TRAINING COURSE
ON

APPLICATIONS OF REMOTE SENSING AND GIS IN WATER RESOURCES MANAGEMENT

<u>ORGANISED UNDER</u>

HYDROLOGY PROJECT PHASE II

AT

NATIONAL INSTITUTE OF HYDROLOGY, ROORKEE

<u>OCTOBER 20-24, 2008</u>

LECTURE NOTE

ON

INTERPRETATION OF REMOTE SENSING DATA

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INTERPRETATION OF REMOTE SENSING DATA

The main objective of image interpretation is to extract information about features displayed in an image. It is defined as the act of examining images for the purpose of identifying objects and finding their significance. The extraction of information depends on image analyst's experience, power of observation, imagination and patience. It also depends on his understanding of the basic principles of an image. The synoptic view provided by satellite images is of great importance in water resources in detecting large features and understanding their inter-relationships.

Digital Data

In a most generalized way, a digital image is an array of numbers depicting spatial distribution of a certain field parameters (such as reflectivity of EM radiation, emissivity, temperature or some geophysical or topographical elevation. Digital image consists of discrete picture elements called pixels. Associated with each pixel is a number represented as DN (Digital Number) that depicts the average radiance of relatively small area within a scene. The range of DN values being normally 0 to 255. The size of this area effects the reproduction of details within the scene. As the pixel size is reduced more scene detail is preserved in digital representation.

Remote sensing images are recorded in digital forms and then processed by the computers to produce images for interpretation purposes. Images are available in two forms - photographic film form and digital form. Variations in the scene characteristics are represented as variations in brightness on photographic films. A particular part of scene reflecting more energy will appear bright while a different part of the same scene that reflecting less energy will appear black. Digital image consists of discrete picture elements called pixels. Associated with each pixel is a number represented as DN (Digital Number), that depicts the average radiance of relatively small area within a scene. The size of this area effects the reproduction of details within the scene. As the pixel size is reduced more scene detail is preserved in digital representation.

Data Formats For Digital Satellite Imagery

Digital data from the various satellite systems supplied to the user in the form of computer readable tapes or CD-ROM. As no worldwide standard for the storage and transfer of remotely sensed data has been agreed upon, though the CEOS (Committee on Earth Observation Satellites) format is becoming accepted as the standard. Digital remote sensing data are often organised using one of the three common formats used to organise image data . For an instance an image consisting of four spectral channels, which can be visualised as four superimposed images, with corresponding pixels in one band registering exactly to those in the other bands. These common formats are:

- Band Interleaved by Pixel (BIP)
- Band Interleaved by Line (BIL)
- Band Sequential (BQ)

Digital image analysis is usually conducted using Raster data structures - each image is treated as an array of values. It offers advantages for manipulation of pixel values by image processing system, as it is easy to find and locate pixels and their values. Disadvantages becomes apparent when one needs to represent the array of pixels as discrete patches or regions, where as Vector data structures uses polygonal patches and their boundaries as fundamental units for analysis and manipulation. Though vector format is not appropriate to for digital analysis of remotely sensed data.

IMAGE INTERPRETATION

Analysis of remotely sensed data is done using various image processing techniques and methods that includes:

- Analog image processing
- Digital image processing.

Visual or Analog processing techniques is applied to hard copy data such as photographs or printouts. Image analysis in visual techniques adopts certain elements of interpretation, which are as follow:

The use of these fundamental elements of depends not only on the area being studied, but the knowledge of the analyst has of the study area. For example the texture of an object is also very useful in distinguishing objects that may appear the same if the judging solely on tone i.e., water and tree canopy, may have the same mean brightness values, but their texture is much different. Association is a very powerful image analysis tool when coupled with the general knowledge of the site. Thus we are adept at applying collateral data and personal knowledge to the task of image processing. With the combination of multi-concept of examining remotely sensed data in multi spectral, multi temporal, multi scales and in conjunction with multidisciplinary, allows us to make a verdict not only as to what an object is but also its importance. Apart from this analog image processing techniques also includes optical photogrammetric techniques allowing for precise measurement of the height, width, location, etc. of an object.

