CHAPTER 4

METHODOLOGY

4.1 STUDY AREA

The selected study area is part of an institutional area of Anna University, Guindy campus (Figure 4.1), about 50 hectare comprises of building, road, open area (includes playground) and vegetation. Most of the buildings are multi story structures (> G+1 to G+3) as well as large size of roof type (workshops). The common practice of building and its roof constructions are reinforced concrete floors, tiled roof and asbestos / cement sheets. In some of the old concrete roof top has light green tone because of the presence of the stagnated rainwater (fungus) and in some of the roof structure has tar coating on a tiled roof. The road is made-up of tar and major portion of road is coved by the vegetation. The study area has a large open area (includes play ground), where the preparation of football ground is in progress, which is shown in different tone. Vegetation covers major portion of the area (> 60%), of which has different tones such as light tone and dark tone. The spectral profile of the selected few location (Figure 4.2) such as, building (concrete, AC sheet, Tiles), open area (playfield, sand), vegetation (dark tone, light tone and grass) is shown in fig 4.3 of the spectral profile. From Figure 4.3 it’s inferred that building roof and parapet wall have produced high reflectance in band green and red. Building old tiles (tar coated) have very low reflectance at Infrared band. Vegetation have high reflectance in Infrared band and Open area (soil) have high reflectance almost in all bands.
Figure 4.1 False Color Composition of Quickbird data for Anna University campus

Figure 4.2 Spectral profile locations in the study area
Figure 4.3 Spectral profile of the selected location (feature)

The study area is flat to gentle slope in terrain, but elevation difference between the ground level and building tops, provides an ample opportunities for the delineation of feature.

In this regard, the site provides a good opportunity to extract the urban features and it can be one of the model area, where it contains or comprises of all urban features. So that the object based approach ensembles for urban feature extraction rather than pixel based approach. The preference for the selection of this study area is, due to the availability of aerial photographs for the creation of Digital Surface Model (DSM) to separate buildings from other features.

4.2 METHODOLOGY

The overall methodology adopted for the study is presented in the form of flowchart and given below in the Figure 4.4.
Figure 4.4 Overall methodology adopted for the study
4.3 DATASET

The preparation of the dataset for this study involves the preparation of merged (PAN + MSS) Quickbird data and Digital Surface Model generated from available aerial photographs because the stereo satellite data was not available. The above steps are described below.

4.3.1 Higher Resolution Satellite data (QUICKBIRD)

The high resolution satellite data, (ie) Quick bird satellite data acquired from Digital Globe, which is having a spatial resolution of 0.60m of PAN and 2.4 m of MSS has been used. The products were merged using PCA method, to produce the new image with the spatial resolution of the PAN and spectral resolution of the Multi Spectral Sensor. While doing so, each band, gets sharpened, maintains its original bit range, number of bands as well as spectral values.

Table 4.1 Specification of Quickbird image used in this study

<table>
<thead>
<tr>
<th>Specification</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquisition date</td>
<td>15-02-2005</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>2.40 m Multi – Spectral Bands</td>
</tr>
<tr>
<td></td>
<td>0.60 m panchromatic</td>
</tr>
<tr>
<td>Spectral Wavebands (µm)</td>
<td>0.45 – 0.52</td>
</tr>
<tr>
<td></td>
<td>0.52 – 0.60</td>
</tr>
<tr>
<td></td>
<td>0.63 - 0.69</td>
</tr>
<tr>
<td></td>
<td>0.76 – 0.90</td>
</tr>
<tr>
<td>Map projection</td>
<td>UTM</td>
</tr>
<tr>
<td>View Angles</td>
<td>Nadir</td>
</tr>
<tr>
<td>Swath Width</td>
<td>16.5 KM.</td>
</tr>
</tbody>
</table>
4.3.2 Creation of Digital Elevation Model

a) Aerial Photographs

Because of the non-availability of stereo Quickbird satellite data, the DSM was generated from the available aerial photographs, using the ground control points, collected through GPS. The Black and White aerial photographs in the scale of 1:6000 of the study area were chosen. The photographs were scanned at the resolution of 30μm using the high resolution scanner, to process the aerial photographs in softcopy photogrammetry software. Using the camera calibration parameters the Interior Orientation was carried out using the above software.

b) Ground Control Point (GCP)

