CHAPTER 2
LITERATURE REVIEW

2.1 INTRODUCTION

This chapter presents literature review on vegetation identification using remote sensing.

2.2 CONVENTIONAL METHODS FOR VEGETATION IDENTIFICATION

Ramstein, 1989, state that, remotely-sensed images present a simple structure specific to the remotely-sensed field. Using the concepts of variogram and fractal dimension, they propose a classification of the textures of images based on simple models. Applications are given to segmentation and resampling.

Cecchi, 1994, demonstrated the usefulness of laser induced fluorescence in the monitoring of vegetation. In order to better investigate the link between fluorescence and plant physiology, in vivo experiments under controlled conditions were carried out for different kinds of samples and vegetation stresses. They describe the employed measurement technique, and report on the experimental results obtained during the last three years both in laboratory and in field. The data mainly refer to laser-induced fluorescence spectroscopy, fluorescence Lidar and passive remote sensing measurements compared with climatic and physiological parameters.
Chen and Tsay, 1996, described the application of a neural network to the segmentation of remote sensing images of multispectral SPOT and fully Polari metric SAR data. The structure of the network is a modified multilayer perceptron and is trained by the Kalman filter theory. The internal activity of the network is a nonlinear function, while the function at output layer is linearized through the use of a polynomial basis function, thus employ the theory of Kalman filtering as the learning rule. The network is therefore called the dynamic learning (DL) neural network. It is found that, when applied to SPOT and SAR data, the DL neural network gives a good segmentation results, while the learning rate is very promising compared to the standard back propagation network and other fast-learning networks. For Polari metric SAR data, optimum polarizations for discriminating between different terrains are automatically built in through the use of Kalman filter technique.

Ryherd, 1996, described image segmentation as a method of defining discrete objects or classes of objects in images. Addition of ‘n’ spatial attribute like image texture, improves the segmentation process in most areas where there are differences in texture between classes in the image. Such areas include sparsely vegetated areas and highly textured human-generated areas, such as the urban-suburban interface. A simple adaptive-window texture program creates a texture channel useful in image segmentation. The segmentation algorithm is a multi-pass,
pair-wise, region-growing algorithm. The test sites include a simulated conifer forest, a natural vegetation urea, and a mixed-use suburban area. The simulated image is especially useful because polygon boundaries are unambiguous. Both the weighting of textural data relative to the spectral data, and the effects of the degree of segmentation, is explored. The use of texture improves segmentations for most areas. It is apparent that the addition of texture has no influence on the accuracy of the segmentation, and can improve the accuracy in areas where the features of interest exhibit differences in local variance.

Raimundo, 1997, discussed the combined use of image merge, segmentation and region-classification techniques, as a new approach in the semi-automatic mapping of land-cover types. In the first step of the procedure, a digitized panchromatic aerial photograph was co-registered with Landsat-TM images. A hybrid image set with high-spatial resolution was then produced by merging the Landsat images and the aerial photograph, through intensity (I), hue (H) and saturation (S) color transform. Using segmentation techniques, hybrid images were partitioned into homogeneous regions, and classified according to a region-based classification algorithm. The analysis of the hybrid IHS color composite supported by field data information permitted to identify the classes on the classified image, so producing an accurate thematic mapping of different soil-vegetation assemblages in the study area.
Mas, 1999, described six change detection procedures that were tested using Landsat Multispectral Scanner (MSS) images for detecting areas of changes in the region of the Tearminos Lagoon, a coastal zone of the State of Campeche, Mexico. The change detection techniques considered were image differencing, vegetative index differencing, selective principal components analysis (SPCA), direct multi-date unsupervised classification, post-classification change differencing and a combination of image enhancement and post-classification comparison. The accuracy of the results obtained by each technique was evaluated by comparison with aerial photographs through Kappa coefficient calculation. Post-classification comparison was found to be the most accurate procedure and presented the advantage of indicating the nature of the changes. Poor performances obtained by image enhancement procedures were attributed to the spectral variation due to differences in soil moisture and in vegetation phenology between both scenes. Methods based on classification were found to be less sensitive at these spectral variations and more robust when dealing with data captured at different times of the year.

Steward, 1999, stated that in the field conditions under daylight, variability in lighting occurs, and hence practical segmentation algorithms must have the ability to adjust to such changes. Thus, a second class of methods treats the segmentation problem as a pattern recognition problem with the RGB values
individually treated as class features. A Bayes classifier is then trained to accomplish segmentation by dividing up the color space with a decision surface. The use of such a classifier allows the training to be accomplished for individual images that represent various lighting conditions typically encountered in outdoor conditions. In addition, because of its general quadratic form, the decision surface produced by the Bayes classifier can take on many different shapes based on class statistics. Pixel values are affected by the specific configuration of a color vision system, including factors related to intensity and spectral distribution of illumination, the lens and lens aperture, properties of RGB color filters, the image sensor response and the digitizer. Thus, the optimal values of the decision surface parameters will vary from image to image as lighting condition changes. Lighting will affect relative RGB values and their distribution. Hence, the first order statistics of the image RGB values were used to determine the optimal parameter values. [Gonzalez, 2000].

Crippen, 2001, stated that near-infrared and red image bands are used to estimate spatial variations in vegetation abundance. They determine the statistical relationship between the values in each band and the vegetation index. Band values are then adjusted so that the average band value for each index level is uniform across all vegetation index levels.
Shiewe, 2001, described landscapes are complex systems, which by their very nature necessitate a multiscale approach in their monitoring, modelling and management. To assess such broad extents, remote sensing technology is the primary provider of landscape sized data sets, and while tremendous progress has been made over the years in terms of improved resolution, data availability, and public awareness, the vast majority of remote sensing analytical applications still rely on basic image processing concepts: in particular, per-pixel classification in multi-dimensional feature space. They describe and compare two technically and theoretically different image processing approaches, both of which facilitate multiscale pattern analysis, exploration, and the linking of landscape components based on methods that derive spatially-explicit multiscale contextual information from a single resolution of remote sensing imagery.

Yamamoto, 2001, implemented a method for detection of the temporal changes using three-dimensional (3D) segmentation. The method is a kind of clustering methods for temporal changes. In the method, multitemporal images form image block in 3D space; x-y plane and time axis. The image block is divided into spatially uniform sub-blocks by applying binary division process. The division rule is based on the statistical t-test using Mahalanobis distance between spatial coefficient vectors of a local regression model fitted to neighboring sub-blocks to be divided. The divided sub-blocks are then merged into clusters using a clustering
technique. The block-based processing, like the spatial segmentation technique, is very effective in reduction of apparent changes due to noise. Temporal change is detected as a boundary perpendicular to the time axis in the segmentation result. The proposed method is successfully applied to actual multitemporal and multispectral LANDSAT/TM images.

