

## Calculating the vegetation area using satellite imaging through two transformation methods

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### حساب المساحة الخضراء باستخدام التصوير الفضائي من خلال طريقتي تحويل

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#### المستخلص

تم في هذا البحث استخدام تحويل NDVI لتحديد أماكن تواجد المناطق الخضراء للمنطقة تحت التصوير بعد ذلك تم توظيف هذه النتائج كمعلومات أساسية لأجراء التصنيف الموجه للمركبة الأساسية الأولى -First- PCA بعد إجراء تحويل KL-Transformation كونها تحوي اغلب المعلومات الموجودة في صور القمر الصناعي ذات المتحسس TM بعد ذلك تمت المقارنة بين طريقتين للتصنيف الموجه وبالرجوع إلى معلومات ال NDVI وكذلك الإحصائيات. وأخيرا تم حساب نسبة المنطقة الخضراء في صور القمر الصناعي بالاعتماد على أفضل تصنيف.

#### Abstract

In this paper, we use of NDVI Transformation to determine where a bouts of the green areas (Vegetation) of the region under the imaging, then employ these results as background information to apply the supervised classification for the first principal component (PCA) after making a turn KL-Transformation they contain most of the information in the satellite image of sensor TM, after that is the comparison between the two methods of classification directed by reference to the NDVI and statistical measurements. Finally, we choose the best classification to calculate percentage of the Green areas in the satellite image.

#### Introduction

"Remote sensing is the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it (1). This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information." In much of remote sensing, the process involves an interaction between incident radiation and the targets of interest. This is exemplified by the use of imaging systems where the following seven elements are involved. Note, however that remote sensing also involves the sensing of emitted energy and the use of non-imaging sensors (2). Principal Component Analysis has been widely used to identify relevant features in remote sensing data due to its good performance in

reconstruction error after dimensionality reduction. Different applications include compact representation of spatio-spectral information (3). The Normalized Difference Vegetation Index is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum, and is adopted to analyze remote sensing measurements and to assess whether the target being observed contains live green vegetation or not. (4).

- **Digital image processing in remote sensing**

The enormous development in industry and technology of computers has helped greatly in dealing with massive digital image data making it easier for the possibility of applying the techniques leading to the digital image data storage and improved, analyze, and display and classified or interpreted manually and automatically and get as much information from them. These techniques are rapidly evolving and form an important part of remote sensing systems and digital imaging space, and it is called: Digital Image Processing. Image processing operations can be divided into four basic operations: Image Restoration, Image Enhancement, Image Classification and Image Transformation.

- **Image transformation**

Digital Image Processing offers a limitless range of possible transformations on remotely sensed data. Two are mentioned here specifically, because of their special significance in environmental monitoring applications: Principal Component Analysis (PCA) and Normalized Difference Vegetation Index (NDVI).

### **The work methodology**

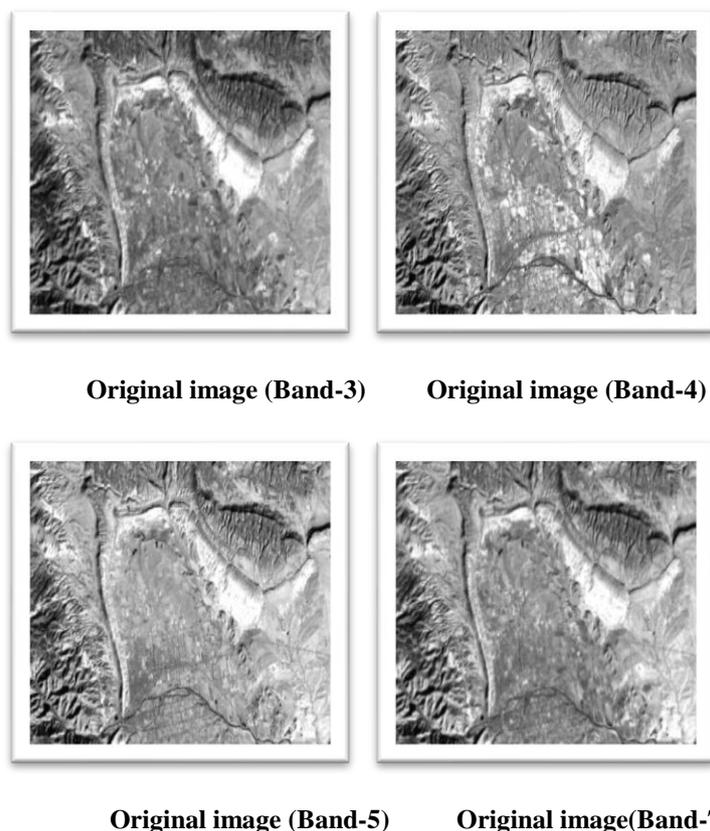
At first, we unfold the satellite image into its bands. as fig (1) and the wave length for each band, shown in table(1).