The GCP was collected for the study area using the Differential Global Positioning System (DGPS). The points were collected, over the buildings.

c) Creation of Digital Surface Model (DSM)

After the relative orientation and absolute orientation process, the DSM was created at the accuracy of 0.36m grid cell resolution and 0.2m of vertical accuracy. Then using the interactive editing the trees and other features were edited to the ground level and the DSM for buildings were created. Then the DSM was converted in to TIN and exported into the TIFF format, which is the collateral data for the imagery and presented in Figure 4.5. Different color indicates the elevation difference of various classes.
4.4 URBAN LANDUSE CLASSES

The National Urban Information system (NUIS) of Government of India has developed urban landuse classification GIS data structure (Given in Annex 1.) for the creation of spatial database for entire country from remote sensing as well as from the recorded data. This includes built-up, agriculture,
forest, wasteland, and water bodies in the level 1 and builtup of rural, urban, in level 2 and residential commercial vacant, vegetation, and transportation information in level3. Based on the above urban landuse classification standard, literatures and possibilities and limitation of the remote sensing data following class were taken up for the urban feature extraction.

Table 4.2. Urban landuse classes

<table>
<thead>
<tr>
<th>Sl.No</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
<th>Level 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Built-up</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1</td>
<td>Builtup_Urb an feature</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.1</td>
<td>Building</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.1.1</td>
<td>Cement Concrete</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.1.2</td>
<td>Building –Asbestos sheet / tar coated roof</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.2.</td>
<td>Open Area (Vacant Land)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.2.1</td>
<td>Open Area - Sand</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.2.2</td>
<td>Open Area – Soil</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.3</td>
<td>Road</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.3.1</td>
<td>Road</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.3.2</td>
<td>Railway</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.4</td>
<td>Vegetation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.4.1</td>
<td>Light tone of grass</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.4.2</td>
<td>Dark tone of grass</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1.5</td>
<td>Waterbodies</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
4.5 OBJECT ORIENTED IMAGE ANALYSIS

The image segmentation and classification are the major tasks in object oriented image analysis. The following step describes those processes.

4.5.1 Image Segmentation

It is a bottom up region merging technique, starting with one pixel of an object and in subsequent steps the smaller objects are merged into larger ones (more pixels).

The prepared dataset (sec 4.2.1) such as merged satellite data and Digital Surface Model (DSM) is taken as an input layer for the segmentation process. DSM has been taken into account of height information during the segmentation process. Using the region growing algorithm, the local homogeneity criteria describing the similarity of adjacent image objects in terms of size, shape and spectral parameter the pixel gets grouped into the object formed (Baatz and Schape 2000 and Schieve 2002)

a) Creation of an Object

In subsequent steps, the smaller image objects are merged into bigger ones by pair wise clustering process. The underlying optimization procedure minimizes the weighted heterogeneity \( n \times h \) of resulting image objects, where \( n \) is the size of a segment and \( h \) is the parameter of heterogeneity. In each step, that pair of adjacent image objects are merged which results in the smallest growth of the defined heterogeneity. If the smallest growth exceeds the threshold defined by the scale parameter, the process stops. A strong and experienced evaluator of segmentation technique is the human eye / brain combination.
b) Segmentation Parameters

There are five parameters which are having functions for defining the heterogeneity while doing the segmentation in the object oriented image processing. Such parameters are Scale, Color, Shape, Compactness and Smoothness (Baatz and Schape 1999), which is explained in the section 3.4.3.

The region growing algorithm extract the buildings, by considering the different range of elevation values, which are indicated by different color values. During this process all the objects which are having a height difference more than the threshold value, get segmented.

c) Segmentation parameter - optimization - fuzzy approach

Fuzzy logic is used to deal with vague and imprecise input in a manner similar to human decision making (Kaehler 1998). The concept of partial truth-truth values between completely true and completely false. Rather than regarding fuzzy theory as a single theory one should regard the process of fuzzification as a methodology to generalize any specific theory from a crisp (discrete) to a continuous (fuzzy) form (Bellman 1975). In geographical phenomena, many of which do not conform to the sharp boundaries imposed by Boolean logic (Altman 1994 and Banai 1993).

