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Irrigated Crop Inventory by Classification of Satellite Image Data

Classification of bands 5 and 7 Landsat multispectral scanner data is used to produce inventories with high accuracies of irrigated crops.

Abstract: *Mixed unsupervised/supervised classification of band 5, band 7 Landsat Multispectral Scanner image data is used as a procedure for determining area of cropland under irrigation in an arid region of the state of New South Wales in Australia. Classification using two analysis systems is described. One is a dial-in bureau service which supports the* ORSER *software package and the other a Dipix Aries II interactive image analysis system. Results obtained agreed to within 1 to 5 percent with information provided by field studies. Density slicing using a vegetation index is also described, but with an accuracy of approximately 8 percent.*

A rough cost-effectiveness comparison is made with irrigated crop inventory studies of other investigators.

Introduction

Much of the western region of the state of New South Wales in Australia experiences arid to semi-arid climatic conditions with low average annual rainfalls accompanied by substantial evapotranspiration. Consequently, a viable crop industry depends to a large extent upon irrigation from major river systems. Cotton growing in the vicinity of the township of Bourke is a particular example. With an average annual rainfall of 360 mm, cotton growing succeeds by making use of irrigation from the nearby Darling River. This river also provides water for the city of Broken Hill further downstream and forms part of a major complex river system ultimately that provides water for the city of Adelaide, the capital of the state of South Australia. The Darling River itself receives major inflows from seasonal rains in Queensland, and in dry years can run at very low levels or stop flowing altogether, leading to increased salination of the water supplies of the cities downstream. Consequently, additional demands on the river made by irrigation must be carefully controlled. In New South Wales such control is exercised by the issue of irrigation licenses to farmers. It is then necessary to monitor their usage of water to ensure licenses are not infringed. This, of course, is the situation in many parts of the world where extensive irrigation systems are in use.

The water demand by a particular crop is very closely related to crop area, because most water taken up by a plant is used in transpiration (Keene and Conley, 1980). As a result, it is sufficient to monitor crop area under irrigation as an indication of water used.

There are several means by which irrigated crop area inventories can be performed. One is to depend upon information supplied by farmers who make use of irrigation. This can suffer in accuracy and timeliness owing to the need to coordinate and expedite a large number of farmer returns, all provided with perhaps varying degrees of objectivity. A second method, and one which is widely used, is to employ so-called extension officers who visit the regions under irrigation and make assessments of irrigated areas. This can be both expensive and time consuming; moreover, it is possible that patterns of irrigation could change over the period required to complete field visits.

* Mr. Moreton passed away on 22 October 1982, before this paper was completed. He is missed sadly by his many friends and colleagues in the Australian remote sensing community.

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A third means by which crop area under irrigation could be determined is to make use of image data of some sort. Aerial photography would in general have to be acquired for a given project and thus would be an expensive avenue to follow. However, imagery from remote sensing satellites is a viable medium for area inventories owing to its timeliness and to its relatively low cost. The spatial resolution of the Landsat Multispectral Scanner (0.4424 ha) is sufficient to permit crop area inventories in most circumstances with sufficient accuracy, and the wavelength bands employed can generally provide the necessary ground cover type discrimination. This paper is addressed to this approach.

Landsat Multispectral Scanner (MSS) image data have been used by several investigators to determine irrigated crop area. Draeger (1977), Heller and Johnson (1979), Keene and Conley (1980), and Thiruvengadachari (1981) have used photointerpretation of bands 4, 5, and 7 color composite Landsat MSS image products at scales of 1:1,000,000 and 1:250,000. In principle, photointerpretation as a means for identifying irrigated cropland works well owing to the marked color contrast of healthy irrigated fields and the (semi-arid) background. Moreover, a human analyst/interpreter is able easily to ignore other regions of healthy vegetation not associated with crops, such as those bordering streams. These investigators reported accuracies of between 4 percent and 10 percent which, for most requirements, would be adequate. However, analyst time required is excessive, ranging up to 200 man hours.

Keene and Conley (1980) have also employed digital analysis methods to determine areas. In particular they chose a band 5 MSS image in which healthy irrigated fields normally show as substantially darker than their surroundings. They then performed a density slicing of the brightness values in this image in order to count the number of pixels with brightness below a predetermined threshold. While this method can be fast compared with photointerpretation, its accuracy suffers if there are other cover types present in the image which also appear dark in band 5; these would include background vegetation in regions of moderate rainfall, and water bodies. Accuracy also depends upon the value of the slicing threshold used.

