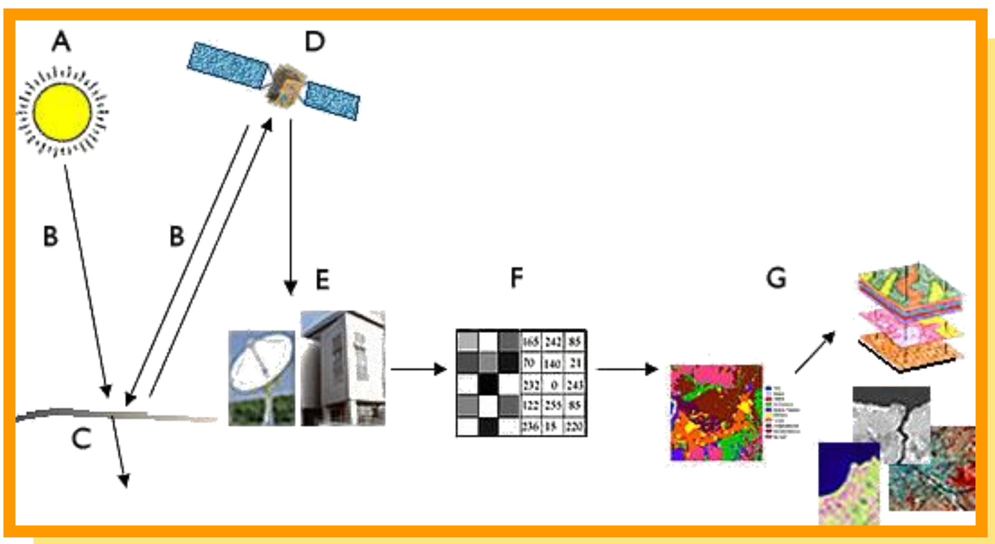
United Arab Emirates University
Humanities & Social Science Collage
Geography Department
GIS Program

Digital Imaging Analysis



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Introduction

This report is a summary of which we take in digital image analysis course; it is very important and formative course for the image analyst. For that in my report I use the internet, textbook for the course, and my notes to write a complete report. So I write about the image and how interpret it by visual, then the difference between the hard image and digital image and how to get the digital image by the satellite. Beside that I mention the function of digital image, which are the image pre-processing, image enhancement, image transformation, image classification, and digital change diction.

Photo Interpretation

The visual interpretation of images based on features tone, pattern, shape, size, shadow, texture and association which consider as indicators. The indicators can be classifying in three ways spatial, spectral, and temporal, the following show the difference between them:

Spatial: related to dimension or location such as, (size, shape, and position-association).

Spectral: depend on the electromagnetic response, such as (tone, colour), as result of reflection and emitted EM energy.

Temporal: it mean the change in spatial or spectral characteristic with time, it can be cyclic (daily, seasonal, annual), or permanent (cleaning, construction).

In addition, when we use the visual interpretation we use our eye and brain for that they will be different on interpretation between people depend on their skill, experiences, and knowledge of area.

Photo Indicators:

Color: the color characteristics of an object, relative to other objects in the photo, are used to identify the feature, we can use RGB (red, green, blue), for example the forest is green and water is blue…etc.

Figure (1): difference between water an land depend on theirs color

Tone: refers to the grey level, or the brightness and darkness of object, the light tone mean high reflectance, and dark tone mean low reflectance, for example sand has a bright tone, while water usually has a dark tone.

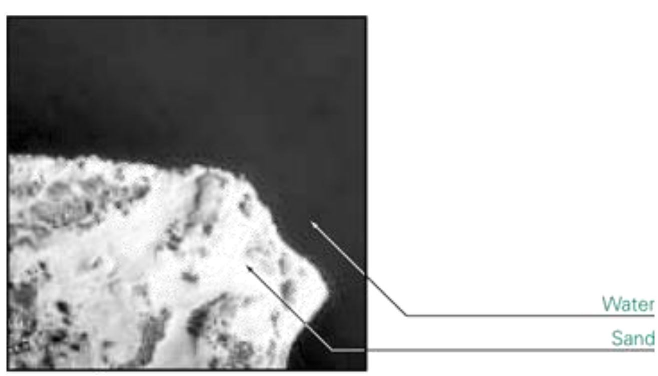


Figure (2): difference between water an sand depend on the tone

Shape: refers to the general form, structure, or outline of individual objects. Shape can be a very distinctive clue for interpretation. Straight edge shapes typically represent urban or agricultural (field) targets, while natural features, such as forest edges, are generally more irregular in shape, except where man has created a road or clear cuts. Farm or crop land irrigated by rotating sprinkler systems would appear as circular shapes.

Figure (3): difference between shapes

Size of objects in an image is a function of scale. It is important to assess the size of a target relative to other objects in a scene, as well as the absolute size, to aid in the interpretation of that target. A quick approximation of target size can direct interpretation to an appropriate result more quickly. For example, if an interpreter had to distinguish zones of land use, and had identified an area with a number of buildings in it, large buildings such as factories or warehouses would suggest commercial property, whereas small buildings would indicate residential use.

Figure (4): difference between sizes

Pattern refers to the spatial arrangement of visibly discernible objects. Typically an orderly repetition of similar tones and textures will produce a distinctive and ultimately recognizable pattern. Orchards with evenly spaced trees, and urban streets with regularly spaced houses are good examples of pattern.

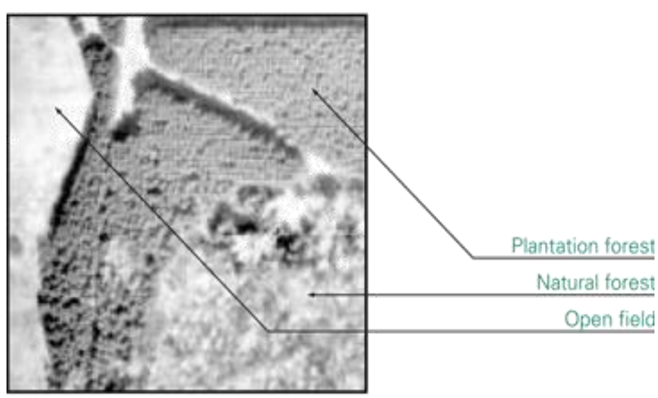


Figure (5): difference between pattern

Texture refers to the arrangement and frequency of tonal variation in particular areas of an image. Rough textures would consist of a mottled tone where the grey levels change abruptly in a small area, whereas smooth textures would have very little tonal variation. Smooth textures are most often the result of uniform, even surfaces, such as fields, asphalt, or grasslands. A target with a rough surface and irregular structure, such as a forest canopy, results in a rough textured appearance. Texture is one of the most important elements for distinguishing features in radar imagery.

Figure (6): difference between texture

Shadow is also helpful in interpretation as it may provide an idea of the profile and relative height of a target or targets which may make identification easier. However, shadows can also reduce or eliminate interpretation in their area of influence, since targets within shadows are much less (or not at all) discernible from their surroundings. Shadow is also useful for enhancing or identifying topography and landforms, particularly in radar imagery.

Figure (7): difference between shadow

Association/site: takes into account the relationship between other recognizable objects or features in proximity to the target of interest. The identification of features that one would expect to associate with other features may provide information to facilitate identification. In the example given above, commercial properties may be associated with proximity to major transportation routes, whereas residential areas would be associated with schools, playgrounds, and sports fields. In our example, a lake is associated with boats, a marina, and adjacent recreational land.

Figure (8): difference between shapes association/ site

Stereo perspective: seeing an area in stereo, or 3-D, is important for determining the t Stereoscopic imagery is the result of overlap, which is the amount by which one photograph includes an area covered by a neighboring photograph. Air photo coverage is generally designed to provide about 60 percent forward overlap between photographs. This allows stereoscopic, or 3D, viewing when the two overlapping photos are used with a stereoscope. In addition, from 20 to 40 percent lateral (side) overlap is allowed when complete coverage of an area is required. For mapping, inventory and vegetation studies, for example, a survey is flown in a series of to-and-from parallel strips with side overlaps between strips over the entire area. Topographical relief of an area, as well as the height of objects such as trees and building.

Figure (9): stereoscope

Remote Sensing Image Forming

To get an image from satellite, we must know the process. First thing we must have a source of light and there is two type, natural which is sun, and artificial -made by human- such as battery (flash), RADAR, LASER. This energy source will provides electromagnetic energy to the target of interest.

Before radiation used for remote sensing reaches the Earth's surface it has to travel through some distance of the Earth's atmosphere. Particles and gases in the atmosphere can affect the incoming light and radiation. These effects are caused by the mechanisms of **scattering** and **absorption**.

> **Scattering** occurs when particles or large gas molecules present in the atmosphere interact with and cause the electromagnetic radiation to be redirected from its original path. How much scattering takes place depends on several factors including the wavelength of the radiation, the abundance of particles or gases, and the distance the radiation travels through the atmosphere. There are three (3) types of scattering which take place.
>
> **Absorption** is the other main mechanism at work when electromagnetic radiation interacts with the atmosphere. In contrast to scattering, this phenomenon causes molecules in the atmosphere to absorb energy at various wavelengths. Ozone, carbon dioxide, and water vapor are the three main atmospheric constituents which absorb radiation.

<u>There are a reaction between the object and radiation, and the reactions can affected by:</u>

1. Types of material, some type reflect the radiation, or absorb it or scatter, for example the steal reflect, but water scatter same of radiation.

2. Angle of incidence is a measure of deviation of something from "straight on"

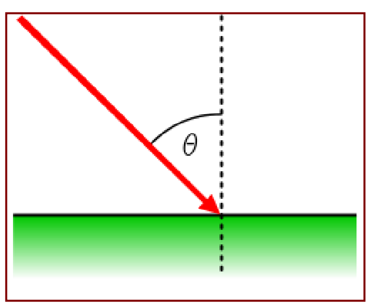


Figure (10): angle of incidence

3. Season: the image which takes in summer will be different from the image taken in winter (rainy day) even for same area.