Fuzzy logic allows for more flexible combinations of different parameters which can be used to find the best segmentation parameters for the feature extraction. All methods are in the empirical models, with the rules, weights or fuzzy membership values are being assigned subjectively using knowledge of the process involved to estimate the relative importance of the input maps.
These fuzzy membership values represent the importance of the weighted values of the each parameter at different levels. Membership values are calculated for each parameter and in turns used to optimize the segmentation parameters. (Carter 1996).

d) **Fuzzy membership value to each parameter**

Fuzzy membership functions for the segmentation parameters are calculated based on the optimized segmentation parameter value. If ‘x’ is the attribute value of different features of a map, \( \mu(x) \) is the fuzzy membership function. Every value of \( x \) is associated with a value of \( \mu(x) \), and the ordered pairs \([x, \mu(x)]\) are known collectively as a fuzzy set.

Fuzzy membership values must lie in the range of \((0,1)\) but there are no practical constraints on the choice of fuzzy membership values. The presence of the various classes or features of a map may be expressed in terms of fuzzy memberships of different sets, storing them as attribute table (Carter 1996 and Westen 1999).

The segmentation parameters are optimized by trial and error process and the values are taken as input for the development of fuzzy membership function which inturn, will be useful for the development of automation. The imprecise nature of segmentation and selection of its associated parameters make fuzzy logic well suited to the task of segmentation parameter determination.
4.5.2 Image Classification

a. Object Classification

Classification means assigning the number of objects to a certain class based on the typical properties or conditions, the classes have. Then the object becomes assigned (classified) to whether they have or they have not met these properties.

b. Knowledge based classification – Fuzzy Approach

The objects are extracted or classified by means of describing the object by several features. The features which are embedded in the image object hierarchies are tone, shape, texture, hierarchy and thematic attributes. The class related features are in relation to the neighbor objects and its relation to sub-objects and super objects etc.

The tone feature is described by the following features, such as mean, brightness, Max difference and Standard deviation (Baatz and Schape 2000).

c. Tone Features

i) Mean

Layer mean value $\overline{C_l}$ calculated from the layer values $C_{li}$ of all $n$ pixels forming an image object.

$$\overline{C_l} = \sum_{i=1}^{n} C_{li}$$  \hspace{1cm} (4.1)
ii) **Brightness** ($b$)

Sum of the mean values of the layers containing spectral information divided by their quantity computed for an image object ($n_L$) (mean value of the spectral mean values of an image object).

$$b = \frac{1}{n_L} \sum_{i=1}^{n_L} \bar{C}_i$$  \hspace{1cm} (4.2)

iii) **Standard deviation** ($\sigma_L$)

Standard deviation calculated from the layer values of all $n$ pixels forming an image object.

$$\sigma_L = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (\bar{C}_i - \bar{C}_L)^2}$$  \hspace{1cm} (4.3)

iv) **Ratio** ($r_L$)

$r_L$ is the ratio of layer $L$ is the mean value of the layer $L$ of an image object divided by the sum of all spectral layer mean values of sub object(SO). Again, only layers containing spectral information can be used to achieve reasonable results.

$$r_L = \frac{\bar{C}_L, Object}{\bar{C}_L, SO}$$  \hspace{1cm} (4.4)
v) **Mean difference to neighbors** \((\Delta CL)\)

For each neighboring object the layer mean difference is computed and weighted with regard to the length of the border between the objects (if they are direct neighbors, feature distance = 0) or the area covered by the neighbor objects (if neighborhood is defined within a certain perimeter (in pixels) around the image object in question feature distance > 0).

The mean difference to direct neighbors is calculated as follows:

\[
\Delta C_L = \frac{1}{l} \sum_{i=1}^{n} l_{Si}(\bar{C}_L - \bar{C}_{Li}) \tag{4.5}
\]

where

- \(l\) - Border length of the image object of concern
- \(l_{Si}\) - border length shared with direct neighbor
- \(\bar{C}_L\) - layer mean value of the image object of concern
- \(\bar{C}_{Li}\) - layer mean value of neighbor \(i\)
- \(n\) - Quantity of neighbors

**d. Generic shape features**

i. **Area**

In non-georeferenced data, the area of a single pixel is 1. Consequently, the area of an image object is the number of pixels forming it. If the image data is georeferenced, the area of an image object is the true area covered by one pixel times the number of pixels forming the image objects.

Length/width ratio(\(\gamma\)).
There are two ways to compute the length/width ratio of an image object.