An alternative approach, utilizing satellite imagery, is to employ classification of more than one band of data to ensure acceptable discrimination of irrigated fields from other cover types. It is the intention of this paper to describe an investigation of classification procedures used for irrigated crop inventory, based upon two software/hardware systems. One is the ORSER package developed at Pennsylvania State University, and the other is the combined applications software and interactive hardware of a Dipix Aries II image analysis system. With these in mind, the specific intentions of the paper are

- to report the results of the study and thereby allow a comparison to be drawn with the image based methods of other workers and with more traditional techniques for gathering irrigated area information,
- to present a comparison of the approaches adopted using ORSER (as a dial-in bureau image processing service) and the Dipix system (as a dedicated interactive facility), and
- to provide a case study of the use of combined unsupervised/supervised classification methodologies.

Methodologies for Image Classification

Successful utilization of supervised classification procedures depends upon having determined beforehand the spectral structure of the data. Often, the simple approach of choosing training data by field studies is not sufficient, in the case of maximum likelihood classification, to ensure that the data have been resolved correctly into a set of single Gaussian modes that will yield accurate results. By comparison, unsupervised classification using clustering is a convenient and usually reliable means by which single modes (or so-called spectral classes) can be determined. However, it is an expensive procedure and is not often used in place of supervised maximum likelihood classification except on small images. Other supervised methods, such as minimum distance (to class means) classification, also depend for their success upon having discovered the structure of the data spectrally. To a first approximation, the spectral classes used naturally by minimum distance classification are hyperspherical and, unless the spectral domain is resolved into sets of non-overlapping approximate hyperspheres, error can result in applying this classifier. Again, clustering is a useful procedure for determining data structure as a precursor to classification.

While straightforward supervised and unsupervised methods are used extensively and show very good results, a more reliable approach is to use the hybrid supervised-unsupervised (modified clustering) approach recommended by Fleming *et al.* (1975), in which clustering is used on a representative and heterogeneous subset of data to discover the spectral modes necessary for use with a supervised algorithm. In this, a set of regions in the image is chosen for clustering such that all apparent cover types (information classes) are present and so that each region contains several cover types. In this way any significant boundary modes will be detected. Application of clustering then produces not only an identification of the spectral classes but also their statistics or signatures. Once these spectral classes have been associated with ground cover types by use of reference or field data, then supervised classification of the full image is carried out.

The hybrid approach is adopted in this paper. In one case the supervised algorithm is of the minimum distance variety whereas in the other it is a maximum likelihood procedure.

Systems Available to the Project

CSIRO-ORSER

The ORSER software package, developed at Pennsylvania State University, is available in Australia as CSIRO-ORSER via the CSIRO computer network CSIRONET . Access is obtained generally over 300 baud telephone lines by means of dial-up modems. Input/output, therefore, is often accomplished using a single terminal such as a Decwriter, which has significant implications both for producing thematic maps and for locating features in images. The restricted image width of 132 pixels (characters) means that only small image or map segments can be displayed conveniently.

CSIRO-ORSER , at the time of the project, did not have a maximum likelihood algorithm implemented. Consequently, supervised results were obtained using a minimum distance classifier.

The CSIRO-ORSER clustering procedure is of the single pass variety and requires the user to enter parameters which seed the generation of, and control the size of, the clusters found. A little experience is required to use this algorithm effectively, but once mastered it can be used to determine data structure very readily.

DIPIX ARIES II A2ASP

Both authors' institutions possess a Dipix Aries II image analysis system which supports an applications software package known as A2ASP . This includes a maximum likelihood classification algorithm along with a clustering procedure based upon peak selection in multidimensional histograms. This clustering algorithm also requires considerable care to use and can give misleading results if due consideration is not given to the mechanism by which it delineates clusters.

The CSIRO-ORSER Based Study

THE STUDY REGION

A band 7 Landsat Multispectral Scanner image of the region considered in the study, consisting of 927 lines of 1102 pixels, is shown in Figure 1a. This is a portion of scene number 30704-23201 acquired on February 1980 (Path 99, Row 81). Irrigated cotton fields are clearly evident in the central left and bottom right regions, as is a further crop in the top right. The township of Bourke is just south of the Darling River, just right of the center of the image. The white border encloses a subset of the data, shown enlarged in Figure 1b. This smaller region was used for signature generation in both the ORSER and DIPIX approaches.

