Object Recognition of Very High Resolution Satellite Imagery using Ontology

Thesis submitted to the Andhra University, Visakhapatnam in partial fulfilment of the requirement for the award of *Master of Technology in Remote Sensing and GIS*

Submitted By
Rigved Ashok Ranade

Supervised By

Ms. Shefali Agrawal
Scientist/Engineer 'SG'
Photogrammetry & Remote Sensing Department
Indian Institute of Remote Sensing
Dehradun

Mr. Raghavendra S
Scientist/Engineer 'SD'
Photogrammetry & Remote Sensing Department
Indian Institute of Remote Sensing
Dehradun

Indian Institute of Remote Sensing,
Indian Space Research Organization,
Department of Space, Govt. of India
Dehradun – 248001
Uttarakhand, India
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Disclaimer

This work has been carried out in partial fulfilment of Masters in Technology program in Remote Sensing and Geographic Information System at Indian Institute of Remote Sensing, Dehradun, India. The author is solely responsible for the contents of the thesis.

Dedicated to my beloved aai and baba…

Acknowledgement

I dedicate this thesis which is part of my M.Tech project work carried out at the Indian Institute of Remote Sensing (IIRS), ISRO, Dehradun to my beloved parents.

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Rigved Ranade (M.Tech 2013-2015)

CERTIFICATE

This is to certify that the project entitled **“Object Recognition in Very High Resolution Satellite Imagery using Ontology”** is a bonafide record of work carried out by **Mr. Rigved Ashok Ranade** during 01 Aug 2014 to 14 Aug 2015. The report has been submitted in partial fulfilment of requirement for the award of Master of Technology in Remote Sensing and GIS with specialization in Satellite Image Analysis and Photogrammetry, conducted at Indian Institute of Remote Sensing (IIRS), Indian Space Research Organisation (ISRO), Dehradun from 19 Aug 2013 to 14 Aug 2015. The work has been carried out under the supervision of **Ms. Shefali Agrawal, Scientist/Engineer ‘SG’**, and **Mr. Raghavendra S, Scientist/Engineer ‘SD’,** Photogrammetry and Remote Sensing Department.

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Ms. Shefali Agrawal
Scientist/Engineer ‘SG’ and Head
Photogrammetry and Remote Sensing
Department
IIRS, Dehradun

Mr. Raghavendra S
Scientist/Engineer ‘SD
Photogrammetry and Remote Sensing
Department
IIRS, Dehradun

Dr. S. P. S. Kushwaha
Dean, Academics & Group Director
ERSSG
IIRS, Dehradun

Declaration

I, ***Rigved Ashok Ranade***, hereby declare that this dissertation entitled "***Object Recognition in Very High Resolution Satellite Imagery using Ontology***" submitted to Andhra University, Visakhapatnam in partial fulfilment of the requirements for the award of ***M.Tech in Remote Sensing and GIS***, is my own work and that to the best of my knowledge and belief. It is a record of original research carried out be me under the guidance and supervision of **Ms. Shefali Agrawal**, Scientist 'SG' and **Mr. Raghavendra S**, Scientist 'SD', Photogrammetry and Remote Sensing Department, Indian Institute of Remote Sensing, ISRO, Dehradun. It contains no material previously published or written by another person nor material which to a substantial extent nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgement has been made in the text.

Place: Dehradun Rigved Ranade

Date: August, 2015

Abstract

The world over the past decade has seen a consistent rise in the number of high resolution satellite sensors being developed. These sensors help in capturing the earth data with finer spatial resolution. The increase in spatial resolution has increased the scope for feature extraction with an increase in the number of land cover classes. Extracting out the desired ground feature information from the image is dependent on the context of the underlying layers. Object Oriented Image Analysis has always tried to extract the meaningful information using the contextual analysis. But the underlying semantics of various land cover classes are not explored since object oriented tasks relies on the knowledge of the expert. This knowledge is not formalized or structure so as to share with other users. Thus there is a need for a knowledge representation technique such as Ontology in formalizing the expert knowledge. The knowledge formalized for a particular domain can always be extended further to a specific problem domain through such structured knowledge base.

The study is based on two major aspects – to develop an object oriented ruleset to segment and classify Very High Resolution satellite imagery & secondly to develop an Ontology, which helps in establishing more defined criteria for image object recognition. The study represents a methodology for integrating the satellite image object domain with the Ontological concepts by formalizing the image object concepts in Ontology, in a structured manner. This helps in relating the concepts more easily.

The overall methodology involves the use of Very High Resolution Satellite Imagery of Worldview-2 satellite. The work performs pan sharpening to fuse the obtained imagery. Further object oriented approach is used to classify the very high resolution satellite image and the classification is exported into a GeoJSON format so as to preserve its object features. The GeoJSON objects are converted as instances in Ontology so as to validate the concepts from Ontology. Reasoner system is used to validate these instances by inferring the knowledge constraints mentioned in the Ontology. To implement the steps mentioned in proposed methodology the study makes use of Worldview-2 Satellite data.

The work has focused on enhancing the existing classification techniques by establishing relations for the satellite image objects and provide semantic meaning with the help of Ontology. The study acts as a baseline for future researchers to integrate more advance techniques for satellite image object recognition.

Keywords: very high resolution satellite imagery, Ontology, geojson, semantic, object oriented image analysis, knowledge base

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1 Introduction

1.1 Background

Over the past few years, Earth Remote Sensing (RS) data acquisition has increased significantly. The large number of satellite images are generated from variety of sources. With the advancement in sensor technology, different sensor systems are also on rise. Eventually, in the past decades, the spatial resolution of satellite imagery has been substantially improved (Moser and B. Serpico, 2008). The increase in spatial resolution has increased the amount of spatial content available in satellite imagery. This has facilitated various application areas such as Urban planning, Farming, Traffic Control, Agricultural mapping, etc. But, such high resolution imageries require a large amount of data storage. At the same time, image processing on such huge data sets require more computation time. The need for such huge datasets has motivated the researchers to optimize the satellite image processing algorithms to better process satellite images.

Satellite images hold information about the geographic features. But this information is extracted by the experts as per the requirement of the application domain. To extract out the information in an efficient manner the image segmentation, classification and feature extraction algorithms have always been in research over a few years. The advancement in sensor technology in providing higher spatial and spectral sensors has triggered the image processing domain to develop better methods to extract relevant information efficiently. Last decade has seen an impressive growth in the integration of various interoperable technologies coming together for information extraction. The chapter further introduces to the important aspects on which the overall work is based.

Hence large number of image processing algorithms are being developed to work on identifying the spatial content efficiently and to optimize the existing algorithms for processing High resolution satellite images. The high spatial resolution imagery has further advanced into the concept of very high spatial resolution satellite imagery with spatial resolution coming down below 1m.

1.1.1 Evolution of High and Very High Resolution satellite imagery

The world over the past decade has seen a consistent rise in the number of high resolution satellite sensors being developed. These sensors help in capturing the earth data with finer spatial resolution. In (Dey et al., 2010) review paper on various image segmentation techniques author mentions that the optical RS imagery has been to a paradigm shift in the decade after year 1999. If we see the various sensors launched, we can clearly see the way world has progressed in sensor advancements. After 1999, a lot of development in Satellite sensors helped the RS community with better quality of satellite images. Sensors such as that of Landsat 7(with 30m spatial resolution for Multispectral (MS) and 15m for Panchromatic (Pan) respectively) was launched in 1999. There after a series of satellites with increased spatial & spectral resolution were launched. This included, IKONOS launched in 1999 (MS:

4.0m & Pan: 1.0m), Quickbird launched in 2001 (MS: 2.44m & Pan, 0.61m), Cartosat-1 launched in 2005 (Pan:2.5m), WorldView-1 launched in 2007 (Pan: 0.5m), Cartosat-2 launched in 2007 (Pan: 1m), GeoEye-1 launched in 2008 (MS: 1.65m & Pan: 0.42m), WorldView-2 launched in 2009 (MS: 1.8m & Pan, 0.46m) and WorldView-3 launched in 2014 (MS: 1.8m & Pan, 0.31m) (Dey et al., 2010).

This has allowed the new phase of High Resolution (HR) and Very High Resolution (VHR) satellite sensors to come up. HR satellite imaging of the earth and its environment represents an important technology for the creation and maintenance of geographic information systems (GIS) databases (Opitz and Blundell, 2008). The increase in spatial resolution helps in collecting more ground information and thus the content captured by HR & VHR sensors is huge. Along with this, the spectral information can also be used for feature extraction as the spatial resolution in multispectral bands has also considerably come down.

1.1.2 Feature Extraction in Satellite Imagery

The increase in spatial resolution has increased the scope for feature extraction. Extracting out the desired ground feature information from the satellite image is dependent on the context of the underlying layers. The satellite image consist of various geographic feature and every feature shows certain characteristics. Thus contextual information is necessary to be considered while extracting out the desired feature. At the same time to extract out a feature from an image, the image should be segmented in such a way that the underlying segment showcases the required characteristics or properties. Segmentation, thus helps in dividing the image into homogenous sections where each segment shows certain characteristics. For identifying the objects, segmentation helps in exploring the granularity of the image. Famous techniques which are still being used by the researchers are Edge Detection, Threshold, Histogram, Region-based methods, and Watershed Transformation (Waseem Khan, 2014). The use of HR and VHR satellite imagery has provided a lot of contextual based segmentation methods to come up where the image object attributes are taken into consideration rather than the traditional segmentation approaches which were mostly pixel-based. The image segmentation process of RS imagery purely depends on the problem domain and no such technique can be completely ruled out. Hence Image segmentation has always remained a hot topic of research.

For satellite images the image pixels belong to a particular land cover class. Thus it is important to classify the image content so as to extract out the required feature. Classification of RS imagery has acquired a lot of attention over last few decades. The initial RS datasets were of a coarser resolution and the image analysis was performed at an image pixel level. As the pixel size reduced due to increase in spatial resolution of sensors, researchers moved towards Object Based Image Analysis (OBIA). (Blaschke, 2010) Image object consisted of a group of homogeneous pixels which helped in retrieving the content from it. The earlier classifiers made use of the spatial and spectral characteristics of an image in performing classification. This was enhanced by taking into account the contextual information with the help of identifying image objects from the imagery. This helped in extracting the desired feature by using the object characteristics. In the last decade, a lot of developments have been done over integration of the image content into classification. Researcher are making use of the contextual characteristics along with the spatial and spectral properties. The contextual information helps in identifying the content layer from satellite image. The use of Ontology as a knowledge conceptualization for classification is used by many of the researchers for interpreting various RS image objects.(Belgiu and Thomas, 2013)(Durand et al., 2007)(Puissant et al., 2007). Hence there was a need to analyse the content driven approaches and to encapsulate the concepts so as to apply the same on the imagery. Ontology helps in organizing geographic concepts in RS Domain.

1.1.3 Ontology – An approach

Moving from the pixel level analysis to an object based image analysis is not enough. The relationships explaining the actual semantics for a particular ground feature are not taken into consideration. This can be achieved with some external vocabulary mentioning the relationships for a particular ground object identified in a satellite image. Ontology is an explicit specification of conceptualization (Gruber, 1995). It intends to identify the concepts and their relationships within a scientific domain (Arvor et al., 2013). The explicit specification of conceptualization involves translating the knowledge from one domain to more specific intended domain (Obitko, 2007). This can be understood with the help of Figure (1.1). With the help of Ontology, a shared hierarchical model consisting of the classes, attributes and the interrelationships among them, can be framed. Hence Ontology can be defined as how well the things (information) is organized. From past few decades, Ontology is playing an important role in knowledge conceptualization. Geographic Information System (GIS) are making use of Ontology for feature extraction. The topic has huge scope in the RS domain as it is still an emerging topic as far as its depth is considered in more specific domains of RS. Ontology can take into consideration the various geographic land use classes and can establish a relationship among them.

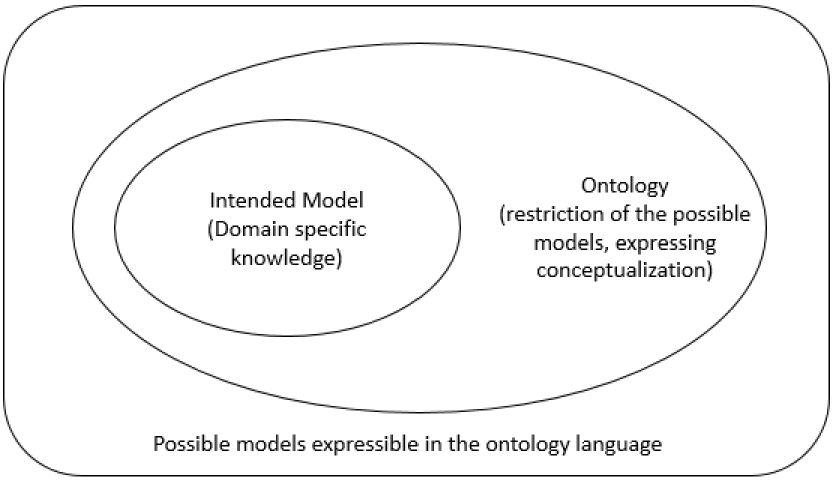

Figure 1.1 - Ontology expressing the domain specific knowledge (Intended Model)(Obitko, 2007)

With respect to the RS domain, various concepts can be integrated so as to form a conceptualization. This conceptualization can be further linked with the image object domain to identify and classify the satellite image objects. The RS domain knowledge needs to be exploited to form a better conceptualization.

The conceptualization should be able to relate the RS things efficiently. Overall better ways are to be explored for image segmentation and object recognition in HR & VHR imagery.

1.2 Motivation and Problem Statement

Over the last few years, sensor development is on rise and advance sensors for earth observation are being developed efficiently. This has allowed us to have a better spatial and spectral resolution in satellite imagery. As spatial resolution increases the clarity of the available content on Earth increases. The spectral profiles helps in understanding the responses of ground objects from the satellite imagery. Thus it is becomes necessary to classify content on basis of overall contextual information available. The user needs to take into account all the characteristics of the image objects and needs to classify on the basis of the contextual conceptualization formed. This requires a semantic understanding of various attributes associated with the classes and their relationships with various land cover classes. Also the increase in spatial resolution, increases the number of land use classes. Hence such classes can be classified if the content information is properly taken into account.

Notable work has been done regarding classification of HR Imagery, but a lot of issues such as improper object delineation, over segmentation, etc. are still under research. Segmenting a satellite image has always been an area of research. The image objects are not properly delineated from the satellite imagery by the earlier segmentation algorithms. Issues regarding over segmentation is a common scenario. The segmentation algorithms segment the image into relevant objects but not all the objects are properly segmented. The segmented blocks also show the spectral properties of its underlying content but not all the spectral profiles are used at all the time. These days the spatial resolution is improving and finer details are captured by the satellite imagery. This details need to be explored by making use of spatial spectral and contextual information. The use of contextual information in segmenting the image helps in delineating the objects according to the content.

For the purpose of HR and VHR imagery a lot of attention needs to be given on various aspects. In HR & VHR, the image objects are delineated by the segmentation algorithm that require input parameters to be tuned by the expert, usually following a trial-and-error process (Arvor et al., 2013). Second challenge is that the decreased resolution in the spectral domain increases the spectral ambiguity of the different land-cover types (Jiayi Li et al., 2014). Thirdly the features are also in various shapes, sizes and scale. Thus there arises a need for a better segmentation algorithm particularly for the HR and VHR satellite imagery.

The second aspect which needs to be address for the HR and VHR imagery is the image feature and object classification. In the last decade, Object Based Image Analysis (OBIA) has been accepted as an effective method for classifying HR datasets(Blaschke, 2010). For performing the classification and recognition of such image objects a strong expert knowledge is required. The object analysis depends on the knowledge and experience of the domain and how the same can be applied for object identification. Image interpretation has always been a challenging task. During classification of images, image content is not always identified and there exist a semantic gap between the classified output and the exact content available. To solve this problem, we need to specify the a priori knowledge used to extract information from satellite imageries into consistent models and to make these models intrinsic to the image analysis systems(Belgiu and Thomas, 2013). Thus there needs to be a system which can take into account the domain knowledge and apply the same on the images which needs to be classified. The concept of Ontology, which helps in specifying the conceptualization of a particular domain can be linked with the geographic scenarios to better classify the content. The concept of Ontology is an emerging topic for the RS community.

The study is aimed at identifying image objects from VHR imagery with the help of a domain conceptualization which can better identify the content semantically. To better classify the image contents, the study proposes a rule based segmentation approach to segment VHR image on basis of the content available in satellite imagery. It takes into account the spatial, spectral and contextual characteristics. This helps in addressing the issues of earlier segmentation algorithms.

The study further aims in developing an Ontology in RS domain to take into account the image object concepts. The conceptualization involves various land cover classes and their attributes and establishing a relationships among them. Ontology will make use of Image Interpretation keys to establish relationships among classes. The conceptualization involves the forming of controls and class axioms to establish relationships among the instances of classes. This helps in exploring the contextual information from the satellite datasets. Study also performs a similarity measure between the segmented block and the developed Ontology. The Ontology should help in identifying the characteristics of segmented block and to eventually identify the objects from imagery. Since the work is yet to evolve, particularly for the HR and VHR satellite image feature and objects, it motivates the user to draw more attention in developing a vocabulary which can eventually relate and classify the features.

1.3 Research Objectives

The research objectives for the project are as follows:

- To formulate a rule based image segmentation & classification algorithm for delineation of objects in Very High Resolution imagery.
- To develop an Ontological Model for image object recognition in high resolution satellite imagery.

1.3.1 Sub-Objectives

- To form an Ontological Model with use of various Image Interpretation keys.
- To develop a system for associating the knowledge conceptualization from Ontology to the features and annotate them.

1.4 Research Questions

- What method is applied to segment the high resolution image so as to get better results?
- What Ontological approach is used for Image object recognition?
- Are there any existing ontological frameworks which can be applied?
- Can the ontology be exported onto other systems (Interoperability)?
- What are the ways to improve the overall efficiency in annotating the relevant content?

1.5 Structure of Thesis

The structure of thesis includes the Introduction, Literature Review, Methodology, Study area and Data set used, Results and Discussion, Conclusion and References.

Chapter 1 – This section introduces the background, motivation and problem statement for this project work. It further introduces the research objectives and the research questions in thesis work.

Chapter 2 – This chapter discusses the overall work done by various researchers across globe related with Object based image analysis & Ontology. It discusses the various aspects in Image segmentation, Object Based Image Analysis, Ontology and Ontology in Remote Sensing.

Chapter 3 – The chapter describes the study area on which the methodology is implemented. The chapter also gives details about the various software and hardware requirements in project and the field survey performed.

Chapter 4 - This chapter details about the methodology adapted to accomplish the desired objectives for the proposed project.

Chapter 5 – Chapter 5 describes the overall results obtained in recognizing the ground objects in VHR satellite imagery. The chapter further discusses the results obtained and how the project leaves a scope for further researchers to enhance classification and object recognition in VHR satellite imagery.

Chapter 6 – The chapter describes the conclusion that is derived after the overall project is implemented. It further states the future recommendations for future researchers so as to work in this domain.

2 Literature Review

In this chapter, we discuss about the varied works in the field of satellite image object recognition and classification. The process starts from the core concepts of segmenting the satellite image and moves towards object interpretation with the use of Ontological modelling. The chapter moves from the initial segmentation algorithms to the recent developments to form rule based systems for segmenting and classifying the image. Further the chapter defines the Ontology and the ontological developments from GIS perspective. Along with this, the chapter also defines the theoretical concepts from both the domains (Image Domain & Ontology).

2.1 Image Segmentation

Image segmentation is defined as a process of partitioning an image into homogenous groups such that each region is homogenous but the union of no two adjacent regions is homogenous (Pal and Pal, 1993). Image segmentation, still today, happens to be a hot area of research in image processing field (Waseem Khan, 2014). Different approaches to segment various image has been a main research focus in the area of image processing over the past few years. The main concern is to extract the objects of interest in image in an effective manner. But more often this does not yield the same expected outcome and needs to be handled by an expert (Baatz and Schäpe, 2000). In RS, it is often viewed as an aid to perform change detection and land use land cover classification. Above scenarios state that the segmentation process is present in every kind of image analysis. This constitutes a plethora of literature on the image segmentation. Thus there is a necessity to categorise the segmentation algorithm according to the problem domain (Dey et al., 2010).

The general approach of image segmentation can be categorised into the bottom-up and top-down approaches. This was termed as the first categorisation of image segmentation by (Dey et al., 2010). In image segmentation, they are often stated as model driven (top-down) and image driven (bottom-up) approach (Guidon, 1997). It can also be stated as segmentation control based categorisation. However, in eCognition/Definiens developer software top-down and bottom-up approach refers to hierarchy of segmentation("eCognition User Guide," 2013). From this it is clear that bottom-up approach helps in forming object by combining/merging pixels or group of pixels together according to the heterogeneity criteria whereas top-down approach moves from splitting the whole image into image objects again based on some heterogeneity criteria (Benz et al., 2004). Thus in eCognition software bottom-up approach is used for multi-resolution segmentation. Also such algorithms can be performed at different image levels depending upon the level of homogeneity.

However, this is not the only definition. The second stage of categorisation points to features or homogeneity measures based approaches used to delineate image objects. The third categorisation is based on operations on image used to generate image objects. These are edge detection, region growing/splitting and may be both of them. It is important to note that these stages are highly interrelated and generally developed methods pick up one or more methods from the list at different stages to perform final segmentation (Dey et al., 2010).

2.1.1 Image Segmentation – A Review

Image segmentation was well established and a lot of research was going on throughout the late 1970s and the 1980s (Haralick and Shapiro, 1985). Initially, Image driven approach operated directly on the image pixels and detected objects solely based on the image features (Maxwell, 2005). Image driven approach extracts image objects based on the statistical features of the image derived through image pixels. These are the edge based segmentation techniques. Edge based techniques helps in detecting edges and then closes the regions with the help of contour generating algorithms (Schiewe, 2002). During the early 170s many image processing algorithms were developed on classifications of individual pixels utilizing the concept of a multi-dimensional feature space (Blaschke et al., 2014). This proved to be a major limitation for the pixel based analysis. Hence the next approaches that evolved were based on the object background. Object Background models are based on histogram thresholding. These are primitive models for image segmentation. They follow a concept of background and foreground objects consisting of a uniform background with objects being irregularly placed on this background (Rosenfield and Davis, 1979). They are mainly based on spectral properties. Spectral variation is represented through image histogram. This makes image histogram the choice for object delineation. Hence, finding a proper threshold between object and background helps in achieving the task of object identification. Many such threshold based methods follow an image model. Maximisation of entropy which was based on the probability distribution model was proposed by (Pal and Pal, 1991).

Different segmentation techniques such as Markov random field (MRF), Neural techniques, Fuzzy theory model, Multiresolution methods, watershed etc. also evolved with a distinctive approach for image segmentation. MRF model is not so old in remote sensing applications as compared to histogram thresholding. MRF model was conceptualised from Ising model (Kinderman and Snell, 1980). MRF model takes into account the neighbourhood relationship which allows for modelling texture and contexture of images. Sarkar et al. (2000) developed a modified technique to reduce the difficulty of MAP-MRF estimation. Instead of directly working on image pixels, authors used a two-step algorithm for an over segmented image. On first step, region adjacency graph was plotted for those regions. Energy function of MRF model was defined based on intra-region homogeneity and inter-region dissimilarity. Further step included performing the region merging based on these energy equations value compared with a threshold based on Fischer distribution. This was an unsupervised MRF model based region merging approach which used the spectral, spatial and textural properties (Sarkar et al., 2002). (Zadeh, 1965) conceptualized the Fuzzy theory which has been applied in various fields of engineering applications. Fuzzy segmentation adds fuzzy boundary for objects. (Tzafestas and Raptis, 2000) used an iterative fuzzy clustering which could take into account the image properties namely, spectral, spatial, texture and frequency in a fuzzy manner for segmentation. The algorithm applied was locally adaptive and number of output clusters/segments were not fixed a priori. Thus, it could produce optimum number of segments till it reached it predefined threshold. Watershed model is a mathematical morphological approach and derives its analogy from a real life flood situation (Beucher, 1992). It transforms image into a gradient image. This image is seen as a topographical surface and the pixel values determine the surface elevation for that particular location. It depends on the flooding process which starts with the water effusing out from the minimum grey value. With this the flooding encountered at two minima converges and a dam or a barrier to stop further flooding is built so as to identify the boundary between them. This method is .an edge based technique (Carleer et al., 2005). The original watershed algorithm tends to over-segment so a modified marker-controlled based watershed algorithm was proposed by (Beucher, 1992). Watershed algorithm produces over-segmentation because of noise or textured patterns. Watershed algorithms can be seen to be applied in varied applications in the RS domain but this model is more recent than the other models.

Various segmentation approaches are used to segment different images according to the need of the domain. Edge-based segmentation techniques helps in detecting the boundaries between image objects and they are located where the intensity changes occur in an image. There are various ways to further delineate boundaries. The image segmentation is based on the representativeness values of each pixel. Region growing algorithms start from seed points and grows into regions until a certain threshold is reached. This helps in combining areas till all the input criteria for region merging are achieved. This threshold is usually a homogeneity criterion or a combination of size and homogeneity. A region grows when all the pixel in an image are attributed to any of the image segments else the process is repeated as per the conditions. This continues until the whole image is segmented (Blaschke et al., 2000).

