Canonical Analysis: The Use of Transformed Landsat Data for Crop Type Discrimination

Thomas Mark Holm

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CANONICAL ANALYSIS:

THE USE OF TRANSFORMED LANDSAT DATA FOR CROP TYPE DISCRIMINATION

BY

THOMAS MARK HOLM

A thesis submitted
in partial fulfillment of the requirements for the
degree Master of Science
Major in Geography
South Dakota State University
1982
CANONICAL ANALYSIS:

THE USE OF TRANSFORMED LANDSAT DATA FOR CROP TYPE DISCRIMINATION

This thesis is approved as a creditable and independent investigation by a candidate for the degree, Master of Science, and is acceptable for meeting the thesis requirements for this degree. Acceptance of this thesis does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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Thank you!
Chapter I
INTRODUCTION

Accurate crop type discrimination has been recognized as one of the essential components for developing crop production information. Historically, remote sensing has played an important role as a tool for deriving geographically based resource data including agricultural information. Remote sensing can provide a synoptic view of the Earth from a distance and can give a unique vantage point from which agricultural characteristics can be evaluated. However, remote sensing has been used with limited success for accurately discriminating crop types in a diverse agricultural region. Therefore, a need exists for a more effective and efficient method of crop type identification (a prerequisite to deriving crop production estimates) for large and diverse geographic areas.

Several needs for effective and efficient crop type discrimination can be identified, such as its use in managing production, storage, and transportation and in determining the market place of crops. The United States Department of Agriculture (USDA) uses crop production information in designing national farm programs and establishing import/export policies (Bauer and Cipra, 1972, 205). Needs for an effective and efficient method of crop type identification for large and diverse geographic areas can be further documented. On January 14, 1975, Dr. William L. Ruble, Deputy Administrator, Management, Agricultural Stabilization and Conservation Service, USDA,
made the following comment about the need for developing space-age remote sensing crop monitoring techniques: "The gathering of accurate crop production information is becoming increasingly important to the United States and the world, particularly in regard to our nations expanding capacity for exporting feed and food grains." In the past decade, much research has been performed in the area of satellite remote sensing applications to crop production gathering. While many of these research results are inconclusive, enough success was met to warrant additional investigative studies in this area. Several remotely sensed data types and analysis methods must be evaluated to effectively and efficiently utilize remote sensing as a tool for gathering crop production information.

Of the remote sensing systems being employed for agricultural information, the acquisition and manual interpretation of large scale aerial photographs is still a commonly-used tool. However, the variability of the human interpreters and the amount of man-hours required for interpretation seems to be a significant problem. Landgrebe and Phillips estimate that it would take 100 man-days to interpret crop types and measure the area of each field for an area 20 miles on a side or approximately 80 hours per township (Colwell, 1972, 11). In addition, the limited availability of aerial photography, in terms of timeliness and coverage is another restricting factor for its use as a tool for agricultural information gathering.

To a certain extent, Landsat satellite data has eliminated this problem of timely coverage. Landsat imagery have been used as a
photographic tool for agricultural applications using manual photo interpretation methods, similar to those employed using aerial photography. However, problems exist in manual photo interpretation of Landsat imagery as in photo interpretation of aerial photography. For example, the variability of the human interpretation and the amount of man-hours involved in interpretation remains a significant problem, and for some applications, manual photo interpretation of Landsat imagery does not yield the level of spatial detail required.

For those applications needing increased spatial resolution, digital Landsat data in the form of computer compatible tapes (CCT's) provides a spatial resolution or "pixels" of .45 hectare (1.1 acre), which provides more detailed information than standard Landsat photographic products. Digital data also provides increased spectral sensitivity as compared to Landsat photographic products. The human interpreter, using black and white photographic imagery, can only discriminate 16 levels of gray. Conversely, with Landsat digital data, a relatively large spectral range is represented. Landsat digital data stores the spectral sensitivity of individual pixels as a numeric value for each of the 4 multispectral scanner (MSS) bands. The numeric range for each MSS 4, 5, and 6 pixel is 0-127 and for MSS 7 is 0-63. These quantitative representations of gray tones are also known as brightness values (BV). The surface features, which may be crops, have unique brightness values in each of the 4 MSS bands. A Landsat scene contains 7.5 million pixels per MSS band or 30 million digital values for the entire 4-band scene.
The use of digital image processing allows for the manipulation of those 30 million pixels by rationally, objectively, and accurately assigning the pixels to a category of importance by means of a classification process. This classification process uses statistical equations that sorts the Landsat pixels into spectrally similar classes using a predefined decision rule. Furthermore, when attempting to classify Landsat data into homogeneous crop type classes (a prerequisite for acquiring crop production information), one must insure that the remotely sensed data represents a time during the growing season when maximum contrast exists between crop type classes. When mapping and identifying diverse crop types within an area, a single Landsat image may not have the necessary spectral contrast for all crop types represented. Two very distinct crop types on the ground may be spectrally similar at one point during the growing season and as the crops mature and/or are harvested the two crops may become spectrally unique. The use of multi-date (multi-temporal) analysis permits the tracking of phenologic changes of crop types and these changes can be incorporated into decision criteria for crop type classification. The use of digital analysis techniques works best when using multi-temporal data sets for crop type identification (Loveland, 1982, interview).

Considering the importance of crop production estimates to managing our world's food supply, it is obvious that research investigating new and perhaps superior methods of crop type identification is essential. Landsat satellite digital data, offering advantages of high availability, repetitive coverage, and increased
spectral sensitivity, is a source of crop type data that has been used with some success. The research described herein was an attempt to obtain accurate irrigated crop type data by subjecting multi-date Landsat data to a relatively unexplored digital analysis technique.

The Problem

The primary goal of this thesis is to investigate the usefulness, accuracy, and efficiency of canonical analysis (a linear transformation technique) for the classification of crop types using multi-date multispectral scanner (MSS) Landsat digital data. The accuracy statistics and the computer processing efficiency of the crop type classification developed using a canonical transformation will be compared with accuracy and efficiency figures of a crop classification developed for the Columbia River and Tributaries Irrigation Withdrawals Analysis Project (Johnson, Loveland, Anderson, 1981) in which multi-date Landsat data covering the same area was classified. The Clarke, Oregon 7.5 minute USGS quadrangle was chosen as the study site because of the availability of timely Landsat data and the existing maximum likelihood classification from the Columbia River and Tributaries Project.

In a general sense, the problem investigated is a method of gathering crop type information using remotely sensed data. As discussed in the Introduction, an important method for crop type identification is the classification of multi-temporal Landsat digital data. Using remotely sensed data in the form of Landsat computer
compatible tapes (CCT's) allows for the analysis of the full spatial resolution of Landsat data (.45 hectare pixels) and the analysis and manipulation of the numeric sensitivity of digital data.

Again, as mentioned in the introduction, a full 4 band MSS image contains 30 million digital values representing the spectral characteristics of various surface features. When introducing the classification of multi-date Landsat data, the dimensionality (data set size) becomes increasingly large. In the case of this study a 12 band MSS data set (three 4 band MSS scenes combined) was used. Traditionally, when classifying multi-temporal Landsat data sets, a direct relationship exists between increased data set size and increased computer processing time. The problem of reducing the large dimensionality of multi-temporal data and improving computer processing efficiency while maintaining classification accuracy is the main problem investigated in this thesis.

Scope of the Study

The general scope of the study was to gather crop type information using remotely sensed data analysis techniques. The type of remotely sensed data used and the general technique chosen was a 12 band MSS Landsat data set subjected to digital classification. The following discussion will explain the general process of digital classification of Landsat data and more specifically emphasize an additional classification step used in this research. This additional step attempted to reduce the dimensionality (data set size) of multi-temporal
Landsat data while maintaining statistical accuracy and computer processing efficiency. A large number of remote sensing terms are used throughout this thesis. For a definition of these terms, please refer to Appendix A, Glossary of Terms. All definitions were taken from Welch and Poulton, 1979.