CLUSTERING

Figure 2 shows the location of four regions selected for clustering using the ORSER single-pass algorithm. A fifth clustering region was chosen which partially included the triangular field in the bottom right region of Figure 1a. These regions consist of up to 500 pixels each and were selected so that a number of the irrigated cotton fields were included, along with a choice of most of the other major ground covers thought to be present. These include bare ground, lightly wooded regions, such as trees along the Darling River, apparently non-irrigated (and/or fallow) crop land, and a light colored sand or soil.

Each of the regions shown in Figure 2 was clustered separately. With the parameters entered into the ORSER clustering processor, each region generated between five and 11 spectral classes. The centers of the complete set of 34 spectral classes were

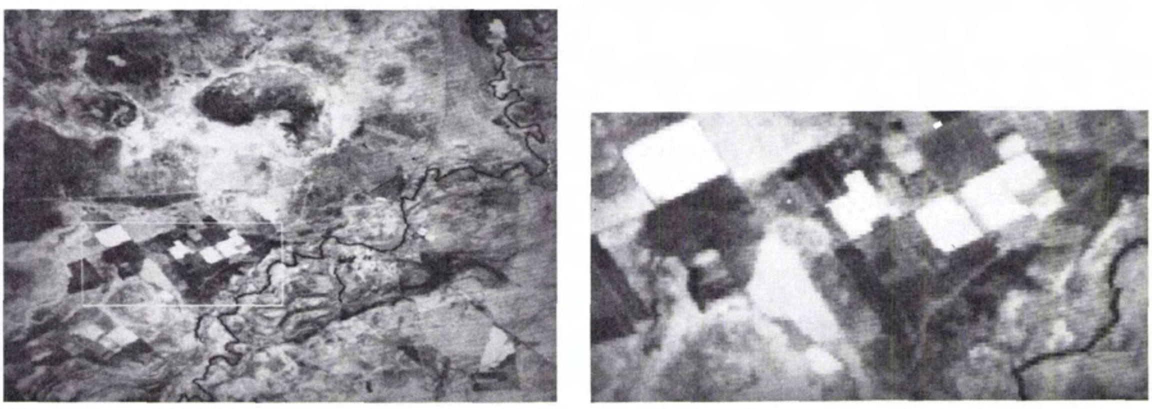

FIG. 1. (a) Band 7 Landsat MSS image of the region of the investigation, showing irrigated fields (white). The area enclosed by the white border is shown expanded in (b) and was used in signature generation.

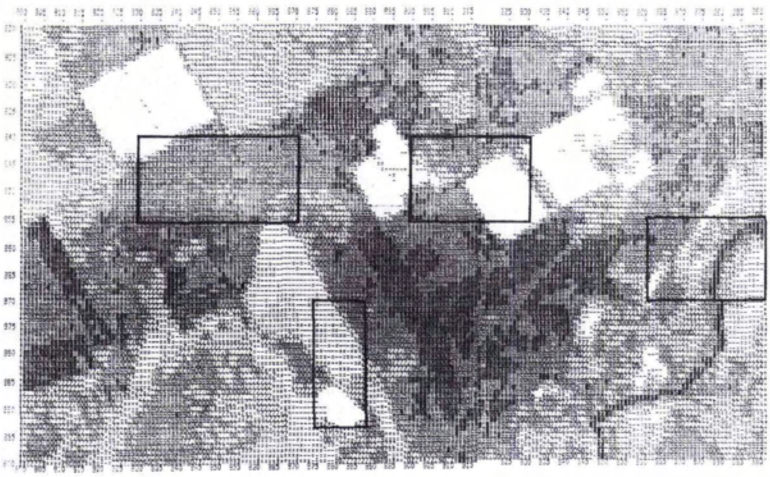

FIG. 2. Line printer map (band 7) of the region shown in Figure 1b, with cluster regions indicated by the black borders.

then located on a bispectral plot. Generally, such a plot consists of the average of the visible components of the cluster means (Landsat bands 4 and 5) versus the average of the infrared components (bands 6 and 7). In this exercise, however, owing to the well-discriminated nature of the data, a band 5 versus band 7 bispectral plot was used; moreover, the subsequent classification also made use only of bands 5 and 7. This reduced the cost of the classification phase; however, the results obtained suggest that accuracy was not prejudiced. The band 5 versus band 7 bispectral plot showing the clustering results is illustrated in Figure 3.