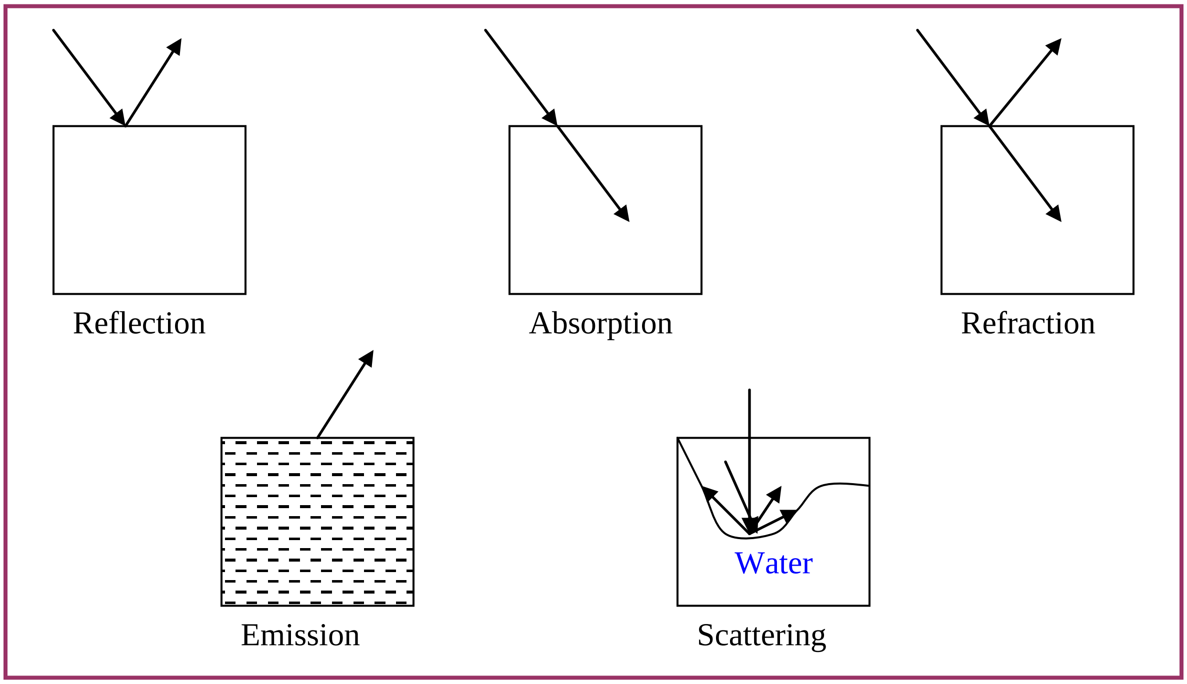


Figure (11): figures shows how the reaction between object and radiation

After know how reaction between radiation and features, we know that some radiations are reflected to the satellite, for that we must know how the lights convert as a signal, the figure below show that operation:

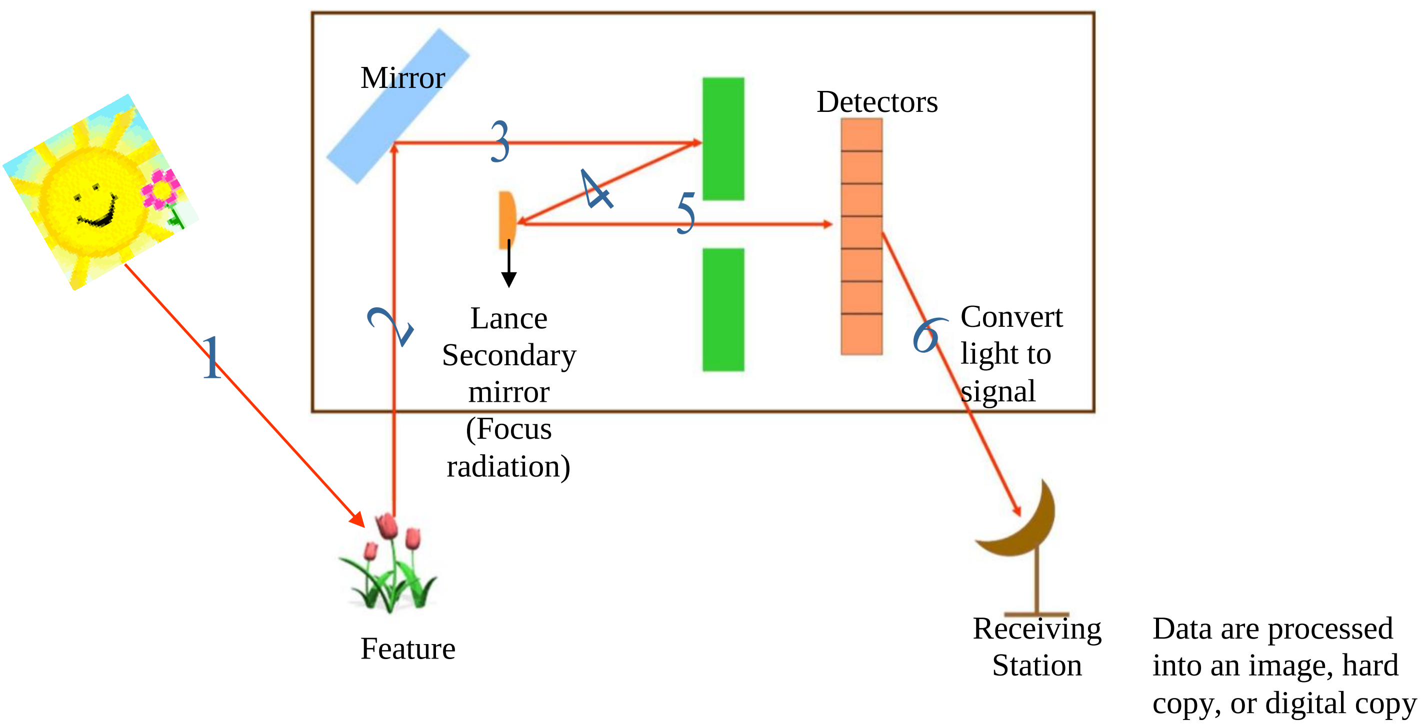


Figure (12): figures shows how to get the digital image

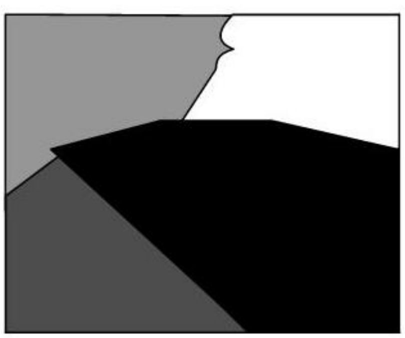
There is an example of different land use type and its reflection:

Land use	Reflection Amount	Why
building	higher	Material maybe steal or concrete
Green areas	low	Photo-synthesis because the radiation is absorbed by trees for making food $6H_2O + 6CO_2 \rightleftharpoons H_{12}C_6O_6 + 6O_2$
Water	Lower	Absorb / Scatter
Desert	high	Sand (stone, rocks), minerals are good reflector.

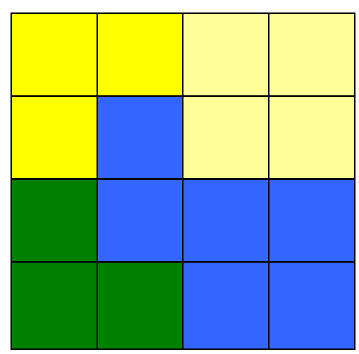
After knowing the amount of reflection, we will give each type digital number depend on it reflect high or low. for example, we will assume we have four land use, and we know the digital number range between 0 and 255.

First, we must find the class interval, it will be 255/4= 63

Class#	Range	Land use	colour
Class1	0-63	Water	Blue
Class2	64-127	green area	Green
Class3	128-191	Desert	Yellow
Class4	192-225	Building	Light Yellow



140	130	199	200
145	10	225	230
75	20	25	30
80	70	50	40



Land use image   land use image with digital number   Finally image

Figure (13): how to get the final image from the digital number

Final step, we make a histogram which is a graph showing the relationship between digital number and frequency, it is useful because it provide summary in clear way.

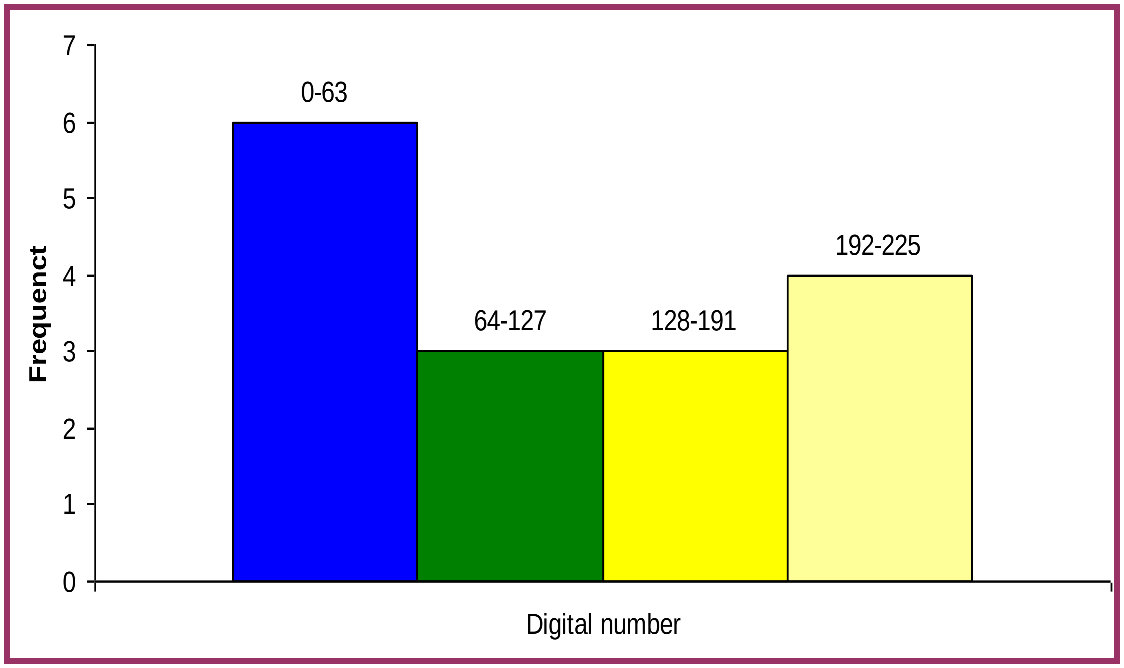


Figure (14): histogram show the relation between frequency and digital number

From the histogram we know that the water cover most of the land, also the green area are low in that land, building and desert have same space of that land.

