DATA VOLUME REDUCTION OF AIRBORNE THEMATIC MAPPER
DATA SET FOR CROP AREA ESTIMATIONS

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ABSTRACT

Results of a study using digital analysis applied to Airborne Thematic Mapper (ATM) data are described. An approach seeking improvements in multispectral agricultural land cover classification is used with particular attention given to the specific characteristics of early season crop data. In order to achieve data volume reduction a method for subset band selection is used along with different sampling schemes for area estimations through the estimations of the proportions of agricultural land cover classes. Results show improvements in classification accuracy of the optimum subset of bands and data volume reduction was achieved by feature selection and by the use of sampling techniques. Low errors were obtained in area estimations using systematic sampling strategy.

KEY WORDS: Subset band selection, sampling, area estimations.

1. INTRODUCTION

High spatial ground resolution and high spectral resolution remotely sensed data is often required to produce the desired information for agricultural applications. High resolution data sets together with multitemporal data sets resulted in an associated increase in data volume. In the field of crop inventory activities, this presents a data handling problem (Hallum and Perry, 1984). One of the most efficient method for data volume reduction is the use of sampling strategies (Hallum and Perry, 1984; Moreira *et al.*, 1986). Another approach when dealing with multispectral data, is to reduce the number of bands producing an optimum subset of bands (Labovitz, 1986; Mausel *et al.*, 1990; Sheffield, 1985).

This study will be concerned with data volume reduction using 11 band Airborne Thematic Mapper (ATM) imagery acquired in the early part of a crop season. Data volume reduction will be achieved by subset band selection and by the application of sampling strategies. The investigation into optimum band selection techniques will focus on the possibility of using only a fraction of the entire available data set and the consequent level of accuracy reached in the classification. The sampling strategies will be used to investigate what size of sample is necessary to estimate the proportions of different land cover classes within an acceptable error and assess the performance of three different sampling strategies.

2. STUDY AREA AND DATA SOURCES

The study area is located near Gedney Hill, Lincolshire, England, UK, about 25 kilometres north-east of Peterborough and 20 kilometres south-east of Spalding. The area is topographically flat containing regularly shaped parcels used almost exclusively for cropping. Records shown that annual crops such as sugar beet, oil seed rape, barley, wheat, beans and potatoes, as well as fruit trees have been grown in the area.

Ground data, which was used as reference data for the training process of the classifier and to assess the classification accuracy, was collected on 27th April, 1989, the day after image acquisition. In the study area selected, crop type was recorded over 18 parcels distributed among 7 classes (i.e., early stage wheat, mid stage wheat, late stage wheat, barley, early stage beans, grass, bare soil ploughed). In addition to the information of crop type in each parcel, the average heights of wheat, barley, and beans were recorded along with estimations of percentage cover biomass. Wheat in the different phenological stages exhibit heights of 12, 20 and 30 centimetres respectively.

A Daedalus AADS 1268 ATM 11 Channel Scanner was used to acquire the image data which was provided by the National Environment Research Council (NERC), under a research grant contract number GR3/7020. Characteristics and technical descriptions of the ATM are given by Williams (1984) and White (1989). The acquisition date was 26th April, 1989, at 09:35 (GMT) and the characteristics were the following: Site number 891/4; flight line 4; flight orientation south-west (i.e., 225 degrees); solar zenith angle of 48.8999 degrees; solar azimuth angle of 130.2617 degrees; and flying height of 2,000 metres (nominal spatial resolution of approximately 5 metres).

A potential problem with the ATM imagery is the effect of viewing geometry, which has two major components (Barnsley, 1984). Firstly, the wide swath angle of the sensor (42.96 degrees each side of nadir), and secondly, the relative azimuth angle between the sun and the sensor. Although the study area was at nadir position, ideally the data set should have been corrected for view angle effects and sun illumination, atmosphere effects, and geometrically and radiometrically corrected. Considering the major aim of the research and that multi-date data will not be used, these possible errors and effects were not considered.

The ground data information was digitised and the average error of the warp was between 2 and 3 pixels and this magnitude of error was considered as unacceptable for the study. One of the main reasons for such large errors is caused by the unstable nature of the aircraft platform. Changes in altitude, roll, pitch and yaw can seriously effect the geometric integrity of the image. Since this type of correction is far beyond the scope of

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this study and in order to overcome the problem, it was decided to digitise the ground data using the imagery itself. Problems emerging from the use of less stable platforms and the steps involved in geometric corrections of ATM imagery can be found in Devereux *et al.* (1989).

