ISTANBUL TECHNICAL UNIVERSITY ★ INSTITUTE OF SCIENCE AND TECHNOLOGY

PROCESS – BASED IMAGE ANALYSIS FOR AGRICULTURAL MAPPING USING MEDIUM RESOLUTION SATELLITE DATA

Ph.D. Thesis by
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Department : **Geodesy and Photogrammetry Engineering**

Programme : **Geomatics Engineering**

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FEBRUARY 2011

İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

TARIMSAL HARİTALAMADA ORTA ÇÖZÜNÜRLÜKLÜ UYDU VERİLERİ İLE PROSES-TABANLI GÖRÜNTÜ ANALİZİ

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FOREWORD

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To my mother and father I dedicate this thesis.

September 2011 Z. Damla UÇA AVCI

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ABBREVIATIONS

RS : Remote Sensing
EM : Electromagnetic
TOA : Top-of-atmosphere
GRS : Ground Receiving Station
UV : Ultraviolet
IR : Infrared
NIR : Near infrared
TIR : Thermal Infrared
DN : Digital Number
GSD : Ground Sampling Distance
AOI : Area of Interest
GIS : Geographical Information System
SWIR : Shortwave Infrared
NDVI : Normalized Difference Vegetation Index
SAR : Synthetic Aperture Radar
ISODATA : Iterative Self-Organizing Data Analysis Technique Algorithm
GLCM : Gray Level Co-occurrence Matrix
TTA : Training and Test Area
GSI : Geographical Survey Institute
SPF : State Production Farm
QL : Quick Look
GCP : Ground Control Point
GSI : Geographical Survey Institute
RMS : Root Mean Square

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PROCESS–BASED IMAGE ANALYSIS FOR AGRICULTURAL MAPPING USING MEDIUM RESOLUTION SATELLITE DATA

SUMMARY

Technology, today, is in progress to automate various kinds of work conducted by people to get more accurate products in more systematic and faster ways with less effort. As in many fields of information technologies, the need for timely and accurate geo-spatial information is steadily increasing. Although expert interaction and feedback is needed today, in the future, more of the steps will be done automatically by intelligent systems. The main motivation of this thesis was the automation in remote sensing applications, and a design of a process-based image analyzing procedure was performed.

In context of this thesis, a process tree was developed for agricultural mapping based on the thought that the agricultural activities are suitable for process based systems since they recur on a periodic cycle. The process tree written is using multi-temporal image dataset as an input, and then giving the classified output image by using an incremental automated system. Two different procedures were developed and executed for optical and radar image datasets separately. The datasets are composed of 5 images of SPOT 4 data acquired on 2007 and 6 images of JERS data acquired on 1997. The study area was selected as Turkgeldi State Production Farm. The crop maps taken from Türkgeldi State Production Farm were used as ancillary data.

Object-based image analysis was used through the process. This method provides the advantage of using class descriptions maintained by considering object properties such as shape, texture and neighborhood relations as well as spectral properties. As a first step, segmentation was applied on multi-temporal data. After the determination of the criteria for each parameter and the expression of related distribution functions, classes were defined. Logical terms were used to combine class descriptions where needed. As the second step, membership values were assigned to the image objects for each possible class based on fuzzy theory. Classification was executed on multi-levels. The hierarchical structure enables a parent-child relation between classes. The final classification output was produced by taking the advantage of a hierarchical structure. The results were interpreted in perspectives of evaluating both the process-based remote sensing applications and the efficiency of object-based image analysis. As the process runs, the classification process is realized incrementally and outputs the final result.

To evaluate the success of the application, the accuracy assessment of the object-based image classification was performed. The problems of segmentation and classification operations, and the solution approaches were evaluated for both process trees of optical and radar datasets to assess the success of the process in scope of automation.

TARIMSAL HARİTALAMADA ORTA ÇÖZÜNÜRLÜKLÜ UYDU VERİLERİ İLE PROSES-TABANLI GÖRÜNTÜ ANALİZİ

ÖZET

Günümüzde teknoloji pek çok alanda insanoğlunun günlük hayatta kullandığı işleri daha sistematik, doğruluklu, hızlı ve minimum insan etkileşimi ile otomatikleştirmek üzere gelişmektedir. Bilgi teknolojilerinin birçok alanında olduğu gibi geo-enformasyon alanında da daha hızlı ve hassas bilgiye ihtiyaç artmaktadır. Bugün, uzaktan algılama alanındaki görüntü analizlerinde proses tabanlı sistemler hala uzman etkileşimi gerektirmesine rağmen, gelecekte çok daha fazla işlem adımının tam otomatik olarak gerçekleştirilebileceği akıllı sistemler yer alacaktır. Bu tezin hazırlanmasındaki ana motivasyon uzaktan algılama uygulamalarındaki otomasyon olup, görüntü analizi için proses-bazlı bir prosedür tasarlanmıştır.

Tez kapsamında, tarımsal faaliyetlerin periyodik nükseden yapısı nedeni ile proses bazlı tasarım için uygun olduğu düşünülerek, tarımsal haritalama amaçlı görüntü işleme prosesi hazırlanmıştır. Hazırlanan proses çok-zamanlı görüntü setini girdi olarak kullanmakta ve otomatik aşamalı sistem ile sınıflandırılmış görüntü çıktısı sağlamaktadır. Optik ve radar olmak üzere iki ayrı veriseti için iki ayrı proses yazılmıştır. Uydu veri setleri olarak 2007 yılına ait 5 adet SPOT 4 ve 1997 yılına ait 6 adet JERS görüntüsü kullanılmıştır. Çalışma alanı olarak Türkgeldi Tarım İşletmesi seçilmiştir. Çalışmada Türkgeldi Tarım İşletmesi'nden alınan ürün haritaları yardımcı veri olarak kullanılmıştır.

Proseste görüntü analizi yöntemi olarak nesne-tabanlı sınıflandırma yöntemi seçilmiştir. Bu yöntemde sınıfların hem spektral özellikler hem de şekil, doku, komşuluk gibi diğer özellikler ile tanımlanması avantajı sağlanmaktadır. Çok-zamanlı verisetleri üzerinde ilk adım olarak segmentasyon işlemi yapılmıştır. Sınıf tanımları yapılarak her parametre için sınıf aidiyet kriteri ve sınıflar için dağılım fonksiyonları belirlenmiştir. Gerektiğinde sınıf tanımlayıcı parametreler mantık operatörleri ile birleştirilmiştir. İkinci adım olarak oluşturulan görüntü nesnelerine fuzzy teorisine dayalı olarak yapılan sınıflandırma işlemi ile üyelik değerleri atanmıştır. Sınıflandırma gerektiği kadar seviyede gerçekleştirilmiştir. Sınıflar hiyerarşik bir ağ yapısı altında birbirleri ile alt-üst sınıf ilişkisi içerisindedirler. Uygulamada proses çalıştırılarak aşamalı olarak sınıflandırma işlemlerini tamamlamakta ve sonuç çıktıya ulaşmaktadır.

Çalışmanın değerlendirilmesi amacı ile nesne-tabanlı görüntü sınıflandırma işleminin doğruluk analizi yapılmıştır. Her iki veriseti için ayrı ayrı olmak üzere segmentasyon ve sınıflandırma işlemlerinde karşılaşılan sorunlar ve çözüm yaklaşımları değerlendirilerek otomasyon açısından hazırlanan prosesin başarısı değerlendirilmiştir.

1. INTRODUCTION

1.1 Thesis Statement

In the broadest sense, agriculture comprises the entire range of technologies associated with the production of useful products from plants and animals, management of crop and livestock, processing and marketing activities [1].

Agriculture is known to be first developed most likely in South Asia and Egypt, and then spread to the rest of the world [2]. Continued growth in the world's population makes the continuing ability of agricultural act critical, to provide all needed food and fiber. Therefore, technology and management is very important globally to have efficient and sustainable agriculture.

Today, information systems are being used for successful agricultural management. An agricultural information system integrates many information sources and types such as field maps, crop types and planting dates, soil moisture data, satellite images, irrigation data, topography data for planning and managing the agricultural activities, monitoring tools for crop development, softwares for analyzing and interpretation of data, technologies to increase the efficiency and accuracy of forecasting of product yield, modeling tools for diseases and taking accuses for protection etc.

Remote Sensing technology is one of the most important tools for agricultural applications. It is the process that involves the detection and measurement of radiation reflected, emitted or scattered from distant objects or materials at different wavelengths; and also the processing of this data for recognizing, identifying and categorizing the materials as classes or types to get quantitative information.

Remote sensing technology is used for agricultural applications in many ways such as determining crop species distribution, crop condition monitoring, extraction of crop productivity and yield forecasting, crop damage assessment, soil classification and soil water content investigation and farm decision making and management [3].

As in a remote sensing process, the analysis of these application areas is based on data produced from electromagnetic interaction with the surface of the field environment (crops, soil etc.) and also on the correct analysis, information extraction and interpretation. Still there are many limitations such as spectral mixing. New technologies are trying to be a solution by using hyperspectral data on sensor technology side and spectral unmixing methods on processing side. For some regions or some seasons, acquiring cloud free images is an important problem for optic data analysis; therefore radar data is being used more and more each day. In addition to these, for detection of small objects (as small fields for agriculture) classification accuracy is a problem, which now is better with higher spatial resolution. Another parameter needed for temporal analyses is the acquisition frequency of satellites over the same area. This has been reduced both by using side looking sensors instead of nadir looking ones and growing number of satellites launched.

Hence, technology is developing in all ways for better results in sensor side such as increasing the abilities and resolutions. In addition to these, ancillary data is also being obtained by higher technology, such as high accuracy spectroradiometers and some advanced field measurement equipments.

On data processing side, today, database systems and information technologies are making the analysis, search and use of data much easier. Besides, new softwares offer user friendly tools, and provide new approaches and methods to produce more accurate and successful results. In this context, neural network applications, object-based image processing systems, are new approaches used for data extraction and image analysis.

In this thesis, as image datasets, two (optical and radar) multitemporal datasets of medium-resolution satellite images were used. As an image processing approach, object-based image processing method was preferred to get benefit of evaluating remotely sensed data with topology, neighborhood relations, shape and textural properties etc. The efficiency, advantages, limits and capabilities of medium-resolution optical and radar satellite images for object-based image processing were discussed and outlined.

The application was designed as a process-based system since the need for automatized data extraction is increasing each day in today’s world. The need of data systematization and the worldwide increase in use of geo-information catalyzes the development of new methods to exploit image information more ‘intelligently’. Over the last years, advances in computer technology, earth observation sensors, remote sensing and GIS technology have led to the emerging field of process-based analysis.

A process-based system is a good approach for agricultural purposes since the agricultural activities occur according to a cycle. Observation of crop development, detecting yearly changes, determining regional parameters, accurate assessment of crop damage and/or crop yield can be applied more successful if realized by a repeatable system. In this thesis, a process-based image analyzing system for crop mapping was developed.

1.2 Research Objectives

The main motivation of the thesis is the increasing trend for automated systems which seems to be used widely for various remote sensing applications in near future. In this study, agriculture, which is one of the main application areas of remote sensing, was selected as a topic of interest and a process-based image analysis was applied to optical and radar datasets to produce thematic crop mapping. Under the process-based analyzing structure, object-based image processing method was employed.

The aim of the study was to perform successful process trees, to be executed on raw data. The application was done using two image datasets belonging to 1997 and 2007. For further work, the intension is to apply the developed process tree to other multitemporal (including similar periods) dataset of the same region and modify it by comparing with the earlier results obtained in this study.

The results were evaluated as in perspectives for the efficiency of process-based remote sensing application and object-based image analysis.

1.3 Structure of the Thesis

In Chapter 1, thesis statement, research objectives and structure of the thesis was summarized.

In Chapter 2, fundamentals of remote sensing science and its process were defined, digital image properties and characteristics were given.

In Chapter 3, remote sensing of agricultural applications was given for both optical and radar data.

In Chapter 4, pixel-based and object-based image processing steps were given, classification methods were outlined, and both of the approaches were evaluated and compared.

In Chapter 5, process-based image analysis and its future were explained.

In Chapter 6, information on study area, datasets and ancillary data used were given. The preprocessing and processing steps were described in detail. The results of analysis and accuracy assessment were given.

In Chapter 7, the results of the thesis were discussed and concluded.

2. REMOTE SENSING

The term "remote sensing" (RS) was coined by geographer Evelyn L. Pruitt, to replace the limiting terms as "aerial" and "photograph". After promoting the new term throughout a series of symposia at the Willow Run Laboratories of the University of Michigan, it gained immediate and widespread acceptance [4].

Today, its widespread definition states Remote Sensing as “the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation” [5]. In more detail, remote sensing refers to getting information from digital geospatial data which is acquired from overhead perspective, using sensors which sample and record electromagnetic radiation in one or more regions of the electromagnetic spectrum that is reflected or emitted from the surface of the Earth [6].

The importance of space-based remote sensing is that this new source of information cannot be easily obtained in other ways with that much promise in both aspects of economical and social benefits [7]. Using RS instrumentation to observe the environment with EM radiation outside the visible part of the electromagnetic spectrum makes the invisible become visible. RS produces measurable physical data; hence enabling objective observations. Also, the data is both in quantitative and qualitative form. The data is flexible and varied since there is a variety of observation techniques, and it is suitable to be studied on by many digital image processing algorithms. Moreover RS data can be reproduced at any time. It can be viewed in more detail and contrast by the possibilities of RS instruments and softwares. RS also allows an image recording of a large area in a very short time [8]. It provides synoptic views of large portions of Earth. Satellite imagery can expand the spatial dimensions of limited and/or costly fields and provide consistent repeat coverage at relatively frequent intervals, making detection and monitoring of change feasible [7].

The ultimate goal of remote sensing is to extract information from the gathered data about the material properties of the Earth's surface with geographical relationships [6]. This process involves the detection and measurement of radiation of different wavelengths that are reflected or emitted from earth objects/materials, by which they may be identified and categorized by class, type, substance, and spatial distribution [9].

2.1 Remote Sensing System

A critical element in producing information of value from satellite imagery is processing, which involves two steps: preprocessing (data acquisition) and the conversion of data to information (data processing and evaluation). The first step turns raw data into accurately calibrated measures of precisely located physical variables such as reflectance, emittance, temperature, and backscatter. The second step is transforming technical data into a form that is meaningful to non-technical users which often includes either the integration of remote sensing data with other types of data or scientific research to characterize the data (or both) [7]. Finally, the information is useful for the qualification, quantification and mapping of the earth and the phenomena [8].

In general, a remote sensing process involves of two main components which are "Data acquisition" (A-E in Figure 2.1) and "Data processing and evaluation" (F-G in Figure 2.1).

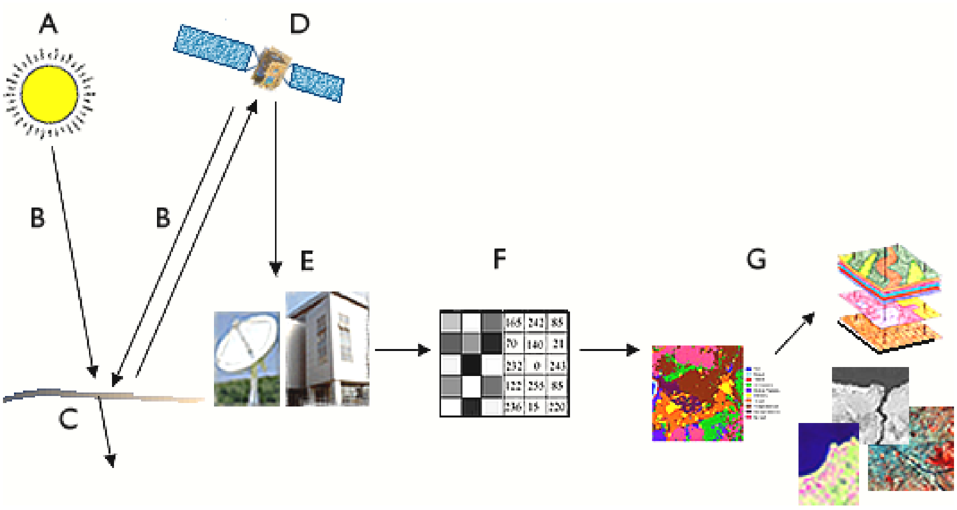


Figure 2.1 : Remote sensing process [10].

2.1.1 Data Acquisition

The first phase of the process is the “data acquisition”. As shown in Figure 2.1 the first component is the energy source which illuminates or provides electromagnetic energy to the target. Regarding to energy source (A), remote sensing systems can be divided into two groups as passive systems and active systems.

Passive systems have optical, thermal, and microwave sensors that receive the naturally emitted or the sun's reflected energy from the surface of Earth. Passive instruments sense only radiation emitted by the object being viewed or reflected by the object from a source. Reflected sunlight is the most common external source of radiation that is sensed by passive instruments [9].

Active instruments provide their own electromagnetic radiation to illuminate the object they observe. They send a pulse of radiation from the sensor to the object, and then, receive the reflected or backscattered from that object [9].

Second component in the data acquisition system is the radiation and the atmosphere (B). The energy that travels from the source to the target interacts with the atmosphere which is the environment in between.

However, the presence of atmosphere puts limitations on the spectral regions that can be used for observation. Atmosphere can also cause some effects on the sensed electromagnetic (EM) radiation such as errors, distortions and decrease of real sensed measurements, which causes the requirements to apply some corrections on the data acquired.

The aim of atmospheric correction is to convert the 'at sensor' or 'top-of-atmosphere' (TOA) radiance to ground-leaving radiance [11].

Next component is the interaction with the target (C). After passing through the atmosphere, the energy reaches the target, and the interaction coming out depends on the properties of both the target and the radiation.

Remote sensing science is mostly dealing with this step of the process. By a reverse operation, the input image which is a composition of values assigned to pixels is being tried to associate with the target parameters by analyzing with various methods to solve the target - EM interaction mechanism.

Another component in the process is the recording of energy by the sensor (D). The imaging systems are composed of a sensor on a platform. The sensor collects and records the energy that has been reflected, scattered by, or emitted from the target. To collect and record energy reflected or emitted from a target or surface, the sensor have to reside on a stable platform. Remote sensing systems can have various platforms regarding to the vehicle to carry the sensor. Acquiring images of

Earth from satellites is the most commonly used platform in the recent years, mostly by being successfully stable.

Sensors used or developed for remote sensing can be classified according to their scanning and imaging properties [12].

Last component is called as transmission, reception, and processing (E). Data acquired from satellite platforms are electronically transmitted to Earth, since the vehicle - satellite - continues to stay in orbit during its operational lifetime [13]. The energy recorded by the sensor is transmitted to a ground receiving station (GRS) by an antenna where the data are processed into an image [10]. The data are received at the GRS in a raw digital format and then, if required, processed to correct systematic, geometric and atmospheric distortions that are inherent in the imagery, and finally translated into a standardized format. The data are written to some form of storage medium such as tape, disk or CD and archived at GRSs. Full libraries of data are managed by government agencies as well as commercial companies responsible for each sensor's archives [13].

2.1.2 Data Processing and Evaluation

The second phase of the process is called as “data processing and evaluation”. As a first step, the image is interpreted, visually, digitally or electronically and this step is known as interpretation and analysis (F).

In visual interpretation, recognition of targets is the key for interpretation and information extraction. Observing the differences between targets and their backgrounds involves comparing different targets based on some of the visual elements of tone, shape, size, pattern, texture, shadow, and association [13].

Digital image processing may involve many procedures including formatting and correcting of the data, digital enhancement to facilitate better visual interpretation, classification of targets and features done entirely by computer [13].

Last component in the process is the “application” (G). The image is processed to extract information about the target. Data can be integrated with data from other sources.

2.2 The Physical Fundamentals of RS Science

The fundamentals of RS Science is based on the physics of electromagnetic energy, interaction of this energy with any surface, sensing and recording principles, producing and processing the data operation and obtaining plus using the information abilities.

Electromagnetic energy is the means by which information is transmitted from an object to a sensing device. Information could be encoded in the contents of frequency, intensity, or polarization of the electromagnetic wave. The information is propagated by electromagnetic radiation at the velocity of light from the source directly or indirectly by the reflection, scattering, and reradiation mechanisms to the sensor [14].

Nuclear reactions within the sun produce a full spectrum of electromagnetic radiation, which is transmitted through space without major changes. As this radiation approaches the Earth, it passes through the atmosphere before reaching the surface. Some of the radiation is reflected upward from the Earth's surface; this radiation forms the basis for photographs or similar images. Some of the solar radiation is absorbed at the surface of the Earth, and is reradiated as thermal energy. This thermal energy can also be used to form remote sensing imagery. The man-made radiation, such as that generated by imaging radars, is also used for remote sensing [15].

An electromagnetic wave consists of a coupled electric and magnetic force field. In free space, these two fields are at right angles to each other and transverse to the direction of propagation [14] (Figure 2.2).

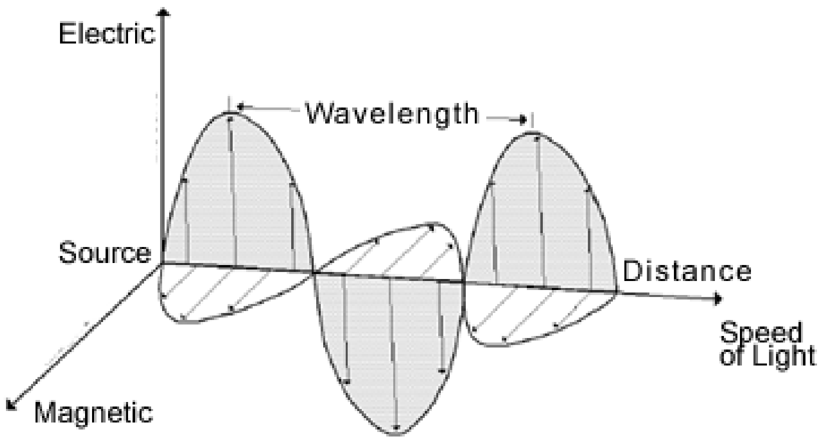


Figure 2.2 : Electromagnetic radiation [16].

Waves in the electromagnetic spectrum vary in size from very long radio waves as the size of buildings, to very short gamma-rays smaller than the size of the nucleus of an atom. Visible light waves are the only electromagnetic waves human eye can see.

In a full spectrum of solar energy the names of division are as indicated whereas subdivision names are established by traditions within different disciplines (Figure 2.3).

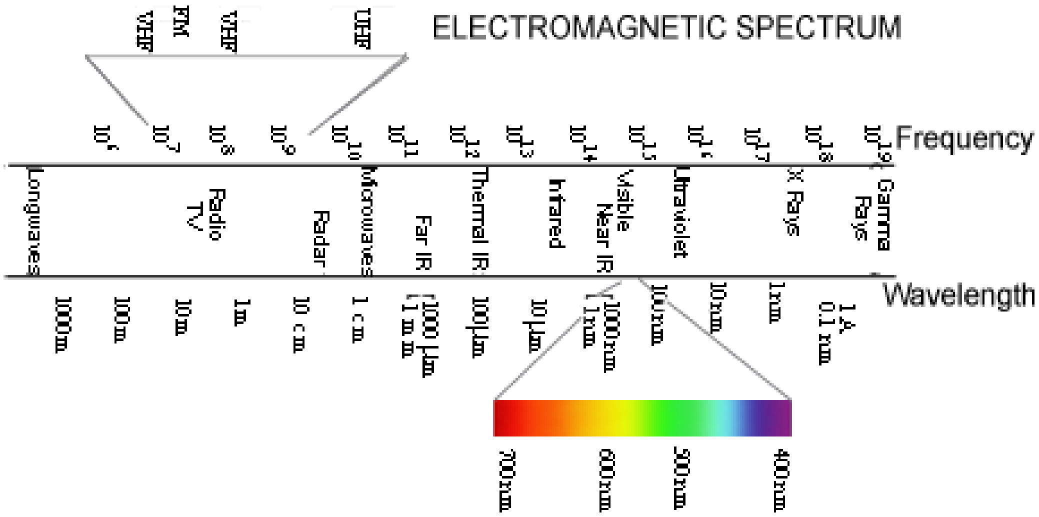


Figure 2.3 : Electromagnetic spectrum, adopted from [5, 17].

The properties of EM portions and the usage in scope of RS are given in Table 2.1.

Table 2.1 : Usage of EM portions in remote sensing [13, 17 - 19].