**Original image (Band- 1)**



**Original image (Band-2)**



**Figure (1):** Represent samples of six visible bands of multi-spectral images.

**Table (1):** Represent the wave length for each band.

Band 1	0.45-0.52 $\mu\text{m}$	visible light, blue
Band 2	0.52-0.60 $\mu\text{m}$	visible light, green
Band 3	0.63-0.69 $\mu\text{m}$	visible light, red
Band 4	0.76-0.90 $\mu\text{m}$	near infrared
Band 5	1.55-1.75 $\mu\text{m}$	middle infrared
Band 7	2.08 -2.35 $\mu\text{m}$	middle infrared

### Principal component analysis (PCA)

Principal components analysis transform are utilized as a tool to extract the significant inter-band information and eliminating the redundancy existed between different bands. KL-Transformation has been widely applied in many applications, such as image enhancement, feature extraction, image classification, image segmentation, temporal change detection, and image compression (5,6) The KLT is a linear transformation which uses the signal statistics to define the orthogonality between rotated axes of the original images and to pointing the direction of decreasing order of the variance (7).

**Mathematical description**

PCA is a statistical tool which has many applications especially in database processing (8),(9). Suppose there are  $M$  square  $N \times P$  monochrome images. This obligation doesn't make any restriction for colored images, since colored images can be supposed as 3 monochrome images that are red, green, and blue color components for each individual pixel.  $N \times P$  Monochrome images are equivalent to  $N \times P$  matrixes that the values of the components of the matrixes are the light intensities of the corresponding pixel's location. Suppose  $N \times P = Q$ . By reshaping the matrixes, the image can be expressed as  $1 \times Q$  vectors  $F_i$  in equation 1. In proposed approach, images are transferred to another field. All images are put in  $X$  matrix that its elements are the intensity values of images.

$$X = \begin{bmatrix} F_1 \\ \vdots \\ F_M \end{bmatrix}_{M \times Q}, F_i = (x_{i1}, x_{i2}, \dots, x_{iQ})_{1 \times Q} \dots \dots \dots (1)$$

The term  $F_i$  indicates the  $i^{th}$  image that converted to a vector. Now, in order to applying PCA method, we make some definitions; The mean vector,  $\bar{M}_x$ : that contains mean values of each image and expressed as:

$$\bar{M}_x = \frac{1}{Q} \begin{bmatrix} \sum_{K=1}^Q X_{1K} \\ \sum_{K=1}^Q X_{2K} \\ \vdots \\ \sum_{K=1}^Q X_{MK} \end{bmatrix}_{M \times 1} = \begin{bmatrix} m_1 \\ m_2 \\ \vdots \\ m_M \end{bmatrix} \dots \dots \dots (2)$$

$\tilde{M}_x$  matrix, that contains the values of  $\bar{M}_x$  for  $M$  times and expressed as:

$$\tilde{M}_x = [\bar{M}_x, \bar{M}_x, \dots, \bar{M}_x]_{M \times Q} \dots \dots \dots (3)$$

Covariance matrix  $C_x$  for  $M$  row of  $X$  matrix[8]:

$$C_x = [C_{i,j}]_{M \times M}$$

That:

$$C_{i,j} = \frac{1}{Q-1} \times \sum_{K=1}^Q [(X_{ik} - \bar{M}_x(i,1)) \times (X_{jk} - \bar{M}_x(j,1))] \dots \dots \dots (4)$$