3. SUBSET BAND SELECTION

An optimum subset of 3 bands from the original 11 band ATM multispectral data set was selected. The use of a limited number of bands will reduce the data volume and therefore, reduce the data to be processed. There has been a great deal of attention paid to the selection of band subset during the mid 80's and it is still the subject of several studies. Sheffield (1985) considered the fact that the human eye uses three primary colours, and consequently the number of bands in a subset should be equal to three. Such a band combination provides colour composites images ideal for visual interpretation.

Regarding the acquisition of information and thematic maps, Labovitz (1986) raised the question: 'How good are remote sensing spectral bands as surrogate measures of ground attributes, e.g., biomass mapping, crop inventorying, and lithologic mapping?'. It was stated that in order to answer this question, the investigator should include selection of bands in the process of classification. Similarly, a question has been raised by Shen and Badhward (1986): 'How well can the classes be separated by observing the values of some feature vectors for a set of samples?'. The former question identifies the need to define an optimum sub-set of bands, while the latter necessitates a measure which allows the quantification of the amount of information.

The amount of information content in a multispectral data set can be expressed in terms of the separability of the classes within a multidimensional feature space. This can be evaluated using a measure of statistical separability between bands. Swain (1978) illustrates the statistical separability in relation to the probability of error. Errors are proportional to the overlap region in feature space and the area of this region changes according to a defined 'normalise distance between the means', i.e., the absolute value of the difference between the means divided by the sum of the standard deviation. This distance is referred to a statistical separability measure. There are several methods for the calculation of the separability between bands (Mausel *et al.*, 1990; Shen and Badhwar, 1986; Shearn, 1986). Transformed divergence analysis was used by Toll (1984) to assess and investigate land cover discrimination using the best sub sets of two and three bands. Several conclusions were drawn concerning the elimination of specific bands to improve classification accuracy and reduce cost of processing. Mausel *et al.* (1990), investigated the performance of four different methods of separability plus eigenvalue and eigenvector analysis used in agricultural applications to determine which would best identify a sub set of four channels. The J-M Distance and Transform Divergence separability methods showed the best results over the Bahattacharyya Distance and Divergence. However, it was concluded that the original number of channels, the number and nature of classes involved, and the method used can all have effect upon the results.

With the aim of selecting a sub set of three bands from the seven bands of Landsat Thematic Mapper, Sheffield (1985) used a method which provides a single preferred choice of a subset. The three band subset which is defined to contain most of the variance, is selected from the largest diagonal elements from the variance - covariance matrix. One problem that remains is the appropriate assignment of colours to the bands. The above study has shown that the natural colour combination (band 1,2,3) and the standard false colour composite (band 2,3,4), are low in the ranking of best band combination. This was claimed to be the result of high band correlations. Several of the methods to determine the statistical separability are multivariate while others consider each band independently. Most of the multivariate methods consider pairwise divergence which increases the computation. Fisher criteria lies in the latter category (McMorrow, 1985) and does not take into account any inter-band correlation.

3.1. Method Adopted for Subset Band Selection

In consideration to the fact that one of the aims of the project is to reduce processing time, Fisher criteria was chosen as an appropriate method for the calculation of statistical separability, and hence for the optimum band selection. Furthermore, the decision was also based on the following factors: (1) the calculation involved in the method is simple and uses basic statistics, (2) computer time required is minimal, (3) previous applications have shown good results. As mentioned above, the method chosen does not consider the inter band-correlation. To overcome this deficiency the use of a correlation matrix was adopted. Additionally, the utilisation of the knowledge of vegetation spectral responses in the range of the electromagnetic spectrum covered by the ATM bands was adopted. Toll (1985) concluded that the best spectral discriminations were obtained from the visible, near infrared, and middle infrared regions.

In summary, the selection of the optimum subset was based on (a) Fisher criteria, (b) Correlation between bands, and (c) Knowledge of vegetation spectral responses in the ATM bands. To calculate the 'Fisher criteria values' for each of the 11 ATM bands, the following equations were implemented in a Fortran program. The Fisher criteria method is based on the statistics of each class pair. It uses a measure of interclass distance, and as such estimates the effectiveness of a single band at separating the classes. Bands are then ranked in order of effectiveness. The method which is adapted from Siegel and Gillespie (1980) is calculated as:

$$d_{ijk} = [(M_{ik} - M_{jk})^2 / (U_{ik} + U_{jk})]^{0.5} \qquad (1)$$

Where d_{ijk} is the distance separating class i from j in band k, M_{ik} and M_{jk} are the (kth) means of each class in band k, U_{ik} and U_{jk} are the variance of each class in band k. The Fisher criteria values for the 11 bands (Table 1) was calculated with the following equation where m is the number of classes:

$$D_k = \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} d_{ijk} \qquad (2)$$

