Digital Analysis of Multitemporal Landsat Data for Land-Use/ Land-Cover Classification in a Semi-Arid Area of Nigeria

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ABSTRACT: This paper focuses on computer-assisted analysis of multitemporal Landsat data of a semi-arid area of Nigeria to examine the possibilities and constraints of digital classification of land use/land cover. The procedure followed includes sub-area creation, image to grid and image to image registration, various enhancement techniques, and a supervised classification technique (maximum likelihood).

Although individual crops could not be mapped owing to land management practices in the area as well as the limitations imposed by the characteristics of the data, the nine broad land-use/land-cover classes established were tested and found to be separable and statistically accurate at above 85 percent. The results indicate that best Landsat acquisition periods for the study area are January/February (for dry season inventory) and August/September (for wet season inventory). Differences in densities of tree canopies, mixed cropping of small farm plots, varying ground moisture conditions, and atmospheric attenuation are factors to be considered in mapping land use/land cover of the study area.

INTRODUCTION

One of the serious problems inhibiting the process and progress of development in Nigeria is the lack of basic resource information (FAO, 1966; Mabogunje, 1978; Hunting Technical Services Ltd., 1981; ILO, 1981; Areola, 1982; Hildreth *et al.*, 1984; Adeniyi, 1979, 1984a). Two basic causes of this problem are (1) the national perception of resources and (2) the "inadequate" recognition, and consequently, "unavailability" of modern procedures for the collection and presentation of basic resource information.

It is generally and locally believed that Nigeria is blessed with a plentiful supply of land. This perception has led to the false philosophy of inexhaustibility as well as the failure to recognize that neither the environment as such nor parts of the environment are resources until they are capable of satisfying human needs (Zimmermann, 1951). Because resources only become available to a society through the combination of increased knowledge and expanding technology, the presence of abundant land area in Nigeria is nothing more than "neutral stuff" until means are devised to apprise and evaluate the lands prior to their utilization.

Remote sensing technology has revolutionized the methodology of resource surveys. In Nigeria, this method has been applied largely through *ad hoc* arrangements. Most applications have been based on visual analysis of imagery (Bejarano and Okoye, 1979). In spite of these *ad hoc* arrangements, much research is still needed to document the possibilities and constraints of applying remotely sensed data, especially Landsat MSS data, to resource surveys in Nigeria.

The main objective of this paper, therefore, is to examine the applications of computer-assisted analysis of multitemporal Landsat MSS data for land-use/land-cover classification of a semi-arid area of Nigeria. Specifically, the paper investigates the possibilities and the constraints of digital classification of land use/land cover during both dry and wet seasons with a view to providing general guidelines for operational procedures.

THE STUDY AREA

The Bakolori irrigation project area, located in the Talata Mafara and Maradun local government areas of Sokoto State, is selected for this study. The area (97650 hectares), located within the Sokoto-Rima Basin, lies approximately within longitudes 5°53′E and 6°20′E and latitudes 12°30′N and 12°50′N (Figure 1).

The area is semi-arid with mostly hot and dry weather which creates two distinct seasons—prolonged dry season (October to May) with a short wet season (end of May to early October). While

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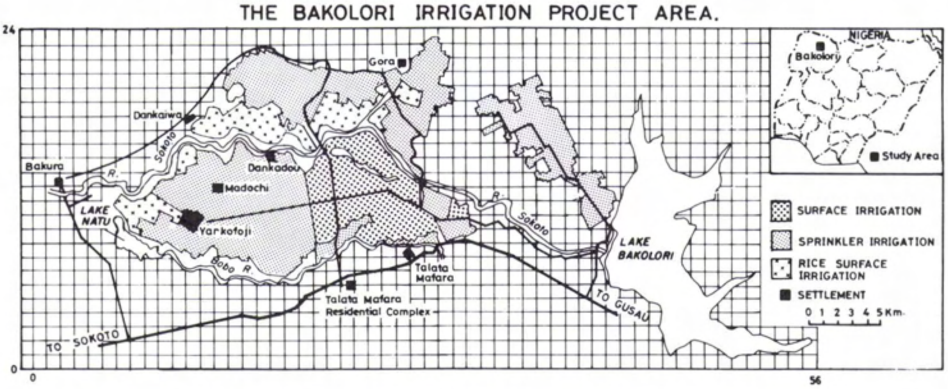

FIG. 1. A design and the location map of the Bakolori Irrigation Project Area. (Note: The expected size of the Bakolori reservoir is shown on the map. The size and shape of the reservoir as of 10 June 1980 is shown in Figure 3 (bottom) and Plate 1. The grid interval is one kilometre.)

over 75 percent of the annual rain falls between July and September, November to February are virtually without rain. Within the Sokoto-Rima Basin, the wet season varies from 180 days in the south (Yelwa area) to less than 110 days in the north. The mean annual potential evapotranspiration is over 1800 mm while the mean annual water deficit is above 750 mm (Adejuwon, 1971). Thus, although temperatures are generally sufficient in the dry season to allow plant growth, insufficient rainfall and high evapotranspiration limit cropping activities, without irrigation, to the wet season.

The study area lies wholly within the Sudan Savanna belt. The Sudan Savanna is dominated by mixed woodland—a vegetation of small trees with light canopies. The grasses are generally short (1 to 1.5 m) except the acquatic types. Gallery forests, called thickets, are found along rivers.

The traditional activity of most of the people in the basin is subsistence agriculture and herding. There are two forms of farming activities—permanent cropping and once-a-year cropping. Year round farming is carried out in the low-lying areas that are subject to seasonal flooding or water-logging along the banks of rivers or depressions (such areas are locally called "fadama"). The once a year farming is carried out in the old terraces adjacent to the fadama land. Crops such as maize, cotton, millet, guinea corn, cowpea, and groundnut are grown. Farm sizes are generally small, ranging from 0.2 ha to 0.9 ha in the fadama areas while the average for the upland is about 0.53 ha (Iliya and Sidhu, 1982). However, households may have several of these plots scattered between the upland and the fadama areas.

