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REFLECTANCE OF VEGETATION, SOIL, AND WATER

Craig L. Wiegand, Principal Investigator
Co-Investigators: H. W. Gausman
R. W. Leamer
A. J. Richardson
A. H. Gerbermann
Contributors: R. J. Torline
M. R. Gautreaux
J. H. Everitt
J. A. Cuellar
R. R. Rodriguez
J. R. Noriega

Agricultural Research Service
U.S. Department of Agriculture
P. O. Box 267
Weslaco, TX 78596

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16. Abstract

Bands 4, 5, and 7 and 5, 6, and 7 were best for distinguishing among crop and soil categories in ERTS-1 scenes 1182-16322 (1-21-73) and 1308-16323 (5-21-73), respectively. Plant parameters (leaf area index, population, cover, and height) explained 95.9% of variation in band 7 digital counts for cotton and 78.2% of variation in digital counts for combined sorghum and corn crops. Chlorotic sorghum areas 2.8 acres or larger in size were identified on a computer printout of band 5 data. Reflectance of crop residues was more often different from bare soil in band 4 than in bands 5, 6, or 7. Simultaneously acquired aircraft and spacecraft MSS data indicated that spacecraft surveys are as reliable as aircraft surveys. ERTS-1 data were successfully used to estimate acreage of citrus, cotton and sorghum, and idle cropland; recognition of agriculture and rangeland was 85.7% and 78.1%, respectively, in 1-21-73. Classification results for 1-21-73 and 5-27-73, improved when fields greater than 15 acres, more than 25% plant cover, and plants taller than 30 cm were used. Combined Kubelka-Munk and regression models, that included a term for shadow areas, gave a higher correlation of composite canopy reflectance with ground truth than either model alone.

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PREFACE

The research by the U.S. Department of Agriculture at Weslaco, Texas, with ERTS-1 data was based on three objectives: (1) to compare results using ERTS-1 data with predictions of analytical models for interaction of light with vegetation, (2) to determine the seasonal spectral changes of the various crops and soils in Hidalgo County, Texas, and discriminate among them by means of reflectance measured from ERTS-1, and (3) to gain experience developing an operational system of satellite data analysis to fit the needs of the U.S. Department of Agriculture. Several substudies relating to the three objectives were conducted under three categories: (1) crop vigor and potential crop yield, (2) crop discrimination, and (3) soil. The crop vigor and potential crop yield studies were based on laboratory and aircraft experience that resulted in an understanding of the interaction of light with vegetation and the subsequent definition of most useful wavelengths for indicating physiological plant stress and for discriminating among crop genera. Analytical models were also produced relating reflectance to crop vigor and leaf area index. Crop discrimination and soil studies were based on computer identification procedures. Procedures developed using film optical densities and aircraft scanner data were applied to ERTS-1 data.

Considerable expertise has been developed and substantial progress has been made toward defining elements of an operational data analysis system to meet the needs of the U.S. Department of Agriculture. Hidalgo County, Texas, a subtropical area of about 1,000,000 acres, was chosen as the base unit from which data were collected and analyzed. Preprocessing steps for ERTS-1 data have been refined and algorithms for rapid analysis, display, and tabulation have been implemented. Leading crops can be characterized for the subtropical test county by ground surveys and space data acquired in December and January or May; certain crops (citrus, cotton and sorghum, and possibly vegetables as a composite category) and land uses (rangeland, cropland, and idle land) can be inventoried from space; and chlorotic (iron deficient) sorghum areas larger than 2.8 acres (1.1 hectares) can be identified in otherwise uniform fields.

Further studies should make possible the development of models to relate ERTS-1 multispectral scanner measurements with plant canopy parameters because the relations discovered among plant parameters and multispectral scanner digital counts promise to advance efforts to identify crops at immature stages of development and to assess vegetative vigor and cover of crops that will be helpful in relating space observations to crop yields.

CONTENTS

ILLUSTRATION

FIGURES

TABLES

ABBREVIATIONS

ANOV	Analysis of Variance
ARS	Agricultural Research Service
CCT	Computer Compatible Tape
CRT	Cathode Ray Tube (dark-trace storage-type)
EREP	Earth Resources Experiments Package
ERTS-1	First Earth Resources Technology Satellite
K-M	Kubelka-Munk
LAI[a/]	Leaf Area Index
MSS	Multispectral Scanner
NASA	National Aeronautics and Space Administration
NDPF	National Data Products Facility
SCS	Soil Conservation Service
SRS	Statistical Reporting Service
TCLRS	Texas Crops and Livestock Reporting Service
USDA	United States Department of Agriculture
WLI	Wavelength Interval

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a/ LAI is the ratio of total leaf area of plants to ground area occupied by plants.

INTRODUCTION

The work planned under this contract had three stated objectives:

1. To compare experimental results using ERTS-1 data with predictions of analytical models for interaction of light with vegetation.

2. To determine the seasonal changes of the various crops and soils in Hidalgo County, Texas, and discriminate among them by means of reflectance measured from ERTS-1.

3. To gain experience developing an operational system of satellite data analysis to fit the needs of the USDA.

The objectives can be logically grouped into substudies in the following categories:

1. Crop vigor and potential crop yield

   a. Relation to LAI and to MSS signal strength
   b. Chlorosis detection (iron deficiency)
   c. Crop vigor categories within crops and their relation to yield.

2. Crop discrimination

   a. Cotton versus sorghum
   b. Among vegetables
   c. Optimum time of year to discriminate citrus
   d. Dominant rangeland plants
   e. Rangeland condition.

3. Soil

   a. Bare versus cropped land
   b. Major soil types
   c. Spectral contrast between freshly irrigated and non-irrigated soil
   d. Spectrum of saline soil and distribution of salt-affected soil.

The crop vigor and potential crop yield studies are based on laboratory and aircraft experience that resulted in an understanding of the interaction of light with vegetation and the subsequent definition of most useful wavelengths for indicating physiological plant stress and for discriminating among crop genera. Analytical models were also produced relating reflectance to crop vigor and LAI.

The second and third groups of studies are based on computer identification procedures. Procedures developed using film optical densities and aircraft scanner data were refined and applied to ERTS-1 data.

PROCEDURES

Ground Data Collection

Hidalgo County, Texas, has been chosen as the base area from which data are collected and analyzed. The county was chosen as the base unit because this is the governmental unit by which agricultural census data are collected and summarized, and it is the unit by which crop allotment and acreage restrictions are most commonly administered.

Because of the need for extensive ground truth representative of the county to use as a basis for comparing the reliability and accuracy of the ERTS-1 data interpretations, statisticians of SRS, USDA, were asked to design a sampling procedure for the county that would allow a valid summary of data for the county from the sample. Hidalgo County contains three major agricultural areas that may be designated as northern, central, and southern. The northern region is mainly pasture and rangeland with a little irrigated farming located around local water supplies. The central region is practically all irrigated. The cultivated land is generally broken into small fields--typically medium-textured terrace soils devoted to mixed field and vegetable row-crops, citrus, and miscellaneous farm enterprises. The southern region of Hidalgo County is generally fine-textured soil that is used extensively for winter vegetable production. The majority of land in the southern region is irrigated. Urban and other non-agricultural areas are found mainly in the central region. The urban areas are not included in the survey.

The sampling procedure used divided the county into 1,000-acre segments in the northern region, 160-acre segments in the central and southern regions, and assigned each segment a number. By the random start and increment method, four interpenetrating samples of 43 segments each were selected. These were distributed through all three regions. Four more interpenetrating samples were selected, but only segments located in the southern region were designated sampling sites. These 25 additional segments in the southern region were chosen because of the concentration of winter vegetables in the southern region when few crops are growing in the other regions. A total of 197 sampling segments was chosen from the 3,927 segments listed for the county. The sampling area is thus approximately 4% of the total area.

Each of the 197 segments was located on a base aerial map of the county and assigned a unique number designation. Each field in each segment was ground-truthed and numbered. Fields are, by definition, areas operated as separate units. The number of fields fluctuates slightly. The total number of fields ground-truthed for each satellite pass was approximately 1,400.

After each sample segment was visited, the field information was coded by the technician in charge of ground-truthing and recorded on 80-column computer punch cards. The data on the computer cards were later edited and stored on magnetic tape for use in the analysis of the satellite data. A print-out of these tapes was given to the ground truth personnel. The magnetic tapes and computer cards are stored in separate buildings to minimize chances of data loss.

Considerable information of agricultural importance can be extracted from these ground truth data; however, the main reason for collecting such a complete set of records is their use as an independent data set to judge the reliability and accuracy of the county-wide interpretation of ERTS-1 data. Such data also provide the training and test fields used in computerized recognition algorithms.

Ground truth information was obtained on several items pertaining to crops, crop histories, and farming practices by interviewing approximately 400 land operators or managers. Typical ground truth included crop species, stage of maturity, row spacing, plant height, percent ground cover, row direction, Munsell color of soil, recent cultural practices such as tillage, irrigation, harvest, defoliation, and such additional qualitative information as notes on weediness, general plant vigor, and plant stand.

Weslaco ERTS-1 Data Analysis System

The NDPF provided MSS radiometrically scene-corrected digital counts (ERTS-1 Data Users Handbook) recorded on four CCT's for a 100 by 100 nm area, including Hidalgo County where detailed ground truth were available for evaluation of ERTS-1 agricultural surveys. All four of the ERTS-1 MSS bands were used covering the 0.4- to 1.1-μm spectral region. Ground truth in the county was compiled from 197 sample segments containing approximately 1,400 fields that comprise the statistical sample for ERTS-1 crop, soil, and water reflectance studies in Hidalgo County conducted by the USDA at Weslaco, Texas. Ground truth provided actual crop and soil field condition status and identity at the time of each ERTS-1 overpass as well as acreage of each field.

Computer compatible digital tapes from the NDPF were displayed on a CRT, and a coordinate system was overlaid to aid in locating the 1,400 fields in Hidalgo County. Digital data were selected for each ERTS-1 MSS band from the CCT for each of the 1,400 test fields. The average digital values for each field and band were determined for use in test and training field selection procedures.

The average digital values from the sample fields for ERTS-1 MSS bands 5 (0.6 to 0.7 μm) and 7 (0.8 to 1.1 μm) were displayed in a scatter diagram format to determine the major distinguishable categories. Training fields were chosen (from the 1,400 available fields) that would be representative of these distinguishable categories (Driscoll et al., 1972). The computer was programmed to classify these categories, using ERTS-1 MSS data from the training fields, by determining the mean vector and covariant matrix for each category that is used in a maximum likelihood classifier (Fu et al., 1969). The optimum channels to be used in the classifier were determined using a channel (ERTS-1 MSS bands) optimization program CHOICE (Jones, 1973). The classifier and optimum bands were then implemented in a table look-up procedure suggested by Eppler (Eppler et al., 1971).

Classification and acreage estimation results were reported using Anderson's land use classification scheme (Anderson et al., 1972). Four level one categories (urban, agriculture, rangeland, and water) and various level two categories such as vegetables, citrus, cotton and sorghum, idle cropland, dry debris, grass, mixed shrub, and non-agriculture were considered. Ground truth was not available for level one urban and water categories, but classification and acreage estimation results were usually developed for all categories with ground truth. Idle cropland was resolved into McAllen--Brennan and Harlingen, Mercedes--Raymondville soil association categories.

A classification (land use survey) was determined for every pixel or resolution element (849,000 pixels in January and 948,000 pixels in May of 1973) in Hidalgo County, and a comparison was made, using Student's t-test, between actual[a/] and computer acreage estimates of Hidalgo County for level one categories agriculture and rangeland, and level two categories vegetable, citrus, cotton and sorghum, idle cropland, grass, and mixed shrub. A ratio of actual to computer acreage estimates was also provided to aid in comparing results.

A line printer recognition map of the county land use survey was also generated. The county was divided into successive 5 x 5 pixel matrices (25 pixels per matrix). Each matrix was classified by the category having the majority of pixels (out of 25). The final line printer recognition map of the county was derived by printing a symbol for every other matrix of every other line of the matrix classification map so that a classification map with a resolution of 115.5 acres per pixel was created. The final classification map is a 100 to 1 reduction of the original ERTS-1 MSS data as delivered by the NDPF.

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b/ Actual data are synonymous with the county estimate from the sample of 1400 fields that were ground-truthed for the county.

The processing steps used by the Weslaco data analysis system are:

1. Determine ERTS-1 CCT Data Quality

   A section of each of the four ERTS-1 CCT's received from NDPF are displayed on the DICOMED M36 CRT using each band (MSS 4, 5, 6, and 7) to check for data quality (RANGE)[c/]. If data quality is good, the original CCT's sent from NDPF are copied and the duplicated tapes are used as working copies (MCOPY). If data quality is judged not good (from visual CRT interpretation), then the tapes are sent back to the NDPF for reprocessing, or the scene is reordered from NDPF.

2. Merge ERTS-1 CCT For Study Area

   Portions of the working tapes covering the study area (Hidalgo County) are merged onto another tape so that all data for Hidalgo County is readily accessible on one tape (MERGE). Usually, the study area is contained on three CCT's that are merged onto one CCT (Merged tape).

3. Subdivision of Merged Tape

   The study area on the merged tape is subdivided into smaller areas that are of the right width to be displayed on the computer line printer as gray maps by defining magnetic tape coordinates (record number and word count) for these smaller areas that are roughly estimated from ERTS-1 transparencies, allowing for some overlap between areas.

4. Generate Gray Maps

   The digital ERTS-1 MSS data for these subdivided areas are stored on another magnetic tape (segment tape) using a computer program called TEST5. Another program (GRMAP) is used to read this tape and generate the gray maps for image interpreters to use in locating the 197 test segments in the complete Hidalgo County study area. The gray map symbols are usually based on the digital value range of MSS band 5 with MSS band 7 overriding MSS band 5 when water bodies are present.

[c/] Computer program name.

5. Location of Training and Test Fields

Image interpreters locate training and test fields, within the 197 county segments, using ground truth for every field, high altitude aircraft photomosaics with the 197 county test sites marked, ERTS-1 transparencies, and line printer gray maps of the segment tape. The segment magnetic tape and coordinates of each field within the 197 segments are determined from the line printer gray maps and punched on cards along with ground truth identification segment numbers. A computer program (SELT4) is used to create a third magnetic tape (field tape), containing only the MSS digital data selected from training and test fields by using the segment tape and field coordinates on punched cards. Most of the effort in this data processing step is used in image interpretation to locate segments and fields.

6. Select Training Fields

After the test and training fields have been selected and recorded on a third digital magnetic tape (field tape), a large library of statistical programs is available to analyze these data.

One program (SSNCH) is used to calculate means, standard deviations, degrees of freedom, maximum and minimum values, and the range for each of the selected fields using the field tape, and it automatically stores these basic statistics on computer disks for other statistical analyses.

Selection of training fields is accomplished using program SCATT that generates a two-dimensional scatter diagram using means determined from SSNCH and ground truth stored on disk.

Another program (PURE1) is used to locate selected training fields from each field's tape for use in pattern recognition programs. One pattern recognition program (CENSR) has the ability to censor outlying data values for each training category and retain only data values that are correctly classified for each training category. As many censoring iterations as needed can be performed until recognition results for training data are high enough for use with test fields.

7. Select Best Channels

Two programs are being used at Weslaco for evaluation of ERTS-1 MSS channels. One program (FACTO) determines the number of major components of variability (factors) present in the original number of MSS channels. The second program (CHOIC) selects the best 2 or 3 channels (user option) by five divergence critera that will optimally distinguish among a given set of land use categories.

8. Classify Test Fields

Once the training data have been edited and the best channels selected, the resulting training statistics are further evaluated by classifying test fields using a table look-up program (LOKUP), based on procedures developed by Eppler (Eppler, 1971). The table look-up program is a procedure for speeding up the maximum likelihood classification rate by an order of magnitude over previous programming approaches. If the recognition results are not high enough, then it may be necessary to reselect training fields that are more representative and begin the whole process over again.

When test field recognition results are satisfactory, acreage estimates can be developed for the crop and soil categories used, and larger study areas can be classified.

9. Classify Study Area

All ERTS-1 MSS pixels in the complete Hidalgo County study area are classified using a program (DISC) based on the table look-up procedure. A classification map and acreage estimates are the two main outputs of this program.

Image Processing Programs.--The following programs have been developed for image processing:

1. Program RANGE - Displays either ERTS-1 CCT's or merged tapes in either actual or extended digital count range and overlays a grid that is referenced to the MSS data on the ERTS-1 CCT or merged tape.

2. Program COPY - Copies ERTS-1 CCT's to a set of other tapes for back up purposes.

3. Program MERGE - Combines an area on three ERTS-1 CCT's into one merged tape to eliminate the splitting of study area between ERTS-1 CCT's.

4. Program TEST5 - Reads data from either ERTS-1 CCT's or merged tape of quadrilateral defined areas (called sectors) determined from ERTS-1 imagery and records only these areas on a secondary tape for further processing.

5. Program GRMAP - Makes a line printer gray tone map of the area on secondary tapes by assigning print-out symbols to user selected digital count ranges found in these areas.

6. Program SELT4 - Creates a third tape (fields tape) from the secondary tape by using quadrilateral defined areas for each field obtained from gray maps.

7. Program SSNCH - Prints out selected areas (either of sectors or fields as found on secondary or third tapes, respectively) and calculates basic statistics (mean, standard deviation, maximum, minimum, range, and distribution) for each area or field and channel.

Pattern Recognition Programs.--The following programs have been developed for pattern recognition:

1. Program SCATT - Generates a two-dimensional scatter diagram of the mean digital MSS data from aircraft or spacecraft sensors to study MSS data groupings and select training fields.

2. Program PURE1 - Reads digital field tape and locates training fields determined from a two-dimensional scatter diagram and records training data on temporary disk file for use with pattern recognition programs.

3. Program CENSR - Censors outliers in each training category using the maximum likelihood ratio pattern recognition classifier.

4. Program FACTO - Determines the number of major components of variability that exist in the original number of aircraft or spacecraft MSS and calculates principal axis factor weights that optimally represent most of the variation in the ERTS-1 data.

5. Program PLOT - Generates a scatter diagram, using the first two principal components determined by FACTO, for further study of training data groupings.

6. Program CHOIC - Selects the best 2 or 3 channels (user option) out of the total number of MSS channels available by five divergence criteria.

7. Program LOKUP - Classifies test fields selected from Hidalgo County stored on a field CCT and develops pattern recognition classification results on per field and per pixel bases.

8. Program DISC - Classifies all ERTS-1 MSS data in Hidalgo County and develops acreage estimates for each training category on a per pixel basis.

Three-Dimensional Display of ERTS-1 Data.-- Two methods have been developed to present ERTS-1 MSS signal strengths in three dimensions. One method displays the points in a two-dimensional drawing representing the distribution three variables would take in three-dimensional space. The proportions and angle of perspective are adjusted to match the limits of a single page of computer printout. Both ends of a rectangular box are drawn by the computer, and the edge lines are indicated on the drawing. Data points are located within the box in proportion to their vector lengths along the X, Y, and Z axes. The vectors along the three axes can represent signal strength, ratios between signal strength, numerical differences between signals, variation from the mean signal strength, or proportion of the total signal strength from each channel. Any of the three axes can represent any of the desired variables.