At this stage, it was necessary to rationalize the number of spectral classes and to associate spectral classes with ground cover types (so-called information classes). While a sufficient number of spectral classes must be retained to ensure classification accuracy, it is important not to have too many, because the number of class comparisons, and thus the cost of a classification, is directly related to this number. Because the classifier to be employed was known to be of the minimum distance variety, which implements linear decision surfaces between classes, spectral classes were grouped together into approximately circular groups (provided they were from

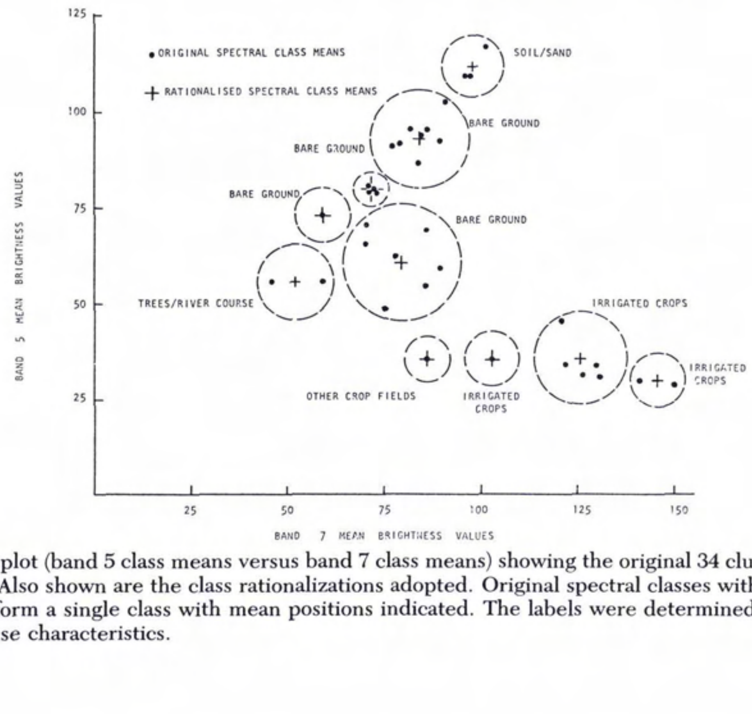

FIG. 3. Bispectral plot (band 5 class means versus band 7 class means) showing the original 34 cluster centers (spectral classes) generated. Also shown are the class rationalizations adopted. Original spectral classes within the dotted circles were combined to form a single class with mean positions indicated. The labels were determined from reference data and spectral response characteristics.

the same broad cover type) as shown in Figure 3. In this manner, the number of classes was reduced to ten. Labels were attached to each of those (as indicated in Figure 3) by comparing cluster maps to black-and-white and color aerial photography, and to band 7 line printer maps of the satellite data. The relative band 5 and band 7 brightness values were also employed for class recognition; fields under irrigation were evident by their low band 5 values (~30 on a scale of 255, indicating high chlorophyll absorption) accompanied by high band 7 reflectance (~100 to 150, indicating healthy, well-watered vegetation).

SIGNATURE GENERATION

Signatures for the rationalized spectral classes were generated by averaging the means of the constituent original set of spectral classes. This was done manually, and is an acceptable procedure for the classifier used. Minimum distance classification makes use only of class means in assigning pixels and does not take any account of class covariance data. On the contrary, maximum likelihood classification incorporates both class covariance matrices and mean vectors as signatures, and merging of constituent spectral class signatures to obtain those for rationalized classes cannot readily be done by hand. Rather, a routine that combines class statistics, such as MERGESTATISTICS available in LARSYS, is required (Phillips, 1973). Such a facility is not available in CSIRONET-ORSER (CSIRO-ORSER Users Manual, 1979). The rationalized class means are indicated in Figure 3.

CLASSIFICATION AND RESULTS

With spectral class signatures determined as above, Figure 1a was checked for crop fields that indicated use of irrigation. A classification map of the Figure 1b (6,957 ha) region is shown in Figure 4. Fields under irrigation are clearly discernible by their shape, as well as by their classification. By retaining several other ground-cover types as separate information classes (rather than giving them all a common symbol representing 'non-irrigated'), other geometric features of interest are evident. For example, the Darling River is easily seen, as are some neighboring fields that are not irrigated. This was useful for checking the results of the classification against maps and other reference data.

