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Evaluating TM Data for SRS Crop Acreage and Production Estimates

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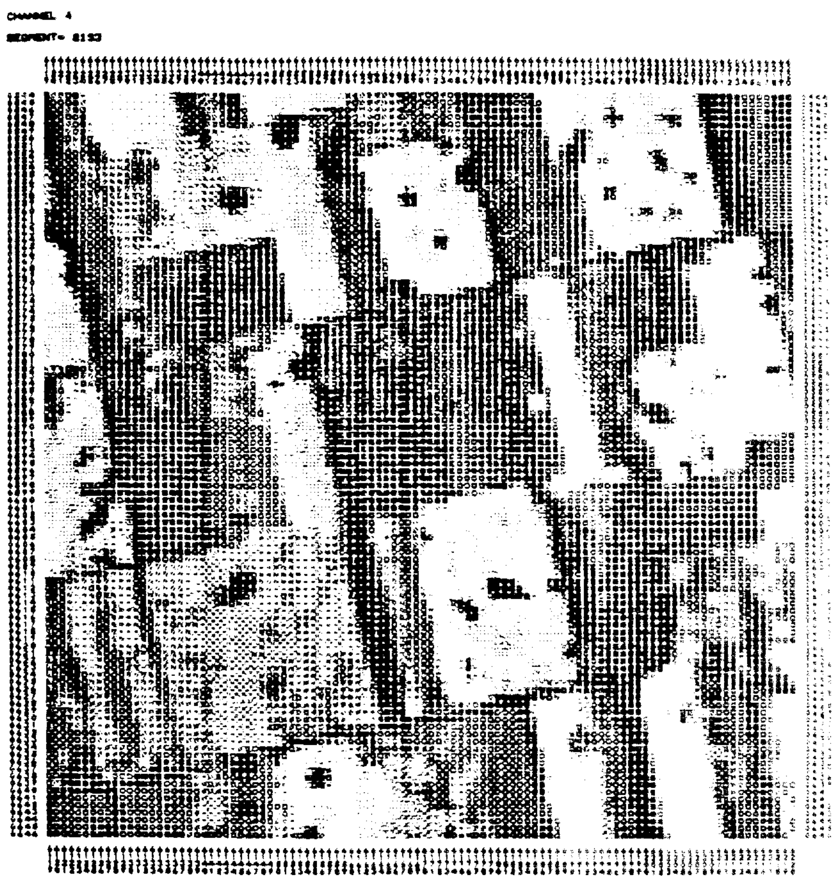

Evaluating TM Data For SRS Crop Acreage and Production Estimates.

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ABSTRACT

The U.S. Department of Agriculture's Statistical Reporting Service (SRS) is researching the use of remotely sensed data to improve the statistical characteristics of its crop estimates. This study compares the corn and soybean area estimation performance of Thematic Mapper (TM) to Multi-Spectral Scanner (MSS) Landsat data. Corn regression relationships are improved using TM data. Data reduction designs involving pixel averaging and channel selection make TM processing competitive with MSS. Correlations between TM field reflectance and farmer-reported crop yields are much higher than the respective Objective Yield correlations. Recommendations include additional research for yield applications, for sampling frame development, and for resolving questions relating to the statistical characteristics of the estimates.

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GLOSSARY

A-Format: Digital data from Landsat Multi-Spectral Scanners (MSS) are available to users in several different CCT formats. A-format data are processed with radiometric corrections only. P-format data are also processed with geometric corrections and Cubic Convolution Resampling (CCR). CCR produces a pixel with higher spatial resolution (representing a smaller area on the ground) and is generated by combining the weighted values of 16 A-format pixels [25]. (Underscored numbers in brackets refer to items in References section.)

Bands: Satellite sensors are equipped with detectors that measure the amount of light energy reflected from the surface of the Earth up to the satellite. Light energy is part of the electro-magnetic continuum of wave energy which includes X-rays, ultra-violet light, visible light, infra-red waves (near, middle, and thermal), and communications frequencies. Detectors are engineered by selective filtering to register energy within narrow wavelength intervals (bands) of this continuum. The MSS sensor has four bands within the visible to near infrared portion of the spectrum while TM has seven bands. Two of the additional TM bands are in the middle infrared range and the third is in the thermal range. Thermal energy is radiated or emitted rather than reflected.

Benefit/Cost Analysis: An economic analysis of a process which seeks to determine if expended resources are effectively and efficiently used.

Boundary Width: A representation of Landsat pixels corresponding to a June Enumerative Survey (JES) segment contains information about the relative location of pixels within the segment. Boundary pixels are those which "touch" the segment border or the within segment border between two JES-identified fields. Boundary pixel reflectance values are assumed to represent a mixture of covers on either side of the boundary and are usually excluded from signature development. For MSS processing, the number of pixels defining the boundary width is usually one. However, the boundary width for TM analyses is increased because the TM pixel represents a smaller ground-area.

Calibration: This is a procedure (a first-order linear transformation) to locate JES segments in terms of latitude and longitude (map-based coordinate system). Corresponding points (such as road intersections) observed in the segment photo are located on U.S. Geological Survey quadrangle maps. In this way, Landsat pixels corresponding in area to the location of the segment on the ground can be further identified as belonging to specific fields (and therefore specific crops) within the segment [3,6,13].

CCT: Computer Compatible Tapes are magnetic tapes (6,250 or 1,600 bits per inch) containing the Landsat digital data and sold by EROS Data Center to users.

Channels: Used interchangeably with Bands but also used in a computer processing sense to identify a data stream from a specific sensor band of a CCT.

Classifier: The collection of discriminant functions identified during signature development (supervised clustering) and used to label pixels in the scene with a cover or crop identifier. Classifier development is the decision process used by the analyst to produce the classifier. Included are decisions about spectral class inclusion and the use of prior probabilities. (See Priors and Clustering.)

Clustering: A process to determine spectral classes within a sample of Landsat data. The algorithm used is CLASSY [15], which alternates maximum likelihood iterative techniques for estimating the parameters of a mixture distribution with an adaptive procedure for splitting, combining, and eliminating the resultant components of the mixture, and leads to an estimate of the number of multivariate normal components in the mixture. Two approaches to clustering are supervised and unsupervised. Supervised clustering uses as input the pixels from a single known cover like corn. Spectral differences within the cover are identified. Unsupervised clustering uses as input unlabeled pixels, presumably from a mixture of crops. The output from unsupervised clustering are spectral classes which most likely are representative of a mixture of covers having similar or identical reflectance patterns. (See Signature.)

Commission Error: This is one measure of classifier accuracy and indicates the degree to which particular crops or covers are "overclassified." It is computed for each specific crop or cover. The commission error for corn, for example, is the number of non-corn pixels (according to the ground reference data) classified to "corn" and expressed as a percentage of the total number of pixels classified as corn. (See Percent Correct.)

Cubic Convolution Resampling: One of the differences between the A-Format and P-Format Landsat CCT. The P-Format pixel is generated by combining with various weights the values of 16 nearest neighbor A-Format pixels. This process produces pixels of higher spatial resolution (representing a smaller ground area) and serves as a vehicle for geometric correction to the P-Format data [25].

Discriminant Functions: These are derived from the probability density functions of the spectral classes defined during clustering and collectively form the maximum likelihood classifier. Formulas for the discriminant functions may be found in Section 3.3 of Appendix II. (See Priors.)

EDITOR: The collection of software developed under the auspices of USDA to process Landsat data and produce regression estimates of crop acreages.

EROS Data Center: The Earth Resources Observation Systems (EROS) is a program of the U.S. Department of the Interior and administered by the Geological Survey. Together with NOAA (National Oceanic and Atmospheric Administration), the Center provides remotely sensed data products (primarily Landsat products) to users.

Field-Level Edit: A quality control measure designed to monitor the accuracy of the JES data used for ground reference in signature development and regression parameter estimation.

Field Pixel: A generated reflectance vector that is the average within each channel of Landsat pixel values making up a JES field. The 50-pixel field pixel (FP) is computed in the same manner but instead of generating a single FP per field, one FP is created for every 50 pixels in the field. Field boundary pixels are usually excluded from the computation.

Jackknife: A method developed by Quenouille (1956) and so named because of its flexibility as a statistical tool [17]. It is used in this paper to identify designs which subset the sample to allow independent classifier development and regression parameter estimation without losing degrees of freedom.

Landsat: A series of NASA Earth observing and resource monitoring satellites. The five satellites in the series to date all carried the MSS. Landsat-4 and Landsat-5 also carry the newly developed high resolution, high data rate TM scanner. MSS captures reflectance data for areas on the ground as small as 57 meters square (after resampling), in a four component vector (bands), with measurement values (quantization) ranging from 1 to 64. The TM scanner produces 28.5 meter resolution pixels with seven vector components measured in 256 quantization levels.

MSS: Multi-Spectral Scanner, one of the first satellite-borne, Earth-observing sensors. (See Landsat.)

P-Format: One of the available CCT formats. (See A-Format.)

P-value: In this study, it is the probability of obtaining a t-value equal to or greater than the observed t-value under the conditions stated by the null hypothesis. If the null hypothesis is rejected, the P-value is the probability of committing a Type I Error.

Percent Correct: One measure of the overall quality of a classifier. It is reported for individual crops as well as for all crops or covers in the sample. It is the percentage of JES-defined sample pixels correctly labeled; that is, those pixels having agreement between the classifier cover label and the JES ground cover label. (See Commission Error.)

Pixel: A term derived from "picture element," the basic unit of an image-forming system, and generalized to mean the basic unit for recording satellite-acquired remotely sensed data. The pixel is an N-component vector with N corresponding to the number of channels (bands). Each component is an integer value within the quantization range of the sensor, indicating the level of energy (within that band) reaching the satellite sensor. The pixel is used somewhat differently by the two basic approaches to remote sensing applications: image processing and numerical analysis. Images are generated by equating shades of gray or tones of color to pixel-vector patterns or relationships. Numerical analysis relies more on pattern definition and pattern recognition (in a mathematical sense) of the actual numbers making up the pixel vector. A scene can be thought of as a giant matrix in which every element (pixel) is referenced by a row and column.

Priors: A variation of maximum likelihood classification which allows "expectations" of finding a particular cover of interest in the scene to modify the classification criterion.

Relative Efficiency: A measure of the effectiveness of this use of Landsat data relating the efficiency of the JES direct expansion estimate to the efficiency of the Landsat regression estimate. See section 3.7 of Appendix II.

Scene: A Landsat scene. The continuous acquisition of the satellite sensor is broken at certain intervals defined by orbit row and path in such a way that each division (scene) contains the same number of pixels and covers the same land area.

Segment Landsat Window: A block of Landsat data containing pixels belonging to a specific JES segment.

Signature: Signature development is a process involving a particular Landsat scene and a specific crop or cover. Its goal is to identify the spectral classes (categories) that define the reflectance patterns of the cover as observed in the sample and assumed to hold across the scene. The set of spectral classes found define the signature of the cover in that scene. Cover signatures are developed from supervised clustering.

TM: Thematic Mapper is the newest sensor available on Landsat satellites. (See Landsat.)