The data for the ground-truthed areas in Hidalgo County are grouped into categories that represent similar ground cover. For example, one grouping used is: vegetables, citrus, forage, weeds, field crops, bare soil, harvested fields, and non-agricultural areas. A three-dimensional diagram can be generated from each category, or any combination of categories.

The completed scatter diagram shows the relation between the three variables chosen. The center of the cluster of points for each category is indicated by a distinctive symbol so the center of the various clusters can be compared with clusters formed by other categories.

The other three-dimensional technique is a cubic histogram in which the three edges of a cube are ratioed to three variables similar to the isometric drawing. The cube is divided into cells arranged in rows, columns, and layers along the three axes. The number of data points falling into each cell within the cube is counted as the data are read by the computer. When all data points have been read, each layer of the cube is printed as a two-way histogram with the number of data points in each row and column shown for each layer.

Where the data are divided into multiple categories, two cubes are generated simultaneously. One cube contains the number of data points falling in each cell; the other lists the categories having data falling in each cell. The two cubes are printed side-by-side, layer-by-layer, making it possible to locate clusters of data points along the three axes and to tell which categories are represented in each cell. Clusters of data points and their distribution pattern are thus readily apparent as well as overlapping of clusters and the categories included in the overlapping.

Digital Data Display

A paper entitled "System of Digital Display Subroutines (SODIDS)" has been prepared by R. J. Torline.

Prior to the contract period, it was realized that some means of displaying the CCT's of ERTS-1 data would be necessary for humans to interact with them to edit them, select training sites, etc. In conjunction with a DICOMED Model 36 Display, an operational System of 25 Digital Image Display Subroutines (SODIDS) has been developed. These subroutines provide a tool for the interaction among user, digital image display, and computer. The use and function of the subroutines are described in the above paper.

Crop and Soil Category Determination and Training Field Selection

A paper entitled "ERTS-1 Crop and Soil Category Determination and Training Field Selection" has been prepared by A. J. Richardson, C. L. Wiegand, M. R. Gautreaux, and R. J. Torline. An abstract follows:

One of the problems of automatic land use mapping of agriculture scenes is the difficulty in matching ground truth to spectrally distinctive agricultural discrimination categories (training field selection). Supervised and unsupervised training field selection techniques of crop and soil land use categories in Hidalgo County, Texas, were investigated using two-dimensional scatter diagrams to study ERTS-1 MSS data grouping structure of crop and soil categories.

The ERTS-1 MSS data used were average digital data corresponding to 1,290 ground-truthed fields (supervised method) in Hidalgo County on the January 21, 1973, ERTS-1 overpass, and average digital data determined from a one-pass clustering program (unsupervised method) for 25 clusters extracted from each of the northern, central, and southern regions of the county. Ground truth, consisting of crop identity, plant cover, plant height, crop and soil condition, and size of field in acres, were also obtained at the time of the overpass for each of the 1,290 fields.

Factor analysis and divergence channel optimization programs indicated that ERTS-1 MSS bands 5 (0.6 to 0.7 μm) and 7 (0.8 to 1.1 μm) were the best choices for the two axes of two-dimensional scatter diagrams used to study MSS digital data groupings of crop and soil categories in Hidalgo County, Texas. Two scatter diagrams, using average MSS digital data from supervised and unsupervised ERTS-1 MSS data sources, exhibited similar data grouping structure that correspond to crop and soil conditions in the county. Therefore, data groupings whose crop or soil identity were known in terms of ground truth in the unsupervised scatter diagram could be identified by association to corresponding data groupings in the supervised scatter diagram whose identity were known in terms of ground truth. Thus, these results indicate that scatter diagrams plotting MSS digital averages from unsupervised clustering programs could be used to select representative training fields with only a minimum amount of ground truth required to identify groupings within the data.

Two-dimensional scatter diagrams, using ERTS-1 MSS average digital data from either supervised or unsupervised data collection methods, allow the investigator to efficiently determine distinguishable groupings of ERTS-1 MSS data and to select the most representative members of these groups as training data. Results indicate that unsupervised clustering programs provide the most efficient approach to training field selection because of their minimum ground truth requirements.

A Quadrilateral Algorithm for Image Processing

A paper entitled "A Quadrilateral Algorithm for Image Processing" has been prepared by A. J. Richardson and M. R. Gautreaux. An abstract follows:

A mathematical algorithm has been developed, based on quadrilaterals, that can be used to instruct a digital computer to efficiently find digital data, of a particular ground area of interest, recorded on magnetic tape. The use of this algorithm in conjunction with a DICOMED D-36 CRT Display permits efficient search of digital data from MSS sources such as the NASA 24-channel, ERTS-1 4-channel, and EREP 13-channel scanners.

RESULTS

Simultaneously Acquired Aircraft and ERTS-1 MSS Data Comparison

A paper entitled "Land Use Classification and Ground Truth Correlation from Simultaneously Acquired Aircraft and ERTS-1 MSS Data" has been prepared by A. J. Richardson, M. R. Gautreaux, R. J. Torline, and C. L. Wiegand. An abstract follows:

MSS data simultaneously collected by the NASA 24-channel MSS (flown at 10,000 feet, 3.048 km) and by ERTS-1, 4-band MSS on January 21, 1973, were used to compare crop recognition results and acreage estimates.

Optimum channel selection programs selected aircraft channels 3, 5, and 8 (0.466-0.495 μm, 0.588-0.643 μm, and 0.770-0.810 μm, respectively) and spacecraft channels 4, 5, and 7 (0.5-0.6 μm, 0.6-0.7 μm, 0.8-1.1 μm, respectively) as the best channels for distinguishing among five training categories: Carrot, cabbage, onion, broccoli, and mixed shrubs. Actual test field recognition results were based on vegetable, rangeland, bare soil, and water categories. Correlations among aircraft, spacecraft, and ground truth data (plant cover, maturity, height, and condition) indicated that aircraft and spacecraft MSS data agreed more closely than either data source agreed with ground truth data. Aircraft MSS data were related slightly better than spacecraft MSS data to ground truth data. On a per field basis, overall recognition performance using data for 94 agricultural test fields (Table 1), was low for both aircraft and spacecraft data (61.8 and 62.8%, respectively). When classifications were limited to vegetable fields larger than 10 acres and with plants taller than 25 cm, recognition results for vegetables improved to 88.9 and 100.0% for aircraft and spacecraft, respectively. Thus, the main difficulty in recognizing vegetable fields was that fields with little vegetative cover and short plants were misclassified as bare soil, the category they most spectrally resembled.

Both spacecraft and aircraft acreage estimates for one aircraft flight line (61.6 square km) and 94 test fields, indicated that spacecraft agricultural surveys are as reliable as aircraft agricultural surveys, although aircraft and spacecraft MSS data acreage estimates did not agree closely with ground truth acreage.

Table 1. Classification results for a common set of 94 aircraft test fields using MSS data for January 21, 1973. Results are given on a per field basis using a majority rule classification procedure for each field.

		AIRCRAFT CLASSIFICATION RESULTS				
Classification category	Total	Vegetables	Immature crops and mixed shrubs	Bare soil	Threshold*	Percent Recognition
Vegetables	28	14	4	10	0	50.0
Immature crops and mixed shrubs	19	8	6	4	1	31.6
Bare soil	47	1	8	38	0	80.8
Total	94	23	18	52	1	61.8

		SPACECRAFT CLASSIFICATION RESULTS				
Classification category	Total	Vegetables	Immature crops and mixed shrubs	Bare soil	Threshold*	Percent Recognition
Vegetables	28	14	5	9	0	50.0
Immature crops and mixed shrubs	19	4	4	9	2	21.0
Bare soil	47	2	0	41	4	87.2
Total	94	20	9	59	6	62.8

* Any field not classified as any of the three training categories were placed in an "other" category called "threshold."

ERTS-1 Aircraft Support Data Analysis

A paper entitled "ERTS-1 Aircraft Support, 24-Channel MSS CCT Experiences and Land Use Classification Results" has been prepared by A. J. Richardson, M. R. Gautreaux, and C. L. Wiegand. An abstract follows:

MSS data collected by the NASA 24-channel MSS on July 26, 1972, (Mission 207) over the USDA, Research Farm at Weslaco, Texas, were used for agricultural land use investigations. MSS data from 24 areas of the Research Farm were selected for crop, soil, and water discrimination studies.

The standard error of estimate for each of the 24 channels for a very uniform surface (a water reservoir) was used as an indicator of electronic noise. By this criterion, channels 22 (12.0-13.0 μm), 20 (10.1-11.0 μm), 15 (4.50-4.76 μm), and 21 (11.1-12.0 μm) were of low quality. More odd than even value digital counts were found in all channels, and it was concluded that the data were really seven bit precision. As expected, signatures for diverse areas such as water, highway, roof tops and bare soil differed from those of vegetal categories. Among vegetal categories, sugarcane and cotton had distinctive signatures that distinguished them from grass and citrus. An optimum channel selection program selected channels 7 (0.72-0.76 μm), 8 (0.770-0.810 μm), 3 (0.466-0.495 μm), and 18 (8.8-9.3 μm) as the best four channels for distinguishing among seven vegetation categories: Stoneville 213 cotton, Anton SP-21 cotton, Valencia orange, Red blush grapefruit, sugarcane, coast-cross 1 bermudagrass and African stargrass. These same channels also distinguished the nonvegetal categories satisfactorily. Classification accuracies improved to about 81% when the intra-plant genera categories (such as the two cotton varieties) were combined into one. Most misidentifications were among vegetation categories. Acreage estimates from the number of resolution elements in the categories agreed well with field sizes and acreages estimated from aerial photographs for categories with few misidentifications.

ERTS-1, 4 Channel MSS Signatures and Land Use Classification Results

A paper entitled "ERTS-1, 4 Channel MSS Signatures and Land Use Classification Results" has been prepared by A. J. Richardson, M. R. Gautreaux, and C. L. Wiegand. An abstract follows:

ERTS-1 MSS data from 292 fields in Hidalgo County were selected from the December 16, 1972, pass (scene 1146-16323) for crop and soil discrimination studies.

An editing process that censored outlying data values from each training category increased correct classification of the training set from 89.6 to 98.1%. The edited data were then used in an optimum channel selection program. Channels 5 (0.6-0.7 μm), 6 (0.7-0.8 μm), and 7 (0.8-1.1 μm) were the best three channels for distinguishing among seven training categories: bare soil, carrots, cabbage, tomatoes, mixed grasses, mixed shrubs, and citrus. Classification results from 292 test fields, using the training statistics for the seven training categories, indicated that only three broad categories could be distinguished: vegetables, citrus, and a category composed of immature row crops, bare soil, weeds, and grasses. On a per field basis the overall correct recognition for these three categories was 80.1%. For fields with a 0 to 40% plant cover, recognition results were low for vegetables and citrus (20.0 and 50.0%) and high for bare soil (87.4%). For fields with 40 to 100% plant cover, recognition results were higher for vegetables and citrus (100.0 and 65.0%, respectively) and 80.4% for the group of fields composed of weeds, mixed grasses, and mixed shrubs (80.4%). When stratified according to size, fields in the 0 to 20 acre range were most poorly recognized (74.1%). The 20 to 40 acre fields were recognized more often (81.1%), probably because training fields were in the 20 to 40 acre range. The 40 to 100 and 100 to 1,000 acre fields had overall correct recognitions of 79.1% and 92.9%, respectively.

Shadow Contribution to MSS Digital Counts

In addition to the plant parameters LAI, plant population, plant cover, and plant height, the shadows cast by plants should influence the MSS digital counts. A model has been developed that uses sun azimuth and elevation, row direction (angle), and plant height to estimate the amount of interrow area viewed by the sensor that would be shaded by row crop plants.

Fractional shadow is defined in terms of plant and sun geometry by

$$fs = \frac{PH \circ SIN/\theta - \emptyset/}{RW \circ TAN\ (\alpha)}$$

wherein PH is plant height, θ is sun azimuth east of true north, $\emptyset$ is row azimuth east of true north, RW is row spacing, and α is sun altitude above the local horizon.

Multiple regression equations have been developed relating the MSS digital counts for the May 27, 1973 (scene ID 1308-16323) overpass to LAI, plant population, plant cover, plant height, and shadow. The proportion of the MSS digital count sum of squares explained by the plant parameters alone and by the plant parameters plus the shadow term are as follows:

Crop	Band	Plant parameters alone	Plant parameters plus shadow	Plant parameters, except LAI, plus shadow	Plant parameters, except plant population, plus shadow
Cotton	4	0.899	0.952	0.818	0.935
	5	.853	.854	.754	.805
	6	.934	.951	.922	.942
	7	.959	.962	.949	.893
Sorghum and Corn	4	.590	.795	.731	.762
	5	.653	.804	.826	.799
	6	.873	.890	.780	.828
	7	.782	.921	.753	.912

The R^2 values show that when plant parameters alone explained a low proportion of the variation, addition of a shadow term resulted in a very substantial improvement in the R^2 values.

When the LAI term was deleted, and the shadow term retained with the other 3 plant parameters (third column of R^2 values from left), less of the variation in digital count for cotton was explained than by the plant parameters alone. For corn and sorghum, the R^2 were larger in the visible (bands 4 and 5) when a shadow term was added and LAI was deleted, but were lower in the infrared (bands 6 and 7). Thus the shadow term helps most to explain the visible band response of corn and sorghum.

Plant Canopy Models

A paper entitled "Models for Extracting Plant, Soil, and Shadow Reflectance Components of Row Crops" has been prepared by A. J. Richardson, C. L. Wiegand, H. W. Gausman, J. A. Cuellar, and A. H. Gerbermann. An abstract follows:

The ERTS-1 MSS data and the measured geometry of sun and plant canopies were used to remove plant, soil, and shadow reflectance components of vegetated surfaces using three plant canopy models (Kubelka-Munk (K-M), a regression model, and a combination of the K-M and regression models).

The ERTS-1 MSS data used were average digital data for 3 corn, 10 grain sorghum, and 10 cotton fields in the scene of the May 27, 1973, satellite overpass. Ground truth, consisting of fractional crop cover, fractional shadow cover (determined from sun elevation, sun azimuth, row direction, plant height, and row width), and LAI were also obtained at the time of the satellite overpass.

In the reflective infrared portion of the spectrum (band 6, 0.7 to 0.8 μm; and band 7, 0.8 to 1.1 μm), the K-M model gave high reflectance values for mature corn and sorghum and low values for immature cotton that had a low LAI and ground cover. The K-M theory explained up to 84% of the variation in the band 6 and 7 composite reflectance of cotton.

The regression model did not express crop and soil reflectances well; it explained up to 69% of the variation in the observed reflectance in the visible (band 5, 0.6 to 0.7 μm) for corn and sorghum, but a maximum of only 56% in the reflective infrared (band 6, 0.7 to 0.8 μm) for cotton.

Combination of the K-M and regression models integrated the best features of each model. The combined model gave a higher correlation, in general, between composite canopy reflectance and ground truth than the first two models. It explained 86% of the variation in the visible light reflectance (band 5) of corn and sorghum and 90% of the variation in the reflective infrared (band 6) for cotton. The infinite plant canopy and soil reflectances determined from the combined model were reasonable for both corn and sorghum and cotton data. Shadow reflectances were more reasonable for young cotton with exposed interrow soil than for older corn and sorghum. Corn and sorghum averaged 72% ground cover, with their leaves touching between rows, making the contribution of shadows to reflectance more difficult to estimate for these two crops than for cotton that averaged only 30% ground cover.

(The full text is presented as Appendix A of this report.)

Leaf Area Index Prediction

Two plant canopy models, the Kubelka Munk (K-M) and combined K-M and regression models were used to predict LAI. Prediction of LAI has application to crop yield forecasting by relating LAI predictions from ERTS-1 MSS measurements to per acre crop yield estimations.

The ERTS-1 MSS data used were average digital data for 3 corn, 10 grain sorghum, and 10 cotton fields for the May 27, 1973, overpass. Ground truth consisting of fractional crop cover, fractional shadow cover (determined from sun elevation, sun azimuth, row direction, plant height, and row width) and LAI were obtained at the time of the satellite overpass. These data were used in a previous study (Appendix A) to determine the plant canopy model equation coefficients (optical constants a and b, soil reflectance Rg, and shadow reflectance Rs) that yield the best prediction of the composite plant canopy reflectance in terms of LAI, fractional crop cover, and fractional shadow cover for the K-M and combined plant canopy models. These equation coefficients were then used to evaluate the prediction of LAI in terms of composite plant canopy reflectance, fractional crop cover, and fractional shadow cover for both the K-M and combined plant canopy models, when the equations for each model were solved for LAI rather than composite plant canopy reflectance.

The correlation coefficient range for the K-M model ($R = 0.48$ to 0.91) was higher than the combined model ($R = 0.14$ to 0.86) for prediction of LAI from composite plant canopy reflectance, fractional plant cover, and fractional shadow cover. The correlation coefficient range for the K-M model ($R = 0.43$ to 0.92) was lower than the combined model ($R = 0.72$ to 0.95) for prediction of composite plant canopy reflectance from LAI, fractional plant cover, and fractional shadow cover (Tables 2 and 4, Appendix A).

These correlations show that the equation coefficients predict composite plant canopy reflectance better than LAI because these coefficients were optimized in the sense of least squares for predicting composite plant canopy reflectance. These results also indicate that the combined model yields a generally higher correlation when equation coefficients are optimum. The combined model correlations are degraded more when equation coefficients are not optimum because the model is more complex than the K-M model.

Models should be useful for forecasting crop yields when more optimal equation coefficients become available by development of complex partial differential coefficients for $\partial N/\partial a$, $\partial N/b$, $\partial N/Rg$, and $\partial N/Rs$ (where $N = LAI$) for least square curve fitting procedures.

Relation of ERTS-1 Digital Data to Vegetation Density

A paper entitled "Vegetation Density as Deduced from ERTS-1 MSS Response" has been prepared by C. L. Wiegand, H. W. Gausman, J. A. Cuellar, A. H. Gerbermann, and A. J. Richardson. An abstract follows:

Reflectance from vegetation increases with increasing vegetation density in the 0.75- to 1.35-μm wavelength interval. Therefore, ERTS-1 bands 6 (0.7 to 0.8 μm) and 7 (0.8 to 1.1 μm) contain information that should relate to probable yield of crops and animal carrying capacity of rangeland. On the other hand, reflectance from vegetation is typically less than from bare soil, and it is essentially constant in the visible wavelengths as vegetation density increases; consequently, the decreased response observed in ERTS-1 bands 4 (0.5 to 0.6 μm) and 5 (0.6 to 0.7 μm) as vegetation increases is mainly caused by vegetation obscuring soil reflectance. The ratio of band 5 to band 7 (5/7) or band 7 minus band 5 (7-5) are, in addition to bands 6 and 7, practical indicators of vegetative cover and density for users of ERTS-1 data.

