University of Southern Queensland

Faculty of Health Engineering and Sciences

Object-Oriented Image Analysis of Cotton Cropping Areas in the Macintyre Valley Using Satellite Imagery

A dissertation submitted by

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In fulfilment of the requirements of

Course ENG4111/ENG4112 Research Project

Towards the degree of

Bachelor of Spatial Science (Honours)

Dissertation Submitted on the 29th October 2015

ABSTRACT

The use of extraction of polygons using software (segmentation) such as eCognition on satellite imagery to produce object based data is becoming more apparent. The technique is impressive on large areas, extracting information which can be processed for whatever purpose, with export options allowing compatibility for use in other software packages. The research is to use Landsat7 imagery with its multispectral bands, applying the object-oriented technology through ENVI 5 software and acquiring an image data set for cotton area estimates and possible infield crop analysis if time permits. The ability to create polyline data sets of specific identities from a remote sensing image has been unachievable efficiently in the past. The rate of computer, computer software technology has enhanced human computer interaction to a level that now makes data extraction of desired properties from a remote sensing image effective and is now a present reality. The intricate options of classification and rule sets within the object-oriented software selection process, is open to the users interpretation and analysis of the required data extracted. The thematic mapper (TM) bands collated from satellite imagery, allow specific features to be isolated from other features by various combinations of TM bands which can highlight the feature or features of interest to be extracted. The following dissertation investigates the desired method used through ENVI 5 software to extract the cotton area data from a cotton property, create the segmentation data sets and test the accuracy, efficiency and effectiveness of this relatively new object-oriented technology.

LIMITATIONS OF USE

CERTIFICATION

University of Southern Queensland

Faculty of Health, Engineering and Sciences

ENG4111/ENG4112 Research Project

Certification of Dissertation

I certify that the ideas, designs and experimental work, results, analyses and conclusions set out in this dissertation are entirely my own effort, except where otherwise indicated and acknowledged.

I further certify that the work is original and has not been previously submitted for assessment in any other course or institution, except where specifically stated.

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ACKNOWLEDGEMENTS

I would like to thank Dr Glenn Campbell for his guidance in the initial idea of the object-oriented concept.

I would like to thank my supervisor Prof. Armando A. Apan for his fresh approach, assistance and professionalism in my endeavor's into the object-oriented phenomena.

I would like to thank Dean Beliveau for permission of access to the ENVI software used on the University of Southern Queensland Toowoomba campus for the dissertation.

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GLOSSARY OF TERMS

Remote Sensing - Image generation of the earth by satellite or aircraft to obtain information from it illustrates the term Remote sensing (Oxford Dictionary 2015).

Pixel - A satellite image is made up of tiny squares (pixels) the same as a picture on your television set (Graham 1999).

Kernal – The mapping of each pixel data vector into finite set of discrete spectral catorgories (i.e., types, labels, and strata), which are called kernel spectral types or spectral candidate areas ((Baraldi et al. 2006 p.2564).

Multispectral Image – is the spectral responses of various features in different spectral bands (Navulur 2007 p.12).

Thematic mapper (TM) – the mapping of light and heat from image sensors across the electromagnetic range.

Segmentation – the creation of vectors (polylines) of a classified feature by computer software from an image.

Classification - Image classification applies knowledge of the image by identifying a group of pixels into clusters (kernals) to be categorized into a certain class in the image such as trees (Navulur 2007 p.47).

Object-oriented – An object can be defined as a grouping of pixels of similar spectral and spatial properties, thus object oriented refers to analyzing the image in object space rather than pixel space (Navulur 2007 p.3).

Workflow – a term used in ENVI software for step by step process of an extraction method used for segmentation.

Chapter 1 INTRODUCTION

1.1 Introduction

Satellite imagery technology has been in existence since the early seventies, however it was not cost effective to use for the general public. Since this time the development of computers to this modern day has been a technological explosion. The general public are now technologically equipped with smart phones, own or have access to a computer that can handle high data rates which allows access to information worldwide via the internet. This modern era now allows access to satellite imagery which can be utilized as a measuring base to extract any information that is of interest provided you have the software to accomplish your desired task. This research proposal aims to use the satellite imagery in extracting information in regard to cotton development over a given area at a caption of time with the availability of satellite images from today, dating back to 1986. The data set of these images are large, hence an automated process is required to extract the polygons of interest from the numerous geo-referenced tiles available. The development of automated data extraction from the satellite images will be the focal point of my research.

1.2 Idea Initiation

The initial research proposal had been inspired by approaching Doctor Glenn Campbell as a possible supervisor, who had offered to assist in my research topic. The topic of object-oriented image analysis from satellite imagery was one suggestion in which I found of interest. Since this meeting a number of ideas were proposed from water storage within a temporal range and crop analysis within a temporal range utilizing appropriate software. At the start of Semester 1 2015, Glenn had advised it would be of benefit to myself if Professor Armando A. Apan would be my new supervisor for the project as he is well versed in this field of remote sensing. Professor Apan has been kind enough to accept the responsibility of being my supervisor for the 2015 term of the dissertation. Hence from further meetings with Professor Apan the focal point of the proposal has changed to a more realistic approach in regard to the time frames allocated to complete the dissertation proposal. The changed proposal entails the data output to be now the analysis of cotton areas and production on the property of “Eukabilla” and surrounds situated in a section of the Macintyre Valley, with the data image sets captured in a certain point in time. This however does not change the principal research in object-oriented image analysis in extracting the desired polygon information from the satellite image. The area is well known to myself as I was involved in the initial survey and design of most of these developed cotton properties whilst being employed by SMK Pty. Ltd. Goondiwindi from 1985 - 2012.

1.3 Locality

The Macintyre Valley is a rich area of cotton development in which meanders along the Macintyre River and subsidiary tributaries. The property “Eukabilla” is depicted in this project being part of a section of the Macintyre Valley is shown below from Landsatlook Images website, the image depicts the month of February 2014, being around the optimum visual effect of planted cotton.

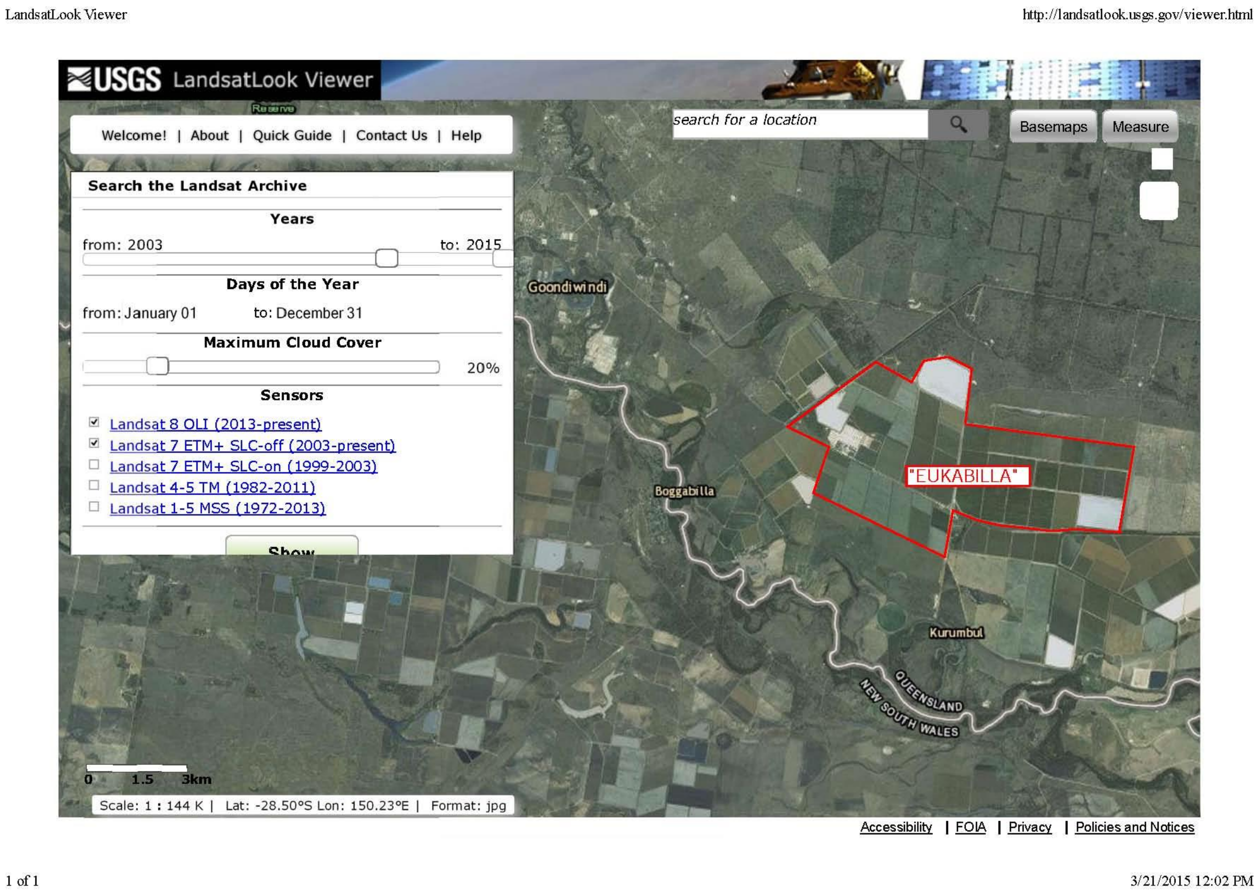


Figure 1.1: LandsatLook Viewer image of property “Eukabilla” cotton development (LandsatLooK 2015)

1.4 Objectives and Scope

The research involves evaluating cotton production at a caption of time in a section of the Macintyre Valley by a method of object-oriented image analysis on a satellite image. The software ENVI 5 shall be used to derive the polygon information with the process of ENVI 5 described in depth with verification of results. This verified data shall then be applied to the accuracy of identification of cotton areas at a caption of time. The data derived can then be utilized as a tool for cotton production analysis by others.

1.5 Benefits and Outcomes

Satellite imagery data extraction in a temporal environment should provide an inexpensive exercise of reporting information specific to the user's needs. The data can be harvested from large areas at minimal cost. The project is envisaged to provide an example of information potential for other user's in incorporating their information requirements from this technology.

The purpose of this project is to apply a data set of rules using ENVI 5 software on one satellite image over a given area at a point in time, validate the rule set. Apply the excepted rule set in extracting information from satellite imagery cumulating in deriving cotton area data.

1.6 The Organization of the Dissertation

The dissertation entails researched data including a list of figures, list of tables and other information in appendices that represent part of the journey involved in this project. Chapters include in the following order the Introduction, Literature review, Research Methods, Results, Review and Conclusion and Recommendations.

Chapter 2 LITERATURE REVIEW

2.1 Introduction

The dissertation is based on remote sensing principles with the addition of Object-Oriented Image analysis, the following review touches on the basis of the technology through to the concepts of Object-Oriented paradigm. The review is a confirmation of the advancement in technology from a scientific base of evidence from various people and organizations from around the world.

2.2 Remote Sensing

Image generation of the earth by satellite or aircraft to obtain information from it illustrates the term Remote sensing (Oxford Dictionary 2015). Remote sensing refers to the ability to collect, measure and analyze data without directly coming into contact with it (Graham 1999).

2.2.1 Radiation

Electromagnetic radiation is where an object reflects, absorbs or emits energy dynamically and continuously. The temperature of an object is directly proportional to the energy it emits or reflects. Energy is transferred in waves from one place to another, these wavelengths vary depending on the objects characteristics such as trees, stars, water etc. (Graham 1999). Electromagnetic radiation is the variation of wavelengths of energy that are captured by a device such as a camera to form an image of objects taken at that point in time. The shorter the energy wavelength the brighter the object, conversely the longer the energy wavelength the darker an object is.

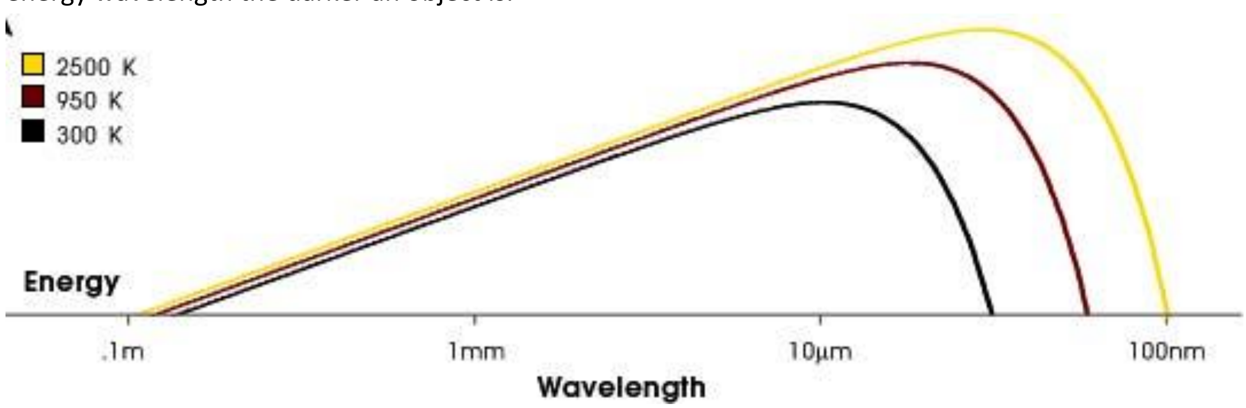


Figure 2.1: Energy wavelength diagram shown in kelvin (Graham 1999, *p.4*)

2.2.2 Solar Radiation

Solar radiation is the form of energy emitted from the sun that generates the electromagnetic spectrum of energy reflected from the earth's objects on its surface, which in turn generates a remote sensing image from the electromagnetic range from a satellite or planes image capture device.

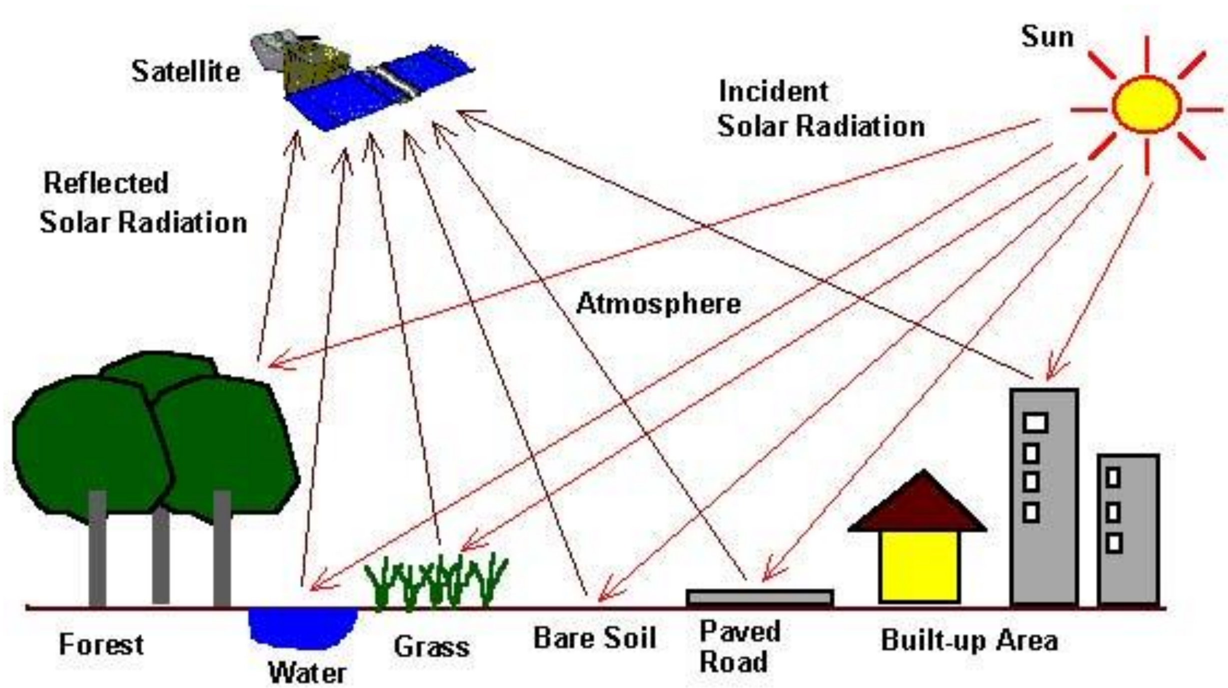


Figure 2.2: What is Remote Sensing, Optical and Infrared Remote Sensing *(Crisp 2015)*

2.2.3 Electromagnetic Spectrum

Electromagnetic radiation (EMR) travels at the speed of light (c=3x10^8 meters/second) in a sinusoidal pattern similar to a wave travelling through water. The electric and magnetic fields of electromagnetic radiation have defined wavelengths and frequency, the frequency is the number of peaks passing through a fixed point per unit per time and wavelength the difference in distance between peaks (APEC 2015). EMR is classified in wavelength measured in micrometers (1 µm = 10^{-}6 µm) and the electromagnetic spectrum comprises of cosmic rays (<10^{-7} µm), gamma rays (~10^{-7} µm), X-rays (~10^{-4} µm), Ultraviolet (0.1—0.4 µm), visible light (0.4—0.7 µm), near infrared (0.7—1.3 µm), thermal infrared (3-- 10µm), microwave (~10^5 µm) and TV/radio (~10^8 µm) (APEC 2015).

