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FORECASTS OF WINTER WHEAT YIELD AND PRODUCTION USING LANDSAT DATA

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16. Abstract

The feasibility of forecasting winter wheat yield and production using Landsat data is examined. The topics considered include: 1) relationships that form the basis for Landsat wheat yield forecasts; 2) temporal/spectral aspects of those relationships, including optimum Landsat spectral bands or band transforms and optimum data acquisition times (dates); 3) the capability of extending Landsat/wheat yield relations over time and space; 4) the relative utility of Landsat approaches, alternative approaches and combination (hybrid) approaches; 5) considerations involved in large area applications; and 6) the possibility of making simple direct wheat production forecasts (yield x acreage) using a single Landsat procedure. The fundamental conclusion drawn is that there is considerable information related to winter wheat yield in Landsat data, and that the prospects for utilizing this information are promising, but require additional work before operational use can be made of the information.

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PREFACE

This document reports on the results of an investigation to establish the feasibility of forecasting winter wheat yield and/or production using Landsat data. The research was carried out by personnel of the Infrared and Optics Division of the Environmental Research Institute of Michigan (ERIM) under NASA/Goddard Space Flight Center (GSFC) contract NAS5-22389 during the technical performance period from May 1975 through October 1977. Mr. G. R. Stonesifer (902) of NASA/GSFC served as the Technical Officer and Mr. Richard F. Nalepka of ERIM served as the Principal Investigator for this contract.

The authors wish to acknowledge the technical guidance and administrative assistance provided by Mr. G. R. Stonesifer throughout the contract period. ERIM personnel who deserve recognition for their continuing involvement and substantial contributions to the technical activities include Ms. A. Metzger and P. Bresnahan. Mr. F. Sadowski, G. Thomas, and J. Lewis contributed significantly to the collection of the field data and Ms. D. Rebel helped collect and reduce the data gathered. Drs. E. Jebe and G. Suits were consulted and provided important technical inputs throughout the program. Secretarial support was provided by Ms. E. Hugg, D. Dickerson, J. Watters, and M. Warren.

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1 SUMMARY

As the world population increases and the weather conditions remain uncertain, the adequacy of the world food supply is becoming an increasingly serious concern. The adequacy and availability of food is very important to the stability of world peace. Major potential social and economic consequences could develop due to either worldwide food shortages or the inequitable distribution of available supplies during conditions of severe local shortages. To avoid such serious problems better overall management of world food resources is required.

The first necessary component of better management is the availability of accurate and timely information as to the state or condition of the crops as related to their production potential. This is especially important for those crops which are a major part of the staple diet of large segments of the world population and for those crops (e.g., wheat, corn and rice) which are subject to significant international trade.

There are many ways that improved information might be made available. One means of generating such information which has not been examined in sufficient detail is the use of present day satellite sensors (e.g., Landsat MSS). Such sensor systems, with their potential for repeated coverage of most of the Earth, offer potentially cost-effective means by which to carry out the large area surveys.

Of the many possible agricultural crops which are of interest we have selected one, winter wheat, on which to concentrate our efforts. Over the last two years we have been examining the utility of the Landsat MSS to help forecast the yield and production of wheat over a large ground area in a timely and accurate fashion. Although our interest was for large area application, small area performance was also investigated. This was done in an effort to determine the fundamental accuracy with

which estimates could be made on a local basis, which is useful in analyzing the precision with which estimates can be made on large areas. In addition, more accurate local estimates may be desirable.

Many of the existing approaches to estimating crop production are either independent of current remote sensing data, or else use remote sensing (e.g., Landsat) data only for estimation of crop acreage, with the yield component of production being estimated by alternative procedures such as geographically coarse agrometeorological yield models (e.g., LACIE).

In our approach we use Landsat data as a means of obtaining forecasts of crop yield by using the Landsat data as a measure of current vegetation condition as it relates to potential yield. The advantage of this approach is that it permits us to take advantage of the fact that the vegetative condition of a wheat crop integrates the effects of all the factors affecting its growth, including non-meteorological factors (e.g., soil type, planting density, irrigation, fertilization) which are normally not considered in traditional yield models. In addition, given that Landsat data can provide a reasonable measure of crop type and crop condition at appropriate times in wheat's growth cycle, it may also be possible to forecast production (yield x area) early in the season directly from Landsat data. Of course, as with any early forecast, extreme or unusual conditions occurring between the time of the forecast and harvest will affect the ultimate production. Therefore, it is necessary to occasionally update the forecast. Agrometeorological models and data from meteorological satellites would serve this purpose well.

In order to reach the present stage of development of our present approach a number of basic questions needed to be addressed. First it was necessary to establish whether useful information related to yield or production could in fact be extracted from Landsat data and, if so, to define under what circumstances this was possible. Therefore, we began by searching for and examining relationships between: (1) Landsat data and field condition, (2) field condition and yield, and then naturally, (3) Landsat data and yield. As a part of these investigations other aspects of the problem were also examined. The optimum Landsat bands to use for this problem as well as the optimum time or times during the growing season were studied. When these factors were established and estimates of yield were made, we compared the results using Landsat data on both local segments and relatively large areas with results using more traditional methods. The purpose of these comparisons was to determine if our approach could potentially contribute to those now being employed for estimating yield. In addition, we attempted to improve the cost-effectiveness of the approach through geographic extension of yield-predictive relationships.

Finally, as a result of knowledge and insight gathered throughout the investigation, a possible approach to direct Landsat production forecasts was identified and tested.

The approach to assessing production presently being pursued by us offers some specific advantages over other approaches when it comes to applying them operationally on a worldwide basis. These potential advantages include: (1) early season forecasts, (2) elimination of the need during the operational phase to locate and identify fields, (3) providing a means not now available for operating in regions of small or irregularly shaped fields, (4) accounting for non-uniformities within fields, (5) incorporating in the production forecast effects due to disease, drought, etc., (6) possibly eliminating the need for training each growing season, (7) eliminating the need for identifying specific sites in advance, and (8) as a result of (7), reducing the effects of cloud cover on useful data acquisition and the sampling error that results therefrom.

The investigation described above centered on a number of sites in the U.S. Southern Great Plains in the state of Kansas. As a result of the investigation we found that:

1. Landsat data can be effectively used to estimate certain variables which are required in existing yield models (such as LAI or percent cover).
2. Landsat indicators of yield are as highly correlated with individual field yield as are estimates using traditional field sampling methods, even when using Landsat data collected several weeks before the field samples are made.
3. A considerable amount of the variation in individual field yield which is not explainable by meteorological data can be accounted for by Landsat data.
4. In order for Landsat data to be of maximal use in an operational system, improvements in the ability to remove the external effects (including atmospheric effects) are required.
5. It may be possible in certain situations to make useful direct wheat production forecasts using early-season Landsat data.

With regard to item 5, results achieved to date in evaluating our direct winter wheat production forecast technique are very encouraging. For a region of approximately 21,000 km^2 (8000 $miles^2$) in the U.S. Southern Great Plains which included both large and small fields, we were able to forecast the end of season (June) production with an error of only 2.6% using Landsat data gathered in mid-April. Uncertainties still exist, however, as to whether equally accurate results could be achieved under differing circumstances.

As a result of the investigation reported herein we recommend that activities be undertaken which:

1. Continue to investigate validity of fundamental hypotheses and reasons for departures therefrom.
2. Continue to investigate large area/large sample investigations with emphasis on analyzing randomness of errors, training and testing procedures, and data handling.

3. Continue to investigate ways to calibrate or stratify data for optimal use of Landsat-wheat yield relations. As part of the above we include:
   a. investigate better haze correctors
   b. investigate better phenology indicators
   c. consider the use of Landsat data for indicating only relative yield on a local basis, to be calibrated by other procedures (field sampling, etc.)
4. Further investigate hybrid yield models that incorporate Landsat, meteorological and cultural factors as perturbations from normal.
5. Continue to investigate direct wheat production approach to determine the generality of its usefulness.

2
INTRODUCTION

Accurate monitoring of various food supplies is a vital input to their efficient and equitable production and distribution. It has been estimated that a reduction from three to two percent in the error of United States national corn, soybean, and wheat production estimates could result in 14 million dollars net social benefit to the country [1], and that more frequent and timely estimates alone, even without an accompanying improvement in accuracy, should result in additional benefits [2]. For crops that are subject to international trade, estimates of domestic production need to be accompanied by estimates of global production.

In view of the very large inventory problem the above discussion implies, and in view of the need for timely production estimates, the use of satellite data (such as Landsat) could potentially be quite useful. The purpose of the investigation described in this report is to determine the feasibility of using Landsat data to improve winter wheat crop production forecasting capabilities.

The production of an agricultural crop can be thought of as the product of the crop yield and the area of that crop. Remote sensing data, and Landsat data in particular, can potentially be used to help assess and estimate both crop yield and crop acreage. In this study we consider first the problem of estimating wheat yield using the data known to be from wheat fields. This problem is addressed by demonstrating the nature of yield prediction using Landsat data, by comparing such yield prediction to other methods, and by studying the consistency of Landsat yield relations from one site or acquisition to another. Second, we consider the possibility of forecasting total wheat production using a procedure which does not require the prior classification of the data as wheat and non-wheat. An initial test of a technique designed to make such forecasts using early-season Landsat data is presented.

Wheat was chosen as the crop of interest for this investigation because of its relatively distinct spectral/temporal character, and because it is a crop that is subject to international trade. Events such as the 1972 US/Soviet wheat sale also seemed to underline the need for improved forecasts of production. The state of Kansas was chosen as the study site, since it is the largest wheat producing state in the country, and since activities in Kansas carried out as part of other programs would be complementary to this investigation.

It seems appropriate at this time to discuss some of the background of wheat production forecasts.

There are several steps in making accurate and timely wheat production forecasts using conventional approaches. These steps include:

1. reliable crop identification
2. reliable acreage determination
3. reliable forecasts of yield per acre
4. an efficient information processing system.

Most of the work that has been done with respect to contributing to wheat production estimates using Landsat data has concerned steps 1 and 2. Recently, additional emphasis has been given to step 4 as part of the Large Area Crop Inventory Experiment (LACIE) [3]. Some effort has been devoted to step 3 [e.g., 4, 5, 6], but it appears to be the one step that is presently least understood, and farthest from operational implementation. Accordingly, this investigation has concentrated on the use of Landsat data (with or without ancillary information such as agrometeorological data) to improve forecasts of yield.

There are several different approaches that have historically been taken for predicting crop yields. Most attempt to relate meteorological parameters such as rainfall to crop yields. We believe that another variable should be added, namely crop vegetation density (e.g., percent cover or leaf area index [LAI]). Vegetation density is potentially measurable using remote sensing, and therefore, it is an important consideration for this investigation insofar as it is indicative of yield. The rationale for using vegetation density is developed later in this section, after more conventional alternative techniques and existing U.S. Department of Agriculture (USDA) procedures are discussed.

Efforts to relate meteorological parameters to crop yield have produced high correlations in some situations and statistically insignificant correlations in others. This variability in results may have many explanations but is most likely due to the fact that the cause-effect relationships are extremely complicated and that the interactions among environmental parameters are not well understood. In addition, the meteorological parameters chosen (e.g., monthly rainfall) frequently have been too coarse to be consistently useful, and are not always the limiting factors to growth and yield.

One of the problems with using only meteorological parameters to predict yield is that other parameters also are relevant. These parameters include fertilization, irrigation, planting density, disease and mechanical injury. Most of the increases in yield for a number of types of crops over the last several decades can be attributed to the use of more and better fertilizers and to irrigation. Mechanical injury, such as lodging, has been shown to reduce yields, and the amount of reduction is dependent on the timing of the lodging [7]. In addition, it has been estimated that disease, insects, and weeds account for an average reduction in yield of wheat of 32%, although these losses may vary considerably from year to year and region to region. Another problem is that meteorological variables are sometimes poorly correlated with the parameters that are actually directly associated with the growth processes. For example, the relationship between precipitation and soil moisture is a complex function of the temporal distribution and amount of rainfall, soil texture and other factors.

The crop forecasting methods currently used by the Statistical Reporting Service (SRS) of the USDA are of two kinds--operator subjective condition surveys, and objective enumerative surveys. One form of subjective condition model is described in Reference 8, and is as follows:

$$Y_c = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4$$

where Y_c = computed yield per acre

X_1 = condition (or reported probable yield per acre) by farmer's estimate

X_2 = precipitation for specified months prior to date of forecast

X_3 = expected precipitation for specified months after date of forecast

X_4 = time.

The constants are obtained by multiple regression using historical data. The application of this relation is made using regions stratified in accordance with climatic factors.

Objective enumerative field surveys [9] are based on actual samples of plant characteristics in portions of selected fields. Only major crops are subjected to enumerative surveys. The principal advantage of this approach is that yield estimates are based on actual samples of parameters directly related to yield, such as average weight of developing grain on selected wheat plants. The principal disadvantage is that such yield estimates cannot be made until late in the growing season. Additional difficulties arise from sample size limitations, bias in field measurement, and lack of information on the amount of the crop that is lost (e.g., not harvested) after field measurement.

There is a considerable amount of evidence that the potential yield of agricultural crops is correlated with the vegetative density of the crop, including such parameters as percent vegetation cover, leaf area index, and standing biomass. In the initial stages of crop development, for example, vegetation cover may be an indicator of the number of plants that have been sown and germinated. In subsequent stages, vegetation cover may be indicative of the status of the crop in response to accumulated weather and disease.

A correlation between the vegetative development of a crop and its yield is, of course, not surprising. And, in fact, the farmer's estimates of crop condition, and even previous attempts to estimate yield using remote sensing, have almost certainly been based on some aspect of crop vegetative development. It is hoped that by use of satellite digital data, we may be able to generate a large number of samples of vegetation condition over large areas in an objective, timely, cost-effective manner.

A theoretical model of the yield of an agricultural crop as a function of the leaf area index, the structure of the crop, and a number of important environmental parameters has been developed at ERIM [10]. This model shows the close interaction of these factors, and indicates that the effect of environmental parameters is highly dependent on the vegetative development of the crop, including the value of peak leaf area index and also leaf area duration (LAD).

The fundamental propositions on which our investigation of Landsat forecasts of wheat yield are based are that:

1. a good early-season indicator of potential wheat grain yield is the degree of vegetative development
2. the degree of wheat vegetative development can be estimated using Landsat data.

Until recently, it has been difficult to get precise and timely field observations of crop condition over large areas, so estimates of potential yield based on such observations have not generally been practical. However, the advent of earth resources satellites such as Landsat has presented the possibility of monitoring actual crop condition over large areas in a timely fashion. The purpose of this investigation is to explore that possibility.

In the remainder of this report we present the details of our investigation. The material is organized in the following way. In Section 3 we describe the general approach of the investigation and discuss the study area, the field data collection, and various types of data used. Section 4 provides a discussion of the basic relationships which may make Landsat forecasts of yield possible. We follow this section with a discussion of the results of our investigation into the optimum Landsat bands for useful yield relationships and the optimum times during the growing season to gather Landsat data. In Section 6 we discuss the relative utility of Landsat data, meteorological data, and ancillary (cultural) data for forecasting yield on a local (field-by-field) basis. The question of extending the Landsat/yield relations is presented in Section 7, and the results of making yield forecasts over a geographical region as large as a Crop Reporting District are discussed in Section 8. Section 9 describes an initial effort in implementing a direct winter wheat production forecasting approach. Finally, in Sections 10 and 11 we present the conclusions drawn and recommendations made as a result of this investigation.

3
GENERAL APPROACH

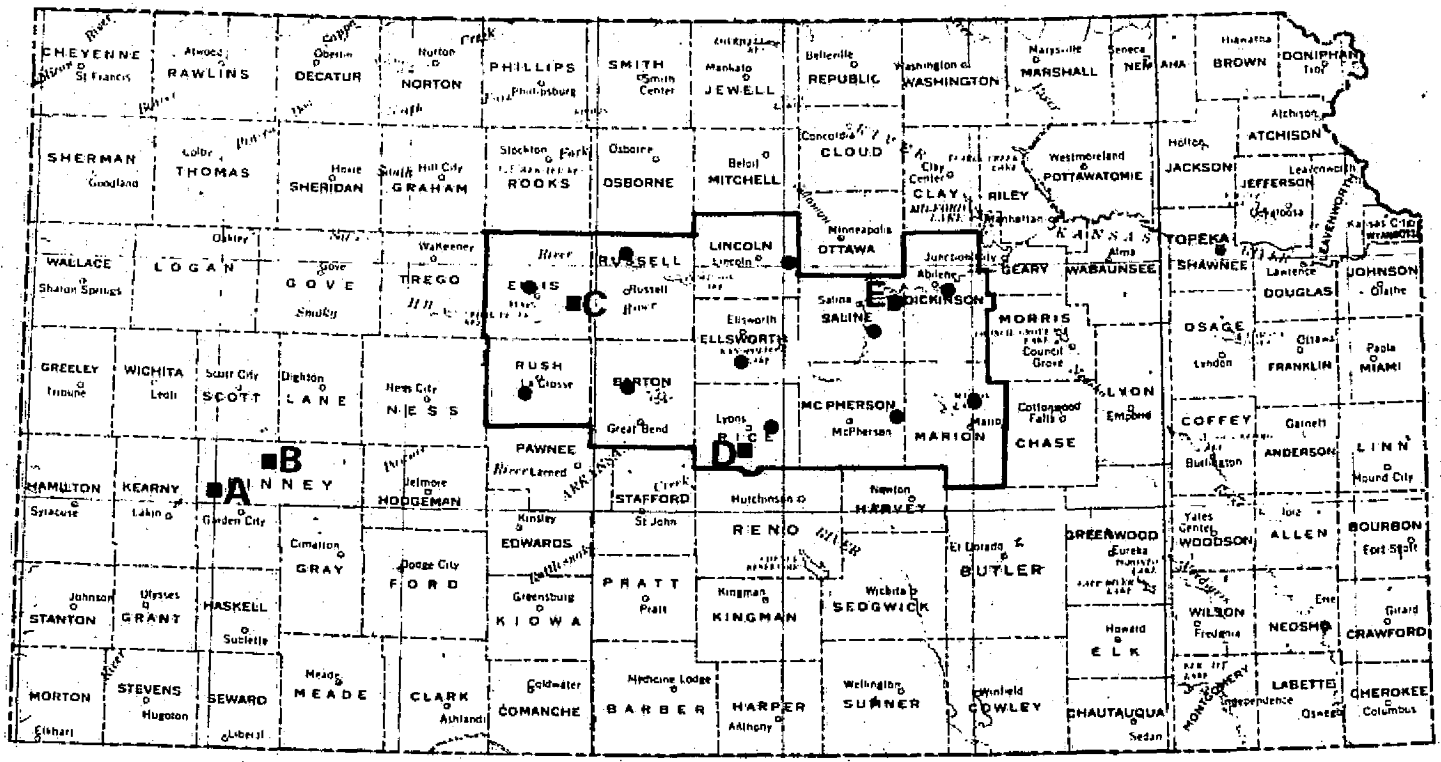
In this section we describe the data used in this investigation and the data acquisition, reduction, and processing methods employed. These data include ERIM-collected field data, yield information, meteorological and other ancillary information, digital Landsat data, and imagery and photography covering Landsat scenes. As was indicated in the introduction, this investigation utilized data gathered in the State of Kansas, with the majority of work confined to specific study areas.

3.1 FIELD DATA COLLECTION

Two Finney County sites (A and B) shown in Figure 1 were involved in ERIM field data collection. Site A is a 5x6 mile area characterized by continuous-cropping practices and fields that were fertilized and irrigated, either by circular pivot sprinkler systems or by flood irrigation. This site was visited during the 1974-75 growing season. Site B is a 5x6 mile area that had predominantly non-irrigated, non-fertilized wheat fields grown in summer-fallowed land, and was visited during the 1975-76 growing season.

A total of six trips of approximately five days duration each were made to the Finney Site A. These trips began in late April 1975 (before heading) and terminated with a trip in mid-June, when essentially all of the wheat had turned yellow. The trips were planned so that the field team could be on location at the time of the Landsat (1 and 2) overpasses. The specific 1975 Landsat overpasses for which the ERIM team was in the field at Site A are listed in Table 1.

The first two trips to the Finney A test site were planned primarily to check out field data collection techniques. Data that could be used to characterize specific fields was not collected until the May 22 trip. Field data that was collected included measurements of leaf area index, percent cover, and biomass, plus radiometric properties



Key:

■ - Sites for which wheat yield information is available

A - Finney Site A
B - Finney Site B
C - Ellis Site
D - Rice Site
E - Saline Site

● - Other sites used in large area investigations

FIGURE 1. LOCATION OF KANSAS SITES

TABLE 1. LANDSAT OVERPASSES FOR WHICH ERIM PERSONNEL WERE AT FINNEY SITE A

Satellite	Date
Landsat 2	4/25/75
Landsat 2	5/13/75
Landsat 1	5/22/75
Landsat 2	5/31/75
Landsat 1	6/9/75
Landsat 2	6/18/75

of wheat components (and soil). The methods employed to obtain these quantities are discussed in Appendix I.

In 1976, measurements of percent cover and radiometric properties were made at Site B. Field measurements of percent cover were made at three different times in 1976, corresponding to the times of Landsat 1 or 2 overpasses. The specific Landsat overpasses for which the ERIM field measurement team was in the field are listed in Table 2.

TABLE 2. LANDSAT OVERPASSES FOR WHICH ERIM PERSONNEL WERE AT FINNEY SITE B

Satellite	Date
Landsat 2	4/18/76
Landsat 2	5/6/76
Landsat 1	6/2/76

3.2 USE OF LANDSAT DATA

Landsat data collected over Finney Sites A and B, and the Ellis site were used for much of the early investigations of relationships between yield, field measurements, and Landsat data. The acquisitions used are given in Table 3. In addition to these three sites, two additional sites,

TABLE 3. LANDSAT DATA PROCESSED

Site	Date	Frame No.*
A (Finney)	22 Nov 1974	1852
A (Finney)	15 Apr 1975	1996
A (Finney)	21 May 1975	5032
B (Finney)	6 May 1976	2470
Ellis	3 May 1975	5014
Ellis	11 May 1975	2109
Ellis	20 May 1975	5031
Ellis	21 May 1975	5032
Ellis	17 June 1975	2146

*Prefix of: 1 or 5 - Landsat 1
2 - Landsat 2

Rice and Saline (see Figure 1), had wheat yield information available, and were used in the investigation of large-area yield and production estimation techniques.

In order to obtain Landsat information that corresponds to field measurement, yield, and other ancillary information, all quantities were made to characterize individual fields. To do this, fields identified on high altitude photography were located using a coordinate digitizer, and a transformation was determined using selected control points so that the field locations were established in the Landsat data. As described in Appendix V, an inset from the actual field boundaries was established so that only pixels whose centers do not lie nearer to the boundary than the size of one pixel would be used. This was done to insure that radiation from adjacent fields would not influence the statistics representing the field of interest. Once field locations and insets were established, the mean signal value in each Landsat band was obtained for each field. These mean values and the associated field measurements, yield, and other information were then stored in a computer file for subsequent analyses.

For purposes of examining large-area techniques, a number of 5x6 mile segments shown in Figure 1 also were used in the Central Kansas Crop Reporting District. The use of these sites is described in Section 8.1.

3.3 OTHER SOURCES OF DATA

In addition to Landsat data and to the field data collected by ERIM personnel, a variety of data was available from other sources, as indicated in Table 4. Much of this data was provided through the courtesy of NASA/JSC.

TABLE 4. DATA USED IN THIS INVESTIGATION

Data Type	Source
Landsat Digital Data	- Earth Resources Observation Systems (EROS) - Johnson Space Center (JSC)
Landsat Imagery	- Agricultural Stabilization and Conservation Service (ASCS) - JSC
Ground Truth Information (including crop inventory, overlays, and other information)	- JSC, (and ASCS)
Yield Estimates	- JSC, ASCS
Environmental Data (rainfall, temperature, wind, humidity)	- JSC, (and ASCS)
Soil Maps	- Soil Conservation Service (SCS)
Aerial Photographs; Field Radiometric Information	- Texas A&M University (TAMU) - Colorado State University (CSU)
County, District, and State Wheat Production Figures	- Kansas Crop and Livestock Reporting Service
Soil and Vegetation Measurements	- ERIM
Ground and Low-Altitude Aircraft Photographs	- ERIM

The most important information of this type for the purposes of this investigation was wheat grain yield. Actually, several different types of estimates of yield were generally available. However, unless otherwise indicated, we used the farmer's combine (harvested) weight yield estimates, since they are believed to be the most accurate. Yield per harvested acre was used, unless otherwise stated.

Other data that was available and that was used included: (1) percent cover estimates, (2) stand height, (3) phenological state, (4) soil moisture (subjective), (5) cultural practices such as fertilization, irrigation, summer-fallowing, (6) wheat variety, (7) notes on anomalous crop conditions (e.g., lodging, disease), (8) subjective stand quality ratings, and (9) meteorological information.

In addition to data used for the field-by-field analyses of fundamental relationships, additional forms of data were used to investigate large area wheat yield and production techniques. In particular, Kansas Crop and Livestock Reporting Service (KCLRS) production figures on a county-by-county basis were used.

3.4 GENERAL METHODS OF ANALYSIS

Once data on a field-by-field basis was stored in a computer file, a number of manipulations and standard statistical methods were performed in carrying out the investigation. Correlation and regression analyses were used to determine the relationship between such parameters as yield, Landsat data, ancillary data, and field measurements. In addition, F- and t-tests were used to analyze yield prediction extension techniques, and t-tests were used to assess the performance of Landsat large area yield prediction techniques. In general, our analyses were based on expected cause-effect relationships, in the hope that this would lead to generally optimum procedures, rather than procedures that would work best on one data set.

4
BASIC RELATIONSHIPS

As indicated earlier, the hypotheses on which Landsat forecasts of wheat yield are based are that: 1) there is a relationship between Landsat data and vegetation density; 2) there is a relationship between vegetation density and yield; and 3) there is, therefore, a relationship between Landsat data and wheat yield. These basic relationships will be illustrated and discussed in this section. Additional material that further explores these relationships is contained in Section 5.

4.1 LANDSAT DATA/VEGETATION DENSITY

A number of investigations have indicated the existence of a relationship between remote sensing (Landsat) data and vegetation density* [e.g., 5, 11, 12]. An example of the relationships found during this investigation between individual Landsat band data values and vegetation density when essentially all of the vegetation is green is indicated in Figure 2. Here we see that both Landsat visible bands (MSS4 and MSS5) are significantly negatively correlated with vegetation density (LAI), Band 7 is significantly positively correlated with vegetation density, and Band 6 is nearly uncorrelated with density. Of the four Landsat bands, the red band (MSS5) exhibits the highest individual band correlation with vegetation density. These findings are generally consistent with our expectations based on previous work [13]. A plot of the individual Band 5 data values vs vegetation density is shown in Figure 3. It can be seen that the Band 5 data values are quite sensitive to changes in vegetation density at low values of LAI, but lose sensitivity at high values of LAI. Here again, this result should be expected based both on recent reports [14] and previous work [13].

*In this investigation, the relationship of Landsat data and yield with LAI and with percent cover have been found to be quite similar. Therefore, the two indicators of vegetation density are used more or less interchangeably.