The results of an experiment designed specifically to test the relations among LAI, plant population, plant cover and plant height, and the ERTS-1 MSS responses for 3 corn, 10 sorghum, and 10 cotton fields are also given. Because of clouds, only one ERTS-1 pass (May 27, scene 1308-16323) yielded MSS data and that for only bands 4, 5, and 6. The coefficient for the linear correlation between LAI and band 6 digital counts was 0.823** for the 10 cotton fields and 0.841** for the combined sorghum and corn fields. The correlation coefficient between LAI and band 6 minus band 5 digital counts was 0.888** for cotton fields and 0.768** for the corn and sorghum fields. The four plant parameters explained 87 to 93% of the variability in the band 6 digital counts and from 59 to 90% of the variation in bands 4 and 5. Plant population was as useful as LAI for characterizing sorghum and corn fields, and plant height was as good as LAI for characterizing cotton fields. These findings generally support the utility of ERTS-1 data for explaining variability in green biomass, harvestable forage, and other indicators of productivity.

(Note: When data for band 7 (0.8 to 1.1 μm) became available, the plant parameters leaf area index, plant population, plant height, and plant cover explained 95.9% of the variation in band 7 digital counts for cotton and 78.2% of the variation in digital counts for the combined crops sorghum and corn.)

MSS Individual Sensor Response Variability

A phenomenon called "banding" is observed in some ERTS-1 MSS imagery if one or more of the six sensors within a specific channel yields a signal sufficiently higher or lower, on the average, than the other sensors in that channel. The consequence is "bands" at regular intervals in the imagery. Thus, a study was conducted to find out if the six sensors within each channel actually responded alike.

The ERTS-1 MSS uses six sensors per channel to measure reflected radiance from scenes on the earth in each of four channels. These four channels (six sensors per channel) are sensitive over WLI's 0.5 to 0.6, 0.6 to 0.7, 0.7 to 0.8, and 0.8 to 1.1 μm. Since the ERTS-1 MSS senses the earth at a six scan line per sweep rate, each individual sensor forms a separate image scan line.

A uniform earth target, the Gulf of Mexico (May 27, 1973), was used as the MSS data source for a statistical experiment that was designed to test the null hypothesis of no difference among the six sensors within each channel using a simple randomized complete block ANOV. The experiment was replicated seven times (six sensors x four channels equals 24 total sensors per sweep (replication) of the ERTS-1 MSS with 25 pixels sampled per sweep). The 25 pixels per sweep were averaged within each sensor, channel, and replication to obtain the basic data for the experiment.

The ANOV was run separately for each channel to avoid unwanted interaction from natural differences among the four ERTS-1 channels. The F-Test among sensors was highly significant (0.01 probability level) for all four channels. The replications were not significant (0.01 probability level) in any of the four channels because the Gulf of Mexico water apparently gave a uniform response for each replication. Channels 4 and 5 had considerably lower calculated F's than did channel 6 or 7, indicating that the calibration and/or the digitizing process for channels 6 and 7 are more critical than for channels 4 or 5.

A Duncan's multiple range test was used to statistically rank the six sensor means within each ERTS-1 MSS channel. Within ERTS-1 channel 4, sensor 5 had a significantly different mean than all other sensor means in that channel. (There is no way of knowing which sensor is which, therefore, all sensors are relative to the first sensor used in ANOV.) Possibly this sensor was responsible for the "banding effect" for channel 4. Similarly, since sensor 5 in channel 5 (a different detector than sensor 5 of channel 4) was significantly different from all other sensors in that channel, it is possibly responsible for the "banding effect" in channel 5. Sensor 1 in channel 6 and sensors 1 and 6 in channel 7 also may have caused "banding effects."

The six sensors of channel 5 had the least variability indicating that channel 5 may be better than the other channels on the basis of uniform response among sensors. On that basis, channel 6 appears to be the worst channel, because every mean was statistically different from every other sensor mean.

The implications of this finding impact heavily on the results obtained in applying the data for discriminating among crops and differentiating among soils and soil conditions. It is evident that the non-uniformity in response of the six sensors per channel introduces variability in the spectral signature among individual pixels in the data. Consequently, the spectral differences have to be larger between any two categories to distinguish between them than if the sensor responses were the same. Subtle differences such as those between soil types become indistinguishable.

All the ERTS-1 MSS data from a scene could be preprocessed, as the Canadians are doing, to establish the mean for the whole scene for each sensor. Then the response of each sensor can be adjusted on a pixel by pixel basis to the mean response of all sensors or to one sensor in the mid-range of responses encountered. This procedure should improve overall recognition accuracy some, perhaps up to 10%. The disadvantage is that it adds a preprocessing step to the analysis procedures. If adjustments are incorrectly made, the data could be degraded rather than improved. Also, the procedure would be very time consuming.

Reflectance Differences Between Crop Residues and Bare Soils

A paper entitled "Reflectance Differences Between Crop Residues and Bare Soils" has been prepared by H. W. Gausman, A. H. Gerbermann, C. L. Wiegand, R. W. Leamer, R. R. Rodriguez, and J. R. Noriega. An abstract follows:

The objective was to find the best spectral waveband to remotely identify crop residues that reduce soil erosion by wind and water. Consequently, reflectance differences between crop residues and soils were studied, reflectance spectra of standing and littered crop residues were compared, and the utility of ERTS-1 MSS data for distinguishing soils with crop residues from bare soils was tested.

Laboratory spectrophotometric results indicated that the near-infrared waveband (0.75 to 1.35 μm) should be the best spectral region to distinguish crop residues from bare soils. Within this waveband, reflectance of crop residues for six crops was 15.3 to 24.5% higher than the reflectance of six respective soils.

Field spectroradiometric investigations were conducted using the 0.5- to 1.8-μm waveband. Crop residue littered on the soil had greater reflectance than bare soil. Standing crop residue gave lower reflectance than bare soil.

The ERTS-1 MSS digital counts (signal strengths) were statistically different between soils with and without crop residues more times (8 out of 12) for band 4 (0.5 to 0.6 μm) than for bands 5 (0.6 to 0.7 μm), 6 (0.7 to 0.8 μm), and 7 (0.8 to 1.1 μm), or for band ratios 4/7, 5/7, 4/6, and 5/6. In the majority of the comparisons for band 4, soils with crop residues had less reflectance than bare soils.

Present reflectance techniques are unable to distinguish quantities of crop residue on the soil, and better parameters are needed to describe crop residues.

Additional study of ERTS-1 MSS data relating crop residues to wind and water erosion susceptibility of the soil is merited.

Use of ERTS-1 to Detect Chlorotic Grain Sorghum

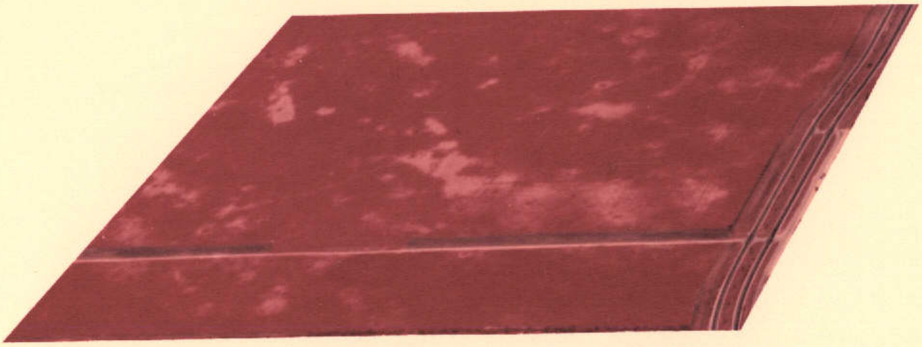
A paper entitled "Use of ERTS-1 to Detect Chlorotic Grain Sorghum" has been prepared by H. W. Gausman, A. H. Gerbermann, and C. L. Wiegand. A summary follows:

This study was conducted to determine if ERTS-1 MSS data could be used to detect differences in chlorophyll concentration between chlorotic (iron deficient) and green grain sorghum (*Sorghum bicolor* (L.) Moench) plants.

The upper oblique photo in Plate 1 is a positive print of an infrared transparency that readily shows the color difference between chlorotic and normal areas; chlorotic areas appear white, and normal areas appear magenta. Oblique photographs delineated chlorotic areas better than overhead photographs. The lower photo in Plate 1 depicts the computer printout for band 5 (0.6 to 0.7 μm). Although the difference in mean digital counts between the normal area and the largest chlorotic area was statistically significant ($p = 0.01$) for all bands (4, 5, 6, and 7), band 5 was selected because it contains the chlorophyll absorption band at the 0.65-μm wavelength; differences in mean digital counts were 5.3, 7.7, 7.2, and 2.4 for channels 4, 5, 6, and 7, respectively.

A comparison of encircled areas in the lower photo (Plate 1) with the chlorotic areas in the upper photo shows that most of the chlorotic areas can be identified on the computer printout of the ERTS-1 band 5 data. Chlorotic areas on the printout have higher digital counts (higher reflectance) than normal areas (see Plate 1 caption for explanation of symbols) because chlorotic plants have less chlorophyll than normal plants and, therefore, chlorotic plants absorb less radiation than normal plants at the 0.65-μm chlorophyll absorption band.

Chlorotic sorghum areas 2.8 acres (1.1 hectare) or larger were identified on the computer printout of band 5 data. This resolution is sufficient for practical applications in detecting chlorotic areas in otherwise homogeneous grain sorghum fields.



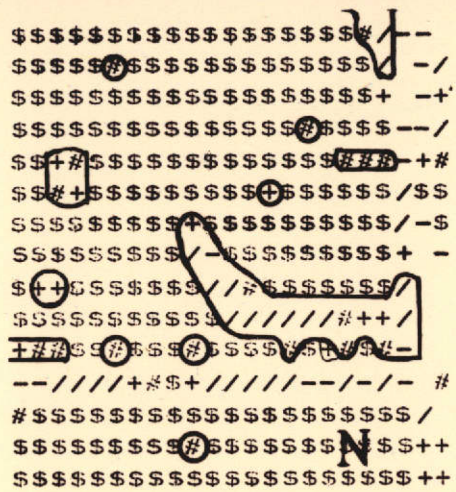


Plate 1. Upper photo is a positive print of an infrared transparency showing areas of white-appearing chlorotic sorghum and magenta appearing normal (N) sorghum. Lower photo is a printout of ERTS-1 band 5 data; chlorotic areas corresponding to those in the upper photo are encircled. Digital counts corresponding to the printout symbols are:

$ = 30 to 33, # = 33 to 36, + = 36 to 39,

/ = 39 to 42, - = 42 to 45, and blank = $\geq$ 45.

Acreage of Vegetables in Hidalgo County

A paper entitled "Acreage of Vegetables in Hidalgo County in 1972 and 1973" has been prepared by A. H. Gerbermann, C. L. Wiegand, and J. A. Cuellar. An abstract follows:

Ground surveys from the fall of 1972 through the spring of 1974 on approximately 1,400 fields in Hidalgo County provided a replicated sample that permitted calculation of county acreage estimates, and standard errors of the estimates, for 16 vegetable crops produced in the county.

Acreage estimates not previously available are listed in Table 2 for 7 crops (bean, beet, mustard greens, turnip, parsley, peas, and squash) along with comparative acreages for 9 others (broccoli, cabbage, carrot, cantaloupe, cucumber, lettuce, onion, green pepper, and tomato) that are estimated by TCLRS. The ground survey consistently overestimated the acreage of onion and tomato compared with TCLRS estimates, and the ground survey inadequately sampled the melon and potato areas of the northern and western parts of the county; however, it appears to yield representative estimates for about 15 vegetable crops. Since the acreage of citrus, cotton, grain sorghum and other commodities can be obtained from the same survey that yields vegetable acreages, there is merit in the various commodities jointly sponsoring such a survey; one in April for warm season crops and one in December for fall-planted crops would suffice.

Citrus Acreage of Hidalgo County

A paper entitled "Citrus Acreage of Hidalgo County by Varieties and Tree Age Groups" has been prepared by J. A. Cuellar, A. H. Gerbermann, and C. L. Wiegand. An abstract follows:

Ground surveys and ERTS-1 MSS digital data were used to estimate citrus acreage in Hidalgo County, Texas, for January 1973. The acreage estimates from these two sources were 89,000 and 81,000 acres, respectively. Interviews with managers or owners of 119 plantings were also conducted to obtain information on citrus acreage by early and midseason orange, late orange, and grapefruit categories and the age of the trees by 0 to 3, 4 to 7, and 8 year or older age groups. The interviews resulted in estimated acreages of 19,400 acres of early and midseason (Marrs, Hamlin, Pineapple, Jaffa, Navel) oranges; 19,000 acres of late orange (Valencia), and 46,600 acres of grapefruit (ruby red, star ruby, Marsh pink, and white). When plantings were grouped by age, results showed that ruby red grapefruit has been the overwhelming choice for recent plantings. None of the early orange varieties is popular, as indicated by no plantings in the 0 to 3 year old group, although Marrs oranges appeared popular several years ago as indicated by the number of groves in the 4 to 7 year old group. Grapefruit plantings appear to be continuing at a rate of about 3,000 acres per year. These findings should be valuable to the citrus industry for projecting nursery tree demand and for planning harvesting and marketing operations.

Table 2. Comparison of TCLRS and ARS ground survey estimates and standard errors of the estimates ($s_{\bar{x}}$) of vegetable acreages in Hidalgo County in 1972 and 1973, and ground survey estimates of spring-planted vegetables in 1974.

CROP	1972 (Spring & Fall) TCLRS estimates	1972 (Fall, only) Ground survey	1973 Spring & Fall TCLRS estimates	1973 Spring & Fall Ground survey	1974 (Spring, only) Ground survey
	Acres Harvested	Acres ± $s_{\bar{x}}$ Planted	Acres Harvested	Acres ± $s_{\bar{x}}$ Planted	Acres ± $s_{\bar{x}}$ Planted
Bean	--	2401±1589	--	1706±792	445±445
Beet	--	1399±791	--	945±570	Fall planted
Broccoli	1600	2555±1100	1100	1091±763	" "
Cabbage	9300	9698±2387	10700	13768±3513	" "
Carrot	11800	10546±3112	11200	10890±2260	" "
Cantaloupe	5400	796±796	5400	4581±1438	7645±1333
Cucumber	2800	992±651	2300	4346±2514	429±429
Lettuce	2300	3916±1425	1900	3145±1538	Fall planted
Mustard Greens	--	1864±862	--	540±399	" "
Turnip	--	1348±857	--	840±533	" "
Onion	10200	17667±3535	10600	13540±3422	" "
Parsley	--	187±187	--	861±487	" "
Peas	--		--	4869±2203	
Squash	--	441±441	--	940±448	0
Green Pepper	3200	1850±1116	2700	2716±1078	2118±880
Tomato	4200	4756±2354	2400	5025±1500	3178±1015

Description and Remote Inventory of Hidalgo County Rangelands

A paper entitled "Description and Remote Inventory of the Rangelands of Hidalgo County, Texas" has been prepared by J. H. Everitt, C. L. Wiegand, A. J. Richardson, and A. H. Gerbermann. An abstract follows:

Hidalgo County, Texas, was used as a test site for developing a data analysis system for investigating the feasibility of assessing agricultural land use and growing conditions using data acquired by ERTS-1. Although more noted for its production of vegetables, citrus, and field crops, there are large areas of rangeland in the county. The rangelands are comprised of three major range sites: deep sand, red sandy loam, and gray sandy loam. Botanical descriptions for each site are given.

ERTS-1 MSS digital counts were used to classify the county into major land uses. Rangelands were represented by the "mixed shrub" and "grass" categories. The remote inventory yielded an estimate of 470,000 acres in "mixed shrub" and "grass"; the acreage estimate from a ground survey was 450,000 acres. The categories "mixed shrub" and "grass" occurred also for naturally vegetated areas such as wildlife refuges, canal and road rights of way, rural homesites and for irrigated pastureland. These data indicate that useful range inventories are possible using spectral measurements from space.

Use, Management, and Productivity of Hidalgo County Rangelands

A paper entitled "Use, Management, and Productivity of the Rangelands of Hidalgo County, Texas" has been prepared by J. H. Everitt, J. A. Cuellar, C. L. Wiegand, and D. G. Akers. An abstract follows:

Data on the predominant animal species grazing the range, grazing pattern used, stocking rates, brush control practices, potential productivity, and forage species seeded to the range were obtained by owner-operator interviews, field observations, and SCS sources on a sampling of 41 management units, totaling 8,473 acres, in Hidalgo County, Texas. The data permitted a compilation of representative management practices and uses for the 350,000 acres of range in the study county. The range is used primarily for cow-calf operations, although wildlife management is an important consideration and source of income. Continuous year-long grazing was practiced on 18 management units (63% of acreage) and an intermittent or some type of rotational system was used on 23 units (37% of acreage). Brush control was practiced on 47% of the sampled acreage; mechanical control was practiced on 35% and chemical control on 12% of the sampled acreage. Buffelgrass was seeded to 21% of the total acreage. Little fertilizer is used. This information shows range management practices and uses for this portion of the South Texas Plains.

Field Size Distribution and Land Use in Hidalgo County, Texas

A paper entitled "Field Size Distribution and Land Use in Hidalgo County, Texas" has been prepared by R. W. Leamer and A. H. Gerbermann. An abstract follows:

Data on field size and land use from randomly selected sample areas show that the average field size in Hidalgo County, Texas, is 30 acres. In the northern, central, and southern geographical regions of the county, the average size is 160, 17, and 22 acres, respectively. The northern region is mainly devoted to range and pasture because of low rainfall and lack of irrigation water. The central region is a general farming and citrus growing area on medium textured soils where small fields predominate. The southern region fields are commonly used for production of winter vegetables on fine textured soils and warm season row crops.

Land Use Survey Comparison, January 21 and May 27

A paper entitled "Land Use Survey Comparison of Hidalgo County for January 21 and May 27, 1973 ERTS-1 Overpasses" has been prepared by A. J. Richardson, C. L. Wiegand, M. R. Gautreaux, and R. J. Torline. A comprehensive summary follows:

ERTS-1 MSS data collected on January 21 and May 27, 1973, were compared for land use survey investigations of agricultural categories in Hidalgo County, Texas. Classification and acreage estimation results were reported for the following land use categories: agriculture (vegetable, citrus, cotton, sorghum, and idle cropland) and rangeland (mixed grass and mixed shrub).

Optimum channel selection programs selected ERTS-1 MSS bands 4 (0.5 to 0.6 μm), 5 (0.6 to 0.7 μm), and 7 (0.8 to 1.1 μm) as the best combination to use for classification and acreage estimation studies for the January 1973, overpass. Bands 5, 6 (0.7 to 0.8 μm), and 7 were selected as the best ERTS-1 MSS band combination for the May 1973 overpass. Thus, ERTS-1 bands 5 and 7 are more important for distinguishing crop and soil categories than bands 4 and 6 that are alternatively of secondary importance depending on time of year and specific crop and soil conditions.

