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Extraction of land use map under arid and semi-arid conditions using frequency-based classifier

A. Salah
National Research Centre (NRC) and National Authority for Remote Sensing and Space Sciences, Soil and Water Use Department, Ministry of Scientific Research and Technology, Cairo, Egypt
salahtohamy@hotmail.com

G. Ahmed
University of Assuit, Faculty of Agriculture, Soil & Water Department, Assuit, Egypt
ghallabahmed@hotmail.com

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ABSTRACT: In this study a cover frequency-based classifier approach was tested in an attempt under arid and semiarid conditions to extract a land use information map from TM multispectral images. This classification procedure involves two stages. In the first stage, the TM data were first classified into 14 land cover types using a supervised maximum-likelihood classifier (MLC). In the second stage, the pixel window size 7*7 was moved all over the land cover map obtained from the first stage to extract the cover frequency tables for each of the 7 land use classes. These frequency tables were then employed in the classification of 7 land use classes using a supervised minimum city-block distance classifier. Also the study area was classified using the conventional MLC method for comparison. For each land use map, a confusion matrix was obtained by comparing the classification results for the test samples with the ground truth map. A Kappa Index of Agreement (KIA) was compared for two classification error matrices. Also the accuracy of the individual category was measured using a coefficient of condition Kappa. The overall accuracy measured by Kappa Index of Agreement (KIA) was 0.86 for MLC method. It was significantly improved to 0.91 with the cover frequency method.

1 INTRODUCTION

Classification approaches currently used in remote sensing applications suffer from drawbacks related to the per-pixel range treatment, whereby a large number of computations is required to classify each pixel. One of the most common and frustrating problems in multispectral classification using statistic decision rules is the misclassification in the identification of information classes (Brodley and Friedl, 1999). This misclassification occurs because of similarities in spectral classes response. Different information classes may have the same or similar spectral response in all spectral bands (Lillesand and Kiefer, 1994). For these reasons, the differentiation among them could be difficult (Hansen et al., 2000). However, these classes can be visually separated by the interpreter. On the contrary, per-pixel class-ification algorithms could be used relatively easily to generate a land cover map because the land cover information is directly related to the pixel values on the image.

On the other hand, information about human activity on the land (land use) cannot always be inferred directly from land cover (Homosura and Palewatta, 1994). This information cannot be reasonably interpreted from imagery. For instance, the cultivated land in arid and semiarid areas is often divided into small and heterogeneous agriculture fields, unlike in Europe and North America. Under these conditions, relating spectral groups of pixels to land-use classes cannot be straightforward because the land-use classes can be composed of a wide range of spectral classes. In addition, under arid and semiarid conditions, land cover types are often smaller than the maximum size that most remote sensors can resolve. Spectral classes are mostly made up of mixed pixels. However, the high spatial frequency nature of the image means that a lot of mixed pixels derived from the boundaries between two adjacent land cover types can be generated. Furthermore, the effect of relief on the pixel values is significant in some portion of the image. Under these conditions a land cover type is not perfectly reflected by a spectral class. Consequently, generating a land cover map using the standard per-pixel classifier can be inaccurate.

Cover frequency methods have been employed in a wide range of environmental conditions to derive land use maps. Zhang et al. (1988) have applied the cover frequency method in an urban area. They first

classified the TM image into 13 land cover components using a clustering method. Supervised training was then applied to the land cover map to define five land use types. Gong and Howarth (1992a) derived 14 land use classes under rural-urban fringe from SPOT High Resolution Visible (HRV) images. They first obtained 12 land cover classes using a supervised (MLC) classification. Fourteen land use classes were then generated from the land cover map using a supervised minimum-city block distance classifier. Bandibas (1995) developed a frequency based contextual classifier for land-use identification. He applied this algorithm for the classification of spatially heterogeneous land use under tropical conditions.

This study aims to develop an accurate image classification method under arid and semiarid conditions using the cover frequency-based classifier approach. The resulting approach was successfully applied for the mapping of the land-use/land cover types of the Landsat TM image in Ismailia Province and in a portion of El-Sharkyia Province in Egypt.