For applying KL transform,  $M$  eigenvectors  $V_i, i = 1, 2, \dots, M$  and  $M$  eigenvalues  $\lambda_i, i = 1, 2, \dots, M$  can be found, which satisfy equation 5:

$$\forall i \in \{1, 2, \dots, M\} C_x \cdot v_i = \lambda_i \cdot v_i$$

$$V_i = \begin{bmatrix} [V_1(i)] \\ [V_2(i)] \\ \vdots \\ [V_M(i)] \end{bmatrix} \dots\dots\dots(5)$$

If we put all eigenvectors in a matrix, the modal matrix "Λ" will be obtained that its columns are the eigenvectors of  $C_x$  as shown below[9]:

$$\Lambda = [V_1, V_2, \dots, V_M]_{M \times M}^T \dots\dots\dots(6)$$

Now we can define V matrix:

$$V = \Lambda^{-1} \dots\dots\dots(7)$$

Λ is a unitary matrix. So:

$$\Lambda^{-1} = \Lambda^T \Rightarrow V = \Lambda^T \dots\dots\dots(8)$$

$$\Rightarrow V = [V_1, V_2, \dots, V_M]_{M \times M}^T \dots\dots\dots(9)$$

So:

$$V = \begin{bmatrix} [V_1(1)] & \dots & [V_M(1)] \\ \vdots & \ddots & \vdots \\ [V_1(M)] & \dots & [V_M(M)] \end{bmatrix}_{M \times M} \dots\dots\dots(10)$$

Applying KL transform makes Y matrix:

$$Y = V.(X - \tilde{M}_x) \dots\dots\dots(11)$$

Now we can obtain X with the inverse process of equation 11:

$$Y = V.(X - \tilde{M}_x) \Rightarrow V^{-1} \cdot Y = X - \tilde{M}_x$$

$$\Rightarrow X = V^{-1} \cdot Y + \tilde{M}_x \dots\dots\dots(12)$$

According to equation 8 we can write:

$$V^{-1} = (\Lambda^T)^{-1} = (\Lambda^{-1})^{-1} = \Lambda = V^T \dots\dots\dots(13)$$

Now, X matrix can be retrieved using equation 14:

$$X = V^T \cdot Y + \tilde{M}_x \dots\dots\dots(14)$$

In order to compress X some definitions are made as below[10]: Eq. 15

$$Y_k \triangleq \begin{bmatrix} [Y(1,1)] & \dots & [Y(1,Q)] \\ \vdots & & \vdots \\ [Y(K,1)] & \dots & [Y(K,Q)] \end{bmatrix}_{K \times Q} \dots\dots\dots(15)$$

$$\hat{X} \triangleq V_k^T \cdot Y_k + \tilde{M}_x \dots\dots\dots(16)$$

Considering the first k Eigen vectors from the M Eigen vectors (K<M), the  $\hat{x}$  matrix that is slightly different from X matrix, can be retrieved. The values of  $\hat{x}$  are near to values of X .

**Algorithm for PCA**

- Step 1: Formation of vectors from the given matrix (x).
- Step 2: Determination of covariance matrix.
- Step 3: Determination of Eigen values of the covariance matrix.