Elements of Image Interpretation

Primary Elements Black and White Tone

	Color
	Stereoscopic Parallax
	Size
Spatial Arrangement of Tone & Color	Shape
	Texture
	Pattern
Based on Analysis of Primary Elements	Height
	Shadow
Contextual Elements	Site

DIGITAL IMAGE PROCESSING

Image processing in the context of remote sensing refers to the management of digital images, usually satellite or digital aerial photographs. Image processing includes the display, analysis, and manipulation of digital image computer files. The derived product is typically an enhanced image or a map with accompanying statistics and metadata. Digital Image Processing is a collection of techniques for the manipulation of digital images by computers. The raw data received from the imaging sensors on the satellite platforms contains flaws and deficiencies. To overcome these flaws and deficiencies inorder to get the originality of the data, it needs to undergo several steps of processing. This will vary from image to image depending on the type of image format, initial condition of the image and the information of interest and the composition of the image scene. Digital Image Processing undergoes three general steps:

- Pre-processing
- Display and enhancement
- Information extraction

The important digital image processing functions required to analyse remotely sensed data for hydrology and water resources management applications are summarized in Table 1.

(A) Pre-processing of the Remotely Sensed Images

When remotely sensed data is received from the imaging sensors on the satellite platforms it contains flaws and deficiencies. Pre-processing refers to those operations that are preliminary to the main analysis. Preprocessing includes a wide range of operations from the very simple to extremes of abstractness and complexity. These categorized as follow:

1. Feature Extraction
2. Radiometric Corrections

3. Geometric Corrections
4. Atmospheric Correction

The techniques involved in removal of unwanted and distracting elements such as image/system noise, atmospheric interference and sensor motion from an image data occurred due to limitations in the sensing of signal digitization, or data recording or transmission process. Removal of these effects from the digital data are said to be "restored" to their correct or original condition, although we can, of course never know what are the correct values might be and must always remember that attempts to correct data what may themselves introduce errors. Thus image restoration includes the efforts to correct for both radiometric and geometric errors.

Geometric Corrections

Rectification is the process of projecting image data onto a plane and making it conform to a map projection system. Registration is the process of making image data conforms to another image. A map coordinate system is not necessarily involved. However rectification involves rearrangement of the input pixels onto a new grid which conforms to the desired map projection and coordinate system. Rectification and Registration therefore involve similar sets of procedures for both the distortions.

1. **Locating Ground Control Points** This process employs identification of geographic features on the image called ground control points (GCPs), whose position are known such as intersection of streams, highways, airport, runways etc. Longitude and latitude of GCPs can be determined by accurate base maps, where maps are lacking GPS is used to determine the Latitude and Longitude from navigation satellites. Thus a GCP is located in the field and determining its position using GPS. Accurate GCPs are essential to accurate rectification. GCPs should be Reliably matched between source and reference (e.g., coastline features, road intersection, etc.) Widely dispersed throughout the source image
2. **Re-sampling Methods** The location of output pixels derived from the ground control points (GCPs) are used to establish the geometry of the output image and its relationship to the input image. Difference between actual GCP location and their position in the image are used to determine the geometric transformation required to restore the image. This transformation can be done by different resampling methods where original pixels are resampled to match the geometric coordinates. Each resampling method employs a different strategy to estimate values at output grid for given known values for the input grid.

Nearest Neighbour The simplest strategy is simply to assign each corrected pixel, the value from the nearest uncorrected pixel. It has the advantages of simplicity and the ability to preserve original values in the altered scene, but it may create noticeable errors, which may be severe in linear features where the realignment of pixels is obvious.

