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CORN AND SOYBEAN LANDSAT MSS CLASSIFICATION PERFORMANCE AS A FUNCTION OF SCENE CHARACTERISTICS

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ABSTRACT

In order to fully utilize remote sensing to inventory crop production, it is important to identify the factors that affect the accuracy of Landsat classifications. The objective of this study was to investigate the effect of scene characteristics involving crop, soil, and weather variables on the accuracy of Landsat classifications of corn and soybeans. Segments sampling the U.S. Corn Belt were classified using a Gaussian maximum likelihood classifier on multitemporally registered data from two key acquisition periods. Field size had a strong effect on classification accuracy with small fields tending to have low accuracies even when the effect of mixed pixels was eliminated. Other scene characteristics accounting for variability in classification accuracy included proportions of corn and soybeans, crop diversity index, proportion of all field crops, soil drainage, slope, soil order, long-term average soybean yield, maximum yield, relative position of the segment in the Corn Belt, weather and crop development stage.

I. INTRODUCTION

Previous research has demonstrated that satellite remote sensing has the potential to provide accurate, timely crop production information (MacDonald and Hall, 1978) or when combined with conventional survey data to improve the accuracy and efficiency of area estimates (Hanuschak et al., 1980). But, to fully develop and utilize Landsat data to inventory crop production, it is important to identify and understand the factors that affect Landsat crop classification accuracy.

Classification accuracy of Landsat MSS data depends on a number of variables including scene characteristics; procedures for training, classification, and area estimation; and the general quality of the data. The variability in accuracy found using the same classification procedure and the similar distributions of Landsat data acquisition dates, at different locations is due primarily to scene variability. Understanding the way scene characteristics affect classifier performance is an important step in determining not only the accuracy that can be expected for a particular area, but also the amount of effort required for training, classification, and area estimation procedures to achieve an optimal accuracy and efficiency.

The primary objective of this research was to investigate the accuracy of Landsat MSS data classifications of corn and soybeans as a function of scene characteristics in the U.S. Corn Belt. The scene characteristics involved several aspects of crop, soil, and weather variables. A second objective was to examine the interrelationships among the scene characteristics.

The study has an immediate potential application in the design of a crop inventory system using remote sensing. For example, areas with high expected classification accuracy could be sampled with lower frequency than areas where local characteristics are known to induce poorer classification results.

II. REVIEW OF PREVIOUS FINDINGS

Many remote sensing researchers have found that a difference exists among the Landsat classification and area estimation accuracies in different sites. Bizzell et al. (1975), reporting on the results of CITARS project, found two site characteristics, field size and proportion of corn and soybeans, to be correlated with proportion estimation accuracy. They attributed the effect of field size to the decreasing percentage of mixed pixels as field size increases. Further, areas with predominantly larger fields tended to be more uniform and have fewer cover types, thus decreasing the amount of spectral variation. Field size effects have also been noted by Bauer et al. (1978), Hixson et al. (1980) and Pitts et al. (1980).

The LACIE project, involving large-area production estimates, dealt with a wider source of errors. Pitts et al. (1978) identified sampling and classification errors as the two major components of area estimation errors. Classification error, which is the subject of our study, was viewed by LACIE as composed of analyst-labeling error sources and machine-classification error sources. The magnitude of the labeling error was affected by Landsat acquisition date, crop development stage, and a number of confusion crops, while classification error was associated with field size, training statistics, and classification algorithm selected. Both labeling and classification were affected by the general quality of the data, such as registration accuracy and atmospheric effects. In addition to these scene characteristics, soil and weather variability were noted as contributing factors to classification accuracy by Bizzell et al. (1975) and Bauer et al., (1979).

In summary, the literature on remote sensing applications has extensively demonstrated the feasibility of using Landsat data and computer-aided analysis for crop identification and area estimation. Although several studies have indicated that scene characteristics, including weather variations, affect classification performance, no work, to our knowledge, has been carried out with sufficient supporting data to define satisfactory functional relationships between specific scene characteristics and performance of a classification system for crop inventory.

III. APPROACH

A. DESCRIPTION OF STUDY AREA AND LANDSAT DATA

Multitemporally registered Landsat-2 and -3 MSS data acquired over the U.S. Corn Belt during the summer of 1978 were analyzed. The data set consisted of 23 sample segments, each 5 x 6 n. miles in size. The locations (Figure 1) of the test sites were selected to represent a broad range of conditions in terms of climate, soil, topography, field sizes, cropping practices of corn and soybeans, and confusion classes (e.g. oats, sorghum, sunflowers, and trees).