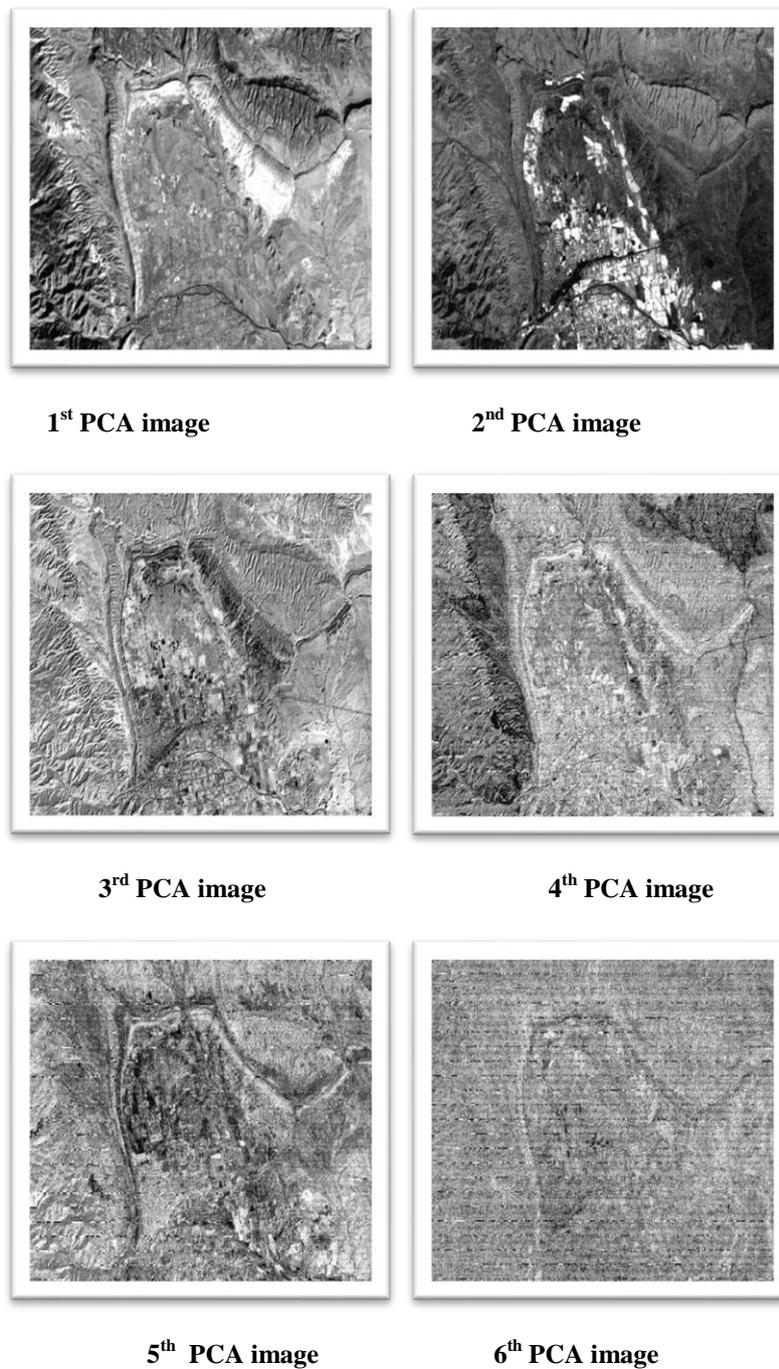
Step 4: Determination of Eigen vectors of the covariance matrix.

Step 5: Normalization of the Eigen vectors.

Step 6: Compute the KL transform matrix from the Eigen vector of the covariance matrix ( $v$ ).

Step 7: KL transform of the input matrix,  $y = v(x)$ .

Step 8: Reconstruction of input values from the transformed coefficients,  $(x = v' * y)$ .