Scale of an object is stated as level of aggregation and abstraction at which an object can be described (Benz et al., 2004). An object smaller than the spatial resolution of image (pixel size) will be difficult to identify. This is because of inappropriate scale of object. Two notable problems can be seen from this scenario. Firstly, if the size of object is bigger than the spatial resolution of image, then the object will be a collection of group of pixels in that image. Secondly, if the size of object is lower than the spatial resolution of satellite imagery the object will not be distributed by the image pixels and will be included in one pixel itself and it will not be recognized properly. The HR sensors have addressed the second scenario and object identification is possible in HR imagery. To address the first problem idea of multi-scale and multi-resolution approach arose. Multi-scale segmentation can go both ways from coarse to fine (top-down) and fine to coarse (bottomup) levels (Zhong et al., 2005).

Multi-resolution/hierarchical segmentation was proposed using Fractal Net Evaluation approach (FNEA) by (Baatz and Schäpe, 2000). The authors brought an important approach which helped the future researchers in performing multi-resolution segmentation. The main concept was on the similarity approach of Fractals and the FNEA represents this collection of fractals as a hierarchy. In terms of image segmentation the approach included an input from the finer level to the coarser level on the top. During the process whenever an object is detected its representation at a finer level is achieved through similarity. This algorithm also merges region and it starts from each pixel while considering the pixel itself as an object and then further merging regions based on the heterogeneity criteria. Spectral, spatial, texture, size and contextual properties of image were also considered during execution. This approach is included in the eCognition/Definiens Developer software ("eCognition User Guide," 2013). This software revolutionised the field of remote sensing image segmentation with its immense possibility to provide GIS ready information (Blaschke, 2010)(Benz et al., 2004). But this approach requires an intervention of an expert who provides the values for the scale, smoothness and compactness factors for a multi-resolution segmentation process. Due to this the approach is semi-automatic and few parameters are tuned as per the experts. (Maxwell, 2005) proposed a fuzzy approach which automatically selects the parameter of the segmentation used in multi-resolution approach.

Many experts have worked on developing segmentation techniques according to the problem domain. (Narkhede, 2013)(Waseem Khan, 2014)(Dey et al., 2010) have provided a detailed review of various segmentation algorithms in different problem domain. According to (Narkhede, 2013), the image segmentation algorithms can be divided into Edge detection, Thresholding, Region-based, Fuzzy Technique & Neural Network. The review of (Dey et al., 2010), gives an idea of Image segmentation techniques which can be particularly used in RS domain. It particularly highlights the works in Multiresolution Model for Remote Sensing Domain.

The strong motivation to develop techniques for the extraction of image objects stems from the fact that most image data exhibit a characteristic texture which is neglected in common classifications. Smoothness, Intensity patterns and coarseness are responsible for defining the texture in an image. Industrial vision is one such field where the texture analysis plays an important role. This area includes image processing so as to judge the surface texture to assess the quality of the products. Many such methods are based on the statistical properties of an image as well as the spectral or Fourier characteristics of airborne data, radar or VHR-satellite data which are playing an increasing role in remote sensing (Blaschke et al., 2000).

The concept of 'ideal' object scale does not exist and depending on the application, the objects from different levels and of different meaning can be combined together (Blaschke et al., 2000). The human eye is able to recognise large and small objects at the same time but this is not the case along totally different dimensions (Blaschke et al., 2000). In RS, a single sensor correlates highly with a specific range of scales. Hence detecting an object in an image can be directly related with the sensor's capability or its resolution. A simple rule is that the scale of image objects to be detected must be significantly bigger than the scale of image noise relative to texture. This ensures that subsequent object oriented image processing is based on meaningful image objects (Baatz and Schäpe, 2000). Therefore, among the most important characteristics of a segmentation procedure is the homogeneity of the objects. Good results are expected only if contrasts are treated consistently (Baatz and Schäpe, 2000). It is also a requirement that the results of a segmentation process should be reproducible. This allows for the applications to have a variety of data. Further the authors argue that multi-resolution image processing based on texture and utilisation of fractal algorithms can alone fulfil all main requirements at once. Their 'fractal net evolution approach' uses local mutual best-fit heuristics to find the least heterogeneous merge in a local vicinity following the gradient of the best-fit (Baatz and Schäpe, 2000). (Rizvi et al., 2011) proposed an efficient method for image segmentation based on a multi-resolution application of a wavelet transform and marker-based watershed segmentation algorithm. The method was able to addresses the issue of excessive fragmentation usually caused due to watershed segmentation.

2.1.2 Image segmentation in High Resolution Satellite Imagery

Optical remote sensing imagery evolved in the last decade and much of these developments can be seen after year 1999. As stated in the Section 1.1.1, many high resolution satellites were launched in last decade. During this time, inevitable change in RS data acquisition was seen due to the increase in the spatial and spectral resolution of the sensors. Hence these are the evidence of a drastic shift that happened during this time. Prior to this period, the pixel size used to include two or three buildings where as the pixel size got reduced to a size lesser than that of a car. Eventually the earlier algorithms which use to work only at a pixel level failed as these algorithms were unable to address the complexity of scene. Thus research for better segmentation and classification algorithms for such high and very high resolution image evolved (Dey et al., 2010).

The segmentation of HR and VHR satellite imagery has allowed the researchers to explore various capabilities to improve segmentation process. Since the HR imagery holds more details, most of the earlier segmentation techniques happen to over segment the image objects. Thus a single object in context is over segmented. To overcome this, researchers included the use of hybrid models that included the aspects like scale, homogeneity criteria, image layer weightage and wavelet analysis & statistical methods in segmenting the imagery according to the need (Moser and B. Serpico, 2008)(Belgiu and Drăguţ, 2014)(Cui and Zhang, 2010)(Baatz and Schäpe, 2000)(Parvathi et al., 2009)(Rizvi and Mohan, 2011).

In (Cui and Zhang, 2010), the authors shows a Graph-based multispectral high resolution image segmentation method, with the use of an edge based auto threshold select method. Parameters like the band weight and NDVI (Normalized Difference Vegetation Index) is used. This helps to calculate the edge weight. This was implemented on a Quick-bird multispectral imagery. In (Moser and B. Serpico, 2008) a method was developed for classifying the high resolution images with MRF fusion and Multi-scale segmentation. The method was adopted so as to exploit the capability to detect bigger objects in coarse-scale and to improve the identification and recognition of spatial characteristics at a finer scale. D. Barbosa (Barbosa et al., 2012) proposed a new segmentation technique which joins the edge and region based information with spectral method using Morphological watershed algorithms. B. Mathivanan (Mathivanan and Selvarajan, 2012) proposed an edge embedded marker based watershed algorithm for high spatial resolution RS image segmentation. To make it effective, the authors proposed two improvements, which were able to handle the segmentation in HR imagery by using a two key steps of marker extraction and pixel labelling. In (Blaschke, 2010), the author defines segmentation algorithm to divide the image into (a) relatively homogeneous and (b) semantically significant group of pixels called the object candidates.

The researchers have also tried to work on performing wavelet analysis to segment the HR and VHR images. Wavelet tries to decompose the signal into its high and low frequency components. This can be explored to perform multi-resolution segmentation where the segmentation at different levels is to be performed depending on the scale. (Parvathi et al., 2009) proposed a segmentation method for HR image analysis. The technique included a wavelet transform, which was applied to the image, producing detailed (horizontal, vertical, and diagonal) and approximation coefficients. The image gradient with selective regional minima was calculated using the grey-scale morphology for the approximation image at a resolution defined. Further the watershed algorithm was applied to the gradient image so as to avoid over segmentation. This helped in performing watershed segmentation efficiently. The decomposed images did not over segment and the overall segmentation remained better than the traditional watershed segmentation. For exploring the very high resolution content and to find an effective method (Belgiu and Drăguţ, 2014) compared various supervised and unsupervised multi-resolution segmentation approaches. This work involves a comparison between the multi-resolution algorithms either available online or accessible from the developer.

Multi-scalar image segmentation is a fundamental step in OBIA, yet there is a need for a tool to address the problem for appropriate scale selection. Since it is difficult to select a proper scale for segmentation. To extract meaningful content from the image identifying proper scale is of utmost importance. Since the scale is an abstract term, no specific scale can be determined. In (Drăguţ et al., 2010), the author has proposed new customized algorithm, which helps in estimating the scale for a segmenting a high resolution satellite image. The algorithm works on the principle of local variance (LV) of object heterogeneity within a scene. Estimation of scale parameter (ESP) was developed by which generates iteratively image-objects at different scale levels in a bottom-up approach. At the same time it also calculates the LV for each scale. LV is plotted against the corresponding scale and this helps in finding the variation in heterogeneity. The thresholds in rates of change of LV indicate the scale levels at which the image can be segmented and is relative to the data properties at the scene level (Drăguţ et al., 2010).

(Esch et al., 2008) in his work proposed an approach which helped the quality of image segmentation in HR Synthetic Aperture Radar (SAR) imagery using the Definiens Developer software. The method focused on minimizing the over and under segmentations so that the overall segmentation results are accurate. The process being developed make use of iterative sequence of multi-scale segmentation, feature-based classification, and classification-based object refinement (Esch et al., 2008). The developed method has been applied to various remotely sensed data and when compared to the results achieved with use of Definiens Developer software gave 20-40% better results than the earlier segmentation processes. In (Anders et al., 2011) the authors have used stratified object-based image analysis to semi-automatically extract contrasting geomorphological features from HR digital terrain data. It shows that different geomorphological features require different segmentation parameters. Authors performed through a semi-automatic method to assess the segmentation result by comparing 2D frequency distribution matrices of training samples and image objects.

2.2 Object-Based Image Analysis (OBIA)

In the absence of a formal definition, (Hay and Castilla, 2006) proposed that Object- Based Image Analysis (OBIA) is a sub-discipline of GIScience devoted to partitioning remote sensing (RS) imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale. (Hay and Castilla, 2006) further stated that OBIA's key objective is to develop proper theory, methods and tools so as to replicate human interpretation of RS imagery in some automated or semi-automated processes. This will eventually increase repeatability and production and at the same time will help in reducing the subjectivity, labour and time costs involved.

2.2.1 Concept of Image Objects

Image object is defined as a set of pixels which are grouped together on basis of some homogeneity criteria such as colour, compactness, shape. The object and pixel relationship can be defined through Equation (2.1).

$$o = (P_1, P_2, P_3 \dots\dots.. P_n) \qquad (2.1)$$

where,
o is the Object in an image
n is the number of pixels
P is the pixel in an image
Relation of pixel level to object level can be understood through Figure (2.1).

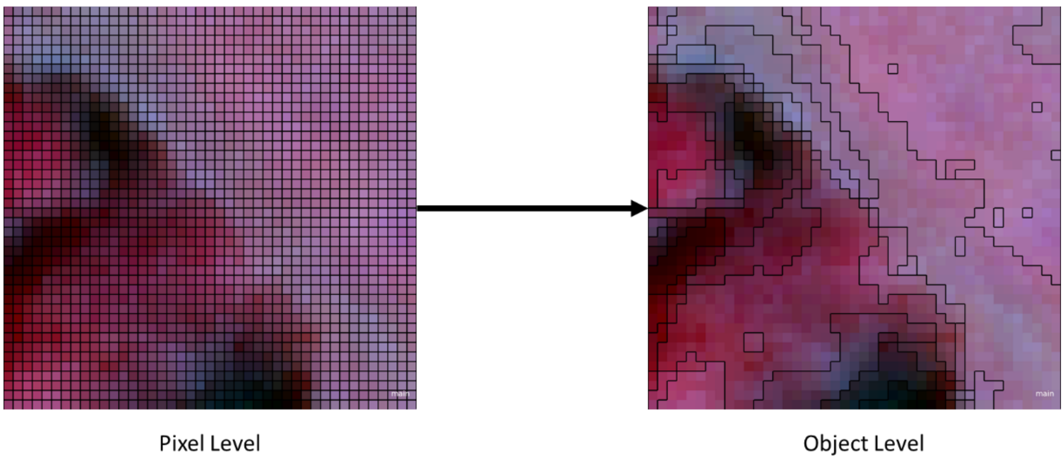

Figure 2.1 - Description of Pixel and Object level

2.2.2 Image Object hierarchy

Image Objects are arranged into levels when performing object analysis on image. The pixels form the ground level or the zero level from where the initial segmentation algorithms work to create objects on a level above the pixel level. The level above the pixel level consist of a certain group of pixels combined together to form image objects. This can be explained through Figure (2.2).

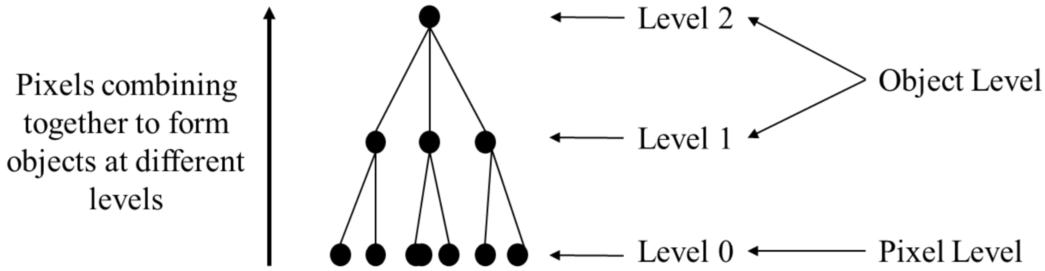

Figure 2.2 - Image Object Hierarchy

The Remote Sensing imagery needs to be converted into useful information to be used with other Geographic Information Systems (GIS). To extract meaningful information it is important to explore the granularity of image. Since the image is made up of pixels, it is important how we extract the information from pixel data. The initial work consisted of pixel by pixel analysis. With the increasing spatial resolution due to advent of new sensors in the 21st century, the pixel size has gradually reduced. Over the past decade a lot of study has been into object analysis rather than the pixel analysis. This is because of the increase in spatial resolution of satellite imagery. The HR satellite imagery is able to hold more detailed information due to this. It is not easy to work only on a pixel by pixel basis as a single ground object when captured by the HR sensor now holds much more information in the form of group of pixels. Thus these pixels together tend to exhibit similar characteristics.

Segmentation is not a new topic of research and notable work can be found since the 1970s but the work in Geospatial domain started after the 1980s (Blaschke, 2010). The image segmentation forms the basis for segregating the image into its various contents. In last decade, GIS and Image processing evolved through Object Based Image Analysis (OBIA). As stated by (Blaschke, 2010), Segmentation provides the building blocks for OBIA. Homogeneity helps in forming various image segments. OBIA involves the processing of such group of pixels or ‘Objects’. Thus a group of pixels help in holding more contextual information than a single pixel. The grouping of pixels proves to be useful for removing the salt and pepper effect.

Geographic Object-Based Image Analysis (GEOBIA) is a sub-discipline of Geographic Information Science (GIScience) devoted to developing automated methods to partition RS imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scales, so as to generate new geographic information in GIS-ready format (Hay and Castilla, 2008). For the purpose of Object Recognition in satellite imagery, it is important to understand the group of pixels showcasing a ground object on an image. The use of geographic OBIA is a useful tool in identifying content from satellite imagery. Notable work has been done in the field of Geographic OBIA. In (Arvor et al., 2013), the author has made a detailed review and analysis of GEOBIA and Ontology for performing image analysis stating that GEOBIA presents four new components that are not typically used in pixel based classifiers. These include the integration of expert knowledge and feature space optimization which allows improving how the classification of Remote Sensing Imagery is performed.

In, (Gao et al., 2007) the author made use of OBIA to map the land cover in a forest area. The initial classification consisted of a pixel level Maximum likelihood classification while the others were object based. The second classification was based on the spectral values of image features. The third and fourth classification was purely OBIA conceptualization and included the Multiresolution segmentation and the SEaTH (SEperability and Thresholds) algorithm. The accuracy of OBIA based classification was highest as they not only made use of the image objects but the Multiresolution and SEaTH approaches could delineate the features on the contextual properties. The Multiresolution algorithm made use of the spatial, spectral, scale and homogeneity parameters to extract meaningful information. The most important aspect of OBIA is that it makes use of object features during the classification process. This includes objects' spectral, spatial, texture and contextual information and through this the authors have tried to minimize the misclassification rate.

According to (Opitz and Blundell, 2008) Geographic feature classes such as road networks, building footprints, vegetation, etc. form the backbone of GIS mapping services. These services are used for military intelligence, telecommunications, agriculture, land-use planning, and many other vertical market applications. Keeping geographic features current and up-to-date, however, represents a major bottleneck in the exploitation of high resolution satellite imagery. The author states that the Feature Analyst software is also one such tool which proves to be effective for users as they can form rule sets strong enough to extract meaningful information from the HR satellite imagery. The tool makes use of object specific and geographic features. It also includes the use of panchromatic and multi-spectral imagery. Thus authors mentions that such scenarios help in saving time, cost and labour needed if the traditional means were to be used. With this a new workflow process for maintaining the temporal currency of geographic data can be introduced.

(Opitz and Blundell, 2008) states that there were two approaches for identifying and extracting objects of interest in remotely sensed images: manual and task-specific automated. The manual approach involves the use of trained image analysts, who find out the feature of interest according to the need of domain and their expertise and manually perform image analysis over it. Features are hand-digitized, attributed and validated during geospatial, data-production workflows. Even if this is a predominant approach it has shortcomings in meeting the expectations from the commercial sectors. This involves lack of expertise in a particular domain and the time consumption in performing the feature extraction tasks manually. Also as the manual tasks increases the overall cost increases. Thus such shortcomings and tend to ask for a system which can automate the overall scenario. In (Opitz and Blundell, 2008), the author states that using Feature Analyst, the user can provide the system with several examples of desired features from the image. This acts as a learning method for the system to take the image features as input. The system then automatically develops a model that correlates known data (such as spectral or spatial signatures) with targeted outputs (i.e., the features or objects of interest). Once such structural model is prepared, the image analysis becomes easier and the system can easily identify and relate the contextual information with the image segments. Thus the use of objects from image can be related in better approach. The resulting learned model then uses the gained information to perform classification and to extract the desired targets and objects from the image. Feature models can be stored in a repository, called the Feature Model Library. The accompanying workflow and metadata (information on spectral bandwidth, date and time stamp, etc.) can be used to quickly compose new models for changing target conditions such as geographic location or hour of day.

According to Blaschke, the first stage of OBIA development was mainly devoted to the software, algorithms and infrastructure which required to generate and exploit objects (Blaschke, 2010). Today, the ultimate focus of OBIA literature and applications is not to focus on building better segmentation methods, but rather to include and develop geographic based intelligence, i.e., appropriate information within a geographical context. Implementation is more on focusing on these developments. The next phase of OBIA research from 2005 is directed more towards the automation of image processing. As a consequence of the rapidly increasing widespread of HR imagery and improved access to such imagery, more and more authors and researchers are discussing automatic object delineation. Author further states that even if automated object recognition seems to be the ultimate goal, in real it is still performed step by step which includes interlinked processes building workflows or rulesets or breaks in these workflows. In both cases the steps involve addressing various multi-scale instances of related objects within a single image (Blaschke, 2010).

Over the last decade, OBIA has been accepted as an efficient method for extracting detailed information from high and very high resolution satellite imagery (Blaschke, 2010). Object oriented (OO) concepts and methods have been successfully applied to many different problem domains, and there is great opportunity to adapt and integrate many of its beneficial components to GEOBIA (Hay and Castilla, 2008), as the majority of early GEOBIA research was conducted without OO software, tools or languages. In (Blaschke, 2010), author describes about the evolution of OBIA and how OBIA helps in better image analysis than the earlier pixel level analysis. (Hay and Castilla, 2006) published a SWOT (Strength, Weaknesses, Opportunities and Threats) analysis of OBIA. It mentions that key issues is to ensure that an easily defined Ontology which is also properly understood can be integrated into the software that is being developed for OBIA. Thus OBIA basically takes into account the contextual information and the same information can be modelled for further use. Thus it is has been into research since the last decade extensively. The SWOT analysis helps in knowing the threats and the ways to deal with issues still persisting with OBIA. In (Blaschke et al., 2014), the author states that GEOBIA is strongly associated with Image segmentation and remains the only way to delineate the objects in satellite imagery.

2.3 Ontology – A Conceptualization

The widely accepted definition of Ontology is the one proposed by Gruber, which says, Ontology is a formal, explicit specification of a shared conceptualization (Gruber, 1995). An ontology helps in identifying the concepts and their relationships within a scientific domain (Arvor et al., 2013).

In philosophy, ontology is the study of the kinds of things that exist. In Artificial Intelligence (AI), the term ontology has largely come to mean one of two related things. First of all, ontology is a representation vocabulary, often specialized to some domain or subject matter. More precisely, it is not the vocabulary as such that qualifies as an ontology, but the conceptualizations that the terms in the vocabulary are intended to capture. Thus, translating the terms in an ontology from one language to another, for example from English to French, does not change the ontology conceptually. In its second sense, the term ontology is sometimes used to refer to a body of knowledge describing some domain, typically a common sense knowledge domain, using a representation vocabulary (Chandrasekaran et al., 1999).

As described by the W3C Recommendations, on the Semantic Web, vocabularies define the concepts and relationships (also referred to as "terms") used to describe and represent an area of concern. Vocabularies are used to classify the terms which are used in a particular application, characterize possible relationships, and define possible constraints on using those terms. In practice, vocabularies can be very complex (with several thousands of terms) or very simple (describing one or two concepts only). There is no clear division between what is referred to as "vocabularies" and "ontologies". The trend is to use the word "ontology" for more complex, and possibly quite formal collection of terms, whereas "vocabulary" is used in general terms. Vocabularies are the basic building blocks for inference techniques on the Semantic Web ("Ontologies - W3C," 2015). In the semantic web stack, languages used for defining ontologies are RDF Schema and the Web Ontology Language OWL ("OWL Web Ontology Language Overview," 2004).

Ontology is a formal representation of concepts and their relationships within a domain of interest. Ontologies may contain definitions about categories and their relations (such as CONTINENT and COUNTRY) as well as instances (such as "EUROPE is a CONTINENT"). With this there are two such concepts in Ontology, the first is called terminological knowledge and refers to as T-Box, the latter is called assertion knowledge and often referred to as A-Box (Paulheim, 2011). The ontologies are divided into Framework Ontology and the Domain Ontology. The framework ontology helps in defining the higher level concepts while the domain ontology moves towards defining the detailed concepts of a particular domain. Thus domain ontology is a part of framework ontology. Thus ontologies are a way to facilitate knowledge sharing and reuse and can be formalized with standardized languages such as OWL. Thus, they can serve to structure the semantic interpretation of images (Andrés et al., 2013). Ontology is still an emerging field in RS domain and some notable work has been done over the past few years.

2.3.1 Components of Ontology

The components of Ontology help in designing the conceptualization. The ontological components depend on the domain for which the Ontology is prepared. Hence the components vary but the core concepts remain the same and are used by author according to the need of knowledge requirement. These components are classes, relations, individuals, etc. These components are described in detail below,

Axioms – Axioms help in defining the conditions that hold true for the mentioned domain. These conditions help distinguish the concepts defined in ontology (Agarwal, 2005).

Class – Classes defines the structure of what type of individual is to be created. The set of such individuals or objects which is the basis for knowledge representation is called a class as mentioned in (Agarwal, 2005). These individuals are the instances of a class.

Relations – Relations represent what type of interactions exists between classes. Relations help in specifying the role for an individual. They are categorised into the object and data property. The object property relates two individuals. The data property is the property an individual holds with a specific literal value which can be a string, integer, a double value etc.

Individual – Individuals are the instances of classes which are responsible for asserting the properties defined for them.

Attributes – Attributes define the relationships between the individuals of classes and the values which individuals hold.

2.3.2 Ontology Life Cycle

Below methodology was developed within the Laboratory of Artificial Intelligence at the Polytechnic University of Madrid, 1998 by (Fernández et al., 1997). It covers a methodology for planning the overall knowledge formation and mentions the steps through which the Ontology flows. Author termed the methodology as the 'METHONTOLOGY' and mentions to be one of the process for efficient planning of Ontology. It adopts a life cycle by prototypes, as mentioned in Figure (2.3), and proposes certain number of techniques for every step of the management of the cycle (prevision, control, quality assurance), development (specification, conceptualization, formalization, implementation, maintenance) and of support (acquisition of knowledge, integration, evaluation, documentation, management of the configuration). It also considers the independences between the life cycles of several ontologies managed in parallel (Belhadef and Kholladi, 2009).