Bilinear Interpolation The strategy for the calculation of each output pixel value is based on a weighted average of the four nearest input pixels. The output image gives a natural look because each output value is based on several input values. There are some changes occurred when bilinear interpolation creates new pixel value.

(B) Image Enhancement. The major advantage of remote sensing data lies in the ability to visually evaluate the data for overall interpretation. An accurate visual interpretation may require modification of the output brightness of a pixel in an effort to improve image quality. Here are a number of methods used in image enhancement. This paragraph examines the operations of 1) contrast enhancement, 2) band ratio, 3) spatial filtering, and 4) principle components. The type of enhancement performed will depend on the appearance of the original scene and the goal of the interpretation.

Image Enhancement

Raw satellite data are stored as multiple levels of brightness known as the digital number (DN). Data stored in an 8-bit data format maintain 256 levels of brightness. This means that the range in brightness will be 0 to 255; zero is assigned the lowest brightness level (black in gray- and color scale images), while 255 is assigned the highest brightness value (white in gray scale or 00% of the pigment in a color scale).

When a satellite image is projected, the direct one-to-one assignment of gray scale brightness to digital number values in the data set may not provide the best visual display. This will happen when a number of pixel values are clustered together. For instance, if 80% of the pixels displayed DNs ranging from 50– 95, the image would appear dark with little contrast.

Enhancing Pixel Digital Number Values: Images can enhance or stretch the visual display of an image by setting up a different relationship between the DN and the brightness level. The enhancement relationship created will depend on the distribution of pixel DN values and which features need enhancement. The enhancement can be applied to both gray- and color-scale images.

Contrast Enhancement Techniques. The histogram chart and lookup table are useful tools in image enhancement. Enhancement stretching involves a variety of techniques, including contrast stretching, histogram equalization, logarithmic enhancement, and manual enhancement. These methods assume the image has a full range of intensity (from 0–255 in 8-bit data) to display the maximum contrast.

Linear Contrast Stretching. Contrast stretching takes an image with clustered intensity values and stretches its values linearly over the 0–255 range. Pixels in a very bright scene will have a histogram with high intensity values, while a dark scene will have low intensity values. The low contrast that results from this type of DN distribution can be adjusted with contrast stretching, a linear enhancement function performed by image processing software. The method can be monitored with the use of a histogram display generated by the program. It is therefore possible to perform a temporal analysis on data collected at different times of the day or even at different seasons.

Histogram Equalization. Low contrast can also occur when values are spread across the entire range. The low contrast is a result of tight clustering of pixels in one area. Because some pixel values span the intensity range it is not possible to apply the contrast linear stretch. Histogram equalization evenly distributes the pixel values over the entire intensity range.

Logarithmic Enhancement. Another type of enhancement stretch uses a logarithmic algorithm. This type of enhancement distinguishes lower DN values. The high intensity values are grouped together, which sacrifices the distinction of pixels with higher DN.

Manual Enhancement. Some software packages will allow users to define an arbitrary enhancement. This can be done graphically or numerically. Manually adjusting the enhancement allows the user to reduce the signal noise in addition to reducing the contrast in unimportant pixels.

Image Arithmetic Operations

The operations of addition, subtraction, multiplication and division are performed on two or more co-registered images of the same geographical area. These techniques are applied to images from separate spectral bands from single multispectral data set or they may be individual bands from image data sets that have been collected at different dates. More complicated algebra is sometimes encountered in derivation of sea-surface temperature from multispectral thermal infrared data (so called split-window and multichannel techniques).

Addition of images is generally carried out to give dynamic range of image that equals the input images.

Band Subtraction Operation on images is sometimes carried out to co-register scenes of the same area acquired at different times for change detection.

Multiplication of images normally involves the use of a single'real' image and binary image made up of ones and zeros.