INTRODUCTION

This paper reports the performance of TM (Thematic Mapper) satellite data used for crop acreage estimation and examines its potential for crop yield assessment. TM is compared with MSS (Multi-Spectral Scanner) data using the Landsat crop-area estimation procedure developed by the Statistical Reporting Service (SRS) [7]. Holko and Sigman [9] describe the current SRS procedure for MSS data. Their paper is reprinted here as Appendix II.1/

For this study, a Landsat scene simultaneously acquired by both the TM and MSS satellite sensors is analyzed according to the current procedure. Several TM-specific modifications to the current procedure are outlined. Performance results between MSS and TM and within the TM specific designs are compared at the sample level in terms of cost and precision of estimates produced.

Processing starts after the collection of ground reference data during the annual SRS June Enumerative Survey (JES). The JES is a longstanding survey designed to provide direct expansion estimates of crop acreages early in the crop year [18]. All ground covers within specific land plots called segments are identified through personal interviews with farmers and drawn off on aerial photographs.

The JES photographs and Landsat scenes are registered to a map base in latitude/longitude coordinates. This common referencing allows pixels corresponding in location to the JES fields to be so identified and manipulated. Pixel reflectance vectors from all fields within segments in the scene for a specific cover, such as corn, are clustered to produce signatures. Signatures are discriminant functions defined by mean vectors and covariance matrices describing the multivariate normal distributions assumed to underlie reflectance patterns. The collection of these statistics for all covers in the scene constitutes the scene classifier [23].

Pixels within segment Landsat windows are assigned a cover identifier by the classifier. Counts of pixels assigned to a specific crop are regressed against the crop hectares obtained during JES enumeration. These sample level regression coefficients are usually applied to the counts from full-scene classification and aggregated across scenes to obtain State-level crop-area estimates. (For this study, full-scene processing and aggregation are unnecessary because measures of precision and processing costs are obtained from sample-level processing.)

1/ First occurrence of Glossary terms are underlined. Underscored numbers in brackets refer to items in References section.

EVALUATION CRITERIA

The measure used to evaluate MSS results in previous SRS studies is the relative efficiency (RE) [18]. It is defined as the ratio of the variance of the JES direct expansion estimate to the variance of the Landsat regression estimate. The RE indicates the factor by which the JES sample size (and corresponding survey costs) would have to be increased to produce direct expansion estimates having the same precision as that of the Landsat regression estimates. The RE is used in benefit/cost analysis to compute the benefits of Landsat as indirect savings in data collection costs from not increasing the JES sample size. The goal is to "save" more than the costs associated with acquiring and processing Landsat data.

One shortcoming of the RE measure is that it ignores the time differential. JES estimates are available in early July while Landsat regression estimates are not available until December. To some information users, this time delay severely diminishes the value of the information, no matter how precise the later estimates might be.

Expanding the JES sample size would have statistical and operational benefits to SRS not taken into account by the RE measure. Estimates of all crops, livestock inventories, prices, grain stocks, and crop yields would be affected, directly or indirectly. The increased precision (assuming no change to the current level of non-sampling errors) from expanding the JES sample size would be available at earlier dates.

It is, therefore, misleading to view the RE in any absolute sense. However, for purposes of comparing the performance of the different satellite sensor formats, this measure is satisfactory because it does measure relative improvements between designs producing estimates for the same crops within the same time interval.

DATA SETS

Three sets of data are discussed: Landsat, yield, and ground reference.

Landsat Data

Scene 40049-16264 over west-central Iowa (path 27, row 31) simultaneously acquired by the Landsat-4 MSS and TM sensors on September 3, 1982, is used in the comparative analyses that follow. TM bands 6 (thermal) and 7 (far-infrared) are switched to processing channels 7 and 6, respectively, so that channel numbers correspond to increasing band wavelengths. The computer compatible tapes (CCT) for both MSS and TM are in the P-format.

The TM CCT received from the EROS Data Center contained some errors. (CCT's provided during that time were primarily for engineering studies, not user-application work.) Channel 7

(Thermal Band 6) was found to have a four pixel column left shift relative to the other channels. The problem was corrected by shifting this band to the right during the conversion to standard EDITOR tape format.

This CCT was also missing "long records" 470 and 1038 corresponding to scan image lines 1877 through 1880 and 4149 through 4152, respectively. None of the segment Landsat windows used for analysis spanned these scan lines, so the loss of data was not a factor in the analyses. NASA Conference Publication 2326 contains the proceedings of the Landsat-4 Early Results Symposium and Landsat Science Characterizations Workshop. Several papers included in that publication discuss similar problems and describe further the mechanical operations and performance of the MSS and TM sensors [1,4].

The TM data set contains four pixels for every MSS pixel with TM pixels accumulating reflectance over a 28.5-meter square area compared with MSS at 57 meters square. The TM pixel reflectance measurement vector contains seven values compared with the four for MSS. Each TM vector component value may range from 0 to 255 while the MSS range is 0 to 63. These differences result in a sevenfold increase in the volume of TM data.

Yield Data

The yield study utilized Objective Yield [18] survey data in sample fields falling in the 60 JES segments used for the area estimation study. Farmer Reported Field Yield is from the Form D: Postharvest Interview for both corn and soybeans. Objective Yield estimates of field yield are from the monthly summary tables provided to the Iowa State Statistical Office (SSO) during September and November.

Ground Reference

Sixty JES segments approximately 1 square mile each enumerated in 1982 are used in the designs identified below. These ground-gathered data were subjected to the routine JES editing process and the field-level edit. Ground data are unchanged from that used for the MSS processing in 1982 [24]. However, several segments were found to have minor calibration problems. Figures 1 through 3 graphically show the problem. The minor errors are undetectable in MSS processing but show up plainly in the TM designs. The miscalibration probably has no effect in the MSS analysis (because of the larger size MSS pixels) but are corrected for TM processing to avoid using incorrectly labeled pixels for signature development.

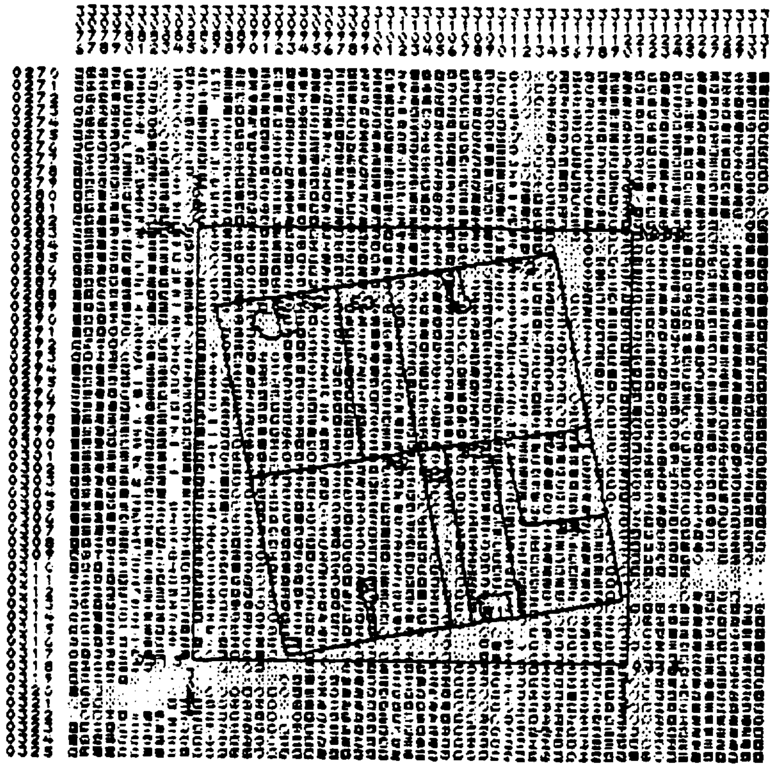

Figure 1. MSS greyscale of Band 2, Segment 8153 overlayed with line plot of digitized field boundaries using the calibration developed for MSS processing. A calibration problem is not obvious in this figure.

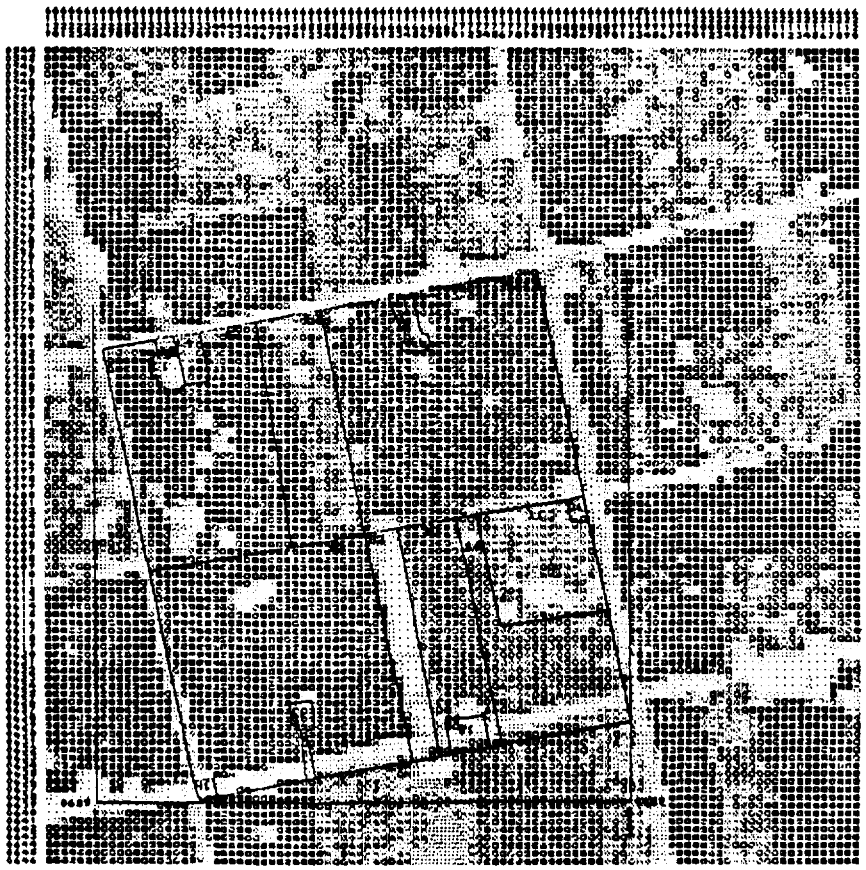

Figure 2. TM greyscale of Band 7 (Channel 6) Segment 8153 overlayed with line plot of digitized field boundaries with the same calibration used in Figure 1. Note evidence of a problem along the left and bottom edges of the segment. By definition the segment extends from the middle of the road to the middle of the road.