Aerial photography and a subsequent wall-to-wall inventory of crop types was digitized and registered to the Landsat data to provide a digital map of each site for evaluation of the classification results. Two data acquisition windows of the corn development stages, based on the investigations by Hixson et al. (1982), were selected for analysis: (1) preplant to 12 leaves, and (2) tassel to dent.

Color composites of Landsat imagery for all segments and all acquistions, along with full-frame Landsat color imagery were used to select cloud-free dates of Landsat data and for visual assessment of the contextual aspect of a segment in relation to the county where the segment was located.

B. TRAINING AND CLASSIFICATION

A systematic sample of the 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 in a field, the cover type in the field was identified from the ground inventory. Only field center pixels were selected.

From 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 a per point Gaussian maximum likelihood classifier from LARSYS (Phillips, 1973).

C. MEASURES OF CLASSIFICATION PERFORMANCE

Classification performance was evaluated for corn, soybeans and overall by three categories of performance measures: (1) wall-to-wall accuracy, obtained by comparing Landsat classifications of all pixels of a segment to the ground inventory identification; (2) test field accuracy, obtained by comparing test field classifications to the ground inventory; and (3) proportion estimate error, obtained by comparing the ground inventory proportions with the

Landsat proportions. The latter measure used RMS error for corn and soybeans to represent an overall error. Corn and soybean proportion estimate errors were defined as the absolute relative difference between the Landsat proportion and ground truth proportion of corn.

D. SCENE CHARACTERISTICS

Twenty-nine variables were defined to express the scene characteristics. They were grouped into four categories: (1) soil variables, (2) "ground truth" variables, (3) productivity variables, and (4) seasonal variables.

Soil variables were defined and estimated from available publications.

SLOPE - Average slope: 0-nearly level to moderately sloping (0-12%), 1-strongly sloping to very steep (12-25%).

DRAIN - Natural drainage: 1-poor to somewhat poor, 2-moderately well, 3-well.

PARM - Parent material: 0-not loess or not loess on till, 1-loess or loess on till.

ORDER - Taxonomic order: 0-not Mollisol, 1-Mollisols.

VARI - Soil variability: 1-low, 2-medium, 3-high, 4-very high.

VAXOR - Interaction of VARI and ORDER.

DRXOR - Interaction of DRAIN and ORDER.

DRXVG - Interaction of DRAIN and original vegetation.

"Ground Truth" Variables. These variables were obtained from the ground inventory data.

CORN - Proportion of corn.

SOYB - Proportion of soybeans.

PAST - Proportion of pasture, alfalfa, grass, hay and clover.

TREE - Proportion of trees and orchards.

ELSE - Proportion of homesteads, water bodies, non-agriculture, and idle fields.

ALL - Proportion of all field crops together.

ALLAC - Coded field size for all field crops: 1-small, 2-medium, 3-large, 4-very large.

MIX - Proportion of mixed pixels.

ALXMI - Interaction of ALL and MIX.

SWI - Shannon-Wiener diversity index, using 22 cover types:

$$SWI = e^H \text{ and } H = -\sum P_i \log_e P_i$$

where P is the proportion (0.0 to 1.0) of cover type i. A scaling was used to make this index vary from 0 (least diverse) to 1 (most diverse).

Productivity variables were:

MAX - 1978 soybean "maximum yield" (range 40.0 to 73.1 bu/ac). Maximum yield as proposed by Holt et al. (1979) is the yield that would have been obtained if weather was not limiting throughout the growing season. Maximum yield values were computed on a county basis.

CYLDAVE - Long-term (approximately 20 years) average corn yield for the counties where the segments were located (range 56.1 to 100.4 bu/ac).

SYLDAVE - Long-term (approximately 20 years) average soybean yield for the counties where the segments were located (range 18.1 to 35.5 bu/ac).

BELT - A qualitative variable that reflects the relative position of the segment in the Corn Belt. Two levels were defined: 0=Corn Belt fringe area (9 observations) and 1=inside the Corn Belt (14 observations).

Seasonal variables were:

WF - 1978 "weather factor" for representing the environmental limitations on soybean yield prevailing during the growing season (Holt et al., 1979). Low values of WF correspond to severe limitations on yield.