	Wavelengths(m)	**Frequencies (Hz)**	**Energies (eV)**	**Relation with RS**
Gamma ray	$< 1 \times 10^{-11}$	$> 3 \times 10^{19}$	$> 10^{5}$	Entirely absorbed by the Earth's atmosphere. Not available for RS.
X-ray	1×10^{-11} to 1×10^{-8}	3×10^{16} to 3×10^{19}	10^{3} - 10^{5}	Entirely absorbed by the Earth's atmosphere. Not available for RS.
Ultraviolet (UV)	1×10^{-8} to 4×10^{-7}	7×10^{14} to 3×10^{16}	3 - 10^{3}	Some Earth surface materials fluoresce or emit visible light when illuminated by UV radiation. However, it is easily scattered by the Earth's atmosphere and not generally used for RS.
Visible	4×10^{-7} to 7×10^{-7}	4×10^{14} to 7×10^{14}	2 - 3	Common wavelengths of colors, visible region to human eye.
Infrared (IR)	7×10^{-7} to 1×10^{-3}	3×10^{11} to 4×10^{14}	0.01 - 2	Radiation in the reflected IR region is used for remote sensing purposes in ways similar to the visible portion. The thermal IR region is used for sensing the radiation emitted from the Earth's surface in the form of heat.
Microwave or radar	1×10^{-3} to 1×10^{-1}	3×10^{9} to 3×10^{11}	10^{-5} - 0.01	Ka, K, and Ku bands are not common today. X-band is used for military reconnaissance and terrain mapping. C-band is common on research systems. S-band, L-band and P-band are used on experimental research systems.
Radio	$> 1 \times 10^{-1}$	$< 3 \times 10^{9}$	$< 10^{-5}$	This region is not normally used for RS.

2.3 Sensing Principles

As indicated by Elachi, C. and Zyl, “The radiation emitted, reflected, or scattered from a body generates a radiant flux density in the surrounding space that contains information about the body’s properties.” A detector is used to measure the properties of this radiation [14].

The physics of the energy-atmosphere-target interactions, recording data and image formation are different for various EM portions [8]. Also, depending on the type of the sensor, different properties of the field are measured. Optical spectrometers measure the energy of the fields at a specific location as a function of wavelength [14]. Synthetic-aperture imaging radars measure the amplitude, polarization, frequency, and phase of the fields. Below, sensing principles are explained according to these spectrum windows.

2.3.1 Passive Sensing

- **Optical Sensing**

The simplest form of recording the detected energy is for the reflection of solar radiation from the Earth's surface. This form of remote sensing mainly uses energy in the visible and near infrared portions of the spectrum and atmospheric clarity, spectral properties of objects, angle and intensity of the solar beam, choices of films and filters, and others are the key variables for the analysis [15].

The reflectivity of surfaces in the visible and near infrared regions is actually governed by the top few microns’ reflectivity [14]. Therefore, penetration is not very effective as it is in microwave sensing.

- **Thermal Sensing**

The other form for remote sensing deals with the short-wave energy that has been absorbed, and then reradiated at longer wavelengths. Emitted radiation from the Earth's surface reveals information concerning thermal properties of materials. This information can be interpreted to suggest patterns of moisture, vegetation, surface materials, and man-made structures [15].

- **Passive Microwave Sensing**

Passive microwave sensing is similar to thermal remote sensing. All objects emit microwave energy of some magnitude, but in very small amounts. A passive microwave sensor detects this naturally emitted microwave energy. The information gathered is related to the temperature and moisture properties of the surface [13].

2.3.2 Active Sensing

Some remote sensing instruments generate their own energy, send to the object to be observed and then record the reflection of that energy. These are called "active" sensors and they are independent of solar and terrestrial radiation. Typical active sensors are the imaging radars [15]. Microwave radiation can penetrate through cloud cover, haze, and dust, which is a problem for shorter optical wavelengths. This property allows data collection at any time including almost all weather and environmental conditions, and moreover at night.

2.4 Energy - Atmosphere / Target Interactions

2.4.1 Energy - Atmosphere Interactions

Energy must pass through the entire atmosphere and reach to the sensors [15]. The atmosphere between the sensor and the object is not homogeneous, but variable locally and in time.

This exists as a limitation for the multispectral passive methods of measurement [8]. For radar imaging, atmosphere is not a problem however, rain and other forms of precipitation can cause echo signals that mask the target's real echoes.

Under these conditions, it can be said that atmospheric effects may have substantial impact upon the quality of images and data that the sensors generate. Therefore, the practice of remote sensing requires knowledge for concerning the interactions of electromagnetic energy with the atmosphere.

As solar energy passes through the Earth's atmosphere, it is subject to modification by several physical processes such as absorption, scattering etc. [15] (Figure 2.4).

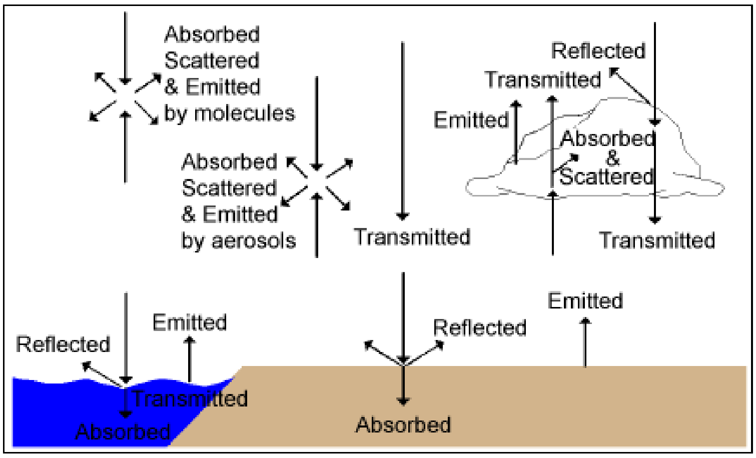


Figure 2.4 : Various radiation obstacles and scatter path [16].

- **Absorption**

Absorption of radiation occurs when the atmosphere prevents or attenuates the transmission of radiation through the atmosphere. Some gases are responsible for most absorption of solar radiation [15]. The most efficient absorbers of solar radiation which result effective loss of energy are, water vapor, carbon dioxide, and ozone [20]. Thus, the Earth's atmosphere is not completely transparent to electromagnetic radiation because of the gasses forming important barriers to the transmission. So the energy is selectively transmitted of certain wavelengths through the atmosphere which are referred to as “atmospheric windows” [15] (Figure 2.5). The effects of absorption on RS can be summarized as; all RS equipment must “look” through the atmosphere, where it is transparent to EM waves [8].

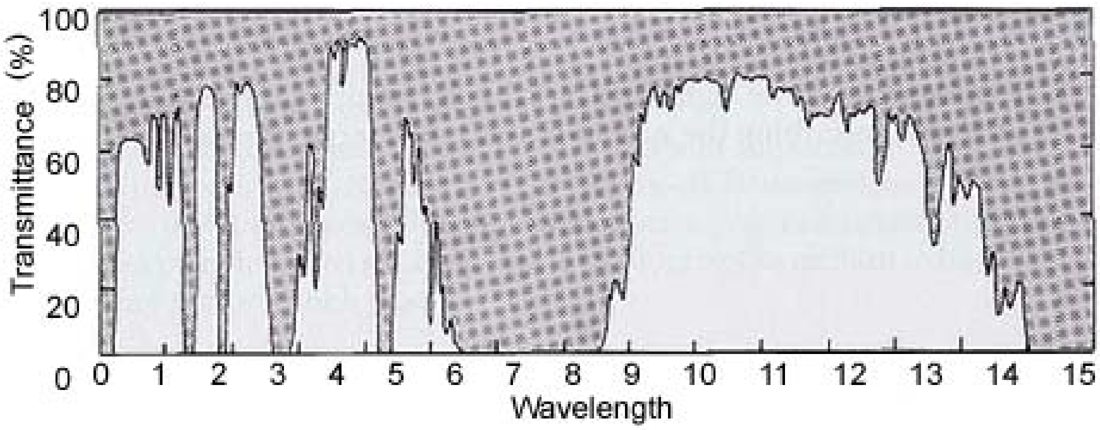


Figure 2.5 : Atmospheric windows [21].

- **Scattering**

Scattering is the redirection of electromagnetic energy caused by particles suspended in the atmosphere or sometimes large molecules of atmospheric gases can cause this. The amount of scattering depends on the size of particles, their abundance, the wavelength of the radiation, and the depth of the atmosphere through which the EM is passing. The effect is the redirection of the radiation, so a portion of the incoming solar beam is directed back toward space, and some toward the Earth's surface [15].

If atmospheric particles have diameters that are very small relative to the wavelength of the radiation, then it is Rayleigh scattering. This type of scattering is wavelength dependent and the amount of scattering increases with decrease in wavelength. If scattering is caused by large atmospheric particles including dust, pollen, smoke, and water droplets, it is called Mie scattering. Mie scattering have diameters that are nearly equivalent to the wavelength of the scattered radiation. In other words, it occurs when the particles that cause the scattering are larger than the wavelengths of radiation in contact with them. Nonselective scattering is caused by particles that are much larger than the wavelength of the scattered radiation. Water droplets and large dust particles can cause this type of scattering. In non-selective scattering, all wavelengths are scattered about equally [15, 23].

The effects of scattering for remote sensing is that, it causes skylight, forces the brightness of the atmosphere to be recorded in addition to the target, besides it directs reflected light away from the sensor aperture and outside the sensor's field of view toward the sensors aperture so it decreases the spatial detail by making the image fuzzier, and it tends to make dark objects lighter and light objects darker so that the contrast between them reduces [22].

- **Refraction**

Refraction occurs in the atmosphere according to the pass of light through varied clarity, humidity, and temperature layers [15].

Effects on RS are that it bends the light, cause mirages and especially for hot and humid days it degrades spectral signatures [22].

2.4.2 Energy - Target Interactions

- **In Visible - Near Infrared Region**

“On average, 51% of the in-coming solar radiation reaches the Earth's surface. Of this total, 4% is reflected back into the atmosphere and 47% is absorbed by the Earth's surface to be re-radiated later in the form of thermal infrared radiation” [22]. There are three forms of interaction that can take place when energy strikes upon the surface. These are: absorption (A); transmission (T); and reflection (R).

The total incident energy (I) will interact with the surface in one or more of these three functions of wavelength. The proportions of each interaction type will depend on energy and the material (Figure 2.6). The incident energy equals the sum of the absorbed, the reflected and the transmitted energy through the law of conservation [22].

$$I = A + R + T \qquad \textbf{(2.1)}$$

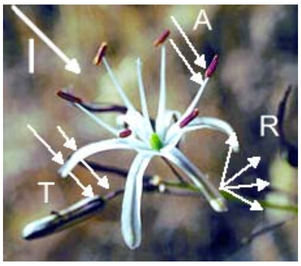


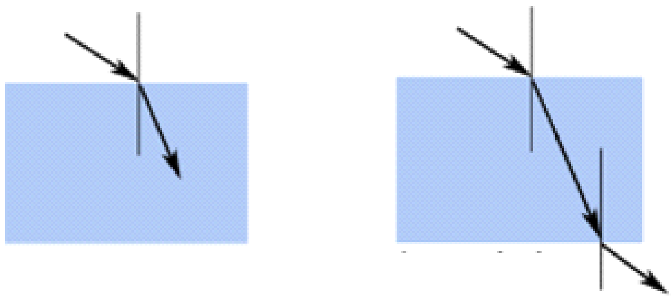
Figure 2.6 : Energy - target interactions.

- **Absorption**

Some of the incident radiation is absorbed within the medium; a portion of this energy is then re-emitted, usually at longer wavelengths, and some of it remains and heats the target (Figure 2.7a).

- **Transmission**

Some of the incident radiation penetrates into certain surface materials. If the material is transparent and thin in one dimension, it normally passes through, generally with some diminution (Figure 2.7b).



(a) (b)

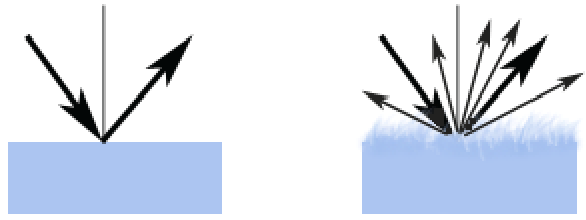
Figure 2.7 : Energy-target interactions (a) absorption, (b) transmission.

- **Reflection**

Some of the incident radiation moves away from the target and scatters away from the target at various angles depending on the surface roughness and the angle of incidence of the rays, it is called “reflection”.

When the surface is so smooth relative to the wavelength and causing almost all of the incident radiation to be redirected in a single direction, it is called specular reflection [15] (Figure 2.8a).

Diffuse reflection occurs when a surface is rough relative to a wavelength acting as a diffuse reflector, and when the energy is scattered more or less equally in all directions [15] (Figure 2.8b). As a special case a perfectly diffuse reflector is termed as Lambertian surface and reflective brightness is same when observed from any angle.



(a) (b)

Figure 2.8 : Reflection (a) specular, (b) diffuse.

For any given material, the amount of solar radiation that reflects, absorbs, or transmits varies with wavelength or with time. In RS, the key property is the reflectance factor. Reflectivity is the fraction of incident radiation reflected by a surface. ρ is the measure of the reflectance percentage of an object where G_{ref}: reflected spectral intensity and G_{incid}: Incident spectral intensity.

$$\rho = G_{ref} / G_{incid} \qquad \textbf{(2.2)}$$

The two important properties of matter that make possible to identify different classes and separate them by the reflectance related properties are the spectral and temporal signatures.

Spectral signature: The relationship between the intensity of EM radiation and wavelength is called the spectral signature. A single feature or a pattern in the spectral reflectance curve could be diagnostic in identifying the object. Figure 2.9 shows the average reflectance spectra of some Earth surface materials.

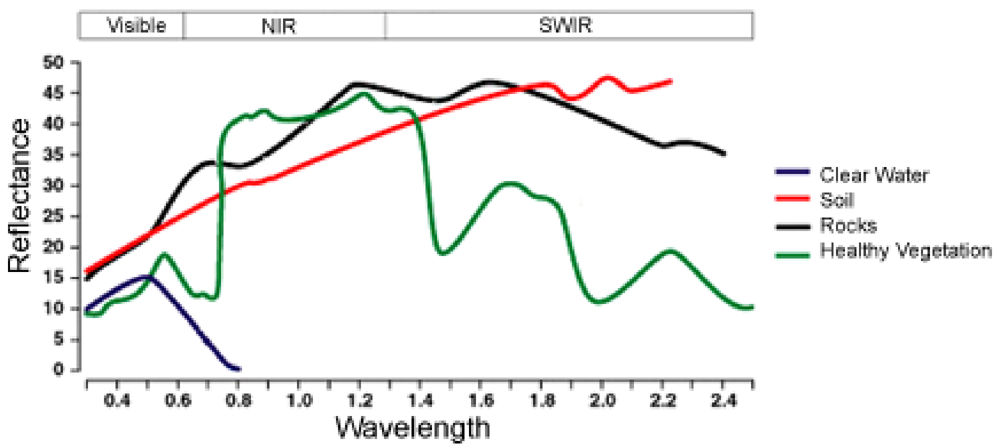


Figure 2.9 : Reflectance spectra of some materials [10].

As spectral signatures show the available spectral intervals of the spectrum to discriminate the objects that are intended to be distinguished, it is the base step for choosing the suitable sensor and satellite for the purpose. Two features that are indistinguishable in one spectral range may have very different reflectance values in another portion of the spectrum. This is the essential property of matter allowing different features to be identified and separated using their spectral signatures.

To overcome the problem of distinguishing objects having very similar spectral signatures, hyperspectral data can be used. Using spectro-temporal signatures can be another solution if the observed objects have regular changes in time.

Temporal reflectance signature: Temporal signature is also a reflectance-related signature which is represented as a function of time. It is mostly used for vegetation and crop observations since the varied growing stages in time provide a new dimension for discrimination (Figure 2.10).

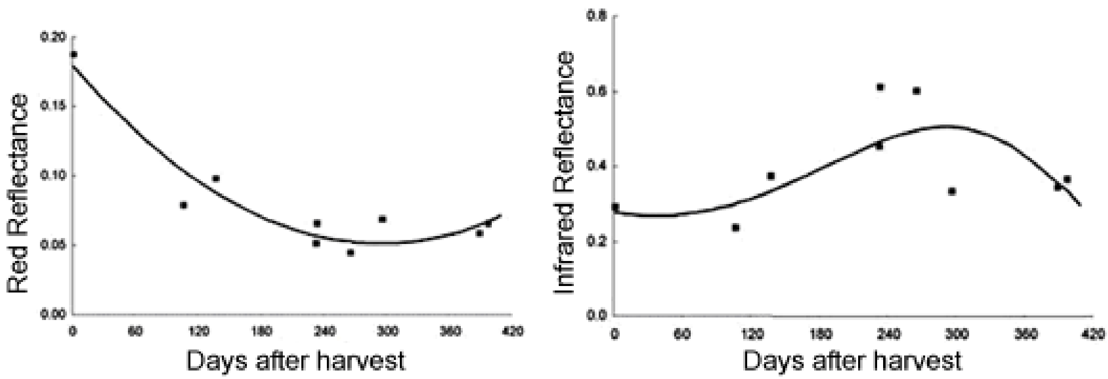


Figure 2.10 : Temporal reflectance signatures of a sugarcane.

- **In Thermal Infrared Region**

Any object at a physical temperature that is different from absolute zero emits electromagnetic radiation which is described mathematically by Planck's radiation law. Planck's results were announced in 1900, and researches on the topic are followed by Rayleigh, Jeans, Wien, Stefan, and Boltzmann, who all studied different aspects of the problem. Planck's radiation law is a description for radiation that occurs at all wavelengths. The radiation makes a peak at a wavelength that is inversely proportional to the temperature. For most of the natural bodies, the peak thermal emission occurs in the infrared region. All natural terrains have a lower efficiency than blackbody and it is expressed by the spectral emissivity factor ε, which is the ratio of the radiant emittance of the terrain to the radiant emittance of a blackbody at the same temperature. It is expressed in Equation 2.3.

$$\varepsilon(\lambda) = S'(\lambda, T) / S(\lambda, T) \quad \textbf{(2.3)}$$

Here, λ: wavelength of the radiation T: absolute temperature of the radiatior in K and $S(\lambda,T)$: spectral radiant emittance in W/m3 (Watts per unit area per unit wavelength).

Natural bodies are also characterized by their spectral emissivity. Spectral emissivity expresses the capability to emit radiation due to thermal energy conversion relative to a blackbody with the same temperature. A single measurement of surface-emitted heat measurement depends on a number of independent parameters; however, if difference in emitted heat is measured at two times of the day, it would allow the derivation of the thermal inertia *P* on a pixel-by-pixel basis. Thus a thermal inertia map can be used to classify surface units. The thermal emission is dependent on the surface thermal inertia, which in turn is a function of the surface material [14].

- **In Microwave Region**

Microwave energy is reflected in the same manner as visible light however this reflection is called scattering. The microwave pulses carrying the energy sent out by imaging radar and are scattered upon contact with the Earth's surface. The way the pulse is scattered is known as the scattering mechanism (Figure 2.11).

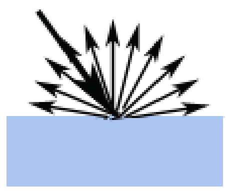
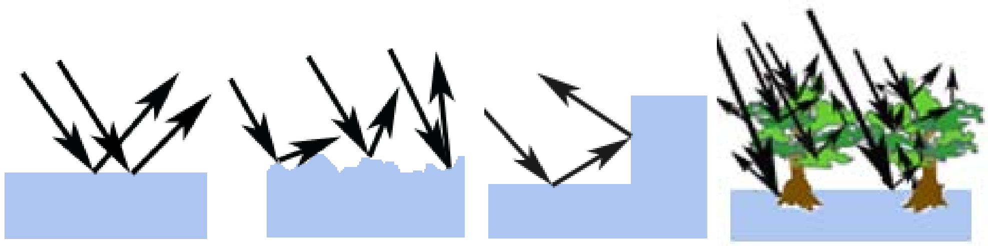


Figure 2.11 : Scattering.

It's important that the measured energy is scattered back towards and therefore it is called the backscatter [23]. Basically, there are four types of scattering mechanisms due to scattering from four types of surface [13, 26]:

- When radar interacts with a smooth surface, “smooth surface scattering” occurs; most of which the scattering is in the forward direction, away from the radar and only a very small fraction of the energy is reflected back towards the radar (Figure 2.12a).
- When the surface is rough the scatter is in all directions. Some fraction of the energy in the transmitted pulse is reflected back towards the radar. The rougher the surface is, the higher the backscatter (Figure 2.12b).

- The other type of scatter is from two surfaces, one flat on the ground being horizontal, the other upright being vertical. The reflected pulse hits one of the surfaces after the other. This type of scattering is known as "double-bounce" scattering. Most of the scatter for a double-bounce mechanism is in the backscatter direction (Figure 2.12c).
- "Volume scattering" or "vegetation layer scattering" is called when the pulse is scattered from a layer of randomly oriented scatterers. It is more complicated than the other three scattering types since the radar pulse penetrates the vegetation layer, then it is scattered after hitting one of the randomly oriented branches or leaves in the canopy (Figure 2.12d).



(a) (b) (c) (d)

Figure 2.12 : Surface scattering (a) smooth (b) rough (c) double-bounce (d) volume.

Besides all these, moisture affects the scattering mechanism. The presence (or absence) of moisture affects the electrical properties of an object or medium, which influences the absorption, transmission, and reflection of microwave energy. Thus, the moisture content influences how targets and surfaces reflect the EM energy from radar and effect how they will appear on an image. Generally, reflectivity increases with increased moisture content.

Radar backscatter is used to identify and discriminate different objects in an image by evaluating the radar signatures. Radar signatures can also be examined up to their dependencies on parameters like incidence angle, polarization, time and frequency.

For spaceborne imaging radars, the amount of energy scattered back toward the sensor is important. This is characterized by the surface backscatter cross section $\sigma(\theta)$, where θ is the incidence angle. The backscatter cross section is defined as the ratio of the energy received by the sensor over the energy that the sensor would have received if the surface had scattered the energy incident on it in an isotropic fashion. The backscatter cross section is given in decibels as:

$$\sigma = 10.\log(\text{energy ratio}) \quad \textbf{(2.4)}$$

Temporal radar signature: Radar backscatter can also be represented as a function of time like optical reflectance signature. As shown in Figure 2.13, it is possible to monitor crop growth and to retrieve acreage, using the unique temporal signature of fields.

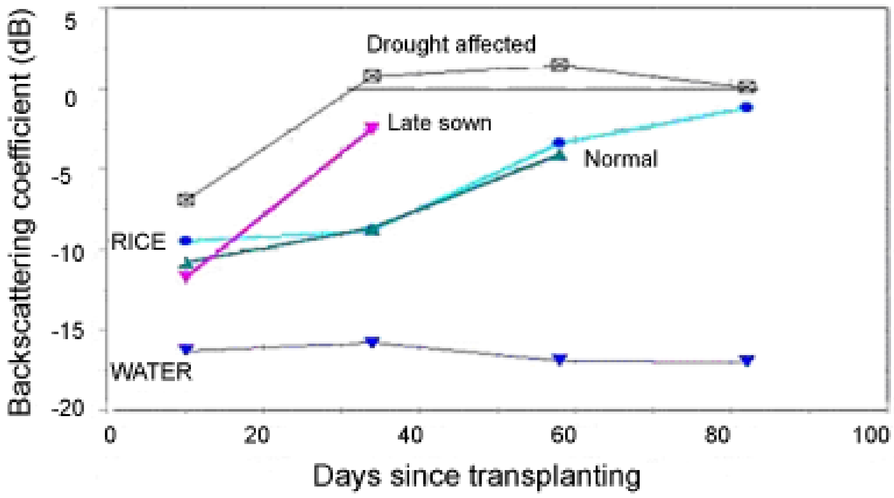


Figure 2.13 : Temporal radar backscatter values of rice planted fields.

2.5 Digital Image and Resolution

2.5.1 Digital Image

Digital RS techniques are concerned with the recording of EM entering the sensor. The quantity (Q) is measured and arranged as image matrix with coordinates i, j. The set of quantities Q (i, j) for all available values gives a latent RS image [8].

For optical imaging, the acquired table of numbers in the rows and columns of a digital image are unique brightness values (gray values).

For radar imaging, the usual presentation of echo signals after processing results in an image are the intensity values, by which a measured radar cross section is reproduced as a gray tone [8].

For both, a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are called picture elements, image elements, and pixels. Pixel is the term used most widely to donate the elements of a digital image [24] (Figure 2.14).

Each pixel is a number represented as “digital number” (DN), which is about the average radiance of the pixel area. The range of DN values is normally between 0 and 255 values for 8 bit optical images. The pixel intensity values for radar images are often converted to a physical quantity called the backscattering coefficient or normalized radar cross-section. The measurement unit is decibel (dB) and the values range from +5 dB for very bright objects to -40 dB for very dark surfaces [20].