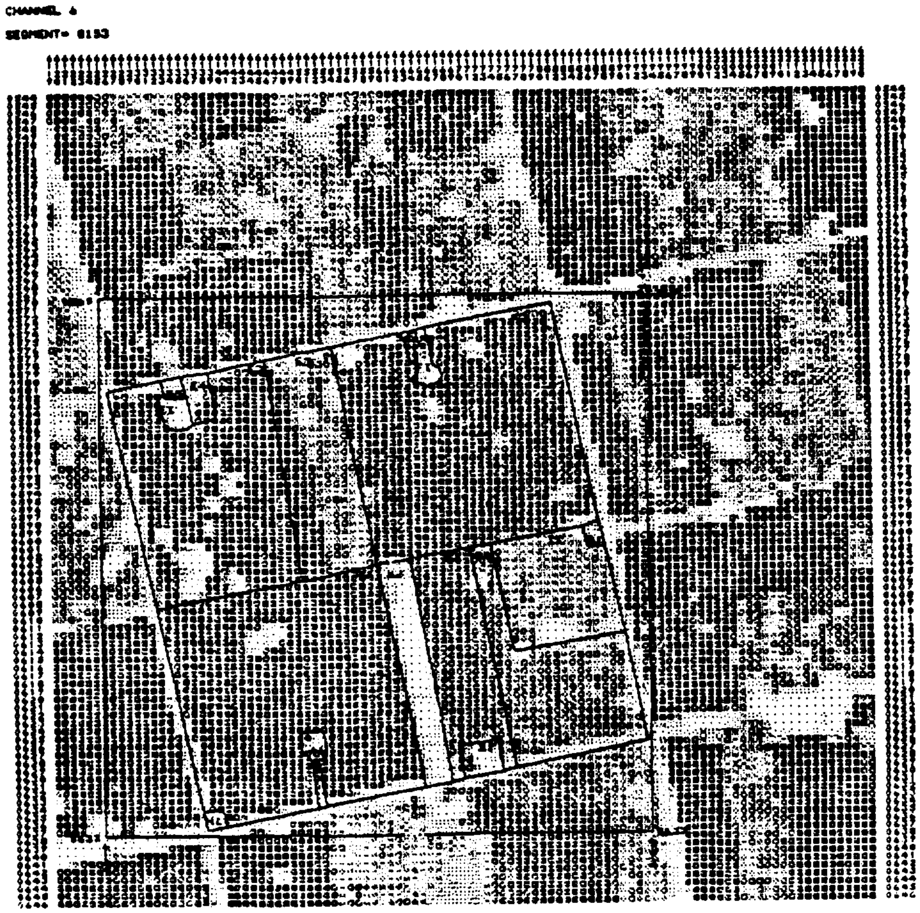

Figure 3. TM greyscale of Band 7 (Channel 6), Segment 8153, overlayed with line plot of digitized field boundaries using the corrected calibration. Note the alignment of all four segment boundaries along the roads showing up "light" in the greyscale. Note also the rightmost field in the upper left section of the segment. There appears to be a boundary problem with this field as evidenced by the changing printer symbol occurring about two-thirds the field width measured from the right side of that field. This may be an example of a partially harvested field showing two different signatures or it may be that the left part of this field really belongs to the field adjoining to the left.

The difference between the TM and MSS greyscales gives a good idea of the degree of additional information present in TM. The MSS greyscale print quality is somewhat degraded in this example, but even at its best, little improvement would be noted.

CROP AREA ESTIMATION DESIGNS

Three basic designs are presented. Within each the best of several variations is selected on the basis of Benefit/Cost considerations. Each successive design builds on the characteristics of the previous one.

Design TM-1: MSS Mimic

In the TM-1 design, TM processing duplicates whenever possible the MSS processing. All seven bands (with the thermal band renumbered as channel 7) are used for signature development and ensuing classification. All field interior pixels are used for signature development. As with MSS processing, pixels on field boundaries are not used. Specifics of the analysis for both TM and MSS are presented in table 1.

The boundary width is increased from the MSS single 57-meter pixel to three TM 28.5-meter pixels or 85.5 meters. This lessened the chance of using TM mixed pixels for signature development. The digitized field boundary may not coincide exactly with the true field boundary location and exact alignment of MSS pixels to TM pixels is not guaranteed; therefore, the three TM pixel boundary is used instead of two, even though it "thickens" the boundary compared with MSS. Tying up this additional pixel in the boundary acts in a minor way to systematically reduce the volume of data used for clustering.

Table 1--Specifics of the TM-1 design

Characteristic	Design: MSS		Design: TM	
Channels	4,5,6,7		1 thru 7 1/	
Boundary width	1 pixel		3 pixels	
Clustering:				
Cover	Pixels	Categories	Pixels	Categories
Corn	11,663	4	32,413	10
Soybeans	8,679	5	23,717	5
Other crops	5,247	12	11,199	31
Total	25,589	21	67,329	46
Pixels classified	47,890		192,541	
Percent correct 1	65.4		61.9 2/	
Percent correct 2	73.6		77.7	

1/ Channels 6 and 7 correspond to TM bands 7 and 6, respectively.
2/ Percent correct 1, the standard, takes into account misclassification among the covers that constitute "other crops" while percent correct 2 treats "other crops" as a single cover.

Table 2 shows the results of sample classification for both the TM and MSS designs and lists by strata the R^2 value and B(1), the slope coefficient, of the regression equations. Ignoring strata is desirable from a hypothesis testing point of view because of the increased degrees of freedom and the more definitive nature of a single test. Ignoring strata (pooling) in Iowa is more easily justified than in other States because Iowa's strata are more a geographic separator than an agricultural intensity identifier and sampling fractions differ very little between strata. Any loss in estimation efficiency resulting from pooling should have a similar effect in both analyses; therefore, pooling is not expected to confound the test results. The P-values listed are computed from observed B(1) values under the null hypothesis that a stratum slope coefficient is equal to the pooled strata (ALL) slope coefficient. Student's t is used for each stratum test [5].

Table 3 compares the performance of simulated TM data with the results of these real TM data. As reported by Sigman and Craig [21], the simulated data were acquired over northern Missouri in early September 1979 by an aircraft-borne sensor.

Table 2--TM-1 sample level regression characteristics

Crop Strata / N	MSS R^2	MSS RE	MSS B(1)	MSS P-Value	TM R^2	TM RE	TM B(1)	TM P-Value
Corn:								
14/26	0.44	1.71	0.72	0.50	0.87	7.38	0.96	0.72
15/17	0.40	1.56	1.07	0.55	0.94	15.63	1.05	0.45
17/12	0.82	5.05	0.97	0.46	0.92	11.36	1.01	0.90
18/ 5	0.85	5.00	1.01	0.59	0.96	18.75	0.86	0.26
ALL/60	0.49	1.93	0.86	N/A	0.88	8.19	1.00	N/A
Soybeans:								
14/26	0.86	6.85	0.99	0.85	0.91	10.67	0.95	0.54
15/17	0.92	11.72	1.02	0.90	0.88	7.81	1.00	0.88
17/12	0.87	6.99	1.00	0.96	0.88	7.58	1.23	0.11
18/ 5	0.93	10.71	1.23	0.34	0.86	5.36	1.52	0.23
ALL/60	0.89	8.94	1.01	N/A	0.91	10.92	0.99	N/A

N/A = Not appropriate. Strata = JES strata. N = Sample size.

Table 3--Comparison of TM-1 results with simulated TM results

Cover	Missouri 1979 R^2 S-MSS	MSS	S-TM	P-TM	Sample	Iowa 1982 R^2 MSS	TM	Sample
Corn	0.55	0.51	0.89	0.85	11	0.49	0.88	60
Soybeans	0.97	0.93	0.99	0.95	11	0.89	0.91	60

To account for atmospheric differences between the low level aircraft acquisition and the satellite acquisition, predicted TM values (P-TM) are derived. They are computed by applying the difference between simulated (S-MSS) and real MSS R^2 to the simulated TM (S-TM). The Iowa TM results are remarkably similar to the simulation levels given the difference in sample sizes and the higher Missouri MSS levels.

Returning to the results of the TM-1 design, Hotelling's T test for equality of correlation coefficients [8,12] is used to test for significant improvement in the TM pooled strata R^2 values against the null hypothesis of no differences between TM and MSS. Table 4 shows the r0, r1, r2, and D value elements of the test; the computed T; the P-value under the null hypothesis of no difference; and the degrees of freedom associated with the test. There is little statistical reason to accept the corn null hypothesis of no difference in classifier performance between sensors. However, the test results for soybeans do not support rejecting the null hypothesis.

The classification percent correct information presented in table 5 shows that the improvement in the corn regression comes not so much from the TM classifier's ability to correctly identify a higher percentage of corn and soybean pixels as it does from the classifier's ability to label noncorn and non-soybean pixels to covers other than corn and soybeans. This shows up in the TM classification's reduced commission error rates and its higher "other crops" percent correct. No strong correlation between percent correct levels and R^2 levels is evident in this classification. The overall percent correct (which does not consider misclassification among the covers that make up the "other crops" grouping) is only slightly better for TM than for MSS.

Table 4--Hotelling's T test of TM-1 R^2 values

Crop	Degrees of freedom	---Components of the test--- r0	r1	r2	D	T-value	P-value
Corn	57	.774	.950	.699	.0378	9.19	0.00
Soybeans	57	.971	.949	.942	.0053	0.72	0.24

r0: Correlation between the MSS and TM segment level pixel count from classification.
r1: Correlation between the segment reported area and TM classified pixel count.
r2: Correlation between the segment reported area and MSS classified pixel count.
D: Determinant of matrix whose diagonal elements are 1 and whose off-diagonal elements are r2, r0, and r1.

Table 5--TM-1 classification percent correct by sensor

From:	Number of pixels classified To: Corn	Soybeans	Other Crops	Total	Percent Correct	Commission Error Percent
	TM classification:					
Corn	56,589	1,912	19,965	78,466	72.1	10.0
Soybeans	2,167	39,811	13,747	55,725	71.4	6.9
Other	4,138	1,035	53,177	58,350	91.1	38.8
Total	62,89	42,758	86,889	192,541	77.7	N/A
	MSS classification:					
Corn	14,064	1,098	4,312	19,474	72.2	22.9
Soybeans	1,099	10,540	2,226	13,865	76.0	15.7
Other	3,070	861	10,620	14,551	73.0	38.1
Total	18,232	12,499	17,158	47,890	73.6	N/A

N/A = Not appropriate.

The benefits of TM, expressed in terms of higher RE's have costs associated with them, a function of higher acquisition and processing costs of the TM data. To evaluate the gain from a particular design, a benefit/cost (B/C) ratio is calculated. Appendix I explains in detail the inputs and the method used to obtain the ratio. Cost-efficient designs are those which increase the precision of the estimates, but do so at a cost below that of an expanded-sample JES. B/C values greater than 1 indicate a cost-effective design.

If a single classification is used to estimate a number of crops, then some question arises as to how the benefit component of the B/C for the analysis ought to be computed. This is particularly true if several major or important crops are estimated. (An alternative measure proposed by Holko [11] does not have this drawback.) Averaging of the RE's is not attractive. Information users are generally interested in the precision of the estimate for a particular crop, not in some average across all crops.