1. The ratio of length/width \((l/w)\) is identical to the ratio of the eigen values of the covariance matrix \((eig(S))\) with the larger eigen value \((eig(S))\) being the numerator of the fraction.

\[
\gamma = \frac{l}{w} = \frac{eig_1(S)}{eig_2(S)}, eig_1(S) > eig_2(S)
\]  

(4.6)

where, \(\gamma\) ratio of \(l/w\)

2. The ratio length/width can also be approximated using the bounding box.

\[
\gamma = \frac{l}{w} = \frac{a^2 + ((1 - f)b)^2}{A}
\]  

(4.7)

where

- \(a\) – Length of bounding box
- \(b\) – Width of bounding box
- \(f\) – Degree of filling.
- \(A\) – Area covered by image object

ii) **Length \((l)\)**

The length can also be computed using the length-to-width ratio derived from a bounding box approximation. It is approximated as follows:

\[
l = \sqrt{A \gamma}
\]  

(4.8)
Another possibility which works better for curved image objects is to calculate the length of an image object based on its sub-objects.

iii) **Width (w)**

Also the width of an image object is approximated using the length-to-width ratio. In eCognition the width is approximated as follows:

\[ w = \sqrt{\frac{A}{y}} \]  

(4.9)

Again, for curved image objects the use of sub-objects for the calculation is the superior method.

iv) **Border length (e)**

The border length \( e \) of an image object is defined as the sum of edges of the image object that are shared with other image objects or are situated on the edge of the entire scene. In non-georeferenced data the length of a pixel edge is 1.

v) **Shape index (S)**

Mathematically the shape index is the border length \( e \) of the image object divided by four times the square root of its area \( A \). Use the shape index \( S \) to describe the smoothness of the image object borders. The more fractal an image object appears, the higher its shape index.

\[ S = \frac{e}{4\sqrt{A}} \]  

(4.10)
vi) **Density** (\(d\))

The density \(d\) can be expressed by the area covered by the image object divided by its radius. Where \(n\) is the number of pixels forming the image object and the radius is approximated using the covariance matrix:

\[
d = \frac{\sqrt{n}}{1 + \sqrt{\text{Var}(X) + \text{Var}(Y)}}
\]  

(4.11)

vii) **Asymmetry** (\(k\))

The lengthier an image object, the more asymmetric it is. For an image object, an ellipse is approximated which can be expressed by the ratio of the lengths of minor and major axes of this ellipse. The feature value increases with the asymmetry.

\[
k = 1 - \frac{n}{m}. \quad (4.12)
\]

where

\(n\) – Length of minor axis
\(m\) – Length of major axis

viii) **Compactness** (\(c\))

In eCognition the compactness \(c\), used as a feature, is calculated by the product of the length \(m\) and the width ‘\(n\)’ of the corresponding object and divided by the number of its inner pixels \(A\).
\[ c = \frac{n.m}{a} \]  

(4.13)

e. **Line features based on sub-objects**

The information for classification of an object can also be derived from information provided by its sub-objects. A specific method is to produce compact sub-objects for the purpose of line analysis.

i) **Line so: length**

Of the image object of concern, the object center is known, among all the sub-objects those two objects are detected which are situated furthest from this center point. From one end point to the other, the distances between the center points of adjacent sub-objects are added together (red lines). The radii of the end objects are also considered to complete the approximation (green) which is shown in Figure 4.4.

\[ l_{so} = r_1 + r_2 + \sum_{i=1}^{n} d_i \cdot \]  

(4.14)

\[ \gamma_{so} = \frac{l_{so}}{w_{so}} = \frac{l_{2so}^2}{A} \]  

(4.15)
The grey level co-occurrence matrix (GLCM) is a tabulation of how often different combinations of pixel grey levels occur in an image. A different co-occurrence matrix exists for each spatial relationship. To receive directional invariance all 4 directions ($0^\circ$, $45^\circ$, $90^\circ$, $135^\circ$) are summed before texture calculation. An angle of $0^\circ$ represents the vertical direction, an angle of $90^\circ$ the horizontal direction.

i) Homogeneity

If the image is locally homogeneous, the value is high if GLCM concentrates along the diagonal. "Homogeneity" weights the values by the inverse of the “Contrast” weight with weights, decreasing exponentially according to their distance to the diagonal.

\[
\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}.
\]  

