# IMAGE CLASSIFICATION
# WITH REMOTE SENSING
# USING DATA-MINING TECHNIQUES

by

Mohammad Tanveer Alam

Submitted in Partial Fulfillment of the Requirements
for the Degree of
Master of Science
in the

Mathematics program

YOUNGSTOWN STATE UNIVERSITY
May, 2011

Image Classification for Remote Sensing Using Data-Mining Techniques

Mohammad Tanveer Alam

I hereby release this thesis to the public. I understand that this thesis will be made available from the OhioLINK ETD Center and the Maag Library Circulation Desk for public access. I also authorize the University or other individuals to make copies of this thesis as needed for scholarly research.

Signature:

*Mohammad Tanveer Alam*, Student — Date

Approvals:

*John Sullins*, Thesis Advisor — Date

*Bradley A. Shellito*, Committee Member — Date

*Jamal K. Tartir,* Committee Member — Date

Peter J. Kasvinsky, Dean of School of Graduate Studies & Research — Date

ABSTRACT

Remote Sensing engages electromagnetic sensors to measure and monitor changes in the earth's surface and atmosphere. Remote Sensing Satellites are currently the fastest growing source of geographical area. Using data-mining techniques enables more opportunistic use of data banks of remote sensing satellite images. This thesis focuses on supervised and unsupervised classification, the two data mining techniques on the high resolution satellite Imagery from satellite IKONOS and satellite LANDSAT taken of the area around Kent State University, Ohio The image was classified into ten distinct class; 1) Water, 2) Forested, 3) Agriculture, 4) Urban Development, 5) Vegetation1, 6) Vegetation2, 7) Vegetation3, 8) Vegetation4, 9) Grass, 10) Road. ERDAS Imagine was used in manipulating the images and creating the classification and analysis. The result obtained in form of accuracy helps to decide which image and classification technique is better to identify geographical patterns related to land use.

ACKNOWLEDGEMENTS

I would like to thank Dr. John Sullins and Dr Bradley Shellito for the many opportunities of doing research with them, especially on the topic of Remote Sensing. This research allows me to pursue my academic goals to the fullest. I would like to thank Dr. Jamal Tartir for being the committee members of my thesis and helping me out on too many occasions to count at YSU. Also, I would like to thank Dr. Shellito for the academic help and moral support provided in and out of the class room.

# TABLE OF CONTENTS

# LIST OF TABLES

# 1 Introduction

Remote Sensing have been used to monitor land use changes; this has an important role in urban development and very useful for the production of land use and land cover statistics which can be useful to determine the distribution of land use in vegetation and watershed [7, 8]. Using remote sensing techniques to develop land use classification mapping is a useful and detailed way to improve the selection of areas designed to agricultural, urban and/or industrial areas of a region. The evolution in technology of remote sensing has caused it to become one of the most commonly used techniques in the world [4].

The area of study is located in Kent, Ohio, United States. The area covers the major portion of Kent State University including the Dix Stadium. In this study two different classification methods were used: Unsupervised and supervised classification. Unsupervised classification is the identification of natural groups, or structures, within multispectral data. Supervised classification is the process of using trained samples, samples of known identity to classify pixels of unknown identity. For this work the ERDAS Imagine computer software will be used to develop a land use classification using IKONOS image and LANDSAT Image. The generated land use classification will be compared with a land use generated using Google Earth to find the Accuracy with each method and to decide which method provides better land use classification.

# 2 Literature Review

## 2.1 The Landsat Program

The purpose of the Landsat program is to provide the world's scientists and application engineers with a continuing stream of remote sensing data for monitoring and managing the Earth's resources [4]. In 1967, the National Aeronautics and Space Administration (NASA), encouraged by the U.S Department of the Interior, initiated the Earth Resource Technology Satellite (ERTS) program. This program resulted in the development of five satellites carrying a variety of remote sensing systems designed primarily to acquire Earth resource information. The most noteworthy sensors were the Landsat Multispectral Scanner (MSS) and Landsat Thematic Mapper. The landsat Program is the United States oldest land-surface observation satellite system, having obtained data since 1972. It has had a tumultuous history of management and funding sources [13].

Landsat-5 was equipped with a Multispectral Scanner (MSS) and Thematic Mapper(TM). MSS is an optical sensor designed to observe solar radiation, which is reflected from Earth's surface in four different spectral bands, using a combination of the optical system and the sensor. Thematic Mapper is a more advanced version of the observation equipment used in the multispectral scanner, which observes the Earth's surface in seven spectral bands that range from visible to thermal infrared regions.

The Thematic Mapper(TM) is an advanced, multispectral scanning, earth resources sensor designed to achieve higher image resolution, sharper spectral separation, improved geometric fidelity, and greater radiometric accuracy and resolution than that of the MSS sensor. This sensor also images a swath that is 185km (115 miles) wide, but each pixel in a TM scene represents a

30m × 30m ground area, except in the case of the-infrared band 7, which uses a larger 120m × 120m pixel. The TM sensor has seven bands that simultaneously record reflected or emitted radiation from Earth's surface in the blue (band1), green (band2), red (band3), near-infrared band (band 4), mid-infrared (band 5 and 7), and far-infrared (band6) portion of the electromagnetic spectrum. TM band 2 can detect green reflectance from healthy vegetation, and band 3 is designed for detecting chlorophyll absorption in vegetation. TM band 4 is ideal for near – infrared reflectance peaks in healthy green vegetation, and for detecting water-land interfaces. TM band 1 can penetrate water from for bathymetric (water depth) mapping along coastal areas, and is useful for soil-vegetation differentiation, as well as distinguishing forest types. Two mid-infrared bands on TM are useful for vegetation and soil moisture studies, and discriminating between rock and mineral types. The far-infrared band on TM is designed to assist in thermal mapping, and for soil moisture and vegetation studies [14]. Landsat 5 was originally designed for a three-year mission, and remains in service after 25 years. Landsat 7 is still operating with a faulty scan line corrector. The next NASA land surface imaging mission is called the Landsat Data Continuity Mission and is scheduled for launch in December 2012.

**Characteristics of the Landsat Thematic Mapper (TM) Spectral Bands**

- Band 1: 0.45 to 0.52 µm (blue). Band 1 is useful for mapping water bodies as blue band penetrates in water, and other bands of the electromagnetic spectrum are reflected back. It also supports analyses of land-use, soil, and vegetation characteristics.

- Band 2: 0.52 to 0.60 µm (green). Green band spanning between blue and red chlorophyll absorption bands, this band shows the green reflectance of healthy vegetation. It is useful for differentiating between types of plants, determining the health of plants, and identifying manmade objects.

- Band 3: 0.63 to 0.69 µm (red). The visible red band is one of the most important bands for discriminating among different kinds of vegetation. It is also useful for mapping soil type boundaries and geological formation boundaries. Red band may exhibit more contrast than blue and green band because of the reduced effect of the atmospheric attenuation.

- Band 4: 0.76 to 0.90 µm (reflective infrared). This band is especially responsive to the amount of vegetation biomass present in a scene. It is useful for crop identification, for distinguishing between crops and soil, and for seeing the boundaries of bodies of water.

- Band 5: 1.55 to 1.75 µm (mid- infrared).This band is sensitive to the turgidity- amount of water in plants. Such information is useful in crop drought studies and in plant vigor investigations. In addition, this band can be used to discriminate between clouds snow, and ice.

- Band 6: 10.4 to 12.5 µm (thermal infrared). This band measures the amount of infrared radiant flux (heat) emitted from surfaces. It is useful for locating geo-thermal activity, thermal inertia mapping for geologic investigations, vegetation classification, vegetation stress analysis, and soil moisture studies.

- Band 7: 2.08 to 2.35 µm (mid- infrared). This band is particularly helpful for discriminating among types of geologic rock formations [8].

## 2.2 IKONOS

IKONOS, the world's first commercial high-resolution imaging satellite, operated by GeoEye was successfully launched in September of 1999. IKONOS collects imagery in four multi spectral bands and a single panchromatic band. The IKONOS multispectral bands approximate LANDSAT bands 1 through 4. Its applications include both urban and rural mapping of natural resources and of natural disasters, agricultural and forestry analysis, mining, engineering, construction, and change detection. Both the panchromatic and all four multispectral bands have 11-bit dynamic range. With 11-bit resolution, details in shadows, highlights, and low contrast scenes can be more easily discerned than in 8-bit images from Landsat, IKONOS produces panchromatic (black and white) imagery at 1 m resolution and multispectral (color) imagery at 4 m resolution. In 1 m panchromatic image, objects that 1 m in size on the ground can be distinguished, providing they have separate and distinct visual characteristics from other neighboring objects. For example, objects such as cars, tennis courts are all recognizable because of their context within their surroundings. Multispectral 4 m imagery does not have the spatial clarity of the panchromatic imagery due to its lower resolution however the 4 m multispectral imagery has much higher spectral resolution due to its four bands in the blue, green, red and near- infrared part of the spectrum. The higher spectral resolution allows the user greater scope for distinguishing between vegetation and soil types and other land use and landcover applications. The panchromatic imagery is available in one band has a spectral wavelength from 0.45 to 0.9 μm while the multispectral imagery is available in four bands in the blue, green, red and near-infrared part of the spectrum also ranges from 0.45 to 0.9 μm [15].

## 2.3 Spatial, Spectral and Radiometric Resolution

The High Resolution satellite digital image comprises of a two dimensional array elements called pixels arranged in columns and rows. Each pixel represents an area on the Earth's surface. A pixel has an intensity value and a location address in the two dimensional image. The intensity of a pixel is digitized and recorded as a digital number. A digital number is stored with a finite number of bits and the number of bits determines the radiometric resolution of the image. For example, an 8-bit digital number ranges from 0 to 255. Several types of measurement may be made from the ground area covered by a single pixel. Each type of measurement forms an image which carries some specific information about the area. By "stacking" these images from the same area together, a multilayer image is formed. Multilayer image can also be formed by combining images obtained from different sensors. For example, a multilayer image may consist of four layers from IKONOS multispectral image. Multispectral image consists of a few image layers, each layer represents an image acquired at a particular wavelength band. A multi spectral Landsat Thematic Mapper image consists of seven bands: blue, green, red, reflective infrared, two mid- infrared and thermal infrared. Spectral resolution of a sensor system is the number and width of spectral bands in the sensing device. A sensor with three spectral bands in the visible region of the Electromagnetic spectrum would collect similar information to that of the human vision system. The Landsat Thematic Mapper sensor has seven spectral bands located in the visible and near to mid infrared parts of the spectrum. Spatial resolution specifies the pixel size of satellite images covering the earth surface. And refer to the smallest possible feature that can be detected. A High Resolution image refers to one with a small resolution size. Fine details can be seen in a high resolution image. On the other hand Low Resolution image is one with a large resolution size, only coarse features can be observed in the image [7].

## 2.4 Classification

Remotely sensed data of the Earth may be analyzed to extract useful thematic information. Data are transformed into information. Multispectral classification [3] is one of the most often used methods of information extraction. This procedure assumes that imagery of a specific geographic area is collected in multiple regions of the electromagnetic spectrum and that the images are in good geometric registration.

Two methods of classification are commonly used: Unsupervised and Supervised. The logic or steps involved can be grasped from the following flow diagrams:

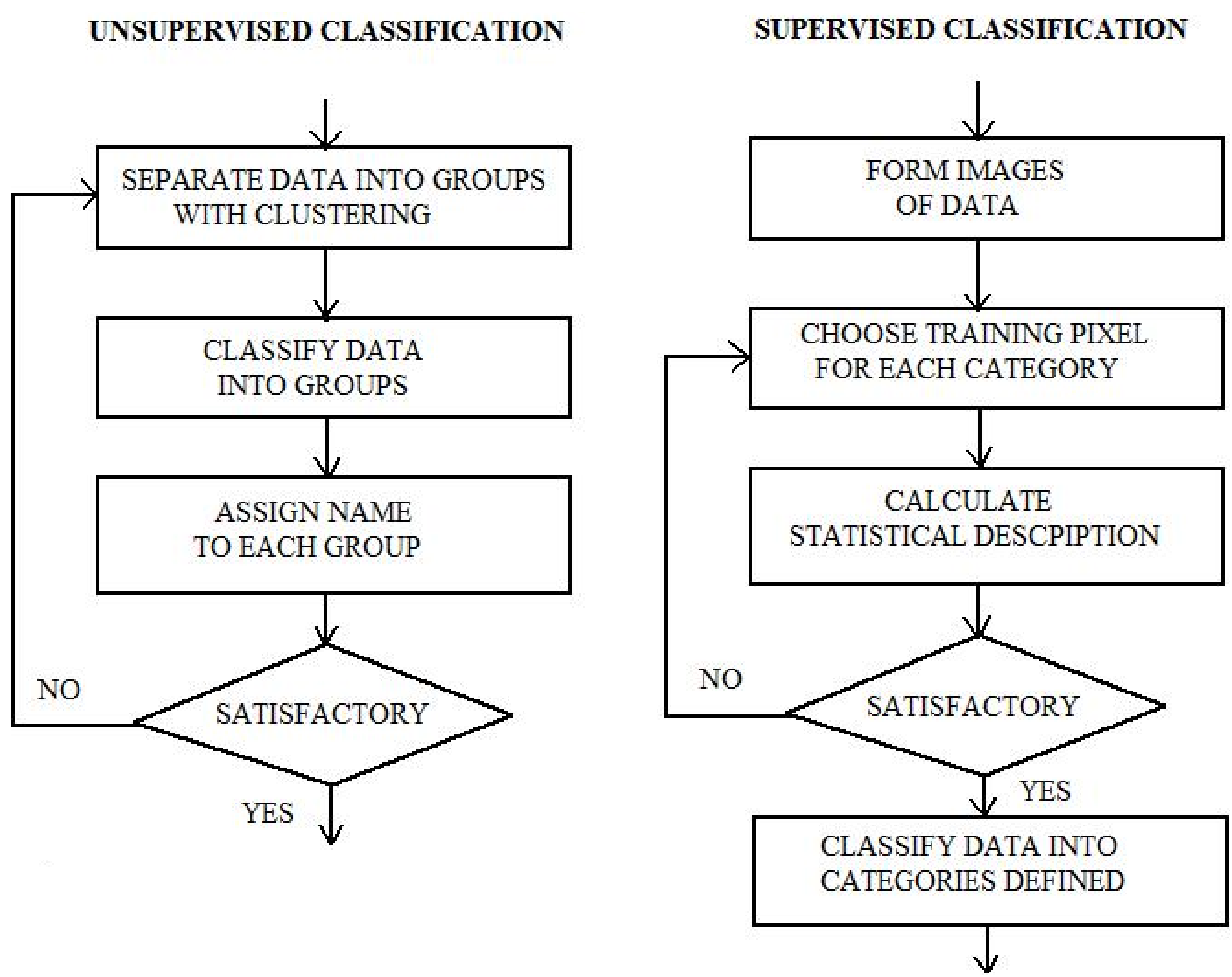


*Figure from F.F. Sabins, Jr., "Remote Sensing: Principles and Interpretation"*

In an unsupervised classification, the identities of land-cover types to be specified as classes within a scene are not generally known a priori because ground reference information is lacking or surface features within the scene are not well defined. The computer is required to group pixel with similar spectral characteristics into unique clusters according to some statistically determined criteria [5]. The analyst then combines and relabels the spectral clusters into hard information. Any individual pixel is compared to each discrete cluster to see which one is closest to. A map of all pixels in the image, classified as to which cluster each pixel is most likely to belong, is produced. This then must be interpreted by the user as to what the color patterns may mean in terms of classes, etc. that are actually present in the real world scene; this requires some knowledge of the scene's feature/class/material content from general experience or personal familiarity with the area imaged.