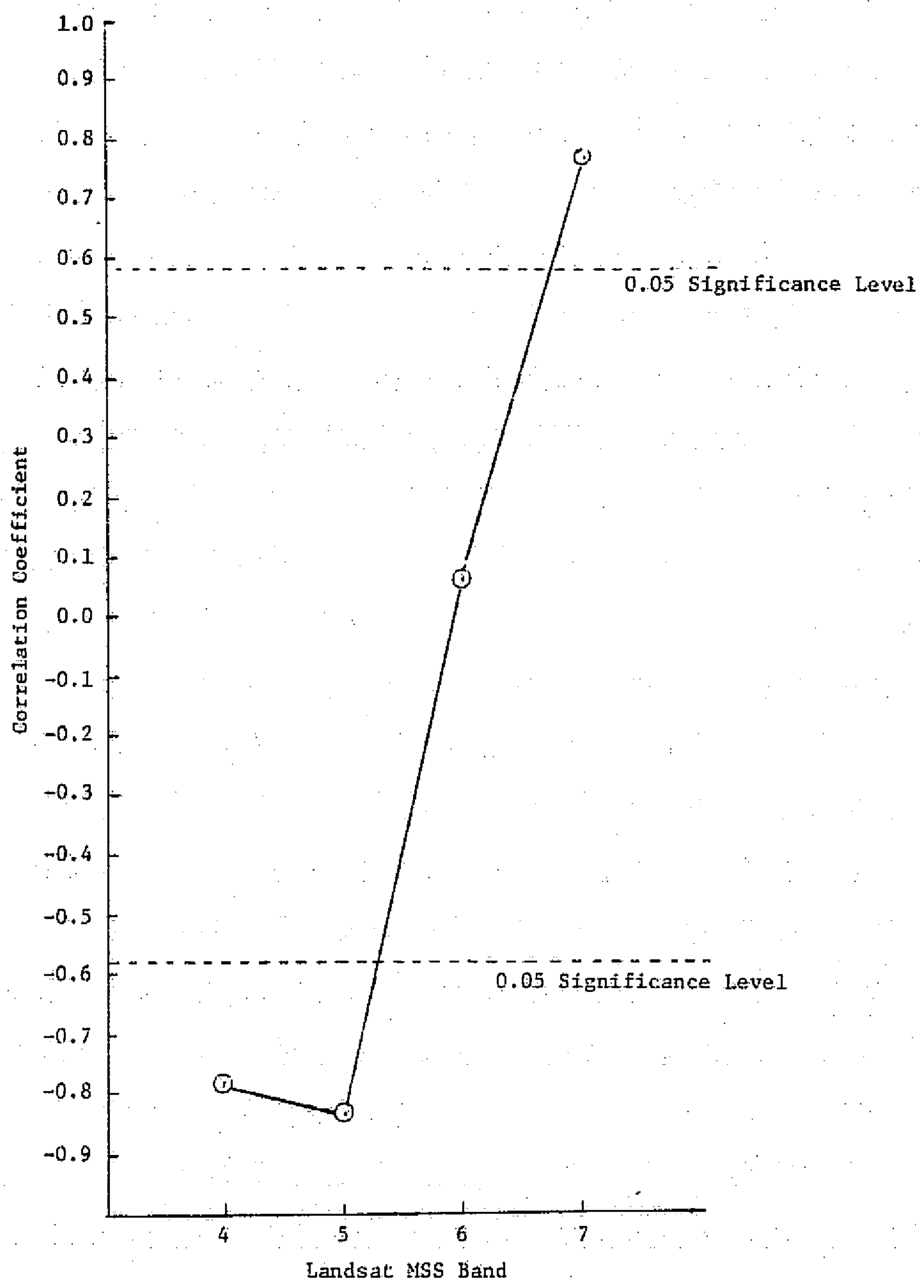


FIGURE 2. CORRELATION OF LANDSAT INDIVIDUAL BANDS WITH LAI, FINNEY A SITE, 21 MAY 1975

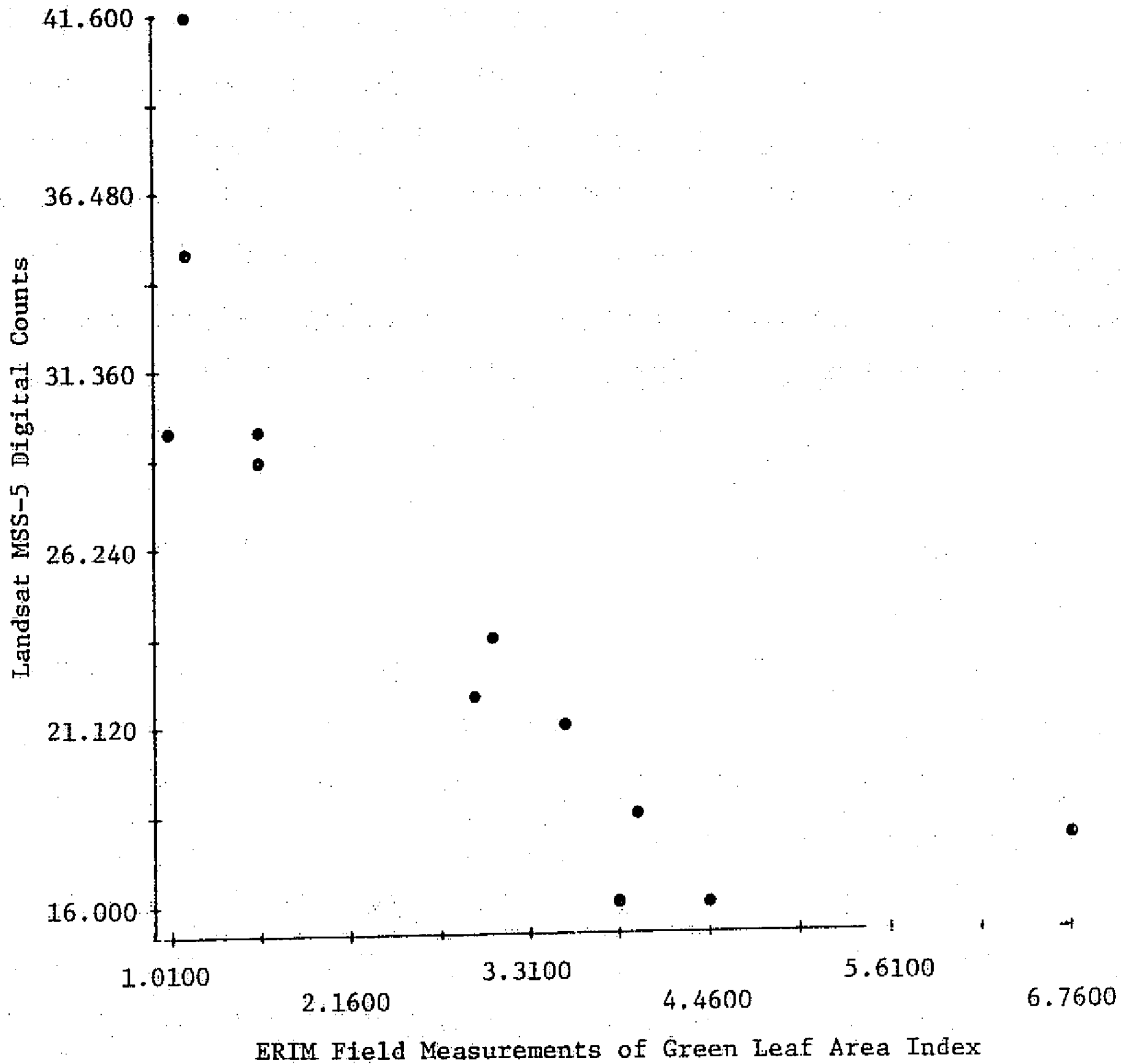


FIGURE 3. LANDSAT RED BAND (MSS-5) VALUES VS GREEN LEAF AREA INDEX. FINNEY A SITE, 21 MAY 1975

In order to extract all of the available information concerning vegetation density, all four Landsat bands would have to be used. However, there would be advantages if transformations of the Landsat data were available that maintained most of the information on green vegetation density while simultaneously being insensitive to other variables. Previous studies [e.g., 10] have suggested a number of Landsat data transformations which satisfy these requirements. Included among these is the ratio of Band 7 to Band 5. In Figure 4, which plots this ratio against vegetation density we see that a high correlation (>0.80) between Landsat data and vegetation density exists. As a part of this investigation we briefly examined other green measure transforms*. Comparative results using some of these transforms are shown in Figure 5. As this figure suggests, we have found the various green measure transforms to generate roughly equivalent results. Therefore, throughout the remainder of the text we use the green measure transforms more or less interchangeably. (A more detailed discussion of green measure transforms is contained in Appendix III.) The point to be remembered is that there is a high correlation relationship between Landsat data and vegetation density or field condition.

4.2 FIELD CONDITION/YIELD

An example of the relationship found between vegetation density and yield is shown in Figure 6. Although these data show a generally positive correlation, it is clear that the correlation is better at low values of vegetation density than at high values. In this data

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* Among the green transforms examined are:

RAT75 = MSS7/MSS5

SQ75 = $\sqrt{MSS7/MSS5}$

RAT65 = MSS6/MSS5

TVI = $\sqrt{\frac{MSS7-MSS5}{MSS7+MSS5} + 0.05}$

XGREEN = Tasselled Cap Green Measure (See Appendix III)

SQGRE = Square Root of XGREEN

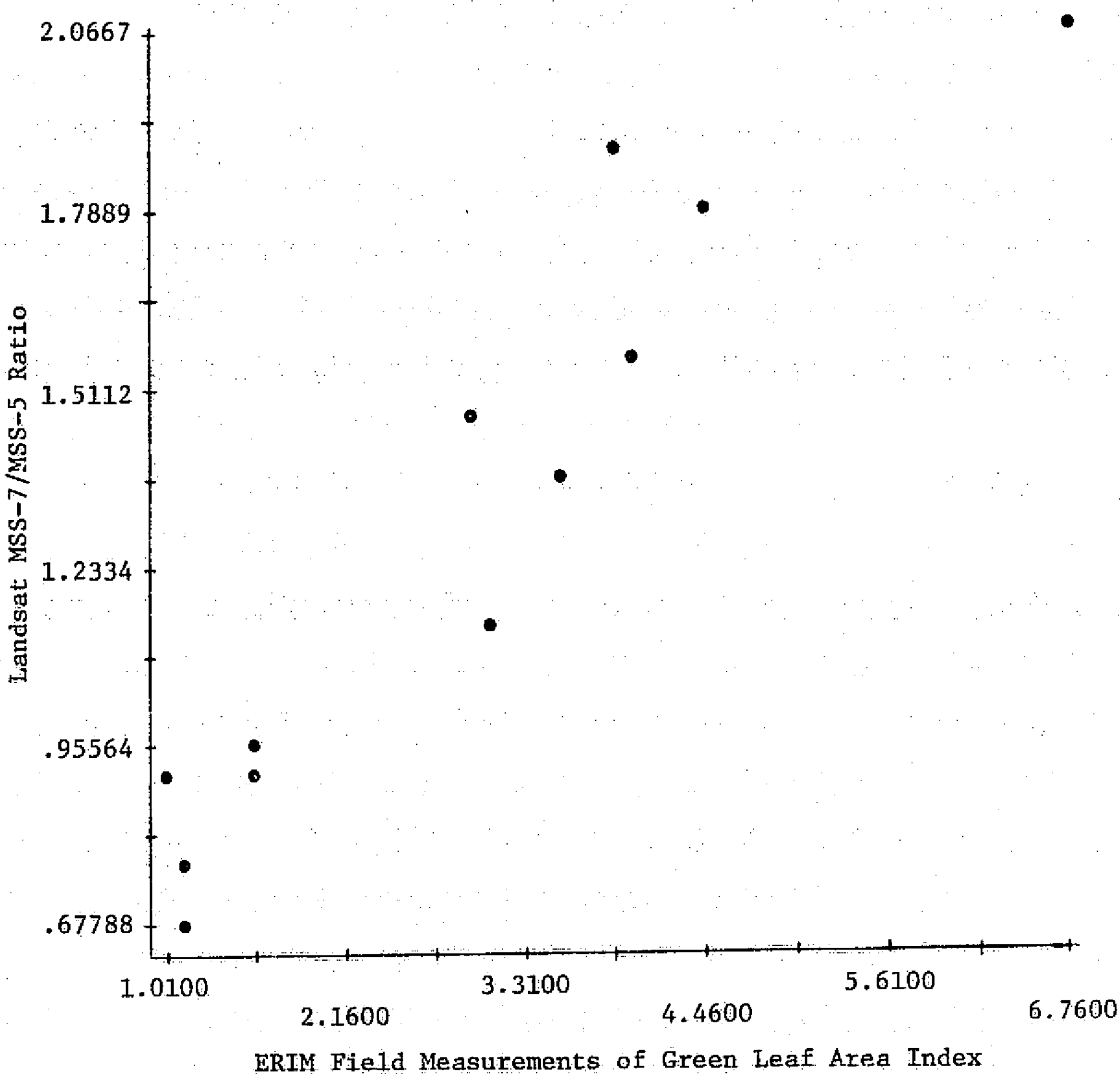

FIGURE 4. LANDSAT MSS-7/MSS-5 RATIO VALUES VS GREEN LEAF AREA INDEX. FINNEY A SITE, 21 MAY 1975

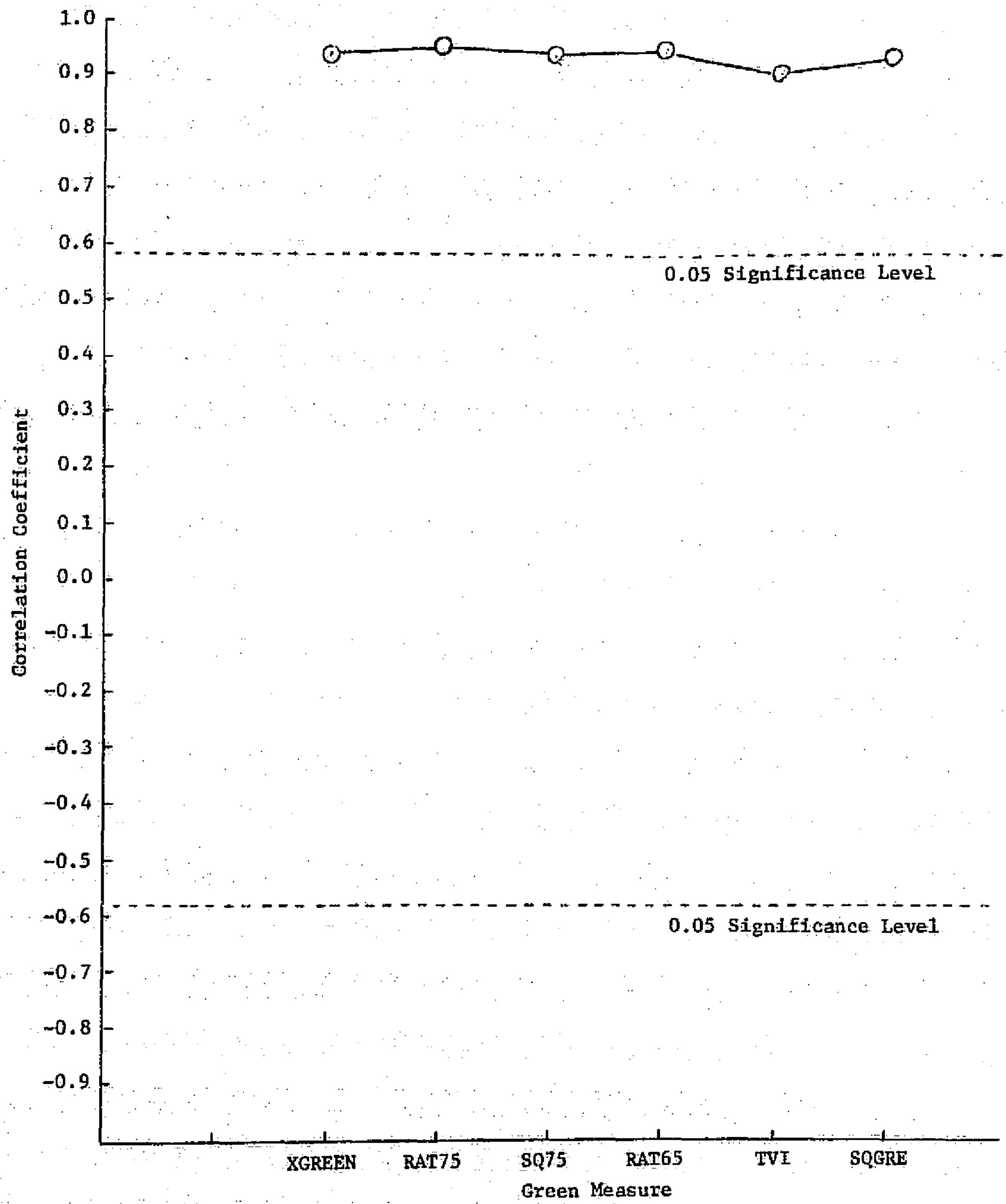

FIGURE 5. CORRELATION OF LANDSAT "GREEN MEASURES" WITH FIELD MEASUREMENTS OF GREEN LAI, FINNEY SITE, 21 MAY 1975

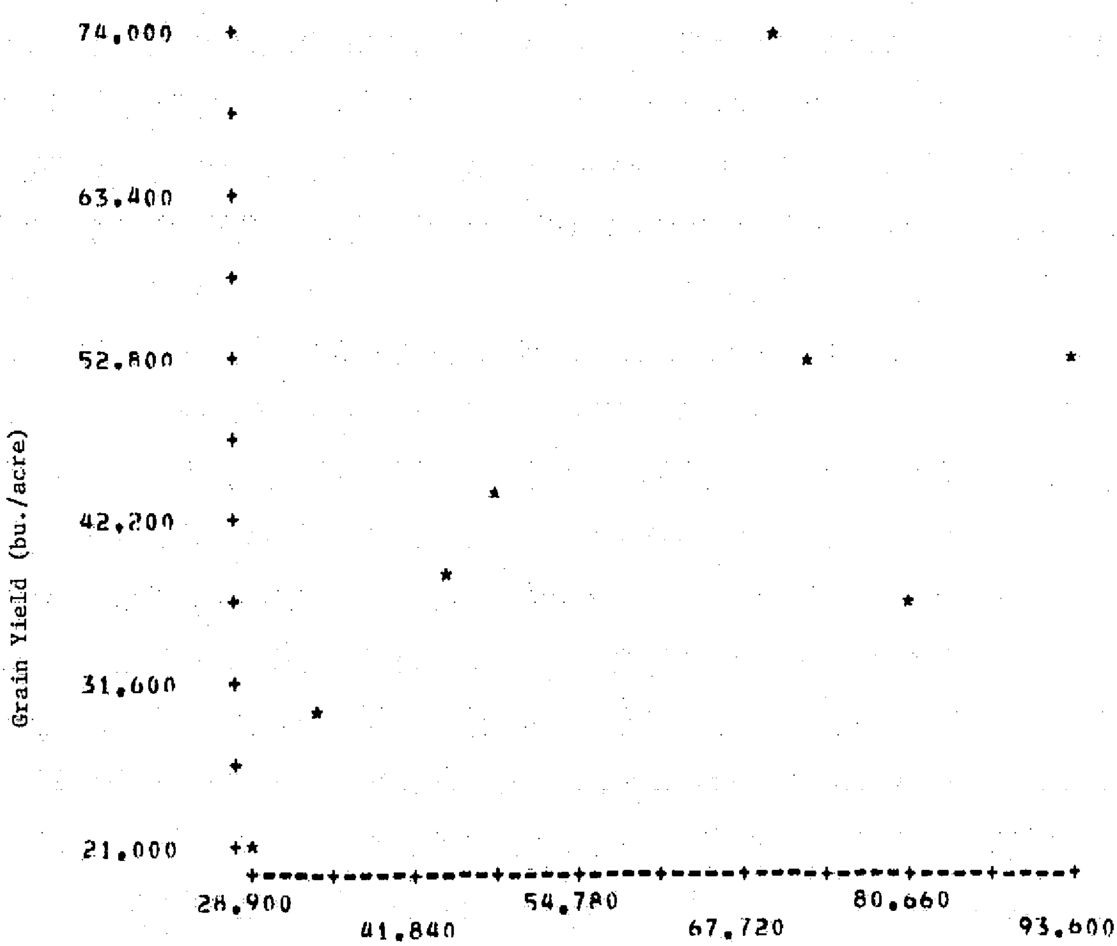

FIGURE 6. SCATTER PLOT OF HARVESTED GRAIN YIELD VS. ESTIMATES OF PERCENT GREEN VEGETATION COVER, FINNEY A SITE, 21 MAY 1975

set the low vegetation densities are from non-irrigated fields and high densities are from irrigated fields. In other data sets, we have noted correlations between vegetation density and yield which vary somewhat as a function of time, as indicated in Section 5.2.1. In order to get a more dependable result based on more data we combined data from measurements made on two separate years at about the same phenological stage, and incorporating both irrigated and non-irrigated crops. These data are plotted in Figure 7 and suggest that a useful relationship does exist between field condition and yield.

It should be noted that the relationship between Landsat data and vegetation density discussed in the previous section is a much more straightforward relationship than the relationship between vegetation density and yield. The relationship between Landsat data and vegetation density is basically a physical-electromagnetic relationship which connects two observations at the same point in time in a more or less causal fashion. Yield, on the other hand, has a much more complicated relationship with field condition which has a strong plant physiological component and which is the integrated effect of a host of conditions over time. The relationship may be affected by conditions occurring before or after the observation of field condition. For example, one of the fields on which we made measurements developed significant mosaic virus after the measurement, which undoubtedly altered the relationship between vegetation cover before the onset of the virus and eventual yield. In addition, observations at one point in time do not necessarily compare fields at similar phenological stages. We have observed different fields within the same site, and even different portions of the same field which differ significantly in phenological development.

The point of the above discussion is that an accurate measure of vegetation density at a point in time (whether from field measurements or Landsat data) does not necessarily guarantee a good measure of eventual wheat grain yield on <u>all</u> fields at <u>all</u> times. The potential success

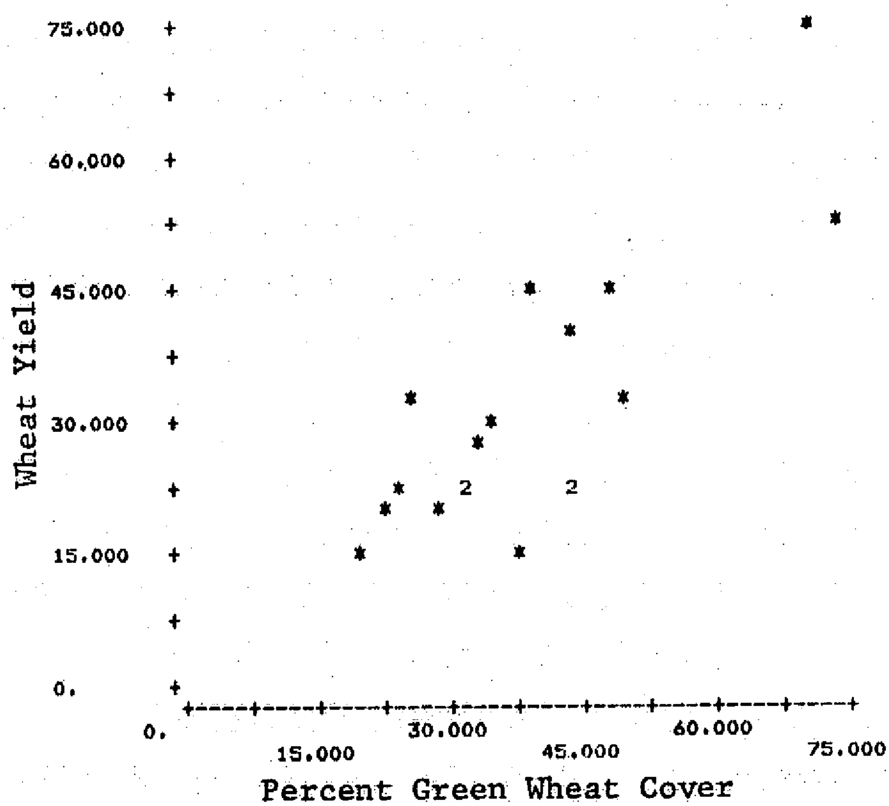

FIGURE 7. ERIM MEASUREMENTS OF PERCENT COVER VS WHEAT YIELD (Combined 1976 and 1975 Data)

of this approach depends on the relationship being generally useful most of the time.

4.3 LANDSAT DATA/YIELD

The most important test, of course, is whether Landsat data is indicative of potential yield. Figure 8 shows that the individual Landsat band correlations between Landsat data values and yield are similar to the correlations between Landsat data values and vegetation density. The fact that Band 5 and Band 7 have the highest individual correlations with yield suggests, once again, that some form of difference or ratio of these two bands may be a useful single-parameter indicator of yield (green measure). The correlation between several types of green measures and yield is indicated in Figure 9, and again suggests that they are all approximately equivalent. Figure 10 is an example of the relationship found between a Landsat green measure and wheat grain yield on a number of fields.

4.4 CONCLUSION

Although the generality of the fundamental relationships can only be determined by examining more data, the data we have examined suggest that the basic relationships on which Landsat forecasts of yield are based may be correct much of the time, and we will proceed on that assumption.

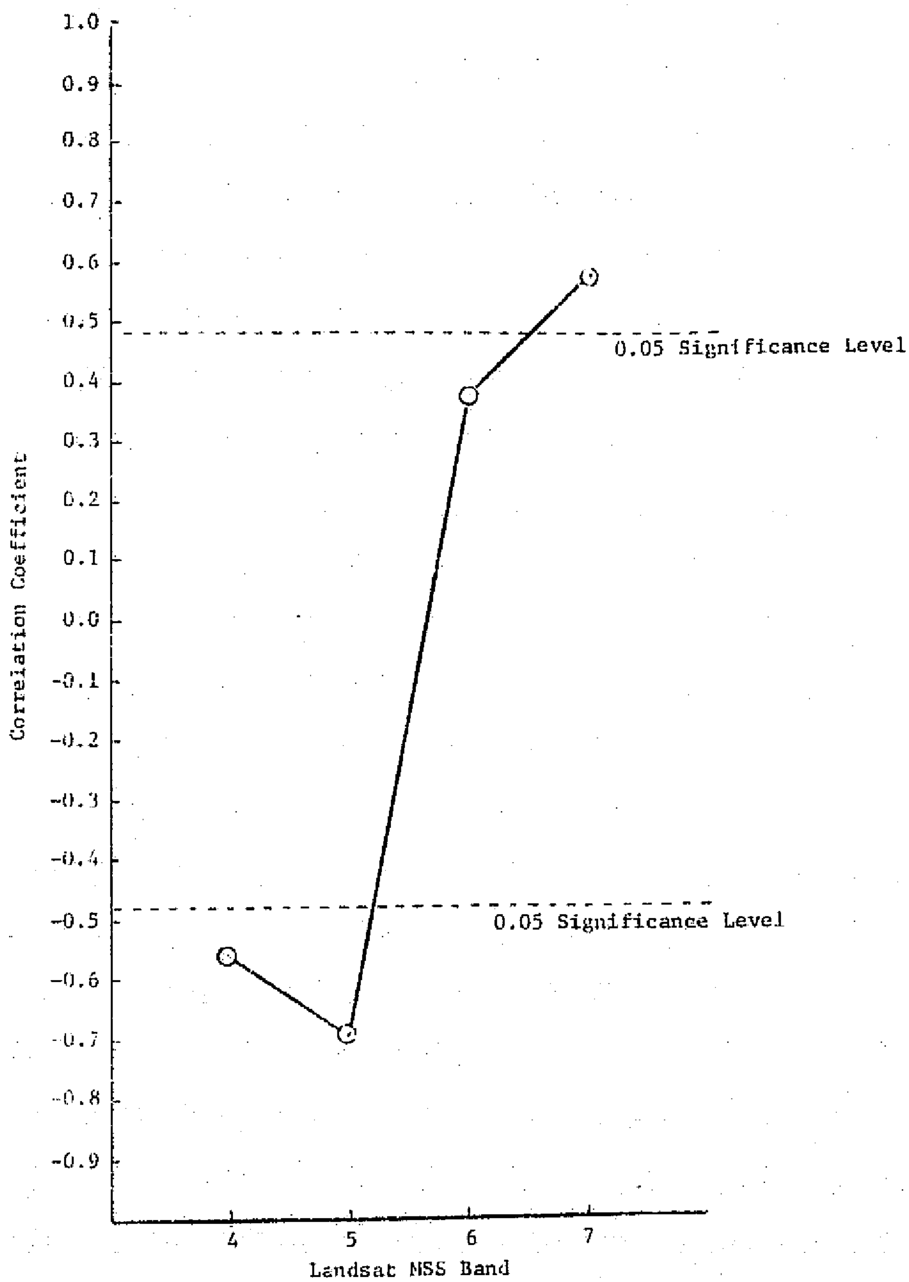

FIGURE 8. CORRELATION OF LANDSAT INDIVIDUAL BANDS WITH FIELD YIELD, FINNEY SITE A, 21 MAY 1975

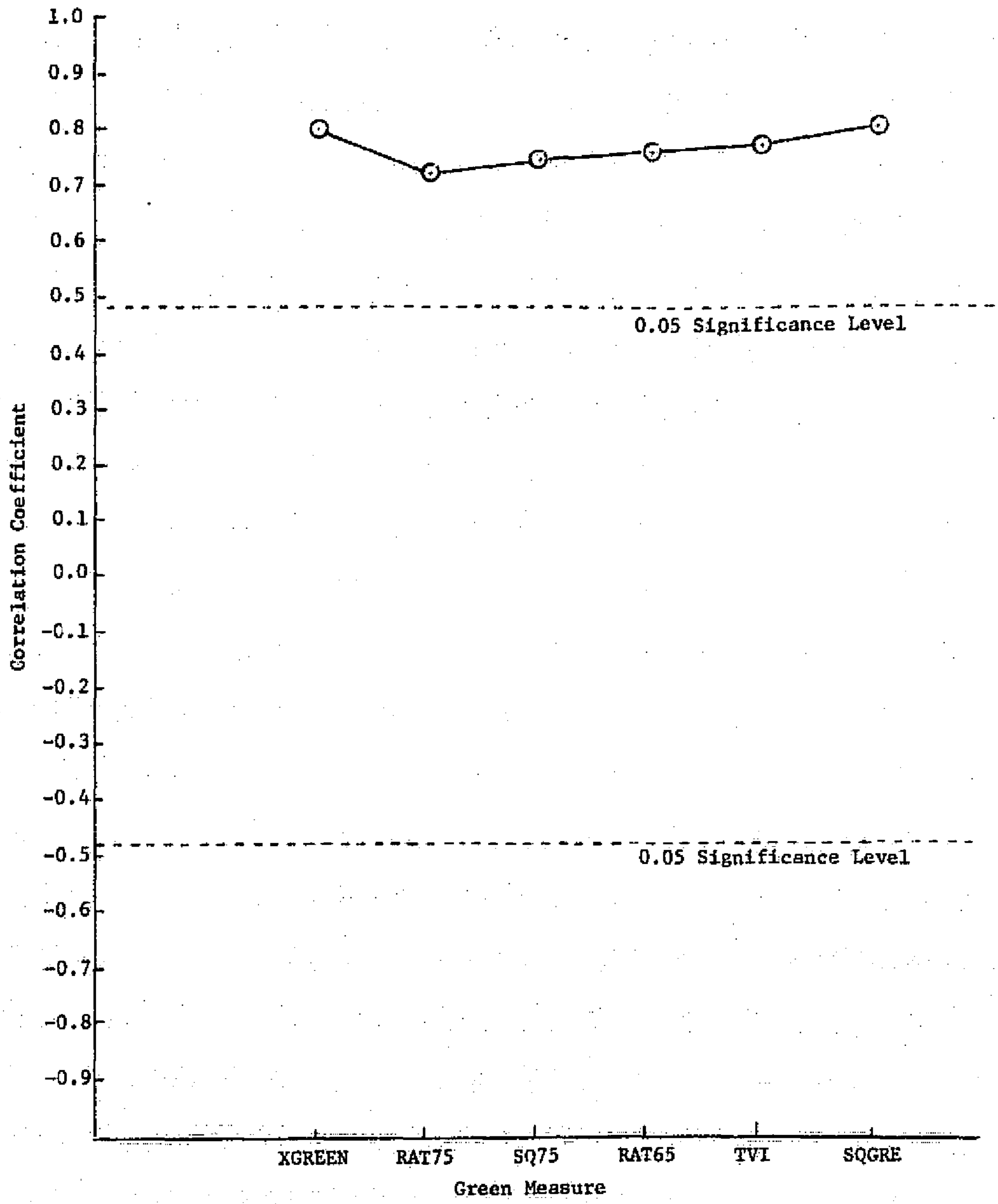

FIGURE 9. CORRELATION OF LANDSAT "GREEN MEASURES" WITH FIELD YIELD, FINNEY SITE A, 21 MAY 1975

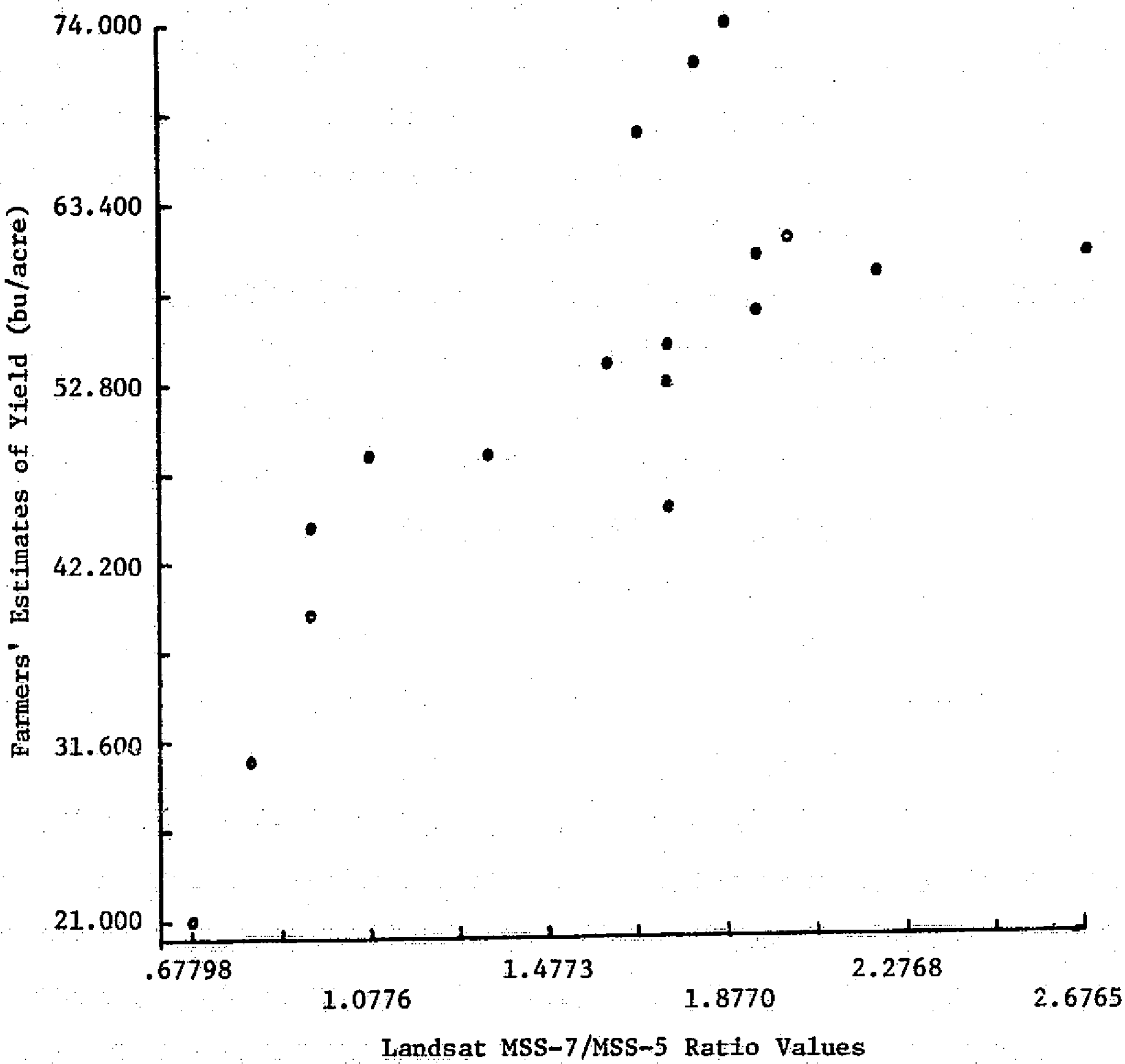

FIGURE 10. LANDSAT MSS-7/MSS-5 VALUES VS YIELD, 21 MAY 1975, FINNEY SITE A

5
TEMPORAL/SPECTRAL ASPECTS OF YIELD RELATIONSHIPS

Given the indications in the previous section that there are relationships that may permit Landsat forecasts of yield, additional questions that need to be addressed are: (1) what the optimum bands or transformations of bands for forecasting yield using Landsat data are, and (2) what the optimum date or combination of dates for forecasting yield using Landsat data is. These two questions will be addressed in this section.

