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ANALYSIS OF AL KUBUB DUNES AREA AND WEST BURAYDAH CITY LAND COVER ALONG WADI AR RUMAH IN ALQASSIM, SAUDI ARABIA USING LANDSAT/TM

AlSultan, Sultan*; M. Z. MatJafri#; K. Abdullah# and H. S. Lim#

* Al Sultan Environmental Research Center. Al Madina Rd., P.O.Box. 242 Riaydh Al Khabra, Al Qassim, Saudi Arabia.
Tel: +966504890977, Fax: +96663340366
E-mail: allssultan7@hotmail.com

\# School of Physics, Universiti Sains Malaysia, Minden 11800 Penang, Malaysia.
Tel: +604-6577888, Fax: +604-6579150
E-mail: mjafri@usm.my, khirudd@usm.my

ABSTRACT

Mapping of Alkubub dunes land Cover within an Urban-desert environment using LANDSAT Thematic Mapper (TM) imagery is the main objective of this study. Regional and urban planning analysis studies for Land Cover mapping has proved to be an effective tool to monitor natural and human-induced environmental changes. In this study supervised classification using maximum likelihood classifier has been used to identify surrounding dunes terrain. It has been proved that the proposed scheme is capable to delineate different features including vegetation, roads, Moderate Arable Land (MAL), Good Arable Land (GAL), Non-agricultural land (NAL), and urban with high classification accuracy.

INTRODUCTION

Changes in vegetation cover are amongst the more obvious of the alterations that mankind has caused to the global environment. Historically these changes have been local or regional in effect, though widespread. The production of the thematic maps, such as those depicting land cover, using an image classification is one of the most common applications of remote sensing[1]. Many researchers used this technique to achieve this aim[2][3][4]. For many reasons, then the detection and monitoring of vegetation cover dynamics is highly desirable[5]. Remote sensing clearly has a potential role to play in order to monitor fragile arctic ecosystems, although they have yet to be fully investigated[6]. The natural environment in the Arabian Peninsula is strongly governed by solar radiation, vegetation and water. The current study examined whether space observations are useful to study the region phenomena[10]. Numerous of researches on the land cover change analysis considering only the temporal analysis. Land covers classification and change detection using temporal series a good knowledge of the relationships between these biophysical parameters in different ecological conditions. In this paper, Alkubub area in AlQassim land cover change feature space was studied. Studying Alkubub in AlQassim area along Wadi Ar Rumah is important for several reasons: i) understand the real condition of land cover/use of desert feature and its vegetation, ii) the importance of observing the land cover system in an active agricultural and populated area for the benefit of the desert agriculture and settlement landscape. Finally, the total water supply, which comes from ground water, is of about 75-85%. The total volume is estimated to be 900000 million m^3 in the ground water reserves, which was formed in the last Ice age, 15000 to 30000 years ago[8]. For the last 30 years, It has been advantageous to perform the crop cultivation by center pivot irrigation system in Saudi Arabia. This agricultural method is mainly progressing in the Al Qassim district[9].

STUDY AREA

The selected study area is centered on the Alkubub dunes land Cover in Al-Qassim state, which is situated along Wadi Ar Rumah, Saudi Arabia. Figure 3 shows a false color composite image of Alkubub dunes land Cover and its surrounding desert terrain. Sand dunes occupy large portions of the image, and the western portion of Buraydah City is dominated by Date Palm Grove vegetation and agriculture. There are definitely areas of Buraydah that are clearly being affected by dune encroachment. The preliminary analysis clearly indicates that satellite imagery and the use of Land Cover Mapping provide means to identify and quantify the effects of desert processes upon urban areas.

The Alkhubub study area in the *Arabian Peninsula* is located between 12°N and 32°N latitudes and between 20°E and 35°E longitudes. This particular geographical position gives the area a great bioclimatic diversity. The desert of the Arabian Peninsula is located as a part of the hot desert, which extends from the *Sahara* in Africa in the west to the *Thar* desert in Indo-Pakistan sub-continent in the east. The overall climate falls within desert and arid climates, except the *Asir* province where the temperature is lower and the rainfall is greater than that of the remaining part of the peninsula. The area is also subjected to a significant problem with regard to desertification. The focus will be made on Wadi Ar Rumah watershed mainstream path with their left and right sides especially at the midstream, Anafud desert and downstream levels. Its midstream part comes through Al Qassim Oasis located at the center of the peninsula desert.

