Dirasat, Agricultural Sciences, Volume **33**, No. **2**, 2006

Mapping Land Cover in the Dead Sea Basin from Landsat TM Satellite Imagery

*Mahmoud M. Rababa'a and Jawad T. Al-Bakri **

ABSTRACT

A study was carried out to investigate the use of digital classification techniques of Landsat TM imagery to map vegetation pattern and land cover in the Dead Sea basin. Unsupervised classification methods, K-means and ISODATA, and density slicing of the Normalized Difference Vegetation Index (NDVI) were applied to the TM imagery to derive digital maps of land cover in the study area. Output maps were checked and verified in the field to assess their accuracy and to correct area estimate of each output class. Results showed differences in the overall accuracy of the three methods with the highest accuracy of 78%, obtained from NDVI method. Mapping accuracy was also variable at the class level, with lowest mapping accuracy of urbanized areas. Area estimate, therefore, was corrected using ground data included in the confusion matrices, originally used in accuracy assessment of maps. Results of area estimate were improved when correction of area estimate was made. The study suggests the possibility of using remote sensing data to map land cover and emphasize the role of ground data in correcting output maps.

KEYWORDS: Remote sensing, Unsupervised classification, NDVI, Mapping accuracy.

1. INTRODUCTION

Jordan is characterized by arid to semiarid climate with noticeable rainfall variation within and among years, where annual rainfall ranges from less than 50 mm in the eastern parts of the country up to more than 600 mm in the north-west of the country. The rainfed area in Jordan (areas receiving more than 200 mm annual rainfall) is limited and restricted to the western and northern highlands with vegetation presence being variable through time and space depending on the actual rainfall (Juneidi and Abu-Zanat, 1993). Thus, for monitoring the vegetation and land cover of these zones, medium and high-resolution satellite imagery, with high frequency, is required. Earth observation systems, particularly Landsat Thematic Mapper (LTM) has been shown to be effective in mapping vegetation, land use and land cover in different ecological zones all over the world (Ayyad *et al*., 1997; Khreim and Lacaze, 1997; Baban and Luke, 2000; Hirata *et al.,* 2001). Recently, different digital classification techniques of the TM visible and near infrared bands have been widely used to map land resources (Harris, 2003; Shupe and Marsh, 2004; Muttitanon and Tripathi, 2005; Yuan *et al*., 2005). This research attempts to investigate the use of digital image processing techniques of Landsat TM imagery to map land cover in the Dead Sea basin. Specific objectives of the study are:

1- To compare, evaluate and assess the digital maps of land cover derived from three classification methods of Landsat TM imagery.
2- To analyze land cover patterns in the study area.

The first objective provides a possible alternative to conventional ground surveys that consume time and money while the second objective provides means for managing land use in the study area.

Vegetation Mapping from Remote Sensing

Spectral reflectance of healthy vegetation is low in the red and blue, medium in the green and high in the near infrared portions of the electromagnetic spectrum (Lillesand and Kiefer, 2004). Therefore, multi-spectral images of visible and near infrared bands provide means for mapping vegetation at local and regional levels.

* Former Graduate Student, Al-Al-Bayt University, Mafraq, Jordan; Department of Land, Water and Environment, University of Jordan. Received on 1/3/2004 and Accepted for Publication on 6/3/2006.

Vegetation can be either visually or digitally mapped from satellite imagery and further field-check is usually made to verify the output maps. The use of visual interpretation of satellite imagery is not preferred for large study areas as it is usually demanding, as far as effort, time and money are concerned. Therefore, digital classification of satellite imagery provides alternative tool for visual interpretation. Additionally, it provides digital maps that are readily available for further analysis and studies.

Several studies have shown successful applications of digital classification of remotely sensed images for mapping vegetation, land use and cover. Ayyad *et al.* (1997) used the supervised classification of Landsat TM to map vegetation and land cover in Egypt with an overall accuracy of 90%. The same technique was used in Syria (Hirata *et al*., 2001) to produce vegetation and land cover maps with an overall accuracy of 85%. Supervised and unsupervised classification techniques were also used to map vegetation, land cover and use in different study areas around the world (e.g. Abdalla, 1994; Brondizio *et al*., 1996; Grignetti *et al*., 1997; Miller *et al*., 1997; Azzali and Meneti, 2000; Baban and Luke, 2000). Results from the above studies varied depending on the digital classification method, vegetation type, accuracy assessment method and the various land/used image characteristics.