The Bakolori project area is designed to provide irrigation water for 23,200 ha (net) out of which 33.6 percent will be served with surface irrigation and the rest by sprinkler irrigation. Out of the area to be served with surface irrigation (7,800 ha), about 41 percent are planned to be used for rice production. Farm plots vary from 0.25 to 1 hectare and 0.16 to 0.5 hectare for the surface and sprinkler irrigation areas, respectively. The farmers are given as many plots as the number they had before or as they could cope with, but the plots are also scattered all over the project area (Iliya, 1981). Thus, fragmentation prevalent prior to the project is still maintained.

METHODOLOGY

DATA SOURCES AND THEIR CHARACTERISTICS

Table 1 shows the type and characteristics of the data sources used in this study. Multitemporal Landsat computer compatible tapes (CCTs) were the primary sources of data. The available dry and wet seasons Landsat CCTs were acquired for the digital classification and mapping of land use/land cover during the two seasons.

Radar mosaics (1:250,000) and vegetation maps derived from them were used to delimit the study area. The radar mosaic depicts clearly the broad landform types and the major settlements.

Aerial photographs and topographic maps cover only the western half of the study area. The topographic map (sheet 31) for the eastern half of the study area was still under compilation. The Bakolori irrigation project design map (redrawn and shown in Figure 1) was used for general orientation and for the geometric registration of the Landsat subscenes covering the study area. In addition to these data sources, two brief reconnaissance surveys of the study area were carried out in December 1983 prior to the analysis and in September 1984 after the digital processing.

IMAGE ANALYSIS SYSTEM

The main processing of the multitemporal Landsat MSS data was carried out on the Dipix image system (A Resource Image Exploitation System-

TABLE 1. DATA SOURCES AND THEIR CHARACTERISTICS

Type	Date	Scale	Cloud	Quality	Code	Aquisition Source
Landsat-1, MSS (CCT)	7 Nov 1972	1:3,369,000	0%	5888	8110709255500	Eros Data Centre, Sioux Falls, SD. U.S.A.
Landsat-2, MSS CCT	7 Dec 1975	1:3,369,000	0%	8888	8231909120500	Federal Dept. of Forestry, Ibadan (Nigeria)
Landsat-3, MSS CCT	10 Jun 1980	1:1,000,000	10%	5555	83082809062X0	Federal Dept. of Forestry, Ibadan (Nigeria)
X-band (3 cm) Radar Mosaic	Nov 1976	1:250,000	—	—	ND31-16 and ND32-13	Federal Dept. of Forestry, Ibadan (Nigeria)
Vegetation Map	1978	1:250,000	—	—	ND31-16 and ND32-13	Federal Dept. of Forestry, Ibadan (Nigeria)
Aerial Photos (Black and White)	Nov 1976	1:25,000	—	—	Sheet 30	Federal Survey Dept. Lagos (Nigeria)
Topographical Map	Puld 1978 Based on 1962 Air Photos	1:50,000	—	—	Sheet 30 S.E.	Federal Survey Dept. Lagos (Nigeria)
Bakolori Irrigation Project Design Map	NA	1:100,000	—	—	—	SRDDA Project office, Talata Mafara, Sokoto State, (Nigeria).

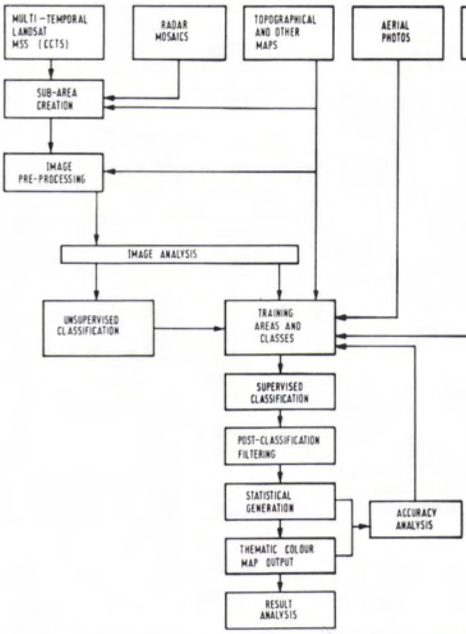

FIG. 2. A flowchart of the procedure for interactive digital image processing.

ARIES II) at the Faculty of Environmental Studies, University of Waterloo, Waterloo, Ontario, Canada. Part of the processing was also carried out on the Image Analysis System (CIAS) at the Canada Centre for Remote Sensing (CCRS) in Ottawa. CIAS and Dipix descriptions have been given by Goodenough (1979) and Shindler (1982), respectively. Figure 2 illustrates the procedure followed.

SUB-AREA CREATION

The whole Landsat scene for each date was loaded into the VMA (Video Memory Array), then viewed through the color monitor (CM). With the use of cursor and roam functions on the bit-pad of the Dipix system, line and pixel coordinates of the top left and the bottom right corners were recorded. The vegetation map and the Bakolori project design map were consulted for the choice of the corners. The sub-area so created contained original radiometric data. The first sub-area for each date was made larger than the area of interest. After the sub-areas had been geometrically corrected, new sub-areas were then created through the same procedure.

GEOMETRIC CORRECTION

Two forms of geometric corrections were carried out: (i) Image to grid and (ii) image to image.

Image to grid registration requires visual identification of identical points on the image and on the map. Coordinates of points identified on the map (Eastings and Northings) are then used for the polynomial transformation. Because the study area had not been completely covered by topographic maps and the vegetation map covering the area had only the Northings, the gridded 1:100,000 project design map (Figure 1) was therefore used for the registration. The grid interval on the map is 1,000 m.

The 1980 Landsat MSS which was relatively and temporally compatible to the design map was registered to the map grid. The map contained fewer roads than the image and some of the roads on the map were not visible on the image. In addition to using road intersections, some other landmarks were also used.

Geometric registration was carried out using the image registration and resampling package of the Dipix system. After several attempts, 17 points were used with the third-order polynomial transformation. The standard error of pixel estimate is 40.52 m and that for the line is 37.99 m. Thus, image to grid registration was accomplished with an error of less than 50 m. The original pixel ground resolution was then resampled to 50 m by 50 m.

The image to image registration follows the same procedures as the image to grid except that, instead of reading the coordinates of points from a map, the cursor is placed on the identical points identified on the slave image (i.e., the image to be registered) and the master image which have been loaded automatically by the image to image registration program.