Five geographic regions can be recognized: (i) the Western Highlands, (ii) the Central Plateau, (iii) the Northern Deserts, (vi) the *Rub al Khali* desert, and (v) the Eastern Lowlands. The Central Plateau geographic region, the mountains of *Hejaz* and *Asir* slope eastward toward the Central Plateau, also called *Najd*. Little vegetation can be found in most of this region (see Fig. 1). In parts of the rocky plateau, fertile oasis support large farm communities; Al Qassim is one of these oases. During the raining season in the peninsula, nomadic herders bring their animals to feed on patches of grass that grow in the region for a short time after occasional rainfall. The peninsula terrain is varied but on the whole fairly barren and harsh, with salt flats, gravel plains, and sand dunes but few lakes or permanent streams. In the south is the *Rub Al Khali* (Empty Quarter), the largest sand desert in the world. In the southwest, the mountain ranges of *Asir* Province rise to over 2700 m. There is no precipitation during the months from June to September

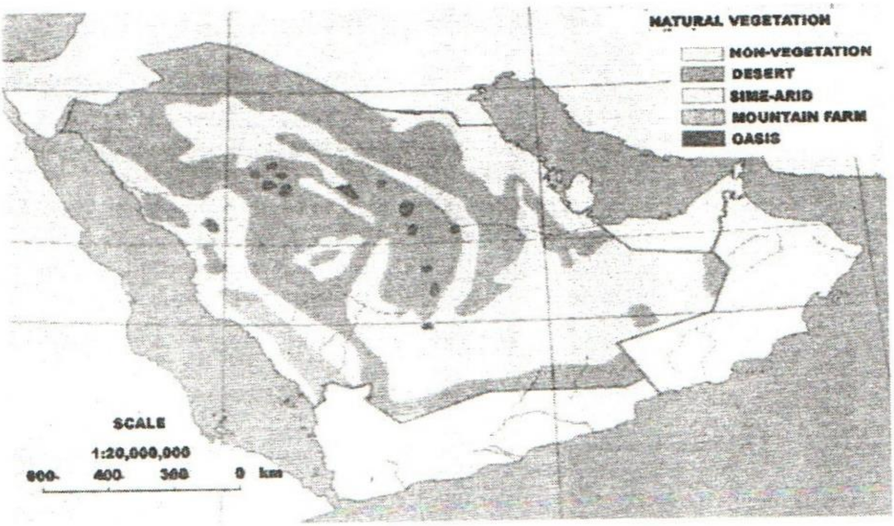

Figure 1. Natural vegetation (Atlas of Saudi Arabia and World, 1996)

IMAGE CLASSIFICATION

The overall objective of image classification procedures is to categorize all pixels in an image into different classes or themes. The spectral pattern present within the data for each pixel is used as the numerical basis for classification that is, different feature types manifest different combination of pixel values based on their inherent spectral reflectance and emittance properties. In this, a spectral pattern is not at all geometric in character. Rather, the term pattern refers to the set of radiance measurements obtained in the various wavelength bands for each pixel. In image classification, there are two main approaches, supervised and unsupervised classifications.

1 Supervised Classification

In this type of classification, the image analyst supervises the pixel categorization process by specifying, to the computer algorithm, numerical descriptors of the various types of features present in the scene. To do this, representative sample sites of previously known features type, called, training area, are used to compile a numerical "interpretation key" that describes the spectral attributes for each feature type of interest.

Each pixel in the data set is then compared numerically to each category in the interpretation key and labeled with the name the category it "looks most like." There are number of numerical strategies that can be employed to make this comparison between unknown pixels and training set pixels (Lillesand, 1994).

THE PROPOSED SCHEME

The minimum distance decision rule (also called spectral distance) is used to calculate the spectral distance between the measurement vector for the candidate pixel and the mean vector for each signature. In Figure 2, spectral distance is illustrated by the lines from the candidate pixel to the means of the three signatures (three classes). The candidate pixel is assigned to the class with the closest mean. The equation for classifying by spectral distance is based on the maximum likelihood.