Digital Image

In this section I will write the digital image definition, Advantage of digital image, formats, and the processing of digital image.

Digital image mean the image which is in digital format, and there is differences between digital image and hard copy image. In hardcopy image we use brain and eye to analysis it (subjective), but in digital image analysis we get exact result (objective).

There is advantage for visual interpretation:

1. No need for computer (hardcopy, softcopy) → less cost.
2. No need for programmers or analyst → Less cost

But the advantage of digital is better:

1. Faster when we have huge data.
2. More details, if we forget something in visual interpretation, the computer will analysis everything and all features.

Digital image format:

- Bitmap File (.bmp)
- GIF (.gif)
- JPEG (.jpg)
- Photoshop File (.psd)
- PICT (.pct)
- Pixel EPS (.eps)
- PNG (.png)
- TIFF file (.tif)

Digital photo Composition

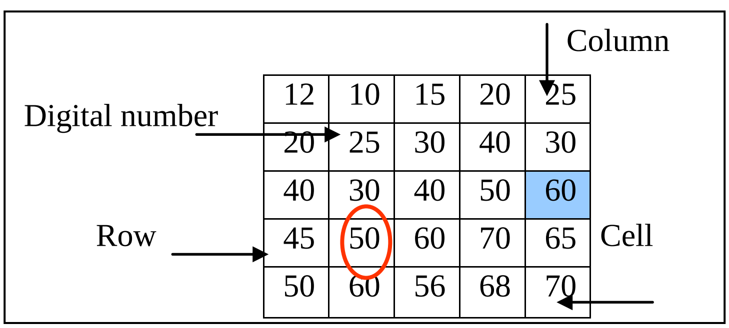


Figure (15): Digital photo Composition

There are many processing for the digital image:

1. Pre-processing, before any process.
2. Enhancement, improve the appearance.
3. Transformation, map geo-referencing
4. Classification and analysis.

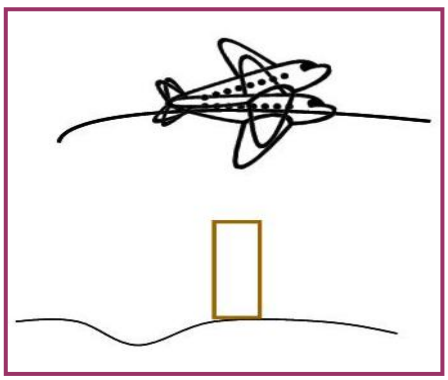
Digital Image Pre-Processing

Preprocessing functions involve those operations that are normally required prior to the main data analysis and extraction of information, and are generally grouped as radiometric or geometric corrections. Before digital images can be analyzed, they usually require some degree of preprocessing. This may involve radiometric corrections, which attempt to remove the effects of sensor errors and/or environmental factors. A common method of determining what errors have been introduced into an image is by modeling the scene at the time of data acquisition using ancillary data collected. Geometric corrections are also very common prior to any image analysis. If any types of area, direction or distance measurements are to be made using an image, it must be rectified if they are to be accurate. Geometric rectification is a process by which points in an image are registered to corresponding points on a map or another image that has already been rectified. The goal of geometric rectification is to put image elements in their proper planimetric (x and y) positions.

First we must know the errors of geometric and radiometric, and there is two type of errors, internal (within sensor), and external (outside the sensor), then how to solve it by the geometric and radiometric correction.

Source of geometric errors:

1. Tilt, due to wind (attitude), there is 6 tilts in 3 axes.



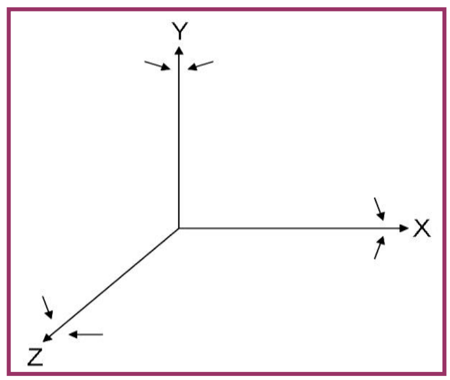


Figure (16): tilt error

2. Altitude, (height, elevation). More high more error. H2 more error.

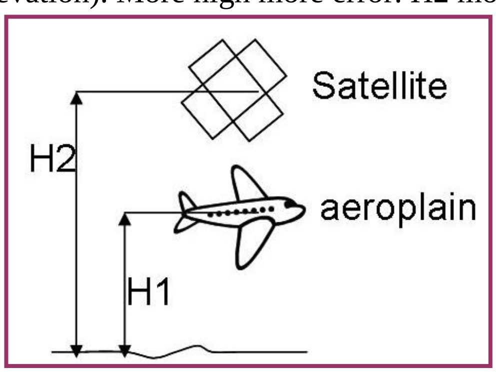


Figure (17): attitude error

3. Topography, change in elevation

Relief displacement → shift in the position of the object due its height.

Figure (18): elevation error

4. Rotation of the earth and the movement of the satellite. (Systematic every time some amount of error), and not random. Because Earth rotates from west to east, satellite rotates from north to south.

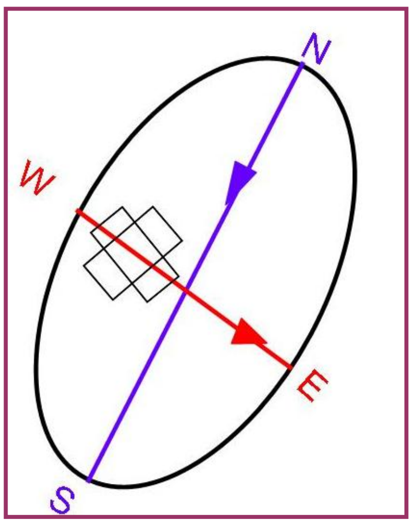


Figure (19): rotation of earth and satellite error

5. Speed of mirror, internal errors. Problem with mirror speed due to malfunction of the mirror parts.

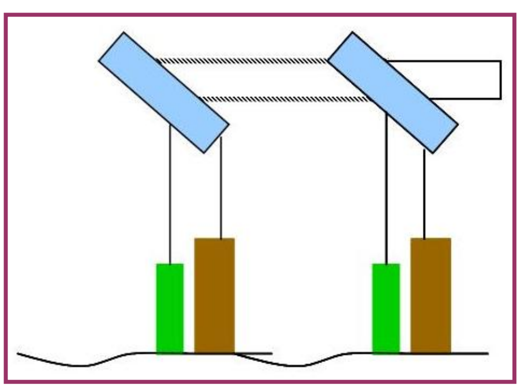


Figure (20): speed of mirror in satellite error

To solve those errors we apply the Geometric correction and it is include correcting for geometric distortions due to sensor-Earth geometry variations, and conversion of the data to real world coordinates (e.g. latitude and longitude) on the Earth's surface. For that we apply the geo-referencing technique for it, for example bring map for same area and shoes a clear feature on it and sign it in the image also for same area by the GCP (ground control point), such as the road intersection. The GCP it must be well distributed, better more than four.

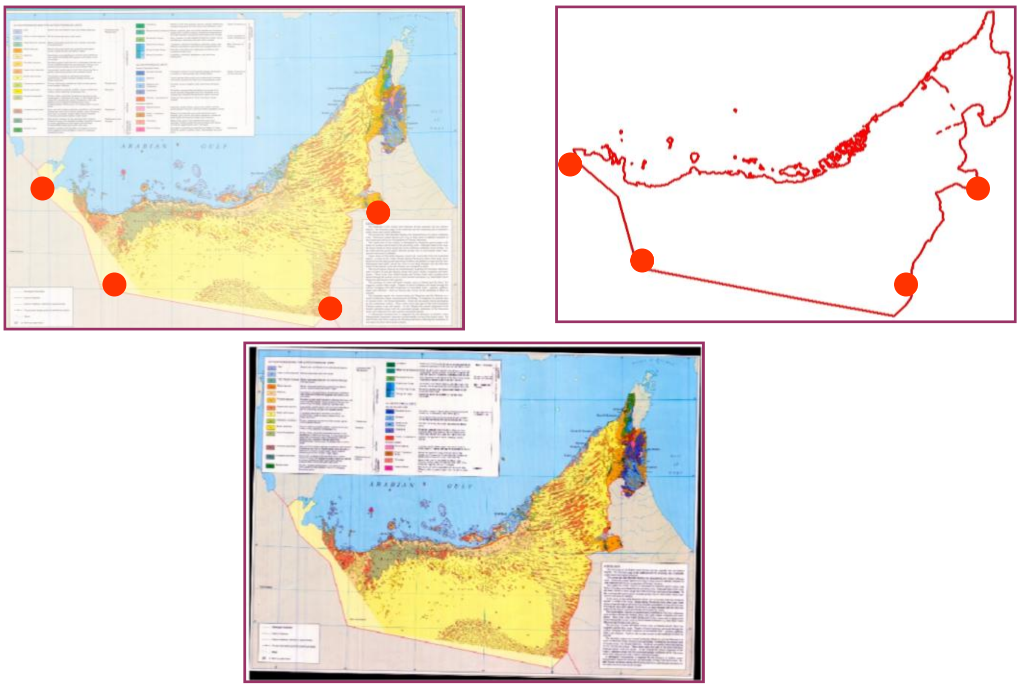


Figure (21): Georeference method

The geo-referenced image becomes curve because of the curvature of earth.