Upon examination of the correlation matrix, the highly correlated bands can be spotted quite easily (Table 2), i.e., those with a value approaching 1.0. The high correlations between the visible bands are an example of this. In the near infrared, bands 6 and 7, and bands 7 and 8 exhibit correlations of, 0.940 and 0.955, respectively. Bands 6 and 8 also shown a high coefficient (0.817).

Band	Fisher Criteria
1	15.2139
2	38.2585
3	36.5790
4	45.5791
5	35.2813
6	136.2813
7	157.1967
8	154.9301
9	49.0035
10	39.5124
11	75.6195

Table 1. Values of the Fisher Criteria for the ATM band 1 to 11

Bands	1	2	3	4	5	6	7	8	9	10	11
1	1.000										
2	0.846	1.000									
3	0.817	0.944	1.000								
4	0.651	0.905	0.903	1.000							
5	0.838	0.950	0.957	0.900	1.000						
6	0.533	0.223	0.294	-0.041	0.299	1.000					
7	0.318	-0.030	0.060	-0.260	0.036	0.940	1.000				
8	0.134	-0.170	-0.058	-0.341	-0.119	0.817	0.955	1.000			
9	0.705	0.665	0.730	0.592	0.723	0.571	0.440	0.391	1.000		
10	0.506	0.759	0.749	0.800	0.772	-0.097	-0.250	-0.279	0.667	1.000	
11	0.262	0.521	0.478	0.626	0.526	-0.390	-0.572	-0.633	0.268	0.714	1.000

Table 2. Correlation Matrix for the ATM Band 1 to 11

By examining Table 1 alone, the selection of an optimum subset is straight forward, i.e., bands 6, 7 and 8 due to their high Fisher Criteria values. However, the correlation matrix in Table 2, shows that the above subset should be rejected because of high correlation. Thus in order to achieve an optimum subset of bands, the methods have been combined with a knowledge of the spectral response of vegetation. Consequently, band 7 (near infrared), band 9 (middle infrared) and band 4 (visible) were selected as the optimum subset of bands.

4. DIGITAL CLASSIFICATION

A supervised minimum distance classifier was used for the digital classification. The decision rule of the method is computationally simple and spreadly used. Hixson *et al.* (1980), when comparing several classification methods, ranked the minimum distance algorithm as the least complex, and with respect to cost per square kilometre for classification (not including cost for developing training statistics), the most cost effective.

Training statistics were used based in more than one training area for each land cover class. Since ground data information was available from the area to be classified and not from outside areas, contiguous pixels were adopted (Labovitz, 1986). The shape chosen for each area was a rectangle and each of them was displaced perpendicularly along the larger axis of the field. The number of pixels used for each class was accordingly Richards's (1986) recommendation. Two data sets were selected for classification, i.e., standard false colour composite (bands 7,5,3) and the subset selected by optimum band selection process (bands 7,9,4). The data sets were modified according to some preprocessing techniques such as masking and spatial filtering. Masking techniques were used in order to (a) eliminate unwanted areas surrounding the site, (b) to eliminate unwanted areas within the site and (c) to eliminate boundary pixels.

Spatial filtering techniques can be used to improve the accuracy of multispectral classifications and this is achieved by reducing the within class variance. However, a factor which should always be considered when using spatial filters, is the inclusion of boundary pixels within the filter. Many authors have dealt with the relationship between the type and size of spatial filters, image pixel size, type of land cover, and classification accuracy (Atkinson *et al.*, 1985; Cushnie, 1987; Cushnie and Atkinson, 1985; Gong and Howarth, 1990; Harris, 1985). With particular reference to per-point classification of fine spatial resolution data, Cushnie and Atkinson (1985) suggested some guidelines regarding the use of spatial filtering as follows: (1) blurring or smoothing of the imagery is potentially useful for reducing the variability of the digital values within individual land cover units, (2) the smoothing operation should avoid blurring all forms of boundaries between different land cover units in every orientation and at any scale, (3) neither of these operations must take place at the expense of the other, i.e., the variability must be smoothed without removing or distorting the boundaries. Since the use of spatial filtering modifies the frequency and spatial distribution of boundary pixels, the filters were applied to reduce the within field variability and were not concerned with the proportions of boundary pixels and the like. Masking techniques were used to eliminate boundary pixels and pixels from unwanted areas (e.g., from farm houses and canals) within the site selected. Thus masking and spatial filtering techniques were always used together.