The 1975 and 1972 Landsat MSS images were individually registered to the geometrically corrected 1980 image. The image to image registration program allows only one Landsat band from each of the two Landsat MSS data to be loaded onto the CM. The registration was time consuming because of the following reasons: (1) the master image was a wet season image whereas the two to be registered were dry season images; (2) the change in land use, consequent on the irrigation project, had altered the land cover on the 1980 image (the roads in the master image were absent on other images), (3) the shape of the river that crosses the area was, in several places, different owing to natural movement of the channel, and (4) use of only one band each from each Landsat MSS image further enhanced the above problems (see Figures 3 and 4).

In spite of these problems, 20 and 22 points were used for the 1980/1975 and 1980/1972 registrations, respectively. The standard error of estimates for pixel and line are 1.14 and 1.0 respectively for 1980/1975 and 0.99 and 0.94 for the 1980/1972. The accuracy achieved for the geometric registration of the multitemporal Landsat MSS data is comparable to the 1 to 2 pixels achieved by other researchers (Rasmussen, 1982; Zafiryadis, 1982). However, the accuracies reported here seemed not to be uniform for the whole subscene. This non-uniformity is perhaps caused by the distribution of the points which, in turn, is influenced by the reasons already given

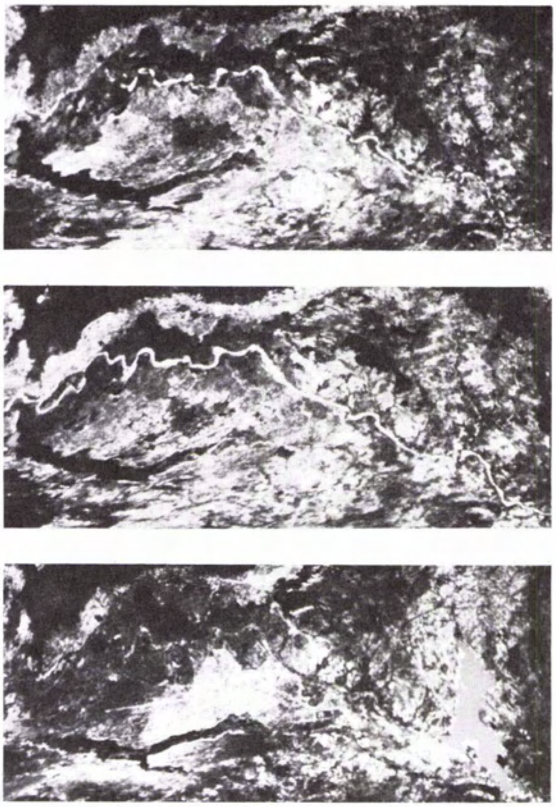

FIG. 3. Geometrically corrected composite (multitemporal) Landsat images of the study area. Upper image, 7 November 1972; middle image, 7 December 1975; bottom image, 10 June 1980. (These images are reproduced from the original color composites.)

above. Also, it should be noted that the accuracy of the image to image registration, executed in this study, is a function of the accuracy of the master image.

IMAGE PROCESSING

Various digital image processes, including enhancement techniques and unsupervised and supervised classification techniques, were carried out (see Adeniyi (1984b) for details). This paper reports the supervised classification technique only.

Supervised classification involves three major steps: (1) Selection of training areas, (2) generation of the spectral signatures for training areas, and (3) classification of the sub-scene on the basis of signatures generated for training areas. Supervised classification was carried out both on the Dipix and CIAS systems.

Because of the nature of the data, and the physical and cultural settings, only broad classes which reflect the combination of similar land use/land cover were considered. This decision allowed the use of the 1978 vegetation map, the 1976 aerial photography, and radar mosaics as guides for selection of training areas. However, heavy reliance was placed on the stereoscopic examination of aerial photos for the final selection of training areas (see Figure 5).

Eight and nine training areas were selected for 1980 and 1975/1972, respectively. Additional training areas were required for 1975 and 1972, as a result of burnt areas not apparent in the 1980 data.

Selection of the training areas was followed by

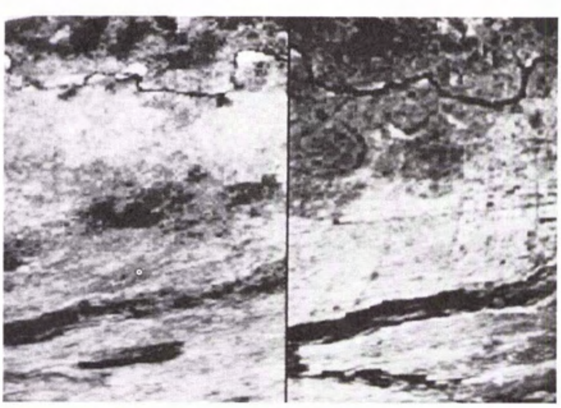

FIG. 4. Multitemporal Landsat images (band 7). The images were created to illustrate the difficulty of image to image registration. The 1972 (dry season) image is shown on the left and the 1980 (wet season) image on the right. Observe the shape of the river on the two images. Also note that the roads on the 1980 image are absent on the 1972 image (see text for detail).

FIG. 5. Aerial photograph (taken November 1976 and reproduced here at an approximate scale of 1:70,000) of part of the study area: (1) The flood plains (fadama), (2) rainfed agricultural land, (3) dug-up wells used locally for irrigation during the dry season, (4) settlement, (5) River Sokoto (dry), (6) alluvial fans (designated as bare surface area in the classified land-use/land-cover map, Plate 1), and (7) wooded shrubland/thicket.

generation of spectral signatures for each training area.

The Interactive Training (IT) function of the Dipix system was used. An undecimated color composite of each Landsat MSS subscene for each date was automatically loaded onto the color monitor by the task IT for the definition of the training areas. Each training area was composed of several small polygons, depending upon the size and distribution of each land-use/land-cover type. The boundary of each polygon was drawn by the cursor using the write annotation function of the graphic pad.

Each class as defined by the training area was composed of the recording of pixel intensity vectors (for bands 4, 5, 6, and 7 of the Landsat subscene). Means and the covariance matrix were then calculated to develop spectral signatures representing land use/land cover from which the training area was drawn. These parameters were then examined to determine spectral homogeneity of each class.