CPER1 - Corn development stage at first Landsat acquisition.

SPER1 - Soybean development stage at first Landsat acquisition.

CPER3 - Corn development stage at second Landsat acquisition.

SPER3 - Soybean development stage at second Landsat acquisition.

CYLD - 1978 county average corn yield (USDA data).

SYLD - 1978 county average soybean yield (USDA data).

F. STATISTICAL ANALYSES

The Statistical Analysis System (SAS Institute, 1979) was extensively used in this study. Initially, plots of each independent variable versus the dependent variables were obtained to examine the form of the relationships and, secondly, simple correlations of all possible combinations of variables were run. Plots and correlations were also used to examine the interrelationships among the independent variables.

A separate multifactor analysis was performed for each dependent variable. Several regression models using the STEPWISE procedure of SAS with the MAXR option were run. Initially only the ground truth variables were allowed to enter the model. After the selection of a subset of the ground truth variables based on the ability to explain the variability in the dependent variables, a subset of the soil variables was selected. Following the same procedure, productivity variables were entered, and finally a subset of the seasonal variables was selected after the ground truth, soil, and productivity variables, previously selected, were already in the model.

An additional analysis consisted of all possible regressions of subsets of 4 to 14 of the 29 independent variables. The output of this program lists subsets of independent variables for each subset size in order of amount of variation explained in the dependent variable.

IV. RESULTS AND DISCUSSION

A. CLASSIFICATION RESULTS

Results show that Landsat proportion estimates were strongly related to ground inventory proportions with R greater than 0.90. Figure 2 indicates that the regression lines are close to the 1:1 line between Landsat proportions and ground truth proportions with no major departures from the regression lines in any of the segments analyzed.

Wall-to-wall classification accuracy was linearly related to test field accuracy for corn, soybean, and overall classifications with correlation coefficients around 0.70. Since the computation of wall-to-wall accuracies takes into account all pixels of a segment, including mixed pixels, as opposed to only pure pixels of the test field, it was expected that test field accuracies would be higher than wall-to-wall accuracies. In fact, the average test field accuracies were 14, 15 and 12% higher, respectively, for corn, soybean and overall.

Table 1 presents the overall test field performance for all segments together. Omission error was smaller for corn than for both soybean and "other" classes. More soybean and "other" were classified as corn than vice versa in most of the segments. This was associated with the predominance of corn in the study area rather than with analyst bias.

B. SINGLE FACTOR ANALYSIS

This analysis involved the study of the relationship between each dependent variable and each independent variable. Plots of all possible pairs of variables were examined, and only linear relationships appeared to be present. Correlation coefficients were computed for all possible pairs of variables (Table 2). Both productivity and ground truth variables were linearly related to more dependent variables than either soil or seasonal variables.

Corn accuracy measures were related to more independent variables than either overall or soybean accuracies. Proportion error for soybeans (ARSD) did not have a significant relationship with any independent variable. Test field accuracies for both overall and soybeans were related to more independent variables than wall-to-wall accuracies.

The effect of field size on classification accuracy was investigated using the test fields previously selected for test field accuracy assessment. The advantage of using test field size in addition to average field size (ALLAC) as previously presented was that test fields were composed of only pure pixels, therefore the effects of mixed pixels and of small fields, which are otherwise confounded, could be separated. Another advantage was the considerable increase in the number of observations.

Figure 2 presents the relationship between average classification accuracy and average test field size where each observation corresponds to the average of all individual test fields for each classification class, i.e., corn, soybean, and others for each segment. Although a wide range of average accuracies was observed for small field sizes, the average accuracies were usually higher and less variable for larger test fields. The effect of small fields was associated not only with an increase in the proportion of mixed pixels, but also with the intrinsically large spectral variability of small fields.

C. MULTIFACTOR ANALYSIS

To investigate the interrelationships between the independent variables and to understand the nature of the independent variables better, a multicollinearity analysis was performed. Table 3 shows the significant correlations between all possible pairs of independent variables. The correlation between variables of the same group was generally strong except for some of the seasonal variables. Although soil variables were not correlated with many productivity or seasonal variables, they were significantly correlated with ground truth variables. Ground truth variables were also strongly correlated with the productivity variables, with the exception of the maximum yield (MAX) variable. Productivity variables, as expected, were strongly related to both 1978 corn and soybean yields (CYLD and SYLD). Field size (ALLAC), proportion of all field crops (ALL), crop diversity index (SWI), proportion of trees, slope, and proportion of corn were significantly correlated with many other independent variables. In addition, proportion of mixed pixels (MIX), proportion of soybeans, long-term average soybean yield (SYLDAVE), soil order and relative position of the segment in the Corn Belt (BELT) were also significantly correlated with several other independent variables.