4.1. Classification Accuracy Assessment

In a general context, if remotely sensed data, derived products and respective numerical data are to be applied by a user community, a methodology must be implemented for the assessment of classification. There are several methods which can be adopted and there is no simple, standardised, generally accepted methodology for determining classification accuracy. The classification accuracy assessment was carried out as a site specific procedure where the classified images were compared to the ground data information and the output of the comparisons were drawn in confusion matrices. A program was designed to enable the selection of the sampling procedures (random and stratified random sampling), and the total number of pixels to be tested. Classification accuracy tests were performed on the classified images using five sample sizes, (i.e., 665, 1040, 1849, 4160, and 16641 pixels), corresponding to a confidence level of 99% and using random sample and stratified random sampling techniques. In terms of number of pixels, the sample sizes represent 0.25%, 0.40%, 0.70%, 1,60%, and 6.35% respectively of the total area (512 x 512 pixels).

4.2. Classification Results

Figure 1 and Figure 2 show the overall accuracy percentages for the two data sets using random sampling and stratified random sampling with different sample sizes. Additionally, Figure 3 and Figure 4 outline the per class accuracies including errors of omission and errors of commission. The errors of omission are the opposite of the overall accuracies, and errors of commission are related to the reliability, i.e., the lower its percentage the higher its reliability. Examination of the resultant overall accuracies (Figures 1 and 2) show that it is not possible to detect a common pattern as a result of the utilisation of different sample sizes.

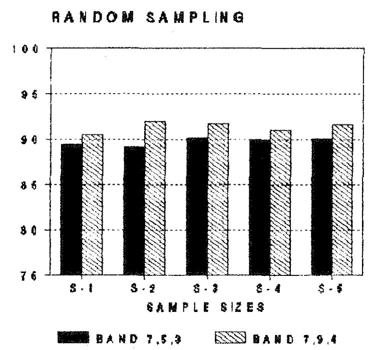

Figure 1 *Overall accuracies (%) in Band 7,5,3 and Band 7,9,4 using different sample sizes (random sampling)*

However, better results are achieved with the use of the optimum subset, Bands 7,9,4. When using Bands 7,5,3 the overall accuracy range from 88.63% to 91.40%, and for Bands 7,9,4 from 90.53% to 93.45%. Also, there are similar factors in the tests. Firstly, the very similar accuracies when larger sample sizes were used, and secondly, slightly better accuracies when using stratified random sample.

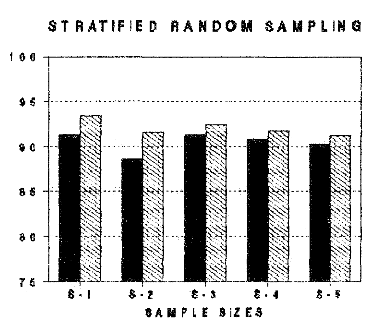

Figure 2 *Overall accuracies (%) in Band 7,5,3 and Band 7,9,4 using different sample sizes (stratified random sampling)*

Analyzing the results when using a sample size of 1848 pixels (264 per class) with stratified random sampling, greater overall accuracy is achieved using the optimum subset selected, Band 7,9,4, (i.e., 92.41%) rather than the standard false colour subset, Band 7,5,3, (i.e., 91.40%). Normally a sample size equal to 100 pixels per class is recommended (Hay, 1979), (see Figures 3 and 4). In the per class accuracies, the advantage of Band 7,9,4 is very clear. The per class accuracies increased in most of the classes with exception of class 1 and 3. Errors of commission drop dramatically in all the classes proving the reliability of using Band 7,9,4. This leads to the conclusion that the inclusion of a middle infrared band in the optimum sub set selected (i.e., band 9) contributed to class separability, particularly those classes with early stage crops where the vegetation present has a high moisture content.