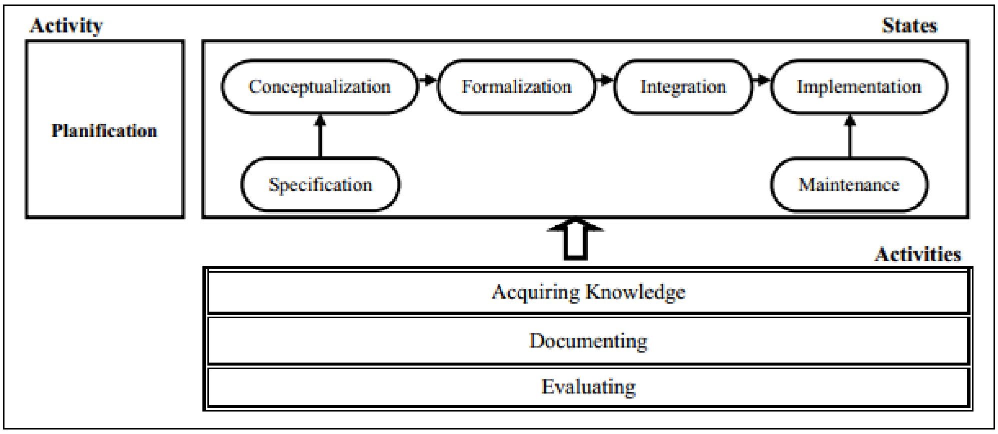

Figure 2.3 - Methontology, Source: (Fernández et al., 1997)

The phase of conceptualization helps in structuring the knowledge in a conceptual manner. The conceptual way combines all the possible domain requirements so as to structure the knowledge according to the problem domain. It constitutes the gathering of complete knowledge and its meaning so as to model it appropriately. By using a set of intermediate representations essentially in the form of tables and graphs data is modelled.

The used intermediate representations are: the taxonomies of concepts, the diagrams of the binary relations, the dictionary of the concepts, the tables of the binary relations, the descriptions of the attributes of instances, the descriptions of the attributes of classes, the tables of constants, axioms and rules.

As seen in Figure (2.3), the Ontology goes through different states. Specification, Conceptualization, Formalization, Integration, Implementation and Maintenance. A conceptualization is an abstract, simplified view of the world that we wish to represent for some purpose. Every knowledge base, knowledge-based system, or knowledge-level agent is committed to some conceptualization, explicitly or implicitly. Therefore the conceptualization consists to identify and structure the knowledge of a domain, from the sources of information. The specification phase is responsible for producing an informal, semi-formal or formal document written in Natural language describing the details. The formalization consists to transform the conceptual model into a formal or semi compatible model, and the authors mentions the need to formalize it using frame-oriented or description logic representation systems. The implementation acts as a phase for implementing the concepts according to the specification mentioned in the documents during the Specification stage. Implementation builds computable models in a computational language, but to make the ontology 'machine-readable' we need to select the formal machine process able implementation language. Authors also mentions that the process involves the intervention of an expert from a specific problem domain in which the Ontology is to be built (Belhadef and Kholladi, 2009).

2.3.3 Combining different Ontologies

The Ontology purely provides information regarding a particular domain and moves towards more specific application oriented task. The knowledge for a particular domain should be available for further use and thus should be reusable, hence there is a certain categorisation of ontologies depending on what type of knowledge is required. The upper ontology is the higher level ontology used for the more general type of knowledge. They are further extended by the domain and task specific ontologies depending upon the specific domain and requirements. The application oriented ontology describe knowledge for a particular application and are more specific.

Figure (2.4), clearly shows the hierarchical structure of higher level ontologies moving to the granularity of an application ontology.

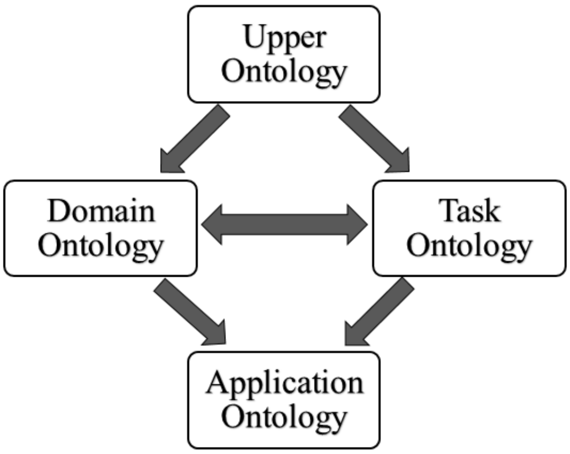

Figure 2.4 - Categorisation of Ontologies

2.4 Ontology – Remote Sensing Perspective

Over the last decade, study related to ontology, focused on relating the knowledge conceptualizations to the geographic objects. In (Mark et al., 1999), the author tries to relate how geographic objects can be related by understanding the object relations with other features in imagery. It is important to know how well the object is connected with other objects. This connections help to relate the objects with specific values or attributes. Thus every geographic objects holds a relational value with respect to other object or scene in a satellite imagery. As stated by (Mark et al., 1999), the knowledge helps in realizing the concepts of objects, relations, boundaries, events, processes, qualities, and quantities of all sorts. Geographic objects can relate to land features and water-bodies, topographic features such as bays, mountains, hills and valleys, roads, buildings, bridges, as well as the parts and aggregates of all of these. These concepts can be used to relate the same objects from a satellite imagery. Geographic objects are earth surface objects with specific characteristics and hold contextual information may be in a more complex form. The same information can be extracted through a satellite imagery for such objects present. Also these geographic objects have features like boundaries, relations with other geographic objects, they are connected with each other or they are found to be scattered on a satellite imagery. Closed geographic objects such as lakes or open like bays can also exist. Thus topology also plays an important role in studying these features. A proper conceptualization of knowledge regarding the geographic objects is needed to distinguish and classify such objects on a satellite imagery (Mark et al., 1999).

In RS images, researchers have tried to relate ontology with various geographic features for classification, feature extraction and object recognition (Belgiu and Thomas, 2013)(Puissant et al., 2007)(Durand et al., 2007)(Mark et al., 1999). Likewise, (Durand et al., 2007) in his work successfully combined ontologies and the use of spectral and geometric characteristics in interpreting the urban objects especially in HR satellite imagery. The work involves the use of an Ontology developed by the experts in recognizing the urban objects. The ontology includes not only the spectral, spatial and contextual information but also certain specific descriptors like as shape properties, elongation, diameter, length of major axis, compactness, solidity, Indices such as Normalized Difference Vegetation Index (NDVI), Soil Brightness Index (SBI), mean spectral value of four bands etc. With the help of a matching score the author tried to compare this with the segmented regions to perform image interpretations.

Since there exists a semantic gap between different ontologies and in between ontologies (Arvor et al., 2013), many studies have tried to bridge the gap so as to enhance the image interpretation process. In (Andrés et al., 2013), the work tries to bridge the semantic gap by using spatio-temporal ontology formalized through geographic standards. It focuses on establishing knowledge related to Image perspective, field viewpoint and the third being the spatio-temporal conceptualization. The work has defined spatio-temporal metamodel which helps in describing the core concepts through geographic standards as per the specification of the OGC (Open Geospatial Consortium) and ISO (International Organization of Standardization). Author uses eight components to describe spatio-temporal knowledge packages: Core, SpatialDimension, TemporalDimensions, Thematic, TemporalRelation, SemanticRelation. Study focuses more on the SpatialRelation package which has defined three relations: topological, projective and metric where topological defined about connections between objects, metric relations were defined by some measurable methods and the projective relationships were established by space projections. The work focused on RCC8 topological relationships (Andrés et al., 2013). The conceptualization was then used for detecting the coastline using the Landsat-5 TM image.

Since past few years, considerable amount of work in object analysis for HR and VHR satellite imagery is in research domain. Many researchers are working towards efficient methods for feature extraction in HR and VHR satellite imagery. The satellite imagery of QuickBird, Ikonos, GeoEye, Worldview series of sensors has allowed the researchers from RS domain to focus on exploring the high resolution content through Ontology. In (Puissant et al., 2007) author proposes a methodology to build an urban ontology which was adapted for multi-level interpretation of multi-source images. The methodology associates segmentation of the images and their classification in regions using low-level descriptors (e.g.

radiometry, texture, shape, size of the elements) and use of domain knowledge in order to transform the segmented regions into semantic objects. In (Puissant et al., 2007), the auhor proposed a framework for ontology based classification of image objects in VHR imagery. The study also focuses on the ontology grounding problem and test the feasibility of visual interpretation keys to extract information from VHR datasets.

For VHR images, (Belgiu and Thomas, 2013) proposed a OBIA based general ontology framework used to classify the objects extracted from VHR imagery. The work makes use of image descriptors such as area, NDVI, Density, Brightness along with Colour, Shape & size. The work has tried to solve the ontology grounding problem by making use of the visual interpretation keys. Thus the classification involves the use of these image interpreters which help in showcasing the object characteristics. In (Belgiu et al., 2014), the work is based on automatically integrating the Ontologies with the OBIA. The work involves the development of a mapping tool to integrate the developed ontology with the class hierarchies formed in eCognition Software. The segmentation and classification were performed through eCognition software and the image objects was assigned to best fitting class. The ontology was developed with an open source tool Protégé. The formal ontology framework for relating the ontology and image domain relied on Extensible Stylesheet Language Transformations (XSLT). This proposed methodology was then applied on a case study to classify the land cover classes. But the author mentions that the operator needs to have a deep understanding of the semantics of the geographic objects and how these objects are presented in concerned satellite imagery. This work represents a domain knowledge problem.

In (Arvor et al., 2013) contributions of Ontologies to the Geographic Object-Based Image Analysis(GEOBIA) have been described, including data discovery, image interpretation, data integration, management of scientific workflows and knowledge sharing within the RS and with each other scientific communities. With such studies on Ontology, there arises a huge scope for further development in object recognition and interpretation.

3 Study Area and Material Used

3.1 Study Area

The study was carried out on a part of Dehradun city, India as shown in Figure (3.1). The study area is geographically located between 78°1'27.9"E to 78°2'29.765"E East longitudes and 30°20'16.3"N to 30°20'17.662"N North Latitudes. The average height of the underlying terrain is 653.573m above mean sea level. Dehradun is located in the Doon valley on the foothills of the Himalayas. Dehradun is home to various National institute and organisations such as Indian Institute of Remote Sensing, ONGC, Survey of India, Forest Research Institute, Indian Institute of Petroleum to name a few.

Study area consist of a subset selected from the actual image tile of Worldview 2 imagery. The study area consist of dense urban area including buildings, schools, hospitals, vegetation cover surrounding the school and open spaces, bare land, road networks. The campus of Doon school is centrally located and includes various features like, swimming pool, open ground, vegetation covers, school building, and playing courts.

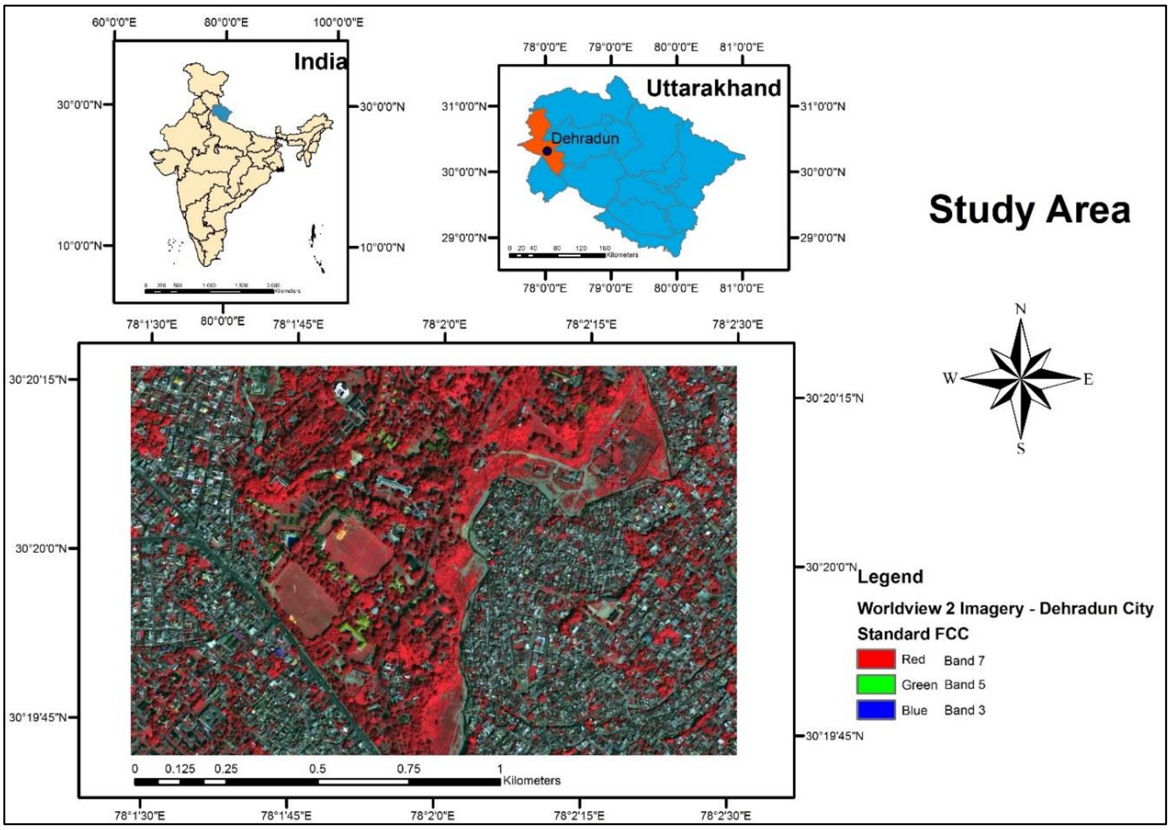

Figure 3.1 Study Area

3.2 Data Used

3.2.1.1 Primary Dataset

The dataset used in study is of Worldview 2 satellite. The data consist of a panchromatic and 8 band Multispectral imagery. The panchromatic band provides a spatial resolution of 0.46m while the multispectral bands provide a spatial resolution of 1.8m.

The specification of Worldview 2 sensor and the Worldview-2 dataset is mentioned in Table (3.1) ("Worldview 2 Datasheet," 2013).

Table 3.1 - Worldview-2 Specification table

Features	**Worldview 2 Specification**
Launch Date	8th Oct 2009
No. of Bands	Panchromatic: 1
	Multispectral: 8
Bands Spectral Range	Coastal (400 - 450nm)
	Blue (450 - 510nm)
	Green (510 - 580nm)
	Yellow (585 - 625nm)
	Red (630 - 690nm)
	Red Edge (705 - 745nm)
	Near Infrared (770 - 895nm)
	Near Infrared 2(860 - 1040nm)
	Panchromatic (450-800nm)
Pixel Resolution	Panchromatic: 0.4m (resampled from 0.46)
	Multispectral: 2m (resampled from 1.84m)
Swath	16.4m at nadir
Radiometric	11bit
Max Viewing angle	+/- 45 degrees off nadir
Orbit Altitude	770 km
Orbit type	Sun synchronous
Overpass Time	10:30am

3.2.1.2 Ancillary Dataset

Ancillary data of road network over the study area is used. The data includes the road network shape file of the study area mentioned in Section 3.1. The data is downloaded from the Open Street Map and consists of the road network.

3.3 Tool and Instruments used

3.3.1 Hardware Tools

The hardware and research field instruments are listed in below Table (3.2).

Table 3.2 - List of Hardware Instruments used in research work

Hardware Used	Purpose
Leica Zeno 5 GPS Handheld	To collect the GPS points for validation
Nikon P510 Camera	To capture the field photographs for validating the study points

Specifications of the Hardware devices are mentioned in detail in Table (3.3) & Table (3.4)

3.3.1.1 Leica Zeno 5 GPS Handheld

Leica Zeno 5 GPS handheld receiver is used for finding the GPS positions of various location during the field survey performed over the study area. The specification of the instrument is mentioned in Table (3.3).

Table 3.3 - Leica Zeno 5 GPS Handheld Specifications("Leica Zeno 5 GPS Handheld Datasheet," 2012)

Specifications	
Processor	Industrial TI AM3715 Sitara microprocessor (ARM Cortex A8) @ 800 MHz
Integrated GPS	1. SirfStarIV GPS with SiRFInstantFix and A-GPS support (48 channel) and active jammer removal 2. GPS Real-Time Accuracy: 2 – 5 m / SBAS (WAAS, EGNOS, MSAS, GAGAN): 1 – 3 m
Integrated communication modules	1. On-board IEEE 802.11a/b/g/n (CCX V4 Certified) radio: i. Security: 802.1X, WPA / WPA2-Enterprise ii. Authentication: FAST-MSCHAPv2; LEAP; PEAPv0-MSCHAPv2; PEAPv1-GTC; TLS iii. Encryption: 64/128 WEP, AES-CCMP, TKIP 2. Bluetooth® v2.0 + EDR radio 3. UMTS 3.8G HSPA+ radio i. Five Band UMTS: 800/850, AWS, 1900, 2100 MHz ii. Quad-Band GSM: 850, 900, 1800, 1900 MHz 4. CDMA EVDO Rev A radio i. Dual Band: 800/1900 MHz 5. Integrated 5 band Antenna, supports both voice and data
Operating System	Microsoft Windows® Embedded Handheld 6.5.3
Optional GNSS Sensors	Leica Zeno GG02 plus SmartAntenna
Optional Software	1. Leica Zeno Field 2. Leica Zeno Connect

3.3.1.2 Nikon Coolpix P510

Nikon Coolpix P510 is used for capturing the various locations over the field area so as to collect the geographic features. Table (3.4) lists all the specifications of P510.

Table 3.4 - Nikon Coolpix P510 Specification details("Nikon | Imaging Products | Product Archive - Specifications - COOLPIX P510," 2014)

Effective pixels	16.1 million
Image sensor	1/2.3-in. type CMOS; total pixels: approx. 16.79 million
Lens	42x zoom NIKKOR; 4.3-180 mm (35mm [135] format angle of view: 24-1000 mm); f/3-5.9; Digital zoom: up to 2x (35mm [135] format angle of view: Approx. 2000 mm)
Motion blur reduction	Motion detection (still pictures)
Focus range (from lens)	50 cm (1 ft 8 in.) to infinity (∞); Macro close-up mode: 1 cm (0.4 in.) to infinity (∞)
Monitor	7.5 cm(3-in.), approx. 921k-dot, wide viewing angle, vari-angle TFT LCD with anti-reflection coating
Image size (pixels)	16M [4608 x 3456], 8M [3264 x 2448], 4M [2272 x 1704], 2M [1600 x 1200], VGA [640 x 480], 16:9 12M [4608 x 2592], 16:9 2M [1920 x 1080], 3:2 [4608 x 3072], 1:1 [3456 x 3456]
ISO sensitivity	ISO 100-1600, ISO 3200/Hi 1 (equivalent to 6400); (Manual setting is enabled in P/S/A/M exposure modes), Hi 2 (equivalent to 12800) (High ISO monochrome in Special effects mode)
Dimensions	Approx. 119.8 x 82.9 x 102.2 mm (4.8 x 3.3 x 4.1 in.) excluding projections*3
Weight	Approx. 555 g (1 lb 3.6 oz) with battery and SD memory card*3

3.3.2 Software Tools

Table (3.5) list all the software tools used during the research work.

Table 3.5 - List of softwares used in research work

Software Tools	**Purpose**
eCognition Developer 8	To perform Object Based image analysis by developing a rule based Image Segmentation and Classification approach
Protégé	To develop an Ontology
ESRI ArcGIS 10.2.2	To perform Map generation
Google Earth	To visualize the study area
Java, OWLAPI	To link the Ontology with image segments

3.4 Field Data Analysis

To properly classify the ground objects in satellite imagery it is important to perform field study. Since the work involves the use of VHR satellite data, the field survey includes the identification of ground objects by visiting few points on the image. The location of these points is collected with the help of GPS handheld unit and the relevant ground features are captured through photographs. The field survey is mentioned in Figure (3.2).

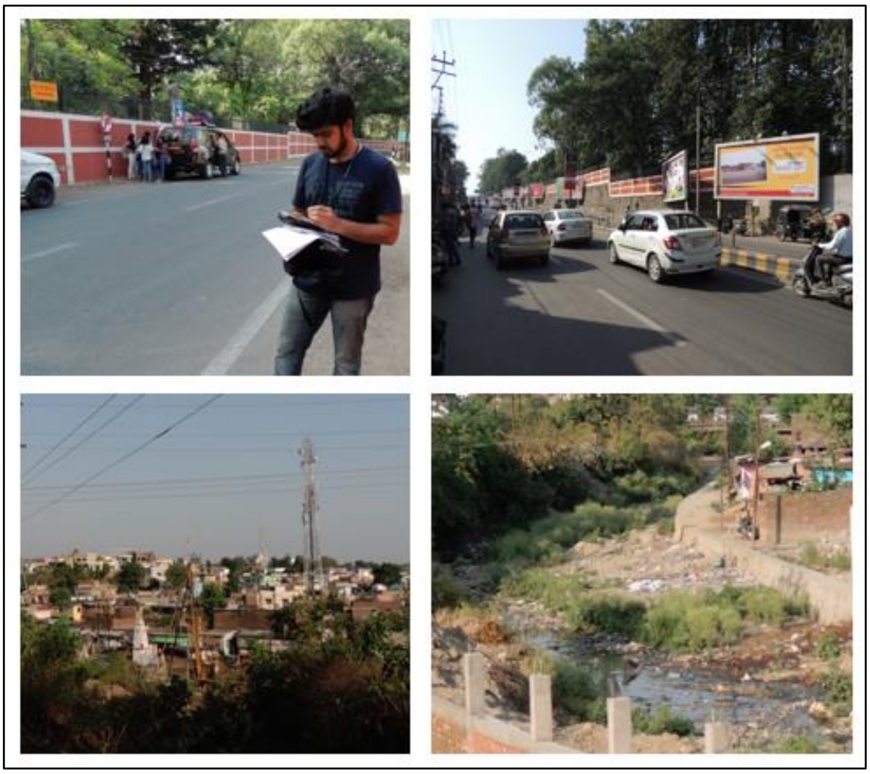

Figure 3.2 - Field Survey

4 Project Methodology

4.1 Approach of the study

The chapter presents the project methodology for identifying the geographical objects in very high resolution satellite imagery using Ontological model.

The project is divided in three phases:

- Phase 1: Image segmentation and Classification through Object based Image Analysis
- Phase 2: Develop an Ontology with respect to the Geographic context
- Phase 3: To link the developed Ontology with the Classified image objects to improve the Classification and perform Object Recognition

The proposed methodology adopted for this project is summarized in below Figure (4.1).

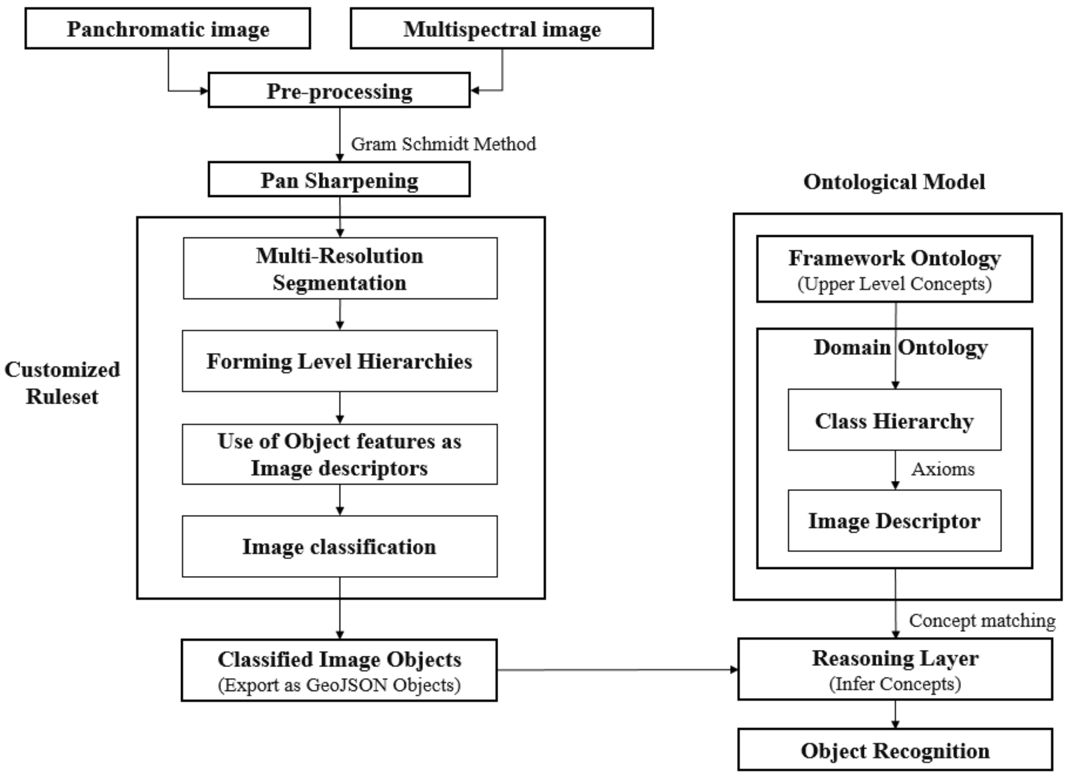

Figure 4.1 - Project Methodology

4.2 Phase 1: Image segmentation and Classification through OBIA

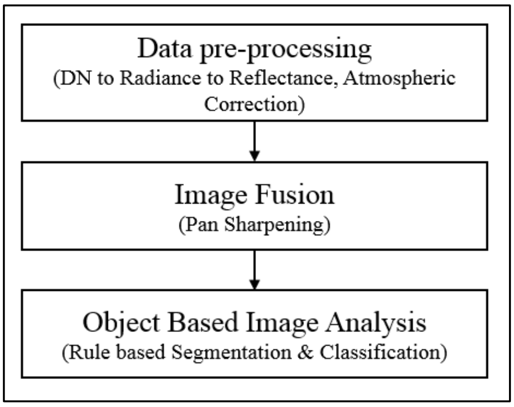

Figure 4.2 – Phase-1 Workflow

The phase 1 of the project includes satellite data acquisition, satellite image pre-processing, image fusion, image segmentation and image classification as illustrated in Figure (4.2). Segmenting the satellite image and classifying the image objects is the main objective achieved in the initial phase of the project. Image pre-processing helps in improving the overall quality of image by removing the atmospheric effects, correction, etc. Initially a subset from actual image is selected for performing the proposed study. Image sharpening method helps in merging the available panchromatic and MS bands together to improve the image spatially and spectrally. Image segmentation helps in dividing the image into various objects or group of pixels with similar characteristics. Classification of satellite images helps to distinguish these segmented objects into various Land cover classes. The various steps followed for obtaining classified objects are as follows.

