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REMOTE SENSOR COMPARISON FOR CROP AREA ESTIMATION USING MULTITEMPORAL DATA

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ABSTRACT

This study compares results of using Landsat Thematic Mapper (TM) versus SPOT Multispectral Scanner data as inputs for estimating crop acreage. The region of interest spanned six counties in east central Arkansas. A multitemporal approach was applied for each sensor with early data coming from May and the later data from August. The crops being investigated were rice and cotton. In all, two TM scenes were utilized along with eight SPOT scenes. Ground truth data came from twenty eight sites approximately one square mile each. Using data from the ground segments, a maximum likelihood pixel classifier was developed through supervised clustering. In turn, this classifier was applied to all the pixels within the segments, and a regression relationship then developed relating the classified results with the ground truth data. The magnitudes of the correlation coefficients were compared across satellites for the crops of interest as an indication of sensor performance. In the analysis, TM data yielded better results than the SPOT data and at a lower cost. Correlational differences were greater for rice than cotton.

Keywords: Landsat TM, SPOT MSS, correlation, multitemporal.

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Introduction

The National Agricultural Statistics Service began research in the early 1970's in an effort to determine the value of satellite data in estimating crop acreage and production. From 1980 through 1987, statistics based on Landsat multispectral (MSS) data were used in setting various crop acreage estimates in several states. A detailed discussion of the progression of the program can be found in Allen and Hanuschak (1988). At the end of 1987, the decision was made to rechannel the resources of the remote sensing applications group back into a research program. A major reason for this was the concern over the anticipated failure of the two current Landsat satellites which had both outlived their expected lives. Additionally, the Landsat satellite due to be launched in 1991 was not going to carry a MSS scanner. The choices of the future were primarily centered upon using MSS data from the French SPOT satellites or using thematic mapper (TM) data from yet to be launched Landsat satellites.

NASS first implemented multitemporal data analysis in its remote sensing program in 1983. Initially, this was used for estimating late season crops in Missouri. It was later expanded to include all major crops in the states of Arkansas and Missouri as well as the winter wheat crop in Oklahoma. Basically, a multitemporal data set consists of spectral readings taken from two or more different dates with the ground area to which they pertain being the same. The purpose of the study presented here is to compare multitemporal results based on MSS data from the French SPOT satellite with those obtained using TM data from the Landsat V satellite.

Methodology

Past applications have shown that the greatest gains in the efficiency of acreage estimates, based on satellite data, have been related to rice and cotton (Allen and Hanuschak, 1988). As a consequence, current sentiment is that once the remote sensing applications program becomes operational again that these two crops would be the first to be considered for inclusion. With this in mind, the state selected for this study was Arkansas which is the nation's number one producer of rice as well as being in the top five in cotton.

In the NASS remote sensing application program, an early season and a late season date have always been utilized for all multitemporal analyses. The choice of the particular dates to use is related to the crops of interest. When cotton and rice are considered jointly, the ideal time frame normally requires that the early scene be from around the first week of May to the first week of June with the late scene being from late July to mid August. The optimum times are dependent upon planting dates and growth progress. Originally, an entire eight county area was to be considered, but unfortunately, cloud free coverage in the needed time frame was not available from SPOT. As a result six counties were included in the study with some having only partial inclusion: Prairie, Lonoke, Jefferson, Monroe, St. Francis, and Arkansas. In essence, the area to be studied was limited by the lack of useable SPOT data. In creating the multitemporal data set, a total of eight SPOT MSS scenes were used; the date of the four early or primary scenes were all May 10, 1988, with the date of the corresponding secondary scenes being August 2 for three areas and August 17 for the fourth. Ideally, with a situation such as this, the fourth scene should be placed in a separate analysis due to the date variation. However, since there were not enough data in the single scene to allow it to be analyzed separately, two approaches were used in this study. First, the area under analysis was reduced so as to exclude that scene; second, a separate analysis was done including that scene as if it had the same date as the other SPOT scenes. The four SPOT scenes were encompassed by a single Landsat TM scene; the date for the primary imagery for TM was May 17 with the secondary scene having a August 5 date.