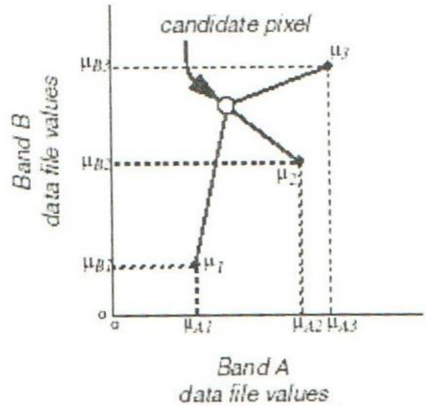

Figure 2 Minimum Spectral Distances

The maximum likelihood algorithm assumes that the histograms of the bands of data have normal distributions. With aid of a prior knowledge (training sets) that the probabilities are not equal for all classes, weight factors for particular classes can be specified. This variation of the maximum likelihood decision rule is known as the Bayesian decision rule. Unless there is a priori knowledge of the probabilities, it is recommended that they may not be specified. In this case, these weights default to 1.0 in the equation. The equation for the maximum likelihood/Bayesian classifier is as follows:

$$D = \ln(a_c) - [0.5 \ln(|Cov_c|)] - [0.5 (X-M_c)T (Cov_c-1) (X-M_c)]$$

Where:

D = weighted distance (likelihood)

c = a particular class

X = the measurement vector of the candidate pixel

M_c = the mean vector of the sample of class c

a_c = percent probability that any candidate pixel is a member of class c (defaults to

1.0, or is entered from a priori knowledge)

Cov_c = the covariance matrix of the pixels in the sample of class c

$|Cov_c|$ = determinant of Covc (matrix algebra)

Cov_c-1 = inverse of Covc

ln = natural logarithm function

T = transposition function

In this algorithm the candidate pixel is assigned to the class, *c*, for which *D* is the lowest. Chart 1 shows the system flowchart for image classification.

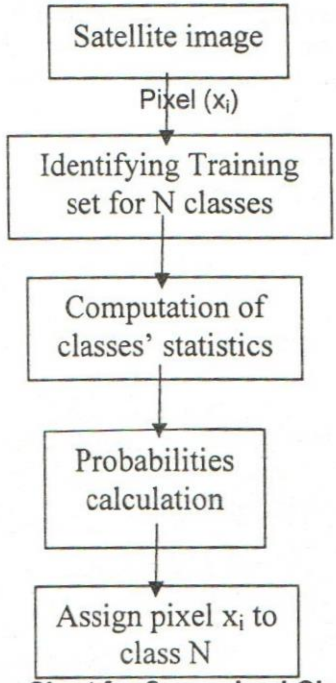

Chart 1 System Flow Chart for Supervised Classification

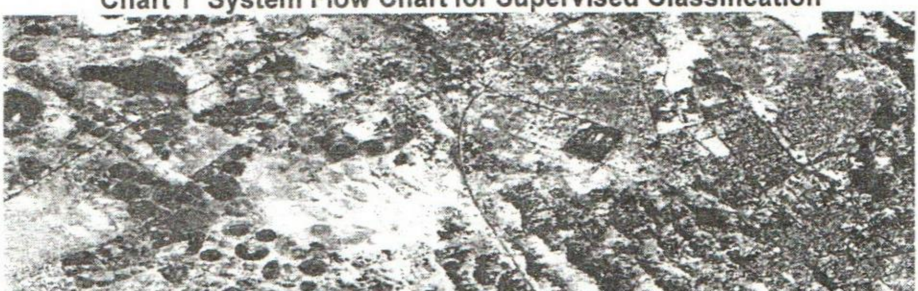

Figure 3. Landsat TM False Color Composite Image of the study area, and its surrounding desert environment.

1 Identifying Training Sites

The classification process was initiated using supervised classification techniques. Representative training sites were selected for each desired land cover class from the Landsat TM imagery, figure 4. Each training site was captured as an AOI, which was representative of the ten known classes of earth surface feature [12] as the following:

* Class 1 Vegetation
* Class 2 Road
* Class 3 MAL Moderate Arable Land (that soil can be used for general cropping after provision of appropriate drainge)
* Class 4 GAL Good Arable Land (well suited to a wide variety of crops inclding ochards
* Class 5 NAL Non-agricultural land (not considered suitable for economic plant production, active high sand dune area
* Class 6 Urban

Figure 4. Landsat TM imagery showing the ten Areas of Interest (AOI) from which spectral signatures were selected and used to classify Urban and desert areas of the City of Buraydah.

