). The first criterion level used the same type of data as Dalhart--L band cross pole. These steps sepayaied corn and


FIG. 21 Dendrogram (tree-classifcation) model using \(\mathfrak{A}\) S001 bands 2, 3, and 4, and C. L and P band cross pole Dalhart data (accuracy \(78 \%\) ).


FIG. 22 Dendrogram (tree-classification) model using all NS001 bands C, L and P band cross pole Dalhart data (accuracy 80\%).

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FIG. 23 Dendrogram (tree-classification) model using \(M^{2} S\) bands 4 , 7, 8 and 9, C and L band cross pole Guymon data (accuracy 70\%).
sorghum from other crops. The next criterion used differences in the sum of \(C\) and \(L\) band cross pole data. The last two steps used \(M^{2} S\) band 9 data to separate vegetation from bare soll. The overall accuracy of the model was 70\%. One bare field, 10, was frequently classified with fields having vegetation. The reason for the misclassification was due to the presence of weeds within the field late in the experiment. The similarity between the two models is striking. Fields with high biomass were separated from other fields using microwave data and vegetation was separated from bare soil using visible and infrared data. The similarity will be discussed further in the next section.

A problem arose when data sets from both Guymon and Dalhart were combined. Due to the fact the visible and infrared regions did not match and no calibration of the scatterometer data was available, no dendrogram for the combined data set was developed.

\section*{Problem 3}

This problem deals with both crop classification and biomass estimations. One technique used to detemine the utility of microwave data in classification was to make a comparison between unsupervised classification result acsuracies using visible, infrared and microwave data and accuracies using only visible and infrared data. As mentioned in the previous subsection, cluster analysis using microwave, visible, and infrared data had classification accuracies equal to or greater than 70\%. Using only visible/infrared data, the classification accuracies decreased to 65\% at Guymon and 78\% at Dalhart. The tree-classification system using visible and infrared data at Dalhart and Guymon are given in Figures 24 and 25, respectively. The major


FIG. 24 Dendrogram (tree-classification) model using all NSOOI data at Dalhart. (78\% accuracy)


FIG. 25 Dendrogram (tree-Glassification) model using \(M^{2} S\) band 4, 7, 8 and 9 data at Guymon (65\% accuracy).
misclassification using visible and infrared data were high biomass fields being classified as one group. For instance, at Guymon twenty-one observations of alfalfa and twenty-two observations of sorghum fields at different biophases were classified into one group. Consequently, result comparisons from the unsupervised technique proved that inclusion of microwave data enhanced classification accuracy.

Supervised classification (discriminant analysis) results also indicated microwave data improved classification accuracy. The contingency table results from classifying fields on August 16 using only NSOO1 data from August 14 and 18 as the training classifier is given in Table 6a. The overall accuracy was 73\%. By including \(K\) band like pole and \(L\) band cross pole data the accuracy increased to \(92 \%\) (Table 6b). To make unbiased comparisons with the Guymon spectral data sets, NSOO1 bands 2, 3 and 4 were analyzed. Following the same techniques, the August 16 classifier accuracy was \(81 \%\) (Table 7a). By including K and \(L\) hand cross pole active microwave data, the accuracy improved only slightly to 84\% (Table 7b). No known reason explained the discrepancy between results using all or parts of the NSOO1 data.

At Guymon, spectral data from August 2 and 17 were used as inputs into the training classifier, and the classifier was tested on August \(5,8,11\) and 14 spectral data. Using only \(M^{2} S\) visible and infrared data, the classification accuracy was 88\% (Table 8a). By including \(K\) band like pole and \(L\) band cross pole data the accuracy remained the same 88\% (Table 8b). Consequently, supervised classification rosults using the Dalhart and Guymon spectral data sets indicated inclusion of microwave data with visible/infrared data maintained or improved

TABLE 6. Dalhart discriminant analysis results using (a) all NS001 channels and (b) all NSOOI channels plus \(K\) band like pole and \(L\) band cross pole ( \(40^{\circ}\) look angle) data from August 14 and 18 as a training classifier. The results are from August 16 testing of the model.
(a)
\begin{tabular}{l|c|c|c|c|c|c|c|} 
& \multicolumn{7}{|c|}{ Number of Observations Classified into Crop Types: } \\
\hline From Crop Types: & Corn & \begin{tabular}{c} 
Bare \\
Soil
\end{tabular} & \begin{tabular}{c} 
Wheat \\
Stubble
\end{tabular} & \begin{tabular}{c} 
Weeds and \\
Bare Soil
\end{tabular} & Pasture & Millet & Weeds \\
\hline 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 & 0 & 3 & 0 & 0 & 0 & 0 & 0 \\
Soil & 0 & 4 & 0 & 0 & 0 & 0 & 0 \\
Pasture & 0 & 0 & 0 & 0 & 0 & 4 & 0 \\
Millet & 0 & 0 & 0 & 2 & 2 & 0
\end{tabular}
*Accuracy of 73\%
(b)
\begin{tabular}{l|r|c|c|c|c|c|c|} 
& \multicolumn{6}{|c|}{ Number of Observations Classified into Crop Types: } \\
\hline Froin Crop Types: & Corn & \begin{tabular}{c} 
Bare \\
Soil
\end{tabular} & \begin{tabular}{c} 
Weeds and \\
Bare Soil
\end{tabular} & Pasture & Millet & \begin{tabular}{c} 
Wheat \\
Stubble
\end{tabular} & Weeds \\
\hline Corn Sil & 16 & 0 & 0 & 0 & 0 & 0 & 0 \\
Bare Soil & 0 & 11 & 0 & 0 & 0 & 0 & 0 \\
Weeds and Bare & 0 & 4 & 0 & 0 & 0 & 0 & 0 \\
Soil & 0 & 0 & 0 & 4 & 0 & 0 & 0 \\
Pasture & 0 & 0 & 0 & 0 & 4 & 0 & 0 \\
Millet & 0 & 0 & 0 & 0 & 4 & 0 \\
Wheat Stubble & 0 & 0 & 0 & 0 & 1 & 0 & 0
\end{tabular}
*Accuracy of 92\%

TABLE 7. Dalhart discriminant analysis using (a) NSOO1 channels 2, 3, and 4 and (b) NSOO1 channels 2, 3 and 4 and \(K\) band like pole and \(L\) band cross pole data. Contingency table results from the model tested on August \(1^{f}\) spectral data.
(a)

Number of Observations Classified into Crop Types:
\begin{tabular}{l|c|c|c|c|c|c|c|}
\hline From Crop Types: & Corn & \begin{tabular}{c} 
Bare \\
Soil
\end{tabular} & \begin{tabular}{c} 
Weeds and \\
Bare Skil
\end{tabular} & Pasture & Millet & Weeds & \begin{tabular}{c} 
Wheat \\
Stubble
\end{tabular} \\
\hline 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 Stubble & 0 & 0 & 0 & 0 & 0 & 4 & 0 \\
Wheat Stubble & 0 & 4 & 0 & 0 & 0 & 0 & 0
\end{tabular}
*Accuracy of \(81 \%\)
(a)

Number of Observations Classified into Crop Types:
\begin{tabular}{l|c|c|c|c|c|c|c|}
\hline From Crop Types: & Corn & \begin{tabular}{c} 
Bare \\
Soil
\end{tabular} & \begin{tabular}{c} 
Weeds and \\
Bare Soil
\end{tabular} & Pasture & Millet & Weeds & \begin{tabular}{c} 
Wheat \\
Stubble
\end{tabular} \\
\hline Corn & 15 & 0 & 0 & 0 & 1 & 0 & 0 \\
Bare Soil & 0 & 12 & 0 & 0 & 0 & 0 & 0 \\
Weeds and Bare & 0 & 3 & & & & & \\
Soil & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
Pasture & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
Millet & 0 & 0 & 1 & 0 & 4 & 0 & 0 \\
Weeds & 0 & 4 & 0 & 2 & 0 & 0 & 0 \\
Wheat Stubble & 0 & 0 & 0 & 0 & 0 & 0 \\
Sorghum & 3 & 1 & 0 & 0
\end{tabular}
*Accuracy of \(84 \%\)

TABLE 8. Discriminant Analysis of Guymon visible/infi, mad data using August 2 and 17 data as the training classifier. Results from classification of August 5, 8, 11, and 14 data.
(a)
\begin{tabular}{l|c|c|c|c} 
& \multicolumn{3}{|c}{ Number of Observations Classifted into Crop Types: } \\
\hline From Crop Types: & Alfalfa & Bare & Paral. Sorghum & Perp. Sorghum \\
\hline Alfalfa & 12 & 0 & 3 & 1 \\
\begin{tabular}{l} 
Bare \\
Parallel Row \\
Sorghum
\end{tabular} & 0 & 32 & 4 & 1 \\
\begin{tabular}{l} 
Perpendicular \\
Sorghum
\end{tabular} & 1 & 1 & 18 & 1 \\
\end{tabular}
*Accuracy is 88\% (assuming parallel sorghum and perpendicular sorghum are one group)
(b)

*Accuracy is 88\% (assuming parállel sorghum and perpendicular sorghum are one group)
classification accuracy compared to using only visible and near infrared data.

Using stepwide regression techniques to determine the utility of intcrowave data, an increare in the coefficient of determination using ilicrowave data is apparent (Tables 9 and 10). At Guymion and Dalhart, the \(C\) band active microwave data were especially sensitive to crop types differences.

Biomass estimation was the second portion of the problem and the results from the previous section have already indicated that combinations of red and near-infrared data may help in estimating biomass. Two such combinations described previously are the perpendicular vegetation index (PVI) and the transformed vegetation index (TVI).