Spectral readings from the satellites provided the first component of the data needed for the analysis. The second component consisted of ground truth data. In order to estimate crop acreage, NASS conducts an annual area frame survey each June. The area frame itself is a stratified population with groupings based on percent of land cultivated. In Arkansas, there are approximately 400 land segments used each year for this survey. Of these, about 275 are agricultural segments (i.e., those 15 percent or more cultivated) with an average size of 640 acres. When all four SPOT scenes were used, there were twenty eight segments from which data could be drawn. The number of useable segments was reduced to twenty three when only three SPOT scenes were utilized. As a quality check, approximately half of the ground data was verified through a visual inspection conducted during the first week of August.

By bringing the two sources of data together, NASS is able to produce a crop acreage estimate that is better than the one that relies solely on the area expansions derived from the ground data. The process begins with the calibration of the area frame land segments to a map base; that is, the exact location of a segment is translated into a set of latitudinal and longitudinal coordinates. During ground data collection, the enumerators not only obtain acreage information but also delineate the fields on a photographic product; as a result, the ground segments provide acreage information by crop as well as by location. Each satellite scene to be used is also registered; this process yields four third order polynomials. The first two can be used to derive row and column values given latitudes and longitudes while the second two can be used to compute latitudes and longitudes given row/column coordinates. This allows one to match the collected ground data to the related satellite data. In the multitemporal case, the mapping of ground segments to the satellite image relies on the registration of the primary scene.

An overlay procedure is used in the multitemporal approach to match pixels (i.e., the individual land areas within a scene to which spectral readings are assigned) in the secondary scene to those in the primary scene. As a first step, points which visually appear to be the same are selected on both scenes. These points are used to produce a scene to scene registration; that is, polynomial relationships between the points in the two scenes are developed. There is one function representing a row mapping and a second representing a column mapping. These serve only as the first approximations for mapping the secondary scene onto the primary. Based on this initial mapping, blocks of satellite data which have corresponding centers are created for both scenes; in most cases there will be approximately 1800 blocks generated for consideration. The primary blocks are squares with sides being 64 pixels each; the secondary blocks are squares with sides being 32 pixels each. The secondary block is then shifted around inside of the primary block until the point where the highest correlation between the contained pixels is found. Blocks with correlations of less than .2 are generally excluded from the formulation of the ensuing polynomials; past experience with Landsat MSS data has shown that correlations typically range from .2 to .4 although they are often quite higher. The shifts which are found are applied to center points of the primary blocks; the resulting row/column coordinates are then used in conjunction with the original row/column centers of the secondary blocks to form two least squares polynomials which relate the scenes to one another. At the next step, residuals are calculated using the new functions. An iterative procedure follows where points with residuals deemed to be too high are removed one at a time with the mapping functions and resulting residuals recalculated at each stage (Ozga et al., 1979). Once the overlay procedure has been completed, the set of pixels in the secondary scene have essentially been shifted so as to fit the primary scene as adequately as possible. Subsequently, the satellite data of each pixel in the secondary scene is then uniquely attached to its matching pixel in the primary scene. In the end, each pixel contained in a segment is associated with a crop type from the area frame survey as well as a set of spectral readings. In the case of SPOT, the satellite signature consists of six values whereas with TM there are fourteen values.