Source of Radiometric errors:

1. Atmosphere errors.

Scattering → particles air pollutant, molecules
Absorption→ gases (CO_2, O_3, and H_2O).
* $O_{3,}$ absorbed ultraviolet which is dangerous to human,

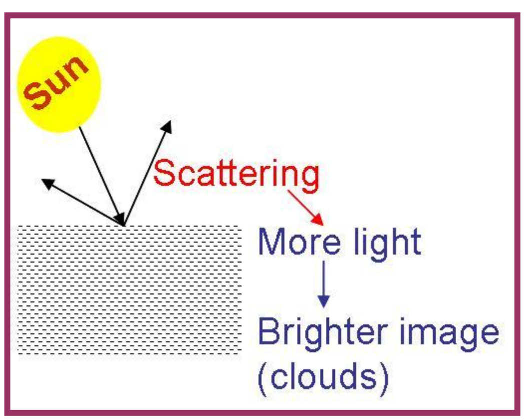


Figure (22): atmosphere error

2. Internal errors

Mainly due to the detectors inside the sensor, as it show below:

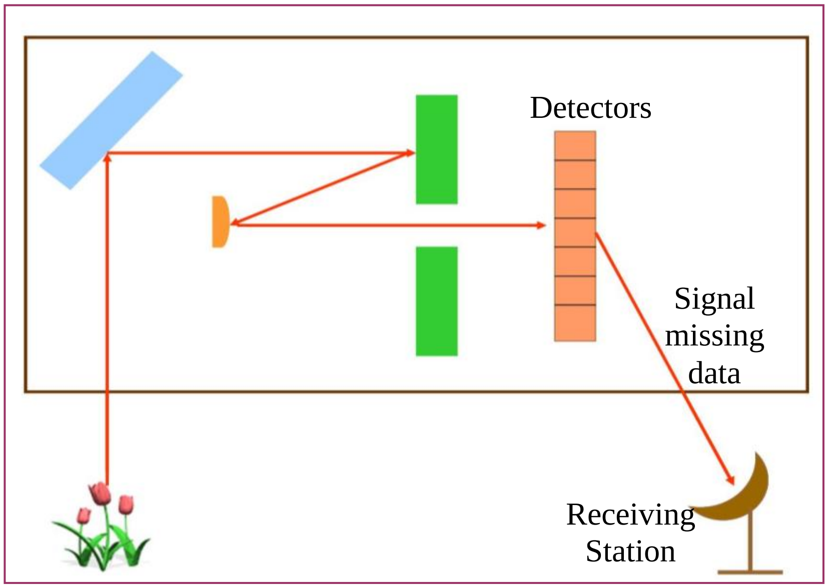


Figure (23): missing data

40	50	60
0	0	0
60	70	80
200	255	210
50	80	20

Dark line

Light line

Stripping

Figure (24): digital image

In this cause we can solve problem by use the De-stripping, that is mean take the average of before and after line, such it show below:

40	50	60
50	60	70
60	70	80
55	75	50
50	80	20

Figure (25): Digital image after correction

Digital Image Enhancement

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide `better' input for other automated image processing techniques.

Image enhancement technique:

One useful, broad categorization of enhancement techniques divides them into point- and region-based operations. Point operations modify pixels of an image based on the value of the pixel independent. By contrast, region-based operations calculate a new pixel value based on the values in a (typically small) local neighborhood, by use crook movement (4 directions), or queen movement (8 direction).

Point operation

Contrast enhancement involves changing the original values so that more of the available range is used, thereby increasing the contrast between targets and their backgrounds. The key to understanding contrast enhancements is to understand the concept of an image histogram. A histogram is a graphical representation of the brightness values that comprise an image. The brightness values (i.e. 0-255) are displayed along the x-axis of the graph. The frequency of occurrence of each of these values in the image is shown on the y-axis, as it shows below:

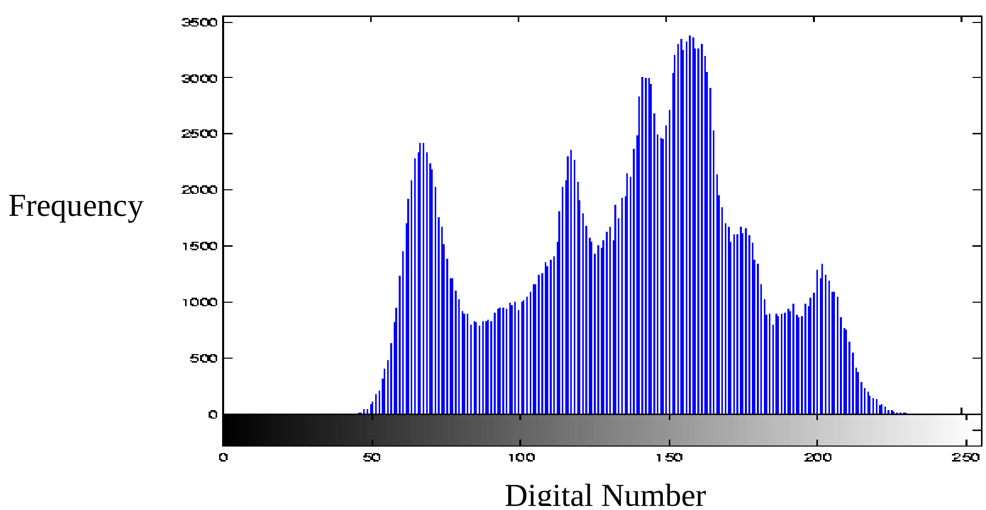


Figure (26): contrast enhancement

There are two type of image contrast enhancement, linear and non linear, so the following will discuss that in more details.

Linear contrast stretch involves identifying lower and upper bounds from the histogram (usually the minimum and maximum brightness values in the image) and applying a transformation to stretch this range to fill the full range. In our example, the minimum value (occupied by actual data) in the histogram is 5 and the maximum value is 100.

Alinear stretch uniformly expands this small range to cover the full range of values from 0 to 255. This enhances the contrast in the image with light toned areas appearing lighter and dark areas appearing darker, making visual interpretation much easier.

22	20	40	45	50	55
30	45	60	70	65	60
40	50	70	60	80	75
55	65	80	60	54	80
70	75	85	70	60	85
60	80	90	95	98	100

Min= 20, Max=100

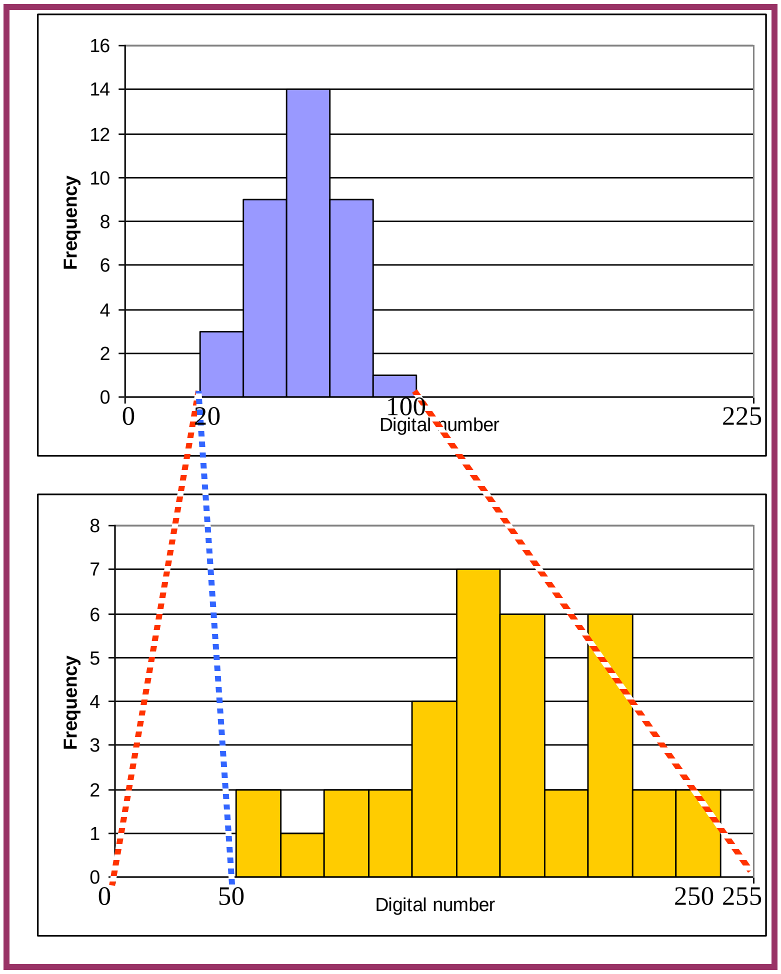


Figure (27): linear contrast stretching

Linear Transformation
$DN_{out} = DN_{in} * constant + constant$

100=225
100x*255
X=255/100=2.5

So we will use 1.6 and multiply all the digital number independent.

55	50	90	100	125	138
75	113	150	175	163	150
90	125	175	150	200	188
138	163	200	150	141	200
175	188	213	175	150	213
150	200	225	238	245	250

Min= 50, Max=250

Non Linear contrast stretch, this stretch assigns more display values (range) to the frequently occurring portions of the histogram. In this way, the detail in these areas will be better enhanced relative to those areas of the original histogram where values occur less frequently. In other cases, it may be desirable to enhance the contrast in only a specific portion of the histogram. For example, suppose we have an image of the mouth of a river, and the water portions of the image occupy the digital values from 40 to 76 out of the entire image histogram. If we wished to enhance the detail in the water, perhaps to see variations in sediment load, we could stretch only that small portion of the histogram represented by the water (40 to 76) to the full grey level range (0 to 255). All pixels below or above these values would be assigned to 0 and 255, respectively, and the detail in these areas would be lost. However, the detail in the water would be greatly enhanced.