The rationale for using multi-temporal digital Landsat data have been discussed in previous sections. However, several attributes of digital Landsat data need to be emphasized. Landsat data are the most common form of digital remotely sensed data available. Landsat data are available as computer compatible tapes which store the spectral characteristics of surface features as numeric values. Each distinct surface feature has a unique digital value representing its spectral response for each of the four MSS bands. These digital values or brightness values are spatially represented as an area with a specific size and location and referred to as picture elements or pixels (.45 hectare or 1.1 acres). Finally, Landsat data are acquired over the same geographic area every 18 days, which allows for the tracking of phenologic changes of crop types.

A fundamental problem is to determine how to utilize the vast amount of information in Landsat data for crop type identification. Digital image classification is a procedure that will reduce this vast amount of data (30 million digital values per 4 band MSS scene) into information classes to solve a predefined problem. Image classification is a process that examines the spectral properties of various surface features (for example, crop type classes) and sorts the spectral data into spectrally similar groups. This general image classification
process is accomplished with four basic steps. They are:

1. Training set selection: This step involves the selection of data that represents the various information classes of interest in the image.

2. Statistical generation: Statistical and mathematical equations that define the unique spectral characteristics for those data selected during training are used.

3. Classify the data: Numeric decision rules that utilize the predefined spectral descriptions are used to assign the Landsat pixels to information classes.

4. Evaluation and refinement: A comparison of classification accuracy and computer processing efficiency is made. Refinement may require returning to Step 1 if necessary.

There are many image classification procedures available that follow these four basic steps. However, there are several variations which can be employed when attempting to classify Landsat data. An explanation of these classification variations is not appropriate for this thesis topic. However, a list of several common variations for classification of Landsat data follows: (refer to Appendix A for definitions)

1. **Training set selection**
   - Supervised
   - Unsupervised
2. **Statistical generation**
   - Generally, statistical computations are generated during training set selection. Typical statistical calculations made include: class means, standard deviation, covariance matrices and correlation matrices.

3. **Classification** - various classification decision rules
   - Density Slicing
   - Parallelepiped
   - Minimum Distance to Mean
   - Maximum Likelihood
   - Spatial/Spectral Classifier

4. **Evaluation and refinement**
   - Sampling
   - Reference Data
   - Contingency Tables (tool for comparison)

There are many arguments as to which combination of classification procedures yield the most accurate classification results and which are the most computer efficient. The landscape characteristics, particularly spectral complexity, the data set size, and the desired results are important considerations when determining a classification procedure. All these variables were considered when selecting the classification procedure for this thesis problem. The following classification procedure was used with an additional step, noted by the *:
1. Supervised Training Set Selection
2. Statistical Generation
* Canonical Transformation
3. Minimum Distance to Mean Classification
4. Reference Data Comparison Using Contingency Tables

As noted, an additional procedure was added to the basic four classification steps. Canonical transformation was used in an attempt to reduce the data set dimensions (channels) before minimum distance to mean classification. Since a 12 band multi-temporal Landsat data set was used for crop type classification, a step that could reduce the dimensionality of the multi-temporal data set before classification would yield a more computer efficient classification procedure.

Simply, the main objective of canonical transformation is to increase the separability of categories defined within the data while minimizing the differences occurring within each category. The transformation places the maximum category separability within the canonically transformed channel 1, with successive channels having the remaining separability (Jenson and Waltz, 1979, 347). Canonical transformation can potentially place approximately 99 percent of the total scene variance in the first three to six canonical transformed channels. The number of channels needed to represent 99 percent of the cover type information is dependent upon the number of channels in the original Landsat data set, the complexity of the data, and separability of the categories defined during training.

After yielding a crop type classification using the canonical transformation of Landsat data, a comparison was necessary to evaluate
the classification accuracy and the computer processing efficiency. The results of a commonly used classification procedure was available for the same study site using the same 12 band Landsat data set from the Columbia River and Tributaries Irrigation Withdrawals Analysis Project (Johnson, Loveland, Anderson, 1981). A comparison of individual crop type accuracies and computer processing efficiency was done using contingency tables as a tool for comparison.

**Literature Review**

There have been few studies published on the use of canonical analysis of multi-date MSS Landsat data. A study done by Lachowski and Borden (1973) reported the results from using two Landsat MSS scenes. The two MSS images were merged or registered to the same map base so an area could be analyzed using an 8 band MSS data set. The study site was located near Harrisburg, Pennsylvania just northeast of its central metropolitan area near the Susquehanna River. The categories that were classified using the canonical transformation of the 8 band multi-date Landsat data were: (1) river, (2) railroad yard, (3) suburban, and (4) vegetation. One should note that the categories for the Lachowski and Borden study are significantly different from the diverse agricultural region used in this thesis. However, a significant result reported by Lachowski and Borden was that by using canonical analysis, all of the separability among the four categories could be recovered in four canonical channels—a definite reduction in data set size which decreased the computer processing time needed for classification.
A paper entitled, "Techniques to Update a Land Management Information System with Landsat Data," (Nelson and others, 1980) demonstrated that the use of aerial photography for updating land use categories for a large-area data base was inefficient. Therefore, their primary objective was to evaluate the use of digital processing techniques of Landsat data for updating land use data in the Minnesota Land Management Information System. Four techniques of training set selection and statistical generation were attempted. They were:

(1) polygons selected from cathode-ray tube displays (supervised),
(2) unsupervised clustering, (3) polygons selected from aerial photographs, and (4) data extracted from the existing land use data base. The resulting statistics were applied to three classification algorithms. They were: minimum distance to mean, maximum likelihood, and canonical analysis with minimum distance to mean. Thus, with these four training set selection and statistical generation techniques and the three classification algorithms, twelve land cover files were produced and compared to ground reference data for accuracy verification. It was found based on analyst and computer processing efficiency that the statistical manipulation using polygons selected from the cathode-ray tube displays was most efficient. However, based on efficiency and accuracy, the results indicate that statistical manipulations via polygons selected from aerial photographs with the canonical transformation before minimum distance to mean classification was most accurate and efficient. Since this study only compared the digital processing techniques for single date Landsat data, Nelson and
others recommend using more appropriate seasonal coverage and the use of multi-temporal Landsat data if available.

There are several articles available concerning the general topic of canonical analysis which do not deal primarily with the applications of canonical analysis as previously discussed. Rather, they document the algorithm and its dimensionality reduction capabilities. Merembeck and Borden, (1978, 1) showed that canonical analysis has proven to be a powerful tool in dimensionality reduction of large or multiple data sets. They demonstrated this by pointing out that canonical analysis preserves, on as few axes as possible, that portion of the total variance which will allow the analyst to discriminate between certain categories of interest within the data. They also state that it is not uncommon to have 98 percent or more of the discriminatory variance explained on the first two or three axes (this is based on a 4 band data set).

Within a paper entitled, "Principal Components Analysis and Canonical Analysis in Remote Sensing," (Jenson and Waltz, 1979, 347) it is demonstrated that Landsat multispectral scanner (MSS) data are excellent candidates for canonical analysis because the bands are typically highly correlated. In addition, Jenson and Waltz note that canonical transformation will make the categories as separable as possible while making each individual category as homogeneous as possible. They point out that to get maximum benefit from analysis it is necessary to choose, during training set selection, categories that are spectrally unique. Jenson and Waltz, (1979, 347), also stated that
with a four band Landsat data set the total scene variance contained in
the first three canonical transformed axes is typically in excess of
99 percent, thus, eliminating the need to classify all canonical axes.

Somewhat more pertinent to this thesis topic are the results
from Jenson and others, 1981, where a maximum likelihood classifier for
a single-date Landsat MSS image was used for the same study area as the
one used for this report (Clarke, Oregon 7.5 minute quadrangle). Jenson
and others revealed an overall crop type classification accuracy of
65 percent. The maximum likelihood classifier did a respectable job of
identifying the three major crops of wheat, potatoes, and alfalfa.
However, maximum likelihood could not produce a soybean category and the
corn category created contains an unacceptably low accuracy (Jenson and
others, 1981, 18). This inability to consistently classify crop types
in diverse agricultural data sets is due to the fact that the analyst
commonly uses spectral data from only one date in the growing season,
and thus does not incorporate seasonal crop changes.