Classification Results.--Low classification results in January and May prompted investigations of the effects of field stratification by size, plant cover, and plant height on recognition results. It was found that the classification results for January and May improved when only fields greater than 15 acres, with more than 25% plant cover, and with plants taller than 30 cm were used. Application of this field stratification criterion improved classification results in January from 65.9% to 85.7% for agricultural categories and 60.7% to 78.1% for rangeland as compared with increases in May from 74.9% to 77.2% for agriculture and 51.5% to 73.7% for rangeland.

Idle cropland was the most reliably classified agricultural category in both January, 82.5% per field recognition, and May, 70.3% per field recognition.

Citrus was not as reliably classified in May (50.6% per field recognition) as in January (71.4% per field recognition) because in May citrus spectrally resembled cotton, sorghum, and the rangeland categories because of their phenological maturity. Thus, January is a better time of the year for classification and acreage estimation of citrus than May.

It was not possible to distinguish cotton from sorghum (crops grown in greater abundance in May as compared to January) according to cluster diagrams used to select training fields. Classification attempts to distinguish irrigated grown cotton and sorghum (24.2% and 25.4% per field recognition, respectively) and dryland grown cotton and sorghum (21.9% and 35.4% per field recognition, respectively) were not successful. Overall classification of cotton and sorghum (56.1% per field classification) was low because of their spectral resemblance to citrus and to each other.

Classification of vegetables (grown in greater abundance in January as compared to May) was low (50.0% per field recognition) because many vegetable fields were immature in January and were misclassified as idle cropland, the category they most closely resembled.

Classification results for rangeland in May (73.7% per field recognition) was lower than for January (78.1% per field recognition) because in May some areas of rangeland spectrally resembled citrus.

<u>Acreage Estimation Results</u>.--There was no significant difference (0.01 probability level) between actual and computer acreage estimates for agriculture and rangeland categories in both January and May. Thus, these two general categories are distinguishable at either time of the year.

In January there was no significant difference (0.01 probability level) between actual and computer acreage estimates for idle cropland, but there was a significant difference in May. The actual idle cropland acreage estimate (22,932 acres) in May seemed low and it is thought that the computer idle cropland acreage estimate (101,821 acres) is probably closer to the true figure.

Citrus actual to computer acreage estimate in January was in significant agreement (0.01 probability level), but the May computer acreage estimate was significantly higher than the actual acreage estimate. As was shown in the classification results, citrus spectrally resembled cotton, sorghum, and rangeland, thus making the complete county estimate for citrus high.

Agreement between actual and computer estimated acreage for vegetables was not significant (0.01 probability level) in January (not a significant crop in May). It is thought that the computer estimate is closer to the truth because much of the acreage actually counted as vegetables (ground truth) was immature and was probably classified as idle cropland--the category these fields spectrally resemble.

The combined cotton and sorghum actual and computer acreage estimate were in significant agreement (0.01 probability level) in May (they are not significant crops in January). If June or July cloud-free ERTS-1 coverage had been available, it may have been possible to develop accurate computer acreage estimates for cotton and sorghum individually because sorghum would be at the harvest stage by July and should have differed spectrally from cotton.

(The full text is presented in Appendix B of this report.)

SIGNIFICANT RESULTS AND PRACTICAL APPLICATIONS

A discrimination study was conducted that involved 11 out of 292 fields from the December 16, 1972, ERTS-1 overpass and six classification categories (bare soil, mixed shrubs, weeds, bell peppers, tomatoes, and citrus). A ratio of MSS bands 5 to 7 (5/7) and 5 to 6 (5/6) signals resulted in a correct recognition of 86.9% of the members of representative crop and soil conditions, compared with recognitions of 60.0, 64.1, 74.1, and 81.4% for bands 4, 5, 6, and 7 taken individually. Based on this result, a satellite channel ratio procedure has been developed that enhances line printer gray maps for more efficient experimental test site location in the CCT data.

Overall recognition of 94 agricultural fields using simultaneously acquired aircraft and spacecraft MSS data was 61.8 and 62.8%, respectively. Thus, these results indicate that spacecraft agricultural surveys are as reliable as aircraft surveys and typically provide more scene coverage. The main reason for low recognition results cited is that four of the five recognition categories used were vegetables (carrot, cabbage, onion, broccoli) that had low vegetative cover resulting in many misidentifications as bare soil. A thermal channel registered with the shorter wavelengths would, we believe, aid greatly in distinguishing bare soil from crops with low soil cover.

Because independent estimates were not available to compare with acreage estimates derived from ERTS-1 data, except for a few crops, an interpenetrating sample constituting 3.5% of Hidalgo County was ground truthed periodically. The crop or land uses and their acreages, respectively, as estimated from the interpenetrating samples, were: cotton, 119,104; sorghum, 168,161; mixed citrus, 53,954; oranges, 16,929; grapefruit, 13,863; rangeland, 137,845; and improved pastures, 57,169.

The majority of the rangelands of Hidalgo County, Texas, are used in cow-calf operations. Continuous year-long grazing is practiced on about 60% of the acreage and an intermittent or some type of rotational system on the rest. Mechanical brush control is used more than chemical control.

Ground surveys gave representative estimates for 15 vegetable crops produced in Hidalgo County. January 1973 ERTS-1 data estimated the acreage of citrus in Hidalgo County very close to the industry figure.

Combined Kubelka-Munk and regression models, that included a term for shadow areas, gave a higher correlation of composite canopy reflectance with ground truth than either model alone. Further investigation of these models seems merited for forecasting crop yield by relating LAI, fractional plant cover, and fractional shadow predictions from ERTS-1 type MSS radiance measurements to yield or to yield parameters such as total dry weight, plant population, and plant height. Yield estimates could be based on the portion of each pixel's response that is due to plant spectra in a system of three equations with three unknowns. (For more detail on the models, see Appendix A).

Channel optimization studies from December 16, 1972, January 21, and May 27, 1973, selected ERTS-1 MSS bands 5, 6, and 7; 4, 5, and 7; and 5, 6, and 7, respectively, as the best three channels for distinguishing among crop and soil categories in Hidalgo County. Thus, bands 5 and 7 are probably the best two ERTS-1 MSS bands for general crop and soil category classification, while bands 4 and 6 are alternatively selected as the third best band depending on the time of year and existing crop and soil conditions.

Forty percent of the fields in the test county (Hidalgo County) are smaller than 10 acres in size, but they occupy only 8.2% of the land area. Field size produced the strongest effect on classification results for both January, 1973, (54.2 to 84.3% overall correct recognition for all fields larger than zero to 100 acres in size) and May, 1973, (41.9 to 93.1% overall correct recognition for all fields greater than zero to 100 acres in size). When only fields that were larger than 15 acres in size or had more than 25% plant cover, or had plants taller than 30 cm were classified on a per field basis, January level I (agriculture and rangeland) category overall classification results improved from 73.0% to 84.3% and May level I category overall classification results improved from 70.2% to 76.0%.

A study was conducted in a 340-acre (139 hectare) field of grain sorghum (Sorghum bicolor (L.) Moench) to determine if ERTS-1 MSS data could be used to detect differences in chlorophyll concentration between chlorotic (iron-deficient) and green grain sorghum. Chlorotic sorghum areas 2.8 acres (1.1 hectares) or larger in size were identified on a computer printout of band 5 data which contains the chlorophyll absorption band at the 0.65 μm wavelength. ERTS-1 resolution is sufficient for practical applications in detecting chlorotic sorghum in otherwise uniform fields.

Complete classification of Hidalgo County in January and May, 1973, using ERTS-1 data indicate that accurate acreage estimation of citrus, vegetable, cotton and sorghum, idle cropland, and general agriculture and rangeland categories that are not significantly different from acreage estimates using conventional ground truthing procedures are feasible. Computer generated classification maps for January show that vegetable, citrus, rangeland, idle cropland, water, and an undefined (all other) category occupied 1.7, 8.2, 48.0, 36.3, 0.7, and 5.1% of the county land area, respectively. In May, cotton and sorghum, citrus, rangeland, idle cropland, water, and undefined or threshold categories occupied 28.5, 12.7, 41.8, 9.3, 0.4, and 7.3% of the county land area, respectively.

Reflectance of crop residues, that are important in reducing wind and water erosion, was more often different from bare soil in band 4 than in bands 5, 6, or 7.

Plant parameters (LAI, population, cover, and height) explained 95.9% of the variation in band 7 digital counts for cotton and 78.2% of the variation in digital counts for combined sorghum and corn crops. Hence, measureable plant parameters explain most of the signal variation recorded for cropland. LAI and plant population were both highly correlated with crop yields. Since plant population can be readily measured (or possibly inferred from seeding rates), it is a useful measurement for calibrating ERTS-1 type MSS digital data in terms of yield.

It was found that the outputs among the six sensors within an ERTS-1 band were significantly different statistically from each other within each of the four ERTS-1 bands. The individual sensors for band 5 had the least variation from the mean of the six sensors, and those of band 6 had the most variation. Improved recognitions might have resulted if the six sensors per band would have yielded the same outputs. Many of the spectral categories were not very distinctive spectrally so that the signal variability (noise) made subtle differences more difficult to recognize. Any advances NASA can make in improving future multisensor band MSS or in preprocessing to reduce the variability among sensors of a band would be helpful to investigators.

Weslaco's USDA personnel have developed considerable expertise and have made substantial progress toward defining elements of an operational data analysis system to meet USDA needs. Preprocessing steps for ERTS-1 data have been refined, and algorithms for analysis, display, and tabulation have been implemented and greatly speeded as compared with time estimates given in the Data Analysis Plan. It has been determined that the leading crops can be characterized for the test county (a subtropical area with year-around growing season) by ground surveys and space data acquired twice yearly, December and January or May; that certain crops (citrus, cotton and sorghum, and possibly vegetables as a composite category) and land uses (rangeland, cropland, idle land) can be inventoried from space; and that chlorotic (iron deficient) sorghum areas larger than 2.8 acres (1.1 hectare) in size can be identified in otherwise uniform fields.

The models developed relating the ERTS-1 MSS measurements with plant canopy parameters and the relations discovered among plant parameters and the MSS digital counts promise to advance efforts to identify crops at immature stages of development and to assess vegetative vigor and cover of crops that will be helpful in relating space observations to crop yields.

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APPENDIX A

MODELS FOR EXTRACTING PLANT, SOIL, AND SHADOW REFLECTANCE COMPONENTS OF ROW CROPS [1]

A. J. Richardson, C. L. Wiegand, H. W. Gausman,
J. A. Cuellar, and A. H. Gerbermann [2]

INTERPRETIVE SUMMARY

Earth Resource Technology Satellite (ERTS-1) multispectral scanner (MSS) data were used to develop three plant canopy models (Kubelka-Munk (K-M), regression, and combined K-M and regression models) for extracting plant, soil, and shadow reflectance components of cropped fields. The combined model yielded the best correlation of ERTS-1 MSS data with ground truth by accounting for essentially all of the reflectance of plants and of soil and shadow between plant rows. Principles presented in this paper can be used to improve crop yield forecasts and acreage estimations.

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[1] Contribution from Soil and Water Conservation Research, Southern Region, Agricultural Research Service, USDA, Weslaco, Texas. The work was supported in part by the National Aeronautics and Space Administration under contract No. S-70251-AG.

[2] Physicist, Soil Scientist, Plant Physiologist, Biological Technician, and Agricultural Research Technician, respectively, Agricultural Research Service, USDA, Weslaco, Texas 78596.

ABSTRACT

Multispectral scanner (MSS) data from Earth Resource Technology Satellite One (ERTS-1) and the measured geometry of sun and plant canopies were used to extract plant, soil, and shadow reflectance components (determined as relative response to maximum digital count in each ERTS-1 MSS band--4, 0.5 to 0.6 μm; 5, 0.6 to 0.7 μm; 6, 0.7 to 0.8 μm; and 7, 0.8 to 1.1 μm) of vegetated surface using three plant canopy models (Kubelka-Munk (K-M), a regression model, and a combination of the K-M and regression models).

The ERTS-1 MSS data used were average digital data for 3 corn, 10 grain sorghum, and 10 cotton fields in the scene of the May 27, 1973, ERTS-1 satellite overpass. Ground truth, consisting of fractional crop cover, fractional shadow cover (determined from sun elevation, sun azimuth, row direction, plant height, and row width), and leaf area index (LAI - ratio of total leaf area of plants to ground area occupied by plants), were also obtained at the time of the ERTS-1 overpass.

Soil and shadow between plant rows decreased the extracted plant reflectance (relative response) of immature cotton (49.1 and 53.1% relative response in ERTS-1 MSS bands 6 and 7) using the K-M model. The K-M model correlated LAI to ERTS-1 MSS measurements (explained 18.7 to 83.9% of the digital count variation in ERTS-1 MSS bands 4 to 7) better than the regression model correlated plant and shadow cover to ERTS-1 MSS measurements (explained 4.4 to 69.4% of the digital count variation in ERTS-1 MSS bands 4 to 7).

The combined model gave a higher correlation between composite canopy reflectance and ground truth (LAI, plant and shadow cover) than the first two models (explained 51.5 to 90.0% of the digital count variation in ERTS-1 MSS bands 4 to 7). It explained 86% of the variation in band 5 reflectance of corn and sorghum and 90% of the variation in band 6 reflectance for cotton. The extracted plant canopy reflectances for band 6 determined from the combined model were not decreased because of between row soil and shadow reflectance components for either the corn and sorghum (77.6 and 93.9% relative response in ERTS-1 MSS bands 6 and 7), or the cotton data (78.3 and 94.2% relative response in ERTS-1 MSS bands 6 and 7). Shadow reflectance values were more reasonable (less than plant and soil reflectance values) for young cotton with 30% ground cover that had exposed interrow soil than for more mature corn and sorghum with 72% ground cover that had leaves touching between rows making the contribution of shadows to the reflectance more difficult to estimate for these two crops than for cotton.

INTRODUCTION

Spectra from vegetated surfaces are a mixture of reflectances from plants, soils, and shadows (Gerbermann et al., 1969) that are created by the sun and by the plant canopy geometry. Intensity and spectral quality of solar irradiance (Gates, 1965), geometry of the plant canopy and the viewing system affect the radiance of vegetated surfaces (Suits, 1971; Smith et al., 1973). Driscoll et al. (1972) points out that crop and soil classification accuracy is affected by varying crop canopy geometry. Nalepka et al. (1973) showed that acreage estimates are degraded by spectra from non-uniform targets within individual resolution elements. Improved understanding of the effects of these factors would aid interpretation of multispectral data.

Radiance of vegetated surfaces will provide useful information to foresters, ecologists, and agriculturalists (Wiegand et al., 1973) interested in forecasting and estimating crop yields and productivity, mapping soil types, and estimating vegetation conditions (Houseman et al., 1966; Merewitz, 1974; Tucker, 1974).

In this paper, we use the composite canopy radiance (radiance reflected from a combined plant, soil, and shadow vegetabled surface), as measured by the multispectral scanner (MSS) aboard the Earth Resources Technology Satellite (ERTS-1), to statistically extract plant, soil, and shadow reflectance components of vegetated surfaces.

THEORY

Three statistical models for studying plant, soil, and shadow reflectance contributions to composite canopy reflectance of vegetated surfaces are presented.

Kubelka-Munk

The Kubelka-Munk model (K-M) (Allen and Richardson, 1968) relates leaf area index (LAI), the ratio of leaf area of plants to the ground area they occupy, to plant and soil reflectance contributions of the composite canopy reflectance.

$$M = \frac{1}{2 \text{ Log } b} \text{ Log } \left[\frac{(a - Rc)}{(a - Rg)} \frac{(1 - aRg)}{(1 - aRc)} \right]. \qquad (1)$$

Composite canopy reflectance (Rc) is measured from space and LAI (M = LAI) is measured in the field. A least square curve fitting process (see appendix) was used to determine optical constants (a and b), and the soil reflectance (Rg) component of the composite canopy reflectance. The reciprocal of optical constant a is the infinite plant canopy reflectance ($R_\infty = 1/a$), defined as the reflectance of an infinite thickness of plant leaves (Allen and Richardson, 1968). This model treats reflectance contributions of plants grown on a soil background, but not sunlit soil or shadows between plant rows.

The optical constants a and b can also be used to determine scattering (s), and absorption (k) coefficients, and the remission function (k/s) of the plant canopy (Allen and Richardson, 1968).

$$s = \frac{2a}{a^2 - 1} \log b, \tag{2}$$

$$k = \frac{a - 1}{a + 1} \log b, \tag{3}$$

$$\frac{k}{s} = \frac{(1 - a^{-1})^2}{2a^{-1}} . \tag{4}$$

Regression Model

Tucker and Miller (1974) and Wiegand et al. (1973) developed regression models that use biophysical characteristics (biomass, chlorophyll, and water content) and plant parameters (LAI, percent cover, and plant height), respectively, for extracting underlying soil contributions of the composite canopy reflectance. The form of this regression model is

$$Rc = A_0 + A_1 (X), \tag{5}$$

where Rc is composite canopy reflectance, A_0 is soil reflectance, and X is the biophysical or plant parameter characteristics. As indicated by the equation, soil reflectance is obtained as the reflectance intercept when the biophysical or plant parameter characteristic (green biomass, plant height, LAI, etc.) goes to zero.

In the present analysis, a regression model was developed, using plant canopy geometry, to partition composite canopy reflectance into plant, soil, and shadow components as shown in Figure 1 and as represented mathematically by the following relation,

$$Rc = fpRp + fsRs + (1 - fp - fs)\ Rg, \tag{6}$$

where fp - fractional plant cover,

fs - fractional shadow cover,

Rp - plant canopy reflectance,

Rs - shadow reflectance,

Rg - soil reflectance, and

Rc - composite canopy reflectance.

This model was developed to consider reflectance from soil and shadow between rows of cultivated fields (Allen et al., 1970a). There is no fractional ground cover term (fg) because this area is taken care of by the (1-fp-fs) term (ie; fg = 1-fp-fs).

Rearranging terms in equation (6) and rewriting we obtain,

$$Rc = Rg + (Rp - Rg)\ fp + (Rs - Rg)\ fs. \tag{7}$$

Equation (7) is of the same form as the standard multiple linear regression equation,

$$Rc = A_0 + A_1 fp + A_2 fs. \tag{8}$$

The following terms of equations (7) and (8) may be equated,

$$Rg = A_0, \tag{9}$$

$$Rp - Rg = A_1, \tag{10}$$

$$Rs - Rg = A_2. \tag{11}$$

Once the regression of composite canopy reflectance (Rc) on fp and fs is determined, Rg is evaluated using equation 9 and Rp and Rs are evaluated as follows,

$$Rp = Rg + A_1, \tag{12}$$

$$Rs = Rg + A_2. \tag{13}$$

Fractional plant cover for row crops is the ratio of canopy width to the row spacing (Figure 1). Derivation of the relation between fractional shadow (fs) and plant height (PH), sun elevation above the local horizon (α), sun azimuth east of true north (θ), and row direction east of true north ($\emptyset$) is given in the appendix.

The main limitation to equation (6), is that the (1 - fp - fs) term cannot be less than zero, the condition where the shadow of one row falls on the canopy of the next row. When this occurs (at large fp or small α), fs can be set equal to 1 - fp so that the (1 - fp - fs) term becomes zero in equation (6), eliminating the soil parameter Rg. In this case there is no reflectance from sunlit soil.