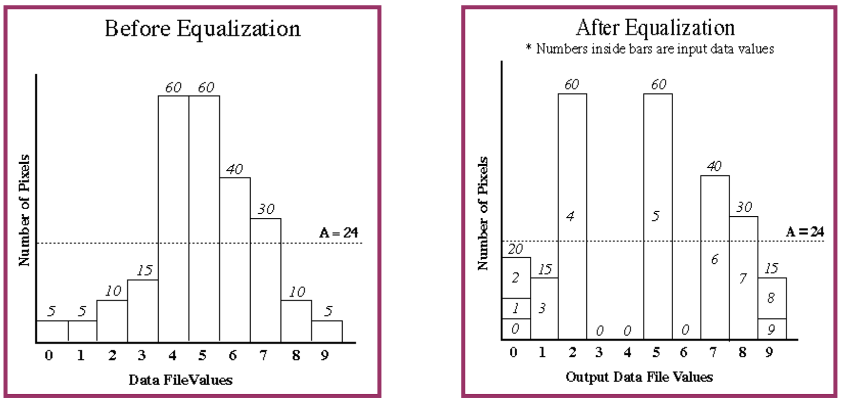


Figure (28): non linear contrast stretch

The first histogram shows values before equalization is performed. When this histogram is compared to the equalized histogram, one can see that the enhanced image gains contrast in the most populated areas of the original histogram. In this example, the input range of 3 to 7 is stretched to the range of 1 to 8. However, the data values at the tails of the original histogram are grouped together. Input values 0 through 2 all have the output values of 0. These results in the loss of the dark and bright characteristics usually associated with the tail pixels (ERDAS Inc. 1995)

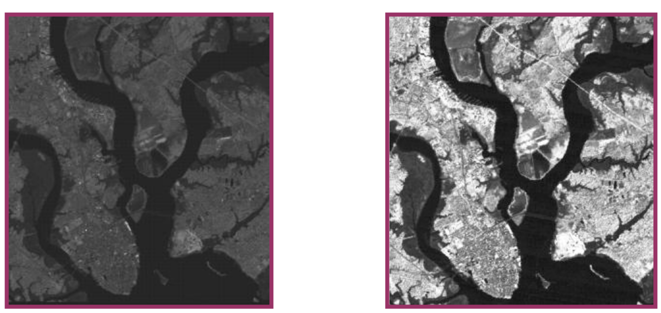


Figure (29): images before and after enhancement

Image analysts must be aware that while histogram equalization often provides an image with the most contrast of any enhancement technique, it may hide much needed information. This technique groups pixels that are very dark or very bright into very few gray scales. If one is trying to bring out information about data in terrain shadows, or there are clouds in your data, histogram equalization may not be appropriate.

To be clearer I will write the non linear transformation formula and give example for it as it show below:

10	20	25	30
12	25	29	28
15	22	30	25
18	19	29	22

$\left.\begin{array}{l}\text{Min= 10}\\ \\ \text{Max= 30}\end{array}\right\}$ Dark image

Non Linear Transformation
F (DN_{out}) = F (DN_{in})

To transfer this image, I will follow this formula ($y = a\,x^2 + b$), first step is get a and b, for that I following show how to get it.
* The stretch will be from 0 to 255, instead of 10 to 30, for that the minimum for new image is 0, and maximum will be 225.

$(0) = a\,(10)^2 + b \rightarrow 100a + b$

$(255) = a\,(30)^2 + b \rightarrow 900a + b$

To get (a):
900a-100a = 800a
255=800a
A=800/255= 0.3

To get b
0= 100*0.3 +b
0=30+b
B= -30

The formula will be $y = 0.3 * (DN)^2 + 30$, so the image which is enhanced look like the image below:

0	90	158	240
14	158	223	206
38	116	240	158
68	80	173	116

$\left.\begin{array}{l}\text{Min= 0}\\ \\ \text{Max= 240}\end{array}\right\}$ Lighter image

Local operation

- Spatial filtering

Spatial filtering encompasses another set of digital processing functions which are used to enhance the appearance of an image. Spatial filters are designed to highlight or suppress specific features in an image based on their spatial frequency. Spatial frequency is related to the concept of image texture. It refers to the frequency of the variations in tone that appear in an image. "**Rough**" textured areas of an image, where the changes in tone are abrupt over a small area, have high spatial frequencies, while "**smooth**" areas with little variation in tone over several pixels, have low spatial frequencies.

Edge enhancement

Improve the difference or exaggerate it between features, such as, (water& land, river & land, geology& fracture- liniment).

10	26	100	150
15	20	110	180
12	22	118	170
15	125	130	160

Water +5
Land – 5

5	21	105	155
10	15	115	185
7	17	123	175
10	130	135	165

Figure (30): edge enhancement

Smoothing enhancement

Suppression of differences between the same features, such as water, land, and vegetation, to do this enhancement we take the average between neighbours as it show below:

10	20	30
20	255	20
30	20	10

Take the average
20+20+20+20/4
=20

10	20	30
20	20	20
30	20	10

Salt and pepper appearance

Figure (31): smoothing enhancement

Also spatial enhancement can done using frequency domain, and convert back to spatial domain frequency domain, by mathematical method to make it easier , such as using Fourier transformation.

- Transformation- method of enhancement.

Image transformations typically involve the manipulation of multiple bands of data, whether from a single multi spectral image or from two or more images of the same area acquired at different times (i.e. multi temporal image data). Either way, image transformations generate "new" images from two or more sources which highlight particular features or properties of interest, better than the original input images.

- Principal Components Analysis

Different bands of multi spectral data are often highly correlated and thus contain similar information. For example, Landsat MSS Bands 4 and 5 (green and red, respectively) typically have similar visual appearances since reflectance for the same surface cover types are almost equal. Image transformation techniques based on complex processing of the statistical characteristics of multi-band data sets can be used to reduce this data redundancy and correlation between bands. One such transform is called principal components analysis**.** The objective of this transformation is to reduce the dimensionality (i.e. the number of bands) in the data, and compress as much of the information in the original bands into fewer bands. The "new" bands that result from this statistical procedure are called components. This process attempts to maximize (statistically) the amount of information (or variance) from the original data into the least number of new components. As an example of the use of principal components analysis, a seven band Thematic Mapper (TM) data set may be transformed such that the first three principal components contain over 90 percent of the information in the original seven bands. Interpretation and analysis of these three bands of data, combining them either visually or digitally, is simpler and more efficient than trying to use all of the original seven bands. Principal components analysis, and other complex transforms, can be used either as an enhancement technique to improve visual interpretation or to reduce the number of bands to be used as input to digital classification procedures.

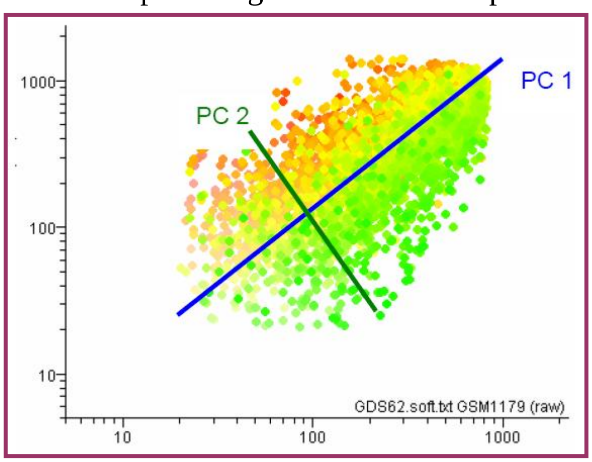


Figure (32): principle component analysis

In the scaterrogram we shift the axis, the rotate it, finally we must find the majority to reduce number if band after transformation. In that case we select the PC1 and remove the PC2.

- Conical Analysis Transformation

Separate the classes, to see the different very clear. Try to maximize the separation between different classes and minimize differences within classes, as it below:

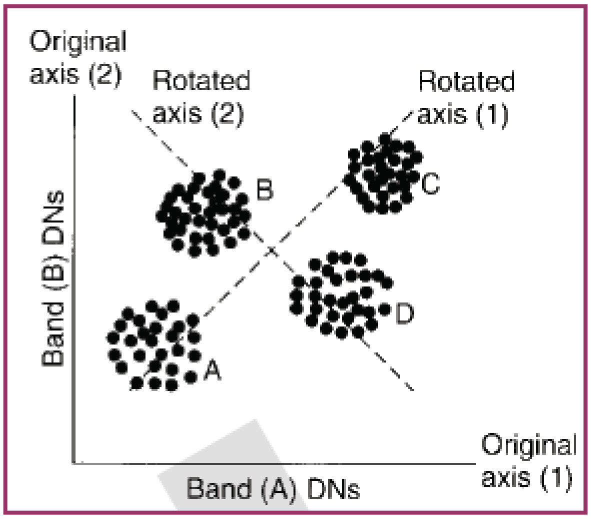


Figure (33): conical analysis transformation

- Intensity – Hue – Saturation (IHS)

A system of producing color imagery that is adapted to human vision. Intensity is the color brightness, hue is the actual color and saturation defines the purity or "grayness" of the color .The IHS color space can be represented by a cone.

  - The intensity is a measure of the brightness of the colour. It is measured along the vertical or height axis where 0% is black, the apex of the cone, and 100% is white, the center of the base of the cone.
  - Hue is the subjective name of the colour e.g. red, yellow, green, and blue. It measured along the circumference of the base of the color cone by degree. For example, red is 0°, yellow is 60°, green is 120°, cyan is 180°, and blue is 240°.
  - Saturation is a measure of how much white is mixed with the colour. A highly saturated colour has little white whereas an unsaturated colour has a lot of white mixed in. It measured along the horizontal axis, the radius of the cone. No color, 0%, is a point at the center of the cone and full color, 100%, is a point on the circumference of the base of the cone.

- Arithmetic Operations

Basic image transformations apply simple arithmetic operations to the image data. Operations between multi-spectral images or multi-temporal images are very useful for image enhancement and feature extraction. One of the multi-image processing is arithmetic operation. Arithmetic operation consists of addition, subtraction, multiplication, division and their combinations. As the results of the operation can be floating value, not integer values. This type of image transform can be useful for mapping changes in urban development around cities and for identifying areas where deforestation is occurring, as in this example.