5.1 OPTIMUM LANDSAT BANDS

In Section 4 we discussed some of our analyses with respect to optimum individual Landsat bands for estimating yield. We now present a more thorough analysis using Landsat data from several dates for sites Finney A, Finney B, and Ellis.

5.1.1 EARLY SEASON RELATIONS

The correlations between individual Landsat bands and yield for observations when the wheat was predominately green (early season) are shown in Figures 11, 12, 13 and 14. For each figure, the horizontal dotted lines are 5% significance lines, so that correlation values which fall between the dotted lines are not considered statistically significant at the 5% level.

Note that the Landsat near-infrared bands (Bands 6 and 7) tend to be positively correlated with yield, while the visible bands (Bands 4 and 5) tend to be negatively correlated with yield. This result is what was expected based on our previous experience [e.g., 10] and is consistent with the discussion presented in Section 4. Note also that in every case Band 7 is more positively correlated with yield than Band 6, and that Band 5 is more highly correlated with yield than Band 4.

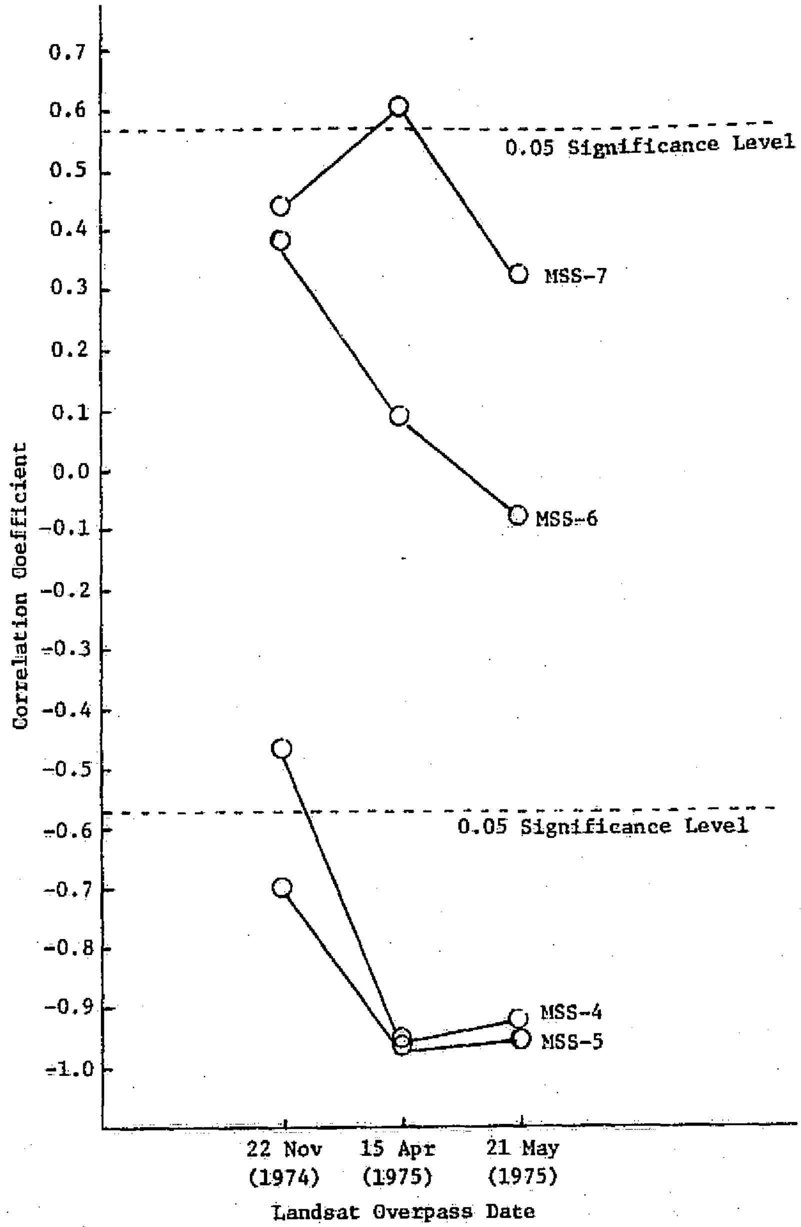

FIGURE 11. CORRELATION OF INDIVIDUAL LANDSAT BAND DIGITAL COUNT VALUES VS YIELD AS A FUNCTION OF DATE, FINNEY SITE A, 1975

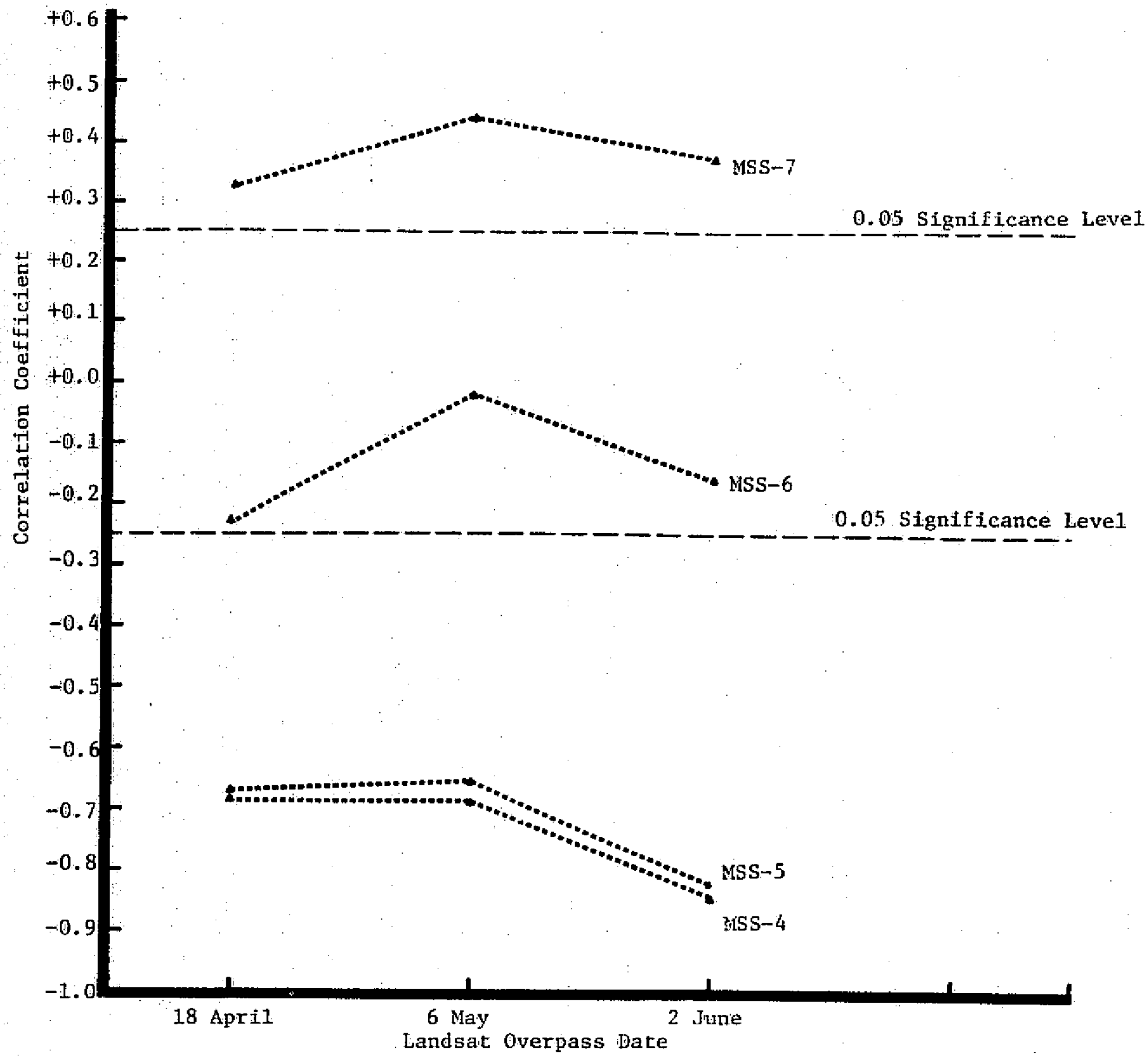

FIGURE 12. CORRELATION OF INDIVIDUAL LANDSAT BAND DIGITAL COUNT VALUES VS. YIELD AS A FUNCTION OF DATE, FINNEY B SITE, 1976

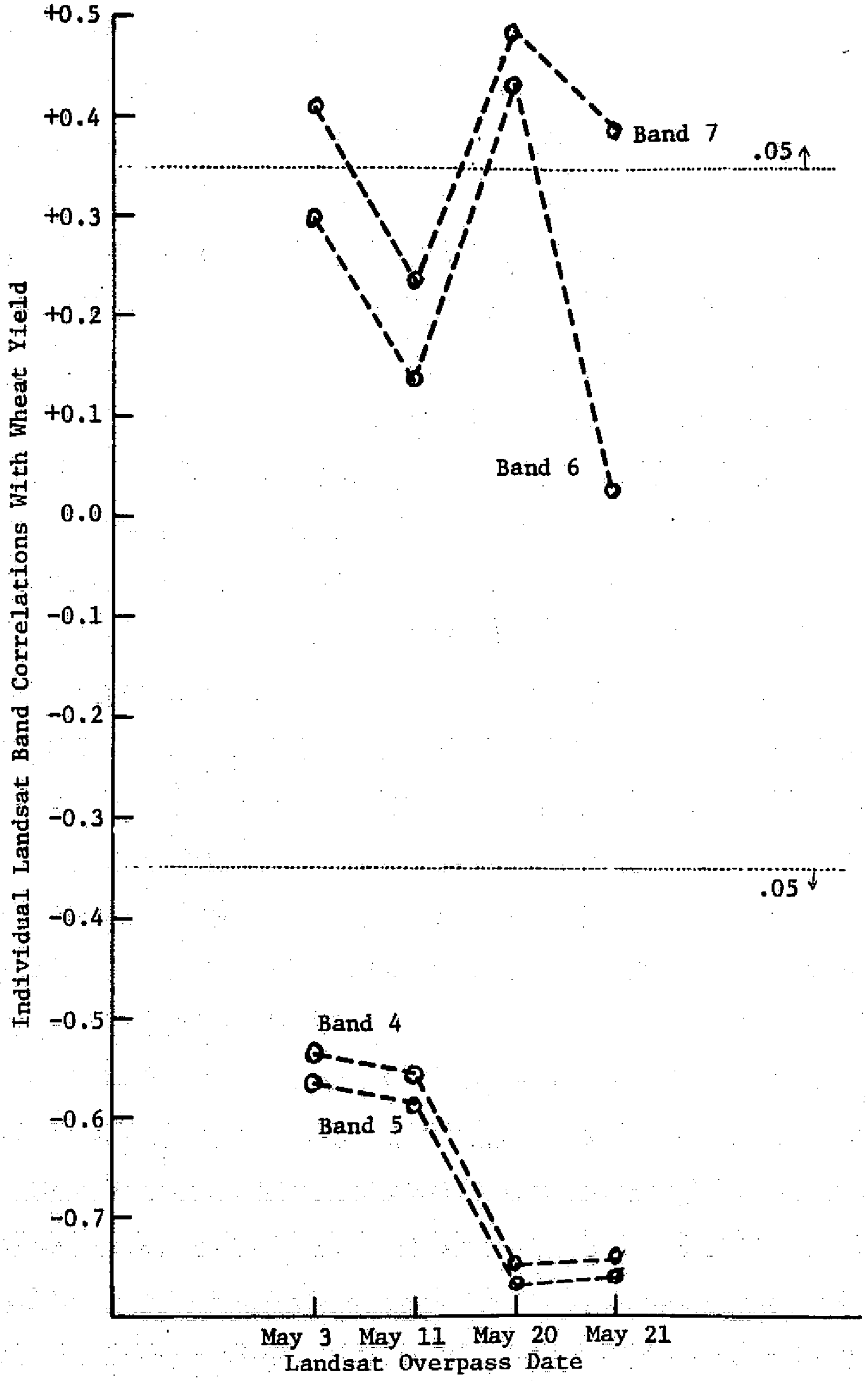

FIGURE 13. CORRELATION OF INDIVIDUAL LANDSAT BAND WITH WHEAT YIELD FOR 5 DATES. An average over 33 fields of 2 pixels or more with a pixel in-set of 1.0 was used for each Landsat band for each date. The horizontal dotted lines specify the 5% significance level (Ellis site, 1975).

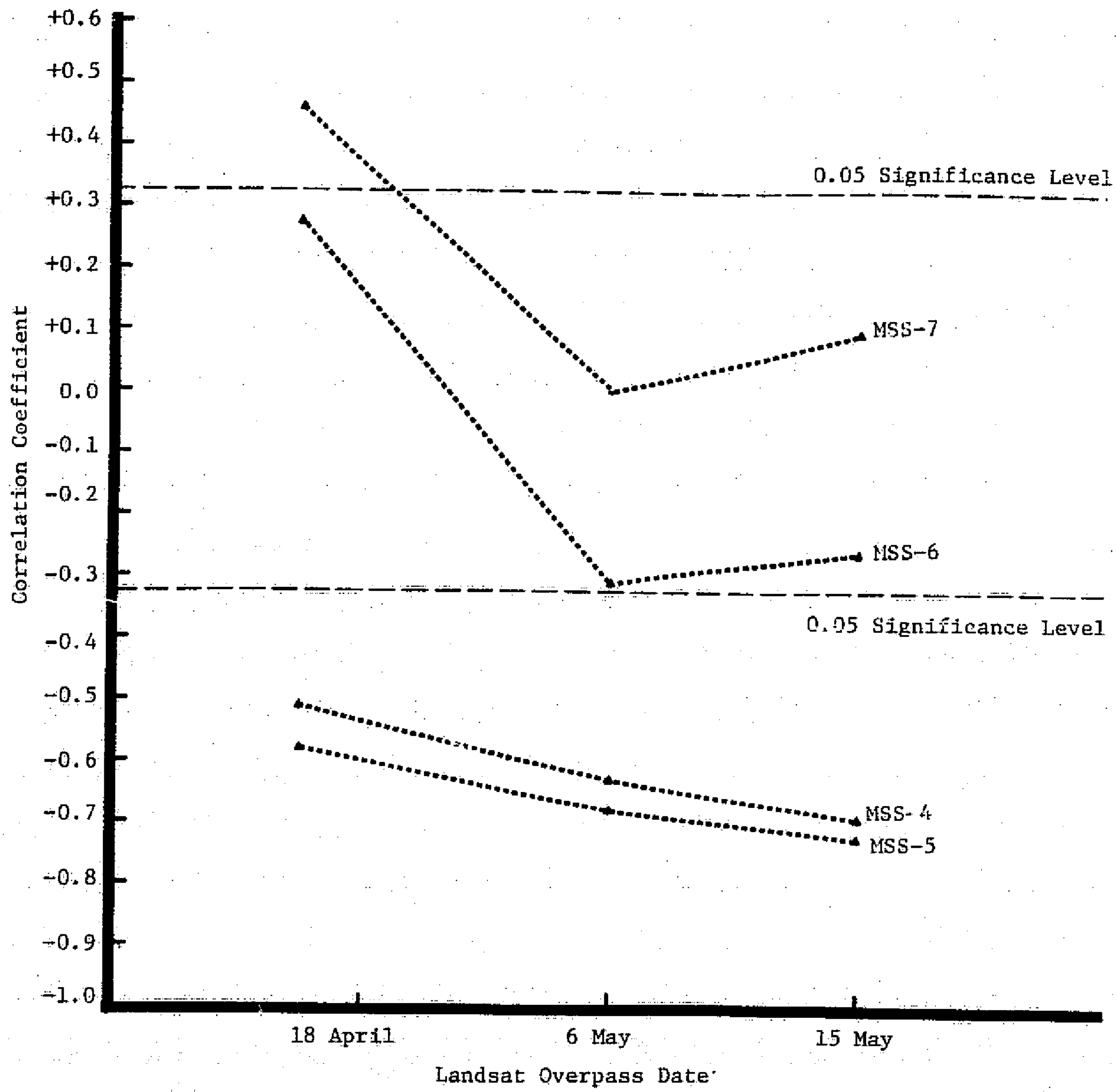

FIGURE 14. CORRELATION OF INDIVIDUAL LANDSAT BAND DIGITAL COUNT VALUES VS. YIELD AS A FUNCTION OF DATE, ELLIS SITE, 1976

Based on these results, the optimum single Landsat band for correlation with yield when the wheat is predominantly green is Band 5. If a two-band green measure transform is desired, a combination of Bands 5 and 7 seem appropriate.

5.1.2 LATE SEASON RELATIONS

Based on previous experience we would expect different correlations between Landsat data and yield (or vegetation density) when the vegetation is predominantly dead (late-season) than when it is predominantly green. We would also not expect, a priori, that a green measure transform would be highly correlated with wheat density or yield when the wheat fields have little or no green wheat present*.

We processed two sets of Landsat data in which the wheat was largely senescent, namely 12 June 1976 Finney B and 17 June 1975 Ellis. A comparison of individual bands and green indicator transforms for the two data sets is presented in Figure 15.

In both cases the green indicator transform is significantly correlated with yield, though barely so on the 17 June 1975 Ellis data. However, in both cases three of the four bands (4,5,6) are significantly negatively correlated with yield. Furthermore Bands 4, 5, and 6 are all more highly correlated with yield individually than is the green indicator transform. It appears as though wheat yield is negatively correlated with crop albedo when the crop is mature. Perhaps this is due to high-yield fields having more stalks and hence casting more shadow (having lower reflectance) than low-yield fields.

The reason that a green measure transform is still significantly correlated with yield in such a situation is not clear, and must be further studied. However, it appears that for late-season (pre-harvest) estimates of yield, some albedo estimator or other stand density estimator could be a better indicator of yield than a green measure.

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* These expectations are consistent with recent analyses by Tucker [14].

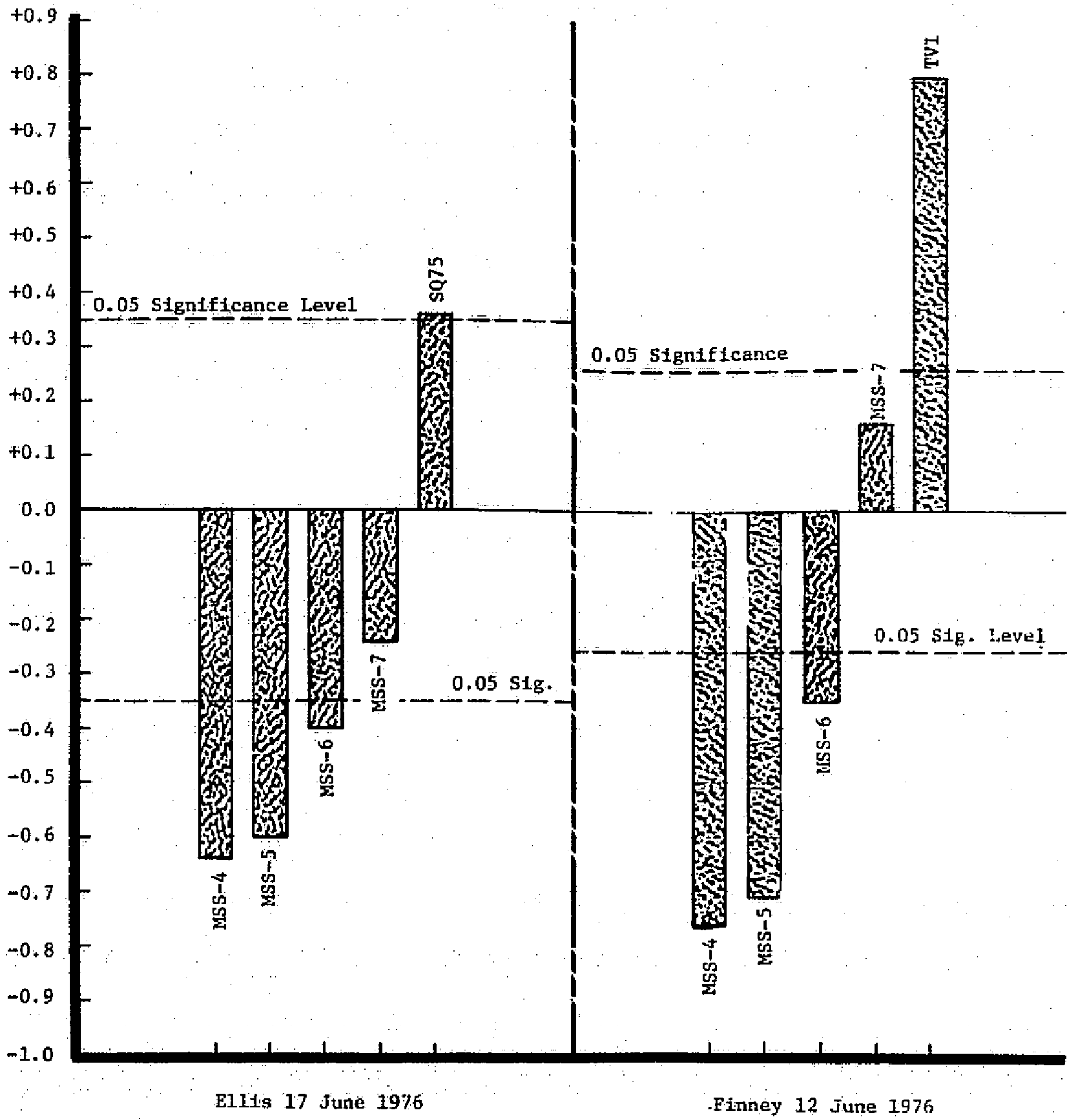

FIGURE 15. CORRELATION OF INDIVIDUAL BAND AND GREEN MEASURE VALUES VS. YIELD LATE IN SEASON

5.2 OPTIMUM LANDSAT ACQUISITION DATE(S)

In addition to considering the spectral relations between Landsat data and yield, we have also considered the temporal aspects of the relationship. It is important to know what data acquisition date produces the most consistently useful information, and if more than one acquisition is considered, what those times are and how they should be utilized.

We were guided in this task by previous empirical and theoretical work. Empirical agronomic studies have indicated that the optimal single data for correlation of wheat vegetation density and yield is at wheat heading, and that better correlations can be achieved by utilizing the integral of green leaf area index over time from heading to senescence (ripe). This integral has been referred to as leaf area duration (LAD)*. The above observations have been supported by a limited amount of wheat growth/yield modeling (simulation) [10] which indicated that heading was the optimum time for correlation between amount of photosynthetic material and ultimate wheat grain yield.

In addition, a regression yield model relating yield and sequential LAI was suggested by the simulation work. A very simple form of such a model might be

$$\text{wheat yield} = A + B \cdot (\text{LAD})$$

It was suggested that a yield model such as this could be implemented using remote sensing indicators of vegetation density (amount of photosynthetic material), and that a useful remote sensing indicator might include a ratio of near-infrared and visible spectral bands.

Since we are interested in establishing relationships between remote sensing data and yield that are of general utility, and which have some empirical and theoretical justification, we chose to be

* Similar concepts would presumably apply for percent cover, and would lead to an integral that might be referred to as percent cover duration.

guided by the above discussion in the course of this investigation in our search for an "optimal" remote sensing yield model. The above concepts are now analyzed using ERIM field measurements of percent cover, and Landsat indicators of percent cover (green measures).

5.2.1 PERCENT COVER/YIELD RELATIONS

The relation between vegetation density at a point in time and grain yield was investigated by calculating the correlation between percent green wheat cover determined from ERIM field measurements and wheat grain yield. Four time periods were available for Finney site A data, namely May 21, (approximately the time of heading), May 30, June 9, and June 18. The results are presented in Figure 16. For this limited set of data on predominantly irrigated fields the highest correlation occurred on May 21, and it decreased monotonically through June 18. Since May 21 was the approximate date of heading, this was not an unexpected result.

An approximation to percent cover duration was computed by successively adding percent cover information to the May 21 data to get a total. Successive summations of percent cover were then correlated with yield to determine if correlations were improved. The results are shown in Figure 17 where it can be seen that none of the summations of percent cover over time improve the correlation with yield obtainable by the values of percent cover on May 21. Similar results were found for LAI and LAD.

The hypothesis that leaf area duration or percent cover duration features improve yield estimation has not been verified for this data set. The lack of verification of the hypothesis may be partly due to the fact that, for the highly irrigated fields in this data set, the amount of grain yield may be more closely related to the amount and timing of irrigation than to the amount and duration of green photosynthetic material.

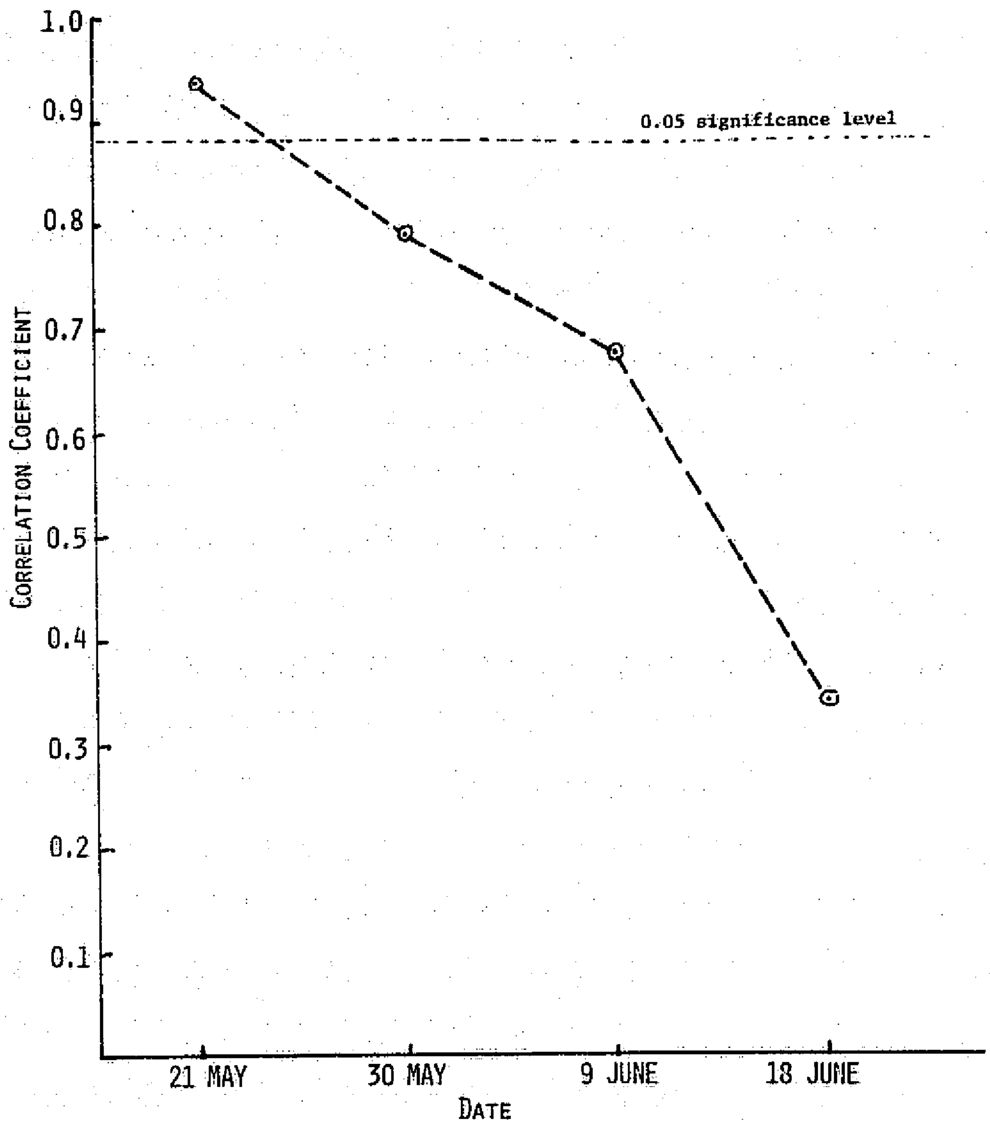

FIGURE 16. CORRELATION OF PERCENT GREEN WHEAT COVER WITH YIELD AS A FUNCTION OF DATE, FINNEY A, 1975

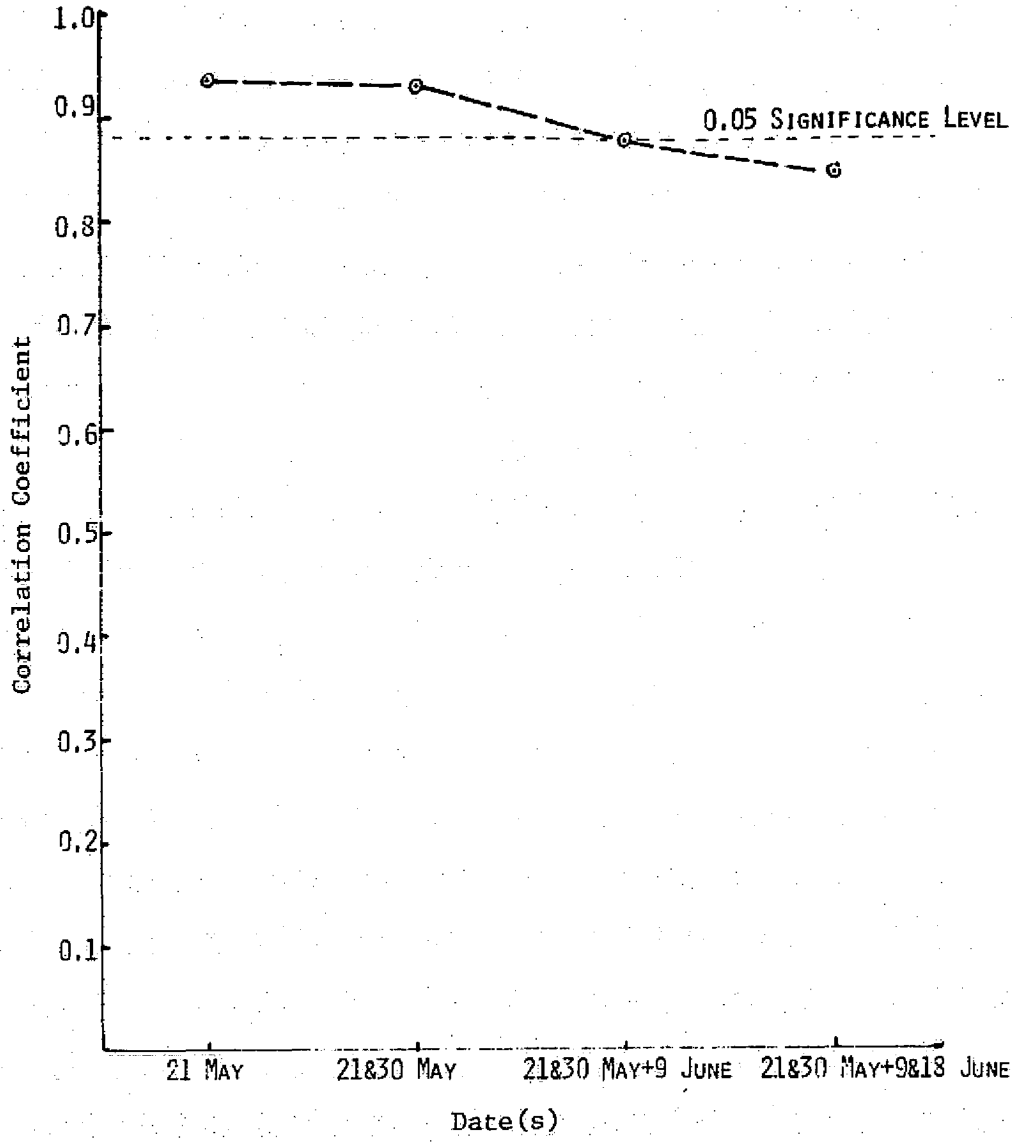

FIGURE 17. CORRELATION OF SUMMATION OF PERCENT GREEN WHEAT COVER WITH YIELD FOR VARIOUS DATES, FINNEY A, 1975

.5.2.1.1 Temporal Aspects of Percent Cover and Wheat Phenology

Another possible reason that the relations between percent cover and yield did not agree with our hypotheses is that some of the other assumptions that were part of this hypothesis were not fulfilled.

