UNIT 13 IMAGE CLASSIFICATION

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13.1 INTRODUCTION

In the previous unit, you have learnt about different image enhancement and transformation techniques which help us better visualise and interpret remotely sensed images. As mentioned earlier, all these techniques aid in providing only better visual information and, therefore, have limited utility.

In this unit, we will move a step further and learn how to make more sense of the landscape by dividing it into separate classes based on surface characteristics. This process is known as *image classification*. It involves conversion of raster data into finite set of classes that represent surface types in the imagery. It may be used to identify vegetation types, anthropogenic structures, mineral resources, etc. or transient changes in any of these features. Additionally, classified raster image can be converted to vector features (e.g., polygons) in order to compare with other data sets or to calculate spatial attributes (e.g., area, perimeter, etc). Image classification is a very active field of study broadly related to the field of pattern recognition. In this unit, we will discuss about different image classification methods, signature evaluation and the guidelines for selecting a classification method.

Objectives

After studying this unit, you should be able to:

- define image classification;
- describe different image classification approaches and algorithms used in remote sensing;
- discuss relative advantages and limitations of commonly used classification algorithms; and
- explain how to evaluate spectral signatures.

13.2 CONCEPT OF IMAGE CLASSIFICATION

Classification is the process of assigning spectral classes into information classes. Spectral classes are groups of pixels that are uniform with respect to their brightness values in the different spectral channels of data. Information classes are categories of interest that an analyst attempts to identify in the image on the basis of his knowledge and experience about the area. For example, a remote sensing image contains spectral signatures of several features present on the ground in terms of pixels of different values. An interpreter or analyst identifies homogeneous groups of pixels having similar values and labels the groups as information classes such as water, agriculture, forest, etc. while generating a thematic map. When this thematic information is extracted with the help of software, it is known as ***digital image classification***. It is important to note that there could be many spectral classes within an information class depending upon the nature of features the image represents or the purpose of the classification. In other words, different spectral classes may be grouped under one information class.

In short, we can define image classification as a process of assigning all pixels in the image to particular classes or themes based on spectral information represented by the digital numbers (DNs). The classified image comprises a mosaic of pixels, each of which belong to a particular theme and is a thematic map of the original image.

13.2.1 Approaches to Classification

There are two general approaches to image classification:

- **Supervised Classification:** It is the process of identification of classes within a remote sensing data with inputs from and as directed by the user in the form of training data, and
- **Unsupervised Classification:** It is the process of automatic identification of natural groups or structures within a remote sensing data.

Both the classification approaches differ in the way the classification is performed. In the case of supervised classification, specific land cover types are delineated based on statistical characterisation of data drawn from known examples in the image (known as *training sites*). In unsupervised classification, however, clustering algorithms are used to uncover the commonly occurring land cover types, with the analyst providing interpretations of those cover types at a later stage. Merits and demerits of both the supervised and unsupervised classification methods are summarised in Table 13.1.

Table 13.1: Merits and demerits of supervised and unsupervised classification methods

	Supervised method	Unsupervised method
Merits	• Analyst has control over the classification • Processing is tied to specific areas of known identity • Errors can be detected and often rectified	• No extensive prior knowledge of the study area is required • Opportunity for human error is minimised • Unique classes are recognised as distinct units
Demerits	• Analyst imposes a structure on data, which may not match reality • Training classes are generally based on field identification and not on spectral properties hence spectral signatures are forced • Training data selected by the analyst may not be representative of conditions present throughout the image • Training data can be time-consuming and costly • Unable to recognise and represent special or unique categories not represented in the training data	• Spectral classes are not necessarily information classes • Analyst has little control over classes • Spectral properties change over time hence detailed spectral knowledge of different features may be necessary

Both these methods can be combined together to come up with a '***hybrid***' approach of image classification. In the hybrid classification, firstly, an unsupervised classification is performed, then the result is interpreted using ground referenced information and, finally, original image is reclassified using a supervised classification with the aid of statistics of unsupervised classification as training knowledge. This method utilises unsupervised classification in combination with ground referenced information as a comprehensive training procedure and, therefore, provides more objective and reliable results.

13.2.2 Stages in Classification

The image classification process consists of following three stages (Fig. 13.1): training, signature evaluation and decision making.

Training is the process of generating spectral signature of each class. For example, a forest class may be defined by minimum and maximum pixel values in different image bands, thus defining a spectral envelope for it. This simple statistical description of the spectral envelope is known as *signature*. Training can be carried out either by an image analyst with guidance from his experience or knowledge (i.e. supervised training) or by some statistical clustering techniques requiring little input from image analysts (i.e. unsupervised training).

There are no specific rules regarding the number of training sites per class but it is advisable to take several training sites for each class to be mapped. If you take very less number of training sites then it may be difficult to obtain a spectral signature which truly represents that class and if you take large number of training sites then a significant time may be getting wasted in collecting and evaluating signatures with significantly improving the final signature.

A general rule of thumb is that training data for a class should be 10 x n where, n is the number of bands. You should also remember that minimum number of pixels in a training site for a class should be n +1 (Jensen, 1986).

Signature Evaluation is the checking of spectral signatures for their representativeness of the class they attempt to describe and also to ensure a minimum of spectral overlap between signatures of different classes. We shall discuss in detail about signature evaluation in section 13.5.

Decision Making is the process of assigning all the image pixels into thematic classes using evaluated signatures. It is achieved using algorithms, which are known as *decision rules*. The decision rules set certain criteria. When signature of a candidate pixel passes the criteria set for a particular class, it is assigned to that class. Pixels failing to satisfy any criteria remain unclassified. We shall discuss in detail about the decision rules in the next two sections.