In Jordan, the Normalized Difference Vegetation Index (NDVI) derived from Landsat TM images was used in a number of studies (e.g. Malkawi, 1997; Al-Qudah, 2000; Al-Momani, 2001) to map vegetation changes in different parts of the country. These studies, however, did not provide information about mapping accuracy and the NDVI values of the different vegetation types. Another research (Al-Bakri, 2000) in the Jordanian Badia showed that supervised classification of Landsat TM produced land cover maps with overall accuracy of 72%. Therefore, further studies are needed to test the various digital classification techniques in Jordan and to verify mapping accuracy values of the output maps.

Study Area

The study area is located between 35° 32' 45" E to 36° 11' 16" E longitude and 30° 57' 18" N and 31° 48' 55" N latitude with an area of 92 km x 62 km (Figure 1). The area covers the Dead Sea basin and includes the following bioclimatic zones (Al-Eisawi *et al*., 2001):

1. *Mediterranean*: This is restricted to the highlands with altitudes ranging from 700 to 1200 m above sea level and mean annual rainfall ranging from 300 to 600 mm, which is the best rainfall in the study area. According to MoA (1995), soils of vertic xerochreptic, entic chromoxerochrept and lithic xerochrept, as denoted by the USDA-SSS system (United States Department of Agriculture, Soil Survey Staff, 1990), dominate this region and supports the natural vegetation. The rainfed cultivation includes wheat, barley, summer crops of chickpea and lentils, in addition to orchards including olives, peach, plum and apricot. Irrigation is also practiced in this area with vegetables as the main irrigated crops.
2. *Irano-Turanian*: This dominates the highlands of altitude ranging from 500 to 700 m and annual rainfall ranging from 100 to 300 mm. Some natural vegetation, such as shrubs and bushes, grow on the sides of wadis where moisture is available. Also, some rainfed barley cultivation is practiced on the poor soils of torriorthents types (MoA, 1995). Irrigation is exercised in different parts of this zone with groundwater.
3. *Saharo-Arabian*: This comprises most of Jordan, known as the Badia, with altitude of 600 to 700 m and a mean annual rainfall of less than 100 mm. Dry hot summers and relatively cold dry winters characterize this region. The region is classified as rangeland and provides home to a wide range of highly diversified adaptive organisms. In addition to low rainfall, poor soils of Paleorthid dominate this zone and restrict the growth of plants and/or rainfed cultivation. Irrigated farms are scattered near groundwater wells in the eastern parts of this zone.
4. *Sudanian Penetration*: This region provides unique ecosystems as the altitude varies from 400 m below the sea level (at the Rift Valley and Dead Sea, lowest point on earth) up to 1200 m in the south. Very hot summer and warm winter characterize this region with mean annual rainfall of 50 mm or less. Acacia sp. in the low-altitude region and scattered shrubs in the high-altitude region are the dominant vegetation. Irrigation is taking place in the low altitude region of Ghor Al-Safi area.

2. MATERIALS AND METHODS

A satellite imagery of Landsat TM, originally acquired at the end of April 1998, was used in this study.

Table 1: Spectral bands of Landsat TM image.

Band	Wavelength (μm)	Nominal spectral location
1	0.45-0.52	Blue
2	0.52-0.60	Green
3	0.63-0.69	Red
4	0.76-0.90	Near infrared
5	1.55-1.75	Shortwave infrared
6	10.4-12.5	Thermal infrared
7	2.08-2.35	Mid infrared

The TM imagery had a spatial-resolution of 30 m and included seven multispectral bands (Table 1) covering visible to thermal infrared wavelengths of the electromagnetic spectrum. Image processing techniques of geometric correction, resampling and registration were done before carrying out digital classification of the imagery.

The raw TM imagery was geometrically distorted and was not in a standard cartographic coordinate system or projection. Therefore, a geometric correction was applied to reduce positional errors and to re-project the imagery in cartographic coordinate system. The raw TM imagery was geometrically corrected using a geocoded panchromatic image of SPOT digitally merged with Landsat TM image, both acquired in 1992. The SPOT image had a spatial-resolution and a geometrical error of 10 m. The image was originally used by the National Soil Map and Land Use Project (NSMLUP) (MoA, 1995). Using the image processing software, image–to–image correction was applied by identifying well defined and distributed Ground Control Points (GCPs) on the geocoded image (SPOT–TM) of 1992 and interactively allocating the corresponding points on the Landsat TM imagery of 1998. More than 30 well–distributed GCP's were used in a third polynomial transformation model as follows (Schowengerdt, 1997):

$$x' = a_0+a_1x + a_2y + a_3x^2 + a_4xy + a_5y^2 + a_6x^3 + a_7x^2y + a_8xy^2 + a_9y^3 \quad \ldots\ldots(1)$$

$$y' = b_0+b_1x+b_2y+b_3x^2+b_4xy +b_5y^2+b_6x^3+b_7x^2y+b_8xy^2 +b_9y^3 \quad \ldots\ldots(2)$$

