112780

AgRISTARS

SR-PO-04023
NAS9-15466

A Joint Program for Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing

Supporting Research

November 1980

Final Report

Vol. II
Research in the Application of Spectral Data to Crop Identification and Assessment

by C.S.T. Daughtry and M.M. Hixson

Purdue University
Laboratory for Applications of Remote Sensing
West Lafayette, Indiana 47907

8.1.-1 0.1 5.2
CR-164266

AgRISTARS

SR-PO-04023
NAS9-15466

A Joint Program for
Agriculture and
Resources Inventory
Surveys Through
Aerospace
Remote Sensing

Supporting Research

November 1980

Final Report

Vol. II
Research in the Application of Spectral Data to Crop Identification and Assessment

by C.S.T. Daughtry and M.M. Hixson

Purdue University
Laboratory for Applications of Remote Sensing
West Lafayette, Indiana 47907

(E81-10152) RESEARCH IN THE APPLICATION OF SPECTRAL DATA TO CROP IDENTIFICATION AND ASSESSMENT, VOLUME 2 Final Report, 1 Dec. 1979 - 30 Nov. 1980 (Purdue Univ.) 120 p HC A06/MF A01 CSCL 02C G3/43

N81-26528

Unclas
00152

SR-PO-04023
NAS9-15466
LARS 112780

Final Report

VOL. II. RESEARCH IN THE APPLICATION OF SPECTRAL DATA TO CROP IDENTIFICATION AND ASSESSMENT

C.S.T. Daughtry and M.M. Hixson

Purdue University
Laboratory for Applications of Remote Sensing
West Lafayette, Indiana 47907

November 1980

Star Information Form

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
SR-PO-04023		

4. Title and Subtitle
Vol. II. Research in the Application of Spectral Data to Crop Identification and Assessment

5. Report Date
November 30, 1980

6. Performing Organization Code

7. Author(s)
C.S.T. Daughtry and M.M. Hixson

8. Performing Organization Report No.
112780

9. Performing Organization Name and Address
Purdue University
Laboratory for Applications of Remote Sensing
1220 Potter Drive
West Lafayette, Indiana 47906

10. Work Unit No.

11. Contract or Grant No.
NAS9-15466

12. Sponsoring Agency Name and Address
NASA/Johnson Space Center
Earth Observations Division
Houston, Texas 77058

13. Type of Report and Period Covered
Final 12/1/79 to 11/30/80

14. Sponsoring Agency Code

15. Supplementary Notes
Principal Investigator: M.E. Bauer
Technical Monitor: J.D. Erickson

16. Abstract

Four investigations of the application of spectral data to crop identification and assessment are discussed in this volume. Part A discusses the development of spectromet crop development stage models. Several "state-of-the-art" development stage models for corn and soybeans were reviewed. One photothermal model and four thermal models were selected and evaluated.

Part B describes an investigation of spectral data as a source of information for crop yield models. Intercepted solar radiation and soil productivity are identified as factors related to yield which can be estimated from spectral data.

Several techniques for machine classification of remotely sensed data for crop inventory are evaluated in Part C. Early season estimation, training procedures, the relationship of scene characteristics to classification performance, and full-frame classification methods have been studied.

In part D, a task to determine the optimal level for combining area and yield estimates of corn and soybeans is discussed. The optimal level is assessed utilizing current technology: digital analysis of Landsat MSS data on sample segments to provide area estimates and regression models to provide yield estimates.

17. Key Words (Suggested by Author(s))
Crop inventory, spectral, Landsat MSS, crop calendar, development stage, crop classification, production estimation, aggregation

18. Distribution Statement

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price*
Unclassified			

*For sale by the National Technical Information Service, Springfield, Virginia 22161

NASA - JSC

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

A. SPECTROMET CROP DEVELOPMENT STAGE ESTIMATION FOR CORN AND SOYBEANS

C.S.T. Daughtry*

1. Introduction

Phenology is the study of periodic biological events in their relation to seasonal climatic changes with emphasis placed on dates of various occurrences. Crop phenology or crop development merges meteorological and biological sciences and will be used here to refer to the entire life cycle of corn and soybeans from soil preparation and planting to maturation and harvest.

During the Large Area Crop Inventory Experiment (LACIE) identification of crops by an analyst required that he integrate all knowledge available to him concerning the spectral appearance of crops, farming practices, and natural events which can change that appearance. One analyst tool was the crop calendar which described the phenology or progression of each crop in a region through detectable or agronomically significant events in its life cycle (Whitehead et al., 1978). Crop development stage information is also an important input to crop growth and yield models.

2. Review of Crop Development Stage Models

Three basic approaches to estimate crop development stage are normal crop phenology, meteorologically-based models and spectrally-based models. Some of the attributes of each approach will be discussed in the following sections.

2.1 Normal Crop Phenology

Normal or average crop phenology is based on the accumulation of days between specific events in a crop's life cycle. Although this method does not account for year-to-year variations in crop development due to weather differences, it does provide a first approximation of when specific events are likely to occur.

----

* The contributions of L. Grant, V.J. Pollara, and J.P. Ward to this task are gratefully acknowledged. Without their work and support this research would not have been possible.

2.2 Meteorological Methods

Crop development involves complex physiological and biochemical processes which are influenced by the crop's environment and are still inadequately understood. Temperature, day length, and the plants' genetic composition are the principal variables influencing crop development. Available moisture and nutrients may affect crop development in some situations.

Thermal Models. During the past century numerous models to describe crop development as a function of environmental variables, particularly temperature, have been proposed. A complete review of literature on the thermal unit concept as it relates to corn and soybeans would comprise a voluminous bibliography. Summaries and conclusions of the research papers on this topic are sufficiently similar that a discussion of several key papers will adequately describe the subject.

There are many different methods of calculating accumulated thermal units, for example Cross and Zuber (1972) report on 22 methods for corn and Major et al., (1975a) report on 11 methods for soybeans. The simplest and most broadly researched method is Growing Degree Days (GDD). A base temperature for growth of 10°C (50°F) is subtracted from the average of the daily maximum and minimum temperatures to give the daily GDD. Most modifications of this simple method impose some upper and lower limits on the daily temperature inputs, while other methods consider day and night temperatures separately. The most common of these limits are 30°C (86°F) for the maximum temperature and 10°C (50°F) for the minimum temperature. A GDD index is obtained by summing the daily GDD from planting to the stage of crop development desired, usually silking or maturity in most studies.

Considerable effort has been directed at trying to predict flowering and maturity dates of various crops on the basis of temperature data. Andrew et al., (1956) used cumulative thermal units to compare development maturation of two corn hybrids at two different locations. They observed that cumulative thermal units above a base of 10°C (50°F) were equally effective in both locations for predicting maturity. They concluded that maturity of corn could be measured successfully by thermal unit accumulations regardless of differences in climate.

Gilmore and Rogers (1958) studied the development of 10 hybrids and 10 inbred lines of corn using 15 different methods of calculating thermal units. Thermal units calculated using temperatures taken at 3-hour intervals did not estimate silking significantly better than those calculated using daily maximum and minimum temperatures. Daily data were as descriptive of the growing conditions for 24-hour period as the data taken at 3-hour intervals. Differences among hybrids in the rate of development based on accumulated thermal units to silking were noted. Stauber et al., (1968) also showed differences in rate of development among hybrids.

Aspiazu and Shaw (1972), Cross and Zuber (1972) and Mederski et al. (1973) compared numerous methods of thermal unit calculations for estimating the silking and maturity stages of corn. Although differences among the methods to estimate a phenological stage were generally small, all methods of accumulating thermal units were better indicators of maturity than calendar days.

Neild and Seeley (1977) using a detailed series of corn development stages showed that development stages could be estimated very well for hybrids of different maturity classes using the simple GDD system with a base temperature of 10°C. Frequent and detailed crop development stage data result in a better measure of the relationship between crop development and GDD than was indicated by previous studies using only one or two development stages.

While thermal units are generally recognized to be superior to calendar days in predicting flowering or maturity dates, there is less than universal agreement as to which method of computing thermal units is best. Thus several methods to predict development stages should be tested and the "best" one for a particular application selected.

Photothermal Models. The thermal unit accumulation concept assumes that photoperiod does not influence the rate of crop development. Thermal models have generally proved to be adequate in predicting development of crops, such as corn. Temperature and photoperiod interact to influence corn development, particularly tassel initiation (Coligado and Brown, 1975). Coligado (1974) developed a model incorporating temperature, photoperiod, and genetic factors to predict tassel initiation of corn. Although Coligado's model appears sound theoretically, it needs further research to extend it to all other stages of development.

Development of soybeans is markedly influenced by photoperiod and cannot be adequately predicted using thermal models alone (Major et al., 1975a). Long daylengths increase the time from flowering to pod set (Johnson et al., 1960) and from flowering to the termination of flowering (Lawn and Byth, 1973). The response of soybeans to photoperiod differs in each development stage.

Obtaining the information necessary to develop mathematical models for predicting soybean development is difficult. Controlled environment studies are nearly impractical when entire life cycles of several cultivars at a number of daylengths and temperatures must be included. Date of planting studies in the field can be used to study numerous cultivars but the parallelism of seasonal daylength and temperature patterns pose problems in analyzing the data.

Major et al., (1975b) modified an iterative regression analysis method (Robertson, 1968) for deriving a mathematical expression relating several stages of development of soybeans to both temperature and daylength. In a comparative study the photothermal model predicted development more accurately than calendar days or various thermal models in several locations (Major et al., 1975b).

3. Objectives

The overall objective of this multiyear task is to develop methods to estimate crop development stages using spectral and meteorological data. The specific objectives are:

1. Define, test and deliver first generation (meteorological) methods to estimate crop development stages for corn and soybeans in the U.S.

2. Identify and begin initial research and development of second generation (spectral-meteorological) crop development models.

3. Define data requirements and approaches for developing and testing crop development models in foreign areas.

The goals of this task are first to aid analyst-interpreters, who will be labeling pixels for classification, and second to provide inputs to crop growth and yield models so that they may be implemented for large geographic areas. Given these two goals, no one method to estimate crop development seemed adequate. A combination of features from the normal, meteorological, and spectral methods was proposed.

Normal crop development models provide preliminary, preseason predictions of when specific crop stages are likely to occur based on previous experience. Meteorological models provide the next increment of information on crop development for crop reporting districts and segments within districts. Meteorological data provides a high degree of temporal resolution (e.g. daily), but relatively poor spatial resolution or sampling. On the other hand, while having relatively low temporal sampling (9 or 18 days with Landsat data), spectral data provides high spatial resolution allowing determinations to be made for individual fields.

This hierarchy of crop development models uses as much information as is available at any given point in the season and allows the user to select the level of detail that he requires. The greater the level of detail required, the greater will be the costs in both time and money. For example, a researcher in the early stages of planning a data acquisition program may need only general information about the crops in a region and when their development stages occur. An analyst-interpreter needs specific information about the crops in a region, in particular he needs to know the probable development stages for each crop on any given date.

4. Description of Data Bases

Initial development and testing of crop development models was conducted in the U.S. Corn Belt, the major corn and soybean producing region of the U.S. Together Indiana, Illinois, and Iowa produced about 92 million metric tons of corn and 21 million metric tons of soybeans in 1979 which represented approximately 47 and 37 percent of the total U.S. production of corn and soybeans, respectively.

Local climatological data for 1969 to 1978 were acquired and reorganized for Indiana, Illinois, and Iowa. These data consist of daily maximum and minimum air temperatures and daily precipitation amounts for more than 100 stations per state representing nearly every county in each state.

Crop development stage data used in this task were acquired primarily from three sources (Table A-1). The most detailed data consisting of observations of approximately 200 plots at irregular intervals (about 7 to 14 days) representing all stages from planting to harvest was acquired at the Purdue Agronomy Farm (Bauer et. al., 1979).

The second data set (Table A-1) consisted of periodic observations of selected fields in Landsat MSS segments throughout the Corn Belt in 1978. Unfortunately there are no data prior to late June or early July and planting dates were not recorded for these fields. Similar data for 1979 were not available for analysis by this year.

The third data set (Table A-1) representing all crop reporting districts in Indiana, Illinois, and Iowa was acquired from annual crop summaries published by the USDA Economics, Statistics, and Cooperative Service (ESCS) in each state. These data were obtained by ESCS from mail surveys of each crop reporting district at weekly intervals and were summarized to represent average crop development for an entire crop reporting district. Dates on which 25, 50, and 75% of the fields in each crop reporting district reached each stage of development were interpolated from the published data (USDA - ESCS, 1970 to 1978).

5. Selection and Evaluation of Meteorological Models

Based on a review of the literature four thermal models and one photothermal model were selected and evaluated. The number of calendar days since planting (ΣDays) was included for comparison. These "state-of-the-art" models described briefly in Table A-2 had been developed using observations of individual plants and fields but had not been tested over large areas using statistical data from ESCS. The relative numbers of thermal units accumulated per day for each of these thermal models are illustrated in Figure A-1.

A base temperature of 50°F (10°C) was used for the Growing Degree Day (GDD), Modified Growing Degree Day (MGDD), and Heat Stress (HS) models. The MGDD model sets an upper limit of 86° F (30°C) on the

Table A-1. Data sets used for initial evaluation of crop development models.

Data Set/Location	Description	Acquisition Frequency	Sensor for Spectral Data
Field Research - Purdue Agronomy Farm	Corn Cultural Practices Expt. - 3 planting dates - 3 plant populations - 2 soil types	7 to 14 days	Exotech 100
	Corn Nitrogen Expt. - 4 levels of N fertilizer - 2 years (1978, 1979)	7 to 14 days	Exotech 20C
	Soybean Cultural Practices Expt. - 4 planting dates - 2 cultivars - 2 row widths	7 to 14 days	Exotech 100
Landsat Segments - IN, IL, IA, MN, MO, SD	Commercial Fields - 10 fields/segment	9 to 18 days	Landsat MSS
USDA-ESCS Data - IN, IL, IA	Crop Reporting District - "average" development stage - "average" cultivars	7 to 10 days	(no spectral data)

Table A-2. Summary of thermal and photothermal models evaluated.

THERMAL MODELS

1. Growing Degree Days, GDD

$$\Sigma GDD = \sum_{i=1}^{n} \left[(T_{max} + T_{min})/2\right] - 50$$

T_{max} = maximum air temperature for day i in °F

T_{min} = minimum air temperature for day i in °F

i = date of planting

n = date of silking or maturity

For daily mean temperatures less than 50, GDD = 0.

2. Modified Growing Degree Days, MGDD

$$\Sigma MGDD = \sum_{i=1}^{n} \left[(T_{max} + T_{min})/2\right] - 50$$

$T_{max} = T_{max}$ if $T_{max} < 86$; $T_{max} = 86$ if $T_{max} > 86$

$T_{min} = T_{min}$ if $T_{min} > 50$; $T_{min} = 50$ if $T_{min} < 50$

3. Heat Stress Units, HS (Cross and Zuber, 1972)

$$\Sigma HS = \sum_{i=1}^{n} \left[(T_{max} + T_{min})/2\right] - 50$$

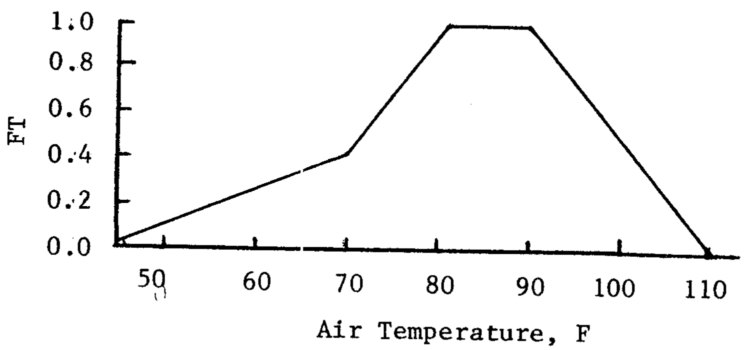
$T_{max} = T_{max}$ if $T_{max} < 86$; $T_{max} = 86 - (T_{max} - 86)$ if $T_{max} > 86$

$T_{min} = T_{min}$ if $T_{min} > 50$; $T_{min} = 50$ if $T_{min} < 50$

Table A-2. (Continued).

4. <u>Temperature Function, FT</u> (Coelho and Dale, 1980)

$$\Sigma FT = \sum_{i=1}^{n} (FT_{max} + FT_{min})/2$$



Temp	FT
43	0.000
70	0.405
82	1.000
90	1.000
111	0.000

FT_{max} = FT for maximum temperature in F

FT_{min} = FT for minimum temperature in F

PHOTOTHERMAL MODEL

<u>Iterative Regression Analysis</u> (Major et al., 1975)

$$M = \sum_{s_1}^{s_2} \left[a_1(L - a_0) + a_2(L - a_0)^2\right] * \left[b_1(T - b_0) + b_2(T - b_0)^2\right]$$

L = day length in hours

T = mean daily temperature

s_1, s_2 = development stages

$\left.\begin{matrix} a_0, a_1, a_2 \\ b_0, b_1, b_2 \end{matrix}\right\}$ = regression coefficients (values given in Table 1 of Major et al., 1975)

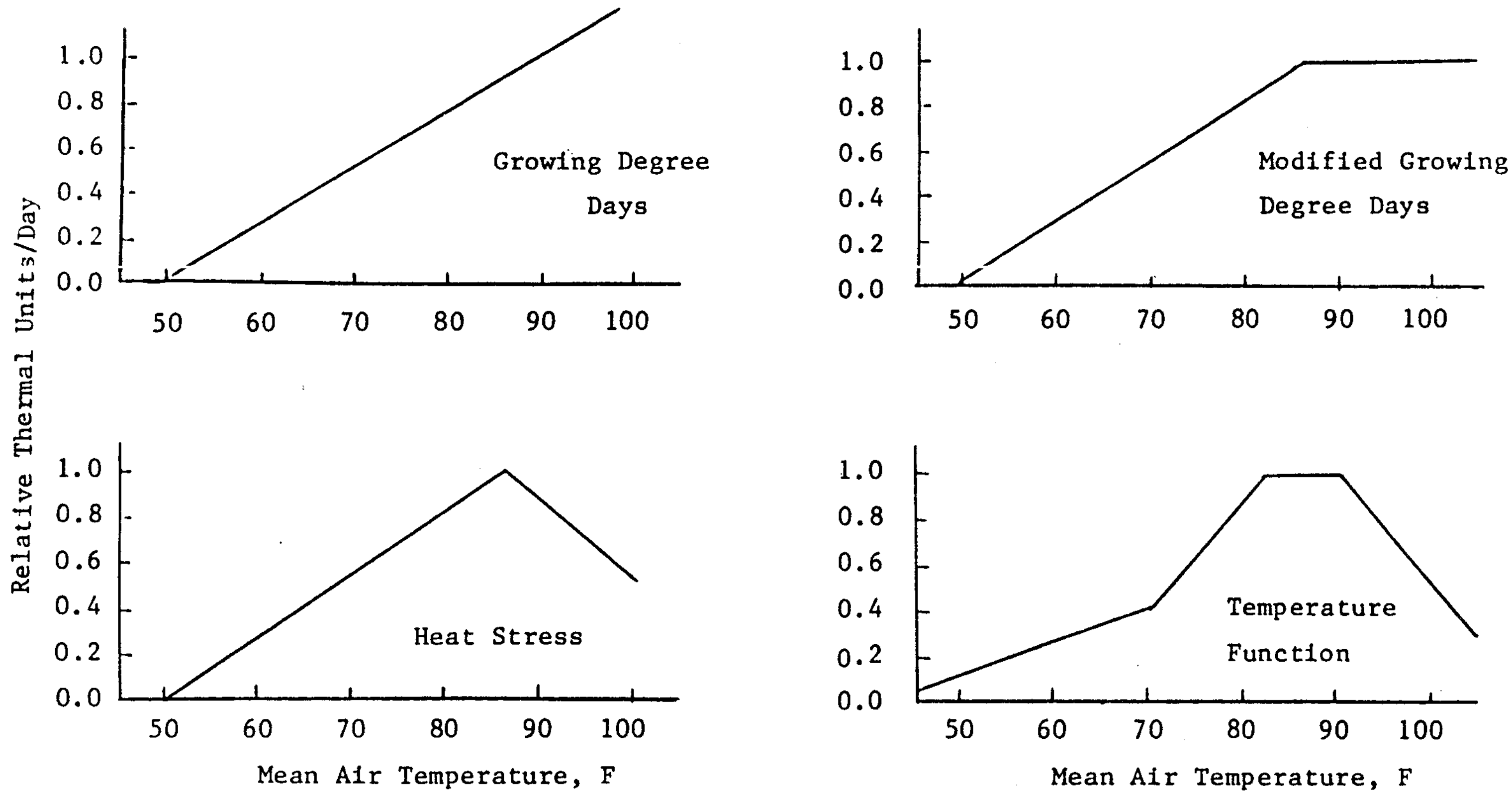


Figure A-1. Comparisons of relative thermal units accumulated per day.

maximum temperature and the HS model decreases thermal unit accumulations for temperatures greater than 86F. No upper threshold was used by the basic GDD model. Daily values of the Temperature Function (FT) by Dale and Coelho (1980) were computed as the mean of the relative growth rates for the maximum and minimum temperatures.

The initial evaluation of these models was a two step process using data from the Purdue Agronomy Farm and then data from crop reporting districts in Indiana and Iowa (Table A-1). Illinois was not included at this stage because only two years of data were readily available for analysis during this task. One meteorological station in each crop reporting district (Table A-3) was used for these initial analyses.

The average thermal unit accumulation for each model from planting to each development stage was computed and used to predict the development stages for the same data series to compare precision and accuracy among the models. Five years (1974-78) and three planting dates per year (25, 50 and 75% of the crop planted) provided 15 planting date-years. The coefficient of variation was computed for each model to compare its relative precision. Low variability in predicting each development stage signified high precision. Accuracy was defined by the mean of the absolute errors in days, that is the predicted date of stage (i) minus the actual date of stage (i). In these initial evaluations actual planting dates were used to start the models. In the subsequent analyses predicted planting date from a planting model will be used to start the models.

The photothermal model developed by Major et al. (1975b) predicted development stages of soybeans directly, thus no preliminary calibrations similar to those of the thermal models were necessary. However, the development stages predicted by the photothermal model do not coincide with those reported by USDA-ESCS. Comparisons of soybean development stages are shown in Table A-4. The Fehr et al. (1971) index provides the most complete and precise description of soybean development. The other two methods, particularly USDA-ESCS's, are more ambiguous in their descriptions of soybean development stages.

This photothermal model consists of a series of regression coefficients for temperature and daylength which were derived for two cultivars from each of five maturity groups of soybeans. To implement the model for large areas with many different cultivars we assumed that the cultivars selected by Major and co-workers sufficiently represented all soybean cultivars in maturity groups I to V. Using data acquired by USDA-ESCS in Indiana, Illinois, and Missouri on the proportion of specific soybean cultivars planted in each CRD, we computed the proportion of the total soybean acreage in each maturity group (Table A-5). Two maturity groups generally comprised more than 90% of the total soybean acreage in any CRD and a simple ratio of the two dominant maturity groups adequately characterized the composition of soybeans planted in the CRD (Table A-5). The mean development stage predicted for a CRD is weighted by the proportion of each maturity group of soybeans historically planted in the CRD.

Table A-3. Meteorological stations used in computing thermal and photothermal indexes.

State	CRD	Station	County	Latitude	Longitude
IN	1	Wanatah 2NW	Porter	41.43	86.93
	2	Rochester	Fulton	41.07	86.22
	3	Columbia City 1S	Whitley	41.13	85.48
	4	Crawfordsville	Montgomery	40.05	86.90
	5	Greenfield	Hancock	39.78	85.75
	6	Farmland 5NNW	Randolph	40.25	85.15
	7	Dubois SIPAC	Dubois	38.45	86.70
	8	Oolitic Purdue Farm	Lawrence	38.88	86.55
	9	Versailles	Ripley	39.07	85.25
IA	1	Primghar	O'Brien	43.08	95.63
	2	Mason City FAA	Cerro Gordo	43.15	93.12
	3	Feyatte	Fayette	42.83	91.80
	4	Castana Exp Farm	Monona	42.07	95.82
	5	Ames 8WSW	Boone	42.03	93.80
	6	Cedar Rapids 1	Linn	42.03	91.58
	7	Shenandoah 1NE	Page	40.78	95.35
	8	Osceola	Clarke	41.02	93.10
	9	Mount Pleasant	Henry	40.95	91.33

Table A-4. Comparisons of soybean development scales.

Fehr et al. (1971)		Photothermal (Major et al., 1975)		USDA-ESCS
Stage	Description	Stage	Description	Description
V0	Planting	0	Planting	Planting
VE	Emergence	1.0	Emergence	
VC	Cotyledon			
V1	1st node			
V2	2nd node			
⋮				
Vn	nth node			
R1	Beginning bloom (>50% with 1 bloom)	2.0	Flowering (>10% with 1 bloom)	
R2	Full bloom (>50% with blooms at top)			Blooming
R3	Beginning pod	3.0	Pod fill (>10% with 2 cm pods)	Pod set
R4	Full pod			
R5	Beginning seed	4.0	End of flowering (<10% new flowers)	
R6	Full seed			
R7	Beginning maturity			Leaves turning
R8	Full maturity	5.0	Physiological maturity (>75% senesced leaves)	Leaves shedding
R9	Harvest	6.0		Harvest

Table A-5. Percent of total soybean acreage in maturity groups II, III, IV, and V for each crop reporting district (CRD) in Indiana, Illinois, and Missouri.

			MATURITY GROUP+				
STATE	CRD	LAT	II	III	IV	V	RATIO*
IN	1	41.17	67.0	32.1	.8		2.32
IN	2	41.15	58.6	40.2	1.1		2.41
IN	3	41.13	50.2	45.1	4.6		2.47
IN	4	39.88	27.6	65.4	7.0		2.70
IN	5	39.90	27.6	63.8	8.9		2.70
IN	6	40.13	12.6	80.8	6.8		2.87
IN	7	38.50	8.3	67.3	24.4		3.27
IN	8	38.65	1.8	71.8	26.7		3.27
IN	9	38.97	4.7	66.3	29.0		3.30
IL	1	41.83	90.0	10.0	0.0		2.10
IL	2	41.75	95.6	4.4	0.0		2.04
IL	3	40.47	20.2	73.6	6.0		2.79
IL	4	40.53	45.9	27.4	0.0		2.54
IL	5	40.47	65.9	34.1	0.0		2.34
IL	6	39.28	5.6	87.6	6.7		2.94
IL	7	39.13	13.0	79.4	7.6		2.86
IL	8	37.90	0.0	73.4	26.6		3.27
IL	9	38.03	0.6	78.5	20.8		3.21
MO	1	39.95		80.0	19.8	0.1	3.20
MO	2	40.00		68.9	31.1	0.0	3.31
MO	3	39.95		71.5	28.4	0.0	3.28
MO	4	38.60		51.6	34.3	14.1	3.40
MO	5	38.40		59.2	39.3	1.5	3.40
MO	6	38.50		65.8	31.3	3.0	3.32
MO	7	37.00		11.5	8.5	80.0	4.90
MO	8	37.10		3.5	22.1	74.5	4.77
MO	9	36.60		.8	1.3	97.9	4.99

+ Data from USDA-ESCS annual summaries for each state. Data are means for 1976 to 1979 in Indiana; 1976 and 1978 in Illinois; and 1976 to 1980 in Missouri.

* Maturity group ratio assumes only two maturity groups in each CRD.

6. Performance of Meteorological Models

The second phase of this task was to evaluate the ability of the models to predict stages of development on a continuous (daily, weekly, etc.) basis. The information most needed by analysts is not on which date flowering occurred but what is the development stage on any given date in the season. To produce this information an overall concept of crop development was required. Ultimately we expect meteorological data will be used by a planting date model to predict starting dates for the crop development stage models which will use meteorological and spectral data to provide information to the analysts and input data for growth and yield models.

6.1 Development Stage Models for Corn

The means, standard derivations, and coefficients of variation (CV) of the four thermal models and ΣDays from planting to silking for three planting dates in 1979 at the Purdue Agronomy Farm are shown in Table A-6. The ΣFT (Temperature Function) provided the smallest CV and ΣDays had the largest. When the means for each model from Table A-6 were used to predict date of silking, the absolute error in number of days for each model was also lowest for ΣFT. Predicting silking as 72 days after planting represented the largest errors. Because dates of physiological maturity were not observed for all planting dates in 1979, comparisons of these models for predicting maturity were not possible with this data set.

Means for the four thermal models and ΣDays from planting to silking (Table A-7) and from planting to maturity (Table A-8) for 15 planting date-years (5 years with 3 planting dates per year) were calculated for each crop reporting district (CRD) in Indiana and Iowa. Coefficients of variation (CV) for each CRD are presented in Tables A-9 and A-10. In Indiana thermal models generally had lower CV's than ΣDays from planting to silking but higher CV's from planting to maturity. However, in Iowa ΣDays had lower CV's than the thermal models which is inconsistent with the theory of thermal unit models (Cross and Zuber, 1972). Comparisons of thermal models and ΣDays by Aspiazu and Shaw (1972) using data from experimental plots in Iowa, showed thermal models to have lower CV's than ΣDays.

To develop methods capable of predicting corn development on a continuous or daily basis, two key assumptions are necessary. First, the development of corn must be linear between specific stages (i.e., planting, silking, and maturity). The relationships of accumulated thermal units and development stages are strongly linear for all planting dates (Figure A-2) and have R^2's greater than 0.98. Thus, intermediate development stages can be estimated using thermal models. Comparisons of the ratio of thermal units at silking (Table A-7) divided by thermal units at maturity (Table A-8) indicate that silking consistently occurs at a relatively constant proportion of the total thermal units.

Table A-6. Accumulated thermal units and ΣDays from planting to silking for 3 planting dates in 1979 at Purdue Agronomy Farm.

	Thermal Units				
Planting Date	ΣGDD	ΣMGDD	ΣHS	ΣFT	ΣDAYS
May 2	1651	1658	1648	40.9	80
May 16	1556	1553	1543	39.6	71
May 30	1408	1397	1386	37.1	65
$\bar{x}$	1538	1536	1526	39.2	72
$s\bar{x}$	123	131	132	1.93	7.55
CV, %	7.9	8.5	8.6	4.9	10.5
$\lvert\overline{\text{error}}\rvert$,days	4.1	4.3	4.0	1.7	5.3

Table A-7. Mean accumulated values for thermal models and ΣDays from planting to date of silking of corn for 15 planting date-years in each crop reporting district (CRD) of Iowa and Indiana.

		THERMAL MODELS				
State	CRD	ΣGDD	ΣMGDD	ΣHS	ΣFT	ΣDays
IA	1	1431	1395	1287	37.2	72.5
IA	2	1345	1334	1244	35.5	72.7
IA	3	1329	1342	1251	36.7	71.9
IA	4	1378	1351	1255	36.2	71.0
IA	5	1404	1378	1301	37.1	70.9
IA	6	1465	1438	1367	38.8	71.1
IA	7	1552	1501	1397	39.2	70.2
IA	8	1389	1344	1239	35.6	67.4
IA	9	1453	1421	1361	37.7	68.3
IN	1	1276	1268	1196	34.1	68.6
IN	2	1321	1308	1237	35.3	68.1
IN	3	1294	1292	1230	35.4	69.7
IN	4	1360	1346	1261	36.3	67.9
IN	5	1388	1360	1294	36.6	68.7
IN	6	1315	1315	1259	35.8	69.1
IN	7	1389	1381	1328	37.2	67.1
IN	8	1369	1362	1301	36.9	68.4
IN	9	1522	1474	1390	39.1	67.6

Table A-8. Mean accumulated values for thermal models and ΣDays from planting to date of maturity of corn for 15 planting date-years in each crop reporting district (CRD) in Iowa and Indiana.