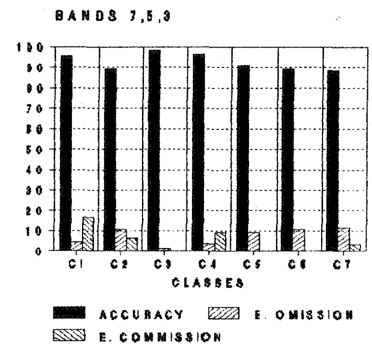

Figure 3 *Per class overall accuracies and errors (%) in Band 7,5,3. Stratified random sampling (sample size 1848 pixels)*

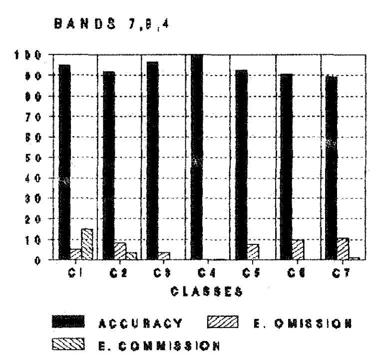

Figure 4 *Per class overall accuracies and errors (%) in Band 7,9,4. Stratified random sampling (sample size 1848 pixels)*

5. THE USE OF SAMPLING IN AGRICULTURAL CROP AREA ESTIMATION

Data volume reduction was successfully achieved by the selection of an optimum subset of bands, using a feature selection technique. This section is concerned with the application of sampling techniques as a further mean of data volume reduction. The sampling techniques investigated include random sampling, systematic sampling and stratified unaligned random sampling and will be evaluated in terms of area estimation.

Sampling is a technique commonly adopted in remote sensing projects. The required information can usually be adequately provided by a sample of the original data (Jolly, 1981). The Large Area Crop Inventory Experiment (LACIE) carried out in the mid 1970's is a well known project which used and generated sampling methodology as part of its area estimation phase (Hixson *et al.*, 1981). Prior to the LACIE project, Bauer *et al.* (1978) used a sample of pixels from full-frame imagery in order to classify Landsat data. The pixel sampling approach demonstrated the capability of producing unbiased and precise results for area estimation. The AgRISTARS (Agriculture Resources Inventory Surveys Through Aerospace Remote Sensing) project which began in 1980 aimed to develop and test procedures using sample surveys of remotely-sensed data. It demonstrated the applicability of the sample survey approach to more than one crop (Hallum and Perry, 1984). Hixson *et al.* (1981) used repetitive sampling with the intention to simulating alternative sampling strategies for full-frame classified images of 80 counties in Kansas USA. Evaluations were made concerning the costs of the sample approach and the precision attained. Results show that the most accurate estimates were obtained from pixel sampling. In the above studies, crop areal estimations were obtained using different sampling approaches. The common feature of each of these methods is the integral selection of a representative sample for further analysis. The motivations behind this are mainly high costs and the time-consuming nature of conventional processing. Several studies have demonstrated that the use of sampling is efficient for crop areal estimations, especially in applications where a complete survey is not economically feasible. Data volume reduction is implicit in all remote sensing projects which employ sampling strategies and procedures.

5.1 The application of sampling to classification

In this study, the parameter population was the ATM optimum subset selected, bands 7,9,4, 512 by 512 pixel size image and the sample unit was taken to be individual pixels. As remotely sensed data from a region or area is spatially autocorrelated, every measurement will contain some information about the neighbourhood of each pixel. The adoption of individual pixels will allow maximum spatial dependence and contribute to the minimisation of the autocorrelation. Techniques including semivariograms can be used to estimate the spatial autocorrelation (Curran and Williamson, 1986; Atkinson, 1987). The evaluation and use of sampling strategies will be determined by the proportions of the different land cover classes already classified. After the digital classification, the number of pixels representing each land cover feature are related to the total number of pixels used in the classification. The result is the proportion of the land cover feature in the whole image. This approach is only used in order to facilitate the handling and computation of the data. The aim and principles of the whole sampling procedure adopted can easily be transferred to a situation where the classified image data is not available and the idea is that only those pixels included in the selected sample from the original data (i.e., in a non-classified image) will then be used in the digital classification. And so, a reduced volume of data would be used in the classification instead of the whole image.

5.2. Sample size

In order to determine the sample size, some basic elements have to be specified. A review of sampling theory is provided by Cochran (1977) and Davis (1986). In a sample, all categories of the entire population (sampled population) require representation (Cochran, 1977). One method of evaluating whether a sample is a good estimator of the population is to use the sampling distribution parameter, which is the distribution of values that the sample mean can take from all the possible samples that could be drawn from the population. An unbiased sample can occur when the mean of the sampling distribution is equal to the mean of the population. Another parameter is the sampling variance (which should be as low as possible), and its equation is as follows:

$$s^2 = \frac{(x - u)^2}{(n - 1)} \quad (3)$$

Where s^2 is the sampling variance, x is the mean of each sample, u is the population mean, and n is the sample size. In order to avoid this calculation for every sample, the sampling variance can be estimated from the population variance. When (N-n) / (N-1) approaches one, the equation becomes $s^2 = Q^2/n$ (4), where s^2 is the sampling variance, Q^2 is the population variance. However, since the population variance is not known, it must be estimated from the variance of the sample. To determine the level of precision (or 'confidence limit') and the degree of certainty (or 'confidence level'), the standard error (s.e.) is used which is $s.e. = Q/n^{0.5}$ (5). This may also be used as an alternative to sampling variance. The confidence limit then becomes; $c = +/- z(s.e.)$, where c is the confidence level, z is the standard error unit for the desired confidence level. The first step in creating a sample size scheme is the calculation of the variance of the proportion: $s^2 = P(1 - P)$ (6). P is the proportion of the population or class of interest and has values between 0 and 1. This value must be estimated, and in this case, is chosen to be different for each land cover class in order to ensure that an adequate sample size is always used. The maximum value of variance is calculated when P is equal to 0.5. Variance decreases as P moves away from 0.5. The sample size is then calculated by the following equation (Curran and Williamson, 1986):

$$n = \frac{(z \cdot v)^2}{c^2} \quad (7)$$

Where n is the sample size, z is the standard error unit for the confidence level chosen with n-1, v is the standard deviation for the proportion of the correctly classified pixels (P(1-P)), and c is the confidence limit. Using the above equation and the desired confidence level and confidence limit, a number of sample sizes were determined to be used in the sampling procedure to estimate the proportions of the classes. The confidence level determines the probability that the estimate will lie within the confidence limit of the true proportions.

5.3. Estimation of the proportions of each land cover class

To estimate the proportions of each land cover class the optimum subset of bands 7,9,4 was used as input. The proportion for each land cover class was calculated by dividing the number of points selected in each class by the total number of points selected. The error of this estimation is the result of the subtraction by the original proportion of the classified pixels in each land cover class. Finally, a weighted error was calculated by relating the percentage estimation error to the original proportions from the classified image. The estimated errors were weighted in relation to the 'true' proportions according to the size of each land cover class in order to take into account the different size of each class. To illustrate this, using the extreme classes in relation to their sizes an estimated error of 1% in class two (Mid stage wheat), corresponds to 399 pixels. The same estimated error in class four (Grass), corresponds to 17 pixels. Furthermore, the weighted error expresses the accuracy of estimation attained by the sampling procedure in relation to the original proportions (i.e., results form the classification of Bands 7,9,4). Different sampling strategies and different sample sizes were adopted and the outputs (estimated proportions and estimated errors) were the result of an average as the computation was run automatically 10 times.

In order to evaluate the performance of each sampling strategy employed, results from three sample sizes were assembled in terms of the weighted errors obtained from all classes. The sample sizes were, 1040, 4160 and 16640 pixels; S-1, S-2 and S-3 respectively (Figures 5, 6 and 7). Furthermore, the 'true' proportions of each class, the estimated proportions and the related weighted errors are displayed in Figure 8.

5.4. <u>Results</u>

It was assumed that the sampling strategies gave an unbiased estimation of the 'true' proportions. It was not possible to obtain the variance of the sampled population, but only the average estimations (run 10 times). Therefore, an evaluation using the confidence limits could not be carried out. Nevertheless, the average estimated errors were low for any sampling strategy and they reside very close to the confidence limit related to the sample sizes which were used. In Figures 5, 6 and 7, the weighted errors start from about zero and in the random sample strategy, reach 14%. The systematic sample gives the lowest errors with a maximum of approximately 3%, and in the stratified unaligned sample, about 5%. This can be explained by the characteristics involving the systematic sample where the sample points are distributed over the entire area, and thus avoiding the possibility of clustering. The latter has a relatively high chance of occurring with simple random sampling.

Results from the systematic sample and the stratified unaligned sample show small weighted errors when compared with random sample. It was clear that sample sizes are related to the resultant weighted error. Using the smallest sample size, weighted errors show a tendency to increase. The lowest errors are related to the biggest sample and a common pattern can be established which is presented in each land cover class; the smaller the sample size, the greater the errors and vice-versa. (The sample sizes in terms of percentage of the whole image represent 0.4%, 1.6% and 6.4%).