Where x and y are positions in the output rectified image, x' and y' represent corresponding positions in the raw image while a's and b's are the transform coefficients. However, before applying the rectification to the entire image, it was important to calculate the error of transforming the raw image into a geometrically corrected one by calculating the Residual Mean Square of error (RMSerror) for each GCP as follows (Jensen, 2005):

$$RMS_{error} = \sqrt{(x - x_{\text{orig}})^2 + (y - y_{\text{orig}})^2} \quad \ldots\ldots\ldots(3)$$

Where x_{orig} and y_{orig} are the original row and column coordinates of the GCP in the image and x and y are the computed or estimated coordinates in the original image when we utilized the nine coefficients of each transform (Equations 1 and 2). Points with high error (RMS > 1 pixel) were rechecked and eliminated or replaced before registration. By this, the Landsat TM imagery was geometrically corrected with an overall error of less than one pixel (30 m).

The Landsat TM image was re-sampled to a new corrected image using the Nearest Neighbour (NN) resampling method, and was then registered to a new output image file in the Jordan Transverse Mercator (JTM) projection system. The study area was then subset and extracted from the output image to reduce the extraneous data outside the study area and to speed up digital image processing. The output from this stage was a geometrically corrected Landsat TM image with a pixel size of 30 m. All processing techniques were carried out using PCI (Photogrammetry and Cartography Incorporation) image processing software (PCI, 1998).

Digital Classification of Image

The aim of the classification process was to categorize all pixels in a digital image into one of several classes (clusters) to produce thematic maps of land cover units present in the image. The following digital image processing techniques were applied:

1. Unsupervised classification with K-means algorithm.
2. Unsupervised classification with ISODATA algorithm.
3. Density slicing of NDVI.

The first method is an automated one and serves to derive spectral categories (classes) by grouping pixels with similar spectral characteristics. Other statistical parameters such as the mean and standard deviation of groups can also be derived. The second method differs from the first one in that it splits or merges classes based on standard deviation values; and it may therefore increase or decrease the number of classes, depending on the spectral characteristics of the satellite imagery. Both methods are considered advantageous as they do not require any previous information about the area being classified (Schowengerdt, 1997) and include all possible spectral classes with less ground surveys. The third method performs grouping of an output NDVI image into a group of classes that represent land cover. The NDVI image was produced by applying the following standard formula (Jensen, 2005):

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}} \quad \text{……………………………………..(4)}$$

Where, NIR and R represent the near infrared (band 4) and the red (band3) channels of the image, respectively. Values of NDVI are negative for water, around zero for bare soil and between zero and one for vegetation. The high vegetation cover results in high NDVI values (more positive).

Assessment of Classification Accuracy

The expected outputs from the digital classifications were digital maps representing land cover patterns in the area (Figure 2). Identification and reclassification were needed to produce meaningful maps. In this research, a standard procedure (Congalton, 1991) of stratified random sampling, sample size, and the assessment techniques was followed. Several field surveys were carried out with the aid of hardcopy maps and navigational Global Positioning System (GPS), with a 5-m positional accuracy, to identify classes and compare classified images with field data. The output digital maps were also compared with the existing hard copy land cover maps (scale of 1:50 000) of the National Soil Map and Land Use Project (NSMLUP) (MoA, 1995).

Accuracy assessment was made by the confusion-matrix procedure in which a set of random samples of classified data of the TM imagery and reference data collected from the field visits were compared (Congalton, 1991). The approach was implemented by selecting random samples from the classified imagery and comparing these classified pixels with ground data. Detailed example on this matrix is shown in Table (4). The accuracy for each class was calculated by dividing the diagonal element of bold font in Table (4) with the total number of samples. The diagonal element of the confusion matrix represented the agreement between both classified and ground data. The overall accuracy was calculated by dividing the total number of all sample diagonals (agreement) by the total number for all random samples as follows (Congalton, 1991):

$$\mathit{Overall}\ \text{accuracy} = \frac{\sum_{i=1}^{r} X_{ii}}{\mathrm{N}} \quad \text{…………………………(5)}$$

Where X_{ii} is the observations correct (diagonal element), N is the total number of samples and r is the matrix row.