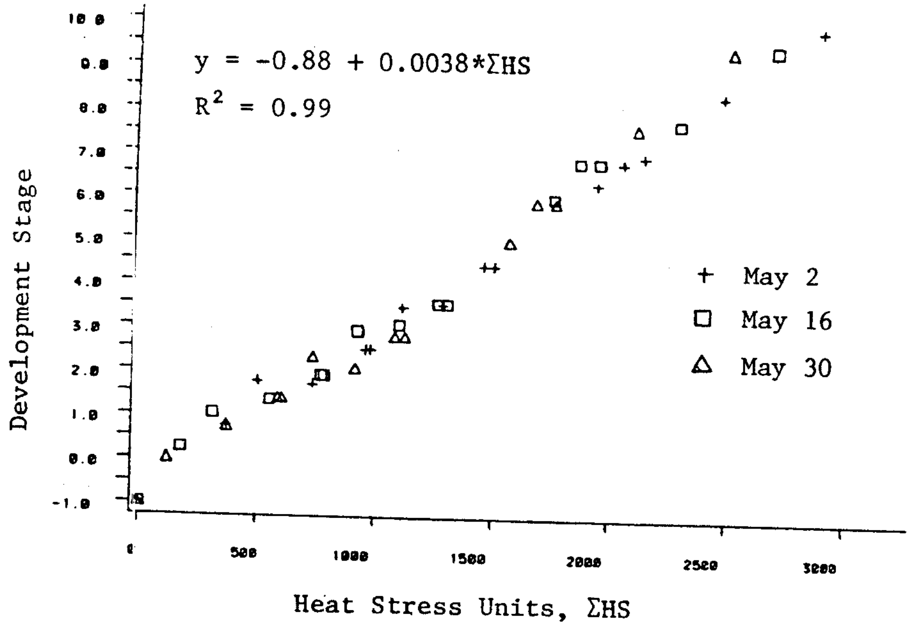
		THERMAL MODELS				
State	CRD	ΣGDD	ΣMGDD	ΣHS	ΣFT	ΣDays
IA	1	2463	2393	2230	64.2	120.5
IA	2	2290	2270	2130	60.9	122.2
IA	3	2277	2299	2153	63.2	122.2
IA	4	2453	2388	2226	64.0	121.0
IA	5	2475	2421	2293	65.3	121.7
IA	6	2532	2484	2368	67.1	121.3
IA	7	2795	2680	2497	69.7	121.0
IA	8	2548	2453	2263	65.0	120.3
IA	9	2641	2578	2473	68.6	121.2
IN	1	2334	2336	2220	63.5	125.5
IN	2	2388	2367	2252	64.7	123.5
IN	3	2334	2343	2239	64.9	127.3
IN	4	2525	2502	2363	67.8	125.3
IN	5	2640	2596	2485	69.8	127.3
IN	6	2424	2436	2333	66.6	127.5
IN	7	2598	2581	2496	69.5	123.1
IN	8	2504	2492	2392	67.7	122.7
IN	9	2762	2675	2526	70.9	122.1

Table A-9. Coefficients of variation (CV) for four thermal models and ΣDays from planting to date of silking of corn for 15 planting date-years in each crop reporting district (CRD) of Iowa and Indiana.

		Thermal Models				
STATE	CRD	ΣGDD	ΣMGDD	ΣHS	ΣFT	ΣDAYS
IA	1	8.1	6.3	6.6	4.9	4.6
IA	2	8.1	7.1	8.6	6.9	4.7
IA	3	7.5	6.1	7.9	5.7	5.6
IA	4	8.9	6.9	7.4	6.3	4.5
IA	5	10.3	8.0	7.8	6.3	3.9
IA	6	6.5	5.6	6.4	5.1	5.5
IA	7	12.1	9.8	9.7	8.1	7.4
IA	8	15.6	13.2	12.6	10.4	8.6
IA	9	8.9	7.8	7.5	6.7	7.7
IN	1	5.5	4.7	5.9	5.0	7.8
IN	2	7.5	6.2	7.2	5.9	8.6
IN	3	7.2	5.9	7.1	6.0	7.3
IN	4	8.4	6.4	7.0	5.5	10.7
IN	5	9.7	8.1	9.2	6.5	9.8
IN	6	8.4	6.8	7.1	6.6	10.3
IN	7	7.2	5.2	6.3	5.1	9.9
IN	8	6.6	5.5	6.0	5.4	11.5
IN	9	7.0	6.2	6.1	5.9	11.0

Table A-10. Coefficients of variation (CV) for four thermal models and ΣDays from planting to date of maturity of corn for 15 planting date-years in each crop reporting district (CRD) of Iowa and Indiana.

		Thermal Models				
State	CRD	ΣGDD	ΣMGDD	ΣHS	ΣFT	ΣDays
IA	1	5.3	5.3	6.0	5.7	5.3
IA	2	6.1	5.1	6.4	5.1	4.9
IA	3	7.6	5.3	7.1	5.2	4.9
IA	4	4.8	4.4	5.4	5.3	5.9
IA	5	9.3	7.9	8.1	6.9	5.3
IA	6	6.9	5.9	6.6	5.6	5.4
IA	7	4.9	4.5	5.4	4.9	6.1
IA	8	10.3	8.9	8.8	7.9	8.6
IA	9	8.1	7.0	6.4	5.9	6.4
IN	1	6.9	5.9	7.0	5.8	4.3
IN	2	5.1	4.3	5.1	3.7	5.8
IN	3	4.8	3.7	4.5	3.3	4.8
IN	4	8.3	6.5	7.2	6.3	6.7
IN	5	9.0	7.4	7.5	5.8	6.3
IN	6	6.9	5.2	6.0	4.5	5.0
IN	7	6.8	5.2	6.0	4.8	7.0
IN	8	5.5	4.4	4.9	4.3	9.0
IN	9	7.0	5.1	5.2	4.2	6.7



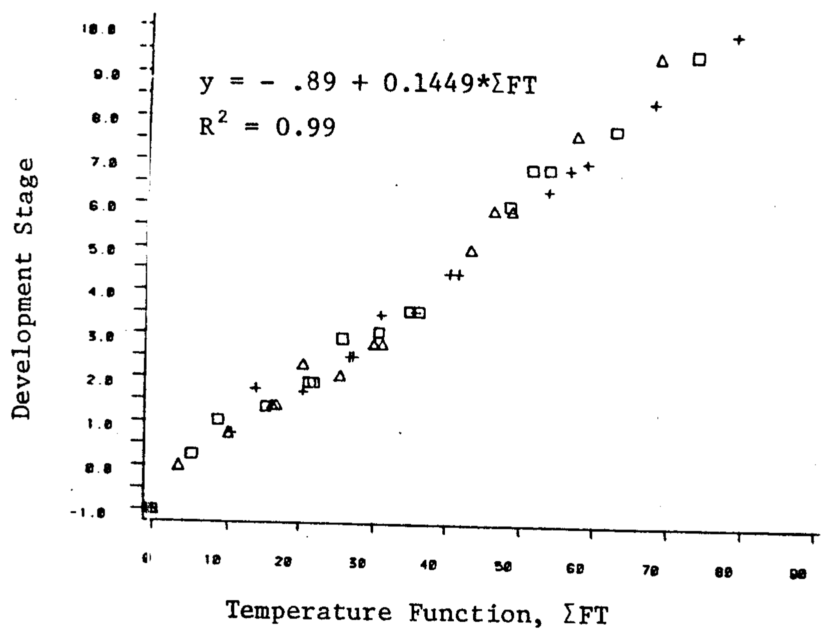


Figure A-2. Relationships of ΣHS and ΣFT units to development stages of corn for three planting dates in 1979 at Purdue Agronomy Farm.

The second key assumption is that the average maturity classes of corn planted in a crop reporting district can be estimated as a function of latitude. To test this assumption mean values of thermal units accumulated from planting to maturity in 15 planting date-years were plotted versus the median latitude of each CRD in Indiana and Iowa (Figure A-3). Although the R-squares for these linear regressions were low (R^2 = 0.52 to 0.56), a first approximation of an adjustment for gross differences in average maturity classes of corn seems possible.

Given that the two assumptions are valid, an approach to estimate corn development stages for segments on a daily basis is proposed. This approach was developed using data for CRD's reported by USDA-ESCS, but should be applicable to segments as well.

The first step is to determine planting dates. Normal planting dates may be used as an initial approximation, but because planting dates are variable depending on weather conditions normal planting dates can induce considerable errors. Planting date models which utilize meteorological data provide a second approximation. These models should be able to depict the progress of corn planting for CRD or county-sized areas and are discussed in a separate section. Spectral models proposed by Badhwar and Henderson (1980) potentially can provide planting dates for specific fields.

The second step in a corn development stage model is to determine the average maturity classes of corn grown in the segment based on latitude (Figure A-4). From the previous discussion of the second key assumption, an estimate of corn maturity classes in a segment is possible. The actual maturity classes of corn planted in a segment may differ due to topography or other local conditions.

The third step is to accumulate the daily increments of thermal units for each planting date. ΣFT and ΣHS (heat stress) models were selected as the best thermal models for predicting corn development stages.

The fourth step is to convert the accumulated thermal units into a widely recognized crop development index, such as Hanway's development stages (Hanway, 1963). Ratios of accumulated thermal units to total accumulated thermal units at maturity can be related to Hanway's development stages for corn. Intermediate stages can be linearly interpolated from the values given in Figure A-2.

6.2 Development Stage Models for Soybeans

The soybean development stage models were evaluated on their ability to predict dates of specific development stages (e.g., flowering, pod set, and maturity). Errors in days for each model were calculated as predicted dates minus actual dates for each stage in 20 planting date-years (5 years and 4 planting dates per year). The best method of prediction was the one where mean error, mean absolute error, and standard deviation were closest to zero.

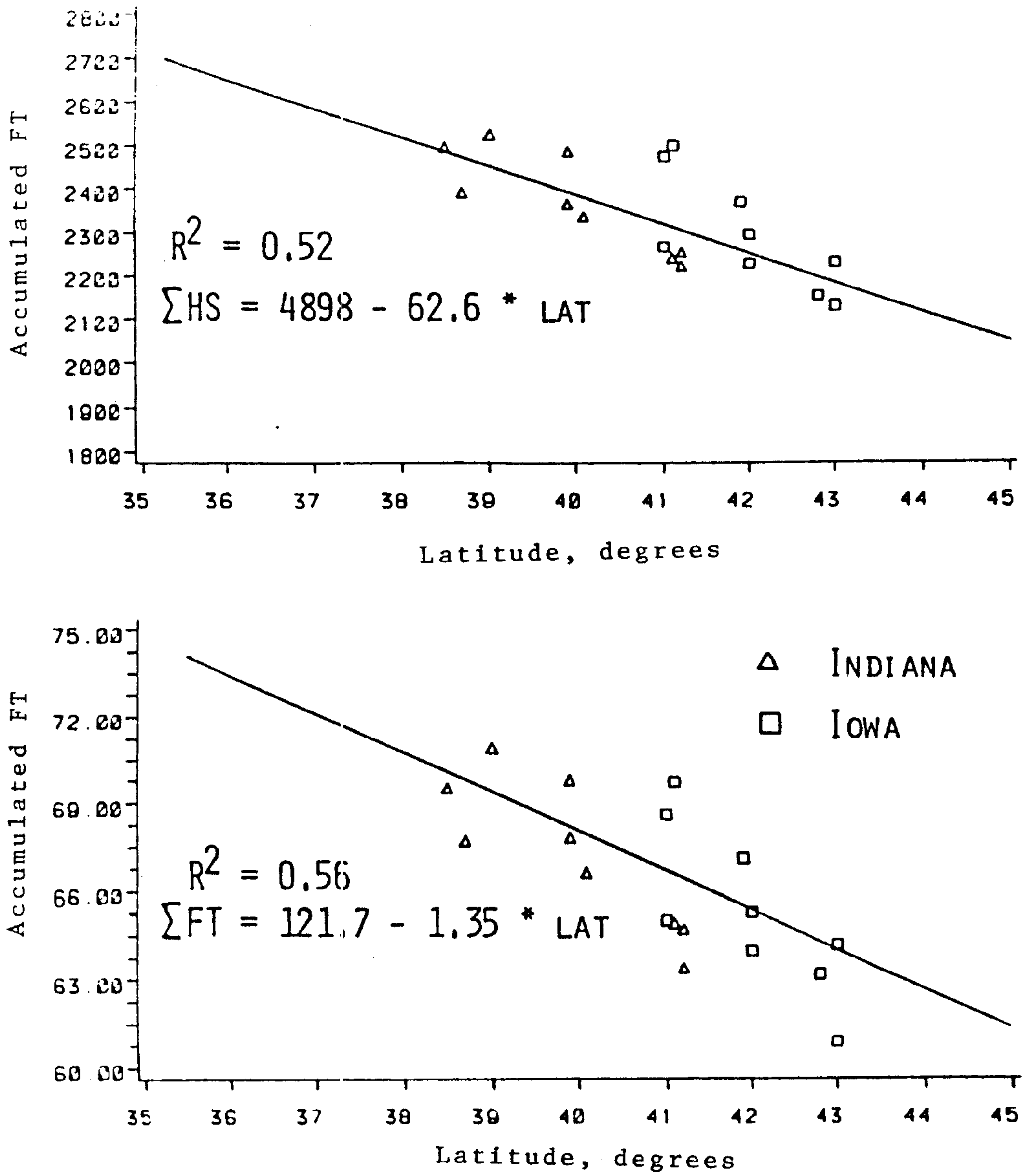


Figure A-3. Mean accumulated ΣHS and ΣFT units from planting to maturity of corn for 15 planting date-years in each crop reporting district (CRD) of Iowa and Indiana plotted as a function of latitude.

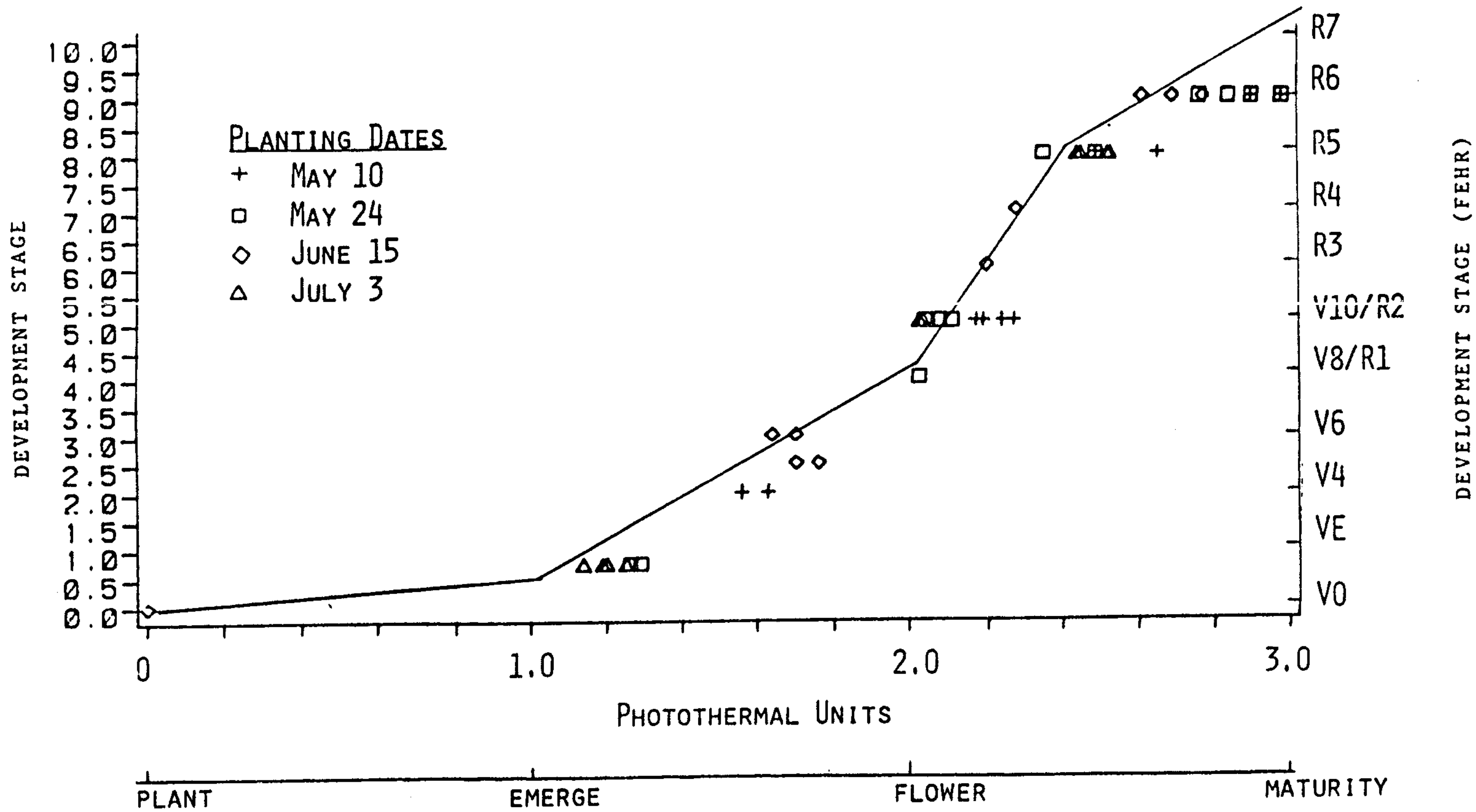


Figure A-4. Relationship of soybean development and photothermal units for soybeans at Purdue Agronomy Farm in 1979.

Preliminary comparisons of thermal, photothermal, and ΣDays models for selected CRD's in Indiana and Iowa indicated that the photothermal model was a better predictor of soybean development than the thermal and ΣDays models, especially for post-flowering stages (Table A-11). The photothermal model accounted for daily changes in both daylength and temperature and thus more nearly predicted soybean development than the ΣDays and thermal models.

The photothermal model consistently had absolute errors as low or lower than the average number of days (ΣDays) models for predicting flowering (Table A-12) and physiological maturity (Table A-13) in each crop reporting district of Indiana and Iowa. The negative errors for flowering indicated that the model consistently predicted that flowering occurred earlier than reported by USDA-ESCS. Some of this negative bias may be due to differences in definition of flowering and physiological maturity. Flowering for the photothermal model occurs when at least 10% of the plants have one flower and physiological maturity occurs when 75% of the leaves have senesced (Major et al., 1975). USDA-ESCS is somewhat less specific in their definitions of soybean development stages. "Bloom" is probably defined as when at least half of the plants in a field have flowers. The USDA-ESCS does not report physiological maturity but does report "leaves turning", "leaves shedding", and in some cases "maturity". Physiological maturity, which is probably analogous to "leaves shedding", was predicted more accurately and consistently than flowering by the photothermal model.

Two key assumptions are necessary to implement this photothermal model for predicting development stage on a continuous basis for large areas. First, the progression of soybean development is assumed to be linear between specified stages (i.e., planting, emergence, flowering, end of flowering, and physiological maturity). The relationships of accumulated photothermal units and development stages of soybeans observed at the Agronomy Farm are illustrated in Figure A-4 for two cultivars and four planting dates. A four segmented line with inflections at emergence (VE), flowering (R1), beginning seed (R5), and physiological maturity (R7.5) was fitted to the data.

The photothermal model as developed by Major et al., (1975b) predicts emergence, flowering, pod fill, termination of flowering and physiological maturity. A simplified version using only equations for "planting to emergence", "emergence to flowering" and "flowering to physiological maturity" appears to adequately describe soybean development (Figure A-4). The inflection point at R5 corresponds to "termination of flowering" and can be estimated as 2.4 photothermal units. Intermediate stages of development may be predicted using linear interpolation between the inflection points in Figure A-4.

The second key assumption is that the portion of the dominant maturity groups of soybeans in a crop reporting district can be estimated as a function of latitude. Because two maturity groups of soybeans comprised more than 90% of the soybean acreage in any crop reporting district, a ratio of the two dominant maturity groups characterized the maturity group distribution (Table A-5). For example,

Table A-11. Soybean development predicted by thermal, photothermal, and ΣDays models minus actual dates. Data are mean absolute errors in days for 20 planting date-years.

STATE	CRD	No. PLANTING DATE-YEARS	THERMAL MODELS ΣGDD	ΣMGDD	ΣHS	ΣFT	Photo-thermal	ΣDAYS
			Planting to Pod Set					
IN	4	20	5.5	4.9	4.1	4.5	2.8	5.5
IA	7	20	2.8	2.8	2.9	2.7	3.0	3.9
			Planting to Maturity					
IN	4	20	21.2	15.3	21.7	16.6	4.7	10.1
IA	7	20	9.1	5.7	9.6	7.3	4.9	4.5

Table A-12. Soybean flowering predicted by a photothermal model and ΣDays model minus actual dates for each crop reporting district (CRD) in Indiana and Iowa. Twenty planting date-years are represented.

	INDIANA			IOWA		
CRD	Photothermal		ΣDays	Photothermal		ΣDays
	$\bar{E}$+	$\lvert\bar{E}\rvert$‡	$\lvert\bar{E}\rvert$	$\bar{E}$	$\lvert\bar{E}\rvert$	$\lvert\bar{E}\rvert$
1	-2	5	11	1	4	9
2	-6	6	11	2	3	11
3	-5	6	10	-2	3	11
4	-7	7	11	0	2	10
5	-7	7	12	2	3	12
6	-7	8	11	-2	2	11
7	-12	12	12	-3	3	10
8	-11	12	11	-1	3	12
9	-12	12	11	-2	2	11
X	-7.7	8.3	11.2	-0.6	2.8	10.8
S_X	3.4	2.9	0.6	1.9	0.7	1.0

+ $\bar{E}$ = Mean error in days for predicted date minus actual date.

‡ $\lvert\bar{E}\rvert$ = Mean absolute error in days.

Table A-13. Physiological maturity (leaves shedding) of soybeans predicted by a photothermal model and ΣDays minus actual dates for each crop reporting district (CRD) in Indiana and Iowa. Twenty planting date-years are represented.

	INDIANA			IOWA		
CRD	Photothermal		ΣDays	Photothermal		ΣDays
	$\bar{E}$	$\lvert\bar{E}\rvert$	$\lvert\bar{E}\rvert$	$\bar{E}$	$\lvert\bar{E}\rvert$	$\lvert\bar{E}\rvert$
1	6	6	8	-4	4	6
2	2	7	8	4	7	6
3	1	7	7	3	8	6
4	1	7	8	-6	7	5
5	-4	9	7	-3	6	5
6	-1	6	8	-9	9	6
7	-4	10	10	-5	5	6
8	-7	9	9	-6	8	7
9	-6	7	9	-10	10	6
$\bar{X}$	-1.3	7.6	8.3	-4.0	7.1	5.9
$S_{\bar{X}}$	4.2	1.4	1.0	4.8	1.9	0.6

+ $\bar{E}$ = Mean error in days for predicted date minus actual date.

‡ $\lvert\bar{E}\rvert$ = Mean absolute error in days.

a ratio of 2.6 indicates that 40% of the soybeans are maturity group II and 60% are maturity group III. Means of these maturity group ratios were plotted versus the median latitude of each CRD in Indiana, Illinois, and Missouri (Figure A-5). A linear relationship appears to adequately describe the mean maturity group distribution. No data were available for Iowa and other northern soybean growing states and caution should be exercised in predicting maturity groups for latitudes greater than about 44 degrees.

If these two assumptions are valid, an approach with five steps to estimate development stages of soybeans on a daily basis is proposed. Although this approach was developed using data reported by USDA-ESCS, it should be applicable to segments.

The first step, which is the same as the corn development stage model, is to determine planting dates. Normal planting date is the initial approximation of planting date, meteorologically-based models provide a second approximation and finally spectral-meteorological models provide planting dates for specific fields.

The second step in this soybean development stage model is to determine the two dominant maturity groups of soybeans in the segment based on latitude of the segment using Figure A-5. Actual proportions of each maturity group planted in a segment may vary slightly due to topography, local preference for particular cultivars, and local climatology.

In the third step the coefficients (Table 1 in Major et al., 1975b) of the four cultivars which represent the two dominant maturity groups in a segment are selected and the daily increments in development stages are computed for each planting date. The regression coefficients were derived for two representative cultivars in maturity groups I to V.

Fourth, the weighted mean development stage which is the average of both maturity groups weighted by their proportion in the segment are computed for each planting date. Alternatively, the predicted development stage for each maturity group may be reported separately.

Finally, the photothermal development units are converted to a standard soybean development stage index, such as reported by Fehr et al. (1971) and illustrated in Figure A-4.

7. Summary and Conclusions

In summary this task reviewed several "state-of-the-art" development stage models for corn and soybeans. One photothermal model and four thermal models were selected and evaluated using data from plots at the Purdue Agronomy Farm and statistical data for crop reporting districts in Indiana and Iowa.

For corn the heat stress and temperature function models performed better than growing degree days, modified growing degree days, and sum

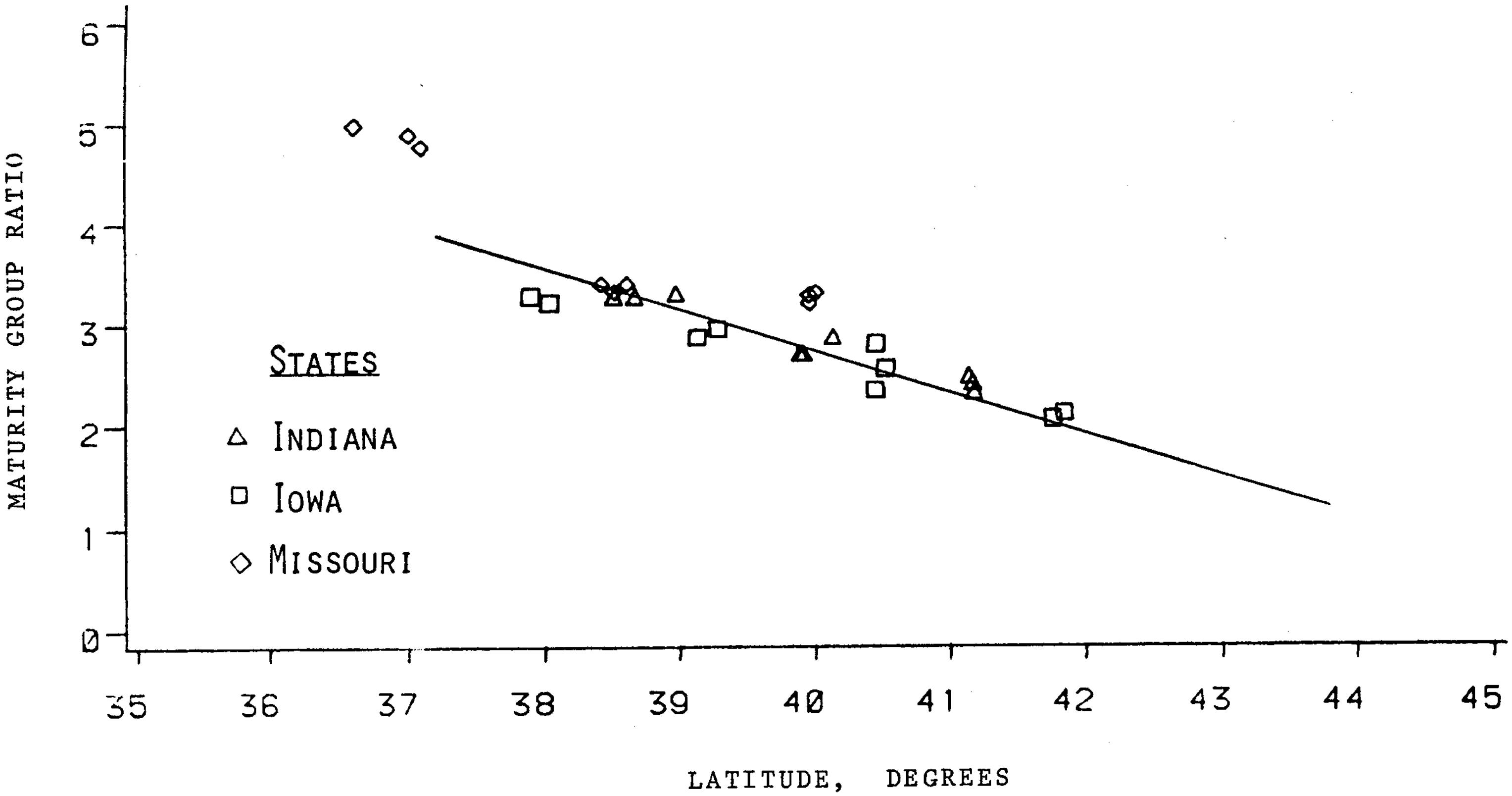


Figure A-5. Soybean maturity group ratio plotted as a function of the median latitude of crop reporting districts in Indiana, Illinois, and Missouri.

of calendar days for predicting silking and maturity. For soybeans the photothermal model provided better predictions of flowering and physiological maturity than any of the thermal models or calendar days. These models were then modified to predict development stages on a continuous or daily basis for crop reporting districts and segments within crop reporting districts.

During the coming year further tests of the meteorological models will be conducted, a planting date model will be implemented and evaluated as a means to "start" the development stage models, and spectral models (Badhwar and Henderson, 1980) and spectral-meteorological models (Hanson et al., 1980) will be evaluated. Finally, these concepts and models will be extended to Argentina and Brazil for initial development and testing.

8. References

1. Andrew, R.H., F.P. Ferwerda, and A.M. Strommen. 1956. Maturation and yield of corn as influenced by climate and production technique. Agron. J. 48: 231-236.

2. Aspiazu, C. and R.H. Shaw. 1972. Comparison of several methods of growing degree unit calculations for corn (Zea mays L.) Iowa State J. Sci. 46: 435-442.

3. Badhwar, G.D. and K.E. Henderson. 1980. Development stage estimation of corn from spectral data - an initial model. AgRISTARS Tech. Report SR-J0-00488, NASA Johnson Space Center, Houston, TX.

4. Coelho, D.T. and R.F. Dale. 1980. An energy-crop growth variable and temperature function for predicting corn growth and development: planting to silking. Agron. J. 72: 503-510.

5. Bauer, M.E., L.L. Biehl, C.S.T. Daughtry, B.F. Robinson, and E.R. Stoner. 1979. Agricultural scene understanding and supporting field research. Laboratory for Applications of Remote Sensing, Purdue Univ., West Lafayette, IN. LARS Contract Report 112879, pp. 1-46.

6. Coligado, M.C., 1974. Tassel initiation studies in corn (Zea mays L.): Temperature and photoperiod effects and a bio-photo-thermal model. Ph.D. Thesis. University of Guelph, Guelph, Ont. 107 pp.

7. Coligado, M.C. and D.M. Brown. 1975. Response of corn in the pre-tassel initiation period to temperature and photoperiod. Agric. Meteorology 14: 357-367.

8. Cross, H.Z. and M.S. Zuber. 1972. Prediction of flowering dates in maize based on different methods of estimating thermal units. Agron. J. 64: 351-355.

9. Fehr, W.R., C.E. Caviness, D.T. Burmood, and J.S. Pennington. 1971. Stage of development descriptions for soybean. Glycine may (L.) Merrill. Crop Sci. 11: 929-931.

10. Gilmore, E. and J.S. Rogers. 1958. Heat units as a method of measuring maturity in corn. Agron. J. 50: 611-615.

11. Hanway, J.J. 1963. Growth stages of corn (Zea mays, L.). Agron. J. 55: 487-492.

12. Hodges, T. and P.C. Doraiswamy. 1979. Crop phenology literature review for corn, soybean, wheat, barley, sorghum rice, cotton, and sunflower. Lockheed Electronics Co., Houston, TX. SR-L9-00409/ JSC-16088.