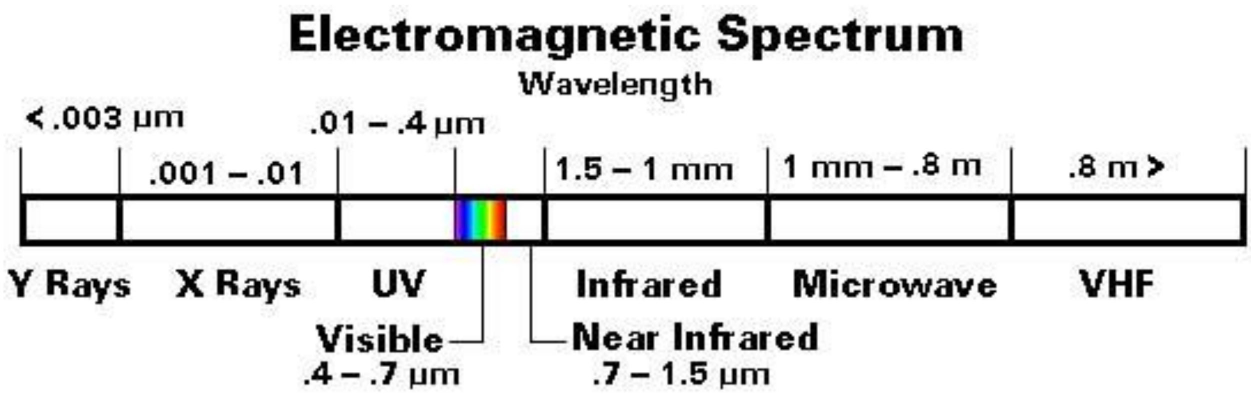


Figure 2.3: Electromagnetic Spectrum (APEC 2015)

2.2.4 Multispectral Image Guide

As mentioned above objects on the earth's surface possess a wide range of properties in which affect the way the objects reflect or emit EMR, figure 2.4 illustrates a simple comparison of some distinct earth objects such as dry bare soil, vegetation and water and how their reflectance properties measure in the EMR range.

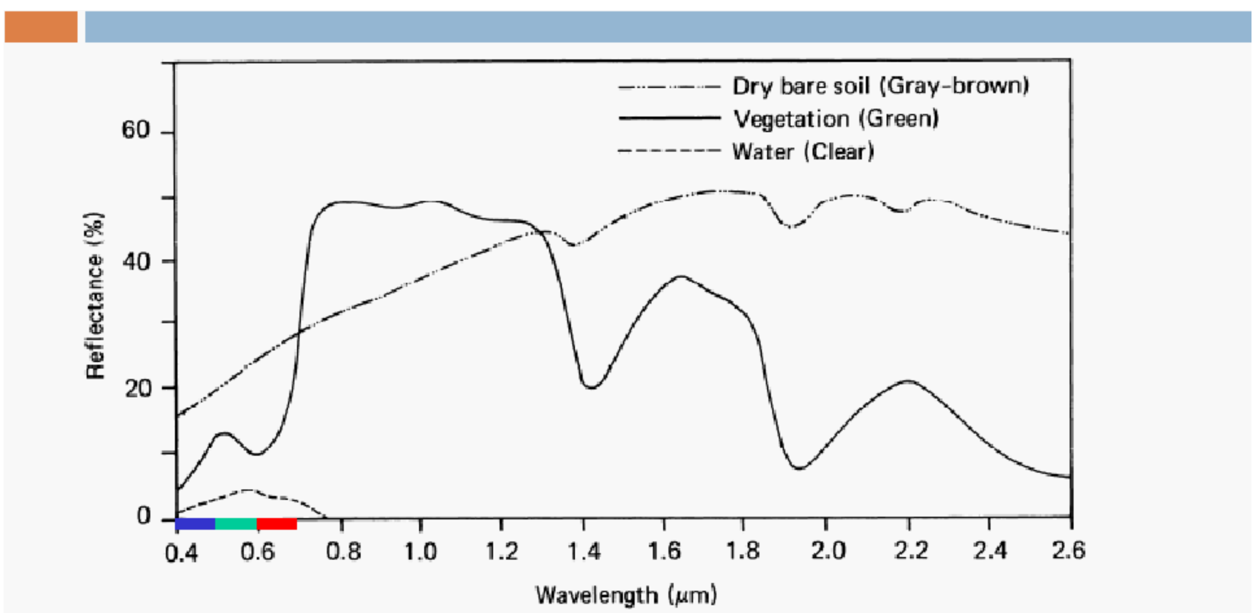


Figure 2.4: A guide to reflectance from various objects in the multispectral range, Google, More images for reflectance spectra, (*Google 2014*)

The spectral range is collected from satellites remote sensing sensors in a series of thematic mapping (TM) capacities in which are bands of TM1-TM7. A combination of these bands allows extraction of an array of collated spectral remote sensing features such as:

- 'Brightness (Bright) – computed from a combination of bands TM1-TM5 and TM7' (Baraldi et al. 2006 p.2568).

- ‘Visible (Vis) - reflectance is the estimated reflectance in the visible portion of the electromagnetic spectrum. It linearly combines bands TM1-TM3 that are individually unfeasible for being employed in land cover discrimination due to their typically small range and high correlation (Baraldi et al. 2006 p.2568).
- ‘Near-infrared (NIR) - reflectance is the estimated reflectance in the NIR portion of the electromagnetic spectrum’ (Baraldi et al. 2006 p.2568).
- ‘Middle infrared (MIR) – reflectance is the estimated reflectance in the MIR portion of the electromagnetic spectrum’ (Baraldi et al. 2006 p.2568).
- ‘Thermal infrared (IR) – reflectance is the estimated reflectance in the TIR portion of the electromagnetic spectrum’ (Baraldi et al. 2006 p.2568).
- ‘Normalised difference vegetation index (NDVI), which is aimed at reducing multispectral (MS) measurements to a single value for predicting and assessing vegetation characteristics such as species, leaf area, stress, and biomass. It should be insensitive to shadow areas’ (Baraldi et al. 2006 p.2568).
- ‘Normalised difference bare soil index (NDVI) – which is aimed at enhancing bare soil areas, fallow lands, and vegetation with marked background response. This single value should be useful for predicting and assessing bare soil characteristics such as roughness, moisture content, amount of organic matter, and relative percentages of clay, silt and sand’ spectrum’ (Baraldi et al. 2006 p.2568).
- ‘Normalised difference snow index (NDSI), which is aimed at discriminating snow/ice from all remaining surface classes, including clouds and cold and highly reflective barren land’ (Baraldi et al. 2006 p.2568).
- ‘Band MIR/TIR composite (MIRTIR), which is aimed at mitigating well-known difficulties in separating thin and warm clouds from ice areas and cold and highly reflective barren land’ (Baraldi et al. 2006 p.2568).

2.2.5 Image Pixel

A satellite image is made up of tiny squares the same as a picture on your television set, these tiny squares are called pixels in which possess variant shades of reflected light at that particular part of the image. The pixels are a measure of a sensors capability of producing the clarity of an object at different sizes, the image resolution. An example is the Enhanced Thematic Mapper (ETM+) on the Landsat 7 satellite has a maximum resolution of 15 meters. This translates a pixel representing 15 x 15 meters on the earth’s surface, any objects smaller than this cannot be defined accurately, the image pixel is proportionate to the sensors capabilities. The resolution of 15 meters represents one pixel being 225m^2 for example pixels in which have similar properties on an image can be classified as vegetation with an area calculated by adding the number of pixels of similar properties (Graham 1999).

2.2.6 Satellite Progression

Satellite imagery emerged in the early 1960's, these satellites were utilized for weather and still photography. The designing for earth imaging satellites initiated in 1967 with NASA launching its first satellite in July, 1972, aptly named Landsat 1 (APEC 2015). In the late 1980s a progression into small satellite designs capable of improved performance with less cost emerged. The technology moved forward rapidly in this field, as there are now a number of satellite constellations operational from different organisations from around the world utilsing the small satellite advancement and technology capabilities. Some of these constellations include,' Global Positioning Systems (GPS), Galileo and GLONASS for navigation and geodesy, RASAT, the Disaster Monitoring Constellation (DMC), RapidEye, COSMO-SkyMed (COnstellation of small Satellites for the Mediterranean basin Observation), and Huanjing constellation (the Small Satellite Constellation for Environment Protection and Disaster Monitoring) for remote sensing' (Yong et al., cited in International Journal of Remote Sensing, August 2008, p.4363).

2.2.7 Landsat

The satellite data obtained for this project has been derived from LandsatLook website with the following providing some insight on the technical aspects of the data. The Landsat project has four decades of imagery data dating back from the launch of Landsat 1 in July 1972 through to the launch of Landsat 8 on May 2013 in which provides high quality data to the present day. The Landsat project is a combined effort between the United States Geological Survey (USGS) and National Aeronautics and Space Administration (NASA) which has provided remote sensing data for the United States of America and world-wide. The purpose of this data produces information for 'commercial, industrial, civilian, military, and educational communities', (Landsat 2013).

2.2.8 Landsat 8 Processing Parameters

The imagery data used for this project is from Landsat 8 with table 1 representing the parameters it provides for its data products.

Table 1.1: Processing parameters for Landsat 8 standard data products (Landsat 2013).
[UTM, Universal Transverse Mercator; World Geodetic System; OLI, Operational Land Imager; TIRS, Thermal Infrared Sensor]

Product Type	Level IT (terrain corrected)
Data type	16-bit unsigned integer
Output format	GeoTIFF
Pixel Size	15 meters/30meters/100meters (panchromatic/multispectral/thermal)
Map projection	UTM (Polar Stereographic for Antartica)

Datum	WGS84
Orientation	North-up (map)
Resampling	Cubic convolution
Accuracy	OLI: 12 meters circular error, 90 percent confidence TIRS: 41 meters circular error, 90 percent confidence

2.3 Image Classification

Image classification applies knowledge of the image by identifying a group of pixels into clusters (kernals) to be categorized into a certain class in the image such as trees. Classification involves the mathematical approach of iterative algorithms within software to extract the desired information from the image. Pixel based classification techniques include unsupervised classification, supervised classification, rule- based classification, neutral net and fuzzy logic classification, classification and regression trees (CART) and decision trees (Navulur 2007 p.47). Identifying and extracting a desired pattern from an image typifies the classification algorithm computation process with traditional methods such as K-nearest neighbor (KNN) and maximum likelihood (ML) (Smits et al. 1997), utilizing appropriate remote sensing software.

2.4 Traditional Pixel Based Classification (supervised, unsupervised and rule-based)

2.4.1 Supervised

Supervised classification entails the details of the image to be verified on the ground, training samples for the purpose of estimating the statistics of the target class (Baraldi et al. 2006 p.2564). The approach uses pixels in the training samples to be associated with a certain class. Pixels outside the training set are compared with the discriminant functions and are assigned to the class they are closest to. Other pixel data outside the discriminant function will remain unclassified (Navulur 2007 p.48). The common techniques in relation to supervised classification include 'the minimum-distance-to-means, parallelepiped classifier, maximum likelihood, nearest neighbor' (Navulur 2007 p.48), naming a few. The nearest neighbor classifier ascertains the minimum-distance-to-means technique which is a function available in eCognition and ENVI 5 software. Some techniques are explained as follows by Navulur:

- 'Minimum-distance-to-means: The minimum distance classifier sets up clusters in multidimensional space, each defining a distinct class. Each pixel within the image range is then assigned to that class it is closest to. This type of classifier determines the mean value of each class in each band. It then assigns unknown pixels to the class whose means are most similar to the value of the unknown pixel' (Navulur 2007 p.49).

- 'Parallelopiped classifier: One of the simplest supervised classifiers is the parallelepiped method. This classifier works by delineating the boundaries of a training class using straight lines. In case of two-band imagery, the boundaries will look like a series of rectangles. After the boundaries have been set, unknown pixels are assigned to a class if they fall within the boundaries of a class. If the unknown pixel does not fall within the boundary of any class, it is classified as unknown. This method is computationally efficient and attempts to capture the boundaries of each class. However, using straight lines to delineate the classes limit's the method's effectiveness. Also, having pixels classified as unknown may be undesirable for some applications' (Navulur 2007 p.48).

-'Maximum likelihood classifier (MLC): The most powerful classifier in common use is the maximum likelihood classifier. Based on statistics mean, variance/covariance, a Bayesian probability function is calculated from the inputs for classes established from training sites. Each pixel is then judged as to the class to which it most probably belongs' (Navulur 2007 p.48).

2.4.2 Unsupervised

Piori knowledge of specific class identified in the remote sensing image in which no target class sample is required , typifies unsupervised classification (Baraldi et al. 2006 p.2563). Baraldi et al. explains utlising priori knowledge in regard to the implementation of design characteristics provide an insight into unsupervised classification such as pattern, spectral colour, categories, statistics, implementation and output (Baraldi et al. 2006 pp.2563-2564). Navulur also defines the unsupervised classification technique as 'to group pixels with similar multispectral response, in various spectral bands, into clusters or classes that are statistically separable. Cluster definition is dependent on the parameters chosen, such as spectral bands, derived spectral ratios, such as Noramalised Difference Vegetation Index (NDVI), and other parameters. Each individual pixel within the scene or image is compared to each discrete cluster to see the closest fit. The final result is a thematic map of all pixels in the image, assigned to one of the clusters each pixel is most likely to belong. Metrics such as Euclidian, Bhattacharya distance, and others are used as a measure to find the closeness of a pixel to a given cluster. The thematic class or cluster then must be interpreted by the end user as to what the clusters mean in terms of ground truth. This approach requires priori knowledge of the scene and the content within the scene. The number of clusters can be modified based on the user's knowledge of features within the scene. One of the drawbacks of this technique is the generalization that can result in arbitrary clusters which do not have any correlation with features on the ground. Further, pixels belonging to clusters that have spectral overlap are often assigned to one of the classes based on a single metric with potential for gross misclassification errors (Navulur 2007 p.47).

Navulur also describes the common or frequently used algorithms to be ‘K-means and the iterative self-organising data analysis technique algorithm (ISODATA) clustering algorithms. Both of these algorithms are iterative procedures’ (Navulur 2007 p.47).

2.4.3 Rule-Based Classification

Navulur states ‘Rule-based classification evolved from the expert systems domain where a given occurrence can be explained by a set of rules and instances. Each instance results in a decision, and the associated rule set is comprised of a series of logical steps that are built on an existing set of variables to explain the occurrence. ERDAS Image from Leica Geosystems has a built-in module called *spatial modeler* for developing the rule bases for image classification. If the user is familiar with the spectral behavior of the objects and the associated phenomenology, a rule base can be developed that can capture the knowledge of the user analogous to the knowledge engineer in expert systems. Following is a simple example of thematic classification of water and vegetation using spectral reflectance values. The rule bases similar to the rules shown here can be created to extract water and vegetation features: If NIR < 20% and Blue < 4%, then pixels belong to water. To classify vegetation, we can use the vegetation index NVDI. The associated rule for classifying vegetation will look similar to the following rule: If NVDI > 0.4, then the pixel belongs to vegetation’ (Navulur 2007 p.47).

Navulur also adds ‘when the user is not familiar with the spectral behavior and phenomenology of various features, there are several data mining techniques available to understand the relationship between a specific thematic class and independent variables, such as spectral bands, derived information layers, such as NVDI, tassel cap, indices, and any ancillary data layers, such as elevation, slope, and aspect. Histogram plots, statistical analyses such as Duncan classification, and multidimensional plots can help the user to select appropriate inputs to feed into these data mining techniques’ (Navulur 2007 p.47).

Baraldi et al. show a good example of rule based phenomena in the form of a table representing the first level of cluster (kernel) spectral rules in regard to the classification of remote sensing features as shown below.

Table 2.1: Logical Expressions Implementing First-Level Kernal Spectral Rules (Baraldi et al. 2006).

Index	Spectral Rule Name	Spectral rule acronym	Expression (where tolerance interval TV1 = 0.7>TV2=0.5; Input features: TM1-TM5, TM7: Landsat TM bands 1-5 & 7
1	ThickCloudsSpectralRule	TKCL_SR	=(min{TM1, TM2, TM3} ≥ (0.7* max{TM1, TM2, TM3})) and (max{TM1, TM2, TM3} ≤ (0.7*TM4)) and (TM5 ≤ (0.7*TM4)) and (TM5 ≥ (0.7*max{TM1, TM2, TM3})) and (TM7 ≤ (0.7*TM4)
2	ThinCloudsSpectralRule	TNCL_SR	=(min{TM1, TM2, TM3} ≥ (0.7*max{TM1, TM2, TM3})) and (TM4 ≥ max {TM1, TM2, TM3}) and not ((TM1 ≤ TM2 ≤ TM3 ≤ TM4) and (TM3 ≥ (0.7*TM4))) And (TM4 ≥ (0.7*TM5)) and (TM5 ≥ (0.7* TM4)) and TM5 ≥ (0.7*max{TM1,TM2, TM3})) and (TM5 ≥ (0.7* TM7))
3	SnowOrIceSpectralRule	SNIC_SR	=(min{TM1, TM2, TM3} ≥ (0.7*max{TM1, TM2, TM3})) and (TM4 ≥ (0.7*max{TM1, TM2, TM3})) and (TM5 ≤ (0.5*TM4)) and (TM5 ≤ (0.7*min{TM1, TM2, TM3})) and (TM7 ≤ (0.5*TM4)) and (TM7 ≤ (0.7*min{TM1, TM2, TM3}))
4	WaterOrShadowSpectralRule1	WASH_SR	=(TM1 ≥ TM2) and (TM2 ≥ TM3) and (TM3 ≥ TM4) and (TM4 ≥ TM5) and (TM4 ≥ TM7)
5	PitbogOrGreenhouseSpectralRule	PBGH_SR	=(TM3 ≥ (0.7*TM1) and (TM1 ≥ (0.7*TM3)) and (max{TM1, TM2, TM3} ≤ (0.7*TM4) and (TM5 ≤ 0.7*TM4)) and (TM3 ≥ (0.5*TM5)) and (min{TM1, TM2, TM3} ≥ (0.7*TM7))
6	DominantBlueSpectralRule	DB_SR	=(TM1 ≥ (0.7*max{TM2, TM3, TM4, TM5, TM7}))
7	VegetationSpectralRule2	V_SR	=(TM2 ≥ (0.5*TM1)) and (TM2 ≥ (0.7*TM3)) and (TM3 < (0.7*TM4) and (TM4 > max{TM1, TM2, TM3}) and (TM5 < (0.7*TM4)) and (TM5 ≥ (0.7*TM3)) and (TM7 < (0.7*TM5))
8	RangelandSpectralRule3	R_SR	= (TM2 ≥ (0.5*TM1)) and (TM2 ≥ (0.7*TM3)) and (TM4 > max{TM1, TM2, TM3}) and (TM3 < (0.7*TM4)) and (TM4 ≥ (0.7*TM5)) and (TM5 ≥ (0.7*TM4)) and (TM5 > max{TM1, TM2, TM3}) and (TM7 < (0.7*max{TM4, TM5})) and (TM5 ≥ TM7)
9	BarrenLandOrBuiltUpOrCloudsSpectralRule4	BBC_SR	=(TM3 ≥ (0.5*TM1)) and (TM3 ≥ (0.7*TM2)) and (TM4 ≥ (0.7*(max {TM1, TM2, TM3})) and (TM5 ≥ max{TM1, TM2, TM3}) and (TM5 ≥ (0.7*TM4)) and (TM5 ≥ (0.7*TM7))) and (TM7 ≥ (0.5*max{TM4, TM5}))
10	FlatResponseBarrenLandOrBuiltUpSpectralRule	FBB_SR	=(TM5 ≥ (0.7*max{TM1, TM2, TM3, TM4, TM7})) and (min{TM1, TM2, TM3, TM4, TM7} ≥ (0.5*TM5)))
11	ShadowWithBarrenLandSpectralRule	SHB_SR	=(TM1 ≥ TM2) and (TM2 ≥ TM3) and (TM3 ≥ (0.7*TM4)) and (TM1 ≥ TM5) and (TM5 ≥ (0.7*TM4)) and (TM5 ≥ (0.7*TM7))
12	ShadowWithVegetationSpectralRule	SHV_SR	=(TM1 ≥ TM2) and (TM2 ≥ TM3) and (TM1 ≥ (0.5*TM4)) and (TM3 < (0.7*TM4)) and (TM5 < (0.7*TM4)) and (TM3 ≥ (0.7*TM5)) and (TM7 < (0.7*TM4))
13	ShadowCloudOrSnowspectralRule	SHCLSN_SR	=(TM1 ≥ (0.7*max{TM2, TM3, TM4})) and (max{TM2, TM3, TM4} ≥ (0.7*TM1)) and (TM5 < TM1) and (TM7 < (0.7*TM1))
14	WetlandSpectralRule	WE_SR	=(TM1 ≥ TM2) and (TM2 ≥ TM3) and (TM1 ≥ (0.7*TM4)) and (TM3 < TM4) and (TM4 ≥ (0.7*TM5)) and (TM5 ≥ (0.7*TM4)) and (TM3 ≥ (0.5*TM5)) and (TM5 ≥ TM7)