Band Ratioing or Division of images is probably the most common arithmetic operation that is most widely applied to images in geological, ecological and agricultural applications of remote sensing. Ratio Images are enhancements resulting from the division of DN values of one spectral band by corresponding DN of another band. One instigation for this is to iron out differences in scene illumination due to cloud or topographic shadow. Ratio images also bring out spectral variation in different target materials. Multiple ratio image can be used to drive red, green and blue monitor guns for color images. Interpretation of ratio images must consider that they are "intensity blind", i.e, dissimilar materials with different absolute reflectances but similar relative reflectances in the two or more utilised bands will look the same in the output image.

Other Types of Ratios and Band Arithmetic. There are a handful of ratios that highlight vegetation in a scene. The NDVI (Normalized Difference Vegetation Index) is known as the "vegetation index"; its values range from –1 to 1.

NDVI = NIR-red/NIR + red

where NDVI is the normalized difference vegetation index, NIR is the near infrared, and red is the band of wavelengths coinciding with the red region of the visible portion of the spectrum. For IRS data this equation is equivalent to:

NDVI = Band 4- Band 3/ Band 4+ Band 3

In addition to the NDVI, there is also IPVI (Infrared Percentage Vegetation Index), DVI (Difference Vegetation Index), and PVI (Perpendicular Vegetation Index) just to name a few. Variation in vegetation indices stem from the need for faster computations and the isolation of particular features.

Principal Component Analysis

Spectrally adjacent bands in a multispectral remotely sensed image are often highly correlated. Multiband visible/near-infrared images of vegetated areas will show negative correlations between the near-infrared and visible red bands and positive correlations among the visible bands because the spectral characteristics of vegetation are such that as the vigour or greenness of the vegetation increases the red reflectance diminishes and the near-infrared reflectance increases. Thus presence of correlations among the bands of a multispectral image implies that there is redundancy in the data and Principal Component Analysis aims at removing this redundancy.

Principal Components Analysis (PCA) is related to another statistical technique called factor analysis and can be used to transform a set of image bands such that the new bands (called principal components) are uncorrelated with one another and are ordered in terms of the amount of image variation they explain. The components are thus a statistical abstraction of the variability inherent in the original band set.

To transform the original data onto the new principal component axes, transformation coefficients (eigen values and eigen vectors) are obtained that is further applied in a linear fashion to the original pixel values. This linear transformation is derived from the covariance matrix of the original data set. These transformation coefficients describe the lengths and directions of the principal axes. Such transformations are generally applied either as an enhancement operation, or prior to classification of data. In the context of PCA, information means variance or scatter about the mean. Multi spectral data generally have a dimensionality that is less than the number of spectral bands. The purpose of PCA is to define the dimensionality and to fix the coefficients that specify the set of axes, which point in the directions of greatest variability. The bands of PCA are often more interpretable than the source data.

Spatial Filtering

Spatial Filtering can be described as selectively emphasizing or suppressing information at different spatial scales over an image. Filtering techniques can be implemented through the Fourier transform in the frequency domain or in the spatial domain by convolution.

Convolution Filters

Filtering methods exists is based upon the transformation of the image into its scale or spatial frequency components using the Fourier transform. The spatial domain filters or the convolution filters are generally classed as either high-pass (sharpening) or as low-pass (smoothing) filters.

Low-Pass (Smoothing) Filters

Low-pass filters reveal underlying two-dimensional waveform with a long wavelength or low frequency image contrast at the expense of higher spatial frequencies. Low-frequency information allows the identification of the background pattern, and produces an output image in which the detail has been smoothed or removed from the original. A 2-dimensional moving-average filter is defined in terms of its dimensions, which must be odd, positive and integral but not necessarily equal, and its coefficients. The output DN is found by dividing the sum of the products of corresponding convolution kernel and image elements often divided by the number of kernel elements. A similar effect is given from a median filter where the convolution kernel is a description of the PSF weights. Choosing the median value from the moving window does a better job of suppressing noise and preserving edges than the mean filter. Adaptive filters have kernel coefficients calculated for each window position based on the mean and variance of the original DN in the underlying image.