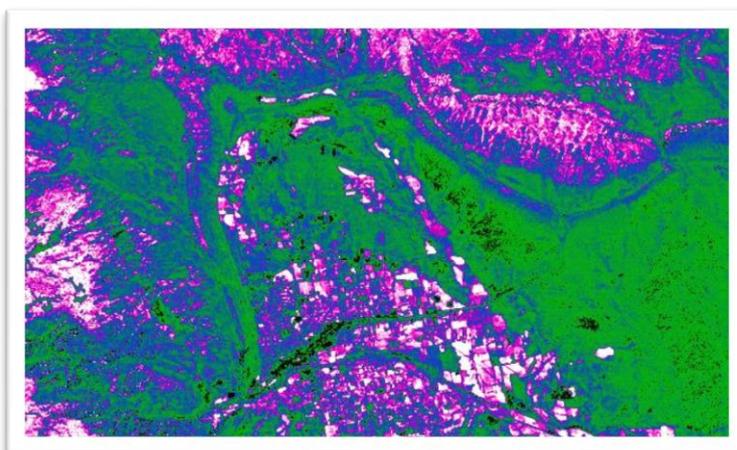


**Figure (2):** Represents the six  $PCA_s$  of the processed images and their normalized versions

### Normalized difference vegetation index (NDVI)

To determine the density of green on a patch of land, researchers must observe the distinct colors (wavelengths) of visible and near-infrared sunlight reflect by the plants. As can be seen through a prism, many different wavelengths make up the spectrum of sunlight. When sunlight strikes objects, certain wavelengths of this spectrum are absorbed and other wavelengths are reflected. The pigment in plant leaves, chlorophyll, strongly absorbs visible light (from 0.4 to 0.7  $\mu\text{m}$ ) for use in photosynthesis. The cell structure of the leaves, on the other hand, strongly reflects near-infrared light (from 0.7 to 1.1  $\mu\text{m}$ ). The more leaves a plant has, the more these wavelengths of light are affected, respectively (11). Fig(3) demonstrate the result of NDVI process which indicate the distribution of the vegetation over the area of field of view. Nearly all satellite Vegetation Indices employ this difference formula to quantify the density of plant growth on the Earth — near-infrared radiation minus visible radiation divided by near-infrared radiation plus visible radiation. The result of this formula is called the Normalized Difference Vegetation Index (NDVI). Written mathematically, the formula is (12):

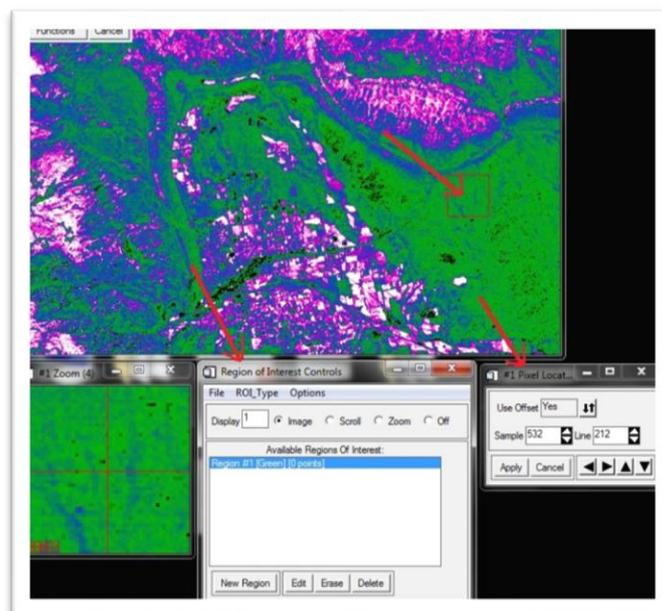
$$\text{NDVI} = (\text{NIR} - \text{red}) / (\text{NIR} + \text{red}) \dots \dots \dots (17)$$



**Figure (3): Resulted image from NDVI transformation**

### Region of interest.

The region of interest process can be achieved by using pixel locator technique as illustrate in fig(4). With reference to the NDVI image we choose the pixel index in green area to the corresponding position in the 1st PCA image. For more accuracy we choose multi pixels (represents classes) in multi homogenous green region



**Figure (4): Pixel locator technique**

## Classification

Image classification is the process of subdividing any image into its constituent parts or objects. Image classification is an important part of the remote sensing, image analysis and pattern recognition. In some instances, the classification itself may be the object of the analysis. For example, classification of land use from remotely sensed data produces a map like image as the final product of the analysis. Supervised and unsupervised classifications are the two broad types of classification processes that are used in satellite remote sensing (13). Some of the supervised techniques do not use probability distribution and use some other kind of mathematical discriminate functions. Maximum Likelihood Classification, Minimum Distance Classification, Parallelepiped and Classification Classifications come under supervised classification techniques. One of the most important method of supervised classification is a Minimum Distance Classification (14,15).