To investigate the amount of variability in the dependent variables that could be explained by a group of scene characteristics, several multilinear regression analyses were run. In building the regression models, ground truth variables were the first variables to be acquired, followed by soil variables, then productivity variables, and finally the seasonal variables. Thus, models for each independent variable were run initially using only the ground truth variables. Then soil, productivity and seasonal variables were entered in order. The results of these analyses are presented in Table 4.

Ground truth variables alone explained much of the variability of corn accuracy measures, especially of corn proportion error (ARCD) where only four ground truth variables gave an R^2 of .89 (Table 4). However, they did not explain much of the variability of soybean proportion error (ARSD), overall proportion error (RMS), and overall accuracy (OV). Corn, soybean, and other proportions and field size (ALLAC) were among the most frequently selected ground truth variables. Proportion of all field crops (ALL) and proportion of pasture were also frequently selected. The ground truth variables selected less frequently (SWI and ALXMI) or never selected (MIX and TREE) were strongly correlated with other ground truth variables.

Soil variables added considerable information to the ground truth variables already in the model, particularly for the overall accuracy measures and for soybean test field accuracy. Drainage, slope, order, and interactions between drainage and order (DRXOR) were the most frequently selected soil variables given that the previously selected ground truth variables were already in the model. Drainage (DRAIN) and parent material (PARM) were important in explaining corn accuracies while slope, order, and interaction variables (DRXOR, DRXVG, VAXOR) contributed more to explaining soybean and overall accuracies.

After ground truth and soil variables were in the model, productivity variables were entered. Although only one or two productivity variables were selected, their contribution to explaining the variability in the dependent variables was large. Long-term average soybean yield (SYLDAVE) and maximum yield were the most frequently selected variables.

Seasonal variables explained a significant portion of the variability of the dependent variables even after the selected variables of all three previous groups were already in the model. They were particularly effective in explaining the variability in the overall and soybean accuracies. The weather factor (WF) was the most frequently selected seasonal variable, followed by soybean development stage at the second acquisition date (SPER3).

Table 5 shows R^2 values obtained by the regression of each dependent variable on an increasing number of independent variables. In these analyses, all 29 independent variables were allowed to enter the model as candidate variables and the best combinations of four to 14 independent variables were selected based on R^2 values. Only four variables were required to explain the variability of corn accuracies compared to six to nine variables for soybean and overall accuracies, except for overall test field accuracy for which only four independent variables explained 81% of its variability. Similarly, it was observed in the single factor analysis previously presented that corn accuracy measures and overall test field accuracy were more strongly related to individual independent variables than either soybean accuracies, overall proportion error (RMS) or overall wall-to-wall accuracy.

V. SUMMARY AND CONCLUSIONS

In summary, this study clearly indicated that several scene characteristics significantly affect classification accuracy. Further investigations should be directed toward modeling classification performance as a function of scene characteristics. Future studies should also include areas with more confusion crops and greater soil variability. Training and classification procedures are the two most controllable sources of variation in classification accuracy after the variability due to scene characteristics has been accounted for. Therefore, after the construction and testing of the model, an investigation of how specific training and classification procedures modify the predicted accuracy based on scene characteristics should be performed.

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Table 1. Mean classification accuracy of 22 segments (segment 883 was not included).

Class	No. of Pixels	Pct. Classified as Corn	Soybean	Other
Corn	13727	85.9	6.6	7.4
Soybean	8534	12.0	81.8	6.2
Other	11872	11.2	5.8	83.0
Total	34133			

Overall Accuracy = 83.9%

Table 5. Coefficients of determination of the regressions of the measures of classification on the best combinations of the scene variables. Total of 29 candidate variables and 4 to 14 variables entering the model (22 observations).