1.1 *Area description*

The investigated area is situated in the Eastern Nile Delta of Egypt. It is located between latitudes 31° 40' and 32° 20' N, and longitudes 30° 25 and 31° 00' E. It includes Ismailia Province and part of El-Sharkyia Province, covering approximately 16,034 km2 (Figure 1). The study area can be divided into two main types of landscape. The first comprises most of the cultivated land in the Eastern Nile Delta region. The topography of this part is level to very gently sloping towards the north and north east from 75 m above sea level in the south, to 0.5-1.0 m close to Manzala lake in the north west of the study area. The second part, representing the eastern part of the area, includes most of the uncultivated land, which extends to the Suez Canal in the east.

The area in general has a fairly flat relief, except in the river terraces and the sand dunes which have an undulating or hummock relief. Most of the promising areas in the Salhiya plains and in the eastern part of the study area are now under reclamation. The climate of the study area is characterised by a hot summer and a mild winter with somewhat cold nights. The type of the growing season is all year round dry. The average annual rainfall is 38 mm. The average annual temperature is 20.7°C, while the reference evapotranspiration is 1524 mm.

2 METHODOLOGY

2.1 *Generalisation of land use map from TM 1994 Imagery using frequency-based classifier*

2.1.1 *Land cover map generation*

In this study a supervised MLC method was used to generate the land cover map. There are some advantages to this approach. First, it is relatively easy to implement because the supervised approach avoids some difficulties such as assigning labels to ambiguous groupings when using clustering methods. Secondly, a supervised approach allows to specify the land cover more explicitly. Thus various land cover components can be more physically related to the land use classes which are to be identified (Gong and Howarth, 1992b).

Therefore, in this procedure, the land cover map was produced using MLC method based on the combination of TM bands 4, 5 and 7 (Figure 2) which has the highest order of optimum index factor (OIF = 43.6). Fourteen spectral classes were generated from the combination of these three bands (Figure 3).

2.1.2 *Supervised training*

The training sites were selected during the field survey in 1995 and 2001 of the study site. Additional training information was obtained from the land use maps. In this step, the classified image map by means of MLC which contains 14 land cover classes, Figure and Table 1) was displayed on the screen. Then, the pixel window (7*7) was moved over the specified training areas for each land use classes. Then training samples were extracted and used to generate the mean frequency tables for each land use class.

2.1.3 *Cover frequency extraction and classification*

The spectral class occurrence frequency $f_l\ (i,j,v)$ is defined as the number of times that a spectral class v occurs in the pixel window centred at (i,j). The window has a square shape with side length l. Spectral classes were labelled from 1 to v, where v is the total number of spectral classes. During the classification, for each pixel at the centre of a pixel window, a cover frequency table was extracted. This was done for every pixel by moving the pixel window over the land cover map (Figure 3). To obtain the cover frequency table, the number (or frequency) of pixels having a specific land cover code can be determined. After the frequency of pixels within the pixel window was counted for each of the 7 land cover codes, 7 frequencies were recorded to form the cover frequency table for identifying the land use to be assigned to the central pixel.