2.5 Object-Oriented

2.5.1 Object-Oriented Image Analysis

An image consists of pixels in which hold various properties of reflected light. The methodology of an object orientated image analysis is to group pixels with similar spatial response using predefined sets of rules and apply pixel-based image techniques to extract features relevant to the applied use (Navulur 2007 p.1). The application of object orientated technology analyses the object space rather than the pixel space. Converting images into multiple objects refers to image segmentation, where polygons created form object shapes that can be interpreted in other software packages. Objects have spatial characteristics as in size, texture, morphology, shape and colour. Object feature extraction from an image enables the exploitation of data such as spatial, temporal, contextual and textural (Navulur 2007).

2.5.2 Computer aided image analysis

Humans have the ability to recognize objects through their data base of memory identifying the properties such as size, shape, colour and texture. The computer aided image analysis uses a set of rules that copies the human interpretation process of an object to extract the specific data required from an image Navulur 2007. This is known as the classification process in eCognition and other software such as ENVI 5.

2.5.3 Object-Oriented History

The development of computers and software was the catalyst of the object-oriented phenomenon, where programming began in the 1960’s consisting of the Simula language, through to Smalltalk and C++ programming languages of the 1980’s (Robinson, Sharp 2009). Java programming language emerged in the 1990’s with object-oriented software technology becoming a dominant feature in human computer interaction (HCI) within the remote sensing arena (Robson, Sharp 2009). Some of the object-oriented language creators are:’ Kristen Nygaard (Simula), Bjarne Stroustroup (C++), Betrand Meyer (Eiffel) and Alan Kay (Smalltalk)’ (Robinson, Sharp 2009 p.221).

2.5.4 Comparisons of Object Orientated and Pixel-Based Classification

Comparisons of Object Orientated and Pixel-Based Classification of Land Use/Land Cover Types Based on Landsadsat7, Etm^{+} Spectral Bands (Case Study: Arid Region of Iran) , (Heck, Alavi Panah, Sarmadian & Matinfar 2007).

The paper is a comparison of pixel based and object based data extracted in the arid region of Iran. Ground truth data had been collated of this area for an error factor in the confusion matrix to be applied to both pixel and object base extraction methods (Heck, Alavi Panah, Sarmadian & Matinfar 2007). Below is the typical Landsat7 parameters that is commonly used in these types of analysis.

Table 2.2: Landsat7 and ETM+ characteristics
Band number Spectral range (micron) Ground resolution (m)
1 0.45 to 0.515 30
2 0.525 to 0.605 30
3 0.63 to 0.690 30
4 0.75 to 0.90 30
5 1.55 to 1.75 30
6 10.40 to 12.5 60
7 2.09 to 2.35 30
8 0.52 to 0.9 15
Swath width 185 Kilometers
Repeat coverage interval 16 days (233 orbits)
Altitude 705 Kilometers
Quantization Best 8 of 9 Bits
Inclination Sun-synchronous, 98.2 degrees

(Heck, Alavi Panah, Sarmadian & Matinfar 2007)

The case study revealed the following results in there comparison.

Table 2.3: Accuracy of pixel-based image classification
Land cover types

Accuracy Agr. Al. DC. NS-S. Or. OC-I. OC-L. Pi. Ru. SS. SC. SD-L. S-SD. Ur
User's accuracy (%) 100 68 92 67 100 93 96 58 60 82 100 94 74 45
Producer's accuracy (%) 93 86 58 100 100 94 88 70 40 99 100 72 94 37
Overall accuracy (%) 81
(Heck, Alavi Panah, Sarmadian & Matinfar 2007)

Table 2.4: Accuracy of object-oriented image classification
Land cover types

Accuracy Agr. Al. DC. NS-S. Or. OC-I. OC-L. Pi. Ru. SS. SC. SD-L. S-SD. Ur
User's accuracy (%) 78 100 100 88 72 100 83 80 83 98 83 100 95 91
Producer's accuracy (%) 87 94 89 95 97 93 89 91 73 94 100 89 91 89
Overall accuracy (%) 91
(Heck, Alavi Panah, Sarmadian & Matinfar 2007)

Their accuracy analysis reveals the object- oriented method using eCognition outperformed the pixel based algorithm classifications method (Heck, Alavi Panah, Sarmadian & Matinfar 2007).

2.5.5 ENVI 5 Software

ENVI 5 is the software to be used in this research proposal which is an available resource at USQ, Toowoomba campus. The software user's guide, tutorials and other material at the EXELIS website, will be helpful in the implementation of the software.

The methods of Unsupervised, Supervised and feature extraction with example-based classifications in the software will be the major component to enable a successful outcome in the data extraction process. Validation of this process by other means such as verification by Google Earth will provide for an error comparison from the anomalies of the three separate processes.

2.5.6 Crop mapping analysis utilizing Object Oriented Phenomena

The automation of segmentation through object-oriented technology of an image has revolutionized the information data extraction capabilities, that in previous times, has been arduous, time consuming and inaccurate. The ability of software to segment an image using user classification in regard to temporal crop mapping analysis has provided a valuable tool for a growers cropping production.

2.5.7 Inter crop analysis (mapping cotton field variability utilizing Object Oriented Phenomena)

Emphasis on crop in-field variability using remote sensing capabilities is now a resource available to the wider community from a technical and affordable perspective. High resolution data is more effective in this situation in capturing the slight reflectance variations that exist in any given field of cropping production. The variations can be related to factors such as gradient problems (water logging), chemical overspray, fertilser utlisation (over or under applying), weather constraints, pest infestations and others. The change in in-field variability cropping factors can be segmented, highlighting areas of concern that can then be ground-truthed to source the issue of reflectance difference compared to a healthy section of a field crop and investigate the cause of this segmented change within the field. Yield monitors are a common source of cropping information however can only be used during the harvest season, whereas remote sensing images can be implemented at temporal intervals leading up to harvest time, providing valuable information for a grower to improve cropping methods for improved output and profit (Yang et al. 2012).

Chapter 3 RESEARCH METHODS

3.1 Objective

ENVI software will be utilized for this project, there are numerous ENVI approaches to the segmentation process. The properties of the satellite image are enhanced through the software allowing a satellite band combination of the image to extract the desired product, in this being cotton fields from its surrounds. In recapping earlier the Image has 7 bands of reflected light properties, this technology has been mentioned in the previous literature review. The approach adopted in this analysis are three ENVI processes being unsupervised, supervised and feature extraction by example- based classifications. These processes will be observed and results shown in the following subsequent sections.

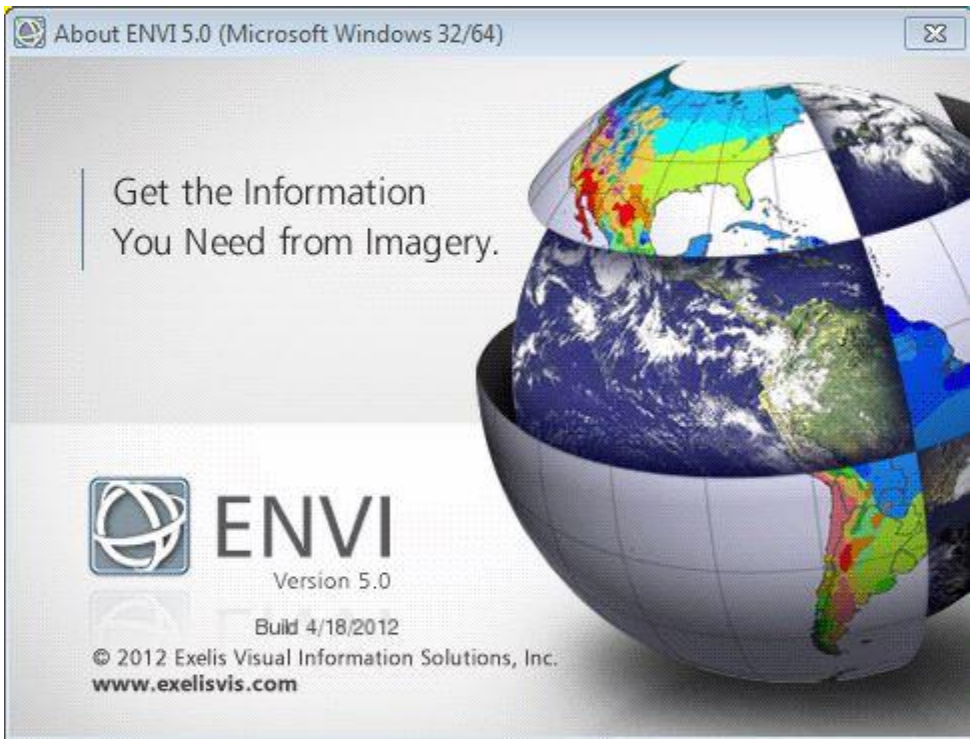


Figure 3.1: ENVI software used (Exelis 2012)

3.2 Classification of Subject Area

Figure 3.2: The clipped satellite image of the subject area representing classifications (Exelis 2012)

The 7 bands of the satellite data can be manipulated to suit the extraction of the desired objects from the image, figure 3.1 represents red-band 6, green-5 and blue-band 4, the designated band assignments in ENVI represent an ideal band sequence for the extraction of cotton field data.

Table 3.1 Class Criteria

Class	
1	Cotton 1 - Bright Green (C1)
2	Cotton 2 -Dark Green (C2)
3	Native Vegetation (NV)
4	Dry Non Photosynthesis Vegetation 1 (DNPV1)
5	Dry Non Photosynthesis Vegetation 2 (DNPV2)
6	Water Dam (WD)
7	Water Natural Tributary (WNT)
8	Gravel (G)

The approach undertaken is to validate the ENVI process by using three methods mentioned above with the key element being the class analysis of the satellite data. A class set has been derived with the purpose of a broad set of labels as to not burden the overall output and objective of analyzing the performance of the methods used and simplifying results obtained to introduce the technology to others for future study. The class set comprises of eight categories as per table 3.1 and figure 3.2 which will be the basis for comparisons to be obtained.

3.3 ENVI Unsupervised

This option of unsupervised is a pixel based workflow in which identifies spectral reflectance of similar properties and assigns a class segmented from the satellite image. The more classes selected creates increased segmented data. The ENVI automated process produces a fast and relatively effective result depending on the data extraction required and relevant settings used.

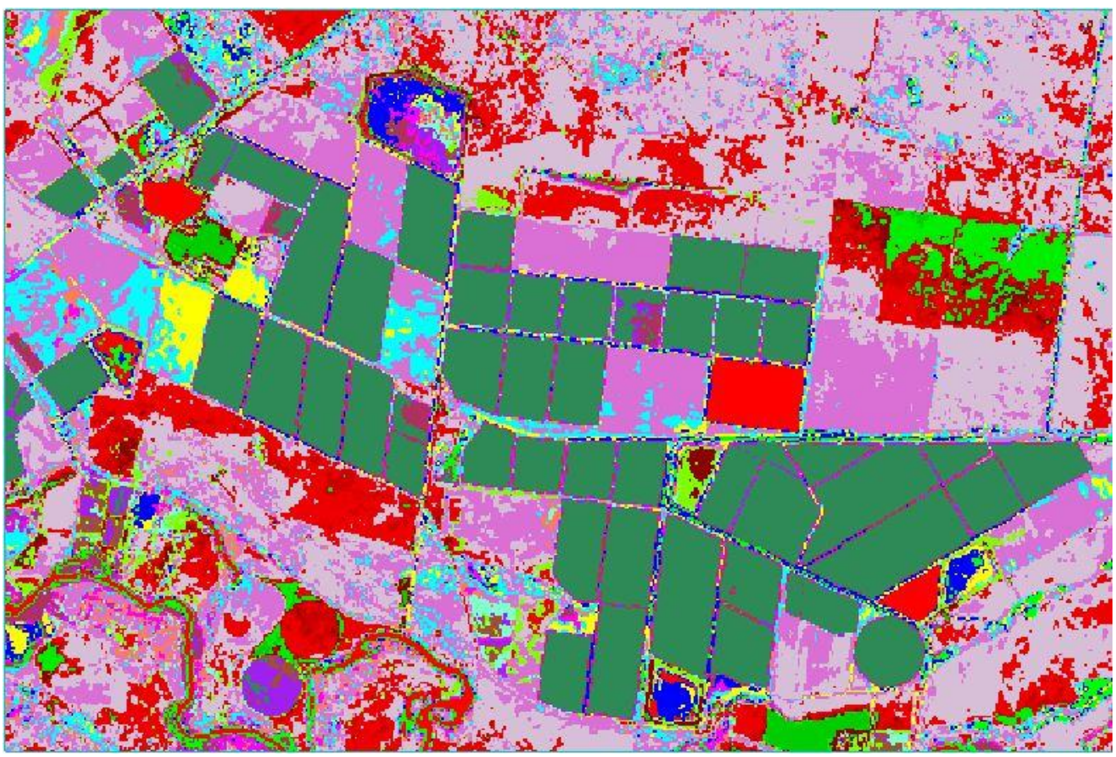


Figure 3.3: The clipped satellite image of the subject area representing an example of unsupervised classification (Exelis 2012)

3.4 ENVI Supervised

Supervised is a pixel based workflow where the user identifies a class from the satellite image. The process entails the user to create a class list by selecting pixels from the image relevant to the assigned class. The colour black represents ENVI class unclassified as this indicates ENVI could not process some spectral data relevant to the user's selection parameters.

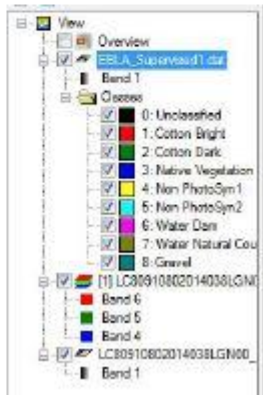


Figure 3.4: Supervised class table (Exelis 2012)

3.5 ENVI Feature Extraction with Example-Based Classification

An object-oriented workflow similar to supervised in the essence of class criteria where the user can use a number of selection methods such as polygon's to select a class from an image hence example based classification. ENVI allows attribute selection in the segmentation process such as spectral, texture, area, length, roundness and form factor to name a few as the algorithm is designed with the object-oriented aspect.

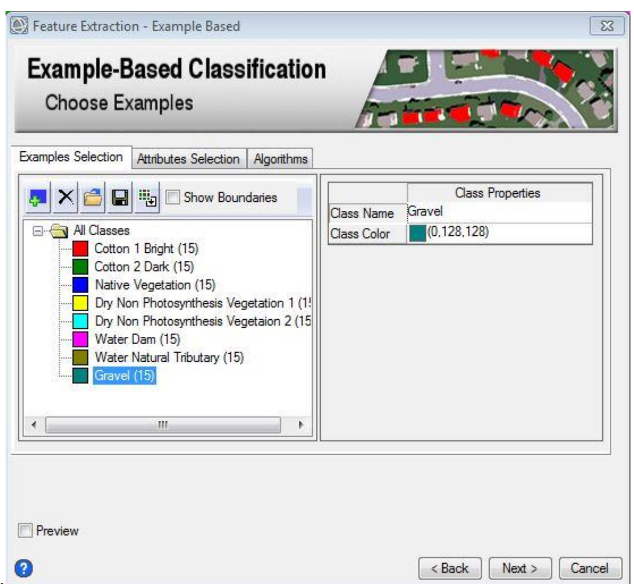


Figure 3.5: Feature extraction with example- based class table (Exelis 2012)

3.6 Google Earth Data Verification

Google Earth has been selected to verify data as it is an independent satellite image source of the area of interest. Specific locations across the data image have been selected and used to determine the class segmentation process. Eight classes have been determined as per table 3.1 with 5 test locations within each class derived e.g. C1 = Class 1 = Cotton 1 Bright Green (C1) etc.