- Spectral ratioing

Spectral ratioing is method of enhancement and one of the most common transforms applied to image data. Image ratioing serves to highlight subtle variations in the spectral responses of various surface covers. By ratioing the data from two different spectral bands, the resultant image enhances variations in the slopes of the spectral reflectance curves between the two different spectral ranges that may otherwise be masked by the pixel brightness variations in each of the bands.

The following example illustrates the concept of spectral ratioing. Healthy vegetation reflects strongly in the near-infrared portion of the spectrum while absorbing strongly in the visible red. Other surface types, such as soil and water, show near equal reflectance in both the near-infrared and red portions. Thus, a ratio image of Landsat MSS Band 7 (Near-Infrared - 0.8 to 1.1 mm) divided by Band 5 (Red - 0.6 to 0.7 mm) would result in ratios much greater than 1.0 for vegetation, and ratios around 1.0 for soil and water. Thus the discrimination of vegetation from other surface cover types is significantly enhanced.

Ratio operation is defined as the division of DN values in one spectral band by the corresponding values in another band, so the formula is $\textit{Ratio} = \text{Band}_j \,/\, \textit{Band}_i$

- Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is method of enhancement, which has been used to monitor vegetation conditions on continental and global scales using the Advanced Very High Resolution Radiometer (AVHRR) sensor onboard the NOAA series of satellites

An index calculated from reflectance measured in the visible and near infrared channels. It is related to the fraction of photo synthetically active radiation. To do this type of enhancement we follow a specific equation which is

"NDVI= (NIR-R) / (NIR+R)"

Equation shows the calculation for **NDVI**, where **NIR** is the reflectance in the near-infrared band, and **R** is the reflectance in the red visible band. The chlorophyll (green pigment) absorbs incoming radiation in the visible band, while the leaf structure and water content is responsible for a very high reflectance in the near-infrared region of the spectrum. NDVI has been correlated to a variety of vegetation parameters, including quantity, productivity, biomass, etc.

Digital Image Classification

The intent of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or "themes". This categorized data may then be used to produce thematic maps of the land cover present in an image. The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground. Image classification is perhaps the most important part of digital image analysis. Two main classification methods are Supervised Classification and Unsupervised Classification as it shows below.

- **Supervised Classification**

Supervised classification relies on the a priori knowledge of the location and identity of land cover types that are in the image. This can be achieved through field work, study of aerial photographs or other independent sources of information.

Training areas, usually small and discrete compared to the full image, are used to "train" the classification algorithm to recognize land cover classes based on their spectral signatures, as found in the image. The training areas for any one land cover class need to fully represent the variability of that class within the image. There are numerous factors that can affect the training signatures of the land cover classes. Environmental factors such as differences in soil type, varying soil moisture, and health of vegetation, can affect the signature and affect the accuracy of the final thematic map.

> A **training area** is a small sample of homogeneous areas selected by the image analyst prior to classification. Each area is determined from maps, ground data, or other information (e.g. land use database). Training sites should be free of anomalies and be large enough to provide good statistical representation. Also, there should be a sufficient number of sites selected for each class to account for small local variations within the class (e.g. age, health, cultivation, moisture content, etc.). Training areas should avoid edge pixels containing the combined backscatter of multiple targets (mixed pixels), and inconsistencies within the area such as roadways, power lines, intermittent cover, etc. Once defined, training areas are used to generate signature statistics for each defined class.

There are numerous aspects that must be considered when conducting a supervised classification. The first is developing an appropriate classification scheme. Training areas must be selected for each of the classes and statistics calculated for them. The appropriate classification algorithm has to be selected, and once each pixel in the image (including the ones used as training areas) are evaluated and assigned to a land cover class, the accuracy of the classification has to be assessed.

Various classification schemes have been developed that can be used for remotely sensed data. The major difference between classification schemes is their emphasis and their ability to incorporate remotely sensed information. One of the more common ones was developed by the United States Geological Survey. Their Land Use/Land Cover Classification System contains four classification levels and places an emphasis on resources, as opposed to other classification schemes that may be "people or activity" oriented. Each level of classification is equated with certain data characteristics, such as image resolution.

Example of digital image classification by use training area:

Figure (34): image classification by use training area

Some common classification algorithms include: Minimum-Distance to the Mean Classifier; Parallelepiped Classifier; and Maximum Likelihood Classifier, as it discussed below.

- **Minimum distance Classification "nearest"**

The simplest classification algorithm, it determines each pixel's 'distance' from the class means, and assigns them to the closest class , if the pixel is further from analyst-defined distance from any category, it remains unclassified or 'unknown'. It does not evaluate differing degrees of variance within the class; therefore it has a lower overall accuracy than the Maximum Likelihood classifier. This classifier is the fastest of the commonly used algorithms because it is mathematically simple.

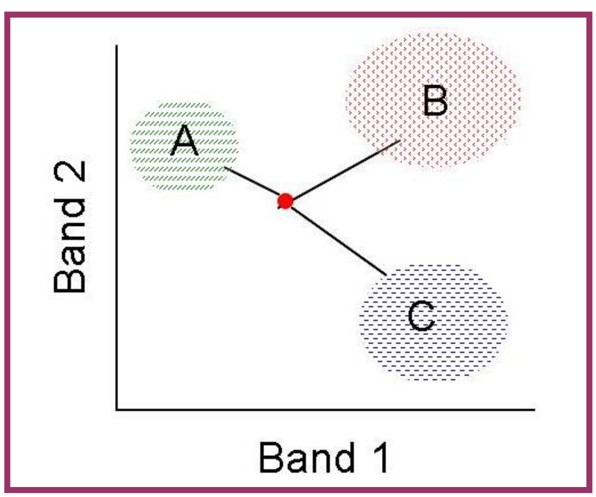


Figure (35): minimum distance classification

- **Parallelepiped Classification**

The parallelepiped classifier uses the class limits and stored in each class signature to determine if a given pixel falls within the class or not. The class limits specify the dimensions (in standard deviation units) of each side of a parallelepiped surrounding the mean of the class in feature space .If the pixel falls inside the parallelepiped, it is assigned to the class. However, if the pixel falls within more than one class, it is put in the overlap class (code 255). If the pixel does not fall inside any class, it is assigned to the null class (code 0). The parallelepiped classifier is typically used when speed is required. The draw back is (in many cases) poor accuracy and a large number of pixels classified as ties (or overlap, class 255). Also Classification rule used for multi-band imagery that considers a range of values within each category of the training set denoted as minimum and maximum values for each image band. It is more sensitive to within class variance than the Minimum Distance classifier. This is because the range limits define a small decision region with clear class segmentation. However, outliers can increase the decision region inappropriately causing errors of commission. Overall, it has a low computational requirement and provides adequate classification accuracies.

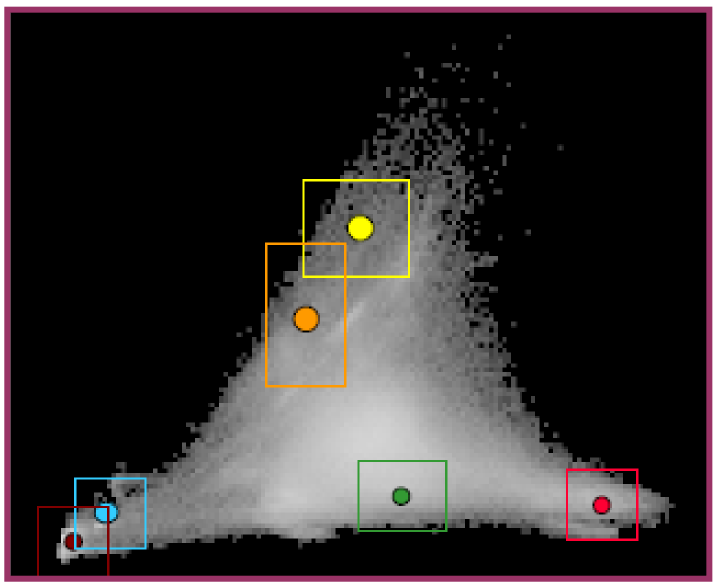


Figure (36): parallel classification method

- **Maximum likelihood Classification**

A statistical decision rule that examines the probability function of a pixel for each of the classes, and assigns the pixel to the class with the highest probability, and also the statistical decision criterion to assist in the classification of overlapping signatures; pixels are assigned to the class of highest probability. The maximum likelihood classifier is considered to give more accurate results than parallelepiped classification however it is much slower due to extra computations. We put the word *`accurate'* in quotes because this assumes that classes in the input data have a Gaussian distribution and that signatures were well selected; this is not always a safe assumption.