The RE indicates the number of replications of the JES sample necessary to achieve direct expansion precision comparable to that of Landsat regression. However, the derived benefit is a synthetic reduction of data collection and data editing costs of a single survey. The maximum value of Landsat versus a single expanded survey in which a number of items are estimated is then a function of the minimum improvement (across items of equal

Table 6--TM-1 B/C ratio by sensor

Crop	R^2		RE		B/C	
	MSS	TM	MSS	TM	MSS	TM
Corn	.49	.90	1.93	8.19	.66	.78
Soybeans	.89	.90	8.94	10.92	N/A	N/A

N/A = Not appropriate.

importance). The B/C analysis based on minimum significant improvement (corn) in table 6 indicates that neither the MSS nor the TM Landsat processing produces cost-efficient estimates.

The RE of a crop at the analysis district (AD) level is usually higher than at the State level [24]. Incomplete Landsat coverage is partly responsible as is the conjectured loss of paper-stratification efficiencies resulting from summarization by analysis district. The 1982 Iowa State soybean RE of 1.2 with 67-percent State coverage is much different from the 8.94 MSS AD RE shown for soybeans in table 6. The MSS RE for corn in the table is low for an AD, presumably because of the late scene date. But it approximates the MSS State corn RE obtained from 1980 through 1983 (table III of Appendix II). Therefore, the corn B/C ratio for the MSS design in table 6 represents a typical Iowa ratio. Until further processing provides State-level observations for TM analysis, the same AD versus State RE relationships are assumed to hold, implying that the TM corn B/C is what typically might be expected in full state analysis.

Design TM-2: Data Reduction by Pixel Averaging

The TM-1 design produced higher RE's and a higher B/C ratio than MSS, but did not produce them cost effectively. The TM data set contains four pixels for every MSS pixel; the TM pixel reflectance measurement vector contains seven values for the four values of the MSS vector; each TM vector component requires eight computer bits while MSS requires only six bits. These differences result in a sevenfold TM data increase which significantly affects EDITOR processing costs. Given the other constraints of this experiment, the only way to improve the B/C ratio is to reduce the amount of data processed.

Data reduction in the signature development step is the focus of the three subdesigns presented here. For the TM-1 design, over 67,000 labeled training pixels are extracted from the segment Landsat windows for submission to the clustering program (Classy). TM-2 modifies that process by computing an average reflectance value from pixels in a field. Significant data reduction results from the use of this field pixel (FP) for signature development.

This data reduction is somewhat attractive for theoretical as well as practical reasons. Distribution-based clustering algorithms such as Classy assume independence within the input data set. Reflectance values of same-field pixels are not independent because of the nature of the data and the resampling process used to produce the P-format pixel. Field pixels do not have this independence problem; therefore, clustering should follow more closely the distribution-based model.

Design A computes a single Field Pixel from all field-interior ("pure") pixels for each field regardless of its size, design B computes an FP from each group of 50 (or fewer) pure raw data pixels in a field, and design C computes a 50-pixel FP using both pure and boundary ("mixed") pixel values. Table 7 shows results from those designs.

Maximizing B/C is the goal of designs beyond TM-1; therefore, B is the winner of the TM-2 design types. Design A probably did not produce a sufficient number of pixels for the clustering algorithm to properly define spectral classes. Using the 50-pixel method in design B more than doubles the original number. Even so, some covers probably have an insufficient number of pixels for good spectral definition. The optimal number to average may be crop-specific or might be a function of field size and number of fields.

Design C performs reasonably well and suggests the advisability of additional research using boundary pixels for classifier development. Perhaps, as Holko suggests, these should be clustered as noncovers and their classification counts (along with real-cover counts) used in a multiple-regression estimation model [8].

Table 7--TM-2 design analysis comparisons

Description	Designs		
	TM-2A	TM-2B	TM-2C
Training pixels (No.)	810	1,839	4,700
Spectral classes (No.)	18	19	24
Overall percent correct	55.7	60.6	60.2
Corn R^2	.87	.88	.84
Corn RE	7.6	8.2	6.1
Percent correct	64.9	69.1	68.3
Percent commission error	21.1	17.5	19.9
Soybeans R^2	.88	.92	.92
Soybeans RE	8.2	12.3	12.3
Percent correct	67.2	76.0	78.0
Percent commission error	13.8	10.5	11.0
B/C ratio	1.2	1.3	0.9

Design TM-2 successfully achieves a higher B/C ratio than TM-1. The improvement comes initially from lower signature development costs. Beyond that, additional savings accrue because the reduced number of spectral classes diminishes classification costs. The concept of data reduction for signature development appears to be sound though more efficient and effective implementations of the concept may be possible. While data reduction in the sample is beneficial, its potential for cost savings is limited to sample intensive processes. Data reduction in the population (full scene) offers broader potential for B/C improvements via lowered classification costs.

Design TM-3: Data Reduction by Channel Selection

Data reduction in the population can be achieved in a number of ways: principal components (PC) transformation [23], population pixel sampling, channel selection, and others. The substantial computer expense necessary to produce the PC transformations is not expected to be offset by savings during later processing and so is not attempted. Channel selection is more attractive than pixel sampling because it reduces both clustering and classification costs and requires no modification to the standard estimation procedure. Pixel sampling would add another element of variance to the estimation model, lowering RE in the process.

EDITOR has marginally useful software tools for optimal channel selection. The choices studied here are based on the following: software considerations (four channels), maximizing interchannel correlation between selected and nonselected channels, minimizing this correlation between selected channels, and differences in these channel correlations by crop. Table 8 shows the interchannel correlations for corn and soybeans computed from the corresponding variance-covariance relationships obtained from training pixels in the JES sample. The upper right triangle is for corn and the lower left for soybeans.

Table 8--TM interchannel reflectance correlations by cover

Channels	1	2	3	4	5	6	7
							CORN
1		.537	.453	.244	.379	.312	.496
2	.571		.660	.158	.554	.456	.280
3	.549	.668		-.168	.487	.593	.231
4	.071	.068	-.250		.322	-.138	.097
5	.389	.326	.173	.711		.687	.291
6	.462	.372	.435	.156	.640		.279
7	.501	.334	.358	-.015	.258	.352	
	SOYBEANS						

Table 9--TM-Scanner band characteristics

TM band No.	EDITOR channel No.	Wavelength (Micrometers)	Name	Subdesign
1	1	0.4-0.5	Blue	A
2	2	0.5-0.6	Green	B
3	3	0.6-0.7	Red	N/S
4	4	0.7-0.9	Near-infrared	A,B
5	5	1.6-1.8	Mid-infrared	B
7	6	2.1-2.4	Far-infrared	A
6	7	10.4-12.5	Thermal	A,B

N/S = Not selected for any subdesign.

Table 10--TM-3 design analysis comparisons

Description	Designs	
	TM-3A	TM-3B
Training pixels (No.)	1,839	1,839
Spectral classes (No.)	17	17
Overall percent correct	58.1	60.0
Corn R^2	.74	.76
Corn RE	3.8	4.1
Percent correct	67.1	69.9
Percent commission error	19.1	17.6
Soybeans R^2	.88	.87
Soybeans RE	8.2	7.6
Percent correct	81.4	79.5
Percent commission error	17.0	13.3
B/C ratio	1.0	1.1

The two designs presented here use pure 50-pixel FP's (described earlier) for clustering. Table 9 gives some band characteristics of the TM sensor and indicates the channels selected for the two subdesigns. Results of the analyses are presented in table 10. There does not appear to be a great deal of difference between the performance of the two designs; however, B has a slightly higher B/C ratio and is the winner. This design reduced data processing costs by two-thirds from the TM-2 winner and by five-sixths from the TM-1 level (See Appendix I table 2). However, accompanying this savings was a substantial reduction in the RE, explaining the rather low B/C for TM-3.

The method of reducing data volume by channel selection looks promising. Additional development of selection criteria (specific to crop area regression estimation needs) and attendant software is needed to maximize the benefits from this approach.

SENSOR EFFECT ON BIAS IN R^2

A key question is whether TM increases the precision of the regression estimate, compared with MSS. Recent studies have questioned how to most accurately measure the precision of regression parameter estimates [8,19]. These studies noted significant differences between R^2 values obtained from the current procedure compared with those from jackknifing methods [17] and seem to dispute the findings of the 1975 SRS study in Illinois [6] which recommended using the same data set for classifier training and parameter estimation.

One possibility explaining the differences is that using the same data to develop a classifier and to evaluate its performance "overfits" the sample data and biases the estimates of the population regression parameters [10]. So, the regression relationships obtained from the current procedure may not hold outside the sample. Thus, it is appropriate to examine if this tendency to overfit the data is a function of sensor type and to determine if differences affect statistical testing. The validity of performance tests may be questionable if differences identified as significant are a function of sensor bias (which negates the testing) rather than of a true measure of enhanced performance.

The design of choice would use two full and independent replications of the JES sample over this area: developing a classifier on one set and estimating the parameters of the regression on the second set. However, only one sample set is available, so a modified jackknife technique is used. The 60 samples in this scene are separated into four groups by quartering the scene into approximately equal-sized vertical strips. JES land use strata are ignored. Segments falling in the first or third strip are called group A; the others group B. Each strip has 15 segments and each group has 30.

The alternating strip design is intended to minimize the effect on classification of the across-scene variability of the TM reflectance values, a function of the physical and mechanical make-up of the TM scanner [2,14]. Within each strip, pixels are sampled at the JES-specified sampling rate. The recent jackknife designs referenced subsample segments over an area so that pixel reflectance is sampled at one-half or one-third the JES-designed rate. The fact that these different designs all produced similar findings lends some power to the assertion that current methods bias estimates of the regression parameters.

Two separate classifiers are developed: one for each group of segments (A and B). The respective discriminant functions are then used to classify both groups (four classifications). Combining appropriate classifications produces an independent and dependent data set having 60 observations each. If segments used for classifier development are designated by lower case letters and segments classified by capital letters, then segments in group A processed with the classifier developed from group B are identified as A/b. The other combinations are A/a, B/a, and B/b. Taken together, A/b and B/a constitute the independent classification, as none of the pixels classified are used for signature development; conversely, the set A/a and B/b make up the dependent classification. The classified pixel counts (first from the dependent then from the independent classification) are regressed against the segment-reported crop acres.

Both MSS and TM are processed in this manner; the results are shown in table 11. Hotelling's T is used to test the null hypothesis that R^2 values from the independent and dependent classification are not different. The P-values reported for comparisons within sensor type do not support the null hypothesis. Since they are different, the independent regression may reflect more accurately the relationship of classified cover to actual cover in the population outside the sample than does the dependent regression.

No unequivocal statement is possible because differences between the dependent and independent R^2 values cannot be attributed wholly to bias caused by overfitting the sample data. The independent classifier is perhaps "inadequate" because it trains on only half the land area that the JES sample design specifies as necessary (within cost constraints) to adequately handle the variability (in the mix of crops) between sampling units. The fact that training samples are designed to be outside the area of the segments classified undoubtedly affects the correlation levels, but is not unlike actual full scene classification in which samples used for training may be some distance from many of the pixels classified.