High-Pass (Sharpening) Filters Simply subtracting the low-frequency image resulting from a low pass filter from the original image can enhance high spatial frequencies. High - frequency information allows us either to isolate or to amplify the local detail. If the high-frequency detail is amplified by adding back to the image some multiple of the high frequency component extracted by the filter, then the result is a sharper, de-blurred image. High-pass convolution filters can be designed by representing a PSF with positive centre weightr and negative surrounding weights. A typical 3x3 Laplacian filter has a kernal with a high central value, 0 at each corner, and -1 at the centre of each edge. Such filters can be biased in certain directions for enhancement of edges.

A high-pass filtering can be performed simply based on the mathematical concepts of derivatives, i.e., gradients in DN throughout the image. Since images are not continuous functions, calculus is dispensed with and instead derivatives are estimated from the differences in the DN of adjacent pixels in the x,y or diagonal directions. Directional first differencing aims at emphasizing edges in image.

(C) Image Classification

Raw digital data can be sorted and categorized into thematic maps. Thematic maps allow the analyst to simplify the image view by assigning pixels into classes with similar spectral values. The process of categorizing pixels into broader groups is known as image classification. The advantage of classification is it allows for cost-effective mapping of the spatial distribution of similar objects (i.e., tree types in forest scenes); a subsequent statistical analysis can then follow. Thematic maps are developed by two types of classifications, supervised and unsupervised. Both types of classification rely on two primary methods, training and classifying. Training is the designation of representative pixels that define the spectral signature of the object class. Training site or training class is the term given to a group of training pixels. Classifying procedures use the training class to classify the remaining pixels in the image.

Supervised Classification. Supervised classification requires some knowledge about the scene, such as specific vegetative species. Ground truth (field data), or data from aerial photographs or maps can all be used to identify objects in the scene.

Firstly, acquire satellite data and accompanying metadata. Look for information regarding platform, projection, resolution, coverage, and, importantly, meteorological conditions before and during data acquisition. Secondly, chose the surface types to be mapped. Collect ground truth data with positional accuracy (GPS). These data are used to develop the training classes for the discriminant analysis. Ideally, it is best to time the ground truth data collection to coincide with the satellite passing overhead. Thirdly, begin the classification by performing image post-processing techniques (corrections, image mosaics, and enhancements). Select pixels in the image that are representative (and homogeneous) of the object. If GPS field data were collected, geo-register the GPS field plots onto the imagery and define the image training sites by outlining the GPS polygons. A training class contains the sum of points (pixels) or polygons (clusters of pixels). View the spectral histogram to inspect the homogeneity of the training classes for each spectral band. Assign a color to represent each class and save the training site as a separate file.

Classification Algorithms. Image pixels are extracted into the designated classes by a computed discriminant analysis. The three types of discriminant analysis algorithms are: minimum mean distance, maximum likelihood, and parallelepiped. All use brightness plots to establish the relationship between individual pixels and the training class (or training site).

Minimum Mean Distance Minimum distance to the mean is a simple computation that classifies pixels based on their distance from the mean of the training class. It is determined by plotting the pixel brightness and calculating its Euclidean distance (using the Pythagorean theorem) to the unassigned pixel. Pixels are assigned to the training class for which it has a minimum distance. The user designates a minimum distance threshold for an acceptable distance; pixels with distance values above the designated threshold will be classified as unknown.

Parallelepiped In a parallelepiped computation, unassigned pixels are grouped into a class when their brightness values fall within a range of the training mean. An acceptable digital number range is established by setting the maximum and minimum class range to plus and minus the standard deviation from the training mean. The pixel brightness value simply needs to fall within the class range, and is not based on its Euclidean distance. It is possible for a pixel to have a brightness value close to a class and not fall within its acceptable range.