The results of the classification agreed remarkably well with ground-based data gathered by field officers of the New South Wales Water Resources Commission and the New South Wales Department of Agriculture. In particular, for the region of 169 651 pixels (75,000 ha) shown in Figure 5, a measure of 803 ha given by the classifier as being under irrigation agreed to better than 1 percent with that given by ground data. This is well within any experimental error that could be associated with the classification and with the uncertainty regarding pixel size (in hectares), and is consistent with accuracies reported by some other investigators (Tinney *et al.*, 1974).

CONCLUDING REMARKS

In general, the combined clustering/supervised classification strategy adopted here works well as a means for identifying a reliable set of spectral classes upon which a classification can be based. The clustering phase, along with a construction such as a bispectral plot, is a convenient and lucid means by which to determine the structure of image data in multispectral space; this would especially apply for exercises that are as readily handled as those described here. The rationalized spectral classes used in this case correspond not so much to unimodal

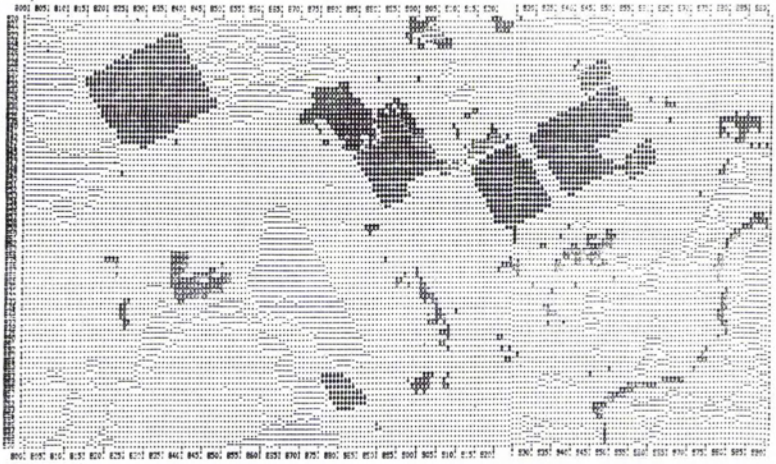

FIG. 4. Classification map of the region of Figure 1b generated using the ORSER software package. Class symbols used are: * irrigated crops; + other crop fields, × trees/river course; − soil/sand; • bare ground.

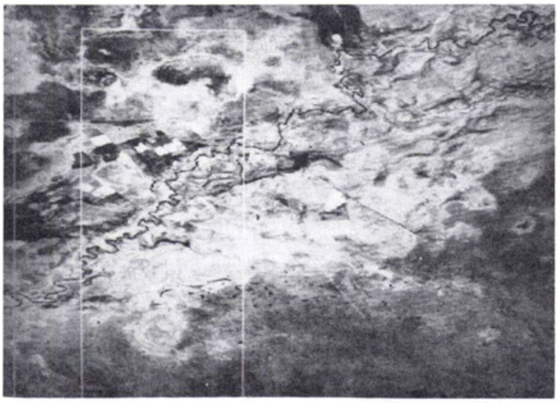

FIG. 5. Region (enclosed in white border) used to assess accuracy of classification using field data.

Gaussian classes normally associated with maximum likelihood classification, but rather are a set that match the characteristics of the minimum distance classifier employed. This is an important general principle: the analyst should know the properties and characteristics of the classifier he is using and, from a knowledge of the structure of the image, choose spectral class descriptions that match the classifier.

THE DIPIX A2ASP APPROACH

A major disadvantage with the ORSER approach to the investigation was the difficulty in locating regions in the image of interest using line printer output. By comparison, using the interactive color display subsystem of a Dipix system, positional location is straightforward.

SIGNATURE GENERATION

Again, only band 5 versus band 7 two-dimensional spectral data were employed for signature generation on the sub-area of Figure 1b. Clustering was used to generate the spectral classes; however, the Dipix histogram peak selection method was not easily controlled when using only two bands. It displayed a tendency to place class means along a line between the river and soil regions in the band 5 versus band 7 scatter diagram and tended to miss the obviously irrigated vegetation classes out along the band 7 axis in Figure 3.

