COMPARISON OF SENSORS FOR CORN AND SOYBEAN PLANTED AREA ESTIMATION

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Michael E. Bellow
National Agricultural Statistics Service
U.S. Department of Agriculture
South Building, Room 4168
Washington, D.C. 20250-2000
U.S.A.

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ABSTRACT

The results of a study comparing the effectiveness of Landsat Thematic Mapper (TM) data and French SPOT Multispectral data for estimation of corn and soybean planted area in a region of Iowa are reported. Ground truth data from USDA's 1988 June Enumerative Survey were used in the estimation process and to :heck results. The survey data covered a sample of 30 land segments. TM and SPOT scenes of the region, imaged during late luly of 1988, were obtained. All bands for each sensor were ıtilized. The ground truth and satellite data were processed hrough USDA's PEDITOR software system. Each pixel in each atellite scene was classified to a specific ground cover based on reviously computed cover signatures. Since the true cover for ach pixel was known from the ground truth data, classification ccuracy could be determined. Statistical criteria used to evaluate ensor performance included percentage of pixels correctly lassified, commission error, and regression determination coeffiient. For both crops of interest, the TM data produced more ccurate area estimates than the SPOT data.

:eywords: Landsat TM, SPOT, classification, regression, clustering

1. INTRODUCTION

his paper reports the results of a study comparing the ffectiveness of two satellite sensors for estimating corn and ybean planted area in a region of Iowa. The sensors are the andsat Thematic Mapper (TM) and the French SPOT lultispectral Scanner. The National Agricultural Statistics ervice (NASS) used the Landsat Multispectral Scanner (MSS) r the Agency's operational crop area estimation program during e 1980-1987 time period. This sensor will not be available in e future, and the choice of a replacement is between TM and OT. NASS is currently evaluating the two candidate systems ith respect to estimation accuracy and cost efficiency.

the NASS operational remote sensing program, MSS data was ocessed and combined with ground truth data from the area rtion of the NASS June Agricultural Survey (JAS), an annual mple survey, to produce crop area estimates. The NASS DITOR software system performed all of the data process- g. A regression estimator was used to relate JAS reported acres a given crop to the classified number of pixels for that crop, d to generate the Landsat area estimates. In comparing the rformance of different sensors, the statistical efficiency of the gression estimator has been the key criterion. This is in contrast other remote sensing studies, where percent correct ssification and commission errors are often used. The gression estimator requires consistency of classification in ler to produce good results; i.e. across all ground sample areas, proportion of pixels from any ground cover classified to the p of interest should remain fairly constant.

The Landsat TM sensor features seven spectral bands, while the SPOT sensor has three. SPOT has a spatial resolution of 20 meters compared with 30 meters for TM, so the area of a SPOT pixel is less than half that of a TM pixel. By comparison, the Landsat MSS sensor has four spectral bands and a spatial resolution of 60 meters. The superior ground resolution of SPOT means that it may be the most useful of the three sensors for land use mapping. However, because TM provides the most spectral information, it may prove to be the best sensor for crop related studies, especially those involving crop condition assessments. In fact, a previous NASS study found that TM was more efficient than SPOT for estimation of hard red winter wheat acreage in Kansas [1]. The extension of that research to other crops is necessary in order for NASS to make the proper choice between the two sensors.

2. RESEARCH AREA

The research site was a nine county region in western Iowa, where corn and soybeans are the predominant crops. Ground truth data from the 1988 June Agricultural Survey were used both in the estimation process and to check results. The survey data covered a statistical sample of 30 land segments, each approximately one square mile. TM and SPOT scenes of the region, imaged during late July of 1988, were obtained. All available spectral bands for each sensor were utilized.

The counties in western Iowa comprising the study area were Ida, Sac, Calhoun, Crawford, Carroll, Greene, Shelby, Audubon, and Guthrie. The sampling frame in use for Iowa in 1988 divided all land area in the state into two strata. One stratum was labelled "cities and towns" and included all area within the legal limits of cities and towns. This stratum was subdivided into agri-urban and residential/business categories. The other stratum, labelled "open country", included all other area in the state and was further substratified by geographic areas. Of the 30 segments available for the study, 28 came from the "open country" stratum and the other two from the agri-urban substratum of "cities and towns". Some prominent covers in the region other than the crops of interest were pasture, oats, and alfalfa.