Subset Image

The acquired dataset covers a vertical area of 360km ("Worldview 2 Datasheet," 2013) on ground. Such a big coverage of data requires huge amount of space. At the same time, computation time required for processing such big image also increases. Thus the project is implemented by taking a subset from the original worldview 2 tile.

4.2.1 Pre-processing Image

The study involves the use of VHR satellite imagery of Worldview 2 satellite. The dataset acquired consist of a panchromatic and 8 band Multispectral (MS) imagery. Before performing any operations it is important that the satellite imagery is corrected for further processing. This includes corrections like DN to Radiance, Radiance to Reflectance conversion, atmospheric corrections, forming desired subsets, etc. The steps followed are illustrated in Figure (4.3) and are as follows:

- DN to Radiance
- Radiance to Reflectance including Atmospheric correction (FLAASH Model)

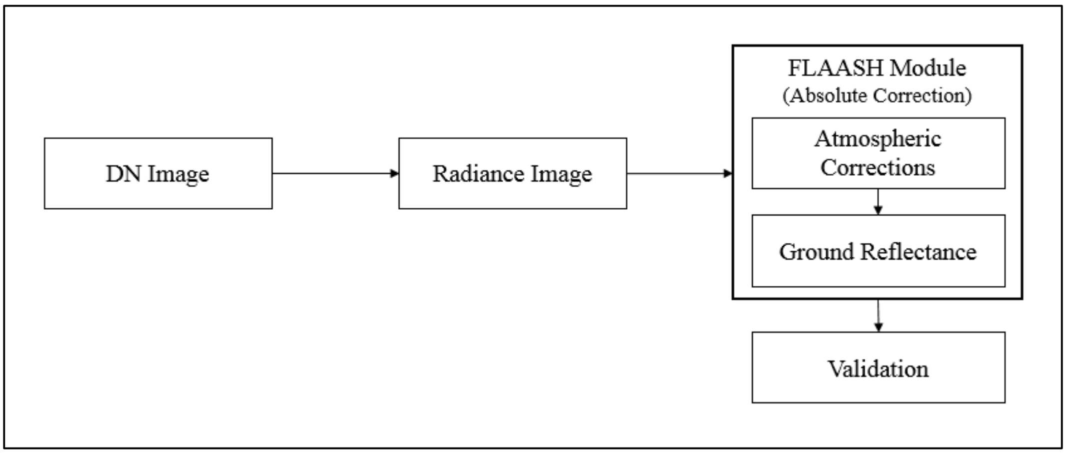

Figure 4.3 - Image pre-processing approach

DN to Radiance Conversion

The Worldview 2 product is a radiometrically corrected image pixel product. The image needs to be corrected so as to have better reflectance values. The process followed is converting the existing DN image into radiance image and then the radiance image to reflectance image. The conversion of radiometrically corrected image pixels to the spectral radiance is performed using below general Equation (4.1)

$$\left(L_{\lambda Pixel,Band}\right)^{n} = \frac{K_{Band}q_{Pixel,Band}}{\Delta\lambda_{Band}} \qquad (4.1)$$

where $L_{\lambda Pixel,Band}$ are top-of-atmosphere spectral radiance image pixels [W-m^{-2}-sr^{-1}-μm^{-1}], K_{Band} is the absolute radiometric calibration factor [W-m^{-2}-sr^{-1}-count^{-1}] for a given band, $q_{Pixel,Band}$ are radiometrically corrected image pixels [counts], and $\Delta\lambda_{Band}$ is the effective bandwidth [μm] for a given band (Updike and Comp, 2010).

The image calibration tool in ENVI is responsible for performing this operation where it takes the absolute radiometric calibration factor for each band and the effective bandwidth from the metadata file (.IMD) of product data.

Atmospheric correction

Satellite images are contaminated due to the presence of various atmospheric effects. Absorption and scattering of the radiations occur because of the various sized particles present in the atmospheric layers. This alters the reflectance values received at the satellite sensor. Atmospheric effects is often a major issue in remote sensing imageries as the presence of the atmosphere always influences the radiation received from the ground onto the sensor. Thus removing the influence of these atmospheric effects is of utmost importance so as to regain the actual reflectance values. To correct the reflectance values various atmospheric correction methods are used. There are two ways of performing atmospheric correction.

- Absolute correction

- Relative correction

Atmospheric correction of satellite images include the downwelling surface-reflected skylight and upwelling path radiance which is to be removed. Here, Absolute atmospheric correction method is applied to the Worldview 2 imagery. This is performed using Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module ("Atmospheric Correction Module: QUAC and FLAASH User's Guide," 2009).

FLAASH is a MODTRAN based model which was developed by the Air Force Phillips Laboratory, Hanscom AFB and Spectral Sciences, Inc. to support multispectral sensors in atmospheric correction (Adler-Golden et al., 1998). FLAASH requires the radiance images as input in BIL format and perform atmospheric correction to convert the radiance values into reflectance values. The same FLAASH converts the radiance image into surface reflectance image. FLAASH makes use of various parameters such as the acquisition time, acquisition date, zenith angle, azimuth angle, multiplying factor for the radiance image, aerosol parameters, etc. to perform atmospheric correction. The conversion from the radiance image to the atmospherically corrected reflectance image is performed through FLAASH. This is available with the ENVI software developed by the Exelis. FLAASH generates an atmospherically corrected reflectance output. The parameters needed by the FLAASH so as to process the radiance image are mentioned in Table (4.1).

Table 4.1 - List of FLAASH parameters needed during atmospheric correction

FLAASH Parameters	Worldview 2
Scene Centre Longitude	78º1´59.15´´E
Scene Centre Latitude	30º19´58.14´´E
Sensor Type	Worldview 2
Flight Date	10th Oct 2010
Average Flight Time	5:54:35
Sensor Altitude	770km
Ground Elevation	0.640km
Atmospheric Model	Tropical
Water Retrieval	No
Aerosol Model	Urban
Aerosol Retrieval	None
Initial visibility	40km
Wavelength Recalibration	No

FLAASH helps in performing atmospheric corrections and converting the radiance image into ground reflectance image. The result obtained from the FLAASH process is validated by comparing the spectral profiles of features with the ideal standard spectral profile of that respective feature. Through the comparison of spectral profiles atmospherically corrected reflectance data is validated.

4.2.2 Image Fusion – Pan Sharpening Process

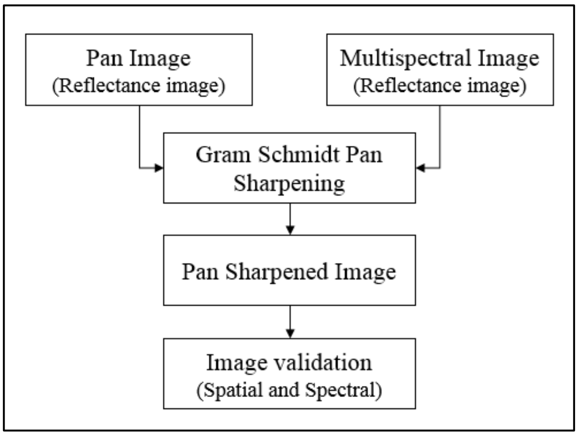

Figure 4.4 - Pan Sharpening Approach

The study involves the use of very high spatial resolution data for identifying the smaller objects on ground whereas the spectral resolution is needed in providing better spectral values for a particular feature on image. The spatial resolution is found to be high in panchromatic band whereas the multispectral bands have lower resolution as compared to its pan band. The spectral information is needed in identifying the ground features on an image as different features have different spectra in different spectral bands. So there arises a need for merging spatial and spectral content when working on object recognition. The Worldview 2 satellite comprises of 8 band MS imagery but with a spatial resolution of 1.8m. The same sensor's pan band has a spatial resolution of 0.46m. The merging of pan band to increase the resolution of MS imagery will help in better object categorisation and classification. Hence there arises a need to make use of both the resolutions for further study. The use of pan-sharpening methods to enhance the spatial resolution in spectral bands involves the merging of High Resolution Panchromatic Image with the Multispectral image. This is achieved with the help of Image fusing methods. Figure (4.4) explains the Pan sharpening approach used for performing Image fusion.

Gram Schmidt Pan Sharpening Method

Since the Worldview-2 dataset is used for study, the pan sharpening is done through a sensor based Gram Schmidt Spectral sharpening method. The spatial resolution of a multispectral digital image is enhanced in a process of the type wherein a higher spatial resolution panchromatic image is merged with a plurality of lower spatial resolution spectral band images (Laben and Brower, 2000). The Gram Schmidt method makes use of the spectral response function of a given sensor. Hence, it is important to understand the spectral responses of various bands for a particular satellite sensor. Since the study makes use of Worldview-2 satellite images the spectral response of every band is shown in Figure (4.5).

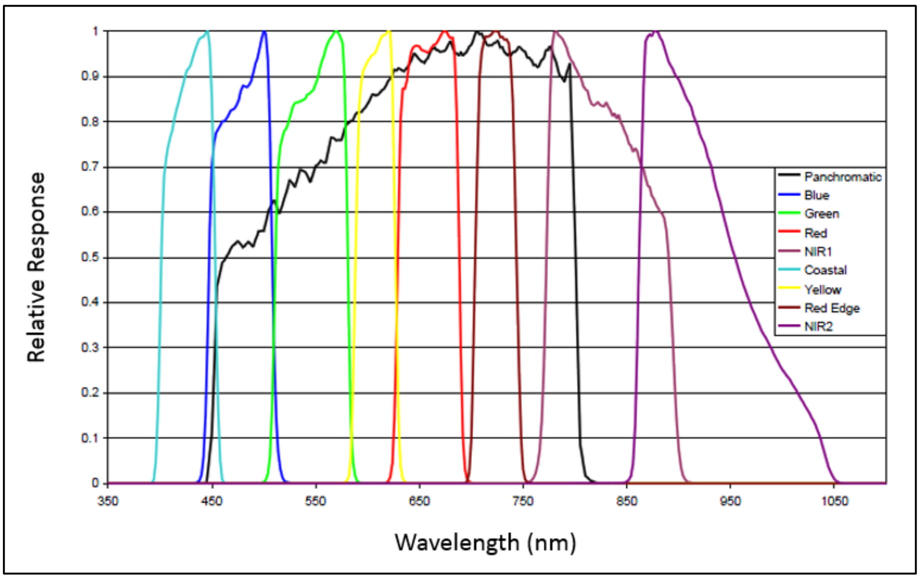

Figure 4.5 - WorldView-2 Relative Spectral Radiance Response (nm) (Updike and Comp, 2010)

The WorldView-2 satellite carries an imaging instrument containing a high resolution panchromatic band with a reduced infrared and blue response and eight lower spatial resolution spectral bands. The first four multispectral bands include blue, green, red and near-infrared bands which are similar but not identical to the QuickBird satellite. Four additional bands are further included, these are shorter wavelength blue band, centered at approximately 427 nm, called the coastal band for its applications in water colour studies; a yellow band centred at approximately 608 nm; a red edge band centered strategically at approximately 724 nm at the onset of the high reflectivity portion of vegetation response; and an additional, longer wavelength near-infrared band, centered at approximately 949 nm, which is sensitive to atmospheric water vapour ("Spectral Response for DigitalGlobe Earth Imaging Instruments," 2010).

The Gram Schmidt method involves the fusion of panchromatic and 8 band MS imagery to form a pan sharpened 8 band MS image. The steps performed are as follows:

- Simulating a panchromatic band from the lower spatial resolution spectral bands.
- Performing a Gram-Schmidt transformation on the simulated panchromatic band and the spectral bands, using the simulated panchromatic band as the first band.
- Swapping the high spatial resolution panchromatic band with the first Gram-Schmidt band.
- Applying the inverse Gram-Schmidt transform to form the pan-sharpened spectral bands

Thus we make use of the spatial content from panchromatic image and spectral content from the MS image.

4.2.3 Object-Based Image Analysis

The pan sharpened image helps in providing better spatial and spectral characteristics. This image can be further used for OBIA to extract out meaningful data in the form of image objects. The OBIA technique is based purely on an expert knowledge and depends on how the expert tunes the steps to get the desired output.

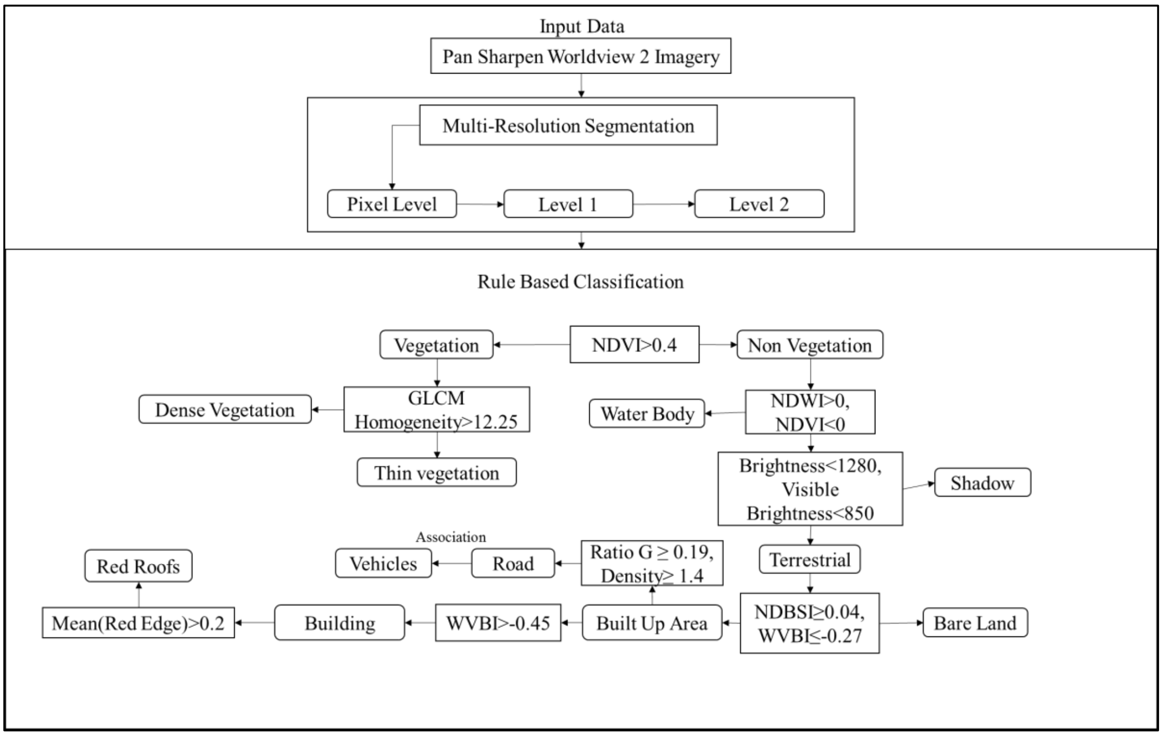

Figure 4.6 - Rule Based Segmentation and Classification Approach

To perform the Object analysis the eCognition Developer software is used. The software helps in forming hierarchical tree based rulesets with each process allowing for various object analysis through various features. The overall methodology for performing the rule-based analysis can be explained from Figure (4.6).

The flowchart in Figure (4.6) illustrates the working of a rule based expert system which starts by segmenting the pan sharpen Worldview-2 image. The segmentation helps in forming objects of the desired size and at different levels. These objects are then classified depending on the object features it represent. The overall process can be detailed into three sections

- Input data
- Image Segmentation
- Image Classification
- Exporting Results to an appropriate format

4.2.3.1 Input Data

The pan sharpen image of Worldview-2 imagery is used. The imagery consist of 8 bands starting from Coastal Blue, Blue, Green, Yellow, Red, Red Edge, Near Infrared 1 and Near

Infrared 2 bands. The pan sharpen image has a pixel size of 0.5m and is geocoded. Along with this ancillary data was used to better delineate the objects. The road network shape file of the underlying study area is used form the Open Street Map.

4.2.3.2 Image Segmentation

The main aim of Image segmentation is to properly delineate the image objects according to their content. Image segmentation helps in grouping and then segregating objects on the basis of some homogeneity criteria. To segment and classify the image a rule set is developed through e-Cognition software and a customized algorithm is prepared as mentioned in Figure (4.6).

Multi-resolution segmentation is used to segment the imagery. The pan sharpened image is segmented so as to extract meaningful objects. Objects of interest typically differ in various scales and size, hence the initial step consist a proper segmentation process. The multi-resolution segmentation makes use of the scale parameter to start the segmentation process. The term scale is abstract and denotes the average size of the object in a segmentation process. It is a trial and error procedure to adjust the scale according to the users need. Segmentation starts with each pixel forming one image object or region. At each step a pair of image objects is merged into one larger object. The merging decision is based on local homogeneity criteria, describing the similarity of adjacent image objects. It is a bottom up approach defined by the eCognition Developers.

The scale parameter of 30 was found to be suitable for initial segmentation. The segmentation is a bottom up approach and makes use of the scale parameter to start the segmentation process. The other parameters include the mentioning of weightage for image bands on which the segmentation should take place. Initially the segmentation was performed with default values of 1 for each band. The segmentation is pixel level segmentation and takes into account the pixel level characteristics. Homogeneity criterion for shape and compactness also needs to be entered into the algorithm process. The value ranging from 0.1 to 0.9 can be given as input. The shape criterion included a value of 0.5 while the compactness included 0.9. These values can be decided by performing the process again and again. The multi-resolution segmentation is used here to produce image object primitives as a first step for a further classification and other processing procedures. Once the segmentation is performed a lot of objects get over segmented and thus it becomes necessary to tune the results according the content. Hence the next step involves the use of a Spectral Difference segmentation which makes use of the spectral differences to club the image objects so as to reduce the over segmented regions.

The spectral difference segmentation is an object level segmentation which is used to merge neighbouring objects according to their mean layer intensity values. Neighbouring image objects are merged if the difference between their layer mean intensities is below the value given by the maximum spectral difference. Image layers can be weighted differently to consider image layers depending on their importance or suitability for the segmentation result. The higher the weight which is assigned to an image layer, the more of its information will be used during the segmentation process, if it utilizes the pixel information. In this segmentation, the image layer weightage was given to the NIR, Red and Green band. The spectral value of 40 was used for merging of image objects. This segmentation also makes use of the thematic bands but no such thematic band was provided during the process.

4.2.3.3 Image Classification

To identify and explore various features from the imagery, normalization indices are used. Indices such as NDVI (Normalization Difference vegetation Index), NDWI (Normalization Difference Water Index), WVBI (Worldview Built-up Index), NDBSI (Normalization Difference Bare Soil Index), Ratio Green, Visible Brightness are used. The major portions of the imagery consists of the vegetation and urban cover. NDVI for the whole image was calculated and the value range for the various image objects was analysed. The vegetation cover showed up a value ranging from 0.4 to 0.8. NDVI helps in highlighting the vegetation cover in imagery and initially the image objects are classified on the basis of NDVI as vegetation and non-vegetation. Further the classification tries to separate the shadows from the image on basis of the brightness index. The water is further extracted through NDWI. The rest of the image objects are classified as Terrestrial objects and the level classification is completed. The level 2 classification includes the objects after using the spectral difference segmentation applied on level 1 to produce level 2 objects.

The next level of classification is a sub classification of the classes obtained at level 1. This includes separating the vegetation into thin and thick vegetation, identifying the building areas, bare soil, parking lots, playing courts from the terrestrial class. The vegetation is further classified on texture basis. GLCM Homogeneity criteria is used to find the homogeneous places. The thin vegetation is more homogeneous than the dense vegetation and the texture homogeneity criteria helps in sub classifying the vegetation class. The Builtup and Bare soil areas are separated on basis of the WVBI and NDBSI respectively. Builtup area is further classified using additional object features. The Builtup features cannot directly be extracted only on the spectral values and spatial attributes are needed. Geometric features such as the Area, Density, Compactness, Asymmetry, Length, Rectangular fit, and Roundness factor are used. The level 2 classification includes separating the road, playing area, vehicles, buildings, bare soil, thin and thick vegetation areas.

The below Table (4.2) highlights the various image descriptors in the form of object features used to classify image objects.

Table 4.2 - List of image descriptors used in proposed methodology

Image Descriptor		Purpose
Spectral	NDVI	Vegetation identification
	NDWI	Water identification
	WVBI	Built-up area identification
	NDBSI	To identify Bare soil
	Visible Brightness	To identify shadows
	Mean values of Band	To be used for customized features like NDVI, NDWI, etc

Spectral	Std. Dev. Coastal Blue	To identify roads
Spatial	Area	To calculate object areas
	Density	to calculate feature density
	Rectangular Fit	To identify building structures
	Length	To find object length
	Texture	To perform texture analysis between various objects
Class	Relations to Neighbour object	To identify features based on class relations
	Relation to sub object	
	Relation to super object	

4.2.3.4 Accuracy Assessment

To validate the results, accuracy assessment is necessary. The methodology includes performing accuracy assessment based on the ground truth collected during the field visit as mentioned in Section 3.4. The accuracy assessment can be performed through various available methods such as Classification Stability, Best Classification Results, Error matrix based on TTA mask, Error matrix based on Samples (Navulur, 2007). Error matrix based on samples is selected and is used for performing accuracy assessment. The samples are selected depending on the field survey performed over the study area.

4.2.3.5 Exporting Results

The rule based classification helps in classifying the image objects by establishing the rules through various object features. Hence we need to be maintain these object features for further detailed classification and analysis. Figure (4.7) illustrates an approach used so that the classified objects can be exported so as to be used in further classification processes.

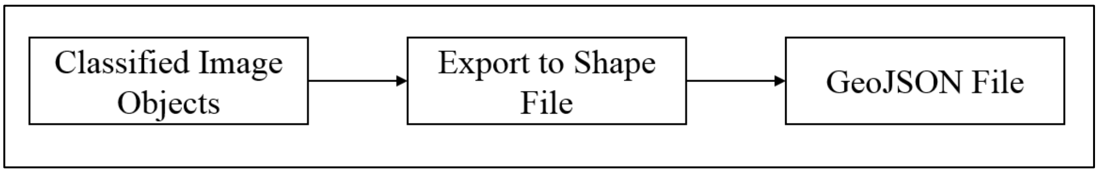

Figure 4.7 - Exporting Classification Results

GeoJSON is a format for encoding a variety of geographic data structures. GeoJSON object helps in representing a geometry, a feature, or a collection of features. Hence the classification results are exported into GeoJSON format so that the object features can be stored structurally.

The overall classification is carried out in eCognition. There is no direct option for exporting the results into a GeoJSON format. Hence the results are exported into a shape file (.shp) file. The required object features and the classification criteria are selected appropriately so that the concerned shape file holds all the information. This is further converted into a GeoJSON file format with the help of available libraries. The GDAL library("GDAL: GDAL - Geospatial Data Abstraction Library," 2015) is a geospatial library used completely for handling various geographic data. The GDAL library is capable of converting the shape file to a GeoJSON file. The main concept of converting to a GeoJSON format is to make sure that the semantics of classification data is maintained. Through the use of various geometry and feature tags the information from the shape file can be embedded into the GeoJSON file. GDAL code is used to convert the shape file to GeoJSON

```
ogr2ogr -f geoJSON kc.json kc.shp
```

The converted GeoJSON file helps in preserving all the information related to object features and classification in a structured form.

4.3 Phase 2: Developing an Ontology with respect to the Geographic context

4.3.1 Ontology

The formation of a conceptualisation is dependent on the type of knowledge required. Every Ontology should start form a particular concept so as to grow the concept further into an application domain. Thus the Ontology is divided into various part with the upper level ontology moving towards to application ontology. The upper level ontology explains the high level concepts in a more general way and the domain ontology is responsible for domain specific concepts. The Ontology is divided into two parts. The formation of Ontology depends purely on the domain concepts. Thus the higher level ontology differs from the domain level concepts. Thus the ontology is divided into two parts

- Framework Ontology
- Domain Ontology

The project proposes a GeoOntology, including the various aspects of the Geographic domain. This aspects include the Land cover classes and relationships between various land cover features.