Table 11--TM-1 dependent-independent R^2 comparisons by sensor

Crop	Count	Within sensor type							
		MSS				TM			
		Dependent (R^2)	Independent (R^2)	T-value	P-value	Dependent (R^2)	Independent (R^2)	T-value	P-value
Corn	60	.488	.140	3.44	.001	.877	.759	3.24	.001
Soybeans	60	.887	.834	2.29	.013	.912	.843	4.36	.001
Other	60	.775	.514	3.35	.001	.926	.876	2.65	.005

Crop	Count	Between sensor types					
		TM Dependent vs MSS Dependent		TM Independent vs MSS Independent		TM Independent vs MSS Dependent	
		T	P-value	T	P-value	T	P-value
(T-values and P-values are calculated from R^2's listed above.)							
Corn	60	8.26	.000	8.03	.000	3.59	.001
Soybeans	60	1.36	.090	0.31	.379	-1.46	.075
Other	60	5.31	.001	7.55	.000	2.41	.010

Intuitively, the range between the dependent and independent R^2 values can be thought of as a confidence indicator; the dependent values represent an upper bound and the independent values a conservative lower bound. Small ranges reinforce confidence that the dependent value is a "good" measure of the population relationship while large ranges tend to weaken that confidence. For example, the large range for MSS corn suggests that .488 is overly optimistic and probably more biased than the MSS soybean value of .887 with its smaller range.

Hypothesis testing in this paper generally examines the null hypothesis of equality between the sensor types (TM and MSS) against the alternative of better TM sensor performance. The probability of a Type 1 Error (falsely rejecting the null hypothesis) is usually only a function of sample variability. In this case, however; another element is present: the different degree to which MSS and TM processing overestimate the respective population regression relationships. The answer to the concern raised earlier is that for these data sets, indicated significant differences for corn and other crops probably are showing true differences; that is, that the improvement in the precision of the corn estimate coming from the TM regression is probably a real improvement.

CROP PRODUCTION POTENTIAL

A previous study examining the usefulness of satellite data in forcasting crop production [20] found marginal potential with MSS data. This study is not so detailed nor theoretical as that and approaches the problem from a different aspect. It explores the proposition that pixel reflectance provides direct information about ground cover yield. Clustering, classification, and regression analysis together indirectly extract the information contained in the pattern of pixel reflectance vectors.

For the test, farmer-reported yields by field are regressed against average field reflectance values; that is, average by field of reflectance values for all pure field pixels. Table 12 shows the results for both corn and soybeans. The best correlation for each n-tuple of channel variables is reported. There are diminishing marginal improvements beyond two channels and rapid fall off after four. This is not surprising in view of other research reporting that for TM "...'four' is the significant dimensionality of the data" [2]. Note that the best four-channel combination for soybeans (1,3,4,6) is not one of those used in data reduction design TM-3 for area estimation.

The best four-channel yield correlations of 0.47 for corn and 0.91 for soybeans are very similar to the respective MSS crop acreage regression correlations of 0.49 and 0.89 reported in table 2. This pattern may be just a coincidence of numbers, but it may indicate that as much yield information is contained in TM data as there is crop or cover information in the MSS data.

Table 12--Correlations between reported yield and reflectance

Number of channels (Independent variables)	Corn (n=21)		Soybeans (n=11)	
	R^2	Best channel n-tuple	R^2	Best channel n-tuple
1	.157	4	.763	4
2	.427	4,7	.825	2,4
3	.449	4,6,7	.903	1,3,4
4	.474	1,4,6,7	.911	1,3,4,6
5	.478	1,2,4,6,7	.922	1,3,4,5,6
6	.479	1,2,3,4,6,7	.924	1,3,4,5,6,7
7	.480	All	.925	All

Table 13--OY versus TM for field yield prediction

Correlations of farmer-reported yield regressed against:						
		TM	OY indicated field yield			
		Best four channels	September		November	
Crop	Sample		Gross	Net	Gross	Net
Corn	21	.47	.06	.06	.21	.15
Soybeans	11	.91	N/C	.22	N/C	.31

N/C = Not computed for soybeans.

The best four-channel reflectance/yield relationships are compared with the operational Objective Yield relationships in table 13. September/November OY estimated field yield is regressed against farmer-reported yield as in the reflectance correlation procedure. Both gross yield and net yield (less harvesting loss) relationships are shown. The differences between reflectance and OY correlations are substantial. However, the subsample is small especially for soybeans.

CONCLUSIONS

The EROS/NOAA TM data delivery system is not yet fully operational and cannot supply the volume of scenes necessary for any sizable operational program.

Conclusions based on a single analysis are by definition tentative. TM performs better than MSS. In every instance the TM regression correlation is higher (absolutely) than its MSS counterpart. The range between the dependent/independent R^2 values for TM are generally smaller than for MSS. The estimate of variance for TM crop estimates is probably more robust and less biased than for MSS. September 3 MSS data are not especially good for estimating corn acreage but TM data are quite satisfactory. Early to mid-August satellite acquisitions have been considered optimal for MSS corn and soybean work [7]. TM may extend that optimal acquisition window. If RE is an adequate measure of the value to SRS of the improved-precision, late-season, crop-area estimates, then data reduction methods can make TM processing-costs competitive with MSS costs.

The seeming contradiction between two measures of classifier quality, lower TM classification percents correct and higher TM R^2 values, might be explained by the interaction of pixel size and field characteristics. Enumerators collecting ground data measure acres over which the crop is seeded; scanners collecting satellite data measure energy-reflectance over that same area. The canopy of the emerged crop is seldom uniform across a field. Primarily because of its increased-resolution pixel, the TM scanner "sees" these canopy irregularities (figure 2). The MSS scanner misses them altogether (figure 1). TM appropriately classifies the irregularities and the crop differently. The resolution of the ground data may be inadequate to measure the correctness of a TM classification.

Substantially more information about yield in a particular field is contained in average field reflectance than is provided by OY methods. TM average field reflectance explains the variability in reported corn and soybean yield about three times better than does the OY. The correlation levels are higher for soybeans than for corn (0.93 vs 0.48) using average reflectance obtained in September. TM reflectance may be valuable for yield estimation and/or forcasting. However, to benchmark the reflectance values to a yield level requires access to end-of-season yields in at least some fields. Therefore, TM midseason yield forecasts are not possible until other relationships are found and exploited.

The evidence in figure 2 of TM's improved ground feature visibility suggests that it may have value for area frame development. Physical features are important for defining strata, count unit, and sampling unit boundaries.

RECOMMENDATIONS

This study shows that processing procedures exist to make TM cost-competitive with MSS for producing crop-area estimates. However, additional research is needed to establish the statistical properties of the regression estimates resulting from the use of either data type. The statistically significant differences between the independent and dependent regression correlations suggest that current procedures underestimate the variance of the crop estimates produced. Recent studies in other areas [10,16] suggest that a bias in the level of the crop estimates may also exist.

Sampling studies, perhaps as part of the 1985 Classifier Study [10], are needed to determine the following: How representative of scene/strata agriculture is the scene/strata JES sample? How representative of scene/strata reflectance is the pixel sample defined by the JES segments? If dependent training and estimation leads to biased results, how can modified jackknife procedures be implemented operationally to reduce or eliminate the bias, to minimize or eliminate the expense of supplemental ground data collection, and to avoid multiple full-scene classifications?

Additional research is needed in the area of improving estimates of crop production using TM data. The potential for end-of-season yield estimates based on the reflectance/yield relationship identified here is limited. That relationship is based on field-specific reflectance. Field boundaries and crop labels outside the JES sample are unknown in the scene. Thus, any use of average field reflectance is limited to the JES sample. If the same high reflectance/yield relationship is found for other crops and in other scenes obtained for different dates, it may be possible to estimate State crop yields from a direct expansion of JES reflectance-imputed field yields.

Corn did not do as well as soybeans in yield analysis. Would a July or August scene have produced better results? How well would OY or plant process models perform if field reflectance were used as an input variable? Would resulting production estimates have sufficient precision to be of any value to the Crop Reporting Board? Future yield/remote sensing research should seek answers to questions such as these.

REFERENCES

[1] Barker, John L., "Relative Radiometric Calibration of Landsat TM Reflective Bands." Landsat-4 Science Investigations Summary, NASA Conference Publication 2326, 1984.

[2] Bartolucci, L.A., M.E. Dean, and P.E. Anuta, "Evaluation of the Radiometric Quality of the TM Data Using Clustering, Linear Transformations and Multispectral Distance Measures." LARS IN #022283, Purdue University, Indiana, February 1983.

Cochran, etc., see [5]

[3] Cook, Paul W., "Landsat Registration Methodology." U.S. Dept. of Agriculture, SRS, Remote Sensing Branch, Miscellaneous Publication. August 1982.

[4] Engel, Jack, "Thematic Mapper (TM) Instrument Description." Landsat-4 Science Investigations Summary, NASA Conference Publication 2326, 1984.

[5] Cochran, William G. Sampling Techniques. 3rd ed. New York: John Wiley & Sons, 1977.

[6] Gleason, Chapman, Robert R. Starbuck, Richard S. Sigman, George A. Hanuschak, Michael E. Craig, Paul W. Cook, and Richard D. Allen. "The Auxiliary Use of Landsat Data in Estimating Crop Acreages: Results of the 1975 Illinois Crop Acreage Experiment." U.S. Dept. of Agriculture, SRS, SRS-21, October 1977.

[7] Hanuschak, George A., Michael Craig, Martin Ozga, Raymond Luebbe, Paul Cook, David Kleweno, and Charles Miller. "Obtaining Timely Crop Area Estimates Using Ground-Gathered and Landsat Data." U.S. Dept. of Agriculture, ESCS, Technical Bulletin No. 1609, August 1979.

[8] Holko, Martin L., "1982 Results for the California Cooperative Remote Sensing Project." U.S. Dept. of Agriculture, SRS, Staff Report No. AGES840305, March 1984.

[9] Holko, Martin L. and Richard S. Sigman, "The Role of Landsat Data In Improving U.S. Crop Statistics." Eighteenth International Symposium Remote Sensing of Environment, Paris, France, October 1984.

[10] Holko, Martin, R. Sigman and J. P. Zuttermeister, "DCLC Regression-Estimator Validation and Classifier Training Study"--research proposal. U.S. Dept. of Agriculture, SRS, November 1984.

[11] Holko, Martin, "A Proposal for Evaluating Landsat Cost Efficiency at the State Level." U.S. Dept. of Agriculture, SRS, RSB memo, December 1984.

[12] Hotelling, Harold, "The Selection of Variates for Use in Prediction with Some Comments on the General Problem of Nuisance Parameters." Annals of Math. Stat., Vol. 11 (1940), pp 271-283.

[13] Kalcic, M.T., "Automatic Segment Matching Algorithm Theory, Test and Evaluation." AgRISTARS Report DC-YZ-04325 (NSTL/ERL-209), June 1982.

[14] LANDSAT-4 Science Characterization Early Results, Volume II--Thematic Mapper (TM), Parts 1 and 2. John L. Barker, Editor. NASA Conference Publication 2355, 1985.