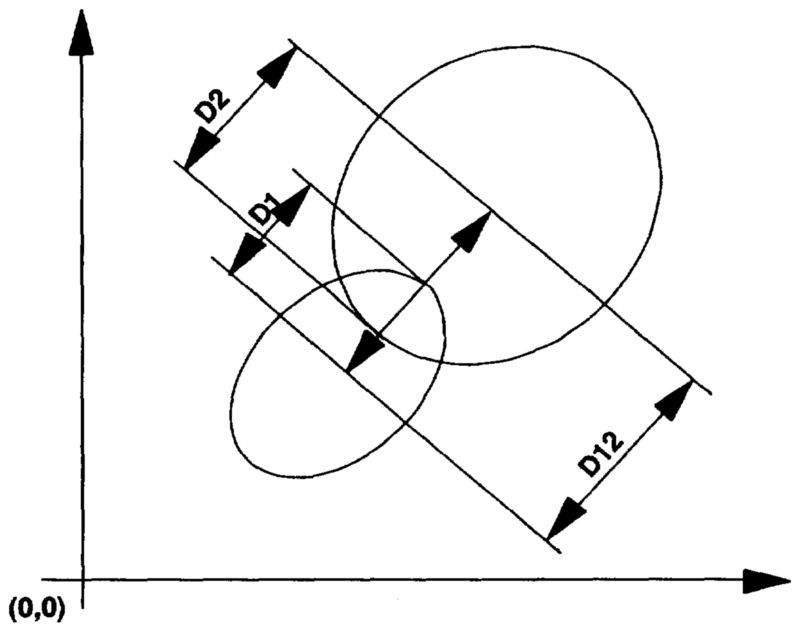
Once this is done, a check for outliers is performed on the sample data. This requires the computation of the principal components for each crop type reported in the ground truth data set. For TM there are fourteen principal components used in the check with six used for SPOT. In this study, all points with computed values over four standard deviations from their corresponding mean were deleted or "clipped" from the set of points that were to be used in the next stage of the analysis. By using principal components, one is able to take advantage of the multivariate properties of the data.

In the next step, clusters are formed by crop; that is, all pixels of a certain crop type are lumped together and a clustering algorithm is then applied to the group. For this study, the modified ISODATA clustering routine in USDA's PEDITOR analysis package for satellite data was used (Bartolucci and Castro, 1979). Basically, the analyst inputs the initial number of clusters (N) to be considered, the minimum number of clusters deemed to be acceptable, the minimum separability between clusters to be permitted, and finally the maximum number of iterations and the minimum convergence to be allowed. The algorithm begins by selecting N points that are equidistant apart along a line in the multidimensional space. Each pixel is then assigned to the cluster (i.e., center point) to which it is closest based on Euclidian distances. The mean vectors and covariance matrices for each cluster are then computed. The new means represent the new center points; the pixels are then reclustered using these points. This continues until either the specified iterations or the indicated convergence is met. Next, the interval between clusters is checked against the limit which was specified. The value used for this check is the Swain-Fu distance measure:

$$\text{Swain-Fu Distance} = \frac{D12}{D1 + D2}$$

where D12 is the Euclidian distance between the two cluster centroids while D1 is the radius of the first cluster's ellipsoid of concentration along the line connecting the two centroids. Distance D2 is similar to D1. Exact computational formulae can be found in Swain (1973). The three variables are shown graphically in two dimensions in Figure 1. If any of the clusters are less than the specified distance apart, the closest two are merged together and new means and covariances again computed. The process then repeats itself until all of the restraints specified by the user are satisfied. Once this is done, the analyst is left with one or more clusters for each crop, and associated with each cluster is a signature consisting of a mean vector and a covariance matrix.

Figure 1 : Illustration of Variables Used in Swain-Fu Distance Calculations



A statistics file containing all the cluster information is then created. This allows for the comparison of clusters across crops. If there are clusters with similar means and covariances, some confusion may result in the classification process. There are two approaches for handling this situation. First, clusters can be dropped thereby excluding them completely from any ensuing analysis. The disadvantage in this is that some data will not be used. A second alternative is to save the data but to force it out of the unwanted clusters. This is done by reclustering the particular crops in question with the minimum number of allowable groupings specified to reflect the merging of some of the original clusters. At the conclusion of this step, each crop has a set of statistics assigned to it. In the study presented here, no clusters were dropped or merged based on an analysis of the statistics file.