## Minimum-distance classification

Template matching can easily be expressed mathematically. Let  $x$  be the feature vector for the unknown input, and let  $m_1, m_2, \dots, m_c$  be templates (i.e., perfect, noise-free feature vectors) for the  $c$  classes. Then the error in matching  $x$  against  $m_k$  is given by  $\|x - m_k\|$ . Here  $\|m\|$  is called the norm of the vector  $m$ . A minimum-error classifier computes  $\|x - m_k\|$  for  $k = 1$  to  $c$  and chooses the class for which this error is minimum. Since  $\|x - m_k\|$  is also the distance from  $x$  to  $m_k$ , we call this a minimum-distance classifier [16]. Fig(6) demonstrate the result of minimum distance classification process, statistical measurements for minimum distance classification shown in table (2). Clearly, a template matching system is a minimum-distance classifier as figure(5) below.

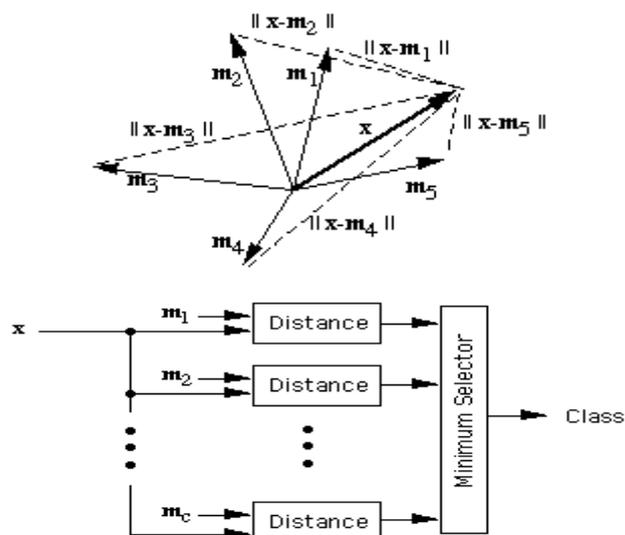


Figure (5): Scheme of the minimum distance classifier with its block diagram.

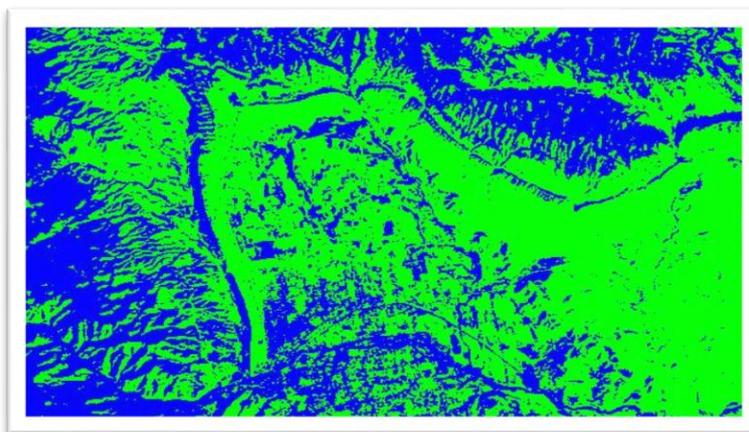


Figure (6): Resulted image from minimum distance classification for 1<sup>st</sup> PCA image.

Table (2): Statistical measurements for minimum distance classification

Class Name	Npts	Pct
Green	[151680]	59.2500%
Blue	[104320]	40.7500%

### Maximum likelihood classification

It applies the probability theory to the classification task (17). A statistical decision rule that examines the probability function of a pixel for each of classes, and assigns the pixel to class with the highest probability(18). Equation for Maximum likelihood /Bayesian classifier as follows

$$D = \ln(a_c) - [0.5 \ln(|C_{ovc}|)] - [0.5(X - M_c)^T (C_{ovc}^{-1})(X - M_c)] \dots \dots \dots (18)$$

Where

D = likelihood,

c = a particular class,

X = measurement vector of candidate pixel,

$M_c$  = the mean vector of sample of class c,

$a_c$  = percent probability that any candidate pixel is a member of class c,

$C_{ovc}$  = the covariance matrix of the pixels in sample of class c,

$|C_{ovc}|$  = determinant of  $C_{ovc}$ ,

$C_{ovc}^{-1}$  = inverse of  $C_{ovc}$ ,

Find likelihood for each pixel for each class. Pixel goes to class which has highest likelihood for this pixel, this way classification will be performed. Fig(7) demonstrating of the result of maximum likelihood classification process, statistical measurements for minimum distance classification shown in table (3).