One hypothesis was that the optimum single date for forecasting probable yield by estimating field condition (vegetation cover) using Landsat data is approximately at the time of heading. This was based in part on the assumption that heading date corresponded approximately with the time of maximum vegetation cover. In this section we examine the timing of heading and vegetative development between and within fields for the Finney B site.

Our field observations indicated that some of the fields were almost completely headed on 14 May, whereas other fields were not completely headed by 2 June. In addition, some fields reached peak vegetative cover before 14 May, and did not head until considerably later. Our field measurements of percent green wheat cover indicated that four of the fields sampled on both 18 April and 14 May had less green wheat cover on 14 May than on 18 April, whereas four other fields had greater green wheat cover on 14 May. Furthermore, there were even variations in timing of heading and peak vegetative cover within a given field. For example, in one field the dense portions of the field decreased from 62% green wheat cover on 18 April to 41% vegetative cover on 14 May, while on the sparse portions of the same field the green wheat cover increased from 29% on 18 April to 36% on 14 May.

The considerable variability in phenology for the fields which were observed, even though meteorological conditions for all fields were probably quite similar, suggests that being able to accurately account for variations in phenology based on meteorological factors (e.g., day and night temperatures and photoperiod) may not always be possible.

5.2.2 TEMPORAL LANDSAT GREEN MEASURE/YIELD RELATIONS

Since only a few fields existed for which percent cover measurements over time and wheat yield were both available, our analysis of percent cover/yield temporal relations is limited. If we use Landsat indicators of percent vegetation cover (green measures) we have a larger data base with which to work. However, a limitation of this approach results from the fact that, to the best of our knowledge, a reliable green measure does not exist for largely senescent canopies.

5.2.2.1 Optimum Single Date

We begin our analysis by examining the optimum single date for correlation between Landsat indicators of vegetation density (green measures) and yield. The available data for Finney A, Finney B, and Ellis for mainly green wheat is plotted in Figures 18-21. Based on these data, we conclude that there appears to be a range of times over which reasonably equivalent correlation between Landsat data and wheat grain yield could be obtained in different situations (times, places). There are many possible reasons for these results. They include:

1. Our data base is not large enough for general trends to emerge.
2. We are missing data at potentially "critical" times.
3. The apparent optimal time may depend, in this small data set, on conditions that occur <u>after</u> a particular Landsat observation (e.g., disease), conditions that may not generally occur.
4. Variation in crop phenology (heading date) makes it impossible to select a single date for which all fields in a single date are in the same phenological stage. (For example NASA/ASCS data, based on ground observations indicates a normal time span of 3-4 weeks between 10% of fields headed and 90% of fields headed in the Central Crop Reporting District of Kansas.)

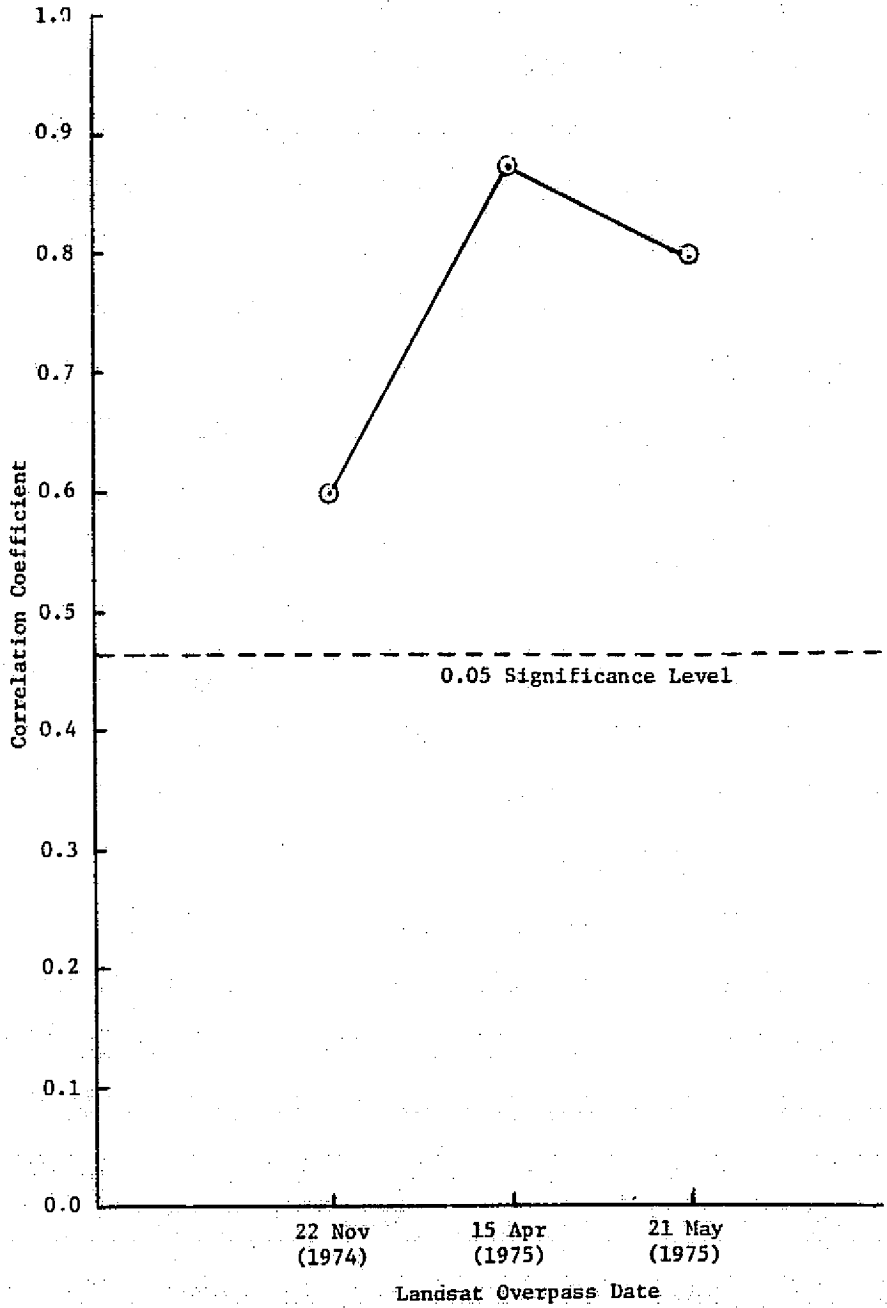

FIGURE 18. CORRELATION OF GREEN MEASURE (SQ75) VALUES VS YIELD AS A FUNCTION OF DATE, FINNEY SITE A, 1975

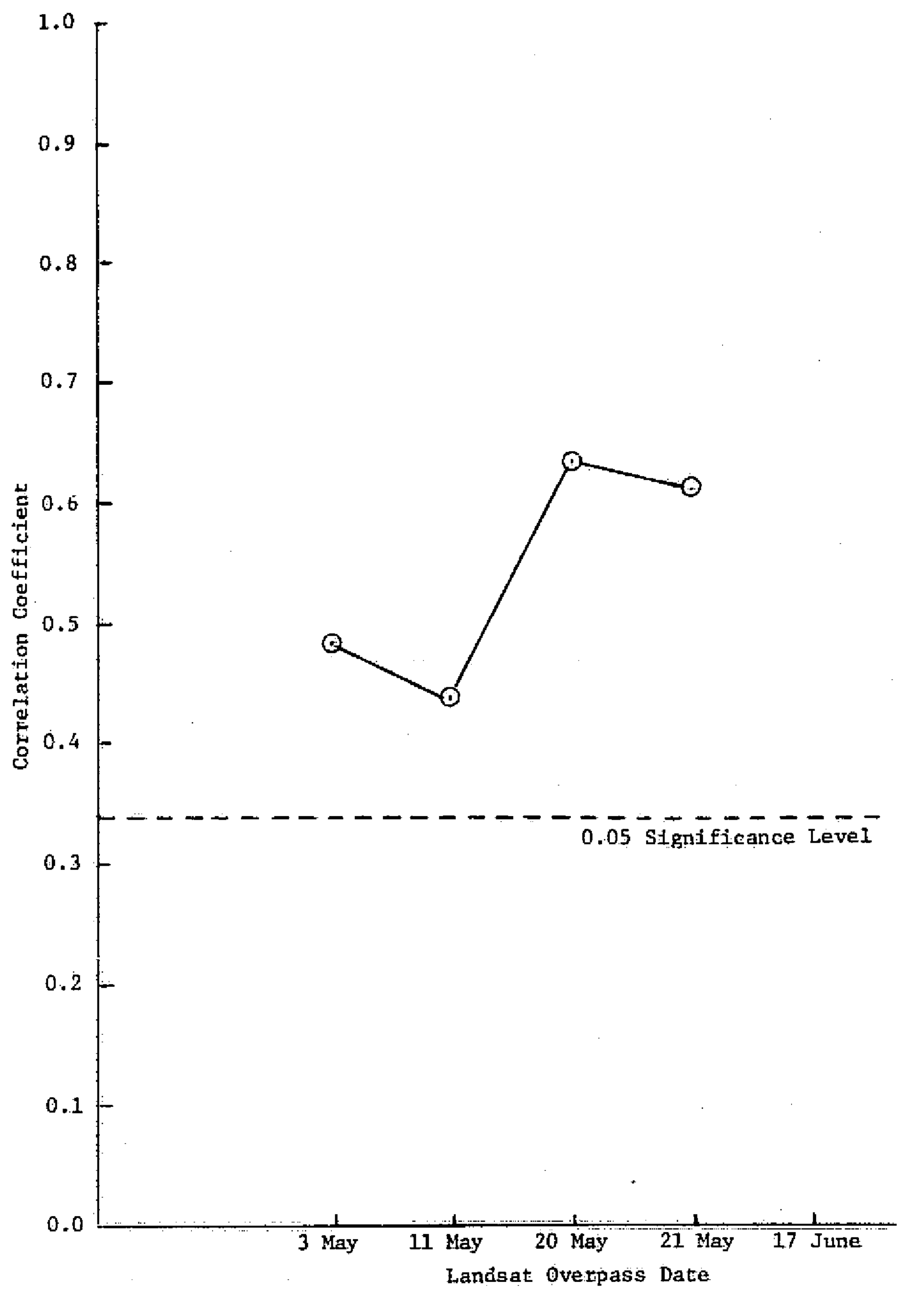

FIGURE 19. CORRELATION OF GREEN MEASURE (SQ75) VALUES VS YIELD AS A FUNCTION OF DATE, ELLIS, 1975

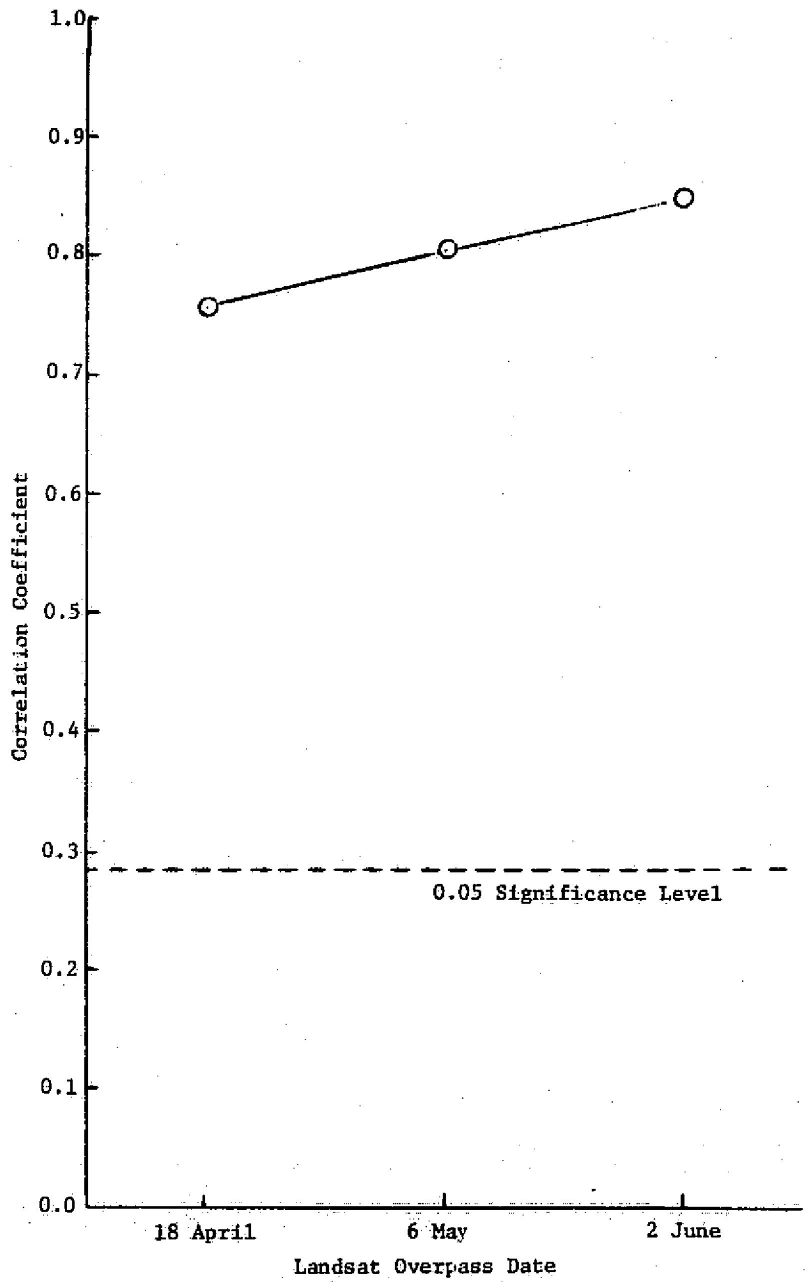

FIGURE 20. CORRELATION OF GREEN MEASURE (SQ75) VALUES VS YIELD AS A FUNCTION OF DATE, FINNEY SITE B, 1976

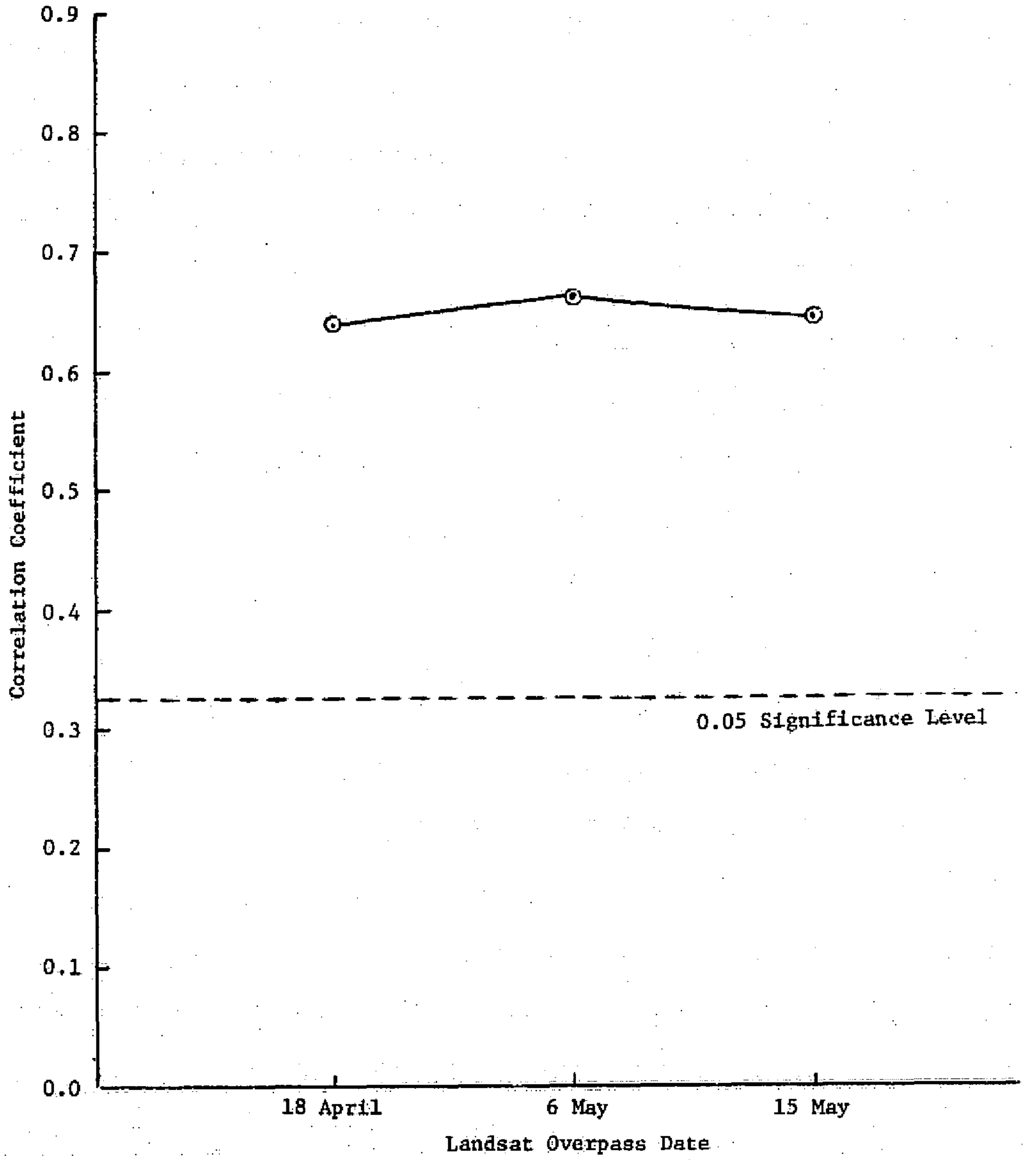

FIGURE 21. CORRELATION OF GREEN MEASURE (SQ75) VALUES VS YIELD AS A FUNCTION OF DATE, ELLIS, 1976

5. In dense canopies, Landsat data will not give as good differentiation between canopy densities as in sparse canopies (see Section 4), so correlation between Landsat data and yield may be a function of the correlation between actual vegetation density and yield, plus the capability of Landsat to monitor vegetation density. This might occur before or after peak vegetation density (approximately at heading).

6. Our fundamental hypotheses concerning optimal time(s) may not be correct.

Our tentative conclusion is that the "optimal date" is somewhat variable, depending especially upon conditions 3-5, and that one Landsat data set within a "window" of up to several weeks may give reasonably equivalent results over time and space. In general, Landsat data collected in May appears to be consistently useful for assessing winter wheat yield in Kansas

5.2.2.2 Optimum Combinations of Dates

We again turn to the hypothesis that LAD or percent cover duration may be a better indicator of yield than any single date, using Landsat surrogates (green measures) for green vegetation density.

The Landsat green indicators from 18 April, 6 May and 2 June from Finney B were used to approximate percent cover over that span of time. This sum was then correlated with wheat yield, and the correlation was found to be 0.89. The best single date has a correlation between Landsat green measure and yield of 0.81. If 18 April, 6 May, and 2 June are used as independent variables for regression with yield, the multiple correlation is 0.92, somewhat better than if the data were summed.

A similar analysis was performed using Ellis A Landsat data as surrogates for percent cover. In this case, we did not have Landsat data from heading to senescence, so we used the May 20 data (the best single date) and summed backwards to May 11 and May 3. The correlation with yield was greater for May 20 SQ75* data than was the correlation with the sum of SQ75 May 20 and SQ75 May 11, which in turn was greater than the correlation with yield for the sum of SQ75 May 20 and SQ75 May 11 and SQ75 May 3 (see Figure 22). No sum of dates was as highly correlated with yield as the best single date (May 20).

5.2.3 CONCLUSIONS

Based on the ERIM field data on actual vegetation density and on Landsat indicators of vegetation density discussed above, it is not clear that a summation of amount of photosynthetic material over time is more highly correlated with yield than is information at a point in time for the cases investigated so far. Although the hypothesis is not fully supported by the data analyzed thus far, the encouraging implication is that it may not be necessary to have all of a certain sequence of dates to perform accurate yield prediction. In other words, the initially proposed ERIM yield prediction method based on Landsat indicators of LAD [10] may be more elaborate than is required. However, multitemporal data used independently (i.e., not summed) has proven to be useful in improving yield prediction.

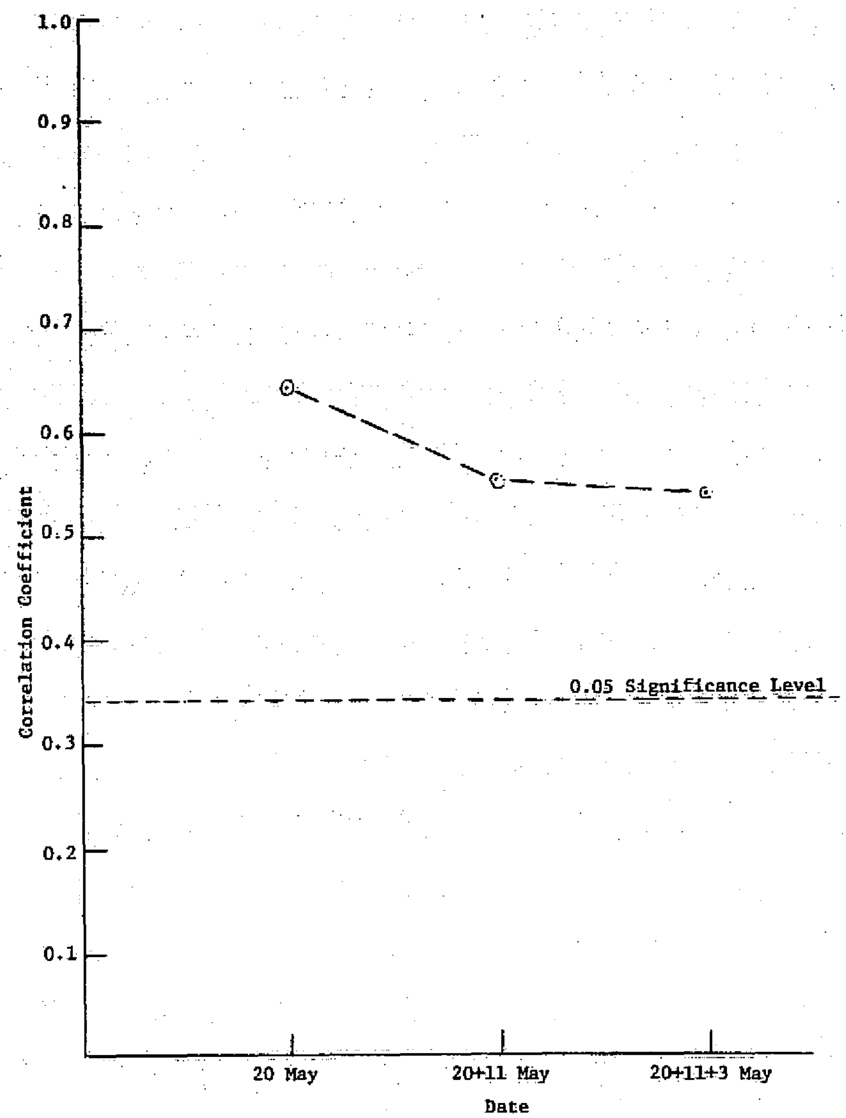

FIGURE 22. CORRELATION OF SUMMATION OF LANDSAT INDICATORS OF GREEN WHEAT COVER WITH YIELD, ELLIS, 1975

6
LANDSAT VS ALTERNATIVES ON A LOCAL BASIS

In previous sections we have examined the utility of Landsat data for estimating yield. It is also important to assess the relative utility of Landsat data, meteorological data, and some combination of Landsat, meteorological, and/or ancillary data for predicting wheat yield. This section discusses analyses carried out to address the above goal and some resulting conclusions.

6.1 METEOROLOGICAL DATA

One of the hypotheses of this project is that there is important wheat yield-related information contained in crop appearance as monitored by Landsat data that is not provided by standard meteorological data. This hypothesis has been cursorily examined for both a predominantly irrigated site (Finney A) and a predominantly non-irrigated site (Finney B).

We assume that meteorological conditions were undoubtedly similar over the small 5 x 6 mile test sites. That this is true is suggested by data from the 30 rain gauge stations on the Finney A site. During the important growing months of May and June the coefficient of variation (σ/m) in precipitation between the rain gauge stations was only about 0.10 (see Table 5).

TABLE 5

RAINFALL DATA FOR 30 RAIN GAUGE
STATIONS AT FINNEY A SITE, 1975

Month	Mean Value Of Rainfall	Standard Deviation	Coefficient of Variation (σ/m)
May	3.76	0.43	0.11
June	2.85	0.27	0.09

Despite the relative constancy of precipitation (and presumably other important meteorological conditions), the yield on the Finney A site varied substantially (21.0 bu/acre to 74.0 bu/acre) from field to field. These differences in yield are more likely related to such factors as soil type, planting density, fertilization, cropping practices in a field, and irrigation, all of which do vary appreciably from field to field (see Section 8.2), but none of which are specifically included in most meteorological models. In any event, aside from special experimental arrangements, a single weather station is generally used to characterize an area much larger than a 5 x 6 mile test site, and thus a meteorological yield model would not indicate any of the known field-to-field differences in yield on a local basis.

We do not have detailed meteorological information for the Finney B site. Again, however, there are substantial differences in yield from field to field on this site (from 3 bu/acre to 65 bu/acre), most of which we are quite certain are not due to differences in meteorological conditions.

As indicated elsewhere in this report (Section 5.1), the differences in crop condition and eventual yield found between fields on both the Finney A and Finney B sites are, to a substantial degree, manifested in Landsat data. Thus, it appears that Landsat data can better account for local variations in yield than can meteorological data.

While we do not minimize the usefulness of meteorological information to roughly estimate yield on a regional average basis, or to help assess approximate status of phenological development, we feel that accuracy of a large area wheat survey could be enhanced by the use of field-by-field information, such as could be provided by Landsat data.

(A discussion of the relations between meteorological conditions and yield on a large-area basis is given in Section 8.0.)

6.2 ALTERNATIVE FIELD ESTIMATES

Some yield models require as inputs certain measures of field conditions. For example, one model depends on periodic estimates of leaf area index (LAI) [15]. Landsat data may be a reasonable source for such inputs.

To assess the utility of Landsat data, several questions can be raised with regard to these variables:

1. How accurately can these variables be estimated by field personnel?
2. How well are these field estimates of variables related to yield?
3. How well can the variables be estimated using Landsat data?
4. How well are the Landsat estimates of the variables related to yield?

If we assume that the carefully made ERIM <u>objective</u> field measurements of percent cover are correct, we can assess how well other field personnel make estimates of such a parameter, relative to how well Landsat data can be used to make such estimates. For the Finney A Site, the May 21 ASCS (Agricultural Stabilization and Conservation Service) <u>subjective</u> visual estimates of percent cover and the ERIM objective field measurements of percent cover have a correlation of 0.52. This correlation is not statistically significant at the 5% level, which suggests that ASCS estimates are not in good agreement with the ERIM measurements. On the other hand, the correlation between a Landsat green measure (Band 7/Band 5) and ERIM objective field measurements for the same fields at the same time is statistically significant, which suggests good agreement in the relative ratings of the fields examined. For the Finney B site, the 18 April ASCS subjective estimates of percent cover and the ERIM field measurements of percent cover have a correlation of 0.71. The corresponding correlation between a Landsat green measure (SQ75) and ERIM percent cover measurements is 0.97. Therefore, preliminary indications are that for yield models that require estimates of degree of crop vegetative development, Landsat data may furnish a better estimate than some subjective estimates made by field personnel using traditional approaches.*

It should be noted that the amount of crop vegetative development also might be estimated by use of meteorologically-based growth models. However, it seems highly unlikely that any meteorologically-based growth model would have predicted the large variation in vegetative percent cover that was found to exist between fields (e.g., on 21 May at the Finney A site fields which were sampled by ERIM varied from 29% green wheat cover to 94% cover). Therefore, using Landsat data one apparently can estimate amount of vegetative development (a possible variable in some yield models) better than growth models that are based on meteorological data.