This literature review is not intended to be all inclusive. A
more detailed explanation of canonical analysis will be discussed in
Chapter III under Canonical Analysis.

The Study Area

The project study site, Clarke, Oregon 7.5 minute quadrangle,
lies within the Columbia River Basin of northern Oregon on the
Deschuttes-Umatilla Plateau (physiographic region of Oregon). The
Deschuttes-Umatilla Plateau lies east of the Cascades and between the
Blue Mountains and the Columbia River. It is a true lava plateau, weathered and dissected by streams. Between the rivers, the surface is nearly level and slopes gently to the north (Loy, 1978, 108). The study site is approximately 6- by 9-miles (9.6- by 14.4-kilometers) in area (34,560 acres or 13,824 hectares), equivalent to a 7.5 minute United States Geological Survey quadrangle. Figure 1 identifies the location of the study site as it relates to its geographic location within the United States and the state of Oregon. The 7.5 minute Clarke quadrangle is illustrated by Figure 2.

The study site can be characterized as a steppe zone with an average annual precipitation rate of 10 inches (25 centimeters) or less (Loy, 1976, 134). Its low elevation in respect to its proximity to the Columbia River gives this region a warmer, drier climate than any other area in Oregon.

This somewhat arid climate is not conducive to dryland agriculture. The dry climate, relatively flat land, and association with the Columbia River and its tributaries are the major factors for the extensive irrigation development which began in the 1930’s and has continued into the 1980’s. More recently, center-pivot irrigation systems, with an average field size of 130 acres, (53 hectares) have come to dominate the area. The dominant crop types within the study site are wheat, alfalfa, and potatoes. Other crops grown include corn, soybeans, rangeland, and apples.

The Clarke, Oregon quadrangle was chosen as the study site because of the crop diversity and existing data base available from the
Figure 1.--A map showing the geographic location of the Clarke, Oregon quadrangle study site. This figure shows the study site location relative to the United States and its location within the state of Oregon.
Figure 2.—Reduced representation of the Clarke 7.5 minute quadrangle. This map shows topographic information of the study area.
Columbia River and Tributaries Irrigation Withdrawals Analysis Project. During the Columbia River and Tributaries Project, field data describing crop types were acquired, which aided in the accuracy evaluation and comparison stage of this thesis research.

In summary, Chapter I has outlined the basic need for gathering crop production information, using digital, multi-temporal Landsat data, and outlined the basic procedure the study followed to solve the defined problem. Chapter II will further explain the data requirements to achieve the objectives of this thesis research.
CHAPTER II

Data Requirements

Three basic requirements for the preparation, classification, and evaluation stages of the study are presented in Chapter II. They are: (1) ground reference data, which was used to compare classification accuracies, (2) digital multi-temporal Landsat multispectral scanner (MSS) data, which is the source for spectral crop type information, and (3) results of a classification procedure developed for training and used for comparison to the results of this thesis research.

Collection of Reference Data

The crop type reference data (part of the Columbia River and Tributaries Project) was acquired primarily from field data collected during the 1979 growing season in the Umatilla Basin. Color-infrared aerial photography at a scale of 1:24,000 were acquired during the 1979 growing season to support the field collected crop type data. The field reference data was transferred to the 1979 color-infrared aerial photography (1:24,000) and then transferred to the 7.5 minute USGS Clarke quadrangle map (1:24,000) for digitizing. A clear acetate overlay was used for both transferring field data to the photographs and transferring the field data to the 7.5 minute Clarke quad.

The crop type reference data, which were field collected and partially interpreted from 1:24,000 color-infrared aerial photographs and transferred to the 7.5 minute map base during the Columbia River and
Tributaries Project, were converted to a machine readable format and registered to a map base by means of digitizing. Digitizing is an interactive technique for entering, editing, and storing geographic information taken directly from a map surface (Stauss and others, 1978, 34). The digitizing was done using the Interactive Digital Image Manipulation System (IDIMS) at the EROS Data Center's Data Analysis Laboratory.

Digital Multispectral Scanner Landsat Data

Before discussing the information requirements and data needs for the multi-temporal Landsat MSS data, a brief review of the Landsat Systems would be appropriate.

The beginning of the Landsat satellite program, formerly Earth Resource Technology Satellites (ERTS) of the National Aeronautics and Space Administration (NASA) and the Earth Resources Observation Systems (EROS), United States Geological Survey Survey (USGS) was the first program devoted to acquiring land resource data from space. Approximately 1.6 million images of land areas worldwide have been collected by three orbital satellites, which were launched in 1972, 1975, and 1978 respectively. Data are collected at altitudes of approximately 950 kilometers (570 miles). The primary data collection instrument on board each satellite is a multispectral scanner (MSS), collecting data in four bands of the electromagnetic spectrum. Landsat's MSS ground instantaneous field of view is 79 by 79 meters (261 by 261 feet), but the effective minimum resolution is 79 by 57 meters (261 by 188 feet). Landsat MSS data are acquired as
digital values and may be produced as black-and-white or false-color images or computer compatible tapes (CCT's). This new vantage point from space provides a means of a regional and synoptic evaluation of the Earth's surface while providing 18 day repetitive coverage (timely) and a cost efficient source of remotely sensed data.

As discussed in Chapter I, a proven method for tracking the phenologic changes of crop types is the use of multi-temporal Landsat data. Because of the diversity of crops within the study site and the various stages of growth of each crop, multi-temporal data was needed to spectrally differentiate the various crop types. Three different dates were chosen from throughout the 1979 growing season. They were: (1) June 3, 1979, ID 30455-18094, which was selected to represent the early portion of the growing season, (2) July 18, 1979, ID 21638-18025, which represents a time during the growing season when the wheat fields have been harvested, and (3) September 10, 1979, ID 21692-18040, which again represents harvested wheat and shows a more predominant vegetation cover for corn and soybeans. The following crop calendar (Table 1) will better illustrate the various stages of growth for each crop type at the time of acquisition of the three Landsat images used.

As illustrated by Table 1, each of the three dates show some crop growth overlap. No matter which single Landsat image is used, there are spectral similarities between two or more crop types. However, by incorporating the spectral characteristics of all three dates at one time, spectrally unique crop type signatures (descriptions), can then be defined.
Table 1.--Umatilla Basin, Oregon Crop Calendar for wheat, alfalfa, potatoes, corn, and soybeans.

<table>
<thead>
<tr>
<th>Crop Type</th>
<th>April</th>
<th>May</th>
<th>June</th>
<th>July</th>
<th>August</th>
<th>September</th>
<th>October</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alfalfa</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corn</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soybeans</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Indicates planting and crop growth cycle

Indicates harvesting of crops
Additional Classification for Comparison

In order to evaluate the accuracy and efficiency of the canonical transformation and classification, an additional classification was needed for comparison. The additional multi-temporal classification for the Clarke, Oregon study site was produced as a training aid during a portion of the Columbia River and Tributaries Project. The following are the four basic steps used for this classification:

1. Unsupervised training set selection
2. Clustering to define spectral characteristics (statistical generation) and subsequent assignment of spectral categories to crop type classes.
4. Evaluation and comparison to ground reference data to determine classification accuracy.

The following description of each step of the unsupervised maximum likelihood classification will provide an appropriate explanation of the classification used for comparison to the canonical transformation classification results.

An unsupervised approach to training set selection was used which involved the random selection of training areas from a predetermined sample of the data (20 percent in this case). From this unsupervised training, a clustering algorithm was applied which divided the pixels within the training area into homogeneous spectral groups.
Statistics are determined for each cluster of pixels (Johnson, 1979, 20). The result of applying cluster analysis is simply the identification of spectrally distinct classes in the image data. After the data were clustered, the analyst used reference data to associate the spectral classes with the cover types of interest (Lillesand and Kiefer, 1979, 479).