In spite of the difference in the sensor wavelength regions, the soil regression lines for both Guymon and Dalhart data sets were quite similar. Consequently, it was felt PVI and TVI were reasonably comparable at Guymon and Dalhart. The equations used to calculate PVI at Guyllon and Dalhart were
\[
\begin{align*}
& \text { PVI }=\sqrt{(R G 5-Z 15)^{2}+(R G 7-Z 25)^{2}}  \tag{16}\\
& \text { RG5 }=(0.176 * 215)+(0.381 * 225)  \tag{17}\\
& \text { RG7 }=(0.381 * 715)+(0.825 * 7.25) \tag{18}
\end{align*}
\]
where 215 is the sfene radiance from band 9 at Guymon or band 3 at Dalhart, and Z25 is the scene radiance from band 8 at Guymon or band 5 at Dalhart. Both combinations were strongly related to total biomass at Dalhart (Figure 26) with PVI showing slightly greater sensitivity at higher bionass levels. Due to the higher sensitivity and strong relationship to biomass, PVI was used as the basic combination which

TABLE 9. Dalhart stepwise classification regression equat*ons using (a) all NSOO1 band (Cli) data and (b) all NSOO1 data plus scatteroneter data ( \(40^{\circ}\) look angle) [Crop Type: \(10=\) corn, 8 * sorghuin, 6 weeds, 4 mare soil and weeds, 3 . pasture, 2 wheat stubble, 1 = bare soll].
\(R^{2}\)(a) Crop Type \(=-(\operatorname{cn} 3 * 1.99)+(\operatorname{ch} 4 * 0.71)+3.03\)0.94
Crop Type \(=(\operatorname{Cn} 2 \star 1.78)-(\mathrm{Ch} 3 * 3.60)+(\operatorname{Ch} 4 * 0.60)+3.26\) ..... 0.95
Crop Type \(\left(\operatorname{Ch}^{\star \star} 1.90\right)-(\operatorname{Ch} 3 \star 3.66)+(\operatorname{Ch} 4 \star 0.63)-(\operatorname{Ch} 5 * 0.07)\) \(+3.26\) ..... 0.95
Crop Type \(=(\operatorname{Ch} 2 \star 1.87)-(\operatorname{Ch} 3 * 3.69)+(\operatorname{Ch} 4 * 0.60)-(\operatorname{Ch} 6 * 0.05)\) \(+(\mathrm{Ch} 7 * 0.11)+3.31\) ..... 1). 95
\(\begin{aligned} \text { Crop Type } \approx & -(\operatorname{Ch} 1 \star 0.04)+(\operatorname{Ch} 2 \star 1.87)-(\operatorname{Ch} 3 \star 3.67)+(\operatorname{Cn} 4 \star(0.60) \\ & -(\operatorname{Ch} 6 \star 0.05)+(\operatorname{Ch} 7 \star 0.12)+3.35\end{aligned}\) ..... 0.95
(b) Crop Type \(=(\operatorname{Cn} 7 * 1.08)+(\operatorname{Cn} 5 * 1.44)+3.38\) ..... 0.96
\(-(\) Ch3*2.07 \()+(\operatorname{Ch} 4 *(0.65)+3.85\) ..... 0.95
\(-(\operatorname{Ch} 3 * 1.25)+(\operatorname{ch} 5 * 1.39)-(\operatorname{Cn} 7 * 0.60)+3.06\) ..... 0.97
Crop Type \(\equiv(\operatorname{Cn} 2 \star 2.03)-(\operatorname{Ch} 3 * 3.90)+(\operatorname{Ch} 4 * 0.54)+3.83\) ..... 0.96
\(\left(\operatorname{Ch} 2^{\star} 1.84\right)-(\operatorname{Ch} 3 * 2.33)+(\operatorname{Ch} 5 \star 1.19)-(\operatorname{Ch} 7 * 0.77)+3.330 .97\)
Crop Type \(=-(\mathrm{Ch} 3 * 2.35)+(\operatorname{Ch} 4 * 0.63)-(\mathrm{L}\) band cross pole * 0.13 ) \(+(C\) band like pole*0.13) +0.88 ..... 0.96
\(-(\) '゙h3*0.73) \(-(\operatorname{Ch} 4 * 0.56)+(\operatorname{Ch} 5 * 2.33)-(\operatorname{Ch} 7 * 0.96) \quad 0.98\)
Crop Type \(=(\operatorname{Ch} 2 * 2.38)-(\operatorname{Ch} 3 * 4.34)+(\operatorname{Ch} 4 * 0.55)+(L\) band like pole* 0.15 ) - (L band cross pole*(0.15)+2.39 ..... 0.96
\(+(C\) band like pole*(0.13)+4.22
Crop Type \(=(\mathrm{Ch} 2 * 1.73)-(\operatorname{Ch} 3 * 3.83)+(\operatorname{Cn} 4 * 0.55)+(\mathrm{L}\) band like pole* 0.14 ) \(-(L\) band cross pole*0.19)+(C band ..... 0.98 like pole*0.07) ..... 0.96
(Ch1*4.20)-(ch3*0.91)-(Ch4*1.13)+(Ch5*3.82.)
-(Ch6*0.58)-(Ch7*0.92)+2.71

TABLE 10. Guymon stepwise classification regression equations using (a) only visible/infrared data and (b) scatterometer ( \(40^{\circ}\) lonk angle) and visible/infrared data LCrop Type: 8msorghum, gaalfalfa, \(0=\) bare solld.
(a) Crop Type \(\left.\begin{array}{rl} & \left(M^{2} S C h ~\right.\end{array}{ }^{\star} 17.350\right)-\left(M^{2} S C h \quad 7 \star 14.76\right)-\)
\(R^{2}\) 0.59
(b) Crop Type \(=\left(P\right.\) band cross pole \({ }^{\star}(0.26)+(C\) band cross pole*(0.49) +26.147
\(\begin{array}{rlr}\text { Crop Type }= & \left(\mathrm{P} \text { band cross pol } e^{\star 0} 0.27\right)-(C \text { band like } & \\ & \mu 01 e^{\star(0.57)}+\left(C \text { band cross pole }{ }^{\star 0} 0.88\right)+28.07 & 0.73\end{array}\)
Crop Type \(:(L\) band cross pole*0.25)+(L band cross pole
\(* 0.23)-(C\) band 1 ine pole*0.76)+( \(C\) band cross pole*0.80) +28.22

Crop Type \(=\left(M^{2} S 1 C h 5 * 0.27\right)+(K\) band like pole*0.32) \(+(L\) band cross pole*0.32) \(+(P\) band cross pole*0.17)-(C band like pole*(0.11)+(C band cross pole*(0.60)+24.2 0.76



other combinations were compared. However, the "saturated" zone of PVI and TVI, where sensitivity decreased for moderate biomass changes, was at biomass levels above \(1000 \mathrm{~g} / \mathrm{mi}^{2}\).

The relationship between PVI, TVI and crop yield is less significant than the relationship to biomass due a dependence on crop type (Figure 21). This dependency is expected because the economic or grain yteld collurises a different proportion of the biological or vegetative yield for each crop type.

With the additional narrow wavelength bands for the NSOO1, a study of the intercorrelations between bands was needed to evaluate other potential visible/infrared combinations. Figures 28 through 36 display intercorrelations of each NSOO1 band to bands 1,2 and 3. The relationship between band 4 and 6 (1.00-1.30 \(\mu^{919}\) and 1.55-1.75 \(\mu \mathrm{ml}\) ) (Figure 33) was simflar to the visible/near infrared relationship, which PMI is based. All of the bare soil and low biomass fields fell along the lower right line; corn and dense sorghum fields fell along the left side of the line. The reiationship suggested another possible PVI relationship using a near-infrared band and a water absorption band. The equations used to calculate the new PVI were
\[
\begin{align*}
\text { PVI64 } & =\sqrt{(\text { RG4 }-Z 20)^{2}+(R G 6-235)^{2}}  \tag{19}\\
\text { RG4 } & =-1.919+0.365(Z 35)+0.158(Z 20)  \tag{20}\\
\text { RG6 } & =0.831+0.842(Z 35)+0.365(Z 20) \tag{21}
\end{align*}
\]
whare 220 is the scene radiance in NSOO1 band 4 and 235 is the scene radiance in NSOO1 band 6. A plot of the new PVI versus total biomass is shown in Figure 37. A definite similarity exists between the conventional PVI and PVI64. A plot of the two combinations revealed

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FIG. 27 The relationship between final crop yield ( \(\mathrm{Kg} / \mathrm{Ha}\) ), and TVI and PVI at Dalhart.
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FIG. 29 Field radiance reflectance values of NSOO1 bands 4 and 5 versus band 3 at Dalhart

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TM4 (760-900NM) VS TM2 (520-600NM)


FIG. 31 Field radiance reflectance values of N5001 bands 1 and 2 versus band 4 at Dalhart

TM4 (760-900NM) VS TM1 (450-520NM)


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TM4 (760-900NM) VS TM7 (2300-2500NM)



LEGEND: CROP
TM5 ( \(1000-1300 \mathrm{NM}\) ) VS TM2 (520-600NM)
TM5 ( \(1000-1300 \mathrm{NM})\) VS TM1 ( \(450-520 \mathrm{NM}\) )

FIG. 31 Field radiance reflectance

TM5 (1000-1300NM) VS TM4 (760-900NM)


FIG. 35 Field radiance reflectance values of NSOO1 bands 3 and 4 versus band 3 at Dalhart in \(10^{-4}\) watts \(\mathrm{cm}^{-2}\) ster \({ }^{-1}\).




LEGEND: CROP


the new PVI (PVI64) gave more information on corn fields compared to PVI and TVI--corn gave a higher PVI64 compared to PVI and TVI (Figure 38). Not enough ground data were collected to explain this PVI difference.

Figures 39 through 41 demonstrate the variability of PVI 64 within corn, alfalfa and sorghun fields at Dalhart. The most striking example was the detection of moisture stressed areas in corn fields 1 and 2. The severely stressed ring-shaped areas within the field are demonstrated by the red color which corresponded to PVI64 values of 4 or less. Dark green areas represent healthy areas within the field with PVI64 values of 6 or greater. Biomass differences are also evident in several alfalfa and sorghum fields.

Summarizing, spectral data from Dalhart suggesed the additional proposed thematic mapper wavelength regions provided slightly more information on crop characteristics than present techniques using visible/infrared data.

As mentioned, a hormalization technique applied to the active microwave data was needed to help remove roughness and soil moisture effects in the Guymon and Dalhart data sets. Based on the \(\sigma^{\circ}\) response with look angle, as biomass increases, the vegetative response at high look angles should also iricrease compared to the \(\sigma^{\circ}\) response from the lower look angles. This was especially noted in the line plots (Figures 19 and 20). Figure 42 demonstrates this effect for \(L\) band cross pole data from corn (high biomass) and bare soil (low biomass). Biomass differences were strongly evident at the larger look angles, especially greater than \(15^{\circ}\) off nadir. Figure 43 represents changes in the \(L\) band cross pole \(\sigma^{\circ}\) due to soil moisture differences wititin a


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FIG. 39 A photo indicating difference PVI64 levels within a stressed corn field (1 and 2) at Dalhart.

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FIG. 40 A photo indicating difference PVI64 levels within a sorghum field (V2) at Dalhart.

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FIG, 41 A photo indicating different PVI64 levels wichin alfalfa fields (V11, V12, V13) at Dalhart.
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FIG. 42 The relationship between \(L\) band cross pole \(\sigma^{0}\) and look angle for a corn field (field 9 ) and bare field (field 15).

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FIG. 43 The relationship of \(L\) band cross pole \(\sigma^{0}\) and look angle for a millet field (field 3 ) under different soil moisture con-
millet field at Lalhart. Any significant soil moisture increase caused a similar response as the biomass increased. However, by calculating the difference between the response from a large and small look angle, the soil molsture effect was diminished while maintaining a high degree of sensitivity to biomass differences. For example, the difference between the \(40^{\circ}\) and \(10^{\circ}\) look angles was roughly the same under different surface ( \(0-2 \mathrm{cmI}\) ) moisture conditions, 12.5 dB . The last effect, surface roughness was minimized by analyzing cross rather than like polarized data.