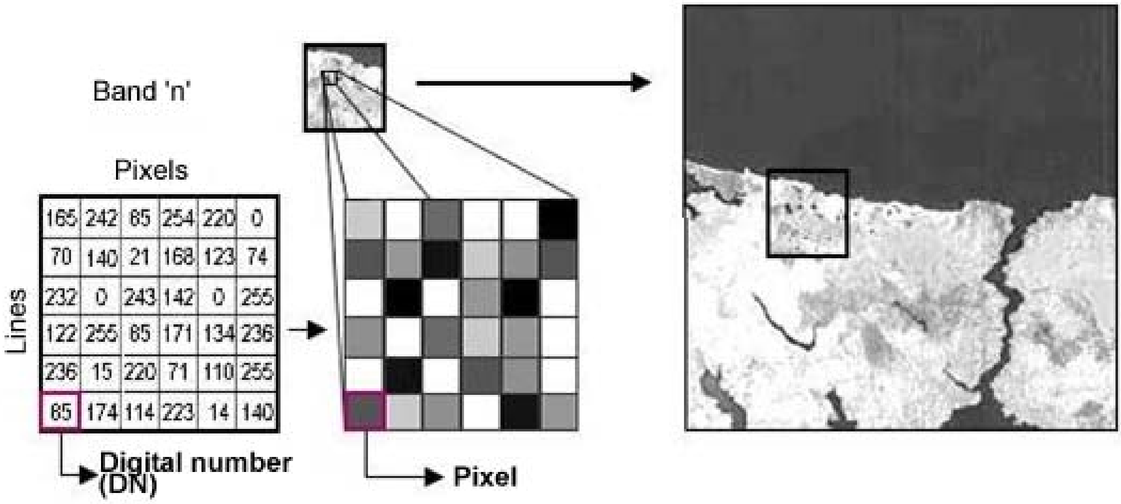


Figure 2.14 : Optical digital image.

2.5.2 Resolution

Resolution can be defined as "the ability of an imaging system to record details in a distinguishable manner" [10].

For a digital image there are four types of resolution.

Radiometric Resolution: The sensitivity to the magnitude of the electromagnetic energy is determined as the radiometric resolution which can be described as the ability of imaging system to discriminate very slight differences in energy. In other words, it refers to the number of gray levels available for analysis.

The value range can be computed using equation 2.5:

$$N = 2^R \tag{2.5}$$

where N is the range and R is the radiometric depth.

Spectral Resolution: Spectral resolution is an ability of a sensor regarding to the wavelength intervals. The narrower the wavelength range for a particular channel or band, the finer the spectral resolution is. Also the spectral resolution increases by the number of bands.

In remote sensing industry, depending on the number of bands, various terms are used such as multi-, super-, and hyperspectral to categorize the sensors. “Commonly used definitions in the industry state that multispectral sensors have less than ten bands, superspectral sensors have bands greater than ten bands, and hyperspectral sensors usually have bands in hundreds" [25].

Spatial Resolution: Spatial resolution is often expressed in terms of ground sampling distance and refers to the area covered on the ground by an image unit of the sensor –the pixel. Spatial resolution is based on various factors, such as the field of view, altitude of the sensor, the number of detectors etc. Moreover the spatial resolutions of the sensors vary with the viewing angle, and influenced by the terrain on the ground [25].

Spatial resolution plays an important role in object recognition and identification. Commercial satellites provide imagery with many various resolutions in a wide range, to meet the requirements of different applications.

"Although different terms are used in the industry to refer to types of spatial resolution, the following are some of the rough guidelines for definitions of spatial resolution: (1) low resolution is defined as pixels with ground sampling distance (GSD) of 30 m or greater resolution, (2) medium resolution is GSD in the range of 2.0–30 m, (3) high resolution is GSD 0.5–2.0 m, and (4) very high resolution is pixel sizes < 0.5 m GSD" [25].

Temporal Resolution: It is an important parameter for analyzing changes over time. This type of resolution refers to the time frequency with which the system can acquire an image of the same area of interest (AOI) on the Earth. The revisit capability depends on parameters such as the satellite orbit, the side looking capability of the sensor and the latitude of the AOI. At higher latitudes, the frequency of revisits increases as compared to the equator.

In Figure 2.15, all resolution types, which are number of bands, pixel size, brightness value range and period frequency of image acquisition, are shown. Higher resolutions increase the dimension of the analyzing space.

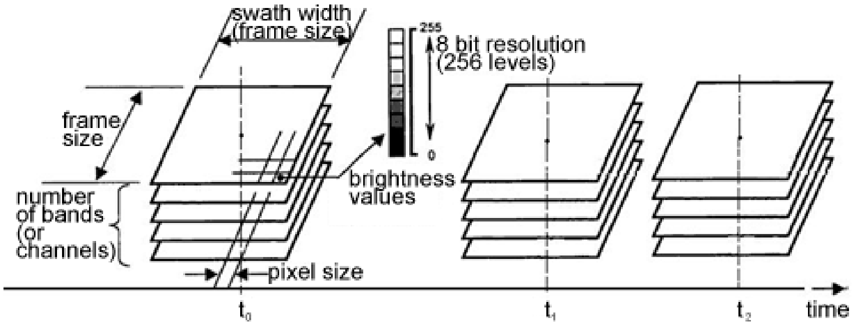


Figure 2.15 : Image resolution types, adopted from [8].

2.6 Image Processing

Digital image processing refers to a processing procedure of digital images by means of a digital computer [24]. The computerized processes that can be applied on digital images can be categorized in three types [24]: Low-, mid- and high-level processes.

- Low-level processes involve preprocessing operations to reduce noise, enhance contrast, and make image sharpening. A low-level process is characterized by the fact that both inputs and outputs of the mechanism are images.
- Mid-level processing on images involves tasks as segmentation, merging image objects and classification (recognition) of individual objects. A mid-level process is characterized by the fact that its inputs generally are images, but the outputs are attributes like edges, contours or the identities of objects which are derived from the image.
- Finally high-level processing involves performing cognitive functions associated with vision, as in image analysis.

From another point of view, the processing operations can be classified as 'Image Preprocessing', 'Image Enhancement', 'Information Extraction' and 'Integration and Interpretation'.

2.6.1 Preprocessing

Preprocessing is an important set of image preparation steps which the DN values are recalculated. Atmospheric effects, sun illumination geometry, surface-induced geometric distortions, spacecraft velocity and attitude variations, effects of Earth rotation, elevation and curvature, abnormalities of instrument performance, loss of specific scan lines are the causes of distortions in an optical data and thus data needs corrections as preprocessing. For radar data, a geometric distortion effect called foreshortening, the noise that causes random variations in the radar signal called speckling are the distortions which have to be reduced by preprocessing procedure. [28]

2.6.2 Enhancement

After performing appropriate atmospheric, radiometric and geometric corrections on the raw data, image enhancement operations can be applied. Contrast stretching, density slicing, spatial filtering, principal components analysis and rationing are some tools that improve scene quality and can be categorized as an image enhancement methods for image (both optical and radar) data [28].

2.6.3 Information Extraction

Extraction of a reliable feature is very important for the improvement of classification accuracy and it has been one of the main tasks in digital image processing. The aim of feature extraction is to extract the most relevant information from the original data in the sense of minimizing the intra-class pattern variability while enhancing the inter-class pattern variability [27]. There are many methods used as information extraction methods.

Image transformations such as principal components analysis, are mathematical techniques that use statistical methods to decorrelate data and reduce redundancy. Arithmetic operations such as rationing are image manipulation techniques, to display or highlight certain features. They both are used for information extraction and interpretation. In addition to these, change detection, pattern recognition and classification are image extraction methods. For optical data, the most used methods of traditional classification are unsupervised classification which is the process of grouping multispectral images and assigning colors that represent either clusters of statistically different sets in correlation with separable classes/features/materials, and supervised classification which uses the training sites as representative areas of particular classes and data is grouped and specified by associating with one of these classes. For radar, mostly segmentation, segmentation based classification, pattern recognition, texture analysis and target recognition methods are operated in the context of information extraction methods [13, 29].

2.6.4 Integration and Interpretation

After information extraction, the product can be used as an input to other systems. In general, remote sensing products are integrated into a Geographical Information System (GIS). GIS integrates hardware, software, and data for capturing, managing, analyzing, and displaying all forms of geographical and geographical referenced information and allows to view, understand, question, interpret, and visualize data in many ways that reveal relationships, patterns, and trends in the form of maps, globes, reports, and charts [28]. Satellite remote sensing provides a very important source of spatial data for GIS and GIS improves interpretation besides remote sensing. Integration of remote sensing and GIS technologies significantly promote the ability to handle geo-information. Benefits are not simply higher accuracy and greater precision, but also some types and levels of information are not available by either one or the other technology alone [26].

3. REMOTE SENSING FOR AGRICULTURE

Agricultural resources are very important renewable and dynamic natural resources. With increasing population pressure and the concomitant need for increased agricultural production (food and fiber crops as well as livestock), there is a definite need for improved management of the agricultural resources.

To accomplish a successful resource management, it is necessary to obtain reliable data with high accuracy in quality, quantity of the resources. For developing countries, this has been traditionally conducted by collecting information from field survey and evaluating them with the associated statistics on crops, rangeland, livestock and other related agricultural resources.

In the recent years, remote sensing takes an important role in data collection procedure and provides large amounts of data for the mission. Besides, remote sensing is very important and an inseparable tool for not only acquiring data, but also for producing comprehensive, reliable and timely information. Hence, remote sensing technology is a requirement and necessity to organize agricultural activities at local, regional and district levels in today's world.

Considering the countries whose mainstay of economy is agriculture, the importance of the agricultural management is obvious for being a backbone of planning and allocation of the limited resources to different sectors of the economy.

Remote sensing has many advantages when compared to traditional methods. However, its excellence is significantly for i) providing a synoptic view, ii) sensing capability on wide regions of EM spectrum, iii) allowing periodic data collection and iv) saving time and money.

i) Synoptic viewing: In particular, all environmental and ecological researches at regional and continental scale require a vast amount of information to characterize the spatial and temporal patterns of landscape dynamics, which are hardly obtained by field survey. Certainly, remote sensing can resolve such limitation of under-sampling by providing view over large geographic area. The environmental measurements become available at regional and even global scales by the use of satellite data which make it more practical for monitoring and analyzing of vegetation activities.

ii) Sensing wide EM spectrum: Sensors on satellites provide spectral information of the observed object in various EM regions. A well combination of knowledge about the spectrum with the spectral properties of the features will direct effective analyses.

iii) Monitoring: Well organized periodic acquisition of land cover is valuable for temporal analysis of features that are variable in time.

iv) Saving time and money: Time, money and manpower used to gather information are less than traditional ground field surveys, hence it is more economic.

Remote sensing technology is used for agricultural applications more than two decades in many ways such as [3, 27]:

- Determining Crop Species Distribution, Crop Classification and Mapping
- Crop Condition Monitoring
- Extraction of Crop Productivity and Yield Forecasting
- Disease Detection, Nutrient Deficiency and Crop Damage Assessment
- Soil Classification and Soil Water Content Investigation
- Farm Decision Making and Management

These topics can be enriched, since there are many subtopics under these titles. In the recent years, the new agricultural approach called precision agriculture promises very effective use of resources, which is very important for sustainable agriculture activities.

Another agricultural demand for today's world is organic agriculture. Organic agricultural activities need to be carried in a fast, accurate and practical way. Balaselvakumar et.al. indicates that many sub applications can be added to the list above, most of which are very useful for organic agricultural applications such as crop identification, acreage, vigor, density, maturity; soil toxicity, moisture, fertility; water availability, quality; irrigation requirement, canal locations; insect and other disease infestations; growth rates, actual yield and yield forecasting [28].

Remote sensing plays an important role as auxiliary variable in the production of agricultural statistics. It can be used at the design level as well as at the estimation level [29].

Consequently, as indicated in the literature, by using remote sensing technology, vast amount of data is collected, analyzed and converted to information, and then integrated into other information systems for agricultural decision making.

With the very recent developments, remote sensing and GIS technology are also gaining importance as very useful tools in sustainable agricultural management and development. Various studies clearly carried out in several applications that the integrated use of aerospace data and RS & GIS technology are very effective tools for suggesting action plans / management strategies for agricultural sustainability of any region [30].

3.1 Remote Sensing of Agricultural Features

Identifying vegetation in a remote sensing image depends on several various plant characteristics. The spectral variations facilitate precise detecting, identifying and monitoring of vegetation on land surfaces. Thus, continually changes in forests, grasslands, crop fields etc. can be observed and obtained often at quantitative levels.

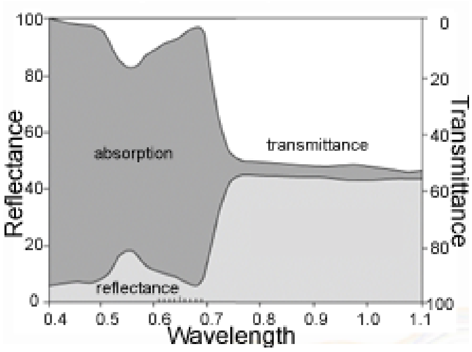
Because vegetation is the dominant component in most ecosystems, remote sensing is very useful to monitor, detect and routinely gather valuable information for characterizing and managing these organic systems [31].

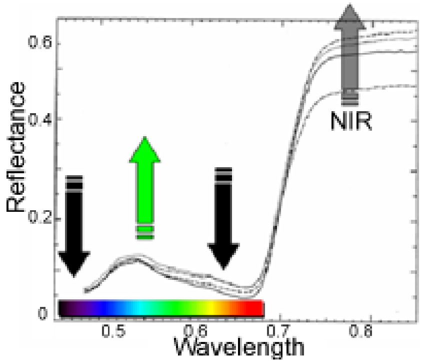
3.1.1 Optical Remote Sensing

3.1.1.1 Reflectance Properties of Vegetation in Agricultural Environments

Vegetation is composed of a limited set of spectrally active compounds [32]. The relative abundances are dependent on species and are indicators of the vegetation's and the surrounding environment's condition [32]. Many remote sensing devices operate in the visible and near infrared regions of the electromagnetic spectrum, and are capable of discriminating the radiation absorption and reflectance properties of vegetation. In Figure 3.1a, a general vegetation spectrum showing the absorption, transmittance and reflectance properties is given.

Mostly, canopy is the main reflector of the vegetative surface and reflectance of vegetation is the most important property in the analysis. One of the most important advantages of optical remote sensing is the detection of properties of the vegetation on infrared portion of the electromagnetic spectrum since vegetation gives the most valuable information in this region (Figure 3.1b).





(a) (b)

Figure 3.1 : General vegetation a) spectra [32] b) reflectance in optical region.

The energy interaction that occurs on leaf can be shown in Figure 3.2.

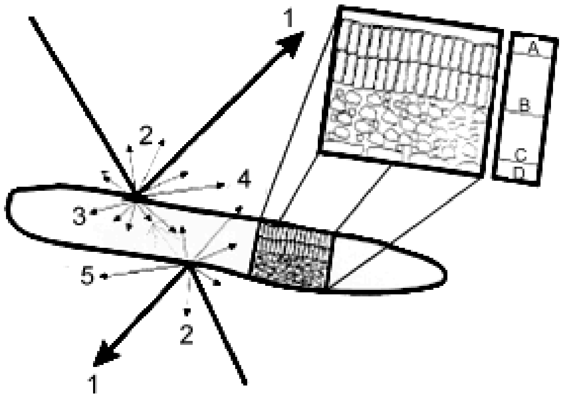


Figure 3.2 : Schematic cross-section of a leaf showing light-photon interactions [32].

In the Figure 3.2, the components of a leaf are shown and the possible interactions of energy on leaf are visualized. Leaf components are as A: upper leaf cuticle, B: palisade mesophyll cells containing the majority of chloroplasts, C: spongy mesophyll cells with a large area of cell wall interfaces, D: lower cuticle containing stomates. The possible interactions that can happen to a photon are to be (1) specularly reflected, (2) diffusely reflected, (3) absorbed in leaf photosynthetic apparatus, (4) scattered from inside the leaf back in the general direction but adding to the leaf reflectance, (5) transmitted or scattered out of the leaf as it originally traveled, adding to leaf transmittance [31].

In general, absorption centered at nearly 0.65 μm (red) is controlled by chlorophyll pigment of green-leaf chloroplasts in the outer leaf. However, absorption occurs at a similar extent in the blue. Hence, the predominant but diminished reflectance of visible wavelengths is concentrated in the green. In other words, most vegetation has a green-leafy color [31].

There is also strong reflectance between 0.7 and 1.0 µm (near IR) in the spongy mesophyll cells that reside in the interior or back of a leaf. The intensity of this reflectance is commonly greater than from most inorganic materials, so vegetation appears much brighter in near-IR region of the spectrum [31] (Figure 3.3).

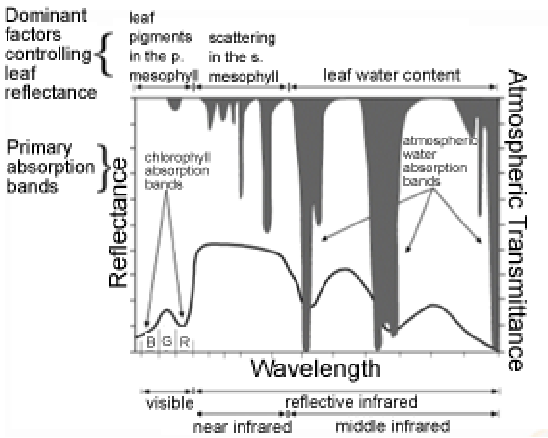


Figure 3.3 : Factors effecting leaf reflectance [32].

There are discontinuities in the refractive indices of a leaf determine the near infrared reflectance. The discontinuities occur within the upper and lower half of the leaf, between membranes and cytoplasm; and individual cells and air spaces of the spongy mesophyll respectively. These can be called the effects of physiological structure of the vegetation.

Healthy leaves act as excellent diffuse reflectors of near-infrared wavelengths due to their internal structure. Since it’s a great indicator, scientists use measurement of the near-IR (NIR) reflectance to determine how healthy or unhealthy vegetation is [32]. Any unhealthy condition of vegetation or anything affecting or blocking a plant's metabolism, growth or development, is regarded as “stress” [33]. If the amount of chlorophyll is reduced because of actual changes in chlorophyll concentration, then canopy architecture changes, branch-scale changes in architecture, and changes in vegetation cover produces shift in the red edge [32].

Reflectance of a vegetation in the shortwave infrared (SWIR) (800 to 2500 nm) is dominated by absorption from water consistence in the plant’s tissue which is Spongy Mesophyll. The three major water absorption regions which also affect the reflectance spectra of healthy leaves are 1.4, 1.9, 2.7 µm. In addition to these, there are two minor absorption features at 0.96 and 1.1 µm. Reflectance in the SWIR is modified by minor absorption features associated some compounds such as starches, proteins, oils, sugars, lignin and cellulose [32].

As a combination of the effects of pigmentation and physiological structure, healthy green vegetation shows low reflectance in the red and blue, medium reflectance in the green, high reflectance in the near infrared portion. In other words, healthy vegetation’s tonal signatures on multispectral images are as: darker tones in the blue and, especially red bands, somewhat lighter in the green band, and notably light in the near-IR bands [34].

When considering the energy interaction on leaf and the related spectral reflectance of vegetation, it has to be taken into account that single leaf reflectance is different from effect of multiple layers of leaf. Multiple layers of leaf have different reflectance mechanism from single leaf reflectance. These have to be considered mostly for the tree crop types.

Time is the main factor that effect spectra, which is also the basic characteristic of vegetation for remote sensing analysis. In addition to the effect of seasonal change, plant age has an effect on tree crops.

For agricultural applications, since the observed objects are mostly crops; seeding, growing, and harvest time periods are the main variables for the decision of data acquisition times.

The growth stages of rice crop and the related crop growth calendar are given in Figure 3.4. The measurements and satellite image acquisitions have to be planned for the most suitable periods to monitor the vegetation status in consideration with growing effect.

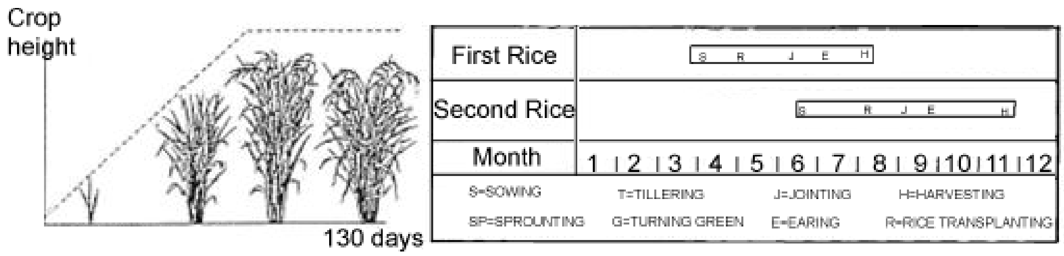


Figure 3.4 : The growth stages [35] and calendar of rice crop [36].

In the image analysis, vegetation indexes can be used successfully as an important information source of vegetation analysis. The most generic index for mapping vegetation is the Normalized Difference Vegetation Index (NDVI), used by many researches. As shown, NDVI is directly related to the photosynthetic capacity and hence energy absorption of plant canopies [37 - 39].

The principle is to use reflectance of vegetation in red region where chlorophyll causes considerable absorption and near infrared region where plant leaf structure creates considerable reflectance in NDVI ratio, and to get high NDVI values for healthy vegetation [40]. The NDVI formula is given as:

$$NDVI = (NIR - RED) / (NIR + RED) \tag{3.1}$$

The NDVI values vary between -1.0 and +1.0 [41]. It can be seen from its mathematical definition that the NDVI of an area containing a dense vegetation canopy will tend to have positive values (0.3 to 0.8), and soil, which generally exhibits a near-infrared spectral reflectance somewhat larger than in the red portion, will tend to generate rather small positive NDVI values (0.1 to 0.2).

Subsequent work has shown that the NDVI is directly related to the photosynthetic capacity and hence energy absorption of plant canopies [38, 39]. NDVI provides a crude estimate of vegetation health and changes in vegetation over time, with the spatial distribution information [42]. NDVI products are especially useful in multispectral remote sensing applications, since these transformations highlight relationships and differences in spectral intensity across the multiple spectral intervals of the spectrum [43].

In this study, NDVI values and the differences in reflectance of different crop types were used as the main keys for crop discrimination.

3.1.1.2 Reflectance Properties of Other Landcover/use Features in Agricultural Environments

Soil, water and urban are the other landcover/use features of an agricultural environment.

- **Soil**

Most of the energy incident on soil is either absorbed or reflected, however there is usually little transmission. The reflectance for most soil types is similar, with an increase in reflectance by wavelength size. The main factors affecting soil reflectance are soil texture, soil structure, moisture content, organic content, iron oxide content.

Soils of different texture indicate different overall structure and roughness. The presence of moisture has a reducing effect on the reflectance of soil across the short-wave spectrum. This occurs until the soil is saturated, beyond, it has no further effect. In near and middle infrared regions, there is also a negative relation with the moisture and the soil reflectance.

Organic matter has a strong influence on soil reflectance. The presence of organic matter decreases the reflectance across the short-wave spectrum. Soil organic matter is characteristically dark. It can be said that soil with an organic content of above 5 %, will effectively appear black.

Iron oxide selectively reflects red and absorbs green light giving a rusty red hue to soil by coating or staining individual particles.

Effects of other parameters on soil reflectance are topography, slope, seasonal parameters etc.

In agricultural applications, soil reflectance is important to determine the field boundaries, to detect the field status at the time of acquisition mostly for the regions that have various crop types with different planting times. It can be an identifier for sparse crop fields by changing the total reflectance per unit area.

In this study, temporal changes in soil reflectance were used to determine the planting period of fields.

- **Water**

Unlike vegetation or soil, the major radiant energy incident upon water is not reflected; it is either absorbed or transmitted. In visible wavelengths < 5% is absorbed or reflected and the rest is transmitted. In near and middle infrared wavelengths, water have strong absorption, and very little radiation is reflected or transmitted.

The three most important factors affecting water reflectance are depth of water, materials within the water, and surface roughness.

If there is suspended sediment present in the surface layer (or in close ranges) of the water body, the reflectivity increases, and water appears brighter. The color will show a slight shift to longer wavelengths. Suspended sediment is easily confused with shallow clear water, since these two phenomena have similar appearances.

Chlorophyll in algae absorbs more of the blue wavelengths and reflects the green; therefore, the water seems greener in color when algae are present.

The topography of the water surface (roughness, smoothness, containing floating materials, etc.) can also lead to complications for water-related interpretation due to potential problems of specular reflection and other influences on color and brightness.

In this thesis, the river being one of the main geographic features in the region is detected by its reflectance and shape properties. The crops in the study area are not analyzed with the use of water content properties, since no ground control measurements such as soil moisture were available.

- **Urban**

Compared to other land cover types, urban environments are spatially and spectrally complex, since they include mixed features such as impervious surfaces, vegetation, water, bare soil etc.

The reflectance of urban area is mostly effected by the type and aging of roof material [44].