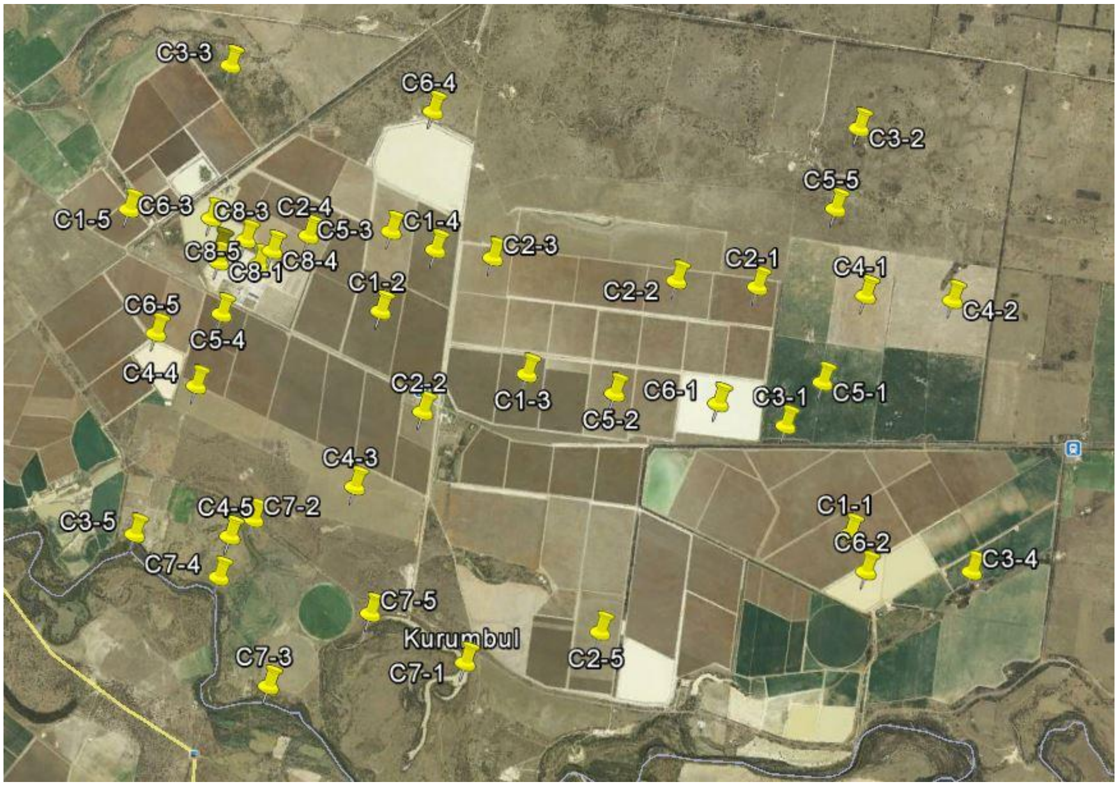


Figure 3.6: Google Earth Image of class locations (Google Earth 2015)

Table 3.2: Google Earth test sample locations

Class Label	Latitude	Longitude
C1-1	28˚37'48.58"S	150˚31'04.48"E
C1-2	28˚35'49.86"S	150˚26'29.70"E
C1-3	28˚36'23.69"S	150˚27'55.87"E
C1-4	28˚35'18.10"S	150˚27'02.25"E
C1-5	28˚34'54.68"S	150˚24'00.45"E
C2-1	28˚35'39.70"S	150˚30'12.65"E
C2-2	28˚35'35.92"S	150˚29'24.89"E
C2-3	28˚35'22.68"S	150˚27'36.22"E
C2-4	28˚35'09.79"S	150˚25'47.14"E
C2-5	28˚38'37.07"S	150˚28'37.25"E

Class Label	Latitude	Longitude
C5-1	28˚36'29.89"S	150˚30'50.18"E
C5-2	28˚36'34.39"S	150˚28'47.39"E
C5-3	28˚35'08.14"S	150˚26'36.09"E
C5-4	28˚35'50.17"S	150˚24'55.62"E
C5-5	28˚34'29.10"S	150˚30'59.89"E
C6-1	28˚36'40.10"S	150˚29'48.35"E
C6-2	28˚38'07.83"S	150˚31'13.35"E
C6-3	28˚34'59.96"S	150˚24'49.43"E
C6-4	28˚34'04.95"S	150˚27'01.26"E
C6-5	28˚36'00.03"S	150˚24'16.82"E

C3-1	28˚36'52.16"S	150˚30'27.85"E	C7-1	28˚38'51.90"S	150˚27'18.28"E
C3-2	28˚34'16.71"S	150˚31'14.78"E	C7-2	28˚37'36.93"S	150˚25'14.46"E
C3-3	28˚33'38.99"S	150˚25'00.52"E	C7-3	28˚39'02.47"S	150˚25'23.20"E
C3-4	28˚38'08.56"S	150˚32'15.43"E	C7-4	28˚38'06.50"S	150˚24'54.26"E
C3-5	28˚37'43.91"S	150˚24'04.67"E	C7-5	28˚38'26.14"S	150˚26'22.85"E
C4-1	28˚35'44.98"S	150˚31'16.54"E	C8-1	28˚35'22.97"S	150˚24'53.80"E
C4-2	28˚35'47.98"S	150˚32'08.04"E	C8-2	28˚35'15.82"S	150˚24'54.13"E
C4-3	28˚37'20.92"S	150˚26'13.99"E	C8-3	28˚35'11.64"S	150˚25'09.76"E
C4-4	28˚36'27.54"S	150˚24'40.59"E	C8-4	28˚35'17.47"S	150˚25'25.54"E
C4-5	28˚37'45.62"S	150˚25'00.62"E	C8-5	28˚35'24.56"S	150˚25'17.47"E

Chapter 4 RESULTS

The results of all options include all 7/7 bands of the spectral subset.

4.1 Unsupervised

The unsupervised ENVI software settings used are as follows:

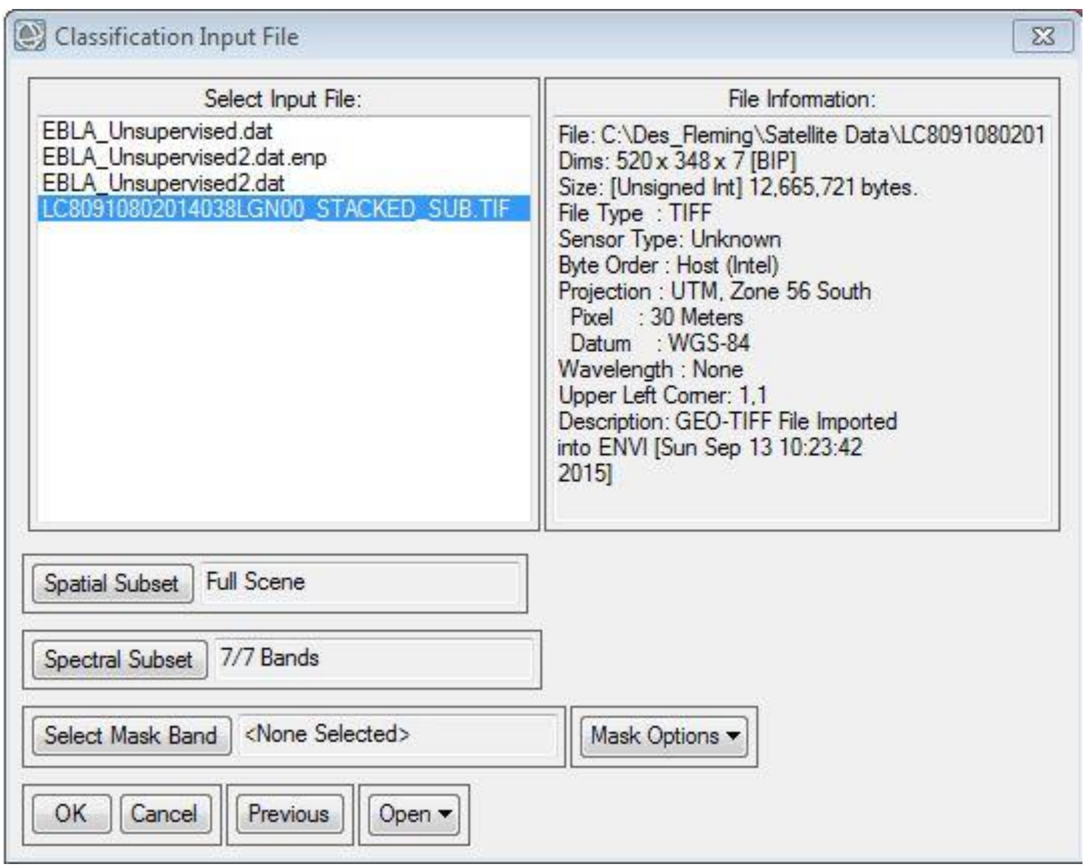


Figure 4.1: Input file setting of ENVI unsupervised (Exelis 2012)

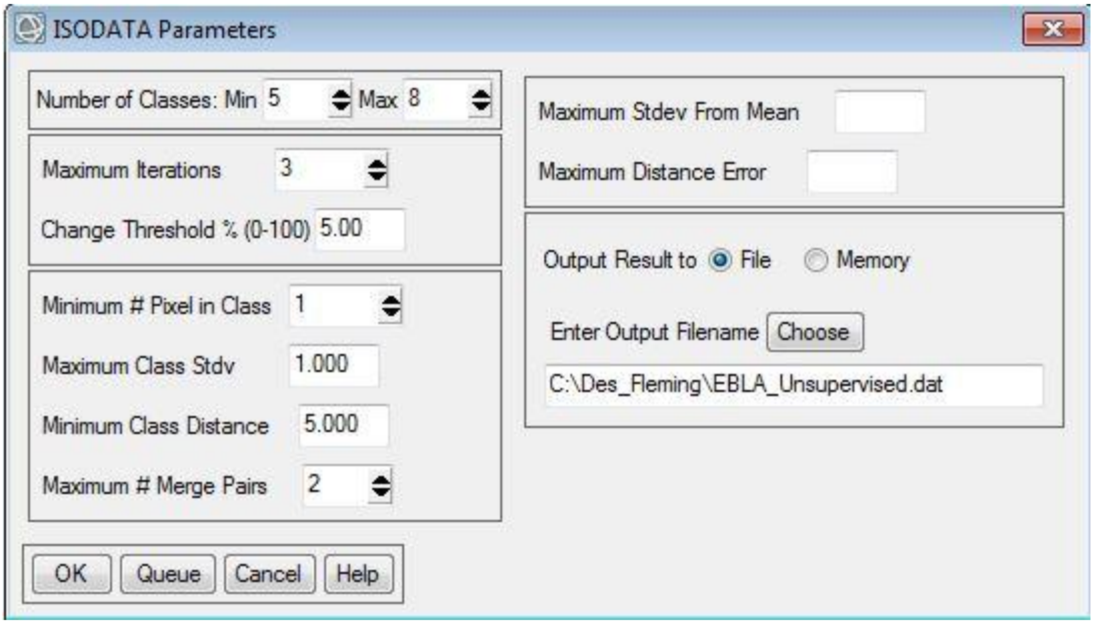


Figure 4.2: ISODATA setting of ENVI unsupervised (Exelis 2012)

The above setting to note in the ISODATA option is the eight class criteria with three iterations used.

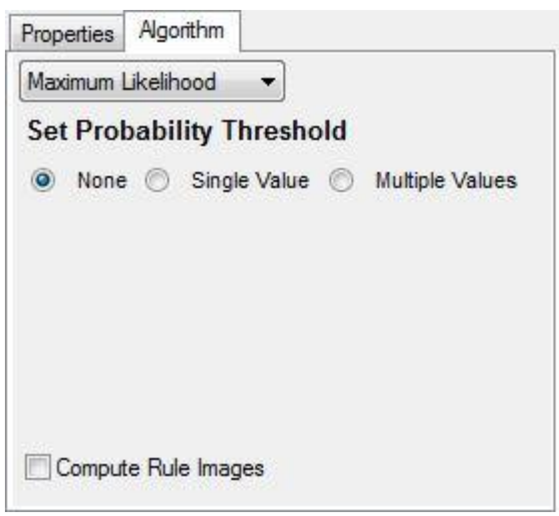


Figure 4.3: Algorithm setting of ENVI unsupervised (Exelis 2012)

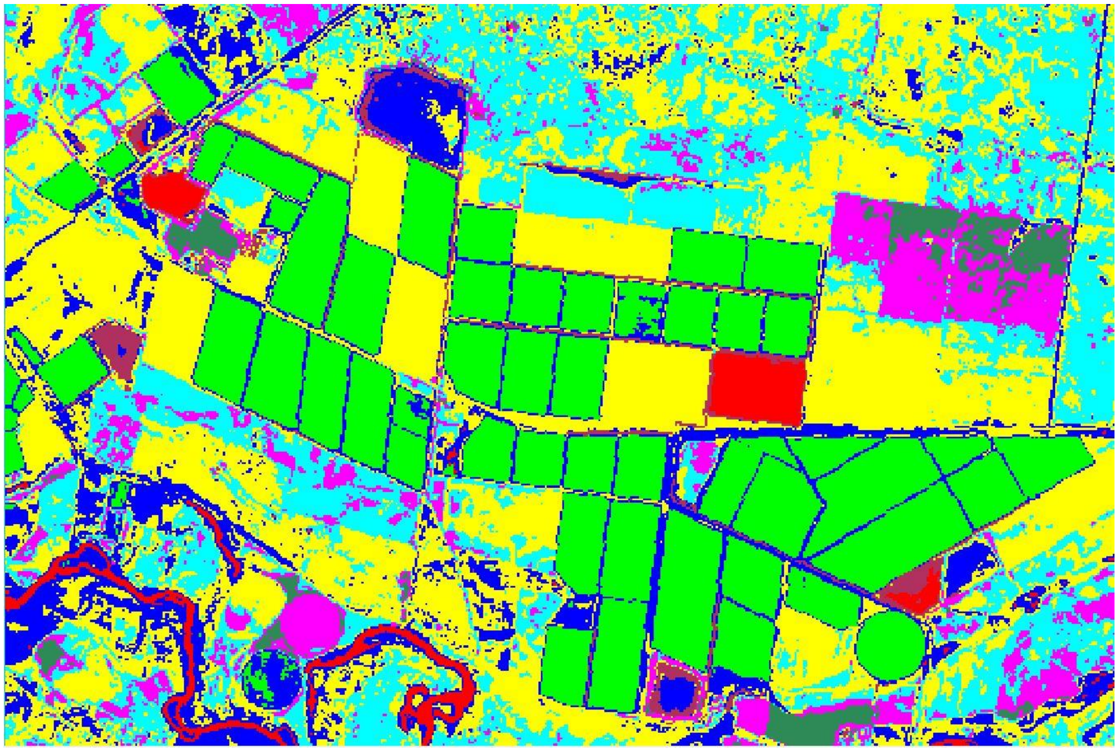


Figure 4.4: ENVI unsupervised segmented result of eight classes(Exelis 2012)

Table 4.1: Unsupervised class result

Unsupervised

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C1-1	28˚37'48.58"S	150˚31'04.48"E	1	1	1
C1-2	28˚35'49.86"S	150˚26'29.70"E	1	1	1
C1-3	28˚36'23.69"S	150˚27'55.87"E	1	1	1
C1-4	28˚35'18.10"S	150˚27'02.25"E	1	1	1
C1-5	28˚34'54.68"S	150˚24'00.45"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C2-1	28˚35'39.70"S	150˚30'12.65"E	1	0	0
C2-2	28˚35'35.92"S	150˚29'24.89"E	1	0	0
C2-3	28˚35'22.68"S	150˚27'36.22"E	1	0	0
C2-4	28˚35'09.79"S	150˚25'47.14"E	1	0	0
C2-5	28˚38'37.07"S	150˚28'37.25"E	1	0	0
Total %					**0%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C3-1	28˚36'52.16"S	150˚30'27.85"E	1	1	1
C3-2	28˚34'16.71"S	150˚31'14.78"E	1	1	1
C3-3	28˚33'38.99"S	150˚25'00.52"E	1	1	1
C3-4	28˚38'08.56"S	150˚32'15.43"E	1	1	1
C3-5	28˚37'43.91"S	150˚24'04.67"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C4-1	28˚35'44.98"S	150˚31'16.54"E	1	0	1
C4-2	28˚35'47.98"S	150˚32'08.04"E	1	0.5	0.5
C4-3	28˚37'20.92"S	150˚26'13.99"E	1	1	1
C4-4	28˚36'27.54"S	150˚24'40.59"E	1	1	1
C4-5	28˚37'45.62"S	150˚25'00.62"E	1	1	1
Total %					**90%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C5-1	28˚36'29.89"S	150˚30'50.18"E	1	1	1
C5-2	28˚36'34.39"S	150˚28'47.39"E	1	1	1
C5-3	28˚35'08.14"S	150˚26'36.09"E	1	1	1
C5-4	28˚35'50.17"S	150˚24'55.62"E	1	1	1
C5-5	28˚34'29.10"S	150˚30'59.89"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C6-1	28˚36'40.10"S	150˚29'48.35"E	1	1	1
C6-2	28˚38'07.83"S	150˚31'13.35"E	1	1	1
C6-3	28˚34'59.96"S	150˚24'49.43"E	1	1	1
C6-4	28˚34'04.95"S	150˚27'01.26"E	1	0	0
C6-5	28˚36'00.03"S	150˚24'16.82"E	1	0	0
Total %					**60%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C7-1	28˚38'51.90"S	150˚27'18.28"E	1	0	1
C7-2	28˚37'36.93"S	150˚25'14.46"E	1	0	1
C7-3	28˚39'02.47"S	150˚25'23.20"E	1	0	1
C7-4	28˚38'06.50"S	150˚24'54.26"E	1	0	1
C7-5	28˚38'26.14"S	150˚26'22.85"E	1	0	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C8-1	28˚35'22.97"S	150˚24'53.80"E	1	1	1
C8-2	28˚35'15.82"S	150˚24'54.13"E	1	1	1
C8-3	28˚35'11.64"S	150˚25'09.76"E	1	1	1
C8-4	28˚35'17.47"S	150˚25'25.54"E	1	1	1
C8-5	28˚35'24.56"S	150˚25'17.47"E	1	1	1
Total %					**100%**
Unsupervised Total %					**81.25%**

Table 4.2: Class Criteria

Class	
1	Cotton 1 - Bright Green (C1)
2	Cotton 2 -Dark Green (C2)
3	Native Vegetation (NV)
4	Dry Non Photosynthesis Vegetation 1 (DNPV1)
5	Dry Non Photosynthesis Vegetation 2 (DNPV2)
6	Water Dam (WD)
7	Water Natural Tributary (WNT)
8	Gravel (G)