3. RESULTS AND DISCUSSION

Initial results of the unsupervised classifications showed output maps with 16 classes. Visual inspection of classes and comparison with the NSMLUP maps, in addition to field surveys, showed less distinctive classes in the study region. The final land cover classes for the unsupervised classification methods are shown in Table (2).

The same classes were identified for the output map of the third method (the NDVI density slicing). In this method, the non-vegetation areas (e.g. water, bare soil and rocks and urban areas) were merged in one class. Results showed that land cover could be classified, according to NDVI, into five distinct classes (Table 3) including all types of vegetation. Output maps of the three classifications are shown in Figure 2. Generally, both unsupervised methods resulted in similar classifications of land cover in the study area and different spatial distribution of vegetated areas than with the NDVI method.

Table 2: Classification scheme of land cover used with K-means and ISODATA methods.

Class	Description
Water	Part of Dead Sea and small earth dams.
Bare soil	Bare soils where no vegetation or urban structure exist.
Bare rock	Bare rocks, mainly limestone.
Farms	Irrigated orchards including fruit trees and olives. Vegetable grown under drip irrigation.
Medium / high density field crops	Rainfed wheat in the high rainfall areas and barley in the low rainfall areas with ground cover more than 35 %.
Low density field crops/ rangeland	Rainfed barley with groundcover less than 35 %. Sparsely vegetated shrubs and herbaceous rangeland.
Rangeland/bare rock	Heavily grazed shrub and herbaceous rangelands mixed with exposed rocks.
Urban	Residential, built-up, industrial and commercial areas.

Table 3: Land cover classes derived from the NDVI density slicing method.

Land cover class	NDVI range
Non-vegetation areas	< 1.00 for Water 0.00 for bare soil, rocks and urban
Sparsely vegetated areas	0.00 – 0.04
Low density field crops	0.04 – 0.10
Medium and high density field crops	0.10 – 0.29
Farms	> 0.29

Results of accuracy assessment (Table 5) showed that the overall accuracy was 67 % for K-means, 71 % for the ISODATA and 78 % for the NDVI method. Results of accuracy assessment showed variations in mapping accuracy among the different classes. The highest accuracy of the unsupervised classification was 93 % for farms. This indicated the possibility of separating farms from other land cover classes in the study area. Other classes were mapped by unsupervised classification with less accuracy. The high accuracy of classification of farms could be attributed to the distinguished spectral characteristics and the high percentage cover of this class, particularly under irrigation. The low accuracy for other classes could be attributed to the mixed patterns of cultivation and the low groundcover of vegetation.

Generally, all classes were mapped with an accuracy of 63% or more, except urbanized areas. These accuracy levels are in line with the results obtained by other researchers, e.g. Al-Bakri (2000), Brondizio *et al*. (1996), Lawan (1996), Miller *et al*. (1997), with differences at the class level, depending on ecological zone and land cover classification schemes. The low mapping accuracy of urban class could be attributed to the spectral heterogeneity of urbanized areas which were mixtures of small residential blocks and landholdings surrounded by small groups of trees. Such patterns resulted in mixed

Table 4: Accuracy of various classes obtained from K-means classification.

		Reference data									
	Class	W	BS	BR	F	MHFC	LFC/R	BR/RL	U	Totals	Mapping accuracy (%)
Classified image data	W	**6**	--	--	--	--	--	--	--	6	6/6 = 100
	BS	2	**26**	--	5	--	1	--	1	35	26/35 = 74
	BR	--	--	**145**	--	1	5	41	--	192	145/192 = 76
	F	--	--	--	**26**	2	--	--	--	28	26/28 = 93
	MHFC	--	--	--	8	**160**	33	5	10	216	160/216 = 74
	LFC/R	--	--	--	--	1	**55**	23	2	81	55/81 = 68
	BR/RL	--	1	17	--	--	65	**207**	--	290	207/290 = 71
	Urban	--	15	1	--	40	32	17	**47**	152	47/152 = 31
	Totals	8	42	163	39	204	191	293	60	1000	Overall accuracy = 67%

Class abbreviations: W = Water, BS= Bare Soil, BR=Bare Rock, F = Farms, MHFC = Medium & High density Field Crops, LFC/RL = Low density Field Crops/Rangeland, BR/RL = Bare Rock /Rangeland**,** U= Urban.

Table 5: Comparison of mapping accuracy (%) of classes obtained with K-means, ISODATA and density slicing of NDVI.

Class	**K-means**	**ISODATA**	**NDVI**
Non-vegetation areas	63	67	85
Bare rock/rangeland	71	71	81
Low density field crops/range land	68	70	75
Medium/high density field crops	74	83	71
Farms	93	82	73
Overall accuracy	**67**	**71**	**78**

Table 6: Area percentage for the different land cover in the Dead Sea Basin obtained with the various classification methods before and after the correction of estimate from confusion matrix.