Instead of using clustering on the full range of spectral data in one pass, the following procedure was used and led to an acceptable set of unsupervised signatures. It was based upon foreknowledge of the bispectral plot in Figure 3 but could have been based upon a scatterplot of the data from Figure 1b, along with a sampling of the lower triangular field in Figure 1a. Figure 6 shows the bispectral plot of Figure 3 with four distinct spectral regions identified. Three correspond to well defined irrigated classes and the fourth to remaining cover types as indicated. Clustering was used to generate six classes in the last zone by limiting the (two-dimensional) spectral range over which the histogram of data was constructed. Only one class was generated for each of the other three spectrally limited zones. These classes, which can be identified as 'irrigated' by reference to the image data, could have been generated by parallelepiped classification; however, clustering was used to ensure that the regions chosen correspond acceptably to single Gaussian spectral modes.

CLASSIFICATION AND RESULTS

Together, all regions gave nine spectral classes, the signatures for which were used in a maximum likelihood classification of the image segment of Figure 1b. The classification map so generated is shown in Figure 7. Only the three irrigated classes are shown (as white), with the other six cover types not shown. For the larger region of Figure 5, maximum likelihood classification based upon the set of signatures generated above gave an irrigated area of 765 ha. This is within 5 percent of the figure obtained by field personnel and of the value obtained by the ORSER study.

USE OF A VEGETATION INDEX

A classification exercise as moderately straightforward as detection of irrigated crops in an arid or semi-arid background is easily handled by the construction of a simple vegetation indicator. As a cross check of the previous results, a simple band 7 divided by band 5 index was set up. This shows vegetated regions as bright and other regions (including sand) as dark. This ratio for Figure 1b is shown in Figure 8. Classification amounts to single dimensional parallelipiped classification by determining a value of the ratio that is a transition between the irrigated and non-irrigated classes. On an interactive image processing system, such as the Dipix Aries II, such a transition is easily established by using a test area such as that in Figure 1b, and color density slicing it. The Dipix allows color density slicing, of data stored in the system's video memory, in real time. Consequently, a large number of trials can be carried out to determine a transition that slices the fields from the background in an acceptable manner using the ratio data. This transition can then be used in parallelepiped classification of the full image data of interest, which is generally too large to be accommodated in video memory. This procedure was adopted for this investigation as well and led to results for Figure 5 of 860 ha of irrigated crops. Agreement with field studies is to within 8 percent.

CONCLUDING REMARKS

The availability of an interactive image processing system makes an investigation such as the present

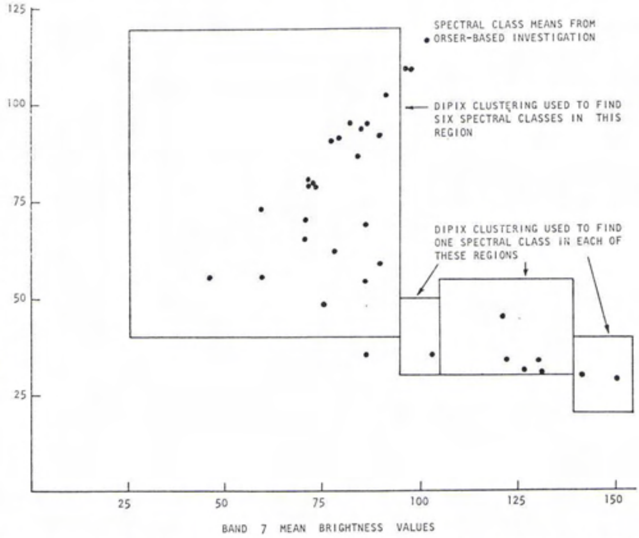

FIG. 6. Bispectral plot of the original class means developed in the ORSER-based approach by clustering, showing also the spectrally-limited zones used for spectral class determination in the DIPIX study.

one quite simple, with several alternative approaches available. Finding regions of interest in the image is straightforward, and real time manipulation of image data, such as color density slicing, using the display subsystem means user familiarity with the particular data under consideration can be gained quickly. The trade-off, however, is that the user requires expertise to operate such a system and to utilize its hardware and software effectively. This is particularly so with the clustering technique available on the Dipix system.

CONCLUSIONS AND COST COMPARISONS

With the limited and diverse data available, it is difficult to carry out an accurate comparison of cost-effectiveness of irrigated crop inventory using classification as against photointerpretation or ground studies. However, some general comments of interest can be made, and these form the basis of a rough comparison.