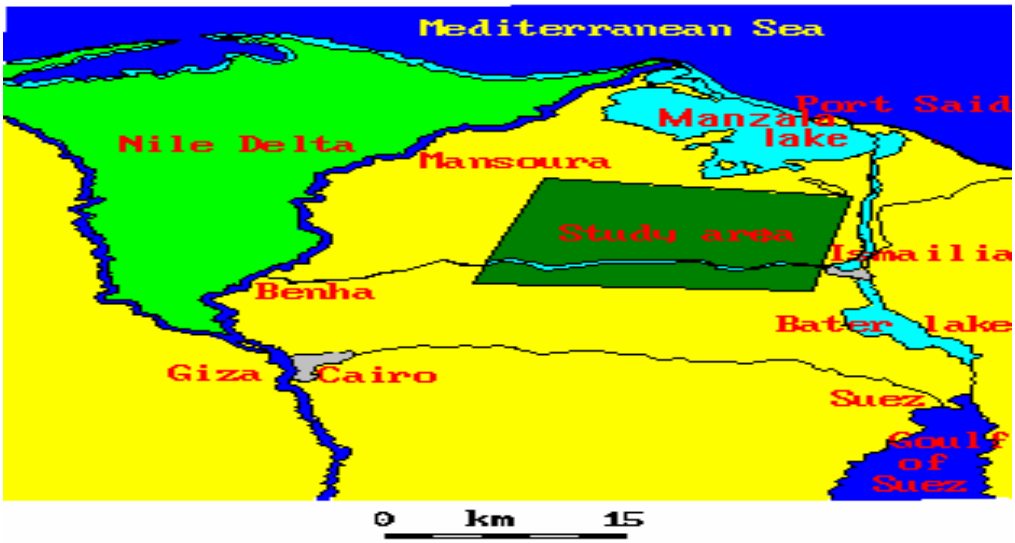


Figure 1. Location of the study area.

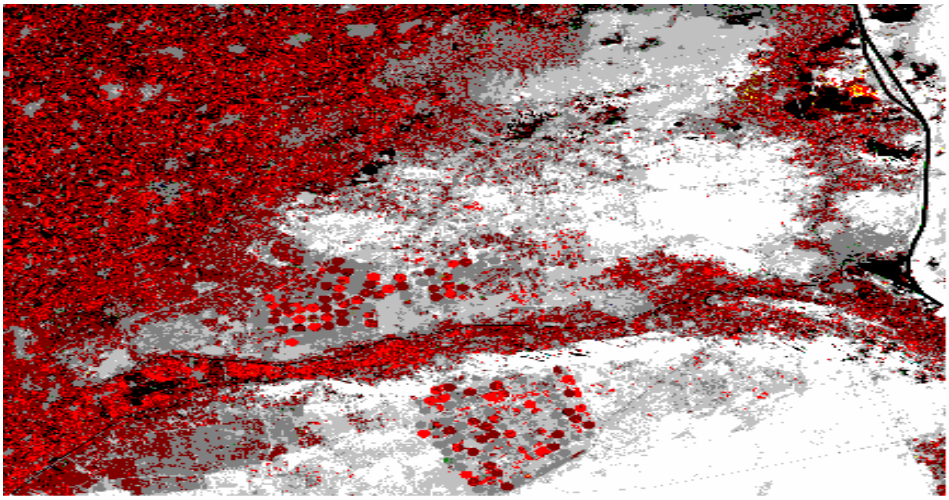
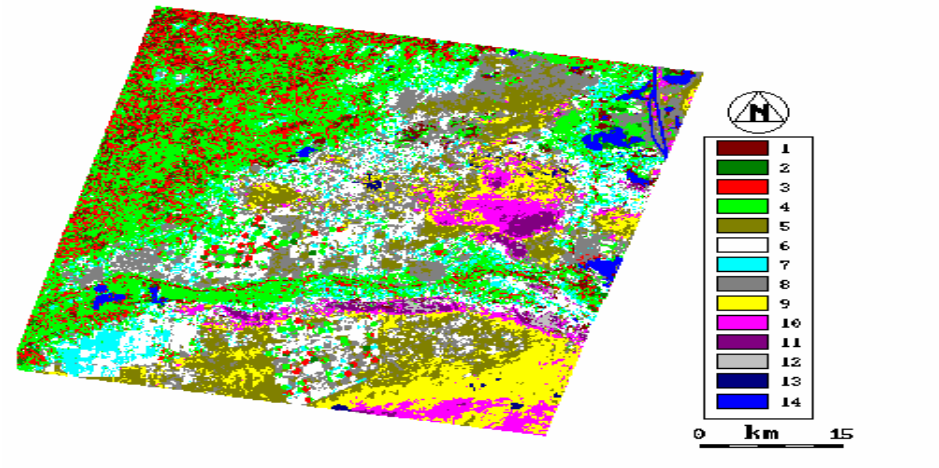


Figure 2. The standard false colour composite of TM-1994 bands 4, 5 and 7 of the study area.



Legend:

<u>Alluvial areas</u>

1. annual crops 1
2. annual crops 2
3. annual crops 3
4. old crops

<u>New agricultural areas</u>

5. low-density cultivated areas (very recent extension)
6. density cultivated areas (old extension) 1
7. density cultivated areas (old extension) 2

<u>Artificial surfaces</u>

8. urban areas

<u>Natural areas & water bodies</u>

9. bare soils 1
10. bare soils 2
11. bare soils 3
12. bare soils 4
13. bare soils 5
14. inland water

Figure 3. Land cover map obtained from TM-1994 using MLC method (before merge).