The term *classifier* is widely used as a synonym of the term *decision rule*.

Fig. 13.1: Stages in the process of image classification

In the following sections, we will discuss unsupervised and supervised classifications in more detail.

13.3 UNSUPERVISED CLASSIFICATION

As the name implies, this form of classification is done without interpretive guidance from an analyst. An algorithm automatically organises similar pixel values into groups that become the basis for different classes. This is entirely based on the statistics of the image data distribution and is often called *clustering*.

The process is automatically optimised according to cluster statistics without the use of any knowledge-based control (i.e. ground referenced data). The method is, therefore, objective and entirely data driven. It is particularly suited to images of targets or areas where there is no ground knowledge. Even for a well-mapped area, unsupervised classification may reveal some spectral features which were not apparent beforehand. The basic steps of unsupervised classification are shown in Fig 13.2.

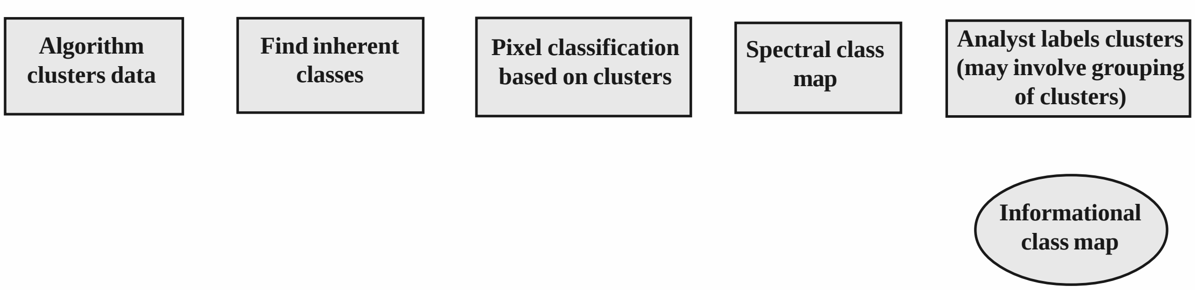

Fig. 13.2: Steps of unsupervised classification

The result of an unsupervised classification is an image of statistical clusters, where the classified image still needs interpretation based on knowledge of thematic contents of the clusters. There are hundreds of clustering algorithms available for unsupervised classification and their use varies by the efficiency and purpose. K-means and ISODATA are the widely used algorithms which are discussed here.

13.3.1 K-Means Clustering

K-means algorithm assigns each pixel to a group based on an initial selection of mean values. The iterative re-definition of groups continues till the means reach a threshold beyond which it does not change. Pixels belonging to the groups are then classified using a minimum-distance to means or other principle. K-means clustering algorithm, thus, helps split a given unknown dataset into a fixed number (k) of user defined clusters. The objective of the algorithm is to minimise variability within the cluster.

The data point at the center of a cluster is known as a *centroid*. In most of the image processing software, each centroid is an existing data point in the given input data set, picked at random, such that all centroids are unique. Initially, a randomised set of clusters are produced. Each centroid is thereafter set to the arithmetic mean of cluster it defines. The process of classification and centroid adjustment is repeated until the values of centroids stabilise. The final centroids are used to produce final classification or clustering of input data, effectively turning set of initially anonymous data points into a set of data points, each with a class identity.

Advantage

- the main advantage of this algorithm is its simplicity and speed which allows it to run on large datasets.

Disadvantages

- it does not yield the same result with each run, since the resulting clusters depend on the initial random assignments
- it is sensitive to outliers, so, for such datasets k-medians clustering is used and
- one of the main disadvantages to k-means is the fact that one must specify the number of clusters as an input to algorithm.

Outliers in remote sensing images represent observed pixel values that are significantly different from their neighbourhood pixel values.

13.3.2 ISODATA Clustering

ISODATA (Iterative Self-Organising Data Analysis Technique) clustering method is an extension of k-means clustering method (ERDAS, 1999). It represents an iterative classification algorithm and is useful when one is not sure of the number of clusters present in an image. It is iterative because it makes a large number of passes through the remote sensing dataset until specified results are obtained. Good results are obtained if all bands in remote sensing image have similar data ranges. It includes automated merging of similar clusters and splitting of heterogeneous clusters.

The clustering method requires us to input maximum number of clusters that you want, a convergence threshold and maximum number of iterations to be performed. ISODATA clustering takes place in the following steps:

- k arbitrary cluster means are established
- all pixels are relocated into the closest clusters by computing distance between pixel and cluster
- centroids of all clusters are recalculated and above step is repeated until the threshold convergence and
- if the number of clusters are within the specified number and distances between the clusters meet a prescribed threshold, then only clustering is considered complete.

Advantages

- it is good at finding "true" clusters within the data
- it is not biased to the top pixels in the image
- it does not require image data to be normally distributed and
- cluster signatures can be saved, which can be easily incorporated and manipulated along with supervised spectral signatures.

Disadvantages

- it is time consuming and
- it requires maximum number of clusters, convergence threshold and maximum number of iteration as an input to algorithm.

13.4 SUPERVISED CLASSIFICATION

Supervised classification, as the name implies, requires human guidance. An analyst selects a group of contiguous pixels from part of an image known as a *training area* that defines DN values in each channel for a class. A classification algorithm computes certain properties (data attributes) of set of training pixels, for example, mean DN for each channel (Fig. 13.3). Then, DN values of each pixel in the image are compared with the attributes of the training set.