Although there is no *a priori* criteria for rejecting a class on the basis of the mean vector and the covariance matrix, some classes where the standard deviations seemed to be too high were "purified" either by deleting some of the polygons making up the original training area or by redefining the entire "training polygons." The spectral signatures so generated for each training area were then used for the maximum-likelihood classification.

To remove the speckled effect caused by unclassified pixels, a post-classification filtering was carried out. Unclassified pixels were common along class boundaries. The post-classification filtering program of the Dipix systems allows the operator to specify the minimum size groups of pixels representing any theme (class) which will be allowed to remain. This is equivalent to specifying a size for the minimum mapping parcel. The program first searches for the minimum contiguous pixel size of land-use/land-cover unit present in the classified image. This information allows the operator to specify the size of the pixel to be merged with the neighboring class. It is possible to indicate the minimum "eat-in-depth" for each class but, without adequate information about the behavior of the spectral reflectance of different features in relation to the climatic and soil characteristics, such a procedure will lead to artifacting. A minimum of five pixels was therefore used for all the classes.

The Dipix system has a software package to superimpose grid lines at either a 1000-m or 10,000-m interval on the theme (classified) images; a grid interval of 10,000 m was selected. Also, the area and the percentage of each land-use/land-cover category were calculated.

RESULTS AND DISCUSSION

LAND-USE/LAND-COVER CLASSIFICATION SCHEME

There is no *a priori* land-use/land-cover classification scheme for Nigeria; hence, the classification employed is pragmatic. Only the major land-use/land-cover classes were classified (Table 2). The 1980 color coded thematic map is shown in Plate 1. The classification includes three Agricultural classes, two Vegetation classes, and one each for Bare soil, Wetland, Water, and Burnt areas.

Three points about the classification should be noted: (1) The three classes within the agricultural category refer only to the land area used for cultivation and not to any specific crop. The reasons for this derive from the fact that

- the 1972 and 1975 Landsat MSS data were acquired at the end of the dry season when nearly all the crops have been harvested;
- the acquisition date for the 1980 Landsat MSS data coincided with the start of the wet season when farm lands were being prepared for cropping; and
- even if the images were acquired during the middle of the growing seasons (January/February and August/September), the complex spatial organization of agricultural land, marked by heterogenous association of many crops on small size plots, would have made the classification of different crops difficult, at least, at the resolution and scale of the imagery used.

(2) Although irrigated farming began in the 1979/80 farming season, cropping patterns had not yet stabilized sufficiently to permit separate classification for irrigated agriculture. For the reason given in (1) above, the areas that depict some irrigation activities have similar spectral reflectance as the rainfed agricultural areas which were under preparation. However, the irrigated areas have different spatial characteristics (see Figure 3, bottom). (3) The two vegetation classes are dominated by shrubs, dotted here and there by drought resistant trees. Wooded shrubland is characterized by woody communities separated by areas of low shrubs. While open, low shrubland areas are extensively used for grazing, the woodlands are exploited for production of firewoods.

Given the above situation, the primary concern is to examine within-class variability and class separability of the land use/land cover established for this study.

TABLE 2. LAND-USE/LAND-COVER CLASSIFICATION SCHEME

Class	Description	Color As On the Original
1	Cultivated Fadama	Red
2	Rainfed Agricultural Land Area 1	Green
3	Rainfed Agricultural Land Area 2	Yellow
4	Mixed Shrubland/Thicket	Orange
5	Wooded Shrubland	Magenta
6	Bare Soil	Cyan
7	Wetland	Dark Blue
8	Water	Blue
9	Burnt Areas	Burgundy

WITH LAND-USE/LAND-COVER CLASS VARIABILITY AND CLASS SEPARABILITY

There have been many comments on accuracies of digital classification of land use/land cover based on spectral data alone (Alfredo, 1981; Rasmussen, 1982; Pokrank and Gaboury, 1983; Satterwhite *et al.*, 1984). It is therefore pertinent to examine briefly the spectral characteristics of the data set *vis-a-vis* the variability of each land-use/land-cover class (as defined by spectral signatures of their training areas) as well as the separability (or otherwise) of the classes.

Various methods have been devised to examine within-class variability and class separability. Markham and Townshend (1981) suggested the use of coefficient of variation as a measure of the degree of spectral heterogeneity (what Townshend (1980) called "scene noise"). Confusion and divergence matrices (Kalensky *et al.*, 1981) have been used to determine the accuracy and separability of classes. Similarly, field data are also used. Because of lack of temporally compatible ground truth data, the following methods were adopted:

- coefficient of variation for within-class variability;
- two tail test concerning the means of the spectral signature of the training areas used in defining each class; and
- confusion and divergency matrices.

WITHIN-CLASS VARIABILITY

In order to appreciate within-class variability, Table 3 and Figure 6 show the characteristics of spectral reflectance values in terms of mean (X), standard deviation (SD), and maximum and minimum values as well as the spectral range for Landsat subscenes of the whole study area. The spectral range varies from only 30 to 84 in all the Landsat bands. In spite of this relatively narrow spectral range (see 1980 band 4), standard deviations shown in Table 3 are relatively high. The high standard deviations of the relatively narrow spectral range are an indication of spectral heterogeneity. For 1980 and 1975, percentages of coefficient of variation ($SD/X \cdot 100$) for bands 7 and 5 range from 14.6 to 31.3. Thus, it was observed, as Satterwhite *et al.* (1984) noted, that the accuracy of a land-cover classification in an arid to semi-arid region, such as the study area, is conditioned by the spectral range of the Landsat bands as well as the environmental complexity of the area.

In order to investigate the effect of this phenomenon as it relates to within-class variability of the classes established for this study, the coefficients of variation (CV) were calculated for the spectral signatures of training areas for some of the land-use/land-cover classes for each date. The values for 1980 are shown in Table 4 for illustration.

An examination of the CVs reveals a lack of any uniform pattern of within-class variability among the Landsat MSS bands. However, certain land-use/land-cover categories, especially the 1980 data, have relatively higher within-class variability indices than the other data set. This, of course, is due to differences in soil moisture, topography, and rates of vegetation growth resulting from the advent of precipitation.

Two classes—wetland and water—consistently have relatively very high variability indices in two of the bands (bands 6 and 7). Variability of the wetland is probably caused by the mixture of sedimented water and aquatic vegetation. Variability of the spectral signature of water is caused by grouping the clear, shallow, and deep water and partly sedimented water into one class. Although there is enough spectral disimilarity within the water class to allow its breakdown into further classes, this was not done in this study.