Table 1. Multispectral cover classification of TM-1994.

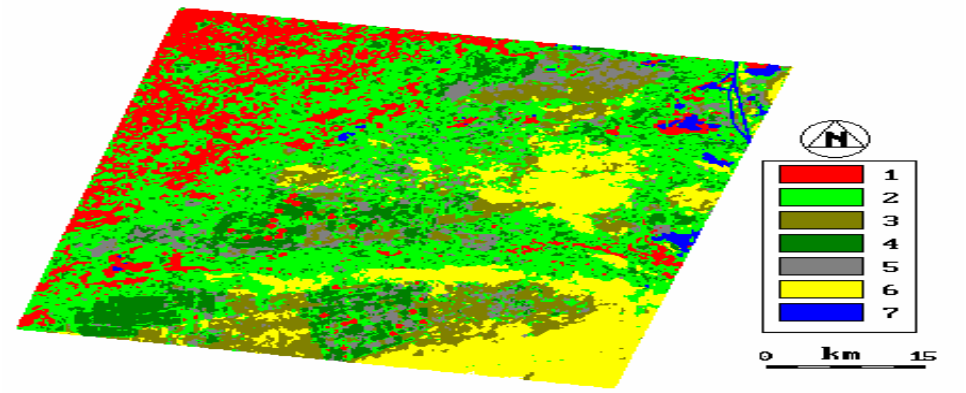
Spectral class	Information class	Land cover class	Area (%)	Area (km^2)	Description
1	1	annual crops 1	17.9	2870	They have high density vegetation cover. They are mainly occupied most of the fertile land of the study area.
2	1	annual crops 2			
3	1	annual crops 3			They include clover, wheat, beans, and flax.
4	2	old crops	12.8	2052	The land use of this classes showed the appearance of a healthy vegetation cover. They are mainly occupied most of the fertile land of the study area. They include fruits and vegetables.
5	3	low-density cultivated areas (very recent extension)	17.6	2822	They all characterised by low vegetation cover. The soils supported only a spare vegetation cover. They are mainly occupied the new agricultural area (sandy soils) of the study area.
6	4	density cultivated areas (old extension)1	5.9	946	The vegetation within this area has different density of cultivation.
7	4	density cultivated areas (old extension) 2			The reflection properties may influenced by background radiation of the soil surface
8	5	urban areas	1.7	273	This land use class has an irregular shape in the images. It is different from the roads which are characterised by linear pattern. It is distributed as small spots in the fertile land as well as the sandy areas.
9	6	bare soils 1	42.7	6846	These classes are represented the sandy soils and may abandoned from cultivation.
10	6	bare soils 2			They characterised by a very shallow windblow sandy soil overlaying the bedrock's.
11	6	bare soils 3			
12	6	bare soils 4			They have a relatively flat relief.
13	6	bare soils 5			
14	7	inland water	1.5	240	They are abandoned of any agricultural production or support a very poor vegetation cover. They include lakes, canals, streams, and reservoirs.

When average cover-frequency tables for all land use classes had been obtained, the entire land cover map was classified by comparing the city-block distances (Gonzalez and Wintz, 1987) between the cover-frequency table for each pixel and the average cover-frequency tables for all 7 land use classes. A pixel was classified into the land use class for which the average cover-frequency table had the shortest city-block distance to the cover-frequency table of the pixel (Gong and Howarth, 1992b). The city-block distance $d(X, M_i)$ between a cover-frequency table $X = (x_1, x_2, x_7)^T$ and the average cover-frequency table for class i, $M_i = (m_{i1}, m_{i2}, \ldots\ldots m_{i7})^T$ is calculated from following formula:

$$d(X, M_i) = \sum_{j=1}^{7} \left| X_i - M_{ij} \right| \qquad \text{Eqn. (1)}$$

The success of the frequency table method in land use classification depends largely on the appropriate pixel window size being selected for the frequency table generation. If the pixel window is too large, too spatial information from the other land-use types could be included. If the pixel window is too small, sufficient spatial information cannot be extracted from a frequency table to characterise a specific land-use type (Gong and Howarth, 1992b).