Figure 44 demonstrates active microwave returns from the same sorghum field at two different look directions--rows paralle? and perpendicular to the flight line. A general shift higher was evident for the \(\sigma^{0}\) return from rows parallel to the look direction. The difference between the near and far look angles also remained relatively constant under different surface roughnesses. Consequentily, most of the information in the return differences between a near and far look angle in cross-polarized data was related to crop biomass. Since \(\sigma^{\circ}\) is expressed in terms of logarithins, a difference between \(\sigma^{\circ}\) is the same as an arithmetic ratio (a nomalization technique). Also, it was anticipated that comparisons of differences in several frequencies and polarizations indicated biomass differences. Comparison of several differences (i.e. \(40^{\circ} \mathrm{L}\) band cross pole \(\sigma^{\circ}-10^{\circ} \mathrm{L}\) band cross pole \(\sigma^{0}\); \(40^{\circ} \mathrm{C}\) band cross pole \(\sigma^{\circ}-5^{\circ} \mathrm{C}\) band cross pole \(\sigma^{\circ}\) ) indicated the \(C\) band cross pole \(40^{\circ}\) and \(C\) band cross pole \(5^{\prime}\) difference was most independent of roughness and soil moisture and most sensitive to biomass differences.


FIG. 44 The \(L\) band cross pole \(\sigma^{0}\) response as a function of look angle for the same sorghum field (field \(1 X\) ) from two different directions, the flight line parallel and perpendicular to the tillage direction.

Other differences, such as the 1. band cross pole difference between the \(40^{\circ}\) and \(10^{\circ}\) look angle, were sensitive to surface roughness by penetrating through several alfalfa and sorghum canopies. For example, alfalfa gave the similar index values as bare soll. Consequently, the \(C\) band relationship was analyzed and is defined as the scatterometer vegetation index (SVI).

The relationship between SVI and total biomass was similar to the PVI/total biomass relationship (Figure 45). The quadratic relationship between SVI and total biomass ( \(R^{2}=0.88\) ) was better than the relationship between PVI and total biomass \(\left(R^{2}=0.74\right)\), or TVI and total biomass \(\left(R^{2}=0.69\right)\). The relationship between PVI, TVI, and SVI was generally linear with bare fields having low SVI and vegetated fields with higher index values (Figures 46 and 47). Alfalfa fields tended to have lower index values compared to the other vegetated fields. The lower value indicated the scatterometer signal was either penetrating through the vegetation and responding to the soll surface, or the signal was responding to the canopy surface only. Changes of SVI within individual fields attributable to soil moisture differences were negligible (Figure 48). At Dalhart, the soll moisture correction factor for bare fields was \(2 \mathrm{db} / 10 \%\) change in soil moisture \(0 \%\) to \(100 \%\) of field capacity); at Guymon, the factor was \(4.5 \mathrm{db} / 15 \%\) change in soil moisture (a change of \(80 \%\) of field capacity). The effect was also dependent on crop type as SVI values from fields having higher biomass were less dependent on surface soil moisture. Correcting SVI for soil moisture using \(\mathbb{C}\) band passive microwave brightness temperatures improved the relationship only slightly (Figures 49 and 50 ). Part of the variance of SVI within each crop type can be explained by

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FIG. 45 The relationship between total biomass and the scatterometer vegetation index, SVI. (4.75 HV \(40^{\circ}\) look angle - \(4.75 \mathrm{HV} 5^{\circ}\) look angle) ( \(R^{2}=0.88\) ).


FIG. 47 The relationship between SVI(db), and TVI ard PVI at Guymon.
\[
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& \text { op ory on whilly }
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\]


SVI(db), and TVI and PVI at Dalhart.
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roughness differences. For example, at Guymon, SVI values fron fields having rows parallel to the flight line were slightly higher, 2-3 db , then values from fields with rows perpendicular to the flight line. Attempts to remove the roughness effects were fruitless as the vegetation effect was also lost. Analysis of Figures 49 and 50 indicated that SVI was insensitive to low PVI or TVI changes; however, at higher PVI and TVI (PVI greater than 1.5 and TVI greater than 1.06) levels SVI became sensitive to changes in biomass. Indications also show that SVI was slightly more sensitive to biomass changes at high biomass levels than PVI or TVI.

Other attempts to determine combinations that normarized the scatterometer data proved fruitless. Consequently, each data set could only be analyzed separately.

\section*{Problem 4}

Considering the results from the previous three problems, diomass was a strong indicator of crop type differences within the active microwave region--crops with greater biomass had higher active microwave responses and were classified separately from other low biomass groups. If the tree classifcation model were applied to an agricultural region which has a crop with different biomass or biophase, misclassification with other crops is likely. For example, the unsupervised classification technique tended to confuse immature sorghum with alfalfa. To fully understand the utility of the tree-classification inodel under different biophases and adjust the classification model for applications under different biomass levels, visible/infrared and active microwave responses needed to be considered. The sorghum
fields at Dalhart and laymon covered a wide range of biomass and biophases ranging from crops that were just emerging to fully headed. Analysis of the response difference within a given crop type due to biomass differences indicated possible errors of misciassification and gave physical explanation for the tree classification model.

The visible/infrared response showed a definite trend as biomass incredsed and crops matured. Figure 51 represents the red/near infrared responses at Dalhart and Guymon, respectively. In both cases, data from bare soil and low biomass fields were linearly related. As the crop matured, the distance from the soil line to the data point increased. Data from fields with the highest biomass and at the reproductive biophase had the largest distance from the soil line. The perpendicular distance had been defined as the perpendicular vegetation index (PVI). As the crop matured from heading, leaves began to senesce and PVI decreases. No fields at Guymon or Dalhart were in the last biophase.

The active microwave response from several fields at Dalhart-22, V2 and V6, and 12--indicated differences at far look angles which appeared to represent different biomass levels. Field 22 was a bare field at Dalhart; V2 was an irrigated sorghum field at Dalhart that had reached the heading stage; V6 was a dryland immature sorghum field only 60 cm tall at Dalhart; and 2 was a corn field with a high biomass at Dalhart. The \(K\) band data indicated no significant differences between the different biomass levels (Figure 52) while the \(C\) band cross pole data indicated some differences (Figure 53). The inmature sorghumi field, V2, had slightly higher returns than the bare field,
MiS7 (652-701NM) VS MMS9 (770-863NM)
TM3 (630-690NM) VS TM4 (760-90CNM)



FIG. 52 The \(K\) band like pole \(\sigma^{0}\) response as a function of look angle for bare soil (field 22), sorghum (field V2 and V6), and corn (field 2) at Dalhart.


FIG. 53 The \(C\) band cross pole response as a function of look angle for bare soil (field 22), sorghum (field V2 and V6), and corn (field 2) at Dalhart.
22. The largest difference was between the vegetation (mature sorghum, corn) and the bare soil-as much as 10 db in the \(40^{\circ}\) look angle. The L band cross pole data also indicated some differences between different biomass levels. Again, the corn and mature sorghum fields had higher returns at high look angles compared to the bare and low bionass fields--as much as 7 db (Figure 54). However, the responses at the high look angles in the \(P\) band cross pole data were sensitive to fields only with high biomass (Figure 55). The analysis therefore implied high frequency active microwave responses "saturated" at relatively low biomass levels while low frequency responses "saturated" at very high biomass levels. \(C\) band would then best separate lower biomass crops, L. band would separate moderate biomass crops and \(P\) band would separate high biomass crops.

The Guymon results also tended to indicate the same situation (Figures 56 through 59). However, roughness from row direction played an important factor also. The best example indicating biomass difference was \(L\) band cross pole from field \(1 X\)--headed, dense sorghum, 15-emerging sorghum, 4-alfalfa, and 14-bare soil (Figure 58). Again the far look angles were responding to high biomass levels. Data from other look angles indicated that surface roughness influenced the return by masking the vegetative differences. Attempts to eliminate roughness effects proved to be unsuccessful, as removal of roughness also reduced the vegetation effect.

Froll the analysis of both spectral data sets, a multifrequency active microwave system using a low and high frequency could improve classification and biomass estimation accuracy. Given the scatterometer vegetation index (SVI), which was strongly related to biomass


FIG.' 54 The \(L\) band cross pole \(\sigma^{0}\) response as a function of look angle for bare soll (field 22), sorghum (field V2 and V6), and corn (field 2) at Dalhart.

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FIG. 55 The \(P\) band cross pole \(0^{0}\) response as a function of look angle for bare soil (field 22), sorghum (field V2 and V6), and corn (field 2) at Dalhart.


FIG. 56 The \(K\) band like pole \(\sigma^{0}\) response as a function of look angle for bare soil (fteld 14), alfalfa (field 4), emerging sorghum (field 15) and headed sorghum (field 1X).


FIG. 57 The \(C\) band cross pole \(\sigma^{0}\) response as a function of look angle for bare soil (field 24), alfalfa (field 4), emerging sorghum (field 15) and hesded, sorghum (field 1X).


FIG. 58 The \(L\) band cross pole \(\sigma^{0}\) response as a function of look angle for bare soil (field 14), alfalfa (field 4), emerging sorghum (field 15) and headed sorghum (field 1 X ).


FIG. 59 The \(P\) band cross pole \(\sigma^{0}\) response as a function of look angle for bare soll (field 14), alfalfa (field 4), emerging sorghum (field 15) and headed sorghum (field 1 X ).
and PVI, a similar combination using \(40^{\circ} \mathrm{P}\) band cross cole \(0^{\circ}-\mathrm{P}\) band cross pole \(\sigma^{0}\) was included with SVI. The resulting modified index (SVIM) is defined as
\[
\begin{align*}
\text { SVIM }= & \left(40^{\circ} \mathrm{C} \text { band cross pole }-5^{\circ} \mathrm{C} \text { band cross pole }\right) \\
& +\left(40^{\circ} \mathrm{P} \text { band cross pole }-5^{\circ} \mathrm{P} \text { band cross pole }\right) \tag{22}
\end{align*}
\]

The modified SVI was also strongly related to total biomass at Dalhart \(\left(R^{2}=0.73\right)\) (Figure 60). In comparison, the relationship of SVIM to biomass at Dalhart was not as strongly related to PVI or TVI at Guymon (Figure 61). Again, alfalfa did not have high SVI values indicating active microwave penetration through the canopy for \(P\) band data. Higher frequency scatterometer data may indicate the presence of dense alfalfa fields. The SVIM responses froll sorghum fields were, however, greater than low biomass or bare fields.

With the sensitiviey of the \(P\) band cross pole data to differences in high biomass, the only change needed in the classification model was to use \(P\) band aross pole differences as a first step to separate the high biomass fields from fields with medium and low biomass. Higher frequency \(L\) or \(C\) band cross pole data were then used as criteria to separate fields with medium and low biomass levels. Using these criteria, the corn and dense sorghum fields at Guymon were separated--anything having a return of -47 db or higher would he classified as corn at Dalhart and -36 db or higher at Guymon. Using these criteria, the accuracy of the tree classifier improved slightly at Dalhart and Guymon--81\% at Dalhart and \(76 \%\) at Guymon.