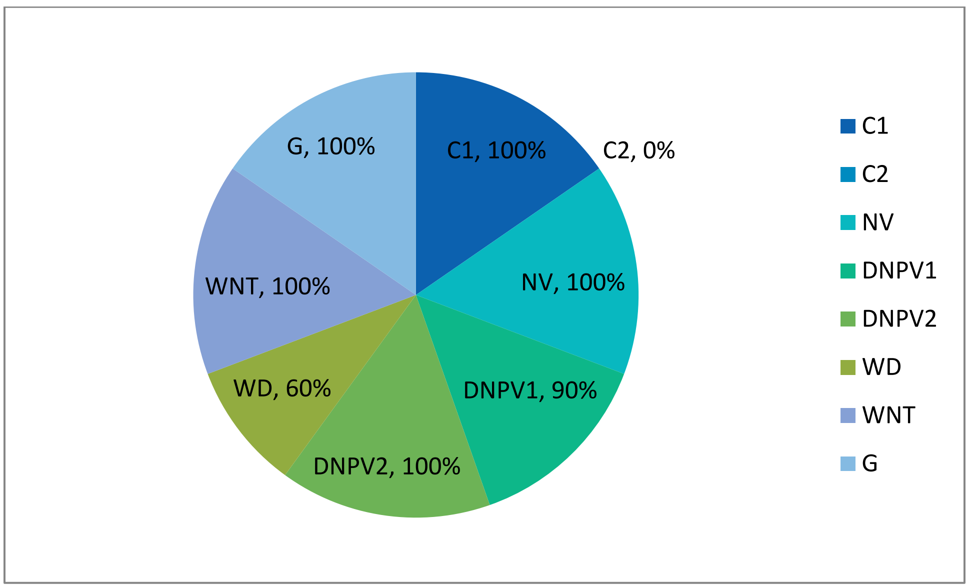


Figure 4.5: Pie chart of ENVI unsupervised segmented result of eight classes

4.2 Supervised

The supervised ENVI software settings used are as follows:

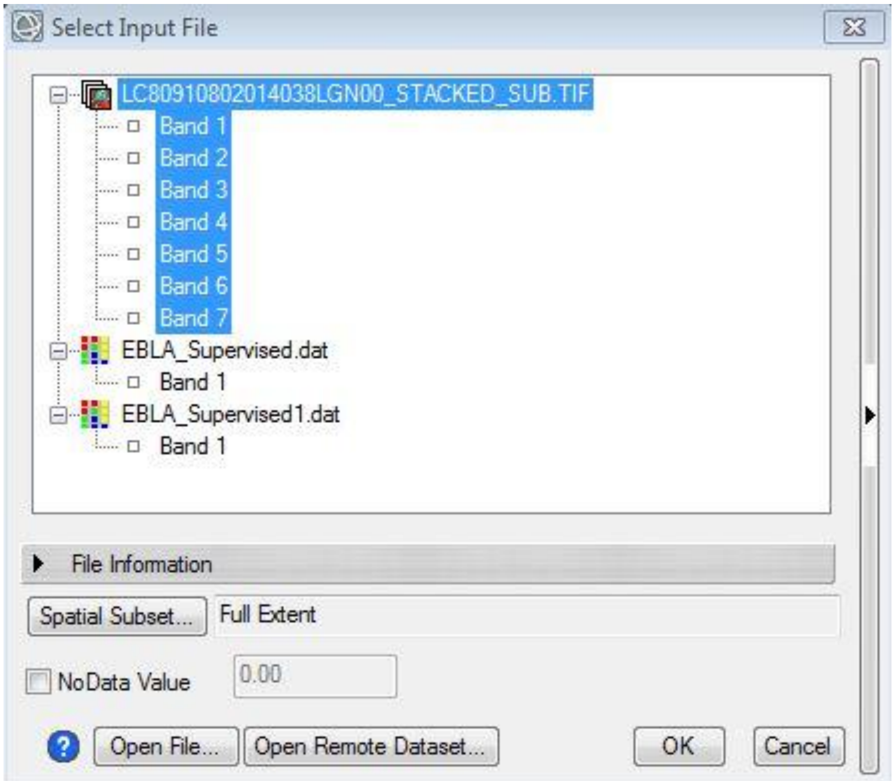


Figure 4.6: Input file setting of ENVI supervised (Exelis 2012)

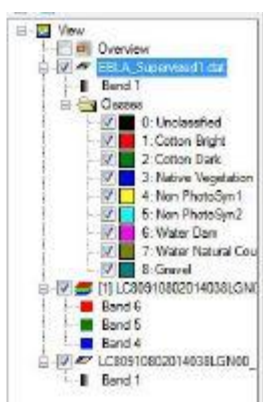


Figure 4.7: Supervised class table by user defined (Exelis 2012)

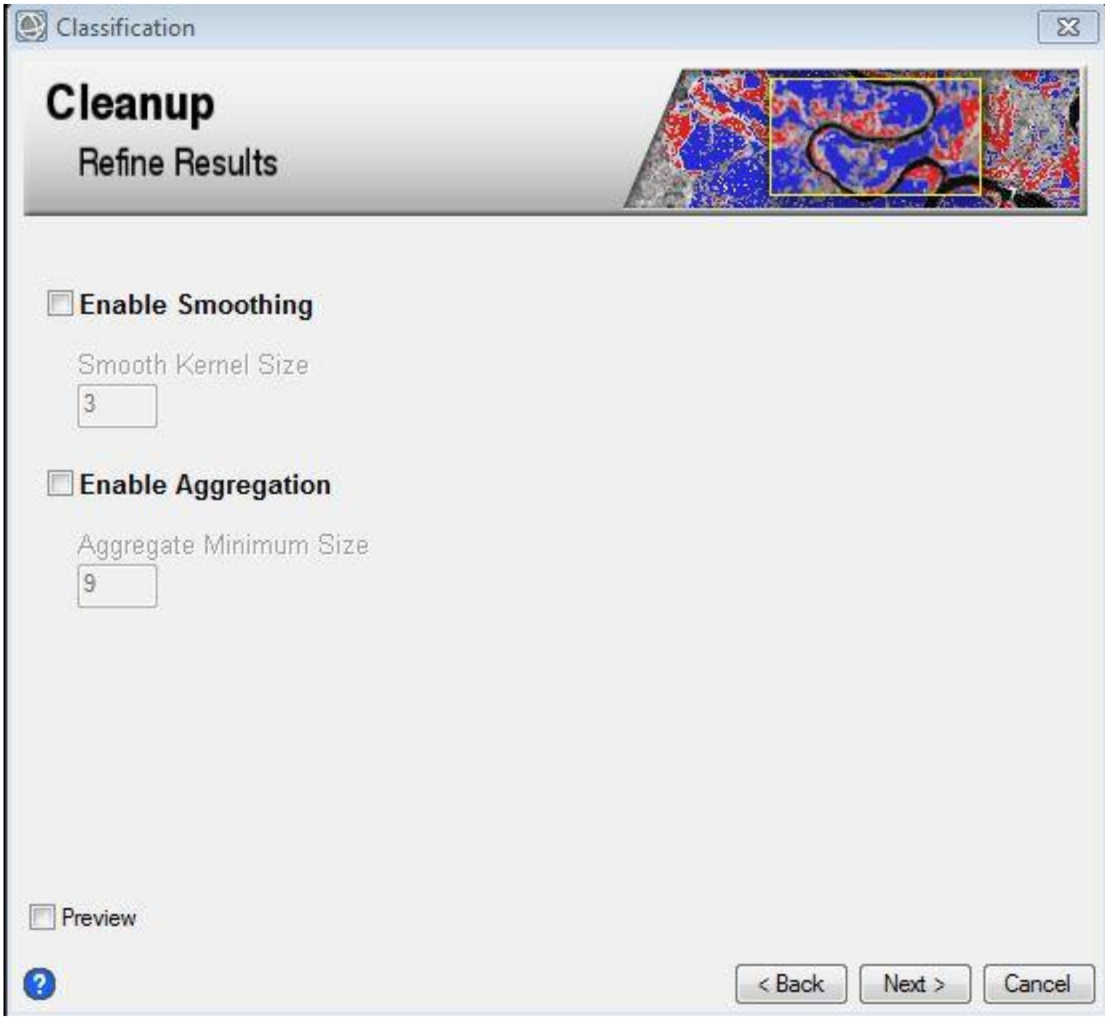


Figure 4.8: Refine results setting of ENVI supervised (Exelis 2012)

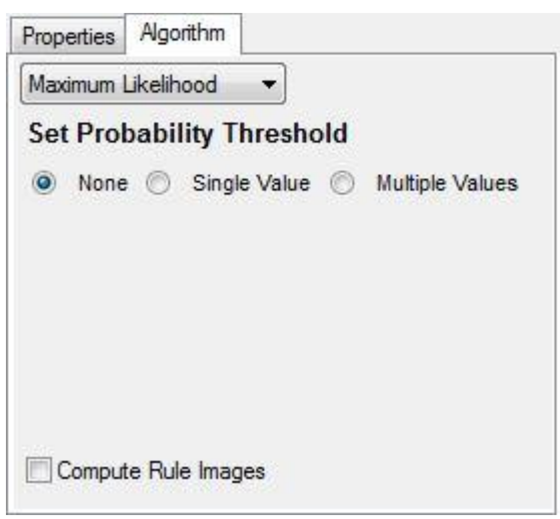


Figure 4.9: Algorithm setting of ENVI supervised (Exelis 2012)

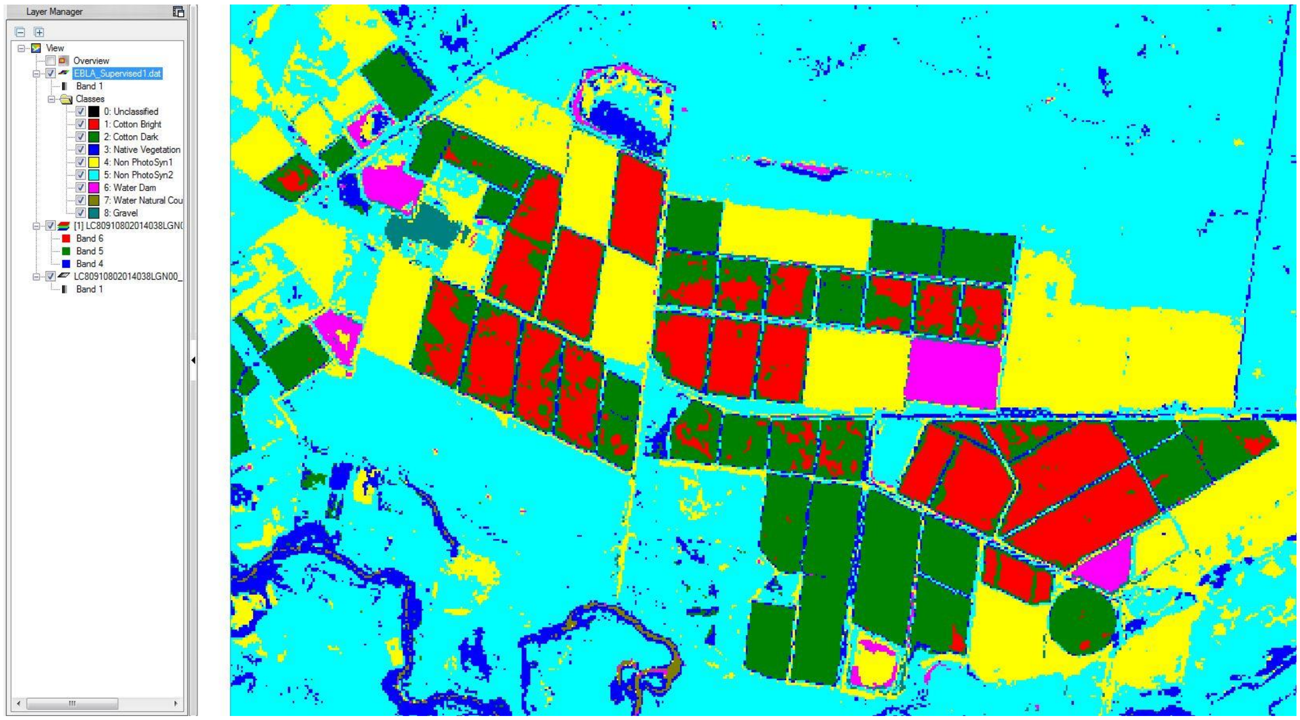


Figure 4.10: ENVI supervised segmented result of eight classes from user predefined class set (Exelis 2012)

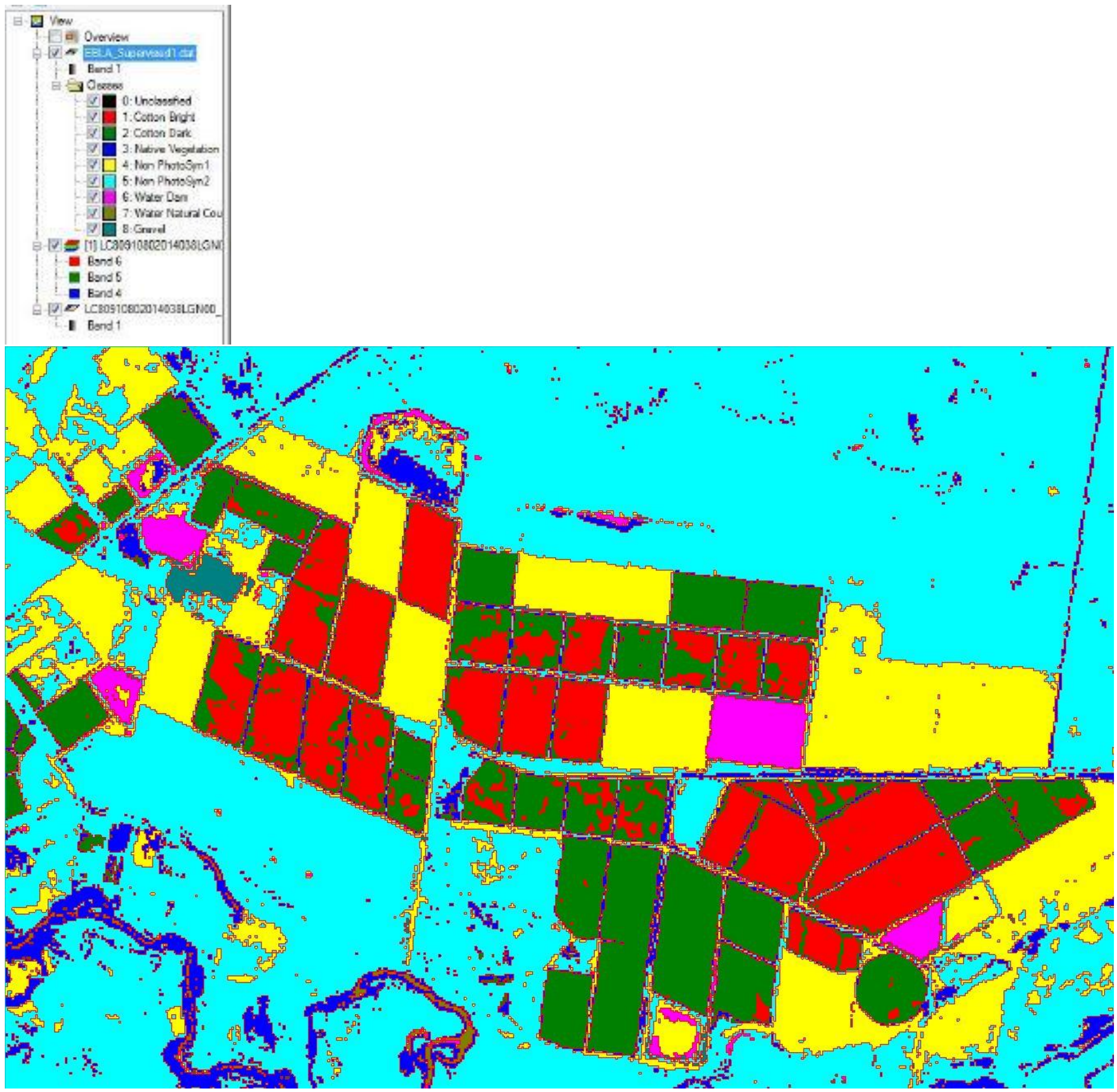


Figure 4.11: Enlarged ENVI supervised segmented result of eight classes from user predefined class set (Exelis 2012)