Correlations between various estimates of field vegetative condition and farmer's yield for a Finney A data set are shown in Table 6. The ERIM objective measurements of percent green wheat cover on May 21 were significantly correlated with yield, as were measurements of green LAI and Landsat data. However, ASCS estimates of percent cover and height were not significantly correlated with yield.

The correlations between various estimates of field vegetative condition and actual yield for a Finney B site data set are shown in Table 7. None of the correlations with yield are statistically significant for this sample. However, the correlations are highest for ERIM objective measurements of green cover and for Landsat data (SQ75). It appears, therefore, that for yield models that require periodic estimates of vegetation condition that are correlated with potential yield, Landsat estimates

*Traditional methods using trained field personnel can certainly be more precise than Landsat data, but the traditional methods are sufficiently time-consuming so that they cannot routinely be made on enough samples to characterize large, variable fields. The advantage of using Landsat data is that it samples the whole field.

of these inputs are as good as or better than the traditional subjective field estimates.

Other yield models require actual (subjective or objective) estimates of probable yield. For example, the USDA/SRS pre-harvest yield forecasts are based on weather variables such as actual and predicted precipitation, plus field condition or probable yield as reported by farmers or other field personnel [8].

TABLE 6. CORRELATIONS BETWEEN VARIOUS INDICATORS OF CROP CONDITION AND YIELD, 21 MAY FINNEY A DATA (N = 6)

Variable	Correlation*
Percent Cover (ASCS)	0.601
Height (ASCS)	0.795
Green Cover (ERIM)	0.912
Green LAI (ERIM)	0.826
SQ75 ($\sqrt{7/5}$)	0.916

*5% significance level = 0.811

TABLE 7. CORRELATIONS BETWEEN VARIOUS INDICATORS OF CROP CONDITION AND YIELD, 18 APRIL 1976, FINNEY B DATA (N = 9)

Variable	Correlation*
Percent Cover (ASCS)	0.18
Height (ASCS)	-0.17
Green Cover (ERIM)	0.52
SQ75 ($\sqrt{7/5}$)	0.45

*5% Significance level = 0.67

We now address the question of whether Landsat data could improve on some traditional estimates of probable yield. One way of making this comparison is to examine the correlations between yield and Landsat data and alternative methods of estimating probable yield. Such alternative methods might include stand quality ratings (made by ASCS personnel), and objective estimates of yield made by ASCS from field sampling just prior to harvest (FCIC). The available comparisons for three sites for which we have processed Landsat data are indicated in Table 8.

On the basis of the results shown in Table 8 our preliminary conclusion is that Landsat indications of probable relative yield are as good as or better than the traditional field alternatives which we examined, even when the Landsat estimates are made as much as two months before the estimates using alternative methods.

We make the following preliminary conclusions as a result of the material presented in this section.

1. Landsat data can provide at least as good an indicator of field condition (percent cover, LAI) as can subjective field estimates for use in existing yield models.
2. Landsat indicators of probable wheat yield are as good an indicator as are subjective, and some objective, field estimates of probable yield, for use in existing yield models.
3. Therefore, suitably calibrated Landsat data can be used as a substitute for field estimates of field condition or probable yield in wheat yield models that require such inputs.

6.3 LANDSAT DATA VS ANCILLARY DATA

Many meteorological yield models do not specifically include potentially important environmental/cultural factors which are not routinely available from local weather stations. The relative importance of some of these environmental/cultural factors and the degree to which they can be accounted for by Landsat data, is discussed in this section.

TABLE 8. CORRELATIONS BETWEEN YIELD OF INDIVIDUAL FIELDS AND ASCS ESTIMATES AND LANDSAT DATA

	SITE						
	FINNEY A, 1975 N=11		ELLIS, 1975 N=18		FINNEY B, 1976 N=11		Average
	Date	Correlation	Date	Correlation	Date	Correlation	Correlation
FCIC Estimate	Pre-harvest	0.95	Pre-harvest	0.74	Pre-harvest	0.45	0.71
Stand Quality Rating	Pre-harvest	0.47	Pre-harvest	0.89		----	0.68
Landsat Predicted Yield (4 bands)	April 15	0.94	May 21	0.79	May 6	0.87	0.87
Landsat Predicted Yield (TVI)	April 15	0.93	May 21	0.64	May 6	0.77	0.78

6.3.1 FINNEY A ANALYSIS

The relationships between several environmental/cultural factors and wheat yield have been investigated for the 1975 Finney A test site. The specific factors investigated were:

1. wheat variety
2. irrigation/no irrigation
3. fertilization/no fertilization
4. amount of irrigation.

An analysis of variance was performed for the above factors by regression with wheat yield for the 16 fields for which such data was available. From this analysis it was possible to determine the percent of the variance in yield accounted for separately by each of the factors, and also the percent of yield variance accounted for by Landsat data for the three dates analyzed. The site used for this analysis is a predominantly irrigated site, and the environmental/cultural factors are not entirely independent. In fact, all fields which were irrigated were also fertilized, and the converse, so these two variables were combined into a single irrigation-fertilization variable. Other factors had lesser, but non-zero correlations. The results of the analysis are presented in Table 9.

The analysis shows that there was not a large amount of yield variance accounted for by wheat variety. This is not surprising since farmers in a given location might be expected to use wheat varieties that are "best" for that location and cultural practices, and therefore the varieties may not differ appreciably from each other. The three principal wheat varieties represented in this analysis are Eagle, Scout, and Satanta. Although we do not have information on yielding ability of Satanta variety, Eagle and Scout varieties of wheat are known to have virtually identical "yielding ability" [16].

TABLE 9. PERCENT OF VARIANCE IN YIELD ACCOUNTED FOR SEPARATELY BY SEVERAL ENVIRONMENTAL, CULTURAL, AND LANDSAT VARIABLES (Finney Site A, 16 Fields)

Variable	Variance in Yield Accounted for by Variable (%)
1. Wheat Variety	18.5
2. Irrigation-Fertilization (yes or no)	24.9
3. Amount of Irrigation	79.9
4. Landsat Data (22 Nov 1974) [TVI]	59.8
5. Landsat Data (15 Apr 1975) [TVI]	85.9
6. Landsat Data (21 May 1975) [TVI]	75.5

Irrigation-fertilization accounts for somewhat more of the variance in yield than wheat variety but surprisingly not a large amount (24.9%). Such cultural practices would not be economically justifiable if there were no effect on yield. The amount of variance in yield accounted for in this analysis by the irrigation-fertilization variable would have been higher (a value of 53.6%) if a field which has been deleteriously affected by a treatment of herbicide was not included in the analysis. The total amount of irrigation (inches) applied to individual fields during the growth of the crop accounted for nearly 80% of the variance in yield. Again, this value would have been higher (85.6%) if the herbicide-treated field had not been included.

Landsat data green measure transforms for the three available dates were analyzed individually for their utility in predicting yield on the fields for which ancillary data was available. Green measure transformations (in this case TVI) for all three dates of Landsat data account for a high proportion of variance in yield.

In addition to the above analysis a coarse evaluation was made of the relative utility of ancillary variables and Landsat variables for predicting yield by determining the percent of variance in yield accounted for by several combinations of variables. The results are presented in Table 10.

TABLE 10. PERCENT OF VARIANCE IN YIELD ACCOUNTED FOR BY SEVERAL COMBINATIONS OF ENVIRONMENTAL, CULTURAL, AND LANDSAT VARIABLES (Finney Site A, 16 Fields)

Variables*	Variance in Yield Accounted for by Variables (%)
1, 2	31.0
1, 2, 3	93.5
1, 2, 3, 5	95.1
4, 5, 6	87.5
4, 5, 6, 1, 2	90.0
4, 5, 6, 3	90.0
1, 2, 3, 4, 5, 6	95.3

*Variable Key

1 -- Variety

2 -- Irrigation/Fertilization (Yes or No)

3 -- Irrigation Amount

4 -- TVI (22 November 1974)

5 -- TVI (15 April 1975)

6 -- TVI (21 May 1975)

In this analysis wheat variety and knowledge of whether the fields were irrigated and fertilized (variables 1 and 2) accounts for 31% of the variance in yield, but addition of information on amount of irrigation (variable 3) raises the variance accounted for to 93.5%. Since precipitation, temperature, and solar irradiance were in all likelihood essentially constant over the entire site, it is not surprising that three factors (variables 1-3) which do vary over the site account for as much of the variance in yield. However, the amount of irrigation, the most important of these three ancillary variables, is not a variable that is likely to be routinely available information, and hence is not a likely candidate variable for a wheat yield model.*

Without any ancillary information, the Landsat green measures for the three Landsat data sets (variables 4-6) account for 87.5% of the variance in yield. When the two ancillary variables most likely to be available (variety and irrigation-fertilization) are included with the three Landsat data transforms, the yield variance accounted for is 90%. A similar result occurs if amount of irrigation is added to the Landsat variables. Apparently much of the variability accounted for by amount of irrigation is also accounted for by the Landsat data. If the best single date of available Landsat data (April 15) is included with the three ancillary variables, 95.1% of the variance is accounted for, while inclusion of all three Landsat data sets raises the value to 95.3%.

The foregoing discussion furnishes the basis for some preliminary conclusions regarding the relative utility of Landsat data and ancillary data for predictions of wheat yield on a predominantly irrigated site in southwestern Kansas. If data on important ancillary variables (especially amount of irrigation) is available, such data is a good indicator of wheat yield on an individual field basis, perhaps somewhat better than several dates of Landsat data (ancillary variables 1-3: 93.5%; Landsat variables 4-6: 87.5%). If both Landsat and ancillary data are simultaneously available, wheat yield prediction performance is improved only

* There is also a significant correlation between amount of irrigation and both percent cover and LAI, thus indicating that amount of irrigation is a factor that should be considered in growth models, as well as yield models.

slightly over either type alone (all variables: 95.3%). Therefore, using Landsat data alone may be an acceptable procedure. In situations where Landsat data, meteorological data, and ancillary data are available, use of some combination of this data will probably improve yield prediction performance. In such situations, the appropriate approach is probably a function of the marginal costs in increasing the complexity of a yield prediction model compared to the marginal benefits.

6.3.2 FINNEY B ANALYSIS

We now examine the wheat yield information accounted for by cultural factors on the 1976 Finney site, and the degree to which Landsat data monitors their effects.

The cultural practices investigated included:

1. wheat variety
2. irrigation (yes/no)
3. fertilization (yes/no)
4. planting date
5. summer fallow (yes/no)
6. amount of fertilizer (lbs per acre).

All of these variables are potentially available early in the growing season, and hence could be available for early yield forecasting.

An analysis of variance was performed for the above factors by linear regression with wheat yield for the 55 fields for which such data was available. From this analysis, it was possible to determine the percent of variance in yield accounted for separately by each of the factors. However, high correlations do exist between some of the variables, so the results cannot be treated as though the variables were independent of each other. The results are presented in Table 11.

Planting date, somewhat surprisingly, accounts for almost none of the variance in yield on these particular fields. Perhaps the over-wintering period tends to reduce potential differences due to planting date.

TABLE 11. PERCENT OF VARIANCE IN YIELD ACCOUNTED FOR SEPARATELY BY SEVERAL CULTURAL FACTORS, FINNEY SITE B

Cultural Factor	Percent of Variance
Planting Date	0.1
Wheat Variety	10.6
Previous Cropping	35.8
Irrigation	56.3
Fertilization	55.0
Amount Fertilization	57.4

Wheat variety accounts for only a small amount of yield variance. This is to be expected, because the principal wheat varieties planted on this site (Eagle, Scout, and Centurk) have similar "yielding abilities" [16].

Previous cropping practice (whether the field was summer fallowed) accounts for an appreciable amount of variance in individual field yield. This is not unexpected since the reason for leaving a field fallow is to improve the soil characteristics for the subsequent crop.

Irrigation, fertilization, and amount of fertilization, all account for a substantial amount of variance in yield. They are highly correlated with each other, however, and the three variables combined do not account for much more variance than each one individually.

The amount of variance accounted for by a Landsat green measure (in this case SQ75) for each of the four dates processed was computed for the same fields that were used in the above analysis. The results are presented in Table 12. Landsat data from either 6 May, 2 June, or

12 June account for more variance in yield than any single cultural factor examined.

TABLE 12. PERCENT VARIANCE ACCOUNTED FOR SEPARATELY BY SEVERAL DATES USING SQ75 (FINNEY SITE A)

Date	Percent of Variance
18 April	54.8
6 May	67.7
2 June	72.0
12 June	67.4

Table 13 gives the results of a comparison of the relative utility of Landsat data, ancillary data, and the combination of the two data sources, for accounting for yield. Note that, together, all of the cultural variables (1-6) account for a substantial amount of yield variance (75%). Nevertheless, the Landsat green measures for the four dates (7-10) account for ev more variance in individual field yield (87%) than all of the cultural variables. The combination of all Landsat and cultural variables accounts for almost all of the variance in yield (94%).

We had previously speculated that field condition as measured by Landsat would account for the integrated effects of the factors governing crop growth and potential yield, including the cultural factors. The effects of cultural factors are most clearly seen on a local area where meteorological conditions are similar, and these cultural factors are almost completely accounted for by Landsat data in this 1976 Finney site. For example, addition of all six cultural factors to the four Landsat variables increased the amount of variance accounted for by only 6.3% (87.3% to 93.6%).

TABLE 13. PERCENT OF VARIANCE IN YIELD ACCOUNTED FOR BY SEVERAL COMBINATIONS OF CULTURAL AND LANDSAT VARIABLES

Variables*	Percent of Variance	Standard Error
1-6 (all cultural variables)	74.9	6.89
7-10 (all Landsat variables)	87.3	4.78
1-10 (all variables)	93.6	3.65

*Variable Key

1 = variety	6 = amount fertilizer
2 = irrigation	7 = SQ75 (May 6)
3 = fertilization	8 = SQ75 (June 2)
4 = planting date	9 = SQ75 (June 12)
5 = cropping	10 = SQ75 (April 18)

6.4 CONCLUSIONS

We draw the following conclusions on the basis of the material presented in Section 6. There is a considerable amount of local yield variance not accounted for by standard meteorological data. Much of this yield variance is accounted for by variation in cultural factors, and it is manifested in Landsat data. For yield models that require estimates of crop vegetative development or potential yield, Landsat data may be as good as some traditional estimates made on the ground by field personnel. Therefore, Landsat data may be quite valuable for making yield forecasts over a large area in a timely fashion.

7
YIELD PREDICTION EXTENSION

In order for Landsat data to be used most effectively as part of a wheat yield forecasting system, a relationship between Landsat data and wheat yield developed under one set of conditions (environmental conditions, cultural practices) should be extendable to Landsat data collected under different conditions at a different place and/or time. In any event, the limitations to the extendability of a relationship between Landsat data and the wheat yield should be known, in order to minimize the possibility of large errors in yield forecasting. There are at least three possible sources of variability that could potentially cause a deviation in a Landsat-wheat yield relationship:

1. changes in environmental conditions (e.g., atmospheric haze and soil reflectance)
2. changes in cultural practices (e.g., irrigation, fertilization, wheat variety)
3. changes in crop history (e.g., planting date, cropping practice, and weather conditions insofar as they affect plant phenology and potential yield).

The following sections discuss the importance of the effects of some of the above sources of variability with respect to extension of a yield prediction relationship, and an investigation of possible ways of minimizing the effects of such variability.

There are a number of ways that yield prediction extension performance could potentially be improved. One way is to transform the data so that it is not as affected by different conditions. These data transformations could be very simple, such as corrections for atmospheric path radiance by subtracting the signal value associated with the darkest objects in the scene. More sophisticated approaches include analytical normalization of the Landsat data set, pixel by pixel, to make it equivalent to some reference data set (e.g., XSTAR). An additional approach is to define a data transformation that maintains much of the desired information (in this case, information related to vegetation density and yield), and which is insensitive to other sources of variation unrelated to the information of interest.

Another way to improve yield prediction extension performance is to apply the yield-predictive algorithms in such a way as to minimize differences in conditions. Yield-predictive relations developed on an area with certain cultural practices (wheat variety, irrigation, fertilization, previous crop) and phenological stage should be applied to areas with similar cultural practices and phenological stage, insofar as this is possible. Effects of different atmospheric conditions could also be alleviated by applying relationships developed on certain atmospheric conditions to areas with similar atmospheric conditions.

In the following discussion we will briefly describe a variety of data transformation techniques, and then examine how some of them perform when applied on sites with different conditions.

7.1 DATA NORMALIZATION TECHNIQUES

One of the simplest traditional ways of normalizing remotely sensed data to account for different atmospheric conditions is to perform a dark level subtraction determined in each data set. This procedure is sometimes useful in minimizing differential additive effects due to differences in amount of atmospheric backscatter. This procedure was not practicable for this investigation, since no sufficiently dark objects were consistently available for examination within the immediate area of the relatively small test sites.

Another traditional way of normalizing data sets is to correct for differences in multiplicative factors caused by different illumination levels by employing large "secondary reflectance standards" with temporally invariant reflectance. None were available for this purpose.

One additional way to mechanically normalize data sets which we examined is to subjectively adjust the envelope of the data values to make them equivalent. The problem with this approach is that the envelope of the data values may be different due to target differences (average vegetation density, etc) which we want to monitor as well as non-target differences (atmosphere, illumination), which we want to normalize.

Since differences in illumination as well as non-Lambertian target reflectance are affected by differences in solar zenith angle, corrections for this effect are sometimes made. However, we were predominantly concerned with extending relationships between data sets with very similar or identical solar zenith angles, so it was not necessary to implement this correction.

The two types of data normalization which we examined in some detail as a part of this investigation were: 1) analytical procedures for normalizing Landsat data sets to a reference data set (EXTEC [17] and XSTAR [18]); 2) green measure transforms, many of which fortuitously normalize multiplicative differences in data sets due to differential atmospheric conditions or soil albedo. (Information concerning various green measure transforms is included in Appendix III.)

7.2 YIELD EXTENSION TESTS

In this section we present the results of three tests of the feasibility of extending a Landsat-wheat yield relationship over time and/or space. The three tests examine three types of conditions:

1. local (adjacent day) yield prediction
2. extension from a predominately non-irrigated site to another predominately non-irrigated site

3. extension from a non-irrigated site to a predominately irrigated site.

In these tests of yield prediction extension, three normalization/extension techniques were examined. The techniques examined were:

1. EXTEC3*
2. SQ75 ($\sqrt{MSS7/MSS5}$)
3. TVI $\left(\sqrt{\frac{MSS7 - MSS5}{MSS7 + MSS5} + 0.5}\right)$

These normalization techniques were compared with yield prediction extension using no normalization of the original four Landsat bands.

The tests were run by computing a regression relation between Landsat data and yield on one data set and analyzing the performance of the regression relation when applied to (extended to) another situation. In order to quantify the degree to which performance changed in extending a yield-predicting regression equation from one data set to another, several statistics were computed. For each test, a mean square error (MSE) was computed for both the original (local) regression and for the new data set according to the formula

$$MSE = \frac{1}{n-m-1} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

where n = number of cases (fields)

m = number of variables (channels used in regression)

Y_i = yield for field i

$\hat{Y}_i$ = Landsat predicted yield for field i.

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* EXTEC3 is an algorithm developed at ERIM under NASA Contract NAS9-14123 to account and correct for variable external effects such as atmospheric condition. Since its application here, it has been superceded by the XSTAR algorithm.

An "F-statistic" was subsequently computed as the ratio of the MSE of the extended equation to the base equation. The larger the F-ratio, the worse the prediction of individual field yields was compared to the base (local) prediction of yield.

Another statistical test performed was to determine how well the average yield for all fields was predicted. This test, a "t-test", was then computed as

$$t = \frac{\hat{\overline{Y}} - \overline{Y}}{s/\sqrt{n}}$$

$\overline{Y}$ = average value of yield

$\hat{\overline{Y}}$ = average predicted value of yield

$s^2 = \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2/n-1$

The null hypothesis is $\hat{\overline{Y}} - \overline{Y} = 0$, or that the mean values of actual and Landsat-predicted yield are the same. The larger the t-value, the less likely the hypothesis is to be true.

7.2.1 ADJACENT DAY YIELD PREDICTION EXTENSION

It was anticipated that the least difficult yield extension situation would be in extending between adjacent days of Landsat data acquisition over the same site. (This test was possible on test sites located in the overlap region of two consecutive (adjacent) Landsat overpasses.) The anticipated ease of extension resulted from the expected minimal to non-existent changes in the three important conditions discussed earlier: 1) environmental conditions; 2) cultural practices; and 3) crop history.

The results of this test (see Table 14) show that for data that is not normalized at all, both the F and t tests are significant. In other words, neither individual field yields nor mean value of yield for all fields is predicted accurately without any normalization. All three of the normalization procedures, however, result in no significant differences (F or t tests) in yield prediction performance by the extension, indicating that for this data set the normalization procedures have been useful in extending yield prediction capabilities.

TABLE 14. PREDICTION OF YIELD FOR ELLIS SITE, 20 MAY 1975, USING (A) RELATION DEVELOPED LOCALLY, AND (B) RELATION DEVELOPED FOR ELLIS SITE, 21 MAY 1975.

Method	A (Local) MSE[1]	B (Non-local) MSE[1]	Mean Difference[2]	F-Statistic	T-Statistic
Original Landsat Bands	19.4	45.0	-5.0	2.3*	4.2*
EXTEC3-Transformed Bands	19.6	20.9	0.4	1.1	0.5
Square Rood of Band 7/ Band 5 Ratio	27.5	25.9	-0.002	0.94	0.002
TVI	25.4	23.9	0.02	0.94	0.02

1. Mean Square Difference Between Actual and Predicted Yield
2. Difference Between Mean of Predicted Yield and Mean of Actual Yield
* Significant at 0.05 level

7.2.2 DRYLAND SITE/DRYLAND SITE PREDICTION

A second and presumably more difficult test of yield prediction extension performance was made using data from two separate sites. (Ellis 11 May 1975 data and Finney B 6 May 1976 data.) Both sites were predominately not irrigated, but the fact that the data is for different locations and different years implies that the weather conditions may have been different during the growing season. Crop phenological development was also somewhat different.

Degree days from March 1 were computed for both sites, and on this basis phenological development of wheat on the Ellis site was slightly ahead of that on the Finney B site on May 6. For this reason, we assume that the Ellis 3 May 1975 Landsat data would have been more analogous to the Finney B 6 May 1976 data in terms of crop phenology.

However, Ellis 3 May 1975 data were collected by Landsat 1, whereas the Ellis 11 May 1975 and Finney B 6 May 1976 data were collected by Landsat 2. Because of the differences in calibration between the two satellites, we chose to use the Ellis 11 May 1975 site, rather than 3 May 1976, for extension from the Finney B 6 May 1976 site.

The May 11 data was used as the base data sec, and yield prediction was attempted using a relationship developed on May 6. The results are presented in Table 15.

TABLE 15. PREDICTION OF YIELD ON ELLIS SITE, 11 MAY 1975, USING (A) RELATION DEVELOPED LOCALLY, AND (B) RELATION DEVELOPED FOR FINNEY B SITE, 6 MAY 1976.

Method	A (Local) MSE[1]	B (Non-local) MSE[1]	Mean Difference[2]	F-Statistic	T-Statistic
Original Landsat Bands	26.6	673.0	-24.7	25.3*	5.4*
EXTEC3-Transformed Bands	26.9	467.0	-20.2	17.4*	5.4*
Square Root of Band 7/ Band 5 Ratio	39.9	91.5	- 2.1	2.4	4.1*
TVI	35.6	77.9	- 3.4	2.2	4.2*

1. Mean Square Difference Between Actual and Predicted Yield
2. Difference Between Mean of Predicted Yield and Mean of Actual Yield
* Significant at 0.05 level

Again, data that had not been normalized failed both the F and t-tests. In other words, neither individual field values nor average yield for all fields were predicted accurately.

In this case the EXTEC3 transformed data yield extension attempt also failed both the F and t-tests, and was not much better than the unnormalized data extension attempt. While the parameters of EXTEC3 were derived for Landsat 1 data, we expected improvement in yield extension between Landsat 2 data sets, as long as both data sets had the same calibration and the Landsat 2 calibration differs not too greatly from the Landsat 1 calibration. But, in fact, NASA's Goddard Space Flight Center modified the calibration procedure for Landsat 2 in July 1975. This change may have contributed to the failure of the transformation in this case.

Both SQ75 and TVI yield extensions "passed" the F test at the 5% level, but only barely so. In other words, prediction of individual fields is not significantly different in a statistical sense due to the extension procedure. However, predicted average value of yield for all fields is significantly different. Apparently, the reason that individual field yields were predicted accurately (F-test), while the average value of field yields was not (t-test), is due to a small but consistent bias in individual field yield prediction.

The F-statistic compared the mean squared value of the individual field yield deviations, and none of the individual field yield predictions were very far in error. However, they all tended to be in error in the same direction. Therefore, the cumulative effect on the average value of predicted yields showed up in a significant t-test.

7.2.3 DRYLAND SITE/IRRIGATED SITE PREDICTION

The third and also difficult test of yield prediction extension performance was made using 21 May 1975 Finney A data and 21 May 1975

Ellis data. The Finney A site is predominantly irrigated and fertilized, whereas the Ellis site is predominately non-irrigated and non-fertilized. The phenological state of the two sites was assumed similar on May 21, based on both ASCS field observations and on the fact that both sites experienced nearly the same number of degree days from March 1 to May 21.

The Finney data was used as the base data set, and yield prediction was attempted using a relationship developed on the Ellis data. The results are presented in Table 16.

TABLE 16. PREDICTION OF YIELD FOR FINNEY A SITE, 21 MAY 1975, USING (A) RELATION DEVELOPED LOCALLY, AND (B) RELATION DEVELOPED FOR ELLIS SITE, 21 MAY 1976.

Method	A (Local) MSE[1]	B (Non-local) MSE[1]	Mean Difference[2]	F-Statistic	T-Statistic
Original Landsat Bands	60.2	460.0	-19.3	7.7*	3.7*
EXTEC3 Transformed Bands	60.2	412.0	-18.6	6.8*	3.8*
Square Root of Band 7/ Band 5 Ratio	71.6	305.0	-15.3	4.3*	3.6*
TVI	56.1	342.0	-16.7	6.1*	3.7*

1. Mean Square Difference Between Actual and Predicted Yield
2. Difference Between Mean of Predicted Yield and Mean of Actual Yield
* Significant at 0.05 Level

Once again, the Landsat data that had not been normalized failed both the F and t-tests. Neither individual field yield values nor mean yield for all fields was predicted accurately. None of the three normalization techniques passed the F and t-tests, either. In other words, none of the normalization techniques tested were able to extend a yield prediction ralationship from one site to the other without statistically significant change.

One of the probable reasons for this poor yield prediction extension is that most of the fields on the Ellis site were low to medium in yield values while most of the fields on the Finney A site were medium to high in yield values. The average value of yield for the Ellis fields was 32.4 bu/acre and the average value of yield for Finney was 52.9 bu/acre. The non-linearity in the relationship between Landsat data and yield may, therefore, have caused some of the problems in extending predictive relationships from one site to another. It is also possible that the irrigated and fertilized fields on the Finney A site have different structural and radiometric (spectral) properties than non-irrigated, non-fertilized fields on the Ellis site. Since no field data were collected at the Ellis site, we cannot confirm this.

Additional tests besides those presented here have been made in an attempt to better understand the factors causing performance of extension of yield prediction relations to vary. However, little consistency in results has been achieved thus far in our analyses. There are many possible sources of variation in performance, and it may be that procedures that are generally optimum can be discovered only by development of a considerably larger base of tests of candidate procedures.

7.3 CONCLUSIONS

From our analyses so far it seems that none of the techniques we have examined for improving yield prediction extension will always be completely effective on every site. A more elaborate normalization and/or stratification of the data might be needed to achieve more consistently accurate results on each site.

However, in terms of a large area survey, the picture is not discouraging. Even with a substantial RMS error on a field-by-field basis, adequate large area or large sample average values may be achieved. This possibility exists because of the central limit theorem, in which the expected error in an estimate of average yield (bias) based on N fields would be smaller by a factor of $1/\sqrt{N}$ if error in predicted yield is normally distributed around zero. Thus, even if average RMS error were 8 bu/acre on a local basis (a value larger than we have observed), a sample of 100 fields could potentially reduce the RMS error of the estimate of the average yield to 0.8 bu/acre. While we have not demonstrated that this is the case, some of our large scale demonstrations (Sections 8 and 9) indicate that there may be some compensating factors that improve results on a large scale average basis.

We would prefer, however, to achieve accurate results on the local, small scale basis, as well as on the large scale average basis.

8
LARGE AREA YIELD ESTIMATION

We have previously indicated that there is a considerable amount of variability in yield on a local basis that apparently can not be accounted for by variations in meteorological conditions, but that can be accounted for by Landsat data. Meteorological yield models, however, are generally used to produce average yield values over large geographic areas. In order to make a comparison between Landsat estimates of yield and meteorological yield model estimates of yield, we made both kinds of estimates over an area large enough that adequate "true" values* of average yield were available. The Central Crop Reporting District (CRD) of Kansas was selected for the comparison since yield estimates for all counties in the Central CRD were available from the Kansas Crop and Livestock Reporting Service (KCLRS). These yield values were used as the "true" values.

In the following material, we first discuss Landsat estimates of yield over the Central CRD, and then NOAA Center for Climatic and Environmental Assessment (CCEA) meteorological yield model estimates of yield. The two methods will then be compared.

It should be noted at the outset that this study had some shortcomings in terms of data comparability and statistical validity. However, since this was an initial attempt to investigate the relative utility and possible problems of using Landsat data to estimate yield over large areas, it was felt that any information that would result would be useful if for no other reason than to better define the requirements of such a comparison for the future.

8.1 LARGE AREA LANDSAT YIELD PREDICTION CAPABILITIES

One reason the Central Crop Reporting District (CRD) of Kansas was chosen for a Landsat large area yield prediction demonstration is

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* Actually "serviceable estimates" according to SRS personnel.

that, of the Kansas CRDs, it best satisfied the requirement for adequate "training" data. Information on individual field yield which is necessary in order to calibrate a Landsat wheat yield relation was available for three sites within the Central CRD.

Tests of the performance of the Landsat yield relation were carried out using Landsat data from individual sample segments in the Central CRD. The rationale for this procedure is that the indicated yield on these sample segments, by appropriate aggregation, could approximate the average yield over the entire Central CRD.

8.1.1 DATA AVAILABILITY

The yield prediction test was initially run using early May 1976 Landsat data. It had previously been established that Landsat data gathered during early May (the approximate time of heading for this region) was correlated with yield. During this time period, two of the three training sites had cloud-free Landsat data. The satellite passes which imaged these training sites occurred on dates separated by 1-2 days. This situation is considered acceptable, and perhaps desirable, for training data since the test data also was acquired on more than one day, and it was desired that the training data encompass the variability likely to be present in the test data.