Fli. 60 The relationship between total biomass and the modified scatterometer vegetation index. SVIM [ (C band cross pole. \(40^{\circ}-C\) band cross pole \(\left.5^{\circ}\right)+\left(P\right.\) band cross pole \(40^{\circ}-P\) band cross pole \(5^{\circ}\) )].

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FIG. 61 The relationship between the modified SVI (SVIM) and TVI and PVI at Guymon.

\section*{SUMMARTY AMD CONCLUSIONS}

Since the study was divided into four problems, results from each will be discussed in detail. Also, an overview summarizing the study and its implications will follow the dicussions of the results.

\section*{Problem 1}

The first problem determined spectral bands which were sensitive to crop type differences. Results implied that several active microwave frequencies were sensitive to crop type differences, especially at look angles greater than \(35^{\circ}\) off nadir. The response differences due to vegetation dominated the effects of roughness and soil moisture. The most sensitive frequencies and polarizations included \(C\) band cross pole, \(L\) band like and cross pole and \(P\) band like and cross pole. Depending on the crop type, responses from certain frequencies discriminated crops. For example, \(L\) and \(P\) band discriminated between sorghum and corn, and \(C\) band was able to discriminated between alfalfa and bare soil. Other active microwave sensors were primarily sensitive to roughness or soil moisture. The visible/infrared sensors were not as sensitive while the passive microwave data were sensitive to soil moisture differences. The biomass differences were detected especially well in the visible/infrared bands. Also, stressed areas were noted using NSOO1 band 6 data (water absorption band). The visible and infrared data were sensitive to the presence or absence of vegetation, but not necessarily certain crop type pairs.

\section*{Problem 2}

The second problem determined the most accurate crop classifying dendrogram for the Guymon and Dalhart spectral data. In this problem, a relatively accurate dendrogram using active microwave, visible, and infrared data was developed for both Guymon and Dalhart spectral data sets. The dendrograin was based first on separating "rough" from "smooth" fields using active microwave data, and second, on separating each class between the bare and low biomass fields from heavily vegetated fields. The preferred active microwave frequencies and polarization were \(L\) and \(C\) band cross pole which were most sensitive to biow mass differences between crop types. Response differences in both frequencies classified different scales of roughness. Classification accuracies using the similar dendrograms were \(77 \%\) for Dalhart and \(70 \%\) for Guymon. Data from other individual bands did not improve the accuracy. The implication was that one model requiring data from four bands (visible through active microwave) could discriminate different crop types with reasonable accuracy. More data sets are needed, however, to thoroughly test the tree classification model.

\section*{Problem 3}

Problem three determined the utility of estimating biomass and discriminating crops using visible/infrared/microwave data compared to visible/infrared data. The primary result in problem 3 was the indication that microwave data improved or maintained classifisation and biomass estimation accuracy in comparison to conventional
classification. The conventional classification technique used only visible/infrared data to classify and estimate biomass. Various statistical techniques such as discriminant analysis and step-wise regression indicated the inclusion of active microwave aided in classifying agricultural crops. With higher accuracy, less frequent visible/infrared/microwave satellite or aircrafi passes would be required for an adequate estimate of crop acreage or biomass.

In addition, the proposed thematic mapper wavelength bands provided more information on vegetation than the Landsat visible/infrared combinations. For example, a combination similar to the perpendicular vegetation index (PVI), but using input data from the near infrared (0.76-0.90 \(\mu \mathrm{ml}\) ) and water absorption band (1.55-17.5 \(\mu \mathrm{m})\) provided additional information on corn compared to the results from brnad band MSS red and near infrared wavelengths. Not enough ground data were collected to determine what physiological parameter within field differences of the the new combination was detecting. The new combination, PVI64, was slightly more related to biomass than the original combination of red and near-infrared data that had been used to calculate PVI. Further studies using these bands are needed.

Finally, an active microwave vegetation index (SVI) was developed using \(C\) band cross pole data from the \(5^{\circ}\) and \(40^{\circ}\) look angles. The combination, which was developed to normalize the two data sets, was highly correlated to PVI. The major implication was that use of this combination would allow a classification and biomass estimation that would be possible regardless of cloud conditions. It is fully recognized that the sensor combination required to collect \(5^{\circ}\) and \(40^{\circ}\)
illagery over the same areas with active microwave is highly impractical and most likely not economically feasible. The result is, however, significant from an academic standpoint and may help in understanding the scattering phenomena that take place in vegetative cover. It is significant to note that \(L\) band differences between \(5^{\circ}\) and \(40^{\circ}\) did not respond to vegetation other than corn and sorghum since the \(L\) band energy was penetrating through the canopy more than \(C\) band. However, further tests of the model are needed in agricultural regions having different management practices.

In spite of the success in discriminating crops and estimating biomass within each data set--Guymon and Dalhart--the sets could not be combined due to the absence of active microwave calibration. Various attempts to normalize the data sets using combinations, such as the SVI, were unsuccessful. Consequently, both data sets were analyzed separately. Any further experiment requiring collection of active microwave data must include some means of calibrating the microwave sensors.

\section*{Problem 4}

The fourth problem determined the effect of biomass differences on the crop classifying dendrogram developed in problem 2. Results from problem 4 indicated that the tree-classification model was significantily dependent upon biomass. Implications are that crops which have similar responses at the same time of year, such as wheat and barley may be indiscriminant. However, at certain biophases physiological differences, such as plant water content may be detectable. Consequently, multi-temporal data are still needed to
accurately separate two "confusion" crops. To make the model even more sensitive, multifrequency microwave data are needed to separate even higher biomass levels. Results proved that the \(p\) band cross pole scatterometer returns are sensitive at high biomass levels at Dalhart. Inclusion of the \(P\) band cross pole data improved crop classification accuracy over the use of \(L\) band and \(C\) band data.

\section*{Overview}

Having answered the questions posed by each problem, the hypothesis--can microwave data help improve classification and biomass estimation compared to present techniques using only visible and infrared data--can be validated. Given the results from Guymon, 0klahoma, and Dalhart, Texas, active microwave data do aid in improving classification and biomass estimation. Results indicated that multifrequency active microwave data would be needed to classify multiplecropped agricultural areas accurately. L and \(P\) band data can discriminate between sorghum and corn; C band can discriminate between bare soil and alfalfa but not between corn and sorghum. In addition, NSOOl data indicated combinations of the water absorption band (1.55-1.75 \(\mu \mathrm{m})\) and the near-infrared band (1.0-1.3 \(\mu \mathrm{m}\) ) gave more crop information than the red/near infrared combinations. Accurate multispectral classification and biomass estimation models were developed from both data sets.

However, two major factors pose problens in using active microwave data-soil moisture and surface roughness. With many of the vegetated crops being irrigated and the non-vegetated field remaining fallow, a bias entered into this analysis due to soil moisture differ-
ences. The most accurate technique to remove the soil moisture effect would be to develop a correction factor using passive microwave data which is primarily sensitive to soil moisture changes, as inputs to the model (Schmugge, 1979). The best method to minimize surface roughness is to use cross-polarized active microwave data, which theoretically isolates the volumetric (dielectric) effects while minimizing the scattering (surface roughness) effects. Other combinations that were developed were unable to remove the effects of roughness alone. Attempts to remove the roughness effect also diminished the vegetation effect.

A second problem dealt with spatial resolution. If large areas of the world are to be covered in a short time period, satellite systems will be required. The question arises as to what should the spatial resolution be and should the resolution be similar for each frequency. Visible/infrared data often have high spatial resolution; passive microwave data have low resolution while active microwave resolution can be controlled by system design and processing. Many fields around the world are too small to be seen even by Landsat. Consequently, by increasing spatial resolution to allow analysis of individual fields implies extremely large amounts of both visible/infrared microwave and active microwave data processing. With lower spatial resolution, knowledge of composite (fields of different crop types, soil moisture, and surface roughness) returns within the cell size is required. For example, what effect would the return from a 32 -hectare field have on the composite return of a 10 km resolution cell, and can classification and biomass information be extracted from
the larger size cells? Consequently, future studies are needed to find the proper resolution size for reasonably accurate estimates of vegetation using visible/infrared/microwave data.

Advantages of using microwave systens are obvious: independence of weather and sunlight and the opportunity for fewer passes with the visible/infrared systems due to higher classification accuracy. Both reasons are advantageous over present visible/infrared systems developed during the LACIE period. Solle foreign agricultural areas that we have previously been unable to monitor froll a satellite due to cloud cover could be monitored in the future. The final results would be two-fold: (1) an improved world-wide agricultural production system which would prevent another event such as the U. S./Soviet Union wheat crisis which occurred in 1974, and (2) domestic food supply planning would be more efficient as better production estimates would induce better domestic storage and production, and stabilize commodity prices.

Consequently, active microwave sensors need to be seriously considered as additional sensing tools in evaluating agricultural areas. With the additional data, potential world food disasters may be averted.

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\section*{APPENDIX A}

\section*{DATA QUALITY, CALIBRATION, AND OMISSIONS}

At both Dalhart and Guymon, data were deleted for various rea-sons--quality and excessive aircraft attitude parameters. This chapter defines the questionable sensor and soil moisture data and the methods used for correcting the data sets. Each sensor system and soil moisture will be discussed in detail.

\section*{NS001/M \({ }^{2} S\)}

Most of the visible/infrared data were of good quality at both Dalhart and Guymon. One of the exceptions was the excessively noisy water absorption hands (bands 6 and 7) on 8/14/80 at Dalhart. Since no means were possible to correct the data, they were eliminated from further data analysis. Also, at Dalhart band 1 data for fields 6,8 , 10,12 and 22 were deleted due to unstable calibration.

With the exception of band \(9(0.77-0.86 \mu \mathrm{~m}) \mathrm{M}^{2} \mathrm{~S}\) data at Guymon, the calibration information proved to be quite stable. Table Ala lists the equations used to convert raw digital courits to radiance values. Note band 9 had three different equations applicable at different periods of the experiment.

All of the working NSOO1 bands had less stable calibration information at Dalhart. Table Alb lists the equations used to convert digital counts to radiance values. Note that several bands had different calibration values on each flight day.