In a supervised classification, the identity and location of some of the land cover types, such as urban, agriculture, or wetland, are known a priori (before the fact) through a combination of fieldwork, analysis of high resolution Image, and personal experience. The interpreter knows beforehand what classes, etc. are present and where each is in one to perhaps many locations within the scene. These are located on the image, areas containing examples of the class are circumscribed (making them training sites), and the statistical analysis is performed on the multiband data for each such classes. Instead of clusters then, one has class groupings with appropriate discriminated functions that distinguish each (it is possible that more than one class will have similar spectral values but that is unlikely when more than 3 bands are used because different classes/materials seldom have similar responses over a wide range of wavelengths). All pixels in the image lying outside training sites are then compared with discriminants derived from the training sites, with each being assigned to the class it is closest to – makes a map of established classes (with a few pixels usually remaining unknown). Result of training is a set of signatures that defines a training sample or cluster. Each signature corresponds to a class, and is used with a decision rule to assign the pixel in the image file to a class. After the signatures are defined, the pixels of the image are sorted into classes based on the signatures by use of classification decision rule and using data contained in the signature, performs the actual sorting of pixels into distinct class values.

## 2.5 Unsupervised Training

Unsupervised training requires only minimal input from the user. However the task of interpreting the classes that are created by the unsupervised training algorithm.

Unsupervised training is also called clustering, because on the natural groupings of pixels in image data when they are plotted in feature space [9,6]. Clusters are defined with a clustering algorithm, which often uses all or many of the pixels in the input data file for the analysis. The clustering algorithm has no regards for the contiguity of the pixels that define each cluster.

Several different unsupervised classification algorithms are commonly used in remote sensing. The frequently used algorithms are the K-mean and The Iterative Self Organizing Data Analysis Technique (ISODATA) clustering algorithm. The ISODATA clustering method uses spectral distance in a sequential method. The Iterative algorithm starts with the first step as assigning arbitrary initial cluster vector. The second step classifies each pixel to the closest cluster. In the third step the new cluster mean vectors are calculated based on all the pixels in one cluster. The second and third steps are repeated until the change between the iteration is small. The change is defined by the percentage of pixels that have changed between iterations. The ISODATA algorithm further refines by splitting and merging of clusters. Clusters are merged if either the number of members (pixel) in a cluster is less than a certain threshold of if the centers of two clusters are closer than a certain threshold. Clusters are split into two different clusters if the cluster standard deviation exceeds a predefined value and the number of members (pixels) is twice the threshold for the minimum number of members. ERDAS Imagine uses the ISODATA clustering for the unsupervised classification [17].

ISODATA Clustering Parameters-

*N* – Represents maximum number of clusters considered. As each cluster is the basis for a class, this number becomes the maximum number of classes to be formed. The ISODATA process first step begins by determining *N* arbitrary cluster means.

*T* – Convergence threshold, which is the maximum percentage of pixels whose class values are allowed to be unchanged between iterations. This threshold prevents the ISODATA utility from running indefinitely. For this study convergence threshold number was set to .95

*M* – The maximum number of times that the ISODATA utility reclusters the data. It prevents this utility from running too long or from potentially getting stuck in a cycle without reaching the convergence threshold. It was set to 24 for our study.

In the first iteration of the ISODATA algorithm, the means of *N* clusters is arbitrarily determined. Every iteration assigns a new mean for each cluster which is calculated, based on the actual spectral locations of the pixels in the cluster. These new means are used for defining clusters in the next iteration. The process continues until there is a little change between iteration.

Cluster means are distributed between the points at spectral coordinates (μ1-σ1, μ2-σ2, μ3-σ3,..μn-σn)

And the coordinates (μ1+σ1, μ2+σ2, μ3+σ3,…....μn+σn).Cluster means are evenly distributed between (μA-σA, μB-σB) and (μA+σA,μB-σB)

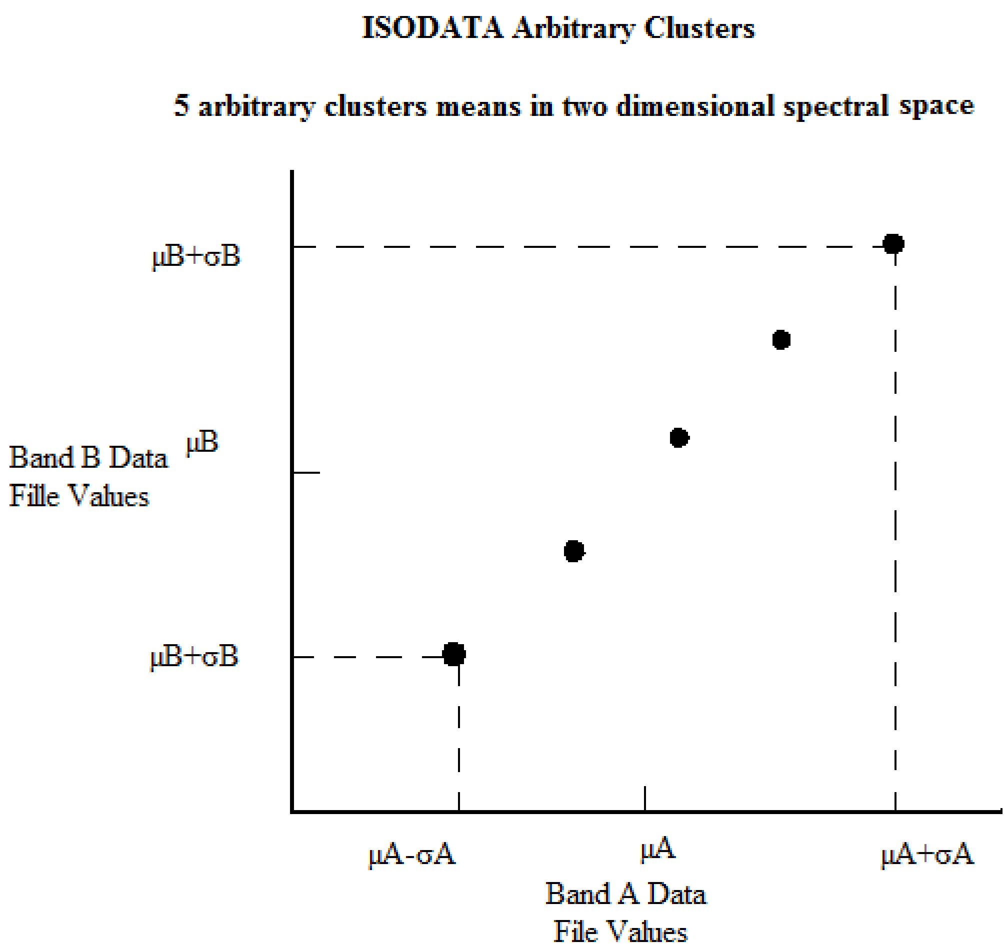


*Figure from ERDAS field guide: ISODATA Arbitrary Clusters*

The analysis of the pixels are done going left to right, from upper left corner of the image and the spectral distance between the candidate pixel and each cluster mean is calculated. The pixel is assigned to the cluster whose mean is the closest. The ISODATA algorithm creates an output image file with a thematic raster layer and/or a signature file as a result of the clustering. At the end of each iteration, an image file exists that shows the assignments of the pixels to the clusters

[17]. After the first Iteration the following figure shown represents the following results in terms of five clusters.

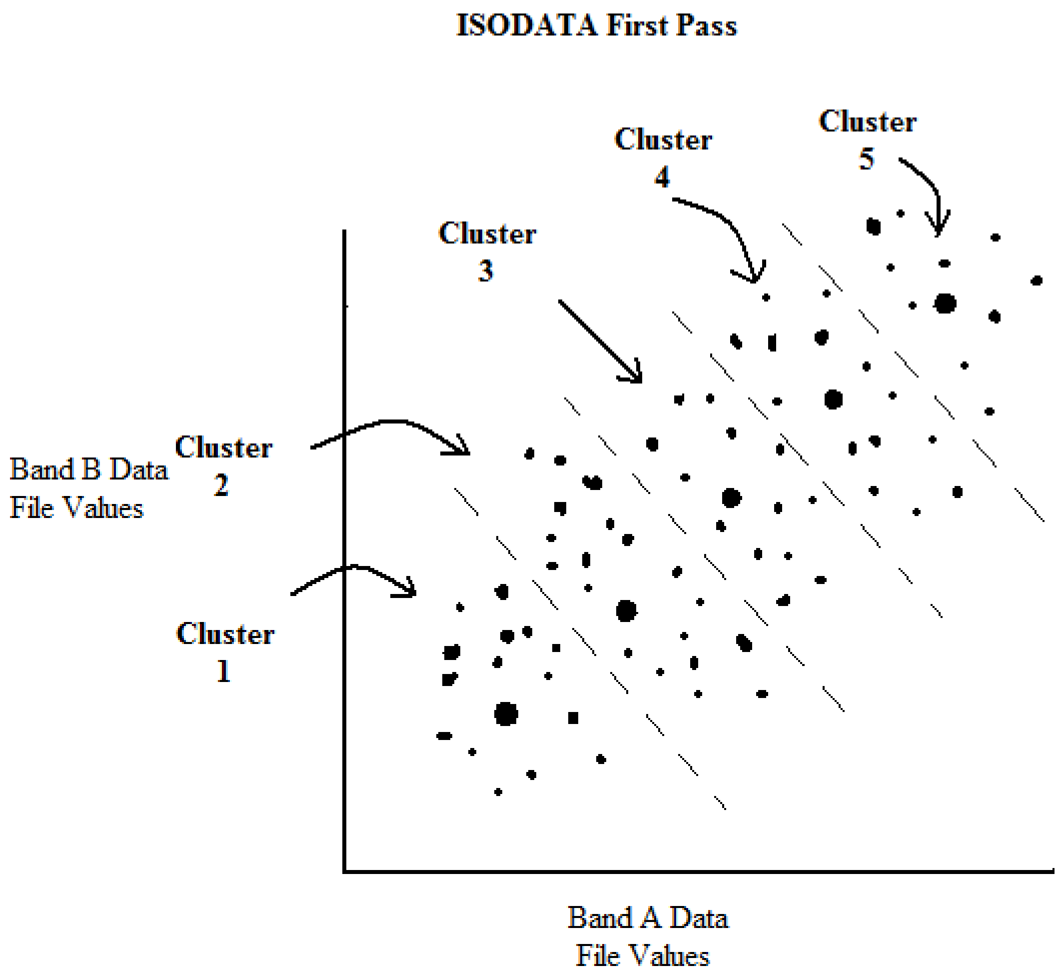


*Figure from ERDAS field guide: ISODATA First Pass*

From the second iteration, the means of all clusters are recalculated, causing a shift in feature space. The process is repeated and each candidate pixel is compared to the new cluster means and assigned to the closest cluster mean.

After each iteration, the normalized percentage of pixels whose assignments are unchanged since the last iteration is displayed in the dialog. When this number reaches *T* (the convergence threshold), the program terminates. It is possible for the percentage of unchanged pixels to never converge or reach $T$ (the convergence threshold). Therefore, it may be beneficial to monitor the percentage, or specify a reasonable maximum number of iterations, $M$, so that the program does not run indefinitely.

**ISODATA Second Pass**

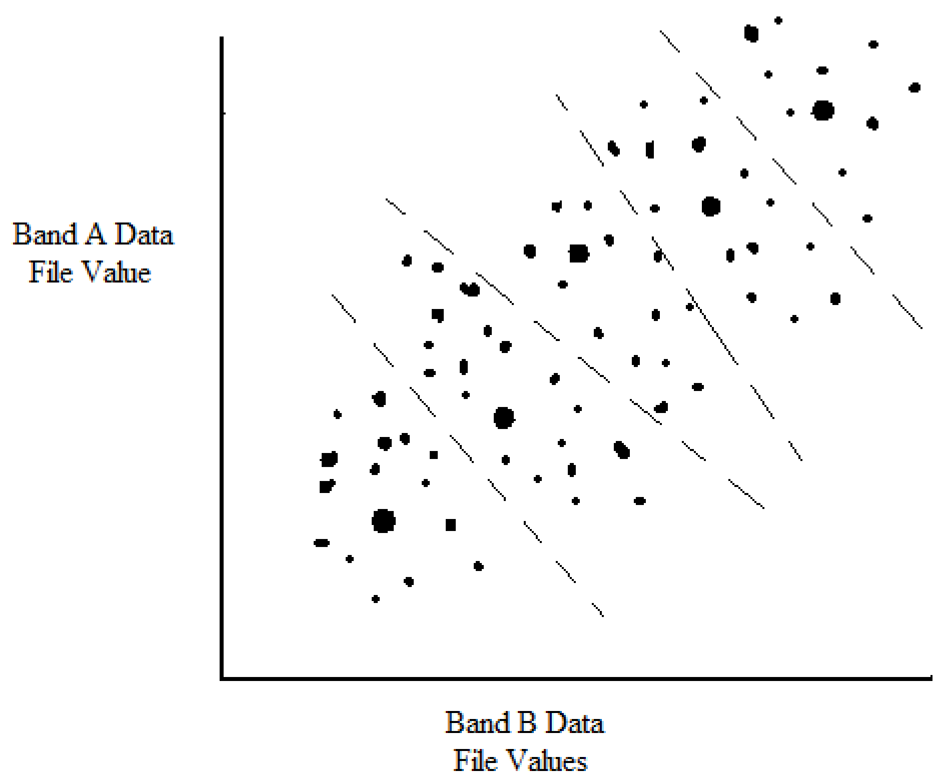


*Figure from ERDAS field guide: ISODATA Second Pass*

## 2.6 Supervised Training

In supervised classification, the image processing software is guided by the user to specify the land cover classes of interest. The user defines “training sites” – areas in the map that are known to be representative of a particular land cover type – for each cover type of interest. The software determines the spectral signature of the pixels within each training area, and uses this information to define the means and variance of the classes in relation to all the input bands or layers [1]. Each pixel in the image is then assigned, based on its spectral signature, to the class it most closely matches. It is important to choose training areas that cover the full range of variability within each land cover type to allow the software to accurately classify the rest of the image. In supervised classification information about the data is already known such as, different types of classes, land cover, vegetation, and the analyst from its prior knowledge help the system to determine the statistical criteria(spectral signatures) for data classification. For collecting training sample or set of pixels selected to represent a potential class, some knowledge either spatial or spectral is known to the analyst from priori, for example if the sample for class water is to be collected, the analyst collect pixels sample from the area which are responsive to blue band as blue band is absorbed by water and so can be easily detected. Ground truth data are most accurate data available about the area of study. Now the Training samples collected for each class has a distinct spectral signature.