While the selection of data for use reflects the optimum choice in terms of both data utility and data availability, there are some problems with data adequacy. Because of cloud cover and other limitations, only 7 of 11 counties within the Central CRD had test sites with useable Landsat data. The training and test data used is indicated in Table 17.

8.1.2 DETERMINATION OF PHENOLOGICAL STAGE

As discussed previously, it is important to apply Landsat yield relations to equivalent phenological stages, not necessarily to similar calendar dates. Therefore, an examination of the comparability in phenologic stage for the training and test sites was conducted.

TABLE 17. LIST OF LANDSAT TRAINING AND TEST DATA

TRAINING SITES

Site (County)	Acquisition Date
Saline	4 May 1976
Saline	5 May 1976
Ellis	6 May 1976

TEST SITES

Russell	6 May 1976
Marion	4 May 1976
McPherson	4 May 1976
Rush	6 May 1976
Ellis	6 May 1976
Rice	4 May 1976
Saline	4 May 1976

The growing degree days (GDD) were calculated using the definition found in Reference [19]. The maximum temperatures above 86°F were entered as 86° and minimum temperatures below 50°F were entered as 50°.

$$\text{GDD} = \frac{\text{Daily Max Temperature } (\leq 86°\text{F}) + \text{Daily Min Temperature } (\geq 50°\text{F})}{2} - 50°\text{F}$$

It was assumed there was no appreciable growth during January and February, so the calculations were started with 1 March 1976. The daily maximum and minimum temperatures were obtained from Reference [20].

The temperatures were from the weather stations located in the counties of the Central Crop Reporting District, since daily temperatures from the actual Landsat sites were not available. Unfortunately, the weather stations for all counties were not adjacent to the Landsat sites in these counties. In Dickenson County the Landsat site and the weather station were fairly close together, while in Russell, Lincoln, and Barton they were relatively far apart. In Marion County the Landsat site is between two weather stations which reported very different temperature ranges. These situations caused uncertainties in the GDD calculations for some sites.

The results of the GDD calculations, tabulated through April 16 and May 4, are presented in Table 18.

TABLE 18. RESULTS OF GROWING DEGREE DAY CALCULATIONS

		Landsat Data Acquisition Date	
	Weather Station	April 16	May 4
1	Russell	273.0	371.5
2	Kanopolis Dam	262.5	382.5
3	Wilson Lake	253.5	388.0
4	Hays	286.0	397.0
5	Saline	289.5	402.5
6	Marion	269.0	410.0
7	Abilene	298.5	428.0
8	Sterling	342.5	468.5
9	Herington	336.5	476.0
10	McPherson	340.5	480.0
11	Great Bend	358.0	473.0
12	Lincoln	367.5	520.0
12	Ellsworth	382.5	541.5
14	Bison	400.5	551.5
15	Florence	454.0	608.0
	μ	327.6	459.87
	σ	±58.23	±71.33

The 15 sites can be loosely divided into three groups. The first seven from Table 18 are in Group 1, the coolest group. The middle group consists of the next four sites (8–11), and the last or warmest group is represented by the last four sites listed in the table. Based on these calculations and an examination of the map in Figure 23 no clear grouping was found either geographically or by date. The most northern weather station (Lincoln) and the most southern (Florence) are both in the warmest group. Similarly, it can be seen that the groups are well scattered throughout the district, with no group predominantly in any one area. The Marion County site is nearly equidistant from the Marion weather station, which is in the coolest group, and the Florence weather station, which is in the warmest group. In addition, there was considerable overlap of the GDD numbers for the first three dates chosen.

As stated earlier, the yield prediction test was run using early May 1976 Landsat data. Landsat yield prediction on the test sites was based on a regression relation between the Landsat green measure, SQ75, and farmers' combine weight estimates of yield per harvested acre on the training sites.

Because of the possible variation in external effects such as atmospheric haze over the training and test sites, it is possible that a correction for such factors would be required. Accordingly, the procedure of training and testing a Landsat yield relationship over the Central CRD was repeated using data that was corrected for amount of haze in the atmosphere by a recently developed ERIM haze normalizing program called XSTAR [17].

8.1.3 RESULTS

The yield predictions that were produced for the test sites are shown in Table 19. Note that the Landsat estimates appear to be sensitive to yield variation, since the uncorrected Landsat county average estimates have a variance of 4.49, which is comparable with

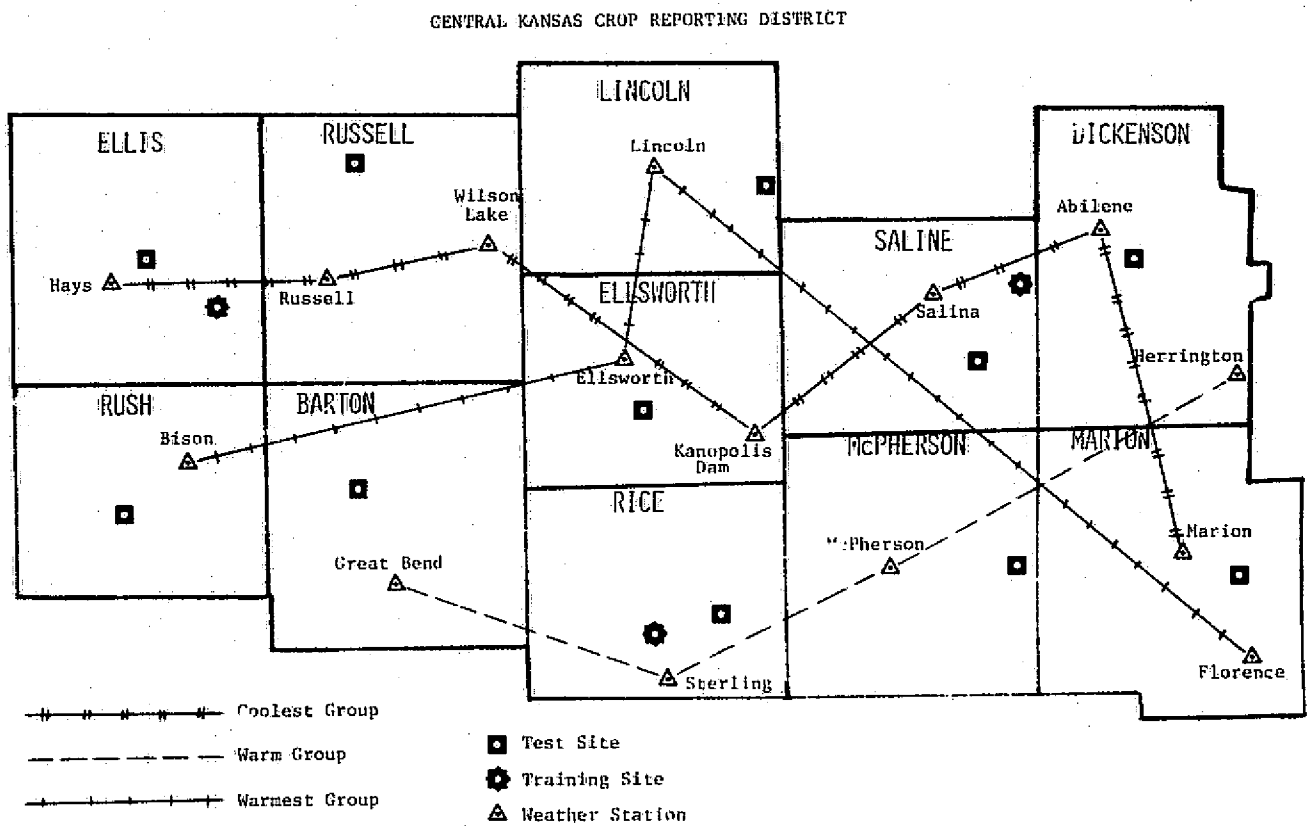

FIGURE 23. SITE LOCATIONS AND COMPARISON OF GROWING DEGREE DAYS

TABLE 19. KCLRS ACTUAL YIELDS AND LANDSAT PREDICTED YIELDS (UNWEIGHTED)

County	"True" Yield (KCLRS)	Landsat Yield (based on SQ75) Uncorrected	XSTAR Corrected
Saline	27.5	37.8	38.0
Ellis	30.6	33.7	34.6
Marion	29.3	30.7	31.3
McPherson	28.5	34.1	36.3
Rush	30.8	35.1	32.5
Rice	34.3	35.2	37.8
Russell	34.5	32.9	33.5
Ellsworth	30.5	32.9	36.1
County Average	30.8	33.7	34.7
Standard Deviation	2.5	2.1	2.5

a variance of 6.35 for KCLRS estimates. The individual correlation between Landsat yield estimates of a particular test site and county KCLRS average yields is not large for either the uncorrected (r = 0.25) Landsat data or for the XSTAR corrected (r = 0.08) Landsat data.

It is not essential that these county estimates be highly correlated for the Landsat estimation technique to be working, since a small sample in a county may not be representative of the entire county. What is hoped, however, is that these county samples, when appropriately aggregated, will be good indicators of average yield over the entire Central CRD. In order to investigate this possibility, the individual county yield estimates were weighted by the number of harvested acres of wheat for the respective county, and aggregated to determine an average value of yield for the Central CRD.

The Landsat average value of weighted county yields was then compared with the KCLRS average yield, using a t-test. The hypothesis was that the average values were identical. This hypothesis was barely accepted at the 5 percent level for the uncorrected Landsat estimate of average yield, but was not accepted for the corrected Landsat estimate. There appears to be a bias in the Landsat estimates of yield, since most Landsat estimates were too high using both XSTAR data (+4.2 bu/acre) and using uncorrected data (+2.9 bu/acre). Apparently the source of bias was not one that could be corrected by only accounting for atmospheric effects (haze), since the haze-corrected (XSTAR) data had a greater discrepancy with the KCLRS estimate than did the uncorrected (but green measure normalized) data. An examination of possible sources of bias is described in Appendix IV.

8.2 AGROMET MODEL YIELD ESTIMATES

Traditionally, agricultural yield has frequently been estimated by using current years' meteorological data as inputs to a "yield model" that is the result of a regression of historical large area yield data and meteorological data. Many of these models have a historical trend term or terms that produce an initial estimate of yield assuming weather is "normal". This initial estimate is modified only if current weather conditions deviate from "normal". For this reason, such models are frequently referred to as perturbation models.

Agrometeorological yield models of the above type produce an estimate of yield that is frequently close to the "correct" answer without use of <u>any</u> data from the current growing season. For example, a winter wheat agrometeorological yield model developed for a region in the USSR has a coefficient of determination (R^2) of 0.80 and a standard error of 2.65 when <u>no</u> meteorological data is used, and this improved to only 0.84 and 2.39, respectively, when March through June meteorological data is included [21]. In other words, the weather data accounts for only 4% of the variance in yield. This approach has both advantages and disadvantages. The chief advantage is the stability of the estimates. Most of the time, when the weather is reasonably "normal", estimates should be quite good. However, the stability associated with a historical regression equation based on large area averages can also make the model insensitive to infrequent large variations in yield that result from large perturbations in weather (or other) factors.

Since agrometeorological yield models are so frequently used for large area yield estimates, they are in some sense a yardstick with which to evaluate alternative approaches. In the following sections we will describe the results of implementation of an agromet yield model, and we will subsequently compare those results with Landsat results.

8.2.1 METHODS

The agrometeorological yield model which was implemented for this investigation was a model developed for Kansas by the Center for Climatic and Environmental Assessment (CCEA) of the National Oceanographic and Atmospheric Administration [22]. The model was implemented for the Central Crop Reporting District (CRD) of Kansas using all readily available meteorological data from meteorological stations scattered throughout the Central CRD. The location of the meteorological stations used is indicated in Figure 23, shown previously.

The CCEA has actually developed a number of models with different times of truncation. For example, one model is implementable as the current years' March meteorological data becomes available, and another is implementable when May meteorological data becomes available. We chose to implement the model for May truncation, since we intended to examine late April and early May Landsat data, and since no April truncation CCEA model was available.

The specific CCEA model used was the following relation:

$$\begin{aligned} \text{yield(bu/acre)} = {} & 12.62441 + 0.24514(X) + 0.73960(Y) \\ & + 0.35817\,[AFP-AFNP] + 1.30843[(MP-MPET)-ND] \\ & - 0.06104[(MP-MPET)-ND]^2 - 0.35332[MAP-MANP]^2 \\ & - 2.07739[MDD] \end{aligned}$$

where

X is the number of years for one historical yield trend (1931-1955) = 25

Y is the number of years for another historical yield trend (1955-1976) = 22

AFP = August to February Precipitation (inches)

AFNP = August to February Normal Precipitation (inches)

MP = March Precipitation (inches)

MPET = March Potential Evapotranspiration (inches)

ND = Normal Difference between March precipitation and potential evapotranspiration

MAP = May Precipitation (inches)

MANP = Normal May Precipitation (inches)

MDD = May Degree Day trigger (=1 if 9 or more days exceed 90°F; =0 otherwise)

The values for normal meteorological conditions were obtained from Reference [22], as were the values for A and I as well as the daylength correction for computing MPET. Potential evapotranspiration (MPET) was calculated according to directions found in References [23] and [24].

After the CCEA estimates were calculated for each meteorological station, an average value was obtained for each county with more than one meteorological station.

8.2.2 RESULTS

It was possible to get complete weather data from ten of the meteorological stations located in the Central CRD. CCEA agromet model estimates of yield were calculated for these stations and compared with KCLRS county estimates. The unweighted CCEA estimates and the KCLRS estimates were found to have a non-significant correlation (r = 0.09). Less than 1 percent of the variance in KCLRS estimates was accounted for by the agromet (CCEA) estimates.

The CCEA estimates were very stable, or conservative. The variance in county CCEA estimates was 1.01, which was considerably less than the variance in KCLRS county estimates of 6.35. One might have expected the point samples (CCEA estimates generally from single meteorological stations) to be more variable than large area averages (KCLRS county estimates). However, the CCEA agromet perturbation model was not very sensitive to changes in weather.* An additional example of this relative insensitivity is that if there had been no precipitation between August and February, the CCEA model for Kansas would have predicted a yield reduction from normal yield of only 3.7 bu/acre. In reality, such a lack of precipitation would likely have had catastrophic effects on wheat yield.

The individual county sample estimates of yield were subsequently weighted by the wheat acreage harvested (in 1976) in the county corresponding with the meteorological station(s). The estimates were then aggregated to a single estimate for the Central CRD, as was done using Landsat estimates. Despite the apparent insensitivity of the CCEA model to meteorological variations (or perhaps because of it), and despite the low correlation between CCEA and KCLRS estimates, the average weighted CCEA value of yield is not far removed from the KCLRS estimate. The difference is 1.6 bu/acre, which has a P-value of 0.18. Therefore, we accept the estimate of yield as being not statistically significantly different from true yield.

The above discussion indicates both the advantages and disadvantages of an agromet perturbation model of the type implemented. Its stability and relative freedom from a constant bias generally guarantees

*Such insensitivity is not a necessary consequence of meteorological yield models, but is a characteristic that generally occurs as a result of construction of the models from large area historical averages.

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that it will not be far in error in reasonably "normal" years. However, its conservativeness also potentially precludes it from adequately reflecting the effects on yield of large or unusual deviations from normal weather.

8.3 COMPARISON OF AGROMET AND LANDSAT ESTIMATES

Unfortunately, the preceding discussion (Sections 8.1, 8.2) may not furnish definitive answers that reflect the relative accuracy of agromet and Landsat yield estimates. For example, whether or not individual county estimates of yield using the two techniques are correlated with KCLRS yield may not be terribly relevant, because of the sampling schemes used. Similarly, the accuracy of prediction of CRD weighted average yield is not necessarily definitive. This is due to the fact that most of the "information" in this particular test seems to be in the acreage weighting factors, which have a substantially larger coefficient of variation than do the yield estimates (see Table 20). Therefore, the county with the largest harvested wheat acreage tends to have the largest weighted yield estimate, regardless of the type of yield estimate (Landsat, KCLRS, or CCEA), and conversely for the county with the smallest harvested wheat acreage. This situation results in, for example, unweighted CCEA estimates having a correlation with KCLRS estimates of 0.09, and the corresponding weighted estimates having a correlation of 0.92.

TABLE 20. COEFFICIENT OF VARIATION (σ/m) FOR PRODUCTION-RELATED PARAMETERS FROM COUNTIES WITHIN THE CENTRAL CRD

Parameter	σ/m
KCLRS Yield	0.08
CCEA Yield	0.03
Landsat Yield	0.06
Acreage	0.22

Despite these difficulties in interpretation, the results do shed some light on characteristics of the two approaches that might be fairly general in nature. Specifically, the agromet model is characterized by relative lack of consistent yield error (bias) and by insensitivity to large changes in yield. The present Landsat model is characterized by potentially large yield bias and by high sensitivity to changes in yield. In other words, either approach has advantages and disadvantages. Either approach might be modified to reduce its disadvantages. Also, agromet and Landsat information could be used together to estimate yield. These possibilities are briefly addressed in the following discussion.

8.4 IMPROVED MODELS

An agromet model could be made more sensitive by making it more physiologically valid. In other words, specific meteorological (and other) effects should have physiologically reasonable consequences. For example, absence of rain from August to February should have drastic effects on yield, and perhaps would even preclude fall planting. Unfortunately, it will be difficult to develop more sensitive agromet models using large area historical averages, because large area average values of yield and meteorological factors do not vary far enough from the norm often enough for simple regression to be sensitive to such variation. Physiologically-based growth and yield models that are sufficiently sensitive may have to be developed under experimentally controlled conditions where environmental conditions and yield can be forced to vary as much as desired, and then tested over large areas for anomalous years to examine their utility.

Present Landsat models already seem to have considerable sensitivity. Regression models with sensitivity using Landsat data are possible to construct, since large variations in field condition and yield can be found in a fairly limited data base.

However, methods need to be developed to make Landsat-yield relations less volatile. One way to accomplish this is to achieve better calibration of Landsat data. Another way to reduce instability of present models is to use a larger training set of data to construct the models, and to implement them on large test sets of data. A way this approach can be simulated on a limited data set is by using average values over an area, rather than individual field values. This approach could be demonstrated by constructing a Landsat perturbation model, in which some normal average value of yield would be calculated, and deviations from this value would occur in response to deviations from normal average values of the Landsat green measure. The general form of such a Landsat perturbation yield model might be:

$$Y = a + c(L - L_o)$$

where

- a is a constant representing average yield at some base time
- L_o is an (historical) average value for a Landsat green measure such as SQ75
- L is the present value for a Landsat green measure
- c is the historically determined change in yield associated with a given change in Landsat green measure.

An example of how the model could be generated and implemented will now be given using 1975 and 1976 Ellis data. The c term in the equation was computed using 1975 Ellis data, in the following manner. Using the 1975 Landsat and yield data we established an algorithm relating the yield and Landsat green measure of the form

$$\hat{Y}_i = d + cL_i$$

where

- d is a constant
- c is the coefficient discussed previously
- L_i is the value of the Landsat green measure for individual fields in 1975.

In this case c was found to have a value of 24.034. Next, an average value of the Landsat green measure for all known wheat fields was determined for both 1975 (L_o) and 1976 (L). The average yield for the 1975 wheat fields on the Ellis site was then input as 32.36($=\overline{Y}_{o75}$) while the average yield for 1976 was 32.70 bu/acre ($=\overline{Y}_{76}$). A Landsat perturbation model generated from this data could be

$$\hat{\overline{Y}}_{(76)} = \overline{Y}_{(75)} + C(\overline{L}_{(76)} - \overline{L}_{o(75)})$$

$$\therefore \quad \hat{\overline{Y}}_{(76)} = 32.36 + 24.034(1.057 - 1.037)$$

$$\therefore \quad \hat{\overline{Y}}_{(76)} = 32.84 \text{ bu/acre vs "correct" value of } 32.7 \text{ bu/acre for the Ellis site}$$

The perturbation part of the model which uses Landsat data has correctly indicated an increase in yield, and the magnitude of the complete yield estimate is within 0.4% of the correct value. A non-perturbation Landsat model approach based on individual field data was implemented and found to produce a yield estimate with an error of 5.6%.

The above example is only intended to be illustrative of a way to decrease the volatility of Landsat-yield relations which are based on a small sample of individual fields. Another way to decrease volatility, as indicated previously, is to use larger training and test data sets. An optimal approach will be one that produces stability and sensitivity, without volatility, in the most cost-effective manner.

An historical trend term could be added to the previous model if that were deemed appropriate. It may not be needed unless some drastic change such as radically new wheat variety is added. And in recent times it is not clear what historical trend, if any, exists. There are some indications that environmental and cultural factors may have slowed or halted the traditional upward trend in yields.

In further refinements of a perturbation model more historical data relating Landsat data and yield could be included. Agrometeorological perturbations could also be added to the model, as well as perturbations in cultural practices not included in an historical trend term (e.g., percent of summer fallow fields planted to wheat).

It is envisioned that an optimal yield model will incorporate all available information, possibly in a perturbation model form, such as

Yield = Historical Trend + Landsat Perturbation
+ Meteorological Perturbation + Cultural Perturbation

It seems certain that if the above type model is skillfully and carefully constructed and implemented, it cannot help but be better than any of the existing approaches which use less than all of the available information.

9
DIRECT LANDSAT WINTER WHEAT PRODUCTION FORECASTS

Thus far we have discussed only the ability to forecast wheat yield (i.e., bu/acre, quintals/ha) using Landsat data. By itself, this information would be valuable as part of a system for forecasting wheat production. However, our work to this point has suggested a method for utilizing the relationship between Landsat data and yield, together with other relationships, to effect direct Landsat forecasts of total winter wheat production, an approach which may overcome certain troublesome problems in some of the existing approaches.

The existing approaches tend to separate the task of forecasting into two separate subsystems consisting of: (1) wheat acreage determination; and (2) regional average determination of per acre yield. The approach discussed below could make it possible to determine production on a pixel-by-pixel basis, using early-season Landsat data, with a single processing step. Thus it may become possible to survey large areas, such as a state or country, much more economically than at present, and achieve more timely information. What follows is a discussion of the rationale of the suggested approach, and a demonstration of its initial implementation.

The basic idea in the direct winter wheat production approach using Landsat data is that, because of the spectrally unique appearance of winter wheat, an appropriate value of yield (per unit area) can be determined for each pixel in the scene, without the need to specify that the pixel is wheat, and that production can be determined as

$$\text{Production} = \sum_{i=1}^{n} \text{yield}_i \times (\text{area of a pixel})$$

where i numbers the set of n pixels covering the area of interest.

We have previously shown that several Landsat transforms are good indicators of green vegetative cover, and that cover, as so measured, in turn is strongly related to wheat yield. An additional fact, which is further discussed below is that in winter wheat regions such as Kansas, wheat tends to develop significant green cover sooner than most non-wheat fields. Thus, if a yield-predictive relation (developed on wheat fields) is applied to non-wheat pixels, in most cases a very low yield indication would be expected, and might be a negligible source of error. If applied to pixels falling on a boundary between wheat and non-wheat, an appropriate intermediate value of green cover, and thus weighted average yield, would be estimated. This intermediate value of yield estimate times the area per pixel could approximate the total amount of wheat production represented by the pixel, which covers an area only partially planted to wheat. Thus, in most cases pixels might tend to contribute only their fair share of the total production estimate.

As mentioned above, our approach depends on the hypothesis that non-wheat fields tend to have a smaller measure of green vegetative cover than wheat fields. Non-wheat classes should be largely separable from wheat using a Landsat indicator of green vegetative cover. In order to test these hypotheses, we examined the green measure SQ75. The measure SQ75 was computed for all sufficiently large fields (wheat and non-wheat) in the Finney County, Kansas site using 6 May 1976 Landsat data. A threshold was selected to optimally distinguish wheat from non-wheat using SQ75. As a result, four of 58 wheat fields fell below the threshold, and two of 38 non-wheat fields fell above, giving an average field classification accuracy of 93.8% correct. A comparison of wheat and non-wheat histograms illustrating the separability is given in Figure 24. The same procedure applied to 6 May 1976 Landsat data for the Ellis County site resulted in an overall classification accuracy of 91.9%. Similar indications of the utility of Landsat green measures for wheat recognition have been demonstrated at ERIM [25].

SQ75	Non-Wheat	Wheat
.66000	0 +	0 +
.68000	3 +XXX	0 +
.70000	15 +XXXXXXXXXXXXXXX	0 +
.72000	11 +XXXXXXXXXXX	2 +XX
.74000	4 +XXXX	2 +XX
.76000	2 +XX	0 +
.78000	2 +XX	3 +XXX
.80000	0 +	1 +X
.82000	0 +	0 +
.84000	1 +X	5 +XXXXX
.86000	0 +	0 +
.88000	0 +	3 +XXX
.90000	0 +	8 +XXXXXXXX
.92000	0 +	4 +XXXX
.94000	0 +	7 +XXXXXXX
.96000	0 +	3 +XXX
.98000	0 +	2 +XX
1.0000	0 +	4 +XXXX
1.0200	0 +	1 +X
1.0400	0 +	1 +X
1.0600	0 +	2 +XX
1.0800	0 +	3 +XXX
1.1000	0 +	3 +XXX
1.1200	0 +	0 +
1.1400	0 +	1 +X
1.1600	0 +	0 +
1.1800	0 +	0 +
1.2000	0 +	2 +XX
1.2200	0 +	0 +
1.2400	0 +	1 +X
1.2600	0 +	0 +

FIGURE 24. SEPARABILITY OF WHEAT FROM NON-WHEAT USING HISTOGRAMS OF THE SQ75 TRANSFORMATION. FINNEY SITE, 6 MAY 1976. (Each x = 1 Field)

We therefore assume that an early-season green measure can give a reasonably accurate classification of wheat and non-wheat in some winter wheat regions.

9.1 LOCAL TEST

Next we examined a simple method of direct production estimation on a local basis. Again using SQ75 as a green measure, we obtained a yield predictive relation based on the wheat fields in a 4x6 mile training area chosen within the Finney B site using 6 May 1976 Landsat data. Using the relation, we computed an estimate of yield for each pixel in a test region consisting of the remaining 1x6 mile area in the site. The yield from each pixel times the acreage associated with a pixel was summed over all pixels in the test region, giving the total production estimated for the 1x6 mile test segment. In doing so, it had been assumed that yield attributed to non-wheat pixels may be negligible, although the assumptions had not yet been checked.

As a result, the production estimate for the test area was 53,900 bushels, compared to the "true" production (as computed from farmer-reported production information) of 40,600 bushels, a 33% overestimate. On examining the assumption of negligible production from non-wheat fields, we found that the average yield/acre associated with non-wheat fields was about 5 bushels per acre. Although this is a rather small yield (compared to typical yields of 30-40 bu/acre and maximum yields around 60 bu/acre for wheat fields), it is multiplied by a very large number of pixels (acres), and so leads to an overestimate of production on the order of what was observed.

Due to the above consideration, we modified the technique to account for the production improperly associated with non-wheat, by selecting a threshold below which a pixel is assumed to be either non-wheat or wheat which is sufficiently marginal as to be possibly not worth harvesting. Initially we chose a threshold so as to approximately make compensating errors in acreage estimation. More specifically, a threshold was determined so as to minimize the difference between the number of wheat pixels below the threshold and the number of non-wheat pixels above the threshold in the training region.

When production estimates were made as described previously, but using a threshold determined using the fields in the training area of the Finney B site, we obtained a production estimate of 42,700 bushels, compared with the actual 40,600 bushels, which represents an error of only 5.2%. In addition, we applied the same procedure to the same site using 18 April 1976 Landsat data, and to a different site (Ellis County, Kansas) using 6 May 1976 Landsat data. For the Ellis site a 6 square mile training area and a separate 3 square mile test area were used. The resulting production estimates are shown in Table 21.

TABLE 21. RESULTS FROM SIMPLE DIRECT WHEAT PRODUCTION ESTIMATION PROCEDURE

Site	Landsat Overpass	True Production (10^3 Bushels)	ERIM Estimate (10^3 Bushels)	Error (%)
Finney B	6 May 76	40.6	42.7	5.2%
Finney B	18 Apr 76	40.6	42.8	5.4%
Ellis	6 May 76	27.9	24.7	11.5%
Finney and Ellis	6 May 76	68.5	67.4	1.6%

Note that the total production estimated for the two sites on the same date with separate training for each site was within 1.6 percent of the correct total production, well within the LACIE desired accuracy [26].

Preliminary indications based on the three local test results give encouragement that the direct wheat production approach using early-season Landsat data might produce reasonable results. Many more tests in different situations will have to be performed in order to assess the consistency in performance. It is anticipated that variations in desired approach or acceptable calibration may occur in other situations, and that stratification of data may be required.

However, the approach does address some problems that may exist in present methods. For example, as indicated in Section 6, local variations in yield can possibly be accounted for with greater precision using Landsat data than using meteorological data. The difficulty in locating field boundaries on Landsat data for determination of wheat acreage is alleviated since all pixels in the test area are included in the proposed new technique, and small or irregularly shaped fields can contribute to the acreage and production estimate even if not a single pixel falls completely within the field boundary. Furthermore, large bare areas within wheat fields will be assigned little or no yield, thereby giving approximately the correct production, without a decision having to be made as to whether the area should be assigned to wheat acreage or not. Finally, marginal wheat fields, ones which are not likely to be harvested, will not be included in early-season production forecasts if they fall below the green measure threshold.

There are some indications that these potential desirable features of the direct wheat production approach are being fulfilled. For example, there were several wheat fields in our Finney test for which no "pure" pixels could be obtained. That is, all pixels covering these fields were on the field boundary, or very nearly so. One such field had a farmer reported production of 1001 bushels and an area of 32.7 acres. Even though not a single pure pixel was present, production of 732 bushels was estimated for this field, based just on the pixels whose <u>centers</u> fell within the field boundaries.

In the Ellis site there was a wheat field which was not harvested because the stand was too sparse. Every pixel within that field boundary had a green transform value less than the minimum threshold. Therefore, even though the field was wheat it could not have contributed to a production estimate, which is the desired result in this case since no wheat was produced on this field.

9.2 LARGE AREA TESTS

Having obtained encouraging results from these preliminary tests, we proceeded to broaden the scope of the experiment by using the direct Landsat production prediction procedure to forecast the production of wheat for a large (21000 km^2) region in Central Kansas.

The area selected for this purpose consisted of 10 out of the 11 counties in the Kansas central crop reporting district, for which useable Landsat data were available. Landsat data covering this area on 16-18 April, 1976 was selected since it was acquired fairly early in the season and because of its relative freedom from clouds.

Training was accomplished by the following steps. The areas for which yield information for individual fields was available in the Central CRD included two 3x3 mile sites as described in Table 22. Acquisitions from these sites were used to develop the yield relation*.

TABLE 22. ACQUISITIONS WITH YIELD INFORMATION USED TO DEVELOP YIELD PREDICTIVE RELATION

Location	Date	No. of Wheat Fields
Rice	4/17/76	11
Saline	4/16/76	25

* For this initial test of direct large area wheat production forecasts we have used yield information to establish the Landsat/yield relation from the same growing season as the data being processed to forecast production. In an operational system, yield relationships will need to be established using historical data.