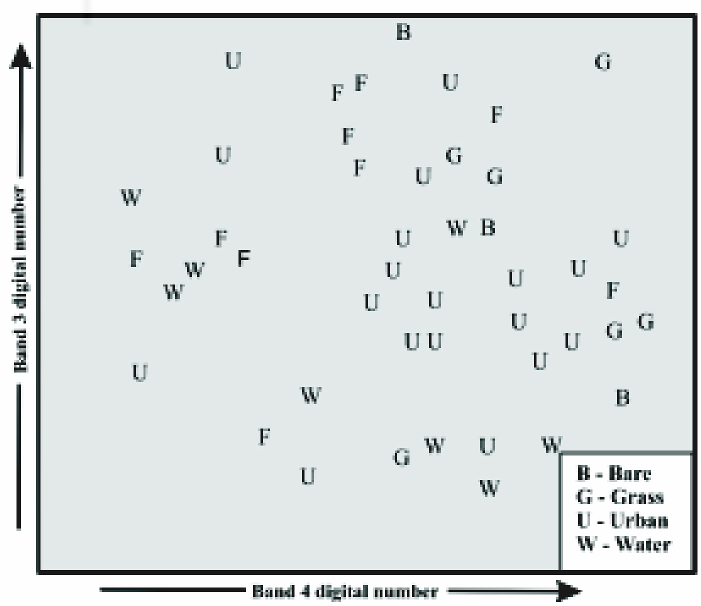

Fig. 13.3: Using supervised classification, pixels are classified into different categories

This is based on the statistics of training areas representing different ground objects (Fig. 13.4) selected subjectively by users on the basis of their own knowledge or experience. Classification is controlled by users' knowledge but, on the other hand, is constrained and may even be biased by their subjective view. Classification can, therefore, be misguided by inappropriate or inaccurate training, area information and/or incomplete user knowledge. Steps involved in supervised classification are given in Fig. 13.5.

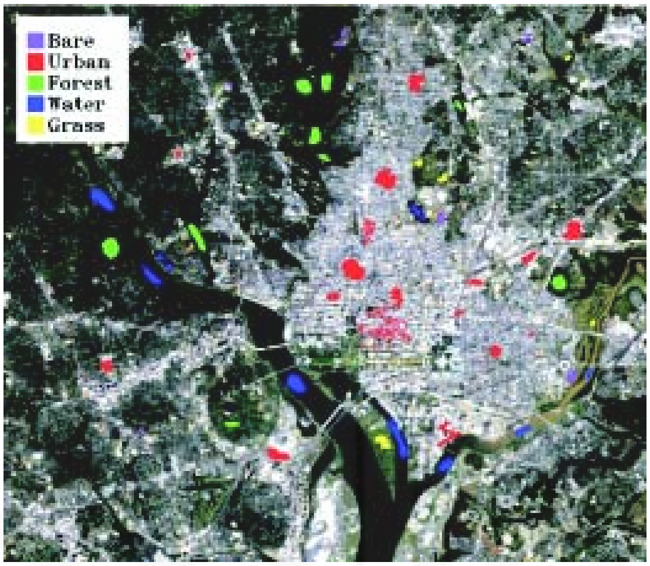

Fig.13.4: Training data in supervised classification

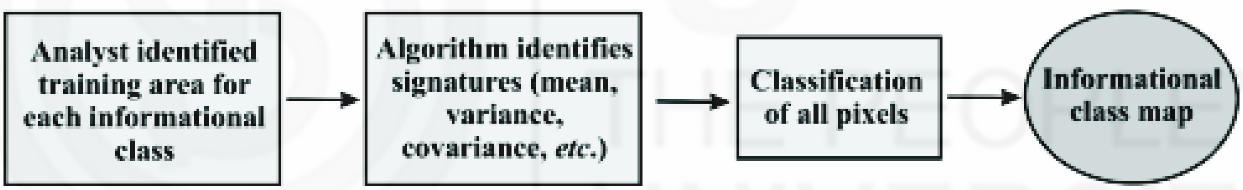

Fig. 13.5: Steps involved in supervised classification

In the following subsections, we will discuss parallelepiped and maximum likelihood algorithms of supervised image classification.

13.4.1 Parallelepiped Classifier

Parallelepiped classifier uses the class limits 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 mean of the class in feature space. If pixel falls inside the parallelepiped, it is assigned to the class. However, if pixel falls within more than one class, it is put in the overlap class. If pixel does not fall inside any class, it is assigned to the null class.

In parallelepiped classifiers, an n-dimensional box is constructed around pixels within each category of interest (Fig. 13.6). The n-dimensional space defined by the parallelepiped delimits different categories.