The vegetation classes (shrub/thicket and wooded shrubland) also have relatively high variability indices, especially for the 1980 data. As already indicated elsewhere above, observed variability is caused by the differential growth rate of vegetation and the presence of open space within the plant communities.

While these variability indices indicate the degree of homogeneity of each class, they do not provide sufficient information concerning the separability of classes. Lack of *a priori* spectral response pattern for the different land use/land cover of the study area preclude the determination of the threshold variability index of each class.

TESTS CONCERNING CLASS SEPARABILITY

Two major tests were employed to determine the class separability. First, means of spectral reflectance values within training areas were compared.

TABLE 3. SPECTRAL REFLECTANCE CHARACTERISTICS OF THREE OF THE FOUR LANDSAT (MSS) BANDS FOR THE STUDY AREA

	1980 Landsat MSS					1975 Landsat MSS					1972 Landsat MSS				
Bands	Max	Min	Mean	SD	Range*	Max	Min	Mean	SD	Range*	Max	Min	Mean	SD	Range*
7	119	18	55.3	8.1	56	41	0	27.5	3.6	25	210	94	159.0	17.7	80
5	85	29	55.3	10.2	59	93	0	52.1	8.6	48	172	75	123.9	15.2	80
4	56	28	39.3	4.7	30	57	0	34.8	4.2	23	228	123	171.4	16.5	84

* The spectral ranges are derived from the limits of the central groupings of the spectral intensity of the data as shown in Figure 7.

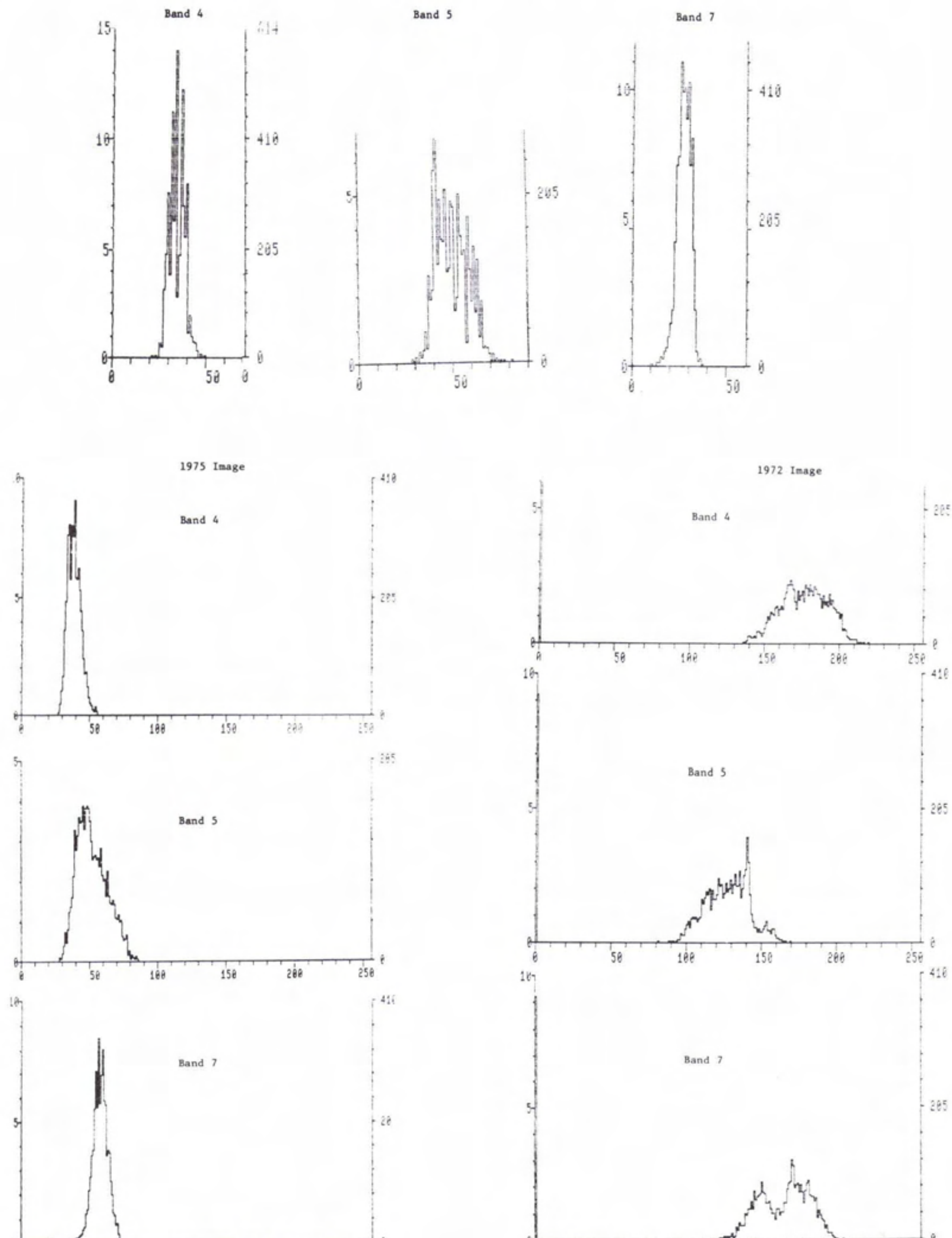

FIG. 6. Histogram for Landsat MSS bands 4, 5, and 7, 10 June 1980, for the study area.

Means of two sets of training areas were compared at a time. Although each training set should normally be compared against all the others (i.e., $n(n - 1)$ combinations, where n = number of classes), only classes with close spectral characteristics were selected for testing (see Table 4).

Basic requirements for the test are

- the number of samples (in this case pixels) are greater than 25,
- the samples are independent of each other, and
- the standard deviation(s) are not equal.