[15] Lennington, R. K., and M. E. Rassback, "Classy--An Adaptive Maximum Likelihood Clustering Algorithm." Proceedings of the LACIE Symposium, NASA Manned Spacecraft Center, Houston, Texas. January 1972.

[16] Lundgren, James C., "A Study of Bias and Variance in Landsat Data Based Regression Estimates for Crop Surveys Using Simulated Data." Lockheed Engineering and Management Services Company, Inc, LEMSCO-20239, December 1984.

Mergerson, etc., see [22].

[17] Miller, Rupert G. "The Jackknife--A Review." Biometrika, 61, 1, p. 1, 1974.

[18] "Scope and Methods of the Statistical Reporting Service." U.S. Dept. of Agriculture, SRS, Miscellaneous Publication No. 1308, September 1983.

[19] Sheffner, E.J., "Crop Area Estimation in Idaho Using EDITOR." NASA contractor report 177327, December 1984.

[20] Sigman, R. S. and G. A. Larsen, "Auxiliary use of Landsat Data in Estimating Crop Yields." U.S. Department of Agriculture, ESCS, December 1980.

[21] Sigman, Richard, and Michael Craig, "Potential Utility of Thematic Mapper Data in Estimating Crop Areas." Fifteenth International Symposium of Remote Sensing of Environment, Ann Arbor, Michigan, May 1981.

[22] Mergerson, James W., George A. Hanuschak, Paul W. Cook, "Applications of Satellite Remote Sensing for U.S. Crop Acreage Estimation, 1980-81 Results." U.S. Dept. of Agriculture, SRS, May 1982 (and subsequent unpublished updates).

[23] Swain, Philip H., and Shirley M. Davis. Remote Sensing the Quantitative Approach. New York: McGraw-Hill, Inc., 1978.

[24] Winings, Sherman B., Paul W. Cook, and George A. Hanuschak, "AgRISTARS DCLC Applications Project 1982 Corn and Soybeans Area Estimates for Iowa, Illinois." Seventh International Symposium on Remote Sensing of Enviornment, Ann Arbor, Michigan, May 1983.

[25] Zuttermeister, J. Paul, and Richard Sigman, "The Effect of Cubic Convolution Resampling on Crop Area Estimates." U.S. Dept. of Agriculture, SRS, Staff Report No. AGES831209, December 1983.

APPENDIX I. BENEFIT/COST COMPUTATIONS

Cost comparisons between MSS and TM processing may be an important consideration when choosing the type of sensor data for a particular application. SRS has little experience in processing TM data and little information concerning the associated costs. Therefore, the cost figures used in the ensuing computations are estimated, often with insufficient data. The following is presented to document the procedure used to obtain the estimates and to explain the method used to compute the ratio elements. The average costs quoted below are 1983 DCLC MSS costs averaged to a State figure [22].

Much of the cost to obtain Landsat-based crop area estimates for a State is not dependent on the Landsat sensor format used. For example, ground data collection and editing costs (averaging $65,000) and personnel, equipment, and supply costs (averaging $80,000) are not dependent on the sensor type. The sensor dependent cost elements are Landsat data acquisition and computer processing costs. These averaged $9,000 and $41,000, respectively, for MSS processing. TM data acquisition costs (under 1984 pricing) would average $38,750 per State. This leaves only TM computer processing costs to be estimated.

Costs to process a full scene are estimated from sample data processing costs and then assumed to hold for all scenes that would be processed in a typical State. Two elements of sample processing form the basis for costing. The observed sample level relationship between these two is used later to extrapolate from State-level MSS to TM costs. The two elements--signature development and sample classification--are used because they represent two fairly intensive computer central processor (CP) activities. Overall computer costs are more a function of the CP demands than they are of input/output operations or storage costs.

Factor Component 1 (FC_1) has to do with clustering (signature development). Clustering costs appear from observing the empirical data to be a function of the number of covers clustered, the number of pixels in each cover, the number of iterations of the algorithm, the number of channels, and the number of multivariate normal distributions found in the data set. This last variable is unknown before clustering and is ignored in the CP usage model formulated. The following ratio appears to approximate the ratio of CP time for different variable inputs as observed in sample data processing:

$$FC_1 = \frac{\Sigma_i \text{ Ln } \#Pix_{1i} * [\#Pix_{1i} * (\#Chan_{1i})^2 * IT_{1i}]}{\Sigma_j \text{ Ln } \#Pix_{2j} * [\#Pix_{2j} * (\#Chan_{2j})^2 * IT_{2j}],}$$

Where:

Ln = natural logarithm,
#Pix = number of pixels for that data set/cover,
#Chan = number of channels,
IT = number of iterations,
i,j = number of covers clustered in data sets 1 and 2,
set subscripts (1,2) = the data sets compared,
Σ = summation notation.

Factor Component 2 (FC_2) is a function of classification; costs are affected by the number of pixels classified, the number of channels in the pixel data, and the number of categories in the classifier. The following ratio approximates the ratio of CP times observed in sample processing:

$$FC_2 = \frac{\#Pix_1 * [\text{Ln } \#Cats_1 * (\#Chan_1)^2]}{\#Pix_2 * [\text{Ln } \#Cats_2 * (\#Chan_2)^2],}$$

Where:

#Pix = number of pixels classified,
#Cats = number of possible classification categories,
and other items are as previously defined.

Appendix table 1 shows predicted and observed behavior of the formulas presented. In both cases, the average predicted factor component is less than the observed. The observed data were obtained from three different systems. No attempt to estimate program CP overhead differences by system was made. Overhead can distort the results, especially on small data sets. The resulting TM processing estimates are probably conservative but serve to form some basis for MSS comparisons.

Appendix table 1--Factor component formula behavior

Predicted---FC1		---Observed	Predicted---FC2		---Observed
0.70		1.00	1.3		1.6
1.70		1.80	3.6		6.2
0.06		0.07	4.0		6.9
2.12		2.25	2.8		3.9
0.70		0.90	3.1		4.5
10.60		13.40	1.1		1.1
22.60		30.29			
2.51		1.83	2.7	average	4.0
0.09		0.07			
3.20		2.40			
4.43	average	5.40			

Factor components for the designs discussed in this paper are presented in Appendix table 2. A simple average of the two components is used as the estimated factor (EF) by which MSS processing costs are adjusted to approximate TM processing costs.

Appendix table 3 shows the cost and benefit computations for MSS and the three TM design winners discussed in the body of this paper. Benefits are calculated only for corn and soybeans as these are the only Iowa crops for which crop area regression estimates are produced.

Appendix table 2--Factor computations for design winners

Design	Clustering (FC1)	Classification (FC2)	Average (EF)
MSS	1.00	1.00	1.0
TM-1	9.00	15.40	12.2
TM-2	0.15	11.90	6.0
TM-3	0.05	3.70	1.9

Appendix table 3--Computations used in benefit/cost analysis

Costs:

			-$1,000 units-		
Design	JES survey	Landsat data	Computer processing	Other costs	Total costs
MSS	65	9.00	EF * 41	75	190.0
TM-1	65	38.75	EF * 41	75	678.9
TM-2	65	38.75	EF * 41	75	424.8
TM-3	65	38.75	EF * 41	75	256.7

Benefits:

			$1,000 units
Design	Crop	RE	Benefit
MSS	Corn	1.93	125.5
	Soybeans	8.94	581.1
TM-1	Corn	8.19	532.4
	Soybeans	10.92	709.8
TM-2	Corn	8.19	532.4
	Soybeans	12.29	798.9
TM-3	Corn	4.10	266.5
	Soybeans	7.56	491.4

Computation of the B/C ratio is as follows:

$$B/C_i = \frac{RE_i * JC}{JC + PC_i + AC_i.}$$

Where:

RE_i = Relative efficiency.
JC = JES survey costs.
PC_i = Landsat processing costs (EF_i * \$41K).
AC_i = Landsat acquisition costs.
EF_i = Estimation $factor_i$ (Appendix table 2).

APPENDIX II.

THE ROLE OF LANDSAT DATA IN IMPROVING U.S. CROP STATISTICS*

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ABSTRACT

Landsat data are used in two ways to improve U.S. crop statistics. Landsat color-composite images are used to stratify areas of land with regard to land use. This stratification is used as a technique to improve the efficiency of an area sampling frame. Also, Landsat digital data are classified and the classified results are used as supplementary information to an agricultural survey. The combination of Landsat classification results and survey data improves the precision of the estimates made.

1.0 Introduction

The Statistical Reporting Service (SRS) is the agency of the U.S. Department of Agriculture responsible for current statistics describing domestic crop and livestock production. For the most part, these statistics are estimates based on sample surveys conducted by SRS personnel.

A major source of data for SRS is its nationwide June Enumerative Survey (JES). It is in conjunction with the JES that SRS uses data from the Landsat satellites. Landsat data are used to improve the precision of the estimates obtained from the JES in two different ways. One use of Landsat data is in the development of an area sampling frame from which the JES sample is selected. A second use is as current, supplemental information that, when combined with the data collected during the JES, increases the precision of calculated area estimates.

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2.0 Use of Landsat Imagery in Area Frame Construction

2.1 Concepts

In area-frame sampling the sample units are pieces of land called _segments_. The boundaries of segments are well-defined, physical features -- such as roads, footpaths, rivers, and railways -- that can be both delineated on maps and aerial photographs and also readily identified by data collection personnel in the field. An _area-sampling frame_ is a complete list (or more frequently a set of specifications that would generate a complete list) of segments that cover a geographical area of interest, such as a state or province. This geographical area of interest is called a _population_.

An area sampling frame is a basic tool for collecting agricultural statistics. It is used in a number of countries to estimate acreage and yield of agricultural products as well as farm-economics parameters such as prices and labor for the current year. Area frame sampling provides accurate information by taking representative samples from only a small portion of the total land area. Estimates can be available five to six weeks after the beginning of data collection.

The construction of an area sampling frame consists of several steps [Houseman, 1975]. The first step is the delineation on a base map of _stratum blocks_. These are large contiguous areas of homogeneous land use. In addition to the mapping symbols on the base map, information from satellite imagery, aerial photography, and other maps are used in this stratification step. All of the stratum blocks of the same land use constitute a _stratum_. Like segment boundaries, the delineated strata boundaries must be identifiable in the field. The purpose of stratification is to increase the precision of sample survey estimates.

The next step is to divide the strata blocks into smaller areas called _primary sampling units_ (PSU's). The PSU's vary in size depending on the stratum but generally contain from 5 to 20 potential segments. Out of each stratum a suitable number of PSU's will be randomly chosen with probability of selection proportional to the area of the PSU.

The purpose of the PSU's is to serve as an intermediate delineation between the large strata blocks and the individual segments. By delineating PSU's all of the segments in the population need not be delineated. Instead, only the segments in the randomly selected PSU's are delineated by subdividing the PSU into the appropriate number of segments based on the area of the PSU and the target segment size. In strata that are predominantly cultivated land, the target segment size is typically one square mile. After the selected PSU has been subdivided, one segment is randomly selected from the PSU for field enumeration.