**Figure (7): Resulted image from maximum likelihood classification for 1<sup>st</sup> pca image**

**Table (3): Statistical measurements for maximum likelihood classification**

Class Name	Npts	Pct
Green	[151625]	59.2285%
Blue	[104375]	40.7715%

## Results and Discussion

As it has been mentioned above, the principal components analysis (PCA) is a technique that can be used to simplify a data set. It is a linear transformation that chooses a new coordinate system for the data set such that the greatest variance by any projection of the data set comes to lie on the first axis (called the first principal component), the second greatest variance on the second axis, and so on, as shown in Table (4).

**Table (4): Statistical measurements for  $PCA_s$**

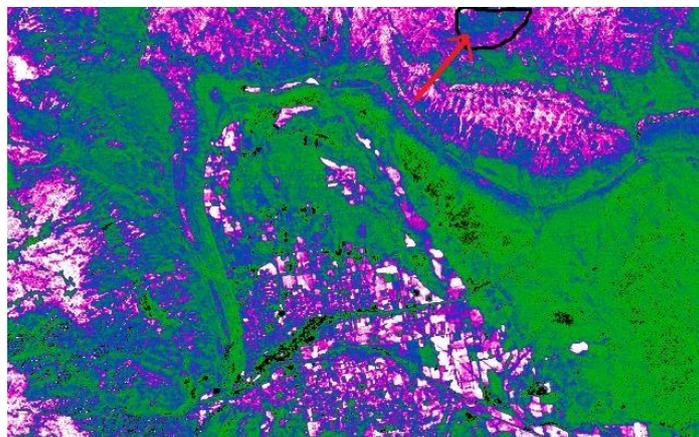
$PCA_s$	Min	Max	Stdev= $\sqrt{\text{var}}$
1	-58.802639	145.237595	20.058790
2	-26.394211	44.749443	5.539415
3	-66.925728	56.851040	4.802076
4	-13.530597	18.554543	1.669205
5	-21.360817	24.032904	1.475337
6	-23.274120	25.102030	1.327521

Supervised classification is the most important technique used for the extraction of quantitative information from a satellite image. It is much more effectual in terms of accuracy in mapping considerable classes whose validity depends largely on the cognition and skills of the image specialist. The technique assumes that each spectral class in the image can be described by a probability function in multi-spectral space. In our research, we choose two regions depending on NDVI transform to see clearly the regions and to select the best region class. Our image dimensions were (640x400), therefore, the percentage for every class was calculated by (number of points in the class(Npts) / 640x400). As we see, figure (6) and figure (7), from the tables under each classified image, vegetation covered 59.25% for minimum distance classification and 59.22% for maximum likelihood classification.

## Conclusion

The NDVI transformation gives the places of the vegetation in the satellite image, but these areas are overlapped with each other as illustrated in fig(3). Therefore we cannot depend on these areas to calculate the vegetation area in the satellite image. Supervised classifications were used for the first principle component after k1-transformation is done, so we get clear and separate regions (classes), because the first PCA has the most information power than the other PCAs for the TM image. Therefore, classified the PCA1 image in supervised method in the first method (minimum distance) we get (59.25%) vegetation ratio as illustrated in fig (6). But in the second method, we get (59.22%) vegetation ratio fig (7). By comparing the two

ratios with NDVI image we see that the first classification method is closest somewhat to the NDVI image. In addition classification gets separation regions than NDVI image. Also the pale regions in the NDVI image appear greenest areas as the index in fig (8),



**Figure (8): The Pale Regions in the NDVI Image**

So, we can study why this vegetation appears pale in NDVI image such as due to disease injury. From the statistical measurement in table (2) and (3) we see that the two supervised classification methods are almost the same, this accuracy of these classifications comes from the prior-knowledge from the NDVI transformation. This process is very important to choose the exact class. The second reason because we used the first PCA which have uncorrelated data. For more accuracy to determine the classes, we choose the region of interest over the pure and homogenous area in order to get closer to actually calculate the proportion of vegetation in the satellite image.

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