Combination K-M and Regression Models

A model was developed from a combination of the K-M and regression model that depends on LAI, fp, and fs to extract infinite canopy reflectance (R_∞), soil reflectance (Rg), and shadow reflectance (Rs). The soil and shadow components were assumed to be partitioned as in the regression model and expressed by fp and fs, but the canopy reflectance (Rp) is described by the K-M model as a function of LAI. Mathematically the combination is accomplished by substituting equation (1) into equation (6).

$$Rc = \frac{a(b^m - b^{-m}) - Rg\ (b^m - a^2\ b^{-m})}{a^2\ b^m - b^{-m} - Rga\ (b^m - b^{-m})}\ fp + Rsfs + (1 - fp - fs)\ Rg. \quad (14)$$

Where m is the LAI of the plant canopy (Figure 1). Equation (14) is equation (6) except that

$$Rp = \frac{a(b^m - b^{-m}) - Rg\ (b^m - a^2\ b^{-m})}{a^2\ b^m - b^{-m} - Rga\ (b^m - b^{-m})}\ , \quad (15)$$

is derived by solving equation (1) for Rc and setting Rc = Rp.

The justification for setting Rc = Rp, in equation (6), can be derived from the basic assumptions of the K-M and regression models. The K-M model, equation (1), makes the assumption that the composite reflectance Rc is equal to the canopy reflectance Rc at a fp corresponding to complete cover by plants on a soil background with reflectance Rg. Therefore, the K-M model applies strictly to only those fields, or parts of fields, with complete ground cover.

Since not all fields have 100% plant cover, the composite plant reflectance term (Rc) in the K-M model, equation (1), was set equal to the plant reflectance term (Rp) in the regression model, equation (6) that allows for reflectance from soil and shadow as well as plant cover. Once the substitution of equation (1) into equation (6) is made to derive the combined model expressed by equation (14), then Rp is eliminated and was not evaluated for this model. The regression model (equation 6) determined canopy reflectance (Rc) at some average LAI value while the K-M and combined model (equation 1 and 14) determines infinite canopy reflectance (R_∞) at LAI equal to infinity. Procedures used to evaluate optical constants a and b, and Rg for the combined model are given in the appendix. Instead of Rp the infinite reflectance ($R_\infty = 1/a$) was determined for the combined model even though they are not equal except for large values of LAI.

None of the models used here treats variation caused by directional reflectance as a function of view or sun angle as has been done in some other models (Suits, 1971; Smith, 1973). The regression and combined models account for shadow caused by plant geometry and sun angle only.

EXPERIMENTAL PROCEDURES

The ERTS-1 MSS digital data collected on May 27, 1973, (scene ID 1308-16323), for 3 corn, 10 grain sorghum, and 10 cotton fields provided the composite canopy reflectance data for this study. Center coordinates of ERTS-1 frame were 26° 02' north and 98° 01' west. Local time of ERTS-1 overpass was 10:32 CST. The average radiance for each field and band, expressed as digital counts, was ratioed to the maximum possible count for each band (127 for bands 4, 0.5 to 0.6 μm; 5, 0.6 to 0.7 μm; and 6, 0.7 to 0.8 μm; and 63 for MSS band 7, 0.8 to 1.1 μm; Table 1). This normalized or relative response is necessary for evaluation of model equations but it deviates from the definition of reflectance (the ratio of exident to incident radiation at a given wavelength).

Ground truth, summarized in Table 1, was also obtained at the time of the ERTS-1 overpass. Percent crop cover was determined for each field as the ratio of the average plant canopy width to the average row spacing, multiplied by a hundred. Four crop cover measurements were made in each field. Percent shadow cover was determined for each field using equation (20) (appendix), multiplied by a hundred, and the required plant and sun geometry are given in Table 1. Percent crop cover and shadow cover were used in fraction form for evaluation of plant model coefficients.

The LAI (Table 1) was determined from ten average-sized plants at each of eight sites in each field. The area of each leaf was determined by a photoelectric planimeter. The area of the leaves was summed for each plant and sampling site. LAI was calculated as the ratio of total leaf area to ground area occupied by the plants.

The K-M model was tested by least square curve fitting (see theory) of the composite canopy reflectance (Table 1), for each ERTS-1 MSS band, to the LAI collected for the cotton, corn and sorghum fields. A set of optical constants (a and b), and soil reflectance (Rg) was calculated (Table 2) for each crop and MSS band.

The regression model was similarly tested by regressing composite canopy reflectance (Table 1) for each ERTS-1 MSS channel on fractional crop cover only and then on fractional crop cover and fractional shadow cover for combined corn and grain sorghum and cotton. A set of regression coefficients was calculated (Table 3) for each crop and MSS band.

The combined model was tested by least square curve fitting (see appendix) of the composite canopy reflectance to LAI, fp, and fs (Table 1) for each ERTS-1 MSS band for combined corn and grain sorghum and for cotton. A set of optical constants (a and b), infinite canopy reflectance (R_∞), soil reflectance (Rg), and shadow reflectance (Rs) was calculated (Table 4) for each crop and MSS band.

EXPERIMENTAL RESULTS

Kubelka-Munk Model

Table 2 presents the results of fitting the K-M model to the composite canopy reflectance data for each ERTS-1 MSS band and for the LAI listed in Table 1. The multiple correlation coefficients, relating the three variables a, b, and Rg, were significant (0.01 probability level) for all four ERTS-1 MSS bands using cotton canopies, and were significant (0.01 probability level) for bands 6 and 7 using combined corn and sorghum canopies.

Relative response in band 7 for corn and sorghum reached 97% (digital count of 61 ratioed to 63 multiplied by 100) of full-scale response, much higher than cotton (53%). Corn and sorghum were more mature and had higher plant cover and LAI than the young cotton plants. Thus, corn and sorghum were strongly reflective in the near-infrared (bands 6 and 7). Bare soil and shadow areas between cotton rows reduced the vegetative reflectance from cotton. Allen and Richardson (1968) showed that infinite reflectance is not reached until 8 (LAI = 8) or more single leaves are stacked. The largest LAI for cotton was 2.9 whereas sorghum reached a maximum LAI of 8.5 (Table 1) so that the band 7 sensor was almost saturated by a pure vegetation response for sorghum.

Plant leaves are strong absorbers of red light (band 5) and are virtually transparent in the near-infrared wavelengths (bands 6 and 7). Thus, the coefficients of absorption k in Table 2 are much larger in bands 4 and 5, than in bands 6 and 7. On the other hand, the scattering coefficients s are much larger in bands 6 and 7, than in bands 4 and 5. The relative differences in k and s for cotton versus corn and sorghum fields are consistent with the differing LAI's.

The least square fit of the K-M model to the composite canopy reflectance and LAI is shown in Figures 2 and 3. In the visible region, bands 4 and 5, the actual data (plotted points) and theoretical curve tend to go from the vertical axis, at a point labeled soil reflectance (Rg), down to an asymptote that is the infinite reflectance (R_∞). In the reflective infrared, bands 6 and 7, the actual data and theoretical curve tend to go from the vertical axis, at Rg, up to R_∞ as an asymptote. In laboratory reflectance measurements of stacked leaves (Allen and Richardson, 1968), the data and theoretical prediction trend was from the reflectance of a single leaf up to the infinite reflectance of many stacked leaves. The reflectance trend for MSS bands 4 and 5, is associated with the fact that spectra from vegetated fields normally have a soil background. Soil exposed between plant rows has reflectance higher in the visible wavelengths than plant leaf or canopy reflectance (Wiegand et al., 1973).

Regression Model

Table 3 presents the results of fitting the regression model to the composite canopy reflectance data, fractional plant canopy cover, and fractional shadow cover listed in Table 1. Correlation coefficients increased in every band when the regression model included shadow cover. Bands 4 and 5 for sorghum and corn registered the largest increases in the correlation coefficient (from 0.689 and 0.695, to 0.804 and 0.833, respectively). Apparently shadows contribute variation to the composite reflectance in bands 4 and 5.

The regression model produced a much higher plant canopy relative response (Rp) in bands 6 and 7 (80 and 86%, respectively; Table 3) for cotton than for corn and sorghum (48 and 58%, respectively; Table 3). Plant canopy reflectance (Rp) for the regression model should have been about the same for both crop categories because between row reflectance edge effects are theoretically accounted for. It was expected that composite canopy reflectance (Rc) from immature cotton plants would have been slightly lower than for mature corn and sorghum.

The relative magnitude of composite canopy (Rc), plant canopy (Rp), soil (Rg), and shadow (Rs) reflectance for cotton, corn, and sorghum canopies produced by the regression model is shown in Table 3. Shadow reflectance for the visible bands 4 and 5 seems too high compared with plant canopy reflectance as calculated in the regression model. The largest difference was for cotton (band 5) where shadow relative response was +26% compared with a plant canopy relative response of 2%.

Combined Model

Table 4 presents the results of fitting the combined model to the composite canopy reflectance data, fractional plant canopy cover, and fractional shadow cover listed in Table 1. The combined model gave a statistically significant correlation between composite canopy reflectance and LAI, fp, and fs for all four ERTS-1 bands for combined corn and sorghum and for cotton compared with the K-M and regression models that were not statistically significant in all bands considered. The combined model also had higher multiple correlation coefficients ($R = 0.717^{**}$ to 0.949^{**}) compared with the K-M model ($R = 0.433$ to 0.915^{**}) and the regression model ($R = 0.201$ to 0.833^{**}).

The combined model gave a more plausible value of infinite canopy reflectance than did the K-M model. Infinite reflectance in the reflective infrared (bands 6 and 7) for combined corn and sorghum and cotton were high (relative response range = 78% to 94%) indicating that the reflectance response from the soil and shadow areas did not reduce the vegetal reflectance of cotton as it did in the K-M model. The K-M model considers a soil background under the plant canopy, but it does not include line-of-sight exposure of soil and shadow to the sensor. The combined model also gave a more realistic plant canopy reflectance than the regression model.

Soil reflectance values calculated from the combined model were as plausible as the values determined by the other two models. Shadow reflectance values determined by the combined and regression models agreed well. The combined model computed lower reflectance values for shadow than for either soil or plant canopy in three of the four bands for the cotton fields. The lower plant cover of cotton may have helped the combined model to estimate shadow reflectance better than for corn and sorghum that had higher plant cover.

INTERPRETATION OF a, b, s, AND k

Both the K-M and combined model yield optical constants (a and b), scattering (s), and absorption (k) coefficients. Both a and b are obtained from curve fitting procedures. The reciprocal of optical constant a is infinite reflectance given in Tables 2 and 4 (Allen and Richardson, 1968). In an important limiting case of high absorption (at water bands) where infinite reflectance and transmittance of a single leaf are small, the reciprocal of b approximates the transmittance of a single leaf in a plant canopy. The absorption coefficient k reduces to Beer's absorption coefficient in the limit of zero scattering (Wendlandt et al., 1966) while the scattering coefficient (s) reduces to the ratio of the reflectance to transmittance of a single leaf in the limit of zero absorption (Allen et al., 1970b).

APPLICATIONS

Optical coefficients a and b and absorption k and scattering s coefficients are basic optical parameters important in modeling the interaction of light with diffuse materials such as vegetated surfaces. These basic parameters help establish the relationship between ground truth measurements (LAI, fp, and fs) and MSS measurements.

Further investigation seems merited for the use of these models for forecasting crop yield by relating (LAI, fp, and fs) predictions from ERTS-1 MSS radiance measurements to various crop yield parameters (total dry weight, plant population, and plant height). Yield predictions might be improved by estimating the proportion of each pixel (picture element or instantaneous ground resolution area) that is plant canopy, soil, and shadow (Nalepka et al., 1973; Driscoll et al., 1972). Yield estimates could then be adjusted by the plant portion for each pixel. These calculations would be based on the models developed in this study as systems of three equations with three unknowns (LAI, fp, and fs). With the 4-band ERTS-1 MSS, four equations could be derived, but only three are needed to effect a solution.

Acreage estimations derived from classifications of agricultural crop and soil categories could be adjusted in much the same way as described for yield predictions. First training data (pixel by pixel) within training categories could be segregated into groups based on their proportions of plant, soil, and shadow areas as determined from the plant canopy models. Training categories could then be established for various strata of plant cover for each crop being surveyed for acreage adjustments.

APPENDIX

Derivation of fractional shadow cover (fs), as used for the regression and combined models, is keyed to Figure 1. The symbols used in Figure 1 and in the derivation are:

PH - Plant height,
RS - Row spacing,
SW - Shadow width,
SL - Shadow length,
Rc - Composite canopy reflectance,
Rp - Plant canopy reflectance,
Rg - Soil reflectance,
Rs - Shadow reflectance,
θ - Sun azimuth east of true north,
ϕ - Row direction east of true north, and
α - Sun altitude above the local horizon.

As can be inferred from Figure 1, SL is related to PH and α by the tangent function

$$SL = \frac{PH}{TAN\ (\alpha)} \ . \tag{16}$$

A SINE relation can be formed relating SL to SW and $| \theta-\phi |$ as follows,

$$\sin | \theta-\phi | = \frac{SW}{SL} \ , \tag{17}$$

such that when equation (17) is solved for SW and equation (16) is substituted for SL we have,

$$SW = \frac{PH \cdot SIN | \theta-\phi |}{TAN\ (\alpha)} \ . \tag{18}$$

From Figure 1 fractional shadow can be defined as a ratio of SW to RS,

$$fs = \frac{SW}{RS} \ , \tag{19}$$

so that substituting equation (18) for SW in equation (19), fractional shadow can be expressed in terms of plant and sun geometry by

$$fs = \frac{PH \cdot SIN | \theta-\phi |}{RS \cdot TAN\ (\alpha)} \ . \tag{20}$$

The K-M and combined model curve fitting procedures for determining optical constants a and b, soil reflectance (Rg), and shadow reflectance (Rs) from ERTS-1 digital data and LAI employ a root finding process to determine Rg and Rs.

Equation (15) along with differential coefficients for ($\partial Rc/\partial a$) and ($\partial Rc/\partial b$), (Allen and Richardson, 1968), are used to evaluate optical constants a and b that determine the best least square fit between Rc and N for the K-M model. The soil reflectance (Rg) is incremented by a delta Rg value systematically until the minimum standard deviation between Rc actual (ERTS-1 MSS data) and Rc predicted is found. The Rg for which the least square curve fitting and root finding procedures yield the minimum standard deviation is taken as the best estimate of optical constants a and b, and Rg. These parameters may be used to test the LAI equation as it appears in equations (1) or (15). The final solution is exact in the sense of least squares for a and b for the Rg determined by the root finding process. The error in determining Rg is related to the smallest increment used in varying Rg.

The combined model employs the K-M model least square estimating process to evaluate optical constants a and b that result in the best fit between Rp and M where Rp is evaluated by,

$$Rp = \frac{Rc}{fp} - Rs\frac{fs}{fp} - \frac{Rg}{fp}(1 - fp - fs). \tag{21}$$

Equation (21) is derived from equation (6) for the purpose of calculating Rp from Rc as Rs and Rg are varied systematically using smaller and smaller increments to find the minimum standard deviation between Rc actual (ERTS-1 MSS digital data) and Rc predicted (equation 14). The error in determining Rg and Rs is related to the smallest increment used in varying Rg and Rs. The values for a and b are exact in the sense of least squares for the Rg and Rs determined by the root finding process.

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Table 1. Ground truth and composite canopy reflectance data collected on May 27, 1973, (scene ID 1308-16323) for 3 corn, 10 grain sorghum, and 10 cotton fields. Sun elevation was 62° and sun azimuth was 93°. Composite canopy reflectances are ERTS-1 MSS digital data ratios to maximum count in each band (127 for bands 4, 5, 6, and 63 for band 7), or normalized response.

Crop Identity	Composite Canopy Reflectance ERTS-1 MSS Bands 4	5	6	7	Crop cover %	Shadow cover %	Plant height cm	Row width cm	Row azimuth °	Leaf area index
Corn	.33	.29	.40	.37	75	25	120	100	20	2.5
	.32	.26	.45	.49	55	43	98	100	37	2.5
	.29	.22	.40	.42	60	40	110	100	1	2.6
Sorghum	.30	.26	.36	.38	75	8	75	92	82	3.0
	.38	.37	.46	.38	35	5	45	100	81	3.9
	.30	.24	.44	.48	90	10	110	100	1	4.1
	.30	.22	.46	.46	80	20	110	100	1	4.2
	.34	.32	.42	.41	65	1	60	100	91	4.2
	.31	.25	.44	.49	65	9	85	100	81	4.9
	.26	.19	.47	.58	70	30	85	100	3	5.1
	.27	.19	.51	.64	90	5	110	92	89	6.9
	.29	.21	.53	.63	85	15	100	100	3	7.3
	.28	.22	.51	.60	90	2	110	92	91	8.5
Cotton	.32	.29	.37	.39	18	15	30	100	19	0.3
	.38	.31	.41	.41	35	3	30	100	81	0.4
	.35	.34	.40	.38	25	14	27	100	1	0.4
	.30	.26	.43	.46	25	0	35	100	91	0.9
	.28	.29	.47	.49	25	4	40	100	81	1.1
	.29	.24	.47	.53	35	4	43	100	81	1.3
	.29	.22	.47	.53	30	21	40	100	1	1.9
	.29	.22	.52	.52	40	1	48	100	90	1.9
	.29	.24	.46	.48	33	4	35	100	80	2.3
	.28	.22	.49	.55	35	24	48	100	19	2.9

Table 2. Optical coefficients A and B, canopy infinite reflectance (RI=1/A), and soil reflectance (RG) using ERTS-1 MSS data, collected on May 27, 1973 (Scene ID 1308-16323) for 3 corn, 10 grain sorghum, and 10 cotton fields. Standard deviation (SD) and multiple correlation coefficients (R) indicate goodness of fit. Scattering (S) and absorption (K) coefficients and remission function (K/S) are also listed.

Plant canopy field	ERTS-1 MSS band	(A)	(B)	(RG)	(RI)	(S)	(K)	(K/S)	(SD)	(R)
Corn and sorghum	4	4.9	1.0	0.35	0.20	0.02	0.03	1.6	0.03	0.43
	5	8.0	1.1	0.33	0.12	0.01	0.05	3.1	0.05	0.46
	6	1.6	1.1	0.29	0.63	0.12	0.01	0.1	0.21	0.84**
	7	1.0	1.0	0.13	0.97	0.17	0.00	0.0	0.06	0.82**
Cotton	4	3.6	2.4	0.40	0.28	0.53	0.49	0.9	0.02	0.86**
	5	5.1	1.4	0.34	0.19	0.14	0.23	1.7	0.02	0.88**
	6	2.0	2.1	0.32	0.49	0.94	0.25	0.3	0.02	0.92**
	7	1.9	2.0	0.30	0.53	1.03	0.21	0.2	0.02	0.92**

** Statistically significant at the 0.01 probability level.

Table 3. Multiple correlation coefficient (MR) of the regression model R=RG+A1(FP)+A2(FS) fit to each band of ERTS-1 MSS data collected on May 27, 1973, for cotton and combined sorghum and corn fields, and, the plant canopy (RP=RG+A1), soil (RG), shadow (RS=RG+A2), and composite canopy (RC) reflectance components, expressed as normalized reflectance, for each band and crop. The linear correlation coefficient (LR) for the regression model RC=RG+A1(FP) fit for each band and crop is also given.