	Before correction			**After correction**		
Class	**K-means**	**ISODATA**	**NDVI**	**K-means**	**ISODATA**	**NDVI**
Non-vegetated areas	38	39	35	32	32	33
Bare rock/rangeland	28	28	21	26	26	22
Low density field crops/rangeland	12	11	13	18	17	15
Medium to high density field crop	18	18	25	17	17	19
Farms	3	4	6	7	8	11

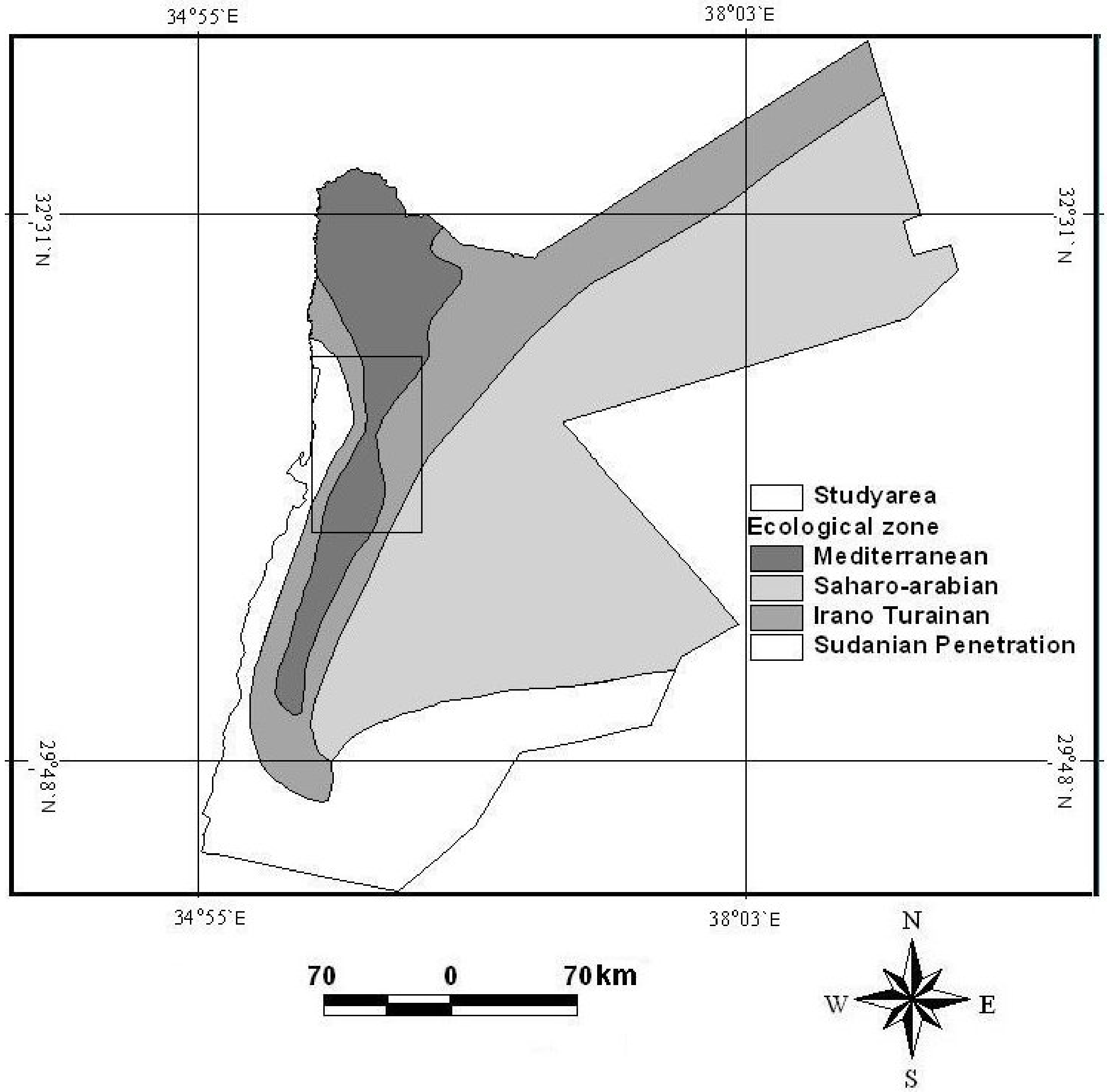

Figure 1: Location of the study area.

pixels at the level of the 30-meter resolution. Similar findings of low classification accuracy of urbanized areas were indicated by Al-Bakri (2000).