Table 4.3: Supervised class result

Supervised

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C1-1	28˚37'48.58"S	150˚31'04.48"E	1	1	1
C1-2	28˚35'49.86"S	150˚26'29.70"E	1	1	1
C1-3	28˚36'23.69"S	150˚27'55.87"E	1	1	1
C1-4	28˚35'18.10"S	150˚27'02.25"E	1	1	1
C1-5	28˚34'54.68"S	150˚24'00.45"E	1	0.5	0.5
Total %					**90%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C2-1	28˚35'39.70"S	150˚30'12.65"E	1	1	1
C2-2	28˚35'35.92"S	150˚29'24.89"E	1	1	1
C2-3	28˚35'22.68"S	150˚27'36.22"E	1	1	1
C2-4	28˚35'09.79"S	150˚25'47.14"E	1	1	1
C2-5	28˚38'37.07"S	150˚28'37.25"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C3-1	28˚36'52.16"S	150˚30'27.85"E	1	1	1
C3-2	28˚34'16.71"S	150˚31'14.78"E	1	0	0
C3-3	28˚33'38.99"S	150˚25'00.52"E	1	1	1
C3-4	28˚38'08.56"S	150˚32'15.43"E	1	1	1
C3-5	28˚37'43.91"S	150˚24'04.67"E	1	1	1
Total %					**80%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C4-1	28˚35'44.98"S	150˚31'16.54"E	1	1	1
C4-2	28˚35'47.98"S	150˚32'08.04"E	1	1	1
C4-3	28˚37'20.92"S	150˚26'13.99"E	1	1	1
C4-4	28˚36'27.54"S	150˚24'40.59"E	1	1	1
C4-5	28˚37'45.62"S	150˚25'00.62"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C5-1	28˚36'29.89"S	150˚30'50.18"E	1	1	1
C5-2	28˚36'34.39"S	150˚28'47.39"E	1	1	1
C5-3	28˚35'08.14"S	150˚26'36.09"E	1	1	1
C5-4	28˚35'50.17"S	150˚24'55.62"E	1	1	1
C5-5	28˚34'29.10"S	150˚30'59.89"E	1	0	0
Total %					**80%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C6-1	28˚36'40.10"S	150˚29'48.35"E	1	1	1
C6-2	28˚38'07.83"S	150˚31'13.35"E	1	1	1
C6-3	28˚34'59.96"S	150˚24'49.43"E	1	1	1
C6-4	28˚34'04.95"S	150˚27'01.26"E	1	1	1
C6-5	28˚36'00.03"S	150˚24'16.82"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C7-1	28˚38'51.90"S	150˚27'18.28"E	1	1	1
C7-2	28˚37'36.93"S	150˚25'14.46"E	1	0.5	0.5
C7-3	28˚39'02.47"S	150˚25'23.20"E	1	0	0
C7-4	28˚38'06.50"S	150˚24'54.26"E	1	0.5	0.5
C7-5	28˚38'26.14"S	150˚26'22.85"E	1	0	0.5
Total %					**50%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C8-1	28˚35'22.97"S	150˚24'53.80"E	1	1	1
C8-2	28˚35'15.82"S	150˚24'54.13"E	1	1	1
C8-3	28˚35'11.64"S	150˚25'09.76"E	1	1	1
C8-4	28˚35'17.47"S	150˚25'25.54"E	1	1	1
C8-5	28˚35'24.56"S	150˚25'17.47"E	1	1	1
Total %					**100%**
Supervised Total %					**87.50%**

Table 4.4: Class Criteria

	Class
1	Cotton 1 - Bright Green (C1)
2	Cotton 2 -Dark Green (C2)
3	Native Vegetation (NV)
4	Dry Non Photosynthesis Vegetation 1 (DNPV1)
5	Dry Non Photosynthesis Vegetation 2 (DNPV2)
6	Water Dam (WD)
7	Water Natural Tributary (WNT)
8	Gravel (G)

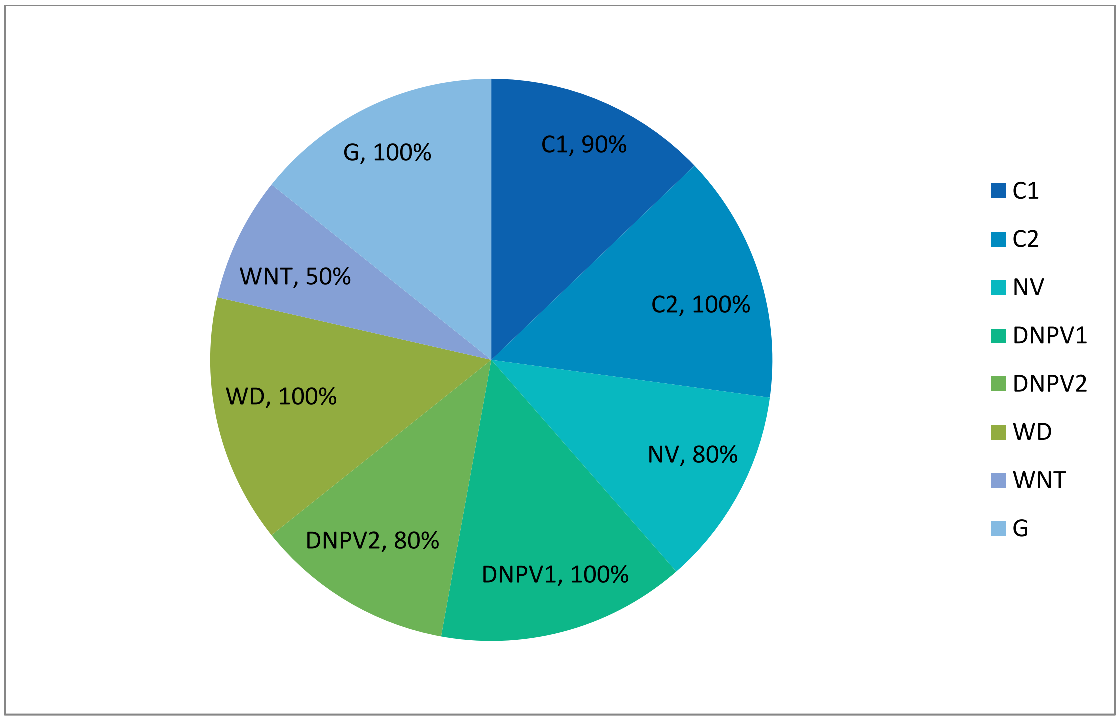


Figure 4.12: Pie chart of ENVI supervised segmented result of eight classes

4.3 Feature Extraction by Example Based Classification

The Feature extraction by example based classification ENVI software settings used are as follows:

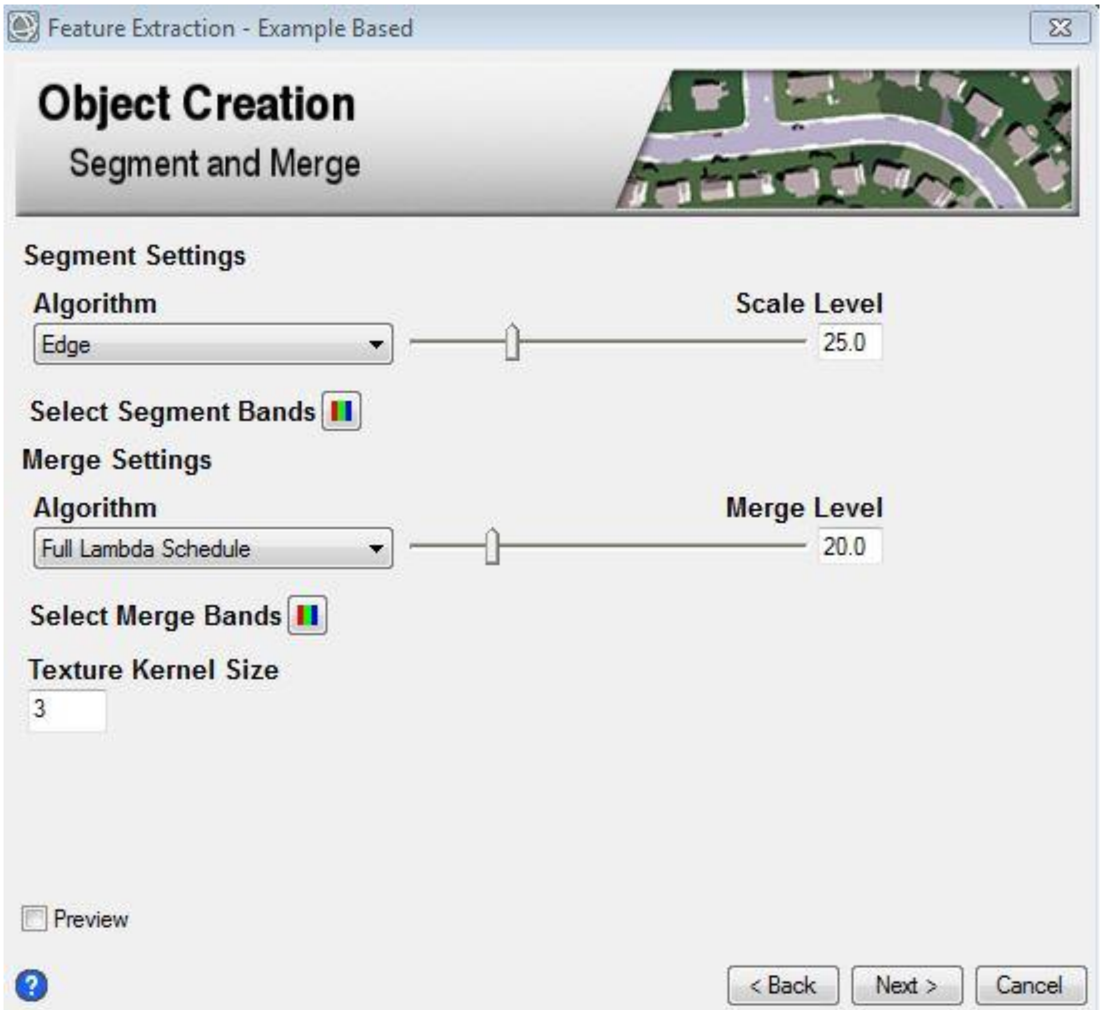


Figure 4.13: Segment and merge setting of ENVI feature extraction with example- based (Exelis 2012

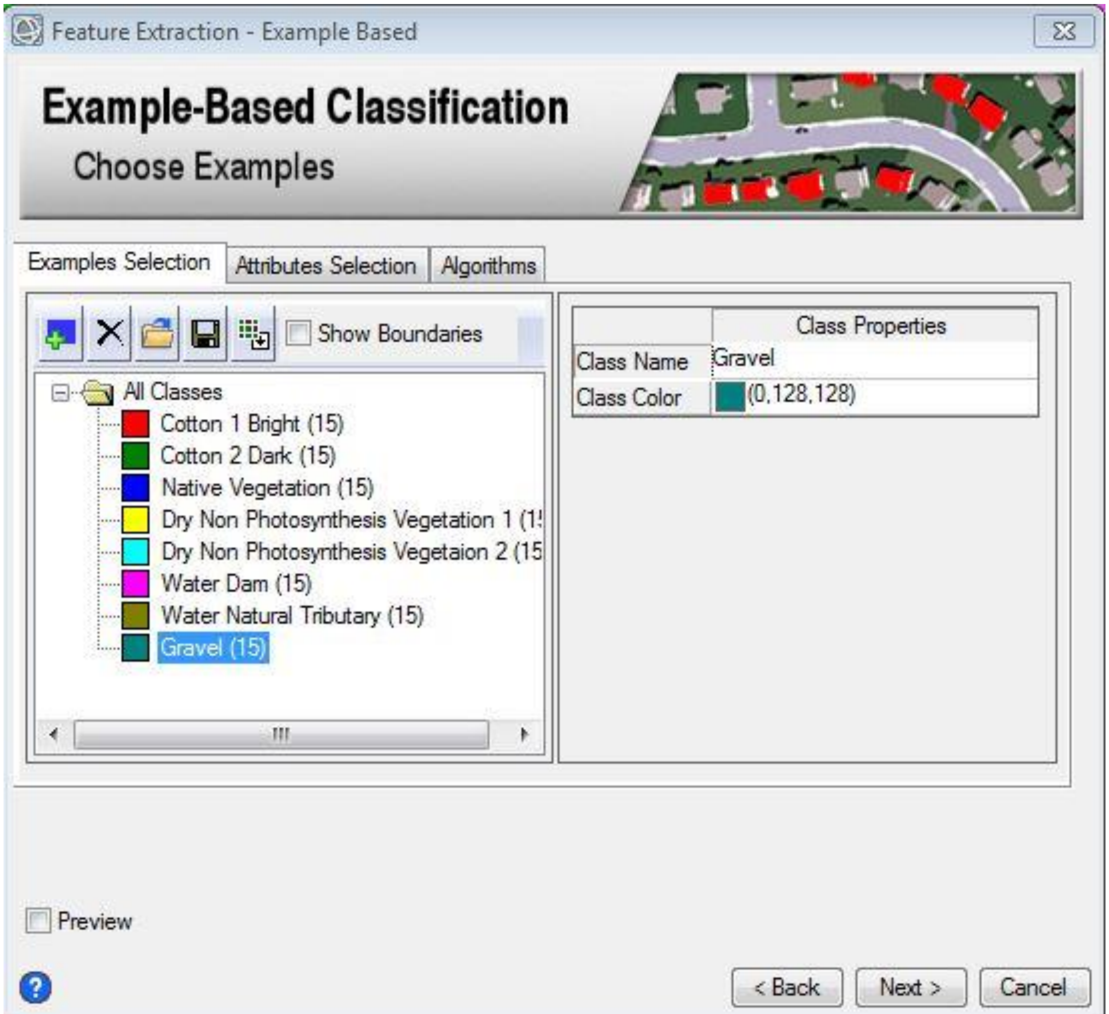


Figure 4.14: User defined class setting of ENVI feature extraction with example- based (Exelis 2012)

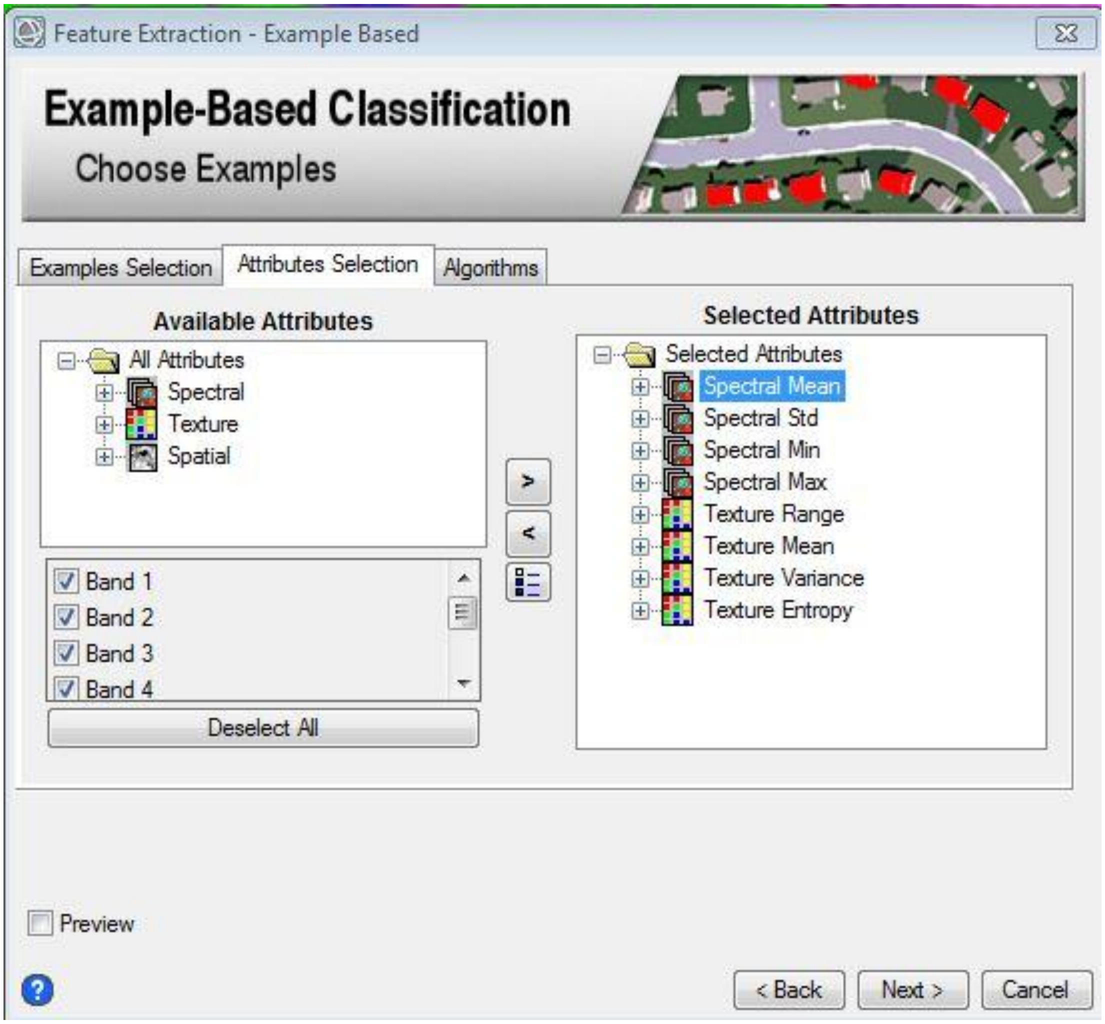


Figure 4.15: Attributes selection setting of ENVI feature extraction with example- based (Exelis 2012)

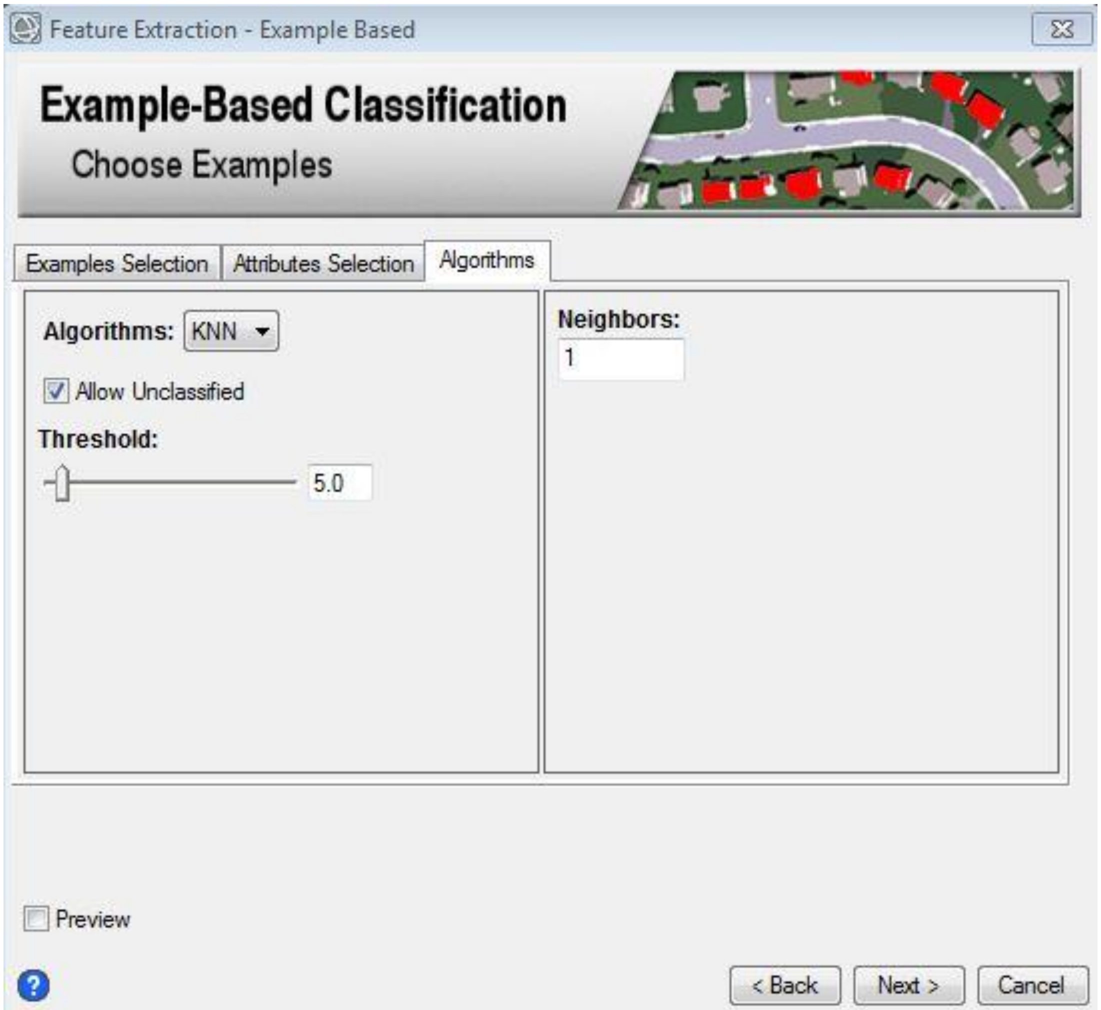


Figure 4.16: Algorithm selection setting of ENVI feature extraction with example- based (Exelis 2012)