13. Johnson, H.W., H.A. Borthwick, and R.C. Leffel. 1960. Effects of photoperiod and time of planting on rates of development of the soybean invarious stages of its life cycle. Bot. Gaz. 122: 77-95.

14. Lawn, R.J. and D.E. Byth. 1973. Response of soya beans to planting date in South-Eastern Queensland. I. Influence of photoperiod and temperature on phasic development patterns. Aust. J. Agr. Res. 24: 67-80.

15. Major, D.J., D.R. Johnson, and V.D. Lueddens. 1974a. Evaluation of eleven thermal unit methods for predicting soybean development. Crop Sci. 15: 172-174.

16. Major, D.J., D.R. Johnson, J.W. Tanner, and I.C. Anderson. 1975b. Effects of daylength and temperature on soybean development. Crop Sci. 15: 174-179.

17. Mederski, H.J., M.E. Miller, and C.R. Weaver. 1973. Accumulated heat units for classifying corn hybrid maturity. Agron. J. 65: 743-747.

18. Neild, R.E. and M.W. Seeley. 1977. Growing degree days predictions for corn and soybean development and some application to crop production in Nebraska. Nebraska Agric. Exp. Sta. Res. Bul. 280.

19. Ranson, K.J., M.M. Hixson, V.C. Vanderbilt, and M.E. Bauer. 1980. Estimation of corn and soybean development stages from spectral measurements. In Field research on the spectral properties of crops and soils. AgRISTARS Report SR-P0-00412, Laboratory for Applications of Remote Sensing, Purdue University, W. Lafayette, IN.

20. Robertson, G.W. 1968. A biometeorological time scale for a cereal crop involving day and night temperatures and photoperiod. Int. J. Biometeorol. 12: 191-223.

21. Stauber, M.S. M.S. Zuber, and W.L. Decker. 1968. Estimation of the tasseling date of corn (Zea mays L.) Agron. J. 60: 432-434.

22. Tsotsis, B. 1958. The use of thermal and photothermal units for describing flowering and maturation in maize. Diss. Abstr. 19: 1156-1157.

23. Whitehead, V.S., D.E. Phinney and W.E. Crea. 1978. Growth stage estimation. Proc. LACIE Symp., pp. 109-114. JSC-16015. Oct. 1978. NASA Johnson Space Center, Houston, TX.

24. USDA Economics, Statistics, and Cooperatives Services. 1970-1979. Illinois Agricultural Statistics Annual Summary. Illinois Dept. Agric. Bull. 80-1. Springfield, IL.

25. USDA Economics, Statistics, and Cooperatives Services. 1970-1979. Indiana Crop and Livestock Statistics Annual Summary. Agric. Exp. Stn., Purdue University, West Lafayette, IN.

26. USDA Economics, Statistics, and Cooperatives Service. 1970-1979. Iowa Agricultural Statistics. Iowa Dept. Agric., Des Moines, IA.

27. USDA Economics, Statistics, and Cooperatives Service. 1970-1979. Annual Crop Weather Summary. Iowa Dept. Agric., Des Moines, IA.

28. USDC. Environmental Data Service. 1969-1978. Climatological data, Indiana, Illinois, Iowa. Natl. Climatic Center, Asheville, NC.

29. Wang, Jenyu. 1960. A critique of the heat unit approach to plant response studies. Ecology 41: 785-790.

B. DETERMINATION OF THE VALUE OF SPECTRAL INFORMATION IN ESTIMATION OF AGRONOMIC VARIABLES ASSOCIATED WITH YIELDS OF CORN AND SOYBEANS

C.S.T. Daughtry and N.C. Fuhs*

1. Introduction

In recent years the world food situation has emphasized the need for accurate and timely information on world-wide crop production. This information is vitally important for efficient planning of production and distribution of grains. Tests of the feasibility of utilizing multispectral satellite data to identify and measure crop area have been successfully completed (MacDonald and Hall, 1980). However, relatively little research and development has been conducted on the potential capability of similar data to provide information on crop condition.

Weather accounts for most of the year-to-year fluctuations in food production and remains the most important uncontrolled variable affecting crop production (Decker et al., 1976). Considerable attention is being focused on studying and understanding the relationships between weather and crop production. Other more static factors such as soil characteristics, management practices, and economic conditions also significantly affect crop production. Continued research into all aspects of crop production and the development of operational crop yield assessment methods are urgently needed and some steps to expand national and international agrometeorological research activities have begun (Baier, 1977).

1.1 Incorporating Weather Variables in Crop Yield Models

During the last several decades numerous studies developed crop yield models. In general, there are three basic types of crop models: statistical; physiological; and "hybrid" models. The statistical models which incorporate weekly or monthly mean weather and crop performance into prediction equations require extensive historical data, typically 20 to 30 years, to derive the equations. Because crop yields and production have increased dramatically over the past 30 to 40 years with the introduction of new technology, statistical models must include terms describing those trends in technology and farming practices. Such equations tend to be specific to certain areas of the country which necessitates a rederivation of the equation when applied to new areas. The corn models of Thompson (1969) and the wheat models of Strommen and

----

*The contributions of D.A. Holt, C.E. Seubert, R.A. Weismiller, and L. Grant to this task are gratefully acknowledged.

coworkers (1979) are examples of statistical models. Baier (1977) reviewed and discussed the uses and limitations of several statistical models for assessing the impact of weather on crop production and found them useful for assessing large scale weather and crop production.

The physiological models describe crop performance as a series of functions of hourly or daily weather conditions (Holt et al., 1975). These models are designed to simulate responses of basic physiological or biological plant processes to the crop's environment and, ultimately, to predict crop yields. While some simulation models may be too specific to apply to large areas, these models tend to require less detailed historical data for calibration and validation (Holt et al., 1979) than the true statistical models.

In an effort to combine the best features of the statistical and physiological models, "hybrid" models were developed. The Energy Crop Growth model (Dale & Hodges, 1975; Coelho and Dale, 1980) and later the Purdue Soybean Simulator (Holt et al., 1979) condensed the effects of weather on crops into one or two computed variables which were related to yield. These "hybrid" models are less complex than the physiological models because a single weather index is used.

Light, water, nutrients, carbon dioxide, and reasonable temperatures are essential for plant survival and growth. Even though light is the energy source for photosynthesis which converts carbon dioxide and water into photosynthate and ultimately crop yields, other factors may be limiting and thus more important in determining the final outcome of a growing season. Light is only one of many important variables affecting crop yields and must be considered as interacting with other variables, not in isolation. Consequently, single factor crop models have had only limited success in predicting crop yields.

1.2 Incorporating Soil Productivity in Crop Yield Models

In addition to the effects of technology and weather on biological processes related to yield, soil productivity is an important variable in determining crop yields. Soils, though continuous entities, when divided into classes exhibit a range of properties which complicate their inclusion in yield models. Very few yield models directly account for limitations imposed by soil characteristics on crop production.

The classification system is divided into two basic systems (1) the natural soil classification system, grouping soils by properties and characteristics as they exist in nature, and (2) the technical soil classification system, grouping soils by factors which affect use and management. Soil productivity rating systems assess soil features which affect crop production and assign crop production potentials. Proper management in some cases can compensate for limitations imposed by native soil productivity and must be included in crop yield models. Inclusion of soil productivity variables into crop yield models is being investigated.

1.3 Incorporating Remotely Sensed Variables in Crop Yield Models

In general there are many types of information available to improve yield forecasts that potentially can be obtained from remotely sensed data. These include: environmental information such as soil characteristics, meteorological conditions, and episodic events; management variables encompassing technological or trend factors and economic conditions; and plant characteristics including biomass accumulations, stress effects, and development stage information. Remotely sensed data has the most potential for interfacing with physiological and "hybrid" models both in influencing the models' predictions directly and in verifying and updating the models' estimates.

Soil drainage classes, which are related to soil texture and organic matter content, are identifiable from Landsat MSS data (Hinzel et al., 1980). Thus Landsat MSS data may be used to evaluate soil productivity based on soil drainage over large areas. Further research into methods of directly assessing soil productivity with remotely sensed data is in progress.

2. Objectives

The overall objective of this task is to evaluate spectral data as a source of information for use in crop yield models. Specifically this task will:

- Identify important factors in determining yield that can be estimated from spectral data.
- Evaluate those selected factors utilizing spectral and agronomic data acquired in controlled experiments at an agricultural experiment station.
- Extend the factors that best estimate crop yield at the agricultural experiment station level to large areas using Landsat MSS data.
- Compare the results of estimating yield with and without spectral information.

3. Data Bases

Two sources of spectral data were used to assess the value of spectral information for predicting the yield of corn. Data acquired using the Exotech Model 100 radiometer at the Purdue Agronomy Farm in 1979 were used in initial testing and evaluation of the intercepted solar radiation (SRI) variable. These data provided detailed spectral and agronomic observations of approximately 50 plots. The observations were collected at irregular intervals although all crop development stages are represented. Different cultural practices were represented where treatments included three plant populations (25,000; 50,000; and 75,000 plants/ha), three planting dates (May 2; May 16; and May 30), and two soil types (light and dark). Crop development stages (Hanway, 1963) were noted throughout the growing season and grain yields were measured at harvest.

The other set of spectral data included Landsat MSS data acquired in 1978 over commercial corn fields in eleven 5 x 6 nautical mile segments located in five states (Figure B-1). Within each of the segments up to 10 corn fields were identified and means and standard deviations were computed for each field in each spectral band for each date of a Landsat overpass. Crop development stages were observed at 18-day intervals from late June until harvest. Grain yield was estimated by each grower (farmer) after harvest.

Meteorological data ordered from NOAA National Climate Center contained data for all cooperative weather stations in Indiana, Illinois, and Iowa. More than 100 stations per state were available with 10 year (1969-1978) historical data ranging from daily maximum and minimum air temperatures and daily precipitation records for all stations to daily evaporation data collected for selected stations.

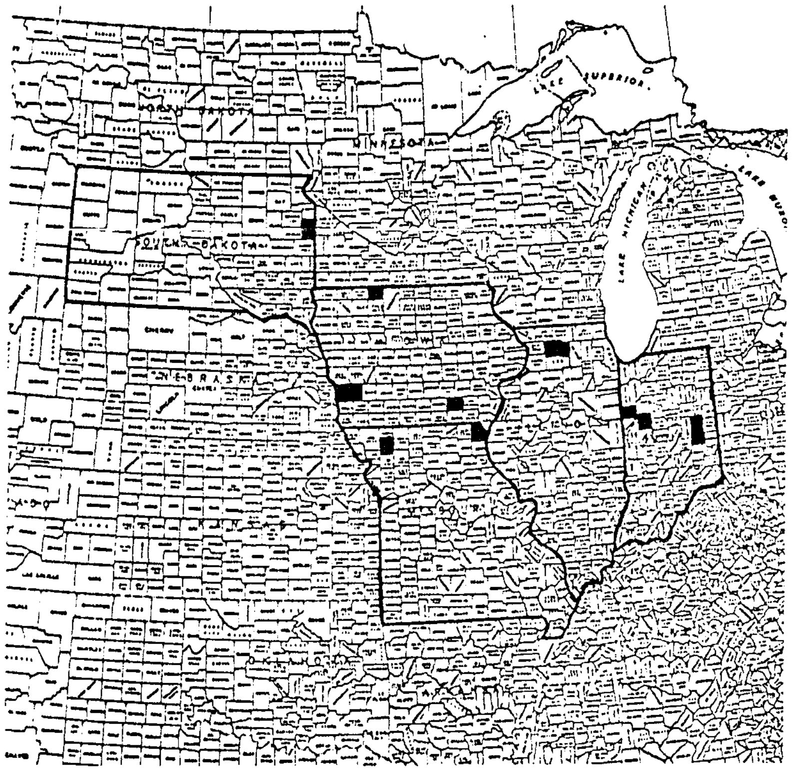
The soils productivity data base available at Purdue/LARS includes digital data for soil series/soil associations for 11 counties. At least 26 additional counties have soil productivity information available at the state offices and more than 60 counties have digital soils data available although this data is not in-house at Purdue/LARS. To complete the soils data base detailed soil surveys, soil productivity ratings for Indiana, Illinois, Ohio, and Nebraska, and soil water holding capacity information for soils for each county in Indiana are currently being assembled.

4. Results and Discussion

4.1 Intercepted Solar Radiation

Solar radiation as an energy source for plants is available only when it interacts with leaves. Considerable effort has been expended to estimate and measure the attenuation of light in crop canopies (Norman, 1980; Hatfield and Carlson, 1977). The ratio of total solar radiation intercepted by a corn canopy has been described as a function of LAI (Linvill et al., 1976) and is shown in Figure B-2. This is an application of Beer's law using LAI of corn canopies and extinction coefficient of 0.79 determined by Stevenson and Tanner (1970). When LAI is 0, no energy is intercepted. When LAI is 2.8 about 90% of the visible solar radiation is intercepted by the canopy and is potentially useful to the crop.

In their work, Dale and coworkers (Linvill et al., 1976; Dale, 1977) measured LAI to calculate intercepted solar radiation (SRI) but suggested a method to estimate an average LAI for corn canopies based on



Segment	Spectral Data Acquisitions
INDIANA	
854	GOOD
843	GOOD
840	GOOD
837	GOOD
IOWA	
836	ONLY 1 DATE IN AUG
867	MISSING JUNE, JULY
144	ONLY 1 DATE JULY
MISSOURI	
209	GOOD
205	ONLY 1 DATE IN JULY 1 DATE IN AUG
ILLINOIS	
809	ONLY 1 DATE FOR EACH JUNE, JULY AND AUG
SOUTH DAKOTA	
241	ONLY 1 DATE IN JUNE

Figure B-1. Location of Landsat MSS data segments.

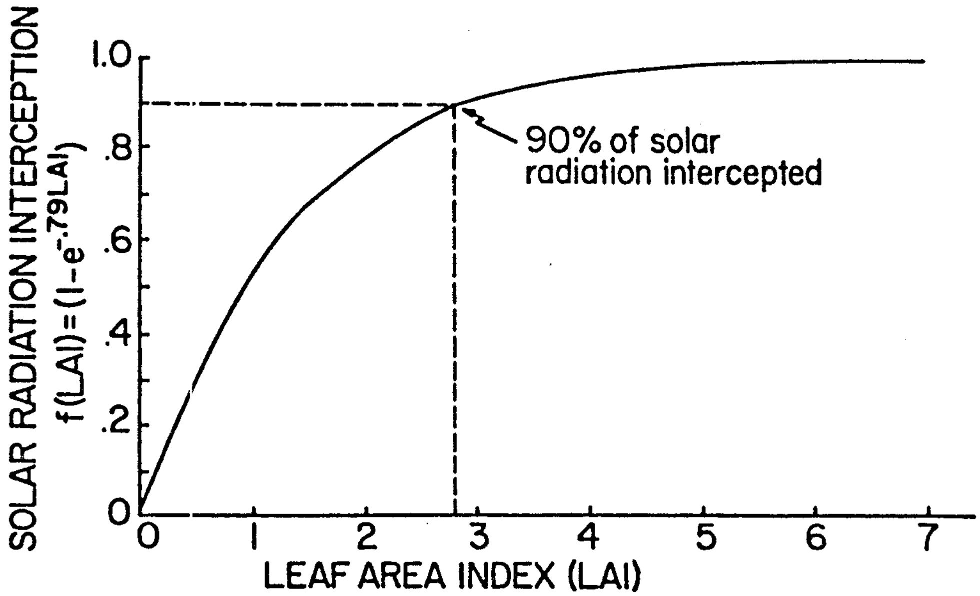


Figure B-2. Solar radiation weighting factor for determining interception of solar energy by corn crop as a function of its leaf area index.

date of silking and plant populations. However, LAIs for corn may vary greatly over large areas due to different planting dates, hybrids, stresses, and row spacings. Remotely sensed data can provide estimates of LAI and percent soil cover (Walburg et al., 1980; Nash et al., 1980). Thus estimates of intercepted solar radiation based on spectrally-derived estimates of LAI should more accurately depict conditions in each field.

Intercepted solar radiation (SRI) values were calculated for each day on which spectral data was acquired and was linearly interpolated for intermediate days throughout the growing season for each field in the data set acquired at the Agronomy Farm. Figure B-3 illustrates three examples of computed SRI over the growing season for fields having the same planting date, May 2, but three plant population densities. These SRI values were derived using an LAI value that was a function of the Greenness Transformation (Malila and Gleason, 1977) adjusted for soil background (Figure B-4). This Greenness function estimated LAI and permitted the results of the Agronomy Farm research to be extended to Landsat MSS data where only spectral response was available.

Although plant populations determine the maximum LAI that maize canopies can achieve, including population as a term in a multiple regression contributed little additional information. More than 79 percent of the variation in LAI was associated with the spectral variables alone i.e., greenness as shown in Figure B-4. Spectral variables plus plant population accounted for only 2 percent more variation. Other cultural practices used in this experiment contributed even less information than plant population to estimating LAI.

The SRI values calculated in this experiment are based solely on spectral data. The SRI values are the accumulated daily SRI's from 6 weeks prior to silking to 6 weeks after silking. SRI values calculated using spectrally-derived LAI and field measured LAI were very similar and did not differ significantly.

One problem in crop response to light research is the confounding of solar radiation and plant moisture stress effects on plant growth and yields. Dale (1977) assumed that the reduction in crop growth was proportional to the reduction in evapotranspiration (ET) from potential evapotranspiration (PET). By combining both intercepted solar radiation and moisture stress functions, Dale computed an Energy-Crop-Growth (ECG) variable which he used to identify weather effects on corn growth and yields. Daily values of ECG were accumulated for a period from 6 weeks prior to silking to 6 weeks after silking.

Three separate spectral variables were examined to determine their relationship to corn yields. First, maximum greenness which occurred at silking was used to represent the maximum LAI and vigor of the canopy. Second, SRI represented the integrated value of intercepted solar radiation during the critical period from 6 weeks before silking to 6 weeks after silking. Third, ECG combined both intercepted solar radiation and moisture stress for the 12 week period centered about silking. Each additional piece of information increased the correlation

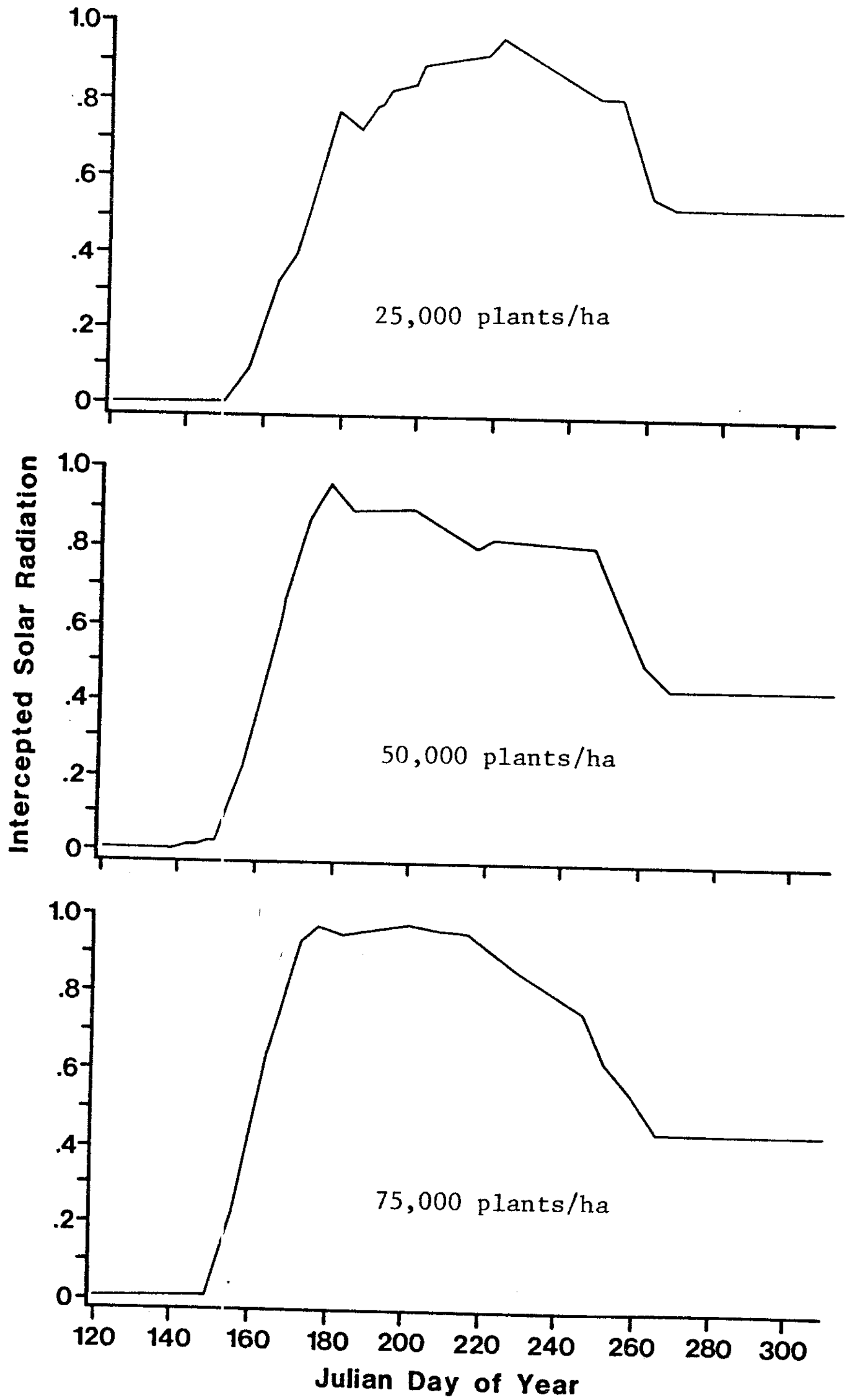


Figure B-3. Intercepted solar radiation computed over the growing season for three plant populations planted on May 2, 1979.

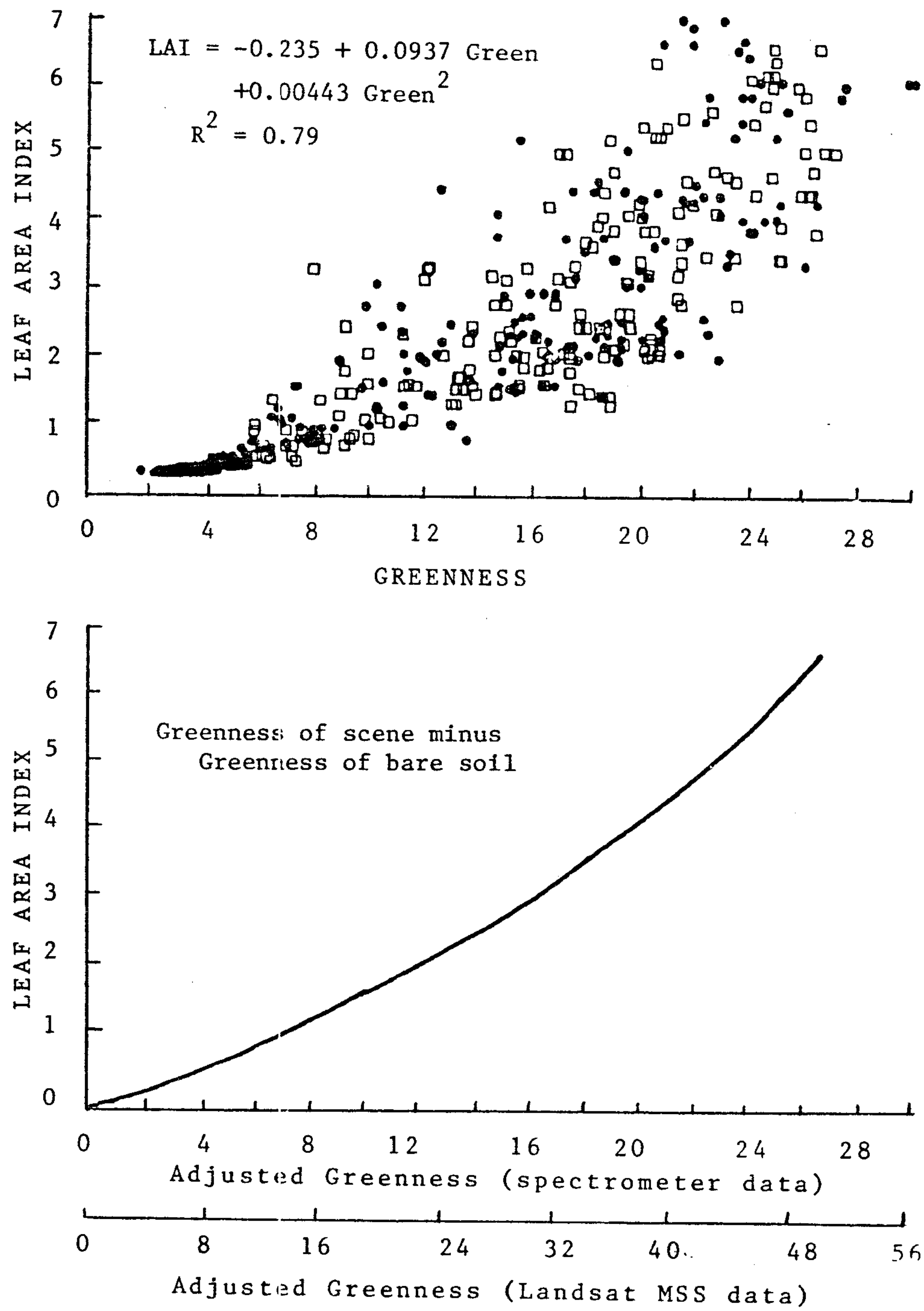


Figure B-4. Leaf area index as a function of greenness adjusted for soil background.

with yields (Figure B-5) and indicated that together spectral and meteorological data can provide more information than either can alone.

These preliminary analyses of spectral data acquired at the Purdue Agronomy Farm indicated that (1) SRI for fields can be estimated from spectral data, (2) SRI and ECG may be more useful in predicting grain yields than a single acquisition of spectral data, and (3) ECG which combines both spectral and meteorological data may provide the most information about crop yield. Since one of the goals of this task is to evaluate spectral variables associated with yields, the next step was to extend these analyses to large areas using Landsat MSS data.

Eleven segments throughout the Corn Belt states were identified (Figure B-1). Based on the Greenness value calculated for each of the 10 selected corn fields within each segment, SRI values for each day of the growing season were computed (Figure B-6). However, when the SRI summed over a period of six weeks before silking and six weeks after silking were correlated with yield (Figures B-7, B-8, B-9), the results were disappointing. Even in segment 854 which was spatially adjacent to the Purdue Agronomy Farm, SRI was not correlated (r=0.05) with yield (Table B-1). The only segments which produced high correlations, Deuel (.77) and Clark (.88), were segments where there was a large range in yields in the 10 fields.

When all fields produced similar yields, there was little or no correlation between yield and SRI. Figure B-10 illustrates the relationship between SRI and yield for all Landsat MSS segments. The lower correlation (r=0.47) of SRI and yields for fields in these segments compared to the correlation (r=0.62) of SRI and yields for plots may indicate differences in the accuracy of measuring grain yields over large areas compared to small plots. The meteorological data needed to calculate ECG are being assembled and further analyses including adding a temperature response function to the ECG model are planned when the data are available. Because the number and timing of Landsat acquisitions differs from segment to segment a curve-fitting technique, such as employed by Badhwar and Henderson (1980), will be investigated to standardize the estimate of SRI.

In summary, the concepts and analysis techniques developed using Field Research data from the Agronomy Farm were successfully implemented and tested using Landsat MSS data. The accumulated intercepted solar radiation (SRI) variable was not highly correlated to corn yields in these fields. Based on previous research at the Agronomy Farm, higher correlations with corn yields can be expected with the inclusion of meteorological data (e.g. ET/PET and temperature) in the accumulated Energy-Crop-Growth (ECG) variable. Further refinement of these and

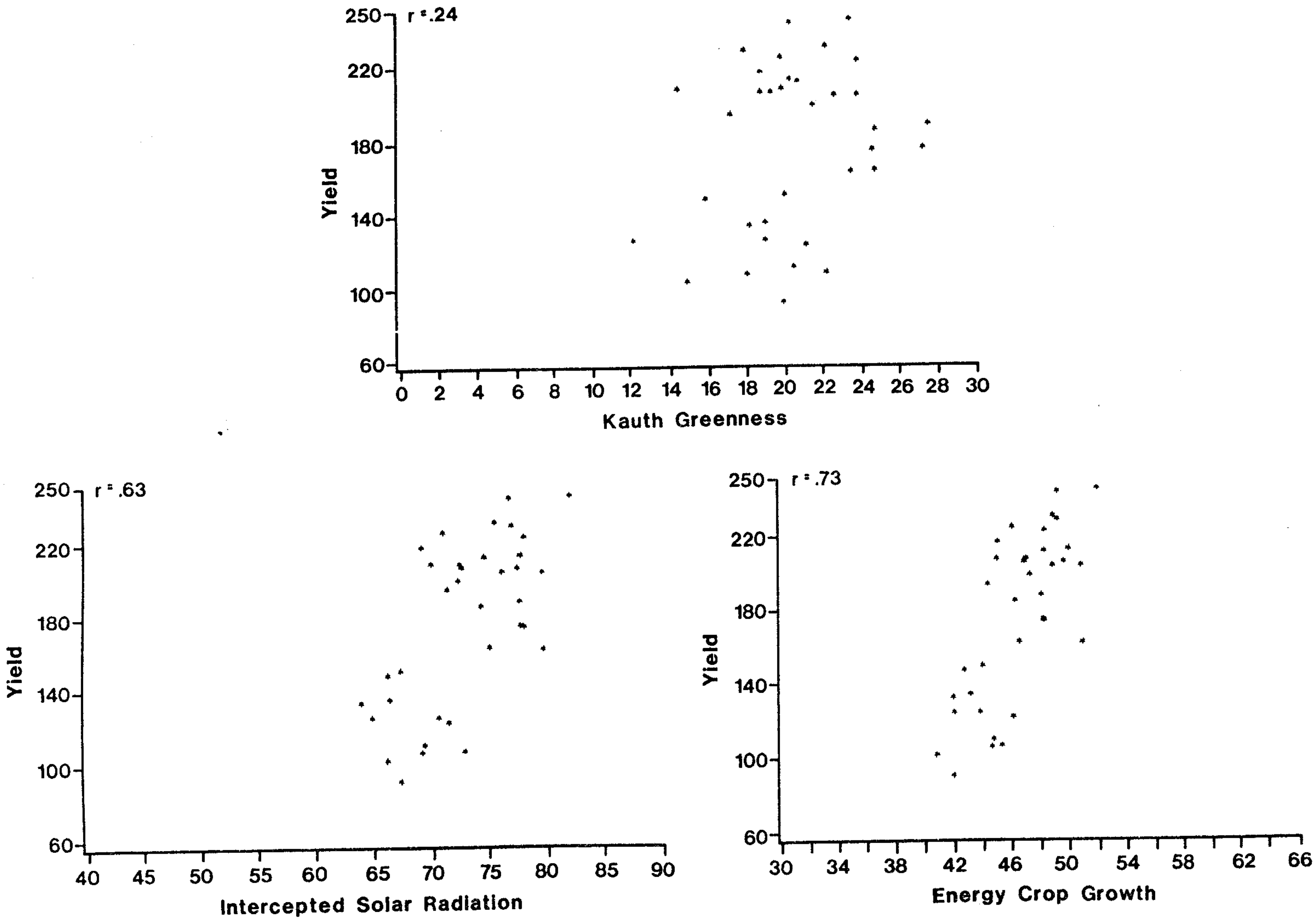


Figure B-5. Correlation of yield with three variables, each adding additional information to the prediction equation.