The relation was developed using a linear regression on SQ75 transformation of wheat field mean signal values with respect to yield. Only 0.1% of the data in the Central CRD was used for this training operation.

The next aspect of training was to determine the threshold on SQ75 values below which a pixel would not be counted in the production estimate, as described in the previous section. Since the sites used to develop the Landsat/yield relation had information for wheat fields, but not for non-wheat fields, they could not be used for threshold setting. We therefore used the four data sets listed in Table 23 for which wheat and non-wheat fields were identified. The amount of information used during this process was only 1.5% of the CRD. To determine

TABLE 23. DATA USED FOR THRESHOLD SETTING

Site	Landsat Acquisition Date
Ellis	17 April 1976
Ellis	18 April 1976
McPherson	16 April 1976
Rush	18 April 1976

the threshold, a histogram of wheat field SQ75 values, and a histogram of non-wheat field SQ75 values was produced. The counts in each bin of the wheat histogram were scaled by a factor such that the total of all counts in the wheat histogram divided by the total of all counts in both histograms equaled the historic percent of acreage planted to wheat in the district. Then a threshold was selected such that the error in production estimate associated with non-wheat counts that fell above the threshold equaled the negative error in production associated with wheat counts that fell below the threshold.

Having established the predictive relation and the threshold, we were then ready to execute the procedure to estimate production. In this initial test, 7.6% of the pixels in each county were processed, by using only the pixels in every 13th scan line. This was done (for reasons of economy) so as to include all six Landsat detectors in the sample. A preliminary test on two areas indicated that the sampling error, compared to using all pixels, was quite small. As a first step in executing the procedure, we applied a screening algorithm [17] to flag pixels that were affected by clouds, cloud shadows, or other problems, and to flag water pixels. These pixels were not included in the initial production tally. However, they were used to adjust the final production estimate in the following way. Water pixels were considered as acreage not available to wheat cultivation and therefore having no production. Cloud, cloud shadow, etc. pixels were assumed to have the same average wheat production as unflagged pixels and therefore did contribute to the wheat production estimate. An operational system could perhaps improve on this approach by using a knowledge of the acreage of lakes, reservoirs, and other known non-agricultural areas which may or may not be hidden by clouds.

The results of the large area production forecast were compared to final KCLRS production figures and are given on a county-by-county basis in Table 24.

The error of the CRD average estimate, 2.8%, is quite low especially compared to the variation of KCLRS estimates made throughout the wheat growing season after the 17 April Landsat overpass.

The above result indicates great potential for such a procedure. A question that remains, however, is how stable the approach is with regard to atmospheric, phenologic, locational, and other variables. In order to begin addressing some of these questions, we examined that portion of each of six counties that had Landsat coverage both on 16 April and 17 April. A histogram based on the 7.69% sampling rate

TABLE 24. RESULTS OF LARGE AREA PRODUCTION ESTIMATE OVER KANSAS CENTRAL CROP REPORTING DISTRICT

County	(10^6 bushels) Landsat Production Estimate	(10^6 bushels) KCLRS Final Production
Ellis	3.72	4.02
Rush	3.74	5.42
Russell	3.35	4.83
Barton	7.52	6.57
Lincoln	3.52	5.34
Ellsworth	4.52	3.95
Rice	7.60	6.48
Saline	4.42	4.62
McPherson	7.45	7.05
Dickenson	6.52	5.51
Total	52.4	53.8
% Difference	2.6%	
RMS Error (over counties)	0.35×10^6 bushels	
Correlation	0.80 (significant at 0.01 level)	

was obtained for the SQ75 green measure in each of the Landsat acquisitions and each of the six areas. By plotting the SQ75 level of corresponding percentiles, the distributions were compared. For example, the Rice County histograms had 16 April and 17 April 20th percentile values of 0.805 and 0.780 for SQ75, respectively, a difference of 0.025 in the full SQ75 range of about 0.7 to 1.7. Figure 25 gives the results of plotting the corresponding SQ75 levels, for each of the six areas. On examining this plot, it appears that in some cases there were substantial differences in SQ75 level between acquisitions, sufficient to potentially cause large errors in production estimation. A number of factors seem to have caused these differences, particularly view angle

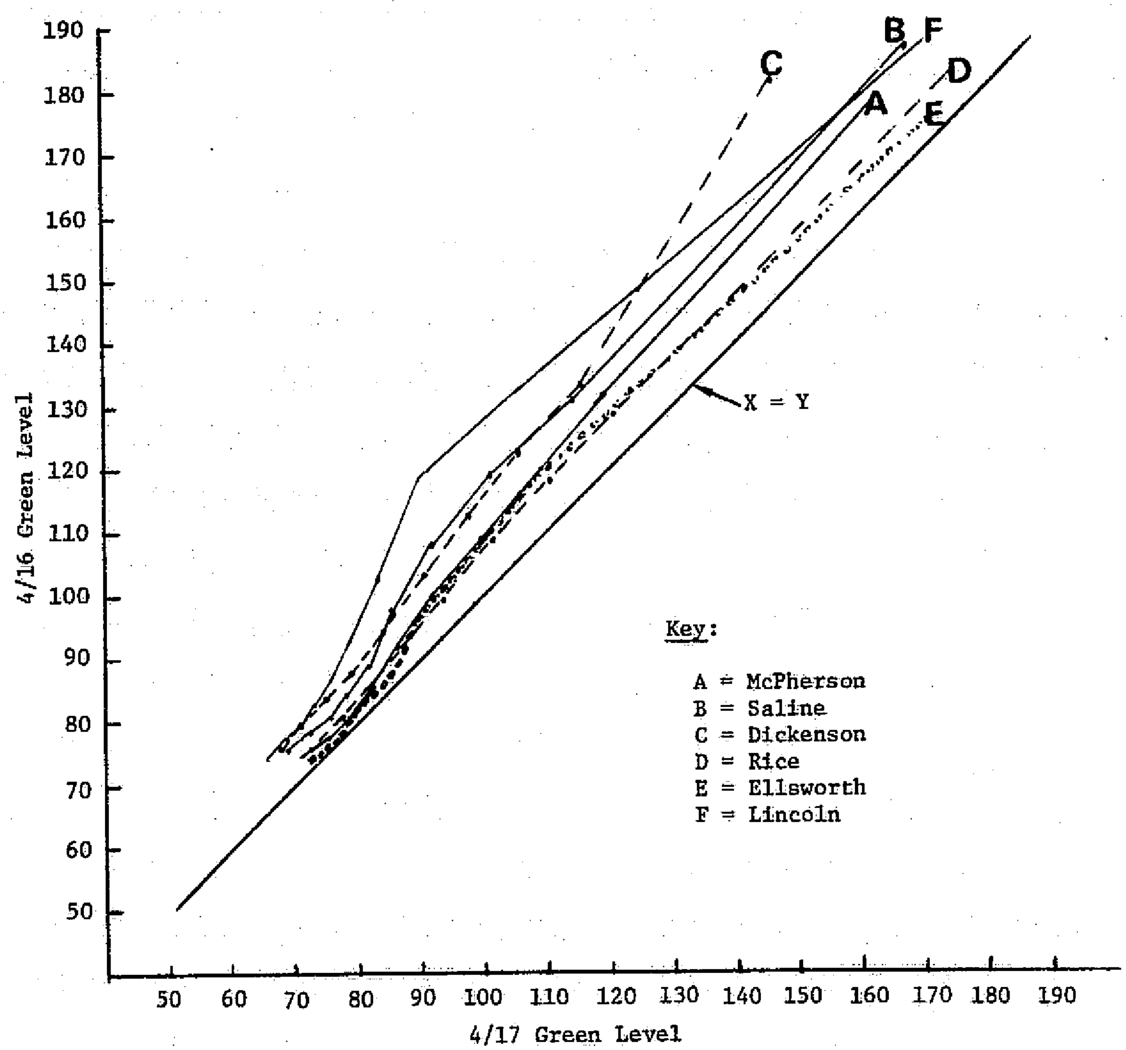

FIGURE 25. 4/16 GREEN LEVEL VS 4/17 GREEN LEVEL OF VARIOUS PERCENTILES

effects (from the west side of one frame to the east side of another) and differing atmospheric conditions. In fact, the three areas showing the greatest between-acquisition differences were those with the greatest number of cloud pixels flagged, suggesting that the effects of clouds and associated atmospheric effects were not completely removed. Improved procedures to handle such problems need to be developed.

Nevertheless, for the initial experiment, a simple direct production approach, featuring a uniform sampling over a large (21000 km^2) region, was carried out and found to offer good potential for providing useful early season winter wheat production information. However, as with alternative satellite-based approaches, some questions still remain as to the repeatability and stability of the procedure over space and time. Particularly noteworthy with this approach are the following: 1) simplicity and economy; 2) avoidance of sampling errors which may arise in systems that depend on identifying fixed location sample segments which sometimes do not receive adequate coverage; and 3) ability to handle mixture or boundary pixels (which are especially prevalent in areas of small fields) in a way not requiring tenuous recognition decisions in borderline cases.

10
CONCLUSIONS

Based on the results of this investigation we draw the following conclusions.

1. There is a considerable amount of yield-related information present in Landsat data.
2. Landsat data can be used to estimate certain variables which are required in existing yield models (such as LAI or percent cover).
3. Landsat indicators of yield are as highly correlated with individual field yield as are estimates using traditional field sampling methods, even when using Landsat data collected several weeks before the field samples.
4. A considerable amount of the variation in individual field yield which is not explainable by meteorological data can be accounted for by Landsat data.
5. In order for Landsat data to be of maximal use in an operational system, improvements in the ability to remove the external effects (particularly atmospheric effects) are required.
6. It may be possible in certain situations to make direct wheat production forecasts using early-season Landsat data.

11

RECOMMENDATIONS

In order to take full advantage and make optimum use of Landsat data for winter wheat production forecasts, the following recommendations should be implemented.

1. Continue to investigate validity of fundamental hypotheses and reasons for departures therefrom.
2. Continue to investigate large area/large sample considerations with emphasis on analyzing randomness of errors, training and testing procedures, and data handling.
3. Continue to investigate ways to calibrate or stratify data for optimal use of Landsat wheat-yield relations. As part of the above we include:
   a. investigate better haze correctors
   b. investigate better phenology indicators
   c. consider the use of Landsat data for indicating only _relative_ yield on a local basis, to be calibrated by other procedures (field sampling, etc.).
4. Further investigate hybrid yield models that incorporate Landsat, meteorological, and cultural factors as perturbations from normal.
5. Continue to investigate direct wheat production approach to determine the generality of its usefulness.

APPENDIX I

TECHNIQUES FOR DETERMINING VEGETATION CONDITION

In the initial phases of this investigation, a considerable amount of effort was devoted to developing a cost-effective way to determine vegetation condition in the field. In this appendix, we first discuss sampling procedures, and then discuss some of the measurement techniques which were investigated. Advantages and disadvantages of the various techniques (such as relative accuracy and efficiency) will be discussed.

I.1 SELECTION OF FIELDS AND SAMPLING STRATEGY

We initially selected fields on the ground which appeared to be indicative of the range of conditions found on the test site. It was apparent from ground observations and previous year's aerial photography that some of the fields were extremely heterogeneous, and therefore, could not be adequately characterized by a small number of random samples. In order to assess the heterogeneity of the fields, the study site was flown over in a light plane and aerial oblique photos of the fields were obtained. These photos enabled a refinement of our original choice of fields, and also enabled us to stratify each field on the basis of general field condition. This stratification reduced the variance of the field condition within strata so that fewer samples within homogeneous strata might be used to assess overall average field condition.

In practice, we made two or more measurements (samples) per homogeneous stratum per field. This procedure resulted in a variable number of samples per field, depending on the heterogeneity of the field condition. The number of ERIM samples was chosen so as to compromise between the desire for precise characterization of field condition and the real-world constraint of limited time, man-power, and funds.

I.2 LEAF AREA INDEX MEASUREMENTS

Some of the fundamental hypotheses of this investigation were based on leaf area index (LAI). This section examines a variety of technques which were used in measuring leaf area. The vegetation samples came from complete harvest of a 30 cm length of a row of wheat. Leaf area was converted to LAI by knowing the length of the row sampled and by measuring the row width.

I.2.1 ELECTRO-OPTICAL LEAF AREA METER

The electro-optical leaf area meter was specifically designed for measuring leaf area. The accuracy of the electro-optical leaf area meter was determined by cutting up a 100 cm^2 piece of paper into a number of pieces and putting all of the pieces through the meter for 10 separate trials. The resulting values obtained from the leaf area meter for the ten trials are presented in Table I.1. It can be seen that the standard deviation is quite small. We also ran some leaf samples through the meter several times and got good repeatability of results. These factors suggest to us that the leaf area meter is quite accurate, and that it gives repeatable results. Therefore, other techniques will be compared against it, or calibrated by it.

Some problems did arise in trying to use the leaf area meter. Perhaps the most severe of these problems was curling of the wheat leaves, and the inability to keep them flat after they were placed in plastic envelopes which were subsequently passed through the leaf area meter.

One attempt to alleviate this problem involved the development of a vacuum technique. A box with perforations on the top was connected to an ordinary vacuum cleaner. The plastic envelope in which the leaves were mounted was perforated on one side with many small holes and placed holes-down on the vacuum box. It was hoped that the resultant suction would hold the leaves flat once they were flattened-out on the plastic envelope. The procedure turned out to be only partially successful and was rather time-consuming. It was abandoned.

Another approach that was tried was soaking the leaves in hot water. This proved to be much more successful. The water retarded curling of the leaves. In addition, when the wet leaves were placed in the plastic

TABLE I.1. LEAF AREA METER READING FOR 10 TRIALS OF PIECES OF PAPER TOTALING 100 cm^2.

TRIAL NUMBER	METER READING
1	100.19
2	101.64
3	101.08
4	99.96
5	100.18
6	99.74
7	100.04
8	99.82
9	100.61
10	99.93
	$\overline{x}$ = 100.32
	σ = .61

sleeve, the surface tension helped to hold them flat. The small amount of water that was included in the plastic envelope had no apparent effect on the performance of the leaf area meter. Eventually, this wetting procedure became standard.

I.2.2 MEASUREMENTS USING MILLIMETER RULE

An approach to measuring the leaf area with a millimeter rule was investigated. The leaf length was measured and an "average" width was estimated. The product of these two numbers was considered to be an approximation to the leaf area.

Leaf area was also calculated from an equation of Teare and Peterson [32], namely:

leaf area (cm^2) = 0.813x - .64

where x is the product of the length times the breadth (maximum width) of the leaf.

The two approaches described above were performed on the same five leaves. The leaf area of the five leaves was then measured using the electro-optical leaf area meter, which had previously been shown to be quite accurate. The results of these three approaches are shown in Table I.2.

TABLE I.2. COMPARISON OF THREE TECHNIQUES FOR MEASURING LEAF AREA

	Technique		
	Length x estimated average width	Teare and Peterson	Leaf Area Meter
Leaf Area (cm^2) for same 5 leaves	52.97	52.96	58.73

Good agreement was obtained between the first two approaches. However, the leaf area meter measurement is almost certainly more correct. Measurements using the first two techniques differ from the leaf area meter measurement by about 10%. Perhaps 10% error is acceptable accuracy. However, the first approach depends on a subjective estimation of average leaf width, so the accuracy will vary with the performance of the individual making the estimates. The Teare and Peterson approach depends on a consistent leaf shape. It is not known how good an assumption that is, but young leaves almost certainly differ somewhat in shape from older leaves.

I.2.3 PHOTOGRAPHING HARVESTED WHEAT SAMPLES

Since the electro-optical leaf area meter is expensive and may not always be available, another optical approach to determining leaf area was investigated. In this approach the leaves (or other components) were stripped from the sampled stalks, and placed upon a white board. The leaves were held flat and in place by a sheet of clear plastic. The board was then photographed at a standard distance with 35 mm high contrast copy film.

The transmittance of a leaf on the negative transparency [τ(leaf)] and the transmittance of the white board [τ(board)] are measured. The frame area, a (frame), is a known constant value, and is equal to the leaf area, a (leaf), plus the area of the board not covered by leaves, a (board).

A densitometer is then used to measure the average transmittance of the entire negative frame, τ(frame). The leaf area for this particular sample can then be determined from the relationship.

$$\frac{a(\text{leaf})}{a(\text{frame})} = \frac{\tau(\text{frame}) - \tau(\text{board})}{\tau(\text{leaf}) - \tau(\text{board})}$$

For properly exposed high contrast film τ(leaf $\approx$1.0 and τ(board) $\approx$0. Therefore,

$$a(\text{leaf}) \approx a(\text{frame}) \cdot \tau(\text{frame}).$$

In practice, this photographic procedure for determing leaf area was not particularly successful. It took considerable time to mount the leaves (or other components) on the board, to photograph the board and to subsequently measure the necessary transmittance values. In addition, we had considerable difficulty with specular reflection from the plastic covering the samples. As a result of the above difficulties we quickly abandoned this procedure, and do not recommend its use.

I.2.4 DETERMINATION OF VEGETATION AREA FROM DRY WEIGHT

An additional technique for estimating vegetation area involved the use of relationships between weight and vegetation area. In this approach, the vegetation samples were separated into components, dried in an oven at 70°C for 24 hours, and subsequently weighed. On theoretical and empirical grounds we would expect a correlation between oven dry weight and some of the properties of the wheat canopy we are interested in. Once such relationships are established for a particular kind of vegetation the dry weight (which is easily and quickly measured) can then be related to vegetation condition. For this reason, we investigated this approach.

The relationship between dry weight and vegetation area depends on the type of vegetation component. For example, there is a different relationship between dry weight and area for leaves and for stems. This is due mainly to the much greater amount of structural material in stems than in leaves. In addition, the relationship may vary with time and type of leaf (thick or thin).

Initially, the relationship between dry weight and green leaf area was investigated. Ten samples from two different dates for which the green leaf area was measured were compared with their corresponding dry weight in a linear regression. This was done after converting dry weight to biomass (g/m^2) and leaf area to L.A.I. (m^2/m^2). The results are presented in Figure I.1. This relationship is significant at the .01% confidence level. The relationship has an R^2 value of .96 and a standard error of 0.48.

One might expect that the relationship between dry weight and leaf area would be the same for both live and dead leaves. However, this was found not to be the case. As the leaves died on the stalk they shriveled and curled to varying degrees. It was virtually impossible to uncurl some of the dead leaves, and if we had succeeded in doing so it would have created an artificial impression of the projected dead leaf area that could be seen in the canopy. Therefore, we did not attempt to uncurl the leaves before measuring their (projected) area with the leaf area meter. This led to a different relationship between "leaf area" and dry weight for live leaves and for dead leaves. The

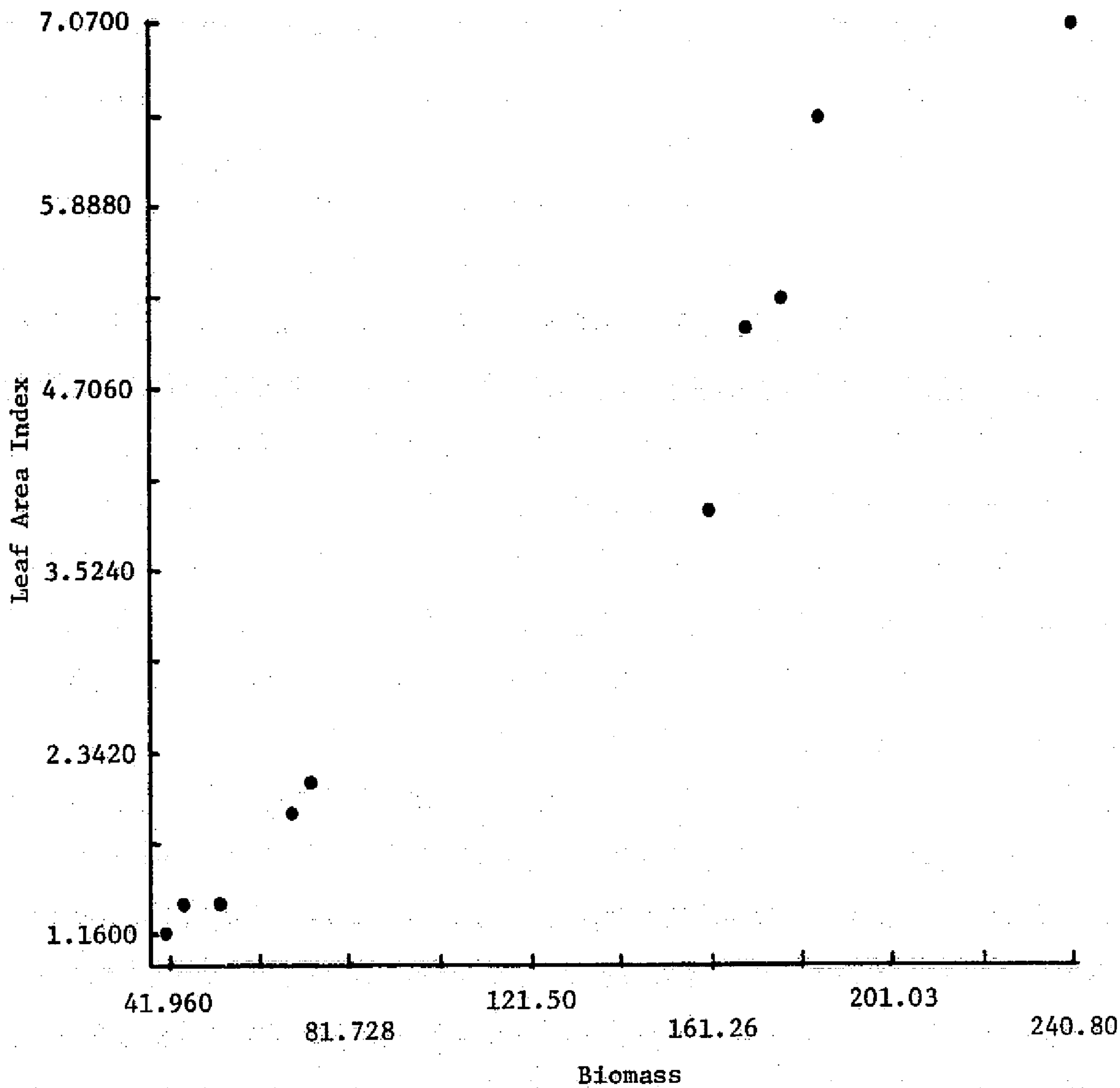

FIGURE I.1. RELATIONSHIP BETWEEN LAI AND BIOMASS variable amount of shriveling and curling of the leaf samples for which the leaf area/dry weight relationship was determined also produced a less predictable relationship. In addition, some photosynthate is metabolized or transported elsewhere during senescense, and it cannot be replaced by the unfunctional photosynthetic apparatus of the dying leaf. Therefore, the dry weight of the leaf will decrease compared to a green leaf.

The relationship between stem (cross-sectional) area and dry weight might be expected to be the same for live and dead stalks because of the structural stability of the stalks. However, some photosynthate is metabolized and/or transported to other parts of the canopy (particularly the developing head) during senescence. Therefore, we determined separate area/weight relationships for live and dead stalks.

We also determined a relationship between wheat head area and dry weight. This relationship is quite variable because the weight of an individual head depends to a considerable extent on the amount of photosynthate which has been transported into it.

Because of the variable geometry of a wheat head, the projected area is not necessarily a good indicator of the total surface area. The rectangular cross-sectional shapes of the heads vary from having one dimension considerably greater than another to being essentially square in cross-section. An alternative procedure for determining the area is to measure the two "widths" and the height of the head. However, it is impossible to account for the "holes" between spikelets, the awns, and other complications. Because of the difficulty in determining a consistent relationship between head weight and area, it is fortunate that the head is generally a small fraction of the area of the wheat canopy. However, this small area is important in that while it is green it is responsible for a substantial amount of the photosynthate which goes into grain production.

I.3 PERCENT COVER MEASUREMENTS

Most of the techniques for measuring L.A.I. are very time-consuming and tedious. The techniques we investigated were also destructive. This section examines a non-destructive technique for providing another measure of vegetation density (percent cover), and describes ways LAI may be derived from such data.

I.3.1 THE MIRROR TECHNIQUE

A "non-destructive" measurement (estimate) of percent vegetation cover was obtained by ground photographs of the wheat in situ. In this approach it is important that all parts be resolved, and that the angular field-of-view of the image is minimized. It is also important, however, that a significantly large area of the wheat canopy is imaged, thereby incorporating (and averaging out) some of the inherent variability. The way we tried to accomplish this was by photographing an image of the field reflected off a large (3 ft by 3 ft) hand-held mirror. The estimates of percent vertical vegetation cover were obtained from 35 mm color pictures of the image in a mirror held at a 45° angle to the wheat canopy (datum). The pictures of the mirror were obtained using a telephoto attachment (200 mm) from a camera station far enough away to image the entire mirror, and with the camera pointing horizontally at the center of the mirror. The geometry of this relation is indicated in Figure I.2. A collimated flash attachment was used in order to fill in any shadows in the canopy. Because the solar illumination fell principally on the top parts of the wheat canopy, these parts were frequently overexposed. Accordingly, we attempted to shade the wheat in the field-of-view from direct sunlight by means of a large piece of cardboard, thereby making the collimated flash the principal source of illumination of the canopy.

High resolution (low ASA) ground photographs were initially obtained. However, wind conditions cause considerable image motion in the vegetation canopy at the fastest useable shutter speeds. We then resorted to

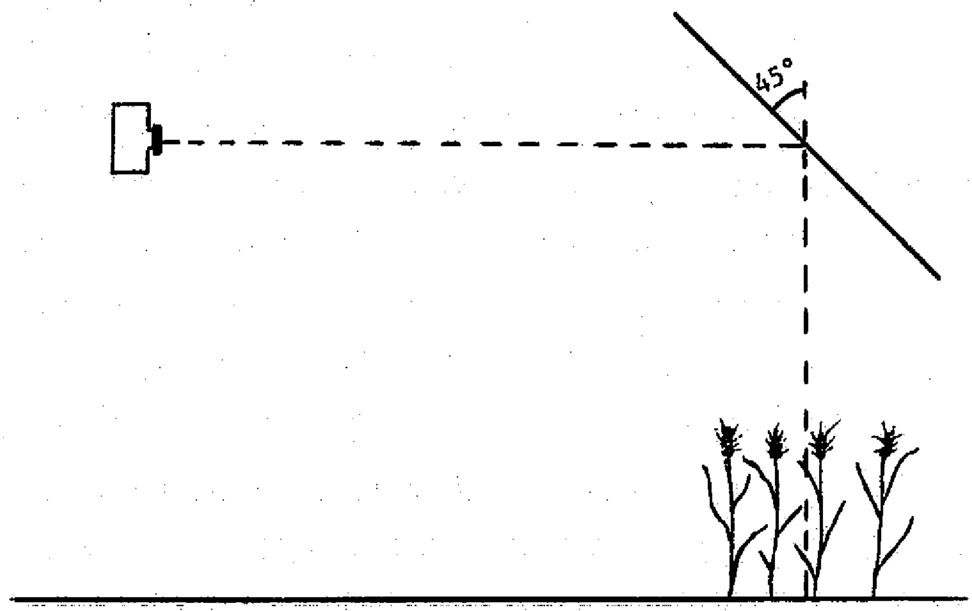

FIGURE I.2. GEOMETRY OF MIRROR PHOTOGRAPHIC TECHNIQUE FOR DETERMINING PERCENT VEGETATION COVER film with a higher ASA so that we could photograph the scene at faster shutter speeds, thereby reducing image motion.

In homogeneous areas of a field, a sample location was generally established by proceeding 15 meters into the field from an arbitrarily chosen point at the edge of the field. An additional sample within the homogeneous area was generally obtained by proceeding an additional 10 meters into the field and then 15 meters parallel to the edge of the field.

An attempt was made to return to the same sample site for harvesting vegetation samples on subsequent dates. However, this was not always possible. Certain sections of certain fields were sometimes inaccessible because of rains. When these conditions prevailed "equivalent" sites in another part of the field were selected for sampling by analysis of the aerial oblique photographs.

The field photographs were subsequently processed and projected onto a large screen on which a transparent grid overlay was taped. The proportion of the canopy representing various components of that canopy was determined by counting the relative number of grid intersections occupied by each of the following components:

1. green leaves
2. green stalks
3. green heads
4. green weeds
5. senescent leaves
6. senescent stalks
7. senescent heads.

The above categories were aggregated into various combinations. The most commonly discussed combination is green wheat cover, which is composed of Items I-3.

The data from the individual photographs was used to produce estimates of vegetation condition for the entire field. The proportion of the field occupied by each stratum was determined from the aerial photos. Then the individual stratum average values were multiplied by the corresponding stratum proportion and aggregated to produce a single value characteristic of the field. In this report percent cover measurements will refer to measurements of percent green wheat cover, unless otherwise stated.

I.3.2 DERIVATION OF OTHER PARAMETERS FROM MIRROR DATA

The mirror/photographic procedure was found to be the most cost-effective technique to measure vegetation density. Modifications of the photographic technique make it theoretically possible to estimate leaf area index from photographic data. That procedure is discussed here.

In order to implement this procedure it is necessary to take simulated vertical photos and oblique photos of the wheat canopy. In practice, this was done by taking telephoto pictures of the image of the mirror tilted at a 45° angle and a 22.5° angle with the vertical, thereby simulating vertical and 45° oblique photos of the canopy. The oblique photos were taken looking both across and down the row direction.

The percent projected cover can be calculated by projection of the images and counting the grid intersections covered. The relationship between these estimates of percent cover and randomly distributed horizontal and vertical projected component areas (H and V) is:

$$\text{percent cover (vertical)} = (1-e^{-H}) \times 100$$

$$\text{percent cover (45° coverage)} = 1 - e^{-(H - \frac{2}{\pi}V\tan 45°)}$$

H and V can then be determined by solution of these two equations. [32]

It is possible to estimate leaf area index from the photographic data by extension of the above procedures. However, a large number of assumptions of canopy conditions must be made in order to obtain such estimates. In all but the very simplest vegetation canopies, these assumptions are probably only fair approximations to reality. In view of the fact that this procedure is both tedious and tenuous, it is not recommended. However, estimates of leaf area index are useful, and some non-destructive means of obtaining such estimates would be desirable. The next section examines a crude, but possibly effective, way of making such estimates.

I.3.3 PERCENT COVER/LAI RELATIONS

A relationship between percent green cover and green LAI was determined empirically using data collected by ERIM during the 1975 field program (see Figure I.3). The data was collected at four points in time between May 14 and June 9 (before heading through almost complete senescence). The LAI data were either actual measurements of LAI using the optical leaf area meter or inferred LAI using a relationship between oven dry weight and leaf area. Very few data points were available for canopies with greater than 70% green vegetative cover. Due to the expected extreme non-linearity of the relationship between percent cover and LAI at high values of percent cover, we chose to generate a relationship which was valid over the range from 0% cover to 70% cover. Most wheat fields will generally fall in this range. The desired relationship was approximated by the least-square fit of a quadratic function of the form

$$LAI = aX + bX^2$$

where X represents the field measured values of percent green wheat cover.