TABLE 4. SELECTED CLASS SEPARABILITY TEST (1980)*

	Class 2			Class 3			
	$\bar{x}$	SD	$CV(\%)$	$\bar{x}$	SD	$CV(\%)$	$|t|$
Band 7	53.33	4.95	9.28	64.17	3.60	5.61	66.34
Band 6	29.44	1.61	5.47	30.41	1.59	5.23	15.32
Band 5	56.28	7.01	12.45	71.83	4.64	6.46	70.35
Band 4	38.01	2.66	7.00	45.47	3.45	7.59	58.75
PTA		1845			969		
	Class 4			Class 5			
Band 7	56.94	3.20	5.62	53.96	3.45	6.56	28.68
Band 6	24.81	2.54	10.24	23.63	4.01	16.97	10.94
Band 5	39.27	3.85	9.80	48.73	5.31	10.90	63.96
Band 4	31.57	1.64	5.19	36.55	2.66	7.28	69.87
PTA		2478			1776		
	Class 7			Class 8			
Band 7	39.29	7.20	17.87	30.97	7.47	24.12	18.20
Band 6	22.74	5.69	25.02	21.44	8.59	40.06	2.66
Band 5	37.25	4.56	12.24	69.92	3.64	5.21	133.89
Band 4	31.49	2.40	7.62	47.77	3.46	7.24	82.18
PTA		893			365		

$\bar{x}$ = mean; SD = standard deviation.
$CV = SD/\bar{x}$ = coefficient of variation.
PTA = Number of Pixels in the Training Area.
* Similar calculations made for 1975 and 1972 are not shown here for lack of space.

These requirements are satisfied by the data. Thus, the standard deviation(s) of the sampling distribution of the means ($\bar{x}$) was estimated from

$$S(x_1 - x_2) = \sqrt{S_1^2/N_1 + S_2^2/N_2} \text{ and}$$
$$t = (\bar{x}_1 - \bar{x}_2)/S(\bar{x}_1 - \bar{x}_2)$$

where $N_1 + N_2 - 2$ is the degree of freedom, N_1 and N_2 the number of pixels in the classes being compared, and Ho (i.e., no significant difference between the means) would be rejected when $/t/ \geq t\alpha$; $\alpha = 0.01$. This test was applied to six classes (two at a time). Results for 1980 only are also shown in Table 4. The results for each of the dates show that all the classes, as defined by their training areas, were significantly separable at 99 percent probability. Only wetland and water (band 6, 1980) and shrub/thicket and wooded shrubland (band 5, 1972) are less defined than the other classes in all the bands. This is understandable given the reason regarding their within variability indices as discussed above.

However, this result does not eliminate the possibility of overlap. What it does mean is that the broad classes are significantly defined. This is expected because the heterogeneity of land-use/land-cover classes tends to average out at lower spatial resolution. The averaging effect reduces, according to Townshend (1980), the size of the spectral space for any given cover class. In particular, the averaging effect is greater in the more complex environments such as the study area. Recognition of this effect guided the creation of the broad classes. This explains why the classes resulting from this study are significantly separable. The result also stresses the need to integrate the environmental attributes of a place with the resolution of the data base in establishing land-use/land-cover classification schemes.

The second test further examined the separability of the classes was the confusion and divergence matrices using the CIAS system at the CCRS. Because of limitation of the size of the Landsat subscene that can be loaded on the CIAS TV color monitor (512 by 512), only the western half of the study (420 by 510) was used. The same training areas used on Dipix system was also used on the CIAS for the maximum likelihood classification. The test was carried out only for the 1975 and the 1980 data set. The results are shown in Tables 5 (A and B) and 6 (A and B)*.

* The author had limited time on the CIAS system; hence, the use of 1980 and 1975 data set for this test.

TABLE 5A. CLASS SEPARABILITY-CONFUSION MATRIX (1975) (TRUE CLASS ACROSS)

	Water	Wetlands	Bare Soil	Uplands I	Uplands II	Fadama	Shrub/Thicket
Unclassified	0	0	0	0	0	0	0
Water	100	0	0	0	0	0	0
Wetlands	0	95	0	0	0	1	1
Bare soil	0	0	99	1	0	0	0
Uplands I	0	0	1	99	0	0	0
Uplands II	0	0	0	0	98	0	1
Fadama	0	4	0	0	1	77	12
Shrub/thicket	0	1	0	0	1	22	86

Weighted Mean Classification Accuracy = 89.59
Weighted Standard Deviation = 7.18
Standard Error of the Mean = 2.71
STD. ERR. of the Mean = (Weighted STD. DEV.)/SQRT (No. of Classes)

TABLE 5B. DIVERGENCE MATRIX

	Water	Wetlands	Bare Soil	Rainfed I	Rainfed II	Fadama	Shrub/Thicket
Water	0.00						
Wetlands	114.33	0.00					
Bare soil	282.79	332.37	0.00				
Rainfed I	288.03	249.09	76.56	0.00			
Rainfed II	221.99	102.29	114.29	36.09	0.00		
Fadama	227.43	20.84	210.36	121.54	27.49	0.00	
Shrub/thicket	224.09	34.08	103.12	72.09	20.33	3.59	0.00

Only water does not overlap with any class. The 1975 result shows that the fadama and the shrub/thicket class have a relatively large percentage of overlap. Indeed, the spectral characteristics of the two classes are rather similar, particularly where they are adjacent to each other. As already noted, a large proportion of the fadama is dominated by shrub and grasses. The accuracies of these two classes are higher in 1980 (wet season). However, there is a relatively large percentage of overlap between the more moist (upland) rainfed agricultural land area 1 (see Plate 1 and Table 2) and the fadama. These two classes are usually located adjacent to each other.