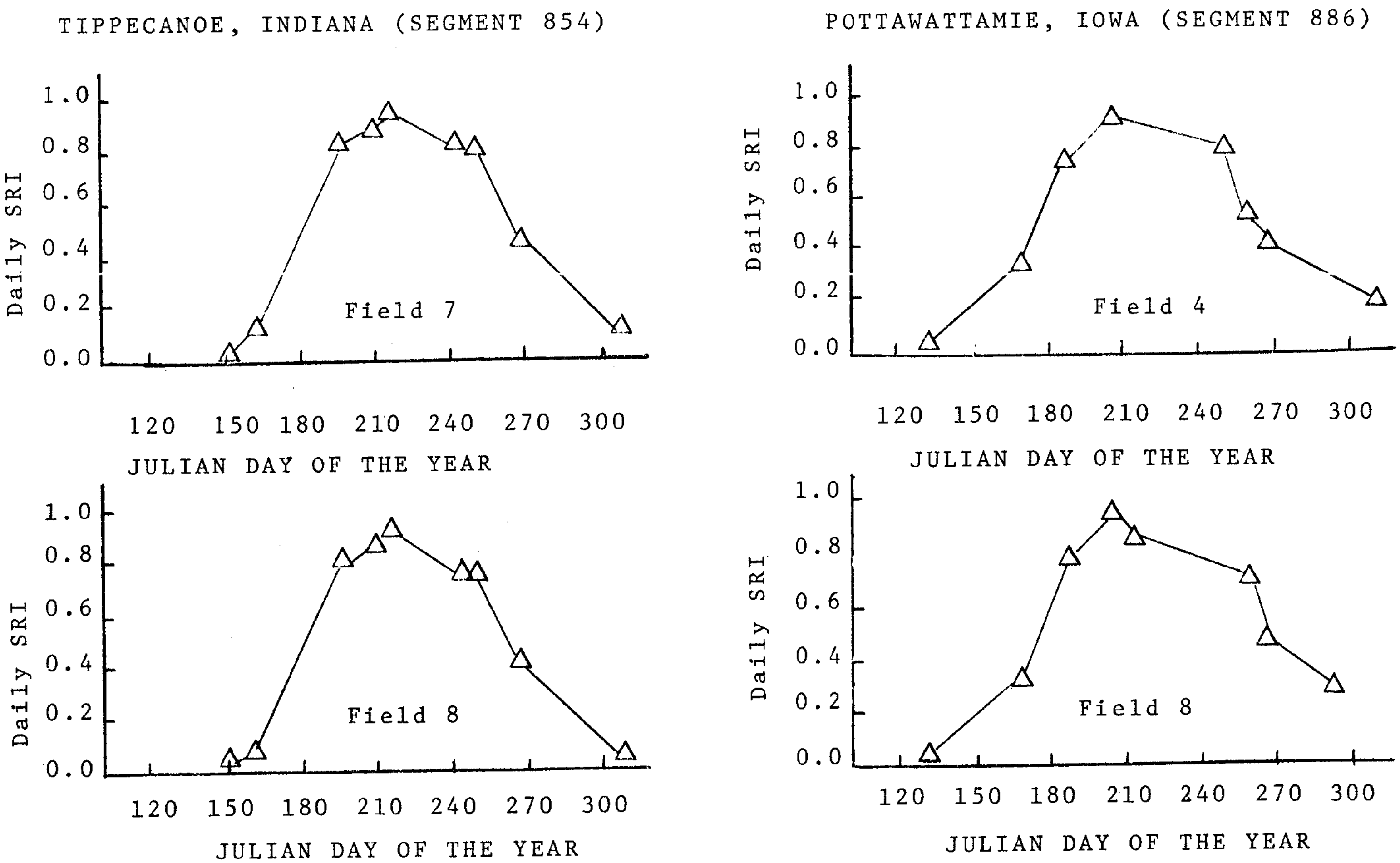


Figure B-6. Daily values of intercepted solar radiation (SRI) determined from Landsat MSS data for selected corn fields in 1978.

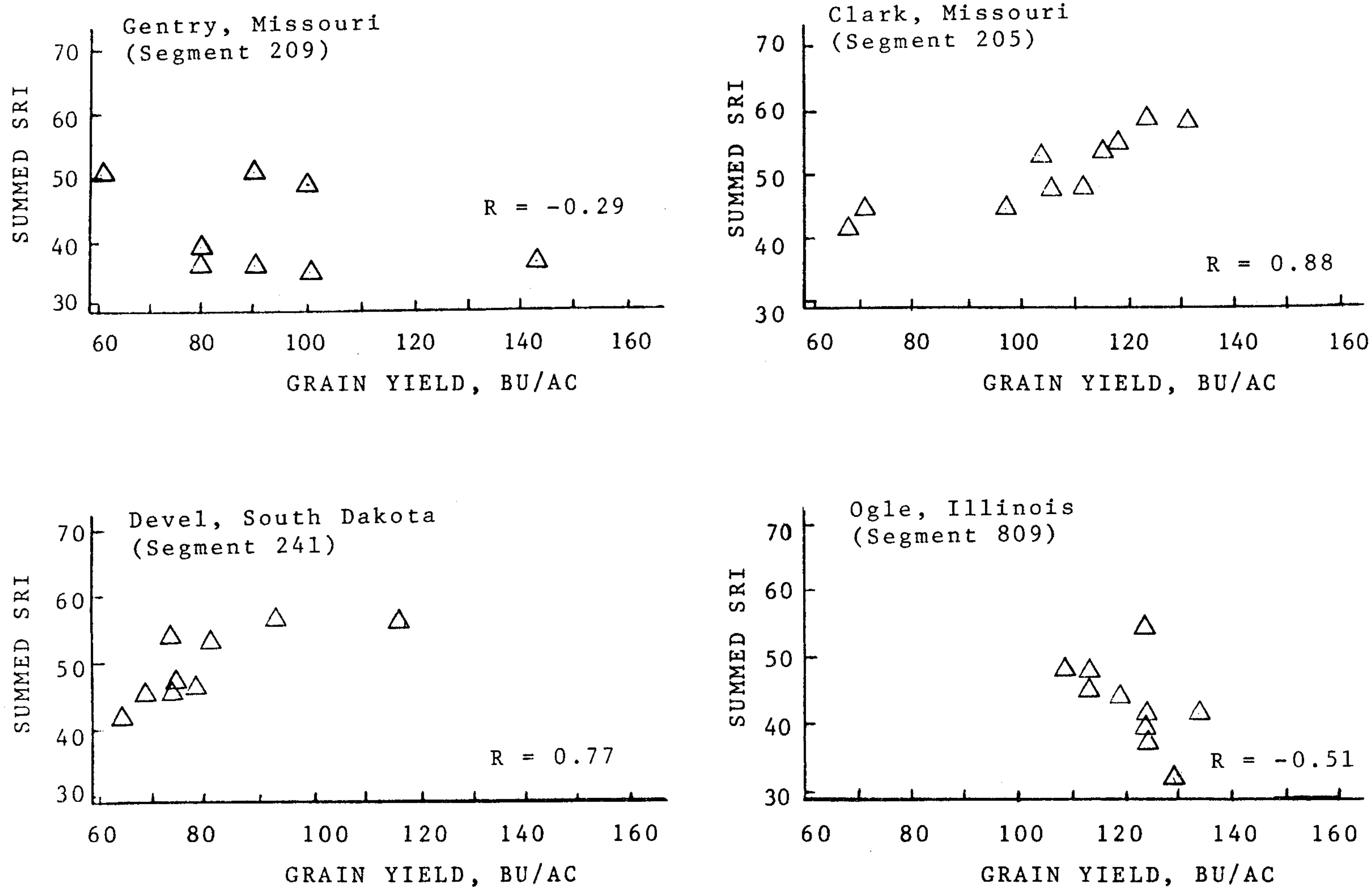


Figure B-7. Daily intercepted solar radiation (SRI) accumulated for ± 6 weeks of silking plotted with corn yields in bushels/acre (segments 209, 205, 241, 809).

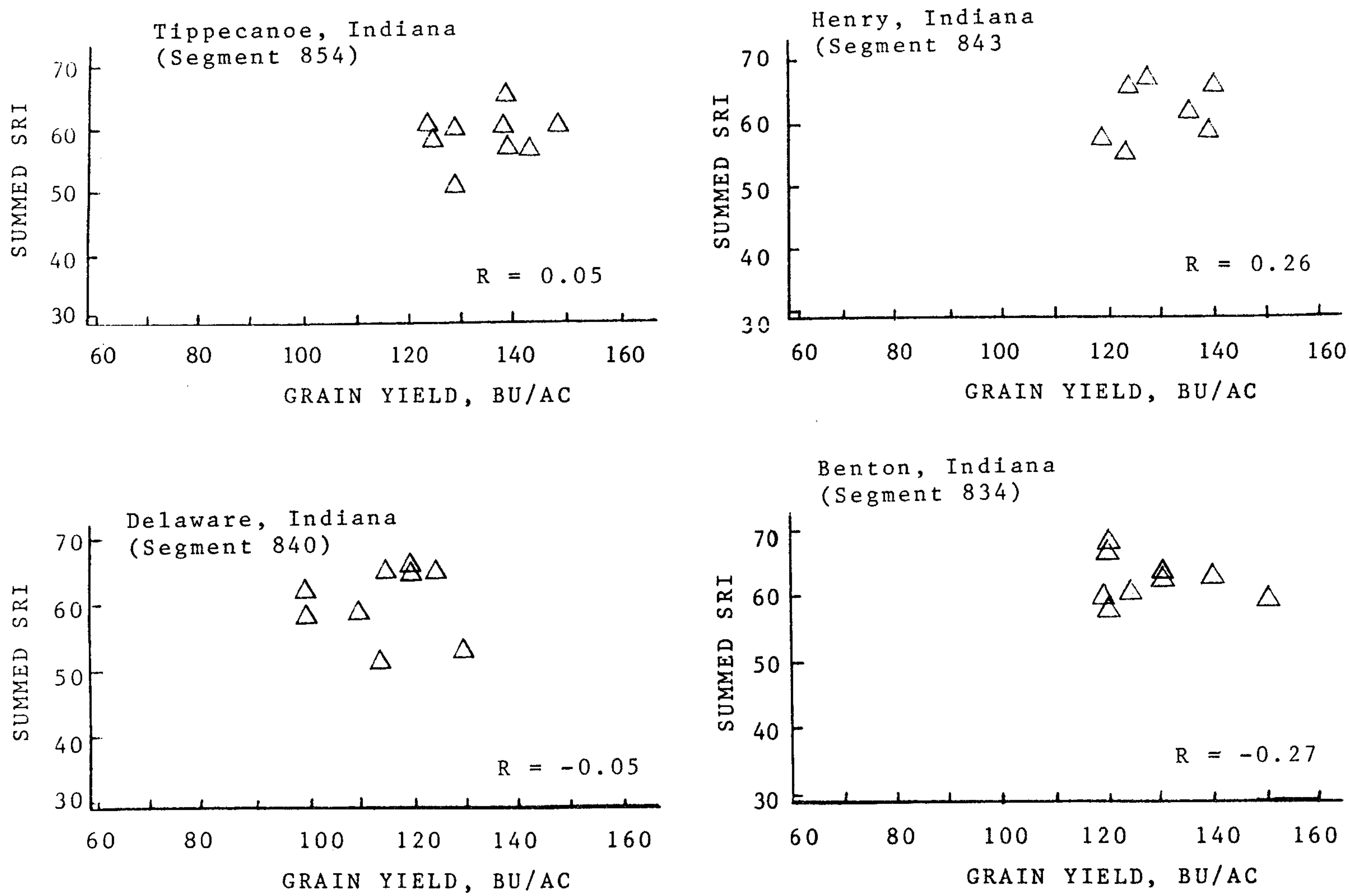


Figure B-8. Daily intercepted solar radiation (SRI) accumulated for ± 6 weeks of silking plotted with corn yields in bushels/acre (segments 854, 843, 840, 834).

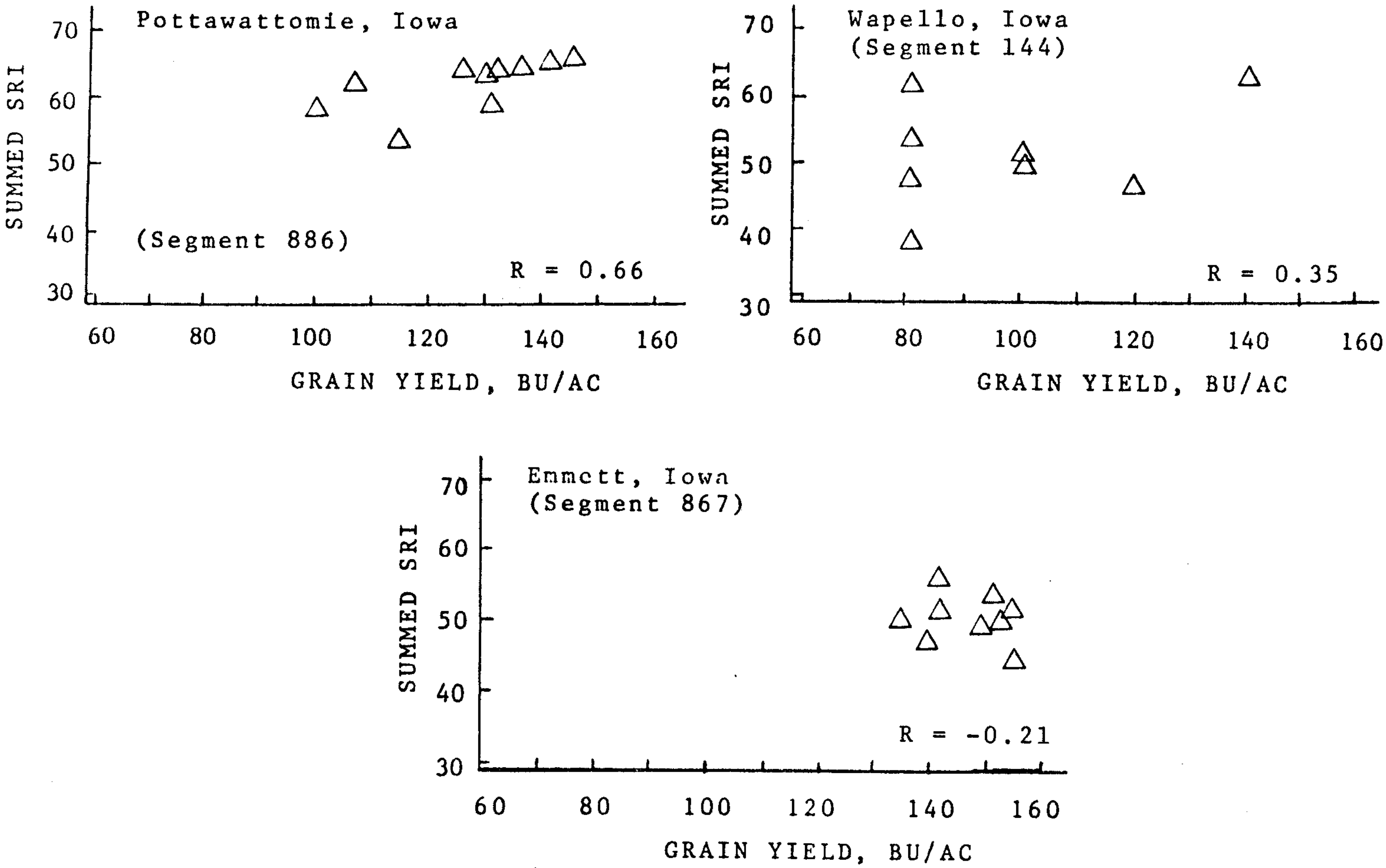


Figure B-9. Daily intercepted solar radiation (SRI) accumulated for ± 6 weeks of silking plotted with corn yields in bushels/acre (segments 886, 144, 867).

Table B-1. Summary of analyses relating intercepted solar radiation and greenness to grain yield.

State	Segment	N	Silking Date†	Corn Yield Mean	Corn Yield Min	Corn Yield Max	SRI±	R±	Green§	R§
				bu/ac						
IL	809	10	200	123	110	135	44.3	-0.51	54.4	-0.56
IN	837	9	216	128	120	150	62.7	-0.27	57.2	-0.88
	840	9	217	115	100	130	60.6	-0.05	61.6	-0.27
	843	7	217	131	120	141	62.2	-0.26	63.8	-0.26
	854	10	204	135	125	150	58.9	-0.05	59.2	-0.33
IA	144	8	297	98	80	140	51.5	0.35	56.5	0.29
	867	9	198	147	135	155	50.5	-0.21	55.6	0.16
	886	10	204	127	101	146	62.0	0.66	63.7	0.46
MO	205	10	208	104	68	130	50.1	0.88	54.1	0.67
	209	8	219	82	55	100	42.9	-0.29	56.9	0.64
SD	241	9	205	81	65	117	50.3	0.77	56.9	0.80
	$\overline{X}$	99	-	116	55	155	54.1	0.42	57.9	0.19

† Average silking date for fields in segment.

± Sum of daily intercepted solar radiation (SRI) variable ±6 weeks of silking. Simple correlation (R) of yield and SRI.

§ Greenness variable of each field at silking. Simple correlation (R) of yield and greenness.

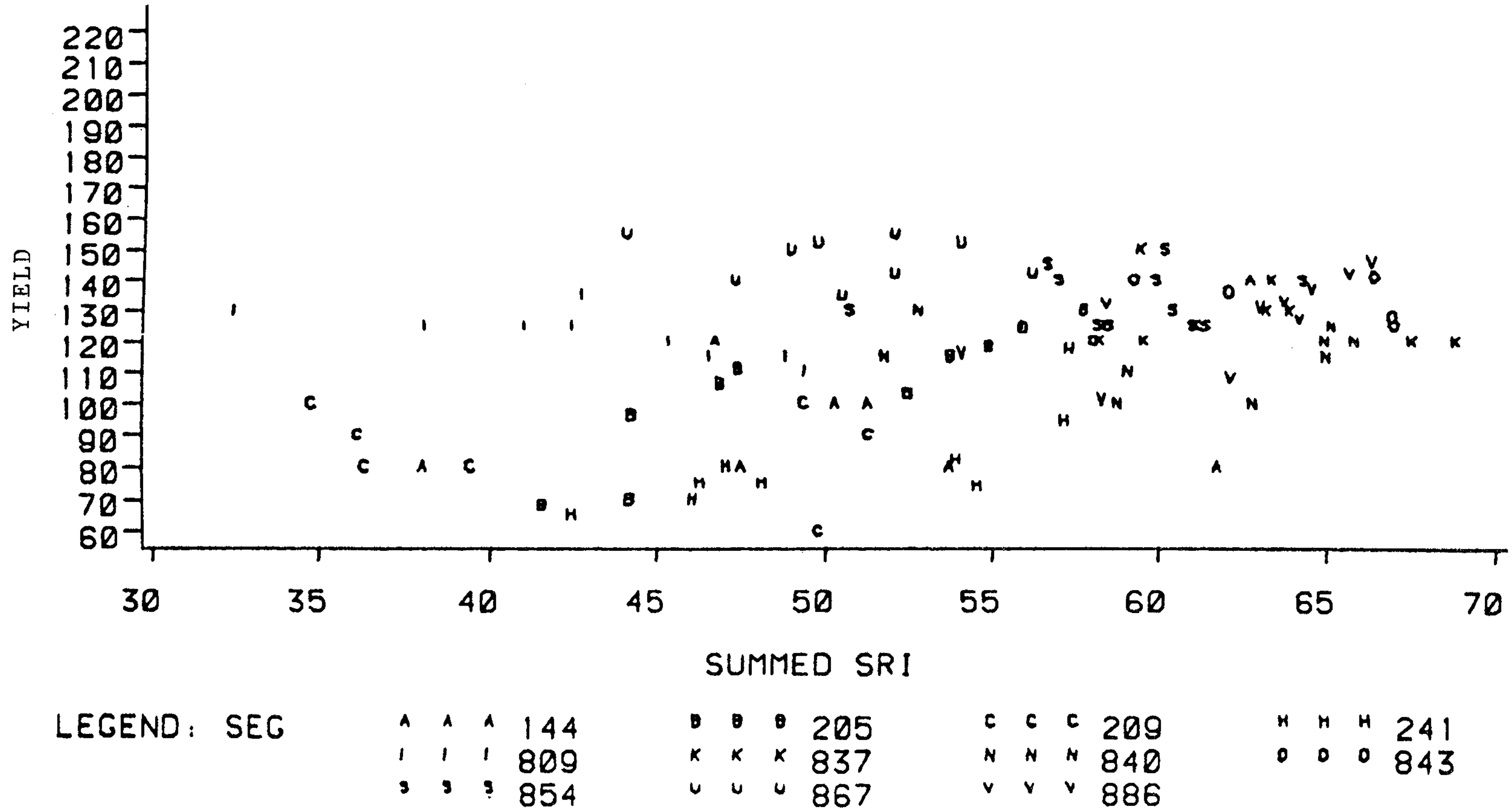


Figure B-10. Corn grain yields as a function of daily intercepted solar radiation (SRI) variable accumulated from 6 weeks before silking to 6 weeks after silking. Data are for 99 fields in 11 segments (5 states) for 1978.

other spectral-meteorological crop yield models are expected.

4.2 Soil Productivity

As the review of current literature on crop yield models indicated, most models use only crop and weather data inputs. Since crop yield is dependent upon a dynamic relationship between crop, soil, weather, and management, incorporation of a soil productivity index into the yield model should improve the estimates of yield. Soil potential productivity ratings are based upon significant physical properties of soils. This measurement is used because definite relationships exist between spectral characteristics of soils and many principal physical properties of soils. This aspect of correlating spectral characteristics of soils using Landsat MSS data to soil properties becomes more important in areas where there is limited historical data and in areas where soil surveys are not available.

Before one approach could be developed for using soil information in crop yield models, the soil properties which affect crop yield and at the same time could be estimated using spectral data had to be identified. The first priority was to develop the ability to stratify soils into soil productivity classes using Landsat data. In order to accomplish this, data bases containing: soil survey maps and profile characteristics; meteorological data; area, yield, and production data; and spectral data were acquired and assembled. Much of this year was spent developing approaches and acquiring data bases.

The second phase consists of evaluating the level of detail required using existing soil productivity ratings for providing soil information to yield models. Three approaches are proposed: (1) the soil series approach using detailed soils survey information, (2) the soil association approach utilizing generalized soil information, and (3) the clustering approach to determine alternative groupings of those properties which are related to soil productivity.

Additional research is in progress to examine classifications of Landsat MSS data which had been used by the Soil Conservation Service to map soils. The spectral data will be correlated with soil properties known to be related to soil productivity. The spectral classes derived through machine classification will be compared to informational classes derived from conventional productivity classes based on a soil productivity rating system (Walker, 1976).

In a series of preliminary sensitivity analyses using the Purdue Soybean Simulator (Holt et al., 1979) and the soil moisture model, SIMBAL, (Stuff and Dale, 1978) soil texture and soil drainage class significantly influenced relative yields of soybeans (Figure B-11). As the amount of rainfall diminished, relative yields of soybeans on coarse-textured soils (e.g., sand) declined more rapidly than yields on fine-textured soils (e.g., silty loam). Capillary movement of water upward from the water table in poorly drained soils supplied enough water for nearly consistent yields over a wide range of rainfall levels.

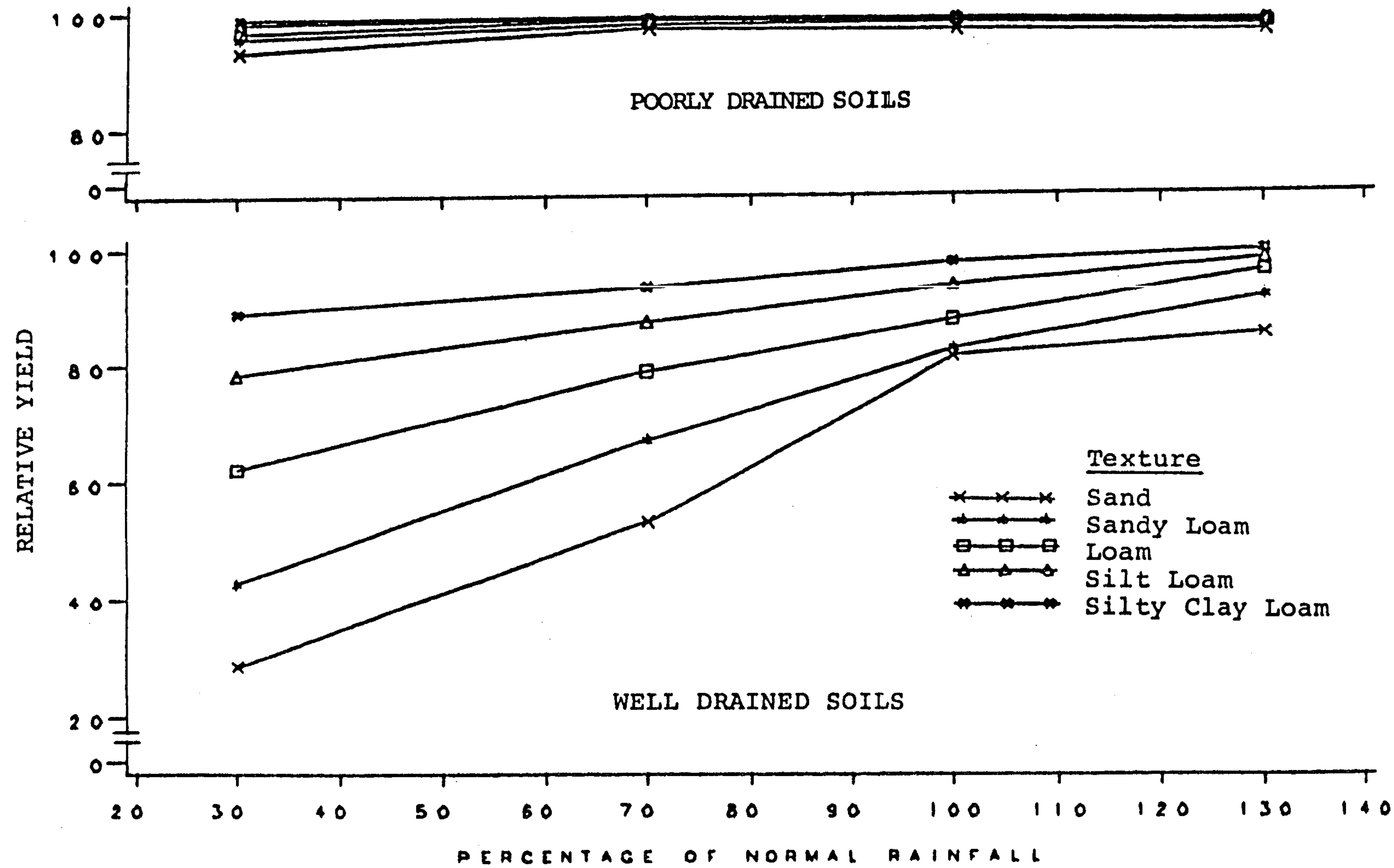


Figure B.11. Sensitivity analysis of soybean yields to varying soil texture, soil drainage, and rainfall.

The crop model together with the soil moisture model appear to reflect reality and offer vehicles to evaluate other soil factors associated with yields of both corn and soybeans. The preliminary findings indicate the necessity of further research in this area.

In addition to completing the analysis to determine the potential utility of soil productivity information in crop yield models, other recommendations include: conducting evaluations to determine the level of detail of soil information needed to be effective, extending evaluation of delineating soil productivity classes to areas analogous to Argentina, and evaluating the contribution of soil productivity ratings.

5. References

1. Badhwar, G.D. and K.E. Henderson. 1980. Development stage estimation of corn from spectral data - An initial model. AgRISTARS Report SR-J0-00488/JSC-16816. NASA/Johnson Space Center. Houston, TX.

2. Baier, W. 1977. Crop-weather models and their use in yield assessments. World Meteorological Organization Technical Report 151. Geneva, Switzerland, p.48.

3. Coelho, D.T. and R.F. Dale. 1980. An energy-crop growth variable and temperature function for predicting corn growth and development: Planting to silking. Agron. J. 72: 503-510.

4. Dale, R.F. 1977. An energy-crop growth variable for identifying weather effects upon maize yield. p. 240-248. In W. Baier, R.H. Shaw, L.M. Thompson, and R.E. Felch (ed.), Agrometeorology of the maize (corn) crop. Proc. Symp. Agrometeorol. Maize (corn) crop, World Meteorol. Organ., Iowa State Univ., Ames, Iowa, USA 5-9 July 1976. WMO No. 481. Geneva, Switzerland.

5. Dale, R.F., and H.F. Hodges. 1975. Weather and corn yield study for Tippecanoe County, Indiana. Final Report to Environmental Data Service, NOAA, on NC-44-72. Agronomy Dept., Purdue University, W. Lafayette, Indiana, 97p.

6. Decker, Wayne L. et al. 1976. Climate and food: Climatic fluctuation and U.S. agricultural production. Committee on Climate and Weather Fluctuation and Agricultural Production. National Academy of Sciences, Washington, D.C. 212p.

7. Hanway, J.J. 1963. Growth stages of corn (Zea mays, L.). Agron. J. 55:487-492.

8. Hatfield, J.L. and R.E. Carlson. 1977. Light quality distributions within three maize canopies. p. 232-239. In W. Baier, R.H. Shaw, L.M. Thompson, and R.E. Felch (eds.). Agrometeorology of the maize (corn) crop. Proc. Symp. Agrometeorol. Maize (corn) crop. World Meteorol. Organ., Iowa

State Univ., Ames, Iowa, USA, 5-9 July 1976. WMO No. 481. Geneva, Switzerland.

9. Hinzel, E.J., R.A. Weismiller, and D.P. Franzmeier. 1980. Correlation of spectral classes derived from Landsat MSS data to soil series and soil conditions for Jasper County, Indiana. LARS Technical Report 080979. Laboratory for Applications of Remote Sensing, Purdue University, West Lafayette, Indiana. 130p.

10. Holt, D.A., R.J. Bula, G.E. Miles, M.M. Schreiber, and R.M. Peart. 1975. Environmental physiology, modeling, and simulation of alfalfa growth. I. Conceptual development of SIMED. Purdue Agr. Exp. Sta. Bull. 907. 26p.

11. Holt, D.A., C.S.T. Daughtry, H.F. Reetz, and S.E. Hollinger. 1979. Separating soil and weather effects in large area yield prediction. Agron. Abstr. 71:12.

12. Linvill, D.E., R.F. Dale, and H.F. Hodges. 1978. Solar radiation weighting for weather and corn growth models. Agron J. 70:257-263.

13. MacDonald, R.B. and F.G. Hall. 1980. Global crop forecasting. Science 208: 670-679.

14. Malila, W.A. and J.M. Gleason. 1977. Investigations of spectral separability of small grains, early season wheat detection and multicrop inventory planning. ERIM Report 122700-34-F. Environmental Research Institute of Michigan, Ann Arbor, MI.

15. Nash, L.M., M.E. Bauer, and C.S.T. Daughtry. 1980. Effects of cultural practices on spectral reflectance of maize canopies. Agron. Abstr. 72:14.

16. Norman, J.M. 1980. Interfacing leaf and canopy light interception models. pp. 49-67. In J.D. Hesketh and J.W. Jones (eds.). Predicting Photosynthesis of Ecosystem Models. Volume 2. CRC Press.

17. Stevenson, K.R. and J.W. Tanner. 1970. Use of plastic plant models for investigating light distribution within a corn canopy. Can. J. Plant Sci. 50:319-329.

18. Strommen, N.D., C.M. Sakamoto, S.K. LeDuc, and D.E. Umberger. 1979. Development of LACIE CCEA-1 weather/wheat yield models. In Proceedings of Technical Sessions, Volume I, the LACIE Symposium, October 23-26, 1978. NASA-JSC, July, 1979, p. 99-108.