The overall mapping accuracy was higher for the NDVI method compared with the ISODATA and K-means methods. Accuracy, however, varied from one class to another within and among the different classification methods. Unexpectedly, the NDVI method resulted in higher mapping accuracy for non-vegetation areas than the unsupervised classification methods. This could be attributed to the inclusion of distinctive spectral classes of water, bare soils and rocks in this class. Medium and high density vegetated areas, on the other hand, were mapped with higher accuracy by the ISODATA than the other classification methods. This could be attributed to the nature of the ISODATA algorithm which enabled splitting of cluster when its standard deviation was high or exceeded a threshold value.

Using the image processing software, the percentage area of each class was calculated (Table 6). As a result of variable accuracy, results showed variations in area estimate of each class. Therefore, it was necessary to correct area estimate of each class to obtain more accurate area estimates. Previous researchers, e.g. Al-Bakri (2000); Gonzáles-Alonso and Cuevas, (1993); Gonzáles-Alonso *et al*. (1997); Taylor and Eva, (1992); Taylor *et al*., 1997), suggested the use of confusion

matrices or regression estimator to correct the area estimate from remote sensing data. The regression estimator was not used as it required more ground data and digitizing of ground segments, i.e. it would consume more time and money. The confusion matrices data, therefore, were used in this research to correct the area of each class. Detailed calculations and corrections of area estimate were shown by Rababa'a (2003). In this method, the area of a particular class was corrected by multiplying its area before correction by its mapping accuracy and adding the proportion of this class included in the other classes. For example, the area of Urban class (U) obtained from K-means (Table 4) was corrected as follows:

Corrected area = area of U × (47/152) + area of BS × (15/152) + area of BR × (1/152) + area of MHFC × (40/152) + area of LFC/R × (32/152) + area of BR/RL × (17/152)

Results showed obvious improvement in area estimate when correction was made with confusion matrices data. Areas of the different classes were improved and variations decreased. This was particularly true with classes of larger proportions (non-vegetation areas, bare rock/rangeland). These findings seem to be in agreement with those reported by Al-Bakri (2000), Taylor and Eva (1992) and Taylor *et al*. (1997). Less variations were observed in area estimates between the K-means and ISODATA methods before and after correction, while obvious variations occurred in estimating the area of farms and medium to high density field crops from the NDVI method. This could be attributed to the spectral mixing which resulted in low accuracy of estimation. Furthermore, comparing the area percentage for each class before and after correction indicated that the three methods could result in inconsistent area estimate for some classes, unless area correction is made. For example, the use of digital classification and NDVI methods resulted in the overestimation of the non-vegetation areas and under-estimation of the farms and vegetated areas. This was mainly due to spectral mixing of these classes which could be attributed to crop density, small landholdings and farm sizes and in many cases the mixed cropping pattern in the area. The non vegetated areas, on the other hand, were distinct land cover classes and were mapped with high accuracy, particularly by the NDVI method.

4. CONCLUSIONS AND RECOMMENDATIONS

The following conclusions and recommendations can be drawn from the present study:

1. The overall unsupervised classification accuracy was higher for the ISODATA method than for the K-means and is therefore more recommended for mapping land cover in the area while the density slicing of NDVI is recommended to separating vegetated and non vegetated areas.
2. Spectral confusion, mixed pixels and class definition were the main factors contributing to reducing the accuracy of land cover maps in the region.
3. Low accuracy mapping of urbanized areas was observed. It seems appropriate then to mask urban areas when digital classifications are applied to map land cover in the region. This is a point that needs further investigation.
4. The use of confusion matrices to adjust area estimates of each class is recommended to improve estimation of class area.
5. The work showed the suitability of the methodology to map land cover in the Dead Sea Basin. The three methods were applied with their appropriate classification schemes and NDVI ranges being determined for the different vegetation classes. Therefore, application of the approach to larger areas is a future objective. Possible improvements of the future work will include the use of better spatial and spectral resolution satellite imagery with possible modification of the classification scheme. In this way, spectral confusion between land cover types may be reduced and more accurate maps may be obtained.

REFERENCES

Abdalla, J. D. 1994. *The Evaluation of Satellite Imagery in a GIS for Monitoring Land Cover Changes in a Semiarid Area of Northeastern Nigeria.* Unpublished PhD Thesis, Silsoe Collage, Cranfield University, UK.

Al-Bakri, J. T. 2000. *Remote Sensing Techniques for Environmental Monitoring of the Semiarid Zone of Jordan.* Unpublished PhD Thesis, Silsoe College, Cranfield University, UK.