After some preliminary experiments, a 7*7 pixel window showed optimum classification accuracy. This window size was used throughout the experiment. For a pixel window size (7*7), a land use classification map was produced and a total of 7 classes has been obtained using a supervised minimum city-block distance classifier (Figure 4).



Legend:

Alluvial areas

1. Annual crops

2. Old crops

New agricultural areas

3. low density cultivated areas (very recent extension)

4. density cultivated areas (old extension)

Artificial surfaces

5. urban areas

Natural areas and water bodies

6. Bare soils

7. inland water

Figure 4. Land use map obtained from TM-1994 using cover frequency method.

2.2 *Generalisation of land cover map from TM-1994 imagery using conventional Maximum-Likelihood Classification (MLC)*

In this study the TM images recorded on April 9, 1994 were classified using following steps:

1. *processing*: Landsat Thematic Mapper (TM) data were geo-referenced to a Universal Transverse Mercator (UTM) projection using 14 control points and a second order algebraic transformation equation. The accuracy of the registration was 0.45 pixel;
2. *selection of optimum bands combination*: for the land use classification of TM dating from 1994, the theory of OIF (Optimum Index Factor) which is described by Greenbaum (1987) was employed. The best 3-bands combination (highest OIF) was used. This combination ranked first (OIF=43.6) corresponding with the TM bands 4, 5, and 7 (Figure 2). This 3-bands combination has been used for a supervised classification of the land cover types in the study area; and
3. ***multispectral*** *classification*: visited sites (field work, 1995 and 2001) and reference data such as land use, geology, soil and topography maps were made to help the supervised classification. The selection of the training sites is based on the field investigation and a land use map produced by Ministry of Agriculture in Egypt (1990). Spectral classes (those are inherent in the remotely sensed data) were selected according to the interpreter's knowledge of the area using the false colour composite displayed on the screen. The variability within and between spectral classes was analysed by evaluating the mean and standard deviation of each spectral class and the distance between classes during the entire sampling procedures (training sample). These classes were refined by adding or deleting individual samples through continuous analysis of the class statistics. The separation between classes was evaluated by displaying two dimension feature spaces of relevant band combinations on the screen using SIGCOMP option of IDRISI (Eastman, 1999).

The performance of these spectral classes and the possible need for additional classes were checked by running a classification algorithm. This proved useful in identifying the major misclassification problem. The evaluation also helped in defining classes to be added and in identifying those classes that should be deleted.

This analysis generated 14 spectral classes that were expected to model the spectral variability of the area (Figure 3). A maximum likelihood classifier was run on three selected bands (TM 4, TM 5, and TM 7) chosen after evaluating their potential information content using OIF theory. The 14 spectral classes were labelled into 7 information classes (information classes are those which are defined by the analyst) using EDIT and ASSIGN options in IDRISI, so that the variability of each class was represented by its constituent spectral classes forming the information classes. The successful classification results are presented in Table 1 and Figure 5

The results obtained with cover frequency method have been compared with the results obtained using the conventional MLC approach. The overall accuracy measured by the Kappa coefficient was 0.86 for MLC method (Table 2). It was improved significantly to 0.91 for cover frequency method (Table 3). The classification result obtained using cover frequency method was used for the updating of the land use map of the study area.