19. Stuff, R.G. and R.F. Dale. 1978. A soil moisture budget model accounting for shallow water table influence. Soil Sci. Soc. Am. J. 42:637-643.

20. Thompson, L.M. 1969. Weather and technology in the production of corn in the U.S. corn belt. Agron. J. 61:453-456.

21. Walburg, G., M.E. Bauer, and C.S.T. Daughtry. 1980. Spectral information for discriminating nitrogen treatment levels in maize canopies. Agron. Abstr. 72:16-17.

22. Walker, C. 1976. A model to estimate corn yields for Indiana. M.S. Thesis. Purdue University, West Lafayette, IN.

C. APPLICATION AND EVALUATION OF LANDSAT TRAINING, CLASSIFICATION, AND AREA ESTIMATION PROCEDURES FOR CROP INVENTORY

Marilyn M. Hixson*

1. Introduction

Accurate and timely crop production information is a critical need in today's economy. During the past decade, satellite remote sensing has been increasingly recognized as a means for crop identification and estimation of crop areas.

An extensive experiment, the Large Area Crop Inventory Experiment (LACIE), was conducted by NASA, the USDA, and NOAA from 1974 through 1977 (1). Its data analysis objective was to distinguish small grains from nonsmall grains using Landsat multispectral scanner (MSS) data. Several other investigations have shown that the potential also exists for identification and area estimation of corn and soybeans (2,3,4,5).

This task is the third year of a specific LARS task which resulted initially from a proposal in response to the Applications Notice. As a study of area estimation technology for corn and soybeans, this task is supportive of the AgRISTARS program.

During the first year of the study, 1978, activities were conducted in three areas:

1. Development of the experiment design and definition of data requirements for the major part of the study. As an extension of this objective, a stratification and sampling plan for the NASA/JSC 1978 corn/soybeans data acquisition program was defined and carried out by LARS.

2. Recommendations for reference data acquisition. Data to be acquired as inventory and periodic observations were recommended. Flightlines and dates for aerial photography acquisition were recommended.

----

*Data analyses were conducted by D.K. Scholz, M.E. Swenson, S.M. Davis, and G.T. Batista. Dr. M.E. Bauer and Dr. V.A. Anderson acted as consultants and advisors to the project.

3. Evaluation of the training and classification procedures used in LACIE Procedure 1 for a corn/soybeans/other crop identification program and investigation of changes to improve the performance of Procedure 1 on corn and soybeans.

Several additional topics were studied during the second year using a 1978 data set:

1. Feature selection in training and classification. Results using channels two (.6-.7 μm) and four (8-1.1 μm) from each of four Landsat acquisitions were not significantly different from those obtained using all channels. Use of fewer than eight bands caused a decrease in performance.

2. Classify, classifypoints, minimum distance, layered, and ECHO classifiers were evaluated. No significant differences in performance were found among classifiers when the same training method was used, except that the sum-of-densities classifier (classify) showed significantly higher small grain classification accuracies. A modified supervised training approach provided a consistent improvement over the ISOCLS training method.

3. In the Corn Belt, the accuracy of classification into corn and soybeans was not high until after the corn had tasseled. No combination of acquisitions which did not include the post-tassel, pre-harvest time period was able to yield high classification performance. Acquisitions from a date around emergence and a date after tasseling of the corn seem to provide a minimal data set for accurate identification of corn and soybeans.

4. Minimum distance, maximum likelihood, and sum-of-densities classifiers compared on additional band and date combinations. Differences in overall classification accuracies were significant, with the sum-of-densities classifier having the highest accuracies and the minimum distance classifier having the lowest. Most of the performances were within 1-2% for all classifiers, so classification costs (which increased in the same order performances increased) should probably be considered in the choice of a classifier.

2. Objectives

Previous work has shown that the accuracy and precision of area estimates obtained from Landsat data are affected by choices of training, classification, and area estimation procedures. The specific technical objectives of this task in 1980 were to:

- Evaluate the accuracy of early season estimates.
- Compare several methods for obtaining training statistics.
- Relate classification performance to scene characteristics.
- Assess the effect of separating the functions of sampling for training and sampling for area estimation.

3. General Approach

The data set used to address the first three objectives was drawn from the data set acquired in 1978 over the U.S. corn and soybean sites. The primary data were selected from 81 sample segments located in four test areas in the U.S. Corn Belt (Figure C-1). A secondary data set sampled segments in the Corn Belt fringe areas, using segments in Kentucky, Missouri, Minnesota, Wisconsin, and Michigan. Multitemporally registered MSS data on segments were used. Training and test data were labeled using ground observations.

The final objective was addressed using Landsat full-frame data covering a region where segment data were also acquired. A stratification of the frame was performed, and each stratum was classified using training statistics derived from ground data over the segments contained within it. Results evaluation was based on ground observations and comparison with USDA/ESCS county estimates.

The specific approach used in addressing each of the objectives will be discussed in the section of the report dealing with that objective.

4. Experimental Results

4.1 Early Season Estimation Accuracy

The objective of this study was to assess the accuracy of early season estimates. The data set analyzed consisted of eight sample segments, selected to represent a broad range of conditions found in the Corn Belt. The segments were 843 and 860 in eastern Indiana, 837 and 854 in western Indiana, 862 and 883 in north central Iowa, and 886 and 892 in west central Iowa.

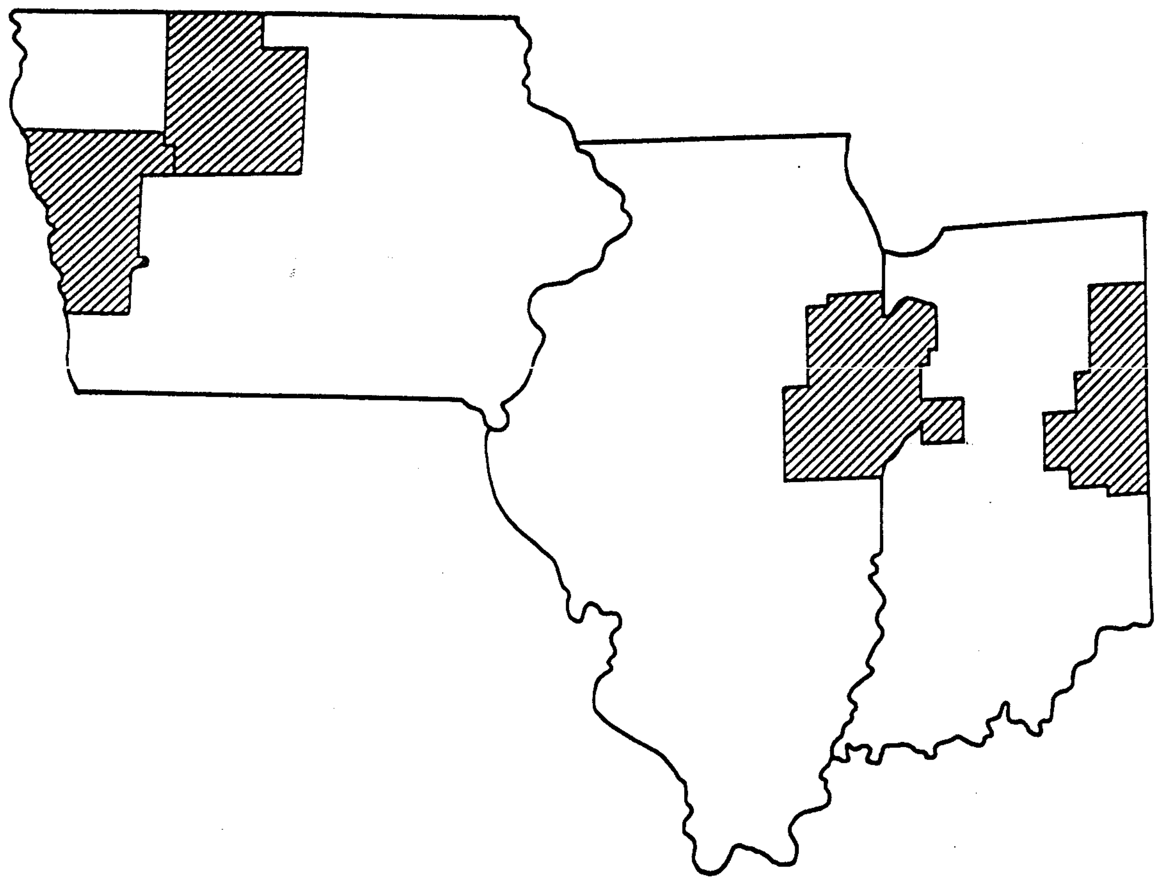


Figure C-1. Locations of the four test areas in the U.S. Corn Belt used to study training, classification, and area estimation procedures for corn and soybeans.

A modified supervised training approach was used. After refinement of the statistics was complete, the entire segment was classified using a minimum distance classifier. One acquisition was used from each of four time periods based on corn development stage: (1) preplant to eight leaves, (2) 10 leaves to tassel, (3) tassel to beginning dent, and (4) dent to mature. One visible (0.6-0.7 μm) and one near infrared (0.8-1.1 μm) band were used in the multidate analyses.

Accuracy of early season estimates is illustrated in Figure C-2. During the first time period, corn and soybeans were not spectrally separable as indicated by the low overall classification accuracy (60.0%). In the Corn Belt, however, relatively accurate differentiation of corn and soybeans from other cover types can be made at that time. Over the same set of segments, it was found that overall identification into two classes (corn and soybeans, else) was 92.0% correct, while the three-class classification (corn, soybeans, else) was only 60.0% correct. The area estimates for total corn and soybeans were generally close to ground inventory estimates (Figure C-3).

Consistently high classification accuracies were not obtained until an acquisition after the corn had tasseled (growth stage three) was included in the analysis. The classification accuracy did not improve by using later season information when the crops of interest had reached maturity.

4.2 Comparison of Training Procedures

Previous work has shown that the method used for obtaining training statistics has a greater influence on accuracy than the classification algorithm utilized (5). This result prompted this study to compare two alternative methods of obtaining training data.

The primary training method used in this investigation was a modified supervised training approach. A systematic grid was placed over the segment of interest. The field containing each of the grid intersections was selected for training and labeled using ground inventory information. Field center pixels of each of the major cover types (corn, soybeans, other) were clustered within cover type.

This training procedure was demonstrated as capable of producing classification results of high accuracy (5). There is, however, a potential bias in the use of this method since variable sized fields are used as sampling units in training. A bias in the statistics may be introduced if certain cover types appear consistently in large or small fields. A potential solution to this problem is to select a fixed training sample unit size (e.g., 3 x 3 pixels) rather than permitting a variable size. A shortcoming of the fixed size method may be that small fields are missed entirely.

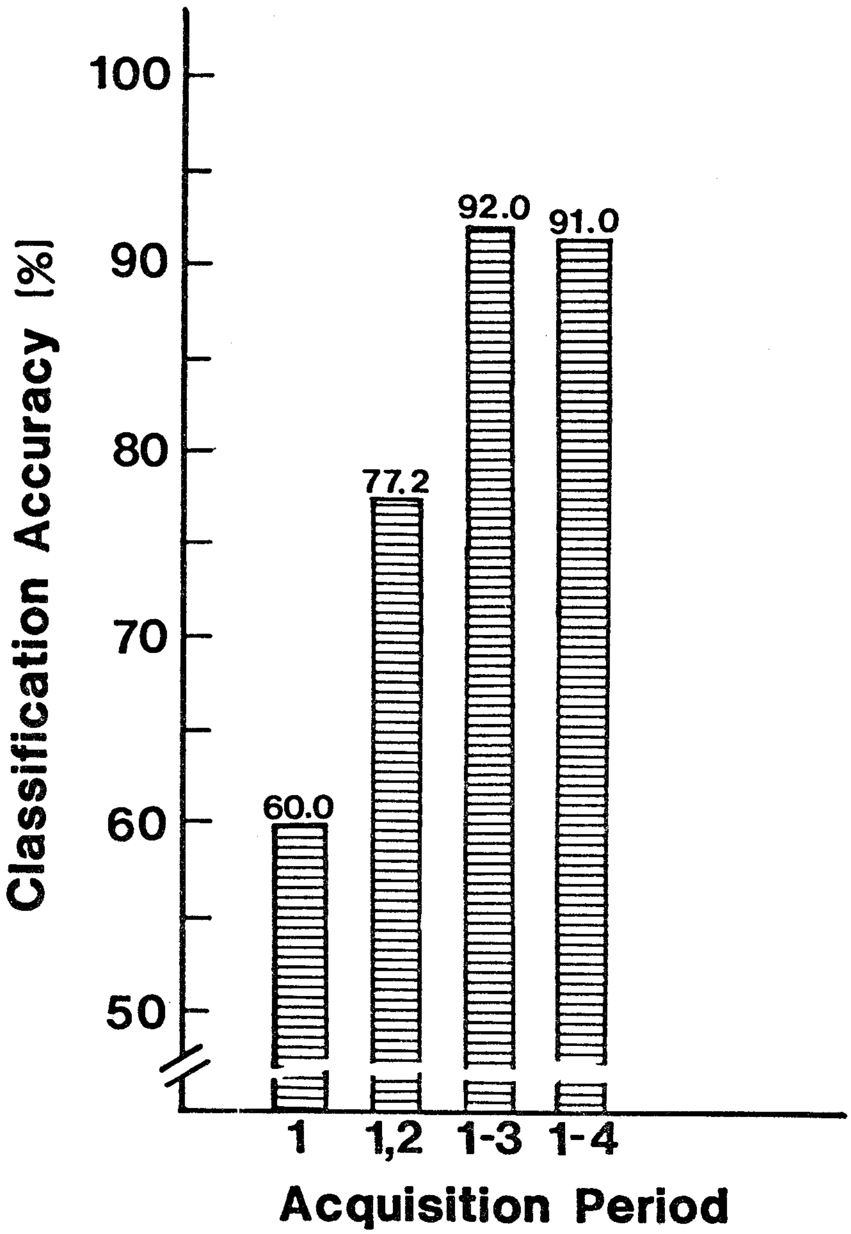


Figure C-2. Overall classification performance using cumulative spectral information with a minimum distance classifier and subsets of two, four, six, and eight channels.

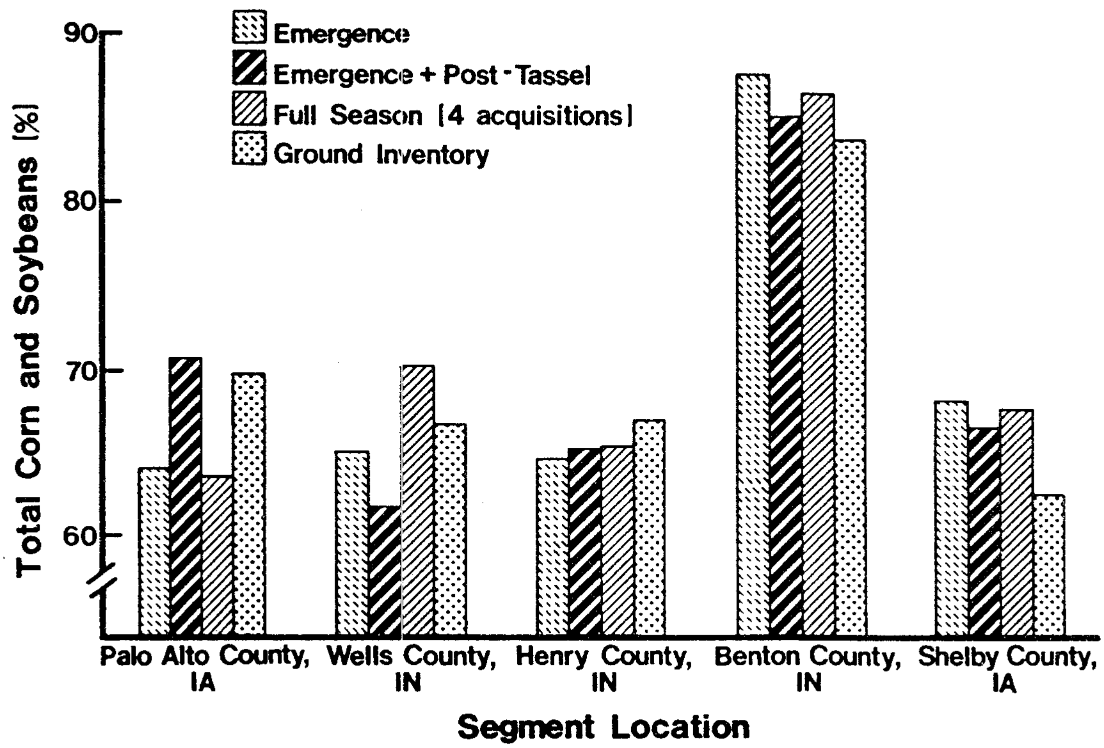


Figure C-3. Comparison of classification estimates to total corn and soybean areas with ground inventory proportions.

The objective of this study was to compare two methods for obtaining classifier training data. The comparison dealt with the size of the training sample units: a fixed size (3 x 3 pixels) compared with a variable size (field center pixels). Evaluation was made by comparing classification accuracies and resulting proportion estimates of corn and soybeans.

Approach. Three test areas in Indiana were selected for study. Each of the test areas was 5 x 6 nautical miles in size. The three segments used were 837 in Benton County, 843 in Henry County, and 860 in Wells County. The locations of the segments are shown in Figure C-4. The segments represent some variability in field sizes observed in the U.S. Corn Belt. Benton County is an area of fairly large, rectangular fields. The other two counties are located in eastern Indiana where smaller field sizes prevail.

Multitemporally registered Landsat-2 and -3 MSS data acquired during the summer of 1978 were analyzed. Aerial photography was acquired over the test areas, and a wall-to-wall inventory of crop types in each site was subsequently conducted. Four data acquisition windows were defined based on the corn growth stage, and high quality Landsat data had to be available in each of the time periods. The four time periods were: (1) preplant to eight leaves, (2) 10 leaves to tassel, (3) tassel to beginning dent, and (4) dent to mature. The dates of Landsat acquisitions used are given in Table C-1.

A systematic sample of the inventory data was used for training and testing the classifier. The pixel at every tenth line and column of the Landsat data was examined. If that pixel fell into a field, the cover type in the field was identified from the ground inventory. For variable size training data, a rectangular area containing only field center pixels in that field was defined as a training field. For fixed cell sizes, a 3 x 3 pixel field was defined if that field contained only field center pixels. Otherwise, the next grid intersection was considered.

The fields selected by this procedure were randomly assigned for either training the classifier or testing classification accuracy. From those fields selected for training, three sets of data were clustered: all fields of corn, all fields of soybeans, and all fields of other cover types. This procedure insures "pure" cluster classes (i.e., clusters containing pixels from only one cover type).

After refinement of the statistics was complete, the entire segment was classified using the Gaussian maximum likelihood per point classifier. One visible (0.6-0.7 μm) and one near infrared (0.8-1.1 μm) band from each acquisition were used in the multidate analyses.

Several measures of performance were evaluated. Percent correct classification of corn, soybeans, "other" cover types, and overall

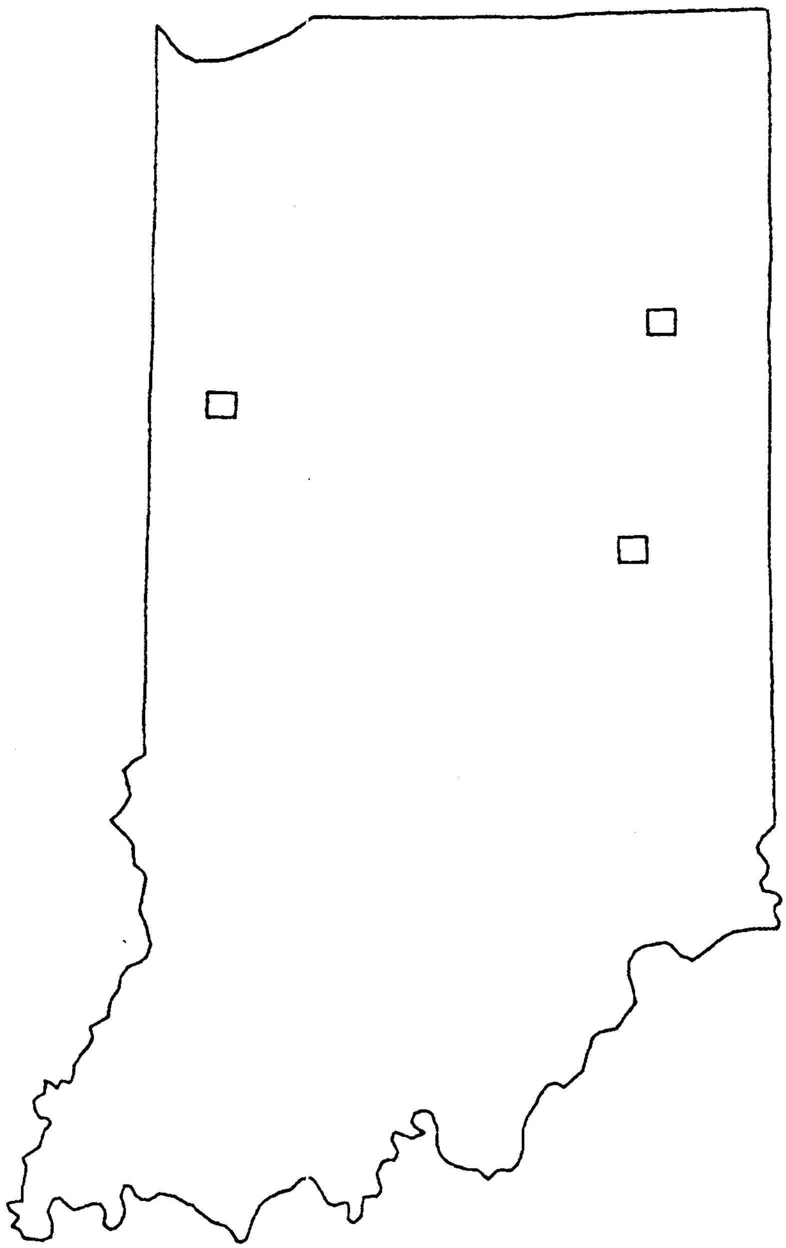


Figure C-4. Locations of the three test areas used in a comparison of training sample unit sizes.

Table C-1. Dates of Landsat acquisitions used for study of training methods.

Segment Number	Time Period			
	1	2	3	4
837	6/29	7/17	8/22	9/27
843	6/9	7/16	8/20	9/26
860	6/1	7/16	8/21	9/25

performance were computed based on the test fields. Proportion estimates were computed from the classifications using the stratified area estimate technique (6) and were compared with ground inventory proportions. Analysis of variance was used to determine differences.

Results and Discussion. Table C-2 shows the percent correct classification for corn, soybeans, "other," and overall for the two training methods described. Tukey one degree of freedom for nonadditivity found interactions nonsignificant at the 25% level, so that the interaction term was pooled with the error term. Analysis of variance showed that the percent correct classification of "other" cover types was significant at the 10% level, and the two methods differed in overall accuracy at the 15% level. The variable size training fields resulted in a higher performance for "other" cover types and overall accuracy in each case.

It was noted, however, that there was a discrepancy between the two methods in the total number of pixels used in training the classifier. For one segment, 2200 points were used in the variable method while only 1400 points were used in the fixed training size method. The use of more training data can increase performance, so a second analysis was run keeping nearly constant the total number of training points used by the two methods.

The results of the second analysis are shown in Table C-3. Again, the interaction between segment and method was not significant. Analysis of variance showed that the percent correct classification of "other" cover types was significantly different at the 10% level. For "other" cover types, the variable size training field method had higher accuracies in all three segments.

The evaluation of the two methods should not be based on the classification accuracies alone, but should also consider the accuracy of proportion estimates. The estimates of corn and soybean proportions are compared with inventory proportions in Table C-4. The analysis of variance showed that the proportion estimates for corn and soybeans did not differ significantly for any of the training methods.

4.3 Relationship of Classification Performance and Scene Characteristics

In the analyses previously conducted in this investigation, segment-to-segment variability was found to have a significant effect on classification performance. Information about the relationship of classification performance to characteristics of the scene would be valuable in the design of a crop inventory system. For example, in areas where classification performance was high, sampling could occur with a lower frequency than in areas having characteristics known to lead to poorer classification performances.

Table C-2. Comparison of classification accuracies of three segments using two different training unit sizes.

Segment	Training Method	Percent Correct Classification				No. of Points
		Corn	Soybeans	Other	Overall	
837	Variable	99.5	91.2	86.8	94.3	2040
	Fixed	94.9	91.3	80.9	91.9	1768
843	Variable	75.1	90.0	84.4	83.0	2211
	Fixed	81.1	91.1	74.2	82.6	1422
860	Variable	71.0	88.3	87.6	82.1	1020
	Fixed	74.6	81.5	72.4	78.4	1278

Table C-3. Comparison of classification accuracies of three segments using two different training unit sizes and keeping the total sample size relatively constant.

Segment	Training Method	Percent Correct Classification				No. of Points
		Corn	Soybeans	Other	Overall	
837	Variable	99.8	93.9	85.3	95.6	1735
	Fixed	94.9	91.3	80.9	91.9	1768
843	Variable	73.7	88.0	81.2	80.9	1485
	Fixed	81.1	91.1	74.2	82.6	1422
860	Variable	71.0	88.3	87.6	82.1	1020
	Fixed	68.6	81.6	85.6	77.3	1035

Table C-4. Proportions of corn and soybeans estimated from the two analysis methods and from the wall-to-wall inventory.

Segment	Cover Type	Proportion		
		Variable Method	Fixed Method	Ground Inventory
837	Corn	42.0	42.2	43.2
	Soybeans	39.4	41.4	40.7
843	Corn	37.0	35.4	32.4
	Soybeans	28.6	30.4	34.3
860	Corn	36.1	32.9	28.4
	Soybeans	43.0	47.4	38.4

An analysis procedure was selected to apply to all of the test segments analyzed. The selected procedure was the Gaussian maximum likelihood classification rule trained in a modified supervised approach using ground observations. The specific procedure was that described in the training methods study using fields (Section 4.2). The amount of training data was kept relatively constant among segments. Acquisitions from around emergence of the summer crops (development stages 0-2 for corn) and after tasseling of the corn (development stages 4.5-8) were used for all analyses.

The segments classified were selected from the 1978 data set over the U.S. Corn Belt and the Corn Belt fringe areas. The selected segments had acquisitions during the two time periods selected for analysis, and digital ground truth tapes were available for all segments. A total of 24 segments in eight states were analyzed (Figure C-5).

A data base of the classification results was constructed, and this was merged with a data base of scene characteristics. The variables contained in the data base are listed in Table C-5.

A general description of some characteristics of the segments analyzed is given in Table C-6. The segments analyzed sampled a wide variety of conditions present in the U.S. Corn Belt and its fringe areas. Several of the areas had relatively large rectangular fields of primarily corn and soybeans. Corn and soybeans in small fields were also sampled, as were scenes containing various confusion crops. One segment contained a lot of sunflowers, one segment was 40% spring wheat, and a third contained orchards. Several of the segments had a substantial amount of pasture and trees (Table C-7).

The accuracies of the segment classifications were as varied as the scenes (Table C-8). The overall accuracy for test fields ranged from 59 to 93%. Wall-to-wall accuracies (including mixed pixels) were about ten percent lower on the average. All except one of the segments in the fringe areas had accuracies less than 85%. A few of the segments in the central Corn Belt had low accuracies. The most notable of these is segment 860 which contains a large area owned by the U.S. Army Corps of Engineers which appeared to be agricultural and was confused with corn and soybean fields. Two other notable exceptions are segments 135 and 144. Segment 135 has small fields, including a few strip fields. Segment 144 is a very complex scene including a variety of field sizes and shapes with a substantial amount of trees and pasture. Table C-9 compares the resulting proportion estimates.

Quantitative analysis of the relationship of scene characteristics to classification performance is well underway at this time. These results will be described in a later technical report.

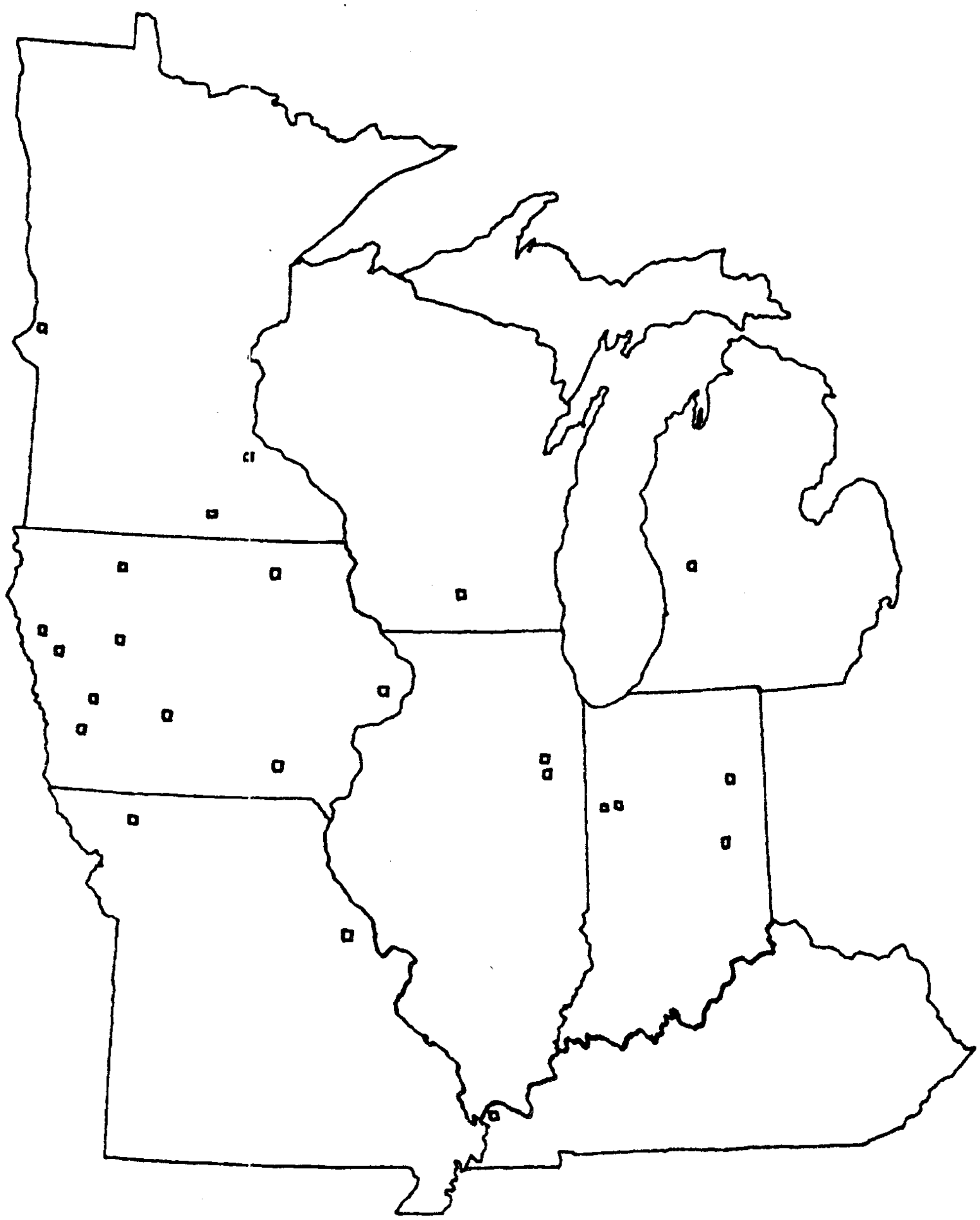


Figure C-5. Locations of segments analyzed for a study of the relationship of scene characteristics to classification performance.

Table C-5. Variables included in data base for study of relationship of scene characteristics and classification performance.