At the next stage, all the sample data are classified using the signatures which were developed. Multivariate normality is assumed which seems justified for most remote sensing applications and specifically considering the methodology used in forming the clusters. Additionally, Swain and Davis (1978) have indicated the robustness of violations to this assumption. In particular, quadratic discriminant scores based on multivariate normality are calculated for each pixel in the sample:

$$d_i^Q(\mathbf{x}) = -.5 \ln\{\det S_i\} - .5(\mathbf{x} - \bar{\mathbf{x}}_i)^T S_i^{-1} (\mathbf{x} - \bar{\mathbf{x}}_i) + \ln p_i$$

where i = 1, 2, ..., g represents the individual clusters. In the formulation, p_i represents the prior probability that a pixel belongs to population i and S_i is the sample covariance matrix. So for each pixel, g discriminant scores are computed. A pixel then would be assigned to population k if

$$d_k^Q(\mathbf{x}) = \text{largest of } d_1^Q(\mathbf{x}), d_2^Q(\mathbf{x}), \ldots, d_g^Q(\mathbf{x}).$$

The classification is normally performed with equal prior probabilities as well as with distinct priors. There are several ways in which to derive the values for unequal probabilities. The most common procedure is to assume that the ground data is completely "true" and then to compute the number of pixels corresponding to each ground cover; a weight reflecting the resulting proportions is subsequently assigned to each land cover category. Since each land cover category may consist of several clusters, this weight is further proportioned to reflect the percent of pixels that are in each cluster within a category. This assignment of proportions excludes boundary pixels as well as those from fields which are considered to have questionable ground data.

Next, a regression relationship is developed between the reported segment data and the corresponding classified pixels. The annual area frame survey yields a direct expansion estimate for crop acreage which is based on the survey ground data alone while the regression estimator utilizes that data as well as the satellite data. In the regression scheme, the ground data is treated as the dependent variable with the satellite data treated as the independent variable. The end result of this approach is a regression estimate which has a lower variance than an estimate based solely on the area frame data. Typically, a classifier is evaluated by examining its confusion matrix. However, if a classifier is to be used to estimate crop acreage, it should be judged instead on how well it does just that (Gleason et al., 1977). This suggests, that in order to compare two classification results, an examination of their correlations with the ground data can be done. In this study, there were eight correlation coefficients to look at for each crop. Initially, there were two results for each satellite, one for cotton and another for rice. Then there was a division based on the number of segments used (23 or 28), and finally, a division based on whether or not prior probabilities were used.

Results

The overlay procedure for the TM data yielded good results. Initially, there were 1,980 blocks used in this step. Of those, 1,758 were used in the initial estimates of the mapping functions (i.e., 42 blocks were eliminated due to poor correlations). After the iterative process, there were 1,415 points used to produce the final functions. The association between SPOT scenes was somewhat less (see Table 1).

Table 1: Results from Overlaying Primary and Secondary SPOT Scenes

Primary Scene Identification	Initial Number Of Blocks	Points Used In Initial Function	Points Used In Final Function
596-280	1892	1820	918
594-280	1806	1709	1161
596-281	1600	1559	967
594-279	1980	1822	1215

The minimum number of points considered necessary for producing a sufficient mapping function typically ranges from 800 to 1,200 depending upon their spread across the scene. The deviations in the initial number of blocks used in the overlay procedure for the SPOT were due to the fact that these scenes vary in size. In some instances, there were discrepancies between the physical area covered by the SPOT data tapes and their corresponding photographic products. This caused some problems in establishing the first approximations for the mapping functions.

Once the overlays were completed, each pixel effectively had assigned to it satellite readings from both the primary and secondary scene. At the succeeding step, outliers were "clipped" from each crop's file using principal components. This resulted in about 2 percent of the pixels being deleted from the TM data set with only about 1 percent dropped from the SPOT data set.