Al-Eisawi, D., El-Oqlah, A., Oran, S., Lahham, J. and al-Khaser, I. 2001. Jordan Country Study on Biological

Diversity: Plant Biodiversity and Taxonomy. The General Corporation of Environment Protection (GCEP), Amman, Jordan.

Al-Qudah, A. N. 2000. *Study of Desertification in Ibn Hammad Basin Using Remote Sensing and Geographic Information System.* Unpublished MSc Thesis, Al Al-Bayt University, Mafraq, Jordan.

Al-Momani, M. A. 2001. *The Use of Remote Sensing and Geographic Information System to Study Urban Expansion on Forest Areas: Applications in Ajloun.* Unpublished MSc. Thesis, Al Al-Bayt University, Mafraq, Jordan.

Ayyad, M. A., Salem, B. B., Clarke, J. and Noin, D. 1997. Monitoring Human Impact on Land Cover by Remote Sensing: Case Study of Mediterranean Desert of Egypt. In: *Population and Environment in Arid Regions,* Proceeding of a Conference on Population and Environment in Arid Regions*,* 24-27 October 1997, Amman, Jordan, 89-101.

Azzali, S., and Meneti, M. 2000. Mapping Vegetation-Soil-Climate Complexes in Southern Africa Using Temporal Fourier Analysis of NOAA-AVHRR NDVI Data. *International Journal of Remote Sensing*, 21 (5): 973-996.

Baban, S. M. J. and Luke, C. 2000. Mapping Agricultural Land Use Using Retrospective Ground Referenced Data, Satellite Sensor Imagery and GIS. *International Journal of Remote Sensing*, 21(8): 1757-1762.

Brondizio, E., Moran, E., Mausel, P. and Wu, Y. 1996. Land Cover in Amazon Estuary: Linking of the Thematic Mapper with Botanical and Historical Data. *Photogrammetric Engineering and Remote Sensing*, 62(8): 921-929.

Congalton, R. G. 1991. A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sensing of Environment*, 7(1): 35-46.

Gonzáles-Alonso, F., Cuevas, J. M., Arbiol, R., and Baulies, X. 1997. Remote Sensing and Agricultural Statistics: Crop Area Estimation in North-Eastern Spain Through Diachronic Landsat TM and Ground Sample Data. *International Journal of Remote Sensing*, 18(2): 467-470.

Gonzáles-Alonso, F., and Cuevas, J. M. 1993. Remote Sensing and Agricultural Statistics: Crop Area Estimation Through Regression Estimators and Confusion Matrices. *International Journal of Remote Sensing*, 14(6):1215-1219.

Grignetti, A., Salvatory, R., Casacchia, R. and Manes, F. 1997. Mediterranean Vegetation Analysis by Multi-Temporal Satellite Sensor Data. *International Journal of Remote Sensing*, 18 (6): 1307-1318.

Harris, R. 2003. Remote Sensing of Agriculture Change in Oman. *International Journal of Remote Sensing*, 24(23): 4835–4852.

Hirata, M., Koga, N., Shingo, H., Fujita, H., Gintzburger, G. and Miyazaki, A. 2001. Vegetation Classification by Satellite Image Processing in Dry Area of North-Eastern Syria. *International Journal of Remote Sensing*, 22(4): 507-516.

Jensen, J. R. 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective*, 3rd edition (New Jersey: Prentice Hall).

Juneidi, J. M., and Abu-Zanat, M. M. 1993. Jordan Agricultural Sector Review: Low Rainfall Zone. Agricultural Policy Analysis Project, Phase II (APAP II), USAID, Amman, Jordan.

Khreim, J. F. and Lacaze, B. 1997. Land Cover Change Detection in a Mediterranean Area (Maritime Syria) from Remotely Sensed Data. In: *Geosciences and Water Resources: Environmental Data Modeling*, C. Bardinet and J. J. Royer (editors), Springer, Heidelberg, Berlin, 197-214.

Lawan, A. I. 1996. *The Application of High Spatial Resolution Satellite Data for Land Use and Land Cover Mapping and Inventory in North East Nigeria*. Unpublished PhD Thesis, Silsoe Collage, Cranfield University, UK.

Lillesand, T. M. and Kiefer, R.W. 2004. *Remote Sensing and Image Interpretation*, 5th edition (New York: John Wiley and Sons).

Malkawi, O. A. 1997. *Study of Desertification in the Azraq Basin using Remote Sensing.* Unpublished Msc. Thesis, Al Al-Bayt University, Mafraq, Jordan.