4.3.1.1 Framework Ontology

The framework ontology defines the high level concepts. The proposed Ontological model will be responsible for associating the high level concepts to the low level features. Ontology will include the acquisition, conceptualization, integration and implementation of the formed hierarchical vocabulary. The ontology used is a hierarchy of classes with attributes and their relationships between them. The conceptualization involves a semantic approach by establishing relationships using various class descriptors. The model will take into account the spectral, spatial and contextual factors related to the RS imagery.

The Ontology is created from a point of view of identifying ground features in a satellite imagery. The ontology will only be complete when it is provided by a certain domain specific knowledge background. The use of upper ontology or framework ontology is needed to provide more general concepts which need to be further extended. GeoOntology makes use the Land Cover Classification System (LCCS) (Di Gregorio, 2005) concepts to develop a general upper level ontology. This includes the various land cover classification scheme. The classification scheme defines the Land cover classes as mentioned in Appendix section.

The classification scheme described in Figure (4.9) mentions the capability of expanding the land cover classification. To prepare the ontology, the above classification concepts are used. The classes defined in the ontology based on LCCS are as mentioned in Figure (4.8).

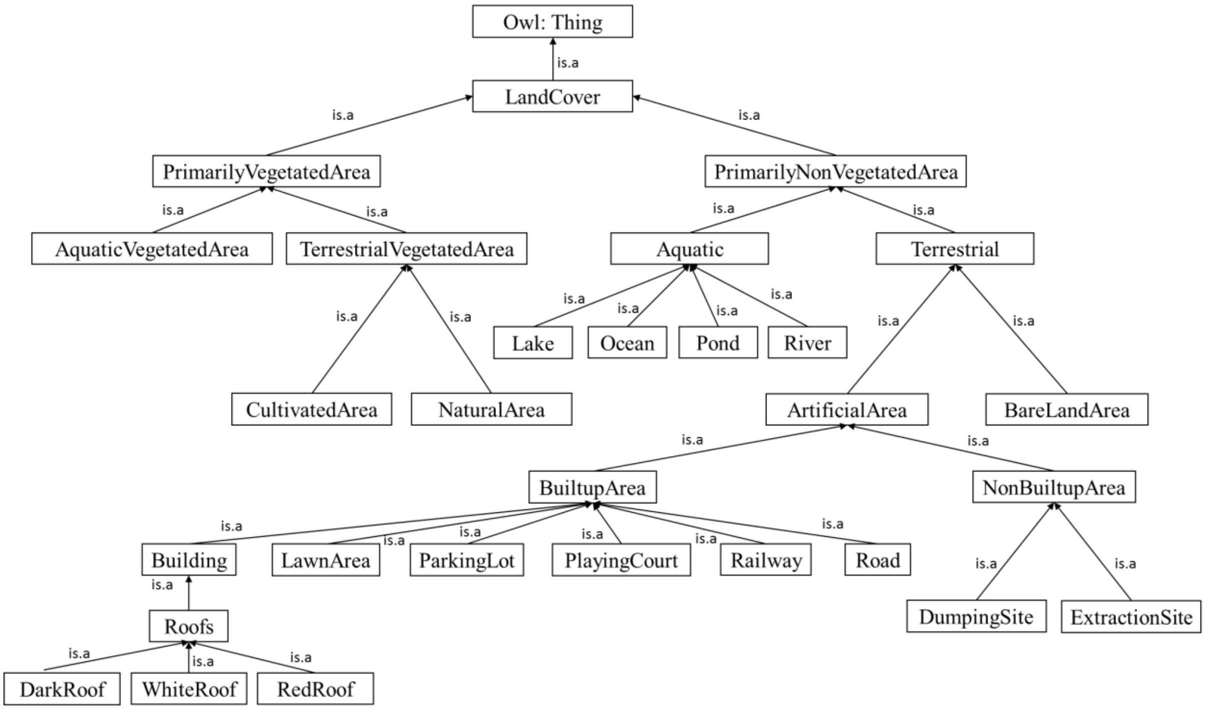

Figure 4.8 - LandCover class hierarchy in proposed Ontology. Every subclass is shown with an "is.a" relationship

4.3.1.2 Domain Specific Extension

The Domain ontology is a conceptualization related with a specific domain. It makes use of a framework ontology from high level concepts and then it further describes the details for a specific domain. Here we have made use of the land cover classes in Remote Sensing Domain and how various individuals make use of such concepts.

The ontology is further extended with including the various other classes regarding the land cover attributes that are seen in a satellite image. The ontology involves the use of Classes, Object properties which exist between the two individuals, and the data property which exists between an individual and a literal. The classes included are extended further to the Land Cover Property class. This include the Geometric, Spectral, Contextual Property classes. The overall class hierarchy used in proposed Ontology is described in Figure (4.9) and Figure (4.10).

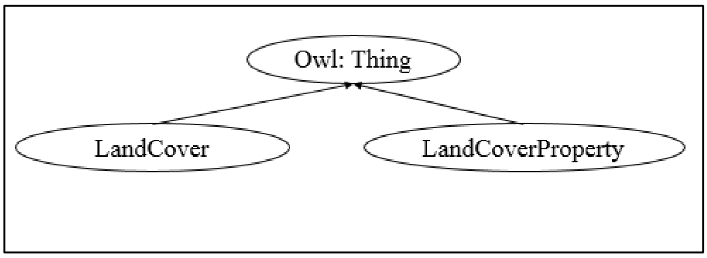

Figure 4.9 - Ontology classes divided into Land cover and its properties

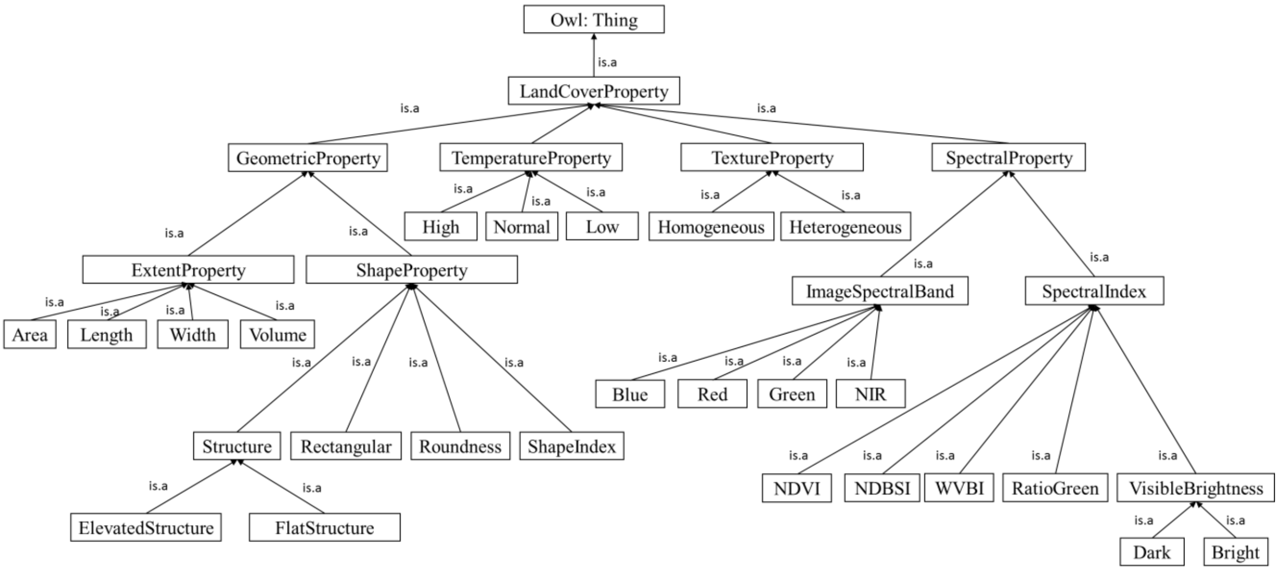

Figure 4.10 - LandCoverProperty class hierarchy in proposed Ontology. Every subclass is shown with an "is.a" relationship

The object properties establishes a relationship between the individuals of classes. These individuals are instances of the classes. The object properties developed with respect to the land cover classes are mentioned in below diagram.

The project tries to move the concepts from a point of view of land cover classification to a more specific object recognition in VHR satellite imagery. The worldview subset image used for study includes majorly the urban area where many ground objects such as Buildings, Trees, Vehicles, Playing Court, Swimming Pool, are located. To include these concepts in Ontology so as to classify them is the main aim of GeoOntology. Every object property explains the mechanism to connect the individuals of classes so as to classify them on some relationship.

Object property hasSpectralResponse is used to establish connection between the individuals of LandCover class through some spectral response. Since every land cover form shows some spectral response on image we try to establish a relationship. This is well explained through Figure (4.11). Similarly, the Object properties are established in the Ontology for various land cover classes.

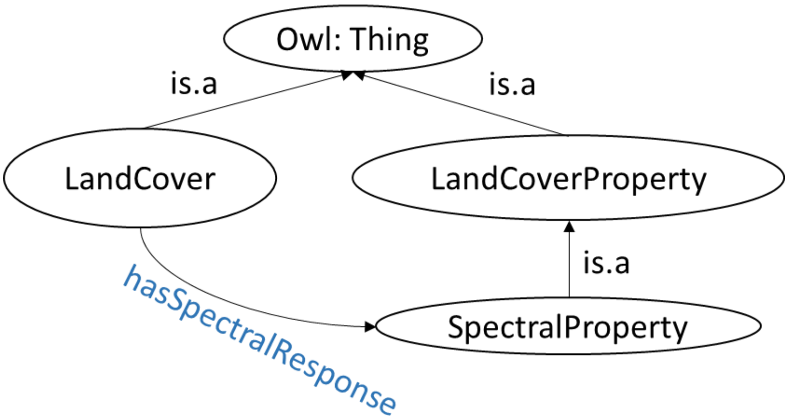

Figure 4.11 - Object Property hasSpectralResponse

Since we know that the spectral index, NDVI, helps in extracting out the vegetation cover in an image, we describe a sub object property of hasSpectralResponse property as hasVegetationIdentity and the same tries to establish a relationship between the vegetation class, classified here as Primarily Vegetated Area and the NDVI class under SpectralProperty. Through this the nested property is established in Ontology. The same scenario is being developed by visualizing the concept in Figure (4.12).

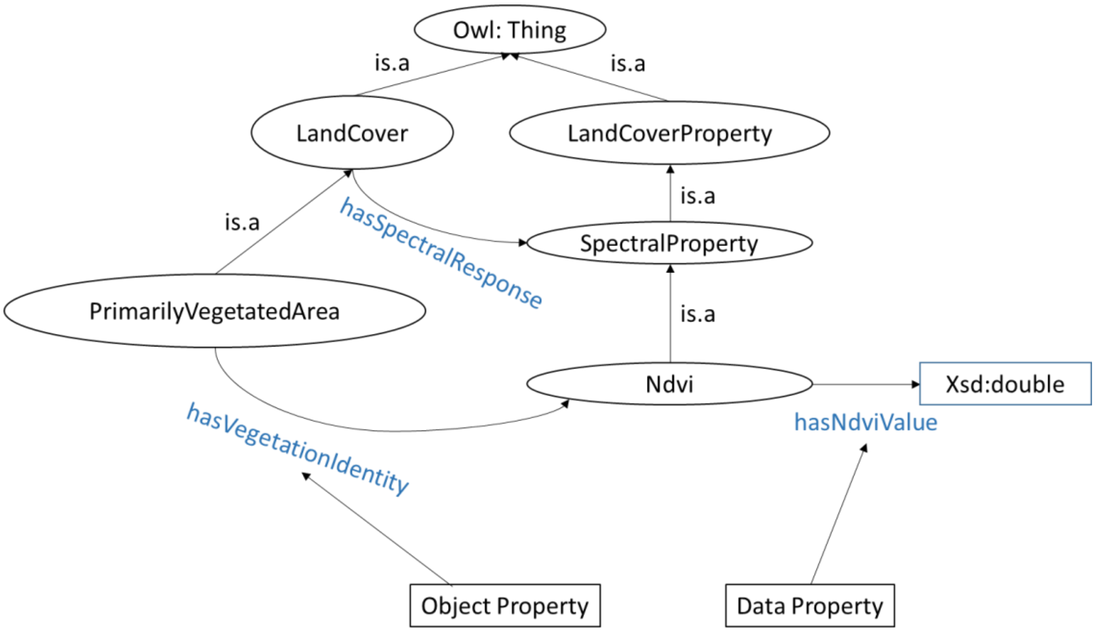

Figure 4.12 - Object Property and Data Property

4.3.2 Reasoner – Inference Engine

Every Ontology needs to be validated by the inference engine which checks for the developed axioms and conditions. The GeoOntology is also validated with the help of a Reasoner. The reasoner is used to infer logical consequences from a set of asserted facts or axioms. The Reasoner used for above study is Fact++. The Reasoner is used to query the developed class axioms and to verify that the ontology is in sync with the developed concepts.

The complete Ontology is constructed using the Protégé open source software (Stanford Center for Biomedical Informatics Research, Stanford, CA, USA). This work was conducted using the Protégé resource, which is supported by grant GM10331601 from the National Institute of General Medical Sciences of the United States National Institutes of Health ("Protégé," 2015).

4.4 Phase 3: Linking Ontology with Image objects

4.4.1 Linking the Ontology and Classified Objects

The sections describes the way of linking the proposed GeoOntology with the image segments earlier classified by the proposed rule set. The module is responsible for connecting the Phase 1 and Phase 2 of the methodology. The phase one consist of image processing techniques to classify the image and the phase 2 is responsible to generate the ontology in order to form a knowledge conceptualization regarding the geographical domain and their attributes on a satellite image. The main purpose of the module is to link the ontological concepts with the image object concepts. Since both the concepts are from different domain it is important to bring the concepts into a single form so that the semantics is preserved.

4.4.1.1 Approach

The approach used for linking of image objects so as to classify further according to ontology is as follows.

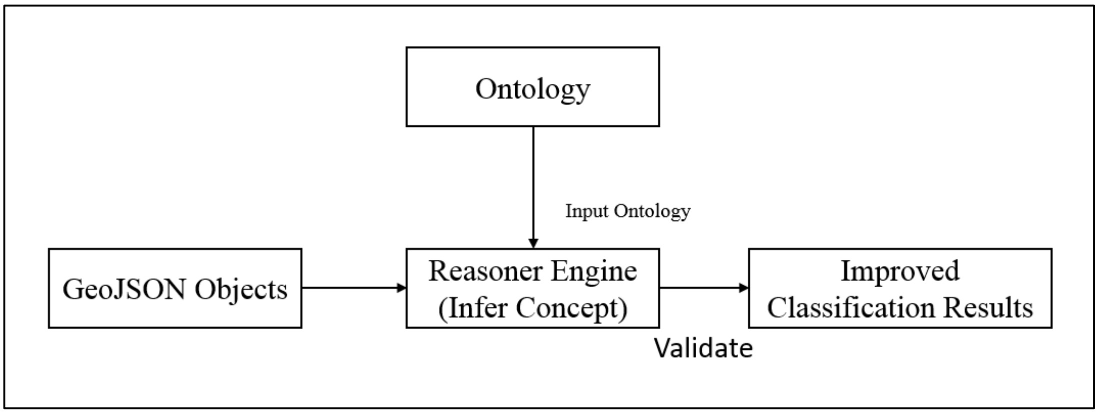

Figure 4.13 - Approach to link Ontology and Image Objects for Object Recognition

The approach as mentioned in Figure (4.13), mentions the process of linking the ontology concepts with image objects. The inputs to the system are the GeoJSON objects already exported as stated in Section 4.2.3.5. The exported GeoJSON objects are a way to preserve the semantics of the features the image objects exhibits. Thus classified objects already exported in GeoJSON format helps in retrieving the object features of interest. On the other part, system also takes the proposed ontology into consideration. Thus, system takes classified objects and Ontology as an input.

The main concept behind linking of Ontology depends on the problem domain and how the user wants the linkage between the image domain and Ontology. Ontology helps in reducing the semantic gap that exists between the image object domain (Arvor et al., 2013). Thus to allow the semantic understanding of various image object terms it is important to combine image concepts into the knowledge formalization. This is achieved by inserting the image concepts into the Ontology. The image objects belong to a specific class and are thus noted as the instances of those specific classes. In the similar manner the concepts in Ontology are formalized in a class hierarchy and the image object concepts needs to be inserted into the specific required class. Thus it is important that the relevant problem domain is formalized inside ontology.

This is achieved by creating the instances for the classes of the relevant image objects in Ontology. This class information is read through the GeoJSON file which holds the information in a structured format. This individuals hold the concepts which are formulated for its relevant class in Ontology. The concepts are then validated using a Reasoner system which infers the rules on the created individual. The facts are thus transferred into the knowledge formalization from the image domain. The overall process is performed using the OWLAPI, specially designed for handling the OWL ontologies. The individuals are created through OWLAPI and by using a reasoner system the concepts are inferred.

To interpret the data a reasoner needs:

- Ontology containing the domain conceptualization.
- Image object information to be validated through Ontology.

The Fact++ reasoner is used to infer, so as to find out the relationship every individual holds. The system not only does a comparative study but also tries to find out the correct classification according to the developed ontology. The reasoner lets the user know about the various relations the individual hold. This helps in further enhancing the concepts used in Ontology. The object recognition purely depends on how well the conceptualization is developed.

5 Results and Discussion

This chapter discusses the results and analyses the outcomes at various stages of the project work. The results are the outcomes of the three phases earlier discussed in chapter 4 methodology. The chapter analyses the outcomes of the phases in detail. Accuracy assessment and validation of results is also analysed and discussed further.

5.1 Phase 1 Image segmentation and Classification through OBIA

5.1.1 Atmospheric Correction of Worldview 2 Panchromatic Image

The panchromatic band is converted from the initial DN image to the top of atmosphere reflectance values along with the atmospheric correction. The results obtained are mentioned in the Figure (5.1).

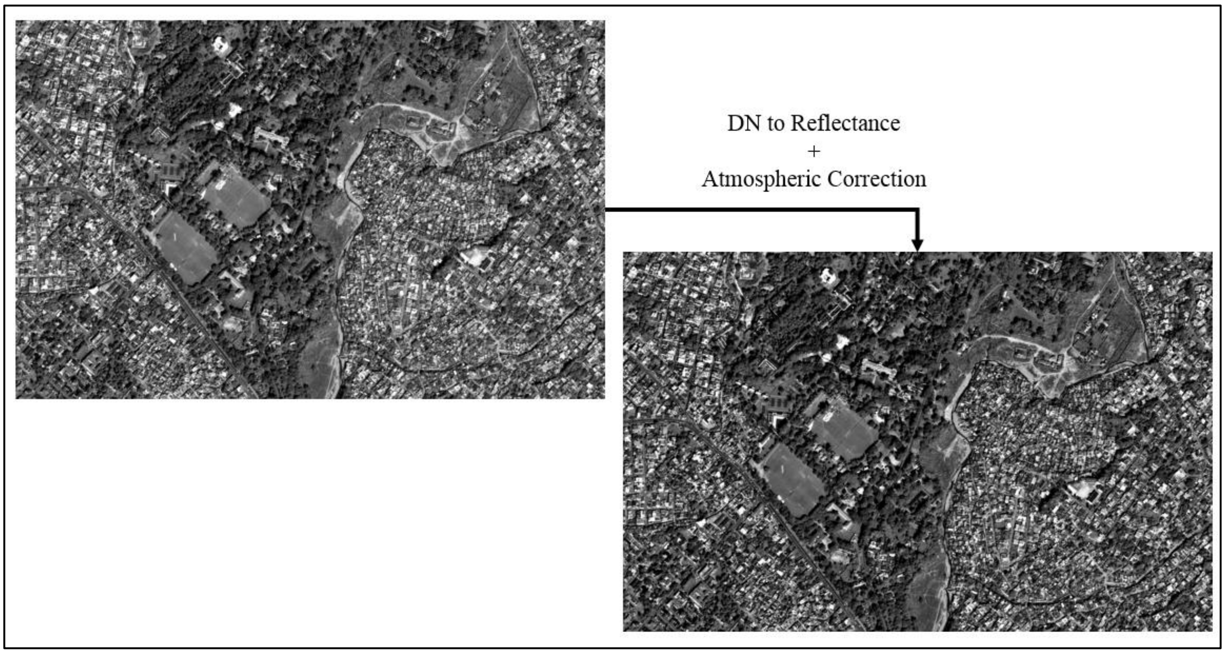

Figure 5.1 - Atmospheric Correction of Panchromatic band of Worldview 2 Dataset

5.1.1.1 Analysis of Atmospherically corrected reflectance panchromatic image

On visual observation slight changes are seen in the image contrast. The image being corrected shows better contrast values and contrast enhancement can be seen. The pixel values for the original image hold undue brightness values due to the atmospheric effects and this need to be corrected. The overall brightness is adjusted in the corrected image. The difference is less and can be very well identified by referring to the Figure (5.2). The image shows a small patch over a vegetation area where the difference in the pixel values of original and atmospherically corrected image is prominent.

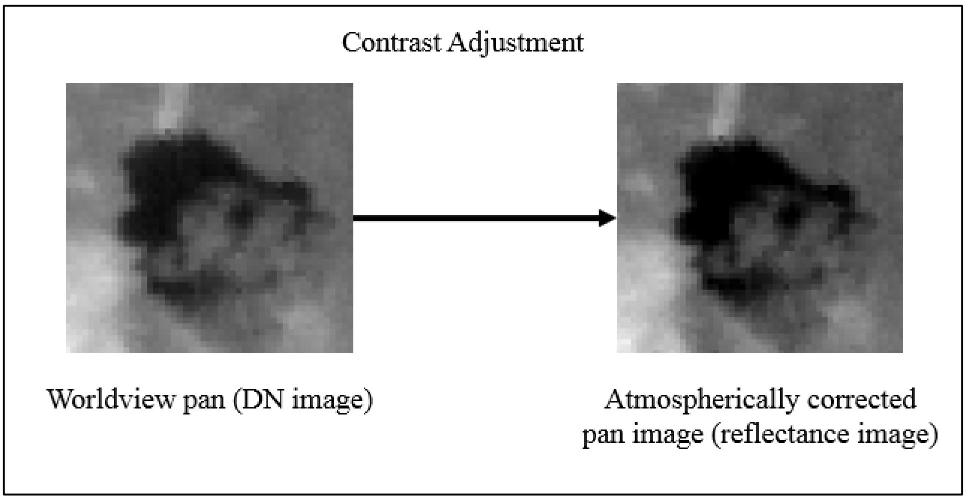

Figure 5.2 - Contrast enhancement due to atmospheric correction

The statistics for both the images are described in Table (5.1) and Table (5.2) respectively.

Table 5.1 - Worldview pan image (Before Correction) - Statistics

Pan image (Before correction)				
Basic Stats	Min	Max	Mean	Stdev
Band 1	156	1971	291.783779	70.244196

Table 5.2 - Worldview pan image (After Correction) - Statistics

Pan Image (After correction)				
Basic Stats	Min	Max	Mean	Stdev
Band 1	0	9398	489.867089	359.057806

5.1.2 Atmospheric Correction of Worldview 2 Multispectral Image

The initial phase of project consisted of data pre-processing steps including the conversion from DN to reflectance and atmospheric correction of imagery. The Worldview multispectral imagery was converted from DN to surface reflectance.

To validate the atmospherically corrected reflectance image it is important to understand the actual spectra of certain ground features like vegetation, urban areas, water body, etc.

Vegetation

For vegetation, the red and blue wavelength is absorbed while the green wavelength is reflected (Agarwal, 2004). The vegetation spectra when viewed in standard false colour composite with NIR showed as Red shows a high shoot in NIR values. This happens due to the chlorophyll content in plants. Vegetation is well identified in the near infrared regions of electromagnetic spectrum.

Water

For water most of the radiations in visible and near IR are either absorbed or transmitted (Agarwal, 2004). Water almost absorbs all the incoming NIR radiations and thus there is no reflectance from the water bodies in the NIR region. Thus the spectral profile of water shows values nearing zero in the NIR region of electromagnetic spectrum. High values are found in the Blue band since it is reflected back.

Bare Land or Built-up Areas

For bare land surface, most of the radiations are either reflected or absorbed and a little portion is transmitted (Agarwal, 2004). Bare land tends to reflect the incoming radiations and thus we can see an increasing trend in the spectral profile of bare land. This includes the reflectance occurring in the river bed, bare land areas, urban features such as buildings, roads, etc. The spectra in such areas are not regular and the spectral profile may vary over a same identified region due to irregularity.

Figure (5.3) shows the atmospherically corrected multispectral image. After applying the atmospheric corrections specific results are obtained and the results can be seen through the spectral profiles of various features.