TABLE 6A. CLASS SEPERABILITY-CONFUSION MATRIX (1980)

	Water	Wetlands	Bare Soil	Rainfed I	Rainfed II	Fadama	Shrub & Thicket
Unclassified	0	0	0	0	0	0	0
Water	100	0	0	0	0	0	0
Wetlands	0	97	0	0	0	0	0
Bare soil	0	0	98	6	0	0	0
Rainfed I	0	0	2	94	0	0	0
Rainfed II	0	0	0	0	92	10	0
Fadama	0	3	0	0	8	89	1
Shrub & thicket	0	0	0	0	0	1	99

Weighted Mean Classification Accuracy = 95.07
Weighted Standard Deviation = 3.99
Standard Error of the Mean = 1.51
STD. ERR. of the Mean = (Weighted STD. DEV.)/SQRT (No. of Classes)

TABLE 6B. DIVERGENCE MATRIX FOR 1980

	Water	Wetlands	Bare Soil	Uplands I	Uplands II	Fadama	Shrub & Thicket
Water	0.00						
Wetlands	95.28	0.00					
Bare soil	1490.35	1265.47	0.00				
Uplands I	234.19	127.33	40.81	0.00			
Uplands II	101.61	37.18	252.43	31.17	0.00		
Fadama	49.43	26.61	472.47	48.17	9.96	0.00	
Shrub & thicket	144.76	40.26	426.06	74.11	27.78	26.28	0.00

Separation of classes in spectral space is indicated by the covergence matrix (Tables 5B and 6B). Some classes are separated by large spectral space (e.g., water and bare soil in 1980). Given the relatively narrow spectral range of the data set, the result confirms the separability of the classes. However, the spectral space between fadama and shrub/thicket is lowest in 1975 (dry season) while it is lowest between fadama and the more moist (upland) rainfed agricultural land area 1 in 1980. This again confirms the overlap within these classes in Tables 5A and 6A.

Another method which could have further established the accuracy is comparison of the classification with the vegetation map derived from radar imagery in 1978. Unfortunately, the map is not temporally compatible with any of the data sets used for this study.

It is, however, pertinent to further remark that, although field work carried out both in 1983 and 1984 did not coincide temporally with the data used, the areas classified as agricultural lands were found to be under cultivation in 1984. Further inquiries from local farmers also confirmed the accuracy of the digital classification of agricultural land.

Although broad categorization of land use/land cover has been successfully achieved in this study, several fine details are generally lost in the process. It was noted that spatial resolution has greater effect on small sized, irregularly shaped, or narrow linear features. In addition, locations of these small linear features has direct effects on their classification accuracy. For instance, River Sokoto had water in certain locations in 1972 but because of the narrowness of the river, *vis-a-vis* the spatial resolution of the Landsat MSS data, those portions were classified with classes occupying the larger proportions of adjacent spectral space. Another example is the settlement. The settlements are mostly located within the agricultural land. Because they are small in areal extent and roofed with grass stocks, their spectral signatures (Figure 5) do not differ much from surrounding agricultural lands.

These phenomena account for the usual unclassified pixels which were found to be common on the boundaries of the classes occupying relatively large area. Prior to post-classification filtering, percentages of unclassified pixels were 7.27, 7.39, and 3.69 for the 1980, 1975, and 1972 data, respectively. By filtering, several of the small-sized, irregularly shaped, linear features were often merged to the adjacent large classes. Thus, the spatial organization of features, particularly as it relates to the size and position of objects in the feature space in relation to the location of other objects is very important for classification. Effects of this phenomenon can be partially eliminated by digitally registering the classified data to a base map containing roads and settlements which have been visually identified and manually delineated.

Land-Use/Land-Cover Distribution

Distribution of the interpreted land use/land cover during the three periods under consideration is shown in Table 7. Agricultural lands dominated the study area by occupying 51.3 percent in 1972, 66 percent in 1975, and 64.1 percent in 1980. In all the years, rainfed agricultural land is nearly twice as large as the cultivated area of the fadama (Plate 1). Based on field observation and the agricultural statistics, millet is found to be the most prominent crop grown in the study area (Table 8). Although cow peas and other crops are grown on the millet fields (when the latter have reached maturity), the fact that millet is contiguously grown by nearly all the farmers indicates the possibility of digitally mapping the areas where they are grown. This, of course, depends on the availability of Landsat MSS data during the middle of the growing season (August-September).

Shrub/thicket and the wooded shrubland occupied more than 25 percent of the study area. In these two classes, pockets of farmland are present; but because of their small sizes as well as their fragmentation, they have not been classified separately

Table 7. Land-Use and Land-Cover Statistics

Class Nos.	1972		1975		1980	
	Hectares	%	Hectares	%	Hectares	%
1	19789.0	20.3	18258.3	18.7	20875.0	21.4
2	13801.3	14.1	22939.3	23.5	26143.8	26.8
3	16493.0	16.9	23613.5	24.2	15518.5	15.9
4	12610.3	12.9	7628.8	7.8	7905.5	8.1
5	20180.0	20.7	16129.3	16.5	18971.3	19.4
6	2689.0	2.8	3642.3	3.7	1757.8	1.8
7	2315.8	2.4	1045.3	1.1	2773.0	2.8
8	113.8	0.1	171.3	0.2	3705.5	3.8
9	9564.3	9.8	4186.5	4.3	—	—
Total	97650	100	97650	100	97650	100

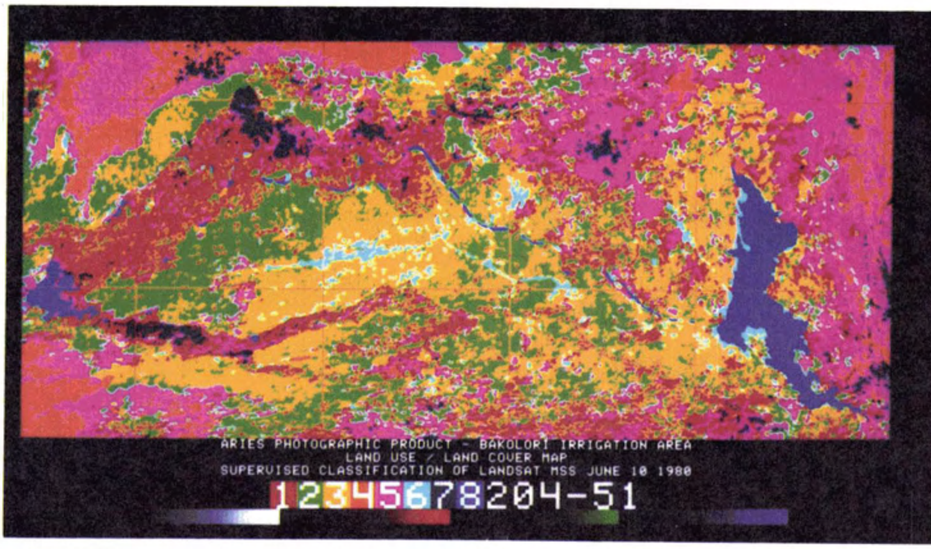

PLATE 1. Land-use/land-cover map of the study area. (1) Cultivated fadama, (2) rainfed agricultural land area 1, (3) rainfed agricultural area 2,(4) mixed shrubland thicket, (5) wooded shrubland, (6) bare soil, (7) wetland, (8) water body. (The interval between the main grid lines on the map is 10 km.)

except where contiguous farm plots are large enough. Other features of the land-use/land-cover distribution include

- The decreasing bare soil area in 1980 (wet season). It is however possible that the larger bare soil area reported for 1972 and 1975 (dry seasons) was caused essentially by climatic variation. Some of the areas may become vegetated or cultivated during the wet season.
- The increasing area occupied by surface water in 1980. This again was due to the new Bakolori reservoir. This reservoir has not been shown in any national or state map. The reservoir was separately classified in order to estimate its (1980) area. It occupied 2442.5 hectares, that is, 65.9 percent of the total surface water area in June 1980.
- The large burnt areas in 1972 and 1975. These burnt areas occur around wetland areas which support tall grasses.