The accuracies of the classification results (1 percent to 5 percent) are as good as those obtained by photointerpretation as reported by Heller and Johnson (1979) and Keene and Conley (1980) (5 percent to 10 percent), when the classification is based upon both band 5 and band 7.

Although a particularly fast method, the use of band 7/band 5 ratio as a vegetation index gave slightly poorer accuracy. More importantly, it depended critically on a careful choice of the threshold value of the ratio which separates irrigated and non-irrigated cover types. This approach is not pursued further in these remarks, but rather, the following apply to the classification of two-dimensional image data.

Both the ORSER and DIPIX based approaches described required approximately 20 hours of analyst

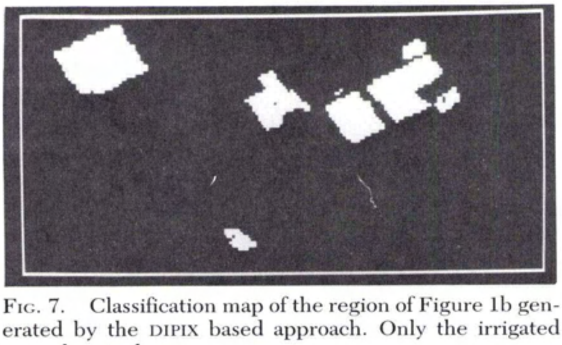

FIG. 7. Classification map of the region of Figure 1b generated by the DIPIX based approach. Only the irrigated crop class is shown.

FIG. 8. Band 7/band 5 ratio of the region of Figure 1b generated with the real time look-up table manipulation facilities of the DIPIX image analysis system.

time. In the former, a large portion was used in locating the study areas using line printer image products. This step was almost insignificant using the Dipix system; however, with the Dipix a considerable amount of the time was taken in deriving suitable class signatures by clustering with the algorithm available. It is conjectured that if a more controllable algorithm could be used on the Dipix for signature generation, then this approach would have taken perhaps only 10 to 15 hours of interactive and batch computing. This would then be the preferred approach. An appropriate clustering procedure would be the migrating means technique adopted in LARSYS (Phillips, 1973), or even the ORSER single pass algorithm.

To make a cost comparison with other studies and methodologies, it is necessary to consider the areas inventoried. To provide a basis for comparison, the number of minutes of analysis time required per 4050 ha (10,000 acres) is used in Table 1 as a means for approximate relative assessment of a number of approaches. A direct dollar cost comparison has been avoided owing to differences in exchange and inflation rates.

From the table it is noted that there is a wide variation in the 'cost' for inventorying by photointerpretation, for results of comparable accuracy. This variation is possibly attributable to relative discrimination difficulties with different data sets, but is probably related also to biases introduced by the relative sizes of the test areas reported. Apart from the results of 3.4 min/4050 ha of Thiruvengadachari (1981), reported for only 6,000 ha, the classification approach of this paper is of comparable or better cost effectiveness. The best approach seems to be the image analysis method used by Keene and Conley (1980) in which a single band is density sliced into irrigated and non-irrigated classes (akin to the vegetation index approach herein). However, accuracy was not reported for that technique. Moreover, it suffers when only a single band is used because non-irrigated and irrigated covers can have similar brightness.

The ORSER based study of this paper was carried out as a professional consulting project at a total cost of approximately $4,000 Australian, in 1983 terms. This represents about $55 (1983) per 4050 ha (10,000 acres), inclusive of data costs, analyst time, computing costs, and other overheads. It would be interesting to compare this to the cost of obtaining the information by ground personnel. Unfortunately, this was not possible in the present situation. However, an interesting comparison can be drawn by considering results from a study by Jensen *et al.* (1975).

They report conventional survey costs (in equivalent 1983 Australian dollars) of approximately $120 per 4050 ha; this is a factor of two higher than the remote sensing based study reported herein. This factor is not inconsistent with the cost savings of remote sensing over and above traditional ground based techniques reported by others. For example, for five selected projects documented by Solomon and Maher (1979), the factors range between 1.9 and 4.4.

A cost component which did not enter into the present study is that associated with geometric correction of the image data. This was not necessary because the crop fields of interest were well delineated, but, more importantly, accurate thematic mapping was not required. Should this not be the case, then the cost of rectification would need to be added.