For collecting training samples in ERDAS IMAGINE the method used in our study was by defining a polygon in the image, this user defined polygon use pattern recognition skill (with or without supplemental ground truth information). The locations of the training sites can be digitized from maps with AOI tools from the software to create signatures [17].

In the supervised learning each pixel in the image is compared with the training samples which are the spectral signature, signature is a set of data that defines a training samples or cluster. The signature is used in classification where decision rule (algorithm) requires signature attributes as input these are stored in the signature file. Once signatures are created, they can be evaluated and merged with signatures from other files, once a set of reliable signatures has been created and evaluated, the next step is step is to perform classification of the data. Each pixel is analyzed independently. The measurement vector for each pixel is compared to each signature, according to the decision rule, or algorithm. Pixels that pass the criteria that are established by the decision rule are then assigned to the class for that signature. The decision rule for the supervised learning used in this study was the statistics and histogram of the signature to make evaluations and comparison, The histogram of signature is formed of the different band combination that is collected from the training samples in IKONOS image it is from four different bands and in Landsat it is from seven different band combination. Each pixel in the image is compared to the histogram of the spectral signature from left to right and top to bottom and check is done that if any of the spectral signature matches with the pixels from image if the match is made the pixel in the image is classified to that particular class which represents that signature. In this study the spectral signature for the different ten classes were collected through the digitized polygon. For example for class water the group of pixels were picked from the area on the image which the used from prior knowledge knows it represents water body. And then signature were collected under .sig files for the comparison to do the supervised classification.

## 2.7 Study Area

The Area around Kent State University, Northeastern Ohio was the Study Area for the thesis the UTM coordinates extending from Upper Left X: 469042.45m, Upper Left Y: 4556861.41, Lower Right X: 475162.45, Lower Right Y: 4550741.41. The two water bodies in the area are the Sandy Lake and Lake Brady. Tom S Cooprrider Bog State Nature Preserve and Plum Creek Park are also the main attractions in the area.

There is Schoonover Stadium in Allerton Sport Complex and Dix Stadium which lies at the far eastern end of Kent State University campus along Summit Street, just east of State Route 261

The important roads in the area are E Summit Street, State Route 261, Kent Ravenna Road, E Main Street, Lake Street and S Walter Street.

This area was well suited for the study as it contains all the geographical land use, it contains bodies, forested area, different vegetations and also a lot of urban development, which was very helpful to have different classes in our classification. The land use was divided into ten different classes 1) Water, 2) Urban development, 3) Vegetation1, 4) Vegetation2, 5) Vegetation3, 6) Vegetation4, 7) Road, 8) Agricultural land, 9) Grass, 10) Forested.

Here Vegetation1 contains the group of trees in the area that had different spectral signature than the dense forest, similarly Vegetation2 are the trees and shrubs having distinct spectral signature than vegetation 1 and forest. Vegetation3 and Vegetation4 also represents vegetation that has different spectral signatures than others.

## 2.8 Image Information

**LANDSAT TM Image Information**

1. Number of Layers(Bands) – 7
    a. Band 1(Blue) : 0.45 to 0.52µm
    b. Band 2(Green) : 0.52 to 0.60µm
    c. Band 3(Red) : 0.60 to 0.69µm
    d. Band 4(Reflective Infrared) : 0.76 to .90µm
    e. Band 5(Mid-Infrared) : 1.55 to 1.75µm
    f. Band 6(Thermal Infrared) : 10.4 to 12.5µm
    g. Band 7(Mid-Infrared) : 2.08 to 2.35µm

2. Data Type - Unsigned 8bit
3. Map Info - Upper Left X: 469042.45m Upper Left Y : 4556861.41m
   Lower Right X: 475162.45m Lower Right Y: 4550741.41m

4. Pixel Size – Pixel Size X: 30m
   Pixel Size Y: 30m
5. Projection - UTM, Zone 17
6. Spheroid - WGS 84
7. Datum – WGS 84

**IKONOS Image Information**

1. Number of Layers(Bands) – 4
   a. Band 1(Blue) : 0.445 to 0.516µm and 0.45 to 0.90µm (1m Panchromatic)
   b. Band 2(Green) : 0.506 to 0.595µm
   c. Band 3(Red) : 0.632 to 0.698µm
   d. Band 3(Near Infrared) : 0.757 to 0.853µm

2. Data Type - Unsigned 16bit
3. Map Info - Upper Left X: 469042.45m Upper Left Y : 4556861.41m
   Lower Right X: 475154.45m Lower Right Y: 4550729.41m

4. Pixel Size – Pixel Size X: 4m
   Pixel Size Y: 4m
5. Projection - UTM, Zone 17
6. Spheroid - WGS 84
7. Datum – WGS 84

## 2.8 Software Used

ERDAS Imagine 2010 is a powerful software package that is most commonly used by remote sensing scientists for manipulating and analyzing data [10]. It is a fully integrated desktop authoring platform, incorporating image analysis, remote sensing and GIS capabilities from company named Earth Resource Data Analysis System (now known as ERDAS)

In this study we used the unsupervised and supervised classification techniques from the Software to analyze the accuracy of image classification on the two high resolution Imagery from Landsat and IKONOS of the described area of study Kent State University.

# 3. Methodology

The High Resolution Image from LANDSAT and IKONOS of the area around Kent State University were taken and the images were crop down to have same Area of Interest (AOI) such that both images share the same UTM coordinates. That will help in our study to decide from the accuracy of classification of the classes, which satellite imagery will provide the better classification. Two different classification techniques Supervised and Unsupervised were used for Image classification using ERDAS IMAGINE. Starting with the unsupervised classification creating a thematic raster layer by letting the software identify statistical patterns in the image data without any ground truth data, The software uses ISODATA algorithm to perform an unsupervised classification. The ISODATA clustering method uses the minimal spectral distance formula to form clusters. Beginning with means of an existing signature set, each time the clustering repeats, the means of these clusters are shifted. The new cluster means are used for the next iteration, for our study the maximum Iteration is 24 and Convergence Threshold of .95 which is the maximum percentage of pixel that has cluster assignments that go unchanged between iterations. And 10 number of classes is considered for this study; After the unsupervised classification is performed the different classes are named from the prior knowledge of the area. The different classes are 1) Water, 2) Urban development, 3) Vegetation1, 4) Vegetation2, 5) Vegetation3, 6) Vegetation4,  7) Road, 8) Agricultural land, 9) Grass, 10) Forested.

For the accuracy assessment randomly chosen 150 different UTM coordinate were taken and then accuracy of the classification was done from comparing the UTM coordinates with Google Earth. The following table contains the study of the unsupervised classification on the IKONOS Imagery.

**Accuracy Assessment Methods**

Production of an error matrix is a key stage in classification process. It permits the analyst to determine the accuracy of the classified map displaying statistics for accessing Image classification accuracy, is this study the accuracy assessment is the comparison of classification method and IKONOS and Landsat TM high resolution imagery for each classification and used to derive the Overall Accuracy, Producer's Accuracy and an estimate of Kappa Statistic [7].

Error Matrix compares two thematic maps. This is typically done in a tabular or array form. In remote sensing image analysis, the two thematic maps are often a "ground truth" map or reference map (In this study Google earth was used for the ground truth) and a map derived from automated image classification here we had IKONOS and Landsat High Resolution Image (the classified map). The error matrix permits the calculation of a range of measures that describes the accuracy of the classified map with respect to the reference map. To generate the error matrix, thematic information is recorded from the same pixels that display the same ground area on the two maps done by choosing the same UTM coordinates on the two maps. Calibration data are recorded from the reference map and validation data from the classified map. Information in the horizontal rows normally corresponds to the thematic classes of the reference map. The vertical columns show the thematic information resulting from automated image classification. The cells in the matrix contain a count of pixels, which is based on information derived from the class assignments of pixels in both the classified map and the reference map [11].

Overall Accuracy is commonly used estimate of accuracy in satellite image classification and is computed by dividing the total correct (sum of the major diagonal) by the total number of pixels in the error matrix. Computing the accuracy of individual categories, however, is more complex because the analyst has the choice of dividing the number of correct pixels in the category by the total number of pixels in the corresponding row or column. Traditionally, the total number of correct pixels in a category is divided by the total number of pixels of that category as derived from the reference data. This statistic indicates the probability of a reference pixel being correctly classified and is a measure of omission error. This statistic is called the producer's accuracy because the producer (the analyst) of the classification is interested in how well a certain area can be classified. If the total number of correct pixels in a category is divided by the total number of pixels that were actually classified in that category, the result is a measure of commission error. This measure, called the user's accuracy or reliability, is the probability that a pixel classified on the map actually represents that category on the ground.

A more comprehensive measure of the accuracy of a classification is the Kappa coefficient, also referred to as Kappa hat or K-hat. This measure compares the numbers of pixels in each of the cells in the matrix with a random or chance distribution of pixels. Kappa statistic considers a measure of overall accuracy of image classification and individual category accuracy as a means of actual agreement between classification and observation. The value of kappa lies between 0and 1, where 0 represents agreement due to chance only. Meanwhile 1 represents complete agreement between the two data sets. Negative values can occur but are spurious [12].

**<u>Unsupervised Classification and Accuracy Measurement on High Resolution IKONOS Image of Kent State University.</u>**

**Table1. Dataset collected after unsupervised classification of IKONOS imagery.**

| S.No | Randomly Collected UTM coordinates | Classification according to the Unsupervised Classification | Real World Classification using Google Earth |
|---|---|---|---|
| 1 | 471541.99mE,4555205.82mN | Forest | Urban development |
| 2 | 470000.42mE,4555788.95mN | Road/Parking Lot | Road/Parking Lot |
| 3 | 469936.88mE,4555827.04mN | Vegetation | Road/Parking Lot |
| 4 | 472912.00mE,4553834.37mN | Vegetation | Vegetation |
| 5 | 473701.00mE,4554351.16mN | Vegetation | Road/Parking Lot |
| 6 | 470314.04mE,4552858.39mN | Vegetation | Vegetation |
| 7 | 472603.61mE,4554845.98mN | Vegetation | Vegetation |
| 8 | 473516.43mE,4551935.81mN | Vegetation | Vegetation |
| 9 | 469920.34mE,4556589.09mN | Vegetation | Vegetation |
| 10 | 474053.08mE,4554500.60mN | Vegetation | Vegetation |
| 11 | 473842.31mE,4556575.72mN | Vegetation | Vegetation |
| 12 | 472149.03mE,4555740.60mN | Vegetation | Vegetation |
| 13 | 471501.22mE,4554569.23mN | Vegetation | Urban development |
| 14 | 471484.29mE,4554856.90mN | Vegetation | Urban development |
| 15 | 473508.35mE,4554964.51mN | Forest | Forest |
| 16 | 471542.90mE,4553171.09mN | Forest | Forest |
| 17 | 475028.99mE,4552342.91mN | Forest | Water |
| 18 | 471541.99mE,4555205.82mN | Forest | Urban development |
| 19 | 470577.58mE,4556346.58mN | Forest | Forest |
| 20 | 472366.92mE,4554077.99mN | Forest | Urban development |
| 21 | 471495.33mE,4555053.94mN | Forest | Forest |
| 22 | 473187.10mE,4552341.45mN | Forest | Forest |
| 23 | 469561.84mE,4554368.01mN | Forest | Forest |
| 24 | 469543.84mE,4553979.01mN | Forest | Urban development |
| 25 | 472451.06mE,4556241.97mN | Forest | Urban development |
| 26 | 472051.24mE,4556264.86mN | Forest | Forest |
| 27 | 472279.43mE,4556679.48mN | Forest | Forest |
| 28 | 473475.40mE,4551972.66mN | Forest | Forest |
| 29 | 475088.02mE,4552233.54mN | Forest | Water |
| 30 | 470529.45mE,4552037.14mN | Forest | Forest |
| 31 | 470173.62mE,4553582.24mN | Forest | Forest |
| 32 | 472920.08mE,4553787.21mN | Forest | Forest |
| 33 | 471170.46mE,4556014.23mN | Forest | Forest |
| 34 | 471954.01mE,4556090.95mN | Vegetation 2 | Vegetation 2 |
| 35 | 472710.23mE,4554504.65mN | Vegetation 2 | Vegetation 2 |
| 36 | 473509.51mE,4552393.82mN | Vegetation 2 | Vegetation 2/Shrubs |
| 37 | 471942.47mE,4554757.44mN | Vegetation 2 | Grass Land |

| | | | |
|---|---|---|---|
| 38 | 474477.32mE,4552160.89mN | Vegetation 2 | Grass Land |
| 39 | 471357.76mE,4556227.26mN | Vegetation 2 | Vegetation 2 |
| 40 | 474625.02mE,4552901.06mN | Vegetation 2 | Vegetation 2 |
| 41 | 470989.79mE,4555527.84mN | Vegetation 2 | Vegetation 2 |
| 42 | 472202.95mE,4555421.97mN | Vegetation 2 | Vegetation 2 |
| 43 | 470810.76mE,4554650.63mN | Vegetation 2 | Vegetation 2 |
| 44 | 471685.30mE,4554082.43mN | Vegetation 2 | Grass Land |
| 45 | 473742.90mE,4551908.25mN | Vegetation 2 | Vegetation 2 |
| 46 | 473404.35mE,4554332.84mN | Road/Parking Lot | Road/Parking Lot |
| 47 | 473049.03mE,4554097.42mN | Road/Parking Lot | Road/Parking Lot |
| 48 | 473158.73mE,4554777.61mN | Road/Parking Lot | Grass Land |
| 49 | 471842.18mE,4555910.12mN | Road/Parking Lot | Road/Parking Lot |
| 50 | 470518.47mE,4555901.67mN | Road/Parking Lot | Road/Parking Lot |
| 51 | 474496.00mE,4556281.60mN | Road/Parking Lot | Road/Parking Lot |
| 52 | 472532.50mE,4552309.36mN | Road/Parking Lot | Grass Land |
| 53 | 473927.82mE,4554279.32mN | Road/Parking Lot | Road/Parking Lot |
| 54 | 471929.98mE,4554892.26mN | Road/Parking Lot | Road/Parking Lot |
| 55 | 473060.91mE,4555966.95mN | Road/Parking Lot | Vegetation |
| 56 | 473704.10mE,4556258.66mN | Road/Parking Lot | Road/Parking Lot |
| 57 | 471932.09mE,4554613.40mN | Road/Parking Lot | Grass Land |
| 58 | 471699.05mE,4554560.74mN | Road/Parking Lot | Road/Parking Lot |
| 59 | 470091.73mE,4553766.70mN | Road/Parking Lot | Road/Parking Lot |
| 60 | 469884.97mE,4553825.63mN | Road/Parking Lot | Road/Parking Lot |
| 61 | 470118.31mE,4554275.53mN | Road/Parking Lot | Vegetation |
| 62 | 471315.83mE,4554547.80mN | Road/Parking Lot | Road/Parking Lot |
| 63 | 471206.48mE,4555763.95mN | Road/Parking Lot | Road/Parking Lot |
| 64 | 473151.18mE,4554715.30mN | Road/Parking Lot | Grass Land |
| 65 | 471502.99mE,4554505.73mN | Road/Parking Lot | Urban development |
| 66 | 470748.86mE,4555347.51mN | Road/Parking Lot | Road/Parking Lot |
| 67 | 473704.83mE,4556268.34mN | Road/Parking Lot | Road/Parking Lot |
| 68 | 473340.25mE,4556145.75mN | Road/Parking Lot | Road/Parking Lot |
| 69 | 473273.65mE,4555435.87mN | Road/Parking Lot | Urban development |
| 70 | 473759.96mE,4555621.11mN | Road/Parking Lot | Forest |
| 71 | 471340.84mE,4553997.15mN | Grass Land | Grass Land |
| 72 | 473881.18mE,4554458.11mN | Grass Land | Grass Land |
| 73 | 473826.33mE,4554184.66mN | Grass Land | Grass Land |
| 74 | 472999.09mE,4554292.02mN | Grass Land | Grass Land |
| 75 | 470717.04mE,4555722.64mN | Grass Land | Grass Land |
| 76 | 470610.35mE,4554774.83mN | Grass Land | Grass Land |
| 77 | 471797.93mE,4553336.33mN | Grass Land | Grass Land |
| 78 | 473244.50mE,4553067.69mN | Grass Land | Grass Land |
| 79 | 472186.32mE,4556024.11mN | Grass Land | Urban development |
| 80 | 472886.80mE,4556254.54mN | Grass Land | Grass Land |
| 81 | 471510.75mE,4555420.51mN | Grass Land | Grass Land |
| 82 | 472018.74mE,4554757.51mN | Grass Land | Grass Land |