2 Computation of class statistics

The next step in the classification process involved the generation of statistics for each spectral signature. These statistical measures that were used to calculate category probabilities are necessary for the Maximum

Likelihood Classification. Spectral Means, Variance and Covariance matrices, and Standard deviations, determinant of variance and covariance matrices were calculated for each the 10 defined spectral classes.

3 Probabilities calculation

Once the necessary class statistics were computed, the MLC algorithm estimated a probability distribution for each training class that describes the chance of finding a pixel from a class C(i) at position (x). This set of probabilities is used to compute the relative highest likelihood that any given pixel belongs to each selected AOI earth surface feature class. Pixels that fall outside the signatures of the pre-defined classes are left and defined as unclassified. In some instances, tweaking and proper setting of the parameters are necessary for accurate classification. The algorithm was run three times with different parameters in order to reduce the proportion of unclassified pixels. This was performed by varying the input threshold used to evaluate whether an individual pixel belonged to one of the respective training classes. Threshold values were 3.0 can be seen in table1and the confusion matrix statistics analysis is shown in table 2.

Table 1. Supervised Classification statistics of Alkubub area Landsat TM. Statistics show the variation of class percentages (review unknown class) as a function of increasing threshold value.

Class No.	Name	No. Pixels	% Area	Threshold	Bias
1	Vegetation	114399	26.18	3	1
2	Road	23117	5.29	3	1
3	Moderate Arable Land	117045	26.78	3	1
4	Good Arable Land	51232	11.72	3	1
5	Non-agricultural Land	110683	25.33	3	1
6	Urban	20506	4.69	3	1

Table 2. Supervised Classification on confusion matrix statistics analysis of Alkbub area Landsat TM

Name	Code	Pixels	1	2	3	4	5	6
Vegetation	1	302	84.11	0.66	9.93	0.33	0	4.97
Road	2	178	0	83.15	5.62	2.81	0	8.43
Moderate Arable Land	3	249	1.2	6.02	81.12	10.04	0.4	1.2
Good Arable Land	4	228	0	2.63	32.89	63.6	0	0.88
Non-agricultural Land	5	125	0	0	0.8	0.8	98.4	0
Urban	6	68	1.47	10.29	2.94	7.35	0	77.94

CLASSIFICATION

As indicated by the preliminary classification results the Supervised Maximum Likelihood Classification (MLC) in this case proved to be a more effective and efficient means of creating a Land Cover classification than the unsupervised classification. The methodology of using known training samples required less input and interpretation from the user than the unsupervised classification

The supervised classification was preformed three times consecutive times in order to reduce the percentage of unknown or unclassified pixels found in the image.

Figure 5 exhibits the result of the supervised MLC, which generated a land cover map of the Buraydah area. The percent area coverage of each final class is plotted on Chart 2 and is based on the statistical area coverage class results shown in table 3.

Table .3. Final Land Cover Classification.

Class	Area (km^2)	Class Name
1	102.9591	Vegetation
2	20.8053	Road
3	105.3405	Moderate Arable Land
4	46.1088	Good Arable Land
5	99.6147	Non-agricultural land
6	18.4554	Urban

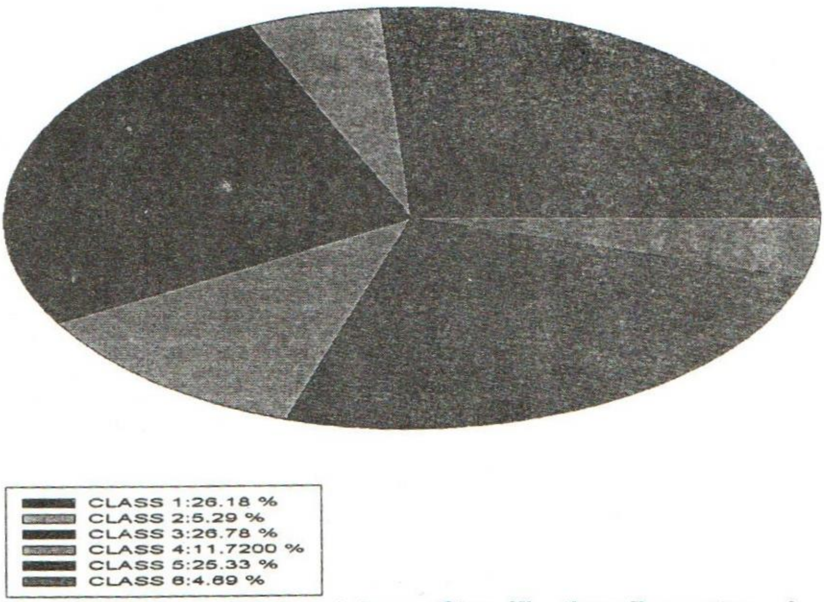

Chart 2. City of Buraydah Land Cover Classification: Percentage Areal Extent of Final Land Cover Classes created using a Supervised MLC (threshold: 4.5).