Segment Number

Dates of Landsat Acquisitions

Ground Truth Proportions

Corn	Hay	Sugar Beets
Soybeans	Pasture	Spring Wheat
Sorghum	Trees	Sunflowers
Winter Wheat	Vegetables	Barley
Oats	Idle	Flax
Clover	Nonagricultural	Orchards
Alfalfa	No ground truth	Beans
Grass	Rye	Potatoes

Classification Accuracy of Test Fields
Wall-to-Wall Classification Accuracy
Analyst Labeling Accuracy*

Corn
Soybeans
"Other"
Overall

Raw Proportion Estimates
Stratified Area Estimates
Variance Reduction Factors

Corn
Soybeans

*For a subset of segments. Analyst labels obtained from NASA/JSC.

Table C-6. General characteristics of segments analyzed for study of relationship of scene characteristics and classification performance.

Segment Number	County	State	APU*	Comments
135	Chickasaw	IA	24E	Small, rectangular fields. A few strip fields.
141	Madison	IA	25W	Small, nonrectangular fields, pasture, and trees.
144	Wapello	IA	17E	Complex scene. Variety of field sizes and shapes. Substantial trees and pasture.
146	Ballard	KY	43	Small, nonrectangular fields. Some tobacco.
180	Kent	MI	29	Complex scene. Irregular fields. Orchards.
183	Freeborn	MN	24	Medium fields, mostly rectangular.
184	Goodhue	MN	24	Complex scene. Many strip and irregular shaped fields. Large amount of trees.
185	Traverse	MN	20	Many confusion crops (sunflowers, sorghum).
209	Gentry	MO	25	Complex scene, nonrectangular fields.
215	Lincoln	MO	30	Relatively small, irregular fields. Trees.
246	Dane	WI	27	Medium fields. Some nonag.
800	Clinton	IA	25E	Primarily corn and soybeans.
824	Iroquois	IL	28	Primarily corn and soybeans. Medium to large fields.
828	Kankakee	IL	28	Primarily corn and soybeans. Medium fields.
837	Benton	IN	28	Primarily corn and soybeans. Larger fields.
843	Henry	IN	28	Small, rectangular fields.
854	Tippecanoe	IN	28	Primarily corn and soybeans.
860	Wells	IN	28	Large area owned by Army Corps of Engineers.
862	Calhoun	IA	24W	Medium size, mostly rectangular fields. Small streams throughout.
881	Monona	IA	14N	Rolling terrain, much pasture.
883	Palo Alto	IA	24W	Large water body.
886	Pottawattomie	IA	14S	Irregular field shapes. Town.
892	Shelby	IA	14S	Small fields. Mostly agricultural.
895	Woodbury	IA	14N	Irregular field shapes. Pasture, some oats.

*As subdivided for yield modeling in Iowa.

Table C-7. Ground truth proportions of crops in test segments.

Segment	Corn	Soybeans	Hay	Pasture	Trees	Spring Wheat	Sun-flowers	Orchard
135	39.9	25.5	11.9	9.1	1.6	0.0	0.0	0.0
141	24.5	19.2	13.2	27.1	7.8	0.0	0.0	0.0
144	20.6	21.3	5.6	8.6	32.9	0.0	0.0	0.0
146	19.8	44.7	0.7	16.3	10.9	0.0	0.0	0.0
180	14.9	0.2	12.2	9.2	32.9	0.0	0.0	15.0
183	48.2	34.5	3.2	0.6	2.0	0.8	0.0	0.0
184	22.9	7.1	15.4	7.7	35.7	0.0	0.3	0.0
185	6.6	8.1	2.1	2.3	0.2	39.9	23.8	0.0
209	9.0	22.9	1.9	36.9	17.5	0.0	0.0	0.0
215	23.1	19.8	3.0	13.5	22.0	0.0	0.0	0.0
246	38.3	2.2	14.2	6.3	9.7	0.0	0.0	0.0
800	55.6	28.2	3.4	3.7	2.0	0.0	0.0	0.0
824	51.4	44.4	0.8	0.3	0.0	0.0	0.0	0.0
828	51.5	35.9	0.7	1.0	0.9	0.0	0.0	0.0
837	44.2	37.9	1.5	4.6	4.2	0.0	0.0	0.0
843	32.8	31.7	3.3	11.6	8.4	0.0	0.0	0.0
854	49.5	41.4	1.2	3.3	0.8	0.0	0.0	0.0
860	30.7	34.0	6.4	2.2	5.7	0.0	0.0	0.0
862	42.1	34.4	6.2	7.7	0.1	0.0	0.0	0.0
881	44.6	7.9	3.3	22.6	9.4	0.0	0.0	0.0
883	33.7	36.2	4.6	12.6	0.6	0.0	0.0	0.0
886	49.1	26.7	3.6	10.5	2.1	0.4	0.0	0.0
892	53.0	15.0	9.3	8.7	1.2	0.0	0.0	0.0
895	56.4	9.6	1.9	14.1	2.4	0.0	0.0	0.0

Table C-8. Classification accuracies (%) on segments assessed using test fields and by comparison with digital ground truth.

	Test Fields				Wall-to-Wall			
Segment	Corn	Soybeans	Other	Overall	Corn	Soybeans	Other	Overall
135	75.3	85.4	84.6	79.2	61.6	67.5	74.5	67.6
141	85.2	89.0	95.3	91.9	65.5	71.4	84.1	77.1
144	76.1	42.8	93.4	77.0	57.0	40.8	85.4	70.1
146	70.7	93.4	71.2	83.4	64.7	84.8	58.0	71.3
180	72.8	66.7	84.2	83.3	50.3	71.1	81.0	76.4
183	77.2	77.8	58.1	75.8	68.5	67.2	54.6	66.1
184	83.8	86.5	84.8	84.6	66.0	63.3	71.0	69.5
185	75.6	49.5	88.9	84.6	63.4	38.0	82.0	77.2
209	30.4	84.4	90.6	79.9	52.5	61.2	79.5	73.4
215	63.3	66.1	71.5	67.8	59.1	59.1	68.0	64.2
246	79.4	88.0	79.3	79.5	72.0	41.6	65.0	67.2
800	94.7	85.6	70.5	89.3	88.0	64.1	54.4	75.0
824	86.0	87.4	14.6	84.3	75.1	81.1	39.5	76.3
828	89.3	73.9	77.4	81.6	82.2	60.2	74.7	73.3
837	91.7	91.1	72.1	89.6	80.3	73.9	66.5	75.5
843	81.6	90.8	83.1	85.3	73.0	80.2	81.3	78.2
854	90.1	82.4	96.7	87.1	79.8	67.9	82.3	75.1
860	55.2	56.5	98.1	59.1	40.8	56.7	75.5	58.5
862	96.9	65.8	93.5	87.2	75.8	47.0	87.9	68.8
881	85.8	78.8	97.6	89.9	69.1	54.0	90.0	78.1
883	99.3	90.6	76.0	88.0	76.8	70.1	57.8	68.6
886	93.8	89.5	98.5	92.8	75.3	66.3	72.2	72.1
892	89.5	97.2	95.6	92.3	76.6	66.7	84.8	77.7
895	92.6	51.9	86.4	87.7	82.3	42.6	67.8	73.3

Table C-9. Comparison of stratified area estimates and ground truth proportions of corn and soybeans.

Segment	Corn		Soybeans	
	Landsat Classification	Ground Truth	Landsat Classification	Ground Truth
135	39.9	51.2	25.5	26.3
141	24.5	25.8	19.2	17.3
144	20.6	21.7	21.3	21.3
146	19.8	17.0	44.7	50.9
180	14.9	8.7	0.2	0.2
183	48.2	57.3	34.5	29.0
184	22.9	29.1	7.1	9.9
185	6.6	13.5	8.1	6.5
209	9.0	12.3	22.9	27.1
215	23.1	28.2	19.8	22.7
246	38.3	46.4	2.2	1.9
800	55.6	60.0	28.2	22.6
824	51.4	47.2	44.4	49.4
828	51.5	49.4	35.9	33.1
837	44.2	44.5	37.9	40.1
843	32.8	34.3	31.7	31.5
854	49.5	51.3	41.4	39.5
860	30.7	28.5	34.0	57.7
862	42.1	35.0	34.4	24.1
881	44.6	44.8	7.9	5.8
883	33.7	33.2	36.2	32.2
886	49.1	50.7	26.7	26.9
892	53.0	50.0	15.0	14.2
895	56.4	60.6	9.6	9.2

4.4 Full-Frame Sampling

The objective of this study is to assess the effect of separating the functions of sampling for training and sampling for area estimation. The frame selected for analysis was acquired over north central Iowa on August 9, 1978. This is during the best time period for detecting corn and soybeans with unitemporal data.

The data analysis procedure consisted of first defining a stratification of the full-frame. The stratification selected was the refined/split strata (defined by NASA/JSC and further refined for the yield modeling activity). Only those counties which fell completely in the frame were analyzed. Figure C-6 shows those counties which fell into each of the two strata within the frame.

Eight sample segments having digital ground truth data were located in the frame and were used to provide training and test data (Figure C-7). Using a modified supervised training approach, statistics were developed for each of the segments. The statistics for all segments within a stratum were pooled to provide a set of statistics describing that stratum.

Three classification and estimation procedures were carried out for comparison. The first method was the method used in the LACIE project: the statistics developed on one segment were used to classify that segment. All segments were classified and an estimate was computed for the region.

The second method also based the estimation procedure on the sample segments, but training was conducted differently. The pooled statistics for a stratum were used to classify all the segments within that stratum. Then an estimate was computed for the region.

The third and final method was to use the pooled statistics from the sample segments in the stratum to classify a systematic sample of pixels in that stratum. The systematic sample was used to provide an area estimate.

The results of this comparison are shown in Table C-10. Using the segment approach, estimates for counties without samples were made using ratios with the 1974 estimates. Comparisons were made to USDA/ESCS estimates by computing root mean square errors. In both strata, the full-frame approach performed better than the standard segment approach for soybeans (Table C-11). Corn in stratum 2 was not as well estimated using the full-frame approach. This may be due to the fact that the training data in this stratum were not well distributed and sampled a very small portion of the total land area. The viability of using one set of statistics for a stratum is illustrated by the generally good performance of the pooled segment approach.

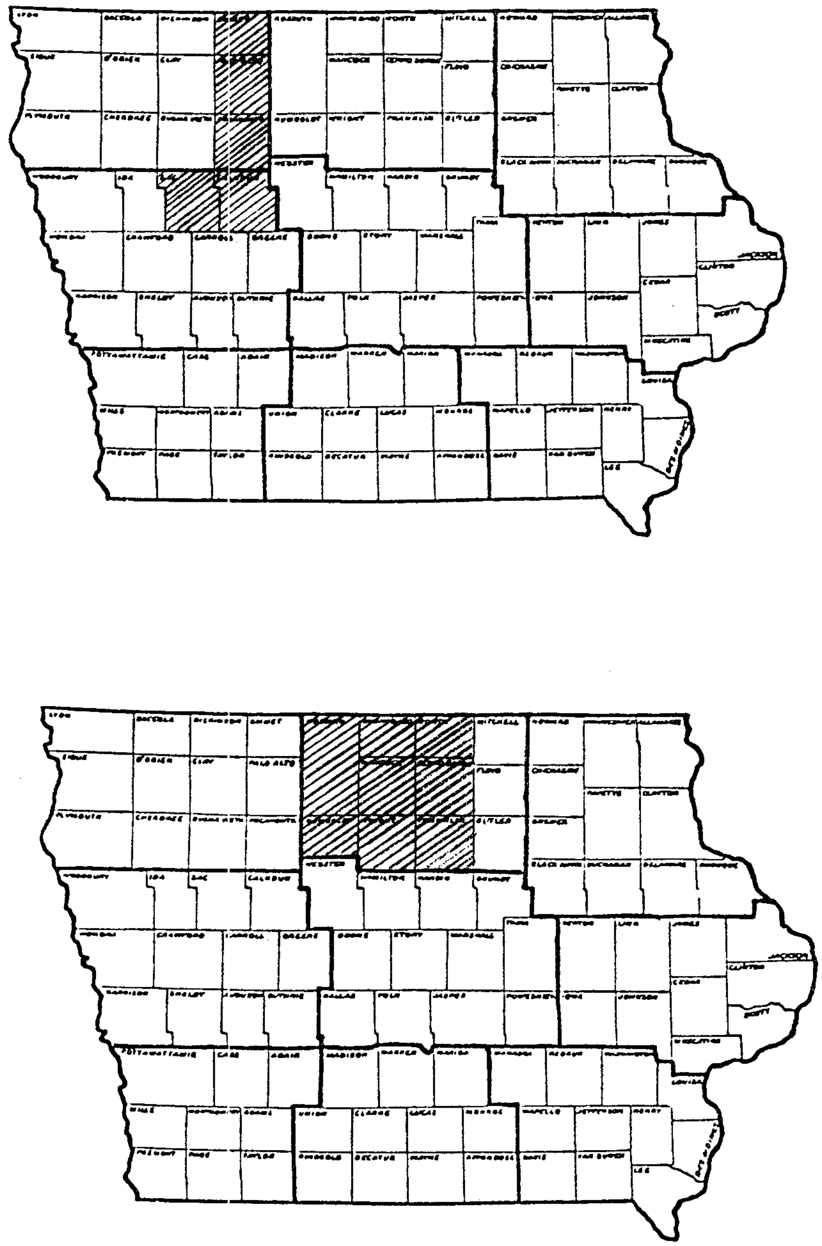


Figure C-6. Counties in the two strata used in the full-frame classification study. The upper map shows those counties in APU 14 and the lower map shows those counties in APU 24.

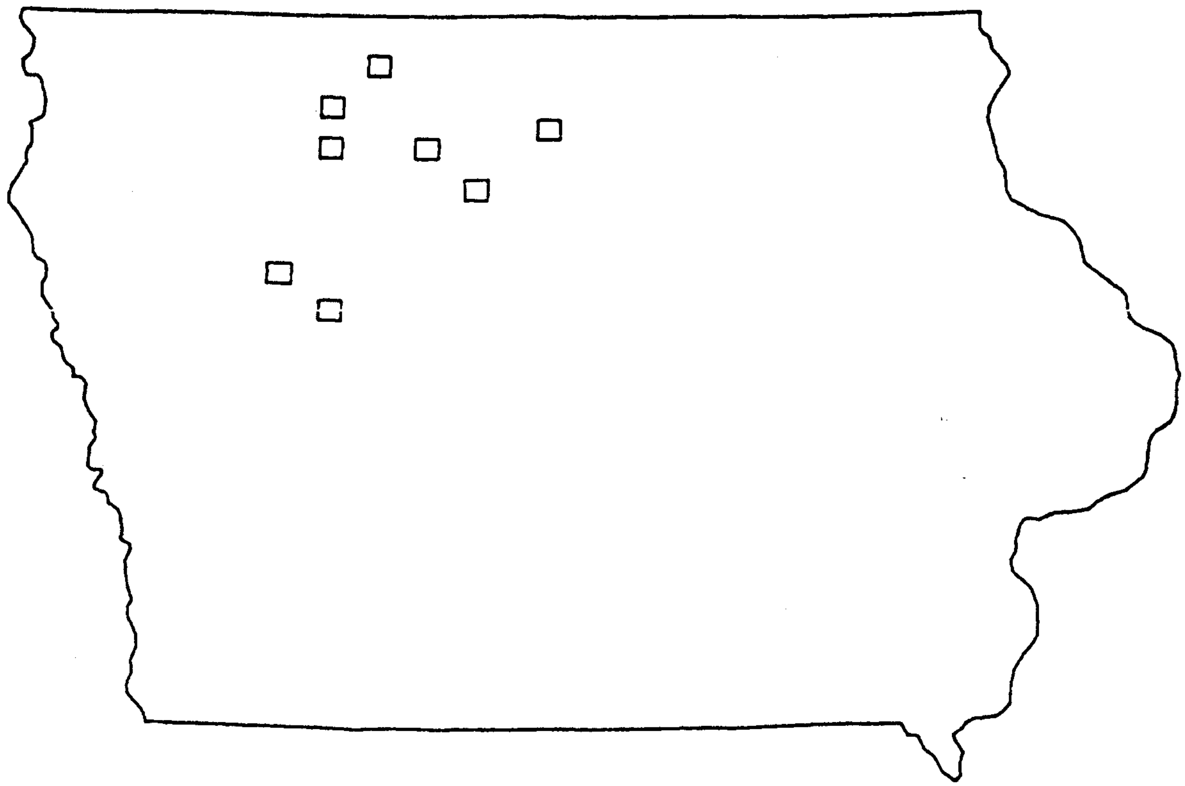


Figure C-7. Locations of sample segments used to provide training and test data for the full-frame study.

Table C-10. Proportion estimates of corn and soybeans made from three methods and compared with USDA/ESCS county level estimates.

Stratum	County	Landsat Estimates						USDA/ESCS	
		Segments with Segment Statistics		Segments with Pooled Statistics		Full-Frame			
		Corn	Soybeans	Corn	Soybeans	Corn	Soybeans	Corn	Soybeans
1	Emmet	38.9	41.4	43.4	41.2	44.4	38.9	40.0	37.1
	Palo Alto	38.6	28.2	32.4	41.5	42.8	41.5	41.8	38.5
	Pocahontas	39.2	35.8	36.6	45.0	41.2	45.1	41.1	39.8
2	Kossuth	43.9	46.8	43.7	46.5	51.6	40.0	43.1	39.6
	Humboldt	49.8	47.8	49.8	48.9	53.0	39.4	45.6	40.2
	Winnebago	46.6	41.2	46.2	41.7	47.4	43.6	42.1	37.8
	Hancock	51.5	31.0	50.4	31.7	51.9	40.5	44.4	34.8
	Wright	50.6	43.1	50.1	43.7	53.6	39.6	47.2	42.8
	Worth	48.1	35.1	47.7	35.6	48.2	42.8	43.0	32.6
	Cerro Gordo	46.5	31.7	46.1	32.1	48.7	41.3	40.8	29.3
	Franklin	46.9	32.2	46.5	32.7	53.7	38.0	44.5	30.7

Table C-11. Root mean square errors of corn and soybean proportions from USDA/ESCS estimates.

Stratum	Corn			Soybeans		
	Segments with Segment Statistics	Segments with Pooled Statistics	Full Frame	Segments with Segment Statistics	Segments with Pooled Statistics	Full Frame
1	3.9	11.0	4.5	11.9	7.3	6.3
2	12.8	11.6	20.6	72.7	13.0	19.5

5. Summary and Conclusions

The results of this task during the past year have addressed many issues in the machine classification of remotely sensed data for crop area estimation. In particular, early season estimation, training procedures, the relationship of scene characteristics to classification performance, and full-frame classification methods have been studied.

Early in the season, at about the time of emergence of the summer crops, corn and soybeans were not spectrally separable. In the Corn Belt, however, relatively accurate differentiation of corn and soybeans from other cover types can be made at that time. This result indicates a potential method for providing early season estimates: estimate the total corn and soybean area from Landsat MSS data and separate the crop proportions using econometric models or historical ratios.

Variable size and fixed size training sample units were compared. Use of the variable size generally resulted in selection of more pixels for use in training. When the total sample size was constrained to be relatively constant on each segment, percent correct classification of other cover types was significantly higher for the variable size method than for the fixed size method. Other accuracy measures were not significantly different. There was, in addition, no significant difference in corn or soybean proportion estimates between the two methods.

Segment-to-segment variability was found to have a significant effect on classification performance. The overall accuracy of test fields varied from 59 to 93 percent. The variability is related to proportion of corn and soybeans in the region, confusion crops present, scene complexity, and field sizes. Quantitative analyses are being conducted to further define these relationships.

A comparison of three methods for obtaining crop statistics over a large region was carried out. A method of sampling pixels throughout the region of interest provided the most accurate soybean estimates. The viability of using pooled statistics for a stratum is illustrated by the generally good performance of the pooled segment approach. This type of training approach used with a systematic sample of pixels seems to merit further investigation due to the variance reduction benefits which could be obtained. In particular, the potential shown for this method should be more fully investigated using multitemporal data which would obtain higher classification accuracies and more accurate area estimates.

6. References

1. MacDonald, R.B., and F.G. Hall. 1980. Crop Forecasting. Science 208: 670-679.

2. Bauer, Marvin E., Marilyn M. Hixson, Barbara J. Davis, and Jeanne B. Etheridge. 1978. Area Estimation of Crops by Digital Analysis of Landsat Data. Photogr. Engin. 44::1033-1043.

3. Bauer, Marvin E., Jan E. Cipra, Paul E. Anuta, and Jeanne B. Etheridge. 1979. Identification and Area Estimation of Agricultural Crops by Computer Classification of Landsat MSS data. Remote Sensing of Environ. 8:77-92.

4. Hanuschak, George, Richard Sigman, Michael Craig, Martin Ozga, Raymond Luebbe, Paul Cook, David Kleweno, and Charles Miller. 1979. Obtaining Timely Crop Area Estimates Using Ground - Gathered and Landsat Data. U.S. Dept. of Agriculture, Economics, Statistics, and Cooperative Service. Technical Bulletin No. 1609.

5. Hixson, Marilyn, Donna Scholz, Nancy Fuhs, and Tsuyoshi Akiyama. 1980. Evaluation of Several Schemes for Classification of Remotely Sensed Data. Photogr. Engin. (To appear).

6. Heydorn, R.P., R.M. Bizzell, J.A. Quirein, K.M. Abotteen, and C.A. Summer. 1978. Classification of LACIE Segments. Proc. LACIE Symposium, NASA, Johnson Space Center, Houston, Texas, October 23-26, pp. 73-86 (JSC-16015).

D. DETERMINATION OF THE OPTIMAL LEVEL FOR COMBINING AREA AND YIELD ESTIMATES

Marilyn M. Hixson*

1. Introduction

The eventual aim of crop inventory studies is production estimation, not area or yield estimates alone. Production estimates can be made only at a level where area and yield strata intersect. The variance of the production estimates is dependent upon the means and variances of both area and yield in the stratum. Thus, it is important that the stratifications for area and yield estimation be coordinated, and that the levels for aggregation be selected so that acceptable variances are obtained.

2. Objectives

The overall objective of this task is to determine the optimal level for combining area and yield estimates of corn and soybeans. Production estimates and their variances will be computed for several levels of area and yield estimates. The estimates and their precisions will be compared.

3. Approach

Iowa was selected to study the optimal level for combining area and yield estimates of corn and soybeans. This state was selected for study as it is included in the 1981 AgRISTARS pilot experiment. The year for evaluation ("current year") was selected to be 1978, the most recent year for which final USDA/ESCS estimates were available when the study was initiated.

----

*Data base development and statistical programs were carried out by Maria Downton, Carol Jobusch, and Pamela Weeda. Carol Jobusch also provided valuable assistance in data base handling and statistical programming. Much appreciation is also due to Prof. K.C.S. Pillai, Prof. V.A. Anderson, and Dr. M.E. Bauer who served as consultants to the project.

The level at which aggregation of area and yield to obtain production should occur is dependent upon the technology being utilized for estimation. If, for example, area or yield estimates made at a given level are biased or not reliable, then aggregation at that level would most likely be undesirable regardless of any potential gains in precision. A change in the technology utilized for estimation, however, might produce reliable estimates at the same level and be a viable candidate for aggregation. This investigation will assess the optimal level with respect to the current technology. Current technology utilizes digital analysis of Landsat MSS data on sample segments to provide area estimates; regression models are developed from historical data and used with current weather data to provide yield estimates. Several levels of obtaining both area and yield estimates will be considered: county, refined strata, crop reporting district, state, and other levels.

The model form and variables considered for inclusion in the regression used by CCEA for yield estimation of corn and soybeans in Iowa were obtained. A weather data base with historical (at least 30 years) and "current year" weather data was needed for all the cooperative meteorological stations in Iowa. Historical and "current year" county area and yield estimates made by USDA/ESCS in Iowa were acquired for the same time period.

Regression equations were derived to predict yield using the historical weather and yield data. A weather smoothing function was utilized to provide estimates of meteorological variables for the various strata studied. Using the 1978 weather data, "current year" yield estimates were made for corn and soybeans in Iowa.

The production estimate ($\hat{P}$) and its variance ($V(\hat{P})$) were computed for all the candidate aggregations. Evaluations will compare the variances with one another and with the results of simulated aggregations and TY aggregations. The production estimate $\hat{P}$ will be compared with USDA/ESCS state estimates to assess any bias due to the yield estimation methodology.

For those levels of aggregation which appear to be improvements over the currently used method, a further investigation into the effects of using the current area estimation methodology needs to be conducted. Within county variances for the crops of interest will be obtained, and variances associated with candidate area strata will be computed.

Utilizing this method for area estimation and the yield estimates computed previously, $V(\hat{P})$ will be computed for all the levels of aggregation which appeared to be promising. The variances will be compared with one another and with the TY and simulated aggregations. These results will be compared with the aggregations using USDA/ESCS area estimates to assess the effect of utilizing the segment approach to area estimation.

3.1 Data Set Utilized

For development of regression models for yield, a historical series of yield estimates and meteorological data were required. The USDA/ESCS county level statistics for yield of corn and soybeans were obtained from the Iowa state office for 1932-78. USDA/ESCS county level estimates of corn and soybean areas for 1978 were acquired for results comparison. Daily observations of temperature and precipitation for all the cooperative meteorological stations in the state of Iowa were purchased from the Iowa Geological Survey (1900-74) and some were supplied by another task (1975-78).

3.2 Levels of Aggregation

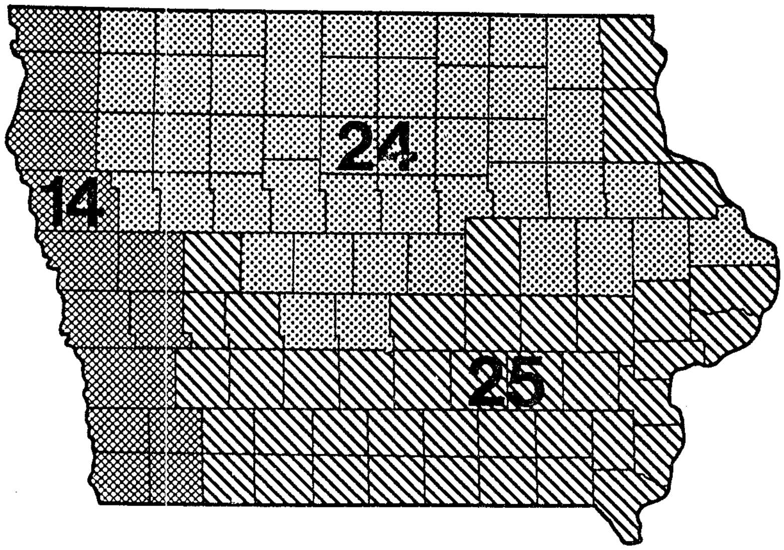
During the Large Area Crop Inventory Experiment (LACIE), aggregation of area and yield estimates to production was done at approximately the state level. Thus, this would be one level for investigation.

For the state of Iowa, yield estimates will be made at the state level and one other level during the 1981 AgRISTARS pilot experiment. NASA/JSC requested that this level be the refined strata in the state (Figure D-1). The yield modeling group, however, thinking that these strata were too broad, suggested a subdivision of them (Figure D-1). This subdivision will be referred to as the refined/split strata in this report. Both of these levels are being considered for evaluation.

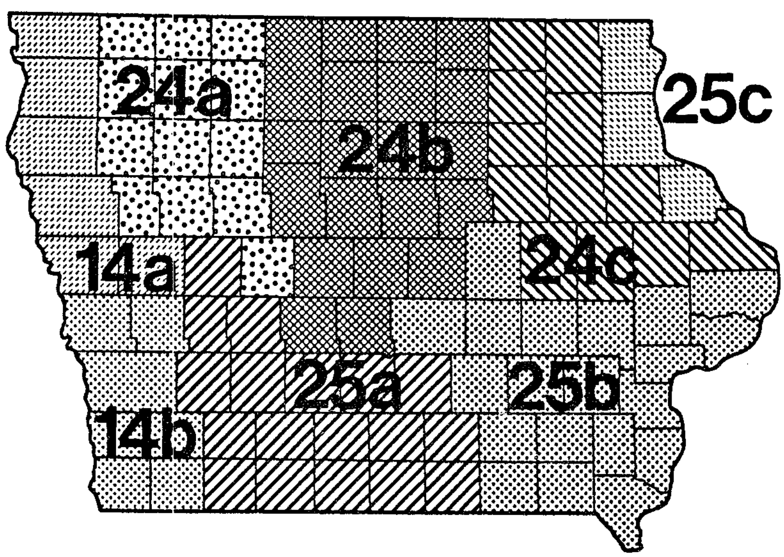
An additional level which seems to be natural to include is the crop reporting district level (Figure D-2) as this has traditionally been a standard unit for the reporting of agricultural statistics. Also, the county level is included as the smallest possible unit using current yield estimation technology, as this is the smallest level for which historical yield estimates are available.

Finally, two other stratification systems were defined at LARS for comparative purposes. These strata were derived based on a five year (1972-76) history of corn and soybean areas and yields. The purpose of these stratification systems was to determine the extent to which improvements in precision could be made if historical data were available for carrying out a stratification in addition to image data.

The two LARS derived stratification systems are shown in Figure D-3. The first, a set of contiguous strata, was developed by examining the five year averages of corn and soybeans yield and area. The strata were refined by evaluating them with respect to the coefficients of variation of the four variables of interest. The second set of strata was defined by using histograms of the four variables of interest to define levels strata which were not necessarily geographically



REFINED STRATA



REFINED/SPLIT STRATA

Figure D-1. Maps of the refined strata developed at NASA/JSC (top) and the refined/split strata as subdivided for the yield modeling effort (bottom).

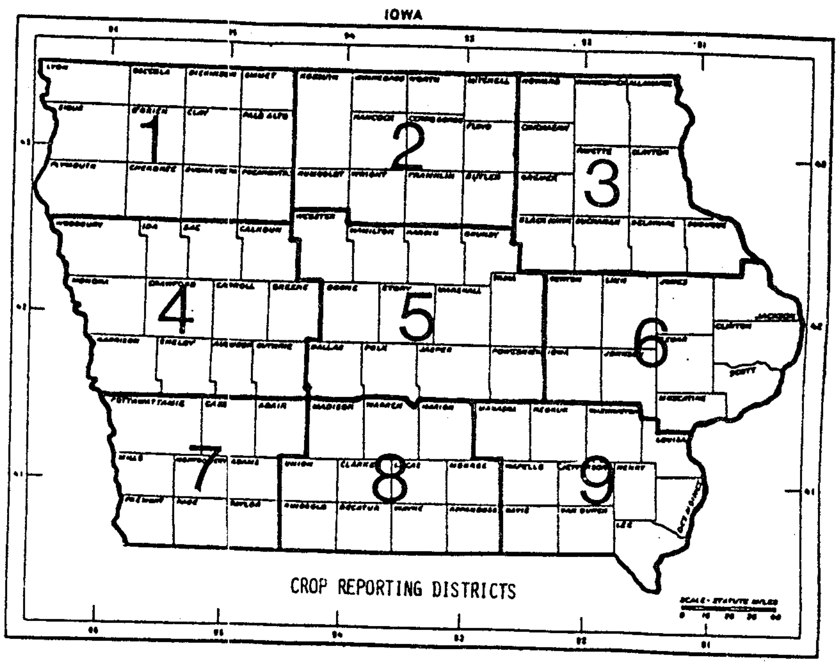
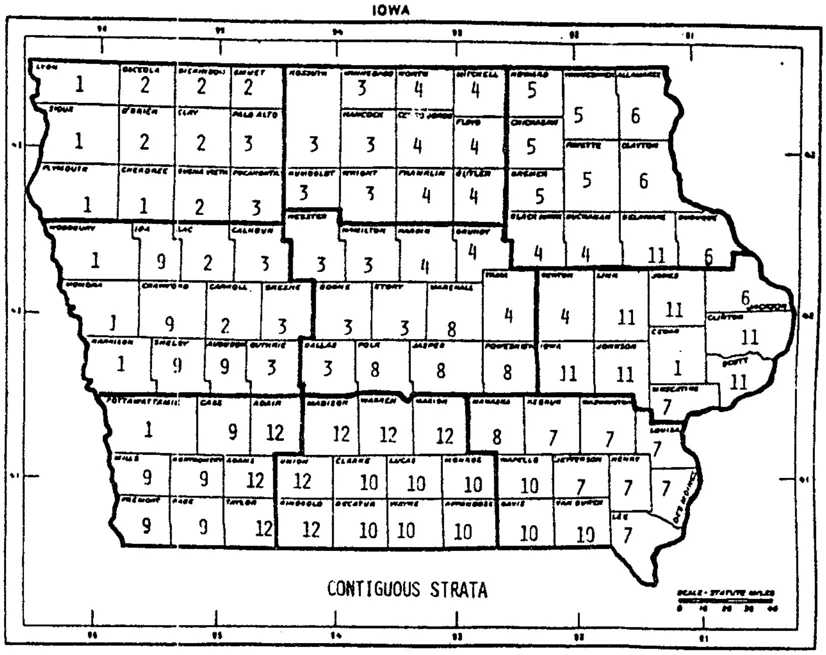


Figure D-2. Map of the crop reporting districts in Iowa.



