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EVALUATION OF THE PROCEDURE 1A COMPONENT OF THE 1980 U.S./CANADA WHEAT AND BARLEY EXPLORATORY EXPERIMENT

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EVALUATION OF THE PROCEDURE 1A COMPONENT OF THE 1980 U.S./CANADA WHEAT AND BARLEY EXPLORATORY EXPERIMENT

Job Order 72-422

This report describes the 1980 Exploratory Experiments activities of the Foreign Commodity Production Forecasting project of the AgRISTARS program.

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For

Earth Resources Applications Division

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NATIONAL AERONAUTICS AND SPACE ADMINISTRATION
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PREFACE

The Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing is a multiyear program of research, development, evaluation, and application of aerospace remote sensing for agricultural resources, which began in fiscal year 1980. This program is a cooperative effort of the U.S. Department of Agriculture, the National Aeronautics and Space Administration, the National Oceanic and Atmospheric Administration (U.S. Department of Commerce), the Agency for International Development (U.S. Department of State), and the U.S. Department of the Interior.

The work which is the subject of this document was performed by the Earth Resources Applications Division, Space and Life Sciences Directorate, Lyndon B. Johnson Space Center, National Aeronautics and Space Administration and Lockheed Engineering and Management Services Company, Inc. The tasks performed by Lockheed Engineering and Management Services Company, Inc., were accomplished under Contract NAS 9-15800.

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FIGURES

1. BACKGROUND

The Foreign Commodity Production Forecasting project of the Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing (AgRISTARS) program was responsible for developing and testing procedures for using aerospace remote sensing technology to provide more objective, timely, and reliable crop production forecasts. One of the components of production estimation is segment area estimation. Since large-area acreage estimates for small grains depend upon segment-level proportion estimates, it is important that those proportion estimates be as accurate and precise as possible. Prior to the AgRISTARS program, several procedures were tested in an attempt to find an accurate and efficient method for estimating small-grain proportions. In the resultant method, Procedure 1 (P1), labels were used in the random selection of training pixels to start a clustering algorithm. Then, cluster statistics were used to produce a maximum likelihood classification of the scene into 2- or 3-class strata. Finally, stratified proportion estimates were made using a second random set of labeled dots. However, this classification component provided no better results than those which could have been produced through simple random sampling. Thus, clustering had not been an effective method.

Consequently, a new clustering algorithm was developed (refs. 1 and 2). Previously, clusters were used to define distributions in the data. The new algorithm used clusters to generate strata within which crop proportions could be estimated. One advantage of this algorithm was that, as an unsupervised routine, a first set of training dots was not needed (as in P1).

In addition, a proportion estimation technique (ref. 3) which used the clusters of this algorithm was developed. This technique involved Bayesian estimation of cluster-level proportions based on historical information concerning cluster purities. The cluster-level estimates were then weighted by their relative cluster sizes and aggregated to produce the segment-level estimate. Use of this technique was expected to provide better proportion estimates. The technique also implemented sequential sampling in an attempt to sample the segment clusters more effectively and further reduce the expected mean squared error (MSE) of the proportion estimation.

Characteristic of this new estimation technique, the Bayesian Sequential Allocation/Bayesian Estimator (BSA/BE), was the selection of dots, one at a time. The sampling technique was an attempt to minimize the MSE of the proportion estimate. Before each sampling of a dot, expected effects to MSE estimates were made for each cluster; and, on the basis of these estimates, a sample was taken from the cluster that was expected to most reduce the MSE. This manner of sampling provided an additional feature: the option of sampling with a fixed sample size or varying the sample size from segment to segment. Varying the sample size could be managed by halting the sampling when a predetermined threshold was obtained for the internal MSE estimate. Varying sample sizes in this manner was to provide uniform accuracy across segments by sampling more frequently from more "difficult" segments.

A 10-segment development test of the BSA/BE (ref. 4) showed that there was at least a 2-to-1 reduction in the MSE from that observed from P1, a reduction in proportion estimation error, and improved analyst labeling accuracy.

2. APPROACH

Flow diagrams of the BSA/BE technique and P1 are presented in figures 2-1 and 2-2, respectively. Table 2-1 shows the four steps involved in stratified areal estimation and a comparison of the BSA/BE to P1 at each level. The BSA/BE differs from P1 at three of the four steps; whereas P1 makes use of approximately proportional allocation of sample dots to Iterative Self-Organizing Clustering System (ISOCLS) clusters and a relative count estimator of cluster-level proportions, the BSA/BE technique makes use of sequential allocation of sample dots to CLASSY clusters and a Bayesian estimator of cluster-level proportions. By incorporating only step 1 of the BSA/BE into P1 (that is, by substituting CLASSY clustering for ISOCLS clustering) and proportionally allocating sample dots to clusters based on cluster sizes, a new estimation technique, the Proportional Allocation/Relative Count Estimator (PA/RCE) is defined. By additionally incorporating step 3 of the BSA/BE, the Proportional Allocation/Bayesian Estimator (PA/BE) technique is defined. Both of these techniques were included for testing in this experiment. A fourth technique, the Random Sampling/Relative Count Estimator (RS/RCE), was also included in the experiment. The RS/RCE, which randomly samples the entire scene without regard to clusters and employs a relative count estimator of segment-level proportions, was included since P1 had not proved to be significantly better than the RS/RCE. The PA/RCE was included to determine the effectiveness of CLASSY clustering. The PA/BE was included to determine the effect of the cluster-level Bayesian estimator with proportional allocation.

For each of these four techniques, the dot sets that were input had labels from one of three possible sources: the integrated labeling procedure (ref. 5), the reformatted labeling procedure (ref. 6), or ground-truth data. Combining the four techniques with the three sources of dot labels and the two sample size requirements (fixed or variable), 24 estimates were made for each segment. The effect of these three factors on the estimates was to be determined.

TABLE 2-1.- PROCEDURE 1 COMPARED TO THE BAYESIAN SEQUENTIAL ALLOCATION/BAYESIAN ESTIMATOR (BSA/BE) TECHNIQUE

Step	Procedure 1	Bayesian Sequential Allocation/ Bayesian Estimator	Proposed advantage
1. Stratification	ISOCLS Use Type 1 labeled dots to collapse clusters into two strata	CLASSY	No need to label dots to create a small number of strata for sampling; thus more efficient.
2. Allocation of dots to be labeled	Approximately proportional to size of strata (post-stratification)	Sequential to minimize mean squared error	Requires less dots for same accuracy by incorporation of 1. Prior information of the distribution of cluster purity. 2. Knowledge of previously labeled samples. More accurate labeling for selected dots.
3. Strata-level estimation	Relative count	Bayes	Reduction in mean squared error for equivalent number of dots by including prior information of distribution of cluster purity.
4. Segment-level estimation	Weighted average over strata	Weighted average over strata	None (same)