Wang, 2001, determined appropriate plot size and spatial resolution for mapping multiple vegetation using remote sensing data for large areas. There were six vegetation cover types which are different in spatial variability. The appropriate plot size and spatial resolution were studied for each vegetation type in order to capture the structures of spatial variability and to improve map accuracy. Semi variogram method was used to model spatial variability. If there is a high correlation between field and image data, the appropriate plot size obtained using the field data will be consistent with the appropriate spatial resolution using the images. The comparison of the vegetation classification at different plot and image sizes by cross validation further proved the appropriate spatial resolution. The appropriate plot size was about 60 m for grass and shrub, 70 m for forbs, and 80 m for tree and half-shrub, and would not be less than 80 m for wood; and the TM images led to an appropriate spatial resolution of 90 m.

Dymond, 2002, compared the effectiveness of image differencing and vegetation indices to improve the forest classification with the input set of
phenologically significant TM scenes. NDVI and Tasseled Cap indices (Brightness (B), Greenness (G), Wetness (W)) were computed using the TM image for each phenological period to test the effectiveness of indices to improve the forest classification. Besides, the changes in TM color composite 3-4-5 and each of the four indices values were subtracted from one phenological period to the next. The area was subdivided into smaller lands which reduced the number of categories and variation within each class. By using hybrid classification, vegetation type map was composed; whereas maximum likelihood method was used for the genera level classification. These procedures were repeated for 6 different input data sets. According to the results of this study the image differencing of the Tasseled Cap indices may have produce the best vegetation classification.

Liu and skidmore, 2002, implemented integrated approaches like consensus builder system (CSB) and a combined expert system (CES) and neural network system (NNC) to improve the classification accuracy. First of the classifiers is Maximum Likelihood Classifier (MLC), in which each pixel is assigned to the class with the shortest modified “Mahalanobis distance” from the pixel to the class mean. The second classifier used in this study is NNC which is composed of two stages; training stage and classification stage. Once the training system is complete, the trained system is used for classification. The third classification
system is the expert system classifier (ESC). The structure of this system composed of two parts. First part is the “knowledge base” to store expert knowledge, and rules, and the “inference engine” for system processing. Classification was performed by the tree individual classifier and two new integrated classifiers using the same training set. An integrated classifier called ESNNC produced the highest accuracy of 80% when compared with the individual classifiers.

Sarkar, 2002, implemented an unsupervised segmentation approach to classification of multispectral image in Markov random field (MRF) framework. They generalized the work on gray value images for multispectral images and is extended for land use classification. The essence of this approach is based on capturing intrinsic characters of tonal and textural regions of any multispectral image. The approach takes an initially over segmented image and the original. Multispectral image as the input and defines a MRF over region adjacency graph (RAG) of the initially segmented regions. Energy function minimization associated with the MRF is carried out by applying a multivariate statistical test. A cluster validation scheme is outlined after obtaining optimal segmentation.

Edward, 2003, stated that farm managers are becoming increasingly aware of the spatial variability in crop production with the growing availability of yield monitors. Often this variability can be related to differences in soil properties
(texture, organic matter, salinity levels, and nutrient status) within the field. To develop management approaches to address this variability, high spatial resolution soil property maps are often needed. Some soil properties have been related directly to a soil spectral response or inferred based on remotely sensed measurements of crop canopies, including soil texture, nitrogen level, organic matter content, and salinity status. While many studies have obtained promising results, several interfering factors can limit approaches solely based on spectral response, including tillage conditions and crop residue. A number of different ground-based sensors have been used to rapidly assess soil properties “on the go” (sensor mounted on a tractor and data mapped with coincident position information) and the data from these sensors compliment image-based data. On-the-go sensors have been developed to rapidly map soil organic matter content, electrical conductivity, nitrate content, and compaction. Model and statistical methods show promise to integrate these ground and image-based data sources to maximize the information from each source for soil property mapping. Photographs and digital images have been analyzed using either manual or computer-aided methods to identify and classify residues and soils. The reflectance of both soils and crop residue lack the unique spectral signature of green vegetation in the 400- to 1000-nm wavelength region (Gausman, 1975, 1977; Wanjura, 1986; Aase, 1991). Crop residues and soils are often spectrally similar and differ only in
amplitude at a given wavelength. This makes discrimination between crop residues and soil difficult or nearly impossible using reflectance techniques in the visible and NIR portions of the spectrum.

Dorren, 2003, stated that the accuracy of forest stand type maps derived from a Landsat Thematic Mapper (Landsat TM) image of a heterogeneous forest covering rugged terrain is generally low. They studied topographic correction of TM bands and adding the digital elevation model (DEM) as additional band improves the accuracy of Landsat TM based forest stand type mapping in steep mountainous terrain. They analyzed object-based classification with per-pixel classification on the basis of the accuracy and the applicability of the derived forest stand type maps. To fulfill these objectives different classification schemes were applied to both topographically corrected and uncorrected Landsat TM images, both with and without the DEM as additional band. All the classification results were compared on the basis of confusion matrices and kappa statistics. It is found that both topographic correction and classification with the DEM as additional band increase the accuracy of Landsat TM-based forest stand type maps in steep mountainous terrain. They found that the accuracies of per-pixel classifications were slightly higher, but object-based classification seemed to provide better overall results according to local foresters.
Van Der Sande, 2003, created detailed land cover maps using IKONOS-2 high spatial resolution satellite imagery. The IKONOS-2 image was first divided into segments and the land cover was classified by using spectral, spatial and contextual information with an overall classification accuracy of 74%.

Walter, 2004, introduced a change detection approach based on an object-based classification of remote sensing data. The approach classifies no single pixels but groups of pixels that represent already existing objects in a GIS database. The approach is based on a supervised maximum likelihood classification. The multispectral bands grouped by objects and very different measures that can be derived from multispectral bands represent the n-dimensional feature space for the classification. The training areas are derived automatically from the geographical information system (GIS) database.

Coppin, 2004, described techniques based on multi-temporal, multi-spectral, satellite-sensor acquired data have demonstrated potential as a means to detect, identify, map and monitor ecosystem changes, irrespective of their causal agents. They summarize the methods and the results of digital change detection in the optical / infrared domain, has as its primary objective a synthesis of the state of the art today. It approaches digital change detection from three angles. The different perspectives from which the variability in ecosystems and the change events have been dealt with are summarized. Change detection between pairs of images (bi-
temporal) as well as between time profiles of imagery derived indicators (temporal trajectories), and, where relevant, the appropriate choices for digital imagery acquisition timing and change interval length definition, are discussed. Pre-processing routines either to establish a more direct linkage between remote sensing data and biophysical phenomena, or to temporally mosaic imagery and extract time profiles, are reviewed. The actual change detection methods themselves are categorized in an analytical framework and critically evaluated. Ultimately, they highlight how some of these methodological aspects are being fine-tuned as this review is being written, and they summarize the new developments that can be expected in the near future.