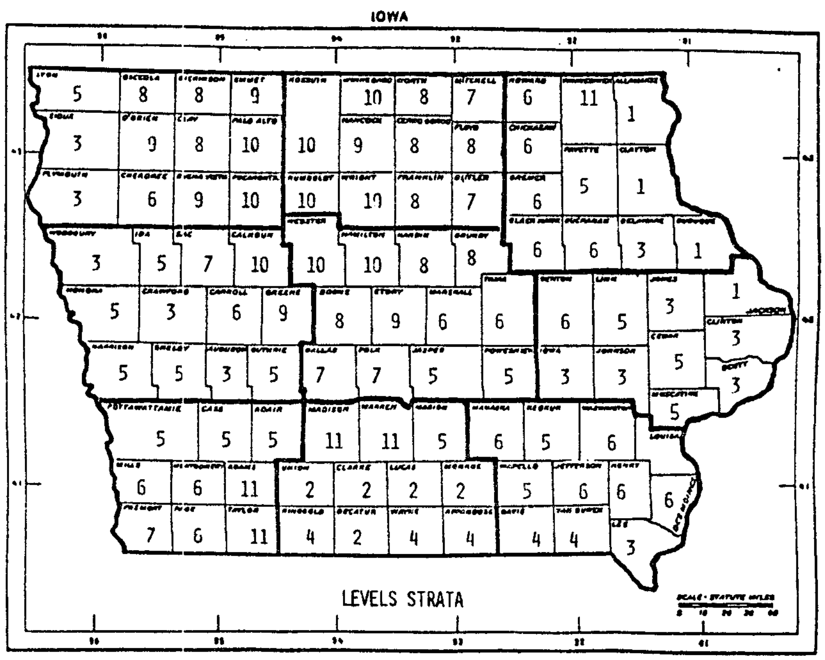


Figure D-3. Maps of two stratification systems developed at LARS. A set of contiguous strata (top) and a set of levels strata (bottom) were developed by examining coefficients of variation of historical crop data.

contiguous. Some characteristics of the strata are presented in Tables D-1 to D-5. Means and variability between counties within the strata are described.

3.3 Meteorological Data Estimation

In order to study the various levels of aggregation, yield estimates were needed at each of the levels. To make yield estimates using current technology, meteorological data were needed for each stratum. Not all counties contain weather stations, and perhaps weighting by nearby weather stations may provide a better estimate of the overall weather of a county than the use of one weather station alone (Figure D-4).

For this reason, a weather smoothing routine was utilized. Wagner (1) devised an objective analysis technique which incorporates a low pass filter and provides a good analysis in sparse data areas or with data containing significant noise. Furthermore, the characteristics of the applied filter function are easily calculated and the analysis technique is quite forgiving in terms of the sensitivity of choosing a filter function for a given data set. This technique was initially devised to remove high frequency fluctuations in the initial condition fields used for numerical weather forecasting. However, the consistency and speed of the technique make it a viable technique for our purposes.

Odell (2) compared ten techniques for interpolation for irregularly spaced sparse data: composite average, nearest neighbor, least squares linear regression, least squares convex hull, average linkage, average linkage with directional correlation, Wagner's objective analysis, modified linkage, and modified least squares. These techniques were tested in terms of their ability to interpolate five years of wheat yield data across the state of North Dakota (45 data points) based on seven stations of wheat yield data. The weighted linear regression technique appeared to be the best technique with the objective analysis, least squares linear regression, and the modified average linkage coming in close behind. However, the weighted linear regression is computationally time consuming, the least squares linear regression is not well behaved on the boundaries, and the modified linkage does not reflect directional trends in the data. The objective analysis approach provides a smooth well behaved surface and is computationally fast. Its major deficiency is that the original data points are not fit exactly. However, if noise exists in the input data, this can be advantageous.

Integration of data fields (raster form) produced by the objective analysis routine is sometimes required in order to obtain averages of meteorological (or other) data over some polygonal area. In order to accomplish this, the subroutines of Rios (3) were utilized. A driver program was written to enable averages, mean square errors, and variances to be calculated for polygonal areas with 39 or fewer

Table D-1. Some characteristics of the refined strata. Means and variability are described for corn and soybeans proportions and yields.

DESCRIPTION OF PROPORTIONS FOR REFINED STRATA

	Corn			Soybeans			Corn + Soybeans			
Stratum	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	No. of Counties
14	37.0	4.3	11.6	16.7	3.8	22.6	53.7	2.9	5.3	13
24	37.7	9.0	35.4	25.5	9.0	35.4	63.2	12.9	20.4	45
25	25.7	8.7	33.7	13.3	5.0	37.3	39.0	12.3	31.5	41

DESCRIPTION OF YIELDS FOR REFINED STRATA

	Corn			Soybeans			
Stratum	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	No. of Counties
14	85.1	23.4	27.5	32.3	3.9	12.1	13
24	99.6	15.7	15.8	32.6	4.0	12.3	45
25	94.7	18.2	19.2	31.0	4.6	14.8	41

Table D-2. Some characteristics of the refined/split strata. Means and variability are described for corn and soybeans proportions and yields.

DESCRIPTION OF PROPORTIONS FOR REFINED /SPLIT STRATA

STRATUM	CORN			SOYBEANS			CORN + SOYBEANS			NO. OF COUNTIES
	MEAN	STANDARD DEVIATION	C.V.	MEAN	STANDARD DEVIATION	C.V.	MEAN	STANDARD DEVIATION	C.V.	
14A	39.3	2.9	7.5	14.1	2.6	18.7	53.4	3.5	6.6	6
14B	35.0	4.4	12.6	19.0	3.1	16.4	54.0	2.4	4.4	7
24A	39.7	2.0	5.1	29.7	6.6	22.1	69.4	6.6	9.6	13
24B	39.7	3.2	8.1	29.3	5.4	18.4	69.0	7.4	10.7	20
24C	32.3	5.2	16.1	14.6	7.1	48.9	4.7	11.1	23.7	12
25A	21.3	8.8	41.1	12.4	3.5	28.4	33.7	11.9	35.4	18
25B	22.2	5.7	25.8	0.9	0.2	20.2	23.1	5.6	24.4	3
25C	30.2	6.7	22.2	16.0	2.9	18.0	46.2	8.1	17.6	20

DESCRIPTION OF YIELDS FOR REFINED /SPLIT STRATA

STRATUM	CORN			SOYBEANS			NO. OF COUNTIES
	MEAN	STANDARD DEVIATION	C.V.	MEAN	STANDARD DEVIATION	C.V.	
14A	81.7	22.9	28.0	32.2	4.8	14.9	6
14B	88.0	23.7	26.9	32.4	3.1	9.6	7
24A	97.5	18.5	19.0	33.5	4.1	12.2	13
24B	103.6	14.1	13.6	33.0	3.8	11.5	20
24C	95.4	13.2	13.8	30.8	3.9	12.7	12
25A	85.6	20.4	23.8	29.1	4.3	14.8	18
25B	102.4	12.5	12.2	32.9	4.2	12.8	20
25C	93.6	8.4	8.5	30.0	2.8	9.3	3

Table D-3. Some characteristics of the crop reporting districts. Means and variability are described for corn and soybeans proportions and yields.

DESCRIPTION OF PROPORTIONS FOR CROP REPORTING DISTRICTS

	Corn			Soybeans			Corn + Soybeans			
Stratum	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	No. of Counties
North West	39.5	2.3	5.7	26.8	8.5	31.7	66.3	8.1	12.2	12
North Central	39.9	2.1	5.2	30.7	5.4	17.5	70.6	6.8	9.7	11
North East	30.2	7.1	23.5	11.7	8.9	75.7	41.9	14.8	35.3	11
West Central	38.3	4.7	12.4	19.3	8.3	43.1	57.6	10.7	18.5	12
Central	37.6	4.9	13.1	25.1	6.5	25.9	62.8	10.4	16.6	12
East Central	33.1	5.3	16.0	13.5	5.4	40.1	46.6	9.6	20.7	10
South West	29.7	5.8	19.6	17.5	4.0	22.8	47.2	9.0	19.0	9
South Central	16.3	4.8	29.3	10.6	2.3	22.0	26.9	6.9	25.6	11
South East	27.0	6.9	25.7	16.5	3.1	18.7	43.6	9.6	21.9	11

DESCRIPTION OF YIELDS FOR CROP REPORTING DISTRICTS

	Corn			Soybeans			
Stratum	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	No. of Counties
North West	93.1	21.0	22.6	33.8	4.3	12.7	12
North Central	99.8	14.1	14.1	32.2	3.5	10.9	11
North East	95.9	12.7	13.2	29.8	3.5	11.7	11
West Central	89.9	21.0	23.4	31.8	3.9	12.3	12
Central	106.8	12.8	12.0	33.9	3.8	11.2	12
East Central	100.5	12.7	12.6	33.8	3.6	10.7	10
South West	85.7	25.1	29.3	31.2	3.4	10.9	9
South Central	86.0	18.7	21.7	28.2	4.7	16.7	11
South East	101.9	12.8	12.6	31.7	4.4	13.9	11

Table D-4. Some characteristics of the contiguous strata. Means and variability are described for corn and soybeans proportions and yields.

DESCRIPTION OF PROPORTIONS FOR CONTIGUOUS STRATA

Stratum	Corn			Soybeans			Corn + Soybeans			No. of Counties
	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	
1	38.8	2.7	6.9	15.7	2.9	18.2	54.6	2.6	4.8	8
2	39.2	2.1	5.4	28.2	3.9	13.9	67.5	4.0	6.0	8
3	39.3	4.1	10.4	32.9	6.0	18.3	72.2	9.7	13.4	15
4	38.9	3.1	7.9	24.6	3.5	14.2	63.5	6.0	9.4	12
5	31.9	3.3	10.3	18.1	2.6	14.1	50.0	4.0	8.0	4
6	22.7	4.2	18.5	1.7	1.2	73.7	24.4	4.6	19.0	5
7	31.3	4.1	13.2	17.6	2.1	11.9	48.9	5.2	10.5	9
8	33.1	4.3	13.0	18.7	2.4	12.7	51.8	5.0	9.7	5
9	35.7	4.7	13.1	17.5	4.0	22.6	53.2	4.0	7.6	9
10	14.3	3.0	20.6	10.6	2.7	25.4	25.0	5.5	22.0	9
11	34.5	4.1	12.0	12.1	2.9	24.3	46.6	4.4	9.4	7
12	21.3	3.5	16.4	12.5	1.8	14.7	33.8	5.1	15.0	8

DESCRIPTION OF YIELDS FOR CONTIGUOUS STRATA

Stratum	Corn			Soybeans			No. of Counties
	Mean	Standard Deviation	C.V.	Mean	Standard Deviation	C.V.	
1	84.5	5.4	6.4	32.6	2.4	7.4	8
2	94.8	6.0	6.3	33.4	1.6	4.7	8
3	103.9	5.8	5.6	33.4	1.4	4.3	15
4	101.0	7.8	7.7	32.7	2.8	8.7	12
5	91.0	10.4	11.4	28.5	3.4	11.8	4
6	94.8	5.4	5.7	29.4	1.5	5.2	5
7	105.8	5.3	5.0	33.1	2.1	6.3	9
8	102.7	5.0	4.8	33.2	1.6	4.7	5
9	87.8	3.4	3.9	32.3	1.3	3.9	9
10	87.8	6.7	7.6	28.0	1.5	5.5	9
11	100.3	3.6	3.6	33.6	1.7	5.2	7
12	85.3	7.6	8.9	29.5	0.9	3.0	8

Table D-5. Some characteristics of the levels strata. Means and variability are described for corn and soybeans proportions and yields.

DESCRIPTION OF PROPORTIONS FOR LEVELS STRATA

	CORN			SOYBEANS			CORN + SOYBEANS			
STRATUM	MEAN	STANDARD DEVIATION	C.V.	MEAN	STANDARD DEVIATION	C.V.	MEAN	STANDARD DEVIATION	C.V.	NO. OF COUNTIES
1	22.7	4.2	18.5	1.7	1.2	73.7	2.4	4.6	19.0	5
2	13.6	2.4	17.7	8.6	0.9	10.7	22.1	3.1	14.1	5
3	36.2	5.1	14.1	12.1	2.0	16.2	48.3	5.5	11.5	12
4	15.0	2.4	16.1	11.3	0.9	7.7	25.3	3.1	11.4	5
5	32.9	6.2	18.8	16.0	1.2	7.2	49.0	6.6	13.6	18
6	33.8	4.2	12.3	20.0	1.1	5.5	53.7	4.7	8.8	19
7	36.2	4.2	11.5	23.1	1.1	4.7	59.3	4.5	7.6	6
8	39.6	2.7	6.9	28.2	1.2	4.4	67.8	2.7	4.0	10
9	40.6	1.1	2.7	31.8	1.6	5.1	72.4	1.7	2.4	6
10	40.5	1.7	4.1	36.4	1.4	3.9	76.9	2.1	2.7	9
11	21.3	1.4	6.4	12.8	1.0	7.5	34.1	1.0	2.9	4

DESCRIPTION OF YIELDS FOR LEVELS STRATA

	CORN			SOYBEANS			
STRATUM	MEAN	STANDARD DEVIATION	C.V.	MEAN	STANDARD DEVIATION	C.V.	NO. OF COUNTIES
1	94.6	5.4	5.7	29.4	1.5	5.2	5
2	82.7	1.9	2.3	27.8	1.2	4.3	5
3	93.0	9.6	10.3	32.9	2.1	6.4	12
4	86.7	4.8	5.5	28.0	1.1	3.9	5
5	94.3	9.1	9.6	32.2	1.9	5.8	18
6	98.5	9.5	9.8	32.6	2.8	8.7	19
7	94.3	6.1	6.5	31.1	1.7	5.4	6
8	100.3	10.0	9.9	32.9	2.6	7.9	10
9	103.6	3.7	3.6	34.2	1.0	2.9	6
10	104.3	3.4	3.3	33.8	1.0	3.0	9
11	84.9	8.6	10.1	29.1	1.0	3.3	4

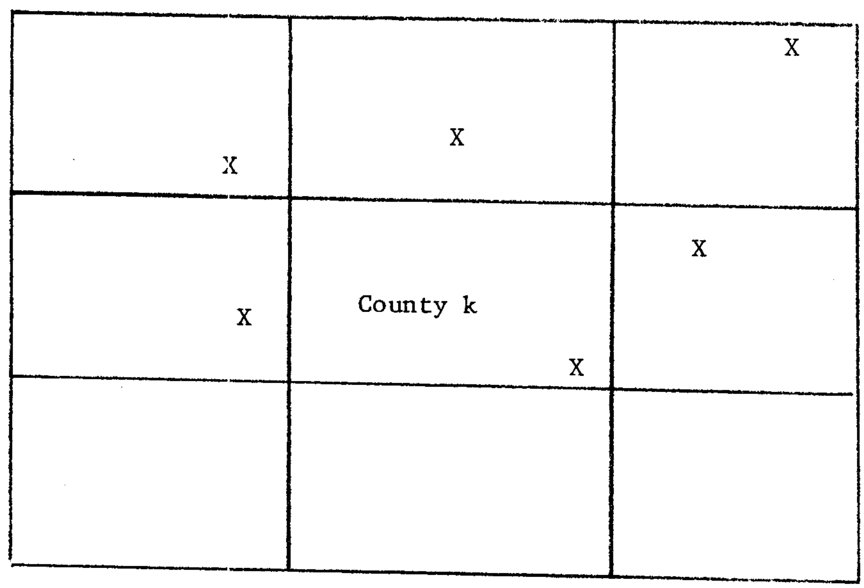


Figure D-4. An example of a situation when weighting by weather stations in adjacent counties may be beneficial in providing good estimates of weather for county K. Each X represents a meteorological station.

vertices. The polygon may contain both convex and concave features. This capability enables averages for a farmer's field, an entire political subdivision or stratum to be calculated.

The general procedure utilized by the objective analysis technique is illustrated by Figure D-5. A grid of a user-selected density is placed over the area of interest. Then the available met station data are used to specify the values at the nearest grid intersection points. The objective analysis procedure then uses gradient and Laplacian weights to specify the values at all grid intersections (1). Finally, an estimate of the smoothed variable can be made over any polygon of interest by averaging over the grid points within that polygon.

The objective analysis technique was found to perform well in interpolating maximum temperature, minimum termperature, and precipitation on both a monthly and a daily basis for a case study in May 1977 in Oklahoma (4).

Based upon the favorable results obtained by other investigators, the Fortran coded programs for objective analysis were obtained from Dr. David E. Pitts of NASA/JSC.

A meteorological data smoothing experiment was conducted to determine how the objective function should be utilized. One month of daily data (June 1974) for all met stations in Iowa was used in the study. There were several factors in the experiment: grid size (25 x 25, 32 x 32, 64 x 64), level of smoothing (daily vs. monthly), gradient weight (1,10), and Laplacian weight (1,10). The results were evaluated by examining the mean square error of fit to station data and the maximum change in specified values.

The first observation from this experiment was that using gradient and Laplacian weights of 10 caused too much change in the specified values. A difference of up to about one inch of precipitation was observed. Thus, the remainder of the experiment was analyzed using weights of one only.

The maximum absolute deviation from specified values was examined for the three grid sizes (Table D-6). The 64 x 64 grid provided estimates much closer to the specified values than the other two grid sizes. The root mean square error was examined for daily vs. monthly averaging (Table D-7). It was found that averaging met data to monthly values and then smoothing the monthly averages performed significantly better than smoothing daily values and then averaging the smoothed values to obtain a monthly estimate.

The parameters selected for use in our study were: grid size 64 x 64 over Iowa, gradient and Laplacian weights of 1.0, and smoothing of monthly average values.

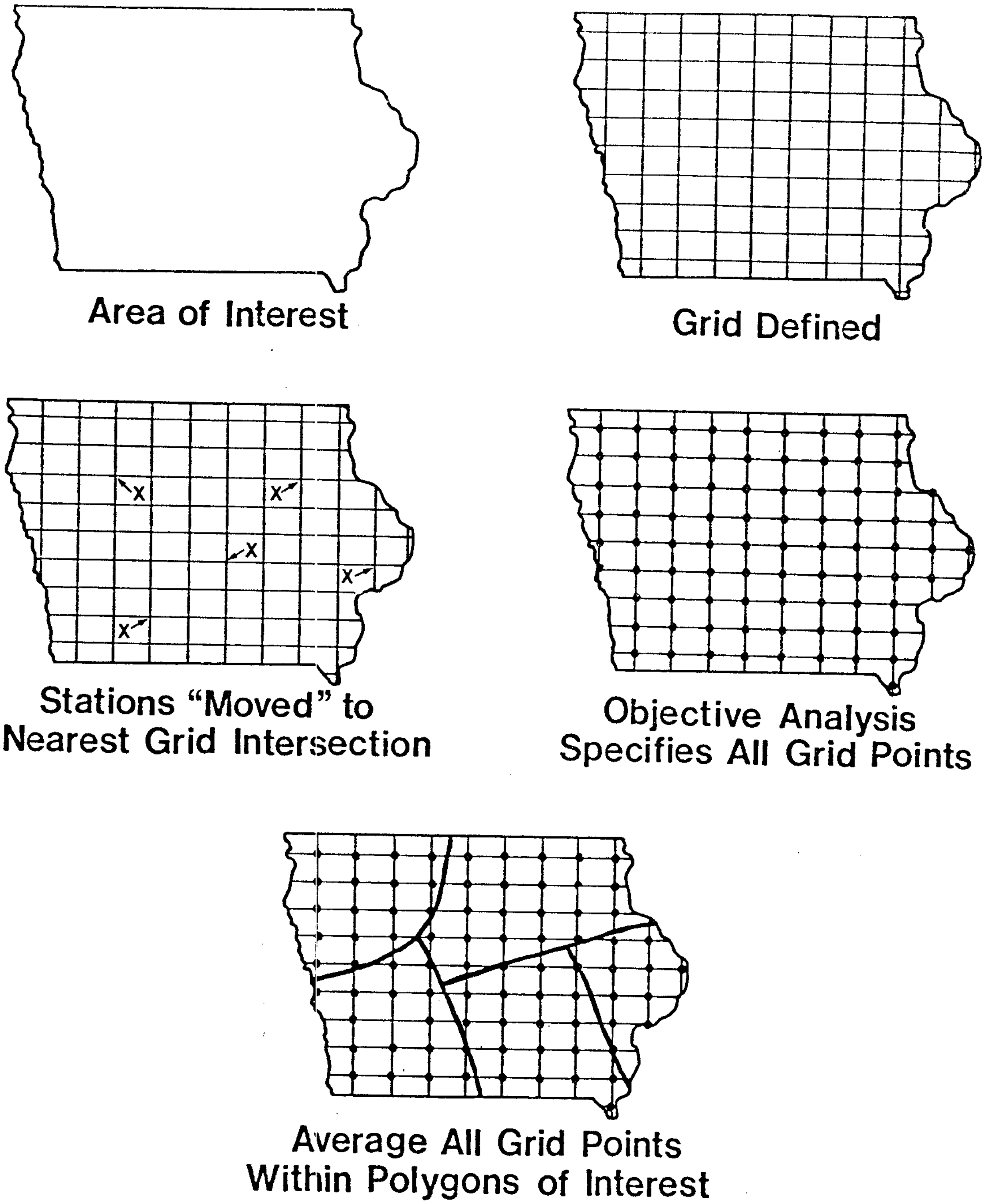


Figure D-5. Schematic diagram of the steps in the meteorological data smoothing routine used to obtain meteorological estimates for polygons of interest in Iowa.

Table D-6. Some results from the meteorological data smoothing experiment. The table shows daily maximum absolute deviations of smoothed values from the specified station values.

Weather Variable	Grid Size		
	25x25	32x32	64x64
Maximum Temperature	2.93	2.45	0.77
Minimum Temperature	2.08	1.39	0.63
Precipitation	0.06	0.04	0.01

Table D-7. Some results from the meteorological data smoothing experiment. The table shows the root mean square error of smoothed values from the specified station values.

Weather Variable	Grid Size	RMS Error	
		Daily Smooth	Monthly Smooth
Temperature	32x32	4.88	0.52
	64x64	NA*	0.17
Precipitation	32x32	6.67	0.92
	64x64	NA	0.17

*NA - Not Available

3.4 Yield Estimation

Estimates of yield at all the levels of aggregation are required for this study. To do this, the variables used in the CCEA state level model were utilized (Table D-8). Regression coefficients were developed for each set of strata utilizing 1931-77 meteorological data and 1932-77 USDA/ESCS estimates of county level yields. The meteorological data inputs were daily reports of minimum temperature, maximum temperature, and precipitation from all the cooperative meteorological stations in the state of Iowa. The meteorological data were smoothed by the Wagner variational analysis technique and were averaged to the polygons describing the strata. Some examples of the resulting yield models are shown in Figures D-6 to D-13.

4. Future Work

This task is continuing into the next contract year. This study will be completed early in that time period. Production estimates and their variances will be computed, and comparisons of the levels of estimation will be made with one another and with the results of simulated and TY aggregations. The production estimate will be compared with the USDA/ESCS state estimates to assess any bias due to the yield estimation methodology.

For those levels of aggregation which appear to be improvements over the currently used method, a further investigation will be carried out for wheat and barley using North Dakota as a test region.

5. References

1. Wagner, K.K. 1971. Variational Analysis Using Observation and Low-Pass Filtering Constraints. Master's Thesis, Dept. of Meteorology, University of Oklahoma, Norman, Oklahoma.

2. Odell, P.L. 1975. Statistical Theory and Methodology for Remote Sensing Data Analysis with Special Emphasis on LACIE. University of Texas at Dallas Annual Report 1, 75N33484, NASA CR-144509.

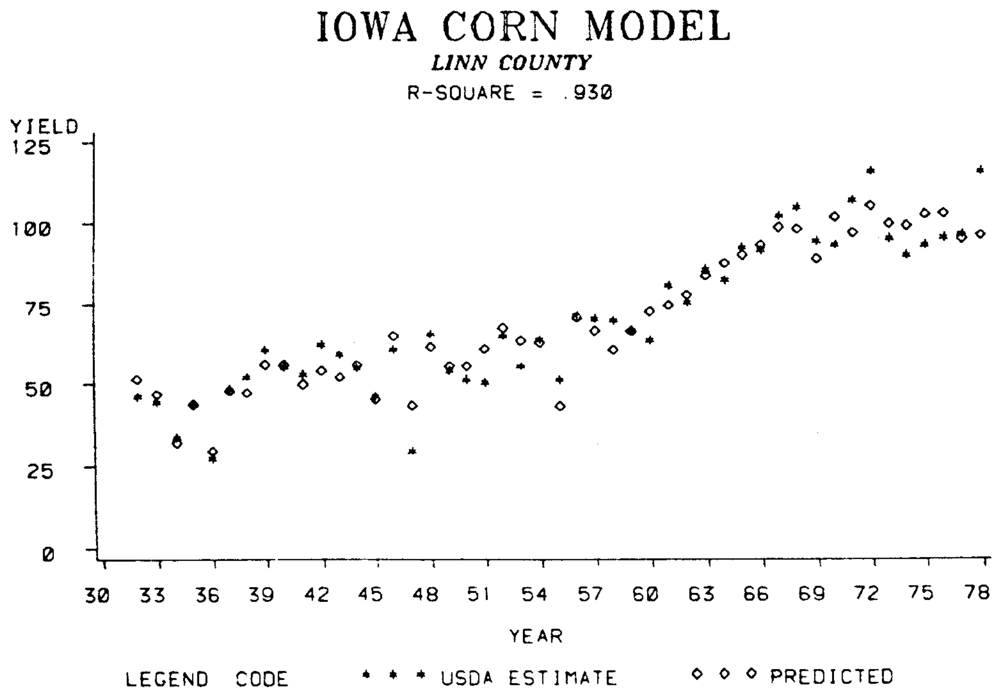
3. Rios, A. 1979. "As Built" Design Specification for BTMAIN Processor Program. NASA, Johnson Space Center, Houston, Texas. JSC-14834, Job Order 71-475, LEC 13322.

4. Pitts, David E. 1980. Interpolation of Daily and Monthly Precipitation and Temperature Using the Wagner Variational Analysis Technique: An Exploratory Experiment. NASA, Johnson Space Center, Houston, Texas. JSC-16504, SR-JO-00457.

Table D-8. Model variables for the regressions predicting yield of corn and soybeans in Iowa.

Iowa Yield Model Variables*	
Corn	Soybeans
Linear Trend 1941-60	Linear Trend 1932-74
Linear Trend 1961-72	Cumulative precipitation October - April DFN
May temperature x precipitation interaction	May temperature x precipitation interaction
June temperature x precipitation interaction	June temperature DFN
June temperature $(DFN)^2$	July precipitation DFN
July precipitation DFN	July temperature DFT
July temperature DFT	August precipitation DFN
July temperature $(DFT)^2$	August precipitation $(DFN)^2$
August temperature DFT	August temperature DFT

*DFN = departure from normal
DFT = departure from trend



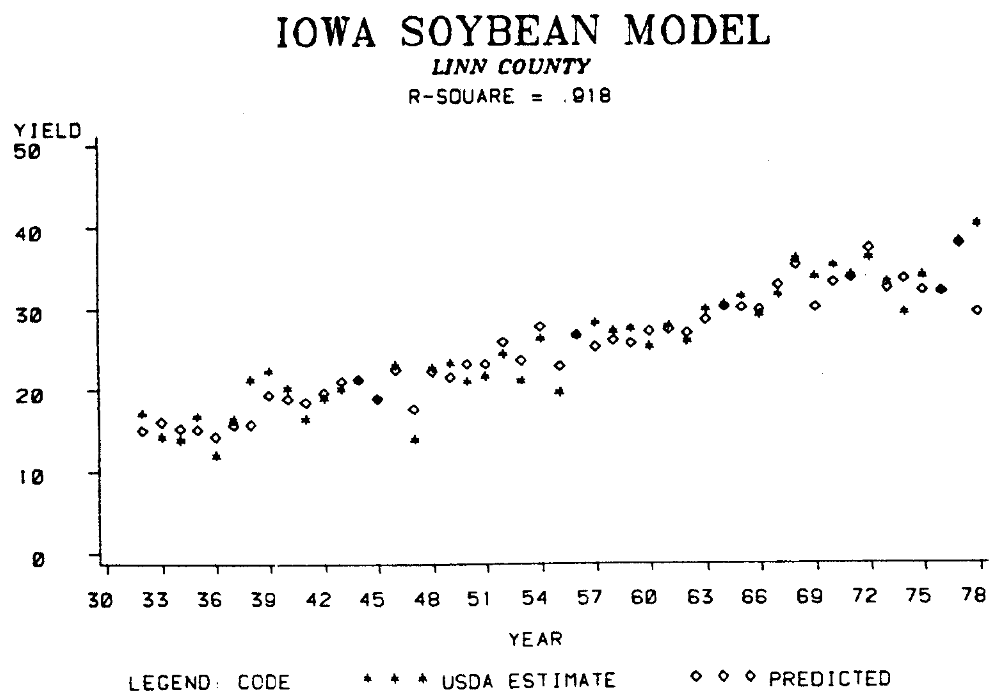
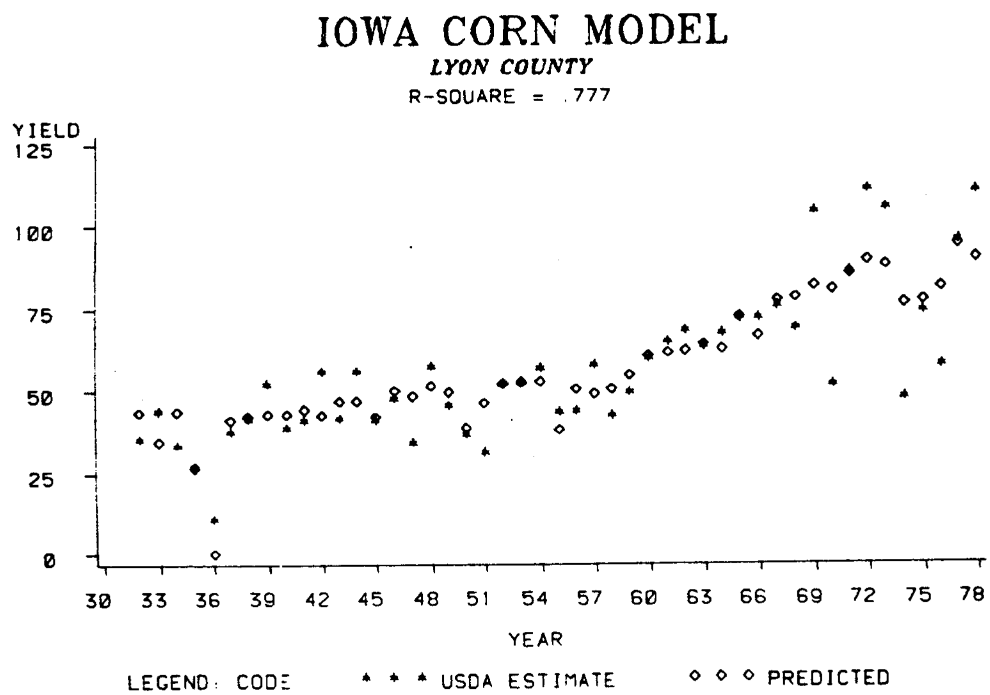


Figure D-6. Comparison of corn and soybean yields predicted by the regression equations with USDA/ESCS estimates for Linn County, Iowa.