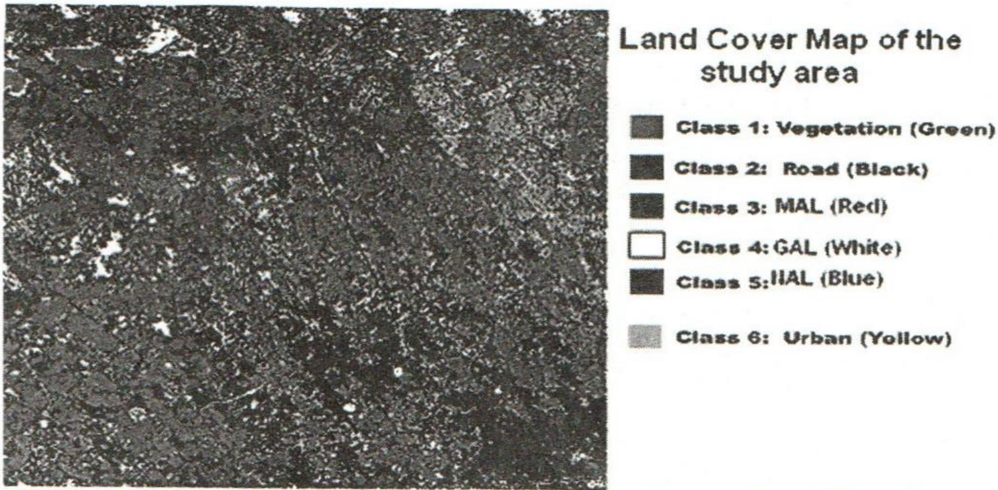

Figure 5. Land cover map of the study area along wadi Ar-Rumah Generated from the supervised classification method

ACCURACY ASSESSMENT

The error matrix indicating the overall accuracy is shown in Table (4). The accuracy of classification based on classified image is calculated to be 90%. This accuracy considered accepted for the purpose of this research.

Table (4): Error Matrix

		Classified land cover map					
		Vegetation	**Road**	**MAL**	**GAL**	**Agricultural area**	**Urban**
Reference Map	Vegetation	2	0	0	0	0	0
	Road	0	2	0	0	0	0
	MAL	0	0	1	0	0	0
	GAL	1	0	0	0	0	0
	Agricultural area	0	0	0	0	2	0
	Urban	0	0	0	0	0	2

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تحليل الغطاء الأرضي للكثبان الرملية لمنطقة جنوب وغرب مدينة بريده على طول وادي الرمة في منطقة العقيم، بالمملكة العربية السعودية باستخدام صور الأقمار الصناعية TM

سلطان السلطان* ، م. ز. ماتجفري، ك. عبد الله** و هـ. س. ليم****

***مركز السلطان للبحوث طريق المدينة القصيم ، الرياض الخبراء، القصيم، ص ب ٢٤٢ السعودية**

****مدرسة الطبيعة، جامعة ماليزيا، ميندن ١١٨٠٠ بيانج، ماليزيا**

إن الهدف الرئيسي لهذه الدراسة هو إنتاج خرائط الغطاء الأرضي للكثبان الرملية من خلال البيئة الحضرية الصحراوية باستخدام صور الأقمار الصناعية TM.
إن تحليل الدراسات الخاصة بالتخطيط الحضري والإقليمي باستخدام خرائط الغطاء الأرضي أصبحت وسيلة ذات فاعلية لمراقبة التغيرات البيئية.
في هذه الدراسة تم تصنيف صور الأقمار الصناعية بواسطة (supervised) بطريقة (MLC) والتي تستخدم لتعريف تضاريس الكثبان الرملية المحيطة بموقع الدراسة.
أثبتت هذه الطريقة أنها قابلة لتحديد حدود المعالم المختلفة التي تشمل النبات والطرق والتربة الحمراء والطين والكثبان الرملية والمناطق الحضارية بدقة تصنيف عالية.