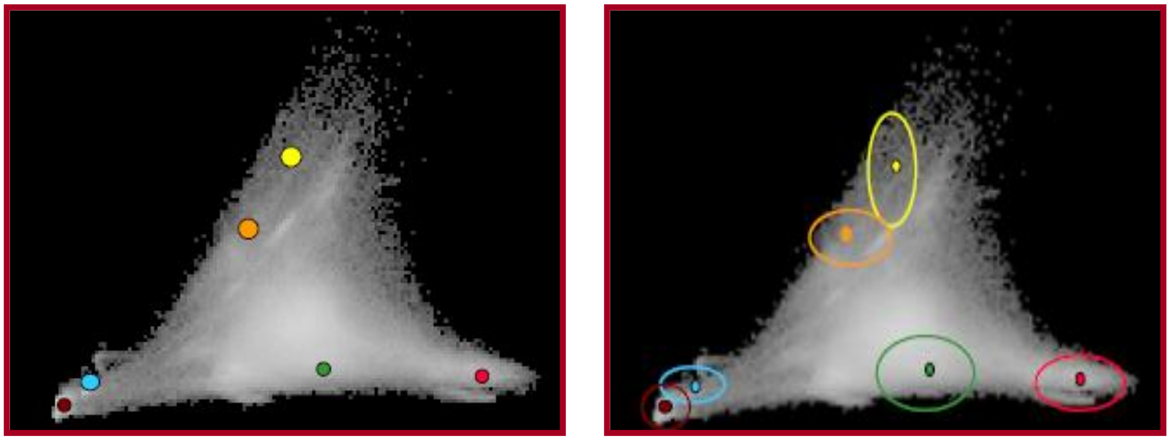


Figure (37): maximum likelihood classification method

- **Unsupervised Classification**

Unsupervised classification is a method which examines a large number of unknown pixels and divides into a number of classed based on natural groupings present in the image values. unlike supervised classification, unsupervised classification does not require analyst-specified training data. The basic premise is that values within a given cover type should be close together in the measurement space (i.e. have similar gray levels), whereas data in different classes should be comparatively well separated (i.e. have very different gray levels) (PCI, 1997; Lillesand and Kiefer, 1994; Eastman, 1995)

The classes that result from unsupervised classification are spectral classed which based on natural groupings of the image values, the identity of the spectral class will not be initially known, must compare classified data to some from of reference data (such as larger scale imagery, maps, or site visits) to determine the identity and informational values of the spectral classes. Thus, in the supervised approach, to define useful information categories and then examine their spectral separability; in the unsupervised approach the computer determines spectrally separable class, and then define their information value. (PCI, 1997; Lillesand and Kiefer, 1994)

Unsupervised classification is becoming increasingly popular in agencies involved in long term GIS database maintenance. The reason is that there are now systems that use clustering procedures that are extremely fast and require little in the nature of operational parameters. Thus it is becoming possible to train GIS analysis with only a general familiarity with remote sensing to undertake classifications that meet typical map accuracy standards. With suitable ground truth accuracy assessment procedures, this tool can provide a remarkably rapid means of producing quality land cover data on a continuing basis.On the next page, example of unsupervised image classification.

First, we must find the class interval,
Class interval= Max-Min/number of class

CI= 255-10/4= 71

Class #	Rang	Land use	Colour
1	10 – 71	Water	Blue
2	72 – 133	Agriculture	Green
3	134 – 195	Land	Orange
4	196 – 257	Urban	Yellow

80	70	60	50	30	25	10
90	95	75	50	45	35	30
100	90	80	70	55	50	40
225	110	120	140	120	60	55
230	220	145	135	140	130	60
240	220	200	190	180	170	160
255	240	230	210	170	180	190

Original image with the digital number

80	70	60	50	30	25	10
90	95	75	50	45	35	30
100	90	80	70	55	50	40
225	110	120	140	150	60	55
230	220	145	135	140	150	60
240	220	200	190	180	170	160
255	240	230	210	170	180	190

Final image

Figure (38) unsupervised classification

Land-use Classification Map Accuracy Assessment

There must be method for quantitatively assessing classification accuracy if remote-sensing-derived; and use or land cover maps and associated statistics are to be useful. Classification accuracy assessment was an after thought rather than an integral part of many remote sensing studies in 1970s and 1980s. Unfortunately, many studies still simply report a single number (e.g., 85%) to express classification accuracy. Such non site-specific accuracy assessments completely ignore location accuracy. In other words, only the total amount of a category is considered without regard for its location. A non site-specific accuracy assessment yields very high accuracy but misleading results when all the errors balance out in a region.

To correctly perform classification accuracy assessment, it is necessary to compare two sources of information: (1) the remote-sensing-derived classification map and (2) what we will call reference test information (which may in fact contain error). The relationship between these two sets of information is commonly summarized in an error matrix. An error matrix is square array of numbers laid out in rows and columns that express the number of sample units assigned to a particular category relative to the actual category as verified in the field. The columns normally represent the reference data while the rows indicate the classification generated from the remotely sensed data. An error matrix is a very effective way to represent accuracy because the accuracy of each category is clearly described, along with both the errors of inclusion commission errors (map producer's accuracy) = incorrect in column / total in column. Measures how well the map maker was able to represent the ground features. And errors exclusion omission errors (map user's accuracy) = incorrect in row / total in row. Measures how likely the map user is to encounter correct information while using the map.

Training versus test reference information

Some analysts continue to perform error evaluation based only on the training pixels used to train or seed the classification algorithm. Unfortunately, the locations of these training sites are usually not random. They are biased by the analyst's a priori knowledge of where certain land cover types existed in the scene. Because of this bias, the classification accuracies for pixels found within the training sites are generally higher than for the remainder of the map. Therefore, this biased procedure is born of expediency and can have little use in any serious attempt at accuracy assessment.

Classification	Residential	Commercial	Wetland	Forest	Water	Total
Residential	70	5	0	13	0	88
Commercial	3	55	0	0	0	58
Wetland	0	0	99	0	0	99
forest	0	0	4	37	0	41
Water	0	0	0	0	121	121
total	73	60	103	50	121	407

Measure of omission error

Residential= 70/73*100= 96 % → 4% omission error
Commercial= 55/60*100= 92% →8% omission error
Wetland= 99/103*100= 96% → 4% omission error
Forest= 37/50*100=74% → 26% omission error
Water= 121/121*100= 100% → 0% omission error

Measure of commission error

Residential= 70/88*100= 80 % → 20% commission error

Commercial= 55/58*100= 95% →5% commission error

Wetland= 99/99*100= 100% → 0% commission error

Forest= 37/41*100=90% → 10% commission error

Water= 121/121*100= 100% → 0% commission error

Overall map accuracy = total on diagonal / grand total

= 70+55+99+37+121/407

= 382/407

=94%

Digital Change Detection

On application of use the digital image is digital change detection, it is use to study the change in land use using remote sensing image, to know if the change positive, or negative (dynamic), or stable (static).So in this section I will focus on factors to consider when study change, then the change detection algorithms, as it is on the following.

Considerations of significance when performing change detection (how to select the satellite)

Remote sensing consideration

a) Spatial resolution

Accurate spatial registration of at least two images is essential for digital change detection. Ideally, the remotely sensed data are acquired by a sensor system that collects data with the same instantaneous field of view on each data. For example, Landsat Thematic Mapper data collected at 30*30 spatial resolutions on two dates are relatively easy to register to one another. Also MMS satellite collected at 80*80 , and IKONOS satellite collected at 4*4 “high resolution”.

b) Temporal resolution

Two important temporal resolutions should be held constant when performing change detection using multiple dates of remotely sensed data. First, the data should be obtained from a sensor system that acquires data at approximately the same time of day. For example, Landsat Thematic Mapper every 16 days, SPOT every 26 days, Metosat every one hour “flood”.

c) Spectral resolution “Band Width”

A fundamental assumption of digital change detection is that a difference exists in the spectral response of a pixel on two dates if the biophysical materials within the IFOV have changed between dates. Ideally, the spectral resolution of the remote sensor system is sufficient to record reflected radiant flux in spectral regions that best capture the most descriptive spectral attributes of the object. For example SPOT satellite band1 (0.4-0.5mm), band2 (0.5-0.6mm), band3 (0.6-0.7mm).

d) Radiometric resolution

An analog-to-digital conversion of the satellite remote sensor data usually results in 8-bit brightness values ranging from 0 to 225. Ideally, the sensor systems collect the data at the same radiometric precision on both dates. When the radiometric resolution of data acquired by one system (e.g., Landsat MSS 1 with 60bit data) is compared with data acquired by a higher radiometric resolution instrument (e.g. Landsat TM with 8-bit data), the lower resolution data (e.g. 6 bits) should be decompress to 8 bits for change detection purposes. However, the precision of decompressed brightness values can never be better than the original, uncompressed data.

2. Environmental characteristic

a) Atmospheric conditions

There should be no clouds, stratus, or extreme humidity on the days remote sensing data are collected. Even a thin layer of haze can alter spectral signatures in satellite images enough to create the false impression of spectral change between two dates. Obviously, 0% cloud cover is preferred for satellite imagery and aerial photography. At the upper limit, cloud cover >20% is usually unacceptable. It should also be remembered that clouds not only obscure terrain, but that cloud shadow also causes major image classification problems.

b) Soil moisture conditions

The soil moisture conditions should be identical for the n dates of imagery used in a change detection project. Extremely wet or dry conditions on one of the dates can cause serious change detection problems. Therefore, when selecting the remotely sensed data to be used for change detection, it is very important not only to look for anniversary dates, but also to review precipitation records to determine how mush rain or snow fell in the days and weeks prior to remote sensing data collection. When soil moisture differences between dates are significant for only certain parts of the study area, it may be necessary to stratify those affected areas and perform a separate analysis, which can be assed back in the final stages of the project.

c) Phonological cycle characteristic

Vegetation grows according to diurnal, seasonal, and annual phonological cycles. Obtaining near-anniversary images greatly minimizes the effects of seasonal phonological differences that may cause serious change to be detected in the imagery. When attempting to identify change in agricultural crops, the analyst must be aware of when the crops were planted. Different species of the same crop can cause the crop to reflect energy differently on the multiple dates of anniversary imagery.