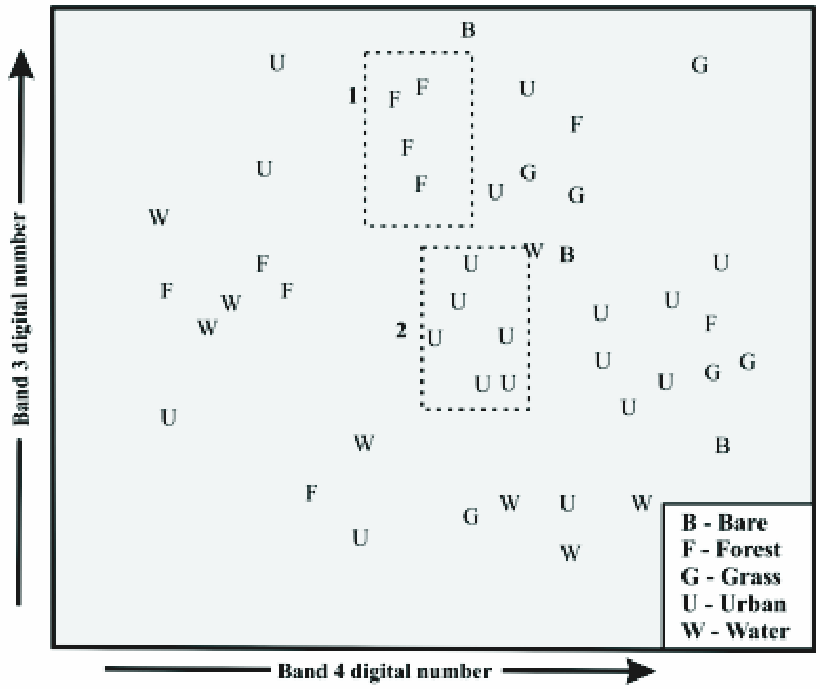

Fig. 13.6: Using the parallelepiped approach, pixel 1 is classified as forest and pixel 2 is classified as urban

Classification using this classifier is carried out in the following steps:

Step 1: Define the range of values in each training area and use these ranges to construct an n-dimensional box (a parallelepiped) around each class.

Step 2: Use multi-dimensional ranges to create different surface categories.

Notice that there can be overlap between the categories when simple method is used. One solution to this problem is to use a stepped decision region boundary.

Advantages

- it is a simple and computationally inexpensive method and
- it does not assume a class statistical distribution and includes class variance.

Disadvantages

- it is least accurate method
- it does not adapt well to elongated (high-covariance) clusters
- it often produces overlapping classes, requiring a second classification step
- it also becomes more cumbersome with increasing number of channels and
- pixels falling outside the defined parallelepiped remain unclassified.

13.4.2 Maximum Likelihood Classifier

Maximum likelihood (MXL) classifier is one of the most widely used classifiers in the remote sensing. In this method, a pixel is assigned to the class for which it has maximum likelihood of membership. This classification algorithm uses training data to estimate means and variances of the classes, which are then used to estimate probabilities of pixels to belong to different classes. Maximum likelihood classification considers not only mean or average values in assigning classification but also the variability of brightness values in each class around the mean. It is the most powerful of the classification algorithms as long as accurate training data is provided and certain assumptions regarding the distributions of classes are valid.

An advantage of this algorithm is that it provides an estimate of overlap areas based on statistics. This method is different from parallelepiped in that it uses only maximum and minimum pixel values. The distribution of data in each training set is described by a mean vector and a covariance matrix. Pixels are assigned a posteriori probability of belonging to a given class and placed in the most "likely" class. This is the only algorithm in this list that takes into account the shape of the training set distribution.

Maximum likelihood classifiers use expected (normal) distribution of DN values to define the probability of a pixel being within a certain class. Plotting the number of pixels with any given DN value yields a histogram or distribution of DN values within a particular band. Studies have shown that for most surfaces DN values from visible or near-infrared (NIR) region of the electromagnetic (EM) spectrum have a normal probability distribution. It means we can define curves based on the mean and standard deviation of the sample that describe the normal probability distribution by selecting category that has highest statistical probability for each pixel. These concentric circles, called *equi-probability contours*, are derived from an assumed normal distribution around each training site. Equi-probability contours define the level of statistical confidence in the classification accuracy. Smaller the contour, higher is the statistical confidence.

Advantages

- it is one of the most accurate methods
- it overcomes unclassified pixel problem (subject to threshold values)
- it provides a consistent way to separate pixels in overlap zones between classes and
- assignment of pixels to classes can be weighted by prior knowledge of the likelihood that a class is correct.

Disadvantages

- cluster distributions are assumed to be Gaussian in each class and band. Algorithm requires enough pixels in each training area to describe a normal population and assumes class covariance matrices are similar
- classes not assigned to training sets tend to be misclassified – a particular problem for mixtures
- it is reliant on the accuracy of training data. Changes in training set of any one class can affect the decision boundaries with other classes
- it is relatively computationally expensive and
- it is also not practical with imaging spectrometer data.

Check Your Progress I

Spend 5 mins

1) Differentiate supervised and unsupervised classification approaches.

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13.5 SIGNATURE EVALUATION

As discussed in subsection 13.2.2, evaluation of signatures is an important step in classification, which is carried out before decision making stage. In this stage, signatures of different classes obtained through training sites from image are checked for their representativeness of class they attempt to describe and also to ensure their uniqueness from other classes. However, let us first review the concept of spectral signature and then about the ways of signature evaluation.

13.5.1 Spectral Signature

The wavelength of any given material determines the amount of solar radiation it reflects, absorbs, transmits, or emits. So, when the amount of solar radiation reflected, absorbed, transmitted, or emitted (usually measured in intensity, as a percent of maximum) by the material is plotted over a range of wavelengths, the connected points produce a curve called the material's *spectral signature*.

The percent reflectance values of similar objects at a selected wavelength will be similar while it will vary for different objects or landscape features. These values can be plotted in a graph and compared. Such plots are called *spectral response curves* or *spectral signatures*. Spectral signatures of like features have similar shapes, for example, concrete will have similar spectral signatures while the spectral signatures of grass and concrete will vary. Differences among spectral signatures are used to classify remotely sensed images into classes of landscape features.

Greater details of recorded spectral information allows for greater information to be extracted from spectral signatures. This important property of matter makes it possible to identify different substances or classes and also to separate them by their individual spectral signatures (Fig. 13.7).

For example, at some wavelengths, soil reflects more energy (absorbs less) than green vegetation but at other wavelengths it absorbs more (like clayey soil) than does the vegetation. These differences in reflectance from various kinds of surface materials make it possible to differentiate them from one another.