The training statistics from the clustering algorithm were then used with the maximum likelihood algorithm to classify the entire data set. The maximum likelihood classifier is based on a statistical decision rule to classify picture elements (pixels) based on predefined spectral statistics based on the calculation of a likelihood of occurrence statistic. A pixel is assigned to the class for which it has the maximum likelihood statistic (Welch, 1979, 23). Simply stated, a maximum likelihood classifier computes the probability of an unidentified pixel occurring in each distribution class or each crop type class. The pixel is then assigned to the most likely class. The maximum likelihood classifier has been the most common tool for digitally classifying agricultural croplands.

Chapter II discussed three data requirements for the preparation, classification and evaluation stages of this study. They are: ground reference data, digital multi-temporal data, and a classification result. The defining and explaining of the data types and their basic required use in the study, will aid the understanding of following chapter on Data Analysis Methods. Chapter III will explain in detail the methodology and use of the three data types.
CHAPTER III
Data Analysis Methods

The basis for the data analysis methodology is the canonical transformation of the 12 band multi-temporal Landsat data set before minimum distance to mean classification. Ultimately, the canonical transformation reduces the total number of bands needed for classification which in turn reduces the computer processing time needed for classification. The primary object of canonical analysis is to maximize the separability of crop type categories while minimizing the differences occurring within crop type categories on as few transformed channels as possible (Jenson and Waltz, 1979, 347).

The digital analysis methods followed five steps in attempting to identify the crop types within the study area.

1. Preparation of the reference data
2. Preprocessing of the Landsat data
3. Supervised training selection and statistical generation
4. Canonical transformation
5. Minimum distance to mean classification

A sixth step involving the evaluation and comparison of results will be discussed in the succeeding chapter. Figure 3, the Data Analysis Methodology Flow Chart, illustrates the basic procedure followed in the classification of crop types and the evaluation and comparison of results.
Multispectral Landsat Data

Radiometric Correction to Landsat Data

Geometric Registration of Landsat Data

June 3, 1979 July 18, 1979 Sept. 10, 1979

Registered 12 Band Data Set

Supervised Training Set
Selection of Crop Types

Statistical Generation from Training Sets

Canonical Transformation of the 12 Band Landsat Data Set Based on Training Statistics

Crop Type Reference Data

Ground Verification and CIR Aerial Photos

Digitizing and Registration of Reference Data

Comparison of Classification Procedures

Evaluation and Comparison of Reference Data to the Canonical Results

Minimum Distance Classification of the Transformed Canonical Channels

Figure 3.—Data Analysis Methodology Flow Chart.
**Preparation of the Reference Data**

As discussed in the preceding chapter, the crop type reference data were compiled by means of field collection and interpretation of color-infrared aerial photography. The crop type reference data were then transferred to the Clarke, Oregon 7.5 minute United States Geological Survey quadrangle map for digitizing and registration. The crop type reference data included the following six cover types: (1) wheat, (2) alfalfa, (3) potatoes, (4) corn, (5) soybeans, and (6) rangeland.

**Preprocessing of the Landsat Data**

The preprocessing of the Landsat data was done to correct for any radiometric anomalies apparent in the data. Such anomalies include striping, bad data lines resulting from sync loss during data transmission or sensor saturation and atmospheric scattering effects (Rohde and Taranik, 1979, 1). These anomalies can be corrected by using normalization or correction procedures. A destriping algorithm was applied to the 3 Landsat images because of striping problems found in each scene.

A second preprocessing step involved the geometric rectification and registration of the Landsat data. Geometric errors, including skew caused by rotation of the Earth under the satellite and variable line length because of varying velocity of the multispectral scanner (MSS)
mirror mechanism, are systematic and predictable (Rohde and Taranik, 1979, 6). These systematic and predictable errors can be corrected using standardized equations.

Other geometric errors include variable and measurable errors. This includes distortions caused by variations in spacecraft velocity, altitude, and attitude. The correction of variable and measurable errors usually involves the geometric registration of the Landsat data to a map coordinate system. This was accomplished in this study by selecting control points which are recognizable ground features in the images whose geographic locations were identifiable on the Clarke, Oregon Quadrangle map. Once the control points were selected, a affine transformation equation was used to assign geographic coordinates to the Landsat pixels. Since the geometrically corrected pixel locations did not coincide with the same pixels in the original distorted images, the distorted images were resampled to determine the brightness values of the pixels in the corrected images. Several resampling methods are commonly used for Landsat data. The Landsat data for this research were registered to Universal Transverse Mercator projection with 63.6 meter by 63.6 meter (1 acre) pixels. A cubic convolution resampling technique was used to assign pixel brightness values to the corrected image. The cubic convolution resampling technique assigns the brightness value to the corrected pixels based on the brightness values of the sixteen uncorrected pixels nearest to that corrected pixel.

After registering all three Landsat images to the same coordinate system, the three Landsat images were united to form a registered 12 band MSS Landsat data set. This registered 12 band image
allowed for the consideration of phenologic changes of the crop types when training areas were selected for the various crop types. Figures 4, 5, and 6 illustrate the three registered false-color composite Landsat scenes which united into a 12 band data set. Figure 7 represents a composite of band 7 from the June, July, and September images which shows three of the twelve bands from the 12 band data set.

**Supervised Training Selection and Statistical Generation**

The first step in digital image classification is the selection of training sets corresponding to the spectral patterns for each of the cover types of interest. This is one of the most critical steps of the classification process. Proper training statistics are a prerequisite for an accurate classification.

Since training set selection is a vital step in an accurate classification, a simple training approach was selected. The method selected was a supervised training approach. Supervised training simply involves the selection and delineation of spectrally unique fields for each crop type of interest. Care was taken to insure that each training field for each crop type was spectrally homogeneous. There are several methods for supervised training set selection. The method used was a digital display selection technique using a cathode ray tube. This method allowed the rapid delineation of training fields based on spectral signatures. After training set selection, the training fields are identified using crop type reference data. The training fields are then grouped into unimodal crop type classes that represent the unique
Figure 4.—This is a geometrically registered subscene (Clarke, Oregon Quadrangle) of a Landsat MSS false-color composite. This image was acquired by Landsat 3 on June 3, 1979, ID 30455-18094.
Figure 5.—This is a geometrically registered subscene (Clarke, Oregon Quadrangle) of a Landsat MSS false-color composite. This image was acquired by Landsat 2 on July 18, 1979, ID 21638-18025.
Figure 6.—This is a geometrically registered subscene (Clarke, Oregon Quadrangle) of a Landsat MSS false-color composite. This image was acquired by Landsat 2 on September 10, 1979, ID 21692-18040.
Figure 7.—This is a false-color image of band 7 (reflected infrared energy) only from each of the three dates illustrated in figures 4, 5, and 6.
conditions of each crop type (such as cut, regrowth and mature alfalfa) (Fleming and Hoffer, 1977, 141).

Descriptive statistics for each of these unimodal crop type training fields were then determined using an Interactive Digital Image Manipulation System (IDIMS) statistics function. The means, standard deviations, covariance matrices, and correlation matrices were computed for each of the crop type training fields. An evaluation was performed to insure informationally homogeneous crop type training fields. After the evaluation and refinement, the individual crop type statistics files were consolidated into one file. The consolidated statistics file, representing the six cover types (wheat, alfalfa, potatoes, corn, soybeans, and rangeland) and a water class was used to define the transformation coefficients for canonical analysis. A further explanation of canonical transformation is appropriate at this time.