| | | | |
|---|---|---|---|
| 83 | 472956.00mE,4554902.27mN | Grass Land | Grass Land |
| 84 | 471459.55mE,4555508.10mN | Grass Land | Grass Land |
| 85 | 471609.84mE,4552206.28mN | Grass Land | Grass Land |
| 86 | 474248.88mE,4551965.19mN | Grass Land | Grass Land |
| 87 | 472062.86mE,4553905.07mN | Grass Land | Grass Land |
| 88 | 473413.60mE,4556725.29mN | Water | Water |
| 89 | 474040.71mE,4552915.39mN | Water | Water |
| 90 | 474968.37mE,4552253.16mN | Water | Water |
| 91 | 469867.58mE,4552223.39mN | Water | Forest |
| 92 | 474062.40mE,4552900.33mN | Water | Water |
| 93 | 471098.51mE,4556738.91mN | Water | Water |
| 94 | 475054.56mE,4551693.62mN | Water | Water |
| 95 | 475128.10mE,4552685.22mN | Water | Grass Land |
| 96 | 473327.19mE,4556719.86mN | Water | Water |
| 97 | 473459.71mE,4556783.04mN | Water | Water |
| 98 | 471903.13mE,4553467.56mN | Water | Water |
| 99 | 472086.60mE,4553406.60mN | Water | Water |
| 100 | 472297.81mE,4553380.70mN | Water | Water |
| 101 | 472296.94mE,4553379.93mN | Water | Water |
| 102 | 472829.48mE,4555954.38mN | Urban development | Road/Parking Lot |
| 103 | 471711.04mE,4555625.76mN | Urban development | Urban development |
| 104 | 471058.01mE,4555294.20mN | Urban development | Urban development |
| 105 | 470856.68mE,4555283.16mN | Urban development | Urban development |
| 106 | 470792.42mE,4555302.39mN | Urban development | Vegetation |
| 107 | 470862.51mE,4555484.79mN | Urban development | Urban development |
| 108 | 470783.46mE,4555509.33mN | Urban development | Vegetation |
| 109 | 470724.72mE,4555539.83mN | Urban development | Urban development |
| 110 | 469791.40mE,4554421.89mN | Urban development | Urban development |
| 111 | 469890.49mE,4554324.26mN | Urban development | Urban development |
| 112 | 472502.40mE,4556258.62mN | Urban development | Urban development |
| 113 | 472383.41mE,4556449.56mN | Urban development | Urban development |
| 114 | 469746.07mE,4553823.45mN | Urban development | Urban development |
| 115 | 469998.48mE,4553913.51mN | Urban development | Urban development |
| 116 | 473989.98mE,4553587.98mN | Agricultural Land | Agricultural Land |
| 117 | 474504.57mE,4553229.55mN | Agricultural Land | Agricultural Land |
| 118 | 474121.37mE,4555289.12mN | Agricultural Land | Agricultural Land |
| 119 | 473615.80mE,4551124.84mN | Agricultural Land | Agricultural Land |
| 120 | 474165.89mE,4551225.27mN | Agricultural Land | Agricultural Land |
| 121 | 474371.89mE,4556584.72mN | Agricultural Land | Agricultural Land |
| 122 | 474658.46mE,4556050.97mN | Agricultural Land | Agricultural Land |
| 123 | 474152.57mE,4553617.29mN | Agricultural Land | Agricultural Land |
| 124 | 474516.08mE,4553229.55mN | Agricultural Land | Agricultural Land |
| 125 | 474502.75mE,4553864.48mN | Agricultural Land | Agricultural Land |
| 126 | 469921.35mE,4551677.38mN | Agricultural Land | Agricultural Land |
| 127 | 469397.90mE,4551685.86mN | Agricultural Land | Agricultural Land |

| | | | |
|---|---|---|---|
| 128 | 470591.42mE,4551558.63mN | Agricultural Land | Agricultural Land |
| 129 | 472394.41mE,4556676.81mN | Agricultural Land | Agricultural Land |
| 130 | 471589.85mE,4556703.47mN | Agricultural Land | Agricultural Land |
| 131 | 472619.03mE,4554554.08mN | Vegetation 3 | Vegetation 3 |
| 132 | 472914.68mE,4554521.97mN | Vegetation 3 | Vegetation 3 |
| 133 | 470182.62mE,4555073.44mN | Vegetation 3 | Vegetation 3 |
| 134 | 470312.73mE,4554993.47mN | Vegetation 3 | Vegetation 3 |
| 135 | 474316.23mE,4555438.76mN | Vegetation 3 | Vegetation 3 |
| 136 | 474060.03mE,4555450.43mN | Vegetation 3 | Vegetation 3 |
| 137 | 471080.64mE,4556111.59mN | Vegetation 3 | Vegetation 3 |
| 138 | 471377.95mE,4556398.42mN | Vegetation 3 | Vegetation 3 |
| 139 | 471890.65mE,4552346.83mN | Vegetation 3 | Vegetation 3 |
| 140 | 472276.50mE,4552027.22mN | Vegetation 3 | Vegetation 3 |
| 141 | 474690.11mE,4552204.31mN | Vegetation 3 | Vegetation 3 |
| 142 | 472604.41mE,4555516.99mN | Vegetation 4 | Vegetation 4 |
| 143 | 472694.68mE,4555568.04mN | Vegetation 4 | Vegetation 4 |
| 144 | 474120.50mE,4556605.43mN | Vegetation 4 | Vegetation 4 |
| 145 | 474206.95mE,4556380.70mN | Vegetation 4 | Vegetation 4 |
| 146 | 469402.41mE,4555425.70mN | Vegetation 4 | Vegetation 4 |
| 147 | 470187.01mE,4555816.81mN | Vegetation 4 | Forest |
| 148 | 470267.02mE,4555812.38mN | Vegetation 4 | Vegetation 4 |
| 149 | 472772.69mE,4555501.70mN | Vegetation 4 | Vegetation 4 |
| 150 | 470638.38mE,4555694.11mN | Vegetation 4 | Vegetation 4 |

The data from the above was used to create the Error matrix. And later the error matrix calculation is done and calculation of the accuracy.

**Table2. Error Matrix for unsupervised classification of IKONOS imagery**

| | Reference Data | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Predicted Class | Vege1 | Forest | Vege2 | Vege3 | Vege4 | Urban | Road | Agri | Grass | Water | Row Total |
| Vegetation1 | 08 | 0 | 0 | 0 | 0 | 02 | 02 | 0 | 0 | 0 | 12 |
| Forest | 0 | 13 | 0 | 0 | 0 | 05 | 0 | 0 | 0 | 02 | 20 |
| Vegitation2 | 0 | 0 | 09 | 0 | 0 | 0 | 0 | 0 | 03 | 0 | 12 |
| Vegitation3 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 11 |
| Vegitation4 | 0 | 01 | 0 | 0 | 08 | 0 | 0 | 0 | 0 | 0 | 09 |
| Urban Development | 02 | 0 | 0 | 0 | 0 | 11 | 01 | 0 | 0 | 0 | 14 |
| Road or Parking | 02 | 01 | 0 | 0 | 0 | 02 | 17 | 0 | 04 | 0 | 26 |
| Agricultural Land | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 0 | 15 |
| Grass | 0 | 0 | 0 | 0 | 0 | 01 | 0 | 0 | 16 | 0 | 17 |
| Water | 0 | 01 | 0 | 0 | 0 | 0 | 0 | 0 | 01 | 12 | 14 |
| Column Total | 12 | 16 | 09 | 11 | 08 | 21 | 20 | 15 | 24 | 14 | 150 |

## Error Matrix Calculations

**Overall Accuracy**

$$= \frac{\text{total \# correct}}{\# matrix\ \ total} * 100 = \%$$

= (08+13+09+11+08+11+17+15+16+12) / 150 * 100

= 120 / 150 * 100

= .8 * 100 = 80%

**Producer's Accuracy**

$$= \frac{total\ \ correctly\ \ predicted\ \ class\ \ X}{total\ \ reference\ \ classX} * 100$$

**User's Accuracy**

$$= \frac{total\ \ correct\ \ class\ \ X}{total\ \ classified\ \ as\ \ classX} * 100$$

**Table 3. Producer's and User's Accuracy from unsupervised classification of IKONOS Imagery**

| **Cover Class** | **Producer's Accuracy** | **User's Accuracy** |
|---|---|---|
| Vegetation1 | 08/12 * 100 = 67% | 08/12 * 100 = 67% |
| Forest | 13/16 * 100 = 81% | 13/20 * 100 = 65% |
| Vegetation2 | 09/09 * 100 = 100% | 09/12 * 100 = 75% |
| Vegetation3 | 11/11 * 100 = 100% | 11/11 * 100 = 100% |
| Vegetation4 | 08/08 * 100 = 100% | 08/09 * 100 = 89% |
| Urban | 11/21 * 100 = 52% | 11/14 * 100 = 78% |
| Road/Parking | 17/20 * 100 = 85% | 17/26 * 100 = 65% |
| Agri Land | 15/15 * 100 = 100% | 15/15 * 100 = 100% |
| Grass | 16/24 * 100 = 67% | 16/17 * 100 = 94% |
| Water | 12/14 * 100 = 86% | 12/14 * 100 = 86% |

## Kappa Statistic

$$\text{K-hat} = \frac{overall\ \ classification\ \ accuracy - \exp ected\ \ classification\ \ accuracy}{1 - \exp ected\ \ classification\ \ accuracy}$$

**Table 4. Matrix of Product for Error Matrix from unsupervised classification of IKONOS imagery**

| | Veg1 | Forest | Vege2 | Vege3 | Vege4 | Urban | Road | Agri | Road | Water | Row totals form above |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Vegetation1 | **144** | 192 | 108 | 132 | 96 | 252 | 240 | 180 | 288 | 168 | 12 |
| Forest | 240 | **320** | 180 | 220 | 160 | 420 | 400 | 300 | 480 | 280 | 20 |
| Vegetation2 | 144 | 192 | **108** | 132 | 96 | 252 | 240 | 180 | 288 | 168 | 12 |
| Vegetation3 | 132 | 176 | 99 | **121** | 88 | 231 | 220 | 165 | 264 | 154 | 11 |
| Vegetation4 | 72 | 144 | 81 | 99 | **72** | 189 | 180 | 135 | 216 | 126 | 09 |
| Urban | 168 | 224 | 126 | 154 | 112 | **294** | 280 | 210 | 336 | 196 | 14 |
| Road/Parking | 312 | 416 | 234 | 286 | 208 | 546 | **520** | 390 | 624 | 364 | 26 |
| Agri Land | 180 | 240 | 135 | 165 | 120 | 315 | 300 | **225** | 360 | 210 | 15 |
| Grass | 204 | 272 | 153 | 187 | 136 | 357 | 340 | 255 | **408** | 238 | 17 |
| Water | 168 | 224 | 126 | 154 | 112 | 294 | 280 | 210 | 336 | **196** | 14 |
| Columns total from above | 12 | 16 | 09 | 11 | 08 | 21 | 20 | 15 | 24 | 14 | 150 |

**<u>Expected Classification Accuracy</u>**

= (144+320+108+121+72+294+520+225+408+196) / 22500

= 2408/22500

= 10.7%

K-hat = (0.80-0.107) / (1-0.107)

= 0.693 / .893

= 0.776

Similarly with the landsat image the unsupervised classification is performed and again 150 randomly chosen UTM coordinates are taken for the study.