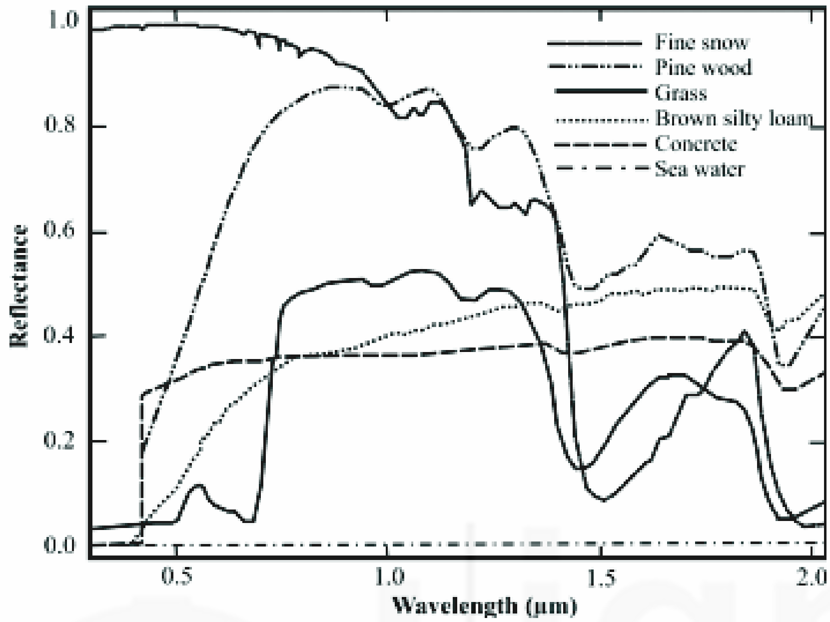

Fig. 13.7: Spectral signature of various features

Spectral response curves of some of the materials are discussed below.

Vegetation contains water, cellulose (tissues and fibres), constituent of wood, lignin (non-carbohydrate nitrogen), chlorophyll (green pigments) and anthocyanin (water-soluble pigments). Depending on how 'active' (i.e. kinds of chlorophyll) a green vegetation is, the combination of transmittance, absorbance and reflectance vary in different bands of the spectrum. Here is a general example of a reflectance plot for a vegetation type, with the dominating factor influencing each interval of the curve so indicated; note downturns of the curve that result from selective absorption in Fig. 13.7.

Chlorophyll strongly absorbs radiation in the red and blue wavelengths but reflects green wavelengths. Leaves appear "greenest" to us in the summer, when chlorophyll content is at its maximum. In autumn, there is less chlorophyll in the leaves, so there is less absorption and proportionately more reflection of the red wavelengths, making leaves appear red or yellow (yellow is a combination of red and green wavelengths). The internal structure of healthy leaves acts as excellent diffuse reflectors of NIR wavelengths. If our eyes were sensitive to NIR, trees would appear extremely bright to us at these wavelengths.

Overall, factors such as leaf damage, sun and shade, leaf water content; leaf air spaces and salinity and nutrient levels can affect spectral response of the leaf.

The spectral response of vegetation canopies is a little different from that of leaves. Transmittance of leaves, amount and arrangement of leaves, structural characteristics such as stalks, trunks, limbs; background (soil, leave litter, etc.); solar zenith angle; viewing angle and azimuth angle influence the spectral response.

Soil tends to have reflection properties that increase approximately monotonically with wavelength. They tend to have high reflectance in all bands. This is dependent on factors such as colour, constituents and especially the moisture content. As described above, water is a relatively strong absorber of all wavelengths, particularly those longer than the red part of visible spectrum (Fig. 13.8). Therefore, as soil moisture content increases, the overall reflectance of that soil tends to decrease. Soils rich in iron oxide reflect proportionally more of the red than other visible wavelengths and therefore appear red (rust colour) to the human eye. A sandy soil on the other hand tends to appear bright white in imagery because visible wavelengths are more or less equally reflected; when slightly less blue wavelengths are reflected this results in a yellow colour. In a nutshell, spectral response curves of soil and rocks are influenced by soil colour, mineral content, inter-molecular vibration of the molecules, organic matter (influences soil colour and moisture), particle size, reflectance and thermal diffusivity and moisture (Fig. 13.8).