Liu, 2004, stated that although change detection algorithms for temporal remote sensing images have been compared using various datasets, there is no general agreement on their performance for separating change and no-change. This study compared image differencing, image rationing, image regression, and principal component analysis (PCA) from a mathematical perspective. Error analysis showed that no-change pixels with errors are expected to be located within an error zone in bi-temporal space. Bi-temporal space consists of two temporal axes of target pixel values observed successively. All algorithms confine a no-change area to a zone delineating change and no-change pixels in the space. Image rationing defines a fan-like sector as a no-change area, generally unsuitable for
change detection. The other algorithms confine a no-change area to a strip-like zone. Image differencing defines a no-change zone with a fixed slope, leading to its inability to specify flexibly the error zone that varies with different conditions. In the examined case, image regression and standardized PCA (SPCA) achieved the best performance for change detection, followed by PCA and image differencing.

Liu and Nishyaman, 2004, stated that seeing the expected technical improvements as to the spatial and spectral resolution, satellite imagery could more and more provide a basis for complex information systems for recognizing and monitoring even small-scale and short-term structural features of interests within nuclear facilities, for instance construction of buildings, plant expansion, changes of the operational status, underground activities etc. The analysis of large volumes of multi sensor satellite data will then definitely require a high degree of automation for (pre-) processing, analysis and interpretation in order to extract the features of interest. Against this background, they focuses on the automated extraction of change information from multispectral satellite imagery.

Lu, 2004, described timely and accurate change detection of Earth’s surface features is extremely important for understanding relationships and interactions between human and natural phenomena in order to promote better decision making. Remote sensing data are primary sources extensively used for change
detection in recent decades. Previous literature has shown that image differencing, principal component analysis and post-classification comparison are the most common methods used for change detection. Spectral mixture analysis, artificial neural networks and integration of geographical information system and remote sensing data have become important techniques for change detection applications. Different change detection algorithms have their own merits and no single approach is optimal and applicable to all cases. Different algorithms are often compared to find the best change detection results for a specific application.

Islam, 2005, described rapid prediction of properties to describe soil variability is essential for site-specific crop management. Accurate predictions require the collection and analysis of a large number of soil samples, which is laborious and costly, and sometimes impossible. On the other hand, the diffuse reflectance spectrum of a soil sample provides multivariate data that are often related to various physical and chemical properties. One way to calculate and plot the spectral variation of different soil types is with the principal component biplot. For the soil that they studied, the first two principal components represent more than 90% of the variation among soil spectra. Their objective was to evaluate the hypothesis that the convex hull biplot area of a geographical region is proportional to the soil variation found in that region. An initial experiment that includes two different geographical regions suggested that the region, which was more variable
in relation to pH, has a larger biplot area than the less variable one. A further analysis of the biplots of five fields and the associated variances of pH, organic carbon and clay showed that there was no direct relationship between the convex hull biplot area and the variation in the above soil properties. In this case, the convex hull biplot area might be a combined result of many soil variables, which we have not measured individually. The question of whether the spectral biplot area is a good and quick method of measuring multi-property soil variation is still open.

Bandyopadhyay, 2005, described land-cover classification of satellite images is an important task in analysis of remote sensing imagery. Segmentation is one of the widely used techniques in this regard. One of the important approaches for segmentation of an image is by clustering the pixels in the spectral domain, where pixels that share some common spectral property are put in the same group, or cluster. Such spectral clustering completely ignores the spatial information contained in the pixels, which is often an important consideration for good segmentation of images. The clustering algorithms often provide locally optimal solutions. They implemented image segmentation by a genetically guided unsupervised fuzzy clustering technique where some spatial information of the pixels is incorporated. A cluster validity index is used as a measure of the fitness value of the chromosomes. Results, both quantitative and qualitative, are
demonstrated for several images, including a satellite image of a part of the city of Mumbai.

Carleer, 2005, stated that very high spatial resolution satellite data represent the surface of the Earth with more detail. Information extraction by per pixel multispectral classification techniques proves to be very complex owing to the internal variability increase in land-cover units and to the weakness of spectral resolution. Image segmentation before classification was proposed as an alternative approach, but a large variety of segmentation algorithms were developed, and a comparison of their implementation on very high spatial resolution images is necessary. Four algorithms from the two main groups of segmentation algorithms (boundary based and region-based) were evaluated and compared. In order to compare the algorithms, an evaluation of each algorithm was carried out with empirical discrepancy evaluation methods. This evaluation is carried out with a visual segmentation of IKONOS panchromatic images. The results show that the choice of parameters is very important and has a great influence on the segmentation results.

Poggi, 2005, described most remote sensing images exhibit a clear hierarchical structure which can be taken into account by defining a suitable model for the unknown segmentation map. A tree structured model like Markov random field (MRF), which describes a means of a sequence of binary MRFs, each one
corresponding to a node in the tree. They propose to use the tree-structured MRF model for supervised segmentation. The prior knowledge on the number of classes and their statistical features allows generalizing the model so that the binary MRFs associated with the nodes can be adapted freely, together with their local parameters, to better fit the data. It allows to define a suitable likelihood term to be coupled with the TS-MRF prior so as to obtain a precise global model of the image. Given the complete model, a recursive supervised segmentation algorithm is easily defined.

Guo, 2005, described high-resolution remote sensing (HRRS) images contain a high level noise as well as possess different texture scales. As a result, existing image segmentation approaches are not suitable to HRRS imagery. They presented an unsupervised texture-based segmentation algorithm suitable for HRRS images, by extending the local binary pattern texture features and the lossless wavelet transform. Their experimental results using USGS 1ft ortho imagery show a significant improvement over the previously proposed LBP approach.

Lucieer, 2005, implemented a region growing segmentation procedure based on texture to extract spatial landform objects from a light detection and ranging (Lidar) digital surface model (DSM). The local binary pattern (LBP) operator, modeling texture, is integrated into a region growing segmentation algorithm to
identify landform objects. They apply a multi-scale LBP operator to describe texture at different scales. They illustrated that involves segmentation of coastal landform objects using a Lidar DSM of a coastal area in the UK. Landform objects can be identified with the combination of a multi-scale texture measure and a region growing segmentation. Uncertainty values provide useful information on transition zones or fuzzy boundaries between objects.