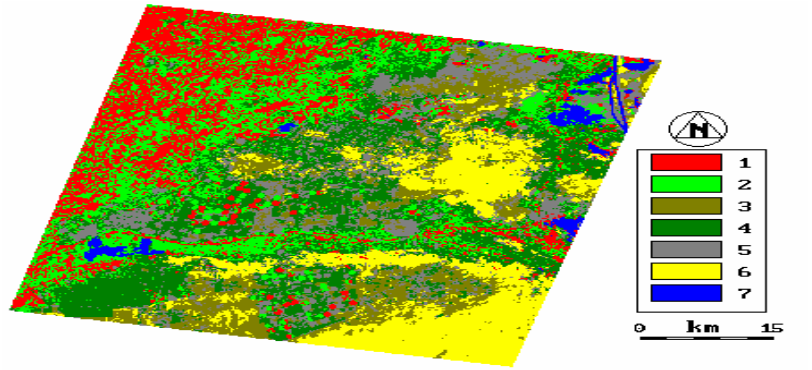
3 RESULTS AND DISCUSSION

In order to study the accuracy of the classification results, the land use map derived from the SPOT-image (Ministry of Agriculture, 1990) was used as ground truth map because: (1) SPOT-image is recent, and (2) the high resolution of the XS-SPOT-PAN (10*10 m) when compared to the resolution of the TM-images (30*30 m). The land use map (reference map) derived from SPOT-image was crossed with TM classified images through CONFUSE option in IDRISI. In turn, for each land use class, a confusion matrix was produced by comparing the classified image with the land use (reference data) map. The error matrix is a comparison between sampled areas on the map generated from the remote sensing and the same areas determined by the same reference data (Congalton, 1991; Congalton and Green, 1993).

In this study, the commission and omission errors were also calculated for each land use class. The Kappa Index of Agreement (KIA) was determined for the interpreted map as a whole, and individually for each interpreted category. The Kappa value is a measure of how well the classification agrees with the ground truth data (Conglaton et al., 1983; Dicks and Lo, 1990). The Kappa coefficient (K) can be calculated from following formula:

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} * x_{+i})}, \text{ Hudson and Ramm (1987)} \qquad \text{Eqn. (2)}$$

where: r is the number of rows in the matrix, x_{ii} is the number of observation in row i and column i *(i.e., the* i^{th} *diagonal element),* x_{i+} and x_{+i} are the marginal



Legend:

Alluvial areas
1. annual crops
2. old crops

New agricultural areas
3. low density cultivated areas (very recent extension)
4. density cultivated areas (old extension)

Artificial surfaces
5. urban areas

Natural areas & water bodies
6. bare soils
7. inland water

Figure 5. Land cover map obtained from TM-1994 using MLC method (after merged into 7 classes).

Table 2. Error matrix, Kappa coefficient and conditional Kappa for land cover map derived from TM-1994using MLC.

	1**	**2**	**3**	**4**	**5**	**6**	**7**	**Total**	**Err. C**	**KIA**
1*	**262**	41	9	14	0	0	0	326	0.20	0.80
2	21	**311**	23	0	0	0	27	382	0.19	0.81
3	0	0	**202**	0	0	49	0	251	0.20	0.80
4	0	22	0	**106**	0	0	0	128	0.17	0.83
5	0	0	12	0	**91**	10	0	113	0.19	0.81
6	0	0	0	0	25	**521**	0	546	0.05	0.95
7	10	0	0	0	0	0	**173**	183	0.05	0.95
To-tal	293	374	246	120	116	580	200	**1929**		0.85
Err. O	0.11	0.17	0.18	0.12	0.22	0.10	0.14			
KIA	0.89	0.83	0.82	0.88	0.78	0.90	0.87	0.85		**0.86*****

* Classified results is given as rows

** Reference map is given as columns

*** Overall Kappa = 0.86

Table 3. Error matrix, Kappa coefficient and conditional Kappa for land use map derived from TM-1994 using cover frequency classifier.

	1**	**2**	**3**	**4**	**5**	**6**	**7**	**Total**	**Err. C**	**KIA**
1*	**192**	0	0	0	0	0	5	197	0.03	0.97+
2	6	**311**	0	0	0	0	0	317	0.02	0.98+
3	0	0	**102**	4	0	0	0	106	0.04	0.96+
4	0	7	0	**235**	0	0	0	242	0.03	0.97+
5	0	0	0	0	**101**	49	0	150	0.33	0.67
6	0	0	7	0	28	**199**	0	234	0.15	0.85
7	0	20	0	5	0	0	**160**	185	0.14	0.86
Total	198	338	109	244	129	248	165	**1431**		**0.90**
Err. O	0.03	0.08	0.06	0.04	0.22	0.20	0.03			
KIA	0.97	0.92	0.94	0.96	0.78	0.80	0.97	0.91		**0.91*****

* Classified results is given as rows

** Reference map is given as columns

*** Overall Kappa = 0.91

totals of row i and column i , respectively, and N is the total number of observations.