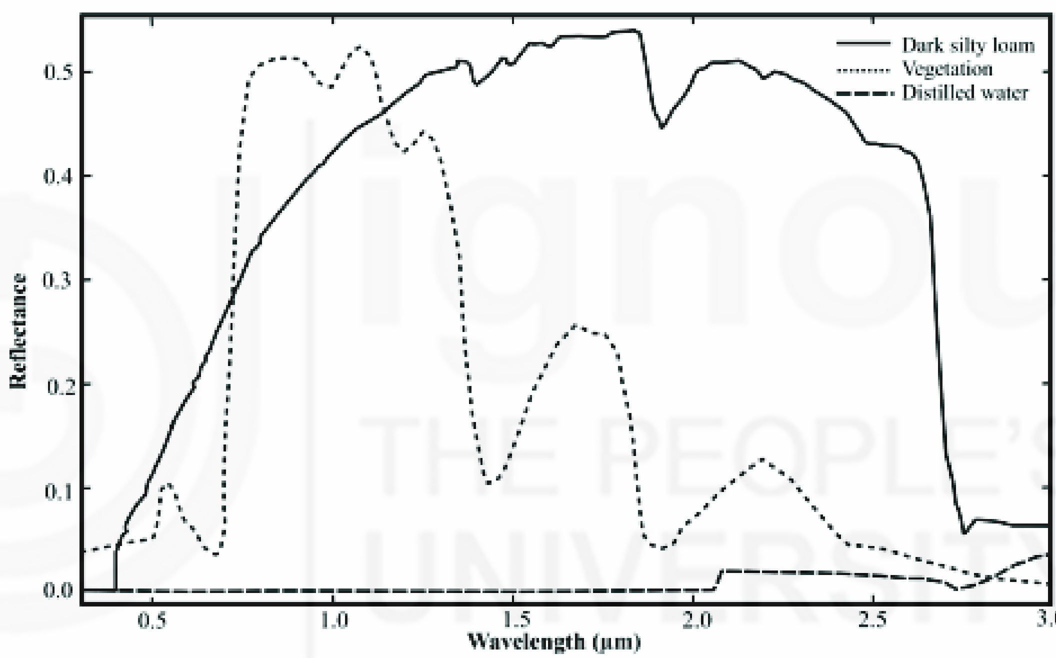

Fig. 13.8: Generalised spectral signatures for some common features

Water absorbs much longer wavelength at visible and NIR radiation than shorter visible wavelengths. Thus, water typically looks blue or blue-green due to stronger reflectance at these shorter wavelengths and darker if viewed at red or NIR wavelengths. If there is suspended sediment present in the upper layers of a water body, then this will allow better reflectivity and a brighter appearance of the water. The apparent colour of the water will show a slight shift to longer wavelengths. Suspended sediment can be easily confused with shallow (but clear) water, since these two phenomena appear very similar. Chlorophyll in algae absorbs more of the blue wavelengths and reflects green, making water appear greener in colour when algae are present. The topography of the water surface such as rough, smooth or floating materials can also lead to complications for water related interpretation due to potential problems of specular reflection and other influences on colour and brightness.

Spectral signatures, however, are not always "pure" which means the sensor might record some signatures that may be emitted by surrounding objects.

"Pure" spectral signature for individual materials or classes can be determined best under laboratory conditions, where the sensor is placed very close to the target (Fig. 13.9). There is no interference in a closed and controlled environment such as a laboratory. Agencies such as ISRO, US Department of Agriculture and several universities maintain large repositories of spectral signatures. Moreover, many image analysis tools have built-in spectral libraries.

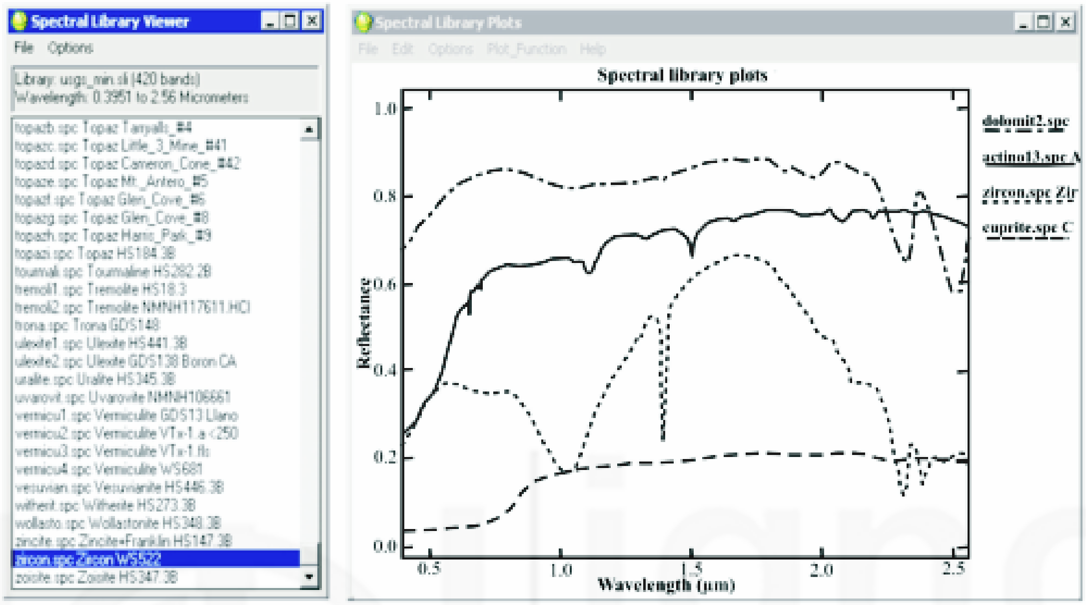

Fig. 13.9: Spectral curves from a spectral library (source: Spectral library of US Geological Survey)

13.5.2 Ways of Signature Evaluation

One of the most common techniques for feature identification is spectral evaluation. Most of the image analysis software provides an interface to plot spectral signature. Fig. 13.10 shows an example of how a spectral image is plotted using an image analysis tool. With knowledge about the spectral profile for a given feature, we can go back and change band combinations to make that feature show up more clearly on the image.