Calibration of the thermal band proved to be different for Guymon and Calhart. The calibration, using the PRT-5 data, showed that at Guymon the low temperature calibration black body aboard the plane was

TABLE Al. Equations used to convert raw NSOO1/M2S digital counts (DC) to radiance values, \(R\), ( \(10^{-4}\) watts \(c^{-1 I^{-2}}\) ster \({ }^{-1}\) ) for Guymon (a) and Dalhart (b)
a. channel \(4 \quad R=\frac{10.46 \times 10^{-4}}{233} *(D C-12)\)
\(7 \quad R=\frac{9.61 \times 10^{-4}}{230} *(D C-13)\)
\(8 \quad R=\frac{8.14 \times 10^{-4}}{230} *(D C-14)\)
\(9 \quad R=\frac{6.98 \times 10^{-4}}{232} *(D C-12)(8 / 2,8 / 5\), and \(8 / 8)\)
\(9 \quad R=\frac{6.98 \times 10^{-4}}{100} *(D C-10)(8 / 11)\)
\(9 \quad R=\frac{6.98 \times 10^{-4}}{160} *(D C-17)(8 / 14)\)
b. channel \(1 \quad R=\frac{1.96 \times 10^{-4}}{207} *(D C-1)(8 / 14 \& 8 / 16\) (Flt 1))
\[
\begin{array}{ll}
1 & R=\frac{1.96 \times 10^{-4}}{151} *(D C-1)(8 / 16 \text { (Flt 2)) } \\
1 & R=\frac{1.96 \times 10^{-4}}{70} *(D C-1)(8 / 18) \\
2 & R=\frac{4.63 \times 10^{-4}}{210} *(D C-21)(8 / 14-8 / 15) \\
2 & R=\frac{4.63 \times 10^{-4}}{140} *(D C-21)(8 / 18) \\
3 & R=\frac{5.61 \times 10^{-4}}{224} *(D C-29)(8 / 14-8 / 16) \\
3 & R=\frac{5.61 \times 10^{-4}}{172} *(D C-29)(8 / 18) \\
4 & R=\frac{11.42 \times 10^{-4}}{232} *(D C-9)(8 / 14-8 / 16 \quad(F 1 t \quad 1)) \\
4 & R=\frac{11.42 \times 10^{-4}}{171} *(D C-9)(8 / 16 \quad(F 1 t \quad 2))
\end{array}
\]

TABLE: Al. (Continued)
\[
\begin{array}{ll}
4 & R=\frac{11.42 \times 10^{-4}}{107} *(D C-8)(8 / 18) \\
5 & R=\frac{5.43 \times 10^{-4}}{232} *(D C-8)(8 / 14.8 / 16(F 1 t \quad 1)) \\
5 & R=\frac{5.43 \times 10^{-4}}{147} *(D C-9)(8 / 16(\text { Flt } 2)) \\
5 & R=\frac{5.43 \times 10^{-4}}{107} *(D C-9)(8 / 18) \\
6 & R=\frac{2.8 \times 10^{-3}}{222} *(D C-12)(8 / 16) \\
6 & R=\frac{2.8 \times 10^{-3}}{166} *(D C-12)(8 / 18) \\
7 & R=\frac{1.43 \times 10^{-3}}{110} *(D C-16)(8 / 16 \& 8 / 18)
\end{array}
\]
too high while the high temperature calibration black body was measuring the proper temperature. This implied that low surface temperatures were as much as \(5^{\circ} \mathrm{C}\) too high. At Dalhart, the opposite condition occurred. The low temperature calibration black body was reading the proper temperature while the high temperature calibration body was reading \(5^{\circ} \mathrm{C}\) too low, suggesting that high surface temperatures were as much as \(5^{\circ} \mathrm{C}\) too low.

The normalization solar correction factors \(\left(\cos \theta_{j}\right)\) for Dalhart are as follows: August 14, 5.7; August 16, (flight 1), 2.0; and (flight 2), 1.1; and August 18, 1.0. For Guymon, the normalization solar correction factors are August 2, 1.7; August 5, 1.6; August 8, 5.0; August 11, 1.0; August 14, 1.6 and August 17, 1.6. To normalize the two data sets, the Guymon data set required a multiplication factor of 1.3 to roughly match the radiance values at Dalhart.

Scatterometer

Due to excessive aircraft roll and drift, several look angles had to be eliminated at Dalhart and Guymon due to the uncertainty of the cell being within the field. At Dalhart, all active microwave data from one field had to be eliminated--field 16 on \(8 / 18 / 80\). Also, data at \(40^{\circ}\) and \(45^{\circ}\) look angles off nadir from several other fields on 8/18/80 were eliminated due to excessive drift (Table A2). At Guynon, flying conditions were much worse; consequently, data from more fields needed to be deleted. A complete list of omitted look angles are given in Table A3. Data from \(8 / 11,8 / 14\), and \(8 / 17 / 78\) were most questionable.

TABLE AR. Questionable scatterometer data for Dalhart
\begin{tabular}{lll}
\hline Date & Field \# & Questionable Analysis \\
\hline \(8 / 14 / 80\) & All data is good & \\
\(8 / 16 / 80\) & All data is good & \\
\(8 / 18 / 80\) & L12 R2 \(20,8,18\) & \(45^{\circ}\) (drift \(9^{\circ}\) ) \\
& L12 R2 14 & \(40,45^{\circ}\left(\right.\) drift \(\left.11^{\circ}\right)\) \\
& L11 R3 16 & All Angles \\
\hline
\end{tabular}

TABLE A3. Questionable scatterometer data for Guymon
\begin{tabular}{|c|c|c|c|}
\hline Date & & Field \# & Questionable Analysis \\
\hline \multirow[t]{4}{*}{8/2/78} & L1 R1 & 2,4,6,7,8,2x,1x & \(40^{\circ}, 45^{\circ}\) ( \(-8^{\circ} \mathrm{drift}, 2^{\circ} \mathrm{roll}\) ) \\
\hline & L2 R1 & 10,13,14,15,2a,2x, 1x & \(45^{\circ}\left(-9^{\circ} \mathrm{drift}\right)\) \\
\hline & L1 R2 & 2,4,6,7,1a,2x,1x & \(45^{\circ}\) (-90 drift) \\
\hline & L. R2 & 15,17,2a & \(45^{\circ}\left(-8^{\circ} \mathrm{drift}\right)\) \\
\hline \multirow[t]{4}{*}{8/8/78} & L2 R1 & 17, 1x & all angles \\
\hline & L2 R2 & 2A & all angles \\
\hline & L4 R1 & 26 & all angles \\
\hline & L1 R2 & 2,6,7 & all angles \\
\hline \multirow[t]{8}{*}{8/11/78} & L1 R1 & 6,8,2x & all angles \\
\hline & L3 R1 & 19,22,1x & all angles \\
\hline & L2 R1 & 2 x , & all angles \\
\hline & L4 R1 & 24,25,27 & all angles \\
\hline & L1 R2 & 4,6,7,1A & all angles \\
\hline & L3 R2 & 22 & all angles \\
\hline & L2 R2 & \({ }_{24,}^{10,17}\) & \(45^{\circ}\) ( \(-4^{\circ}\) drift, \(4^{\circ}\) roll) \\
\hline & L4 R2 & 24,26,27 & all angles \\
\hline \multirow[t]{8}{*}{8/14/78} & L1 R2 & 4 & all angles \\
\hline & L3 R2 & 19 & \(40^{\circ}, 45^{\circ}\) (-80 drift, \(3^{\circ}\) roll) \\
\hline & L2 R2 & 13 & \(45^{\circ} 45^{\circ}\) (90 \({ }^{\circ} \mathrm{drift}\) ) \({ }^{\circ} \mathrm{m}\) \\
\hline & & 10 & \(40^{\circ}, 45^{\circ}\) (90 drift, \(3^{\circ}\) roll) \\
\hline & L1 R3 & all fields & \(40^{\circ}, 45^{\circ}\) ( \(11^{\circ} \mathrm{drift}\) ) \\
\hline & L3 R3 & \(1 \times\) & all angles \\
\hline & L2 R3 & \({ }_{15}^{13,14}\) &  \\
\hline & & & \\
\hline \multirow[t]{5}{*}{8/17/78} & L3 R1 & 21,22 & \(35^{\circ}, 40^{\circ}, 45^{\circ}\left(-12^{\circ} \mathrm{drift}\right)\) \\
\hline & L4 R1 & 2x, 24, 25, 26, 27 & \(35^{\circ}, 40^{\circ}, 45^{\circ}\) (-120 drift) \\
\hline & L3 R2 & 21,22 & all angles \\
\hline & & 1x,19,20 & \(40^{\circ}, 45^{\circ}\) ( \(-10^{\circ}\) drift) \\
\hline & L4 R2 & 24,25,2x & \(45^{\circ}\) ( \(-9^{\circ} \mathrm{drift}\) ) \\
\hline \multirow[t]{4}{*}{8/5/78} & L1 R1 & 2 & \(40^{\circ}, 45^{\circ}\) \\
\hline & L4 R1 & 2 x & \(40^{\circ}, 45^{\circ}\) \\
\hline & L2 R2 & 2 x & \(40^{\circ}, 45^{\circ}\) \\
\hline & L4 R2 & 2x & \(40^{\circ}, 45^{\circ}\) \\
\hline
\end{tabular}

\footnotetext{
*delete these same fields for passive data
}

Signal cross-over between L-band polarizations was quantifiable by Blanchard and Theis (1981). The correction in the cross-polarized data proved to be less than 1 db for the Dalhart and Guymon data sets. There appears to be cross-over in the \(P\) band data collected at Guymon and Dalhart. Figure Al represents like and cross polarized returns with look angle for the same field, \(1 X\), which had rows perpendicular to the flight line. Note the large increase in the like polarized data at \(20^{\circ}\) look angle. Any rapid increase of \(\sigma^{0}\) with increasing look angle can be directly attributed to large scale roughness characteristics. This characteristic is most apparent in like-polarized data; cross-polarized data suppress the roughness effect (Blanchard and Theis, 1981). Consequently, the rapid increase in \(\sigma^{0}\) should not appear in the cross-polarized data. Figures A2a and A2b show \(P\) band like and cross pole responses from a milo field (25) at Guymor. Note the absence of any large increase in \(\sigma^{0}\) at the \(15^{\circ}\) look angle for the cross pole data compared with the like pole data for the first four flight days. In the later flights the rows were tilled and the row height was increased causing a larger increase in \(\sigma^{\circ}\) at \(15^{\circ}\) look angle in both like and cross polarizations. This is an example of data with minimum cross-talk. The cross-polarized data should have smaller decreases in \(\sigma^{0}\) with higher look angles. Note, however, the \(P\) band response for field \(1 X\) in figure Al. At the \(15^{\circ}\) look angle, a large increase in \(\sigma^{0}\) occurs in both like and cross pole data. This suggests excessive cross-talk between the like- and cross-polarized data. No attempt has been made to try and correct for the cross-talk in the \(P\) band cross polarized data. In addition, note the \(\sigma^{0}\) differences in the \(P\) band cross polarized data between the
sets. There appears to be cross-over in the \(P\) band data collected at Guymon and Daihart. Figure Al represents like and cross polarized returns with look angle for the same field, 1 X , which had rows perpendicular to the flight line. Note the large increase in the like polarized data at \(20^{\circ}\) look angle. Any rapid increase of \(\sigma^{0}\) with increasing look angle can be directly attributed to large scale roughness characteristics. This characteristic is most apparent in likepolarized data; cross-polarized data supress the roughness effect (Blanchard and Theis, 1981). Consequently, the rapid increase in \(\sigma^{0}\) should not appear in the cross-polarized data. Figures A2a and A2b show \(P\) band like and cross pole responses from a milo field (25) at Guymon. Note the absence of any large increase in \(\sigma^{0}\) at the \(15^{\circ}\) look angle for the cross pole ata compared with the like pole data for the first four flight days. In the later flights the rows were tilled and the row height was increased causing a larger increase in \(\sigma^{0}\) at \(15^{\circ}\) look angle in both like and cross polarizations. This is an example of data with minimum cross-talk. The cross-polarized data should have smaller decreases in \(\sigma^{0}\) with higher look angles. Note, however, the \(P\) band response for field 1 X in figure A1. At the \(15^{\circ}\) look angle, a large increase in \(\sigma^{0}\) occurs in both like and cross pole data. This suggests excessive cross-talk between the like- and cross-polarized data. No attempt has been made to try and correct for the cross-talk in the \(P\) band cross polarized data. In addition, note the \(\sigma^{0}\) differences in the \(P\) band cross polarized data between the first and fourth--flights as much as 5 db difference. For these reasons we questioned the 0.4 GHz data, especially at Guymon.