TABLE 8. SOKOTO-RIMA BASIN DEVELOPMENT AUTHORITY CROP PRODUCTION DATA 1979/1980. BAKOLORI IRRIGATION PROJECT

	1980	
Crop	Hectarage	Yield (Tons)
Rice	19 w	37
Maize	5 w	6.5
Millet	1,895 w	2,556
Guinea Corn	5 w	3
Wheat	430 d	240
Cowpea	—	—
Vegetable	67 wd	830
Ground-nut	135 w	226
Cotton	640 w	1,024
Sweet Potato	—	—
Others*	80 w	984
Total	3,276	5,906.5

Source: Extracted from the report prepared by the Bakolori Irrigation Project Office, Talata Mafara, 1983.

w = wet season; d = dry season; wd = wet and dry seasons.

* These include sweet potato, tomato, onion etc.

CONCLUSION

The primary objective of this exploratory study was to examine the digital classification of land use/land cover of a semi-arid area of Nigeria—the Bakolori irrigation project area—using multitemporal Landsat MSS data. Landsat MSS computer compatible tapes (CCTs) were the primary data used. Aerial photographs and radar mosaics were used as complementary sources of data.

These data sources are not necessarily the best options for an operational resource investigation for several reasons which include: (1) because of the climatic variations and its effect on crop calendar, an August/September (mid-wet season) and January/February (mid-dry season) Landsat data would have been the most ideal for the land-use/land-cover classification of the study areas; and (2) none of the supplementary data sources was temporally compatible with the Landsat data. Notwithstanding these limitations, the data are considered suitable for this exploratory study.

The major findings of the study reveal that

- The computer-assisted classification of Landsat MSS images can provide rapidly, basic, up-to-date, location specific, as well as quantitative data on broad categorization of land use/land cover for the semi-arid areas of Nigeria.

- As much as possible, soil and landform characteristics in addition to spatial and spectral resolutions should be integrated for the classification of land use/land cover. Specifically for the study area, differences in the density of tree canopy, mixed cropping of small farm plots, varying ground moisture conditions, and atmospheric attenuation are factors which influence the classification as well as causing misclassification.
- The difficulty of mapping individual crop types in the study area is not only caused by the limitations imposed by the Landsat resolution factor and the "inappropriateness" of the data used in terms of their dates of acquisition, it is also caused by the small sizes of farms and the mixed cropping being practiced in the area. Short of developing a new technology that will be suitable for such land management practices, greater benefits will be derived from the current and the near future remote sensing technology by the modification of the current agricultural land management practices in the area. Apart from the need to remove the culturally induced fragmentation of farmlands, the uncontrolled grazing and exploitation of the scant woodland areas further enhance the harsh climatic situation. These activities not only expose the soil to higher evapotranspiration, but also enhance the southward desertification process and the reduction in the available productive land.
- In spite of the second and third factors above, the land-use/land-cover classes established for the study area are quite separable and statistically accurate. Also, the result has provided a useful base for future land-use/land-cover change analyses of the area.
- The best periods for Landsat MSS acquisition for the classification of land use/land cover of the study area are January/February for dry season inventory and August/September for wet season inventory.
- The knowledge of traditional photointerpretation is a necessary prerequisite for the optimal application of computer-assisted analysis of Landsat MSS for classification of land use/land cover of the area. Also, appropriate field surveys should be carried out to coincide with the Landsat overpass of the study area (lacking in resource data) so as to provide a more reliable way of cross-checking and modifying the result of digital classification. A major constraint found in the study area is the lack of adequate motorable roads to enhance field work activity. Apart from the recently established irrigated area, most of the settlements are only accessible by foot or on camels.
- For long-term usage, especially for quantitative analysis and for change detection, the registration of the Landsat MSS data to the national grid is necessary. Because relatively current topographic maps are required for the registration, national classification of land use/land cover in Nigeria will face some difficulties because of the lack of complete topographic map coverage and the age of most of the available maps.
- Although hard copy of the classification resulting from digital analysis of Landsat MSS can be provided rapidly to the resource planner in the form of color coded thematic maps in variety of scales, more cartographic processing is necessary than was achieved in this study in order to provide the additional information that will make the products more comprehensible (e.g., roads, place names, etc.).

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Forum

Optimum Sampling for Digital Terrain Models: A Trend Towards Automation

It is with interest that I recently came across an article by O. O. Ayeni titled "Optimum Sampling for Digital Terrain Models: A Trend Towards Automation" (*PE&RS*, November 1982, pp. 1987-1994). In this article Ayeni is examining some of the approaches to spatial sampling and the tradeoffs for aligned/unaligned, stratified, and random sampling frames. Further in his analysis he suggests the possibility of a ". . . seventh sample pattern—the unaligned systematic stratified random pattern . . ." which ". . . was found to be most efficient in nearly all of the terrains investigated."

This sampling frame is remarkably similar to the stratified systematic unaligned sampling frame proposed by Berry and Baker (1968) about 15 years earlier. It is interesting to note that Berry and Baker came to essentially the same conclusion when they said ". . . if the shape of the autocorrelation function is unknown and linear trends or periodicities may occur, addition of stratification and randomization to the systematic sample to produce a stratified systematic unaligned sample appears to yield both greatest relative efficiency and safety to estimation procedures." Perhaps Berry and Baker's findings will add a bit of perspective to Ayeni's results.

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