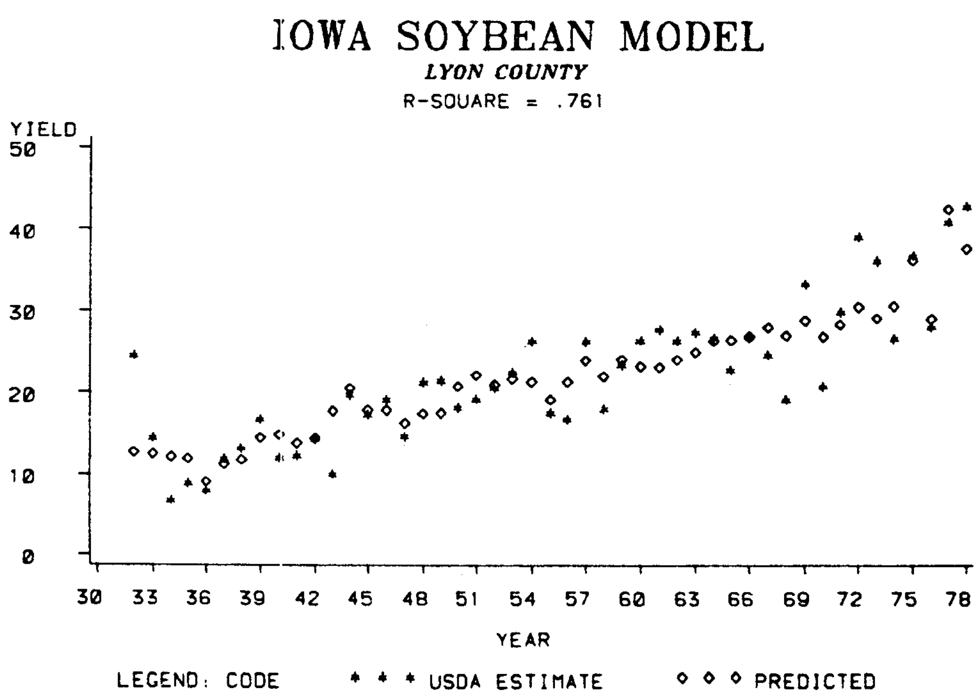
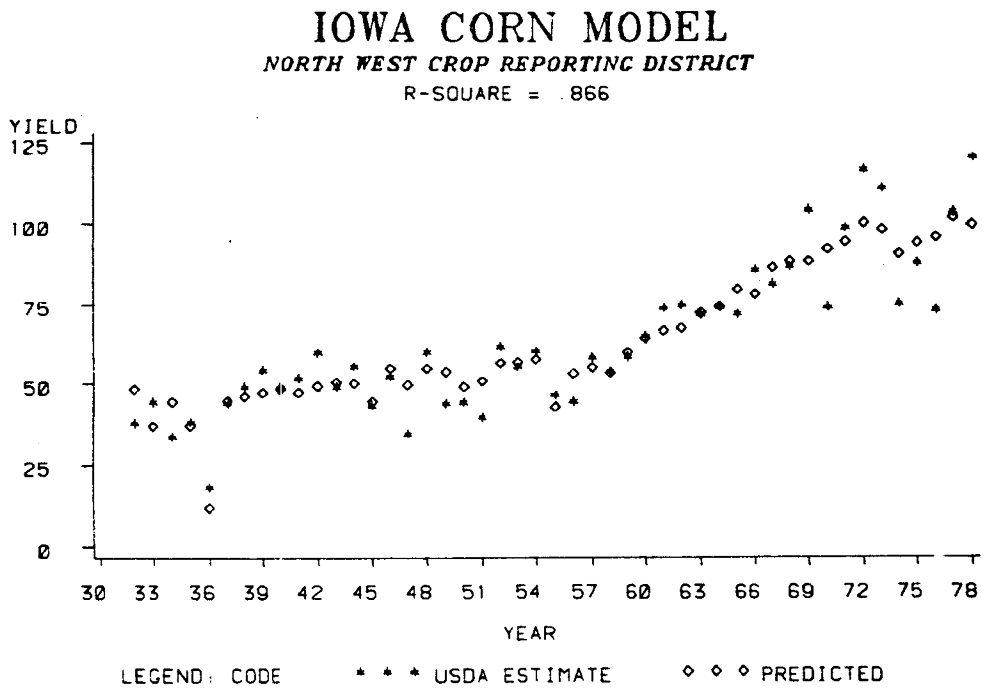


Figure D-7. Comparison of corn and soybean yields predicted by regression equations with USDA/ESCS estimates for Lyon County, Iowa.



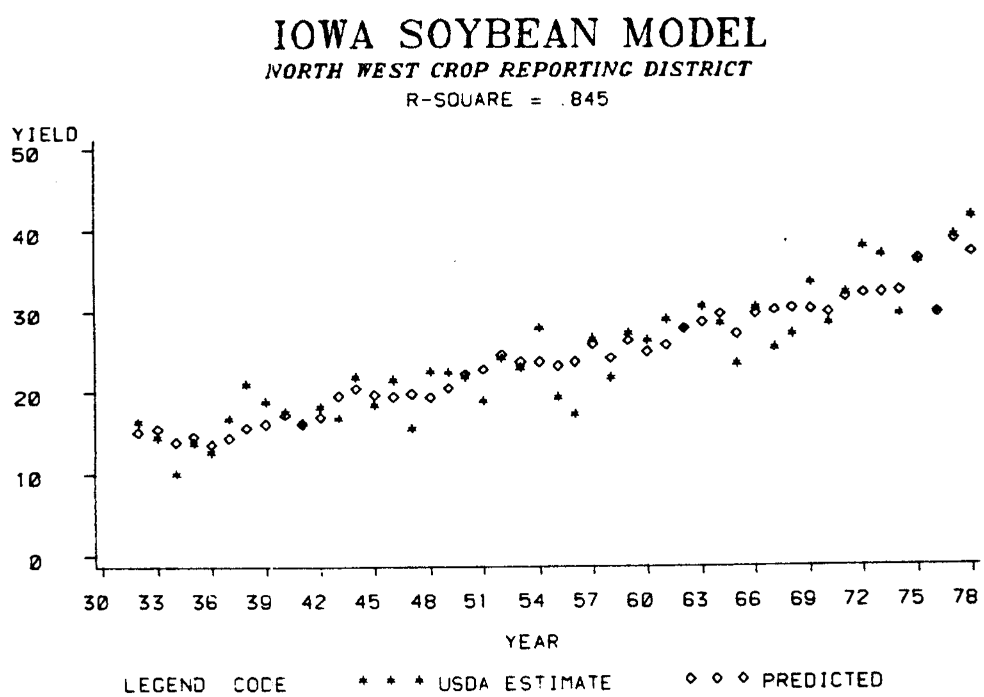
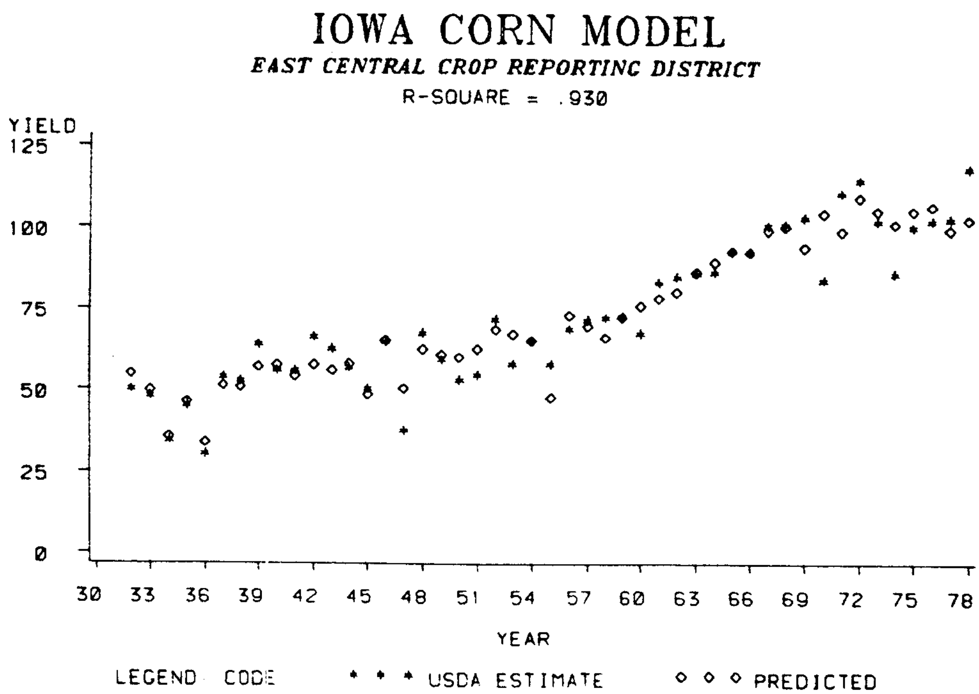


Figure D-8. Comparison of corn and soybean yields predicted by the regression equations with USDA/ESCS estimates for the North West Crop Reporting District in Iowa.



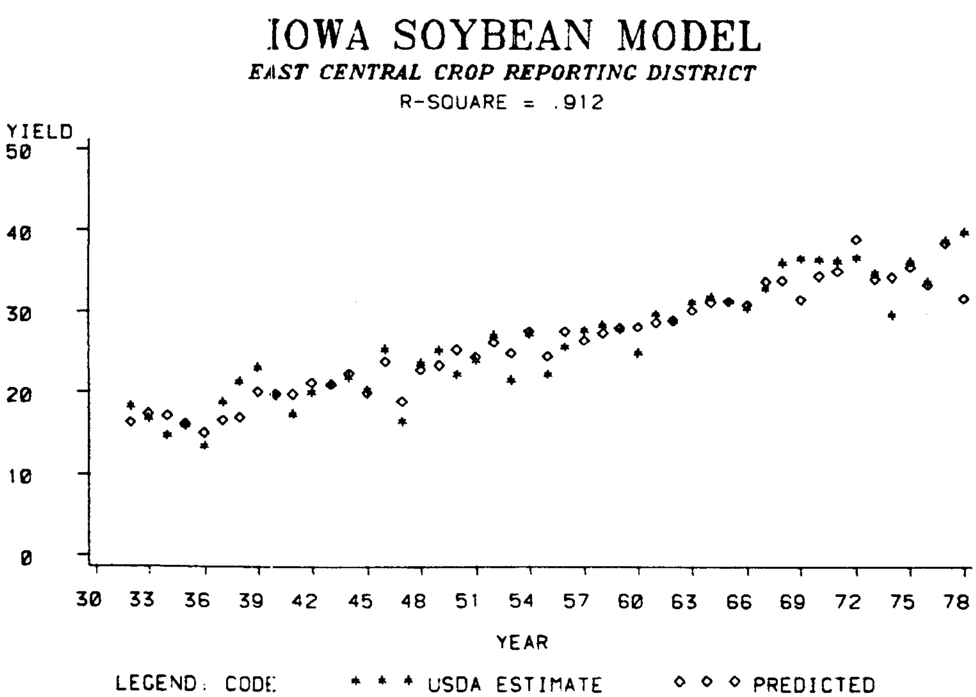
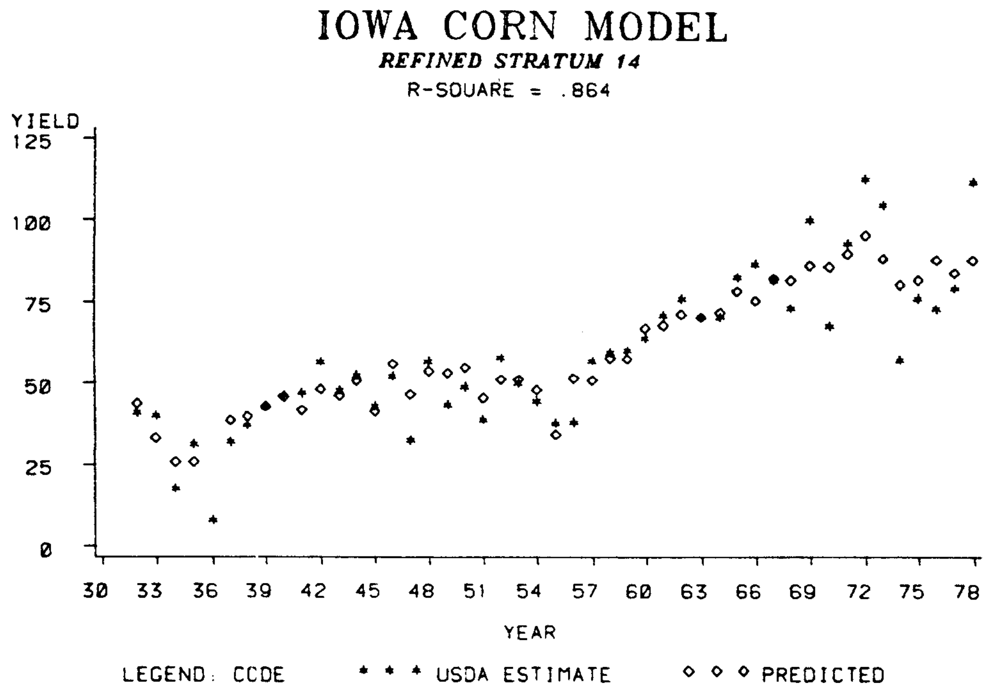


Figure D-9. Comparison of corn and soybean yields predicted by the regression equations with USDA/ESCS estimates for the East Central Crop Reporting District in Iowa.



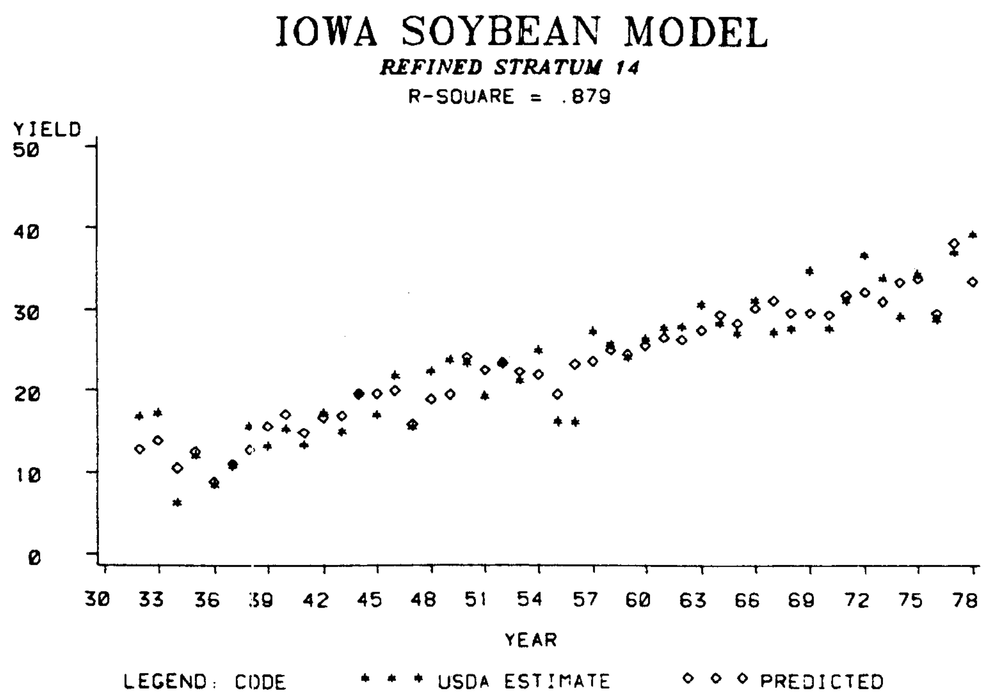
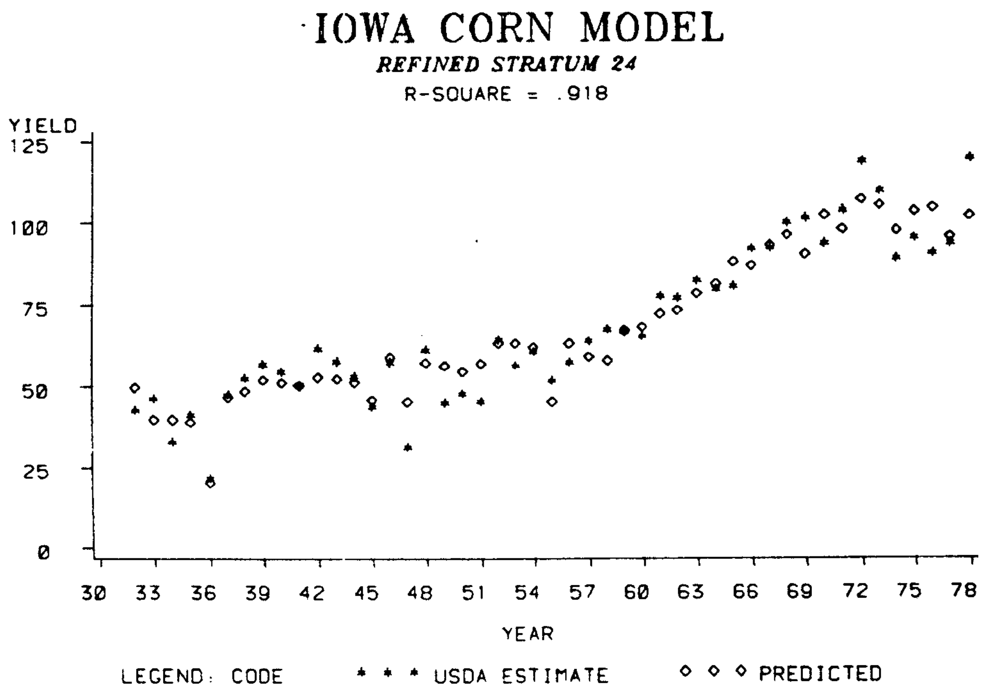


Figure D-10. Comparison of corn and soybean yields predicted by the regression equations with the USDA/ESCS estimates for refined stratum 14 in Iowa.



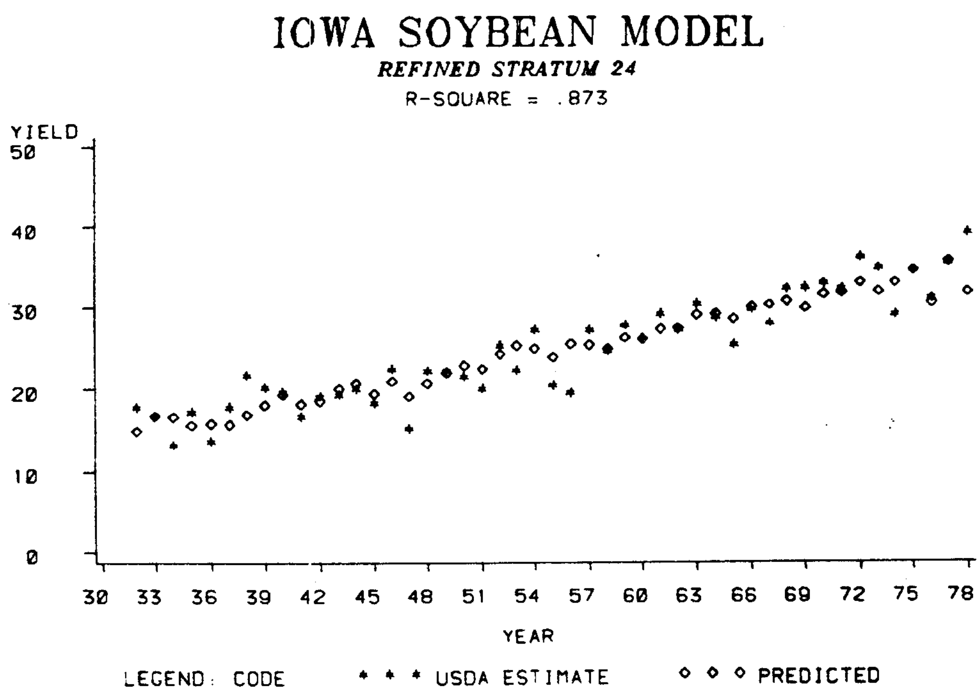
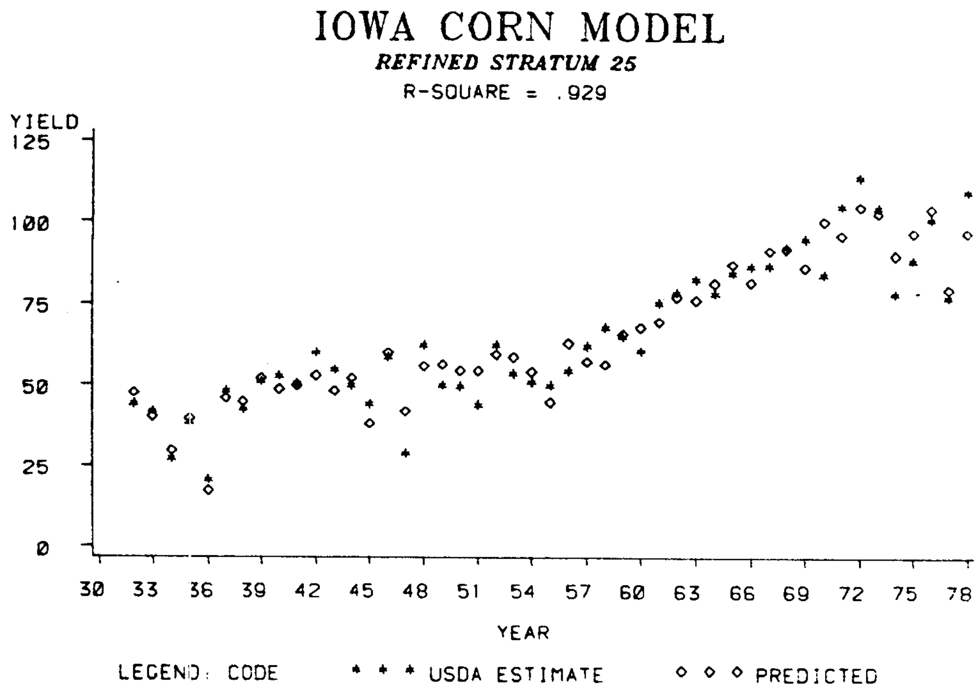


Figure D-11. Comparison of corn and soybean yields predicted by the regression equations with the USDA/ESCS estimates for refined stratum 24 in Iowa.



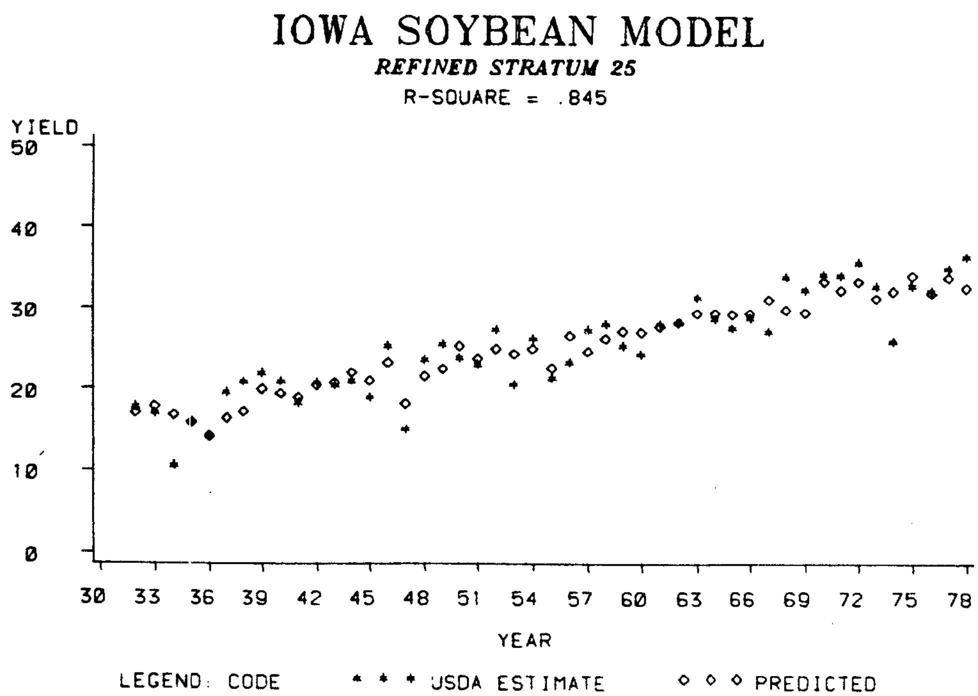
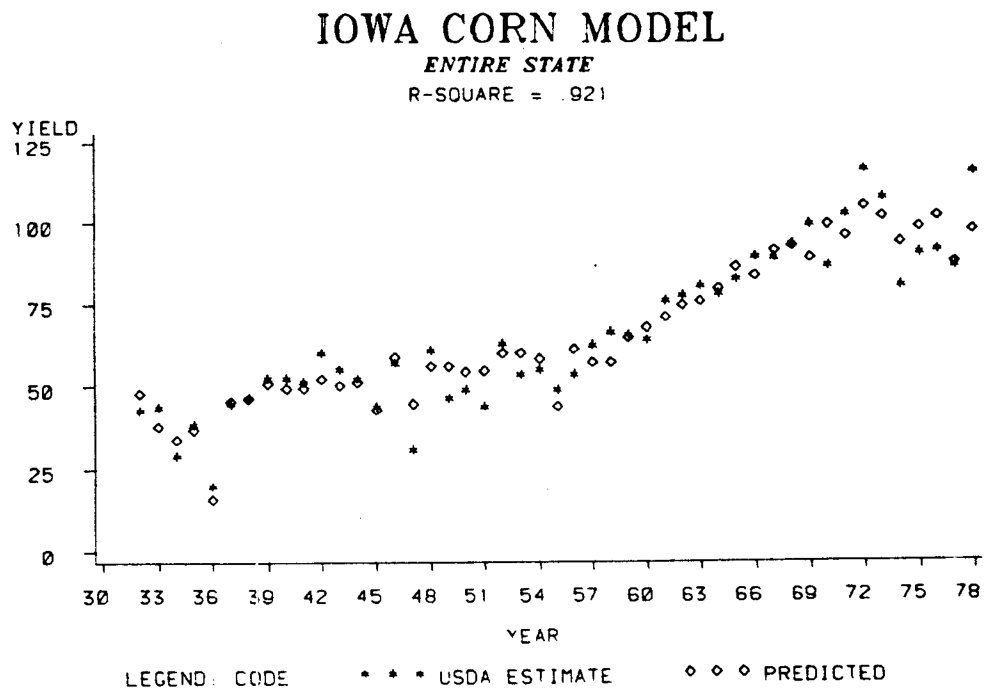


Figure D-12. Comparison of corn and soybean yields predicted by the regression equations with the USDA/ESCS estimates for refined stratum 25 in Iowa.



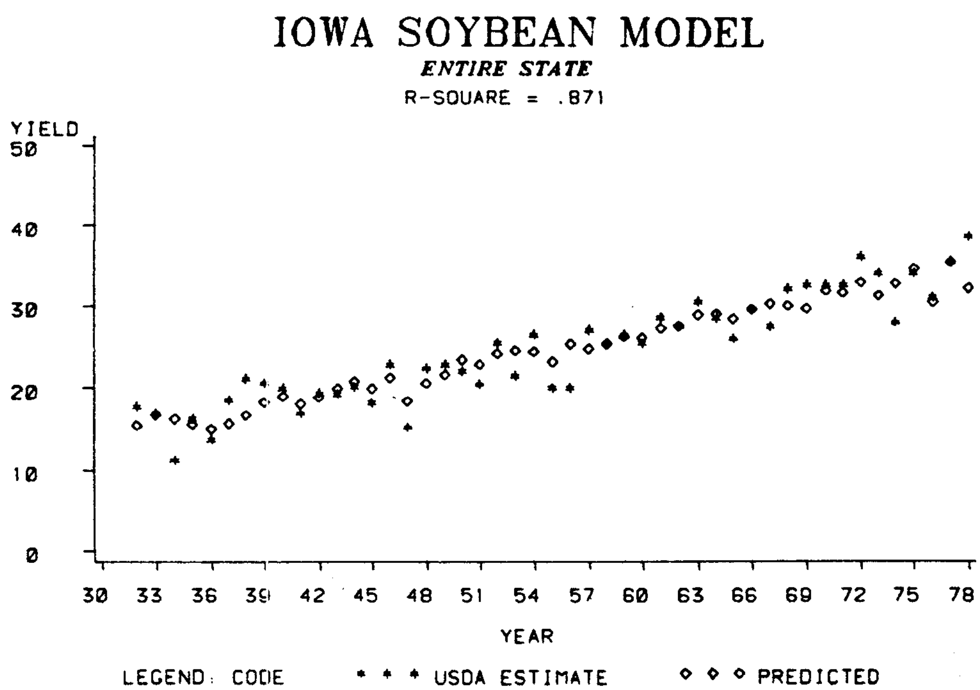


Figure D-13. Comparison of corn and soybean yields predicted by the regression equations with the USDA/ESCS estimates for the state of Iowa.

DISTRIBUTION LIST: VOLUME II

NASA Johnson Space Center

SA:	W. Rice
SK:	R. Erb
SG:	R. MacDonald
SH:	J. Erickson
SG3:	F. Hall
	C. Hallum
	A. Houston
	A. Feiveson
	D. Pitts
	D. Thompson
	K. Henderson
	G. Badwahr
	J. Paris
SH2:	M. Trichel
SH3:	J. Dragg
	R. Bizzell
	R. Eason
	V. Whitehead
JM6:	Technical Library (4)
AP:	Public Affairs Office

NASA Headquarters

ER-2: P. Thome

NASA Scientific and Technical
Information Facility

R. Horvath:	ERIM
W. Malila:	ERIM
R. Cicone:	ERIM
C. Hay:	Univ. Calif.-Berkeley
E. Kanemasu:	Kansas State Univ.
B. Blad:	Univ. Nebraska
J. Heilman:	Texas A&M Univ.
E. LeMaster:	Pan American Univ.
J. Harlan:	S. Dakota State Univ.
F. Ulaby:	Univ. Kansas
J. Smith:	Colorado State Univ.
R. Jackson:	USDA-SEA
C. Wiegand:	USDA-SEA
G. Boatwright:	USDA-SEA
V. Salomonson:	NASA-GSFC
C. Tucker:	NASA-GSFC
J. Barker:	NASA-GSFC
D. Phinney:	LEMSCO
B. Carroll:	LEMSCO

Additional volumes available upon request from Purdue/LARS.

Vol. I. Field Research on the Spectral Properties of Crops and Soils
Vol. II. Research in the Application of Spectral Data to Crop Identification and Assessment
Vol. III. Data Processing Research and Techniques Development
Vol. IV. Computer Processing Support