**Canonical Transformation**

Canonical analysis was the additional step used in the classification procedure. This additional step was used in an attempt to reduce the dimensionality of the 12 band Landsat data set before applying a minimum distance to mean classifier. The reducing of the number of bands (channels) to be classified also reduces the computer processing classification time. In addition, canonical analysis makes the individual crop type classes as separable as possible while minimizing the differences occurring within the crop type classes, which should allow for an accurate classification.
Canonical analysis, which is also known as multiple discriminate analysis simply transforms the spectral characteristics of the crop types (spectral characteristics defined by means of training sets selected by the analyst) into transformation covariance matrices. The covariance matrices are maximized among the crop type classes and minimized covariance matrices are calculated for within crop type classes. The maximizing of among class variance and the minimizing of within class variance is further augmented by the rotating of the original axes to new orthogonal positions. This linear transformation places the maximum separability on the first canonical axis and succeeding axes containing successively smaller amounts of separability. For example, if canonical analysis is performed on an 8 band data set, the last three transformed channels may have near-zero variance. The first five transformed channels contain essentially all of the variance (or effective information) in the original 8 band data set, thus, reducing the number of channels (dimensions) required for classification. The degree of dimensionality reduction (reducing the number of original channels) is related to the amount of correlation in the original data set (Jenson and Waltz, 1979, 345).

Simply stated, the objective of the canonical analysis is to increase the separability of crop type categories defined within the data while minimizing the differences occurring within each crop type category (Jenson and Waltz, 1979, 344). As stated, canonical analysis uses a linear transformation of the data to reduce dimensionality, which in turn makes classifiers more computer efficient (Nelson and others, 1979, 14).
The preceding paragraphs defined the general objective of canonical analysis. The following paragraphs will explain the canonical transformation process as it applies to this specific problem.

As stated earlier, supervised training selection was used to delineate cover type boundaries for statistical generation. Once all training fields were selected for all cover types, statistics were generated for each. Then the statistics for each crop type were consolidated into one statistics file. This one consolidated statistics file represented all cover types within the image. They were: (1) wheat, (2) alfalfa, (3) potatoes, (4) corn, (5) soybeans, (6) rangeland, and (7) water. However, because the water class was not found within the boundaries of the Clarke study site only the first six classes, wheat, alfalfa, potatoes, corn, soybeans, and rangeland were used for final comparison and evaluation.

The consolidated statistics file representing the spectral information for all cover types within the image (7 classes) was then used as input to canonical analysis. Canonical analysis generates two main transformed files based on the spectral statistics information. They are: (1) a transformed coefficient matrix, which defines the increased variance between classes and the decreased variance within classes and (2) the transformed mean vectors (values) for each of the seven cover types for each of the canonical transformed channels. The canonical analysis process defines a maximum number of canonical channels that can be output. The process creates one less transformed channel than the minimum number of one of the following: the number of
cover type classes (7 cover types in this study) or the number of original multispectral scanner bands (12 band data set in this study). Therefore, six canonical transformed channels were generated from the Clarke data from the canonical transformation process.

As stated, canonical analysis performs a linear transformation of the original axes to a new orthogonal position (Larkowski and Borden, 1973, 1). This linear transformation of the original axes is performed to maximize the separability between classes. In addition, a covariance matrix is generated to define the elipsoidal dispersion pattern of points clustering around each class mean. This is done to minimize the within-class variance. The linear transformation places the maximum separability of cover types on canonical channel one and remaining class separability on succeeding canonical channels. The number of canonical channels computed was 6. Table 2 shows the percent of cover type separability on each of the six transformed channels. As illustrated, channel 1 has 47.21 percent of total cover type separability and channels 2 through 6 have 27.43, 14.61, 4.90, 4.67 and 1.18 percent of separability, respectively.

Table 2.—Percent of total cover type separability found in each canonical transformed channel for the Clarke Quadrangle study site.

<table>
<thead>
<tr>
<th>Canonical Channels</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of Total Cover Type Separation per Transformed Canonical Channel</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>47.21</td>
<td>27.43</td>
<td>14.61</td>
<td>4.90</td>
<td>4.67</td>
<td>1.18</td>
<td></td>
</tr>
</tbody>
</table>
In addition, Table 3 is a graphic representation of the cover type separability for each channel. As illustrated, channel one has maximum separability between cover types, with the succeeding channels having less cover type separability. The final graph is a summary of the separability of all six channels combined. This final graph shows total separability for all cover types.

The transformed coefficient matrix file is applied to the 12 band MSS data using a linear equation. This transforms the 12 spectral bands into six canonically transformed channels defined during the transformation. These six transformed channels were used for classification. A black and white print of each transformed canonical channel is found in Figure 8. Again, the maximum cover type information is in channel 1, as illustrated by image 1, with the remaining channels showing less cover type information or less discernable information in the remaining images.

The objective of using the canonical transformation step before classification was to reduce the number of bands or channels to be classified without losing cover type information or decreasing accuracy. The canonical transformation did reduce the original 12 MSS bands to six transformed channels. The six channels represent 100 percent of the total scene information. Therefore, no inherent information was lost and the number of channels to be classified was reduced by 50 percent. A determination of accuracy will be discussed in Chapter IV, Data Evaluation.
Table 3.—Graphs represent cover type separability for six separate canonical transformed channels and one summary of all channels.

<table>
<thead>
<tr>
<th>Channel 1</th>
<th>Channel 2</th>
<th>Channel 3</th>
<th>Channel 4</th>
<th>Channel 5</th>
<th>Channel 6</th>
<th>All Channels</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Crop Types</strong></td>
<td>1 2 3 4 5 6 7</td>
<td><strong>Crop Types</strong></td>
<td>1 2 3 4 5 6 7</td>
<td><strong>Crop Types</strong></td>
<td>1 2 3 4 5 6 7</td>
<td><strong>Crop Types</strong></td>
</tr>
<tr>
<td>1</td>
<td>* - - - - - -</td>
<td>1</td>
<td>* - - - - - -</td>
<td>1</td>
<td>* - - - - - -</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>- * * - - - -</td>
<td>2</td>
<td>- * - - - -</td>
<td>2</td>
<td>- * - - - -</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>- * * - - - -</td>
<td>3</td>
<td>- * - - - -</td>
<td>3</td>
<td>- * - - - -</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>- - * - - - -</td>
<td>4</td>
<td>- - * - - - -</td>
<td>4</td>
<td>- - * - - - -</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>- - - * - - -</td>
<td>5</td>
<td>- - - * - - -</td>
<td>5</td>
<td>- - - * - - -</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>- - - - * * *</td>
<td>6</td>
<td>- - - - * * *</td>
<td>6</td>
<td>- - - - * * *</td>
<td>6</td>
</tr>
<tr>
<td>7</td>
<td>- - - - - * *</td>
<td>7</td>
<td>- - - - - * *</td>
<td>7</td>
<td>- - - - - * *</td>
<td>7</td>
</tr>
</tbody>
</table>

* indicates cover types are not separable
- indicates cover types are separable

Legend

1 Wheat
2 Alfalfa
3 Potatoes
4 Corn
5 Soybeans
6 Rangeland
7 Water
Figure 8.—Black and white print of each of the six transformed canonical channels. The area represented is the Clarke Quadrangle study site.
Figure 8.—Continued.

Channel 5

Channel 6
Minimum Distance to Mean Classification

The applications of a classifier is one of the most time consuming steps in terms of computer processing time. However, by first reducing the number of data channels needed for the classification, the amount of computer processing time needed should also be reduced. Thus, the reduction of channels was accomplished and the six canonical transformed channels were classified using a minimum distance to mean classifier based on the transformed mean vector file output by canonical analysis.

A minimum distance to mean classifier was chosen since this classifier only needs statistics representing the transformed mean vectors for each class, which is one of the products of the canonical transformation. Other classifiers, such as maximum likelihood, could be used. However, a maximum likelihood classifier requires both mean and covariance statistics and canonical transformation does not output a covariance file. For this reason, a maximum likelihood classifier was not practical since training selection would have to be repeated to generate the necessary covariance statistics.