## <u>Unsupervised Classification & Accuracy measurement on the High Resolution Landsat Image of Kent State University</u>

**Table 5. Dataset collected after unsupervised classification of LANDSAT imagery**

| S.No | Randomly Collected UTM coordinates | Classification according to the Unsupervised Classification | Real World Classification using Google Earth |
|---|---|---|---|
| 1 | 473414.06mE,4556725.82mN | Water | Water |
| 2 | 474035.87mE,4552917.29mN | Water | Water |
| 3 | 474967.91mE,4552252.85mN | Water | Water |
| 4 | 473733.24mE,4555923.29mN | Water | Urban development |
| 5 | 470724.50mE,4556851.21mN | Water | Urban development |
| 6 | 472401.08mE,4555777.80mN | Water | Urban development |
| 7 | 474998.02mE,4552332.83mN | Water | Water |
| 8 | 473464.46mE,4556773.18mN | Water | Water |
| 9 | 469226.47mE,4551074.81mN | Water | Water |
| 10 | 469340.40mE,4551127.56mN | Water | Water |
| 11 | 469550.12mE,4555226.42mN | Water | Urban development |
| 12 | 473360.32mE,4556643.99mN | Water | Water |
| 13 | 475086.22mE,4552266.95mN | Water | Water |
| 14 | 473443.82mE,4556837.09mN | Water | Water |
| 15 | 475026.25mE,4552035.16mN | Water | Water |
| 16 | 473490.35mE,4556754.28mN | Water | Water |
| 17 | 475055.29mE,4551808.04mN | Water | Water |
| 18 | 471361.64mE,4554309.05mN | Grass Land | Grass Land |
| 19 | 472408.50mE,4553364.21mN | Grass Land | Grass Land |
| 20 | 473525.19mE,4554449.32mN | Grass Land | Grass Land |
| 21 | 474966.74mE,4553963.54mN | Grass Land | Grass Land |
| 22 | 474269.65mE,4555143.99mN | Grass Land | Grass Land |
| 23 | 471356.78mE,4554321.20mN | Grass Land | Grass Land |
| 24 | 470518.80mE,4555115.45mN | Grass Land | Grass Land |
| 25 | 474411.13mE,4553120.10mN | Grass Land | Road/ Parking Lot |
| 26 | 472672.03mE,4553047.23mN | Grass Land | Grass Land |
| 27 | 474236.25mE,4552027.09mN | Grass Land | Grass Land |
| 28 | 470102.25mE,4552046.52mN | Grass Land | Grass Land |
| 29 | 470252.84mE,4551721.05mN | Grass Land | Grass Land |
| 30 | 470306.27mE,4551963.94mN | Grass Land | Grass Land |
| 31 | 470058.52mE,4551672.47mN | Grass Land | Grass Land |
| 32 | 472424.28mE,4553270.69mN | Grass Land | Grass Land |

| | | | |
|---|---|---|---|
| 33 | 474260.54mE,4552051.38mN | Grass Land | Grass Land |
| 34 | 474482.78mE,4555555.08mN | Grass Land | Grass Land |
| 35 | 474582.37mE,4556616.52mN | Grass Land | Grass Land |
| 36 | 472345.23mE,4553471.20mN | Grass Land | Grass Land |
| 37 | 469893.36mE,4552561.45mN | Forest | Forest |
| 38 | 473471.14mE,4551942.08mN | Forest | Forest |
| 39 | 474293.94mE,4552231.73mN | Forest | Forest |
| 40 | 474068.05mE,4552341.03mN | Forest | Forest |
| 41 | 473961.18mE,4552406.61mN | Forest | Forest |
| 42 | 473606.56mE,4552613.07mN | Forest | Forest |
| 43 | 474748.75mE,4553089.74mN | Forest | Forest |
| 44 | 474792.47mE,4553224.54mN | Forest | Forest |
| 45 | 472962.29mE,4553865.78mN | Forest | Forest |
| 46 | 473267.12mE,4553705.47mN | Forest | Forest |
| 47 | 474023.72mE,4555168.89mN | Forest | Forest |
| 48 | 471133.32mE,4553570.66mN | Forest | Forest |
| 49 | 471548.66mE,4553162.61mN | Forest | Forest |
| 50 | 471616.67mE,4553869.42mN | Forest | Forest |
| 51 | 470620.82mE,4554236.18mN | Forest | Forest |
| 52 | 469180.47mE,4553999.37mN | Forest | Forest |
| 53 | 470622.03mE,4556349.34mN | Forest | Forest |
| 54 | 472612.52mE,4556497.50mN | Forest | Forest |
| 55 | 473686.71mE,4556615.91mN | Forest | Forest |
| 56 | 472875.45mE,4556407.02mN | Forest | Forest |
| 57 | 475057.22mE,4555233.25mN | Forest | Forest |
| 58 | 471264.48mE,4556072.44mN | Vegetation1 | Vegetation1 |
| 59 | 470575.88mE,4556403.99mN | Vegetation1 | Vegetation1 |
| 60 | 474864.12mE,4555229.61mN | Vegetation1 | Vegetation1 |
| 61 | 474912.70mE,4555593.95mN | Vegetation1 | Vegetation1 |
| 62 | 473729.82mE,4556507.22mN | Vegetation1 | Vegetation1 |
| 63 | 472657.46mE,4556666.31mN | Vegetation1 | Vegetation1 |
| 64 | 472076.34mE,4556436.17mN | Vegetation1 | Vegetation1 |
| 65 | 472112.78mE,4555542.33mN | Vegetation1 | Vegetation1 |
| 66 | 472571.23mE,4554551.94mN | Vegetation1 | Vegetation1 |
| 67 | 473890.13mE,4554610.24mN | Vegetation1 | Vegetation1 |
| 68 | 470339.06mE,4552965.86mN | Vegetation1 | Vegetation1 |
| 69 | 470732.55mE,4553347.20mN | Vegetation1 | Vegetation1 |
| 70 | 470447.15mE,4554135.38mN | Vegetation1 | Vegetation1 |
| 71 | 470102.25mE,4552362.28mN | Vegetation1 | Vegetation1 |
| 72 | 470438.65mE,4552285.77mN | Vegetation1 | Vegetation1 |
| 73 | 469571.53mE,4553050.88mN | Vegetation1 | Vegetation1 |
| 74 | 469627.39mE,4553288.91mN | Vegetation1 | Vegetation1 |
| 75 | 470775.05mE,4552240.84mN | Road | Road |
| 76 | 470777.48mE,4552549.31mN | Road | Road |
| 77 | 473153.41mE,4555380.12mN | Road | Road |

| | | | |
|---|---|---|---|
| 78 | 473158.04mE,4554929.52mN | Road | Road |
| 79 | 473020.58mE,4554063.73mN | Road | Road |
| 80 | 472938.00mE,4553981.15mN | Road | Road |
| 81 | 469570.31mE,4554667.32mN | Road | Road |
| 82 | 469733.05mE,4555310.98mN | Road | Urban Development |
| 83 | 469458.58mE,4555230.82mN | Road | Road |
| 84 | 470784.77mE,4551526.74mN | Road | Road |
| 85 | 472225.11mE,4553766.19mN | Road | Road |
| 86 | 472361.13mE,4555447.00mN | Road | Road |
| 87 | 469941.94mE,4551582.60mN | Road | Vegetation1 |
| 88 | 470796.91mE,4552238.41mN | Road | Road |
| 89 | 470532.16mE,4551162.40mN | Road | Vegetation1 |
| 90 | 470563.74mE,4554941.78mN | Vegetation2 | Urban development |
| 91 | 469723.34mE,4555612.16mN | Vegetation2 | Vegetation2 |
| 92 | 469878.79mE,4556532.72mN | Vegetation2 | Vegetation2 |
| 93 | 473740.75mE,4553431.00mN | Vegetation2 | Vegetation2 |
| 94 | 473424.99mE,4553486.87mN | Vegetation2 | Vegetation2 |
| 95 | 472293.12mE,4554193.68mN | Vegetation2 | Urban development |
| 96 | 470547.95mE,4554899.28mN | Vegetation2 | Road |
| 97 | 471911.18mE,4555547.19mN | Vegetation2 | Vegetation2 |
| 98 | 471056.20mE,4555945.53mN | Vegetation2 | Vegetation2 |
| 99 | 471282.70mE,4556821.76mN | Vegetation2 | Urban development |
| 100 | 473950.85mE,4553823.27mN | Vegetation2 | Vegetation2 |
| 101 | 470802.99mE,4553631.39mN | Vegetation2 | Vegetation2 |
| 102 | 470115.60mE,4554233.76mN | Vegetation2 | Road/Parking Lot |
| 103 | 474001.86mE,4556730.68mN | Vegetation2 | Vegetation2 |
| 104 | 474751.18mE,4554072.23mN | Vegetation4 | Vegetation4 |
| 105 | 473930.21mE,4552818.92mN | Vegetation4 | Vegetation4 |
| 106 | 472197.79mE,4551574.10mN | Vegetation4 | Vegetation4 |
| 107 | 470569.81mE,4551535.24mN | Vegetation4 | Agricultural Land |
| 108 | 469515.66mE,4551547.38mN | Vegetation4 | Vegetation4 |
| 109 | 469773.74mE,4556606.19mN | Vegetation4 | Urban development |
| 110 | 471602.10mE,4555302.48mN | Vegetation4 | Vegetation4 |
| 111 | 471998.01mE,4555848.98mN | Vegetation4 | Urban development |
| 112 | 471181.90mE,4555232.04mN | Vegetation4 | Urban development |
| 113 | 470492.69mE,4556657.20mN | Vegetation4 | Road |
| 114 | 470820.60mE,4555916.38mN | Vegetation4 | Vegetation4 |
| 115 | 472740.04mE,4552148.54mN | Agricultural Land | Agricultural Land |
| 116 | 469718.48mE,4553027.80mN | Agricultural Land | Agricultural Land |
| 117 | 474718.39mE,4554814.27mN | Agricultural Land | Agricultural Land |
| 118 | 475018.36mE,4556029.93mN | Agricultural Land | Agricultural Land |
| 119 | 474207.10mE,4556802.33mN | Agricultural Land | Agricultural Land |
| 120 | 471475.79mE,4553607.10mN | Agricultural Land | Agricultural Land |
| 121 | 472554.81mE,4551027.02mN | Agricultural Land | Agricultural Land |
| 122 | 472772.83mE,4552144.89mN | Agricultural Land | Agricultural Land |

| | | | |
|---|---|---|---|
| 123 | 471325.20mE,4551323.92mN | Agricultural Land | Agricultural Land |
| 124 | 471679.82mE,4551906.86mN | Agricultural Land | Vegetation1 |
| 125 | 470105.89mE,4553475.94mN | Agricultural Land | Vegetation1 |
| 126 | 469717.26mE,4553038.73mN | Agricultural Land | Agricultural Land |
| 127 | 471548.66mE,4552897.86mN | Agricultural Land | Agricultural Land |
| 128 | 470121.68mE,4553341.13mN | Vegetation 3 | Vegetation 3 |
| 129 | 471192.83mE,4553195.40mN | Vegetation 3 | Vegetation 3 |
| 130 | 471037.38mE,4552942.79mN | Vegetation 3 | Vegetation 3 |
| 131 | 471632.46mE,4554266.55mN | Vegetation 3 | Vegetation 3 |
| 132 | 472390.28mE,4554745.04mN | Vegetation 3 | Vegetation 3 |
| 133 | 473684.89mE,4554599.31mN | Vegetation 3 | Vegetation 3 |
| 134 | 471514.66mE,4556706.39mN | Vegetation 3 | Vegetation 3 |
| 135 | 472369.63mE,4556645.66mN | Vegetation 3 | Vegetation 3 |
| 136 | 474181.60mE,4556497.50mN | Vegetation 3 | Vegetation 3 |
| 137 | 475005.00mE,4555899.99mN | Vegetation 3 | Vegetation 3 |
| 138 | 474106.30mE,4555200.46mN | Vegetation 3 | Vegetation 3 |
| 139 | 473955.71mE,4554445.07mN | Vegetation 3 | Road |
| 140 | 473367.91mE,4554012.72mN | Vegetation 3 | Vegetation 3 |
| 141 | 472389.06mE,4554425.64mN | Urban development | Urban development |
| 142 | 471497.65mE,4555227.18mN | Urban development | Urban development |
| 143 | 471019.16mE,4555409.35mN | Urban development | Urban development |
| 144 | 469321.35mE,4555164.03mN | Urban development | Agricultural Land |
| 145 | 469962.58mE,4556497.50mN | Urban development | Urban development |
| 146 | 472464.36mE,4556186.60mN | Urban development | Urban development |
| 147 | 471966.43mE,4556172.03mN | Urban development | Vegetation 3 |
| 148 | 472444.93mE,4556108.87mN | Urban development | Urban development |
| 149 | 470540.66mE,4555635.24mN | Urban development | Urban development |
| 150 | 469510.81mE,4555166.46mN | Urban development | Urban development |

**Table 6. Error Matrix for unsupervised classification of LANDSAT imagery**

| | Reference Data | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Predicted Class | Vege1 | Forest | Vege2 | Vege3 | Vege4 | Urban | Road | Agri | Grass | Water | Row Total |
| Vegetation1 | 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17 |
| Forest | 0 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 |
| Vegitation2 | 0 | 0 | 09 | 0 | 0 | 03 | 02 | 0 | 0 | 0 | 14 |
| Vegitation3 | 0 | 0 | 0 | 12 | 0 | 0 | 01 | 0 | 0 | 0 | 13 |
| Vegitation4 | 0 | 0 | 0 | 0 | 06 | 03 | 01 | 01 | 0 | 0 | 11 |
| Urban Development | 0 | 0 | 0 | 01 | 0 | 08 | 0 | 01 | 0 | 0 | 10 |
| Road or Parking | 02 | 0 | 0 | 0 | 0 | 01 | 12 | 0 | 0 | 0 | 15 |
| Agricultural Land | 02 | 0 | 0 | 0 | 0 | 0 | 0 | 11 | 0 | 0 | 13 |
| Grass | 0 | 0 | 0 | 0 | 0 | 0 | 01 | 0 | 18 | 0 | 19 |
| Water | 0 | 0 | 0 | 0 | 0 | 04 | 0 | 0 | 0 | 13 | 17 |
| Column Total | 21 | 21 | 09 | 13 | 06 | 19 | 17 | 13 | 18 | 13 | 150 |

**<u>Error Matrix Calculations</u>**

**Overall Accuracy**

$$= \frac{\text{total \# correct}}{\# matrix\ \ total} * 100 = \%$$

= (17+21+09+12+06+08+12+11+18+13) / 150 * 100

= 127 / 150 * 100

= .846 * 100 = 84.6%

**Producer's Accuracy**

$$= \frac{total\ \ correctly\ \ predicted\ \ class\ \ X}{total\ \ reference\ \ classX} * 100$$

**User's Accuracy**

$$= \frac{total\ \ correct\ \ class\ \ X}{total\ \ classified\ \ as\ \ classX} * 100$$

**Table 7. Producer's and User's accuracy from unsupervised classification of LANDSAT imagery**

| Cover Class | Producer's Accuracy | User's Accuracy |
|---|---|---|
| Vegetation1 | 17/ 21* 100 = 81% | 17/17 * 100 = 100% |
| Forest | 21/21 * 100 = 100% | 21/21 * 100 = 100% |
| Vegetation2 | 09/09 * 100 = 100% | 09/09 * 100 = 100% |
| Vegetation3 | 12/13 * 100 = 92% | 12/13 * 100 = 92% |
| Vegetation4 | 06/06 * 100 = 100% | 06/11 * 100 = 55% |
| Urban | 08/19 * 100 = 42% | 08/10 * 100 = 80% |
| Road/Parking | 12/17 * 100 = 71% | 12/15 * 100 = 80% |
| Agri Land | 11/13 * 100 = 85% | 11/13 * 100 = 85% |
| Grass | 18/18 * 100 = 100% | 18/19 * 100 = 95% |
| Water | 13/13 * 100 = 100% | 13/17 * 100 = 76% |

**Kappa Statistic**

$$\text{K-hat} = \frac{overall\ classification\ accuracy - \exp ected\ classification\ accuracy}{1 - \exp ected\ classification\ accuracy}$$

**Table 8. Matrix of Product for Error Matrix from unsupervised classification of LANDSAT imagery**

| | Veg1 | Forest | Vege2 | Vege3 | Vege4 | Urban | Road | Agri | Road | Water | Row totals form above |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Vegetation1 | **357** | 357 | 153 | 221 | 102 | 323 | 289 | 221 | 306 | 221 | 17 |
| Forest | 441 | **441** | 189 | 273 | 126 | 399 | 357 | 273 | 378 | 273 | 21 |
| Vegetation2 | 294 | 294 | **126** | 182 | 84 | 266 | 238 | 182 | 252 | 182 | 14 |
| Vegetation3 | 273 | 273 | 117 | **169** | 78 | 247 | 221 | 169 | 234 | 169 | 13 |
| Vegetation4 | 231 | 231 | 99 | 143 | **66** | 209 | 187 | 143 | 198 | 143 | 11 |
| Urban | 210 | 210 | 90 | 130 | 60 | **190** | 170 | 130 | 180 | 130 | 10 |
| Road/Parking | 315 | 315 | 135 | 195 | 90 | 285 | **255** | 195 | 270 | 195 | 15 |
| Agri Land | 273 | 273 | 117 | 169 | 78 | 247 | 221 | **169** | 234 | 169 | 13 |
| Grass | 399 | 399 | 171 | 247 | 114 | 361 | 323 | 247 | **342** | 247 | 19 |
| Water | 357 | 357 | 153 | 221 | 102 | 323 | 289 | 221 | 306 | **221** | 17 |
| Columns total from above | 21 | 21 | 09 | 13 | 06 | 19 | 17 | 13 | 18 | 13 | 150 |

<u>Expected Classification Accuracy</u>

= (357+441+126+169+66+190+255+169+342+221) / 22500

= 2336/22500

= 10.38%

K-hat = (0.846-0.1038) / (1-0.1038)

= 0.7422 / .8962

= 0.828

For Performing the Supervised Classification the first step is to define spectral signature for the different classes by using the ERDAS IMAGINE Signature Editor. The signature of every class has a .sig extension, for example for class water two Spectral signatures were created water1.sig and water2.sig similarly for the other classes to the different signature were created and then the supervised classification was performed using the software. So starting with the IKONOS Imagery, 150 random UTM coordinate were chosen.