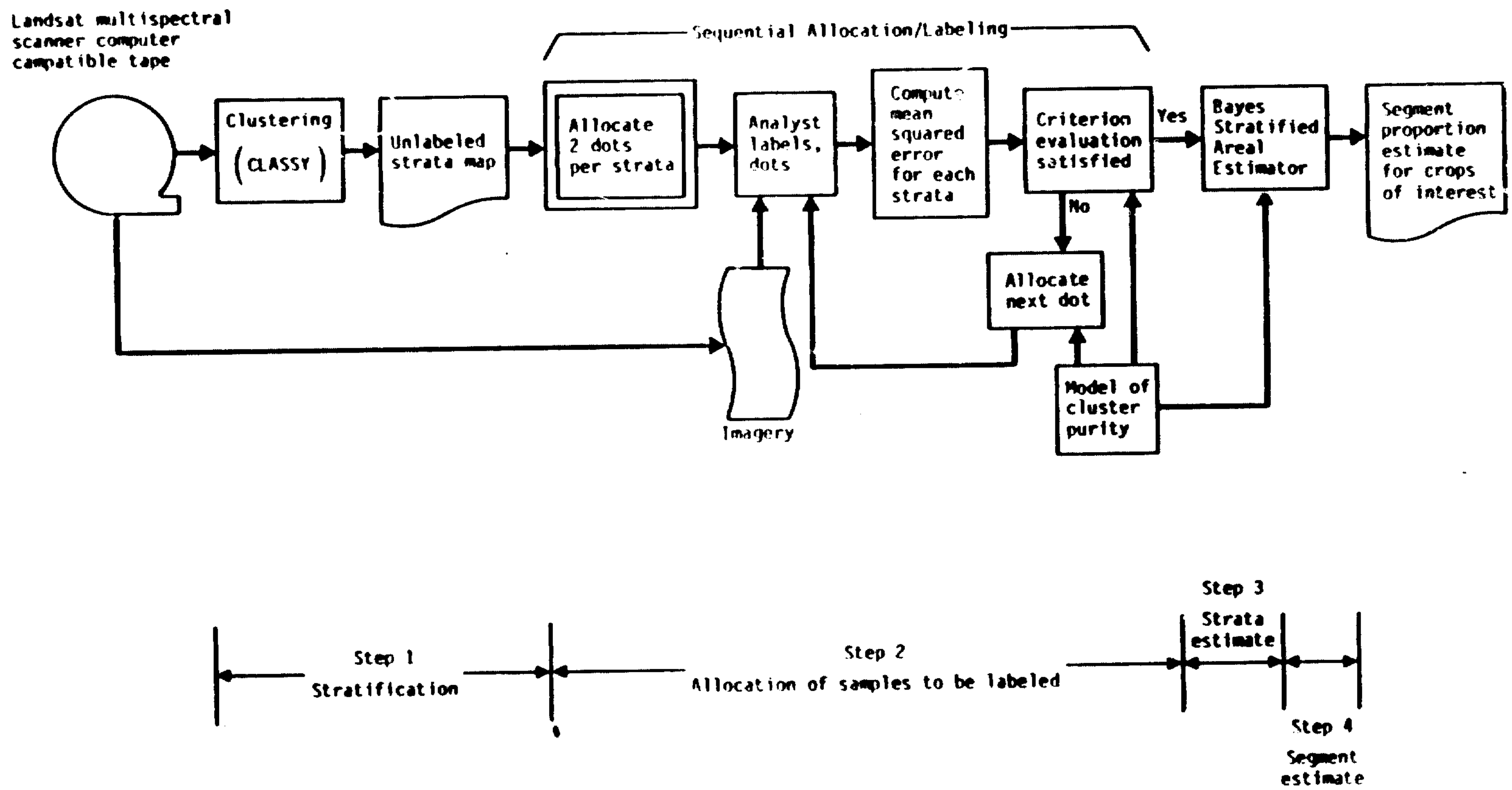

Figure 2-1.- Segment analysis using Bayes Sequential Allocation procedure.

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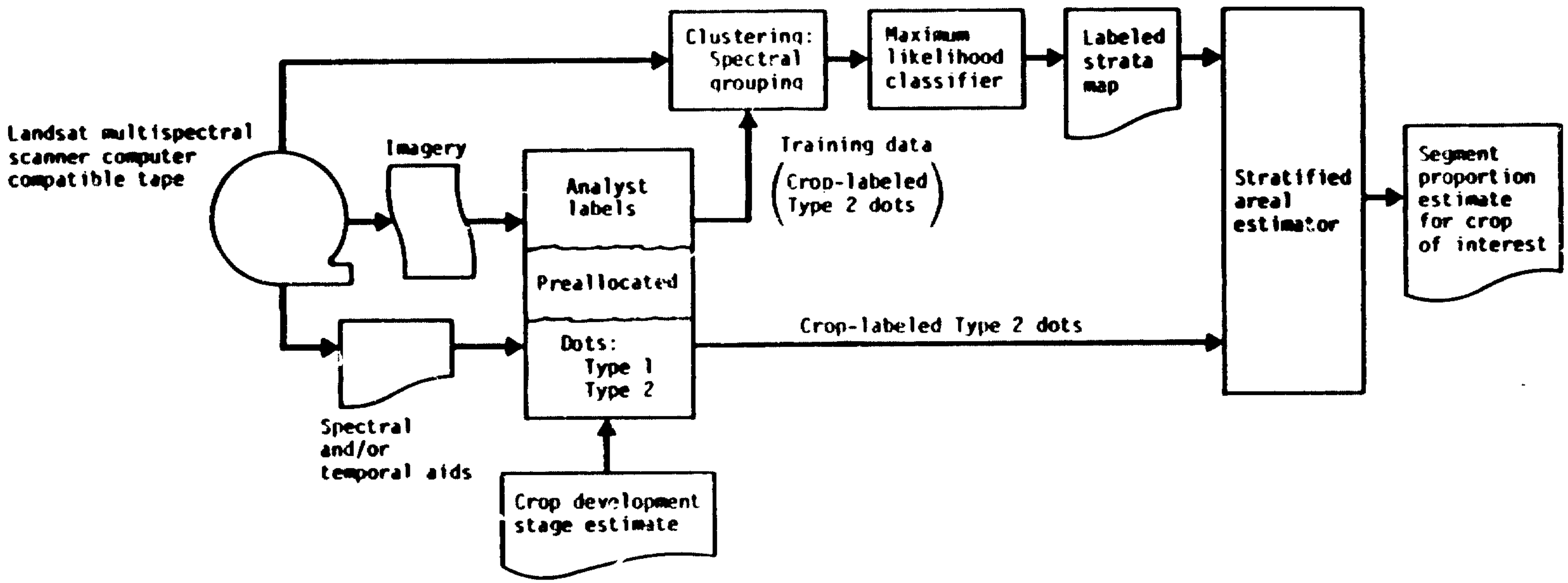

Figure 2-2.- Segment analysis, Procedure 1.

Examination of the effects of the different techniques will, in essence, measure (a) the effect of using stratified random sampling of CLASSY clusters, which are proportional to cluster size, in estimating spring small-grain proportions rather than randomly sampling the entire scene; (b) the effect of Bayesian procedures rather than relative frequency in estimating proportions at the cluster level proportions; and (c) the effect of Bayesian Sequential Allocation rather than proportional allocation in estimating spring small-grain proportions (ref. 7).

3. METHOD

The dot sets from which samples were taken contained dots on one of the four major grids or alternates for grid dots. Enough dots were labeled from each segment so that 75 dots were allocated proportionally to the clusters; this was usually the 209 dots from the first grid plus a few (1 to 10) from grid 2. This was to insure that each cluster would have enough dots for sequential allocations. If it was determined that a grid dot was a boundary dot, an alternate dot was substituted for labeling purposes since boundary dots present special labeling problems; pure dots have been found to have higher labeling accuracies than do boundary dots, but to ignore them by using only pure grid dots in proportion estimation could bias results (refs. 8 and 9). From these dot sets, sample dots were taken for proportion estimation.

Two separate estimation processings were made for 35 spring wheat segments: for one, a fixed sample size of 50 dots was used; and for the other, varying sampling sizes from segment to segment were allowed.

To permit variable sample sizes, two dots were automatically allocated to each cluster so that MSE estimates could be obtained. Then, a threshold was set on the internal segment MSE estimate ($MSE = E(\hat{p} - p)^2 < .0020$). When this threshold was reached, sampling was halted. To achieve comparable results using other techniques, this same sample size was applied to them to obtain proportion estimates. Thus, while the sample size could vary from segment to segment, it was constant among the techniques by which estimates were made for any particular segment.

4. RESULTS

Because there were insufficient data (only nine segments were processible using the reformatted procedure) on which to base an evaluation when the reformatted labeling procedure was used, the part of the evaluation which would include that procedure will not be considered. In appendix A, however, the results are presented for the four estimation techniques for which labels were obtained from the reformatted procedure. Only those results which were obtained when the integrated procedure labels or ground-truth labels were input were considered in the evaluation.

Although estimates were made with fixed and variable sample sizes, emphasis during the evaluation was placed on the fixed sample case. Results of the variable sample case were comparable to those of the fixed sample case; these results, which include biases, MSE's, and plots of proportion estimation errors, are presented in appendix B. Further discussion of the analysis and results will concern only the fixed sample case for input dot sets with labels from the integrated procedure or ground-truth data.

Tables 4-1 and 4-2 present biases of proportion estimates, standard deviations of estimate errors, and MSE's for all 35 segments when dot labels from the integrated procedure were input. The errors are shown in figure 4-1 (ground-truth proportions for these segments are presented in appendix C).

On the basis of analyst-interpreter (AI) labels, the PA/RCE technique provided a significantly less biased estimate and produced less variable errors than did random sampling. The fact that the errors were less variable showed that the clustering algorithm had been effective.