Plant canopy field	ERTS-1 MSS band	Multiple linear regression equation	Linear & multiple correlation coefficient		Reflectance due to plant, soil, shadow, and composite canopy			
		RC= A0 + A1(FP)+ A2(FS)	LR	MR	(RP)	(RG)	(RS)	(RC)
Corn and sorghum	4	RC=0.43-0.16(FP)-0.10(FS)	0.69**	0.80**	0.28	0.43	0.34	0.31
	5	RC=0.46-0.26(FP)-0.17(FS)	0.70**	0.83**	0.21	0.46	0.29	0.25
	6	RC=0.39+0.10(FP)-0.04(FS)	0.34	0.36	0.48	0.39	0.35	0.45
	7	RC=0.23+0.35(FP)+0.05(FS)	0.57**	0.57**	0.58	0.23	0.27	0.49
Cotton	4	RC=0.34-0.09(FP)-0.05(FS)	0.16	0.20	0.25	0.34	0.29	0.31
	5	RC=0.38-0.36(FP)-0.12(FS)	0.54*	0.59*	0.02	0.38	0.26	0.26
	6	RC=0.30+0.50(FP)+0.03(FS)	0.75**	0.75**	0.80	0.30	0.33	0.45
	7	RC=0.28+0.58(FP)+0.18(FS)	0.60**	0.65**	0.86	0.28	0.46	0.47

*Statistically significant at the 0.05 probability level.

**Statistically significant at the 0.01 probability level.

Table 4. Optical coefficients A and B, canopy infinite reflectance (RI), soil reflectance (RG), and shadow reflectance predicted from ERTS-1 MSS data, collected on May 27, 1973 (Scene ID 1308-16323) for 3 corn, 10 grain sorghum, and 10 cotton fields. Scattering (S) and absorption coefficients and remission function (K/S) are also listed. Standard deviation (SD) and multiple correlation coefficient (R) indicate goodness of fit.

Plant canopy field	ERTS-1 MSS band	(A)	(B)	(RI)	(RG)	(RS)	(S)	(K)	(K/S)	(R)	(SD)
Corn and sorghum	4	3.8	1.3	0.26	0.45	0.29	0.13	0.13	1.0	0.87**	0.02
	5	5.7	1.3	0.18	0.46	0.21	0.08	0.16	2.0	0.93**	0.02
	6	1.3	1.0	0.78	0.37	0.44	0.08	0.00	0.0	0.78**	0.03
	7	1.1	1.0	0.94	0.26	0.39	0.19	0.00	0.0	0.88**	0.05
Cotton	4	7.2	1.8	0.14	0.36	0.34	0.16	0.42	2.7	0.72**	0.02
	5	300.0	1.8	0.00	0.34	0.28	0.00	0.58	150.0	0.88**	0.02
	6	1.3	1.7	0.78	0.35	0.32	2.13	0.06	0.0	0.95**	0.01
	7	1.1	1.1	0.94	0.37	0.23	2.18	0.00	0.0	0.82**	0.03

**Statistically significant at the 0.01 probability level.

FIGURE CAPTIONS

Figure 1. Model of a plant canopy showing contributions to the composite reflectance (Rc) of plant canopy (Rp), soil (Rg), and shadow (Rs) reflectance components wherein: I_o = incident radiation, m = instantaneous LAI measured from top of plant canopy, M = maximum LAI, N = north, PH = plant height, RS = row spacing, SW = shadow width, SL = shadow length, α = sun elevation above local horizon, θ = sun azimuth east of true north, and $\emptyset$ = row direction east of true north.

Figure 2. Canopy reflectance, expressed as relative response, versus LAI for corn and sorghum, for each ERTS-1 MSS band. The theoretical curve fit of the K-M model to the data is shown as a solid line. The value of Rg is given at the point where the solid line intersects the vertical axis. Infinite reflectance (R_∞) is shown as a horizontal line.

Figure 3. Canopy reflectance expressed as digital counts versus LAI for cotton, for each ERTS-1 MSS band. The theoretical curve fit of the K-M model to the data is shown as a solid line. The value of Rg is given at the point where the solid line intersects the vertical axis. Infinite reflectance (R_∞) is shown as a horizontal line.

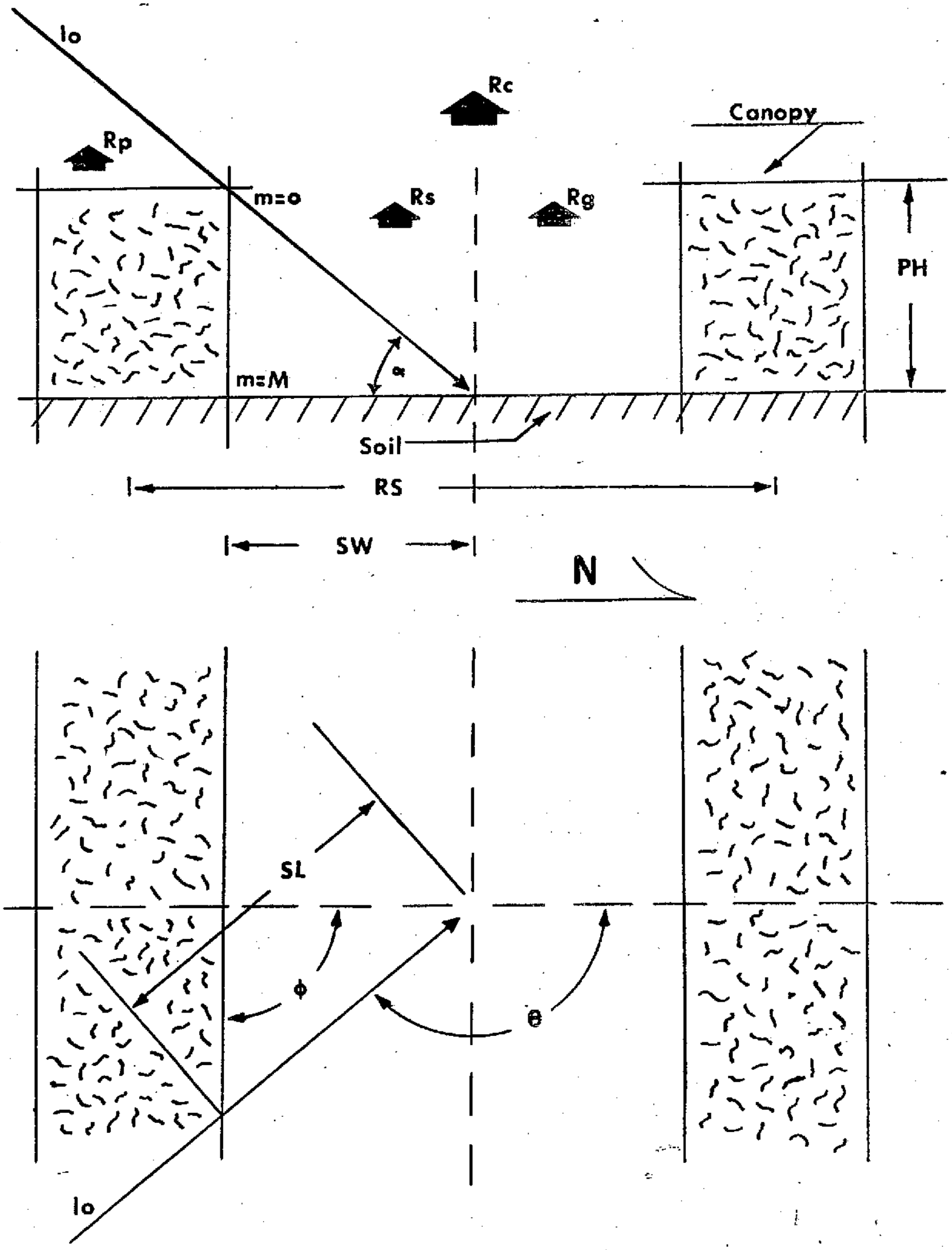

FIGURE 1.

ORIGINAL PAGE IS OF POOR QUALITY

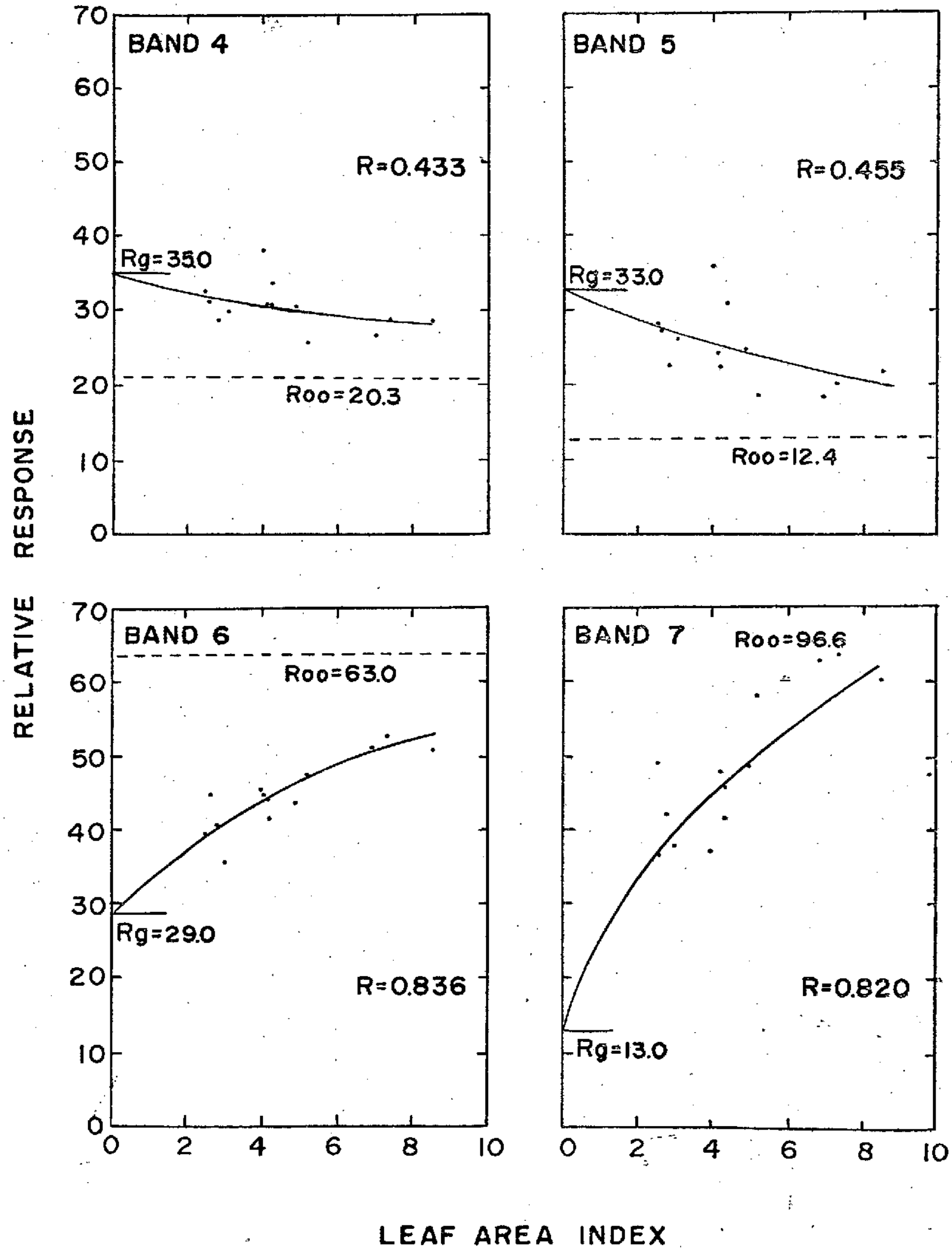
BAND 4
R=0.433
Rg=35.0
Roo=20.3
BAND 5
R=0.455
Rg=33.0
Roo=12.4
BAND 6
Roo=63.0
Rg=29.0
R=0.836
BAND 7
Roo=96.6
R=0.820
Rg=13.0
RELATIVE RESPONSE
LEAF AREA INDEX

FIGURE 2.

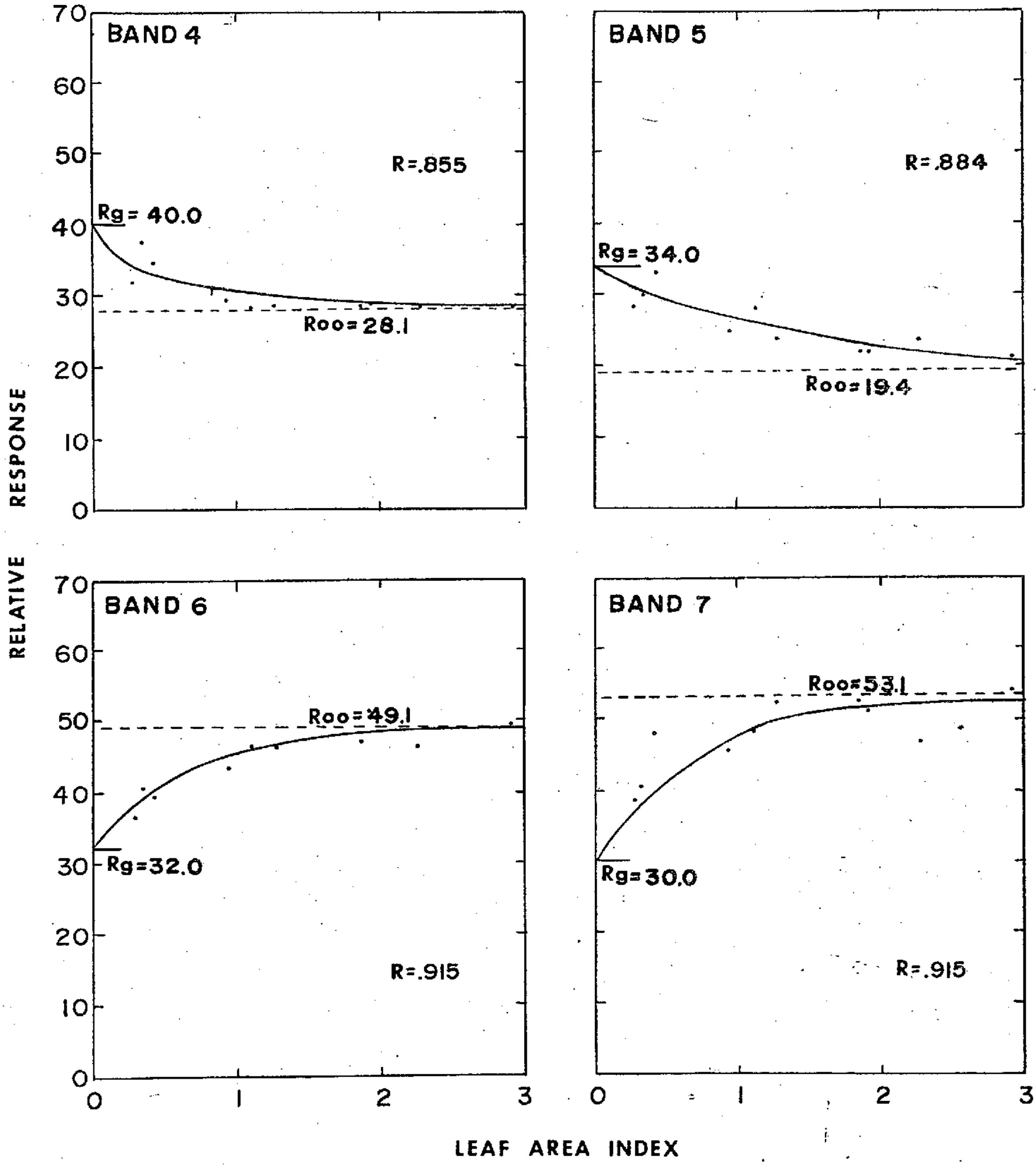
BAND 4
R=.855
Rg= 40.0
Roo=28.1
BAND 5
R=.884
Rg=34.0
Roo=19.4
BAND 6
Roo=49.1
Rg=32.0
R=.915
BAND 7
Roo=53.1
Rg=30.0
R=.915
RELATIVE RESPONSE
LEAF AREA INDEX
0
10
20
30
40
50
60
70
0
1
2
3

FIGURE 3.

APPENDIX B

LAND USE SURVEY COMPARISON OF HIDALGO COUNTY, TEXAS FOR JANUARY 21 AND MAY 27, 1973 ERTS-1 OVERPASSES [1]

A. J. Richardson, C. L. Wiegand, M. R. Gautreaux, and R. J. Torline [2]

INTERPRETIVE SUMMARY

Land use investigations of crop and soil conditions of Hidalgo County, using Earth Resources Technology Satellite (ERTS-1) multispectral scanner (MSS) data, were conducted to develop an operational system of ERTS-1 data analysis for the U.S. Department of Agriculture in the Lower Rio Grande Valley of Texas. Results indicate that a potential exists to operationally survey the general categories of agriculture and rangeland and the specific categories of citrus, cotton and sorghum, and idle cropland, and possibly vegetables.

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[1] Contribution from Soil and Water Conservation Research, Southern Region, Agricultural Research Service, USDA, Weslaco, Texas. The work was supported in part by the National Aeronautics and Space Administration under contract No. S-70251-AG.

[2] Physicist, Soil Scientist, Computer Programmer, and Computer Specialist, respectively, Agricultural Research Service, USDA, Weslaco, Texas.

COMPREHENSIVE SUMMARY

Multispectral scanner (MSS) data collected by the Earth Resources Technology Satellite (ERTS-1) on January 21 and May 27, 1973, were used for classification and acreage estimation studies of crop and soil categories in Hidalgo County, Texas.

Optimum feature selection programs selected ERTS-1 MSS bands 4, 5, and 7 (0.5 to 0.6 μm, 0.6 to 0.7 μm, and 0.8 to 1.1 μm, respectively) as the best three bands for distinguishing crop and soil categories in January. Similarly, ERTS-1 bands 5, 6, and 7 (0.6 to 0.7 μm, 0.7 to 0.8 μm, and 0.8 to 1.1 μm, respectively) were selected as the best three bands in May.

Classification Results

Classification results improved, using fields larger than 15 acres, with more than 25% plant cover, and with plants taller than 30 cm, in January from 65.9 to 85.7% for agricultural categories and 60.7 to 78.1% for rangeland categories as compared with increases in May from 74.9 to 77.2% for agricultural categories and 51.5 to 73.7% for rangeland.

Idle cropland was the most reliably classified agricultural category in both January (82.5% per field recognition) and May (70.3% per field recognition). Citrus was not as reliably classified in May (50.6% per field recognition) as in January (71.4% per field recognition) because in May citrus spectrally resembled the mature cotton, sorghum, and rangeland plants. Thus, January is a better time of the year for classification of citrus than is May. Overall classification of cotton and sorghum (56.1% per field classification) was low because of their spectral similarity to citrus. Classification of vegetables was low (50.0% per field recognition) because many vegetable fields were immature in January and were misclassified as idle cropland.