A supervised clustering of the pixels was then performed. In all cases, the minimum number of acceptable clusters was set at one. Additionally, the percent convergence was to be at least 98.5 with separability set at 0.75. Iterations were performed until these criteria were met. The only input which was varied was the number of initial clusters to consider. For SPOT this was determined by dividing the number of pixels pertaining to a particular crop by 200; this essentially meant, that on the average, the minimum amount of acreage that would be assigned to a cluster was about 20 acres. A similar approach was taken for TM with the divisor being 100. A maximum of 100 initial clusters was arbitrarily set. When twenty three segments were used for the ground data, there were 12,821 acres (369 separate fields) of land used in the classification process; this included 1,665 acres (37 fields) of cotton and 1,688 acres (39 fields) of rice. With twenty eight segments, there were 15,470 acres included (429 fields) with 1,708 acres (38 fields) of cotton and 2,052 acres (45 fields) of rice. Excluded from the clustering were all boundary pixels as well as those "clipped" so the acreage actually used was somewhat less than these indicated totals. Table 2 shows the results for TM data with Table 3 showing those for SPOT. No merging or dropping of categories was done based on the review of cluster separability across crops.

Table 2: Clustering Results for TM Data

For 23 Segments:

Crop	Number of Categories	Total Pixels Clustered
Cotton	1	7,195
Idle Crop	1	7,519
Sorghum	1	820
Woods	1	7,033
Farmstead	1	74
Perm. Pasture	1	1,185
Waste	4	3,043
Grass	1	33
Water	2	451
Corn	1	155
Fallow	3	470
Rice	1	7,165
Soybeans	3	17,949
Winter Wheat	1	106

For 28 Segments:

Crop	Number of Categories	Total Pixels Clustered
Cotton	1	7,290
Idle Crop	1	9,466
Sorghum	1	1,238
Woods	2	9,150
Farmstead	1	77
Perm. Pasture	1	1,934
Waste	3	3,122
Grass	1	33
Water	2	451
Corn	1	155
Fallow	3	470
Rice	1	8,790
Soybeans	1	21,050
Winter Wheat	2	845
Hay	1	541

Table 3: Clustering Results for SPOT Data

For 23 Segments:

Crop	Number of Categories	Total Pixels Clustered
Cotton	1	15,583
Idle Crop	5	16,618
Sorghum	5	1,825
Woods	1	15,628
Farmstead	1	185
Perm. Pasture	2	2,573
Waste	6	6,505
Grass	1	93
Water	3	981
Corn	1	357
Fallow	4	1,030
Rice	1	15,342
Soybeans	3	38,931
Winter Wheat	1	248

For 28 Segments:

Crop	Number of Categories	Total Pixels Clustered
Cotton	1	15,787
Idle Crop	4	20,953
Sorghum	5	2,687
Woods	4	20,120
Farmstead	1	195
Perm. Pasture	4	4,172
Waste	6	6,669
Grass	1	93
Water	3	981
Corn	1	357
Fallow	4	1,030
Rice	1	18,821
Soybeans	3	45,524
Winter Wheat	6	1,801
Hay	2	1,163

Using the mean vectors and covariance matrices which resulted from the clustering, a classification of all the sampled pixels was performed. The number of acres reported on the ground survey for each segment was then regressed on the number of pixels from the classification. As pointed out earlier, the ground data came from a stratified area frame survey. This stratification was maintained in the formulation of the regression equations. Initially, there were three strata included in the sample area. Unfortunately, the sample was such that two of the strata had to be dropped since they contained at most only three segments each and, therefore, would not have provided reliable information. An explanation of the regression estimator used for assessing crop acreage as well as one for the area frame estimator is given in Appendix A.

An examination of the residuals that resulted from the calculated equations was performed in an effort to detect any outliers. Normally, this is viewed as an edit tool which allows the analyst to determine if there are any segments in which the classified acres and reported acres are in disagreement in a disproportion amount. Segments causing major discrepancies are examined for possibly deletion. Caution is needed so as not to delete points that are not a result of faulty data. An analysis of the TM data revealed no problems. However, with the SPOT data, there were several segments which were viewed as problematic due to the fact that the classifier performed so poorly. In the end, one member was dropped from the SPOT data set containing twenty three segments and two from the set of twenty eight segments. Regressions were recalculated accordingly. Both sets were left intact for the TM data. As indicated previously, the correlation coefficient is the basis for determining which data set actually makes the best classifier. This means that, even if the number of sampled pixels classified correctly is rather low, the data can still produce a good classifier if a reliable relationship can be developed between the satellite data and the ground data. The summary in Table 4 shows the percent classified correctly by crop for each data set as well as the commission error (i.e., the number of pixels incorrectly classified to a crop as a percent of the total pixels classified to that crop).