When ground-truth labels were input, the errors produced using the PA/RCE were less variable than those of random sampling (table 4-1 and figure 4-2); but, the disturbing result was the significant bias produced by random sampling. With ground-truth labels input, random sampling was expected to provide an unbiased estimate. Ground-truth labels were input to determine the effect of

TABLE 4-1.- ACCURACY AND PRECISION OF THE INTEGRATED PROCEDURE WITH AI LABELS AND GROUND-TRUTH LABELS

Technique	AI labels			Ground-truth labels		
	Bias	Standard deviation	MSE	Bias	Standard deviation	MSE
Random Sampling/ Relative Count Estimator	-5.7	7.7	90	-2.5	6.9	53
Proportional/ Relative Count Estimator	-4.0	6.2	53	0.0	4.0	16
Proportional Allocation/ Bayesian Estimator	-3.5	6.0	47	0.5	3.8	14
Bayesian Sequential Allocation/ Bayesian Estimator	-2.7	6.8	52	0.4	4.7	22

TABLE 4-2.- RELATIVE ACCURACY AND PRECISION OF THE INTEGRATED PROCEDURE WITH AT LABELS AND GROUND-TRUTH LABELS

Technique	AI labels			Ground-truth labels		
	$\bar{\hat{p}}$ (a)	Relative bias, % (b)	RV (c)	$\bar{\hat{p}}$ (a)	Relative bias, % (b)	RV (c)
Random Sampling/ Relative Count Estimator	23.4	-24.4	32.9	26.6	9.4	25.9
Proportional/ Relative Count Estimator	25.1	-15.9	24.7	29.1	0.0	13.7
Proportional Allocation/ Bayesian Estimator	25.6	-13.7	23.4	29.6	1.7	12.8
Bayesian Sequential Allocation/ Bayesian Estimator	26.4	-10.2	25.8	29.5	1.4	15.9

[a]Average proportion estimate = $\bar{\hat{p}}$

[b]Relative bias = $\dfrac{\bar{\hat{p}} - \bar{p}}{\bar{\hat{p}}} \times 100\%$

[c]RV = $100 \times \dfrac{\hat{\sigma}_e}{\bar{\hat{p}}}$ = relative variation

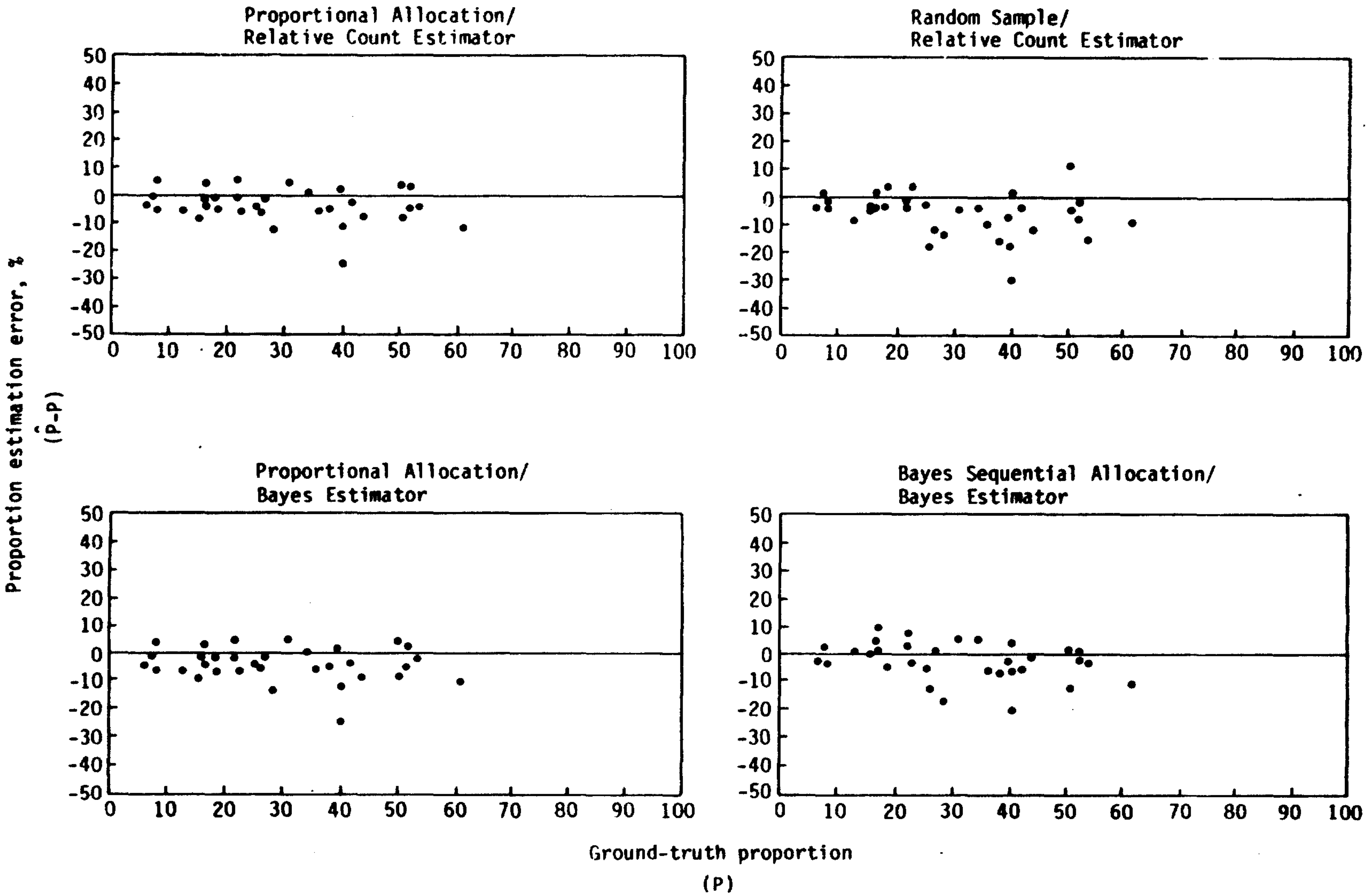

Figure 4-1.- Proportion estimation results with analyst labels.

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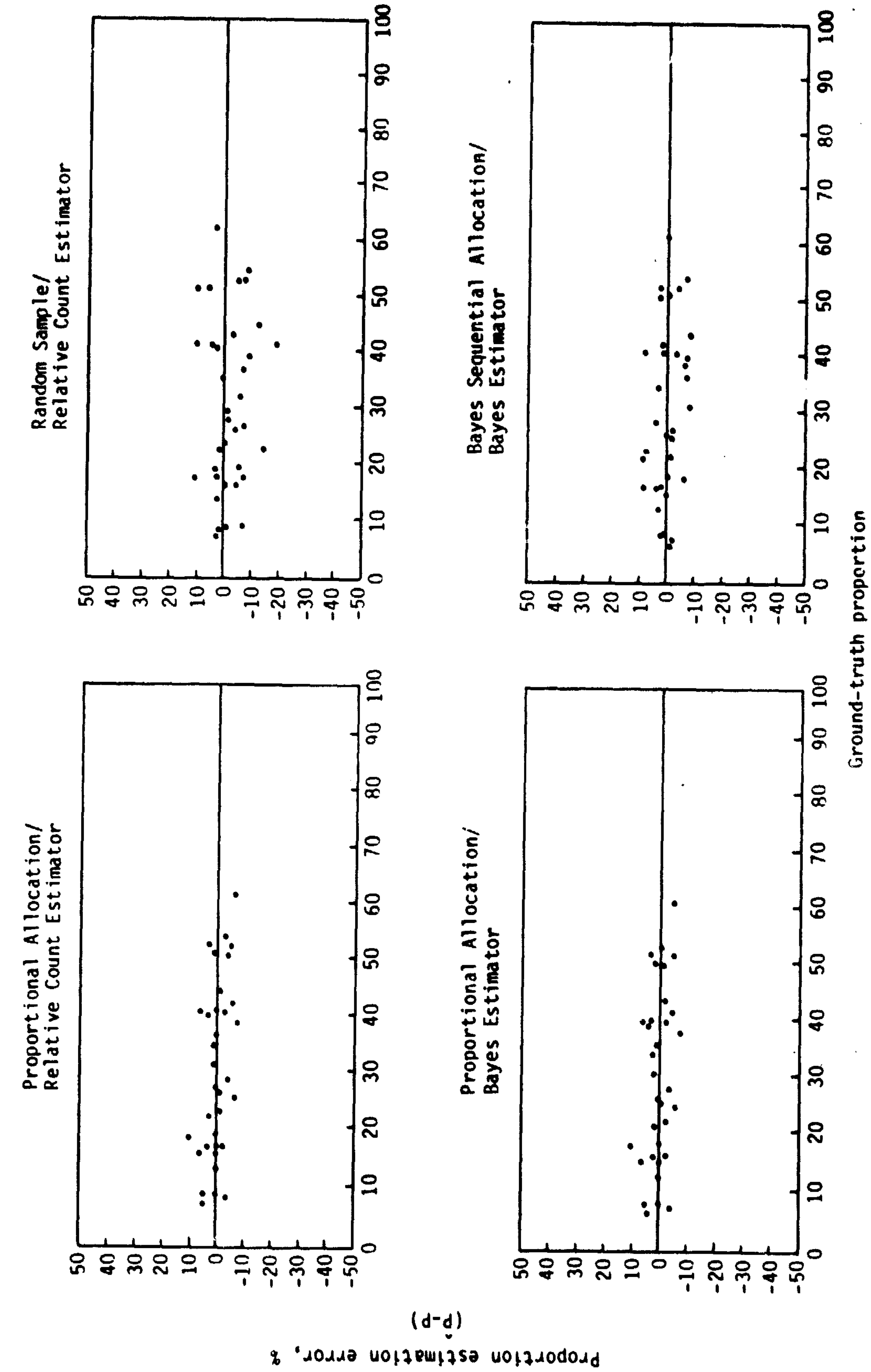