The region was covered by one TM scene with an overpass date of July 25, 1988, and four SPOT scenes, each with an overpass date of July 31, 1988. All scenes were relatively cloud free. It turned out that four segments were completely contained within the TM scene but not within any of the SPOT scenes, while two other segments were completely contained within one of the SPOT scenes but not within the TM scene. These six segments, which included one from the agri-urban category, were dropped from the study. The remaining agri-urban segment contained no corn area and very little soybean area, as indicated by the ground truth data. This segment was included in the training process (supervised clustering) but excluded from classification and statistical analysis. The removal of these segments enabled the exact same ground area to be used for both TM and SPOT, so that a valid comparison between the two sensors could be made.

3. PROCESSING

All data processing associated with remote sensing crop area estimation has been performed using PEDITOR, a special purpose software system developed at NASS [2]. PEDITOR is written mainly in PASCAL, and is maintained on a MicroVax 3500 computer at NASS. It is also maintained to run on IBM compatible personal computers. Satellite scenes are stored on tapes at the CRAY X-MP supercomputer facility operated by Boeing Corporation in Seattle, Washington. Portions of these scenes can be retrieved and transferred to the MicroVax in the form of a multiwindow file. The CRAY supercomputer is also used for large scale classification, estimation, and aggregation, although those tasks were not required for this study.

During the JAS, all field boundaries within segments are drawn off on aerial photographs, which are later transferred to digital form. Questionnaire data from the survey are key-entered in preparation for subsequent ground truth editing. The JAS photographs and satellite scenes are registered to a map base in latitude/longitude coordinates. This allows pixels corresponding in location to the JAS fields to be identified and manipulated. A PC based segment shifting program enables fine tuning of the registration. Using another program, the analyst can select pixels to be used for training and create a packed file containing only those pixels. Boundary pixels are those that "touch" the segment border or the within segment border between two fields. Since reflectance values of boundary pixels are assumed to represent a mixture of covers on either side of the boundary, these pixels are generally excluded from the packed file. A clipping algorithm based on principal components can be used to remove outlier pixels, i.e. those whose multidimensional reflectance vectors are too isolated from the others.

The next step is the training process, which applies supervised clustering to the satellite data. Pixels in the packed file belonging to 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 model reflectance patterns. The collection of these statistics for all covers in a TM or SPOT scene constitutes the scene classifier. The clustering program used in this study implements a modified version of the Isodata algorithm of Ball and Hall [3]. It involves repeatedly assigning pixels to moving cluster centers based on the Euclidean distances between pixel reflectance vectors and the centers, with an option for periodically merging cluster pairs whose Swain-Fu distance is sufficiently small. Swain-Fu distance is a measure of intercluster separation that takes into account the covariance structure of the clusters [4]. The number of clusters in the final output of the program is generally not known prior to clustering, although the user can specify upper and lower limits.

Once the clustering has been performed for each cover, another PEDITOR program allows the analyst to combine all of the clusters into one large statistics file and edit that file. Clusters having too few pixels or excessively high variance can be deleted. If two or more clusters from separate covers are in too close proximity, some of them can be deleted in order to avoid ambiguity in the subsequent classification process. The resulting statistics file contains the defining information for all of the remaining categories (clusters), with each assigned a label and associated with one of the covers in the ground truth data. Prior probabilities can be assigned to the categories based on available information on relative acreage of the different covers in the region of interest. This information may come from a previous survey, the current ground truth data, or other sources. The prior probability for each cover is allocated proportionally among the categories associated with that cover. The use of priors is intended to improve the accuracy of the subsequent classification process.

With the creation of a final statistics file, classification can begin. For the current study, small scale classification was performed, i.e. only pixels within the JAS sample segments were classified. In large scale classification, all pixels within a TM or SPOT scene would be classified. A maximum likelihood classification rule is used [5]. Based on the discriminant functions created during clustering, each pixel in the data set is assigned to its closest spectral class with respect to Mahalanobis distance, a covariance based multivariate distance measure. The user can specify whether or not prior probabilities are to be used. If priors are used, then the classification probability associated with each category is changed in accordance with the prior probability of the cover for that category. Thus a cover having a higher prior probability than another cover is assigned a higher weight in the classification. For each segment, the pixel counts are summed over categories within covers to obtain the number of pixels classified to each cover. By summing these counts over segments, the overall number of pixels classified to each cover can be determined.