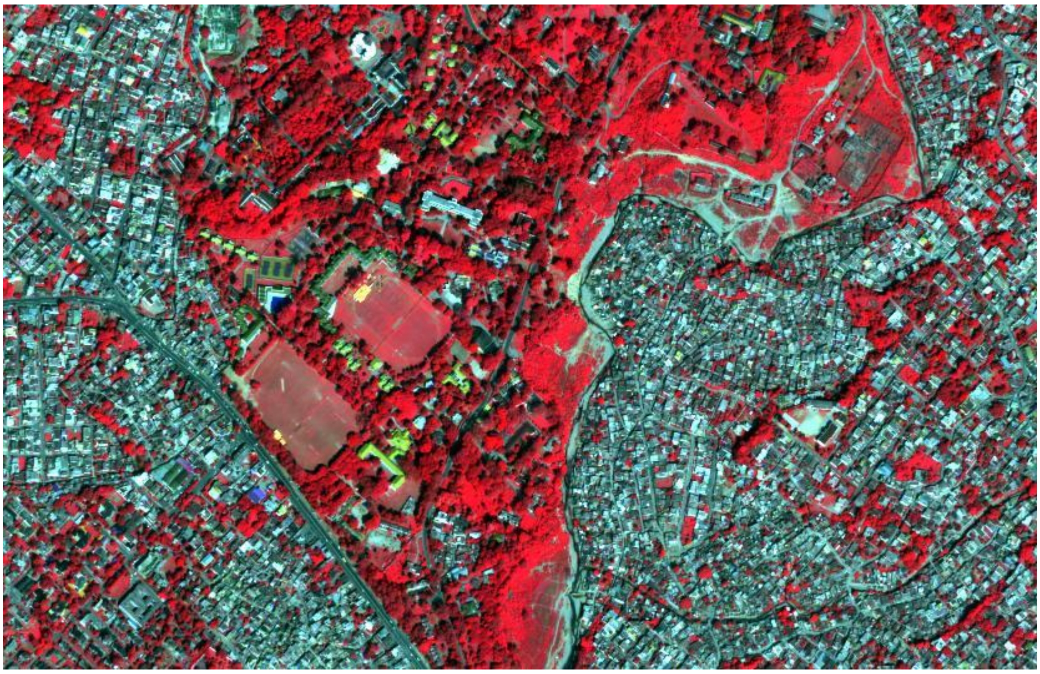

Figure 5.3 - Atmospheric Correction of Worldview 2 Multispectral image (Std. FCC: Band - 7, 5, 3)

5.1.2.1 Analysis over the spectral profiles obtained

Vegetation Spectra

The vegetation spectra in the original image as seen in Figure (5.4) holds irregular reflectance values from the blue band to the NIR region. These values are due the unwanted atmospheric effects which alters the original spectral values. The values also shoot in between the Red and NIR region and later tend to increase in the NIR region. In case of the corrected spectra, a gradual and consistent increasing trend in the spectral values is seen in NIR region. The initial values are also low and the atmospheric effects are also removed. The overall spectral profile of the vegetation feature in image seems to be according to the actual mentioned vegetation spectral profile. Thus we can see that the vegetation profile has been improved from the vegetation profile obtained in the original image.

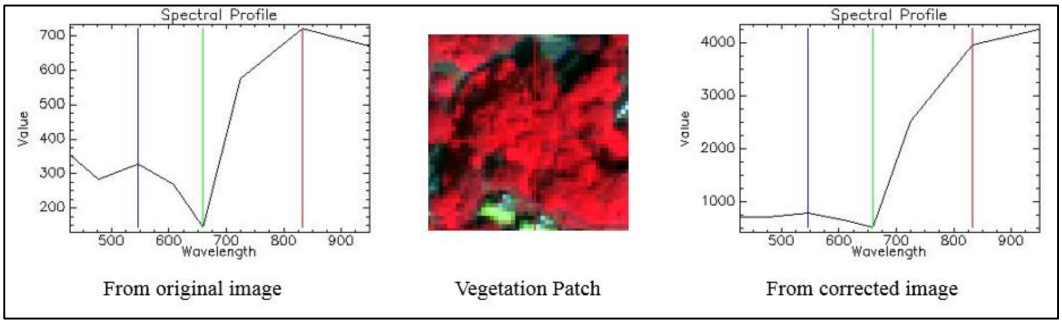

Figure 5.4 - Comparison of Vegetation Spectra between the original DN image and atmospherically corrected reflectance image

Water Body

The spectra of water as seen in Figure (5.5) shows a decreasing trend in the NIR region and then touches almost zero due to the absorption of NIR radiations by the water bodies. The results show that correction is proper with the values decreasing from the blue band towards the NIR band. The values are nearing zero in the NIR region. The spectral profile of the original image shows a poor spectral curve as compared with the spectral profile in corrected image. In the original image, water pixels hold value in the NIR region due to the atmospheric correction. All these effects are properly removed in the corrected image.

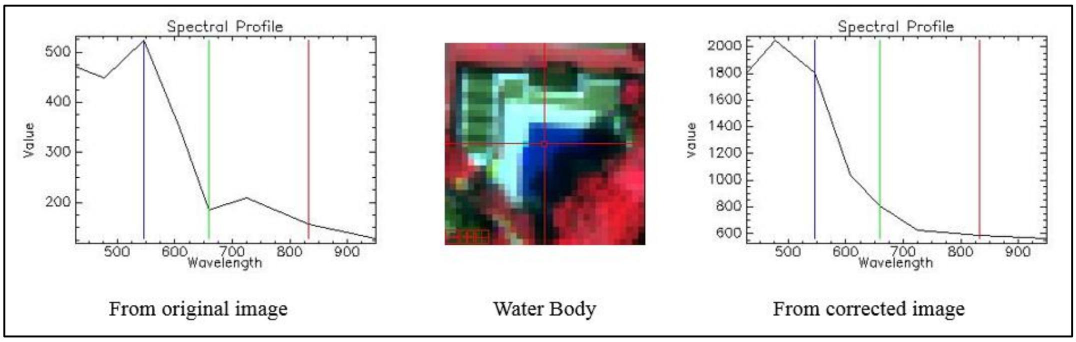

Figure 5.5 - Comparison of Water Spectra between the original DN image and atmospherically corrected reflectance image

Bare Land Area

The spectral profile of bare area as seen in Figure (5.6) shows a proper increasing curve in the corrected image. The spectral profile of bare land in original image shows an irregularity in the spectral values in all the bands. This undulating variation is due the atmospheric effects and the uncorrected values received at the sensor. Thus the spectral profile of bare land seems to be irregular. The spectral profile seems to be improved in the corrected image.

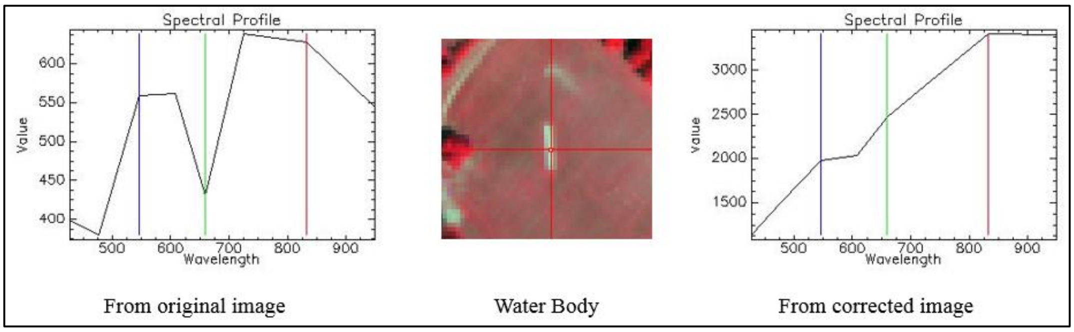

Figure 5.6 - Comparison of Bare Land Spectra between the original DN image and atmospherically corrected reflectance image

5.1.3 Image Sharpening of Worldview 2 Imagery

This section describes the results obtained in the image sharpening task.

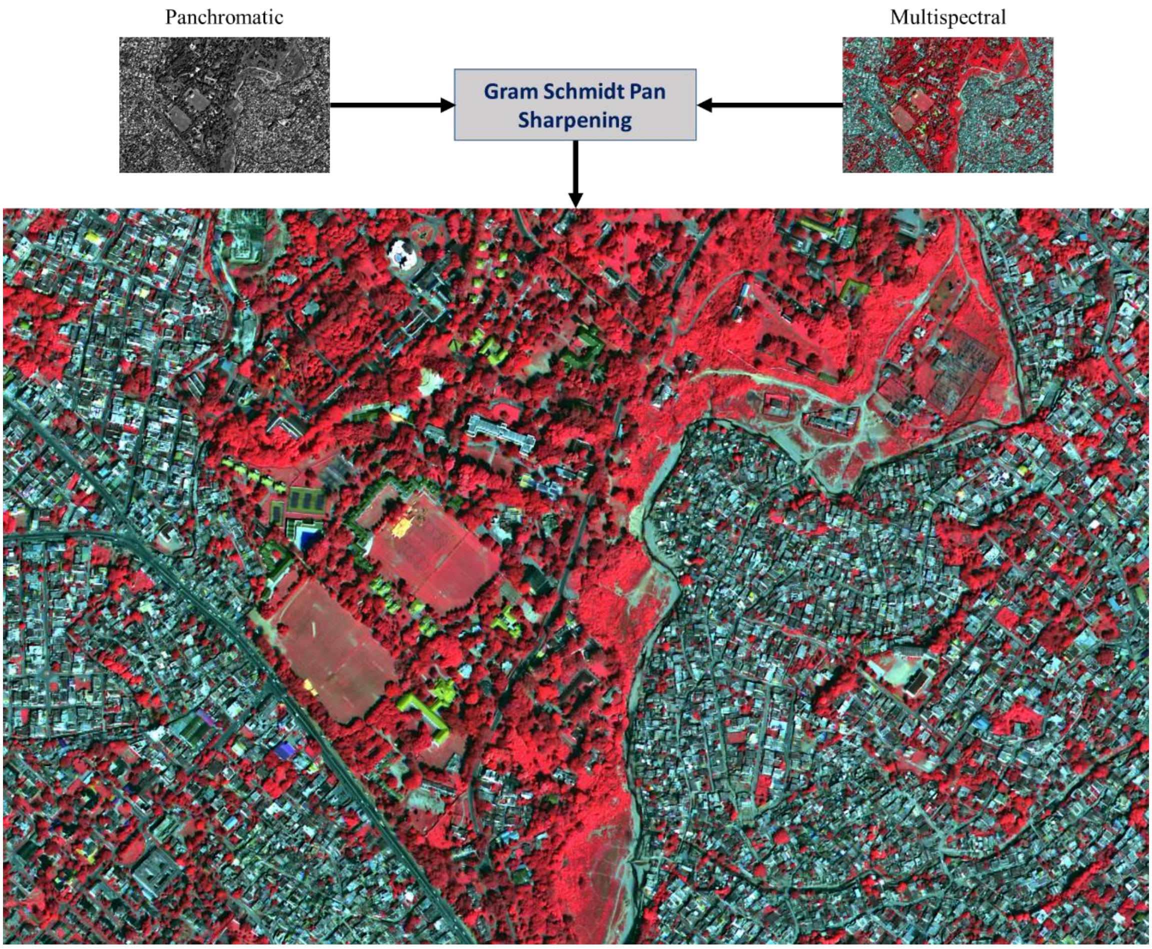

Figure 5.7 - Fused image obtained by applying Gram Schmidt Image Sharpening Technique (Viewed in Std. FCC, 7, 5, 3)

The image sharpening task involves the merging of panchromatic and the multispectral bands together to fuse the spatial and spectral characteristics into a single image. Gram Schmidt algorithm is applied to perform pan sharpening. Figure (5.7) displays the results obtained after performing this step. Figure (5.8) and Figure (5.9) explain the spectral and spatial attributes of pan sharpen image.

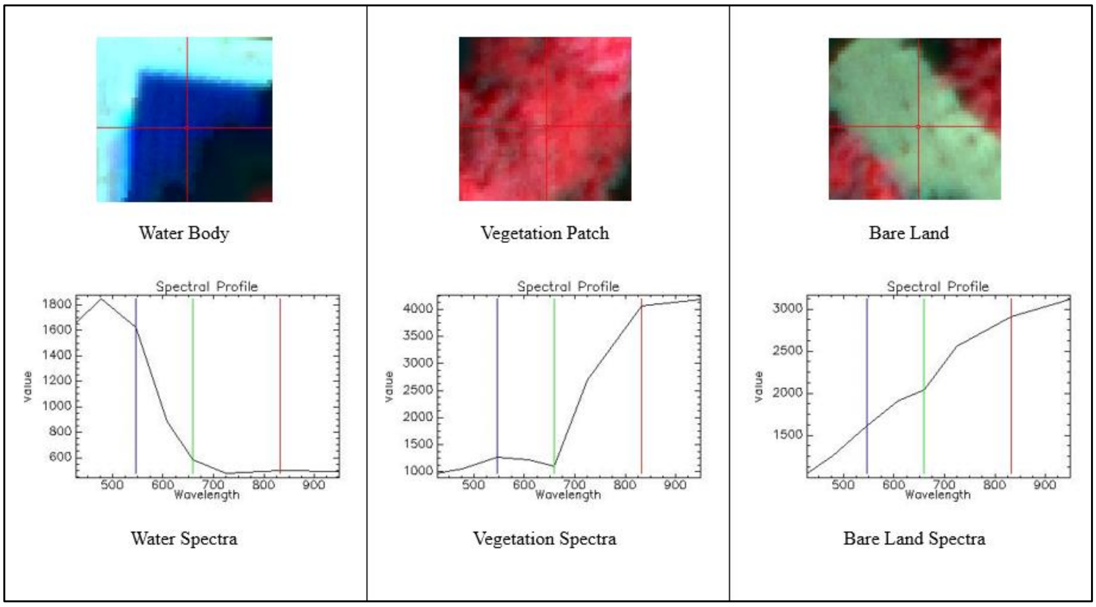

Figure 5.8 - Spectral profiles of Water Body, Vegetation, and Bare Land in pan sharpen Worldview 2 Image

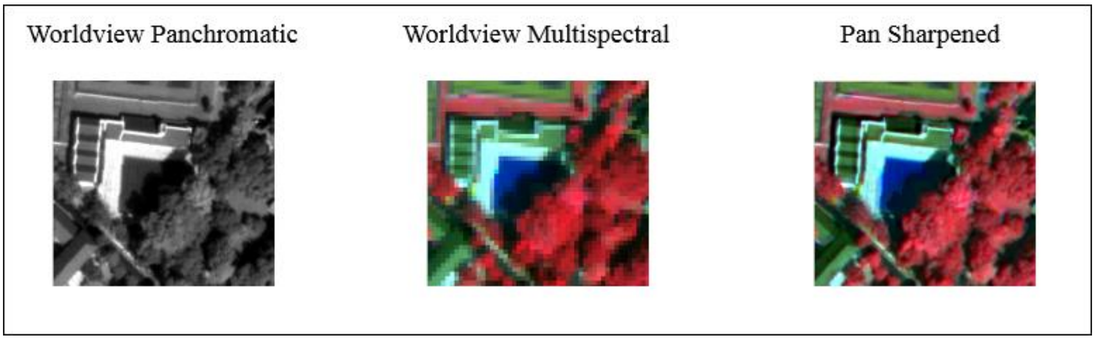

Figure 5.9 - Improvement in the spatial and spectral content of image

Discussion

The fusion of images should not only increase the spatial content but should also preserve the spectral profiles of various ground features in imagery. It is observed initially that the spatial resolution of pan sharpen image has increased to 0.5m equivalent to the pixel size of panchromatic band. The spectral profiles of various ground features are also well maintained. This can be very well understood with the help of Figure (5.8) and Figure (5.9) which describes the improvement in the spatial and spectral aspects of image. Figure (5.9) simply highlights the water body section of image in pan, multispectral and pan sharpen image.

To validate the spectral profiles of water body, vegetation patch and a bare land area from the pan sharpen image are taken into consideration as shown in Figure (5.8). As seen in the Figure (5.8) the profiles are found to be similar to the actual spectral profiles of water, vegetation and bare land respectively. It is observed that the pan sharpen image holds the correct spectral responses along with an increase in the spatial resolution. The observation states that the Gram Schmidt algorithm helps in integrating the spatial and spectral resolution in a single imagery.

The Gram Schmidt algorithm makes use of sensor dependent approaches in performing pan sharpening. This proves to be of great use in sharpening of the worldview 2 imagery. The Gram Schmidt algorithm also maintains the geographic information and the metadata which is well preserved.

The statistical information obtained from the pan sharpen imagery is mentioned in Table (5.3).

Pan Sharpen Image - Full Scene (7,069,712 points)

Table 5.3 - Pan sharpened Worldview-2 image statistics

Basic Stats	**Min**	**Max**	**Mean**	**Std. dev.**
Band 1	-1699	16193	1049.692962	324.503051
Band 2	-305	15957	1125.385578	399.686328
Band 3	-629	13613	1246.950479	459.566498
Band 4	-4636	15960	1252.084482	545.482746
Band 5	-1475	17667	1202.335518	586.339359
Band 6	-284	16102	1977.507563	618.994117
Band 7	413	13827	2557.718041	925.722951
Band 8	65	15102	2686.590035	953.381983

The signal to noise ratio is computed for the pan sharpened image. The region of interest was selected of the same area on pan, MS and pan sharpen image and the overall SNR was calculated for every band respectively. The details of the SNR computed on original DN image, MS image and pan sharpened image is shown in Table (5.4), Table (5.5) & Table (5.6) respectively.

Worldview pan image (Reflectance image)

Table 5.4 - Signal to Noise ratio of Worldview-2 pan band

Basic Stats	**Min**	**Max**	**Mean**	**Stdev**	**SNR**
Band 1	0	2560	874.111111	1121.396043	2.928689463

Worldview 2 MS image (Reflectance image)

Table 5.5 - Signal to Noise ratio of Worldview-2 MS image

Basic Stats	Min	Max	Mean	Stdev	SNR
Band 1	652	3004	1384.529412	1043.336961	2.169690275
Band 2	651	3606	1515.411765	1284.003508	2.379551277
Band 3	572	4015	1616	1514.299508	2.484529703
Band 4	512	4353	1647.941176	1668.131944	2.641477781
Band 5	440	4256	1546.352941	1702.699215	2.752282411
Band 6	679	4693	1854.941176	1733.213506	2.529999366
Band 7	722	4564	1830.294118	1593.872359	2.493588301
Band 8	743	4580	1876.588235	1618.838513	2.440599336

Worldview 2 Pan Sharpen image

Table 5.6 - Signal to Noise ratio of Worldview-2 pan sharpen image

Basic Stats	Min	Max	Mean	Stdev	SNR
Band 1	738	3119	1525.240143	951.527766	2.044923886
Band 2	720	3641	1730.498208	1206.199441	2.104018359
Band 3	730	4169	1864.88172	1425.968409	2.235530519
Band 4	628	4426	1897.010753	1522.342041	2.333144392
Band 5	463	4470	1855.308244	1584.076868	2.409303152
Band 6	733	4670	2121.0681	1632.935025	2.201720916
Band 7	743	4522	2112.11828	1547.891031	2.140978582
Band 8	779	4567	2156.146953	1592.515124	2.118130211

The SNR for the pan sharpen image is above the value of 2 in all bands with band 5 having the highest value.

5.1.4 Rule based Classification of Worldview 2 Imagery

This sections covers the results obtained in the rule based classification process of Worldview 2 imagery. The section mentions the validation of results performed through accuracy assessment. Further the analysis over the classification of imagery at two levels is discussed.

The rule based classification is divided into two levels with the level 1 classifying image into 4 classes and level 2 performing further classification into 11 classes. The results obtained after executing the developed rule based customized algorithm are mentioned in Figure (5.10).

5.1.4.1 Level 1 Classification

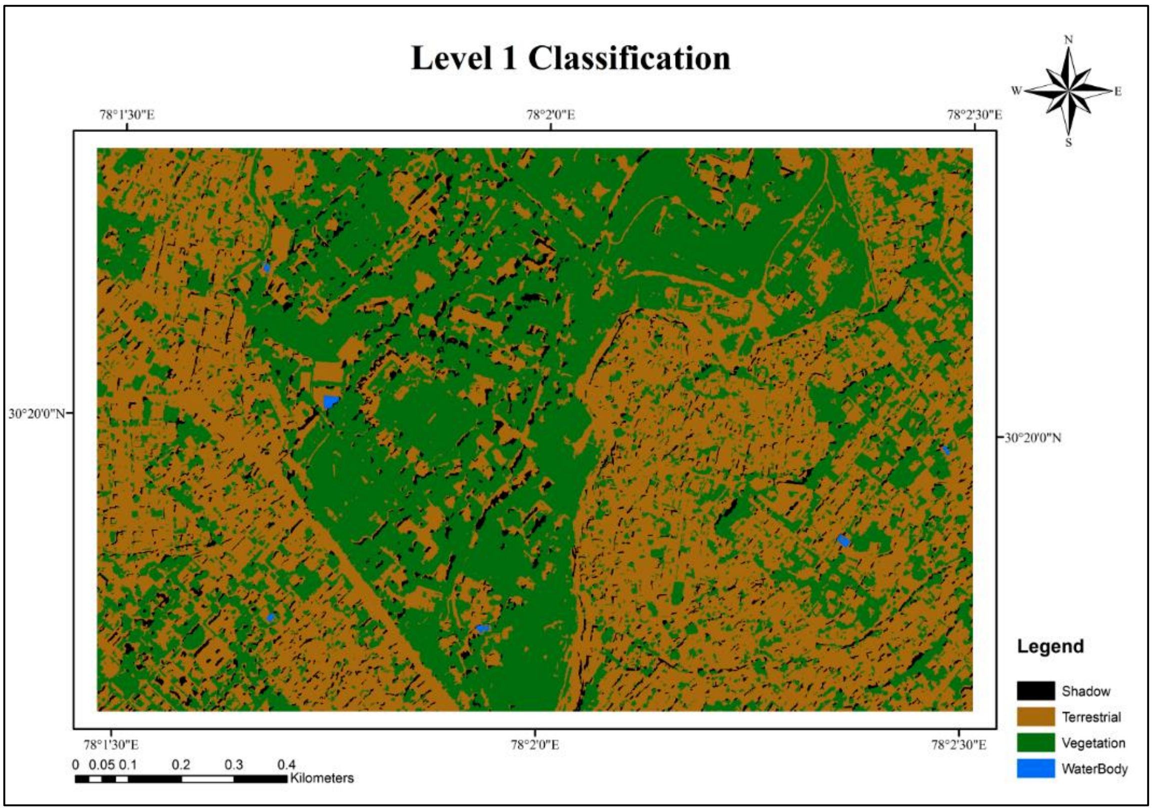

Figure 5.10 - Level 1 Classification

The Level 1 classification shown in Figure (5.10) includes classifying four land cover classes.

- Vegetation
- Water Body
- Terrestrial
- Shadow

To validate the results, accuracy assessment on the above classification was performed using the Error matrix based on samples. The producer and user accuracy obtained is shown in Table (5.7).

Table 5.7 - Accuracy Assessment of Level 1 classification

Class	Producer	User	KIA Per Class
Vegetation	0.9862486	0.9294971	0.9722874
WaterBody	1	1	1
Shadow	0.591	0.8181818	0.575
Terrestrial	0.940.3974	0.9703872	0.89

The accuracy assessment gives an overall accuracy value of 0.9441107 i.e. 94.41% and Kappa coefficient 0.8968539.

The Level 1 classification starts by separating the vegetation cover from the rest of image with the help of NDVI. Since NDVI easily highlights the overall vegetation cover, vegetation is very easy to detect in satellite imageries. The rest of the image is further classified for water body with the help of NDWI. The classification includes the Shadow class since shadow plays an important role particularly in high resolution images. The shadow is separated with the help of Visible Brightness index which is a combination of Red, Blue, Green and NIR band. The shadow class is also separated from the image. The rest of the image is classified as the terrestrial portion which belongs to the land and can contain the built-up area, bare land, artificial content.

The image at level 1 gives a higher accuracy since the image is coarser and not much classes are identified at this level. The major portion of image is classified under vegetation and terrestrial. Shadow class is selected because the image consist of small areas here shadows play a very important role.