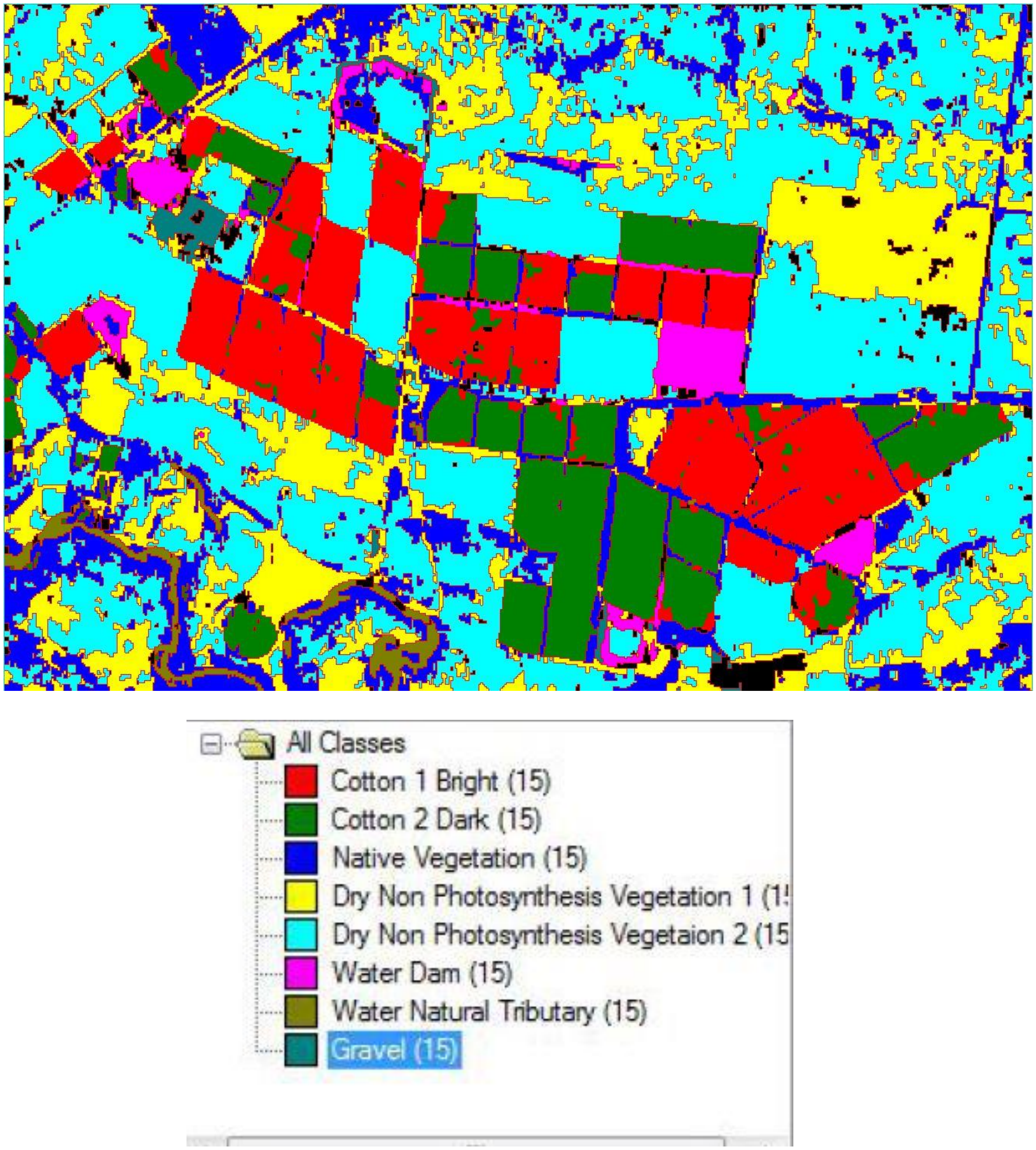


Figure 4.17: ENVI feature extraction with example-based segmented result of eight classes from user predefined class set (Exelis 2012)

Table 4.5: Feature extraction with example-based class result

Feature Extraction with Example-Based

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C1-1	28˚37'48.58"S	150˚31'04.48"E	1	1	1
C1-2	28˚35'49.86"S	150˚26'29.70"E	1	1	1
C1-3	28˚36'23.69"S	150˚27'55.87"E	1	1	1
C1-4	28˚35'18.10"S	150˚27'02.25"E	1	1	1
C1-5	28˚34'54.68"S	150˚24'00.45"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C2-1	28˚35'39.70"S	150˚30'12.65"E	1	1	1
C2-2	28˚35'35.92"S	150˚29'24.89"E	1	1	1
C2-3	28˚35'22.68"S	150˚27'36.22"E	1	0.5	0.5
C2-4	28˚35'09.79"S	150˚25'47.14"E	1	1	1
C2-5	28˚38'37.07"S	150˚28'37.25"E	1	1	1
Total %					**90%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C3-1	28˚36'52.16"S	150˚30'27.85"E	1	1	1
C3-2	28˚34'16.71"S	150˚31'14.78"E	1	0.5	0.5
C3-3	28˚33'38.99"S	150˚25'00.52"E	1	1	1
C3-4	28˚38'08.56"S	150˚32'15.43"E	1	1	1
C3-5	28˚37'43.91"S	150˚24'04.67"E	1	1	1
Total %					**90%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C4-1	28˚35'44.98"S	150˚31'16.54"E	1	1	1
C4-2	28˚35'47.98"S	150˚32'08.04"E	1	1	1
C4-3	28˚37'20.92"S	150˚26'13.99"E	1	1	1
C4-4	28˚36'27.54"S	150˚24'40.59"E	1	1	1
C4-5	28˚37'45.62"S	150˚25'00.62"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C5-1	28˚36'29.89"S	150˚30'50.18"E	1	1	1
C5-2	28˚36'34.39"S	150˚28'47.39"E	1	1	1
C5-3	28˚35'08.14"S	150˚26'36.09"E	1	1	1
C5-4	28˚35'50.17"S	150˚24'55.62"E	1	1	1
C5-5	28˚34'29.10"S	150˚30'59.89"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C6-1	28˚36'40.10"S	150˚29'48.35"E	1	1	1
C6-2	28˚38'07.83"S	150˚31'13.35"E	1	1	1
C6-3	28˚34'59.96"S	150˚24'49.43"E	1	1	1
C6-4	28˚34'04.95"S	150˚27'01.26"E	1	1	1
C6-5	28˚36'00.03"S	150˚24'16.82"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C7-1	28˚38'51.90"S	150˚27'18.28"E	1	1	1
C7-2	28˚37'36.93"S	150˚25'14.46"E	1	1	1
C7-3	28˚39'02.47"S	150˚25'23.20"E	1	1	1
C7-4	28˚38'06.50"S	150˚24'54.26"E	1	1	1
C7-5	28˚38'26.14"S	150˚26'22.85"E	1	1	1
Total %					**100%**

Class Label	Latitude	Longitude	Designated Class	ENVI Class Result	Identification Result
C8-1	28˚35'22.97"S	150˚24'53.80"E	1	1	1
C8-2	28˚35'15.82"S	150˚24'54.13"E	1	1	1
C8-3	28˚35'11.64"S	150˚25'09.76"E	1	1	1
C8-4	28˚35'17.47"S	150˚25'25.54"E	1	1	1
C8-5	28˚35'24.56"S	150˚25'17.47"E	1	1	1
Total %					**100%**
Feature Extraction with Example-Based Total %					**97.50%**

Table 4.6: Class Criteria

	Class
1	Cotton 1 - Bright Green (C1)
2	Cotton 2 -Dark Green (C2)
3	Native Vegetation (NV)
4	Dry Non Photosynthesis Vegetation 1 (DNPV1)
5	Dry Non Photosynthesis Vegetation 2 (DNPV2)
6	Water Dam (WD)
7	Water Natural Tributary (WNT)
8	Gravel (G)

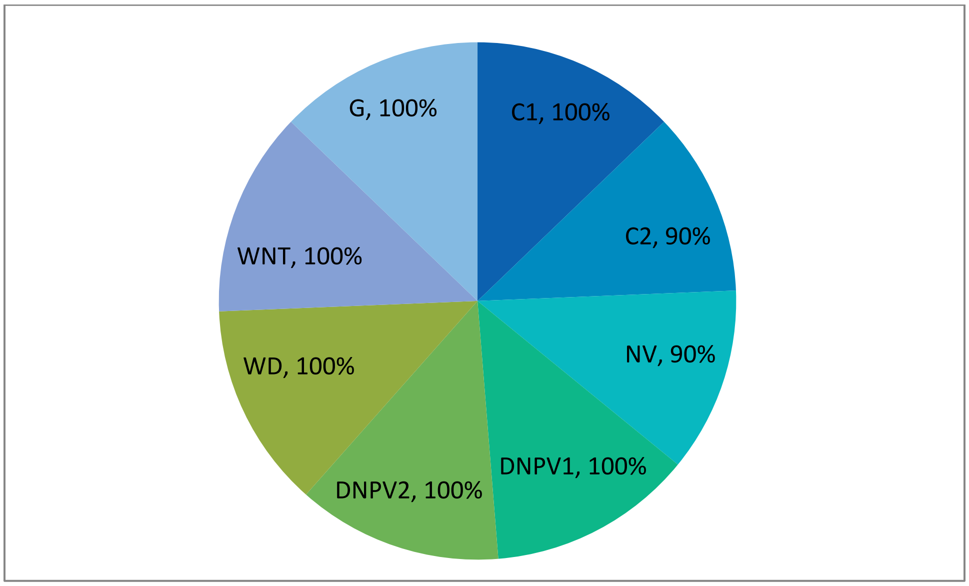
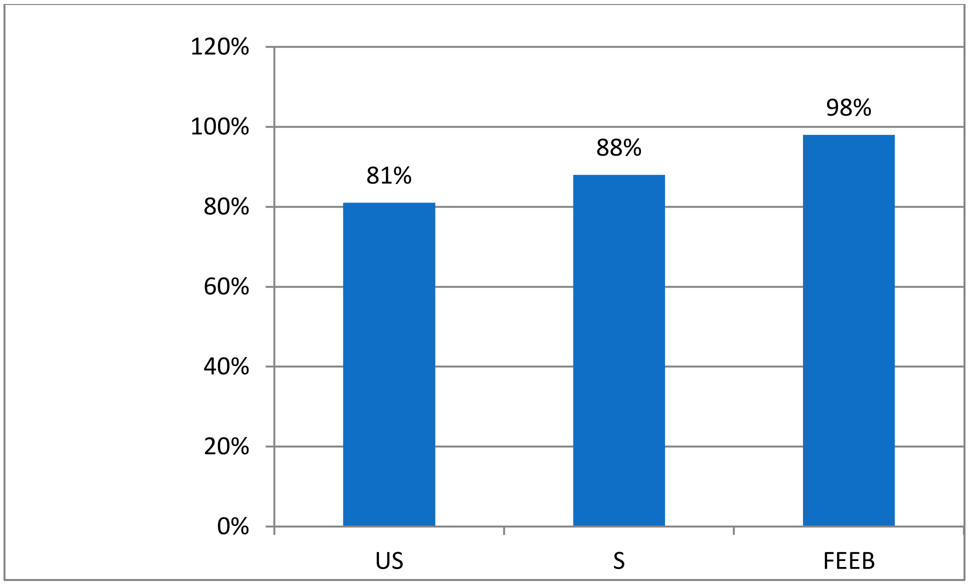


Figure 4.18: Pie chart of ENVI feature extraction with example-based segmented result of eight classes



US = Unsupervised, S = Supervised, FEEB = Feature Extraction with Example-Based

Figure 4.19: Column chart comparing ENVI segmentation method results

Chapter 5 REVIEW

5.1 Unsupervised

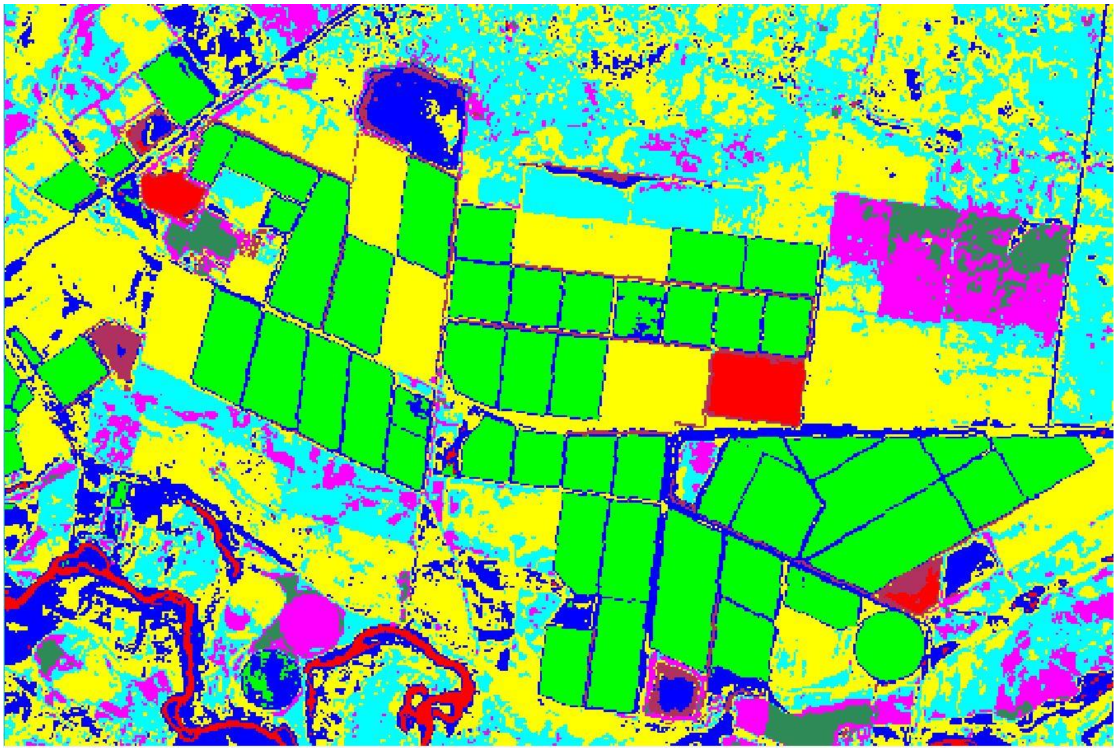


Figure 5.1: ENVI unsupervised review of segmented result of eight classes reviewed (Exelis 2012)

Table 5.1 Unsupervised Class Review

Unsupervised Class Result		
1	Green	C1 & C2
2	Blue	NV & C2 part
3	Yellow	DNPV1
4	Cyan	DNPV2
5	Magenta	DNPV Unclassified
6	Red	WNT & WD part
7	Maroon	WD part
8	Olive	G & Unclassified

Table 5.2: Class Criteria

Class	
1	Cotton 1 - Bright Green (C1)
2	Cotton 2 -Dark Green (C2)
3	Native Vegetation (NV)
4	Dry Non Photosynthesis Vegetation 1 (DNPV1)
5	Dry Non Photosynthesis Vegetation 2 (DNPV2)
6	Water Dam (WD)
7	Water Natural Tributary (WNT)
8	Gravel (G)

The unsupervised method is a quick workflow in ENVI software, as it create's a class set from the users allocated class number selected, in this case 8 were implemented. In the cotton class ENVI has not distinguished between bright and dark green cotton however the outline of the cotton fields has been generally a good result in the essence of extracting cotton field shape and size. Native vegetation has blended in to the dark green patches of in field crop variability, the spot analysis has shown the native vegetation to be the blue class. The dry non photosynthesis vegetation 1 and 2 have shown a high percentage success rate, however an unclassified class as well as gravel have infiltrated these areas such as the colour class of magenta and olive (gravel). The prominent feature of water natural tributary has blended in with the water dam class with maroon being part of water dam class. The overall success rate is high for a simple and fast approach utilizing 7 bands.