(4.16)

where $P_{i,j}$ = image pixel of i,j
ii) **Contrast**

“Contrast” is the opposite of “Homogeneity”. It is a measure of the amount of local variation in the Image. It increases exponentially as \((i-j)\) increases.

\[
\sum_{i,j=0}^{N-1} P_{ij}(i - j)^2
\]

(4.17)

iii) **Dissimilarity**

Similar to “Contrast”, but increases linearly. This will be high if the local region has a high contrast.

\[
\sum_{i,j=0}^{N-1} P_{ij} |i - j|
\]

(4.18)

iv) **Entropy**

The value for “Entropy” is high, if the elements of GLCM are distributed equally. It is low if the elements are close to either 0 or 1. Since \(\ln(0)\) is undefined, it is assumed that \(0 * \ln(0) = 0\).

\[
\sum_{i,j=0}^{N-1} P_{ij}(-\ln P_{ij})
\]

(4.19)
v) **Mean**

The "GLCM Mean" is the average expressed in terms of the GLCM. The pixel value is not weighted by its frequency of occurrence itself, but by the frequency of its occurrence in combination with a certain neighbor pixel value.

\[
\mu_{i,j} = \frac{\sum_{i,j=0}^{N-1} P_{i,j}}{N^2}. \quad (4.20)
\]

vi) **Standard Deviation**

\[
\sigma_{i,j}^2 = \sum_{i,j=0}^{N-1} P_{i,j} (i,j - \mu_{i,j}) \quad (4.21)
\]

\[
\sigma = \sqrt{\sigma_{i,j}^2} \quad (4.22)
\]

"GLCM Standard Deviation" uses the GLCM, therefore it deals specifically with the combinations of reference and neighbor pixels. Thus, it is not the same as the simple standard deviation of grey levels in the original image. Calculating the "Standard Deviation" using i or j gives the same result, since the GLCM is symmetrical. "Standard Deviation" is a measure of the dispersion of values around the mean. It is similar to contrast or dissimilarity.

vii) **GLCM: Correlation**

Measures the linear dependency of grey levels of neighboring pixels.

\[
\sum_{i,j=0}^{N-1} P_{i,j} \frac{(i-\mu)(j-\mu)}{\sqrt{\sigma_i^2 \sigma_j^2}} \quad (4.23)
\]
g. Combining Fuzzy Membership Functions

Given two or more properties with fuzzy membership functions for the same set, a variety of operators can be employed to combine the membership values together. Five operators were found to be useful for combining exploration data sets, namely fuzzy AND, fuzzy OR, fuzzy algebraic product, fuzzy algebraic sum and fuzzy gamma operators (Carter 1996).

i) Fuzzy AND

This is equivalent to Boolean AND (logical intersection) operation on classical set values of (1,0). It is defined as

\[ \mu_{\text{combination}} = \min(\mu_A, \mu_B, \mu_C, \ldots) \]

\( \mu_A \) is the membership value of A at a particular parameter eg. Scale or color.
\( \mu_B \) is the value for Parameter B.

ii) Fuzzy OR

Fuzzy OR is the Boolean OR (Logical Union) in that the output membership values are controlled by the maximum values of any of the input parameter. The fuzzy OR is defined as

\[ \mu_{\text{combination}} = \max(\mu_A, \mu_B, \mu_C, \ldots) \]
iii) **Fuzzy Algebraic Product**

Combined membership function is defined as

\[
\mu \text{ combination} = \prod_{I=1}^{n} \mu_I
\]

where \( \mu_I \) is the fuzzy membership function for the \( I \) th parameter and \( I = 1,2,3,\ldots,n \) parameter are to be combined. The combined fuzzy membership values tend to be small with this operator due to the effect of multiplying several members less than 1. The output is always smaller than or equal to, the smallest continuing membership value.

iv) **Fuzzy algebraic Sum**

This operator is complementary to the fuzzy algebraic product

\[
\mu \text{ Combination} = 1 - \prod_{I=1}^{n} \mu_I
\]

The result is always larger (or equal to) the largest contributing fuzzy membership value and the effect is therefore increasive. Two Pieces of evidence that both favor a hypothesis reinforce or another and the combined evidence is more supportive than either piece of taken individually.

v) **Gamma operation**

\[
\mu \text{ Combination} = (\text{Fuzzy algebraic sum}) \times (\text{Fuzzy algebraic product})
\]
where \( r \) is a parameter chosen in the range \((0,1)\) (Carter 1996) when \( r \) is 1, the combination is the same as the fuzzy algebraic sum; and when \( r \) is 0, the combination equals the fuzzy algebraic product. Judicious choice of \( r \) produces output values that ensure a flexible compromise between the increasive tendencies of the fuzzy algebraic sum and the 'decrease' effects of the fuzzy algebraic product. In this case \( r = 0.7 \) is assigned, the parameter for the combination of membership function is produced (Carter 1996).