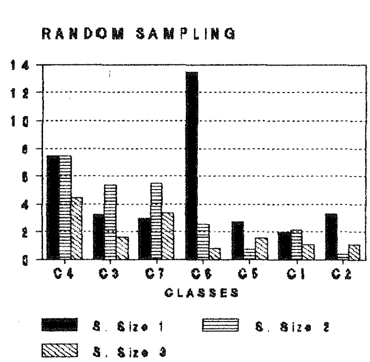

Figure 5 Per class weighted errors (%) using different sample sizes (random sampling)

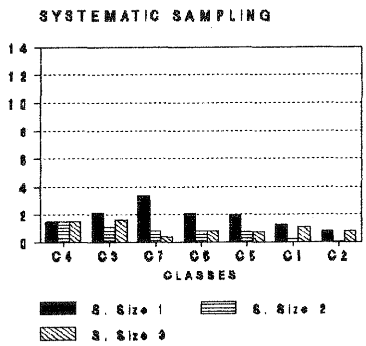

Figure 6 Per class weighted errors (%) using different sample sizes (systematic sampling)

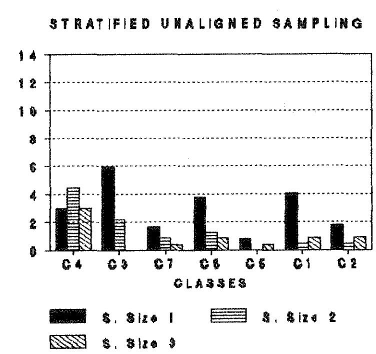

Figure 7 Per class weighted errors (%) using different sample sizes (stratified unaligned sampling)

Better results were obtained from the use of systematic random sampling. When using a sample size of 16641 pixels and systematic random sample (Figure 8), the mean absolute error stays around 1%. In relation to the size of the class, it can be observed that class four, which is the smallest, generally exhibits high errors.

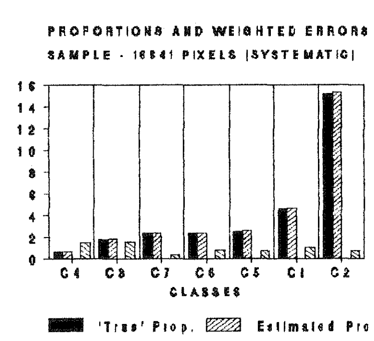

Figure 8 Per class 'true' proportion, estimated proportion and weighted errors (%) using systematic random sampling - 16641 pixels)

6. CONCLUSIONS AND RECOMMENDATIONS

The procedure for feature selection which includes one band from each part of the electromagnetic spectrum will achieve improved results over the standard false colour composite. Results from the optimum subset band selection used (Fisher criteria), show high indices in bands from the visible, near-infrared, and middle-infrared. The comparison of the classified results from both subsets, demonstrate the usefulness of using a non-empirical band selection method in early season agricultural data. Addressing the relationship between sample size and the size of the land cover classes, the lowest errors are obtained from the largest classes. This is a general pattern for half of the classes (i.e., with the exception of classes 4, 3, 7, and 6). Therefore, there is a relationship between sample and size of the classes, and in order to define a sample size for data volume reduction, the above factor should be considered. It can be concluded that a sample size representing 6.4% of the data set will result in the lowest errors and this figure is suggested for this study. Nevertheless, an optimum sample size to be used in the classification of a raw image, could be the sum of specific samples for each of the land cover classes accordingly to their spatial size and autocorrelation characteristic.

7. ACKNOWLEDGMENTS

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8. REFERENCES

Atkinson, P., Cushine, J.L., Townshend, J.R.G. and Wilson, A., 1985. Improving Thematic Mapper land classification using filtered data. *International Journal of Remote Sensing*, 6(6):955-961.

Atkinson, P.M., 1987. The design of efficient sampling schemes for remote sensing. In: *Proceedings of the Annual Conference of the Remote Sensing Society*, Nottingham, UK, pp. 334-342.

Barnsley, M., 1984. Effects of off-nadir view angles on the detected spectral response of vegetation canopies. *International Journal of Remote Sensing*, 5(4):715-728.

Bauer, M.E., Hixson, M.M., Davis, B.J. and Etheridge, J.B., 1978. Area estimation of crops by digital analysis of Landsat data. *Photogrammetry Engineering & Remote Sensing*, 44(8):1033-1043.

Cochran, W.G., 1977. *Sampling Techniques*. John Wiley & Sons: New York.

Curran, P.J. and Williamson, H.D., 1986. Sample size for ground and remotely sensed data. *Remote Sensing of Environment*, 20:31-41.