5.1.4.2 Level 2 Classification

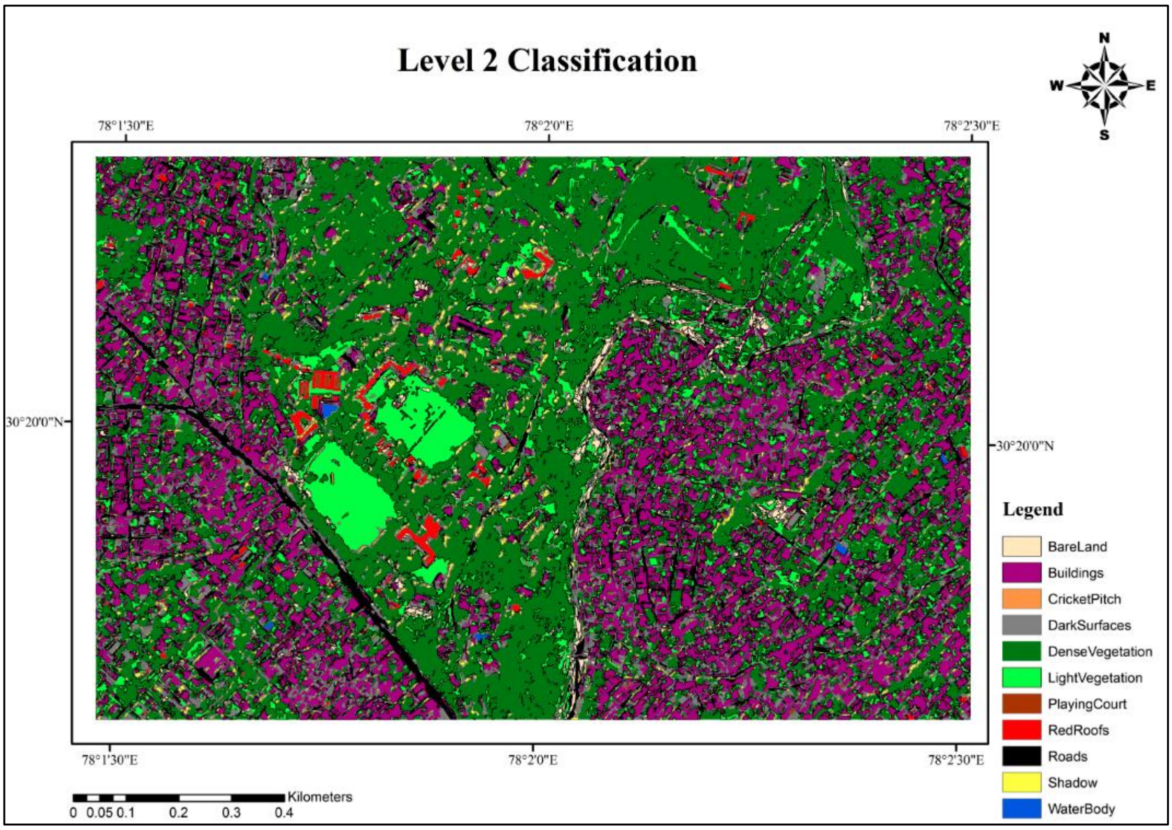

Figure 5.11 - Level 2 Classification

The level 2 classification shown in Figure (5.11) is at more granularity and includes 11 classes. The whole image is classified into

- Bare Land
- Buildings
- Cricket Pitch
- Dark Surfaces
- Dense vegetation
- Light Vegetation
- Playing Court
- Red Roofs
- Roads
- Shadow
- Water Body

The results show a very comparable and satisfactory classification through visual interpretation. To validate these results the accuracy assessment is performed for level 2 classification. The producer and user accuracy for each band class is determined as shown in Table (5.8).

Table 5.8 - Producer and User Accuracy for Level 2 Classes

Classes	**Producer**	**User**	**KIA Per Class**
WaterBody	1	1	1
Shadow	0.926	1	0.895
DarkSurfaces	0.8571429	0.6666667	0.8491571
BareLand	0.673	1	0.5883191
Roads	0.5714286	0.5	0.527
DenseVegetation	1	0.25	1
LightVegetation	1	0.4	1
Buildings	1	0.75	1
RedRoofs	1	1	1
PlayingCourt	1	1	1
CricketPitch	1	1	1

The accuracy assessment gives an overall accuracy value of 0.8352941 (83.52%) and Kappa coefficient 0.7948187 (79.48%).

The overall accuracy in the level 2 classification gets reduced as compared to the level 1 classification. The classification improves for the road and building class whereas many building roofs occur to be dark and do not completely get identified as building roofs. Thus in such places the dark surfaces can be seen. The road class gets delineated properly on basis of spectral blue values, extent, length, density values and thus the road feature extraction. The red roof class is identified but includes the portion near the playing court due to the presence of red colour. The image is classified into 11 classes but some of the classes get mixed due to similar characteristics and more level of relational property needs to be established for separating classes. This brings down the accuracy but still helps in better classifying the content in VHR imagery.

5.2 Phase 2: Developing an Ontology with respect to the Geographic context

This section of thesis details about the Ontology developed from the point of view of classifying the various land cover classes. The results include the Ontology class hierarchy, object properties, data properties included in the developed ontology. This section further analyses the Ontology so as to assess the knowledge formation.

5.2.1 Ontological Model – Class Hierarchy

The knowledge required to further classify the high resolution imagery is developed through Protégé. The ontology is divided into three major classes Land Cover class and the Land cover property classes and the class for manmade objects. The upper level knowledge is used from the Land Cover Classification System (Di Gregorio, 2005). The hierarchy of classes in the developed Ontology are mentioned in below set of images starting from Figure (5.12-5.20) describes the land cover class and land cover property class hierarchy developed in the proposed Ontology.

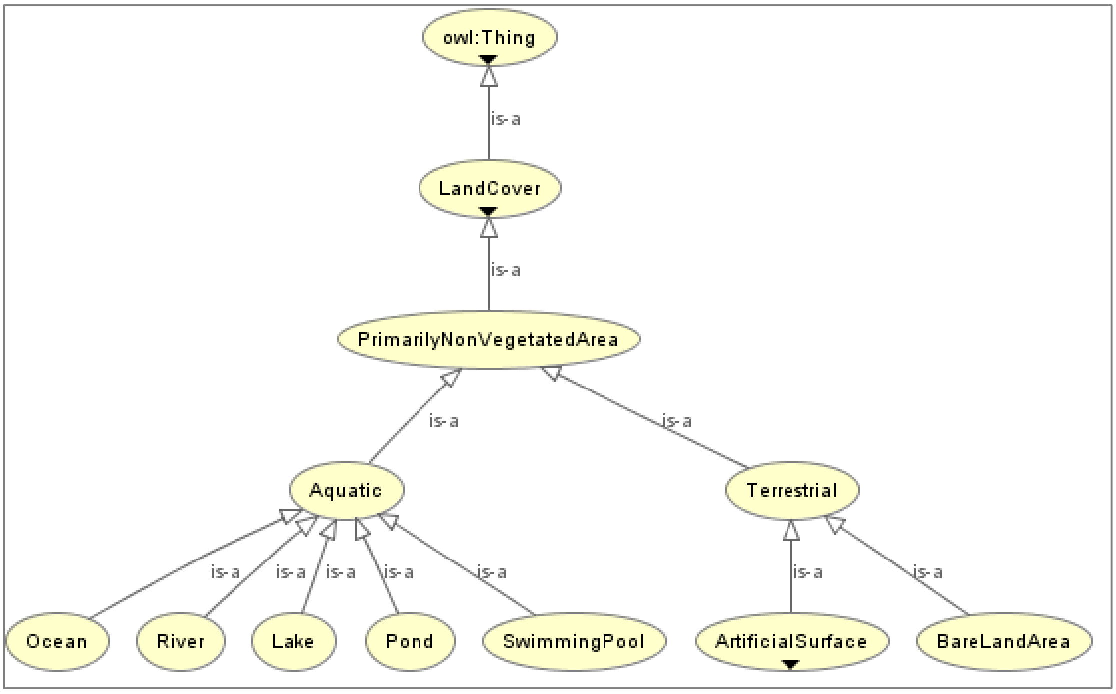

Figure 5.12 - Hierarchical formation of Land cover classes in Ontology

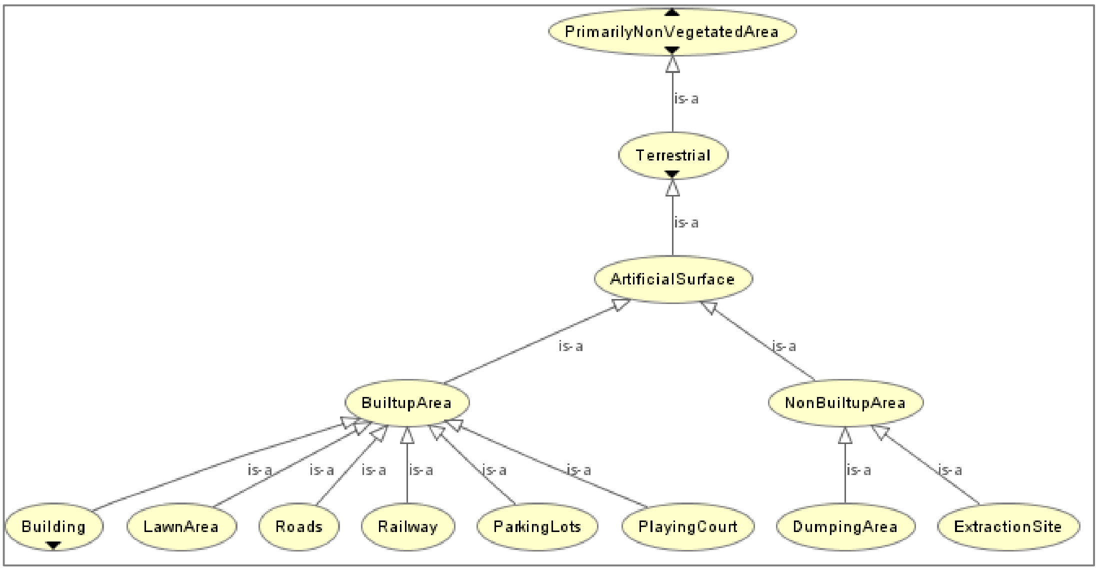

Figure 5.13 - Hierarchical formation of Primarily Non-Vegetated Class in Ontology

From Figure (5.13) it is evident that the Building class extends further and is explained in Figure (5.14). PrimarilyVegetatedArea is described further in Figure (5.15).

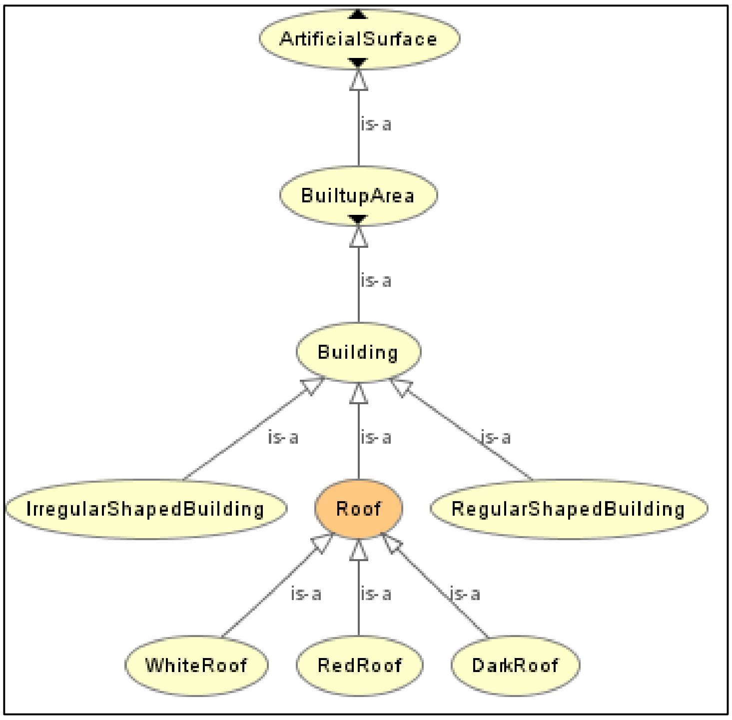

Figure 5.14 - Hierarchical formation of Building class and its subclass

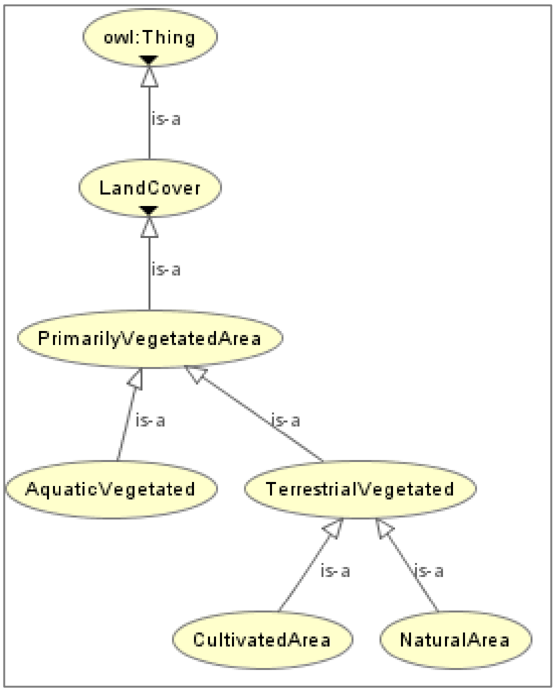

Figure 5.15 - Hierarchical formation of Primarily Vegetation Class

In the similar manner, the land cover property classes are formed. This include the classes which represent attributes the land cover classes hold. The formation of LandCoverProperty class hierarchy is described in Figures (5.16 – 5.20).

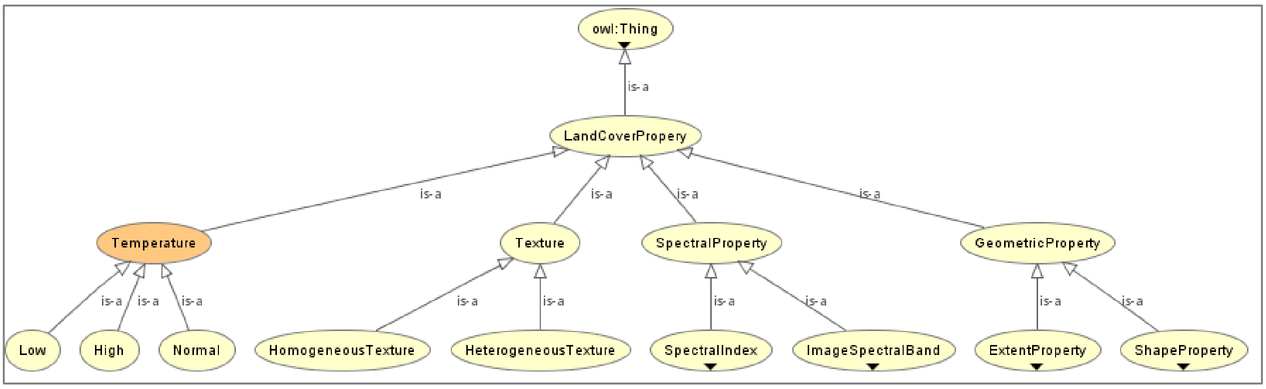

Figure 5.16 - Hierarchical Structure of land cover property classes as mentioned in developed Ontology

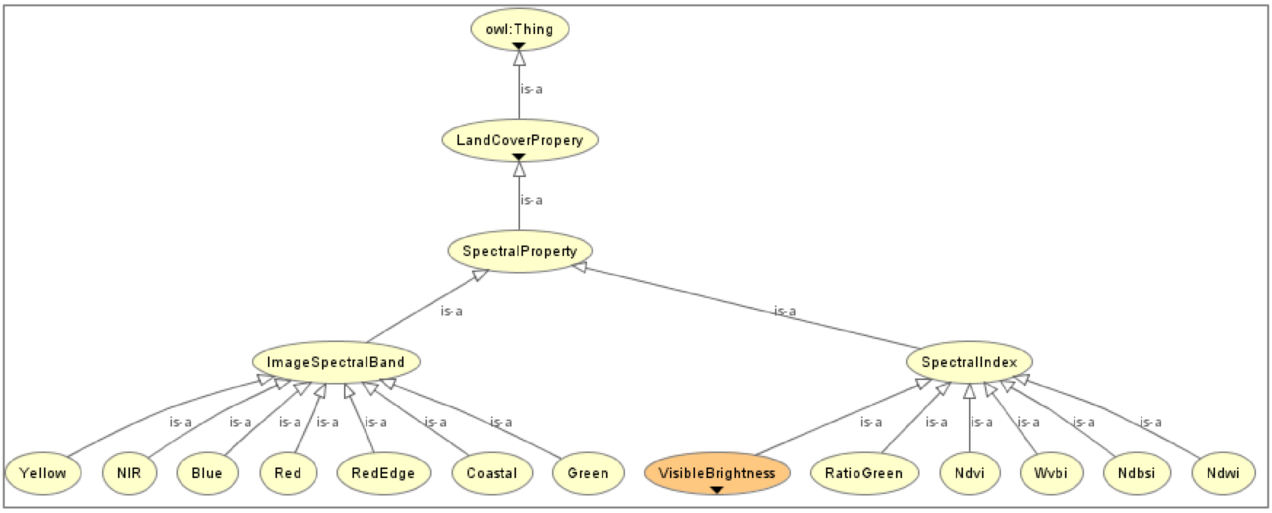

Figure 5.17 - Hierarchical formation of Spectral property classes in developed Ontology

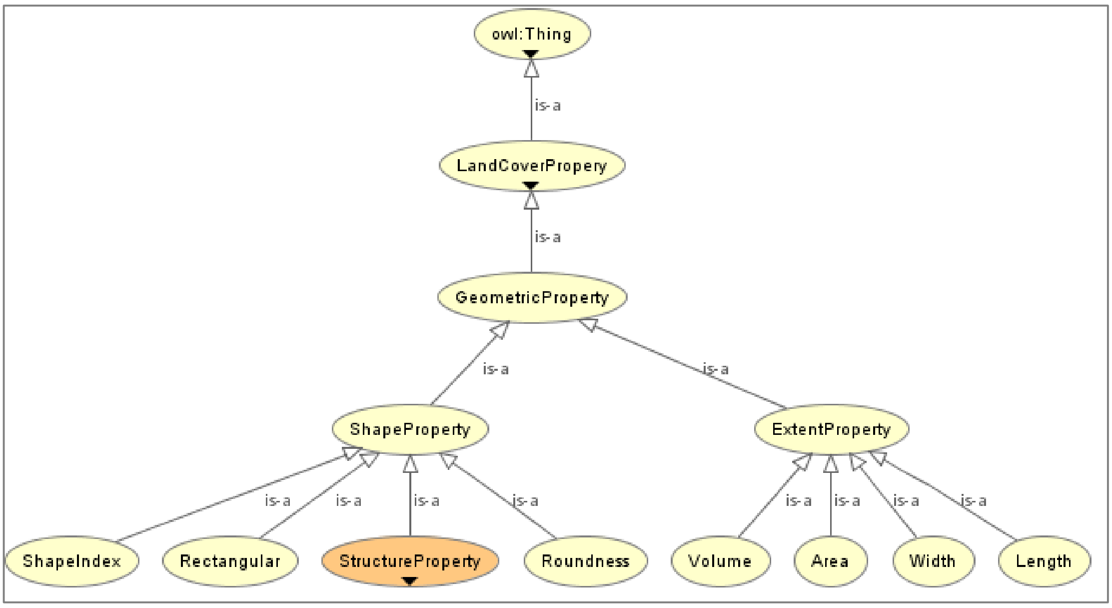

Figure 5.18 - Hierarchical formation of Geometric property classes in developed Ontology

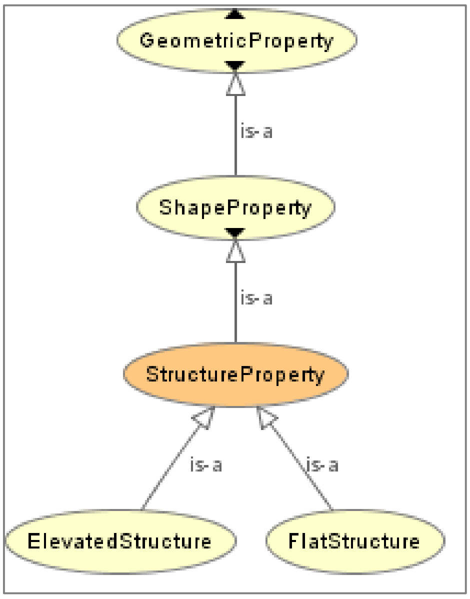

Figure 5.19 - Hierarchical formation of StructureProperty class in proposed Ontology

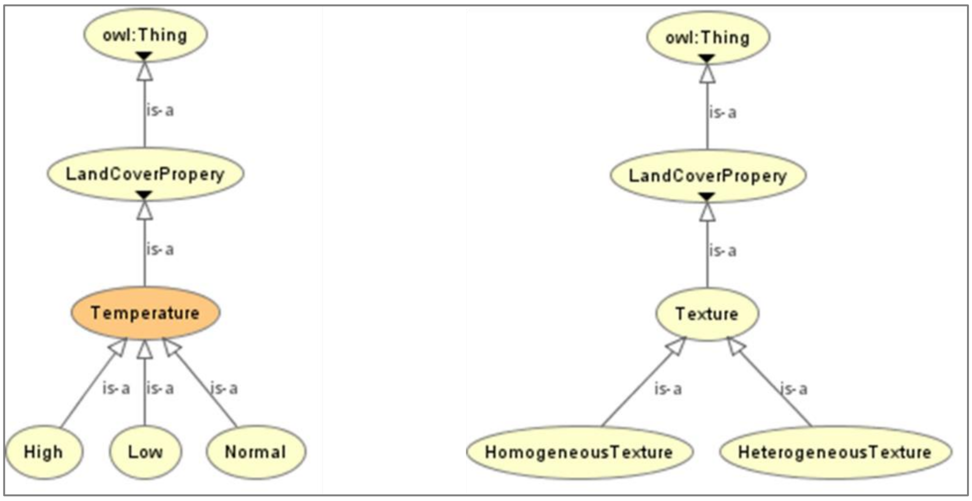

Figure 5.20 - Hierarchical formation of Temperature and Texture property classes in proposed Ontology

The land cover classification involves the use of attributes to establish relationship between them. This is achieved by forming a class hierarchy of all the related attribute information into relevant classes. Figures describe the developed land cover property knowledge in the form of class hierarchy

5.2.2 Object Properties

To establish relationship between the various individuals, object properties were introduced into the ontology. This object properties help bind the individuals of various classes together. The object properties developed in the proposed Ontology as mentioned in Figure (5.21).

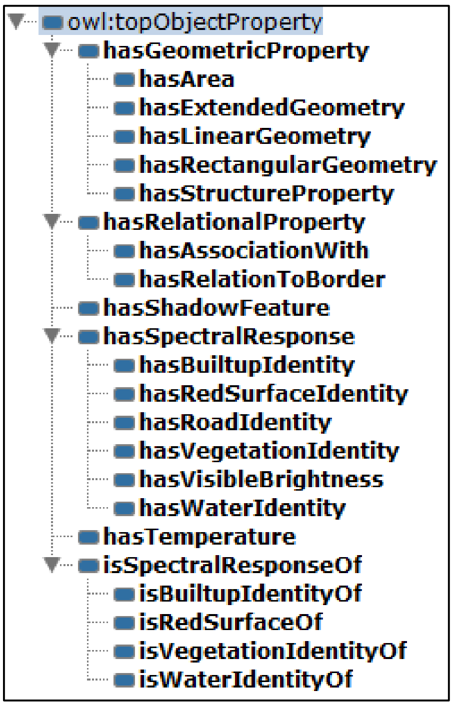

Figure 5.21 - Object property hierarchy in the proposed Ontology

5.2.3 Data Properties

The Data properties establishing a relationship between an individual of a class and a literal is illustrated through Figure (5.22).

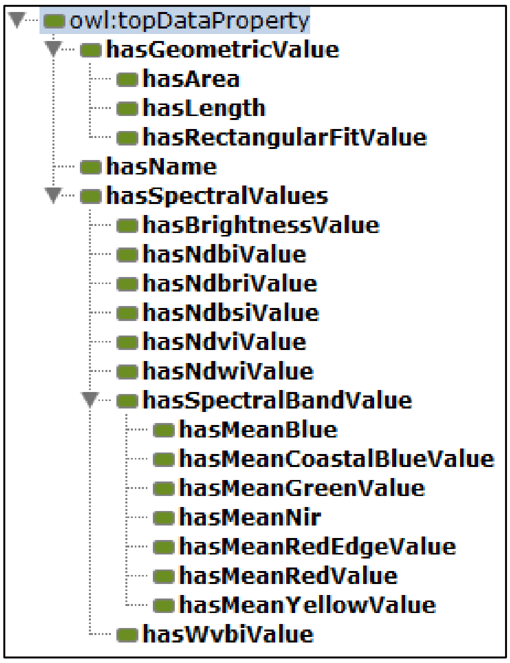

Figure 5.22 - Data Properties used in proposed Ontology

Ontology

The proposed Ontology consist of a total of 74 classes with 23 Object property and 21 data property. The ontology is a developed with OWL2 ("OWL 2 Web Ontology Language Document Overview (Second Edition)," 2012) semantics and thus help in using restrictions to various ontology concepts. The object properties and the data properties can be very well understood since they are segregated under proper domain facts such as spectral and geometric property. The contextual or the content information is also derived with the help of relating these object properties and data properties with the classes. The reasoner validates the information in Ontology on basis of the constraints developed. The reasoner Fact++ was used in the Ontology and all the concepts were inferred and were checked for consistency. The results show that the concepts are consistent. In (Belgiu and Thomas, 2013), the authors have tried to establish relationship on basis of various image descriptors and formed a Ontological model by distributing the concepts as Quantitative and Qualitative. This helped in relating the quantitative and qualitative information together. The proposed study has made use of geographic land cover concepts so as to relate them with geographic objects in satellite imagery. In (Andrés et al., 2013), the author tries to incorporate the knowledge into the Extensible Observation Ontology (OBOE) framework so as to standardised the geographic knowledge. Further OBOE was extended to embed the geographic concepts for image interpretation. In proposed study, the Ontological model makes use of descriptors in the form of land cover properties and tires to establish relationship with the help of spectral, spatial and contextual concepts.