A minimum distance classifier assigns pixels to classes based on closeness of the unknown pixel to the nearest class means. A Euclidean distance measurement was used to determine minimum distance. This is the straight-line distance between the unknown pixel and the cover type class means. Using this approach, a classification depicting crop types resulted.
In summary, the data analysis methods employed a supervised training using a cathode-ray tube, statistical generation, canonical transformation, and a minimum distance to mean classifier. Chapter IV will discuss the evaluation of the canonical transformed classification results and compare the results to a maximum likelihood classification of 12 Landsat channels.
CHAPTER IV

Evaluation of Classification Results

Chapter IV deals primarily in evaluating the classification accuracy and computer processing efficiency of the six channel canonical transformed classification results. In addition, a comparison of the results was made to a commonly used classification procedure for agricultural purposes, a maximum likelihood classification. The maximum likelihood classification used the same 12 band multispectral scanner (MSS) data set for the Clarke, Oregon Quadrangle. The maximum likelihood process was outlined in Chapter II, Data Requirements.

The accuracy evaluation process used contingency tables as a tool for determining classification accuracy. The contingency tables permitted the calculation of three accuracy statistics: (1) the percent of crop types correctly classified, (2) the omission error which, for example, is when a pixel is classified as alfalfa and is not actually an alfalfa pixel, and (3) the commission error which, for example, is when a pixel that is alfalfa is classified as another crop type (Jenson and others, 1981, 8). Computer efficiency was based on computer processing unit (CPU) time for each classification process. The tabulation of CPU time was based on the following three classification analysis steps:

1. Training set selection and statistical generation
2. Transformation of the data
3. Classification of the data

The final comparison of efficiency of the transformed canonical
classification and the maximum likelihood classification was evaluated using the total CPU time required for classification based on the sum of the previous three steps.

For simplicity, the evaluation and comparison of the canonical transformed classification results and the maximum likelihood results will be discussed simultaneously.

**Accuracy Evaluation and Classification Comparison**

The results for the canonical transformation classification were compared to the reference data using contingency tables in order to measure the percent correct, omission errors, and commission errors for the classification. Again, the final cover type classes were:

(1) wheat, (2) alfalfa, (3) potatoes, (4) corn, (5) soybeans, and (6) rangeland. The 6 channel canonical transformed data that was classified using a minimum distance classifier showed an overall classification accuracy of 75.8 percent for all cover types and an overall accuracy of 79.0 percent for the crop type classes only (excluding rangeland areas).

The evaluation of the maximum likelihood classifier showed an overall crop type classification accuracy of 75.9 percent. The individual crop type accuracies vary from 80.3 percent for rangeland to 72.8 percent for soybeans and an overall accuracy of 75.0 percent for the crop type classes only. The 12 band maximum likelihood classification accuracy was measured using the same reference data and assessment techniques. Table 4 is a summarized tabular comparison of the canonical transformation results and 12 band maximum likelihood
results. Table 4 displays the percent correct, omission errors, and commission errors for both the individual crops, and overall.

Table 4: A tabular listing comparing the classification results for the canonical transformation and a minimum distance classifier and the maximum likelihood classifier.

<table>
<thead>
<tr>
<th></th>
<th>Canonical Transformation</th>
<th></th>
<th>Maximum Likelihood</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent Correct</td>
<td>Omission Error</td>
<td>Commission Error</td>
<td>Percent Correct</td>
</tr>
<tr>
<td>Wheat</td>
<td>85.0</td>
<td>13.5</td>
<td>15.0</td>
<td>75.6</td>
</tr>
<tr>
<td>Alfalfa</td>
<td>81.6</td>
<td>29.7</td>
<td>18.4</td>
<td>75.9</td>
</tr>
<tr>
<td>Potatoes</td>
<td>70.3</td>
<td>16.6</td>
<td>48.6</td>
<td>74.3</td>
</tr>
<tr>
<td>Corn</td>
<td>88.8</td>
<td>40.7</td>
<td>11.2</td>
<td>75.6</td>
</tr>
<tr>
<td>Soybeans</td>
<td>70.0</td>
<td>54.7</td>
<td>30.0</td>
<td>72.8</td>
</tr>
<tr>
<td>Range-land</td>
<td>58.6</td>
<td>17.2</td>
<td>41.4</td>
<td>80.3</td>
</tr>
<tr>
<td>TOTAL</td>
<td>75.8</td>
<td>24.2</td>
<td>21.9</td>
<td>75.9</td>
</tr>
</tbody>
</table>

A visual comparison of the ground reference data and the two classifications can be made using Figures 9, 10, and 11. Figure 9 is the classified ground reference data to which the two classifications were compared. The black areas were not used for accuracy comparison because of the lack of ground reference data. Figures 10 and 11 display the final classification for the canonical transformation and minimum distance classifier and the 12 band maximum likelihood classification.
Figure 9.--Ground reference data representing the six major crop cover types for the study site. The color scheme is as follows:
4. Light Blue-Corn, 5. Dark Blue-Soybeans, and
6. Yellow-Rangeland.
Figure 10.—The final six-channel canonical transformed minimum distance to mean classification. This is the final crop type classifications used for comparison to the reference data. The classification scheme is as follows: (1) Brown-Wheat, (2) Red Alfalfa, (3) Green-Potatoes, (4) Light Blue-Corn, (5) Dark Blue-Soybeans, and (6) Yellow-Rangeland.
Figure 11.--The final maximum likelihood classification of the 12 band MSS data from the Columbia River and Tributaries Project results. This is the final crop type classifications used for comparison to the reference data. The classification scheme is as follows: (1) Brown-Wheat, (2) Red Alfalfa, (3) Green-Potatoes, (4) Light Blue-Corn, (5) Dark Blue-Soybeans, and (6) Yellow-Rangeland.
respectively. A test for significance between the two classifications showed there was no significant difference at a 95 percent confidence level.

The most notable difference between the two final classifications is the visual difference in the reduced size of the fields on the canonical transformed classification (see Figures 10 and 11). This difference is also illustrated by Table 4. The rangeland accuracy for the canonical result was 58.6 percent and the maximum likelihood classification showed an accuracy of 80.3 percent. The high percent of commission error of 41.4 percent found in the canonical classification (Table 4) indicates that pixels were classified rangeland but were actually croplands. The spectral relationship of the edge pixels of the irrigated center pivot fields and the spectral characteristics of the non-irrigated class were not appropriately represented when supervised training type was performed. Without sampling these edge pixels during supervised training, the transformation and classification could not assign them to unique cover type class. If this had been done, the classification accuracy may have been improved. This confusion occurred primarily between the wheat class and the rangeland class. When evaluating the original spectral data for all three dates (Figures 4, 5, and 6), the wheat fields appears to be spectrally similar to non-irrigated class on several dates.

Despite the notable difference in classification accuracy for the rangeland class, the nearly identical overall classification accuracy for both methods, the canonical results show better individual
crop type accuracies (see Table 4). The differences were not large enough, however, to be significant.

A summarized evaluation can be made based on the percent correct for each crop class for the two classification procedures. When evaluating the percent correct for the crop type class accuracies, one can make the following statements:

(1) Canonical transformation and a minimum distance classification produced more accurate results for the wheat, alfalfa, and corn classes.

(2) The maximum likelihood classification produced more accurate results for the potato, soybean, and rangeland classes.

(3) The overall crop classification for all six classes, wheat, alfalfa, potatoes, corn, soybeans, and rangeland, produced nearly identical results (75.8 percent canonical, 75.9 percent maximum likelihood).

(4) The canonical results showed a variation of 58.6 percent (rangeland) to 88.8 percent (corn) for the individual class accuracies. Maximum likelihood showed a much smaller range of only 72.8 percent (soybeans) to 80.3 percent (rangelands).

(5) When comparing individual crop class accuracies, such as canonical's corn class (88.8 percent) and maximum likelihood corn class (75.6 percent), there are notable differences. In addition, there is a notable difference in
the rangeland results for canonical (58.6 percent) and maximum likelihood (80.3 percent).

Some general observations can be made for both classifications concerning the omission and commission errors. The maximum likelihood omission errors for soybeans and wheat shows a definite difference from the remaining crop type results. The high omission error of 55.7 percent for soybeans indicates that a significant area (relative to the total area of the soybean class) of soybeans was classified as another crop (see Table 4). After close evaluation of the reference data (Figure 9), the high omission error was due to the classification of an entire center-pivot soybean field as corn. The low omission error of 11 percent for wheat indicates that a small percent of the total wheat area was misclassified as another crop.