FIG. Al Field \(1 X\) (sorghum) \(P\) band like and cross pole response with rows perpendicular to the flight line.


FIG. A2a Scatterometer response from the \(P\) band like pole system over field 25 (sorghum) with rows perpendicular to the flight line.


FIG. A2b Scatterometer response from the \(P\) band cross pole system over field 25 (sorghum) with rows perpendicular to the flight line.

Figure A3 represents like and cross polarized returns from the C and L band scatterometer for field 25 (sorghum), at Guymon. The field was tilled with rows perpendicular to the flight line and polarization. A slight increase in return at the \(20^{\circ}\) look angle for the \(L\) band like pole and cross pole is evident. The increase suggests again that some cross-talk may exist between the polarizations. Note the absence of cross-talk in the c-band data. A slight increase in the like-polarized data at \(10^{\circ}\) look angle off nadir is not evident in the cross polarized data. These data suggest that the other frequencies have sone degree of cross-talk, but on a much smaller scale than the \(P\) band data.

Since scatteroneter power was likely different for the Guymon and Dalhart data sets and no means exists for externally calibrating the system, normalizing the two scatterometer data sets proved to be quite difficult. Figures A4 through A7 represent scatterometer responses for each frequency from two bare fields having approximately the same surface soil moisture and roughness at Guymon (field 14) and Dalhart (field 19). Note the extreme difference in shift of \(L\) band like polarized data between the different frequencies. As much as a 15 dB difference exists between the two data sets in some instances. In addition, the shift in the like polarizaton for all frequencies is not constant nor is it even in the same direction. Note that in figures A4 and A6 field 14 is higher than 19 while in Figure A5 it is slightly lower and in Figure A7 they are alike. The far look angles appeared to be the most comparable between data sets. Since the differences


FIG. A3 Scatterometer response ( \(C\) and \(L\) band like and cross pole) from field 25 at Dalhart in 8/16/80.

ORIGINAL PIGE IS OF FOOR QUALITY


FIG. A4 Scatterometer response (K band like pole) from field 19 at Dalhart on \(8 / 16 / 80\) and fieid 14 at Guymen on \(8 / 5 / 78\). Soil metisture conditions were approximately \(90 \%\) of field capacity.


FIG. A5 Scattidrometer response (C band like and cross pole) from field 19 at Dalhart on \(8 / 16 / 80\) and field 14 at Guymon on \(8 / 5 / \% 8\). Soil moisture conditions were approximately \(90 \%\) of field capacity.


FIG. A6 Scatterometer response (L band like and cross mole) from field 19 at Dalhart on \(8 / 16 / 80\) and field 14 at Guymon on 8/5/78. Soil moisture conditions were approximately \(90 \%\) of field capacity.

\section*{ORIGINAL PACE IS OF POOR QUALITY}


FIG. A7 Scatterometer response ( \(P\) band like and cross pole) from field 19 at Dalhart on 8/16/80 and field 14 at Guymon on 8/5/78. Soil moisture conditions were approximately 90\% of field capacity.
between data sets are not constant with look angle, normáization of the data proved unsucessful. However, one normalization technique used to compare information within a data set was a data combination using a \(\sigma^{0}\) difference between two look angles in the same data set. Since \(\sigma^{0}\) is based on the algorithm of \(\sigma\), a difference implied a ratio between \(\sigma-a\) common normalization technique. It was believed that this technique provided much information on vegetation while minimizing, soil moisture and surface roughness effects, depending on the frequency and polarization.

\section*{Passive Microwave (MFMR)}

Since the passive microwave radiometer was oriented at a constant angle ( \(3^{\circ}\) from nadir), any excessive roll would imply questionable MFMR data. Consequently, any time the airplane had roll greater than \(3.5^{\circ}\) the field average MFMR data were deleted. Table A4 lists the deleted data. With the exception of data from one flight line at Guy-mon--L band data on \(8 / 11 / 7\) had highly erratic brightness temperatures on one occasion--brightness temperatures were quite stable. The nighly variable brightness temperatures indicated local unmeasured variations in the field. Therefore, the following fields at Guymon were deleted from further analysis: fields \(10,13,14,15\) and 17.

\section*{Soil Moisture}

Each sensor has a different cell size. Consequently, to compare data, soil moisture field averages were determined for the area observed by each sensor by averaging only one sample located within the observed area. Unfortunately, in some cases, averaging point locations of soil moisture proved not to be a reliable field average.
\[
\begin{aligned}
& \text { (5) "Lu LAAMTY }
\end{aligned}
\]

TABLE A4. Guymon and Dalhart questionable MFMR data
\begin{tabular}{lll}
\hline Date & Field \# & \(\%\) Roll \\
\hline \(8 / 8 / 78\) & L2 R1 \(1 X\) & 5.3 \\
\(8 / 11 / 78\) & L.3 R1 \(1 X\) & 4.9 \\
& L1 R2 6 & -5.1 \\
& L4 R2 24 & 4.9 \\
\(8 / 14 / 78\) & L2 R1 \(10,17,2 a\) & \(5.4,-8,-5.6\) \\
& L4 R1 27 & respectively \\
& L3 R3 \(1 X\) & 4.9 \\
\(8 / 17 / 78\) & L3 R2 22 & -4.8 \\
\(8 / 18 / 78\) & L1 R1 16 & 5.0 \\
\hline
\end{tabular}

These fields were deleted from the MFMR plots due to excessive roll; drift was not a factor.

For instance, several rows were irrigated and seen by the sensors but not sampled within the field. Also rainfall events occurred at Guymon between sampling periods-on \(8 / 2\) and \(8 / 8 / 78\). An attempt was made to correct the soil moisture by adding the amount. of rainfall or irrigation, assuming complete infiltration. In some cases, this correction did a good job. But in the end the questionable soil moisture data were deleted from the data set. The fields at Gumon with deleted soil moisture data were for \(8 / 2: 22,27,20,25,19,24,8 / 8: 1 x, 2 x\), 2, 10 and 8/17: \(1 x\), (1ine 2).

With the deletions, calibrations, and normalizations the Guymon and Dalhart data sets were complete as possibie. Data for the significant channels are presented in Appendix B and C.
4

DALHART DATATSET
COS=L BAND CROSS POLEE 5 DEGIEE LOOK ANGLE (DB)
PO5=P BAND CRDSS POLE 5 DEGHEE LOOX ANGLE (DB)

PYI =PERPENDICULAR VEGETATION INDEX (DIMENSIONEESS)
TVI =FRANSFORMEO VEGETATTON EADEX (OIWENSIOMESS)
SMOI=0-2 CM VOLUMETRIC SCIIL MOISTURE (X)
PERIODS REPRESENT MISSING VALUES ( \(x\) )
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline FIELO & MONTH & day & C05 & C40 & P05 & P40 & 215 & & & & & \\
\hline 13 & aug & 14 & & & & & & 220 & 235 & PyI & Tvi & Sm01 \\
\hline & AUG & 14 & 0.54 & -20.13 & \(=22.42\) & -58. 18 & 3.47 & 10.58 & - & 1.279 & \(1-003\) & \\
\hline 13 & kig & 16 & 18.29 & -8.91 & -3.79 & -46.97 & 3.17 & & & & 1.003 & 3.8 \\
\hline 13 & AUG & 16 & S.79 & & & & & 9.27 & 18.71 & 1.007 & 0.995 & 11.2 \\
\hline & & & & -6.33 & -16.14 & -50.37 & 3.03 & 9.74 & 21.25 & 1.330 & 1.012 & 8.9 \\
\hline 13 & AUG & 18 & 7.52 & -8.69 & -15.76 & -47.02 & 3.33 & 11.58 & 23.46 & & & \\
\hline 24 & aug & 14 & - & - & - 19.16 & -53, 83 & & & 23.46 & 1.832 & 1:026 & 3.5 \\
\hline 14 & AUG & 56 & 11.36 & -8.87 & & & & 8.62 & - & 0.557 & 0.969 & 1.7 \\
\hline 14 & & & 11.36 & -8.87 & -16.59 & -51.35 & 3.47 & 9.05 & 23.88 & 0.646 & 0.973 & 9.5 \\
\hline & AUG & 16 & 11.0 \% & -6.58 & -16.42 & -51. 54 & 3.82 & 9.29 & 25.46 & 0.428 & & \\
\hline 14 & aug & 18 & 7-03 & - & -14.56 & & & & & 0.428 & 0.956 & 9.5 \\
\hline & & & & & & & 3.82 & 9.47 & 25.33 & 0.497 & 0.96 E & 4.2 \\
\hline
\end{tabular}
DALHART DATATSET
COS=l RAWD CROSS POLE 5 EIEGREE LDOX ANGLE (DB)
DOS=P BAND CRESS POLE \(S\) TIEGREE LOOK ANGLE (DB)

DVI=PERPENDICULAR VEGETATION IMOEX (DIMENSIONEESS)