Regression methodology is used to relate classified pixel counts to the ground truth data. Counts of pixels within each segment classified to a specific crop are regressed against the crop acreage values from the JAS enumeration. A first order regression model is used:

$$Y_i = \beta_0 + \beta_1 X_i \ , \ i=1,\ldots,n$$

where:

n = number of segments
Y_i = reported acres of crop in segment i
X_i = number of pixels classified to crop in segment i
β_0, β_1 = regression coefficients

In NASS operational remote sensing, the 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. These satellite estimates are more efficient than the direct expansion estimates obtained solely from survey data. For the current study, full scene processing and aggregation were not necessary because measures of estimation accuracy could be obtained from processing at the sample level.

)ne such performance measure is the regression determination :oefficient:

$$R^2 = \frac{[\sum_{i=1}^{n} (Y_i - \bar{Y})(X_i - \bar{X})]^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2 \sum_{i=1}^{n} (X_i - \bar{X})^2}$$

vhere $\bar{X}$ and $\bar{Y}$ are the sample means of the X_i's and Y_i's, espectively. This statistic is the square of the correlation oefficient between the independent and dependent variables. It ıeasures the goodness of fit of the regression equation. Closely elated is relative efficiency (R.E.), a measure of the effec- iveness of satellite data in improving the JAS estimates. The elative efficiency is defined to be the ratio of the variance of the irect expansion (JAS) estimate to the variance of the regression satellite) estimate. Equivalently, it is the factor by which the AS sample size would have to be increased in order to produce a irect expansion estimate with the same precision as the satellite stimate. For the current study, since all segments used for lassification occupy the same stratum, the relative efficiency can e computed directly from the determination coefficient:

$$\text{R.E.} = (n-3) / (n-1)(1-R^2)$$

'wo other measures often used are percent correct and ommission error (C.E.). Percent correct is the percent of pixels :ported for a specific crop that are classified to that crop. 'ommission error is the percent of those pixels classified to a rop that actually belong to a different cover according to the round truth data. Percent correct measures a classifier's ability › identify correctly pixels belonging to a crop of interest, 'hile commission error measures its ability to avoid labelling to ıe crop of interest pixels belonging to other covers.

4. THE STUDY

he ground truth data for the study required both internal and dternal editing before being ready for subsequent processing. ıternal editing was used to detect and correct errors within the :ound truth data itself. External editing detected discrepancies :tween the ground truth data and registered satellite imagery quiring corrective action. Some fields were labelled as "bad elds" and removed from the training data set. Fields having too rge a discrepancy between field and planted size, field and ırvested size, or planted and harvested size were included in this ıtegory. Fields for which the reported (survey) acreage differed o greatly from the digitized (image) acreage were also labelled : bad.

ı selecting TM or SPOT pixels for training, all covers ɪntaining fewer than 5 percent of the total number of pixels ere combined into one category, labelled 'other'. This resulted a total of four covers for the subsequent classification process: ɪrn, soybeans, permanent pasture, and other. The covers lumped gether in the 'other' category were farmstead, alfalfa, oats, le crop, waste, woods, crop pasture, and water.

Small scale classification was done both with and without the use of prior probabilities for the four covers. The prior probability for each cover was defined to be the percentage of total pixels in the appropriate packed file (TM or SPOT) belonging to that cover. The packed files used to calculate the priors were the original versions that included the outlier pixels not used for training. The prior probabilities are shown in Table 1.

5. RESULTS

The results of the study are summarized in Tables 2 and 3. Table 2 gives for both corn and soybeans the values of the regression determination coefficent, relative efficiency, percent correct, and commission error for TM and SPOT over the 23 segments used in classification. The values obtained both with and without prior probabilities for the covers are shown. In addition, the number of pixels used for both training and classification are shown. Table 3 gives for both sensors the number of pixels from each cover classified to each cover.

Table 2 indicates that for both corn and soybeans, the TM data resulted in a higher R^2 value than the SPOT data. This was true whether or not priors were used. In addition, percent correct was higher for TM than for SPOT in every case, while commission error was lower. The TM value of R^2 was significantly higher when prior probabilities were used than when they were not, but the use of priors had little effect on the R^2 value for SPOT. The R^2 values obtained for soybeans were higher than the corresponding ones for corn. Corn had higher values of percent correct than did soybeans, but also tended to have higher commission errors.