The omission and commission errors for the canonical results were much more varied for the six crop classes. The high omission error 48.6 percent for alfalfa and the high commission error of 29.7 percent for potatoes appear to be related. The majority of the classification confusion between alfalfa and potatoes is apparent in the area just north of the wheat grouping in the southwest corner. By evaluating the three individual false-color composites (see Figures 4, 5, and 6), there are some spectral similarities which may have been confused during supervised training for alfalfa and potatoes in this area, causing the related high omission and commission errors. For example, spectral similarities in two very unique crop types may occur during the earlier growing season when both crop types are at a stage of vigorous growth,
(wheat and alfalfa on the June 3 image). Both crop types could be reflecting similar amounts of energy due to their vegetation cover (density). Similarly, two unique crop types could be harvested during the same period of the growing season and reflect similar spectral characteristics, thus, generating similar spectral statistics during training set selection.

The high omission error of 54.7 percent for the soybean class was due to the misclassification of the same center pivot field which the maximum likelihood misclassified. This misclassification can be seen when comparing the reference data and the final canonical classification.

**Comparison of Efficiency**

Since the significance test for accuracy showed no significant difference at a 95 percent confidence level between the two final classifications, an evaluation of the total computer processing unit (CPU) time for each method was made. The tabulation of the total CPU time was based on the following three steps:

1. Training set selection and statistical generation
2. Transformation of data
3. Classification of data

Table 5 illustrates there is a significant difference between the two methods based on total CPU time. This notable difference (canonical analysis: 4,240 CPU seconds, maximum likelihood: 14,781 CPU seconds) is contributed primarily to the dimensionality reduction
capabilities of canonical analysis as outlined in previous chapters and the fact that 12 bands were classified using maximum likelihood. For example, the canonical transformation was applied to a 12 band data set. The inherent information contained in the 12 bands was reduced to only 6 canonical transformed channels. Thus, with less data to classify, the amount of CPU time needed for this step was greatly reduced.

Table 5.--This is a tabular comparison of the total CPU seconds used for training set selection, transformation of the data, and classification of the data for the canonical transformation classification and the maximum likelihood classification.

<table>
<thead>
<tr>
<th>Classification Procedures</th>
<th>Canonical Transformation Classification</th>
<th>Maximum Likelihood Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Set Selection and Stat. Generation</td>
<td>3000 CPU Seconds</td>
<td>4860 CPU Seconds</td>
</tr>
<tr>
<td>Transformation of the Multispectral Data Set</td>
<td>380 CPU Seconds</td>
<td>-----</td>
</tr>
<tr>
<td>Classification of the Data</td>
<td>860 CPU Seconds</td>
<td>9921 CPU Seconds</td>
</tr>
<tr>
<td>TOTAL</td>
<td>4240 CPU Seconds</td>
<td>14,781 CPU Seconds</td>
</tr>
</tbody>
</table>

A final consideration must be noted. A maximum likelihood classifier is the most commonly used classifier and the most complex. The classifier is based on a statistical procedure that calculates the probability density functions for each spectral signature. The classifier quantitatively evaluates both the variance and correlation of the category spectral response patterns when classifying an unknown
pixel and assumes the training data is Gaussian (normally distributed) (Lillesand and Kiefer, 1979, 465). Computing the probability density function simply means that the computer computes the probability of a pixel value occurring in the distribution of a class, then the likelihood of it occurring in another class, and so on for each category. It is then assigned to the most likely class (Lillesand and Kiefer, 1979, 466). As shown in Table 5, the maximum likelihood classifier consumed significantly more CPU time based on the fact that the classifier is complex and that it used a 12 band data set for classification.

One must note that the reason for using canonical analysis was to reduce data set size and in return reduce classification processing time. And as stated, minimum distance to mean is a rather simple classifier using distance to category means rather than probability density functions. Furthermore, canonical analysis outputs a mean vector file which can be used directly with minimum distance classification. The maximum likelihood classifier requires both the mean vectors and covariance matrices for classification. The following Chapter V will summarize this research and make some conclusions and recommendations.
CHAPTER V

Summary, Conclusions, and Recommendations

The need for food and fiber for the United States and the world is steadily increasing in importance. As this need increases so does the need for an improved method of collecting agricultural crop production information. Present information gathering techniques have become too time consuming for effective and efficient information gathering of crop production information. Historically, remotely sensed data has played an important role in gathering crop production information, because of its synoptic view of the Earth, its availability, its timely coverage, and its cost effectiveness. To satisfy this need for crop production information, a method which can effectively and efficiently identify crop types (a prerequisite for crop production information) is of prime importance.

Digital analysis of Landsat satellite computer compatible tapes (CCT's) can be used to effectively and efficiently identify various crop types. One of the most common methods of digital image analysis for gathering crop type information is the use of digital image classification of Landsat data. However, when classifying Landsat data for crop identification, a method which can effectively and efficiently analyze the seasonal change of crop types is needed. Therefore, the use of multi-date Landsat data for crop type classification was investigated. This thesis compared the classification accuracy and computer processing efficiency of a commonly used classifier, maximum likelihood, which was used on a 12 band multispectral scanner (MSS) data
set, and the canonical transformation of the 12 band MSS data set with a minimum distance to mean classifier to six transformed canonical channels. This comparison showed no significant difference in terms of classification accuracy. However, there was a significant difference in total computer processing efficiency. The canonical transformation classification used significantly less computer processing unit time.

Conclusions

The need for a useful, accurate, and efficient method for gathering crop production information has been identified in this thesis. The scope of this need is not just a regional or United States requirement, but a worldwide need. The canonical transformation of a 12 band MSS data set with a minimum distance to mean classification of the transformed data, produced a comparatively accurate crop type classification and a more efficient classification as compared to the classification of the entire 12 band data set.

The comparison of the two classification procedures showed no significant difference in terms of overall crop type accuracies. However, the canonical transformation classification used significantly less computer processing unit (CPU) time than the 12 band classification. Several factors contributed to this difference in computer processing efficiency. They are: (1) the maximum likelihood classification was applied to a 12 band multispectral scanner (MSS) data set and canonical transformation classification used only six
transformed channels for classification, and (2) the maximum likelihood classifier uses a very rigorous and complex decision rule for assigning unknown pixels to a cover type class, while a simple minimum distance to mean decision rule for assigning unknown pixels to a class was used for the classification of the six transformed canonical channels.

Despite the obvious difference in classifying 12 bands as compared to six transformed channels and the classifier complexity, one can conclude that the objective to reduce computer processing time by using transformed data for classification was accomplished.

A final conclusion can be made. The use of a canonical transformation of multitemporal digital Landsat data with a minimum distance to mean classification of the reduced transformed channels can be as effective and efficient for gathering crop production information as is the more traditional maximum likelihood classification of large data sets.

Recommendations

In general, before canonical analysis can be accepted as a universally applicable remote sensing tool, canonical analysis should be tested for computer processing efficiency and classification accuracy in various types of landscapes. These areas include forestry, rangeland, various types of agricultural areas, and urbanized areas.

Based on the research of the thesis problem, the following recommendations for further research are suggested:
1. The inherent problems of reduced field size for the canonical transformed classification, which resulted from the inability of supervised training selection to sample all cover types, indicates that an alternative approach to training set selection might be investigated.

2. In addition, canonical analysis for crop type classification should be compared to several other classification procedures, not just a maximum likelihood classification. The available classification procedures were outlined in Chapter I of this thesis.
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APPENDIX A

Glossary of Terms
**Algorithm** - A statement of steps to be followed in the solution of a problem.

**Brightness Value** - A numeric value assigned to each pixel in an image representing the relative reflectance or brightness of that pixel. Bands 4, 5, and 6 have values of 0-127 and Band 7, 0-63.

**Cathode-ray Tube** - A vacuum tube with a phosphorescent screen upon which images are displayed by an electron beam. The abbreviation is CRT.