TVI=TRANSFORNEO VEGETATION INOEX (OIMENSIOALEESS)
PFRIOLS REPRESENT MISSING VALUES (S)
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline FiELD & MONTH & day & \(\cos\) & C4n & pos & P401 & 213 & 220 & 235 & PYI & TVI & SMOI \\
\hline 3* & aug & 14 & 1.st & -17.17 & * & - & - & - & & & & \\
\hline 3* & aug & 16 & 18.72 & -5.17 & -4.51 & -48.55 & 2.19 & 9.88 & 16.58 & 2.153 & 1.ces & 13.2 \\
\hline \(3 \times\) & aug & 16 & 9.94 & -1.94 & - & - & 2.35 & 10.16 & 19.14 & 1.931 & 5.047 & 8.9 \\
\hline 3x & aug & 18 & 7.89 & -5.18 & * & * & 2.77 & 12.26 & 20.95 & 2.623 & 1.068 & 4.7 \\
\hline 419 & A 12 & 14 & - & - & - & - & - & - & - & - & - & . \\
\hline 4Y & Aus & 16 & 8.82 & -6. 22 & - & - & 2.87 & 9.44 & 21. 65 & 1.356 & 1.017 & 9.7 \\
\hline 47 & aug & 16 & 11.22 & \(-5.50\) & * & - & 3.24 & 9.56 & 23.53 & 1.067 & 0.997 & 9.7 \\
\hline 4x & Aug & 18 & 7.E4 & - & \(=\) & & 3.04 & 10.02 & 22.45 & 1.439 & 1.017 & 3.5 \\
\hline
\end{tabular}
DALhART DATATSET
COS＝L bakd cross pole 5 degree loox ahge（DOS） COS＝D EAND CROSS POLE 5 OEGREE LOCK ANGE（OB） PAO＝P EAND CROSS POLE tO DEGREE LOOK ANGE（DB） PVI工PERPEMOICULAR VEGETATION IMDEX COIMENSIONEESS：
TVI＝TRANSFORMED VEGETATIOM IMDEX（DIMERSIONLESS） SMOI \(=0\) O2 CM VOLUNETRIC SOIL MOISTURE（5）
PERIODS REPRESERT MISSING VAUES
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline FTELD & MONTH & O为 & Cos & C40 & P05 & P40 & 215 & 220 & 235 & PVI & TVI & SMO： \\
\hline \％ & AUs： & 14 & 0.85 & － 5.3 & －23．5 & －52．0 & 1－24 & 12.89 & \(\bullet\) & 4.276 & 1－152 & － \\
\hline V2 & avs & 16 & 9．85 & － 2 －1 & \(=19.2\) & －45． 1 & 1．16 & 11．89 & 12.38 & 3.936 & 1－150 & － \\
\hline v2 & AUE & 16 & 10.75 & －0．8 & 021.8 & \(=49.6\) & 1.39 & 12.49 & 15．05 & 3.978 & 1.140 & － \\
\hline V2 & AUG & 18 & e． 35 & \(-4.5\) & －17．3 & －96．8 & － & ＊ & － & & － & － \\
\hline V2 & AU6 & 14. & － & － & －20．0 & \(=48.3\) & 1．24 & 12.89 & － & 4.276 & 1－152 & ＊ \\
\hline \(v 2\) & AUG & 16 & － & － & ＊ & － & 1．15 & 11．89 & ミ2．38 & 3.936 & 1．150 & － \\
\hline V2 & AUG & 16 & 12：45 & －0．3 & 020.7 & －8．9 & 8.39 & 12：49 & 15．05 & 3.978 & 1．140 & － \\
\hline v2 & Aus & 18 & \(\bullet\) & － & － & ＊ & － & － & － & － & － & － \\
\hline V6 & AUG & 14 & EeES & －17．6 & －25． 7 & －34．7 & ＊ & \(\bullet\) & － & － & － & ＊ \\
\hline V6 & AUG & 16 & ＊ & ＊ & \(\bullet\) & ＊ & 4.26 & 12.63 & 14.70 & 1.432 & 0.998 & － \\
\hline Y6 & auc & 16 & 10.75 & －07．4 & －22．1 & －51．9 & － & \(\cdots\) & － & － & ＊ & \(\bullet\) \\
\hline \(\checkmark 6\) & AUG & 18 & S．C5 & \(=9.2\) & －21．8 & －53．5 & ＊ & － & \(\bullet\) & － & \(\bullet\) & ＊ \\
\hline \(v 6\) & AUS & 14 & －0．0．5 & \(-18.0\) & －25．8 & －54．2 & － & － & － & ＊ & － & － \\
\hline V6 & Aut & 16 & 11.15 & －8．7 & －21．4 & \(-50.3\) & 4.26 & 12.63 & 14.70 & 1.432 & 0.988 & ＊ \\
\hline V6 & AUG & 26 & 10．c5 & －7．3 & －23．0 & －51．4 & － & － & ＊ & ＊ & － & － \\
\hline Y6 & AUG & 18 & 2.85 & －18－1 & －20．8 & －52．4 & － & － & － & － & ＊ & － \\
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\] & \(8 \cdot 5\) & 8E0－1 & \(986 \cdot 2\) & 6＜－91 & 9E－If & 96＊1 & 60．cs－ & こでで＝ & S＜゙と－ & 88.5 & 91 & ont & ＊ \\
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\] & \(3 \cdot 5\) & 211＊1 & 06E＊ & 19＊91 & 20021 & ＊8＊1 & 20．150 & 06＊12－ & 8ぎ＊＊ & & & & \\
\hline \multirow[t]{8}{*}{} & \(6 \% 2\) & 960＊\％ & 261＊E & ＊ & 62＊2I & 9102 & 96－Es＝ & 8S・を2－ & 8ぎャ & S0－01 & 91 & onv & \＄0 \\
\hline & 2＊2 & 101＊1 & Es\％＊s & 68＊81 & 88021 & 91＊2 & E1＊s5－ & 22＊12－ & 65＊5 & S8＊2 & 81 & my & ع0 \\
\hline & 上－9 & \(560 \cdot 1\) & 590＊2 & 08.91 & Ot－11 & \(26^{\circ} 1\) & \(00028=\) & 12＊02－ & 95＊ & \(12 \cdot 5\) & 91 & Snv & EO \\
\hline & \(8 \cdot 9\) & OTIEI & 22IEE & 0t－91 & 0＊＊T5 & 92＊I & 99＊2S＊ & S5＊61－ & 96＊＊＊ & 51－3 & 91 & 9nv & co \\
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DALHART DATATSET

dalhart datatiset
COS=L BAND CROSS POLE 5 DEGRIEE LOOX ANGE (08)
CADEL BAND CROSS POLE 40 DEGREE LOOK AMGE (DOB
pao=p band cross pole 40 degire lodk ahge (dsy
PVI IPERPENDICULAR VEGETATION IMDEX CDIMENSIONESS)
tviztransformeo vegetation index coinensioneess)
SMOI=0-2 CM VOLUMETRIC SOIL MOISTURE (X)
PERTODS REPRESENT WISISING VALUES
peritid pepresent misising values
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline fied & month & day & cos & C40 & P05 & P40 & 215 & 220 & 235 & pur & tvi & SkOt \\
\hline 01 & ALS & 14 & 4.20 & -11.25 & -21.40 & -46.83 & 0.95 & 9.89 & - & 3.272 & 1.150 & 6.6 \\
\hline \(0:\) & aug & 16 & 10.74 & -1.91 & -17.54 & -41.78 & \(0: 93\) & 10.52 & 10.18 & 3.565 & 1.156 & 13.2 \\
\hline 01 & aug & 16 & 10.28 & -0.32 & -19.61 & -83.87 & 0.90 & 10.23 & 9.71 & 3.472 & 1-E55 & 13.1 \\
\hline 01 & aug & 18 & 9.43 & -5.49 & -20.10 & -44.44 & 1.13 & 11.29 & 11.75 & 3.709 & 1.148 & 8.1 \\
\hline 02 & aug & 14 & - & - & -22.65 & -45.19 & 1.15 & 10.74 & - & 3.450 & 1.243 & 4.8 \\
\hline 02 & aug & 16 & 10.10 & -1.52 & -18.60 & -43.90 & 1.13 & 11.21 & 11.17 & 3.669 & 1.147 & 17.7 \\
\hline 02 & aus & 16 & 10.54 & 0.57 & -16.40 & -43.78 & 1.05 & 10.12 & 10.28 & 3.282 & 1.145 & 15.6 \\
\hline 02 & aug & 18 & 3.72 & -8.03 & -16. 86 & -46.51 & 1.09 & 9.77 & 10.58 & 3.101 & 1.139 & 8.6 \\
\hline 07 & aug & 14 & \(2.8 \epsilon\) & -11.12 & -21.81 & -43.62 & 0.83 & 12.70 & - & 4.572 & 1.173 & 14.4 \\
\hline 07 & Aug & 16 & 5.12 & -2.94 & -14.68 & -37.74 & 0.86 & 13.37 & 9.93 & 4.829 & 1.175 & 18.3 \\
\hline 07 & aug & 16 & 11.18 & -0.90 & -17.33 & -41.82 & 0.75 & 12.84 & 8.92 & 4.701 & 1.179 & 19.1 \\
\hline 07 & aug & 18 & 7.68 & -3.94 & -15.85 & -42.34 & 0.89 & 13.88 & 9.94 & 5.016 & 1. 275 & 19.2 \\
\hline 08 & aus & 14 & 11.23 & -0.03 & -20.98 & - 22.37 & 0.80 & 12.23 & - & 4.397 & 2.173 & 15.5 \\
\hline 08 & aus & 16 & 9.16 & -1.70 & -17.28 & -41.31 & 0.97 & 14.84 & 10.82 & 5.176 & 1.172 & 19.3 \\
\hline 08 & aug & 16 & 5.74 & -0.52 & -18.13 & -41.80 & 0.80 & 13.23 & 9.75 & 4.754 & 1.177 & 19.3 \\
\hline 08 & aug & 18 & 5.36 & -7.43 & -17.77 & -42.02 & 0.85 & 12.82 & 9.35 & 4.602 & 1.173 & 12.7 \\
\hline 09 & aug & 14 & 3.35 & -19.25 & -20.15 & -46.00 & 0.73 & 11.98 & - & 4.307 & 1.173 & 4.4 \\
\hline
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GUYMON DATA SIET