Table 4: Classification Results for Cotton and Rice

			Cotton		Rice	
	Number of Segments	Prior Probabilities?	Percent Correct	Commission Error	Percent Correct	Commission Error
SPOT	22	YES	76 %	23 %	62 %	37 %
	22	NO	64 %	21 %	38 %	19 %
	26	YES	76 %	23 %	72 %	39 %
	26	NO	65 %	21 %	58 %	25 %
TM	23	YES	84 %	14 %	80 %	22 %
	23	NO	82 %	13 %	78 %	21 %
	28	YES	87 %	25 %	83 %	22 %
	28	NO	87 %	28 %	82 %	23 %

There was a possibility of assigning a pixel to one of fourteen categories for the smaller data set with there being fifteen categories for the larger. Naturally, as the number of possible placements for a pixel increases, the chance of it being misplaced in a random classification increases. With the number of categories used in this study, the probability of randomly classifying a single pixel correctly is 6 to 7 percent; therefore, everything above that was attributed to the effectiveness of the classifier.

Correlation coefficients were calculated for the SPOT data with and without any segments deleted for both the large data set and the smaller. Table 5 and Table 6 summarize the findings by crop for all the data sets considered.

Table 5: Correlation Coefficients for Cotton

	Number of Segments	Prior Probabilities?	Correlation
SPOT	18	YES	.957
	18	NO	.948
	22	YES	.962
	22	NO	.963
	17	YES	.956
	17	NO	.947
	20	YES	.961
	20	NO	.962
TM	18	YES	.993
	18	NO	.990
	22	YES	.976
	22	NO	.967

Table 6: Correlation Coefficients for Rice

	Number of Segments	Prior Probabilities?	Correlation
SPOT	18	YES	.826
	18	NO	.476
	22	YES	.850
	22	NO	.617
	17	YES	.931
	17	NO	.649
	20	YES	.860
	20	NO	.914
TM	18	YES	.963
	18	NO	.963
	22	YES	.963
	22	NO	.962

For rice, the findings for the four TM regressions were all similar. In contrast, with the SPOT data, correlations ranged from .476 to .931. Additionally, the correlations derived from using prior probabilities during classification tended to be higher except in the case of the SPOT data set that consisted of 20 segments. The correlations for all the cotton regressions exceeded .94 with those for the TM data trending higher.

Correlations across sensors were compared in order to assess whether or not actual differences existed for like data sets. These comparisons were made by first applying Fisher's Z transformation to the correlations so as to have normally distributed variables and then calculating the probabilities that the resulting values represented the same population (Fisher, 1967; Shavelson, 1988; Snedecor and Cochran, 1967):

$$Z = .5 [\ln (1 + r) - \ln (1 - r)]$$

where r is the correlation being transformed. The variance of Z is given by 1/(n-3). The three assumptions needed for this approach were 1) normality of the x and y values used in the regression, 2) sufficient sample size, and 3) independence of observations. Based on test procedures outlined in Johnson and Wichern (1988), there was no reason to reject the assumption of normality for the x's and y's; additionally, independence is readily apparent with the two measuring instruments being unrelated in any fashion. The only questionable area was sample size where there is disagreement among various statisticians as to what is adequate. Fisher's work indicated that the Z transformations yielded distributions that were approximately normal even for samples as small as 10. In contrast, Shavelson advocates sample sizes of 20. Snedecor and Cochran suggest that the Z transformation is distributed almost normally independent of sample size.

If crop acreages were to be estimated based on the SPOT data, the regression equations derived from the reduced data set would be used; that is, a small reduction in the correlations for cotton would be accepted in order to obtain some improvement in the correlations for rice. For this reason, only the correlations from the edited SPOT data were used in the analysis.