Likewise, a pixel may be far from a class mean, but fall within the range and therefore be grouped with that class. This type of classification can create training site overlap, causing some pixels to be misclassified.

Maximum Likelihood Maximum Likelihood is computationally complex. It establishes the variance and covariance about the mean of the training classes. This algorithm then statistically calculates the probability of an unassigned pixel belonging to each class. The pixel is then assigned to the class for which it has the highest probability.

Unsupervised Classification

Unsupervised Classification. Unsupervised classification does not require prior knowledge. This type of classification relies on a computed algorithm that clusters pixels based on their inherent spectral similarities.

Steps Required for Unsupervised Classification

The user designates 1) the number of classes, 2) the maximum number of iterations, 3) the maximum number of times a pixel can be moved from one cluster to another with each iteration, 4) the minimum distance from the mean, and 5) the maximum standard deviation allowable. The program will iterate and recalculate the cluster data until it reaches the iteration threshold designated by the user. Each cluster is chosen by the algorithm and will be evenly distributed across the spectral range maintained by the pixels in the scene. The resulting classification image will approximate that which would be produced with the use of a minimum mean distance classifier (see above, "classification algorithm"). When the iteration threshold has been reached the program may require you to rename and save the data clusters as a new file. The display will automatically assign a color to each class; it is possible to alter the color assignments to match an existing color scheme (i.e., blue = water, green = vegetation, red = urban) after the file has been saved.

Advantages of Using Unsupervised Classification

Unsupervised classification is useful for evaluating areas where you have little or no knowledge of the site. It can be used as an initial tool to assess the scene prior to a supervised classification. Unlike supervised classification, which requires the user to hand select the training sites, the unsupervised classification is unbiased in its geographical assessment of pixels.

Disadvantages of Using Unsupervised Classification

The lack of information about a scene can make the necessary algorithm decisions difficult. For instance, without knowledge of a scene, a user may have to experiment with the number of spectral clusters to assign. The unsupervised classification is not sensitive to covariation and variations in the spectral signature to objects. The algorithm may mistakenly separate pixels with slightly different spectral values and assign them to a unique cluster when they, in fact, represent a spectral continuum of a group of similar objects.

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Table 1. Image processing functions required to analyze remote sensor data for hydrology and water management applications.

Preprocessing

1. Radiometric correction of error introduced by the sensor system electronics and/or environmental effects (includes relative image-to-image normalization and absolute radiometric correction of atmospheric attenuation)
2. Geometric correction (image-to-map rectification or image-to-image registration)

Display and Enhancement

3. Black & white (8-bit)
4. Color-composite display (24-bit)
5. Black & white or color density slice
6. Magnification, reduction, roam
7. Contrast manipulation (linear, non-linear)
8. Color space transformations (e.g. ROB to IHS)
9. Image algebra (band ratioing, image differencing, etc.)
10. Linear combinations (e.g., Kauth transform)
11. Spatial filtering (e.g. high, low, band-pass)
12. Edge enhancement (e.g. Sobel, Robert's, Kirsch)
13. Principal components (e.g. standardized, unstandardized)
14. Texture transforms (e.g. min-max, texture spectrum, fractal dimension)
15. Frequency transformations (e.g. Fourier, Walsh)
16. Digital elevation models (e.g. analytical hill shading)
17. Animation e.g.movies of channel detection

Remote Sensing Information Extraction

18. Pixel brightness value
19. Univariate and multivariate statistical analysis (e.g. mean, covariance)
20. Feature (band) selection (graphical and statistical)
21. Supervised classification (e.g. minimum distance, maximum likelihood)
22. Unsupervised classification (e.g. ISODATA)
23. Contextual classification
24. Incorporation of ancillary data during classification
25. Expert system image analysis
26. Neural network image analysis
27. Fuzzy logic classification
28. Hyperspectral data analysis
29. Radar image processing
30. Accuracy assessment (descriptive and analytical)