Rosenfield and Fitzpatric-Lins (1986) have recommended the remote sensing community to use the Kappa index as a whole, and for the individual categories. The advantage of using Kappa value is that it takes all the elements in the confusion matrix into consideration, rather than just the diagonal elements which occur with calculation of overall classification accuracy. This coefficient also uses information in the classification error matrix resulting from errors by commission and omission. Therefore, this coefficient utilises all cell values in the matrix.

Tables 2 and 3 give the confusion matrix, commission and omission errors, Kappa index of agreement for the classification results derived from both per-pixel classification and cover frequency classification, respectively. The row entries of the confusion matrix represent the classified results and the column entries represent the reference data. The overall accuracy obtained from cover frequency method is higher than that obtained from MLC method.

Comparison of Table 2 with Table 3 shows that the agreement between classified results and reference data has been improved for most of the land use classes by using the cover frequency method. The symbol (+) indicates an improvement in classification accuracies with the cover frequency method, when compared with Kappa values derived using per-pixel classification. This is particularly true for the land use class 1 (annual crops), class 2 (old crops), class 3 (low density cultivated areas), and class 4 (density cultivated areas) (Table 3). This indicates that the cover frequency method gives higher classification accuracies in a spatially heterogeneous area. On the other hand, MLC shows higher classification accuracies for the land use class 6 (bare soils), and class 7 (inland water), because these land use classes are spatially homogeneous (Table 2).

Table 3 shows that 33% of the urban areas (class 5) was wrongly classified as bare soils (class 6). The confusion between these classes may refer: to (1) the spectral similarity between them, although they can be easily recognised visually, (2) the rural residences of these areas are mostly built of raw bricks which reflect portion of incident radiation quite similar to those of desert sand and bare land, at different wavelength (Ghabour, 1988), and (3) the roofs of the rural buildings are always covered by dry plant residues which reflect more in the visible light regions and absorb the infrared radiation (Salah, 1992). For urban areas, cover frequency is supposed to give a higher classification accuracy compared to the MLC because this land use is spatially heterogeneous. Basically, it is composed of the spectral classes corresponding to bare soils (class 6), roof and others. However, the urbans in the study area are in small

and elongated clusters along the roads which are often smaller than the selected pixel window (7*7) used in this experiment. This resulted in the inclusion of some spatial information from other land use classes during the training and the classification. Consequently, urban areas give the lowest classification accuracy (0.67), when the cover frequency classifier was used.

Under arid and semiarid conditions, most of the land use classes in the study area are not mainly composed of one land cover type. In case of annual crops (class 1), the area is composed of dry soil for those portions that are newly harvested, wet soil for the parts that are recently irrigated. These differences in field conditions made some spectral classes from different land use types to overlap in the multispectral space. In such case, use of the per-pixel classification, such as MLC, will be difficult to segment this kind of satellite image into different land use classes. The image segmentation is more accurate if the spectral class frequency of each class is used as signature of the land use classes. This indicates that using per-pixel classifications give lower accuracies in a spatially heterogeneous area.

Figures 4 and 5 show the classification results obtained using the cover frequency classifiers and MLC, respectively. Land use classes in Figure 4 seem to be very homogeneous and the map appears more like a product of manual interpretation. The difference between this map and the one obtained by the traditional classification method (MLC) (Figure 5) is readily apparent. The 'pepper and salt' effect observed in Figure 5 has been reduced dramatically. Furthermore, the cover frequency classified image (Figure 4) has more distinct information class boundaries and appears more homogeneous.

4 CONCLUSIONS

From the above analyses, the cover frequency method used in this study proved to be superior for land use classification when compared with the conventional maximum-likelihood classification (MLC). Land use classification accuracies obtained from the MLC method can be improved significantly by using the cover-frequency method. The results showed that the cover frequency method gave higher classification accuracies when compared with the conventional classification, like MLC method, in spatially heterogeneous areas. On the other hand, for spatially homogeneous classes, the classification accuracies obtained using the cover frequency method were generally lower than those obtained using conventional classification methods. More-over, the major drawback of the cover frequency method is the pixel window effect which causes boundary confusion. This occurs when a pixel window is located at the boundary of two different land use types. The cover frequency table extracted from this pixel window will not correspond to either of the two land use classes. Furthermore, this study shows the advantage of using Kappa index as a measure of total map accuracy as a whole, and for individual class.

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