5.2 Supervised

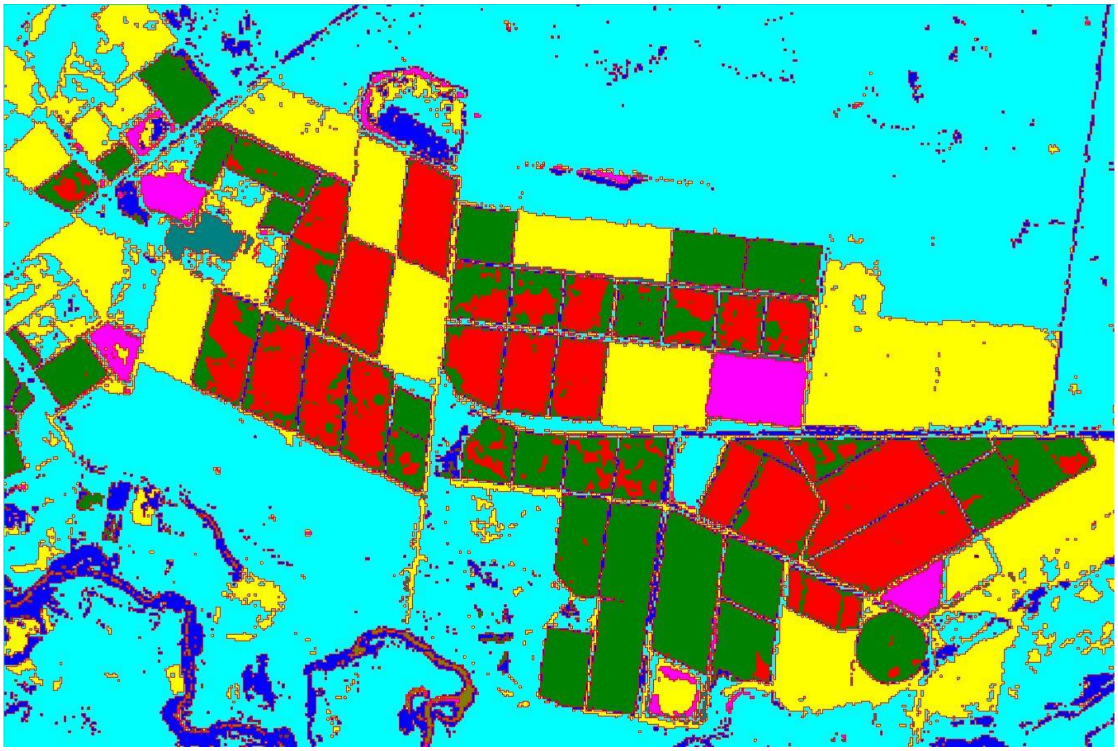


Figure 5.2: ENVI supervised segmented result of eight classes from user predefined class set reviewed (Exelis 2012)

Table 5.3: Class Criteria Review Supervised

	Class
1	Cotton 1 - Bright Green (C1)
2	Cotton 2 -Dark Green (C2)
3	Native Vegetation (NV)
4	Dry Non Photosynthesis Vegetation 1 (DNPV1)
5	Dry Non Photosynthesis Vegetation 2 (DNPV2)
6	Water Dam (WD)
7	Water Natural Tributary (WNT)
8	Gravel (G)

This process involved the selection of twenty pixel based selections from the image for each class to derive the class table applied to the supervised workflow. In this case the result produced no unclassified data in which ENVI shows as black on the class table if it cannot decide on a specified class provided. The deficiency of this workflow was the water natural tributary having the segmented data scattered and non-continuous, the bright and dark green cotton has shown a variable result between the classes, with not all of the bright green classification being evident. The variable class results are based on the user class selection process, a review in gathering more samples per class in the ENVI workflow may correct some of the anomalies that ENVI has produced in the segmented data. Overall an 88 percent success rate is due to the class sampling process of the supervised method.

5.3 Feature Extraction with Example-Based

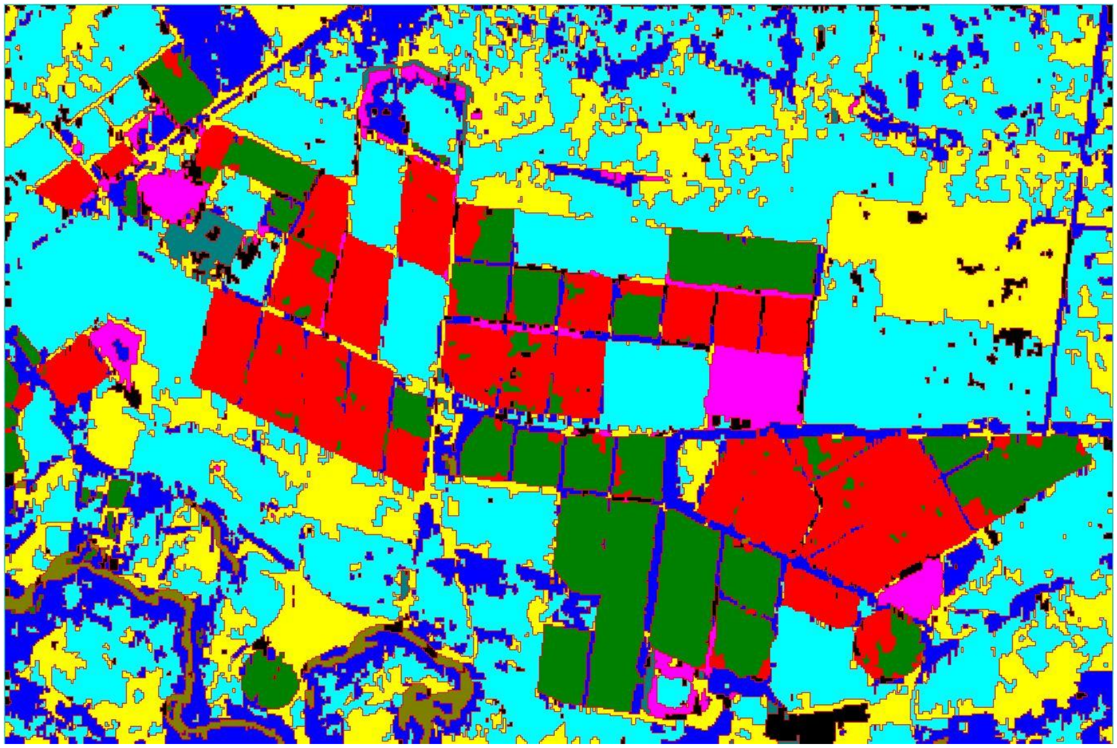


Figure 5.3: ENVI feature extraction with example-based segmented result of eight classes from user predefined class set reviewed (Exelis 2012)

Table 5.4: Class Criteria Review Feature Extraction with Example-Based

	Class
1	Cotton 1 - Bright Green (C1)
2	Cotton 2 -Dark Green (C2)
3	Native Vegetation (NV)
4	Dry Non Photosynthesis Vegetation 1 (DNPV1)
5	Dry Non Photosynthesis Vegetation 2 (DNPV2)
6	Water Dam (WD)
7	Water Natural Tributary (WNT)
8	Gravel (G)

The workflow produced the segmentation data from the user selecting 15 samples of each class, this method has the object-oriented approach with attributes of spectral and texture taken into account. Other attributes available were not selected to allow the segmentation process to run smoothly as the more attributes added the longer the algorithm process to produce the segmented data from the satellite image or worst case, the software freezing whilst in the algorithm process. This option produced the highest class sampling success rate however the classes tended to at some sections blend into each other for example two cotton fields into one. These anomalies can be rectified with possibly more sampling of classes in the class set as parts of the segmented image has also resulted in black areas of unclassified data. Other options can be modifying selected settings in the workflow process, as is encouraged through the workflow example files provided by the ENVI software and company website Exelis http://www.exelisinc.com/solutions/ENVI/Pages/default.aspx.

Chapter 6 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The three segment extraction options used in unsupervised, supervised and feature extraction with example-based from satellite imagery has produced an insight into the ENVI software's successful capabilities. The examples shown have had a high percentage rate in class identification however some broken or scattered data, miss classification, non-classification and merged data tend to distort the shape and size of the feature of interest to extract. This can be rectified by correcting some of the anomalies through the software by:

- Changing the satellite image band selection at the start of the workflow that is best suited for the segmentation process of the object of interest e.g. bands 6,5,4 are a good option for cotton field extraction in this satellite image instance. All 7 bands were used in this comparison to represent the full complement of light reflection properties, however the software allows the user to select whatever the desired band the user requires to ultimately achieve a sound extraction of interest result from the image.
- Manipulating the software settings in the option process, performing workflow iterations until the desired result is obtained.
- Exploring other workflow methods in the data extraction process.
- The quality of the image data set used for extraction.
- Research software manuals and website for available alternatives.

The ENVI software is not designed for the novice user off the street. The software is complex with a wide array of different approaches for data extraction of objects of interest. A sound base knowledge is required in understanding remote sensing technology, terminology and methodology for the user to achieve the optimum result of the extracted data of interest from any image used, as mentioned above many variables effect the outcome of the extraction process with the user needing to have a clear understanding of the processes required.

6.2 Recommendation for Future Research

The above dissertation has revealed that the technology works with the cotton field data extraction being a success, with options of refinement available to improve the outcome. This then therefore can be applied to whatever is in an image can ultimately be measured in some way or form, with this being the case then the user has the ability to extract any form of data the image possesses which makes future research unlimited.

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APPENDIX A: Project Specification

University of Southern Queensland

Faculty of Engineering and Surveying

ENG4111 & ENG4112 Research Project
Project Specification

For: **Desmond Fleming**
Student No. 0038842606

Topic: Object-Oriented Image Analysis of Cotton Cropping Areas in the Macintyre Valley Using Satellite Imagery

Supervisor: Prof. Armando A. Apan

Enrolment: ENG 4111 – Research Project Part 1 – S1 2015
ENG 4903 – Professional Practice 2 – S2 2015
ENG 4112 – Research Project Part2 – S2 2015

Project Aim: To assess and develop object-oriented image analysis techniques in mapping cotton cropping areas using satellite imagery.

Programme: **Issue 2 24th March 2015**

1. Conduct literature review on the use of satellite imagery for crop mapping, and on the principles and applications of object-orientated image analysis techniques.
2. Acquire Landsat imagery and other supporting GIS thematic maps (soil, road, drainage, etc.)
3. Perform data pre-processing tasks, i.e. clipping to the study area, re-projection, mosaicking, etc., as required.
4. Identify sample areas (“training sites” or “ground truth” areas) of various crops (cotton, sorghum, corn, etc.) evident in the image.
5. Conduct object-oriented image analysis by using different parameters and classification algorithms available in the software. Objective to focus on cotton vs others with the possibility of mapping within-field spatial variability, if time permits.
6. Produce classification maps showing areas planted with cotton.
7. Conduct accuracy assessment of the output maps.

8. Write and submit dissertation.

APPENDIX B: Project Procedure

Project Procedure:

- Data Collection & ENVI 5 Software Use
- Data Extraction ENVI 5
- Data Reduction and Compilation
- Dissertation and report results
- Data comparison and analysis using various techniques

Table 3.1: Description of Project Assignments

A	**Data Collection & ENVI 5 Software Use**
A1	Determine satellite imagery tile area
A2	Collate image data
A3	ENVI 5 Tutorials & help menu/Import data into ENVI 5
B	**Data Extraction ENVI 5**
B1	Determine data extraction parameters
B2	Derive the rule set/Extraction methodology
B3	Iteration 1 Process image/determine polylines data extraction
B4	Classification validity by independent technique eg. Digitizing 5 images
B5	Compare results (repeat assignments B2,B3 & B5 until the results are suitable)
B6	Report on accuracies, graphs & determine comparisons
B7	Compile results
C	**Data Reduction & Compilation**
C1	Apply extracted data to calculations on cotton area
C2	Graph results
D	**Dissertation and report results**
D1	Complete dissertation and report
D2	Dissertation draft for supervisor and create power point for PP2
D3	Dissertation amendments

APPENDIX C: Resource Requirements

The entire project is computer orientated with all data electronic based. Time frames to access USQ facilities and resources to be determined with supervisor. Upon email request from my self to Professor Apan (supervisor) for access to ENVI 5 software on the USQ Toowoomba campus he was successful in obtaining permission from the Dean. In acceptance of using USQ facilities I must adhere to all of the relevant USQ policies and procedures such as the Safety Management System Project Zero (USQ 2015).

Table 3.2: Resource Requirements for Project Assignments

A	**Data Collection & EVI Software Use**	**Cost**
A1	USQ facilities, computer, software & internet access	nil
A2	USQ facilities, computer, software & internet access	nil
A3	USQ facilities, software & internet access	nil
B	**Data Extraction ENVI 5**	
B1	USQ facilities, computer, software & internet access	nil
B2	USQ facilities, computer, software & internet access	nil
B3	USQ facilities, computer, software & internet access	nil
B4	USQ facilities, computer, software & internet access	nil
B5	USQ facilities, computer, software & internet access	nil
B6	USQ facilities & home, computer, software & internet access	nil
B7	USQ facilities, computer, software & internet access	nil
C	**Data Reduction & Compilation**	
C1	USQ facilities & home, computer, software & internet access	nil
C2	USQ facilities & home, computer, software & internet access	nil
D	**Dissertation and report results**	
D1	Home resources, computer, software & internet access	nil
D2	Home resources, computer, software & internet access	nil
D3	Home resources, computer, software & internet access	nil

APPENDIX D: Risk Assessment

The research project consists of computer based applications, which will involve computer rooms at USQ and home use of a laptop. These environments are considered to be neutral with no major risk factor evident as shown in table 5.1 derived from figure 5.1 matrix.

HAZARD RISK ASSESSMENT MATRIX

	Hazard Categories			
	1	2	3	4
Frequency of Occurrence	Catastrophic	Critical	Serious	Minor
(A) Frequent	1A	2A	3A	4A
(B) Probable	1B	2B	3B	4B
(C) Occasional	1C	2C	3C	4C
(D) Remote	1D	2D	3D	4D
(E) Improbable	1E	2E	3E	4E

Unacceptable High Medium Low

Figure 4.1 *SMS 2014, Safety Management Services, Hazard Risk Assessment Matrix, viewed 26 October 2014,* http://www.smsenergetics.com/risk-management/process-hazards-analysis/risk-assessment-matrix-2

Table 4.1: Project Assignments Risk Assessment

A	**Data Collection & ENVI 5 Software Use**	**Risk**
A1	Determine satellite imagery tile area	4E
A2	Collate temporal image data	4E
A3	ENVI 5 Tutorials & help menu/Import data into ENVI 5	4E
B	**Data Extraction ENVI 5**	

B1	Determine data extraction parameters	4E
B2	Derive the rule set/Extraction methodology	4E
B3	Iteration 1 Process 3 image/Determine polylines data extraction	4E
B4	Classification validity by independent technique eg. Digitizing 5 images	4E
B5	Compare results (repeat assignments B2,B3 & B5 until the results are suitable)	4E
B6	Report on accuracies, graphs & determine comparisons	4E
B7	Compile results	4E
C	**Data Reduction & Compilation**	
C1	Apply extracted data to calculations on cotton area	4E
C2	Graph results	4E
D	**Dissertation and report results**	
D1	Complete dissertation and report	4E
D2	Dissertation draft for supervisor and create power point for PP2	4E
D3	Dissertation amendments	4E

APPENDIX E: Plan of Communication

The dissertation requires sound content, the inexperience of an undergraduate in this project requires the guidance by his supervisor to enable:

- project problems to be resolved.
- access to USQ facilities implemented.
- project schedules to remain on time.

Communication recommended as per table 4.2 below.

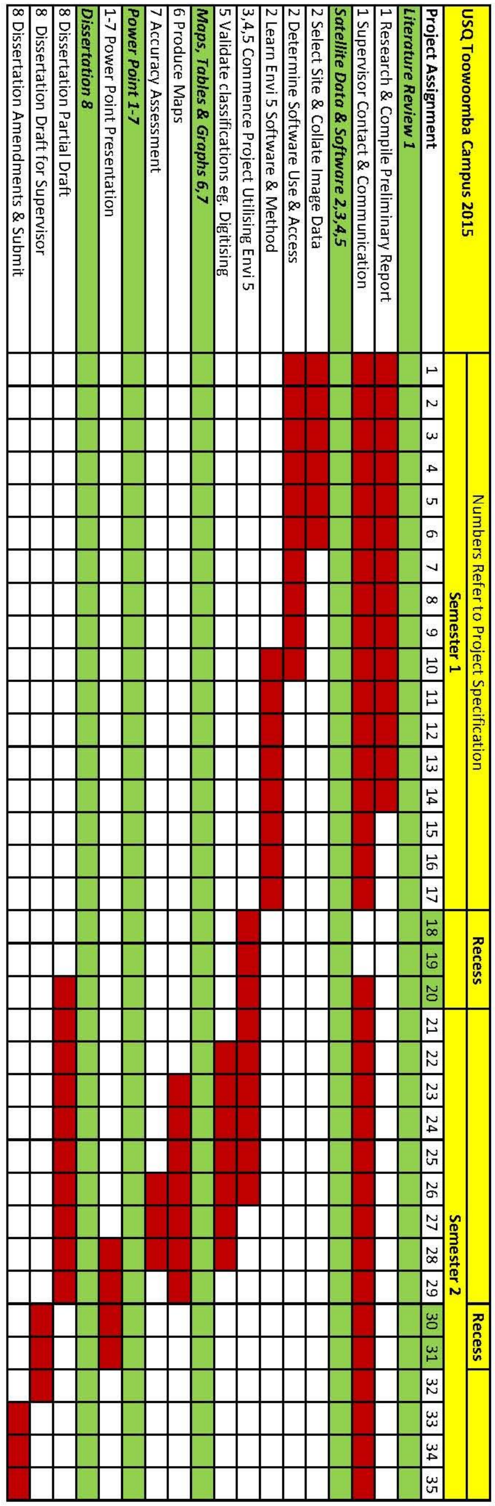
Table 4.2: Communication to Supervisor Guideline

Frequency	Communication used	Description
Weekly	Meeting, Email or Phone	Initial project commencement
Fortnightly	Email or Phone	Project duration

APPENDIX F: Schedule of Project

The figure 4.2 is an estimated project timeline that may be subject to change due to unknown anomalies, however it is a realistic approach of completing the dissertation.

Figure 4.2 Project Schedule



APPENDIX G: Landsat 8 Bit Quality Band

the table below gives the bits and colors associated with the 8-bit quality band:http://landsat.usgs.gov/LandsatLookImages.php

8-Bit LandsatLook QA Band - Read bits from RIGHT to LEFT <- starting with Bit 0								
Bit	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**0**
Description	**Cloud***	**Cirrus***	**Snow/Ice***	**Vegetation***	**Water***	**Terrain Occlusion**	**Dropped Frame**	**Designated Fill**
***Set for highest confidence value (11)**								