**CCT** - Computer Compatible Tape. Digital Landsat data is obtained on a CCT or a set of CCT's.

**Channel** - Usually refers to a band, i.e., Landsat has a four-channel multispectral scanner.

**Classification** - The result of classifying an image by spectral differences.

**Cluster** - Any configuration of elements (pixels) occurring closely together.

**Cluster, Statistics** - The mean, variance, and covariance statistics calculated for a group of pixels.

**Clustering** - The analysis of a set of measurement vectors to detect their inherent tendency to form clusters in multidimensional measurement space.

**Clustering Algorithm** - Unsupervised classifier - finds natural groupings of pixels, in multispectral scanner (MSS) data, on the basis of cluster statistics inherent within the data.
Control Point - Any point in a horizontal and/or vertical control system (e.g., UTM map projection) that is identified on an aerial photograph or Landsat image and used for correlating data shown on the photograph or image to the map.

Controlled Clustering - This approach uses purposive selection of rectangular training areas generally encompassing several resource categories in each training area. The size of the rectangular areas can vary. Calculation of training statistics employs the same clustering algorithm, clustering training areas separately or collectively. Each cluster is identified as representing a resource category with the use of supporting data. Training statistics for clusters representing a mix of resource types can be eliminated.

Covariance - The expected value of the product of the deviations of corresponding values of two variables from their respective means.

Covariance Matrix - A measure of the "spread" of the data.

CRT - A Cathode Ray Tube.

Cubic Convolution - A high order resampling technique in which the brightness value of a pixel in a corrected image is interpolated from the brightness values from sixteen nearest pixels around the location of the corrected pixel.

Density Slicing - A general class of electronic or digital techniques used to assign image points or data vectors to particular classes based on the density or level of the response in a single image or channel; classification by thresholds.
Destriping - Removal of the residual differences after the calibration constants have been applied to the six MSS detectors of that band.

Digital - Of or relating to, or resembling a digit.

Digital Image or Digitized Image or Digital Picture Function - Obtained by partitioning the area of an image into a finite two-dimensional array of small, uniformly-shaped, mutually exclusive regions, called "resolution cells," and by assigning a representative grey-tone to each region. A digital image may be conceived as a function whose domain is the finite two-dimensional set of resolution cells, and whose range is the set of grey tones.

Digital Value - Data is said to have a digital value when it can be represented numerically. Necessary for computation within a computer.

Digitize - To assign or use a digital value to express analog data.

Dimensionality Reduction - Compressing a given amount of information into fewer variables.

Divergence - A statistic that is a measure of the difference between spectral signatures for spectral classes.

Euclidean Distance - The shortest distance between two points.

Gaussian Curve - Normal distribution of data represented by a bell-shaped curve.

Geometric Accuracy - Four types: Geographic (latitude-longitude)—based on the standard Earth-fixed coordinate reference system, which employs latitude and longitude. Positional—
ability to locate a point in an image with respect to a map. Scene Registration—the ability to superimpose the same point in two images of a scene taken at the same time (different spectral bands). Temporal Registration—the ability to superimpose a point in two images of the same scene taken at different times (same or different spectral bands).

Geometric Correction - Spatial reorganization of a data set to match a pre-determined set of spatial conditions.

Gray Level - A shade of gray representing different radiometric levels, or intensities on imagery.

Ground Data - Data obtained on surface/subsurface features to aid in the interpretation of remotely sensed data.

Landsat - An unmanned Earth-orbiting NASA satellite that detects and transmits multispectral images in the 0.5 to 10.6 um region to earth receiving stations (formerly called ERTS).

Maximum Likelihood - A statistical decision criteria to classify picture elements into computer spectral classes based on the calculation of a likelihood statistic. The likelihood statistic is calculated from the value of the pixel in question, mean, variance, and covariance for the computer spectral classes. A picture element is assigned to the class for which it has the maximum likelihood statistic. It can also be used to resolve overlap in classification results from other classifiers.

Minimum Distance to the Means - The unknown pixel is assigned to the class whose mean spectral pattern, determined from a sample of known pixels, is closest to that of the unknown pixel.
**Modified Supervised** - This approach involves the purposive selection of a number of known and homogeneous training areas for each resource class. Training areas need not be spectrally homogeneous. The clustering algorithm is used to derive the training statistics by clustering all training areas for each resource category collectively.

**MSS** - Multispectral Scanner on Landsat 1 and 2 - The MSS system gathers data by imaging the surface of the Earth in four spectral bands in the spectral region from 0.5 to 1.1 micrometers. The object plane is scanned by means of an oscillating flat mirror between the scene and the double-reflector, telescope-type of optical chain. The four bands are usually referred to as: MSS band 4, .5 - .6 um; MSS band 5, .6 - .7 um; MSS band 6, .7 - .8 um; and MSS band 7, .8 - 1.1 um.

**Multi-Digital Image** - Corresponding set of digital images obtained from the images in a multi-image. A multi-digital is often called a multi-image for short when it is understood from context that digital images are involved.

**Nearest Neighbor** - A resampling technique that calculates the brightness value of a pixel in a corrected image from the brightness value of the pixel nearest the location of the pixel in the input image.

**Parallelepiped Classifier** - A classifier which utilizes an upper and lower brightness value in four spectral bands to assign a picture element to a computer training class.

**Parallelepiped Classification** - A classification algorithm which uses lower and upper gray tone limits in each of up to four channels to alarm or classify each pixel. In order to be classified, a pixel must
be within the spectral bounds in each of the channels. This is also called a "one-dimensional" classifier, since only one set of bounds is calculated (from the training pixels) per channel.

**Pattern Recognition** - An automatic procedure for deciding to which class any given pixel should be assigned.

**Pixel** - Picture element. Unit of resolution on Landsat imagery. One pixel on Landsat 1 and 2 data is equal to approximately 57 meters by 79 meters or one video data byte.

**Preprocessing** - Commonly used to describe corrections and processing done to image data before information extraction. Includes geometric and radiometric correction, mosaicking, resampling, and formatting.

**Processing** - Manipulation of data by means of a computer or other devices.

**Radiometric Correction** - Normalization procedures developed to minimize the effect of radiometric distortions such as bad data lines and striping.

**Registering** - Alignment process by which two images or two digital images of the same ground area are positioned coincident with respect to one another so that their respective gray tones at any (x,y) coordinate or any resolution cell represent the sensor output for the same part of the same object.

**Remote Sensing** - Imaging or recording of physical phenomena at a distance by detecting the radiant energy which the phenomena either reflect or emit. In this glossary, the term is used in a restricted
sense to include only those remote sensing activities which involve the
detection of energy characteristically moving at the velocity of light.

Resampling - Techniques used to calculate a brightness value to
a pixel in an image that has been corrected. Include nearest neighbor,
bilinear interpolation, and cubic convolution.

Spatial - That which exists in the physical world and can be
located and described by linear dimensions.

Spatial/Spectral Classifier - Numeric decision rule that
utilizes the spatial relationships between neighborhood pixels as well
as the spectral values when producing a classification.

Signature - A characteristic or series of characteristics by
which a material may be recognized. Used in the sense of spectral
signature, as in photographic (color reflectance).

Spectral Characteristics - Relation, usually shown graphically,
between wavelength and some other variables.

Spectral Response - The variation in sensitivity of a device to
light of different wavelengths.

Spectral Signature - Quantitative measurements of the spectral
energy reflected, transmitted, absorbed, or emitted by an object at one
or more wavelength intervals.

Supervised Training - Process of calculating training statistics
from areas that are known to contain a cover type or information
category of interest to the user.

Temporal - Pertaining to, concerned with, or limited by time.

Training - The process of calculating training statistics or
calculating the spectral signature of a training set.
Training Set - A group of points from which training statistics are calculated.

Training Statistics - Statistics generated through training and used for classification of the data.

Unsupervised Training - Process of finding natural grouping in MSS data and calculating training statistics based on cluster statistics inherent within the data.

UTM - Universal Transverse Mercator; map projection.