Number of Var.	Corn			Soybeans			Overall		
	CO	CT	ARCD	SO	ST	ARSD	OV	OVT	RMS
4	.84	.82	.87	.70	.62	.32	.49	.81	.57
5	.86	.84	.90	.75	.75	.56	.63	.88	.63
6	.87	.86	.91	.77	.80	.70	.66	.91	.67
7	.88	.86	.92	.81	.83	.78	.72	.92	.81
8	.89	.87	.93	.84	.85	.81	.80	.94	.85
9	.93	.88	.94	.90	.90	.87	.82	.95	.87
10	.97	.89	.95	.92	.91	.88	.84	.97	.89
11	.98	.93	.96	.94	.95	.94	.86	.97	.96
12	.99	.94	1.00	.97	.96	.96	.89	.99	.96
13	.99	.97	1.00	.97	.96	.98	.97	.99	.97
14	1.00	.98	1.00	.99	.98	.99	.98	.99	.99

Table 2. Correlation of scene characteristics and several measures of classification performance (for clarity, only the coefficients that were significant at α = 0.15 are presented). All coefficients are based on 23 observations, except for MAX which had 22 observations.

Measures of Classification Performance

Scene Characteristics	Corn			Soybeans			Overall		
	CO	CT	ARCD	SO	ST	ARSD	OV	OVT	RMS
Soil									
SLOPE	-.52	-	-	-	-.33	-	-	-	-.41
DRAIN	-	-	-	-	-	-	-	-	-.34
PARM	-	-	-	-	-	-	-	-	-.46
ORDER	.35	.49	-	-	-	-	-	.43	-
VARI	-.39	-	-	-	-	-	-	-	-.33
VAXOR	-	-	-	-	-	-	.37	-	-
DRXVG	.35	.60	-	-	-	-	-	.63	-
DRXOR	-	.51	-	-	.35	-	-	.59	-
Ground Truth									
CORN	.84	.59	-.56	-	.36	-	-	.34	-
SOYB	.39	-	-.38	.57	.36	-	-	-	-
PAST	-.53	-	-	-	-	-	-	-	-
TREE	-.71	-.43	-	-	-	-	-	-.33	-
ELSE	-	-	-	-.54	-	-	-	-	-
ALL	.74	.36	-	-	-	-	-	-	-
ALLAC	.73	.60	-	-	-	-	-	.32	-
MIX	-.54	-.48	-	-	-	-	-	-	-
SWI	-.72	-.58	.60	-	-.33	-	-	-	-
ALXMI	.57	-	-.35	-	-	-	-	-	-
Productivity									
MAX	-	.47	-.53	-	.37	-	.35	.47	-.33
CYLDAVE	.63	.53	-.57	-	.47	-	-	-	-
SYLDAVE	.67	.63	-.77	.36	.49	-	-	.40	-
BELT	.57	.67	-.51	-	-	-	-	.52	-
Seasonal									
WF	-	-	-	-.41	-	-	-	-	-
CPER1	.37	-	-	-	-	-	-	-	-
CPER3	-	-	-	.44	.40	-	-	-	-
SPER1	.50	.43	-	-	-	-	-	-	-
SPER3	-	-	-	-	-	-	-	-	-
CYLD	.64	.65	-.69	-	.44	-	-	.34	-
SYLD	.75	.70	-.59	-	.48	-	-	.54	-

Table 3. Simple correlation coefficients between pairs of scene characteristics. For clarity, only the coefficients that were significant at $\alpha = 0.05$ are presented (29 independent variables and 23 observations).