Miller, A. B., Bryant, E. S. and Birnie, R. W. 1997. An Analysis of Land Cover Changes in The Northeast Forest of New England using Multi-Temporal Landsat MSS Data. *International Journal of Remote Sensing*, 18 (2): 245-265.

MoA (Ministry of Agriculture, Jordan), 1995. The Soils of Jordan. Report of the National Soil Map and Land Use Project, Volume 2: Main Report, Ministry of Agriculture, Amman, Jordan.

Muttitanon, W. and Tripathi, N. K. 2005. Land Use/Land Cover Changes in the Coastal Zone of Ban Don Bay, Thailand Using Landsat 5 TM data. *International Journal of Remote Sensing*, 26(11): 2311 – 2323.

PCI (Photogrammetry and Cartography Incorporation), 1998. Using PCI Software, 1 (Ontario: PCI Inc).

Rababa'a, M. 2003. *The Use of SAR and Landsat TM Imagery to Study Vegetation Patterns in the Dead Sea Basin.* Unpublished MSc Thesis, Al Al-Bayt University, Mafraq, Jordan.

Schowengerdt, R. A. 1997. *Remote Sensing: Models and Methods for Image Processing,* 2nd edition (London: Academic Press).

Shupe, S. M. and Marsh, S. E. 2004. Cover- and Density-Based Vegetation Classifications of the Sonoran Desert Using Landsat TM and ERS-1 SAR Imagery. *Remote Sensing of Environment,* 93 (1):131-149.

Taylor, J. C. and Eva, H. D. 1992. Regional Inventories on Beds, Cambs and Northants (UK), Final Report to CEC-JRC, Silsoe College, ISBN 1871564522.

Taylor, J. C., Sannier, C. A. D., Delince, J. and Gallego, F. J. 1997. Regional Crop Inventories in Europe Assisted by Remote Sensing: 1988-1993. Synthesis Report of the MARS Project—Action 1, European Commission, EUR 17319.

USDA-SSS (United States Department of Agriculture, Soil Survey Staff), 1990. *Keys to Soil Taxonomy*, 4th edn, SMSS, Technical Monograph 19, Blacksburg, Virginia.

Yuan,F., Sawaya, K. E., Loeffelholz, B. C. and Bauer, M. E. 2005. Land Cover Classification and Change Analysis of the Twin Cities (Minnesota) Metropolitan Area by Multitemporal Landsat Remote Sensing. *Remote Sensing of Environment,* 98(2): 317-328.

استنباط خرائط الغطاء الأرضي في حوض البحر الميت من صور الماسح الغرضي المحمول على متن القمر الصناعي الأمريكي لاندسات

*محمود محمد ربابعة، جواد طالب البكري**

ملخص

أجريت دراسة لاستقصاء إمكانية استخدام وسائل التصنيف الرقمي لصور الماسح الموضوعي (TM) المحمول على القمر الصناعي الأمريكي لاندسات، لاستنباط خرائط الغطاء الأرضي في حوض البحر الميت. تم استخدام طريقتي التصنيف غير المراقب باقتران المسافة الى المتوسط الحسابي واقتران البيانات المتماثلة وطريقة توزيع مدى قيم الفرق المطبع للمؤشر النباتي (NDVI) لاستنباط الخرائط المذكورة. تم في الدراسة إجراء المسوحات الميدانية للتأكد من دقة الخرائط الناتجة وتصحيح مساحة كل صنف. أظهرت النتائج فروقات في مستوى دقة التصنيف الكلية بين الطرق الثلاث مع أعلى مقدار من مستوى دقة التصنيف (78%) للطريقة الثالثة. تباينت دقة الخرائط على مستوى الصنف مع الحصول على أقل دقة تصنيف لصنف المناطق المدنية، لذا فقد تم تصحيح المساحات المقدرة من الطرق الثلاث باستخدام البيانات الميدانية التي تم استخدامها أصلا في تقييم دقة الخرائط. وقد تحسنت نتائج تقدير المساحات بعد استخدام التصحيح. وأظهرت الدراسة إمكانية استخدام بيانات الاستشعار عن بعد لاستنباط خرائط الغطاء الأرضي مع التأكيد على دور البيانات الأرضية في تصحيح الخرائط الناتجة.

* طالب دراسات عليا سابقاً، جامعة آل البيت، المفرق، الأردن؛ وقسم الأراضي والمياه والبيئة، كلية الزراعة، الجامعة الأردنية، عمان، الأردن. تاريخ استلام البحث 2004/3/1، وتاريخ قبوله 2006/3/6.