Cushine, J.L. and Atkinson, P., 1985. Effect of spatial filtering on scene noise and boundary detail on Thematic Mapper imagery. *Photogrammetry Engineering & Remote Sensing*, 51(9):1483-1493.

Cushnie, J.L., 1987. The interactive effect of spatial resolution and degree of internal variability within land-cover types on classification accuracies. *International Journal of Remote Sensing*, 8(1):15-29.

Davis, J.C., 1986. *Statistics and Data Analysis in Geology*. John Wiley & Sons: New York.

Devereux, B.J., Fuller, R. M. and Roy, D.P., 1989. The geometric correction of Airborne Thematic Mapper imagery. *Proceedings of the NERC workshop on airborne remote sensing 1989*, Institute of Freshwater Ecology, Windermere, pp. 19-33.

Gong, P. and Howarth, P.J., 1990. The use of structural information for improving land-cover classification accuracies at the rural-urban fringe. *Photogrammetry Engineering & Remote Sensing*, 56(1):67-73.

Hallum, C.H. and Perry, C.R. Jr., 1984. Estimating Optimal Sampling Unit Sizes for Satellite Surveys. *Remote Sensing of Environment*, 14:183-196.

Harris, R., 1985. Contextual classification post-processing of Landsat data using a probabilistic relaxation model. *International Journal of Remote Sensing*, 6(8):847-865.

Hay, A.M., 1979. Sampling design to test land use map accuracy. *Photogrammetry Engineering & Remote Sensing*, 45(4):529-533.

Hixson, M., Scholl, D. and Fuhl, N., 1980. Evaluation of several schemes for classification of Remotely sensed data. *Photogrammetry Engineering & Remote Sensing*, 46(12):1547-1553.

Hixson, M.M., Davis, B.J. and Bauer, M.E., 1981. Sampling Landsat classifications for crop area estimation. *Photogrammetry Engineering & Remote Sensing*, 47(9):1343-1350.

Jolly, G.M., 1981. Sampling as a cost-reducing tool. In: *Proceedings of an International Conference of Remote Sensing Society*, London, UK, pp. 43-48.

Labovitz, M.L., 1986. Issues arising from sampling designs and band selection in discriminating ground reference attributes using remotely sensed data. *Photogrammetry Engineering & Remote Sensing*, 52(2):201-211.

Mausel, P.W., Kramber, W.J. and Lee, J.K., 1990. Optimum band selection for supervised classification of multispectral data. *Photogrammetry Engineering & Remote Sensing*, 56(1):55-60.

McMorrow, J., 1985. The multispectral classification of upland vegetation at simulated SPOT wavelengths and spatial resolution. Msc. thesis, University of London, unpublished.

Moreira, M.A., Chen, S. and Batista, G.T., 1986. Wheat-area estimation using digital Landsat MSS data and aerial photographs. *International Journal of Remote Sensing*, 7(9):1109-1120.

Richards, J.A., 1986. *Remote Sensing Digital Image Analysis*. Springer-Verlag Berlin Heidelberg, Germany.

Shearn, V.J., 1986. Data volume reduction techniques for land cover classification. MSc.

thesis, University of London, unpublished.

Sheffield, C., 1985. Selecting band combinations from multispectral data. *Photogrammetry Engineering & Remote Sensing*, 51(6):681-687.

Shen, S.S. and Badhwar, G.D., 1986. An information measure for class discrimination. *International Journal of Remote Sensing*, 7(4):547-556.

Siegal, B.S. and Gillespie, A.R., 1980. *Remote Sensing in Geology*. Wiley and Sons, New York.

Swain, P.H., 1978. *Remote Sensing: The Quantitative Approach*, McGraw-Hill: New York.

Toll, D.L., 1985, Landsat-4 Thematic Mapper scene characteristics of a suburban and rural area. *Photogrammetry Engineering & Remote Sensing*, 51(9):1471-1482.

Toll, D.L., 1984. An evaluation of simulated Thematic Mapper data and Landsat Multispectral Scanner data for discriminating suburban and regional landuse and landcover. *Photogrammetry Engineering & Remote Sensing*, 50(2):1713-1724.

White, S.J., 1989. Overview of the 1988 NERC airborne remote sensing campaign. In: *Proceedings of the NERC workshop on airborne remote sensing 1989*, Institute of Freshwater Ecology, Windermere, pp. 1-6.

Williams, D.F., 1984. Overview of the NERC Airborne Thematic Mapper campaign of September 1982. *International Journal of Remote Sensing*, 5(4):631-634.