Brandt, 2005, stated that a Markov random field (MRF) based method using both contextual information and multi scale fuzzy line process for classifying remotely sensed imagery is described. The study area known as Elkhorn Slough is an important natural reserve park located in the central California coast, USA. Satellite imagery such as IKONOS panchromatic and multispectral data provides a convenient way for supporting the monitoring process around this area. Within the proposed classification mechanism, the panchromatic image, benefited from its high resolution, mainly serves for extracting multi scale line features by means of wavelet transform techniques. The resulting multi scale line features are merged through a fuzzy fusion process and then incorporated into the MRF model accompanied with multispectral imagery to perform contextual classification so as to restrict the over-smooth classification patterns and reduce the bias commonly contributed by those boundary pixels. The MRF model parameter is estimated based on the probability histogram analysis to those boundary pixels, and the
algorithm called maximum a posterior margin (MPM) is applied to search the solution. The results show that the proposed method, based on the MRF model with the multiscale fuzzy line process, successfully generates the patch-wise classification patterns, and simultaneously improved the accuracy and visual interpretation.

Xiangyun, 2005, stated that High spatial resolution satellite imagery has become an important source of information for geospatial applications. Automatic segmentation of high-resolution satellite imagery is useful for obtaining more timely and accurate information. The information from the three feature channels are adaptively estimated and integrated into a split-merge plus pixel-wise refinement framework. Segmentation is realized by comparing similarities between different features of sub-regions. The similarity measure is based on feature distributions. Without a priori knowledge of image content, the image can be segmented into different regions that frequently correspond to different land-use or other objects. Experimental results indicate that the method performs much better in terms of correctness and adaptation than using single feature or multiple features, but with constant weight for each feature. The method can potentially be applied within a broad range of image segmentation contexts.

Chen, 2006, stated that the watershed transformation is a well-known powerful tool for automated image segmentation. It is often computationally
expensive and can produce over-segmentation in situations of high gradient noise, quantity error and detailed texture. A method has been designed to overcome these inherent drawbacks. After pre-processing the imagery using a nonlinear filter in order to filter the noise, an optimized watershed transformation is applied to provide an initial segmentation result. A multi-scale, multi-characteristic merging algorithm is used to refine the segmentation. Preliminary results show promise in term of both segmentation quality and computational efficiency.

Maynard, 2006, used Ecological site descriptions (ESDs) based on soil maps, Landsat 7 ETM+ band values, and vegetation index data from 12 scenes as predictive variables in linear regression estimates of total biomass using field data from five Montana ranches. Band wise regression explained the most variability (53%) when ESDs were not included, followed by tasseled cap components (51%), the soil adjusted vegetation index (44%), and the normalized difference vegetation index (41%). ESDs improved the amount of variability explained to 66% for band wise regression and 65% using tasseled cap components.

Yu, 2006, evaluated the capability of the high spatial resolution airborne Digital Airborne Imaging System (DAIS) imagery for detailed vegetation classification at the alliance level with the aid of ancillary topographic data. Image objects as minimum classification units were generated through the Fractal Net Evolution Approach (FNEA) segmentation using e-cognition software. For each
object, 52 features were calculated including spectral features, textures, topographic features, and geometric features. After statistically ranking the importance of these features with the classification and regression tree algorithm (CART), the most effective features for classification were used to classify the vegetation. Due to the uneven sample size for each class, they chose a non-parametric (nearest neighbor) classifier. They built a hierarchical classification scheme and selected features for each of the broadest categories to carry out the detailed classification, which significantly improved the accuracy. Pixel-based maximum likelihood classification (MLC) with comparable features was used as a benchmark in evaluating their approach. The object based classification approach overcame the problem of salt and-pepper effects found in classification results from traditional pixel-based approaches. The method takes advantage of the rich amount of local spatial information present in the irregularly shaped objects in an image. This classification approach was successfully tested at Point Reyes National Seashore in Northern California to create a comprehensive vegetation inventory. Computer-assisted classification of high spatial resolution remotely sensed imagery has good potential to substitute or augment the present ground-based inventory of National Park lands.

Wanga, 2006, stated that High resolution (H-res) satellite sensors provide rich structural or spatial information of image objects. But few researchers study
the feature extraction method of H-res satellite images and its application. They presented a very simple yet efficient feature extraction method that considers the cross band relations of multi-spectral images. The texture feature of a region is the joint distributions of two texture labeled images that are calculated by its first two principal components (PCs) and the spectral feature is that of gray scale pixel values of its two PCs. The texture distributions operated by a rotation invariant form of local binary patterns (LBP) and spectral distributions are adaptively combined into coarse-to-fine segmentation based on integrated multiple features (SIMF). The performance of the feature extraction approach is evaluated with segmentation of H-res multi-spectral satellite imagery by the SIMF approach.

Chen and Zhao, 2006, implemented an optimized watershed transformation to provide an initial segmentation result. A multi-scale, multi-characteristic merging algorithm is used to refine the segmentation. Preliminary results show promise in term of both segmentation quality and computational efficiency.

Myeong, 2006, estimated vegetation in urban areas from satellite images for different purposes, such as carbon storage modeling.

Small, 2007, made comparison of vegetation occurrence in different cities.

Iovan, 2007, presented an automatic approach to derive urban vegetation combining NDVI (Normalized Difference Vegetation Index) and SI (Saturation Index) from a high resolution aerial image and a DSM with 20 cm resolution.
Matikainen, 2007, distinguished buildings, high vegetation and ground using an object-based image analysis (OBIA) approach (Benz, 2004).

Addink, 2007, stated that, object-oriented image analysis has been widely adopted by the remote sensing community. Much attention has been given to its application, while the fundamental issue of scale, here characterized by spatial object-definition, seems largely neglected. In the case of vegetation parameters like aboveground biomass and leaf area index (LAI), fundamental objects are individual trees or shrubs, each of which has a specific value. Their spatial extent does not match pixels in size and shape, nor does it fit the requirements of regional studies. Estimation of vegetation parameters consequently demands larger observation units, like vegetation patches, which are better represented by variably shaped objects than by square pixels. They analyzed optimal object definition for biomass and LAI.

Patel, 2007, conducted a field experiment to study the effect of vegetation cover on soil spectra and relationship of spectral indices with vegetation cover. Multi-date spectral measurements were carried out on twelve wheat fields. Five sets of measurements were taken during the growth period of wheat crop. Field reflectance data were collected in the range of 350 to 1800 nm using ASD spectro radiometer. Analysis of data was done to select narrow spectral bands for estimation of ground cover. The ratio of reflectance from vegetation covered soil
and reflectance from bare soil indicated that spectral reflectance at 670 and 710 nm are the most sensitive bands. Two bands in visible (670 and 560 nm), three bands in near infrared (710, 870 and 1100 nm) and three bands in middle infrared (1480, 1700 and 1800 nm) were found highly correlated with fractional cover. Vegetation indices developed using narrow band spectral data have been found to be better than those developed using broad-band data for estimation of ground cover.