	Soil								Ground Truth										Productivity				Seasonal						
	SLOPE	DRAIN	PARM	ORDER	VARI	VAXOR	DRXOR	DRXVG	CORN	SOYB	PAST	TREE	ELSE	ALL	ALLAC	MIX	SWI	ALXMI	MAX	CYLDAVE	SYLDAVE	BELT	WF	CPER1	CPER3	SPER1	SPER3	CYLD	SYLD
SLOPE		.41	.52	-.54	.48	-	-	-	-.45	-.52	.61	.68	-	-.73	-.61	.64	.51	-.48	-	-	-	-	-	-	-	-	-	-	-.43
DRAIN			.46	-	-	-	-	.42	-	-.69	-	.40	-	-.59	-.46	.43	-	-.47	-	-	-	-	-	-	-	-	-	-	-
PARM				-.46	-	-	-	-	-	-	-	-	-	-	-.46	.42	-	-	-	-	-	-	-	-	-	-	-	-	-
ORDER					-	.69	.75	.56	-	-	-	-.66	-	.57	.59	-.61	-.48	-	-	-	-	.54	-	-	-	-	-	-	.44
VARI						.41	-	-	-	-	-	.53	-	-.40	-	-	-	-.45	-	-	-	-	-	-	-	-	-	-	-
VAXOR							.42	-	-	.41	-	-	-	-	.46	-.48	-.43	-	-	-	-	.40	-	-	-	-	-	-	-
DRXOR								.84	-	-	-	-.44	-	-	-	-	-	-	-	-	-	.49	-	-	-	-	-	-	.45
DRXVG									.40	-	-	-.49	-	-	-	-	-	-	-	-	-	.56	.51	-	-	-	-	-	.48
CORN										-	-.47	-.61	-	.65	.67	-.42	-.81	.55	-	.67	.71	.65	-	-	-	-	-	.81	.79
SOYB											-.46	-.51	-.53	.67	.70	-.67	-.71	-	-	.46	.59	-	-	-	-	-	-	-	-
PAST												-	-	-.77	-.67	.53	.52	-.54	-	-	-	-	-	-	-	-	-.53	-	-
TREE													-	-.85	-.68	.69	.59	.70	-	-	-.41	-.47	-	-	-	-	-	-	-.61
ELSE														-	-	-	-	-	-	-	-.42	-	-	-	-.45	-	-.40	-	-
ALL															.83	-.74	-.71	.79	-	.42	.49	.45	-	-	-	.43	-	-	.53
ALLAC																-.87	-.87	-	-	.53	.59	.52	-	-	-	.50	-	.45	.50
MIX																	.73	-	-	-	-	-	-	-	-	-.50	-	-	-
SWI																		-	-	-.69	-.78	-.61	-	-	-	-	-	-.63	-.65
ALXMI																			-	-	-	-	-	-	-	-	-	-	.52
MAX																				-	.51	-	-	-	-	-	-	.48	.43
CYLDAVE																					.82	.43	-	-	-	-	-	.82	.72
SYLDAVE																						.63	-	-	-	-	-	.80	.82
BELT																							.55	-	-	-	-	.64	.70
WF																							-	-	-	-	-	-	-
CPER1																								-	-	.72	-	-	-
CPER3																									-	-	.68	-	-
SPER1																										-	-	-	-
SPER3																											-	-	-
CYLD																												-	.86
SYLD																													-

Table 4. Variables selected and coefficients of determination as a result of adding a group of scene characteristics given that the selected variables of previous group(s) were already in the model.

Dependent Variables	Ground Truth Variables Entered (R^2)	Soil Variables given Ground Truth Variables (R^2)	Prod. Variables given Ground Truth + Soil Variables (R^2)	Seasonal Variables given Ground Truth + Soil + Prod. Variables (R^2)
Corn				
Wall (CO)	CORN,ELSE,ALL (.77)	DRAIN (.78)	SYLDAVE (.81)	SPER1 (.86)
Test (CT)	CORN,SOYB,PAST, ALLAC (.61)	DRAIN,PARM (.68)	SYLDAVE (.79)	SYLD (.85)
Prop.(ARCD)	CORN,SOYB,ELSE, ALL (.89)	PARM (.92)	SYLDAVE (.95)	
Soybeans				
Wall (SO)	SOYB,ELSE,ALL (.49)	SLOPE (.51)	BELT MAX (.58)	WF (.65)
Test (ST)	CORN,SOYB,PAST, SWI (.47)	DRAIN,DRXOR,DRXVG (.69)	BELT (.76)	WF (.84)
Prop.(ARSD)	PAST,ALLAC,SWI (.10)	SLOPE,ORDER,VARI, DRAIN,DRXVG (.39)	MAX,CYLDAVE (.49)	WF,SPER3,CYLD (.89)
Overall				
Wall (OV)	CORN,SOYB,ELSE, ALLAC (.23)	ORDER,DRAIN,VAXOR, DRXOR (.68)	BELT,MAX (.73)	WF (.85)
Test (OVT)	SOYB,PAST,ELSE, ALLAC (.45)	SLOPE,ORDER,DRAIN DRXOR (.63)	SYLDAVE (.71)	CPER3,SPER3 (.90)
Prop.(RMS)	ELSE,ALL,ALLAC, ALXMI (.16)	SLOPE,ORDER,VARI, DRXOR (.63)	CYLDAVE (.67)	WF,SPER3 (.79)