Desired data are then collected from the sample segments by interviewing farmers who operate land inside the segment. Since the segments within each stratum are statistically representative of the stratum, the data collected from the segments can be expanded to the total area of the stratum. The desired estimate for the entire population is then obtained by summing the results for each stratum.

2.2 SRS Experience

SRS has constructed and maintains an area frame for each of the 48 contiguous states. Since the construction of an area frame for a state is a major effort, SRS is only able to construct approximately three new area frames per year. Once an area frame for a state is constructed, it is used annually for anywhere from 10 to 20 years before it is revised or replaced.

The majority of SRS's area frames contain five basic strata: cultivated land, range and pasture, water, nonagricultural land, and cities and towns. The cultivated land in most states is further stratified by separating "intensively" cultivated land from "extensively" cultivated land. (In Nebraska there are two intensively-cultivated-land strata.) In addition to the five basic land-use strata, the area frames in California and Texas each contain one or more "crop specific" strata. The SRS area frames in Washington, Oregon, and Idaho have strata for dryland grain. [Geuder, 1984]

The use of Landsat imagery to stratify SRS area sampling frames was first demonstrated by Hanuschak and Morrisey [1977]. In this study, county maps at a scale of 1:126,720 were photographically reduced to a scale of 1:250,000 on mylar and overlaid on 1:250,000-scale, color Landsat imagery produced on paper by the EROS Data Center. The Landsat image was photo-interpreted to provide land-use information, whereas the overlaid county map provided physical features for delineating stratum blocks and PSU's. This procedure was then used by SRS in 1979 to construct a new area frame for the state of California [Fecso and Johnson, 1981]. Since 1979, SRS has photo-interpreted Landsat images for constructing new area frames in Arizona, Colorado, Florida, Idaho, New Mexico, Oregon, Texas, Washington, and Wyoming. The majority of these new frames have been in the western United States where much of the cultivated land is irrigated and can thus be readily identified on Landsat images.

In 1982, SRS updated the Nebraska area frame by restratifying the urban stratum and areas where rangeland had been converted to cropland. Used in this restratification effort were plots giving the location of all pivot irrigation in 58 counties. These plots were developed by the University of Nebraska from Landsat data, administrative records for well permits, and field observations by county agents. [Hale, 1983]

Burns [1983] has demonstrated the use of digital Landsat data for updating SRS sampling frames in an area in Louisiana. In this study, unsupervised clustering of the Landsat data was performed, and then stratum labels were assigned to the clusters by an analyst using an interactive image processing system. SRS is further evaluating this procedure for stratifying area sample frames in Wyoming and Florida [Geuder, Blackwood, and Radenz; 1983].

3.0 Landsat Data as Supplemental Information

3.1 Background

SRS conducts the JES annually in late May and early June. The JES survey procedure requires that information be obtained for all the land within each of the sampled segments. To insure that all the land is accounted for, aerial photographs, at a scale of 1:8,000, are used as an enumeration aid. The boundaries for each segment are drawn on individual non-current photographic prints. These segment photographs and corresponding questionnaires are sent to field enumerators for data collection. As part of the data collection procedure, each enumerator is instructed to draw the boundaries of all fields, within each segment, on the segment photograph (a field is defined as a continuous block of land containing the same crop or land cover). On the corresponding questionnaire the enumerator records the cover and size of each field, as well as livestock numbers and other agricultural information obtained from the operator. The information collected during the JES is aggregated to the segment level and direct expansion estimates are then calculated to obtain state level estimates for crop hectares. The formulas for the direct-expansion estimator and its variance are as follows:

Let $\hat{Y}_c$ = the direct expansion estimate for the hectares of crop **c**

$$\hat{Y}_c = \sum_{s=1}^{S} \frac{N_s}{n_s} \sum_{j=1}^{n_s} y_{jsc}$$

where:

y_{jsc} = the hectares reported to crop **c**, in segment **j**, for strata **s**

n_s = number of segments sampled in strata **s**

N_s = the total number of potential segments in stratum **s**

S = the total number of strata.

The estimated variance is:

$$V(\hat{Y}) = \sum_{s=1}^{S} \frac{(N_s-n_s)\ N_s}{n_s\ (n_s-1)} \sum_{j=1}^{n_s} (y_{jsc}-y_{.sc})^2$$

where:

$$y_{.sc} = \sum_{j=1}^{n_s} \frac{y_{jsc}}{n_s}.$$

In 1972 SRS personnel started to investigate the potential of using digital Landsat data to improve the precision of the estimates obtained from the JES. The procedure developed consists of the following steps:

- Analysis District Selection: Landsat data are selected and boundaries of Landsat analysis districts defined.

- Signature Development: Data collected during the JES and corresponding Landsat data are used to develop a maximum likelihood classifier for each analysis district.

- Small Scale Processing: The Landsat pixels representing the area within each segment contained in an analysis district are classified. A relationship is developed between the number of pixels classified to a crop and the hectares recorded for that crop on the JES.

- Full Frame Processing: All of the Landsat pixels within the analysis district are classified. Estimates are calculated at the analysis district level by applying each crop regression relationship to the all-pixel classification results.

- State Level Accumulation: The estimates for all analysis districts are combined to create a state level estimate for each crop of interest.

3.2 Analysis District Selection

An analysis district is an area of land covered by Landsat imagery of the same overpass date. A separate Landsat analysis is done for each analysis district. Depending on the location and availability of Landsat data, each state is divided into a number of analysis districts. The Landsat analysis district location is treated as a geographical post-stratification imposed on the original area frame. As a result of this post-stratification, SRS personnel must determine the number of frame units and the sampled segments which fall into each post-stratum. This results in two types of strata categories:

1) The first stratum category corresponds to the area of the state for which there is no Landsat coverage. This area may be non-contiguous. The portion of each land-use stratum within these geographical areas makes up the post-strata. We let

M_s = the total number of segments in the non-Landsat area in land use strata **s**, and

m_s = the number of sampled segments in the non-Landsat area in land use strata **s**.

2) The second stratum category corresponds to the areas of the state where the land-use strata and the analysis districts are defined. In these areas each stratum consists of the area of intersection between the land use strata and a Landsat analysis district. Here, we let

M'_{as} = the number of frame units in analysis district **a**, land use strata **s**, and

m'_{as} = the number of sampled segments in analysis district **a**, land use strata **s**.

3.3 Signature Development

Signature development is done independently for each analysis district and consists of four phases. The first phase is segment calibration and digitization. Segment calibration is a first-order linear transformation which maps points on the segment photograph to a map base (in our application this map base is the U.S. Geological Surveys quadrangle map series, which uses the latitude/longitude coordinate system of reference). Segment digitization is the process by which field boundaries drawn on the segment photograph are recorded in computer-compatible form. The combined process of calibration and digitization gives us the capability of digitally locating every JES field relative to a map base.

The next phase in signature development is the registration of each Landsat scene. SRS's Landsat registration process is a third-order linear transformation that maps each Landsat pixel within a scene to a map base [Cook, 1982]. Corresponding points selected on a two-degree map and a 1:250,000 Landsat image are used to generate this mathematical transformation. The combination of segment calibration, digitization and Landsat registration provides the capability to locate each JES segment in its corresponding Landsat scene (to within about 5 pixels of the correct location). Since this registration is not accurate enough for selecting training data, line plots of segment field boundaries and corresponding greyscale prints are overlaid and each segment is manually located to within 1/2 pixel of the correct location. With this process we are able to accurately identify all of the pixels associated with any JES field. The result of this is a set of pixels labeled by JES cover.

The third phase of signature development is supervised clustering. In supervised clustering all of the pixels for each cover are processed through one of two available clustering algorithms: Classy or Ordinary Clustering. Classy is a maximum likelihood clustering algorithm developed at Johnson Space Center in Houston, Texas [Lennington and Rassback, 1972]. Ordinary Clustering is an algorithm derived from the ISODATA algorithm of Ball and Hall [1967]. Each clustering algorithm generates several spectral signatures (categories) for each cover. Each spectral signature consists of a mean vector and the covariance matrix for the reflectance values for that category.

In the fourth phase, the statistics for all categories from all covers are reviewed and combined to form the discriminant functions of the maximum likelihood classifier. The formulas for the discriminant functions are as follows:

The <u>maximum likelihood classifier</u> with equal priors:

Classify pixel **k** to category **c** if $D_{ck} \geq D_{ik}$ for all $i \neq c$

The <u>maximum likelihood classifier</u> with priors:

Classify pixel **k** to category **c** if $D^p_{ck} \geq D^p_{ik}$ for all $i \neq c$

where:

$D_{ik} = -\log_e(|Z_i|) - (X_k - U_i)' Z_i^{-1} (X_k - U_i)$

$D^p_{ik} = D_{ik} + \log(p_i)$

U_i = the mean vector for category **i**

Z_i = the covariance matrix for category i

p_i = the prior probability for category **i**

X_k = the reflectance value for pixel **k**

3.4 Small Scale Processing

In small-scale processing each pixel associated with a JES segment is classified to a category. This classification is usually done using both the classifier with priors and the equal priors classifier. For each classifier, pixels classified to each category are summed to segment totals. The category totals corresponding to crops of interest are summed to segment crop totals. These crop totals are used as the independent variable in a regression estimator. Correspondingly, the hectares reported on the JES for each crop are summed to segment totals and used as the dependent variable. The segment totals are used to calculate least-squares estimates for the parameters of a linear regression. Two sets of regression equations are developed for each crop within each stratum (one for the classification with priors, one for the classification with equal priors).

The linear regression equations for analysis district **a**, strata **s**, and crop **c** are of the form:

$$y_{jasc} = b_{0asc} + b_{1asc}\, x_{jasc}$$

where:

y_{jasc} = the reported hectares of crop **c**, from segment **j**, analysis district **a**, land use stratum **s**

x_{jasc} = the crop total classification for segment **j**, analysis district **a**, land use strata **s**

b_{0asc}, b_{1asc} = least squared estimates of the regression parameters for crop **c**, analysis district **a**, land use strata **s**

3.5 Full Frame Processing

The regression equations developed in small-scale processing are evaluated and the classifier giving the best overall regression relationship is selected. This classifier is used to classify every pixel in the analysis district. The classified results are tabulated by category and land-use stratum. For each crop of interest the category totals are summed to stratum crop totals. From these totals the population averages per segment are calculated. Using the population average, a stratum-level regression estimate is made for that analysis district for each crop.

Let $\hat{Y}'_{asc}$ be the analysis district level regression estimator for crop **c** and stratum **s**.