In this thesis, urban is detected by the use reflectance, shape and texture properties.

3.1.2 Radar Remote Sensing

3.1.2.1 Scattering Properties of Vegetation in Agricultural Environments

Radar remote sensing has some advantages upon optical remote sensing. Radar systems have almost all-weather imaging capability, and can be acquired in day or night conditions, increasing the chance of providing useful data [45].

However, the nature of radar interaction with targets is quite different from that of optical signal. Geometric and electrical properties of targets are very important in radar wavebands, while physical and chemical properties are important in optical regions [46]. Radar is reflected in the same manner as visible light. This reflection is called scattering. The radar pulses sent out by imaging radar are scattered upon contact with the earth's surface. The way in which the energy contained in the pulse is scattered is known as a scattering mechanism [24]. Smooth surface, rough surface, double bounce (corner) and volume scatterings are the four types of scattering which were discussed in chapter 2.

A vegetation canopy will interact with radar waves as a group of volume scatterers. The canopy is composed of a large number of discrete plant components, such as leaves, stems, stalks, limbs and so on. In addition, the canopy is underlain by soil that may result in surface scattering of the energy that penetrates the vegetation canopy [47].

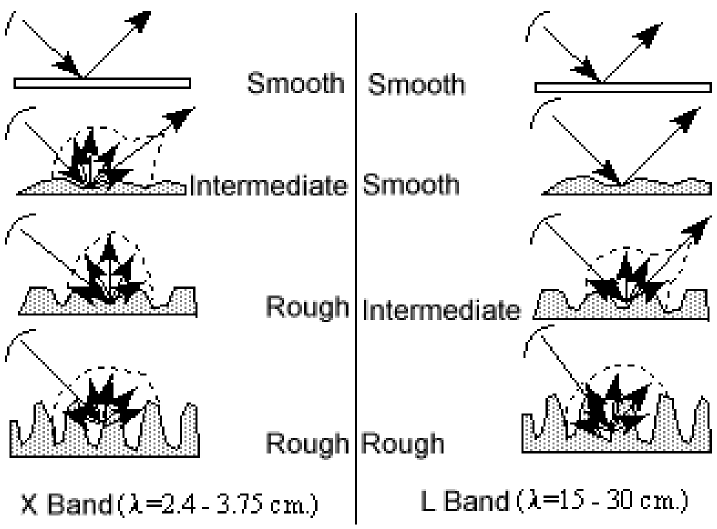
To evaluate the target energy interactions in the radar image, system and target parameters of the radar system must be considered. Wavelength, polarization and incident angle are the system parameters and geometry/shape and dielectric constant are the target parameters that influence the scattering process [48]. When analyzing a radar image, it is important to consider that both parameters would have great effects on the radar backscatter.

- System Parameters

1. Wavelength

The magnitude of radar backscatter from agricultural targets is dependent upon wavelength due to i) differences in the dielectric constant of water as a function of frequency and ii) the relationship between wavelength and plant size and/or penetration depth [48]. As frequency decreases, the signal penetration into crops and/or soil increases.

If the sizes of the target components (i.e. leaves, stems, flowers etc.) relative to the wavelength are small, it acts as a "smoother" target. When the scatterer dimension is approximately the size of the wavelength, the shape of the scatterer becomes very important in determining the backscattered EM fields (Figure 3.5). When the dimensions of the scatterer are much smaller than the wavelength, the scatterer shape is unimportant [48].



(a) (b)

Figure 3.5 : Radar reflection from surfaces of varying roughness (a) X (b) L-band [48].

Since agricultural targets are composed of significant and varying amounts of water, this frequency dependence in the dielectric constant is very important in the interaction process [48]. The backscattering value increases with the water content.

In summary, the higher frequencies are generally preferable for crop type mapping, but this can change regionally depending on the crop mix and seasonally as a function of crop development [48]. In general, shorter wavelengths, of approximately 2 to 6 cm, are best for sensing crop canopies and tree leaves, because at these wavelengths volume scattering predominates and surface scattering from the underlying soil is minimized. However, longer wavelengths, of approximately 10 to 30 cm are best for sensing tree trunks or limbs [47].

2. Polarization

Irrespective of wavelength, radar signals can be transmitted and/or received in different modes of polarization. Being electromagnetic waves, microwaves are transverse; that is the vibrations are perpendicular to the direction of wave propagation. For radar, the waves are typically polarized in a plane, either horizontal or vertical; although it is also possible for the waves to not be restricted to a plane (they could be elliptically or circularly polarized).

Polarization, which refers to the direction of the electric vector in an EM wave, can be a useful discriminator in radar image analysis. For radar applications, the linear combinations of horizontal (H) and vertical (V) polarizations state for the transmitting and receiving antennas giving HH, VV, HV and VH combinations [48].

For vegetation, like-polarized waves (HH or VV) penetrate more than cross-polarized (HV or VH) waves. In addition, more energy is returned from crops having their rows aligned in the azimuth direction than from those aligned in the range direction, especially in the case of like-polarized beams [47].

3. Incident Angle

The angle of incidence of an EM wave to a surface is measured as the difference in angle between the EM wave and the normal vector of the surface at the point of intersection [49].

For steep incident angles penetration increases and more information on background is collected than the surface.

In general, shallower angles provide better crop discrimination (more interaction with the vegetation and less soil contribution). Shallower angles also minimize contributions from soil moisture and maximize differences due to residue cover and tillage type [50].

4. Other system parameters

The other system parameters are range and azimuth resolution, swath width, pulse length, transmitter power, bandwidth etc. These parameters have less effect on interpretation.

- Target Parameters

1. Dielectric properties

One measure of an object's electrical character is the 'complex dielectric constant', which is a parameter that indicates the reflectivity and conductivity of various materials. As reflectivity and conductivity increases, so does the value of this constant [47].

A change in moisture content generally provokes a significant change in the dielectric properties of natural materials. The electromagnetic wave penetration in an object is an inverse function of water content [51].

In the microwave region of the spectrum, most natural materials have a dielectric constant in the range of 3 to 8 when dry, whereas water has a dielectric constant of approximately 80. In other words, the presence of moisture in either soil or vegetation will result in significantly greater reflectivity [47].

2. Geometrical Characteristics

Roughness is a relative concept depending upon wavelength and incidence angle. A surface is considered "rough" if its surface structure has dimensions that are comparable to the incident wavelength [51].

According to the Rayleigh criterion, a surface is considered smooth if:

$$h < \lambda/(8\cos\theta) \qquad \textbf{(3.2)}$$

and considered rough if:

$$h < \lambda/(8\cos\theta) \qquad \textbf{(3.3)}$$

where h: mean height of surface variations, λ: wavelength and θ: incidence angle [51].

One of the most readily apparent features of radar imagery is its side-lighted character, which arises through variations in the relative sensor to terrain geometry [53] and strongly related with the surface roughness. Shadow areas and radar backscatter are affected by different surface properties over a range of incidence angles [47]. Various crops having different surface roughness turn different backscatter values [52].

For agricultural applications, other target parameters are crop growth stages, plant height, soil cultivation density and row direction etc. Row direction effects can be significant at or near perpendicular look directions; for crops, row effects are prominent at incident angles around 40 degrees and at low vegetation densities; sensitivity to these effects may be reduced using cross-polarizations [50]. When row direction is parallel to look direction there is less backscatter, and when row direction is perpendicular to look direction there is more backscatter [50].

To summarize specifically for vegetation, Ulaby et al. (1986) point out the main factors influencing radar backscattering as: (a) the dielectric constant of the vegetation material; (b) the size of canopy diffusing elements, like leaves, trunks, fruits and flowers; (c) the shape and orientation of diffusing elements; (d) the roughness and dielectric constant of the soil beneath the canopy; (e) the geometry of the soil cover (including row direction, row spacing, percent ground cover, and plants height). Most of these factors are discussed in Simýes (1999) [53, 54].

For image interpretation, it is said that determining and describing how various objects reflect radar energy has been mostly derived from empirical observations. It has been found that the primary factors influencing an object's return signal intensity are the target parameters: their geometric and electrical characteristics, as well as their general composition [47].

In this study, multitemporal backscattering values were used for crop discrimination, which indicate mostly the surface roughness characteristic of different types of fields.

3.1.2.2 Scattering Properties of Other Landcover/use Features in Agricultural Environments

Soil, water and urban are the main features of an agricultural environment.

- **Soil**

Over bare soil and moderately vegetated terrain, radar backscatter is sensitive to soil moisture [55]. Magnitude of scattering is governed by dielectric properties of the target and so there is a strong correlation between soil moisture and radar backscatter.

The main factors that affect soil backscatter are;

- Surface roughness (both random and periodic): this complicates estimation of soil moisture using active radar. Radar signal is both attenuated and scattered by vegetation; this has limited application of active radar methods to surfaces with little or no vegetation cover.
- Penetration depth varies depending upon the soil dielectric, incidence angle and frequency; nevertheless synthetic aperture radar (SAR) is sensing moisture in only the top few centimeters of the soil. Frozen soils, regardless of moisture content, have a dielectric constant similar to dry soil [56].
- Other soil parameters such as organic matter, salinity etc. has been shown to have some effect on backscatter although it is less than the roughness and water content effect [48].

- **Water**

Most surface water features are detectable on radar imagery because of the contrast in return between the smooth water surface and the rough land surface. This high contrast ratio is based on a low radar return from the water surface and high return from the rougher land [48].

- **Urban**

The built environment has properties, such as building size, shape, orientation with respect to radar, and material, with which the radiation interacts, and determines the properties of the backscattered radar response. Radar is particularly sensitive to building ‘bulk’ and the orientation of buildings with respect to the radars look direction [44].

The main contribution to radar backscatter in the urban environment is due to corner reflections. Double bounce corner reflection, occurs when the radar look direction is perpendicular to a building wall, the radar wave will bounce from the ground to the wall and back to the sensor, or vice versa which will be observed as bright pixels in the radar image.

3.2 Complementary and Ancillary Data

“Ground truth” implies data collected from the field to control and help satellite image interpretation. In the early days of remote sensing research, ground investigations were mostly used to verify the results of remote sensing interpretation. Today, the same term in remote sensing literature is also used for the reference data that obtained from diverse sources, not necessarily involving ground investigations [57]. There are varying kinds of ancillary and field data. These data may be obtained from maps (e.g. geological units, soil classifications, political boundaries) or may be continuous variables (e.g. digital elevation models, aeromagnetic surveys, and regional economic indicators). Their integration with remotely sensed data requires geometric fidelity and also other alternative analysis strategies available that include deterministic and probabilistic techniques [58]. Ground truth measurements done with radiometers and spectrometers are used primarily to accumulate specific spectral signatures of various materials and features that help to build up a spectral data "bank" [34]. In addition to that, depending on the purpose measurements of other vegetation parameters, plant growth calendar etc. can be used for crop type discrimination, crop yield estimation or other aims of agricultural management. For radar applications soil moisture data is one of the most important types of ancillary data to interpret the relation of backscattering values to roughness and/or moisture content. Remote-sensing studies of complex terrain phenomena can benefit greatly from careful application of digital ancillary data including one or some of these [64].

For agricultural applications, a field crop map is the main information resource. Crop type maps may be used to select training areas, or to verify the thematic maps generated from remote sensing. In this study, crop maps were used as a reference for determining the distribution of membership functions and also for evaluating the accuracy assessment of the classification results.

3.3 Crop Discrimination and Mapping

Crop type identification and mapping are important for national and multinational agricultural agencies, insurance agencies, and regional agricultural boards to prepare an inventory of what was grown in certain areas and when. This serves the purpose of forecasting grain supplies (yield prediction), collecting crop production statistics, facilitating crop rotation records, mapping soil productivity, identification of factors influencing crop stress, assessment of crop damage due to storms and drought, and monitoring farming activity [13]. Today, recording precise crop location and paddock rotational history is becoming an increasingly important part of crop management and product quality assurance [59].

Traditional methods of obtaining this information are census and ground surveying [13]. Advances in satellite imagery allow good results in the calculation of paddock position, area measurement and mapping, when compared with ground survey methods and aircraft-based photography. Satellite data are easy to collect even for wide areas, economic to use, geometrically correct, and it provides more information than that can be gathered by ground surveying.

Developed countries use remote sensing technology for many agricultural purposes. Crop recognition, growth and health monitoring are widely considered achievable goals using satellite imagery [59]. Some scientists and their teams published many high resolution spectral signatures for natural and cultivated species, identifying spectral features associated with normal plant growth conditions and those caused by nutrient deficiency, pests, and abiotic stresses [60-64]. Drought induced effects in vegetation and crops were studied by Bowman, 1989 and Carter, 1991 [65, 66]. Spectral properties of soil and organic matter content were investigated by Condit, 1970, Stoner and Baumgardner, 1981, Price, 1990, Daughtry, 2001, Aase and Tanaka, 1991 and Nagler et al., 2000 [67-72]. Vegetation indices were used effectively in many studies related to vegetation and agricultural applications [73-76]. Hyperspectral approaches have been proposed mostly determining the pest-induced stress in plants [77-80]. Salinity and the spectral properties of plants growing in affected areas were investigated by Wiegand et al., 1994; Wang et al., 2001 [81, 82]. Herbicide damage and also the estimation of its amount was showed by Hickman et al. (1991) [83]. Yield estimation of cotton and vegetable crops were studied by Thomas and Gerberman, 1977, Pearson et al., 1976; Tucker et al., 1981 [84-86]. Remote sensing also provides common data collection and information extraction strategies that standardize measurements [13].

For crop identification and mapping, both optical and radar data can be used. Since reflectivity information is recorded in optical data, crop type identification is easier for the crop types that have highly different reflectance values. The higher the number of bands and the narrower the sensing portions, it will be easier to make a classification. However, there are regions which a cloud free image can be rarely acquired during the critical crop growth periods. Radar data is a solution for this kind of situations. When using radar images, the backscatter is the main identifier for crop types, which is effected mostly by water content and surface roughness of the field. If available, using both of the datasets as complementary for each other will be a better solution.

Independent processes were executed in the application part of this thesis, since the optical and radar datasets used were not belonging to the same year. Crop mapping is performed by taking into account the reflectance and scattering properties of crops and also the textural properties, respectively for the optical and radar datasets.

4. PIXEL-BASED AND OBJECT-BASED IMAGE ANALYSIS

Since the start of the first Landsat satellite in 1972, the Earth's surface is being measured by its reflectance properties. The smallest unit of an image, or called a 'pixel', has the value of this measured spectral reflectance. The traditional information extraction methods developed are usually based on these image pixel values.

Although the referred region of a pixel on Earth is getting smaller as the spatial resolution capabilities increase with the developing technology, the pixel still can consist of more than one object's reflectance which will cause misclassification and reduced accuracy. This problem is called as mixed pixel problem. Mixed pixels were the problematic cases or the difficult parts of image classification. For this reason, some sub-pixel classification methods are developed.

However, both pixel-based algorithms and the sub-pixel analysis only use the spectral properties of the pixels in the image. These approaches utilize spectral information of pixels to classify the image. Normally, the different physical properties of Earth objects have different spectral information and can be specified by these methods. However, the ability of these processes is limited for the objects having similar spectral information. In this circumstance, the image classification accuracy decreases. Therefore, although images are often seen as the most information-rich data, extraction of information frequently had to rely on human interpretation; and compared to visual analysis, digital analysis always had limited success.

The main concept of visual analysis on interpreting image objects is to consider the concepts of neighborhood, distance, location etc., not only spectral reflectance values. The concepts other than reflectivity are actually not new since entire disciplines related to geography are based on these concepts. However, somehow these main concepts in geography have escaped operational use in image processing until recent years. Now, using a new approach, object-based image processing methods, apply the spatial thinking to image processing.

The newly developed object-based image processing combines the spectral information with other information contained in the image as spatial information and use all in classification. Subsequently, images are classified with additional information concerning shape, size, texture and context and relational descriptions to increase the ability to separate the Earth objects with similar spectral information.

To understand the object-based image processing and its advantages, first pixel-based approach and then the object-based approach will be examined.

Pixel-based approach is based on conventional statistical techniques, and classifies an image pixel by pixel and one pixel can only be classified into one class, thus produces a hard classification.

In object-based approach, besides the spectral information in the image, the texture and context information will be combined into classification as well. The image will be segmented into objects to form the classification units which will be treated as a whole in the classification process. Object-based classification approach is based on fuzzy theory, in which one object will be classified into more than one classes with different membership values. These two approaches will be described in detail in the following parts.

4.1 Pixel-Based Image Analysis

Based on the fact that remotely sensed images consist of rows and columns of pixels having measured spectral reflectance, per-pixel approach has been the conventional method for land cover mapping. Pixel-based classification methods, using one or more of the various multispectral classification techniques, assign a pixel to a class fundamentally according to the spectral similarities [87-89]. Ideally, pixels are expected to be grouped as clusters in the multispectral space, corresponding to different land cover types.

In other words, the basic assumption for image classification is that, each specific class exists on a specific part of the feature space. Once the classes are defined in the feature space, each image pixel can be compared with them and assigned to the corresponding one. To run this procedure correctly, classes to be distinguished need to have different spectral characteristics. To find out this, spectral reflectance curves can be compared first. If classes do not have distinct clusters in the feature space, then the result of the classification will only be to a certain level of reliability [90].

The principle of image classification is to assign a pixel to a class based on its feature vector, by comparing it to predefined clusters in the feature space. Repeating the operation for all image pixels result in a classified image [90].

Traditionally classification methods have pixel-based approaches that are based on conventional statistical techniques. Although they perform well, the ability for resolving inter-class confusion is limited.

4.1.1 Feature Space

The intensity of each pixel corresponds to the average brightness measured electrically over the ground area detected for that pixel. Hence each pixel has digital number value corresponding to the average radiance measured for it. Digital image can be defined as a 2D-array of elements storing the DN values. The spatial arrangement of the measurements defines an “image space”. Depending on the sensor, data are recorded in n bands which increase the space dimension (Figure 4.1).

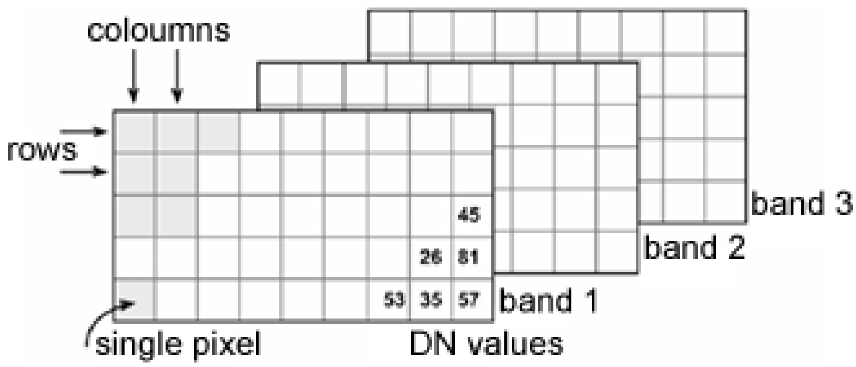


Figure 4.1 : Image space [90].

For one pixel, the values in two bands can be regarded as components of a two-dimensional vector, or called the “feature vector”. As shown in Figure 4.2, the values of the feature vectors are called a “feature space” [90].

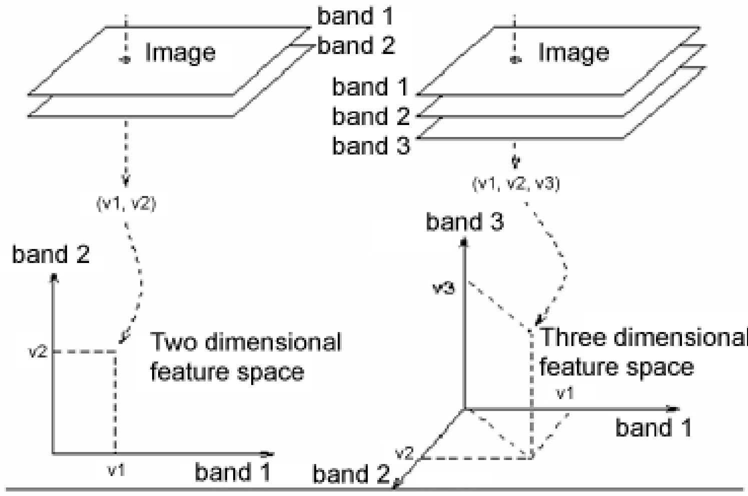


Figure 4.2 : Feature space and a feature vector [90].

4.1.2 Image Classification

"Classification of images involves using a set of rules to decide whether different pixels in an image have similar characteristics" [14]. Pixel-based methods classify remote sensing images according to the spectral information. The procedure follows scanning and evaluating the image "pixel by pixel", and one pixel can only be assigned to one class.

There are a variety of approaches to perform digital classification. However, in pixel-based classification, two main traditional classification methods known as supervised and unsupervised classifications are used. The classes are determined by a priori identification for supervised and by a posteriori identification for unsupervised classification.

4.1.2.1 Unsupervised Classification

These classifiers examine the natural groupings or clusters present in the image values and aggregate the unknown pixels into one of these classes. The basic expectation is that values of a specific cover type should be close together in the measurement space, whereas data in different classes should be comparatively well separated [5].

Unsupervised classification is used when there is little or no external information about the land cover types existing and also about the distribution of them. The results of unsupervised classification are spectral classes that are then associated with the land cover types using reference data by an analyst [91].

There are numerous classification algorithms to determine the natural spectral groupings present in a data or a dataset [5]. The two most frequently used clustering algorithms are the K-means and the ISODATA (iterative self-organizing data analysis technique algorithm) algorithm.

4.1.2.2 Supervised Classification

In supervised classification, the image analyst supervises the pixel categorization process. This supervising is specifying to the computer algorithm, numerical descriptors of the various land cover types present in an image. In other words, training samples are defined to describe the typical spectral pattern of the land cover classes. Pixels in the image are compared to the training samples to be labeled with one of the land cover class that has similar characteristics.

There are two basic stages involved in the supervised classification method: training stage and classification stage.

Training samples are pixel groups that represent the typical spectral information of land cover classes and are selected by the analyst to train the classifier. Training data must be both representative and complete for all classes. Training samples for each information class should be typical. Besides, the analyst have to take into consideration all of the spectral variability within an information class [92].

Classification is performed after specifying a set of training samples and choosing a certain classification algorithm. Pixels in the image are compared to each training sample numerically and are allocated to the land cover classes according to certain algorithms which are called classifiers. The classic classifiers used in pixel-based image analysis are hard classifiers, which assign a membership of 1 or 0 to the pixels, expressing whether a pixel belongs definitely to a certain class, or not.

The commonly used classifiers are minimum distance to mean classifier, parallelepiped classifier, and maximum likelihood classifier. These classifiers use distance in their algorithm steps which is expressed as “Euclidian distance” and having DN as the unit. In simple terms, the distance can be calculated according to Pythagoras’ theorem in a two dimensional feature space [90].

4.1.3 Accuracy Assessment

Classification is not complete until its accuracy has been assessed [5]. By accuracy, ‘the level of agreement between labels assigned by the classifier and the class allocations on the ground collected by the user for testing’ is meant.

To reach valid conclusions about the accuracy, the test samples must be selected without bias. When performing accuracy assessment for the whole classified image, the known reference data should have different set than the sample set used for training the classifier [5]. Failure to meet these important criteria may cause false results in which the true accuracy is over- or under-estimated.

The following are the two methods commonly used for the accuracy assessment.

a) Error matrix

Error matrix is a square matrix having the same number of information classes that will be assessed as the row and column. Numbers in rows are for the classification result and numbers in columns are for reference data. In this square, elements along the main diagonal represent pixels that are correctly classified (Table 4.1).

Table 4.1 : Error matrix.

		Reference Data			
		Class 1	Class 2	Class N	Row Total
Classification Data	Class 1	a_{11}	a_{12}	a_{1N}	$\sum_{K=1}^{N} a_{1K}$
	Class 2	a_{21}	a_{22}	a_{2N}	$\sum_{K=1}^{N} a_{2K}$
	⋮	. .	.	. .	
	Class N	a_{N1}	a_{N2}	a_{NN}	$\sum_{K=1}^{N} a_{NK}$
	Coloumn Total	$\sum_{K=1}^{N} a_{K1}$	$\sum_{K=1}^{N} a_{K2}$	$\sum_{K=1}^{N} a_{KN}$	$N=\sum_{1,K=1}^{N} a_{NK}$

Error matrix is a very effective way to represent map accuracy. It makes it in the way that the individual accuracies of each category are described along with both the error of commission and error of omission. Error of commission is defined as accepting an area into a category when it does not belong to that category. Error of omission is defined as excluding that area from the category in truly belongs.

There are three accuracy indexes (user's accuracy, producer's accuracy and overall accuracy) and their calculation methods are described below.