## Supervised Classification and Accuracy Measurement on High Resolution IKONOS Image of Kent State University.

**Table 9. Dataset collected after supervised classification of IKONOS imagery**

| S.No | Randomly Collected UTM coordinates | Classification according to the Unsupervised Classification | Real World Classification using Google Earth |
|---|---|---|---|
| 1 | 475122.84mE,4555850.13mN | Water | Water |
| 2 | 474982.28mE,4555688.37mN | Water | Vegetation |
| 3 | 475065.28mE,4555593.86mN | Water | Water |
| 4 | 473508.56mE,4556831.30mN | Water | Water |
| 5 | 475066.79mE,4552276.56mN | Water | Water |
| 6 | 473464.33mE,4556832.51mN | Water | Water |
| 7 | 475103.75mE,4552215.37mN | Water | Water |
| 8 | 469872.88mE,4556393.27mN | Water | Urban development |
| 9 | 475069.22mE,4552082.69mN | Water | Water |
| 10 | 470074.02mE,4556795.56mN | Water | Water |
| 11 | 469265.83mE,4551136.96mN | Water | Water |
| 12 | 469280.37mE,4551166.04mN | Water | Water |
| 13 | 474040.71mE,4552915.39mN | Water | Water |
| 14 | 472296.94mE,4553379.93mN | Water | Water |
| 15 | 473413.60mE,4556725.29mN | Water | Water |
| 16 | 469867.58mE,4552223.39mN | Water | Water |
| 17 | 475054.56mE,4551693.62mN | Water | Water |
| 18 | 472086.60mE,4553406.60mN | Water | Water |
| 19 | 473052.36mE,4554098.33mN | Road/Parking Lot | Road/Parking Lot |
| 20 | 473106.89mE,4554276.45mN | Road/Parking Lot | Road/Parking Lot |
| 21 | 472753.07mE,4554232.83mN | Road/Parking Lot | Road/Parking Lot |
| 22 | 471838.25mE,4555911.02mN | Road/Parking Lot | Road/Parking Lot |
| 23 | 472446.51mE,4556015.23mN | Road/Parking Lot | Road/Parking Lot |
| 24 | 473032.97mE,4556086.72mN | Road/Parking Lot | Road/Parking Lot |
| 25 | 473378.30mE,4555050.72mN | Road/Parking Lot | Grass Land |
| 26 | 473928.41mE,4554265.55mN | Road/Parking Lot | Road/Parking Lot |
| 27 | 473424.35mE,4554248.58mN | Road/Parking Lot | Road/Parking Lot |
| 28 | 470792.56mE,4555248.23mN | Road/Parking Lot | Road/Parking Lot |
| 29 | 471358.42mE,4555486.93mN | Road/Parking Lot | Road/Parking Lot |

| | | | |
|---|---|---|---|
| 30 | 472464.69mE,4556016.44mN | Road/Parking Lot | Road/Parking Lot |
| 31 | 473424.95mE,4556155.18mN | Road/Parking Lot | Road/Parking Lot |
| 32 | 470123.70mE,4554284.93mN | Road/Parking Lot | Grass Land |
| 33 | 471929.12mE,4554891.99mN | Road/Parking Lot | Road/Parking Lot |
| 34 | 471469.89mE,4554692.06mN | Road/Parking Lot | Road/Parking Lot |
| 35 | 473699.40mE,4556253.93mN | Road/Parking Lot | Road/Parking Lot |
| 36 | 473423.14mE,4556021.28mN | Road/Parking Lot | Road/Parking Lot |
| 37 | 470137.03mE,4553966.26mN | Road/Parking Lot | Road/Parking Lot |
| 38 | 470315.15mE,4553729.98mN | Road/Parking Lot | Road/Parking Lot |
| 39 | 471316.01mE,4553983.22mN | Grass Land | Grass Land |
| 40 | 471130.01mE,4554589.67mN | Grass Land | Grass Land |
| 41 | 471704.35mE,4554941.06mN | Grass Land | Grass Land |
| 42 | 471492.91mE,4554006.24mN | Grass Land | Grass Land |
| 43 | 472012.12mE,4554771.43mN | Grass Land | Grass Land |
| 44 | 470953.11mE,4554776.27mN | Grass Land | Grass Land |
| 45 | 470558.09mE,4555062.23mN | Grass Land | Grass Land |
| 46 | 472973.60mE,4554878.66mN | Grass Land | Grass Land |
| 47 | 473104.46mE,4555053.14mN | Grass Land | Grass Land |
| 48 | 473300.76mE,4555406.96mN | Grass Land | Grass Land |
| 49 | 470462.98mE,4555050.72mN | Grass Land | Grass Land |
| 50 | 470616.86mE,4554764.76mN | Grass Land | Grass Land |
| 51 | 471446.87mE,4552597.05mN | Grass Land | Grass Land |
| 52 | 470919.78mE,4552432.26mN | Grass Land | Grass Land |
| 53 | 472632.51mE,4553649.40mN | Grass Land | Grass Land |
| 54 | 473383.76mE,4553363.44mN | Grass Land | Grass Land |
| 55 | 473226.84mE,4553264.69mN | Grass Land | Grass Land |
| 56 | 474054.58mE,4554497.43mN | Vegetation1 | Vegetation1 |
| 57 | 472147.98mE,4555740.89mN | Vegetation1 | Vegetation1 |
| 58 | 472226.67mE,4555801.59mN | Vegetation1 | Vegetation1 |
| 59 | 472906.96mE,4553841.23mN | Vegetation1 | Vegetation1 |
| 60 | 470266.99mE,4552723.97mN | Vegetation1 | Forest |
| 61 | 473807.55mE,4553712.71mN | Vegetation1 | Vegetation1 |
| 62 | 473268.34mE,4553790.26mN | Vegetation1 | Vegetation1 |
| 63 | 473788.46mE,4553719.68mN | Vegetation1 | Vegetation1 |
| 64 | 474182.26mE,4553853.57mN | Vegetation1 | Vegetation1 |
| 65 | 473767.26mE,4553881.44mN | Vegetation1 | Vegetation1 |
| 66 | 470369.98mE,4552899.52mN | Vegetation1 | Vegetation1 |
| 67 | 471689.51mE,4556221.97mN | Vegetation1 | Vegetation1 |
| 68 | 471787.05mE,4556250.45mN | Vegetation1 | Vegetation1 |
| 69 | 472558.29mE,4555001.95mN | Vegetation1 | Vegetation1 |
| 70 | 473273.49mE,4554923.19mN | Vegetation1 | Vegetation1 |
| 71 | 473739.69mE,4551905.17mN | Vegetation2 | Vegetation2 |
| 72 | 473664.26mE,4551852.16mN | Vegetation2 | Vegetation2 |
| 73 | 470778.62mE,4554564.53mN | Vegetation2 | Vegetation2 |
| 74 | 471950.33mE,4556093.99mN | Vegetation2 | Vegetation2 |

| | | | |
|---|---|---|---|
| 75 | 472258.10mE,4556244.84mN | Vegetation2 | Vegetation2 |
| 76 | 472356.85mE,4556188.50mN | Vegetation2 | Vegetation2 |
| 77 | 472214.63mE,4555390.45mN | Vegetation2 | Vegetation2 |
| 78 | 472846.68mE,4555529.04mN | Vegetation2 | Vegetation2 |
| 79 | 472994.80mE,4555748.96mN | Vegetation2 | Vegetation2 |
| 80 | 471565.92mE,4550962.02mN | Vegetation2 | Vegetation2 |
| 81 | 470906.61mE,4552537.37mN | Vegetation2 | Vegetation2 |
| 82 | 471693.60mE,4552533.96mN | Vegetation2 | Vegetation2 |
| 83 | 472626.53mE,4554554.27mN | Vegetation3 | Vegetation3 |
| 84 | 472805.10mE,4554433.36mN | Vegetation3 | Vegetation3 |
| 85 | 474083.51mE,4555935.25mN | Vegetation3 | Vegetation3 |
| 86 | 469454.47mE,4551465.40mN | Vegetation3 | Vegetation3 |
| 87 | 469333.15mE,4551398.31mN | Vegetation3 | Vegetation3 |
| 88 | 469758.38mE,4551116.21mN | Vegetation3 | Vegetation3 |
| 89 | 471326.76mE,4551704.94mN | Vegetation3 | Vegetation3 |
| 90 | 471498.67mE,4551780.07mN | Vegetation3 | Vegetation2 |
| 91 | 471785.84mE,4551501.53mN | Vegetation3 | Vegetation3 |
| 92 | 470670.48mE,4554185.73mN | Vegetation3 | Vegetation3 |
| 93 | 471010.06mE,4554309.55mN | Vegetation3 | Vegetation3 |
| 94 | 475002.12mE,4555637.18mN | Vegetation3 | Vegetation3 |
| 95 | 471371.29mE,4556695.89mN | Vegetation3 | Vegetation3 |
| 96 | 474362.50mE,4555628.09mN | Vegetation3 | Vegetation3 |
| 97 | 474493.14mE,4555598.63mN | Vegetation3 | Vegetation3 |
| 98 | 470378.31mE,4554795.05mN | Vegetation3 | Vegetation3 |
| 99 | 470194.66mE,4554892.82mN | Vegetation3 | Vegetation3 |
| 100 | 469303.39mE,4555331.23mN | Vegetation3 | Vegetation3 |
| 101 | 469788.52mE,4554393.18mN | Urban development | Urban development |
| 102 | 469880.09mE,4554158.32mN | Urban development | Urban development |
| 103 | 469260.27mE,4554218.57mN | Urban development | Urban development |
| 104 | 471336.61mE,4554994.98mN | Urban development | Urban development |
| 105 | 471246.34mE,4555063.44mN | Urban development | Urban development |
| 106 | 471060.34mE,4555304.57mN | Urban development | Urban development |
| 107 | 471203.62mE,4555382.42mN | Urban development | Urban development |
| 108 | 471139.25mE,4555458.30mN | Urban development | Urban development |
| 109 | 471608.33mE,4555342.44mN | Urban development | Grass Land |
| 110 | 470985.52mE,4555756.83mN | Urban development | Urban development |
| 111 | 474879.59mE,4556149.72mN | Urban development | Urban development |
| 112 | 473790.88mE,4556247.27mN | Urban development | Urban development |
| 113 | 472149.65mE,4556160.63mN | Urban development | Urban development |
| 114 | 472961.48mE,4555926.77mN | Urban development | Urban development |
| 115 | 473025.70mE,4556200.62mN | Urban development | Road/Parking Lot |
| 116 | 470615.65mE,4551545.30mN | Agricultural Land | Agricultural Land |
| 117 | 470838.60mE,4551925.77mN | Agricultural Land | Agricultural Land |
| 118 | 469869.25mE,4551798.54mN | Agricultural Land | Agricultural Land |
| 119 | 472298.08mE,4551894.87mN | Agricultural Land | Agricultural Land |

| | | | |
|---|---|---|---|
| 120 | 473454.83mE,4553936.84mN | Agricultural Land | Vegetation 4 |
| 121 | 472351.40mE,4550959.45mN | Agricultural Land | Agricultural Land |
| 122 | 474008.38mE,4553686.36mN | Agricultural Land | Agricultural Land |
| 123 | 474163.48mE,4553705.74mN | Agricultural Land | Agricultural Land |
| 124 | 474248.30mE,4553393.13mN | Agricultural Land | Agricultural Land |
| 125 | 474913.52mE,4554637.53mN | Agricultural Land | Agricultural Land |
| 126 | 469903.18mE,4551693.13mN | Agricultural Land | Agricultural Land |
| 127 | 470591.42mE,4551556.21mN | Agricultural Land | Agricultural Land |
| 128 | 470567.18mE,4551744.02mN | Agricultural Land | Agricultural Land |
| 129 | 470723.04mE,4555772.13mN | Vegetation 4 | Vegetation 4 |
| 130 | 470836.33mE,4555540.70mN | Vegetation 4 | Road/ Parking Lot |
| 131 | 472160.56mE,4554467.90mN | Vegetation 4 | Vegetation 4 |
| 132 | 472216.29mE,4554602.40mN | Vegetation 4 | Vegetation 4 |
| 133 | 472520.43mE,4554554.53mN | Vegetation 4 | Vegetation 4 |
| 134 | 473055.39mE,4554541.81mN | Vegetation 4 | Vegetation 4 |
| 135 | 473175.65mE,4554552.72mN | Vegetation 4 | Vegetation 4 |
| 136 | 473448.13mE,4554652.53mN | Vegetation 4 | Vegetation 4 |
| 137 | 474725.70mE,4554330.98mN | Vegetation 4 | Vegetation 4 |
| 138 | 474825.21mE,4554459.87mN | Vegetation 4 | Vegetation 4 |
| 139 | 473510.15mE,4551909.22mN | Forest | Forest |
| 140 | 474023.15mE,4552292.16mN | Forest | Forest |
| 141 | 470253.35mE,4551016.25mN | Forest | Forest |
| 142 | 470590.36mE,4551218.24mN | Forest | Forest |
| 143 | 470266.49mE,4552753.28mN | Forest | Forest |
| 144 | 472637.66mE,4556526.18mN | Forest | Forest |
| 145 | 474695.64mE,4555154.21mN | Forest | Forest |
| 146 | 474070.76mE,4554738.59mN | Forest | Forest |
| 147 | 469931.20mE,4553488.55mN | Forest | Forest |
| 148 | 469638.72mE,4553301.65mN | Forest | Forest |
| 149 | 469170.63mE,4553217.05mN | Forest | Forest |
| 150 | 469086.57mE,4553089.15mN | Forest | Forest |