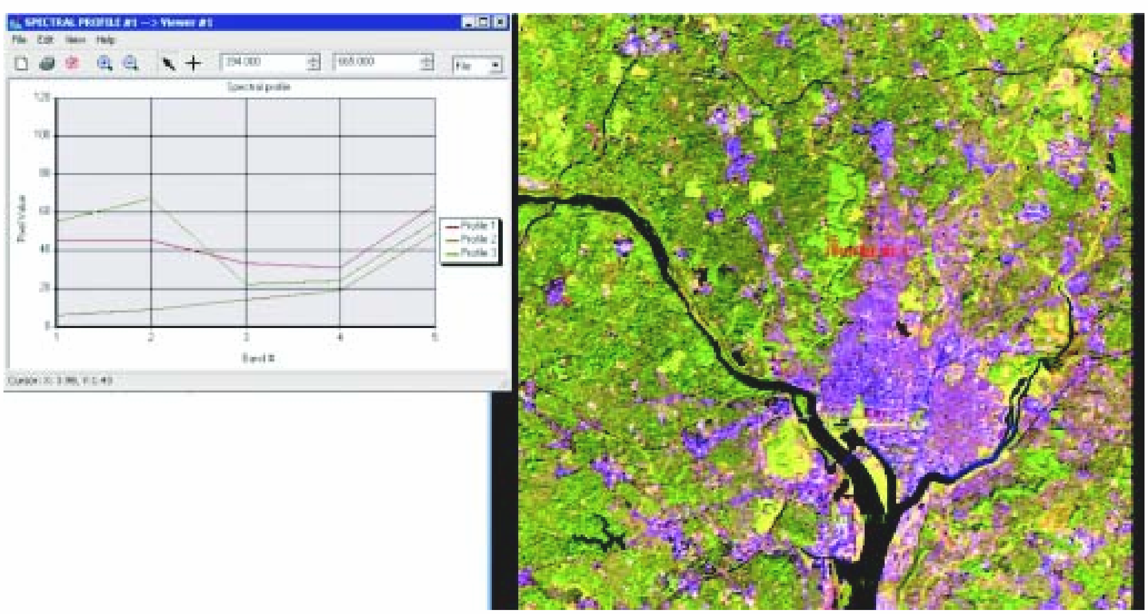

Fig. 13.10: Spectral plots from a satellite image

Spectral signatures are evaluated in the following three ways:

- classification is performed on the pixels within the training samples for each class and is compared with classes as recorded in the field data on those location. Ideally, all pixels in a training sample should classify correctly. However, you can expect high percentages of correctly classified pixels if the signatures taken are appropriate

- measuering spectral distance, i.e. separability by computing divergence, transformed divergence or the Jeffries-Matusita distance. You can find mathematics behind computation of these in a book by Swain and Davis (1978). However, it is important to ensure that there is high separability between signatures from different types of training samples and low separability among signatures from the training samples of a particular class and

- mean and standard deviation of each signature are used to plot ellipse diagrams in two or more dimensions. The plotting allows the analyst to identify similar signatures and hence the classes which are likely to suffer most from misclassification. If the amount of overlap between a pair of signatures is large then those classes are not separable using that image data.

You should note that some of the training samples whose signatures have negative effect on the classification outcome need to be either renamed or merged or deleted.

13.6 OVERVIEW OF OTHER CLASSIFICATION METHODS

As mentioned in the above sections, apart from the supervised and unsupervised classification there exists a third kind of classification method known as ***hybrid classification***. This method uses both the afore-mentioned methods (supervised and unsupervised classifications) and is primarily applied to improve accuracy and efficiency of classification results. The most common example of hybrid classification is the use of unsupervised classification to delineate classes prior to supervised classification in order to aid the analyst in identifying numerous spectral classes. *Guided clustering* is another such method which is useful in analysis involving complex variability in spectral response for each land cover. In this method, analysis delineates numerous supervised training sets for each land cover. These training sets do not have to be homogeneous as opposed to the regular supervised classification. Data from all these training sets are used for supervised classification. The analyst uses his discretion while selecting final spectral classes, so all of the redundant classes are merged or discarded as per need.

There are number of other classification methods such as contextual, decision tree, neural network, etc. Contextual classifiers incorporate spatial or temporal information along with the spectral signatures while deciding at the information classes. Decision tree classifiers are knowledge based classifiers which classify in steps, where the classifier is able to distinguish between two or more classes at each step. In this method, various types of classifiers as deemed appropriate can be combined. Neural network classifiers do not require any assumption about the statistical distribution of data and use machine learning techniques to classify image pixels.

Some classification methods deal with the classification of mixed pixel, which refers to classes with more than one land cover. These methods, referred as *spectral mixture analysis*, are based on physical models providing information on discrete spectral signatures rather than statistical methods.

Linear mixture methods consider spectral classes from one pixel to be linear mixture of all the land cover classes. Fuzzy classification methods account for the transition between various land cover classes, known as fuzzy regions in between two classes. Fuzzy classification does not have definite boundaries and one pixel may belong to more than one class.

Check Your Progress II

Spend 5 mins

1) Discuss hybrid classification.

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13.7 SELECTION OF AN APPROPRIATE CLASSIFICATION METHOD

Classification process involves translating pixel values in a remote sensing image into meaningful categories. In case of land cover classification, these categories comprise different types of land cover defined by the classification scheme that is being implemented. There are number of classification methods that can be used to group image pixels into meaningful categories. Unfortunately, there is not a single best approach to image classification. The choice made depends a lot on the algorithms that are available with the image processing software used and also familiarity and experience with different methods. The choice of classification method is dependent upon many factors, accuracy being one of the most important criteria. Some of the ways to evaluate efficacy and accuracy of classification methods are discussed in next unit. It has generally been found that in areas of complex terrain, the unsupervised approach is preferable over the supervised one. In such conditions, if the supervised approach is used, the user will have difficulty in selecting training sites because of the variability of spectral response within each class.

Consequently, a prior ground data collection can be very time consuming. Also, the supervised approach is subjective in the sense that the analyst tries to classify information categories, which are often composed of several spectral classes whereas spectrally distinguishable classes will be revealed by the unsupervised approach, and hence ground data collection requirements may be reduced. Additionally, unsupervised approach has the potential advantage of revealing distinguishable classes unknown from previous work. However, when definition of representative training areas is possible and statistical information classes show a close correspondence, the results of supervised classification will be superior to unsupervised classification.