Then:

$$\hat{Y}'_{asc} = M'_{as} \left[y_{.asc} + b_{isc}(X_{.asc} - x_{.asc}) \right]$$

where:

$$y_{.asc} = \sum_{j=1}^{m'_{as}} \frac{y_{jasc}}{m'_{as}} \quad \text{and} \quad x_{.asc} = \sum_{j=1}^{m'_{as}} \frac{x_{jasc}}{m'_{as}}$$

M'_{as} = previously defined (3.2)

m'_{as} = previously defined (3.2)

x_{jasc} = previously defined (3.4)

y_{jasc} = previously defined (3.4)

$X_{.asc}$ = the population average for crop **c** in analysis district **a** land use stratum **s**

The estimated variance is:

$$V(\hat{Y}'_{asc}) = \frac{(m'_{as}-1)}{(m'_{as}-2)} (1-r_{asc}{}^2) \frac{(M'_{as}-m'_{as})M'_{as}}{m'_{as}(m'_{as}-1)} \sum_{j=1}^{m'_{as}} (y_{jasc}-y_{.asc})^2$$

where:

r^2_{asc} = the sample correlation between y_{jasc} and x_{jasc}

3.6 State Level Accumulation

The final step of our Landsat analysis is the combining of all of the estimates (one for each post strata) into a state-level estimate of the area of the desired crop.

Let $\hat{Y}'_c$ be the final state level estimate for the hectares of crop **c**.

Then:

$$\hat{Y}'_c = \sum_{a=1}^{A} \sum_{s=1}^{S'_a} \hat{Y}'_{asc} + \sum_{l=1}^{L} M_l\, y_{.lc}$$

where:

$$y_{.lc} = \sum_{j=1}^{m_l} \frac{y_{jlc}}{m_l}$$

M_l, m_l previously defined (3.2)

$\hat{Y}'_{asc}$ is as defined earlier (3.5)

y_{jlc} = the hectares reported to crop **c** for segment j in the non-Landsat post strata **l**

S'_a = The number of land use strata in analysis district **a**

A = The number of analysis districts

L = The number of land use strata that exist in the area where we do not have Landsat coverage

The estimated variance is:

$$V(\hat{Y}'_c) = \sum_{a=1}^{A} \sum_{s=1}^{S'} V(\hat{Y}'_{asc}) + \sum_{l=1}^{L} \frac{(M_l-m_l)M_l}{m_l(m_l-1)} \sum_{j=1}^{m_l} (y_{jlc}-y_{.lc})^2$$

3.7 Evaluation of the Landsat Estimate

Landsat data are used as supplemental information to improve the precision of the area estimates obtained from the JES. Unlike area frame construction, the effectiveness of this use of Landsat data can be measured. The measure used is the efficiency of the Landsat estimator relative to the JES direct expansion estimator. This relative efficiency (RE) is defined as the ratio of the variance of the direct expansion to the variance of the Landsat estimate. Equivalently, this is the factor by which the sample size would have to be increased to produce a direct expansion estimate with the same precision as the Landsat estimate.

$$RE = \frac{V(\hat{Y}_c)}{V(\hat{Y}'_c)}$$

3.8 Implementation

The basic concepts of SRS's Landsat analysis were developed during the 1972-1979 time period. In 1980 as part of the AgRISTARS Domestic Crop and Land Cover Project, SRS's Remote Sensing Branch began making current-year, state-level area estimates for winter wheat, corn and soybeans in selected states. This move to a pseudo-operational mode meant that current year Landsat data (May for winter wheat, August for corn and soybeans) had to be processed to produce estimates by late-November and late-December for winter wheat and corn/soybeans respectively. The original implementation plan called for including two states in 1980 and adding two more states each year to a total of 10 states by 1984. In 1980 winter wheat estimates were produced for Kansas, corn and soybean estimates for Iowa. Table 1 shows the states included in the project, the crops for which estimates were made, and the number of Landsat scenes needed to cover each state. In 1983, SRS deviated from the original plan by adding only one state to the project. No new states were added in 1984. These modifications were necessary due to personnel ceilings and limitations of current processing capabilities. In 1984, under the modified plan, SRS expects to process about 2,000 JES segments contained in 66 Landsat scenes covering most of seven states (Table I).

3.9 Results

The JES direct expansion and Landsat estimates are two of many indications used to determine the official USDA area estimates. For most major crops the JES direct expansion is the key indication used for setting the preliminary area estimates in July. The Landsat estimates for the states in the project (available at the end of the crop year) are reviewed when the final end-of-season estimates are made.

Tables II through VI show the JES direct expansion, the Landsat estimates and the final USDA estimates. The relative efficiencies of the Landsat estimates are mostly in the range from 1.2 to 2.0 for the major crops of winter wheat, corn and soybeans. The relative efficiencies for crops with fewer hectares such as cotton and rice are considerably better. The level of some of the estimates for cotton and rice, however, differ considerably from other data sources used to make the official estimate. Part of the variability in the relative efficiencies for the major crops can be explained by the amount of Landsat coverage available to do each estimate. Figure 1 shows three graphs comparing the percent of each crop covered by Landsat data with the relative efficiency obtained. If the trend apparent in these graphs can be extended, one would expect that the best we could do is relative efficiencies of about 2.5. These results, although promising, are not as good as originally expected. However the continued personnel limitation and the increasing respondent burden being placed on our farm sector may make our Landsat estimator one of few techniques feasible for improving crop statistics in the U.S.

References

Ball, G.H. and D.J. Hall. A Clustering Technique for Summarizing Multivariate data. Behavioral Science, 12 153-155, March 1967.

Burns, G.S. Land Cover Change Monitoring Within the East Central Louisiana Study Site -- A Case for Large Scale Area Surveys with Landsat Multispectral Scanner Data. Technical report, DC-Y3-04418, NSTL/ERL-221. NASA, NSTL Station, Mississippi, June 1983.

Cook, P.W. LANDSAT Registration Methodology Used by U.S. Department of Agriculture's Statistical Reporting Service 1972-1982. 1982 American Statistical Association Meetings, Cincinnati, Ohio, August 1982.

Fecso, Ron and Van Johnson. The New California Area Frame: A Statistical Study. Report SRS-22. United States Department of Agriculture, Statistical Reporting Service, Washington, D.C., September 1981.

Geuder, Jeff; Paul Blackwood, and Ron Radenz. Using Landsat for Sampling Frame Development. Research proposal. Statistical Reporting Service, October 1983.

Geuder, Jeff. Paper stratification in SRS area sampling frames. SF & SRB Staff Report No. 79. Statistical Reporting Service, Washington, D.C., February 1984.

Hale, Bob. An Evaluation of the Nebraska Area Frame. SF & SRB working paper. Statistical Reporting Service, November 1983.

Hanuschak, George and Kathleen Morrissey. Pilot Study of the Potential Contributions of Landsat Data in the Construction of Area Sampling Frames. Staff report. Statistical Reporting Service, Washington, D.C., October 1977.

Houseman, Earl. Area Frame Sampling in Agriculture. Report SRS-20. Statistical Reporting Service, Washington, D.C., November 1975.

Table I: States and Crops for Which Landsat Area Estimates Have Been Made

State	Years in Project	Area Estimates Produced for:	Number of Landsat Scenes Needed:
Kansas	1980, '81, '82, '83, '84	winter wheat	16
Iowa	1980, '81, '82, '83, '84	corn, soybeans	12
Oklahoma*	1981, '82, '83, '84	winter wheat	7
Missouri*	1981, 1/, '83, '84	winter wheat, corn, soybeans, cotton, rice	12
Colorado*	1982, '83, '84	winter wheat	14
Illinois	1982, '83, '84	corn, soybeans	10
Arkansas*	1983, '84	soybeans, rice, cotton	5
TOTAL			66

* major producing areas

Table II: Area Estimates for Winter Wheat Harvested by State and Year

	JES Direct Expansion		Landsat Regression			
State/Year	Estimate	Standard Error	Estimate	Standard Error	Relative Efficiency	USDA Estimate
	(1,000 hectares)		(1,000 hectares)			(1,000 hectares)
Kansas						
1980	5,214	162	5,051	136	1.3	4,856
1981	5,452	158	5,298	104	2.3	4,897
1982	5,677	167	5,611	120	1.9	5,301
1983	4,652	153	4,477	124	1.5	4,371
Oklahoma						
1981	2,612	117	2,483	101	1.4	2,590
1982	2,914	119	2,660	90	1.8	2,792
1983	1,725	85	1,688	74	1.3	1,740
Colorado						
1982	1,276	91	1,132	49	3.4	1,178
1983	1,193	115	1,110	81	2.0	1,214
Missouri						
1983	830	66	866	49	1.9	749

Table III: Area Estimates for Corn by State and Year

	JES Direct Expansion		Landsat Regression			
State/Year	Estimate	Standard Error	Estimate	Standard Error	Relative Efficiency	USDA Estimate
	(1,000 hectares)		(1,000 hectares)		(1,000 hectares)	
Iowa						
1980	5,735	115	5,801	93	1.9	5,666
1981	5,828	128	5,820	103	1.6	5,828
1982	5,601	118	5,568	113	1.1	5,565
1983	3,708	111	3,666	81	1.8	3,683
Missouri						
1981	870	75	775	51	2.2	850
1982 1/	-	-	-	-	-	-
1983	758	60	629	45	1.8	688
Illinois						
1982	4,809	115	4,677	106	1.2	4,735
1983	3,482	113	3,380	102	1.2	3,318

Table IV: Area Estimates for Soybeans by State and Year

	JES Direct Expansion		Landsat Regression			
State/Year	Estimate	Standard Error	Estimate	Standard Error	Relative Efficiency	USDA Estimate
	(1,000 hectares)		(1,000 hectares)		(1,000 hectares)	
Iowa						
1980	3,395	112	3,290	96	1.5	3,359
1981	3,260	104	3,275	82	1.6	3,278
1982	3,539	106	3,433	99	1.2	3,428
1983	3,155	98	3,200	88	1.3	3,238
Missouri						
1981	2,306	115	1,964	86	2.1	2,072
1982 1/	-	-	-	-	-	-
1983	2,275	124	2,008	97	1.6	2,104
Illinois						
1982	3,866	120	3,767	109	1.2	3,743
1983	3,696	107	3,669	99	1.2	3,602
Arkansas						
1983	1,661	78	1,565	70	1.3	1,578

Table V: Area Estimates for Rice by State and Year

	JES Direct Expansion		Landsat Regression			
State/Year	Estimate	Standard Error	Estimate	Standard Error	Relative Efficiency	USDA Estimate
	(1,000 hectares)		(1,000 hectares)			(1,000 hectares)
Missouri						
1981	47	20	31	10	6.8	31
1982 1/	-	-	-	-	-	-
1983	51	21	46	10	3.9	25
Arkansas						
1983	419	48	376	32	2.2	374

Table VI: Area Estimates for Cotton by State and Year

	JES Direct Expansion		Landsat Regression			
State/Year	Estimate	Standard Error	Estimate	Standard Error	Relative Efficiency	USDA Estimate
	(1,000 hectares)		(1,000 hectares)			(1,000 hectares)
Missouri						
1983	26	15	30	4	11.1	44
Arkansas						
1983	144	33	103 2/	19	2.9	138

1/ No Landsat estimates were made for Missouri during 1982 due to insufficient Landsat coverage.

2/ Arkansas had a lot of cotton that was planted and abandoned prior to the satellite overpass. This area was not included in the Landsat regression estimate.

Figure 1: Plot of Percent of Each Crop Covered by Landsat Data Versus the Relative Efficiency of the Landsat Estimate.