The value of zero is used to represent complete membership and values in between are used to represent intermediate degrees of membership. The set \( S \) is referred to as the universe of discrete for the fuzzy subset \( F \). Frequently the mapping is defined as a function, the membership function of \( F \). Fuzzy AND and fuzzy OR may be more appropriate than fuzzy gamma in some situation but not in others, for example suppose that two input maps represent evidence for a preposition that requires the evidence occur jointly.

In fuzzy AND case combination would be controlled by the minimum of fuzzy membership values. In other situations, fuzzy OR is more appropriate. In expert system terminology, the fuzzy membership functions are the 'knowledge base and the inference engine'. Fuzzy logic is one of the tools used in expert systems where the uncertainty of evidence is important.

**h. Class Hierarchy**

It is used for formulating the knowledge base for classifying image object. It contains all classes of a classification scheme in a hierarchically structured form. The relations defined by the class hierarchy are in two ways, such as the inheritance of class description of child class and semantic grouping of classes.
In Inheritance, the parent classes are passed to the child classes, example the Building (New Concrete Str), Building (tiles and tar sheet), Building (Asbestos sheet) are the child class of building parent class. The child classes have the same inherited class of parent class description, eg all the building have the elevation, but roof top will be vary with different tone and texture.

4.5.3 Conventional Classification (Pixel Based)

In the process of satellite image classification, the image pixels are automatically assigned (by the classification software) to one of a number of output classes. Two methods of image classification were utilized such as supervised and unsupervised. Supervised classification, as the name suggests, involves the user defining, by delineating training sites, the output classes to which pixels will be assigned. On the other hand, unsupervised classification or image clustering requires no pre-classification input from the user and pixels are split into a number of groups (to be specified by the user), based on their spectral similarity. Supervised classification formed the core of the classification work, while an unsupervised classification was performed to assist in the selection of training sites.

Table 4.3 lists the classes that were mapped through supervised classification. These classes represent one or more were spectrally inseparable. An example Vegetation dark and light and open area (exposed to soil surface as well as small grass)
Table 4.3 Classes Resulting from Supervised Classification

<table>
<thead>
<tr>
<th>Class</th>
<th>Comprising/Part of the class Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building (Concrete)</td>
<td>Concrete roof top of Single story or multistory building of residential / Institutional / Industrial / Commercial building</td>
</tr>
<tr>
<td>Building (Tiles)</td>
<td>Tiled roof top of building</td>
</tr>
<tr>
<td>Building (AC Sheet)</td>
<td>Workshop / Industries / Godown of Asbestos Cement sheet</td>
</tr>
<tr>
<td>Open Area</td>
<td>Open ground / Area</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Vegetation (Dark / light color</td>
</tr>
<tr>
<td>Road</td>
<td>Bituminous tar road</td>
</tr>
</tbody>
</table>

4.5.4 Accuracy Assessment

In order to measure the quality of the classifier, a comparison is made on the classified objects with the referenced classifier or onsite ground measurement. It is referred to as confusion matrix or error matrix. It contains all the information about the relation between classification and reference classification. However it is often useful to derive from it some characteristic numbers which simplify the accuracy assessment of the classification (Congalton 1991).
4.5.5 Comparison of Accuracy

The accuracy comparison was carried-out on the confusion matrix of conventional method as well as object based method. And the comparison was made on each of the classified features.

4.5 CONCLUSION

The overall methodology was applied over the prepared dataset, such as fused PAN and MSS of QUICKBIRD data. On the prepared DSM and fused QUICKBIRD the multi-resolution segmentation was applied, and the segmentation was fuzzified for semi-automation. And the knowledge base was created on semantic information, performed classification by developing the fuzzy rule. The conventional method of classification also performed on the data. The performed results and methodology were compared.