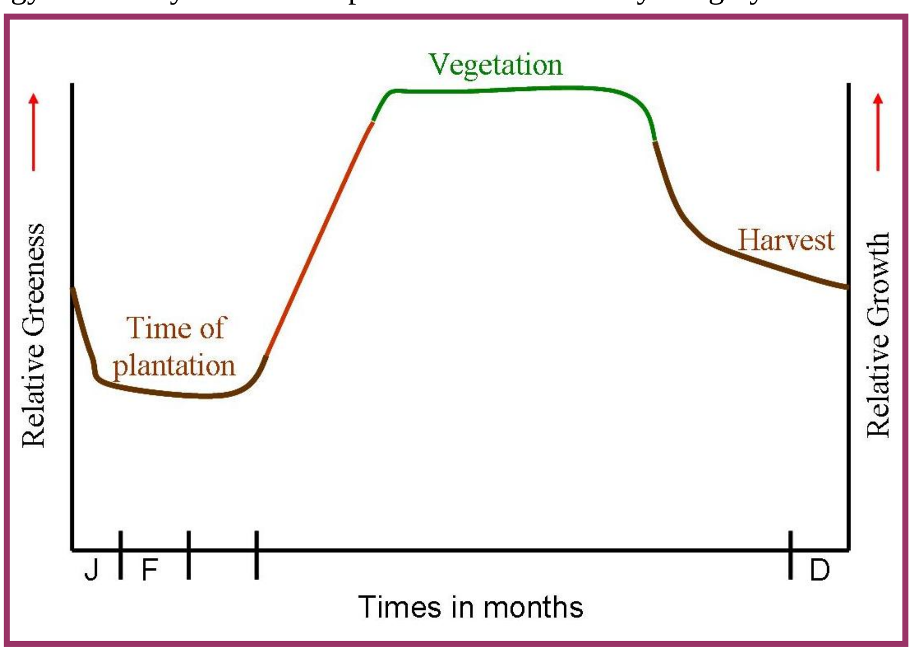


Figure (39) phonological cycle

Change Detection Algorithms

In this section we will discuss nine basic algorithms as classified by Jensen (1996). Certainly, there are other ways in which to classify change detection algorithms. For example, see Coppin and Bauer (1996) for a very thorough review of satellite-based change detection in forest ecosystems. However, Jensen's system is consistent with the C-CAP protocol and our study fits well into Jensen's system. Each method is followed by a brief description and some discussion of studies relevant to that method. The objective of this section is to present change detection procedures so that, in the following section, we can discuss which of these methods can utilize GLMs.

Write function memory insertion

This involves a false color display where blue, green, and/or reds represent various bands from different times. For example, band 1 from a 1988 TM image could be displayed as green and band 1 from a 1994 image could be displayed as red and the blue display could be left blank. The different color then represent differences in band one between the two time periods. (Perhaps a more intuitive name for this type of change detection might be something like "false-color time image". Martin and Howarth (1989) refer to it simply as "multi-date imagery".) Jensen *et al.* (1993b) found this method useful for the detection of Cattail and Waterlily changes using SPOT data. Crapper and Hynson (1983) describe a similar method using Landsat photographic imagery as an economic and efficient method for change analysis.

Multi-date composite image Change detection

This involves combining the images, from two different times, to be used in the change detection as one multi-layer image. This multi-layer image is then subjected to analysis involving the multiple layers. That is, similar to classifying land cover types in a single time with seven band of TM data, the composite image contains 14 bands. There are different ways in which change information can then be extracted from the composite image. change areas become "a class" to be extracted from the multi-layer image using (more-or-less) standard classification techniques. An example would be to use unsupervised classification to create "change" and "no- change" clusters. This approach only works to the extent that change classes are spectrally significantly different (Lillesand and Kiefer, 1994, p. 621). Studies utilizing the composite image approach have used principal component analysis (PCA). PCA applied to composite imagery is described by Richards (1993, section 11.7.5). Working with a composite image, Muchoney and Haack (1994) found principal component analysis superior to an unsupervised classification of the composite. Chavez and MacKinnon (1994) found the first two bands of a composite image PCA to be more effective at detecting change than differences in Normalized Difference Vegetation Index (NDVI). Fung and LeDrew (1987) compare different PCA methods: standardized (correlation-based) versus non-standardized (covariance-based) and total versus specific land cover analysis. They do not attempt to establish which is "better" but show the different methods will produce significantly different results.

Image algebra change detection

This method involves various algebraic manipulations of the reflectance values. A particular example is image subtraction -- the difference between reflectance values for a given band for two images. Image algebra can also involve the subtraction of indices, which, themselves are some function of the reflectance value calculated separately for the two dates. Another image algebra method is to compute the ratio of reflectance values. An area is considered to have changed if the difference or ratio of reflectance values for the pixel representing that area is beyond a set threshold. Image “differencing” and image “ratioing” are discussed in Lillesand and Kiefer’s text (1994, p. 621-2) although they do not give an example using the method. Price *et al*. (1992) use image differencing to detect shrub dieback and found rather poor agreement with field verification (48.4% agreement).

In contrast, Bauer *et al*. (1994) found an overall accuracy near 90% for standardized differencing. Muchoney and Haack (1994) found that image differencing and PCA both offer the potential for monitoring forest defoliation. Townshend *et al.* (1992) considered the impact of mis-registration by looking at differences in Normalized Difference Vegetation Index (NDVI) values for two dates. Similarly, Choung (1992) compares differences in NDVI as well as differences in Tassel-cap transformations. Green *et al.* (1994) found image differencing of a single band to work better than differences in a vegetation index. Another approach to image subtraction is based on image regression where pixel values for date two are estimated using the information from date one. Then, the residual differences between predicted and actual values are used to assess change (Singh, 1989). This approach offers an alternative to direct subtraction which, in the context of longitudinal data, can have correlation effects which often confuse the meaning of the change value (Burr and Nesselroade, 1990).

Post classification comparison change detection

This is the most straightforward method of change detection. It involves the overlay (or “stacking”) of two or more classified images. change areas are simply those areas which are not classified the same at different times. In a review paper, Singh (1989) found this technique had the lowest accuracy when compared to various image algebra techniques and PCA classification of a multi-date composite. Muchoney and Haack (1994) found post-classification inferior to both PCA and image differencing for monitoring defoliation; pointing out that the method does not allow for normalizing differences between multi- temporal data. However, Jensen *et al.* (1995) did post-classification change detection using classified images that were normalized previous to classification. They found the resulting change product satisfactory and useful as a display tool to exhibit an association between Cattail/Sawgrass mixture and high concentrations of porewater phosphorus.

Ferguson *et al.* (1993) used post-classification to produce effective maps of changes in Seagrass habitat and Jensen *et al.* (1987) did a post-classification change detection to monitor wetland change in the Savannah River swamp forest. Augenstein *et al.* (1991) found post-classification acceptable for Kelp monitoring. Jensen *et al.* (1993c) found the method suitable for the C-CAP program as long as the individual data are classified as accurately as possible. Hall *et al.* (1991b) found post classification change detection to provide appropriate input into their land transformation model.

Multi date change detection using a binary mask applied to date 2

This method is a hybrid combination of image algebra and post classification. It involves using image algebra to determine areas likely to have changed. Those pixels determined to have changed are labeled as 1 and those determined to have not changed are labeled as 0. This results in a binary image of 0s and 1s. The areas labeled as zero are "masked out" and the areas labeled as 1 are then investigated with traditional classification methods to determine "from-to" information. By using a binary mask, analysts can focus particular attention on change areas. This may help to reduce errors that might occur in the post-classification alone. Jensen *et al.* (1993) use a binary mask on TM data in the context of a C-CAP study. They found the method to be useful but contingent on selection of the appropriate threshold for the mask.

Multi-date change detection using ancillary data source as date 1

This method is essentially a post classification change detection with the initial classification derived from some source other than remotely sensed data (at least not directly). change areas are determined in a fashion similar to the post-classification method. Westmoreland and Stow (1992) describe a similar, more general, approach of integrating image data and GIS layers for identification of land-use and land-use updates. Maclean *et al.* (1992) describe a general approach of integrating GIS and image data for forest resource monitoring.

Manual, on-screen digitization of change

This approach is analogous to photo interpretation and involves similar considerations.The method visually determines change areas by simultaneously viewing two images. This method is not appropriate for large area, recurrent change detection due to its labor intensive, non-automated nature. However, when the interest is in a very particular change phenomena, the method is appropriate and, perhaps, the only method capable of such refined change determination. Jensen (1996, p. 272 and figure 9-19) review this method as a way to assess housing and geomorphological change caused by Hurricane
Hugo. Martin and Howarth (1989) compare four methods for change - detection at the urban-rural fringe: visual side-by-side inspection, visual write function memory insertion, post-classification, and composite image supervised classification. They found side-by-side visual interpretation and supervised classification of the composite image provided the most detail and had the highest overall accuracy.

Spectral change vector analysis

This method looks at changes in pixel values by considering the pixel locations for the two dates in the multi-dimensional spectral space. For example, the band one and band two values for a particular pixel from one time will be located at a certain place in the band- one/band-two two dimensional space. That same pixel at the later date will also have a location in the two dimensional space. These two points comprise the head and tail of a vector. Change is determined by assessing the magnitude of the change vector. The direction of the vector can help determine "from-to" information (Jensen, 1996, p.275-6; Lillesand and Kiefer, 1994, p. 623; Malila, 1980). Malila (1980) initially proposed the method. (Table 2 in Malila's study provides a more detailed description of this method's advantage.) Michalek *et al.* (1993) investigate the utility of change vector analysis with MSS data for monitoring changes in a Caribbean coastal zone and conclude the method can be a valuable tool for coastal resource surveys, especially for identifying areas suspected to have changed. Attention can then be focused on these areas. Choung (1992) used an Euclidean distance change vector and found this method to provide results similar to image ratioing but superior to other single band algebra methods and composite image PCA. Virag and Colwell (1987) used a combination of vector analysis with write insertion memory function for "an improved method for producing color coded (change) images" p. 1101). Colwell and Weber (1981) apply a change vector analysis to data transformed with the tassel-cap transformation.

Knowledge-based vision system for detecting change.

This method, which attempts to conduct change detection with little human intervention, is in its infancy (Jensen, 1996, p. 276-7). Wang (1993) describes a knowledge-based vision system used for detecting land changes at the urban fringe. He describes the key aspects of preprocessing, spatial representation and manipulation, and incorporation of ancillary data. As knowledge-based systems are developed, they will employ various combinations of the different methods described above (Jensen, 1996). As change detection methods become more automated, a knowledge-based approach will provide a format to integrate these methods into a system that will help to automate the entire process. This concludes the description of the nine basic change detection methods as classified by Jensen (1996). Now we consider these methods with respect to if and how they can be enhanced with GLMs.

Conclusion

At the end of this report I think it is very important to study digital image analysis for the GIS student, because it helps them to do their project when the use remote sensing image. In addition my report is a summary of digital image, for that I recommend who will use or read my report to go through the internet and book to learn more about it because there is new techniques and new software for do the analysis not just what we learn in the university, for that who want to know every thing about the digital image and it function, continue reading about it and learn the new techniques. Finally, I hope to be an integrated and received up to easily.

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