The Ontology refers to a specific domain knowledge. Since the main objective of the study is to identify the image objects in VHR imagery the geographic context is formalized. The ontology can involve additional concepts to enhance the object recognition process but it depends completely on the expert approach. As stated by (Arvor et al., 2013), author describes the Ontology knowledge to be qualitative such as (Vegetation is high) or subjective (depends on expert) but states that the information in image is quantitative which includes the mean values of image bands, pixel values, etc. To link the qualitative with the quantitative is referred to as the challenge faced by the OBIA group. The proposed Ontology has made use of image concepts so as to ease the process of object recognition through simplified relations. Thus the proposed Ontology helps in forming a qualitative knowledge but with various quantitative information such as mean spectral value for image bands, NDVI values along with the subjective information. Thus this approach improves the process of classification of VHR images to identify objects on it.

5.3 Phase 3: Linking Ontology with Image objects

5.3.1 Classified Objects – Converted in GeoJSON format

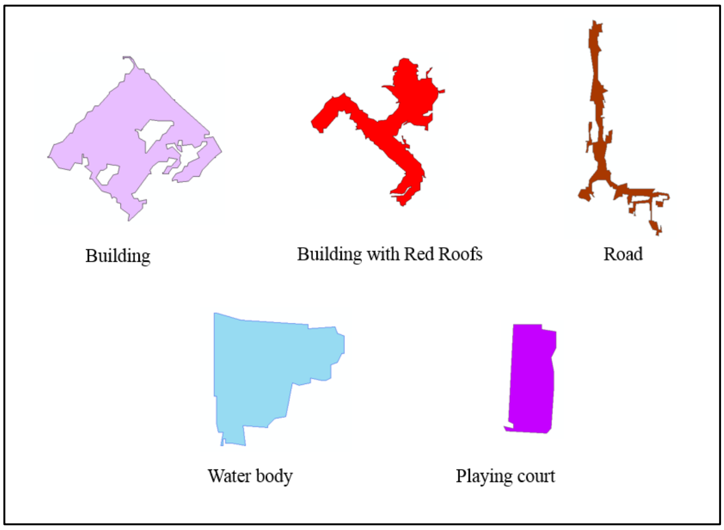

Figure 5.23 - Visualization of classified objects converted into GeoJSON format

The Figure (5.23) mentions the objects selected from the exported results so as to infer the Ontology concepts on them.

5.3.2 Object recognition through Ontological Approach

Individual: Building

After validating by Reasoner

Model	→	No inferred model found
Usage	→	Building1 Building1 hasRectangularGeometry Building_RectangularValue Building1 hasBuiltupIdentity Building_WVBI Individual: Building1 Building1 Type Building Building1 hasName "Doon_Building"^^xsd:string
Explanation	→	• Building_RectangularValue Type Rectangular • Building_RectangularValue has RectangularFitValue "0.7325"^^xsd:double • Building_RectangularValue Type hasRectangularFitValue only xsd:double[<"0.8"^^xsd:double] • Individual: Building_RectangularValue

Figure 5.24 - Ontology output 1

Result: Refer to Figure (5.24). After the reasoner infers the knowledge for Building object, the system generates 5 usages for Building individual but does not yield an inferred model.

This happens because the constraints are not matched properly. The object property hasRectangularFit for Buildings mentions a constraint of RectangularFit value to be greater than 0.8 since most of the buildings are rectangular. The rectangular fit value for this individual is 0.732 which is less than 0.8 and thus the system does not accept the individual as a building.

Since this is the case the same scenario is executed by creating an individual under IrregularShapedBuilding class which relates the property for Building with Rectangular fit less than 0.8. After creating an individual of IrregularShapedBuilding, the values are again validated by a Reasoner, the outcomes are mentioned in Figure (5.25). The inferred model is generated and the individual is validated under IrregularShapedBuilding class.

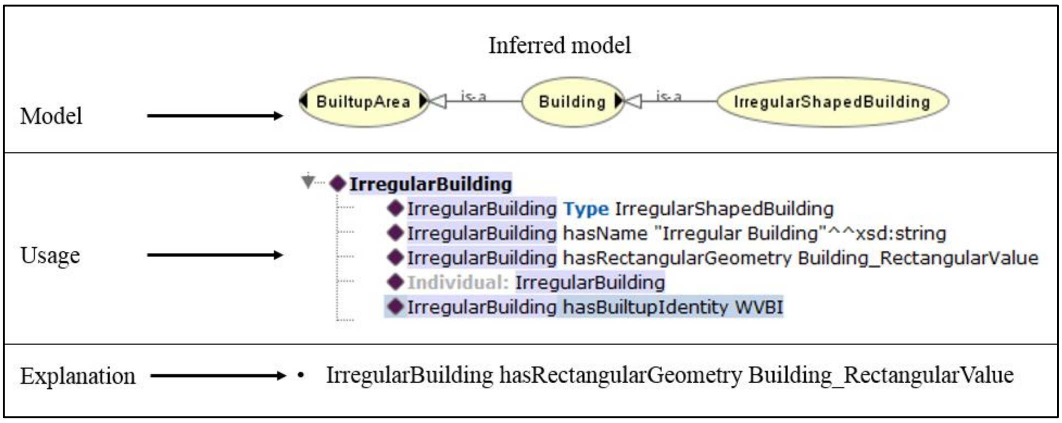

Figure 5.25 - Ontology output 2

.**Individual**: Building with Red Roofs

After validating by Reasoner

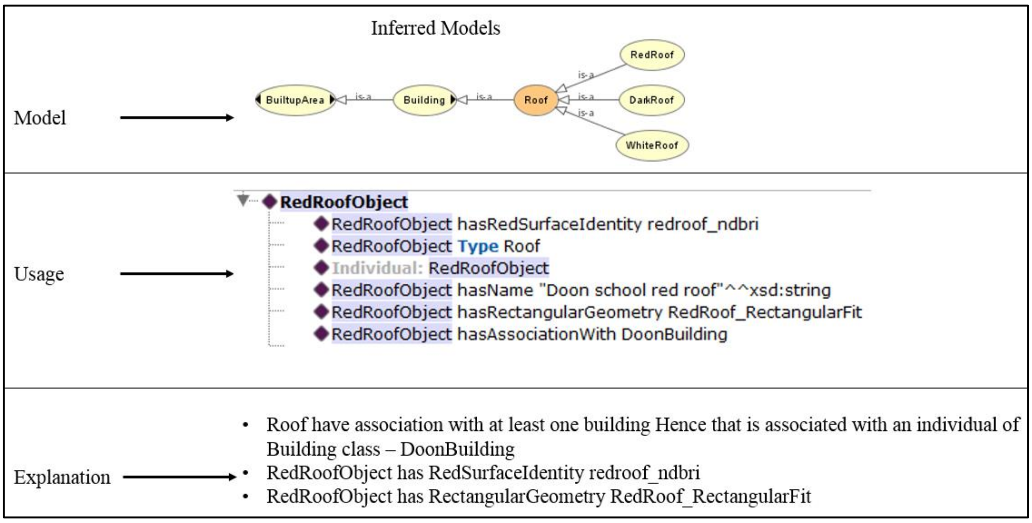

Figure 5.26 - Ontology output 3

Result: Refer Figure (5.26). The red roof object identified in image is inferred by the reasoner and the results show that the red roof object is properly classified as per Ontological knowledge. The red roof class comes under the Roof category which is under building. The inferred model correctly shows the inference of class hierarchy and validates that the roof belongs to building. Since the condition in Ontology specifies the roof to hold value of either dark, red or white, the individual is bound to fall into these classes. To further infer the concepts, the individual also holds a NDBRI (Normalized Difference Brick Roof Index) (Zhou et al., 2012) value which categorises the red content in various surfaces. The conditional statement states that the value of NDBRI should not be less than 0.15 and should be less than 1. This helps in categorising the roof class as the value of NDBRI is 0.226. Also the roof class holds an object property that it is always associated with minimum 1 building. Thus the red roof is associated with an instance of building class.

Individual: Roads

After validating by Reasoner

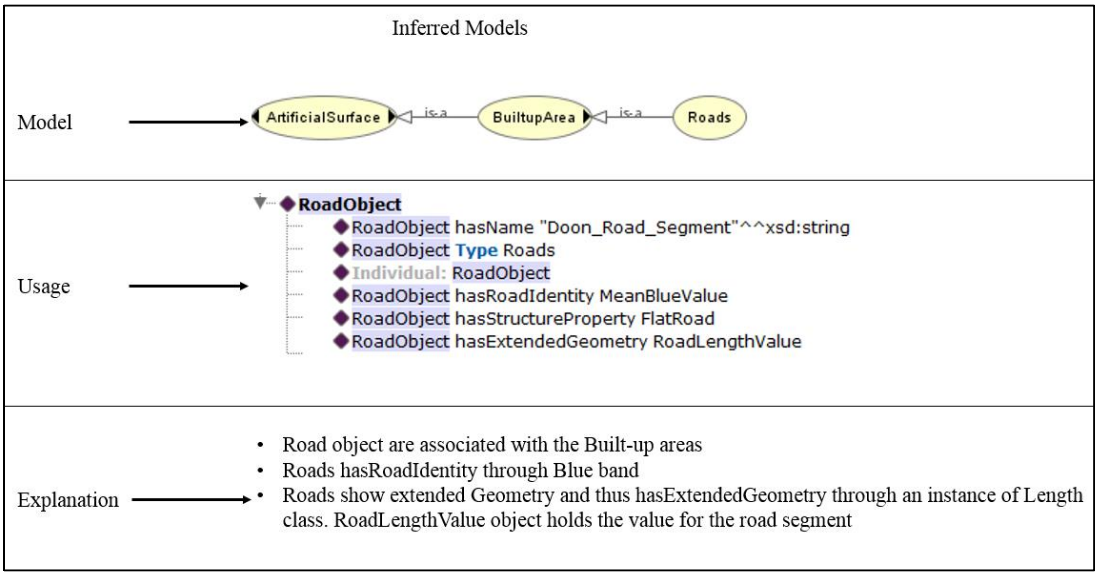

Figure 5.27 - Ontology output 3

Result: Refer Figure (5.27). Results show that the road object is validated by the reasoner system and enhances the existing classification. Since the road network comes under built-up area but is not easily identified through spectral values, geometric properties are used to classify roads. Thus the road object is associated with both the spectral and geometric properties like the 'hasRoadProperty', 'hasStructureProperty' and 'hasExtendedProperty'.

Individual: Water Body

After validating by Reasoner

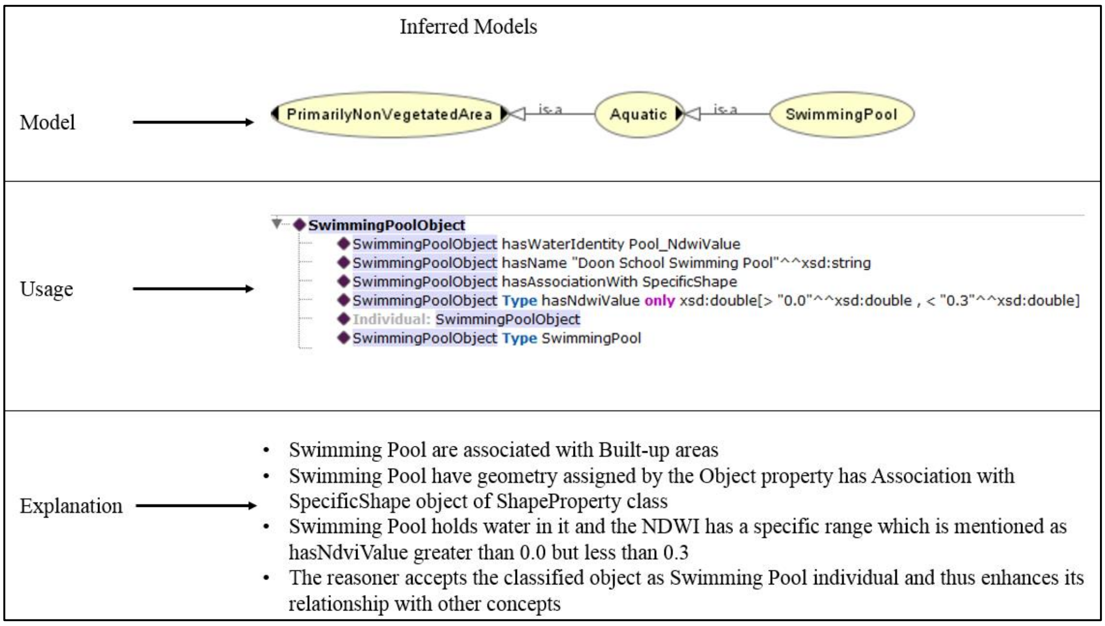

Figure 5.28 - Ontology output 4

Result: Refer Figure (5.28). Swimming Pools are always associated with a Builtup area. The constraints used were of NDWI value greater than 0 for water. The water body object is inferred by the Reasoner to be validated on NDWI count. It is also a fact that swimming pools have some geometric shape.

Individual: Playing Courts

After validating by Reasoner

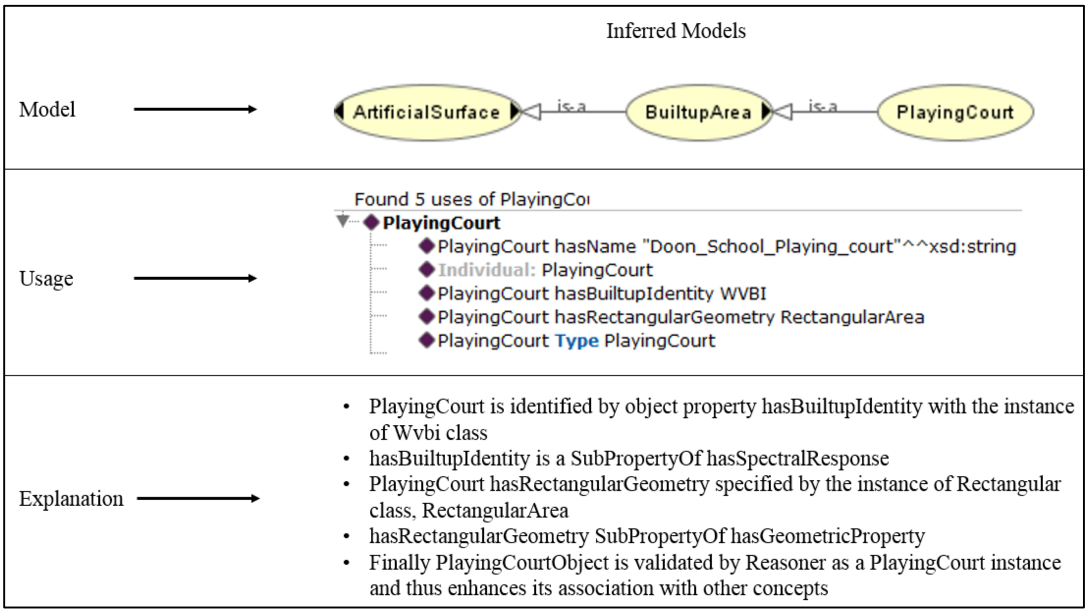

Figure 5.29 - Ontology output 5

Result: Figure (5.29) shows the inferred ontology for the class of PlayingCout. The object is accepted as a playing court by the reasoner as it accepts all the values for the object according to the restrictions formalized in the Ontology.

5.3.3 Visualizing the annotations via Google Earth

The above inferred concepts are visualized on Google Earth with the help of KML file. The KML file is modelled with the data attributes to help visualize the concepts for the image objects inferred through Ontology. Once the concepts are validated through an inference engine, the concepts hold true for the specific object. Here the inferred concepts act as relations for the image objects so as to recognize them. These include the components such as the class, attribute information and is structured with the help of KML file. The KML file helps in visualizing the content for specific geographic object on map. Refer to Figure (5.30).

Figure 5.30 - Ontology linking of Image objects visualized through KML file on Google Earth

The process of image interpretation in geographic domain is an expert process and many of the parameters need to be tuned depending on the problem domain (Arvor et al., 2013). The image objects obtained through object oriented approach can be further improved by tuning the initial segmentation process since it decides the shape and size of the object being formed. Thus it is important to tune the segmentation algorithms as per the need of the problem. The results show that to properly have object recognition in VHR imagery the object parameters should be properly defined. These objects along with their features are the input to the ontology (Derivaux et al., 2007) and thus proper matching mechanisms are required to further classify them. If the knowledge is structured then the sharing of knowledge is easier. This can be explained with the example that a road is an elongated network but this gets altered due to the presence of various objects present on or near road. Thus their presence cause the road characteristics to change over the image. This is to be taken into account when performing object recognition. Figure (5.23) describes various such objects extracted from the satellite image, the road object is not seen to be that linear or smooth along its boundaries. This is due to the fact that the presence of other objects in and around road disturb the actual characteristics of road. The feature might change in satellite imagery due to the presence of other elements. A presence of tree or a tall building casts a shadow on surface which can also disturb the overall spectra received from that region in a satellite image. Thus to improve the object recognition the overall object characteristics should be modelled. From the obtained results it is well understood that the structured knowledge helps in combining various sources. It also helps in transferring information from one source to other. The ontological framework proposed in the study uses the concepts of Land Cover classification System (Di Gregorio, 2005) knowledge as the upper level knowledge to be further extended for the object recognition in VHR satellite imagery. Thus enhanced object interpretation is achieved.

In (Lampoltshammer and Heistracher, 2014), the author proposed an extension plugin for the Protégé tool for converting the GeoJSON objects into OWL relevant files. Similar approach is used in project work so as to perform object recognition. But the approach is not that easy as image objects not necessarily hold values and constraints as mentioned in ontology. Thus the expert knowledge should be properly modelled into the ontology in a manner such that the underlying semantics of the image object are addresses. The results for the image objects selected show that for Building class the instance (individual) when inferred by the reasoner, does not accept the value entered for Rectangular Fit. This happens when the constraints are not properly modelled. Thus there is a need to structure data in an ontological form properly.

The concepts from Ontology, not necessarily match the image objects as the knowledge is never complete. It keeps growing and the interpretation of objects is possible only when the specific knowledge is formalized from the existing knowledge. The results show that the study is able to explicitly assign the concepts from the Ontology to the image objects.

6 Conclusion and Recommendations

6.1 Conclusions

The present study has proposed a knowledge representation framework in the form of Ontology for RS domain with a view of classifying the image objects in VHR satellite imagery. To perform this activity the study concludes certain specific developments and achievements through the various stages of proposed methodology. The study was able to perform better pan sharpening method by reducing the spatial resolution of MS up to the level of panchromatic band and maintaining the spectra for various features. Further the project methodology was able to delineate the objects at two levels. Level 1 image objects were classified into four classes with accuracy of 94.41% and level 2 image objects were classified with an accuracy of 84%.

The study involves the development of an Ontology, specifically for the satellite image object domain consisting of various land cover class hierarchy along with their object and data properties. The Ontology was able to form a class hierarchy of 74 classes including the land cover classes along with their property classes. The study later was able to relate the image object concepts into the Ontology through the form of individuals. These concepts when included into the Ontology, were validated through a Reasoner module. The inferred knowledge after applying the reasoner was asserted to as enhanced classification. The study is able to visualize the enhanced classification on Google Earth by modelling it through a KML file. Thus the study concludes the understanding of image object recognition through visualization step.

The presented work has shown the scope for better classification of VHR satellite imagery through the use of Ontology. The study is able to structure the required knowledge to annotate the image objects with the Ontological concepts. Thus Ontological framework helps in better object recognition through a knowledge domain. The study concludes that the classification results are dependent on the quality of image segmentation (Blaschke, 2010)(Belgiu and Thomas, 2013). The image segmentation process helps in delineating the image objects and then the delineated object parameters rule the further classification process. In this study, image object delineation is better with the help of the proposed methodology and the image segmentation helps in separating a total of 11 classes in level 2.

Ontology not only conceptualizes the domain facts but also helps in building the knowledge for further use. One of the major observations is the improved classification of image objects by signifying the image object relations through Ontology. Ontology not only proves to be a source of knowledge the domain needs but also fills the semantic gap which exists in performing image classification(Blaschke et al., 2014). Thus we conclude that the study is able to perform object recognition with the help of proposed Ontology. The study has proposed two major aspects an rule based object based image classification and developing ontological model for image object recognition. Results show the relevance of proposal.

6.2 Future Recommendations

The study involves two distinct domains, Image processing and the Ontology. The link between the Ontology and image processing for geographic aspects is an important step towards integrating the geographic concepts with OBIA. To improve the segmentation techniques, it is recommended that the ancillary data such as LIDAR data, DEM, can be used to enhance the segmentation of satellite image. The ontology is a knowledge framework and needs to be shared among the experts so as to enhance the framework knowledge. Thus it is recommended that future researchers and experts utilize the existing knowledge to form more domain specific knowledge. From the work it is also recommended to make sure the Ontological analysis involves sharing of knowledge among other experts. The study performed acts as a new horizon for future researchers to further enhance the functionality of linking ontology in Geospatial aspects.

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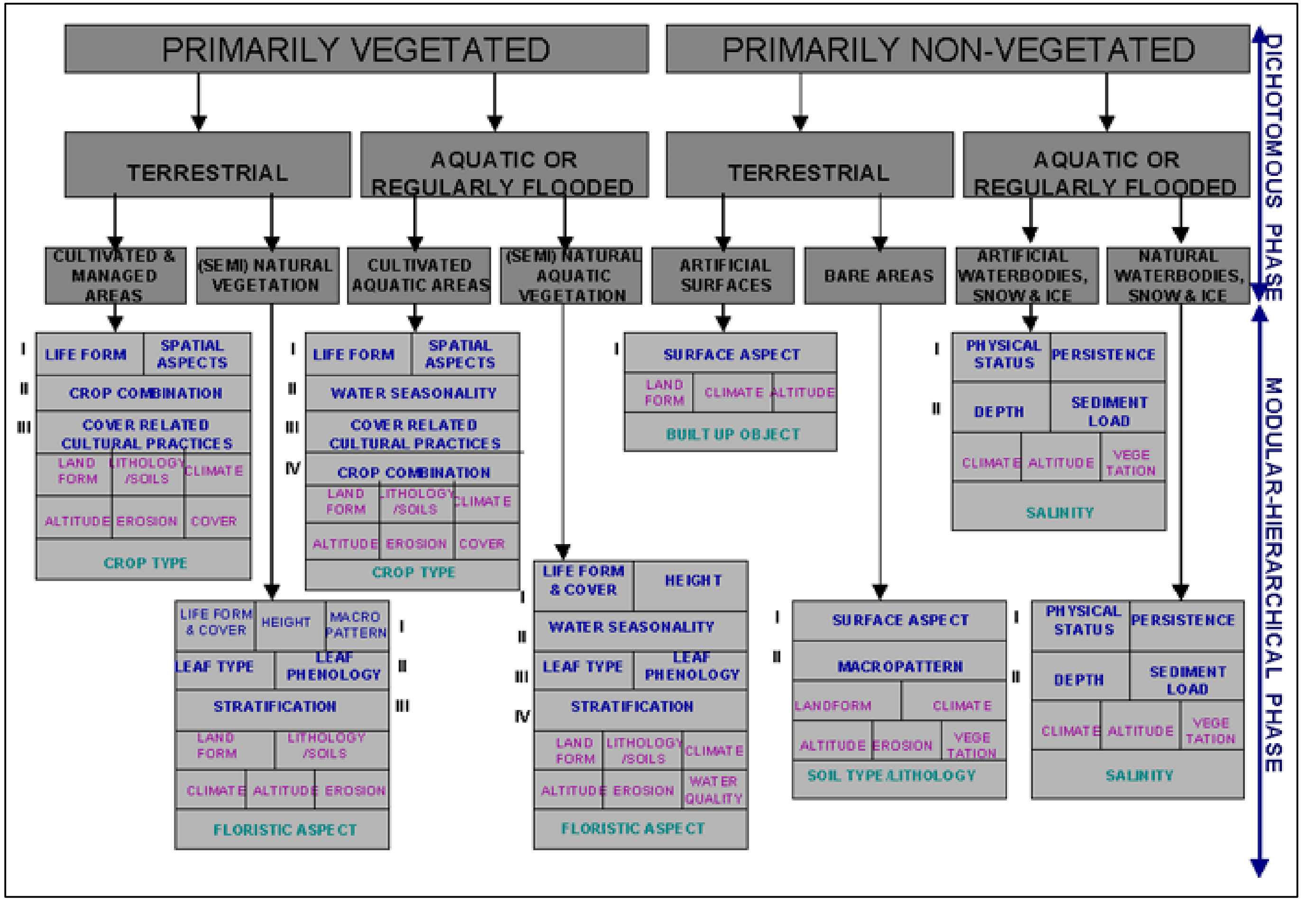
Appendices

Appendix 1: Overview of Land Cover Classification System

This section provides details about the Land Cover Classification System (LCCS) schema utilized for developing proposed Ontology in project work. The details of the schema are provided in the classification schema published by the (Di Gregorio, 2005) in Appendix Figure (1).



Appendix Figure 1 - Overview of Land Cover Classification Scheme (Di Gregorio, 2005)