**Table 10. Error Matrix for supervised classification of IKONOS imagery**

| | Reference Data | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Predicted Class | Vege1 | Forest | Vege2 | Vege3 | Vege4 | Urban | Road | Agri | Grass | Water | Row Total |
| Vegetation1 | 14 | 01 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 |
| Forest | 0 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 |
| Vegitation2 | 0 | 0 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 |
| Vegitation3 | 0 | 0 | 01 | 17 | 0 | 0 | 0 | 0 | 0 | 0 | 18 |
| Vegitation4 | 0 | 0 | 0 | 0 | 09 | 0 | 01 | 0 | 0 | 0 | 10 |
| Urban Development | 0 | 0 | 0 | 0 | 0 | 13 | 01 | 0 | 01 | 0 | 15 |
| Road or Parking | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 0 | 02 | 0 | 20 |
| Agricultural Land | 0 | 0 | 0 | 0 | 01 | 0 | 0 | 12 | 0 | 0 | 13 |
| Grass | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17 | 0 | 17 |
| Water | 01 | 0 | 0 | 0 | 0 | 01 | 0 | 0 | 0 | 16 | 18 |
| Column Total | 15 | 13 | 13 | 17 | 10 | 14 | 20 | 12 | 20 | 16 | 150 |

**<u>Error Matrix Calculations</u>**

**Overall Accuracy**

$$= \frac{\text{total \# correct}}{\# matrix\ \ total} * 100 = \%$$

= (14+12+12+17+09+13+18+12+17+16) / 150 * 100

= 140 / 150 * 100

= .933 * 100 = 93.3%

**Producer's Accuracy**

$$= \frac{total\ \ correctly\ \ predicted\ \ class\ \ X}{total\ \ reference\ \ classX} * 100$$

**User's Accuracy**

$$= \frac{total\ \ correct\ \ class\ \ X}{total\ \ classified\ \ as\ \ classX} * 100$$

**Table 11. Producer's and User's accuracy from supervised classification of IKONOS imagery**

| Cover Class | Producer's Accuracy | User's Accuracy |
|---|---|---|
| Vegetation1 | 14/15 * 100 = 93% | 14/15 * 100 = 93% |
| Forest | 12/13 * 100 = 92% | 12/12 * 100 = 100% |
| Vegetation2 | 12/13 * 100 = 92% | 12/12 * 100 = 100% |
| Vegetation3 | 17/17 * 100 = 100% | 17/18 * 100 = 94% |
| Vegetation4 | 09/10 * 100 = 90% | 09/10 * 100 = 90% |
| Urban | 13/14 * 100 = 93% | 13/15 * 100 = 87% |
| Road/Parking | 18/20 * 100 = 90% | 18/20 * 100 = 90% |
| Agri Land | 12/12 * 100 = 100% | 12/13 * 100 = 92% |
| Grass | 17/20 * 100 = 85% | 17/17 * 100 = 100% |
| Water | 16/16 * 100 = 100% | 16/18 * 100 = 89% |

## Kappa Statistic

$$\text{K-hat} = \frac{overall\ classification\ accuracy - \exp ected\ classification\ accuracy}{1 - \exp ected\ classification\ accuracy}$$

**Table 12. Matrix of product for Error Matrix from supervised classification of IKONOS imagery**

| | Veg1 | Forest | Vege2 | Vege3 | Vege4 | Urban | Road | Agri | Road | Water | Row totals form above |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Vegetation1 | **225** | 195 | 195 | 255 | 150 | 210 | 300 | 180 | 300 | 240 | 15 |
| Forest | 180 | **156** | 156 | 204 | 120 | 168 | 240 | 144 | 240 | 192 | 12 |
| Vegetation2 | 180 | 156 | **156** | 204 | 120 | 168 | 240 | 144 | 240 | 192 | 12 |
| Vegetation3 | 270 | 234 | 234 | **306** | 180 | 252 | 360 | 216 | 360 | 288 | 18 |
| Vegetation4 | 150 | 130 | 130 | 170 | **100** | 140 | 200 | 120 | 200 | 160 | 10 |
| Urban | 225 | 195 | 195 | 255 | 150 | **210** | 300 | 180 | 300 | 240 | 15 |
| Road/Parking | 300 | 260 | 260 | 340 | 200 | 280 | **400** | 240 | 400 | 320 | 20 |
| Agri Land | 195 | 169 | 169 | 221 | 130 | 182 | 260 | **156** | 260 | 208 | 13 |
| Grass | 255 | 221 | 221 | 289 | 170 | 238 | 340 | 204 | **340** | 272 | 17 |
| Water | 270 | 234 | 234 | 306 | 180 | 252 | 360 | 216 | 360 | **288** | 18 |
| Columns total from above | 15 | 13 | 13 | 17 | 10 | 14 | 20 | 12 | 20 | 16 | 150 |

Expected Classification Accuracy

= (225+156+156+306+100+210+400+156+340+288) / 22500

= 2337/22500

= 10.3%

K-hat = (0.933-0.103) / (1-0.103)

= 0.83 / .897

= 0.925

The supervised classification is performed on the landsat Image.

## Supervised Classification & Accuracy measurement on the High Resolution Landsat Image of Kent State University

**Table 13. Dataset collected after supervised classification of LANDSAT imagery**

| S.No | Randomly Collected UTM coordinates | Classification according to the Unsupervised Classification | Real World Classification using Google Earth |
|---|---|---|---|
| 1 | 475122.19mE,4552257.84mN | Water | Water |
| 2 | 474009.15mE,4552914.86mN | Water | Water |
| 3 | 473422.64mE,4553321.78mN | Water | Vegetation 1 |
| 4 | 474989.21mE,4552386.57mN | Water | Water |
| 5 | 473385.04mE,4556850.23mN | Water | Water |
| 6 | 475164.70mE,4552260.27mN | Water | Water |
| 7 | 473326.55mE,4556673.08mN | Water | Water |
| 8 | 473462.90mE,4556777.13mN | Water | Water |
| 9 | 469342.15mE,4551790.88mN | Water | Water |
| 10 | 475150.73mE,4552003.41mN | Water | Water |
| 11 | 475134.04mE,4555654.67mN | Water | Water |
| 12 | 473354.56mE,4556646.88mN | Water | Water |
| 13 | 475173.81mE,4551980.33mN | Water | Water |
| 14 | 475026.86mE,4551765.98mN | Water | Water |
| 15 | 473496.56mE,4556840.03mN | Water | Water |
| 16 | 475056.08mE,4552343.99mN | Water | Water |
| 17 | 473513.65mE,4556825.40mN | Water | Water |
| 18 | 474441.49mE,4555547.80mN | Grass Land | Grass Land |
| 19 | 472942.86mE,4552472.80mN | Grass Land | Vegetation 4 |
| 20 | 474576.30mE,4556629.88mN | Grass Land | Grass Land |
| 21 | 474960.70mE,4553965.45mN | Grass Land | Grass Land |
| 22 | 474268.45mE,4555145.25mN | Grass Land | Grass Land |
| 23 | 471355.56mE,4554320.19mN | Grass Land | Grass Land |
| 24 | 470517.24mE,4555113.15mN | Grass Land | Grass Land |
| 25 | 474984.35mE,4553965.36mN | Grass Land | Grass Land |
| 26 | 472674.10mE,4553046.09mN | Grass Land | Grass Land |
| 27 | 474234.04mE,4552026.11mN | Grass Land | Grass Land |
| 28 | 470103.02mE,4552045.12mN | Grass Land | Grass Land |
| 29 | 470253.11mE,4551722.09mN | Grass Land | Grass Land |
| 30 | 470305.12mE,4551964.12mN | Grass Land | Grass Land |
| 31 | 470056.01mE,4551673.36mN | Grass Land | Grass Land |
| 32 | 472425.14mE,4553269.70mN | Grass Land | Grass Land |
| 33 | 474259.15mE,4552050.87mN | Grass Land | Grass Land |
| 34 | 474483.45mE,4555554.03mN | Grass Land | Grass Land |

| | | | |
|---|---|---|---|
| 35 | 474581.27mE,4556615.14mN | Grass Land | Grass Land |
| 36 | 472343.13mE,4553470.20mN | Grass Land | Grass Land |
| 37 | 469892.14mE,4552562.11mN | Forest | Forest |
| 38 | 473472.05mE,4551941.78mN | Forest | Forest |
| 39 | 474294.05mE,4552232.07mN | Forest | Forest |
| 40 | 474067.43mE,4552343.11mN | Forest | Forest |
| 41 | 473962.02mE,4552405.05mN | Forest | Forest |
| 42 | 473605.13mE,4552612.04mN | Forest | Forest |
| 43 | 474747.44mE,4553090.15mN | Forest | Forest |
| 44 | 474793.23mE,4553225.17mN | Forest | Forest |
| 45 | 472962.07mE,4553866.23mN | Forest | Forest |
| 46 | 473266.13mE,4553704.06mN | Forest | Forest |
| 47 | 474022.45mE,4555167.90mN | Forest | Forest |
| 48 | 471133.23mE,4553571.24mN | Forest | Forest |
| 49 | 471549.13mE,4553163.14mN | Forest | Forest |
| 50 | 471618.04mE,4553868.53mN | Forest | Forest |
| 51 | 470621.25mE,4554235.29mN | Forest | Forest |
| 52 | 469179.02mE,4553997.07mN | Forest | Forest |
| 53 | 470623.03mE,4556348.89mN | Forest | Forest |
| 54 | 472611.89mE,4556496.25mN | Forest | Forest |
| 55 | 473685.23mE,4556616.43mN | Forest | Forest |
| 56 | 472874.23mE,4556406.89mN | Forest | Forest |
| 57 | 475056.97mE,4555234.02mN | Forest | Forest |
| 58 | 471265.15mE,4556071.45mN | Vegetation1 | Vegetation1 |
| 59 | 470574.95mE,4556404.25mN | Vegetation1 | Vegetation1 |
| 60 | 474865.05mE,4555230.45mN | Vegetation1 | Vegetation1 |
| 61 | 474913.23mE,4555594.26mN | Vegetation1 | Vegetation1 |
| 62 | 473730.83mE,4556506.12mN | Vegetation1 | Vegetation1 |
| 63 | 472656.89mE,4556665.79mN | Vegetation1 | Vegetation1 |
| 64 | 472075.56mE,4556437.12mN | Vegetation1 | Vegetation1 |
| 65 | 472113.05mE,4555543.23mN | Vegetation1 | Vegetation1 |
| 66 | 472571.23mE,4554552.13mN | Vegetation1 | Vegetation1 |
| 67 | 473891.02mE,4554611.36mN | Vegetation1 | Vegetation1 |
| 68 | 470341.03mE,4552965.98mN | Vegetation1 | Vegetation1 |
| 69 | 470733.16mE,4553348.13mN | Vegetation1 | Vegetation1 |
| 70 | 470448.13mE,4554136.14mN | Vegetation1 | Vegetation1 |
| 71 | 470103.26mE,4552363.25mN | Vegetation1 | Vegetation1 |
| 72 | 470439.05mE,4552286.13mN | Vegetation1 | Vegetation1 |
| 73 | 469572.12mE,4553051.07mN | Vegetation1 | Vegetation1 |
| 74 | 469626.87mE,4553289.09mN | Vegetation1 | Vegetation1 |
| 75 | 470774.98mE,4552241.04mN | Road | Road |
| 76 | 470776.13mE,4552548.87mN | Road | Road |
| 77 | 473152.92mE,4555379.92mN | Road | Road |
| 78 | 473157.77mE,4554928.42mN | Road | Road |
| 79 | 473021.12mE,4554064.05mN | Road | Road |

| | | | |
|---|---|---|---|
| 80 | 472937.95mE,4553982.05mN | Road | Road |
| 81 | 469571.03mE,4554668.02mN | Road | Road |
| 82 | 469732.77mE,4555311.09mN | Road | Urban Development |
| 83 | 469457.87mE,4555231.06mN | Road | Road |
| 84 | 470785.56mE,4551525.07mN | Road | Road |
| 85 | 472226.08mE,4553767.18mN | Road | Road |
| 86 | 472360.99mE,4555446.98mN | Road | Road |
| 87 | 471114.51mE,4554966.75mN | Road | Road |
| 88 | 470797.01mE,4552237.02mN | Road | Road |
| 89 | 470284.06mE,4553756.89mN | Road | Road |
| 90 | 469939.40mE,4556674.56mN | Vegetation2 | Vegetation2 |
| 91 | 469723.34mE,4555612.16mN | Vegetation2 | Vegetation2 |
| 92 | 469878.79mE,4556532.72mN | Vegetation2 | Vegetation2 |
| 93 | 473740.75mE,4553431.00mN | Vegetation2 | Vegetation2 |
| 94 | 473424.99mE,4553486.87mN | Vegetation2 | Vegetation2 |
| 95 | 469827.96mE,4555939.23mN | Vegetation2 | Vegetation2 |
| 96 | 470547.95mE,4554899.28mN | Vegetation2 | Road |
| 97 | 471911.18mE,4555547.19mN | Vegetation2 | Vegetation2 |
| 98 | 471056.20mE,4555945.53mN | Vegetation2 | Vegetation2 |
| 99 | 469563.14mE,4555358.59mN | Vegetation2 | Vegetation2 |
| 100 | 473950.85mE,4553823.27mN | Vegetation2 | Vegetation2 |
| 101 | 470802.99mE,4553631.39mN | Vegetation2 | Vegetation2 |
| 102 | 469766.35mE,4555816.32mN | Vegetation2 | Vegetation2 |
| 103 | 474001.86mE,4556730.68mN | Vegetation2 | Vegetation2 |
| 104 | 474751.18mE,4554072.23mN | Vegetation4 | Vegetation4 |
| 105 | 473930.21mE,4552818.92mN | Vegetation4 | Vegetation4 |
| 106 | 472197.79mE,4551574.10mN | Vegetation4 | Vegetation4 |
| 107 | 473855.92mE,4552921.73mN | Vegetation4 | Vegetation4 |
| 108 | 469515.66mE,4551547.38mN | Vegetation4 | Vegetation4 |
| 109 | 472053.96mE,4555410.38mN | Vegetation4 | Vegetation4 |
| 110 | 471602.10mE,4555302.48mN | Vegetation4 | Vegetation4 |
| 111 | 474890.75mE,4553005.46mN | Vegetation4 | Vegetation4 |
| 112 | 473831.69mE,4555005.22mN | Vegetation4 | Vegetation4 |
| 113 | 470492.69mE,4556657.20mN | Vegetation4 | Road |
| 114 | 470820.60mE,4555916.38mN | Vegetation4 | Vegetation4 |
| 115 | 472740.02mE,4552148.43mN | Agricultural Land | Agricultural Land |
| 116 | 469718.45mE,4553027.75mN | Agricultural Land | Agricultural Land |
| 117 | 474718.40mE,4554814.20mN | Agricultural Land | Agricultural Land |
| 118 | 475018.36mE,4556029.93mN | Agricultural Land | Agricultural Land |
| 119 | 474207.10mE,4556802.33mN | Agricultural Land | Agricultural Land |
| 120 | 471475.79mE,4553607.10mN | Agricultural Land | Agricultural Land |
| 121 | 472554.81mE,4551027.02mN | Agricultural Land | Agricultural Land |
| 122 | 472772.83mE,4552144.89mN | Agricultural Land | Agricultural Land |
| 123 | 471325.20mE,4551323.92mN | Agricultural Land | Agricultural Land |
| 124 | 471471.54mE,4553597.38mN | Agricultural Land | Agricultural Land |