Morton, 2008, implemented method for automatic radiometric normalization of multi- and hyper spectral imagery based on the invariance property of the Multivariate Alteration Detection (MAD) transformation and orthogonal linear regression is extended by using an iterative re-weighting scheme involving no-change probabilities. The procedure is first investigated with partly artificial data and then applied to multitemporal, multispectral satellite imagery. Substantial improvement over the previous method is obtained for scenes which exhibit a high proportion of change.

Keith, 2009, stated that the contemporary global climate crisis demands mitigation technologies to curb atmospheric greenhouse gas emissions, principally carbon dioxide (CO2). Geologic carbon sequestration (GCS) is a method by which point source CO2 emissions are purified and deposited in subsurface geologic formations for long-term storage. Accompanying this technology is the inherent responsibility to monitor these large-scale subsurface reservoirs for CO2 leaks to
ensure safety to local environments and inhabitants, as well as to alleviate global warming. Elevated CO2 levels in soil are known to cause anoxic conditions in plant roots, thereby interfering with plant respiration and inducing a stress response that could possibly be remotely sensed using aerial imagery. Airborne remote sensing technology has the potential to monitor large land areas at a relatively small cost compared to alternative methods.

Wuest, 2009, presented a modification of a region based approach for unsupervised segmentation of high resolution satellite imagery as a solution to segmentation of land use coverage in QuickBird multispectral 2.44 m imagery. This type of segmentation is important to a variety of applications such as land use classification and urban planning. All region based segmentation approaches require a method for representing image regions / segments and judging the similarity between two given image regions / segments. In the proposed modification, region description is provided through the integration of band ratios. Region similarity measures are performed using Fuzzy Logic. The Hierarchical Split Merge Refinement (HSMR) algorithmic framework for unsupervised image segmentation is the foundation for this modification. Test results demonstrate stable segmentation of land use areas across a variety of high resolution satellite images.
2.3 THRESHOLD TECHNIQUE FOR VEGETATION

Sader, 1992, developed a technique to visualize change using three dates of NDVI imagery concurrently and interpretation concepts of color additive theory. By simultaneously projecting each date of NDVI through the red, green, and blue (RGB) computer display write functions, major changes in NDVI (and, hence, green biomass) between dates will appear in combinations of the primary (RGB) or complimentary (yellow, magenta, cyan) colors. Knowing which date of NDVI is coupled with each display color, the analyst can visually interpret the magnitude and direction of biomass changes in the study area over the three dates. Automated classification can be performed on three or more dates of NDVI by unsupervised cluster analysis (Sader, 2001). Change and no-change categories are labeled and dated by interpreter analysis of the cluster statistical data and guided by visual interpretation of RGB-color composites.

Coppin, 1996, stated that an array of techniques are available to detect land-cover changes from multi-temporal remote sensing data sets. The goal of change detection is to discern those areas on digital images that depict change features of interest (e.g., forest clearing or land-cover land-use change) between two or more image dates. One method, image differencing, is simply the subtraction of the pixel digital values of an image recorded at one date from the corresponding pixel values of the second date. The histogram of the resulting image depicts a range of pixel
values from negative to positive numbers, where those clustered around zero represent no change and those at either tail represent reflectance changes from one image date to the next. This method has been documented widely in change-detection research (Singh, 1986; Muchoney, 1994; Macleod, 1998). Some investigators favor this method for its accuracy, simplicity in computation, and ease in interpretation.

Andreasen, 1997, segmented images by thresholding the median filtered histogram of the green chromaticity coordinates.

Meyer, 1998, segmented the plant and background by thresholding the excess green color index.

Tian, 1998, used a Bayes classifier to do plant and weed segmentation with robustness to lighting variations. In order to train the classifier, individual pixels were first classified in a partially-supervised fashion through cluster analysis. Then a Bayes classifier was trained so that a decision surface was defined to segment images with lighting conditions which are similar to those represented by the training image.

Rees, 1999 stated that the motivation behind the NDI is that it is similar to a vegetative index commonly used in agricultural remote sensing to estimate the amount of vegetation represented by a pixel.
Pérez, 2000, used a normalized difference index (NDI) along with morphological operations for plant segmentation.

Image differencing using band ratios or vegetation indices is another technique commonly employed for land-cover change detection. For example, the normalized difference vegetation index (NDVI) was developed for use in identifying health and vigor in vegetation, as well as for estimates of green biomass. The NDVI, the normalized difference of brightness values from the near infrared and visible red bands, has been found to be highly correlated with crown closure, leaf area index, and other vegetation parameters (Tucker, 1979, 1982, 2001, 2005; Sellers, 1985; Singh, 1986; Running, 1986). Lyon, 1998, compared seven vegetation indices to detect land-cover change in a Chiapas, Mexico study site. They reported that the NDVI was least affected by topographic factors and was the only index that showed histograms with normal distributions. Change in canopy cover or vegetation biomass can be detected by analyzing NDVI values from separate dates.

2.4 WAVELET FOR SEGMENTATION

Eldman, 2003, presented a method for combining multiband information for texture segmentation. It is based on an extension of fractal dimension analyze of texture for multi-channel and is rotational invariant The method allows texture
classification of thematic maps made from combination of ‘N’ wavelength bands. The method was validated using mosaic of natural textures, comparison with others implementations and real satellite images.

Wang, 2004, utilized the extracted features obtained by the wavelet transform (WT) rather than the original multispectral features of remote-sensing images for land cover classification. WT provides the spatial and spectral characteristics of a pixel along with its neighbors, and hence, this can be utilized for an improved classification. Four classifiers, namely, the fuzzy product aggregation reasoning rule (FPARR), fuzzy explicit, multilayered perceptron, and neuro-fuzzy (NF), are used for this purpose. The performance is tested on multispectral real and synthetic images. The performance of original and wavelet feature (WF)-based methods is compared. The WF-based methods have consistently yielded better results. Biorthogonal3.3 (Bior3.3) wavelet is found to be superior to other wavelets. FPARR along with the Bior3.3 wavelet outperformed all other methods. Results are evaluated using quantitative indexes like $\beta$ and Xie–Beni.

Zhang, 2005, stated that a wavelet feature based supervised scheme for fuzzy classification of land covers in multispectral remote sensing images is proposed. The proposed scheme is developed in the framework of wavelet-fuzzy hybridization, a soft computing approach. The wavelet features obtained from
wavelet transform on an image provides spatial and spectral characteristics (i.e., texture information) of pixels and hence can be utilized effectively for improving accuracy in classification, instead of using original spectral features. Four different fuzzy classifiers are considered for this purpose and evaluated using different wavelet features. Wavelet feature based fuzzy classifiers produced consistently better results compared to original spectral feature based methods on various images used in the present investigation. Further, the performance of the Biorthogonal3.3 (Bior3.3) wavelet is observed to be superior to other wavelets. This wavelet in combination with fuzzy product aggregation reasoning-rule outperformed all other methods. Potentiality of the proposed soft computing approach in isolating various land covers are evaluated both visually and quantitatively using indexes like measure of homogeneity and Xie-Beni measure of compactness and separability.