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\hline 22 & aug & 17 & 1 & -1:8.89 & * & -3.67 & - & 2.15 & 0.98 & 5.78 & 1 1-534 & 1.100 & 21.8 \\
\hline 22 & aug & 17 & 2 & & - & - & - & - & - & - & 1.E34 & 1.100 & 11.6 \\
\hline 27 & avg & 2 & 1 & -25.00 & . 19.50 & - & - & 1.22 & 0.95 & 7.14 & 2.131 & -1.125 & - \\
\hline 27 & AUs & 2 & 2 & -23.35 & -49.10 & - & - & - & - & - & 2.131 & 1.125 & - \\
\hline 27 & aug & 5 & 1 & -21.78 & -48.80 & -3.52 & -24.02 & 1.10 & 0.80 & 6.48 & 1.991 & 1.7.31 & 11,2 \\
\hline 27 & AUG & 5 & 2 & -17.00 & -46.24 & - & - & - & - & - & 1.951 & 1.131 & 15.4 \\
\hline 27 & aug & 8 & 1 & -19.76 & -50.80 & 15.40 & -3.10 & 1.15 & 0.70 & 8.20 & 2.803 & 1.159 & 15.6 \\
\hline 27 & aug & 8 & 2 & -16.30 & -49.40 & - & * & - & - & - & 2.803 & 1.159 & 15.6* \\
\hline 27 & aug & 11 & 1 & - & - & - & - & 0.95 & 0.57 & 8.34 & 2.979 & 1.171 & 23.2 \\
\hline 27 & aug & 11 & 1 & - & - & * & - & \(\bullet\) & - & - & 2.979 & 1.171 & 23.2 \\
\hline 27 & aug & 14 & 1 & -15.92 & -47.50 & - & - & 0.91 & 0.51 & 9.46 & 3.503 & 1.182 & 12.1 \\
\hline 27 & aug & 14 & 2 & -19.90 & -4E. 30 & -3.81 & -21.12 & * & - & - & 3.503 & 1.182 & 8.9 \\
\hline 27 & aug & 17 & 2 & -20.39 & - & - & - & 1.39 & 1.15 & 6.91 & 1.853 & 1.102 & 4.3 \\
\hline 27 & aug & 17 & 2 & -15.40 & -47.30 & -4.43 & -21.49 & - & - & - & 1.853 & 1.102 & 5.5 \\
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\hline 2 & aug & 2 & 1 & -25.00 & - & - & - & 1.05 & 2.22 & 2.89 & 0.104 & 0.952 & 2.5 \\
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\hline 2 & AUG & 5 & 1 & -25.70 & - & -4.81 & - & 1.22 & \(1=42\) & 3.54 & 0.155 & 0.953 & 10.5 \\
\hline 2 & aug & 5 & 2 & -24.10 & -48.10 & \(\bullet\) & - & - & - & - & 0.155 & 0.963 & 11.6 \\
\hline 2 & aug & 8 & 1 & -25.97 & -48.50 & 28.20 & -2.70 & 0.95 & 1.10 & 2.95 & 0.238 & 0.978 & - \\
\hline 2 & aug & 8 & 2 & \(\bullet\) & \(\bullet\) & - & - & - & - & & 0.238 & 0.978 & - \\
\hline 2 & aug & 11 & 1 & -24.39 & -46.70 & 12.40 & -11.20 & 1.73 & 1.97 & d. 58 & 0.132 & 0.948 & 5.2 \\
\hline 2 & aug & 11 & 2 & -20.30 & -45.60 & - & - & - & - & - & 0.132 & 0.948 & 5.2 \\
\hline 2 & aUG & 14 & 1 & -25.21 & - & -4.27 & - & 1.52 & 1.88 & 4.16 & 0.108 & 0.945 & 3.6 \\
\hline 2 & aug & 14 & 2 & -24.10 & -46.30 & - & * & \(\bullet\) & - & - & 0.261 & 0.945 & 3.6 \\
\hline 2 & גUG & 17 & 1 & -23.40 & -47.30 & -4.15 & -29.16 & 1.63 & 2.87 & 4.34 & 0.122 & 0.947 & 3.3 \\
\hline 2 & avg & 17 & 2 & -22.40 & -46.30 & \(\bullet\) & - & - & - & - & 0.122 & 0.947 & 3.3 \\
\hline 6 & aug & 2 & 1 & -25-80 & - & - & - & \$.43 & 1.70 & 3.91 & 0.056 & 0.945 & 3.0 \\
\hline 6 & nug & 2 & 2 & -23.70 & -44.90 & -5.67 & -25.26 & - & - & - & 0.098 & 0.945 & 3.0 \\
\hline 6 & aug & 5 & 1 & -24.40 & -49.40 & -4.55 & -24.02 & 1.46 & 1.78 & 4.22 & 0.153 & 0.952 & 13.0 \\
\hline 6 & avg & 5 & 2 & -23.70 & -47.20 & * & - & - & - & - & 0.153 & 0.952 & 13.0 \\
\hline 6 & AUG & 8 & 1 & -21.70 & -51.77 & 14.90 & -5.10 & 1.50 & 1.75 & 4.40 & 0.256 & 0.965 & 6.2 \\
\hline
\end{tabular}

Gillainal pagx Is

\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline field & HCKTH & ony & RUn & C05 & C40 & P05 & P40 & 210 & 215 & 225 & pur & TVI & Smo3 \\
\hline 10 & aug & 27 & \(\pm\) & -22.90 & -46.00 & -4.06 & -29.35 & 2.34 & 2.59 & 5.73 & \(0.0 \leqslant 2\) & 0.937 & 3.6 \\
\hline 10 & aug & 17 & 2 & \(-23.80\) & -47.80 & - & - & - & - & - & \(0.0 \leq 2\) & 0.937 & 3.4 \\
\hline 14 & aus & 2 & 1 & -26.10 & -46.58 & - & - & 4.43 & 1.82 & 4.03 & 0.128 & 0.950 & 22.3 \\
\hline 14 & - aug & 2 & 2 & -23.80 & -47.10 & -3.71 & -19.123 & - & - & - & 0.128 & 0.950 & 21.1 \\
\hline 14 & aug & 5. & 1 & -24.00 & -47.80 & -5.20 & -18.75 & 1.52 & 1.81 & +.27 \({ }^{\text {- }}\) & 0.147 & 0.951 & 20.0 \\
\hline 14 & AUS & 5 & 2 & -25.70 & -46.50 & - & - & - & - & - & 0.147 & 0.951 & 20.4 \\
\hline 14 & aug & 8 & 1 & -24.80 & -50.50 & -6.01 & -26.135 & 2.00 & 2.30 & 6.10 & 0.470 & 0.973 & 10.6 \\
\hline 14 & aug & 8 & 2 & -24.00 & - 52.10 & - & - & - & - & - & 0.670 & 0.976 & 10.8 \\
\hline 14 & aug & 11 & 1 & -24.30 & -48.60 & - & - & 2.07 & 2.35 & 5.53 & 0.1E5 & 0.951 & 5.4 \\
\hline 14 & aug & 11 & 2 & -23.80 & -44.20 & -6.e2 & -25.1ES & - & - & - & 0.185 & 0.958 & 5.3 \\
\hline 10 & aug & 14 & 1 & - & - & - & * & 1.54 & 1.74 & 4.45 & 0.286 & 0.968 & 4.0 \\
\hline 14 & Aug & 14 & 2 & -24.30 & -45.40 & -4.91 & -26.154 & \(\bullet\) & - & - & 0.286 & 0.958 & 4.0 \\
\hline 14 & AUG & 17 & 1 & -26.10 & -48.50 & -2.20 & \(-27.70\) & 2.03 & 2.30 & 5.68 & 0.254 & 0.961 & 3.5 \\
\hline 14 & aug & 17 & 2 & -27.10 & -50.10 & - & \(\bullet\) & - & - & - & 0.254 & 0.981 & 3.5 \\
\hline 17 & avs & 2 & 1 & -27.10 & -50.41 & - & \(\bullet\) & 1.70 & 2.02 & 4.61 & 0.059 & 0.944 & 3.7 \\
\hline 17 & aUg & 2 & 2 & -26.20 & -48.80 & -5.21 & -25.1E2 & - & - & - & 0.659 & 0.944 & 4.2 \\
\hline 17 & aug & 5 & 1 & -28.00 & -50.50 & -4.98 & -24.157 & 1.49 & 1.76 & 4.16 & 0.146 & 0.952 & 5.8 \\
\hline
\end{tabular}


ORIGINAL PAGE IS
OF POOR QUALITY




GUYXOH DATA SET
\[
\begin{aligned}
& \text { POS=P BAND CROSS POLE } 5 \text { DEGREE LJCK ANGLE (DB) } \\
& \text { PAG=P EAND CROSS POLE } 40 \text { DEGREE -LCK ANGLE (DB) }
\end{aligned}
\]
\[
\begin{aligned}
& \text { PVI IPERPENDICLLAR VEGETATICN INDEX (DIMEASIOMEESS) } \\
& \text { TVI=TRAASEORNED VEGETATION UNOEX (DIMEMSIONLESS) }
\end{aligned}
\]
FERIDOS REORESENT MHSSIMG VALUES
ORPMNA PRAE PR
OF POOR QUALHY


\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline fielo & MCNTH & eny & quin & cos & C40 & . P05 & P40 & 210 & 215 & 225 & pys & 7VI & SMOI \\
\hline 8 & aug & 8 & 2 & -28.80 & -38.30 & - & - & - & - & - & 1.475 & 1.112 & 5.0 \\
\hline \(s\) & aug & 11 & 1 & - & - & * & - & 1.20 & 1.11 & 5.73 & 1.355 & 1.084 & 8.5 \\
\hline 8 & aug & 11 & 2 & -27.90 & -33.30 & - & - & - & - & - & 1.395 & 1.084 & E.5 \\
\hline 8 & aug & 14 & 1 & -29.42 & - & -3.42 & - & - & - & - & 0.000 & 0.000 & 4.9 \\
\hline 8 & aug & 14 & 2 & -26.50 & -35.20 & - & - & - & - & - & 0.000 & 0.000 & 4.9 \\
\hline \(\varepsilon\) & aug & 17 & 1 & -26.00 & -34.10 & -3.72 & -211.93 & 1.01 & 0.90 & 5.42 & 1.455 & 1.102 & 3.2 \\
\hline 8 & aug & 17 & 2 & -25.50 & -32.40 & - & - & * & - & & 1.455 & 1.102 & 3.2 \\
\hline 14 & avg & 2 & 1 & -29.80 & -38.70 & * & - & 0.93 & 0.75 & 6.07 & 1.0E4 & 1.131 & 6.1 \\
\hline 14 & aug & 2 & 2 & -26.90 & -37.20 & -6.24 & -18.01 & - & - & - & 1.8es & 1.131 & 6.2 \\
\hline 14 & aug & 5 & 1 & -29:3\% & -40.90 & -5.38 & -16.80 & 0.91 & 0.70 & 5.76 & 1.760 & 1.133 & 5.8 \\
\hline 14 & AUG & 5 & 2 & -26.70 & -39.10 & - & - & - & - & - & 1.780 & 1.133 & 5.8 \\
\hline 14 & aUg & 8 & 1 & -26.90 & -42.75 & 13.60 & 2.00 & 0.80 & 0.65 & 5.70 & 1.200 & 1:138 & 5.8 \\
\hline 1A & AUG & 8 & 2 & -25.50 & -40.00 & - & * & * & - & - & 1.800 & 1.138 & 5.5 \\
\hline 18 & AUG & 11 & 1 & -28.00 & -36.00 & 11.30 & -0., 80 & 1.08 & 0.84 & 5.90 & ©.711 & 1.118 & 4.9 \\
\hline 14 & aug & 11 & 2 & \(\bullet\) & \(\bullet\) & - & * & - & - & - & 1.712 & 1.118 & 4.9 \\
\hline 14 & aug & 14 & 1 & -26. 60 & - & \(=2.47\) & -17.72 & 0.83 & 0.66 & 5.62 & 1.757 & 1.136 & 5.1 \\
\hline 14 & ®ug & 14 & 2 & -25.ec & - 37.90 & - & & - & - & - & 1.757 & 1.136 & 5.1 \\
\hline
\end{tabular}








\begin{tabular}{cccc}
225 & pVI & TVI & 5.601 \\
7.34 & 2.542 & 1.162 & 27.4 \\
. & 2.542 & 1.162 & 27.4 \\
8.37 & 2.810 & 1.154 & 9.7 \\
. & 2.810 & 1.154 & 10.6
\end{tabular}
    st:*(-23)```