Figure 4-2.- Proportion estimation results with ground-truth labels.

techniques with unbiased estimators on the variability of errors and the effect of techniques with biased estimators on both the proportion estimates and the variability of errors. However, random sampling as an unbiased technique, produced a significant underestimate even when ground-truth labels were input. To determine the reason for this result, the biases of the 209-plus pixel input dot sets were examined since these were the sets from which the 50-dot samples were taken. The bias (over all 35 segments) was found to be -0.8 percent, and the estimate produced by random sampling was not really significantly biased with respect to this. This indicates that the use of the PA/RCE technique resulted in the overestimation of the 209-plus dot proportion estimates by 0.8 percent. While this was not a significant overestimate, it should be noted. The important result achieved was the reduction of error variability produced by the PA/RCE from random sampling when AI labels and ground-truth labels were input. This reduction was attributed to CLASSY clustering. Cluster purities are further discussed in appendix D.

Since clustering was effective, the next step was to determine the effect of a Bayesian estimator. For the PA/BE, the same dots that were used for the PA/RCE were again used. Thus, the only difference between the two techniques was the estimator employed; with the PA/BE, a cluster-level Bayesian estimator was used instead of a relative count estimator. It had been hypothesized that the PA/BE would provide improved proportion estimates over the PA/RCE because prior knowledge of cluster purities was being considered. Such results could be expected in the same way that the PA/RCE was expected to provide proportion estimates that were more accurate than those obtained through random sampling because of the use of clustering information. As hypothesized, there seemed to be improved precision; but, the difference was small (table 4-1). Figure 4-3 shows the difference between the PA/BE and the PA/RCE for all 35 segments. A positive difference indicates that the PA/BE produced the larger estimate. As the PA/RCE estimate increased, there was a tendency for a larger positive difference. Whether AI labels or ground-truth labels were input, the PA/BE produced a mean proportion estimate that was five-tenths of a percent larger than that of the PA/RCE. This was attributed to a tendency for positive biasing (with respect to the PA/RCE) by the Bayesian estimator (figure 4-3).

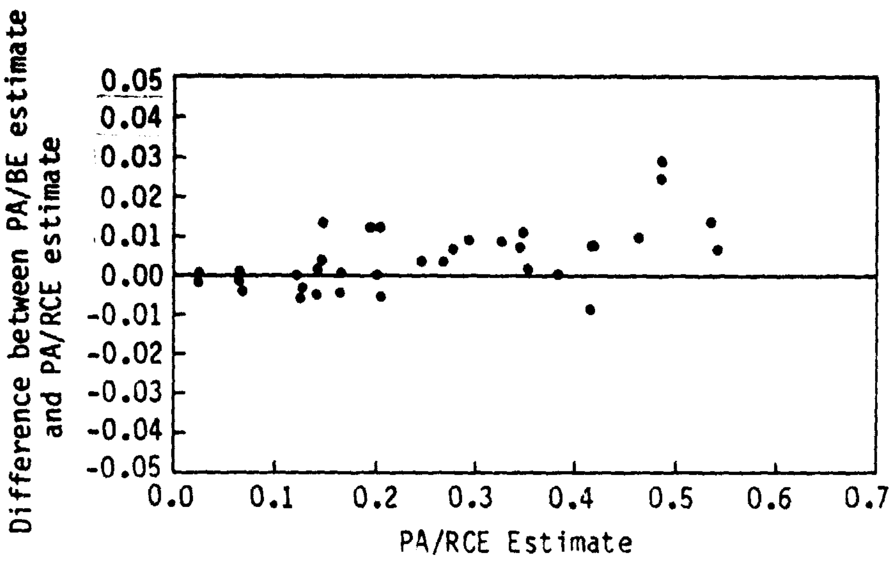

Figure 4-3.- Differences in estimates using proportional allocation with and without Bayesian estimation.

The net effect was a reduction of a negative bias when AI labels were input. With the positive biasing, however, the result was a slight reduction (0.2 percent) in error variability from that of the PA/RCE. This was the case when AI labels were input and also when ground-truth labels were input. In both cases, the MSE's of the PA/BE were slightly reduced from those of the PA/RCE. These results were encouraging because they supported the expectation that Bayesian estimation at the cluster level would provide greater precision (although producing slightly biased results) over maximum likelihood estimation.

The final technique was the BSA/BE, the results for which (as can be seen in table 4-1) showed it to be the least biased technique when AI labels were input. This had been hypothesized since the dots were allocated to clusters one at a time with the intention of minimizing the MSE. Although it produced the least biased results as hypothesized, the BSA/BE produced more variable results than did proportional allocation. This was a disturbing observation.

In an effort to further study these results, an attempt was made to separate the effects of Bayesian estimation and sequential allocation. In order to determine whether or not the results of the BSA/BE followed those of the PA/BE when compared to an unbiased estimation technique, estimates were made using the same sequentially allocated dots and cluster information with a relative count cluster-level (BSA/RCE) estimator rather than the Bayesian estimator. Using the Bayesian estimator in the proportion estimation process increased the estimates by approximately 2 percent. This was true whether input labels were from AI's or ground-truth data (table 4-3). As in proportional allocation, Bayesian estimation produced less variable results at the expense of biasing. However, with sequential allocation, this bias was not as slight as with proportional allocation. A graph comparing the two sequential estimates for each of the 35 segments is presented in figure 4-4. Notice that there was greater overestimation for segments with lesser amounts of small grain.

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TABLE 4-3.- ACCURACY AND PRECISION OF SEQUENTIAL ALLOCATION

Technique	AI labels			Ground-truth labels		
	Bias	Standard deviation	MSE	Bias	Standard deviation	MSE
Sequential allocation (relative count, cluster-level estimate)	-4.9	7.1	73	-1.7	5.3	30
Sequential allocation (Bayesian cluster-level estimate)	-2.7	6.8	52	+0.4	4.7	22

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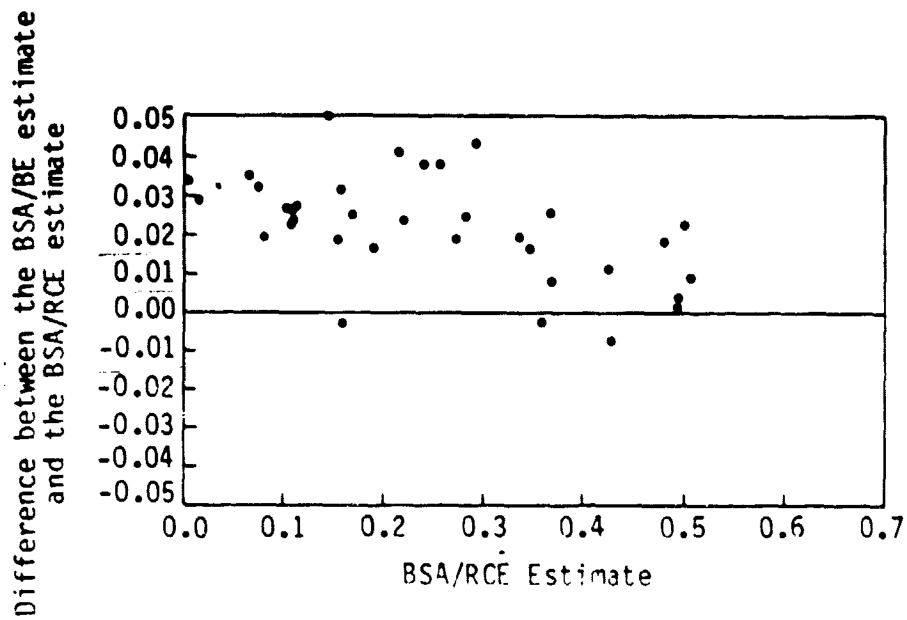

Figure 4-4.- Differences in proportion estimates using sequential allocation.