| | | | |
|---|---|---|---|
| 125 | 471039.87mE,4552446.55mN | Agricultural Land | Agricultural Land |
| 126 | 469717.26mE,4553038.73mN | Agricultural Land | Agricultural Land |
| 127 | 471548.66mE,4552897.86mN | Agricultural Land | Agricultural Land |
| 128 | 470121.68mE,4553341.13mN | Vegetation 3 | Vegetation 3 |
| 129 | 471193.02mE,4553194.45mN | Vegetation 3 | Vegetation 3 |
| 130 | 471039.03mE,4552943.11mN | Vegetation 3 | Vegetation 3 |
| 131 | 471633.23mE,4554267.05mN | Vegetation 3 | Vegetation 3 |
| 132 | 472391.01mE,4554744.95mN | Vegetation 3 | Vegetation 3 |
| 133 | 473685.06mE,4554600.02mN | Vegetation 3 | Vegetation 3 |
| 134 | 471515.06mE,4556707.12mN | Vegetation 3 | Vegetation 3 |
| 135 | 472370.07mE,4556646.23mN | Vegetation 3 | Vegetation 3 |
| 136 | 474182.13mE,4556496.96mN | Vegetation 3 | Vegetation 3 |
| 137 | 475004.89mE,4555900.00mN | Vegetation 3 | Vegetation 3 |
| 138 | 474107.01mE,4555201.02mN | Vegetation 3 | Vegetation 3 |
| 139 | 473955.71mE,4554445.07mN | Vegetation 3 | Road |
| 140 | 473368.03mE,4554013.06mN | Vegetation 3 | Vegetation 3 |
| 141 | 472388.04mE,4554424.98mN | Urban development | Urban development |
| 142 | 471498.05mE,4555226.00mN | Urban development | Urban development |
| 143 | 471018.99mE,4555410.03mN | Urban development | Urban development |
| 144 | 469321.35mE,4555164.03mN | Urban development | Agricultural Land |
| 145 | 469963.05mE,4556498.00mN | Urban development | Urban development |
| 146 | 472464.13mE,4556187.03mN | Urban development | Urban development |
| 147 | 472281.59mE,4554133.39mN | Urban development | Urban development |
| 148 | 472445.04mE,4556109.04mN | Urban development | Urban development |
| 149 | 470541.06mE,4555636.00mN | Urban development | Urban development |
| 150 | 469511.03mE,4555167.12mN | Urban development | Urban development |

**Table 14. Error Matrix for supervised classification of LANDSAT imagery**

| | Reference Data | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Predicted Class | Vege1 | Forest | Vege2 | Vege3 | Vege4 | Urban | Road | Agri | Grass | Water | Row Total |
| Vegetation1 | 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17 |
| Forest | 0 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 |
| Vegitation2 | 0 | 0 | 13 | 0 | 0 | 0 | 01 | 0 | 0 | 0 | 14 |
| Vegitation3 | 0 | 0 | 0 | 12 | 0 | 0 | 01 | 0 | 0 | 0 | 13 |
| Vegitation4 | 0 | 0 | 0 | 0 | 10 | 0 | 01 | 0 | 0 | 0 | 11 |
| Urban Development | 0 | 0 | 0 | 0 | 0 | 09 | 0 | 01 | 0 | 0 | 10 |
| Road or Parking | 0 | 0 | 0 | 0 | 0 | 01 | 14 | 0 | 0 | 0 | 15 |
| Agricultural Land | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 13 | 0 | 0 | 13 |
| Grass | 0 | 0 | 0 | 0 | 01 | 0 | 0 | 0 | 18 | 0 | 19 |
| Water | 01 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16 | 17 |
| Column Total | 18 | 21 | 13 | 12 | 11 | 10 | 17 | 14 | 18 | 16 | 150 |

<u>Error Matrix Calculations</u>

Overall Accuracy

$$= \frac{\text{total \# correct}}{\# matrix\ \ total} * 100 = \%$$

= (17+21+13+12+10+09+14+13+18+16) / 150 * 100

= 143 / 150 * 100

= .953 * 100 = 95.3%

## Producer's Accuracy

$$= \frac{total\ correctly\ predicted\ class\ X}{total\ reference\ classX} * 100$$

## User's Accuracy

$$= \frac{total\ correct\ class\ X}{total\ classified\ as\ classX} * 100$$

**Table 15. Producer's and User's accuracy from supervised classification of LANDSAT imagery**

| Cover Class | Producer's Accuracy | User's Accuracy |
|---|---|---|
| Vegetation1 | 17/ 18* 100 = 94% | 17/17 * 100 = 100% |
| Forest | 21/21 * 100 = 100% | 21/21 * 100 = 100% |
| Vegetation2 | 13/13 * 100 = 100% | 13/14 * 100 = 93% |
| Vegetation3 | 12/12 * 100 = 100% | 12/13 * 100 = 92% |
| Vegetation4 | 10/11 * 100 = 91% | 10/11 * 100 = 91% |
| Urban | 09/10 * 100 = 90% | 09/10 * 100 = 90% |
| Road/Parking | 14/17 * 100 = 82% | 14/15 * 100 = 93% |
| Agri Land | 13/14 * 100 = 93% | 13/13 * 100 = 100% |
| Grass | 18/18 * 100 = 100% | 18/19 * 100 = 95% |
| Water | 16/16 * 100 = 100% | 16/17 * 100 = 94% |

## Kappa Statistic

$$\text{K-hat} = \frac{overall\ classification\ accuracy - \exp ected\ classification\ accuracy}{1 - \exp ected\ classification\ accuracy}$$

**Table 16. Matrix of Product for Error Matrix from supervised classification of LANDSAT imagery**

| | Veg1 | Forest | Vege2 | Vege3 | Vege4 | Urban | Road | Agri | Road | Water | Row totals form above |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Vegetation1 | **306** | 357 | 221 | 204 | 187 | 170 | 289 | 238 | 306 | 272 | 17 |
| Forest | 378 | **441** | 273 | 252 | 231 | 210 | 357 | 294 | 378 | 336 | 21 |
| Vegetation2 | 252 | 294 | **182** | 168 | 154 | 140 | 238 | 196 | 252 | 224 | 14 |
| Vegetation3 | 234 | 273 | 169 | **156** | 143 | 130 | 221 | 182 | 234 | 208 | 13 |
| Vegetation4 | 198 | 231 | 143 | 132 | 121 | 110 | 187 | 154 | 198 | 176 | 11 |
| Urban | 180 | 210 | 130 | 120 | 110 | **100** | 170 | 140 | 180 | 160 | 10 |
| Road/Parking | 270 | 315 | 195 | 180 | 165 | 150 | **255** | 210 | 270 | 240 | 15 |
| Agri Land | 234 | 273 | 169 | 156 | 143 | 130 | 221 | **182** | 234 | 208 | 13 |
| Grass | 342 | 399 | 247 | 228 | 209 | 190 | 323 | 266 | **342** | 304 | 19 |
| Water | 306 | 357 | 221 | 204 | 187 | 170 | 289 | 238 | 306 | **272** | 17 |
| Columns total from above | 18 | 21 | 13 | 12 | 11 | 10 | 17 | 14 | 18 | 16 | 150 |

Expected Classification Accuracy

= (306+441+182+156+121+100+255+182+342+272) / 22500

= 2357/22500

= 10.47%

K-hat = (0.953-0.1047) / (1-0.1047)

= 0.8483 / .8953

= 0.947

# 4. Result

An analysis performed on the extracted datasets has been performed in this section. The goal was to find the out which satellite image and data-mining technique was the best for the classification. Moreover the Unsupervised and Supervised Classification was performed on the high resolution IKONOS and LANDSAT image. And the accuracies and kappa- statistic of the classification was determined to compare the data-mining technique and high resolution image.

From the results obtained the accuracy of the supervised classification is more than unsupervised classification tells supervised classification is better as the different spectral signatures of each class is taken from the imagery by selecting the pixel that hold the same information for example for the classification of water under the supervised classification two different spectral signatures were created selecting the pixels that represented the lake. In this study there are two lakes in the area Sandy Lake and Brady Lake. Therefore when the supervised learning was done the spectral signature compared all the pixels in the image having the same value and this gave the information about the class water in the classification which was easily identified by adding specific color to the class water. Whereas in unsupervised classification its computer aided and uses minimum spectral distance to assign a cluster for each candidate pixel. Each pixel is analyzed beginning with the upper left corner of the image and going left to right block by block. In this study there were ten classes every pixel was distributed under each class using the Iterative Self Organizing Data Analysis Technique (ISODATA) method which ERDAS Imagine uses for unsupervised classification. Now each class was named on the basis of the prior knowledge of the area under study for example the location of the lake was known from before so class that represented that area pixel was taken to be as water. Similarly it is done for the other classes. Therefore accuracy of the classification obtained from unsupervised is less than the supervised learning.

The IKONOS high resolution image contain four band Panchromatic, red, green, blue and the Image has spatial resolution of 4m except for panchromatic which is 1m. The Image classification assumed had good accuracy results and the spatial resolution is too fine but when the comparison with the LANDSAT Thematic Mapper image is done which has seven bands blue, green, red, reflective infrared, mid-infrared, thermal Infrared and mid-Infrared2 having spatial resolution of 30m. It was found in the study that accuracy of classification was better with LANDSAT image than IKONOS Image. The spectral resolution in LANDSAT thematic mapper is greater than IKONOS and it was found from the study that for classification of the land-use the spectral resolution is important than spectral resolution.

The different spatial and spectral resolutions are the limiting factors for the utilization of the Remote Sensing data for different applications. Unfortunately, because of technical constraints, satellite remote sensing systems can only offer the following relationship between spatial and spectral resolution: a high spatial resolution is associated with low spectral resolution and vice versa. That means that a system with a high spectral resolution can offer a medium or low spatial resolution. Therefore, it is either necessary to find compromising between the different resolutions according to the individual application or to utilize alternative methods of data acquisition. So there is a trade-off between spectral resolution and spatial resolution. Best trade off for the classification of the land use to reach higher accuracy as we see from the study is through higher spectral resolution.

Following table has the Accuracy and Kappa-Statistic indicating the land-use classification obtained from LANDSAT image with supervised learning gives the best accuracy result.

**Table 17. Accuracy and Kappa-statistic from different Image classification**

| Image Classification | Accuracy | Kappa-Statistic |
|---|---|---|
| IKONOS Image Unsupervised | 80.00% | .776 |
| LANDSAT Image Unsupervised | 84.60% | .828 |
| IKONOS Image Supervised | 93.30% | .925 |
| LANDSAT Image Supervised | 95.30% | .947 |

# 5. Conclusion

The Study has shown the effectiveness of using supervised learning on Landsat TM image to predict land use. From the accuracy results it was noted that spectral resolution is the most important factor for the land use classification. Different bands help to differentiate between vegetation and also help to monitor the health of vegetation's. Comparison with the IKONOS image and Landsat TM image on the basis of accuracy of classification the Image with more number of bands definitely has a big advantage. Supervised learning is best suited for the land use classification as the user can select as many spectral signatures of each class and obtain more accurate results whereas in unsupervised has to rely on the computer aided classification results for the land use which may not me accurate. The seven band combination for the Landsat TM distinguishes the different kinds of vegetation to give the best result for the classification of the different classes compared to only four band combination for IKONOS image. The trade-off between the spectral resolution and spatial resolution becomes a dilemma for certain uses of the Image classification. But from the study which shows a higher accuracy of image classification for the land use is obtained from the image which has more band combinations, as it is much easier to distinguish between the different classes and it also allows having more number of classes in the study. In that way lot information is gathered from the satellite Image of the particular area. In future remote sensing satellite there should be more combinations of different bands that can be very helpful for studying the land-use and land-cover of the area. New technology is also helping to improve the spatial resolution keeping the spectral resolution the same. Satellite remote sensing will provide a great solution for tomorrow's world.

# 6. References


[1] W.G.M. Bastiaanssen, S. Thiruvengadachari, R. Sakthivadivel and D.J. Molden,"Satellite Remote Sensing for Estimating Productivities of Land and Water", *International Journal of Water Resources Development*, Mar 1999.

[2] Adenberg, M., "Cluster Analysis for Applications", *Academic Press*, 1972.

[3] A. Lazar and B. Shellito. "Comparing Machine Learning Classification Schemes – a GIS Approach. In Proceedings of ICMLA'2005": *The 2005 International Conference on Machine Learning and Applications*, IEEE, 2005.

[4] Jane You and David Zhang,"Smart Sensor: An On-Board Image Processing System for Real-Time Remote Sensing", *International Journal of Image & Graphics*, July 2002.

[5] Murthy Remilla L.N, Srinivasan R, Prakash C.V.S, "Estimation of Potential for Spaceborne Remote Sensing Data Services", *International Journal of Business Research*, Sept 1, 2008.

[6] Nicholas M.Short., "Image Processing and Interpretation", *Academic Press*, 1972.

[7] John R Jensen, *Introductory Digital Image Processing : A Remote Sensing Perspective,* Prentice Hall, Cambridge, New Jersey, 1996.

[8] John R Jensen, *Remote Sensing of the Environment : An Earth Resource Perspective,* Prentice Hall, Cambridge, New Jersey, 2000.

[9] FF Sabins, Jr, *Remote Sensing : Principles and Interpretation,* WH Freeman & Co, New York City, 1987.

[10] Tour Guides, *ERDAS IMAGINE Professional Tour Guides,* ERDAS, Inc, Norcross, 2009.

[11] Daniel J.Getman, Jonathan M. Harbor, Chris J. Johannsen, Bernard A. Engel, and Goufan Shao, Improving the Accuracy of Historic Satellite Image Classification by Combining Low-Resolution Multispectral data with High-Resolution Panchromatic Data, *The Journal of Terrestrial Observation*, Spring 2008.

[12] Mohd Hasmadi Ismail, and Kumaruzaman Jusoff, Satellite Data Classification Accuracy Assessment Based from Reference Dataset, *International Journal of Computer and Information Engineering*, 2008.

[13] Ed Sheffner, Landsat Program, *Ecosystem Science and Technology Branch of the Earth Science Division*, 1999.

[14] Donald T. Lauer, Stanley A. Morain, and Vincent V. Salomonson, The Landsat Program: Its Origins, Evolution, and Impacts, *Photogrammetric Engineering and Remote Sensing*, 1997.

[15] J. Grodecki and G. Dial, IKONOS Geometric Accuracy, *Space Imaging*, 2001.

[16] Robert Sanderson, Introduction to remote Sensing, *New Mexico Space Grant Consortium,* 2000.

[17] Field Guides, *ERDAS IMAGINE Professional Tour Guides,* ERDAS, Inc, Norcross, 2009.