Saroj, 2007, utilized the extracted features obtained by the wavelet transform (WT) rather than the original multispectral features of remote-sensing images for land cover classification. WT provides the spatial and spectral characteristics of a pixel along with its neighbors, and hence, this can be utilized for an improved classification. Four classifiers, namely, the fuzzy product aggregation reasoning rule (FPARR), fuzzy explicit, multilayered perceptron, and neuro-fuzzy (NF), are used for this purpose. The performance is tested on multispectral real and synthetic
images. The performance of original and wavelet feature (WF)-based methods is compared. The WF-based methods have consistently yielded better results. Biorthogonal3.3 (Bior3.3) wavelet is found to be superior to other wavelets. FPARR along with the Bior3.3 wavelet outperformed all other methods. Results are evaluated using quantitative indexes like $\beta$ and Xie–Beni.

Chen and Pan, 2009, stated that landscapes are complex systems composed of a large number of heterogeneous components as well as explicit homogeneous regions that have similar spectral character on high-resolution remote sensing imagery. The multiscale analysis method is considered an effective way to study the remotely sensed images of complex landscape systems. There remain difficulties in identifying perfect image-objects that tally with the actual ground-object figures from their hierarchical presentation results. To overcome the shortcomings in applications of multiresolution segmentation, some concepts and a four-step approach are introduced for homogeneous image-object detection. The spectral mean distance and standard deviation of neighboring object candidates are used to distinguish between two adjacent candidates in one segmentation. The distinguishing value is used in composing the distinctive feature curve (DFC) with object candidate evolution in a multiresolution segmentation procedure. The scale order of pixels is built up by calculating a series of conditional relative extrema of each curve based on the class separability measure. This is helpful in determining
the various optimal scales for diverse ground-objects in image segmentation and the potential meaningful image-objects fitting the intrinsic scale of the dominant landscape objects. Finally, the feasibility is analyzed on the assumption that the homogeneous regions obey a Gaussian distribution. Satisfactory results were obtained in applications to high-resolution remote sensing imageries of anthropo-directed areas.

2.5 NORMALIZED DIFFERENCE VEGETATION INDEX

Crippen, 1990, stated that the near-infrared (NIR) versus red “infrared percentage vegetation index,” \( \frac{\text{NIR}}{\text{NIR} + \text{Red}} \), is functionally and linearly equivalent to the normalized difference vegetation index, \( \frac{\text{NIR}-\text{Red}}{\text{NIR} + \text{Red}} \). It is both computationally faster and never negative.

Barnes and Baker, 2000, described soil maps derived from random or grid-based sampling schemes that are often an important part of precision crop management. Sampling and soil analysis to derive such maps require a large investment of both time and money. Aerial photos have been used as a soil mapping aid for years. Studies have shown that such approach can be useful for defining management units in precision farming, but these studies are often limited to a single field, not an entire farming operation. In this study, multispectral airborne green, red, near infrared (NIR), and thermal and satellite (SPOT and
Landsat TM data were used to derive soil textural class maps for 350 ha of a 770 ha research and demonstration farm in Maricopa, Arizona. These maps were compared to soil textural analysis results from samples in the top 30 cm of the soil profile at an approximate grid spacing of 120 m. Differences in tillage, residue, soil moisture between fields limited the accuracy of spectral classification procedures when applied across the entire study area. Using spectral classification procedures on a field-by-field basis, it was possible to map areas of soil textural class with reasonable accuracy. These results are specific to the study area and may not apply at other locations due to the numerous factors that can contribute to a soil's spectral response. Classification procedures were also used with vegetation present over the study area later in the season.

Moleele, 2001, stated that degraded areas include those suffering from bush encroachment, believed to result from heavy cattle grazing over a number of years. Certain bush encroachment species have been found to be relatively nutrient-rich. The consider the extent to which a series of quantified layers through mainly bush encroachment canopies can be identified using conventional and newly derived vegetation indexes and transforms based on Thematic Mapper (TM) imagery. Field work involved the stratification of green biomass into the herbaceous cover layer; 0.3-1.5 m browse layer; 1.5-2.5 m browse layer; and >2.5 m browse layer. Biomass measurements from these layers were statistically associated with conventional
vegetation indices and transforms such as the Normalized Difference Vegetation Index (NDVI), brightness and greenness values, and relatively newly derived darkening indices involving the mid-infrared bands. When green biomass and transformed pixel data were averaged per classified vegetation unit, weak negative correlations emerged between grass biomass and the transformed pixel data and no significant correlations developed with the woody biomass layers. When point data were used in the analyses, results showed that most indices and the brightness transform were significantly correlated with the lower browse layer. Only the darkening indices and brightness function were sensitive to the browse layers individually and the browse plus grass layers. They showed the limitations of conventional indices such as the NDVI in terms of browse and herbaceous layer assessment.

Johnson, 2002, described vineyard leaf area as a key determinant of grape characteristics and wine quality. In the agriculture, available ground-based leaf area measurements employed by growers are not well suited to larger area mapping. IKONOS high spatial resolution, multispectral satellite imagery was used to map leaf area throughout two commercial wine grape vineyards in California's North Coast growing region. The imagery was collected near harvest during the 2000 growing season, converted to at-sensor radiance, geo-referenced and transformed to normalized difference vegetation index (NDVI) on a per pixel
basis. Measurements at 24 ground calibration sites were used to convert NDVI maps to leaf area index (LAI; m² leaf area m⁻² ground area); planting density was then used to express leaf area on a per vine basis (LAv). Image-based LAv was significantly correlated with ground-based LAv estimates developed at 23 validation sites (r²=0.72; P<0.001). Despite challenges posed by the discontinuous nature of vineyard canopies and architectural differences imposed by shoot positioning trellis systems, remote sensing appears to offer a basis for mapping vineyard leaf area in low LAI vineyards. Such maps can potentially be used to parameterize plant growth models or provide decision support for irrigation and canopy management.

Arnon Karnieli, 2003, described natural vegetation in semi-arid regions characterized by three ground features, in addition to bare surfaces—biological soil crusts, annuals, and perennials. These three elements have distinguishable phenological cycles that can be detected by spectral ground measurements and by calculating the weighted normalized difference vegetation index (NDVI). The latter is the product of the derived NDVI of each ground feature and its respective areal cover. Each phenological cycle has the same basic elements oscillation from null (or low) to full photosynthetic status and back to a stage of senescence. They vary in phase. The biological soil crusts show the earliest and highest weighted NDVI peak during the rainy season, and their weighted NDVI signal lasts longer
than that of the annuals. The annuals are dominant in late winter and early spring while the perennials predominate in late spring and during the summer.