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The fact that the BSA/BE produced more variable results than did the PA/BE was due, in part, to a decreased overall labeling accuracy (table 4-4). In order to determine whether or not these differences were significant, the differences between labeling accuracies of the samples for each segment from those of all labeled dots for each segment were found. The means of these differences are shown in table 4-5. While there was a significant improvement of small-grain labeling accuracy, there was a simultaneous decrease in nonsmall-grain labeling accuracy. The result was a slight decline in total labeling accuracy.

These results indicate that, with a small sample of 50 dots, proportional allocation is the sampling method that produces the most precise and reliable estimates. A slight reduction in variability can be gained at the cost of slight biasing of results by using the Bayesian estimation technique.

Although CLASSY clustering was effective (that is, proportional allocation of dots to CLASSY clusters resulted in greater precision for a given sample size), the same precision could be obtained by random sampling without the need of clustering information if a large enough sample size were taken. If dot sets with AI labels were input with the present labeling accuracy, a random sample of 85 dots would be required to obtain the precision of 50 dots proportionally sampled from CLASSY clusters. If labeling was perfect, a random sample of 166 dots would be required to obtain the same precision of 50 dots proportionally allocated to CLASSY clusters.

Therefore, the biases of proportion estimates, standard deviations of errors, and MSE's of all available labeled dots from the 209 pixels were found when dot sets with AI labels were input and when dot sets with ground-truth labels were input. Table 4-6 presents the results obtained when those dots were treated as a random sample. It was expected that these dots would provide greater precision than a 50-dot proportional sampling of CLASSY clusters because of the larger sample size. Just as we expected, when using all available labeled dots, the RS/RCE showed less variable errors than the PA/RCE when it used only 50-dot samples allocated to CLASSY clusters. Notice in table 4-6 that the use of alternate dots did not introduce a bias; the mean error was very small when

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TABLE 4-4.- LABELING ACCURACY

Technique	Random sampling	Proportional allocation	Sequential allocation	All labeled dots
Small grains	72.06	73.30	75.10	72.56
Nonsmall grains	93.64	94.75	91.62	93.54
Total	88.09	88.62	86.40	87.54

TABLE 4-5.- MEAN DIFFERENCES OF SAMPLE LABELING
ACCURACY FROM OVERALL LABELING ACCURACY

Technique	Random sampling	Proportional allocation	Sequential allocation
Small grains	0.93	1.01	3.14*
Nonsmall grains	-0.07	1.21*	-2.01*
Total	0.45	0.98	-1.18

*Indicates a significant difference at the
10-percent level of significance.

TABLE 4-6.- ACCURACY AND PRECISION OF A RANDOM
SAMPLE OF AVAILABLE 209 DOTS

Dots	AI labels			Ground-truth labels		
	Bias	Standard deviation	MSE	Bias	Standard deviation	MSE
Random sample (all labeled dots)	-3.9	5.8	48	-0.8	2.9	9
Proportional sampling	-4.0	6.2	53	0.0	4.0	16

ground-truth labels were used. This was important since analysts substituted alternate dots for boundary dots in both the integrated and reformatted labeling procedures to provide better labeling targets to eliminate the special labeling problems that boundary dots present.

In order to determine the effect of clustering with larger samples, cluster-level proportion estimates were made with a relative count estimator on the basis of all labeled dots and weighted by their cluster sizes to produce segment-level estimates. These results are shown in table 4-7. As can be seen, clustering had little effect on the accuracy or precision of estimates when these larger samples were taken. These results point to labeling errors as the limiting element in precision.

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TABLE 4-7.- ACCURACY AND PRECISION OF ALL LABELED DOTS WHEN WEIGHTED BY CLUSTER SIZE

Dots	AI labels			Ground truth labels		
	Bias	Standard deviation	MSE	Bias	Standard deviation	MSE
All labeled dots (weighted)	-3.9	5.7	48	-0.7	2.5	6.3
All labeled dots (random)	-3.9	5.8	48	-0.8	2.9	9
Proportional sampling	-4.0	6.2	53	0.0	4.0	16

5. SUMMARY AND CONCLUSIONS

For the first time in Foreign Commodity Production Forecasting (FCPF) project testing, clustering has been an effective method in making proportion estimates. Proportionally allocating 50 dots to CLASSY clusters to estimate proportions resulted in greater precision than using a random sampling of 50 dots. This was observed when dot sets with AI labels from the integrated procedure were input, and it was also observed when dot sets with ground-truth labels were input.

When a cluster-level Bayesian estimator (rather than a relative count estimator) was employed with proportional allocation, errors of proportion estimates were slightly less variable at the expense of a slight positive bias with respect to the estimate of the PA/RCE technique. When dot sets with AI labels from the integrated procedure were input, the results of the PA/BE were less biased with respect to ground-truth proportions. Whether analyst-labeled dot sets or ground-truth labeled dot sets were input, the net result was a reduction in the MSE.

The BSA/BE provided the least amount of bias with respect to ground-truth proportions when analyst-labeled dot sets were input. However, this was due to positive biasing by the Bayesian estimator with respect to an unbiased estimate based on the same dots, also weighted by cluster size. The magnitude of this bias was approximately 2 percent. This same effect was observed when dot sets with ground-truth labels were input. In addition, the errors of estimates from the Sequential Bayesian technique showed greater variability than did those from proportional sampling. This was attributed, in part, to a reduced overall labeling accuracy observed for dots selected through sequential allocation.

It was estimated that in order to obtain the same precision with random sampling as obtained by the proportional sampling of 50 dots with an unbiased estimator, samples of 85 or 166 would need to be taken if dots sets with AI labels (integrated procedure) or ground-truth labels, respectively, were input. Little difference, on the other hand, was observed between random sampling and cluster-weighted estimates when all available labeled dot from the 209 were input. Another important result is that dot relocation by analysts provided dot sets that were unbiased.

6. RECOMMENDATIONS

While automatic labeling would provide large samples at relatively low costs, it is only a goal. With large samples, these clustering procedures do not seem to provide much improvement in proportion estimation. However, it is not recommended that effective clustering algorithms be discarded. Neither should efforts in proportion estimation techniques be defaulted to random sampling. An effective procedure using clustering information is available for use in testing and for future development. Automatic labeling, it should be remembered, is not yet a reality. It is therefore recommended that these proportion estimation techniques be maintained, particularly the PA/BE because it provided the greatest precision. It is recommended also that this estimation procedure be considered as the base line for the 1981-82 FCPF Spring Small Grains Pilot Experiment. Further exploratory testing needs to be conducted for other crops of interest such as corn and soybeans.

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APPENDIX A

RESULTS OF THE FOUR ESTIMATION TECHNIQUES UNDER REFORMATTED PROCEDURE

APPENDIX A

RESULTS OF THE FOUR ESTIMATION TECHNIQUES UNDER REFORMATTED PROCEDURE

Because of biowindow restrictions, only nine segments were processible under the reformatted procedure. Biases of proportion estimates (for fixed samples) along with standard deviations and mean-squared-errors (MSE's) for these segments are presented in table A-1. The errors of the proportion estimates are shown in figures A-1 and A-2. When dot sets with labels from the reformatted procedure were input, large positive biases were produced through the use of all the techniques. Although the estimates produced by techniques using CLASSY clustering were less biased, there was no significant difference among the biases because of the great amount of variation in the errors; as can be seen, the standard deviation of the proportion estimate errors in each of the techniques was approximately 19 percent. Errors in the labeling of dots and the limited number of segments would not permit enough of a basis to warrant an evaluation of the techniques when labels result from the Reformatted procedure. But to be complete, comparable statistics are provided in table A-1 for these same segments when ground-truth labels were used. Interestingly, the standard deviations and MSE's were smaller when CLASSY clustering was used.