The major limitation of classification as a procedure for projects such as irrigated crop inventory seems to be that appropriate analytical skills are required along with expertise in using digital image analysis equipment. Despite this, classification

TABLE 1. 'COST' COMPARISONS OF VARIOUS PROCEDURES FOR IRRIGATED CROP INVENTORY

METHOD	AREA* (ha)	TIME (hr)	'COST' (min/4050ha)	ACCURACY (percent)
Photointerpretation (Heller & Johnson, 1979)	271,500	15	13.4	$6 \rightarrow 10$
Photointerpretation (Thiruvengadachari, 1981)	6,000	0.083	3.4	4
Photointerpretation (Draeger, 1977)	1,480,000	84	13.8	$4 \rightarrow 7$
Photointerpretation (Keene and Conley, 1980)	813,300	200	60	~5
Image Analysis—1 band (Keene and Conley, 1980)	226,900	1	1	not given
Classification—ORSER (This study)	295,424	20	16.5	~1

* The area given in this column is not necessarily the complete area inventoried in the project but rather is an area reported in conjunction with times, thereby allowing 'cost' to be calculated.

yields results of high accuracy with good cost effectiveness, as demonstrated above. In addition, thematic maps can also be produced readily, and incremental costs for additional areas surveyed (once signatures have been generated) are probably significantly lower than by photointerpretation. These would seem to justify the method, and if skills are not readily available, image analysis consultants can be used, this being particularly cost effective when complete project costs are taken into account.

The project reported upon in this paper has been based upon a water resources study in which it was important to know crop areas irrigated but in which crop type discrimination was not significant. Consequently, the classification strategy was straightforward and, as noted, cost effective. Moreover MSS sensor resolution was acceptable to ensure good accuracy for crop fields of the size typically encountered in western New South Wales.

Should crop discrimination be a consideration, then the classification methodology would need substantial refinement to allow a finer segmentation of the spectral domain. Often, this refinement can add significantly to overall project costs. Instead, a more cost-effective approach might be to follow the methods adopted in this paper for an initial stratification of the image data into crop and non-crop regions and then use a second level of sampling to enable crop discrimination within the regions identified as crops. The latter could be carried out by field personnel or by aerial photography.

Acknowledgments

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References

CSIRO-ORSER Users Manual, 1979. CSIRO Div. of Computing Research, Canberra, A.C.T.

Draeger, W., 1977. Monitoring irrigated land acreage using Landsat imagery: An application example. *Proc 11th Int'l Symp. on Rem. Sens. Environ.* Michigan, pp. 515-524.

Fleming, M. D., J. S. Berkebile, and R. M. Hoffer, 1975. *Computer aided analysis of Landsat-1 MSS data: A comparison of three approaches including a modified clustering approach*, LARS Information Note No. 072475, Laboratory for Applications of Remote Sensing, Purdue University, West Lafayetta, Indiana.

Heller, R. C., and K. A. Johnson, 1979. Estimating irrigated land acreage from Landsat imagery, *Photo. Eng. and Rem. Sens.* 45, 1379-1386.

Jensen, J. R., L. R. Tinney, and J. E. Estes, 1975. Analysis of the accuracy and cost-effectiveness of a cropland inventory utilizing remote sensing techniques, *Proc. 10th Int'l Symp. on Rem. Sens. Environ.*, Michigan, pp. 1149-1158.

Keene, K. M., and C. D. Conley, 1980. Measurement of irrigated acreage in western Kansas from Landsat images, *Environ. Geol.*, 3, 107-116.

Phillips, T. L. (Ed.), 1973. *LARSYS User Manual*, LARS, Purdue University, West Lafayette, Indiana.

Solomon, S., and K. M. Maher, 1979. *An economic analysis of five selected Landsat assisted information systems in Oregon*, NASA OSTA Contract No. NASw-2800, Task No. 30.

Thiruvengadachari, S., 1981. Satellite sensing of irrigation patterns in semi arid areas: An Indian study, *Photog. Eng. Rem. Sens.*, 47, 1493-1499.

Tinney, L. R., J. E. Estes, K. H. Thaman, and R. R. Thaman, 1974. Operational use of satellite and high altitude remote sensing for the generation of input data for water demand models, *Proc. 9th Int'l Symp. on Remote Sensing Environ.*, Michigan, pp. 739-757.

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