Overall accuracy: Overall accuracy is the proportion of all reference pixels, which are classified correctly. It is computed by dividing the total number of correctly classified pixels which are calculated as the sum of the elements along the main diagonal by the total number of reference pixels. The overall accuracy for the matrix in Table 4.1 is calculated as the following:

$$OA = \frac{\sum_{K=1}^{N} a_{kk}}{\sum_{i,k}^{N} a_{ik}} = \frac{1}{n}\sum_{K=1}^{N} a_{kk} \quad \textbf{(4.1)}$$

Producer's accuracy: Producer's accuracy estimates the probability that a pixel, which is of a certain class in the reference classification, is correctly classified. It is estimated with the reference pixels of that class divided by the pixels where classification and reference classification agree that class. The producer's accuracy can be calculated using the following equation for class I:

$$PA\ (class\ I) = \frac{a_{ii}}{\sum_{i=1}^{N} a_{ki}} \quad \textbf{(4.2)}$$

Producer's accuracy show how much the classification agrees with reference classification.

User's accuracy: User's accuracy is estimated by dividing the number of pixels of the classification result for a certain class with the number of pixels that agree with the reference data in that class. It can be calculated as:

$$UA\ (class\ I) = \frac{a_{ii}}{\sum_{i=1}^{N} a_{ik}} \tag{4.3}$$

User's accuracy predicts the probability that a pixel classified as class I is actually belonging to class I.

b) Kappa analysis

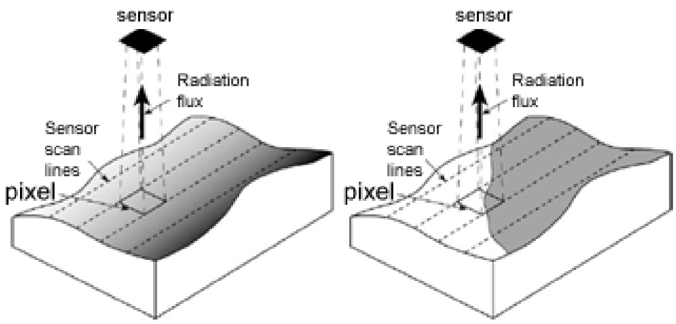
The Kappa analysis is basically a statistical determination of difference of two error matrixes by a discrete multivariate technique used in accuracy assessment [93]. The result of performing a Kappa analysis is a measure of agreement or accuracy. The measure of agreement between a classification and the reference data, is based on the difference between the actual agreement in the error matrix and the chance agreement, which are indicated by the major diagonal and the row and column totals, respectively. K value, the result of Kappa analysis is expressed as:

$$\hat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r} x_{i+} * x_{+i}} \tag{4.4}$$

Here, r is the number of rows in the error matrix, x_{ii} is the number of observations in row i and column i (on the major diagonal), x_{i+} is the total observations in row i, x_{+1} is the total of observations in column i, and N is the total number of observations included in the matrix.

4.1.4 Sub-pixel Classification

In these classification schemes, it is assumed that each pixel would be assigned to only one feature vector class, although in reality, the represented area on the ground by a pixel rarely belongs to homogenous cover type. Instead, these surfaces are generally a mixture of different surface covers with different spectral responses [14] (Figure 4.3).



(a) (b)

Figure 4.3 : Sub-pixel mapping (a) homogeneous pixel (b) mixed pixel [94].

The spectral signature measured by the remote sensing instrument is actually the weighted sum of the individual surface element spectra. The weights of different feature reflectances are relative to the area they cover in the boundaries of representing pixel. Sub-pixel classification algorithms attempt to identify these relative abundances for each pixel [14].

Accuracy assessment is one of the challenging aspects of the sub-pixel classifiers since traditional accuracy assessment methods have structures based on manner of hard classifiers and there is no straightforward approach for this aim [95]. In some cases, the only way to compute the accuracy of a sub-pixel classifier is evaluation of the results after they are hardened [96].

4.2 Object-Based Image Analysis

When human beings use their eyes and actualize the seeing operation, they perform a complex mental process. This cognition process compares the view of objects and their relationships with the existing knowledge of memory. This process is called as “image understanding” and object-based image processing is based on this process.

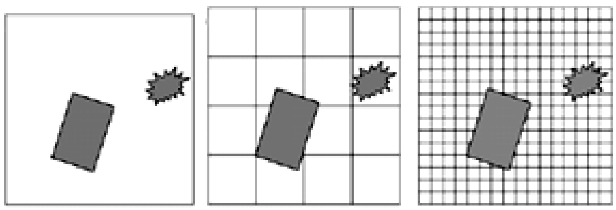
However, in visual analysis, there are some difficulties of interpretation since satellite imagery is different from the daily surroundings especially for being two-dimensional, not having a depth sense, having an unfamiliar perspective and different scales. Also imaging of wavelengths outside of the visible window, make recognition difficult. Hence, even for visual analysis, the elements of visual interpretation are exposed.

In the image analysis, recognizing targets is the key to interpretation and information extraction. Observing the differences between targets and their backgrounds involves comparison based on visual elements of tone, shape, size, pattern, texture, shadow, and association between them [13].

‘Tone’ refers to the relative brightness of objects in an optical image. For radar imagery it can be defined as the average intensity of the backscattered signal [51]. Generally, tone is the fundamental element for target discrimination. ‘Shape’ refers to the general outline of individual objects which can be a very distinctive clue for interpretation. In an image ‘size’ is a property that is a function of scale. For correction, it is important to assess the size of a target relative to other objects in a scene, as well as the absolute size. ‘Pattern’ refers typical orderly repetition of similar tones. ‘Texture’ refers to the arrangement and frequency of tonal variation. ‘Shadow’ is also helpful since it may provide an idea of the profile and relative height of the target although it can sometimes reduce or eliminate interpretation in its area of influence. Association' takes into account the relationship between objects that may provide useful information for identification [13].

Object-based image processing algorithms are based on recognizing objects according to their reflectance/backscatter values with using the additional information. The additional information of objects is based on the values derived for image objects with tools similar to the elements of visual image interpretation. However when it is performed by object-based image processing algorithms, the values are calculated by some statistical analysis.

When the development of object-based image analysis is investigated, it is seen that, at first it was assumed to be a solution for high resolution image analyzes. Different techniques that are required to unravel information from different resolution datasets such as presented in Figure 4.4, were assumed as requiring (a) sub-pixel techniques, (b) pixel-based techniques, and (c) object-based techniques.



(a) (b) (c)

Figure 4.4 : Objects in (a) low (b) medium and (c) high spatial resolution images [97].

However, after many applications in the literature, it was seen that the object-based method gives successful results for medium or coarse resolution data as well [98-102]. Increasing numbers of empirical studies published in peer-reviewed journals have subsequently provided sufficient proof of the improvements that object-based image analysis offers more than pixel-based analyses and in many recent articles it has been claimed that object-based processing techniques are becoming more popular when compared to traditional methods [103]. After a review that includes screening several thousand abstracts, more than 820 OBIA (object based image analysis) related articles comprising 145 journal papers, 84 book chapters and nearly 600 conference papers, T. Blaschke mentioned that the object-based methods are making considerable progress towards a spatially explicit information extraction workflow, such as is required for spatial planning as well as for many monitoring programmes [97].

In this study, Definiens Software was used. In the literature, much of the work also referred to as “Object Based Image Analysis” originated around the software known as “Definiens” (which was previously known as “eCognition”) [104-107]. The methods used in this thesis were described dependent to the algorithms of the software used.

The main two steps of object-based image analyzing are ‘segmentation’ and ‘classification’ which can be described as ‘formation of objects’ and ‘assignment of the objects to classes’.

4.2.1 Segmentation

Object-based classification operates not directly on single pixels, but on image objects which are obtained after a dividing operation. These image objects refer to homogeneous, spatially connected regions of image. The dividing operation of image to image objects is referred as segmentation. Segmentation is the preliminary and very important step in object-based classification. Segmentation can be defined as the subdivision of an image into image objects by a separation operation up to some criteria [108]. Objects are formed by grouping pixels according to some criterion of heterogeneity and homogeneity.

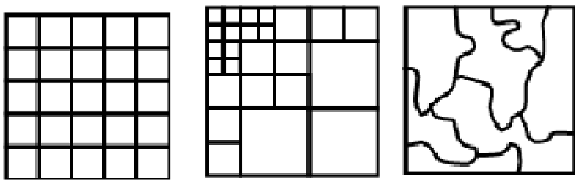
Typical image segmentation techniques follow one of these two processes: (1) region merging by using some measure of homogeneity criterion and (2) separation of objects by finding edges between neighboring pixels [114].

Region-merging approaches can be divided into two approaches: (1) region growing and (2) region split and merging. Region-growing technique starting with a set of seed points involves pixel aggregation. The region grows from these seed pixels by merging neighboring pixels that have similar properties. On the other hand, the region-splitting and -merging approach follows the subdivision step of an image to a set of arbitrary, disjointed regions and then merging step that splits the regions based on the similarity rules for object creation. Thresholding is a region-merging technique useful to discriminate objects from the background [114].

Edge-based methods create image objects based on contours of gray levels. Watershed analysis is a popular edge-based image segmentation technique. Another edge-based technique is the connectivity-preserving relaxation-based segmentation method that starts the segmentation process with an initial boundary shape [114].

Object-based image analysis software used in this thesis provides three kinds of segmentation algorithms to use for creation of unclassified basic image objects (Figure 4.5).

- Chessboard segmentation: Domain is splitted into square objects.
- Quadtree segmentation: Domain is splitted into image objects of maximum size as described by the parameters.
- Multiresolution segmentation: Domain is segmented at user defined resolution meeting the optimized color-shape, smoothness-compactness criteria.



(a) (b) (c)

Figure 4.5 : Segmentation methods (a) chessboard, (b) quadtree, (c) Multiresolution [109].

The chessboard and quadtree segmentations are mostly used as a first step to divide the image into main parts, and then the multiresolution segmentation takes place. The purpose is making the processing easier. The patented multiresolution segmentation algorithm can be defined as the main procedure to create image objects.

Multiresolution segmentation is a bottom up region-merging technique. One-pixel objects are the starting points of this method [108]. To achieve adjacent image objects of similar size and thus of comparable quality, the procedure starts at any point in the image with one-pixel objects and the procedure simulates simultaneous growth of segments in each step till the final result [109].

It uses the objects according to an optimization function given by equation 4.5.

$$w_{sp}\sum_{nb} w_b\sigma_b + (1-w_{sp})\left(w_{cp}\frac{1}{\sqrt{np}} + (1-w_{cp})\frac{l}{lr}\right) \leq h_{sc} \qquad \textbf{(4.5)}$$

where nb is the number of spectral bands, w_b is the within-object standard deviation for the spectral band b, l is the object border length, np is the number of pixels and lr is the shortest possible length given the rectangle bounding the pixels. This function also includes three kinds of user-defined weights: The spectral parameter w_{sp}, the compactness parameter w_{cp}, and corresponding to the threshold of heterogeneity, the scale parameter h_{sc} [110].

Scale is a crucial aspect for image understanding. Scale is the parameter for determining the maximum allowed heterogeneity for the resulting image objects. Thus, a heterogeneous data will have smaller objects than a more homogeneous data with the same scale parameter [109]. The size of image objects is changed related to the scale parameter value, although there is no direct correlation between it and the number of pixels or the object size. Object homogeneity is defined by the homogeneity criterion which is represented color, smoothness, and compactness criteria [114].

The composition of homogeneity criterion is as shown in Figure 4.6 [109]. These variables optimize the object's spectral homogeneity and spatial complexity at a given scale. It is important to understand the effects of each criterion independently and also relationally to segment the image and create objects suitable for a given application [114].

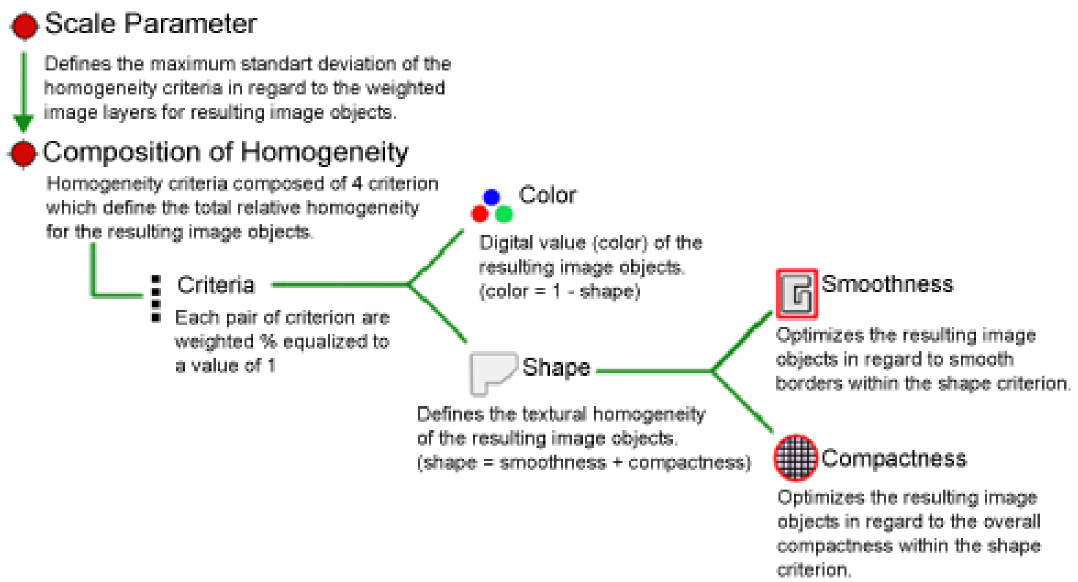


Figure 4.6 : The composition of homogeneity criterion [109].

The color parameter defines the spectral values. The shape factor is defined by two parameters which are smoothness and compactness. The smoothness and compactness factors can be used for optimization of image objects for smoother borders, or more compact image objects respectively [114].

Color / Shape Criterion: This parameter controls the color vs. shape homogeneity during object creation. If shape criterion is weighted high, then less spectral homogeneity influences the object generation [111].

Smoothness / Compactness Criterion: The shape criterion is comprised of smoothness and compactness criterion [109]. When the shape criterion is > 0, smoothness/compactness weights are determined and it affects the resulting objects be more compact or smooth [111].

Computation of the heterogeneity criterion is as in following equations [109]:

Spectral or color heterogeneity is the sum of the standard deviations of spectral values in each layer, weighted with the weights for each layer w_c. (Equation 4.6)

$$h_{spectral} = \sum_c w_c \sigma_c \tag{4.6}$$

where c: color, σ: standard deviation

And, with $0 \leq w_{cmpt} \leq 1$ being the user defined weight for the compactness criterion h_{shape} is given as in equation 4.7:

$$h_{shape} = w_{cmpt} \cdot h_{cmpt} + \left(1 - w_{cmpt}\right) \cdot h_{smooth} \tag{4.7}$$

Heterogeneity as deviation from a compact shape (h_{cmpt}) is described by the ratio of the de facto border length *l* and the square root of the number of pixels forming this image object: (Equation 4.8)

$$h_{cmpt} = \frac{l}{\sqrt{n}} \tag{4.8}$$

Another way of describing shape heterogeneity is the ratio of the de facto border length *l* and the shortest possible border length *b* given by the bounding box of an image object parallel to the raster. (Equation 4.9)

$$h_{smooth} = \frac{l}{b} \tag{4.9}$$

The overall fusion value *f* is computed as given in equation 4.10 based on the spectral heterogeneity h_{color} and the shape heterogeneity h_{shape} as follows:

$$f = w \cdot h_{color} + (1 - w) \cdot h_{shape} \tag{4.10}$$

where *w* is the user defined weight for color with $0 \leq w \leq 1$.

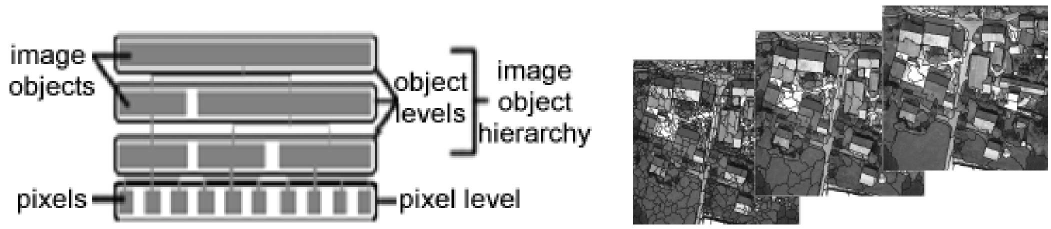
The accuracy of segmentation is so important that its success directly influences the performance of object-based image classification. Only a good segmentation leading to a successful classification will outperform pixel-based classification. Thus, before classification step, segmentation results have to be evaluated. Human interpretation and correction –if needed- is considered as the best way for the evaluation of the segmentation output [112].

In order to be able to produce a satisfying classification result, the image objects have to suit the analyzing tasks of the study. In other words, final image objects have to be as large as possible and as small as necessary [109].

The same imagery can be segmented into smaller or larger objects to work with more than one layer with considering the most practical way to derive information from image objects [109]. Also, this carries the classification level to another dimension where parent–child relationships can be leveraged to improve/enhance feature extraction process [114].

Many different segmentation layers mean many different scale image object levels that are produced up to different color/shape combinations, but are in a hierarchical network relation [113].

Subsequently, the image objects are networked, each image object is related to its neighbor objects at the same level, to its parent objects at higher levels, and to its subobjects in lower levels [114] (Figure 4.7). To assure definite relations, it is restricted that any image object can only have one superobject [109].



(a) (b)

Figure 4.7 : Segmentation hierarchy (a) schematically (b) on imagery [109].

Two trivial image object levels which represent the boundaries of the hierarchy are the pixel level which is a partition of the image into pixels and the project level which is one object covering the entire image [109].

To link image objects regarding to their spatial context, a topological network is created which becomes hierarchical when the relation of image objects of different levels at the same location is defined. Then each object is linked to its neighbors, its sub- and super-objects. This is also a description of hierarchical scale dependencies. Together with classification and mutual dependencies between objects and classes, a network can be seen similar to a spatial semantic network [109].

After the image objects are generated, many methods can be used to classify them. The simple classification can conducted only by comparing the mean grey values of the objects, and the advanced classification will combine ancillary data, such as shape characteristics and neighborhood relationships [112].

4.2.2 Image Object Features

Features are considered as source of information to define the parameters used to classify image objects. In the software used in this application, there are three types of features; object features, class-related features and scene features.

I. Object Features

'Object features' are the features of classes based on the evaluation of image objects themselves.

- **Thematic attributes:** The object's thematic properties may be taken from various kinds of thematic layers.
- **Layer values:** Layer values evaluate the first and second statistical moment (mean and standard deviation) of an image object's pixel value and the object's relations to other image object's pixel values.
- **Shape:** Shape features evaluate the image object's shape in a variety of respects.
- **Texture:** The image object's texture can be evaluated using different texture features.
- **Hierarchy:** This feature provides information about the embedding of the image object in the image object hierarchy.

II. Class-Related Features

'Class-related features' refer to the classification relations through the image object hierarchy. This can be a vertical (as to superobjects and subobjects) or a horizontal relation (as to neighbor objects). The features available are given below with which relation they are based on.

- **Relations to neighbor objects:** Relationship of objects at the same level.
- **Relations to subobjects:** Relationship of a class with the one on a lower level.
- **Relations to superobjects:** Relationship of a class with the one on a higher level.
- **Relations to classification:** These features are for obtaining the potential classification of an image object.

III. Scene Features

'Scene features' used for class definitions relate to the mean values of the entire image and can be described in two ways given below:

- **Class-related:** Features providing information on image objects of a certain class.
- **Scene-related:** Features providing information related to the scene.

4.2.3 Image Classification

One of the most evident differences between pixel-based image analysis and object-based image analysis is the classifiers. The object-based image analysis utilizes soft classifiers that are based on fuzzy logic [114].

The most powerful soft classifiers are classifiers based on fuzzy systems [109]. Fuzzy classification is a probabilistic approach and a powerful classification technique. It uses expert system rules for classification and it is efficient to exploit the spectral family of signatures for a given class and spectral overlap between classes. For a thematic map with n classes, fuzzy classification includes n-dimensional membership degrees, which describe the likelihood of class assignment of an object (obj) for all n classes [114]. (Equation 4.11)

$$f_{class}\,obj = [\mu_{class1}(obj), \mu_{class2}(obj) \dots \mu_{classn}(obj)] \qquad \textbf{(4.11)}$$

where μ: membership degree.

A fuzzy set mathematically is a function, mapping its domain to [0,1]. A fuzzy set A over a domain set D is A: D→[0,1]. For any value $x \in D$, it gives a confidence factor indicating how possible is x belonging to A, i.e. $A(x) = P_{A|\{x\}} = P_{x \in A}$. The membership function of A is notated as $\mu_A(x)$ [115].

The membership value 1 expresses full membership which can be called a complete assignment to a class and 0 expresses absolutely non-membership. The degree of membership depends on the objects fulfillment of the class-describing conditions [114]. The objects are then classified according to whether they have or have not met the required properties [114].

Fuzzy theory allows a greater flexibility compared with binary theory in which a pixel can only have two extreme values of yes or no and as a result belong to one information class, however fuzzy set theory allows one pixel to hold several non-zero membership grades for different information classes [116].

On the other hand, the fuzzy rule set contains information about the overall reliability, stability, and class combination of all the potential classes that the object can belong to. It also allows including an unclassified object that does not meet the membership function requirements of all the n classes [114]. Visually, the maximum membership degree determines the final classification to build an interface to crisp (Boolean) systems.

Fuzzy classification requires a complete fuzzy system that is consisting of fuzzification, fuzzy rule base and defuzzification components. Fuzzification is the input step of variables to form fuzzy sets, fuzzy rule base is using fuzzy logic combinations on the input set for class definitions, and defuzzification is transforming the fuzzy classification results to common crisp classification to get the thematic classification [114] (Figure 4.8).

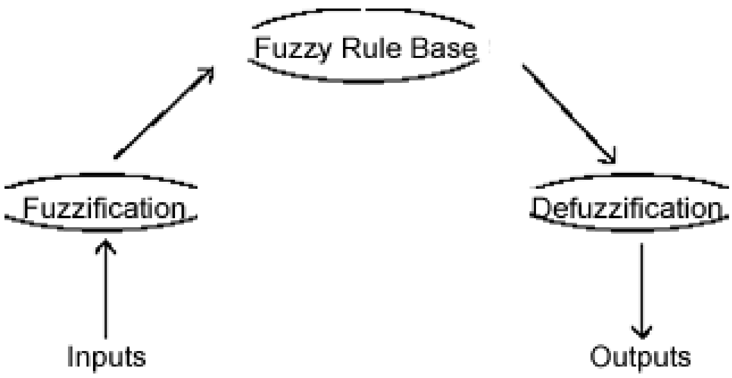


Figure 4.8 : Basic architecture of fuzzy systems [114].

I. Fuzzification: Fuzzification describes the transition to a fuzzy system [114]. The membership value $\mu(obj_i)$ between 0 and 1 is assigned to each feature and defined by membership functions. The most frequently used functions are monotonic, triangular, trapezoidal and bell-shaped [114].

Each membership function generates different membership grades. The more the memberships overlap, the more objects are common in the fuzzy sets, resulting with a vaguer classification.

In Figure 4.9a, rectangular and trapezoidal membership functions to define crisp set M (red) and fuzzy set A (blue) over the feature range X on x-axis by the membership degree μ in y-axis are shown. In Figure 4.9b, the membership functions on feature *x* define the fuzzy set low, medium and high for this feature.

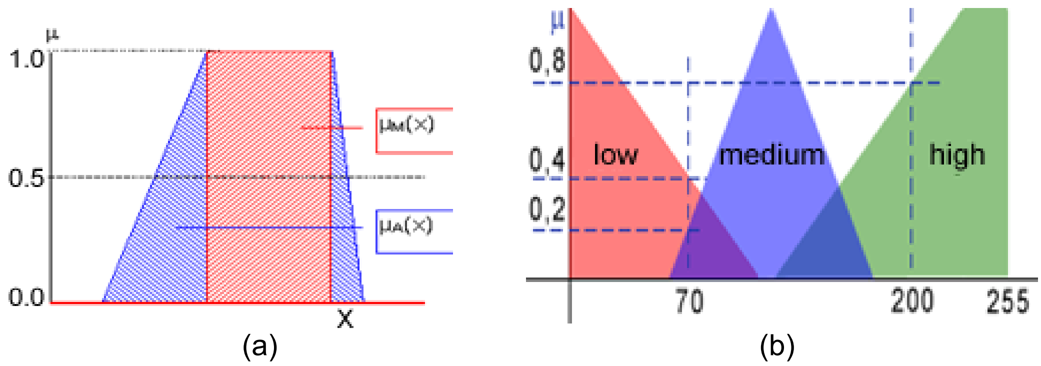


Figure 4.9 : Membership functions for (a) crisp (M) and fuzzy (A) set (b) low, medium and high membership values.