TABLE A-1.- ACCURACY AND PRECISION OF THE REFORMATTED PROCEDURE WITH AI LABELS AND GROUND-TRUTH LABELS

Technique	AI labels			Ground-truth labels		
	Bias	Standard deviation	MSE	Bias	Standard deviation	MSE
Random sampling/ Relative Count Estimator	9.1	19.4	436	-0.8	6.1	36
Proportional Allocation/ Relative Count Estimator	6.2	19.2	382	-1.5	3.9	17
Proportional Allocation/ Bayesian Estimator	6.0	18.8	369	-1.7	3.9	17
Bayesian Sequential Allocation/ Bayesian Estimator	6.3	19.1	381	-2.7	4.0	22

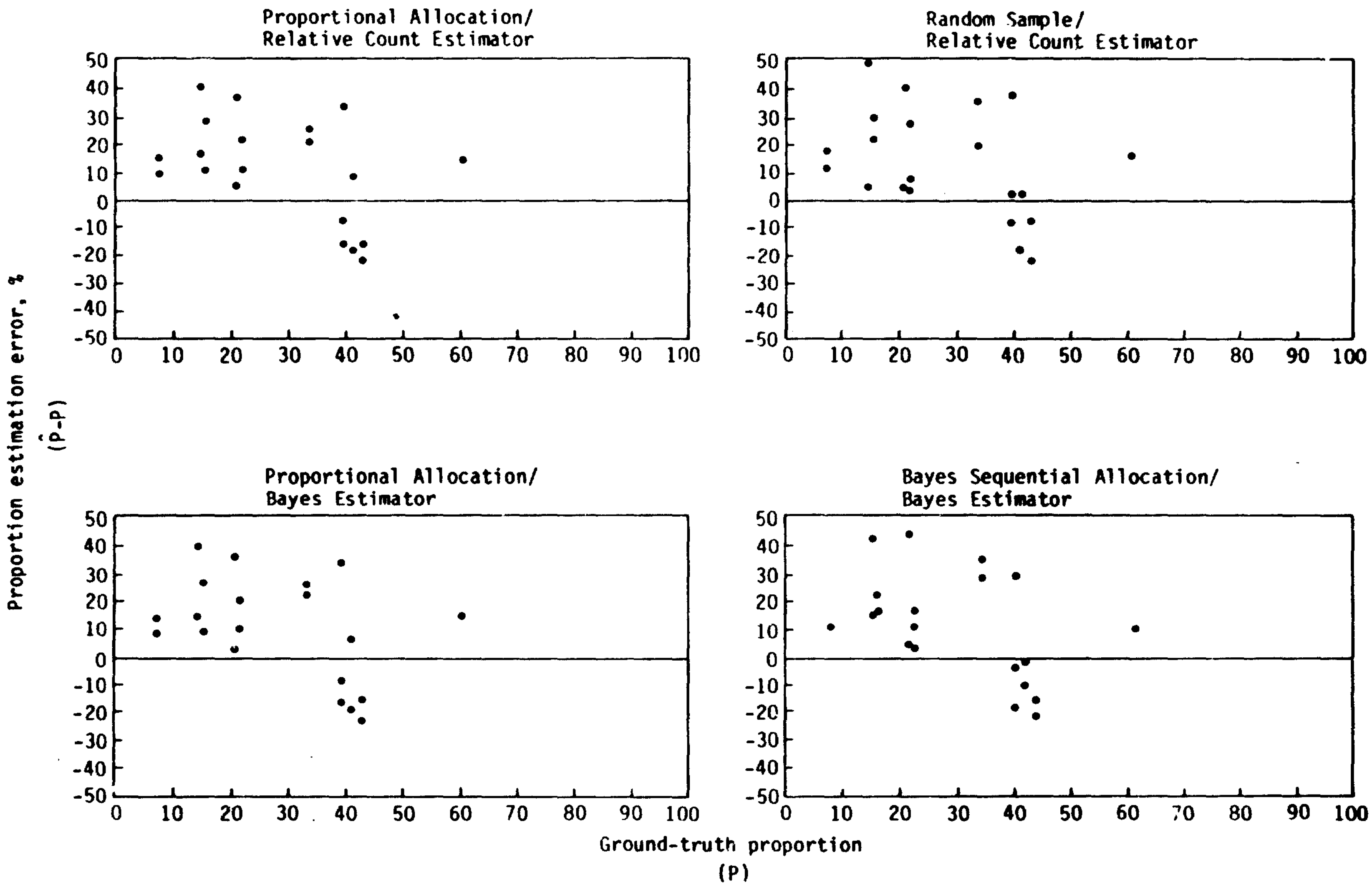

Figure A-1.- Proportion estimation results with analyst labels.

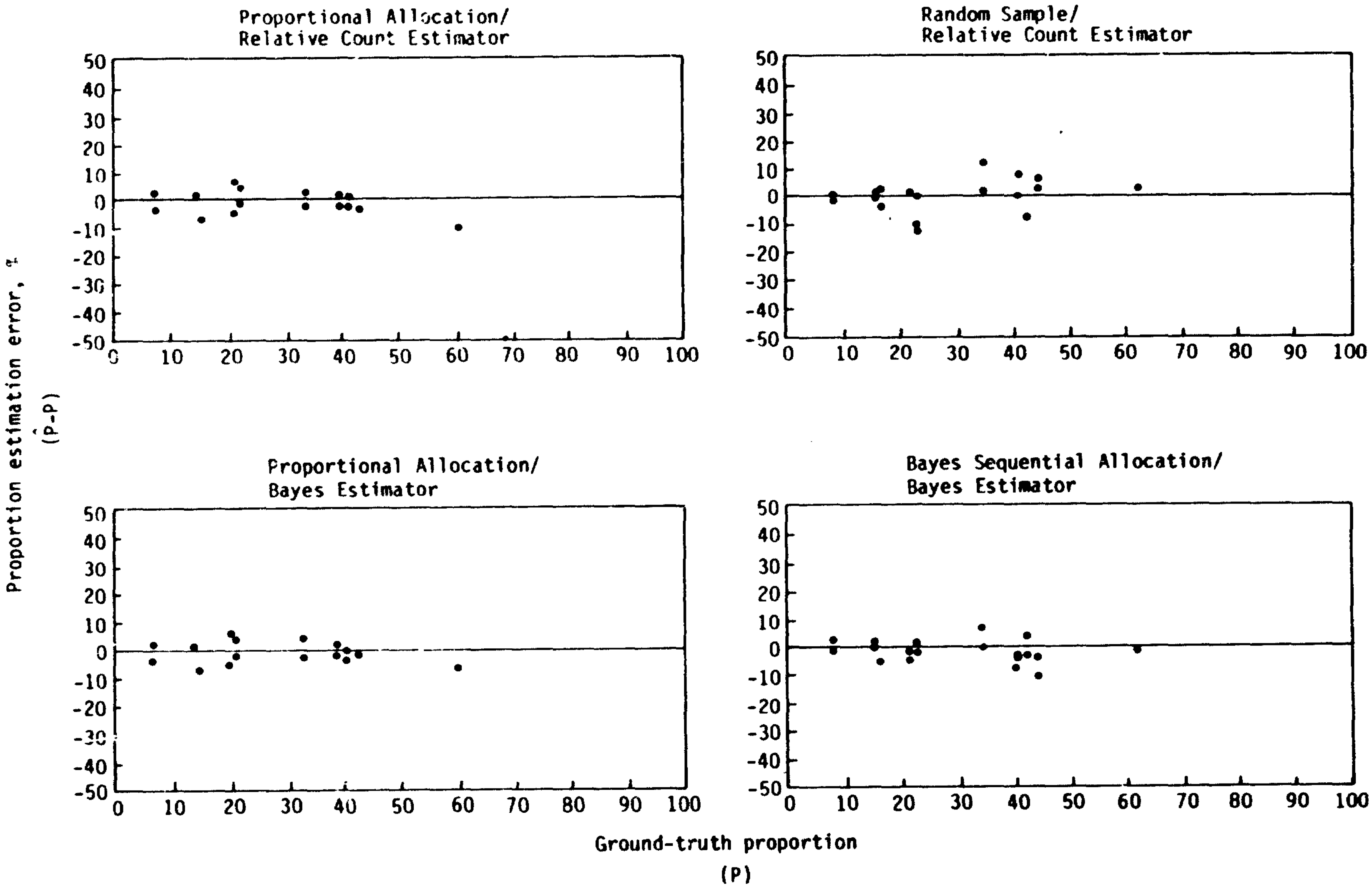

Figure A-2.- Proportion estimation results with ground-truth labels.