Acreage Estimation for Hidalgo County

There was no significant difference (0.01 probability level) between actual and computer acreage estimates for agriculture and rangeland categories in both January and May. Thus, these two general categories are distinguishable at either time of the year.

In January, there was no significant difference (0.01 probability level) between actual and computer acreage estimates for idle cropland but there was a significant difference in May. In January, their was no significant difference between actual and computer acreage estimates for citrus, but the May computer acreage estimate for citrus was significantly higher than the actual acreage estimate. Agreement between actual and computer estimated acreage for vegetables was not significant in January. In May, there was no significant difference between actual and computer estimates for the combined cotton and sorghum category.

These results indicate that an agricultural land use survey system using ERTS-1 MSS data for specific categories as citrus, cotton and sorghum, and idle cropland can yield acreage estimates that are not significantly different from acreage estimates using conventional ground truthing procedures. Cost/benefit studies are needed before implementation of an ERTS survey system can be fully justified.

INTRODUCTION

A study is discussed here concerning the use of the Earth Resources Technology Satellite (ERTS-1) as a land use survey tool (Aldrich, 1971) for inventory of agricultual crop and soil categories existing in Hidalgo County that is located in the Lower Rio Grande Valley of Texas. The purpose of the research was to gain experience and knowledge necessary for development of an operational ERTS survey system in agriculture at Weslaco, Texas. One benefit of an operational agricultural survey system would be the production of timely and accurate forecasts of crop surpluses or deficiencies to allow planning and implementation of domestic economic policies (local, regional, or national). For an ERTS-1 survey system in agriculture to be useful (operational), forecast improvement value (economic benefit) must exceed the cost of the ERTS survey system (benefit/cost) (Castruccio, 1974; Merewitz, 1974).

Classification accuracy for land use categories surveyed and reliability of acreage estimates will in large measure determine the degree of economic success to be expected of an operational land use survey system for agriculture.

EXPERIMENTAL PROCEDURE

Hidalgo County was chosen as an experimental site for an ERTS-1 survey because a county is the logical governmental unit by which agricultural census data are collected and summarized. The January 21 and May 27, 1973, ERTS-1 overpasses provided MSS radiometrically scene corrected digital count data (ERTS-1 Data Users Handbook) recorded on eight computer compatible tapes (CCT), four CCT for each overpass, for a 100 by 100 nm area, including Hidalgo County where detailed ground truth were available. All four of the ERTS-1 MSS bands covering the spectral region of 0.5 to 1.1 μm were used for this study. Ground truth in the county was compiled from 197 sample segments containing approximately 1,400 fields that comprise the total statistical sample for ERTS-1 crop, soil, and water reflectance studies in Hidalgo County conducted by the U.S. Department of Agriculture at Weslaco, Texas. Ground truth provided actual crop and soil field condition status and identity as well as acreage of each field at the time of each ERTS-1 overpass.

Computer compatible digital tapes (CCT) from the National Data Products Facility (NDPF) were displayed on a cathode ray tube (CRT) and a coordinate system overlaid to aid in locating as many of the 1,400 test fields (1,290 fields in January and 1,157 fields in May) in Hidalgo County as possible. Digital data were selected from the CCT for all of the test fields located and for each of the four ERTS MSS bands for both overpasses. The average digital count values for each field and band were determined for use in training field selection procedures for both overpasses.

The average digital values for ERTS-1 MSS bands 5 and 7 were displayed in a scatter diagram format (Figure 1) to determine the major distinguishable categories in the statistical county sampling and to select training fields that would be representative of these distinguishable categories (Driscoll et al., 1972). The 20 fields, marked in Figure 1 with an asterisk, were selected as representative training fields for four distinctive categories: vegetables, citrus, rangeland, and idle cropland in January. The computer was trained to classify these four categories, using ERTS-1 MSS data from the 20 fields, by determining the mean vector and covariant matrix for each category that are used in a maximum likelihood classifier (Fu et al., 1969). The optimum channels to be used in the classifier (Table 1) were determined using a channel (ERTS-1 MSS bands) optimization program CHOICE (Jones, 1973). The classifier and optimum bands were implemented in a table look-up procedure suggested by Eppler (Eppler et al., 1971). A similar procedure was followed to determine training fields and training statistics for May.

Classification and acreage estimation results were reported using Anderson's land use classification scheme (Anderson et al., 1972). Four level I categories urban, agriculture, rangeland, and water, and nine level II categories vegetables, citrus, cotton, sorghum, idle cropland, dry debris, grass, mixed shrubs, and nonagricultural were considered. Ground truth acreage estimates were not available for level I urban and water categories. Classification and acreage estimates were developed for all categories for both overpasses with ground truth except dry debris and nonagricultural. Idle cropland was resolved into McAllen - Brennan soil association and Harlingen and Mercedes - Raymondville soil association categories.

Classification of Test Fields

A stratification process by field size, plant cover, and plant height was used to study source of classification error. This process resulted in the selection of a smaller number of test fields that yielded improved classification results. Classification result improvement was determined by comparing all test fields selected originally with the smaller number of test fields selected by the stratification process.

The proportion of the county in various land use categories was determined from computer classification of ERTS-1 digital data from all test fields to determine improvements in acreage estimates for both overpasses. Actual acreage estimates are based on planimeter measurements of the test fields from aerial photographs. Computer estimated acreages were determined by counting the number of pixels classified into each category and multiplying by a pixel to acre conversion factor (1.155 acres/pixel) determined for the Hidalgo County area in a previous report (Richardson et al., 1974). A ratio of computer to actual or actual to computer acreage estimate, depending on which estimate was the largest, as a comparison measure was determined for all land use categories. A ratio of one is a perfect comparison.

Classification of Hidalgo County

A classification (land use survey) was determined for every pixel (849,000 pixels in January and 948,000 pixels in May) in Hidalgo County and a comparison was made, using Students t-test, between actual and computer acreage estimates of Hidalgo County for level I categories agriculture and rangeland, and level II categories vegetables, citrus, cotton and sorghum, idle cropland, grass, and mixed shrubs.

Two line printer recognition maps of the county land use survey were generated. The county was divided into successive 5 x 5 pixel matrices (25 pixels per matrix). Each matrix was classified by the category having the majority of pixels and represented a larger (degraded) pixel of the classification results. The final line printer recognition maps (Figures 2 and 3) of the county were derived by taking every other degraded pixel and every other line of the degraded classification map so that final classification maps with a resolution of 115.5 acres per pixel were created. The final classification maps are 100 to 1 reductions of the original ERTS-1 MSS data as delivered by the NDPF.

EXPERIMENTAL RESULTS

The channel (ERTS-1 MSS bands) optimization program CHOICE, using ERTS-1 MSS digital data from 20 training fields (Figure 1) for January 1973, ranked ERTS-1 MSS band combination 4 (0.5 to 0.6 μm), 5 (0.6 to 0.7 μm), and 7 (0.8 to 1.1 μm) above ERTS-1 MSS band combination 5, 6, and 7 by two of three divergence criteria calculated by CHOICE as best distinguishing among crop and soil categories in Hidalgo County. The same ERTS-1 MSS band combination (4, 5, and 7) was best for discriminating three of four training categories (vegetables, citrus, rangeland, and idle cropland) from all other training categories. It was concluded that the ERTS-1 MSS band combination 4, 5, and 7 were the best three bands to use in the maximum likelihood classifier for January 1973 MSS data. Similarly, ERTS-1 MSS bands 5, 6, and 7 were selected as the best band combination for May 27, 1973 MSS data. Thus, ERTS-1 bands 5 and 7 are more important for distinguishing crop and soil categories than bands 4 and 6 that are alternatively of secondary importance, depending on the time of year and specific crop and soil category conditions.

Classification Results for Test Fields

All test fields selected from the NDPF CCT were used to determine the classification results for January and May, 1973 in Table 1. It was thought that the five level II category classification results (per pixel basis) for vegetables (16.9%), citrus (49.7%), idle cropland (74.1%), grass (45.9%), and mixed shrubs (44.7%) were not accurate enough to yield reliable acreage estimates for these land use categories in Hidalgo County for January. Similarly, the level II category classification results (per pixel basis) for citrus (33.3%), cotton and sorghum (51.3%), idle cropland (65.9%), grass (41.6%), and mixed shrubs (54.1%) were not good enough for reliable acreage estimates in May. Therefore, classification results for these fields were stratified by field size, plant cover, and plant height to determine whether classification accuracy was dependent on any one or all of these variables.

Stratification by field size produced the greatest effect on classification results for both January (54.2 to 84.3% overall correct recognition for all fields greater than zero to 100 acres in size, respectively, per field basis; Table 2) and May (41.9 to 93.1% overall correct recognition for all fields greater than zero to 100 acres in size, respectively, per field basis; Table 3). Crop cover stratification effects were stronger in January (55.4 to 69.4% overall correct recognition for all fields greater than zero to 80% crop cover, respectively; Table 2) than in May (41.0 to 49.0% overall correct recognition for all fields greater than zero to 80% crop cover, respectively; Table 3). Similarly, crop height stratification effects on classification results were stronger in January than in May. It was concluded that a field stratification criterion that would delete fields less than 15 acres in size, with crop cover less than 25%, and with crops shorter than 30 cm should improve classification results for both January and May.

Table 4 indicates the improvement in classification results after applying the field stratification criterion as compared with using all test fields (Table 1). On a per field basis, for January level I categories (agricultural and rangeland), overall classification results improved from 64.5 (Table 1) to 84.3% (Table 4). The level I per pixel overall classification improvement for January was 74.7 to 78.5%. The May classification results comparing all fields with stratified fields showed similar improvements (Table 1 and 4). The per field recognition results improvement for both January and May was greater than per pixel improvement because the small fields weighted the per field recognition result adversely when using all test fields.

Idle cropland was the most reliably classified level II category in both January (82.2% per field recognition; Table 4) and May (70.3% per field recognition; Table 4). Citrus was the most reliably classified level II category in January (71.4% per field recognition) while combined cotton and sorghum was the next most reliably classified level II category in May (56.1% per field recognition).

Citrus was not as reliably classified in May (50.6% per field recognition) as in January (71.4% per field recognition) because in May citrus resembled cotton, sorghum, and rangeland plants (Table 4). These citrus classification results confirm results of a similar citrus study reported previously (Richardson et al., 1972) using MSS data collected at aircraft altitudes.

It was not possible to distinguish cotton from sorghum in May according to scatter diagrams (such as Figure 1) used to select training fields. Actual classification attempts to distinguish irrigated grown cotton and sorghum (24.2 and 29.4% per field recognition, respectively) and dry land grown cotton and sorghum (21.9 and 35.4% per field recognition, respectively) were not very successful. These cotton and sorghum classification results agreed with previous studies using aircraft MSS classification of cotton and sorghum (Richardson et al., 1972, Discriminant analysis of Bendix scanner data, Fourth Annual Earth Resources Review Program, NASA, Houston). Results of that study indicate that possibly a June ERTS-1 overpass (cloud free) would have allowed better classification and acreage estimates of cotton and sorghum because sorghum would have been mature.

Classification of vegetable in January (50.0% per field recognition; Table 4) was low because many fields were immature and were misclassified as idle cropland. Classification of vegetables was not attempted in May because that is the off-season period for vegetables.

Classification results for rangeland in May (73.7% per field recognition; Table 4) was lower than for January (78.1% per field recognition; Table 4) because in May some areas of the rangeland spectrally resembled citrus.

Acreage Estimates for Test Fields

Comparison between actual and computer estimates for acreage using all test fields and stratified test fields are presented in Tables 5 and 6, respectively. There does not seem to be a general overall improvement in the actual to computer acreage estimates comparing all to the stratified test fields for both January and May . In some instances, as for vegetable, citrus, and idle cropland in January, the ratio of actual to computer acreage estimates indicated an improved estimate comparing all (ratio = 0.370, 0.895, and 0.791, respectively) to stratified (ratio = 0.813, 0.980, and 0.959, respectively) test fields. However, in other instances, as for agriculture in January and citrus, cotton and sorghum, and rangeland in May, the ratio of actual to computer acreage estimates indicated a degraded estimate comparing all (ratio = 0.944, 0.668, 0.886, and 0.988, respectively) to stratified (ratio = 0.904, 0.598, 0.828, and 0.918, respectively) test fields. In general, the results do seem to indicate that classification results improved in January, but they were worse in May when comparing actual to computer acreage estimates for all and stratified test fields.

Acreage Estimate for Hidalgo County

The entire county acreage estimate comparisons for January and May are given in Table 7. Actual acreage figures are based on the average of four independent ground truth samples (172 of 197 sample segments) of the county (approximately 4% of the land area), and computer estimates are based on classification of every ERTS-1 MSS data pixel in the county. The level I actual and computer acreage estimates were not significantly different (0.01 probability level) for agriculture and rangeland in either January or May. Thus these two categories can be distinguished at either time of the year.

The actual and computer estimate comparison for Level II categories citrus and idle cropland were not significantly different (0.01 probability level) in January but were significantly different in May. Idle cropland and citrus were overestimated in May because cotton and sorghum and rangeland spectrally resembled these two categories. Actual and computer acreage estimates for vegetable were significantly different (0.01 probability level) in January. Vegetable acreage was underestimated by the computer because much of the vegetable actual acreage, according to detailed ground truth, was composed of low crop cover, or low plant height and thus resembled idle cropland. The grass and mixed shrubs categories were not estimated very well by the computer in either January or May because of their close spectral resemblance to each other.

Figures 2 and 3 are line printer recognition maps for January and May respectively, with 115.5 acre per pixel resolution. These maps are useful for indicating the geographical occurrence (physical location) of the crop and soil category classification results. Most of the rangeland (/ for grass and - for shrubs) is shown to occur in the northern and southwestern portions of the county in both January and May. There is some scattering of rangeland in the agricultural area (southern half of the county) that probably corresponds to fields of dry debris. The McAllen - Brennan soil (M overprinted with a W) association (light colored highly reflective sandy loam soils) appeared mostly in the western central part of the county in January. In May this area was planted to cotton and sorghum (0 overprinted with a + for dryland cotton and sorghum and # for irrigated cotton and sorghum). The Harlingen and Mercedes - Raymondville soil ($) association (darker color low reflective clayey soils) were classified mostly in the extreme south and east portions of the county in January. In May the area was planted to cotton and sorghum.

Citrus (blank) was classified mostly in the central part of the county in both January and May as expected. Misclassification of citrus as cotton and sorghum in May is evident from a comparison of the citrus area immediately south of the McAllen - Brennan soil in January and/or south of dryland cotton and sorghum in May. In January this area has more citrus, with some grass (/) and McAllen - Brennan soil, than May because of citrus misclassification in May as cotton and sorghum.

In January, vegetables (- overprinted /) appear to be classified in southern part of county as expected. Also the frequency of occurrence of vegetables in this area as compared to Harlingen soil is not high. Thus, the computer acreage underestimation for vegetables compared to actual acreage seems justified.

These results indicate that classification maps for the county should be of benefit to investigators looking at various county land use applications.

SUMMARY

Crop and soil categories of Hidalgo County were inventoried using MSS data collected from ERTS-1. The best three ERTS-1 MSS bands, according to divergence criteria, were 4, 5, and 7 in January and 5, 6, and 7 in May of 1973.

Per pixel classification results, using all test fields for January and May were higher than per field classification results because small fields degraded the per field classification results. Field stratification studies indicated that improved classification results could be obtained by censoring fields less than 15 acres in size, with less than 25% crop cover, and with plants shorter than 30 cm prior to classification for both January and May ERTS-1 overpasses.

Actual to computer acreage estimate comparisons using all test fields and stratified test fields indicated that improved acreage estimate comparisons were obtained in January but not in May.

Actual to computer acreage estimates, based on classification of all pixels in Hidalgo County, indicate that it should be possible to estimate the county acreage of level I agricultural and rangeland categories in either January or May. County acreage estimates for level II citrus, idle cropland, and possibly vegetable should be possible in January but not in May. The combined cotton and sorghum level II category acreage can probably be estimated on a county basis in May but not in January. If a June or July ERTS-1 overpass were available, individual acreage estimates of cotton and sorghum would probably be possible.

Computer line printer classification maps of Hidalgo County in January and May indicated that the geographical occurrence (physical location) of the crop and soil category classification results was good. These classification maps should be of benefit to land use investigators interested in the geographical extent and distribution of crop and soil categories in Hidalgo County. Thus, indications are that a potential exists for an operational land use survey of agricultural and rangeland level I categories, and citrus, cotton and sorghum, and idle cropland level II categories using ERTS-1 MSS data in Hidalgo County.

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Table 1. Recognition results for test fields using MSS data from ERTS-1 collected January 21 and May 27, 1973. Categories are listed using Anderson's land use classification system. A total of 1290 fields (35,351 pixels) were used for the January results and 1157 fields (35,984 pixels) were used for the May results.

	Computer land use category results			
	January 21, 1973		May 27, 1973	
Ground truth land use categories	Percent recognition (per pixel)	Percent recognition (per field)	Percent recognition (per pixel)	Percent recognition (per field)
01 Urban	----	----	----	----
02 Agricultural	74.6	65.9	71.8	74.9
01 Vegetables	16.9	18.4	----	----
02 Citrus	49.7	57.6	33.3	34.7
03 Cotton & Sorghum	----	----	51.3	49.2
04 Idle cropland	74.1	72.2	65.9	58.0
05 Dry debris	----	----	----	----
03 Rangeland	74.9	60.7	74.8	51.5
01 Grass	45.9	51.1	41.6	27.8
02 Mixed shrubs	44.7	43.0	54.1	45.2
03 Non agricultural	----	----	----	----
04 Water	----	----	----	----
Total (Level I)	74.7	64.5	73.0	70.2
Total (Level II)	54.3	57.5	46.3	34.8

Table 2. The effect of field size (1,290 fields), plant cover, and plant height (588 fields) on classification results (per field basis) for ERTS-1 data collected on January 21, 1973. MSS channels 4, 5, and 7 were used.

Field size stratification			Crop cover stratification			Crop height stratification		
Field size in acres	Overall correct recog-nition	Accumu-lative total fields	Crop cover in percent	Overall correct recog-nition	Accumu-lative total fields	Crop height in cm	Overall correct recog-nition	Accumu-lative total fields
0	54.0	1290	0	55.4	588	0	55.4	588
5	57.0	1127	5	56.3	566	10	57.4	533
10	61.3	828	10	56.8	540	20	61.6	451
15	64.2	649	15	58.0	517	30	64.8	378
20	67.6	479	20	59.1	495	40	64.8	353
40	74.4	188	25	59.7	485	100	66.6	303
50	79.1	120	40	61.6	415	200	66.6	276
100	84.3	51	60	63.5	239	300	70.1	164
---	---	---	80	69.4	131	400	62.5	16

Table 3. The effect of field size (1,157 fields), plant cover, and plant height (975 fields) on classification results (per field basis) for ERTS-1 data collected on May 27, 1973. MSS channels 5, 6, and 7 were used.