II. Fuzzy rule base: A fuzzy rule base is used to make up a description of a thematic class by a combination of fuzzy rules [114]. Fuzzy rules have "if-then" structure. If a condition is fulfilled, then the action related takes place [109]. Operators can be used to combine the fuzzy rules such as "and" and "or". "And" represents the minimum value of all return values. "Or" represents the maximum value, returning the maximum value of all returned values. A fuzzy rule base delivers a fuzzy classification and it consists of discrete return values for each of the classes which represent the degree of class assignment. If relatively higher return values exist for the most possible class, the assignment will be more reliable [114]. In Figure 4.10, the image object is a member of all classes to various degrees such as μ_{urban}(object)=0.6, μ_{water}(object)=0.8, $\mu_{vegetation}$(object)=0.3.

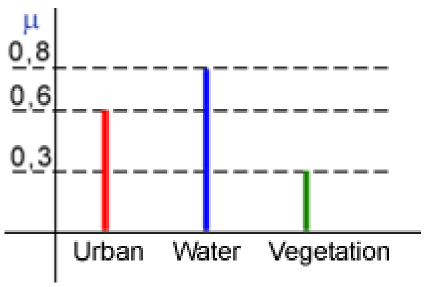


Figure 4.10 : Membership degree values of an image object for different classes [109].

III. Defuzzification. Defuzzification is the reverse process of fuzzification. So, the output of this process is a crisp classification. To produce land cover classification results finally, the fuzzy results have to be translated back to a crisp value, in which an object is either assigned to a class or not [114].

For defuzzification of classification results, the class with the highest membership degree is chosen as the final class. (Equation 4.12)

$$f = max\ \{\mu_{class1}(obj), \mu_{class2}(obj), \dots \mu_{classn}(obj)\} \qquad \textbf{(4.12)}$$

Class assignment equals to the class *i* with the highest members. If the membership degree of a class is below a certain value, no classification is performed and minimum reliability is ensured. As this output discards the uncertainty of fuzzy classification, this step is the final step of information extraction process [114].

Classes are formed by defining a value interval for the descriptive feature or features. All image objects take different membership values for each feature and consequently for each class.

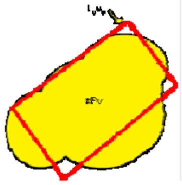
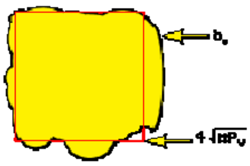
The features used to form classes in this study are given in Table 4.2 with their formulas

where;

P_v:	Set of pixels of an image object v and equals to {(x,y) :(x,y) ε v}
$\#P_v$:	Total number of pixels contained in P_v
$c_k(x,y)$:	Image layer value at pixel (x,y)
c_k^{min}:	Darkest possible intensity value of layer k
c_k^{max}:	Brightest possible intensity value of layer k
$\bar{c}_k$:	Mean intensity of layer k
$\sigma_k(v)$:	Standard deviation of layer k of an image object v
(x,y) :	Pixel coordinates
c_{krange} :	Data range of layer k
c_{krange} :	$c_{kmax} - c_{kmin}$
γ_v^{EV}:	The ratio of the eigenvalues of the covariance matrix with the larger eigenvalue being the numerator of the fraction.
γ_v^{BB}:	Ratio length of v of the bounding box
l_v:	Length of an image object v
w_v :	Width of an image object v
b_v:	Image object border length
$4\sqrt{\#P_v}$:	Border of square with area #Pv
i :	The row number
j :	The column number
$P_{i,j}$:	The normalized value in the cell i,j
N :	The number of rows or columns

***** The gray level co-occurrence matrix (GLCM) is shortly explained in Appendix A1.

Table 4.2 : The features used for class descriptions.

Feature	**Description**	**Formula**	**Feature Value Range**
Mean Value	Layer mean value ck(Pv) is calculated from the layer values ck(x,y) of all #Pv pixels forming an image object.	$\overline{c_k}(v) = \overline{c_k}(P_v) = \frac{1}{\#P_v} \sum_{(x,y) \in P_v} c_k(x,y)$ **(4.13)**	$[c_k^{min}, c_k^{max}]$
Standard Deviation	Standard deviation is calculated from the layer values of all n pixels forming an image object.	$\sigma_k(v) = \sigma_k(P_v) = \sqrt{\frac{1}{\#P_v}\left(\sum_{(x,y)\in P_v} c_k^2(x,y) \sum_{(x,y)\in P_v}\right.}$ **(4.14)**	$[0, \frac{1}{2} c_k^{range}]$
Length / Width	The ratio l/w is identical to the ratio of the eigenvalues of the covariance matrix with the larger eigenvalue being the numerator of the fraction.	$\gamma_v = min\gamma_v^{EV}, min\gamma_v^{BB}$ **(4.15)**	$[0, \infty]$
Width			
Compactness	The compactness of an image object v is calculated by the product of the length l and the width w and divided by the number of its pixels #Pv. 	$\frac{l_v \times w_v}{\#P_v}$ **(4.16)**	**[0, 1]** **1=ideal**
Shape Index	It is the border length e of the image object divided by four times the square root of its area A. 	$\frac{b_v}{4\sqrt{\#P_v}}$ **(4.17)**	
GLCM* Dissimilarity	It is a dissimilarity characteristic of the object decided by GLCM.	$\sum_{i,j=0}^{N-1} P_{i,j}\lvert i-j\rvert$ **(4.18)**	[0,90]
GLCM* Homogeneity	It is a homogeneity characteristic of the object decided by GLCM.	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$ **(4.19)**	[0,90]
NDVI	Spectral arithmetic formula that to identify vegetation areas.	NDVI = (NIR - RED) / (NIR + RED) **(3.1)**	**−1,+1**

As indicated, to define each class, expressions are used. The membership function describes the calculation of membership value for a specific expression. Each membership function is created and defined for a certain feature value of an image object [109].

Setting the minimum, maximum and threshold values, one of these membership functions suitable for the feature can be used: “Larger than, Smaller than, Larger than (Boolean, crisp), Smaller than (Boolean, crisp), Larger than (linear), Smaller than (linear), Linear range / Triangle (V), Linear range / Triangle (inverted V), Singleton (exactly one value), Approximate Gaussian, About range, Full range” (Figure 4.11).

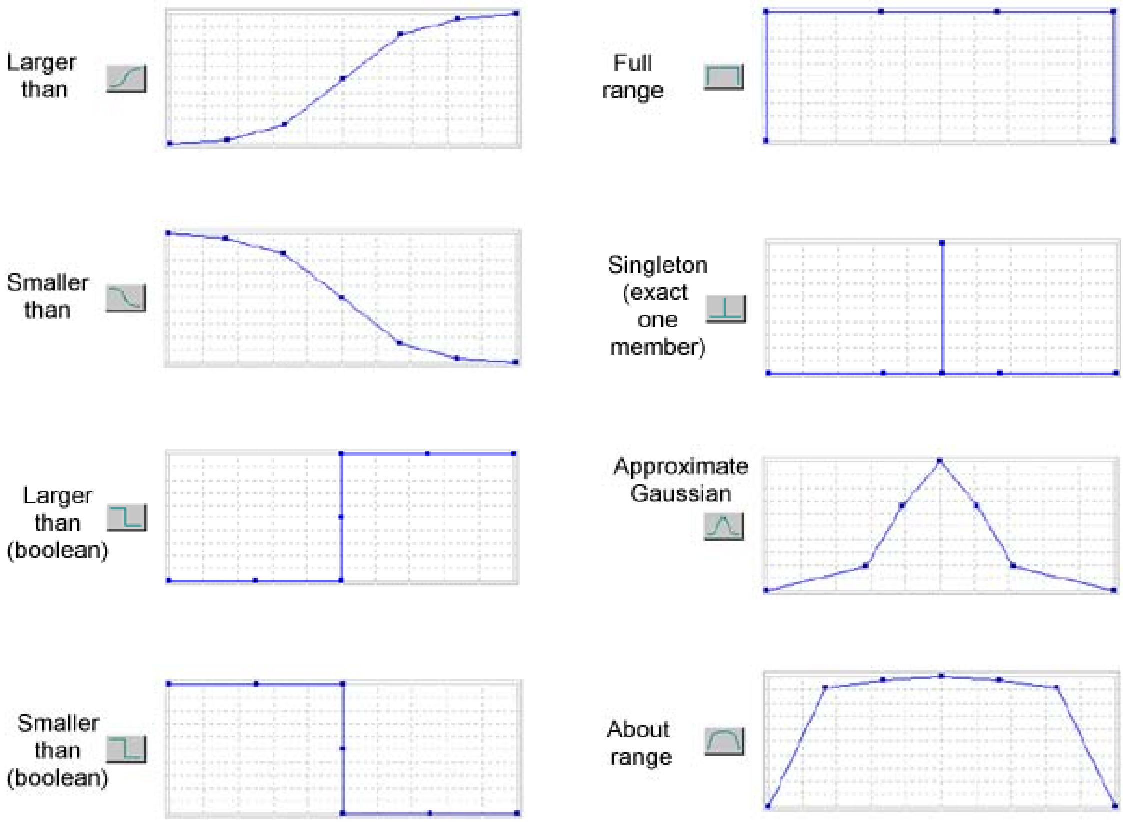


Figure 4.11 : Slopes of the available membership distribution functions [109].

With a specialized knowledge of a feature’s distribution, the function slope can be adapted according to the requirements.

4.2.3.1 Condition-Based Classification

Each class description consists of an expression or a set of expressions. These can be defined by a simple condition or a combination of conditions.

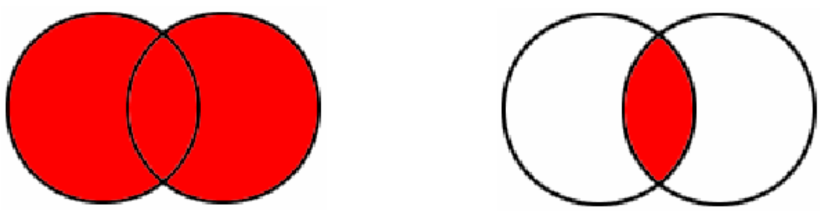
A single condition is defined by a one-dimensional membership function. It is used when all available knowledge can be defined by a single condition to make the class assignment. Its structure is a simple [If -> then] rule sentence representing the class assignment due to only one condition, one single fuzzy feature [114].

Usually, the rules necessary to describe classes cannot easily be defined by only one single condition. Therefore, class descriptions often consist of combinations of conditions connected by operators such as “and”, “or” and “not” [114]. Its structure is as combinations of [If -> then] rule sentences combined by logical operators.

When a class description is composed of expressions, these are connected by logical operators. To represent this kind of conditions, logical combinations of features have to model these multidimensional dependencies in the feature space. The modeling is performed with fuzzy logic concepts such as `and` and `or`.

Or (max): The conditions combined by the maximum operator (combination of conditions) take the highest membership value (Figure 4.12a).

And (min): The conditions combined by the minimum operator (intersection of conditions) take the lowest membership value (Figure 4.12b).



(a) (b)

Figure 4.12 : Fuzzy logic operators (a) or (max) combination (b) and (min) intersection.

In general, the logical operators used are:

Or (max)	: returns the maximum of the fuzzy values
mean (arithmetic)	: returns arithmetic mean of the fuzzy values
And (min)	: returns the minimum of the fuzzy values
mean (geo.)	: returns geometric mean of the fuzzy values
and (*)	: returns the product of the fuzzy values
not	: returns inversion of a fuzzy value

Expressions and logical operators provide flexible and specific definitions to form well-structured class descriptions.

In Figure 4.13 both constellations for a class description represent the same condition using operators in two different ways [109].

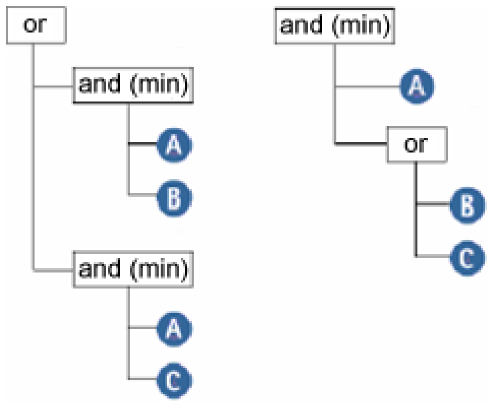


Figure 4.13 : Operators used to describe classes [109].

4.2.3.2 Nearest Neighbor Classification

The Nearest Neighbor classifier is based on given sample image objects within a defined feature space as in a supervised classification [109].

By definition of representative set of sample objects for a feature forms the membership function of that feature and finally the membership functions of each class is formed (Figure 4.14).

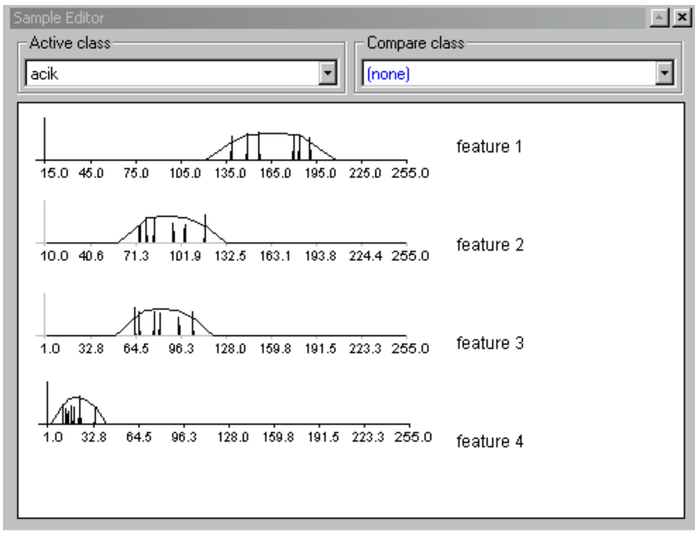


Figure 4.14 : Sample objects' feature values form the related distribution functions.

The principle for the nearest neighbor classification is, declaring the representative set of sample objects for each class and then run the algorithm to make a search for each image object to find for the closest object in the feature space.

The fuzzy realization of the nearest neighbor approach automatically generates multidimensional membership functions. The closer an image object is located in the feature space to a sample of class A, the higher the membership degree to this class. The distance is computed as [109]:

$$d = \sqrt{\sum_f \left(\frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f}\right)^2} \qquad \textbf{(4.20)}$$

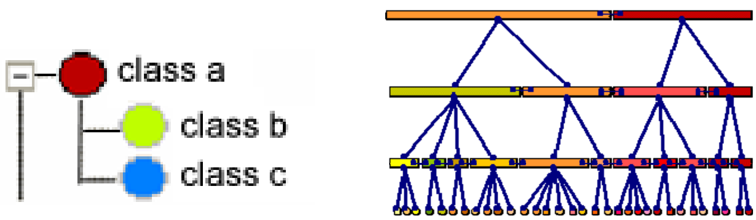
where d: distance between sample object s and image object o, $v_f^{(s)}$: feature value of sample object for feature f, $v_f^{(o)}$: feature value of image object for feature f, σ_f: standard deviation of the feature values for feature f. The distance in the feature space between a sample object and the image object that will be classified is standardized by the standard deviation of all feature values. This allows features in a varying range to be combined in the feature space for classification. Due to the standardization, the distance value d=1 means that, the distance equals to the standard deviation of all feature values of the feature space. Based on the distance d, a multidimensional, exponential membership function is computed which results with different membership values depending on the different distances between image object and sample object [109].

4.2.4 Hierarchical Structure

The classification hierarchy is based on different image object levels and a strong hierarchy allows an advanced multi-scale classification strategies [117].

After all class descriptions are ready for condition-based algorithms or nearest neighbor classifiers, relations can be defined to make up a hierarchical structure.

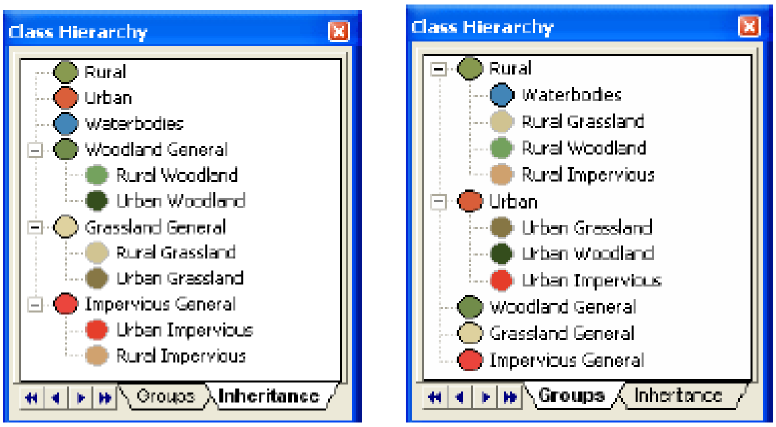
The class hierarchy knowledge can be seen in Figure 4.15a which is the first step to create the knowledge base for a given classification task. It contains all classes and it is organized in a hierarchical structure where image objects are in relation with the other level's image objects through this hierarchy (Figure 4.15b).



(a) (b)

Figure 4.15 : Class hierarchy (a) structure, (b) network of image objects.

Thus a meaningful semantic grouping of classes in the groups' hierarchy is formed (Figure 4.16).



(a) (b)

Figure 4.16 : Hierarchy in two viewpoints: (a) inheritance and (b) groups hierarchy.

Consequently, the analysts have multi-scale classification ability, in which the image objects have sub- and super- relations between each other (Figure 4.17).

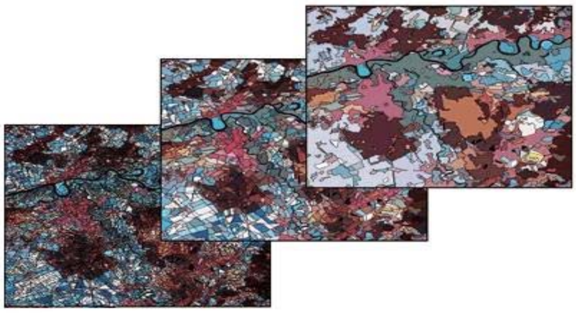


Figure 4.17 : Classification hierarchy [109].

4.2.5 Accuracy Assessment

When using fuzzy classification methods, objects can belong to several classes with different degrees of membership. Hence, if class overlaps exist, then this should be evaluated. In other words, some objects fulfill the criteria of more than one class and their feature values reside in these overlapping ranges. Although fuzzy concepts make it possible to define ambiguities, the main is to define classes as unambiguously as possible [109].

There are accuracy assessment methods producing statistical outputs to check the quality of the classification results.

a) Classification stability

The difference between the best class assignment and the second best one is calculated as a percentage. The statistical output displays basic statistical operations performed on the best-to-second values per class.

b) Best Classification result

The statistical output is evaluated per class. Basic statistical operations such as number of image objects, mean, standard deviation, minimum value and maximum value are applied on classes to perform the best classification result [109].

c) Error matrix based on TTA (training and test area) mask

Test areas are used as a reference set to check classification accuracy by comparing the classification with ground truth, based on pixels.

d) Error matrix based on samples

This is similar to ‘Error matrix based on TTA mask’, however it is not based on pixels but it considers samples derived from manual inputs.

5. PROCESS-BASED IMAGE ANALYSIS

Automation is defined as the use of control systems and information technologies to reduce the need for human intervention [118]. In every field of life, technology is getting things done easier, faster, more accurate and with less requirement of human effort. Automation is currently in use either in a simple or a complex form, and it is obvious that there is a change going from partly to fully automation. Generally, the change is in evaluation and goes step by step with technological development. Improvements start with the transformation of work steps from manual to automated systems and each time more of the steps in a sequence are automatized. By completing the combination of all steps in the future, full automatic systems will be realized.

As in many fields of information technologies, the need for timely, accurate and interoperable geo-spatial information is steadily increasing. It is necessary to synchronize and standardize technologies and harmonize approaches related to the acquisition, processing, and retrieval of multi-sensor, multi-spectral, multi-resolution data from various sensors. The availability of such data, systematization and the increasing worldwide use of geo-information will catalyze the development of new methods to exploit image information more ‘intelligently’ [119].

Over the last years, advances in computer technology, earth observation sensors, remote sensing and GIS technology have led to the emerging field of process-based analysis. Process-based image processing and analyzing systems will be the initial segment for automatic systems.

As indicated by Blaschke and Lang, identifying and extracting objects of interest in remotely sensed images can be distinguished to two types of approaches: manual and task-specific automated approaches. In the first approach, a trained image analyst manually identifies features of interest using various image analyzing and digitizing tools. Features are hand-digitized, attributed and validated by the analyst during geospatial data production workflows. Although today it is still the predominant approach to produce geospatial data, it is not efficient because of the laborious, time consuming nature of manual feature identification. The second approach has been developed by the researchers since 1970s. The researches were attempting to automate the object recognition and feature extraction process from imagery by using task-specific computer programs [119].

The earlier algorithms developed were using traditional image analyzing methods through an automatic process such as the system developed by Geographical Survey Institute (GSI) -the national mapping organization in Japan which performs process-based image analyzing applications by using pixels as information sources [120]. Also, Schneidewind et al. developed an automated approach to find optimal parameter settings for pixel-based visualizations [121].

While a vast majority of remote sensing applications still rely on pixel-based classification methods, the demand for context-based algorithms and object-based image processing techniques is increasing. In recent articles, it has been claimed that “Object-oriented processing techniques are becoming more popular compared to traditional pixel-based image analysis” [103]. Even a first, brief literature search reveals that publications in the early period of object based image analysis (2000 to 2003/04) were dominated by conference proceedings and ‘grey’ literature, but increasing numbers of empirical studies published in peer-reviewed journals have subsequently provided sufficient proof of the improvements that object based analyzing offers over per-pixel analyses [97].

According to the indicated trend of using object-based image analyzing methods, they will probably be used more through process-based systems in the future. For example, better approaches than pixel-based approach are searched in MARS (Monitoring Agricultural Resources) Project of European Commissions’ Joint Research Center Institute for Environment and Sustainability which includes an automatic classification system for an agricultural application. In this project, a number of methods for automatic classification have been proposed. These range from simple pixel based unsupervised classifications to supervised parcel-based classifications. They report that “for automatic classification new classification approaches may have to be considered to exploit or manage the additional texture information” [122].

Yan, 2003 mentioned that, it has shown highly encouraging results in assessing spatial and spectral patterns at varied scales in intelligent classification of aerial and satellite imagery [114]. Filip Hajek mentioned that “The predominant visual interpretation and pixel-based automated techniques are now being gradually replaced by the object-based image classification at multiple levels” [123].

Although it is still a new approach, when the success of the method is considered, it may be thought as a promising one to provide more successful results than traditional ones when used through a process-based system.

A process-based system is a good approach for agricultural purposes since the agricultural activities occur according to a cycle. Observation of crop development, detecting yearly changes, determining regional parameters, accurate assessment of crop damage and/or crop yield can be applied more successful if realized by a repeatable system. However, there may be still some problems such as a process-based system will need many parameters of input data to be same or stable/constant.

In this thesis, the first step of a process-based system is realized. The process tree is written, however, the process steps and the values of the parameters have to be updated and improved with next years' datasets as a further study.

Also a developed process system has to be adapted to future needs, industry demands and repeatable and transferable solutions. The challenge is developing a flexible approach for transferring domain knowledge of a feature extraction model from image to image that is capable of adapting to changing conditions (image resolution, pixel radiometric values, landscape seasonal changes, and the complexity of feature representation) [119].

6. APPLICATION

Turkey has 39 million hectares of agricultural land, hence agriculture is of key importance both in social and economic terms [123]. For developing countries like Turkey, estimation of the yield has a vital importance [124]. Therefore, the ability to crop discrimination (or crop type mapping) which is the essential step for crop yield estimation and agricultural planning activities, is very important.

The main purpose of this thesis is to perform crop discrimination over the study area by process-based image analysis. Object-based classification is used through the process tree. Theobjective was to obtain the most suitable function types and threshold values of the parameters for two different image datasets. An incremental process was executed to obtain the classified image, which was applied on a multitemporal dataset.

6.1 Study Area: Türkgeldi State Production Farm

Türkgeldi State Production Farm (SPF) is located in the Thrace Region of Turkey in Kırklareli City, included by the borders of Lüleburgaz district (Figure 6.1).

Figure 6.1 : Map and satellite image of Türkgeldi region.

Türkgeldi State Production Farm is located on E 27.12º, N 41.41º far from the city center by 65 km. This farm has a total area of 1905 ha. for agricultural usage and has a height of 46 m. above sea level.

There is Mediterranean climate with an average annual rainfall of 557 mm. and average annual temperature of 12.3 ºC [126].

Türkgeldi SPF is made up of two very different characterized physiographic units. One type is the high lands -as 60 km. above sea level- made up of old clay sedimentation. The other is the region all around Ergene stream -as 40-45 km. as above sea level- which is alluvial lands [126].