APPENDIX B

RESULTS OF FOUR ESTIMATION TECHNIQUES UNDER VARIABLE SAMPLING OF SEGMENTS

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RESULTS OF FOUR ESTIMATION TECHNIQUES UNDER VARIABLE SAMPLING OF SEGMENTS

Proportion estimates for segments with varying sample sizes were made only when dot labels were obtained from the integrated procedure or ground-truth data. In table B-1, biases, standard deviations, and MSE's for proportion estimates made under sampling based on a threshold (set at .0020) for an internal MSE estimate are presented.

Proportion errors are shown in figures B-1 and B-2. The results were similar to those of the fixed sample size. The sample sizes averaged approximately 42 dots and ranged from 25 to 75 dots.

TABLE B-1.- BIASES AND VARIANCES

Technique	AI labels				Ground-truth labels			
	Bias	Standard deviation	MSE	Internal MSE estimate	Bias	Standard deviation	MSE	Internal MSE estimate
Random sampling/ Relative Count Estimator	-4.4	8.1	83	42	-2.3	6.8	50	42
Proportional Allocation/ Relative Count Estimator	-3.5	6.1	48	45	-0.4	5.8	33	43
Proportional Allocation/ Bayesian Estimator	+2.9	5.9	43	18	+0.1	5.7	32	17
Bayesian Sequential Allocation/ Bayesian Estimator	-2.5	6.9	53	20	+0.3	4.9	24	20

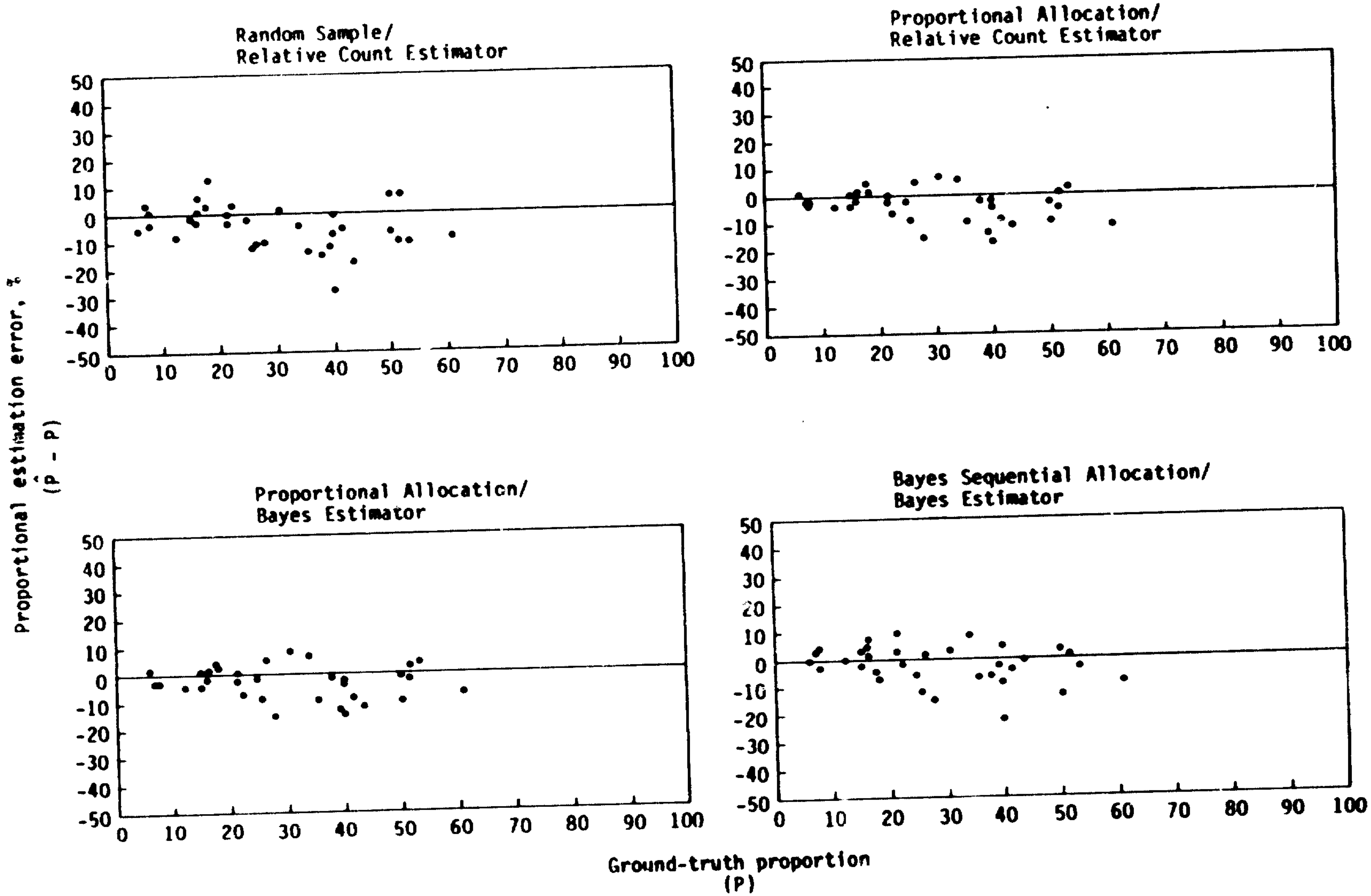

Figure B-1.- Proportion estimation results with analyst labels under varying sample sizes.

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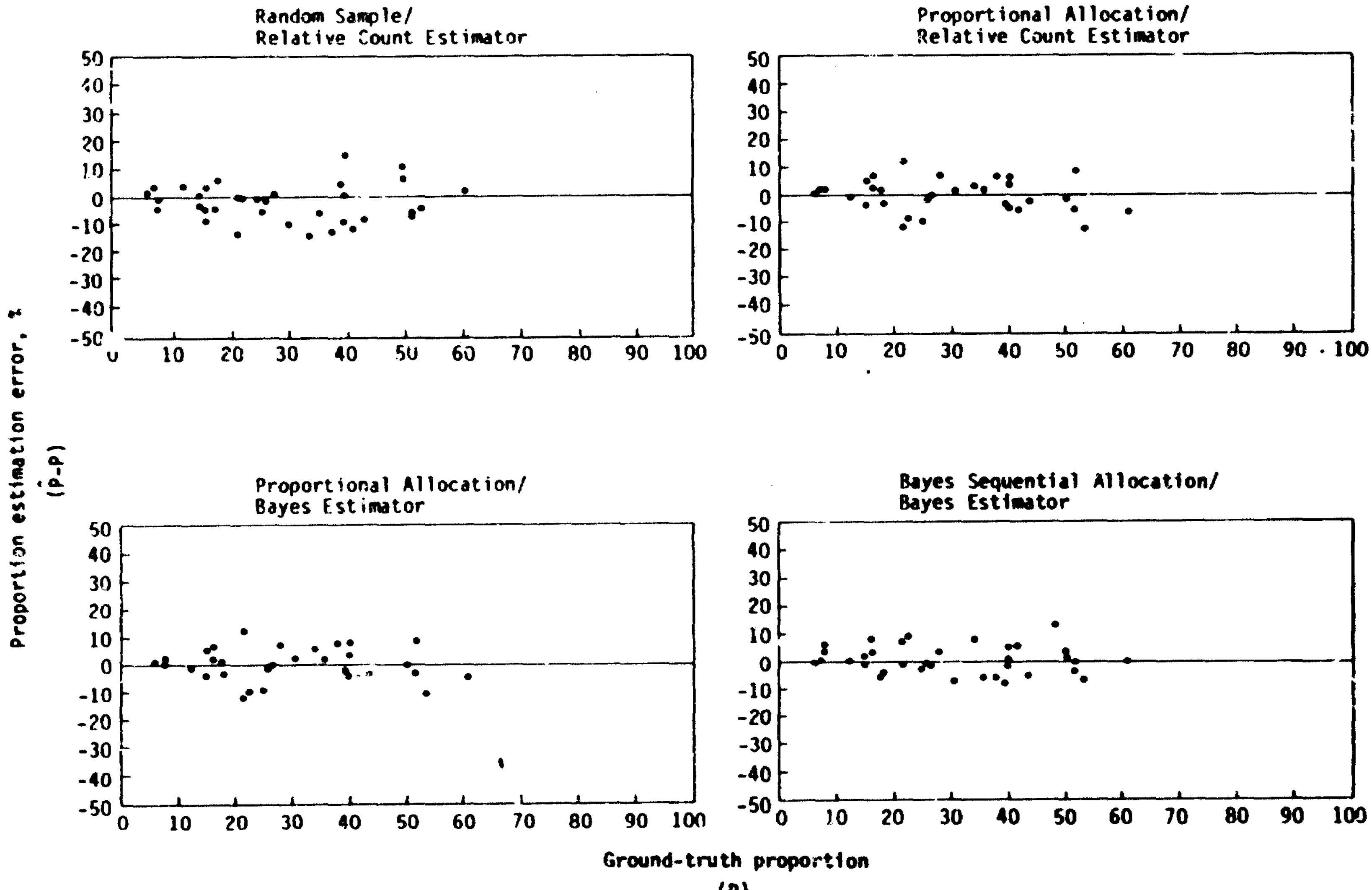