A method for assessing whether one sensor produced a better regression fit than the other is provided by the F-test for equality of residual variances. This test was performed for the 'with priors' case for each crop. The hypotheses are as follows:

$$H_0: \sigma^2_{TM} = \sigma^2_{SPOT}$$

$$H_1: \sigma^2_{TM} < \sigma^2_{SPOT}$$

where σ^2_{TM} and σ^2_{SPOT} are the true variances of the residuals for TM and SPOT, respectively. The test statistic F* is the ratio of the regression mean square error of TM to that of SPOT. Since the number of observations is the same for each sensor, this is equivalent to the ratio between the sums of squared residuals:

$$F^* = \frac{\sum_{i=1}^{n} [\, Y_i - \hat{Y}_i \text{ (TM)} \,]^2}{\sum_{i=1}^{n} [\, Y_i - \hat{Y}_i \text{ (SPOT)} \,]^2}$$

where $\hat{Y}_i$ (TM) and $\hat{Y}_i$ (SPOT) (i=1,...,n) are the fitted values corresponding to the ground truth Y_i for TM and SPOT, respectively. Assuming that the data is normally distributed, the test statistic has an F distribution with n-2 degrees of freedom in oth the numerator and denominator under H_0.

he computed values of F* were .488 for corn and .445 for ›ybeans. By examining tabulated percentiles of the appropriate F istribution, it was found that the null hypothesis could be ;jected at the .06 level for corn and at the .05 level for ›ybeans. The lower residual variances associated with the TM ita are indicative of tighter regression fits than those obtained ›r SPOT.

6. CONCLUSIONS

he results of the analysis provide strong evidence that TM data preferable to SPOT data for estimating corn and soybean anted area. This is probably due in large part to the greater ›ectral information content of TM. It should be noted that the ›rformance measures covered approximately the same ground ea as did the training samples, so the results for both sensors ay reveal a slightly higher level of accuracy than would be ›tained in actual practice. The use of prior cover probabilities ›pears to improve classification efficiency.

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ıble 1. Training pixel counts and prior probabilities

	No. Training Pixels		Prior Probability	
›ver	TM	SPOT	TM	SPOT
›rn	21,296	46,243	.441	.431
›ybeans	15,498	34,016	.321	.317
rmanent Pasture	3,239	7,405	.067	.069
her	8,274	19,549	.171	.183

Table 2. TM and SPOT efficiency comparison

	TM		SPOT	
Description	Priors	No Priors	Priors	No Priors
Corn R^2	.878	.833	.750	.748
Soybeans R^2	.926	.890	.834	.826
Corn R.E.	7.45	5.44	3.64	3.61
Soybeans R.E.	12.29	8.26	5.48	5.22
Corn % Correct	86.65	87.96	85.09	78.65
Soybeans % Correct	83.46	78.08	72.94	73.20
Corn C.E.	22.77	28.23	31.44	29.58
Soybeans C.E.	21.91	25.62	25.28	29.90

Table 3. Complete TM and SPOT classifications

TM (priors) ----------Pixels Classified To:--------------------------------

From:	Corn	Soybeans	Permanent Pasture	Other	Total
Corn	25,441	1,761	541	1,618	29,361
Soybeans	1,813	18,386	446	1,385	22,030
Permanent Pasture	1,143	445	2,869	1,013	5,470
Other	4,543	2,952	2,664	7,362	17,521
Total	32,940	23,544	6,520	11,378	74,382

SPOT (priors) ----------------Pixels Classified To:-------------------------

From:	Corn	Soybeans	Permanent Pasture	Other	Total
Corn	50,504	3,673	1,176	3,998	59,351
Soybeans	8,953	32,475	824	2,268	44,520
Permanent Pasture	2,652	1,219	2,708	4,493	11,072
Other	11,555	6,098	3,353	14,182	35,188
Total	73,664	43,465	8,061	24,941	150,131

TM (no priors)----------------Pixels Classified To:-------------------------

From:	Corn	Soybeans	Permanent Pasture	Other	Total
Corn	25,827	1,843	955	736	29,361
Soybeans	3,474	17,201	681	674	22,030
Permanent Pasture	1,176	499	3,248	547	5,470
Other	5,511	3,582	3,627	4,801	17,521
Total	35,988	23,125	8,511	6,758	74,382

SPOT (no priors) --------------Pixels Classified To:------------------------

From:	Corn	Soybeans	Permanent Pasture	Other	Total
Corn	46,678	5,519	4,750	2,404	59,351
Soybeans	7,574	32,590	2,691	1,665	44,520
Permanent Pasture	1,970	1,375	6,150	1,577	11,072
Other	10,064	7,006	11,106	7,012	35,188
Total	66,286	46,490	24,697	12,658	150,131