There are partly some leftovers of forest consisting of 3-4 oak types and ulmus tree. Makebate is the natural vegetation cover of the land [126].

Agriculture, gardening and livestock activities are the main functions of the SPF. The agricultural activities include mainly the wheat and additionally sunflower, barley, artificial feeding ground (meadow), clover, vetch and gruel production [127]. In gardening activities vegetable seeding (tomato, cruet, aubergine and bean) is maintained over a relatively smaller area [126].

The main water resource of the farm is the 8 deep wells which are drilled to benefit from the underground water resources. Till to the recent years, the Ergene River which flows along the south and east of the SPF was being used as the major irrigation source for the farm. Since the pollution of the river water caused by the contamination of the waste waters of the textile and medical industry, this natural resource has unfortunately lost its employability [127].

There is intense activity with respect to harvesting and regeneration. In this production farm, mostly wheat is the main product and has approximately 3000-ton capacity in a year. In addition, sunflower, corn, canola, clover, and vetch are the other agricultural products that are aggregated.

Field photographs of the Türkgeldi SPF are shown in Figure 6.2.

Figure 6.2 : Field photographs of the Türkgeldi SPF [128].

6.2 Datasets

Two different datasets were used for application:

1. **Optical Dataset:** The images of the dataset-1 were acquired over Türkgeldi region by SPOT-4 satellite.
2. **Radar Dataset:** The images of the dataset-2 were acquired over Türkgeldi region by JERS-1 satellite.

The details of the datasets used are given in Table 6.1:

Table 6.1 : The details of image datasets used.

Dataset #	Study Area	Sensor Type => Satellite	Acquisition Date
Dataset-1	Türkgeldi SPF	Optical => SPOT - 4	26.04.2007 22.06.2007 24.07.2007 30.08.2007 04.10.2007
Dataset-2		Radar => JERS - 1	03.02.1997 19.03.1997 02.05.1997 11.09.1997 25.10.1997 08.12.1997

6.2.1 Optical Image Dataset

The images of the dataset-1 were acquired over Türkgeldi region by SPOT-4 satellite which is one of the sensors in optical sensors category.

The technical properties of SPOT-4 satellite and SPOT-4 images are given in Table 6.2 and Table 6.3, respectively [129].

Table 6.2 : Technical properties of SPOT-4 satellite.

Operator	SPOT IMAGE
Design Life (years)	7
Launch Date	24 March 1998
Mass (kg)	2550
Orbit Type	Polar Sun Synchronous
Orbit Height (km)	832
Orbit Inclination (°)	98.7
Orbit Cycle (day)	26
Equatoral Crossing -Descending	10:30 AM
Onboard Data Recorder (Gb)	240
Data Rate (Mbps)	50
Number of Sensors	3

Table 6.3 : SPOT-4 image properties.

BANDS / PROPERTIES	Wavelength min. (µm)	Wavelength max. (µm)	Spatial Resolution (m)	Swath (km)
Band 1 (Green)	0.500	0.590	20	60
Band 2 (Red)	0.610	0.680	20	60
Band 3 (NIR)	0.780	0.890	20	60
Band 4 (NIR)	1.580	1.750	20	60

The images of dataset-1 were searched upon Sirius SPOT online archive system (Figure 6.3) and five images on suitable dates were selected.

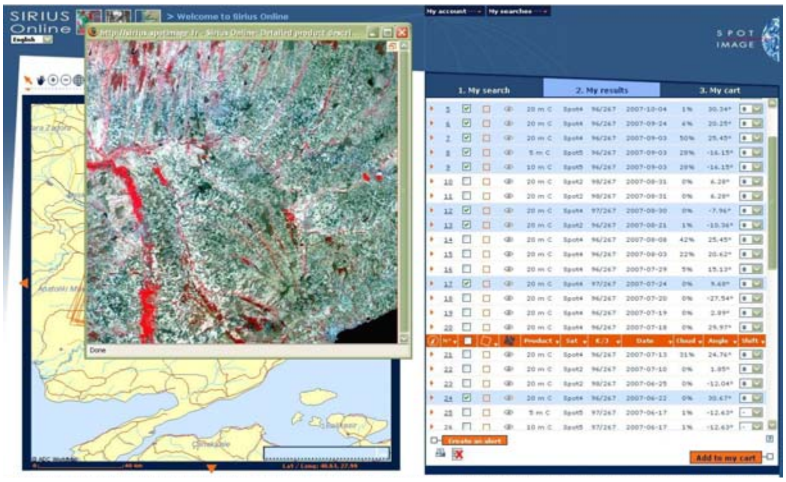
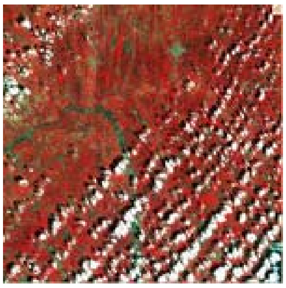
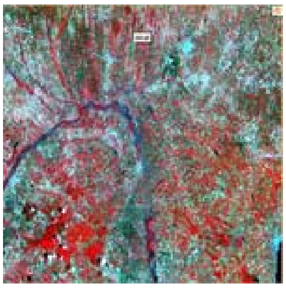


Figure 6.3 : Interface of SPOT online archive search.

Quicklooks (QL)s of the optical images used are shown in Table 6.4.

The problem with the optical dataset was the clouds which existed in the 26.04.2007 dated image. Some of the clouds were over the south part of the study area. However, the data was not neglected since its acquisition date was a good one for applying a multitemporal analyze according to the crop calendar.

Table 6.4 : QL images of optical dataset (Dataset-1).

Date	Quicklook image
26.04.2007	
22.06.2007	
24.07.2007	
30.08.2007	
04.10.2007	

6.2.2 Radar Image Dataset

The images of the dataset-2 were acquired over Türkgeldi region by JERS-1 satellite which is one of the sensors in radar sensors category.

Technical properties of JERS-1 satellite and image properties are given in Table 6.5 and Table 6.6, respectively [130].

Table 6.5 : Technical properties of the JERS-1 satellite.

Operator	NASDA, JAXA
Design Life (years)	2
Launch Date	11 February 1992
Mass (kg)	1400
Orbit Type	Sun Synchronous
Orbit Height (km)	568
Orbit Inclination (°)	8
Orbit Cycle (day)	44
Local Time At Descending Node	10:30-11:00 AM
Onboard Data Recorder (Gb)	240
Data Rate (Mbps)	30
Number of Sensors	2

Table 6.6 : JERS-1 image properties.

Wavelength	24 cm (L-band)
Bandwidth (MHz)	15
Polarization	HH
Look Angle (º)	35.21
Data Quantization (bits)	3
Data Rate (Mbit/s)	60
Spatial Resolution	12.5 m.

The six images of dataset-2 were found upon DESC online archive (Figure 6.4).

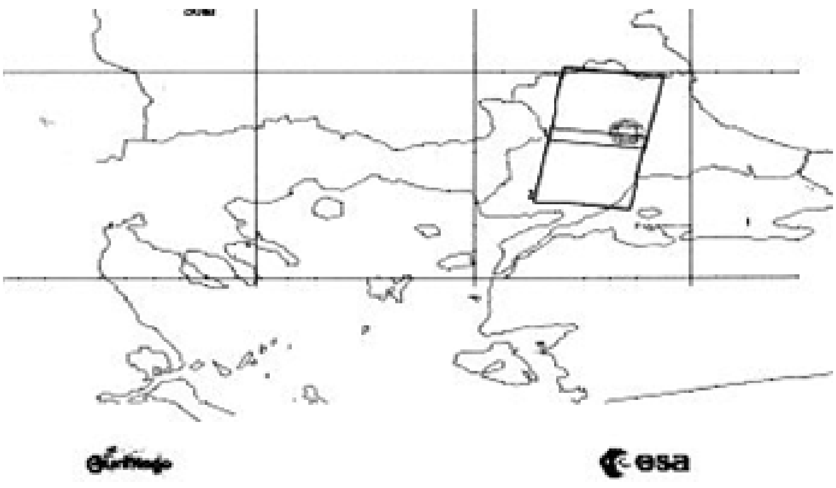
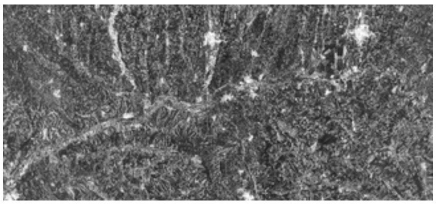
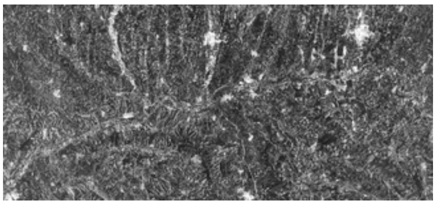
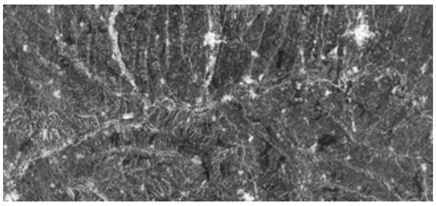
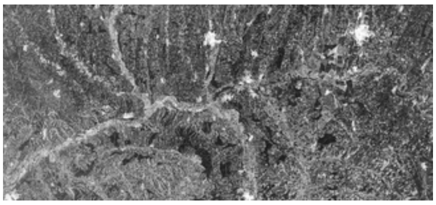
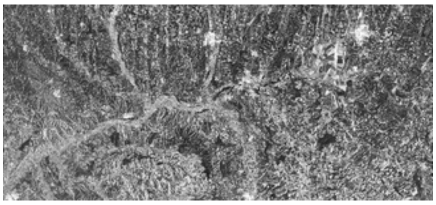
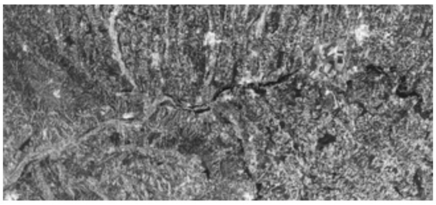


Figure 6.4 : Interface of JERS online archive search.

(QL)s of radar images used are shown in Table 6.7.

Table 6.7 : QL images of radar dataset (Dataset-2).

Date	Quicklook image
03.02.1997	
19.03.1997	
02.05.1997	
11.09.1997	
25.10.1997	
08.12.1997	

The dataset had the ideal dates and also there were no cloud problem as an advantage of radar data.

6.3 Ancillary Data

Ancillary data may include crop maps, crop calendar, any other data about the crop or planting properties, and the related environment. For this study, crop maps of the study area were obtained from the Türkgeldi SPF.

1) **Optical Dataset:** 2007 crop map of the Türkgeldi SPF is given in Figure 6.5.

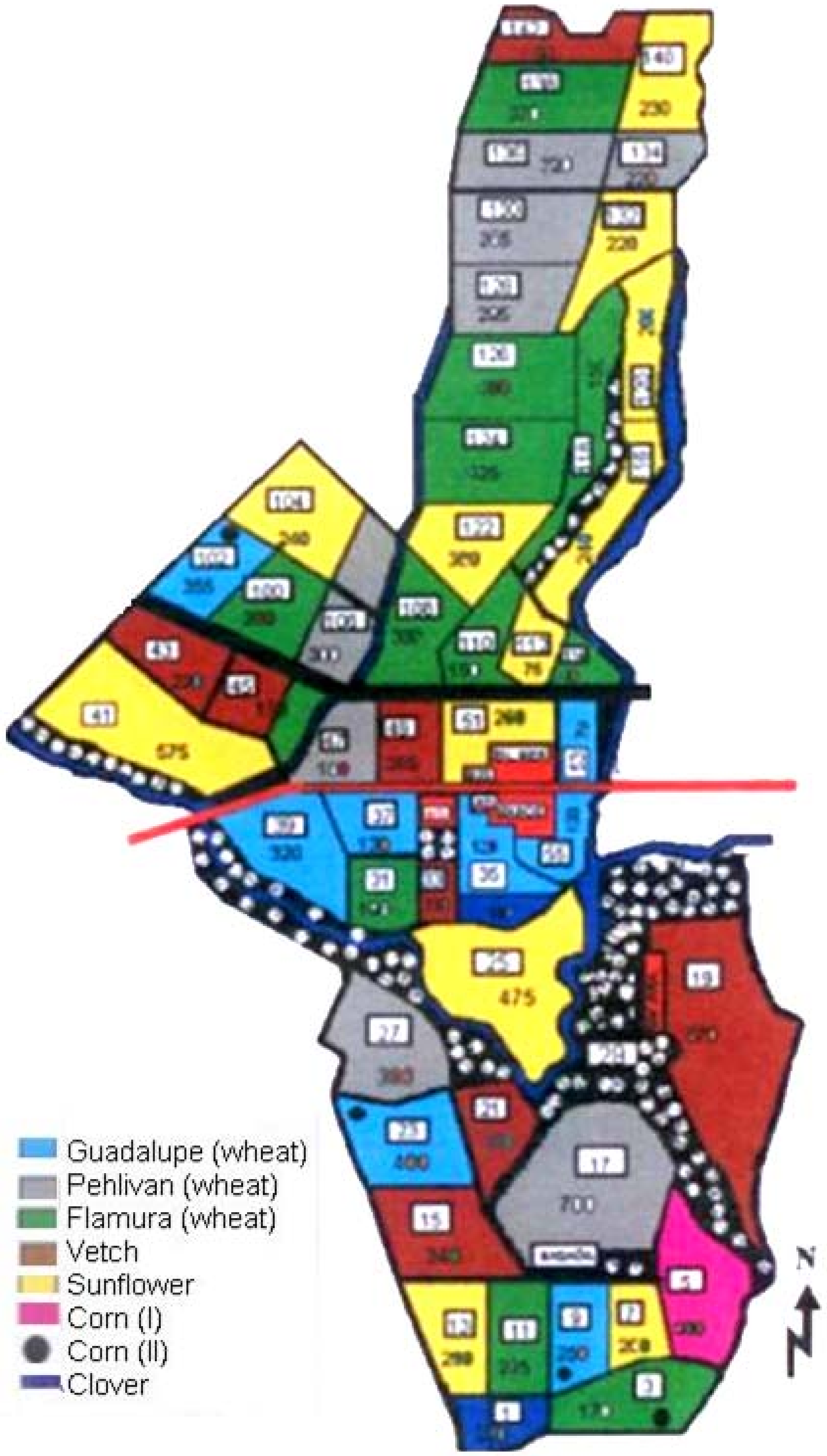


Figure 6.5 : 2007 crop map of Türkgeldi SPF [131].

2) **Radar Dataset:** 1997 crop map of the Türkgeldi SPF is given in Figure 6.6.

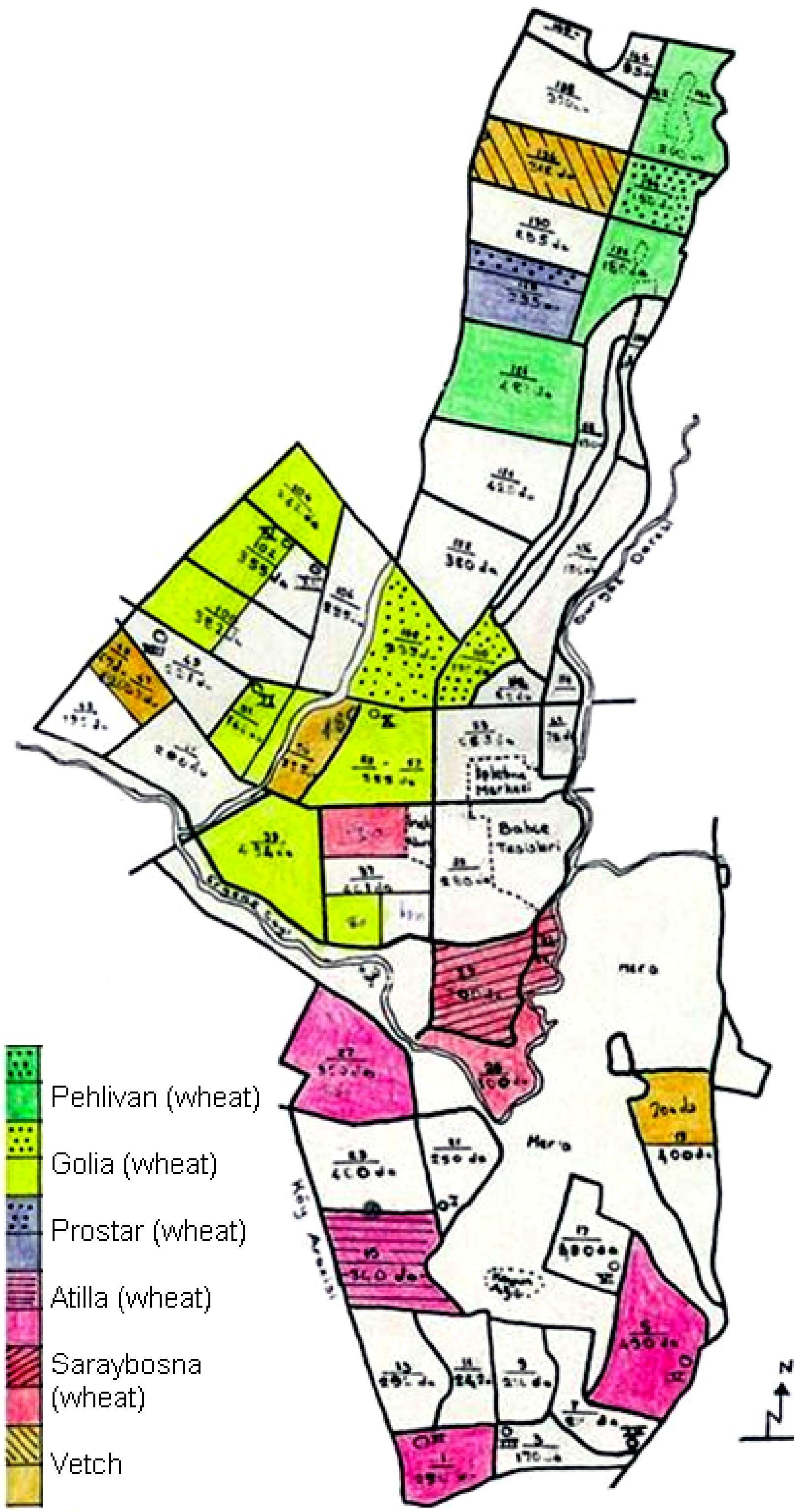


Figure 6.6 : 1997 crop map of Türkgeldi SPF.

The crop type information of the empty represented fields was learned from the Türkgeldi SPF [132].

6.4 Preprocessing

The preprocessing step which includes radiometric, atmospheric and geometric corrections was not applied on the images, since the purpose of this study was testing the success of the process-based image processing applications based on raw data using minimum human interaction. In the same manner, image enhancement methods were also not applied on datasets.

As a preprocessing process, registration (image to image) was performed to form an image dataset.

6.4.1 Application I: Optical Image Dataset

The sub images of about 500 * 600 pixels extracted from the original image frames were registered to each other by 1st degree polynomial and nearest neighbor resampling method.

In Table 6.8, registration parameters used are given.

Table 6.8 : Registration parameters used for optical image dataset.

Date	Number of GCPs	RMS Error
26.04.2007 (base image)	-	-
22.06.2007	8	0.45
24.07.2007	9	0.49
30.08.2007	8	0.54
04.10.2007	7	0.45

In Figure 6.7 co-registered images of the dataset are shown.

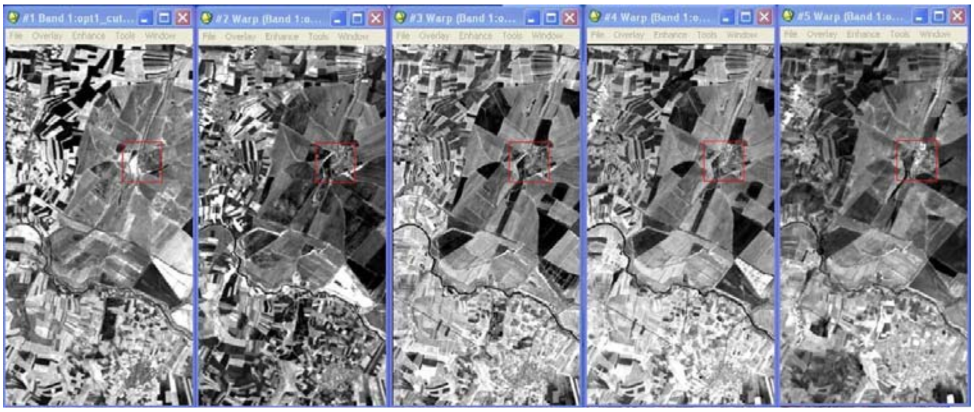


Figure 6.7 : Co-registered optical image dataset.

6.4.2 Application II: Radar Image Dataset

The sub images extracted from the original image frames were registered to each other.

As a first step, the ground control points that represent clearly identifiable points in the images were selected. In Figure 6.8, the GCP points used for registration are shown.

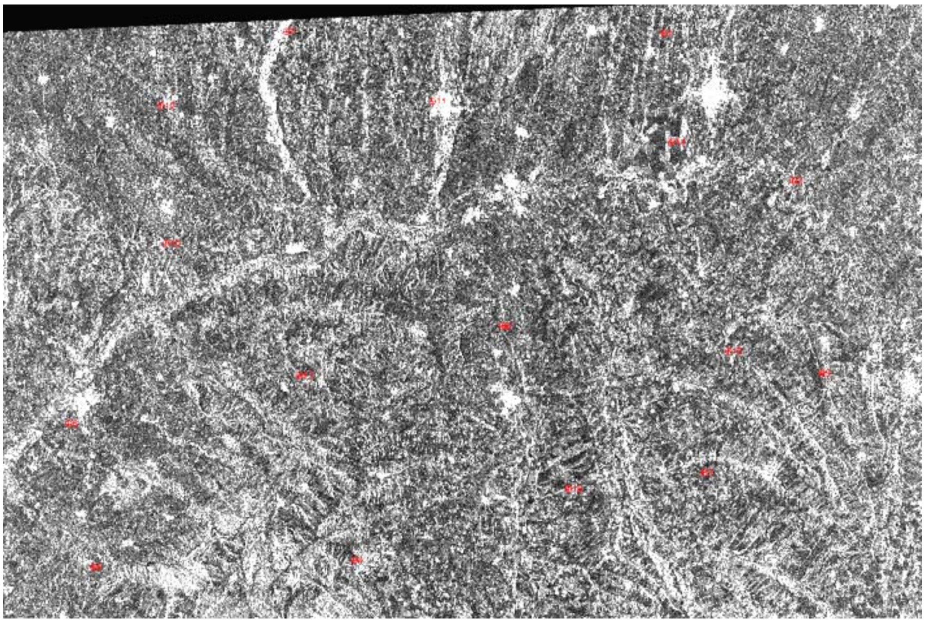


Figure 6.8 : The GCPs used in co-registration of the radar image dataset.

In Table 6.9, the registration parameters used are given.

Table 6.9 : Registration parameters used for radar image dataset.

Date	Number of GCPs	RMS Error
03.02.1997	16	0.353
19.03.1997 (base image)	-	-
02.05.1997	16	0.329
11.09.1997	16	0.329
25.10.1997	16	0.354
08.12.1997	16	0.338

6.5 Process-Based Image Analysis

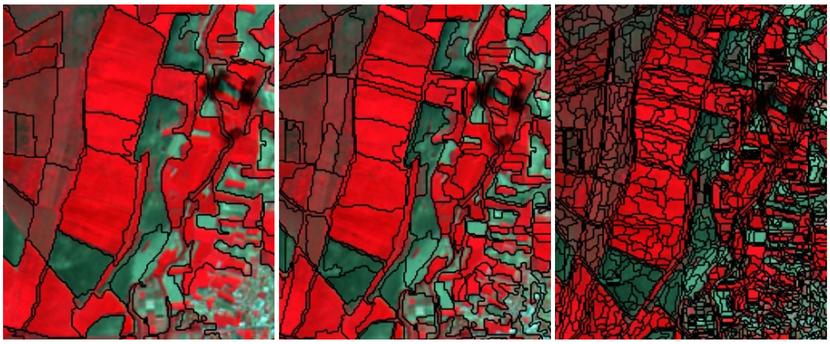
In the application, the Definiens software, a commercial object-based image processing program under the license of Definiens AG Company, was used.

6.5.1 Application I: Optical Image Dataset

6.5.1.1 Segmentation

The segmentation step is very important, since it totally affects the classification success of the study. In this study to obtain the best results, the values of the scale parameter and other parameters were decided after many combinations were tested regarding to visual analysis.