Figure B-2.- Proportion estimation results with ground-truth labels under varying sample sizes.

APPENDIX C

1979 GROUND-TRUTH PROPORTIONS

APPENDIX C

1979 GROUND-TRUTH PROPORTIONS

Segment	Ground-truth type (a)	Barley, %	Other spring small grains, % (b)	Total spring small grains, %
1387	D	8.01	35.36	43.37
1392	D	2.02	28.28	30.30
1394	I	0.31	39.51	39.82
1457	I	3.15	38.24	41.39
1461	I	4.99	48.19	53.18
1467	D	3.09	48.46	51.55
1472	I	4.02	35.16	39.18
1473	D	11.69	39.74	51.43
1485	I	1.35	20.80	22.15
1514	D	4.92	22.77	27.69
1518	D	0.29	25.22	25.51
1524	D	0.00	6.96	6.96
1571	I	0.32	14.60	14.92
1612	I	0.00	16.03	16.03
1617	D	21.18	39.68	60.86
1619	D	10.39	39.76	50.15
1627	I	0.00	15.80	15.80
1630	I	0.67	16.80	17.47
1636	I	0.87	38.91	39.87
1653	I	0.00	16.13	16.13
1658	I	1.44	32.41	33.85
1664	D	1.94	33.50	35.44
1676	I	0.23	7.44	7.67
1755	I	6.55	5.64	12.19
1784	I	4.07	17.29	21.36
1825	D	6.20	19.95	26.15
1835	D	5.61	19.02	24.63
1843	D	0.75	5.13	5.88
1909	I	0.88	17.15	18.03
1918	I	1.14	13.80	14.94
1920	I	0.09	21.11	21.20
1924	I	1.01	36.75	37.76
1948	D	1.95	5.57	7.52
1974	I	4.48	35.25	39.73
1987	D	15.48	34.40	49.88

[a] D indicates 400 dot ground-truth proportions.
I indicates inventoried ground-truth proportions from universal ground-truth tapes.

[b] Other spring small grains include spring wheat, oats, durum wheat, and flax.

APPENDIX D

CLUSTER PURITIES

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CLUSTER PURITIES

In order to determine the appropriateness of a beta prior for cluster proportion estimates, small-grain proportions for each cluster were found from ground-truth data. The percentage of all clusters having small-grain proportions within five-hundreth intervals was then found. These clusters are shown in figure D-1. The continuous line represents the shape of a beta prior with a mean equal to the mean small-grain proportion estimate for those segments (0.26). Thus the beta prior is given as follows:

$$g(\theta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha-1}(1 - \theta)^{\beta-1}$$

where $\alpha = 0.3513$ and $\beta = 1$.

As can be seen, the beta seems to be a reasonable prior.

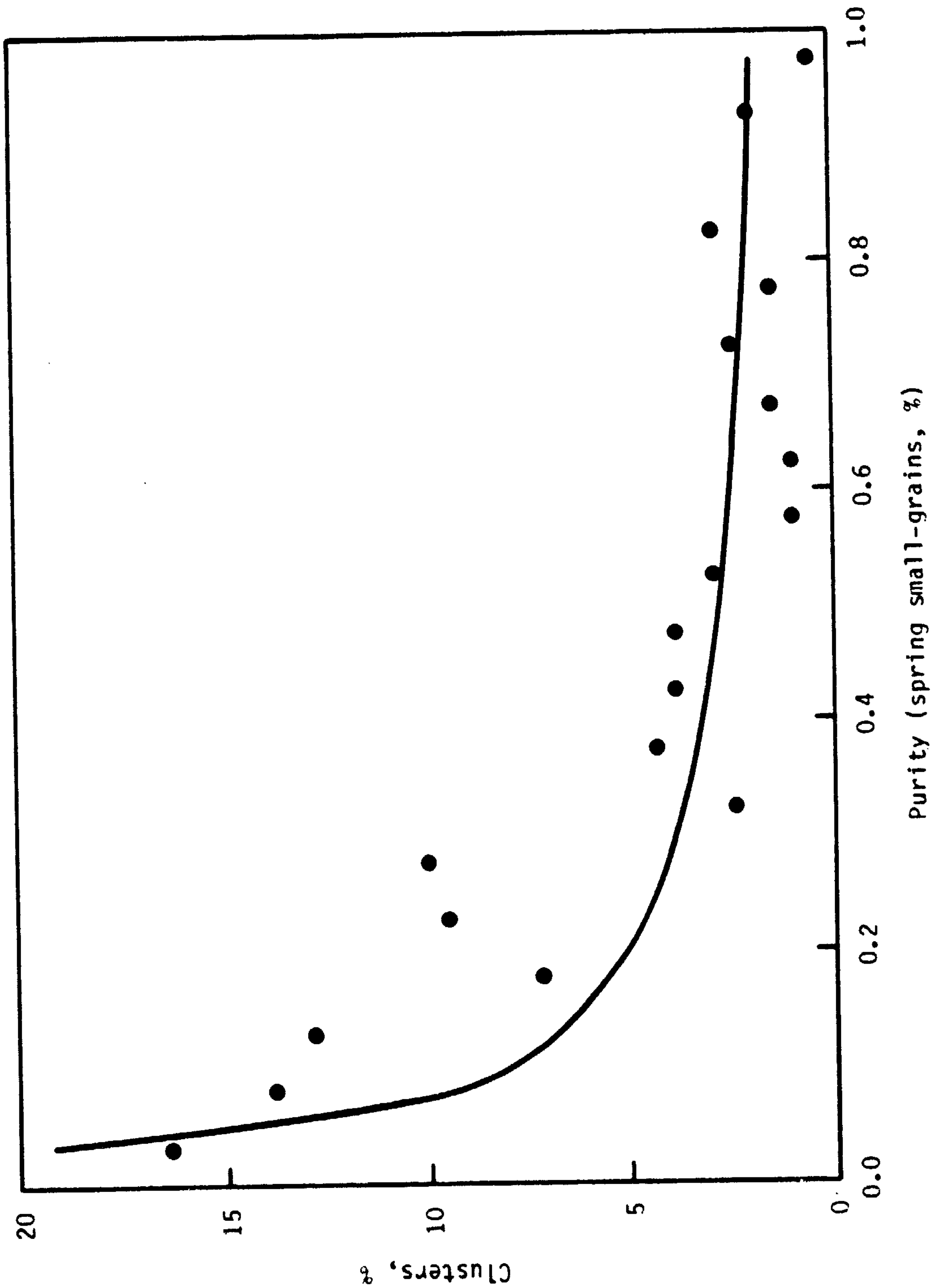

Figure D-1.- Cluster purity.