The least-squares regression was forced to go through the origin (zero intercept) so that biologically impossible results (e.g., prediction of negative values of LAI) could not occur. The resulting

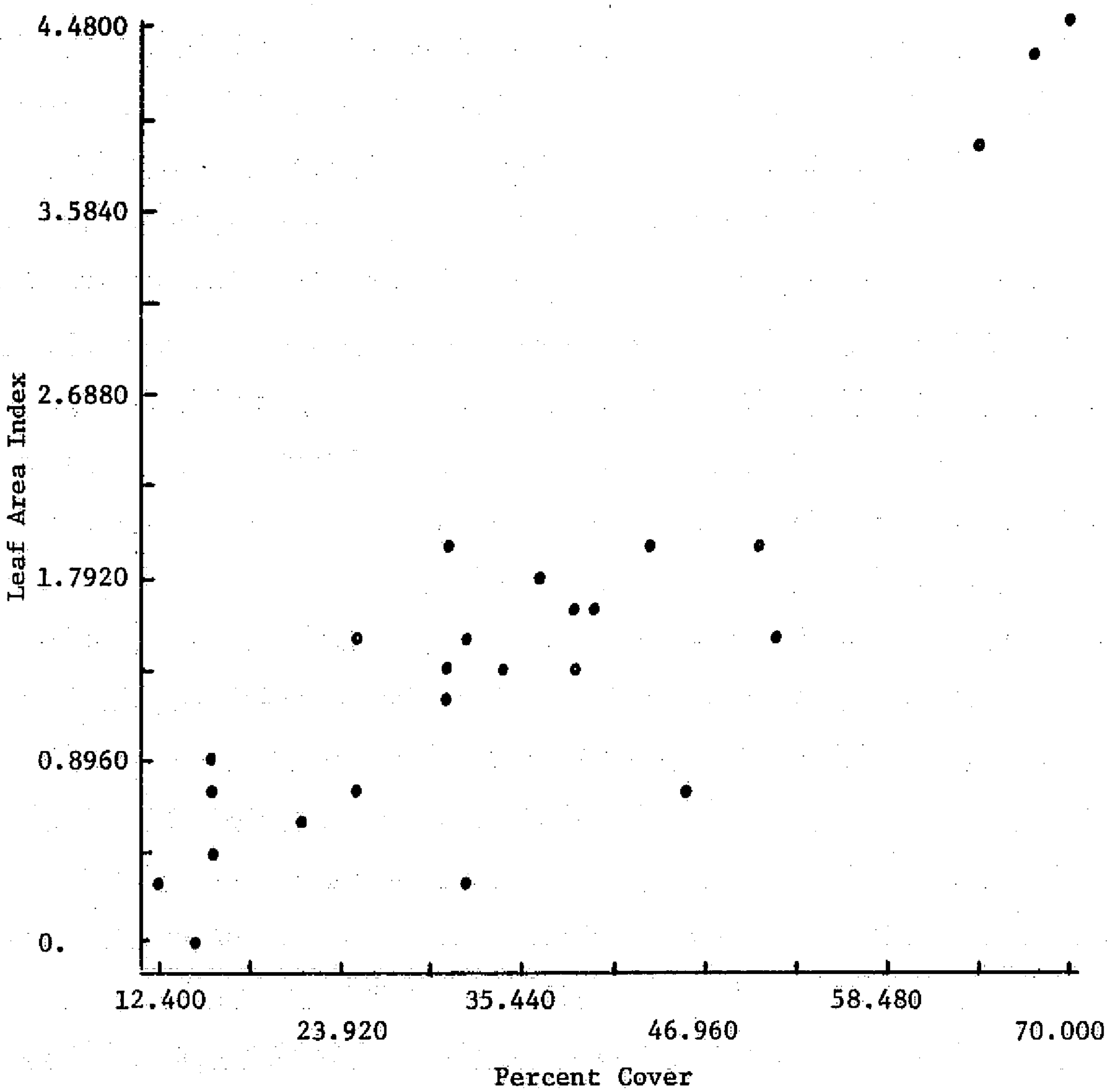

FIGURE I.3. RELATIONSHIP BETWEEN LAI AND PERCENT COVER regression equation for 25 cases was

$$\text{Green LAI} = .0162X + .00062X^2$$

The coefficient of determination (R^2) was 0.82, which is reasonably good considering the data includes several wheat varieties grown under different conditions and covering the period of time from pre-heading to partial senescence. The standard error of the estimate using the above regression relation was 0.50

It should be noted that this algorithm is valid only for percent green leaf cover and LAI data generated in the same way it was for this investigation. Other procedures for measuring percent green leaf cover and LAI, or relations between total plant cover and total plant area index, will require different algorithms.

I.4 INTERPRETATION OF DATA

The various measuring techniques or ways of implementing them produced different kinds of measurements with different accuracy and different biophysical significance. The significance of the measurements is discussed in this section.

Biological leaf area index, percent vegetation cover, and projected leaf area index all have important information and meaning of their own. Biological leaf area index gives the one-sided photosynthetic area per unit area of ground. However, it gives no information about the distribution or orientation of this photosynthetic area within the canopy. In addition, leaf sheaths, leaf stalks, and heads are all important photosynthetic organs which are not normally included in biological leaf area index.

Percent vegetation cover describes the projected area of vegetation which is viewed from the normal (vertical) view angle. In some respects this parameter may give a better indication of the amount of vegetation which is actually photosynthesizing, because it does not include area that is covered by other vegetation when viewed or illuminated from a

0° zenith angle. However, the sun is rarely, if ever, at the zenith (0°), so percent vegetation cover is not a perfect indicator of the photosynthetic area illuminated. Percent vegetation cover also indicates how much vegetation is viewed looking straight down, which is an important factor determining the spectral reflectance, and hence the remote sensing spectral signature. However, the orientation and distribution of the components is also important in that they determine the irradiance on the components and radiance off them, and also the amount of the vegetation canopy that is in shadow. Vegetation density may also be important, especially for reflectance in the near IR bands.

Horizontal and vertical projected vegetation area indices (H and V) are abstractions, but are potentially very useful. They give the structure (orientation) and density of the vegetation components. Both percent vegetation cover and biological leaf area index can be estimated from the projected area indices. The irradiance on and the radiance from the components can be calculated. The amount of vegetation illuminated and seen, and the reflectance of the vegetation canopy for any solar zenith angle and viewing angle, can be approximated. Because of the way the data can be manipulated to get a variety of kinds of information, the horizontal and vertical projected area indices may be the single most complete form in which the vegetation canopy can be described. However, it may be very difficult to obtain such data.

I.5 ADVANTAGE OF IN SITU PHOTOGRAPHIC TECHNIQUE

There are several advantages to the in situ photographic determination of vegetation condition. Perhaps the greatest single advantage is that a reasonably large area (e.g., 1 m^2) can be sampled quickly and non-destructively in the field. A sample unit size this large is probably important, especially in flood irrigated wheat where there are large fluctuations in field condition between rows. In addition, each sample (picture) is easily stored and transported back to the laboratory for analysis at a convenient time without altering its characteristics in any way. Furthermore, the data can be reduced in a variety of ways at various points in time during the investigation. It is also much easier to re-examine "anomalies" that may be discovered during data analysis if a photographic record is available than it would be if the only record were a number written in a field notebook.

There are some limitations to the photographic approach. For example, the photographic record one obtains may not be an accurate indication of the way the crop "looks" most of the time or the way it looked when remote sensing data was obtained. This could occur, for example, if the pictures were taken on an anomalously windy, or wind-free day or moment. However, other ways of characterizing vegetation density suffer from similar limitations.

In addition, it may be difficult to accurately determine the particular type of canopy component one is looking at on the photographic record, particularly in overexposed or underexposed portions of the photograph. Confusing green leaves with dead leaves or vice versa could lead to serious errors in interpretation. Such a problem might be alleviated by using color IR film in conjunction with color film, but such a procedure was not tried.

Despite some difficulties and limitations, the photographic estimation of percent cover (and perhaps other parameters such as LAI) is considered the single most cost-effective means of characterizing field condition. In addition, it is also non-destructive. Therefore, this procedure is the one that is recommended for characterizing vegetation density under most circumstances.

APPENDIX II
RADIOMETRIC MEASUREMENTS

In addition to our measurements of the density and structure of the vegetation components of various wheat fields, we also made measurements of the radiometric properties of the canopy components. This was done by placing samples of canopy components in sealed plastic bags, transporting them back to ERIM, and measuring their radiometric properties using a Beckman DK-2(a) spectrophotometer. Hemispherical reflectance and transmittance measurements (500-1100 nm) were made on: (1) live leaves, (2) dead leaves, (3) live (green) stalks, (4) dead stalks, (5) live (green) heads, and (6) dead heads.

In addition, surface soil samples were also collected, put into sealed plastic bags and transported back to ERIM. These soil samples included both dry and moist (recently irrigated) conditions. The reflectance of the samples (500-1100 nm) was measured using a Cary 14 spectrophotometer.

The value of the above measurements is that using them it is possible to simulate the sequential bidirectional spectral reflectance of any and all fields (if the radiometric properties of the types of components, e.g., green leaves and soil, are assumed to be constant). The simulation is possible by using a model for computing the vegetation canopy spectral reflectance which was developed by Dr. G. Suits of ERIM [32].

There are several advantages of this approach as opposed to making in situ measurements of spectral reflectance of entire vegetation canopies. One advantage is that simulation does not depend on good environmental conditions (e.g., clear skies). Another advantage is that reflectance of various vegetation canopies can be simulated under identical environmental conditions (including solar zenith angle), which is virtually impossible to achieve with empirical <u>in situ</u> spectral reflectance measurements. Perhaps the greatest advantage of modeling is that it furnishes the basis for understanding the causes of the reflectance of particular canopies under particular conditions. An analysis of some simulated reflectance data is presented in Appendix III.

APPENDIX III

GREEN MEASURE TRANSFORMS

A variety of transformations of remote sensing data which contain much of the information on the amount of (green) vegetation present have been developed (e.g., see [14]). These transformations are useful in their own right as diagnostic tools, indicative of a particular parameter, but they do not create "new" information. No transformation will create information that is not present in the raw data, and in fact some information is removed by data transformations of the kind we are discussing here. It is probable that one of the main values of green measure transforms is that many of them minimize signal variations ("noise") unrelated to the amount of green vegetation, such as soil albedo, and perhaps illumination and atmospheric conditions [10,13].

Without pretending to present an exhaustive analysis, we will now briefly examine some of the reasons green measure transforms "work", and their relative utility.

It is known that if soil reflectance varies appreciably, it can interfere with unambiguous assessment of vegetation density. Therefore, we initially analyzed how much soil reflectance varied in the study area prior to examining ways to reduce possible effects of soil reflectance variations. The fact the soil reflectance does vary considerably in the study area is indicated by ground-based measurements of soil reflectance made by Texas A&M field personnel on the Finney A site using an Exotech ERTS radiometer (see Table III.1).

One way that has been suggested to alleviate this problem [10] is to form a ratio of an infrared and a red channel, which in many situations tends to reduce variations due to varying soil reflectance. The ratio also retains much of the information regarding the vegetative development

TABLE III.1. AVERAGES OF BROAD-BAND GROUND SPECTRAL REFLECTANCE MEASUREMENTS MADE BY THE LACIE FIELD MEASUREMENTS TEAM USING AN EXOTECH ERTS RADIOMETER (From [27])

Soil Reflectance	Value In Landsat Band: 4	5	6	7
Mean, m	0.130	0.157	0.216	0.263
Standard Deviation, σ	0.060	0.049	0.057	0.068
Coefficient of Variation, (σ/m)	0.46	0.31	0.27	0.26

(percent cover, LAI) of the wheat canopy, and may even help to normalize data with respect to such factors as variations in solar irradiance, ground slope, and the like.

In order to determine whether an infrared/red ratio would be effective on Kansas soils, we collected samples and made spectral reflectance measurements of a variety of soils from both the old (1975) and new (1976) Finney Intensive Test Sites. The results for the 1976 data (Table III.2 and Fig. III.1) suggest that ratio processing can be effective in normalizing variations in soil reflectance for soil conditions found in Finney County, Kansas. The reflectance ratio of wavelengths 0.75 μm/0.65 μm (approximately equated to Landsat Band 6/Band 5) seems to be the best in this respect. However our analyses suggest that Landsat Band 7 is better than Band 6 as an indicator of vegetative development and potential yield (see Section 4), presumably due to the greater contrast between vegetation and soil in Band 7. Therefore, a Band 7/Band 5 ratio may be more useful for simultaneously reducing significant soil reflectance variation and maintaining information on differences in vegetative development.

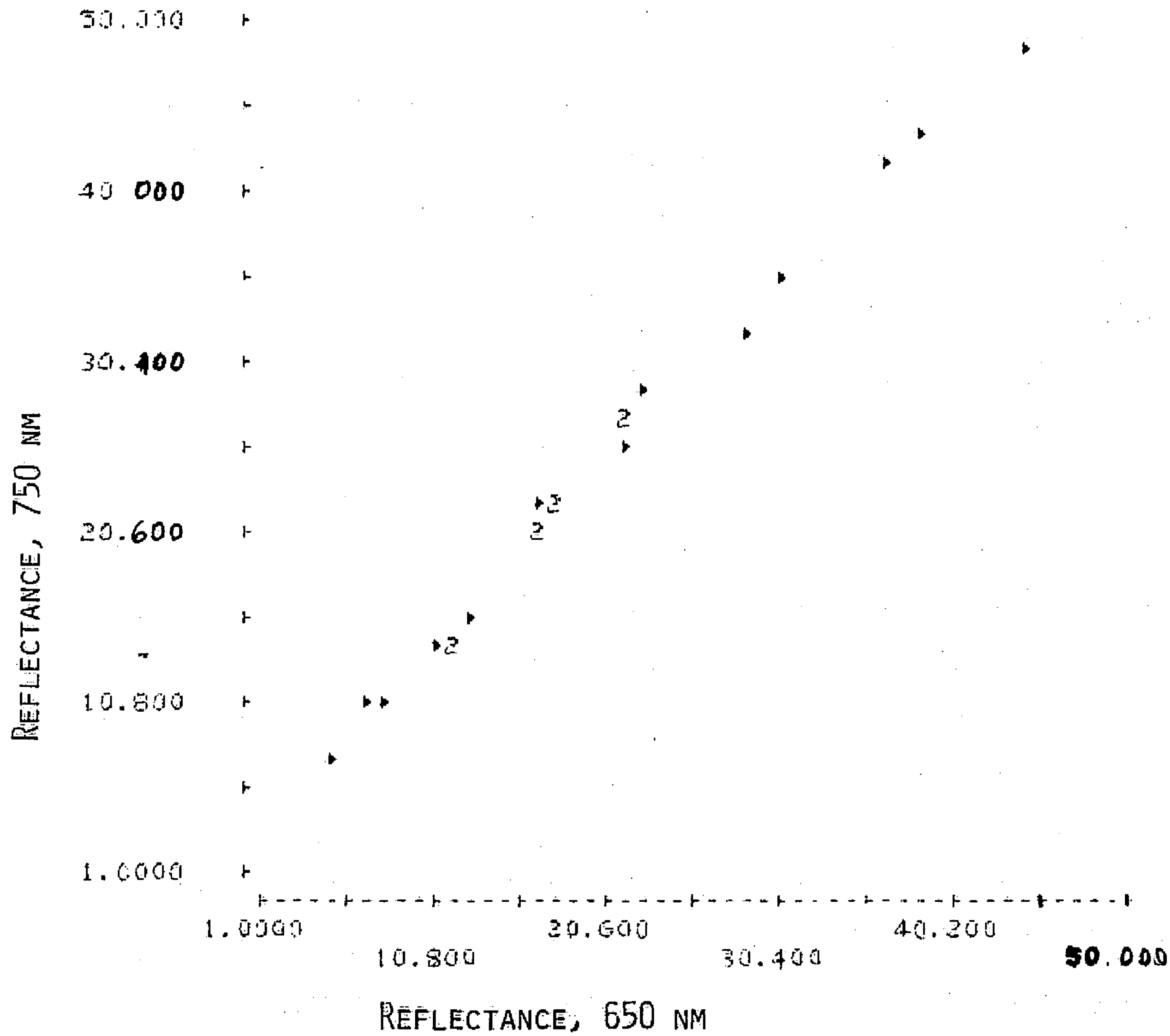

FIGURE III.1. SCATTER PLOT OF 21 SAMPLES OF REFLECTANCE (%) FROM FINNEY SOILS AT 750 nm AND 650 nm (FROM ERIM FIELD MEASUREMENTS)

TABLE III.2. AVERAGE SOIL SPECTRAL REFLECTANCES AND REFLECTANCE RATIO (m), AND CORRESPONDING COEFFICIENTS OF VARIATION (σ/m), FOR 19 SOIL SAMPLES TAKEN FROM THE NEW FINNEY SITE

Wavelength (nm)									
650		750		900		750/650		900/650	
m	σ/m	m	σ/m	m	σ/m	m	σ/m	m	σ/m
20.75	0.53	24.81	0.49	29.18	0.41	1.24	0.09	1.53	0.16

May 6 Landsat data for the 1976 Finney site on three wheat fields that were plowed up prior to harvest shows a substantial variation in soil reflectance. The effect of several green measure transforms on the Landsat data for the three fields is shown in Table III.3. Note that the transformed data exhibits much less variability than the untransformed individual bands.

TABLE III.3. LANDSAT DIGITAL COUNT AVERAGE VALUES FOR INDIVIDUAL BANDS AND FOR THREE TRANSFORMS ON THREE PLOWED FIELDS (6 May 1976)

	Landsat Bands				Transforms		
Field	4	5	6	7	6/5	7/5	TVI
A	46.5	66.5	73.5	32.4	1.11	0.49	0.50
B	32.2	43.2	49.2	21.8	1.14	0.50	0.48
C	47.1	69.0	76.7	33.9	1.11	0.49	0.49

It is more difficult at the moment to indicate empirically what the usefulness of the soil normalizing transforms is in a vegetation canopy using actual Landsat data because insufficient ground data is available. The usefulness of the transforms in a vegetation canopy with variable reflectance can be investigated, however, using a vegetation canopy reflectance model. Malila, et al [27], calculated the canopy reflectance under a variety of conditions using structural and radiometric data collected on the 1975-76 Finney site as part of this project. The reflectance measurements were converted to simulated Landsat radiance values, and some of the results are shown in Table III.4. Note that the variation in individual band simulated Landsat radiances is large for low vegetation cover canopies, but decreases as the vegetation cover increases. The ratio values are nearly constant for a given value of vegetation cover. On the other hand, there is some variability due to soil albedo in a simple difference between two bands (7-5).

Another transformation of the Landsat data which was tested for its yield/vegetative development prediction capabilities is computed as part of the EXTEC3 algorithm. EXTEC3 generates two hybrid axes (directions in Landsat signal space), including one that is nominally in the direction of green development, and another in the direction of variation in soil-brightness. The soil-brightness channel is approximately orthogonal to the "green development" channel. If the green-development channel adequately defines the extent of vegetative development, it should provide a valuable indication of potential yield. Furthermore, it is a direction that in theory can be uniquely and consistently defined for all Landsat data sets.

Initial testing of the information content in the green development channel suggests that the single direction may not be completely satisfactory for quantifying degree of vegetative development or yield.* In fact, there seems to be a considerable amount of yield predicting information in the soil-brightness channel, which is a measure of overall scene brightness. This situation may be due to an increase of shadowing within the canopy as the amount of green vegetation increases, which tends to decrease the overall scene brightness. In addition, there is possibly a correlation between soil reflectance and vegetative development and yield. In non-irrigated areas, the brighter soils may be the

* These findings are similar to those reported by Lambeck [17] and Malila [28], who proposed using a ratio of tasselled cap green to tasselled cap brightness.

TABLE III.4. MODELED VALUES OF LANDSAT RADIANCE AND RADIANCE RATIOS FOR CANOPIES WITH LOW TO INTERMEDIATE VEGETATION COVER AND HIGH SOIL VARIABILITY (After [27])

Stage	Green Cover (%)	Soil	Band 5	Band 6	Band 7	Band 6/ Band 5	Band 7/ Band 5	7-5	7+5	7-5/ 7+5
		1	0.326	0.369	0.477	1.13	1.46	0.151	0.803	5.32
Emergent	3	2	0.459	0.522	0.670	1.14	1.46	0.211	1.129	5.35
		3	0.591	0.676	0.865	1.14	1.46	0.274	1.456	5.31
		1	0.446	0.615	0.819	1.38	1.84	0.373	1.265	3.39
Jointing	10	2	0.606	0.830	1.100	1.37	1.82	0.494	1.706	2.02
		3	0.766	1.052	1.392	1.37	1.82	0.626	2.158	2.78
		1	0.393	0.828	1.196	2.11	3.04	0.803	1.589	2.39
Pre-Heading (Booting)	38	2	0.459	0.964	1.398	2.10	3.05	0.939	1.857	2.80
		3	0.526	1.109	1.619	2.11	3.08	1.093	2.145	3.24

sandier soils, with less available stored water and with less available nutrients. The darker soils may contain more clay and so hold more moisture and possible nutrients. However, it may be risky to take advantage of this information, because other conditions can affect soil brightness but have opposite correlation with yield, and because undetectable soil conditions (e.g., fertilization, subsurface moisture) can cause differences in growth but not in soil brightness.

Yet another transformation which has been observed by some investigators as a quantitative measure of green vegetation cover and/or yield is a component of the "Delta-Classifier" [29] and is defined as

$$G = MSS4 - MSS7 + 96$$

For 21 May Landsat data on Finney site A, the G transformation was highly correlated with both percent green cover and leaf area index, but not as significantly as some of the other green feature indicators we have investigated. It was also highly correlated with yield, but again not to the same degree as other green feature indicators. The same situation was found to be true for both 20 May and 21 May 1975 Ellis data, and also for 6 May 1976 Finney data.

To further study the relationship between G and green vegetative cover, and also to test the sensitivity to external effects, we computed the transformation on simulated Landsat data which was generated using the ERIM Canopy/Atmospheric Model [27]. In addition, the transformations TVI and SQ75 were similarly computed on the simulated data. Nine separate canopies were modeled, each having its own value of percent cover.

When external factors were held fixed, we found that the correlation between percent cover and G using modeled Landsat data was 0.97, and that the standard error in estimating percent cover using G was 8.1 percentage points. The comparison shown in Table III.5 indicates that G is roughly comparable, but slightly superior, to two other transformations for measuring percent cover.

TABLE III.5. COMPARISON OF G AND OTHER TRANSFORMATIONS FOR MEASURING PERCENT COVER USING MODELED DATA (9 Points)

Green Measure	Correlation With Percent Cover	Standard Error in Measuring Percent Cover
G	0.97	8.1
TVI	0.91	12.8
SQ75	0.95	9.6

Again using model-simulated Landsat data, we examined the variation in G one should expect due to normal variations in haze, view angle, and background albedo. For each canopy, a Landsat signal was computed for each of several conditions of each of the four external parameters under consideration, resulting in a total of about 1200 points. Using these points, a regression was run relating percent cover and G transform value. The result was a standard error of 23.7 percentage points in estimating percent cover. Using the same procedure with the transforms TVI and SQ75, the corresponding standard errors were 19.9 and 20.8.

Conclusions

Based on our analyses of various green measure transforms, it appears that those we examined are roughly comparable in differentiating vegetation canopies on the basis of green vegetation density. This conclusion is not inconsistent with other recent analyses of the relative utility of various green measures [14]. Some investigators have indicated that a square root transform is useful because of the statistical properties of the data [30]. We believe that a square root transform of a green measure may be useful for assessing winter wheat yield due to the apparently curvilinear (asymptotic) nature of the relationship of green vegetation density and yield. While we feel that green measure transforms formed by a difference of two bands (such as MSS7-MSS5 or MSS4-MSS7) are sensitive to differences in green vegetation density, such transforms are not as effective as others (e.g., ratios) at normalizing other effects such as soil albedo.

APPENDIX IV

ANALYSIS OF POSSIBLE SOURCES OF BIAS IN LANDSAT ESTIMATES OF YIELD IN CENTRAL CRD OF KANSAS

An investigation into possible sources of bias in Landsat yield estimates reported in Section 8 is discussed in this appendix. Among the possibilities considered were:

1. unrepresentative training or test data
2. phenological sources of error
3. look-angle effects
4. incorrect Analyst Interpreter (A.I.) identification of wheat and non-wheat fields
5. Landsat calibration errors
6. training yield data.

The following material describes this investigation into sources of the discrepancy between Landsat and KCLRS yield estimates.

The Landsat estimates of yield on the test sites were, in all but one case, higher than the KCLRS county estimates. This might occur if training and/or test sites actually had anomalously high yield. In fact, the training ground truth data did have an average value of yield that was 5.33 bu/acre higher than the corresponding KCLRS county average yields. It would be more clear that this were a major cause of bias if similar computations could be made for the test sites. However, ground truth yield on individual fields is not available from the test sites, so such a comparison is not possible.

Another possible source for bias would result if the wheat fields used for training were not adequately representative of the wheat fields in the area. These data were extracted from LACIE Analyst Interpreter (A.I.) identification. It would be more surprising if the average test field as identified by a LACIE A.I. was actually "better" than average, since the A.I. who must visually select and classify a set of fields as wheat and non-wheat wants to make sure that the fields called wheat actually are wheat, and therefore marginal fields might not be selected. Some indication that this may have happened is that the best Landsat estimates of yield using the A.I. identified wheat fields were found where the county yield was high. In counties with high yields, even the locally below average wheat fields (with locally below average vegetative cover) might be sufficiently different from "non-wheat" fields, permitting them to be accurately identified by the analyst interpreter.

Errors could also occur in our Landsat estimates of yield if incorrect yield data were used for training. We used only the data we considered most reliable, namely farmers' estimates made using actual combine harvest weights.

A.I. identification errors could also cause errors in yield estimation. Through discussions with other ERIM employees who were investigating crop identification errors, we were able to correct test data from some of the sites so that only wheat was included in the yield estimation.

If the phenological stage of the wheat on which training was done was different from the phenological stage of the test data, yield estimation errors could be made. It was noted that, with respect to the growing degree day (GDD) calculations described in Section 8, some of the available April Landsat data had a closer agreement with the May training data than did the corresponding May test data. Therefore, for each test site for which Landsat data was available both in mid-April and early May, the specific deviation of the meteorological station indications of GDD from the average value of GDD for the counties in which training was done was computed for the data appropriate to the available Landsat data. About half of the April test data were found to be better phenological matches with the May training data than are the corresponding May test data, based on the meteorological data available.

However, when April Landsat data was used in place of May Landsat data for the indicated test sites, an even greater yield error was made, because the Landsat-indicated green values were generally higher in April than in May. This situation is biologically unlikely, if not impossible, and is a source of concern. There are indications that this apparent error is associated with anomalous weather conditions before and/or during the April Landsat overpass. For example, errors were smallest on the two sites where weather conditions were approximately the same in April and May. Additional work is required in order to determine the cause, and to explore ways to overcome the situtation by avoiding the use of such data or by correcting it for the anomalous conditions.

There is some indication that Landsat look-angle significantly affects the value of the Landsat green measure. For example, best results were obtained when look-angle for training data was similar to look-angle for test data. If such a situation can be shown to be generally true, then data with similar look-angle should be used in training and testing, or the data should be corrected for look-angle effects. Current work at ERIM on other projects is designed to correct Landsat data for effects of look-angle [31].

When Landsat-yield relations were explored, differences were found in the relations using full-frame Landsat data as opposed to LACIE sample segment data for the same fields. This difference could occur because of different calibrations for the two types of data, or because of different field boundaries. Even after the effects of calibration and field boundary differences were corrected to the best of our ability, however, differences remained. This situation is of concern because the Landsat-yield relations tended to be less diagnostic (smaller R^2) using the sample segment data (which we used for our test) than when using full frame data. In other words, there appears to be a loss in yield-predictive information content associated with sample segment data.

At this time one or more of the above mentioned possibilities may be contributing to the bias in Landsat estimates of yield. Unfortunately, insufficient information is available to establish what are the sources of bias.

APPENDIX V

CRITERION FOR DEFINING ACCEPTABLE PIXELS WITHIN A FIELD, AND FOR REJECTING FIELDS WITH AN INSUFFICIENT NUMBER OF PIXELS

In order to form valid Landsat signal mean values for each field, we must determine which pixels are to represent that field. We must avoid using any pixels which are so near the boundary of a field as to risk containing any signal from near the boundary or from an adjacent field. And yet we wish to select a sufficient number of fields, with a sufficient number of pixels within each field so as to carry out meaningful analyses, and to avoid restricting the range of yield values available in the set of fields. Unfortunately, when data are so limited, a compromise between the above desires is required. The discussion which follows describes our efforts to achieve the best compromise.

For much of our analysis with Landsat data for site Ellis, we used pixel inset distance of 1.5 pixel diameters*, which means that the center of a pixel considered safely within the field must be at least 1.5 pixel diameters within the nearest edge of the field. This guarantees a field one pixel separation between the pixel edge and the field edge to guard against error in the location of the field boundary, and therefore against using boundary pixels. This very conservative distance would frequently be used when pixels are relatively plentiful, or when field location errors are believed to be as much as one pixel.

In the case of our data, we believe the field boundaries are located to an accuracy nearly always better than 0.5 pixels. Therefore, we can with reasonable safety use an inset distance of 1.0 pixel. By so doing,

* A pixel diameter is the distance between two adjacent pixels in a scan line, or the distance between two adjacent scan lines, using an aspect ratio for which the two distances are equal.

we have increased the number of fields that have at least one pixel. In the Ellis site this increase in available fields was from 24 (when inset of 1.5 was used) to 36 (with the 1.0 inset). In addition, we included fields with yield less than the previous minimum of 24.5 bu/acre, so that the available range of yield values started at 15.0 bu/acre, an increase of approximately 50% in the range of yield values represented. A similar pattern was found in the other sites.

The standard deviations of the field mean values computed with 1.0 and 1.5 pixel insets were not appreciably different. The mean values varied by an average of less than ±0.5 digital counts. Thus, we suffered no serious deficiency by using a 1.0 pixel inset, but have received significant advantage.

An additional consideration was to decide on a rule for accepting fields, based on the number of pixels selected from each field. Unfortunately, we discovered a positive correlation between number of pixels per field and field yield. Therefore, in order to retain information for the fields with the lowest yields, it was necessary to accept any field with no fewer than two pixels for every date. Keeping a broad range of yield values is considered sufficiently important that for most analyses, a two pixel criterion was chosen as the preferred compromise. The criterion resulted in the elimination of four of the 36 fields mentioned above. Any more stringent requirement for number of pixels would have increased the lowest value of yield in fields to be accepted to 21.4, not much below the value for a 1.5 pixel inset.

Due to the above considerations, we applied the 1.0 pixel inset criterion, and the criterion specifying two or more pixels in each acquisition, to all data sets subsequently processed that required digitized field boundary definitions.

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