Nichol, 2005, stated that very high resolution (VHR) satellite remote sensing systems are capable of providing imagery with similar spatial detail to aerial photography, but with superior spectral information. They investigate the hypothesis that it should be possible to use multispectral IKONOS images to quantify urban vegetation, obtaining similar accuracy to that achieved from false color aerial photographs. Two parameters, vegetation cover and vegetation density are used to represent biomass in the study area (Kowloon, Hong Kong), for which data is collected for 41 field quadrats. Regression equations relating the field measurements of vegetation density to image wavebands obtained similar high correlations for both image types and lower but significant correlations for vegetation cover. Vegetation density is a quantifiable measure of vegetation in multiple layers above ground, representing the total amount of biomass and is thus well able to indicate the diverse structural types of vegetation found in urban areas. It can be accurately measured using the IKONOS green/red ratio (Chlorophyll Index). The superiority of the latter to the more commonly used Normalized Difference Vegetation Index (NDVI), is attributed to the suboptimal timing of the imagery during the dry season, and its greater sensitivity to multiple layering within the vegetation canopy. A time and cost comparison between the two image
types suggests that the use of IKONOS images is much more cost effective than aerial photographs for urban vegetation monitoring.

Joshua, 2010, described practical geologic CO2 sequestration that will require long-term monitoring for detection of possible leakage back into the atmosphere. One potential monitoring method is multi-spectral imaging of vegetation reflectance to detect leakage through CO2-induced plant stress. A multi-spectral imaging system was used to simultaneously record green, red, and near-infrared (NIR) images with a real-time reflectance calibration from a 3-m tall platform, viewing vegetation near shallow subsurface CO2 releases during summers 2007 and 2008 at the Zero Emissions Research and Technology field site in Bozeman, Montana. Regression analysis of the band reflectances and the Normalized Difference Vegetation Index with time shows significant correlation with distance from the CO2 well, indicating the viability of this method to monitor for CO2 leakage. The 2007 data show rapid plant vigor degradation at high CO2 levels next to the well and slight nourishment at lower, but above-background CO2 concentrations. Results from the second year also show that the stress response of vegetation is strongly linked to the CO2 sink–source relationship and vegetation density. The data also show short-term effects of rain and hail. The real-time calibrated imaging system successfully obtained data in an autonomous mode during all sky and daytime illumination conditions.
2.6 VEGETATION INDICES (VI) THRESHOLDS

Lloyd, 1990, and Fischer, 1994, introduced threshold value at a certain level or amplitude, (e.g. 0.09, 0.099, 0.17 or the range of values from 0.1 to 0.35). The SOS is then determined as the day of the year (DOY) that the NDVI crosses the threshold in upward direction; likewise, the EOS is determined as the DOY that the NDVI crosses the same threshold in downward direction. To determine at which DOY the threshold is reached, the time series is filtered to eliminate remaining cloud cover and interpolated to a daily dataset. NDVI threshold for the SOS can vary from 0.08 to 0.40 (Reed, 2003). In the case of one fixed threshold for a larger study area, the thresholds may not measure the same phenological event and the approach becomes inconsistent. There is also an implicit simplifying assumption that crossing the threshold in one direction is functionally equivalent to crossing it in the other. Yet, there is little reason to assume that these systems do not exhibit hysteresis: the timing and rate of greening across the landscape is independent of and different from the timing and rate of senescence across the same landscape.

2.7 THRESHOLDS BASED ON LONG-TERM MEAN VI

Karlsen (2007) introduced a variation in VI threshold. They calculated a 21-year mean value for each pixel, for Fennoscandia only incorporating pixels with positive values of NDVI. The SOS, for each year, was then considered to be the
date when the NDVI value passed the long-term mean value. This threshold was chosen because it showed the highest correlation with the onset of leafing in birch as observed at ground level. The EOS was determined by the date when NDVI passed below 70% of the 21-year mean. Peak timing was determined as the date with maximum NDVI.

Piao, 2006, stated that based on the NDVI ratio the timings of the greatest increase and decrease are determined as well as their corresponding NDVI values. In the last step, the SOS is determined for each year as the day that a smoothed curve passes the NDVI threshold.

Philippon, 2007, developed where the SOS and the EOS were determined as the date of the 10-day period right before the one where NDVI passes the annual mean level upward (SOS) or downward (EOS).

2.8 THRESHOLDS BASED ON A BASELINE YEAR

Shabanov, 2002, determined the SOS and the EOS by comparing years among each other. First, they designated the NDVI values on DOY 120 and DOY 270 as determining the SOS and the EOS thresholds for a baseline year. The median year in the time series was selected as the baseline year. The DOYs at which the NDVI thresholds were reached in each other year determined the SOS and the EOS for that year.
2.9 THRESHOLDS BASED ON NDVI RATIOS

White, 1997, determined the SOS threshold as the 50% point of the NDVI Curve. The NDVI ratio ranges from 0 to 1. NDVI is the daily NDVI, NDVI max and NDVI min are the annual maximum and minimum of the NDVI curve. This ratio method is similar to the Vegetation Condition Index. In White’s et al. case the minimum and maximum NDVI are determined annually. The SOS was determined as the day that the NDVI ratio reached 50% in upward direction. The EOS was determined as the day that the NDVI ratio reached 50% in downward direction. The justification offered for the choice of the 50% threshold is that the increase in greenness is believed to be most rapid at this threshold and if only one phenological date is to be used, then the period of most rapid growth is more important than the first leaf occurrence or budburst. Furthermore, lower vegetation signals are more easily confounded with soil reflectance. A 50% point states that a certain pixel (or study region) has attained 50% of its maximum greenness. The transformation to NDVI ratio is attractive because it allows for a consistent determination of the 50% point of the vegetation, independent of the geographic location and land cover of the observed study area. Furthermore, the NDVI ratio retains high frequency vegetation changes that can be lost if data are first smoothed.
White, 2006, opted for the transformation of NDVI to NDVI\textit{ratio} based on long-term minimum and maximum values. The advantage of long-term average minimum and maximum NDVI values is that they are usually not strongly influenced by outliers. The disadvantage is that the minimum and maximum NDVI might not be stable through time and could change significantly, for example due to disturbance processes, or other changes in the landscape.