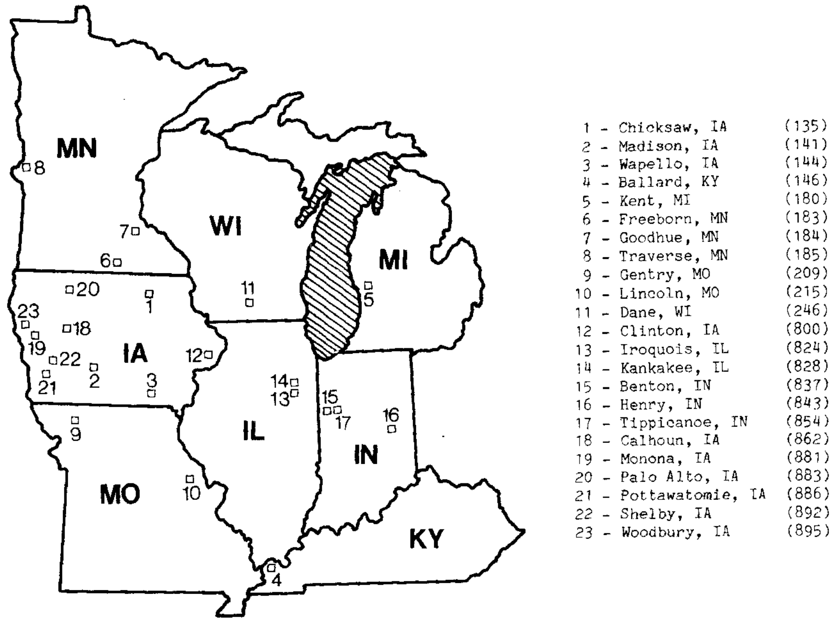

Figure 1. Location of test sites in Corn Belt region (AgRISTARS segment number).

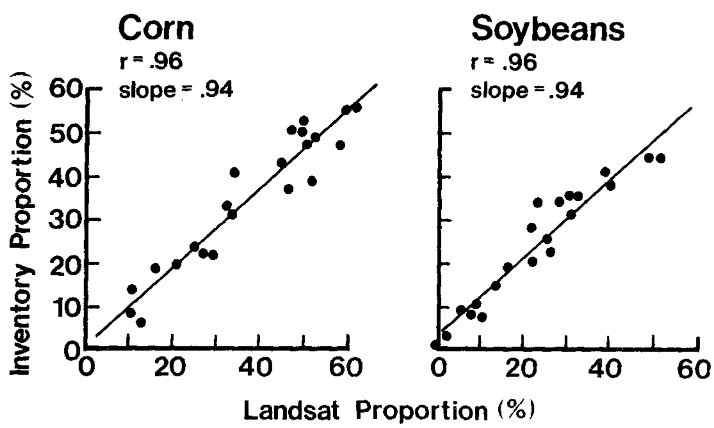

Figure 2. Relationship of Landsat estimates and ground inventory of corn and soybean proportions.

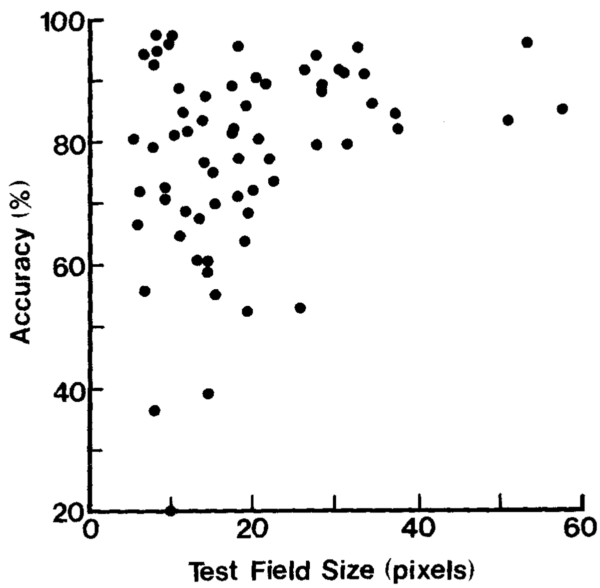

Figure 3. Relationship between average classification accuracy of corn, soybeans, and else and average test field size expressed in number of pixels (66 observations corresponding to 22 segments and 3 classification classes).