Fig. 13.11 shows a Landsat scene of Washington DC, USA which has been classified by supervised as well as unsupervised methods. We can observe that there are many similarities between outputs of supervised and unsupervised methods. However, in this example the outcome of the supervised classification method has more generalised classes than that of the unsupervised method. This is because of the fact that while we use spectral information to create classes in the unsupervised classes, performance of the supervised classes is largely dependent on the training samples. The training samples used for the above classification (Fig. 13.11) is not sufficient to cover the entire spectrum of a particular class and, therefore, we get a generalised image. The results of the supervised classification can be further improved by collecting more training samples which would further help to reduce the differences between classes which may be due to mixtures within each pixel e.g., grass and forest.

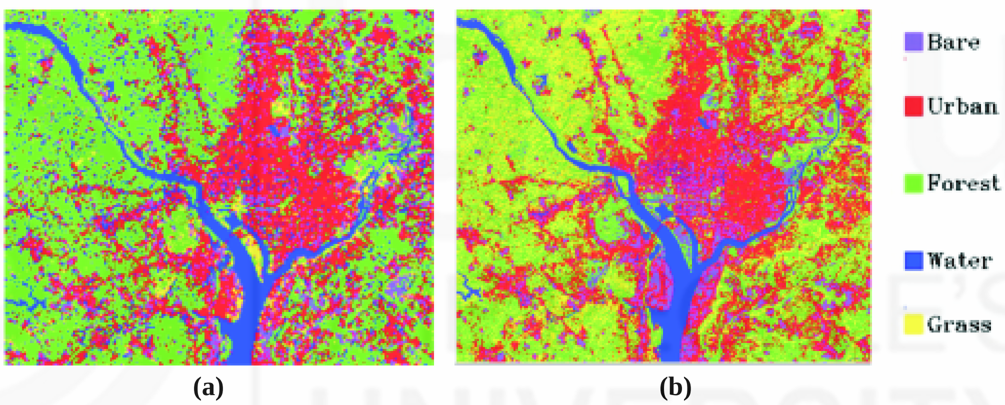

Fig. 13.11: Processing of images. (a) Supervised classification and (b) unsupervised classification with five allowable classes

It is not easy to answer the question which classification method is suitable for a study because different classification results can be obtained from different methods and each method has its own merits and demerits. However, for a general guideline it can be said that factors such as spatial resolution of the remote sensing data, source of data, classification scheme and availability of classification software must be taken into account while selecting a classification method for use.

13.8 SUMMARY

Let us now summarise what you have studied in this unit:

- There are two approaches to image classification, i.e. unsupervised and supervised. Unsupervised classification is useful for complex terrains and it can significantly reduce the cost of ground data collection than the supervised classification.
- Spectral signatures are unique for each material, which allows us to distinguish objects from one another and is the basis of classification in remote sensing.

- Methods of image classification include K-means, ISODATA, Maximum likelihood, Parallelepiped, etc.
- Maximum likelihood method is the most powerful of the classification methods as long as accurate training data is provided and normal distribution of classes is justified. Sometimes, for better image classification, both supervised and unsupervised methods may be used which is known as a hybrid approach.
- Selection of an appropriate image classification method is a challenging task in image classification because there are so many classification methods available. However, the choice for a particular classification method depends on the availability of image processing software along with familiarity and working experience with other methods.
- The next unit (i.e. Unit 14) will introduce you to the relevance of accuracy assessment in image classification.

13.9 UNIT END QUESTIONS

Spend 30 mins

1) What is training data?
2) What are the advantages and disadvantages of unsupervised classification?
3) What are the advantages and disadvantages of supervised classification?
4) What are spectral signatures?

13.10 REFERENCES

- Jensen, J. R., (1986), *Introductory Digital Image Processing: A Remote Sensing Perspective*, Prentice-Hall, New Jersey.
- Swain, P. H. and Davis, S. M., (1978), *Remote Sensing: The Quantitative Approach*, McGraw-Hill International Book Co., New York.
- ERDAS Field Guide, http://www.gis.usu.edu/unix/imagine/FieldGuide.pdf (retrieved in February, 2012).
- US Geological Survey Spectral Library, *http://speclab.cr.usgs.gov/spectral-lib* (retrieved in September, 2011).

13.11 FURTHER/SUGGESTED READING

- Campbell, J. B., (2006), *Introduction to Remote Sensing*, Taylor and Francis, London.
- Lillesand, T. M. and Kiefer, R., (2007), *Remote Sensing Image Interpretation*, John Wiley, New York.

13.12 ANSWERS

Check Your Progress I

Both image classifications differ on the basis of nature of their performance. An unsupervised classification of an image can be done without interpretive guidance from an analyst. It is entirely based on the statistics of the image data distribution. It needs no ground knowledge of area under investigation. Supervised classification requires human guidance. Here, an analyst selects a group of contiguous pixels from part or training area of an image. Calculated attributes of training area are compared on the ground statistics of training area to identify objects correctly on the image. The classification is controlled by knowledge of users.

Check Your Progress II

A combination of supervised and unsupervised classifications is called as a 'hybrid' approach of an image classification. In the hybrid classification of a multispectral image, firstly an unsupervised classification is performed, then the result is interpreted using ground referenced information and, finally, the original image is reclassified using a supervised classification with the aid of the statistics of the unsupervised classification as training knowledge.

Unit End Questions

1) Refer to section 13.2
2) Refer to section 13.3
3) Refer to section 13.4
4) Refer to section 13.5