2.10 **THRESHOLD BASED ON NDWI**

Delbart, 2005, stated that the NDVI is not the optimal index when measuring the SOS and the EOS in areas experiencing snow cover, because the onset of the NDVI increase corresponds with the beginning of snowmelt. Thus, trends in the SOS might not be due to actual earlier vegetation onset but rather due to reduction in the snow cover extent. The Normalized Difference Water Index (NDWI), which is based on reflectances in the Near Infra-Red (NIR) and Short Wave Infra-Red (SWIR) regions, may be more efficient in estimating the start of season for areas where extensive snow cover might be expected.

2.11 **FUZZY LOGIC FOR SEGMENTATION**

Cannon, 1986, developed a segmentation procedure that utilizes a clustering algorithm based upon fuzzy set theory. The procedure operates in a nonparametric
unsupervised mode. The feasibility of the methodology is demonstrated by segmenting a six-band Landsat-4 digital image with 324 scan lines and 392 pixels per scan line. For this image, 100-percent ground cover information is available for estimating the quality of segmentation. About 80 percent of the imaged area contains corn and soybean fields near the peak of their growing season. The remaining 20 percent of the image contains 12 different types of ground cover classes that appear in regions of different sizes and shapes. The segmentation method uses the fuzzy c-means algorithm in two stages. The large number of clusters resulting from this segmentation process is then merged by use of a similarity measure on the cluster centers. Results are presented to show that this two-stage process leads to separation of corn and soybean, and of several minor classes that would otherwise be overwhelmed in any practical one-stage clustering.

Caillol, 1993, used fuzzy random fields for statistical unsupervised image segmentation. A fuzzy model containing a hard component, which describes pure pixels, and a fuzzy component which describes mixed pixels, is introduced. A procedure for simulating, a fuzzy field based on a Gibbs sampler step followed by a second step involving white or correlated Gaussian noises is given. Four different blind segmentation methods are performed: the conditional expectation, two variants of the maximum likelihood, and the least squares approach. The parameters required are estimated by the stochastic estimation maximization
(SEM) algorithm, a stochastic variant of the expectation maximization (EM) algorithm. These fuzzy segmentation methods are compared with a classical hard segmentation method, without taking the fuzzy class into account. The study shows that the fuzzy SEM algorithm provides reliable estimators.

Melgani, 2000, stated that fuzzy classification has become of great interest because of its capacity to provide more useful information for geographic information systems. They describe an explicit fuzzy supervised classification method which consists of three steps. The explicit fuzzyfication is the first step where the pixel is transformed into a matrix of membership degrees representing the fuzzy inputs of the process. In the second step, MIN fuzzy reasoning rules followed by a rescaling operation are applied to deduce the fuzzy outputs, or in other words, the fuzzy classification of the pixel. A defuzzyfication step is carried out to produce a hard classification. The classification results on Landsat TM data demonstrate the promising performances of the method and comparatively short classification time.

Pal, 2000, described effectiveness of various fuzzy thresholding techniques on remotely sensed (IRS and SPOT) images. A quantitative index for image segmentation using the concept of homogeneity within regions is defined. Results are compared with those of probabilistic thresholding, and fuzzy c-means and hard c-means clustering algorithms, both in terms of index value (quantitatively) and
structural details (qualitatively). Fuzzy set theoretic algorithms are seen to be superior to their respective non-fuzzy counterparts. Among all the techniques, fuzzy correlation, followed by fuzzy entropy, performed better for extracting the structures. Fuzzy geometry based thresholding algorithms produced a single stable threshold for a wide range of membership variation.

Shackelford, 2003, investigated the usefulness of high-resolution multispectral satellite imagery for classification of urban and suburban areas and present a fuzzy logic methodology to improve classification accuracy. Panchromatic and multispectral IKONOS image datasets are analyzed for two urban locations in this study. Both multispectral and pan-sharpened multispectral images are first classified using a traditional maximum-likelihood approach. Maximum-likelihood classification accuracies between 79% to 87% were achieved with significant misclassification error between the spectrally similar Road and Building urban land cover types. A number of different texture measures were investigated, and a length–width contextual measure is developed. These spatial measures were used to increase the discrimination between spectrally similar classes, thereby yielding higher accuracy urban land cover maps. A hierarchical fuzzy classification approach that makes use of both spectral and spatial information is presented. This technique is shown to increase the discrimination between spectrally similar urban land cover classes and results in classification
accuracies that are 8% to 11% larger than those from the traditional maximum-likelihood approach.

Benz, 2004, described remote sensing from airborne and spaceborne platforms that provide valuable data for mapping, environmental monitoring, disaster management and civil and military intelligence. To explore the full value of these data, the appropriate information has to be extracted and presented in standard format to import it into geo-information systems and thus allow efficient decision processes. The object-oriented approach can contribute to powerful automatic and semiautomatic analysis for most remote sensing applications. Synergetic use to pixel-based or statistical signal processing methods explores the rich information contents. They explain principal strategies of object-oriented analysis and discuss how the combination with fuzzy methods allows implementing expert knowledge and describe a representative example for the proposed workflow from remote sensing imagery to GIS. The strategies are demonstrated using the first object oriented image analysis software on the market, e-Cognition, which provides an appropriate link between remote sensing imagery and GIS.

Fan, 2009, implemented a remote sensing image segmentation procedure that utilizes a single point iterative weighted fuzzy C-means clustering algorithm. The method solves the fuzzy C-means algorithm’s problem that the clustering
quality is greatly affected by the data distributing and the stochastic initializing the centrals of clustering. After the probability statistics of original data, the weights of data attribute are designed to adjust original samples to the uniform distribution, and added in the process of cyclic iteration, which could be suitable for the character of fuzzy C-means algorithm so as to improve the precision. Appropriate initial clustering centers adjacent to the actual final clustering centers can be found by the proposed single point adjustment method, which could promote the convergence speed of the overall iterative process and drastically reduce the calculation time. The modified algorithm is updated from multidimensional data analysis to color images clustering. With the comparison experiments of the UCI data sets, public Berkeley segmentation dataset and the actual remote sensing data, the real validity of proposed algorithm is proved.

Chengfan, 2010, described the extraction of urban vegetation information is a focal study point of the city remote sensing. To address the limitations of urban regional scale and the features of extraction of urban vegetation from high resolution satellite image based on object-oriented approach, they presented a new approach to use segmentation of high-resolution remote sensing image and the fuzzy classification technique based on multi-thresholds method, and then forests, thin grassland, thick grassland were extracted accurately. The object-based method performances were assessed using Kappa coefficients and overall accuracy. High
accuracy (93.72%) and overall Kappa coefficient (0.8236) were achieved by this new method using Quickbird image; the experimental results demonstrate the new approach is simple for computation in urban regional scale.

2.12 SUMMARY

This chapter presents vegetation identification using conventional methods, fuzzy logic, wavelet and NDVI. Chapter 3 presents data generation for training the network system in identifying the vegetation.