Basically, a normalized value $z = (Z_{r_1} - Z_{r_2}) / s_{r_1 - r_2}$ was computed for each pairing where $s_{r_1 - r_2}$ is the standard error of the difference between the correlations and is given by

$$s_{r_1 - r_2} = [1/(n_1 - 3) + 1/(n_2 - 3)]^{.5}$$

with n_1 and n_2 representing the sample sizes. The probabilities that the correlations for the SPOT data were larger than those for the TM data were then computed using a table of normal values. No hypothesis were formed; if such tests were done, the familywise error rate for conducting multiple z-tests would have to be considered. Findings are shown in Table 7.

Table 7: Probabilities of SPOT Correlations Being Greater Than TM Correlations

Segments (SPOT/TM)	Priors?	Probabilities for Cotton	Probabilities for Rice
17/18*	YES	.006	.195
17/18	NO	.012	.001
20/22**	YES	.231	.019
20/22	NO	.414	.104

* Data set representing overlap between the TM scene and the three SPOT scenes with one segment deleted

** Data set representing overlap between the TM scene and the four SPOT scenes with two segments deleted

Overall, it seems evident that one could conclude that the classification of the multitemporal TM data yielded correlations which were of a greater magnitude than those found using SPOT data.

Relative efficiencies (RE) were calculated on the edited data sets as a final measure of the effectiveness of the SPOT and TM regression estimates:

$$RE = Var\ (\hat{Y}_{DE})\ /\ Var\ (\hat{Y}_R)$$

where $\hat{Y}_{DE}$ is the direct expansion estimate and $\hat{Y}_R$ is the regression estimate. The findings are in Table 8.

Table 8: Relative Efficiencies (RE) for TM and Spot Regression Estimates

		SPOT		TM	
Segments (SPOT/TM)	Priors?	RE for for Cotton	RE for for Rice	RE for for Cotton	RE for for Rice
17/18*	YES	10.2	6.6	70.1	12.3
17/18	NO	8.4	1.5	47.6	12.3
20/22**	YES	11.6	3.4	18.8	12.3
20/22	NO	11.9	5.4	14.2	12.0

* Data set representing overlap between the TM scene and the three SPOT scenes with one segment deleted

** Data set representing overlap between the TM scene and the four SPOT scenes with two segments deleted

The RE's of the TM regression estimates were all greater than those for SPOT. The only estimate deemed to be less than cost effective, however, was the one for rice based on the smaller SPOT data set with no prior probabilities assigned during classification (Allen and Hanuschak, 1988).

Discussion

The results obtained were for a single sample of segments drawn from a six county area of eastern Arkansas. The parcels were randomly selected from a stratified area frame and could be considered to be representative of the area. The sample size itself was somewhat limited due to the cloud coverage that was experienced during the desired time frame. The questions that arise are 1) would SPOT have outperformed TM with a larger sample?, 2) what effects did the variation in dates across secondary scenes of SPOT have on the classifier built from the four scene data set?, and 3) what effects did the variation between scene dates across satellites have? The last of these would be the most difficult to address since there is no control of the passover dates for the satellites; additionally, if by chance the dates did correspond, the possibility of cloud coverage might still prevent the use of coinciding dates. As for the first two questions, the addition of segments even from a different date seemed to enhance somewhat the ability of SPOT to estimate cotton with correlations showing slight increases. Similarly for rice, there was an improvement in correlations in all but one case, that being the edited data set with prior probabilities assigned. The increases in correlations ranged from .02 to .26 with the lone decrease being .07. From this one might conclude that additional segments may help in developing higher correlations for the SPOT classifier. On the other hand, if NASS had an application program that was operational, in all likelihood only a sample similar in size to the one used in this study would be available; given those circumstances, one would be inclined to use the TM data. Additional segments, even with the dates varying, also had a positive influence on percent correct estimates in all cases.