Field size stratification			Crop cover stratification			Crop height stratification		
Field size in acres	Overall correct recognition	Accumulative total fields	Crop cover in percent	Overall correct recognition	Accumulative total fields	Crop height in cm	Overall correct recognition	Accumulative total fields
0	41.9	1157	0	41.0	975	0	41.0	975
5	43.1	931	5	43.5	950	10	44.9	916
10	46.7	671	10	43.9	935	20	46.3	876
15	49.8	528	15	44.1	920	30	49.8	786
20	52.5	386	20	44.5	886	40	54.2	676
40	67.0	161	25	46.0	842	100	55.5	452
50	74.0	104	40	49.0	660	200	46.6	302
100	93.1	44	60	51.1	459	300	45.2	199
----	----	----	80	44.6	179	400	33.3	12

Table 4. Recognition results for stratified test fields using MSS data from ERTS-1 collected on January 21 and May 27, 1973. Categories are listed using Anderson's land use classification system. A total of 502 fields (23,577 pixels) were used for the January results and 498 fields (28,078 pixels) were used for the May results.

Ground truth land use categories	Computer land use category results			
	January 21, 1973		May 27, 1973	
	Percent recognition (per pixel)	Percent recognition (per field)	Percent recognition (per pixel)	Percent recognition (per field)
01 Urban	----	----	----	----
02 Agricultural	77.2	85.7	74.0	77.2
01 Vegetables	34.2	50.0	----	----
02 Citrus	53.8	71.4	38.9	50.6
03 Cotton & Sorghum	----	----	56.1	56.1
04 Idle cropland	76.7	82.2	70.3	70.3
05 Dry debris	----	----	----	----
03 Rangeland	80.7	78.1	78.4	73.7
01 Grass	51.2	61.3	52.4	60.0
02 Mixed shrubs	50.8	56.0	55.3	56.6
03 Non agricultural	----	----	----	----
04 Water	----	----	----	----
Total (Level I)	78.5	84.3	76.0	76.5
Total (Level II)	62.9	74.5	51.8	51.4

Table 5. Comparison of actual acreage (from detailed ground truth of all test fields) to computer estimated acreage (using MSS digital data from all test fields) for land use categories surveyed on January 21 and May 27, 1973. Categories are listed using Anderson's land use classification system.

Land use categories	January 21, 1973 (1290 fields)			May 27, 1973 (1157 fields)		
	Actual acreage estimate	Computer acreage estimate	Actual to computer ratio	Actual acreage estimate	Computer acreage estimate	Actual to computer ratio
01 Urban	-----	-----	-----	-----	-----	-----
02 Agricultural	22172	20926	0.944	20701	22123	0.975
01 Vegetables	2728	1009	0.370	1300	-----	-----
02 Citrus	3613	4039	0.895	3783	5666	0.668
03 Cotton & Sorghum	1761	-----	-----	13255	11744	0.886
04 Idle cropland	12563	15878	0.791	1066	3813	0.280
05 Dry debris	1507	-----	-----	1297	-----	-----
03 Rangeland	17547	17974	0.967	17308	17099	0.988
01 Grass	3769	9710	0.388	3703	7953	0.466
02 Shrub	12071	8264	0.685	13499	9146	0.678
03 Non agricultural	1707	-----	-----	106	-----	-----
04 Water	-----	-----	-----	-----	-----	-----
Threshold	-----	1930	-----	-----	3237	-----
Total	39719	40830	-----	38009	41559	-----

Table 6. Comparison of actual acreage (from detailed ground truth of stratified test fields) to computer estimated acreage (using MSS digital data from stratified test fields) for land use categories surveyed on January 21 and May 27, 1973. Categories are listed using Anderson's land use classification system.

Land use categories	January 21, 1973 (502 fields)			May 27, 1973 (498 fields)		
	Actual acreage estimate	Computer acreage estimate	Actual to computer ratio	Actual acreage estimate	Computer acreage estimate	Actual to computer ratio
01 Urban	-----	-----	-----	-----	-----	-----
02 Agricultural	15800	14291	0.904	15688	15460	0.985
01 Vegetables	637	518	0.813	888	-----	-----
02 Citrus	2349	2397	0.980	2477	4141	0.598
03 Cotton & Sorghum	606	-----	-----	10790	8933	0.828
04 Idle cropland	10907	11376	0.959	906	2386	0.380
05 Dry debris	1301	-----	-----	627	-----	-----
03 Rangeland	11183	11650	0.960	15800	14506	0.918
01 Grass	1849	5872	0.315	2707	6325	0.428
02 Shrub	8805	5778	0.656	13027	8181	0.628
03 Non agricultural	529	-----	-----	66	-----	-----
04 Water	-----	-----	-----	-----	-----	-----
Threshold	-----	1249	-----	-----	2464	-----
Total	26983	27190	-----	31488	32430	-----

Table 7. Comparison of actual acreage (from detailed ground truth) to computer estimated acreage (using ERTS-1 MSS digital data) from the complete county for categories surveyed on January 21 and May 27, 1973. Categories are tested using Anderson's land use classification system.

Land use categories	January 1973 County estimate in acres	January 1973 Computer estimate in acres	May 1973 County estimate in acres	May 1973 Computer estimate in acres	Acreage difference between county and computer estimates January	Acreage difference between county and computer estimates May
02 Agricultural	486860	454048	501448	552654	32812	51206
01 Vegetables	46594	17137	29871	------	29457*	-----
02 Citrus	89215	80729	87833	139035	8486	51202*
03 Cotton & Sorghum	31927	------	358358	311798	------	46560
04 Idle cropland	267444	356182	22932	101821	88738	78889**
05 Dry debris	51680	------	2454	------	------	------
03 Rangeland	453346	470112	432758	457741	16766	24983
01 Grass	97570	244059	84332	175971	146489**	91639**
02 Mixed shrub	315351	226053	316147	281770	89298*	34377
03 Non agricultural	40425	------	32279	------	------	------
04 Water	------	6374	------	4609	------	------
Threshold	------	49670	------	79439	------	------
Total	940206	980209	934206	1094443	------	------

* Significant at the 0.05 probability level.
** Significant at the 0.01 probability level.

FIGURE CAPTIONS

Figure 1. Two dimensional scatter diagram, using ERTS MSS channels 5 and 7, of the mean digital values (January 21, 1973 ERTS-1 overpass) determined for 67 of 1,400 test fields randomly located in Hidalgo County. Training fields are marked with asterisk for four spectrally distinct categories (vegetable, citrus, rangeland, and idle cropland). Definition of four character field identifiers are as follows: class identification (character 1), northern (N), central (C), or southern (S) region of county (character 2), code number ranging from 0 to 9 for 0 to 90% crop cover (character 3), and crop and soil condition code ranging from 0 to 9.

Figure 2. Recognition map of Hidalgo County for the January 21, 1973 ERTS-1 overpass. Resolution is 115.5 acres per pixel. Definition of categories in terms of pixel line printer symbols is given as follows: vegetable (/ overprinted -), citrus (blank), mixed grass (/), mixed shrubs (-), McAllen soil association (M overprinted W), Harlingen soil association ($), water (◦), and threshold (T).

Figure 3. Recognition map of Hidalgo County for the May 27, 1973 ERTS-1 overpass. Resolution is 115.5 acres per pixel. Definition of categories in terms of pixel line printer symbols is given as follows: irrigated cotton and sorghum (#), dryland cotton and sorghum (Θ overprinted with a +), citrus (blank), mixed grass (/), mixed shrubs (-), McAllen soil association (M overprinted with a W), Harlingen soil association ($), water (◦), and threshold (T).

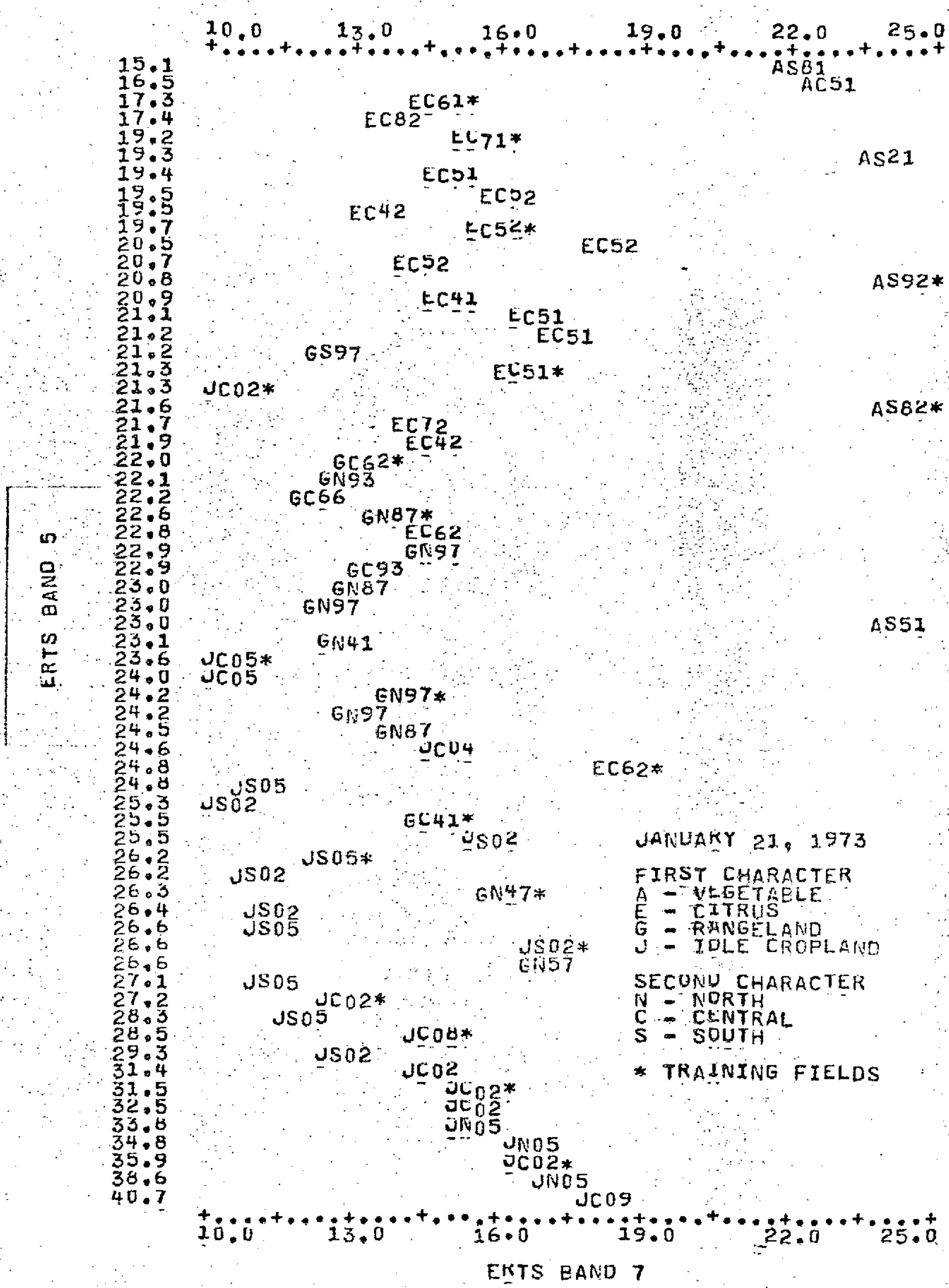

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FIGURE 1.

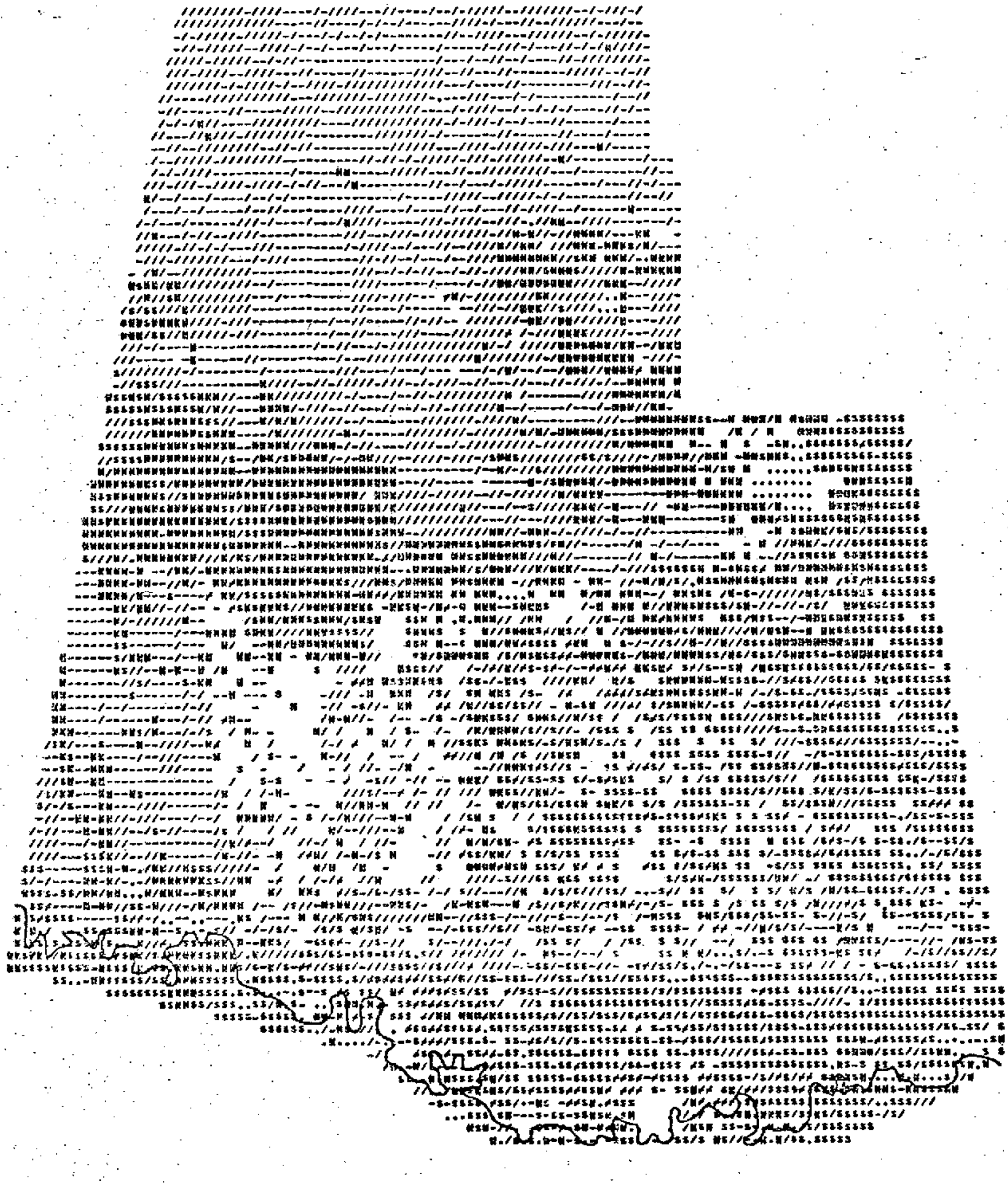

FIGURE 2.

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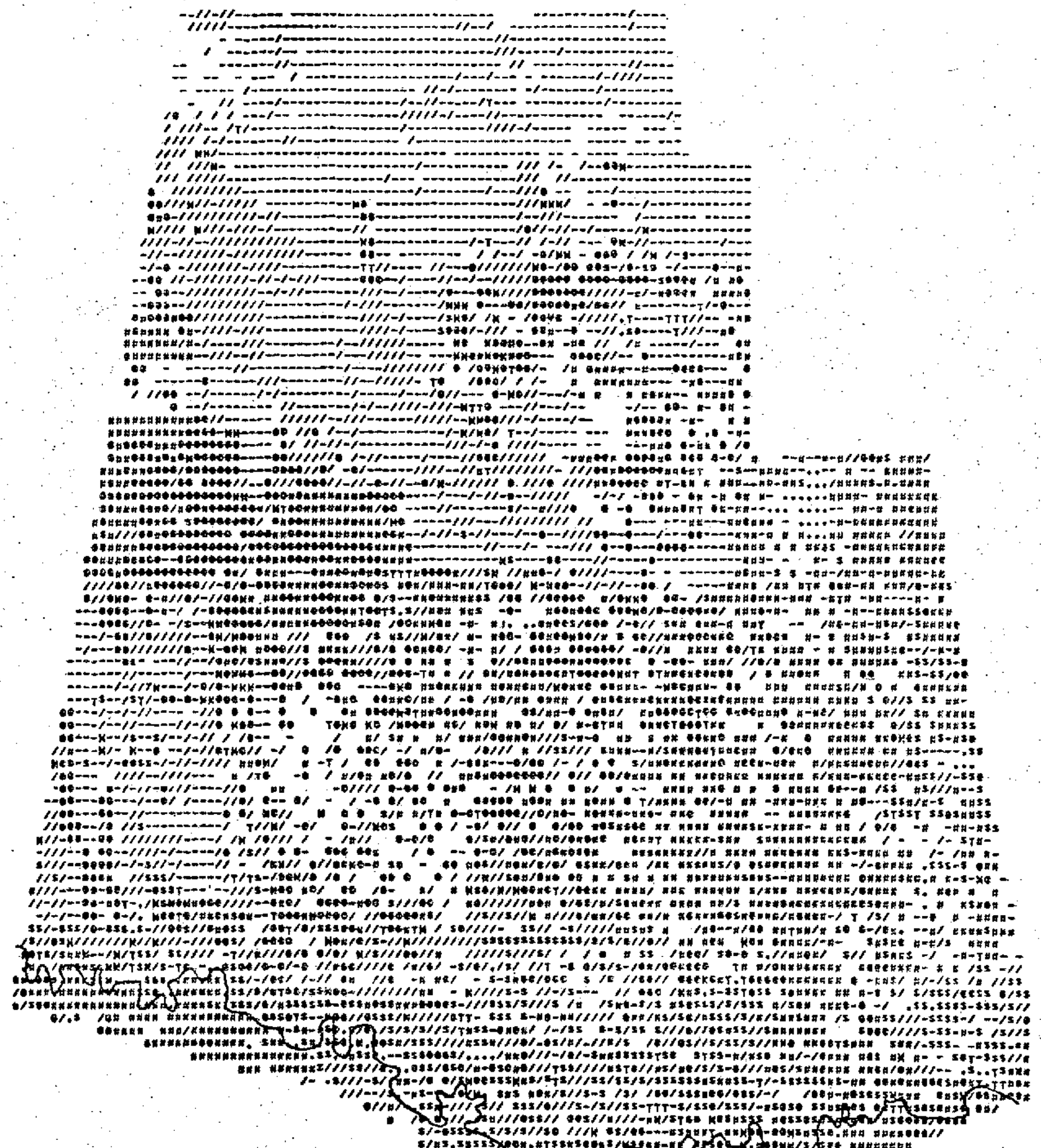

FIGURE 3.