A consideration other than estimator performance would be the cost of the data itself as well as the processing of it. Only the block correlations were performed on a time charge basis; the expenses associated with this study were about 25 percent higher for SPOT than for TM. Note that this excludes costs incurred due to "bad runs" relating to the fact that SPOT data tapes and photographic products did not correspond exactly. In an operational program, the added processing cost would be even greater with a minimum of nine SPOT scenes needed to cover a single TM scene. In the study, eight data tapes and eight photographic products were purchased for SPOT and two of each for TM. The costs were $13,500 for SPOT, significantly higher than the $7,200 for TM. With the assumption that nine SPOT scenes are needed to fill a single TM scene, the data costs in an operational program would be four times higher for SPOT.

With all things considered, this study leads to the conclusion that TM data would probably be more suitable for estimating cotton and rice in an operational program where a multitemporal approach is used. The correlations based on TM were at a higher level at a lower cost. This determination, however, is based on a single study in a given area of Arkansas. Under any circumstance, SPOT costs would be higher. However, a greater reliance could be placed in correlational differences that were found if an additional study were to be done using different data sets in a different area of Arkansas or even possibly in the rice area of Mississippi.

Appendix A

An explanation of the regression and area frame direct expansion estimators for a given crop is given below:

Area Frame Direct Expansion:

For a given state, let h = 1, 2, ..., L denote the land use strata. Within each stratum, the total land area contains N_h area frame units from which n_h units (segments) are selected. Using only the area frame data collected during the survey, the direct expansion estimator for the total acreage of a particular crop in any given state can be expressed as follows:

$$\hat{Y} = \sum_{h=1}^{L} N_h \bar{y}_h$$

where $\bar{y}_h = \sum_{j=1}^{n_h} y_{hj} / n_h$ and y_{hj} is the reported acreage of the specified crop in segment j in stratum h.

The corresponding variance estimate is given by

$$V(\hat{Y}) = \sum_{h=1}^{L} \frac{N_h^2}{n_h (n_h - 1)} \frac{N_h - n_h}{N_h} \sum_{j=1}^{n_h} (y_{hj} - \bar{y}_h)^2$$

Regression Estimation:

$$\hat{Y}_R = \sum_{h=1}^{L} N_h \cdot \bar{y}_h \text{ (reg)}$$

where $\bar{y}_{h(reg)} = \bar{y}_h + \hat{b}_h (\bar{X}_h - \bar{x}_h)$ and $\hat{b}_h$ is the estimated regression coefficient for land use stratum h based on regressing ground reported acres for a particular crop on classified pixels in the n_h sampled segments. Here $\bar{X}_h$ is the average number of pixels classified to the specified crop per frame unit; that is, all frame units are included in the calculation and $\bar{X}_h = \sum_{i=1}^{N_h} X_{hi} / N_h$ where X_{hi} is the number of pixels in the i^{th} area frame unit of stratum h.

Similarly, $\bar{x}_h$ is the average number of pixels classified to the crop in each of the sampled segments in stratum h; that is, only the sampled frame units are included and

$\bar{x}_h = \sum_{j=1}^{n_h} = x_{hj} / n_h$ where x_{hj} is the number of pixels in the j^{th} sample unit of stratum h.

The corresponding variance estimate is given by

$$\text{Var}\,(\hat{Y})_R = \sum_{h=1}^{L} \frac{N_h^2}{n_h} \frac{N_h - n_h}{N_h} \frac{(1 - \hat{R}^2_h)}{n_h - 2} \sum_{j=1}^{n_h} (y_{hj} - \bar{y})^2_h \bullet (1 + \frac{1}{n_h - 3})$$

where $\hat{R}^2_h$ is the coefficient of determination between the reported acreage for the specified crop and the corresponding pixels classified to the crop (Cochran, 1942). Note that the variance of the regression estimator approaches zero as $\hat{R}^2_h$ approaches unity for fixed n_h. In other words, as the correlation increases between the ground data and the classified Landsat data, the variance in the regression estimator decreases.

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