It was observed that scale parameter 50 was convenient to distinguish the river and urban regions. The scale parameter 20 was convenient as a second level, as it was observed that the image objects correctly fit the fields of the study area. However, it was seen that there are smaller fields outside the study area at the surrounding region, Scale parameter 20 was not sufficient for these, so the study was enhanced with one more level, in which the scale parameter was selected as 5 after it was seen that this value is a good segmentation scale for the surrounding fields (Figure 6.9).



(a) (b) (c)

Figure 6.9 : Image segmentation for scale parameters a) 50, b) 20 c) 5.

Also, the other parameters such as color, shape, compactness and smoothness, were tested. The results were evaluated to select the most convenient partitioning related to geographical features of the region. After these tests, the required values shown in Table 6.10 were selected for the study area. It was seen that when the shape parameter value is increased more than 0.1, some of the parts inside the fields were broken (i.e. through the planting rows). When the compactness is increased, it was seen that the fields are broken into smaller regions according to selection of more homogeneous parts. When smoothness is increased, the crops having similar spectral values were grouped as one field.

As experienced, if this region was not a well managed agricultural area, different parts might have been contained within a field such as less irrigated or unhealthy regions. In this case, the fields may require a high scale parameter than a sufficient one bordering the fields, but then they would have to be combined later (such as an less irrigated part and the healthy part of the same wheat field)

Table 6.10 : The most convenient segmentation parameters.

Level	Weight for Layers 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	Scale Parameter	Color	Shape	Compactness	Smoothness
Level 1	0,0,0,0, * 1,1,1,1, 1,1,1,1, 1,1,1,1, 1,1,1,1	50	0.9	0.1	0.5	0.5
Level 2	0,0,0,0,* 1,1,1,1, 1,1,1,1, 1,1,1,1, 1,1,1,1	20	0.9	0.1	0.5	0.5
Level 3	0,0,0,0,* 1,1,1,1, 1,1,1,1, 1,1,1,1, 1,1,1,1	5	0.9	0.1	0.5	0.5

*Since these layers have cloudy data, they were not taken into consideration in the segmentation process.

As seen from the Table 6.10, optical dataset was segmented in three levels. Level 1 was aimed for the extraction of the river and urban mostly. Level 2 was aimed for the extraction of agricultural field boundaries. Level 3 was mostly prepared to make an extraction of the mixing classes which are smaller in regional size. In Figure 6.10, the segmented images of each level are shown.

The number of objects used in each segmentation level are given in Table 6.11.

Once segmentation parameters for the study are defined, it will be constant under the process tree so that the same parameters can be used for future datasets in automated analyzing procedures. This is valid unless the geographical features of the region have main changes. However, it should be also mentioned that the same segmentation parameters are valid for only cloudless images. In that case, clouds have to be taken into account and the weights of the layers have to be checked each time before automated analysis, since the clouds will cause missegmentation of the images. For this study, the weight of the first four layers (bands of first dated image) were chosen as 0 not to effect the segmentation, since this image has a little cloud on top of some agricultural fields.

After segmentation steps were completed, classification procedures were conducted. Every classification level is based on the same level of segmentation.

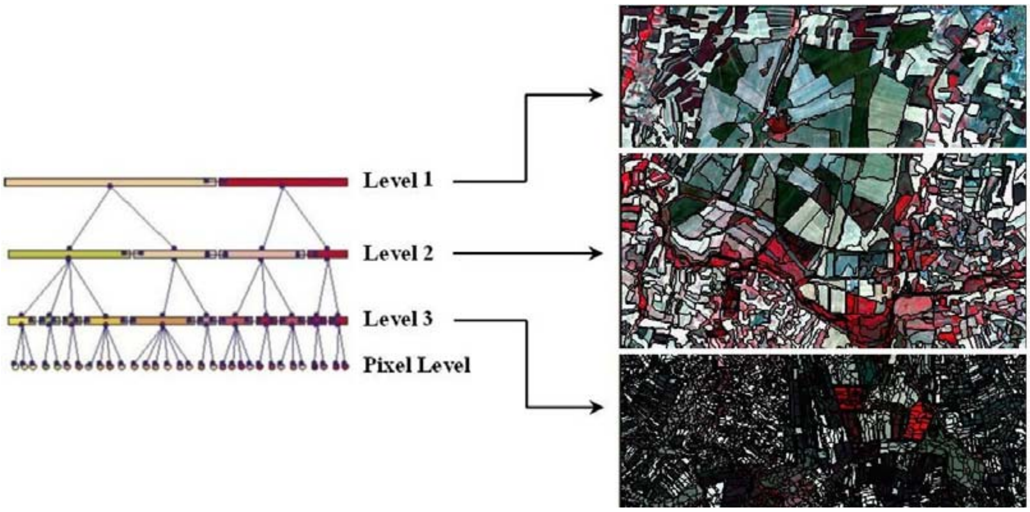


Figure 6.10 : The segmented images of each level.

Table 6.11 : The numbers of the objects used in each segmentation.

Level	Number of Image Objects
Level 1	268
Level 2	1383
Level 3	16631

6.5.1.2 Classification

For each level of classification, classes were defined with features. To decide the features to be used for class definitions, first the criteria that are close to human interpretation were tested such as long and narrow image objects being more likely to belong to river or road classes. As a next step, the features that can only be decided after observing the effects after application (such as texture) were tested for the whole image objects whether this feature can represent a class with a threshold or with a value interval. For example the texture functions such as GLCM homogeneity used for clover was selected after observing its distinguishability from other crops by visual analysis. For this kind of features, all possible choices in the software were tested.

The features or feature combinations that define the classes are shown in Tables 6.12 (for level 1), 6.13 (for level 2) and 6.14 (for level 3). The membership functions were decided to represent the most suitable distribution of the feature and the values were determined.

The same named classes (as river 50 and river 20) have a parent-child relation in a hierarchical network structure. Some classes which exist in the application were not listed in the Tables. These are the classes, for which no criteria were needed, but instead parent-child relations or logical operators were sufficient for these kinds of class descriptions. For example, one of the classes extracted with the use of logical operators through the procedure was river. This class was not redefined with a new criterion since the scale parameter 20 was sufficient for its extraction. In level 3 (where segmentation scale parameter was 5), it was just defined by being a subclass of River 20 class.

Class definitions are listed in the order as appeared in the process tree.

When Tables are examined, it was seen that some classes were defined with a criteria in a low level, and then an additional criteria was defined in the higher level. The reason can be explained with an example. For instance, for urban class example, in the first level the possible urban areas were defined, but final urban class was represented in the second level. Hence, any class having its final level can only be defined by a subclass relation in all higher levels.

Table 6.12 : The features defined in the classes for level 1.

Classes	Subclasses *	Features	Membership Function	Values
River 50		Length / width	Threshold	> 2.9
		Width	Threshold	> 3200 m
Urban 50		Standard deviation for layer 2	Threshold	27
		Standard deviation for layer 4	Full Range	20 – 38
		Standard deviation for layer 13	Full Range	10 – 16

* subclass cells of the Table were left blank since the first level image objects can only be parent objects.

Table 6.13 : The features defined in the classes for level 2.

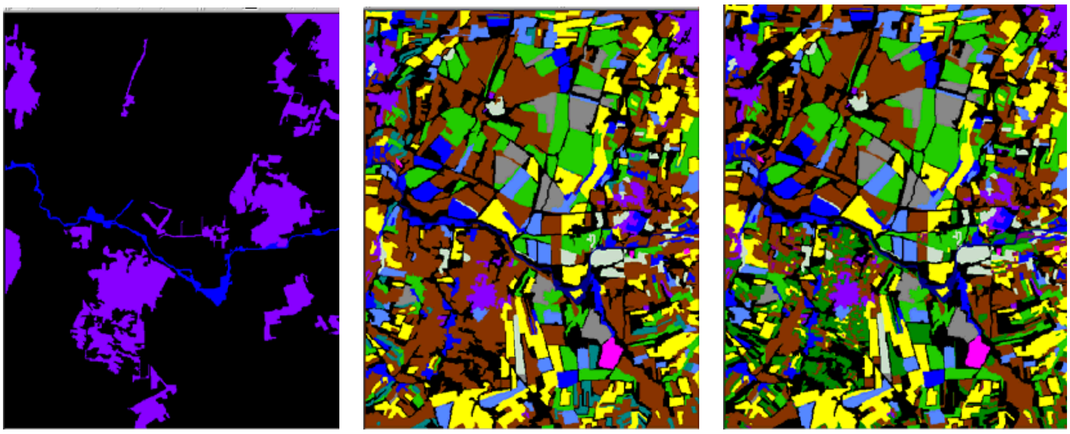
Classes	Subclasses	Features	Membership Function	Values
River 20		Mean layer 9	Full Range	0 – 98
Linearity 20		Compactness	Full Range	3 – 100
Urban 20		Shape index	Threshold	3.2
		GLCM dissimilarity for layer 6 45°	Full Range	13 – 28
		GLCM homogeneity for layer 6	Full Range	0 - 0.08
1st Period Crops 20		NDVI for date 1	Singleton	(-1) - 1
	Wheat or Vetrch (20)	NDVI for date 2	Negative Singleton	(-1) - 1
		NDVI for date 5	Negative Singleton	(-1) - 1
	Corn 2	NDVI for date 5	Singleton	(-1) - 1
	Vetch	NDVI for date 4	Singleton	(-1) – 1
	Vetch type 1	GLCM homogeneity for layer 13 45°	Negative Singleton	0 - 0.3
	Vetch type2	Mean for layer 8	Singleton	50 – 250
	Guadalupe (wheat)	Elliptic fit	Singleton	0 – 1
		Mean for layer 8	About Range	127 – 136
	Pehlivan (wheat)	Mean for layer 5	Linear Range	98.8 - 100.8 89 - 93 102 – 106
2nd Period Crops 20	Sunflower	NDVI for date 3	Negative Singleton	(-1) – 1

Table 6.14 : The features defined in the classes for level 3.

Classes	Subclasses	Features	Membership Function	Values
1st Period Crops 5		NDVI for date 1	Singleton	(-1) – 1
	Wheat - kt or Vetch – kt	NDVI for date 2	Negative Singleton	(-1) – 1
		NDVI for date 5	Negative Singleton	(-1) – 1
	Corn 2 – kt	NDVI for date 5	Singleton	(-1) – 1
	Clover – kt	NDVI for date 4	Singleton	(-1) – 1
	Guadalupe (wheat)-kt	Mean for layer 8	Approximate Gaussian	80 – 180
	Pehlivan (wheat) – kt	Mean for layer 5	Approximate Gaussian	60 – 160
2nd Period Crops 5	Sunflower – kt	Mean for layer 10	Approximate Gaussian	130 - 230
		Mean for layer 11	Approximate Gaussian	110 - 190
		NDVI for date 3	Negative Singleton	(-1) - 1
	Corn 1 – kt	NDVI for date 1	Singleton	(-1) - 1

The classification results of each level are given in Figure 6.11.

The values in the last column of the Table were determined after testing whether they can be used to represent a class. Even it was expected that not to describe features with full range distributions would be a more flexible and better approach, the full ranges gave better results.



(a) (b) (c)

(d)

Figure 6.11 : Classification images at (a) level 1, (b) level 2, (c) level 3 (d) legend.

6.5.1.3 Process Sequence

The classes, features and values were used to determine the final classes and the process was applied through a process tree.

Process sequence had 5 main steps.

Step 1: Segmentation and classification at level 1. In this step, only urban and river classes were determined (Figure 6.12).

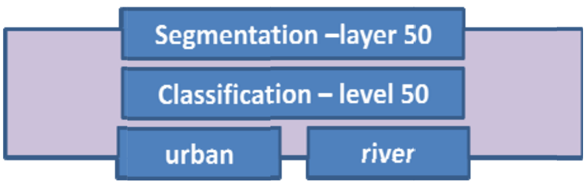


Figure 6.12 : Segmentation and classification at level 1.

Step 2: Segmentation and classification at level 2. In this step, first, road class was determined. After that, Period 1 Crops and Period 2 Crops were determined (Figure

6.13). As a next step, all crop classes were determined in a step by step process (Figure 6.14).

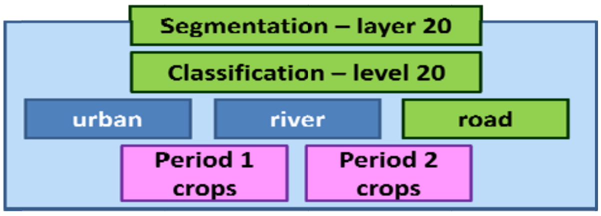


Figure 6.13 : Segmentation and classification at level 2 (Step 1).

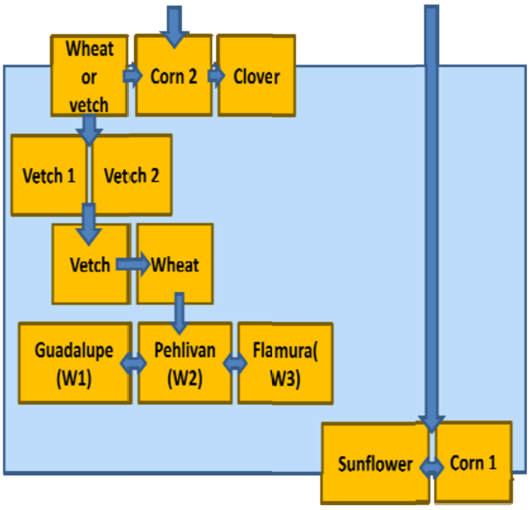


Figure 6.14 : Segmentation and classification at level 2 (Step 2).

Step 3: Segmentation and classification at level 3 was performed. This level was performed for the determination of the crop mapping of surrounding fields. The same procedure was performed for level 5 classification, which was produced from layer 5 segmentation.

Step 4: This step was realized for the final classification. In this step, the classes were extracted from the most suitable level and combined. The best output was obtained by merging the best results for each class. This is the beneficial characteristic of a process-based application and applying object-based approach in a hierarchical structure. By this way, the classification was updated through an iteration process. To reaarange a semantic group and represent a better knowledge, an iterative workflow was proceeded to form the final classification.

Step 5: This step was prepared for the automatic production of the outputs (Figure 6.15).

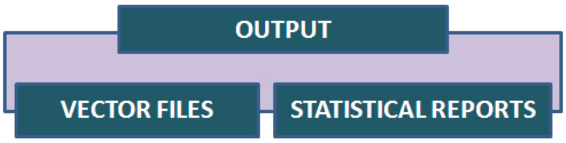


Figure 6.15 : Step for the production of outputs.

Classification result of the optical image dataset is given in Figure 6.16.

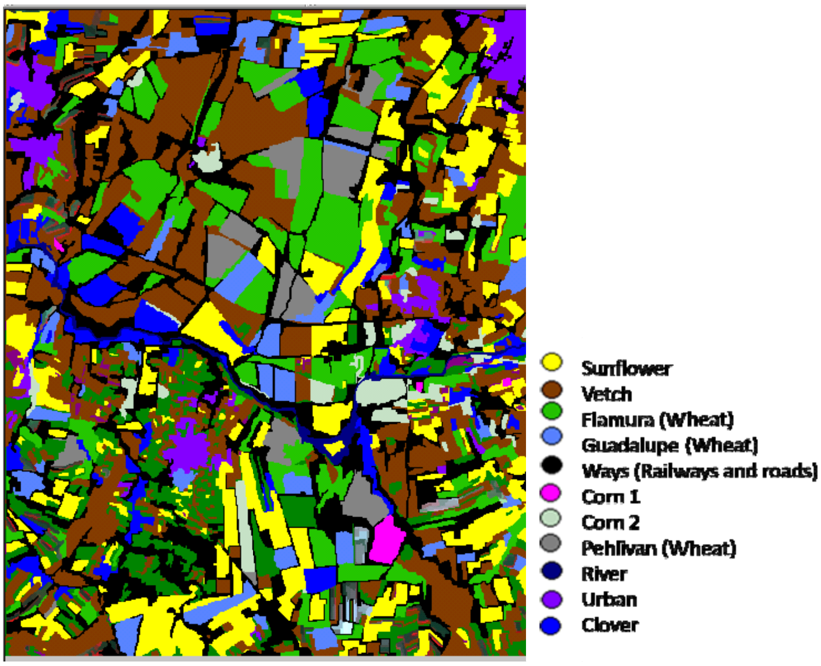


Figure 6.16 : Classified image of the optical image dataset.

It has to be mentioned here that, level 2 classification well represents the study area by means of segmentation and classification for the study area. Therefore, the final classification mainly is based on level 2 classification. However, when considering whole region, it is observed that some classes such as urban or some regions such as small field regions have to be classified in a more high level. Hence, level 3 is created and level 3 classification basically has a more correct classification result for the whole region when evaluated by visual analysis.

Türkgeldi SPF region boundaries were not used in the presentation of the result, since it was not produced as a rectified image.

6.5.1.4 Accuracy Assessment

The error matrix method was applied to obtain the accuracy of the classification. In Figure 6.17, the samples selected as a control set for accuracy assessment is shown. The limitations of this process were; i) random selection was not available, hence, the samples of the control set were selected manually and then compared with the crop map. ii) if some crops are planted only in one (like in corn 1 class in Table 6.15) or in few fields, than the selection of the samples used in the accuracy are restricted and this causes an artificial effect (decrease/increase) in the class accuracy.

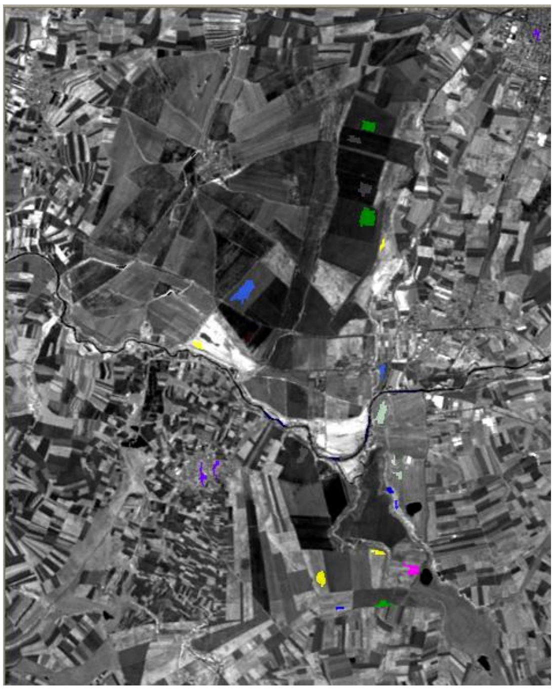


Figure 6.17 : Image objects selected as a control set for accuracy assessment.

The match between the sample objects and the classification is expressed by error matrix given in Table 6.15.

Table 6.15 : Error matrix of the optical dataset classification.

Error Matrix based on Samples

User Class \ Sample	guadalupe	pehlivan	flamura	aycicek	misir1	misir2	yonca	Fig	Ana Nehir Son	Yerlesim Son	Cizgisel Son	Sum
Confusion Matrix												
guadalupe	1	0	0	0	0	0	0	0	0	0	0	1
pehlivan	0	4	0	0	0	0	0	0	0	0	0	4
flamura	1	0	4	0	0	0	0	0	0	0	0	5
aycicek	0	0	0	4	0	1	0	0	0	0	0	5
misir1	0	0	0	0	1	0	0	0	0	0	0	1
misir2	0	0	0	0	0	2	0	0	0	0	0	2
yonca	0	0	0	0	0	0	2	0	0	0	0	2
Fig	0	0	0	0	0	0	0	1	0	0	0	1
Ana Nehir Son	0	0	0	0	0	0	0	0	4	0	0	4
Yerlesim Son	0	0	0	0	0	0	0	0	0	3	0	3
Cizgisel Son	0	1	0	0	0	0	1	0	1	0	3	6
unclassified	0	0	0	1	0	1	0	0	0	0	0	2
Sum	2	5	4	5	1	4	3	1	5	3	3	
Accuracy												
Producer	0.5	0.8	1	0.8	1	0.5	0.6667	1	0.8	1	1	
User	1	1	0.8	0.8	1	1	1	1	1	1	0.5	
Hellden	0.6667	0.8889	0.8889	0.8	1	0.6667	0.8	1	0.8889	1	0.6667	
Short	0.5	0.8	0.8	0.6667	1	0.5	0.6667	1	0.8	1	0.5	
KIA Per Class	0.4857	0.775	1	0.7677	1	0.4706	0.647	1	0.775	1	1	
Totals												
Overall Accuracy	**0.8056**											
KIA	**0.7839**											

reduce expand Close

Accuracy assessment result of error matrix based on samples showed that the overall accuracy is around 80 %.

6.5.2 Application II: Radar Image Dataset

6.5.2.1 Segmentation

After testing many different combinations of segmentation parameters, the most convenient ones observed were selected.

For the weight of layers, the most suitable values that allow the best crop discrimination for each level were chosen. Weights of layers were selected due to the effect and success observed in field boundary extraction, which here was directly related with the time of the data acquisition.

Since the study was focused on crop type mapping and the objects to be extracted were not having different characteristics in shape, the shape parameter was selected at minimum (but not taking 0 value) to evaluate the advantages of compactness and smoothness parameters.

Scale parameter was chosen to fit the suitable image object sizes at each level. The crop field sizes of the study area were extracted at level 3, where scale parameter 20 fits the fields.

Level 1 was designed for extracting the bright areas, so the compactness was important to delineate the boundaries of these kinds of regions. So, compactness was selected as 0.9. However, in level 2, the aim was to divide the image objects of level 1 into parts to extract the urban class from the bright areas. For this purpose, smoothness value was increased not being affected by the scattering effect in radar images.

The results are shown in Table 6.16.

Table 6.16 : The most convenient segmentation parameters.

Level	Weight for Layers 1, 2, 3, 4, 5, 6	Scale Parameter	Color	Shape	Compactness	Smoothness
Level 1	0, 0, 1, 0, 0, 0	60	0.9	0.1	0.9	0.1
Level 2	1, 1, 1, 1, 1, 2	30	0.9	0.1	0.2	0.8
Level 3	0, 0, 1, 0, 0, 0	20	0.9	0.1	0.5	0.5

Since radar data is independent from masking effect of clouds, values can be accepted to be relatively more constant for further studies.

As in optical dataset, it was seen that three levels of segmentation was suitable for the study. Level 1 was aimed for the extraction of the urban and the main bright backscattered pixels. Level 2 was aimed for the extraction of urban, river and planting groups. Level 3 was used to extract the crop types finally. In Figure 6.18, the segmented images of each level are shown.

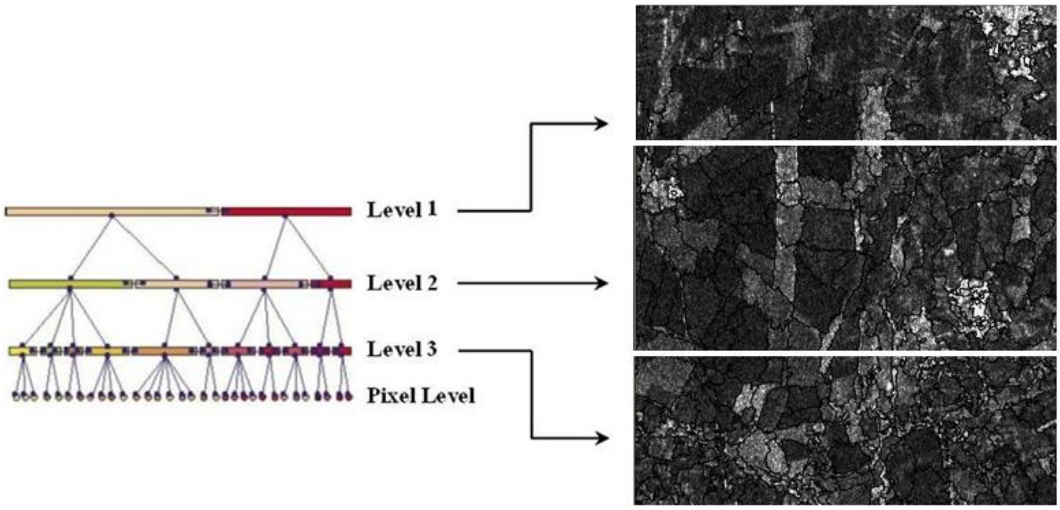


Figure 6.18 : The segmented images of each level.

The numbers of the objects used in each segmentation level is given in Table 6.17.

Table 6.17 : The numbers of the objects used in each segmentation level.

Level	Number of Image Objects
Level 1	120
Level 2	474
Level 3	1129

After segmentation step, classifications at each level were applied.

6.5.2.2 Classification

For radar dataset, the results were given as field types since the data obtained was covering a long time period and, 10 types of planting regimes have been applied in the study area (Table 6.18).

According to the crop regimes, it can be said that the acquisition dates of the crops were convenient for a multitemporal classification.

Table 6.18 : Crop Regimes in the Turkgeldi SPF.

Field Type	February	March	May	September	October	December
1	-	-	Sunflower	Sunflower	Wheat	Wheat
2	Wheat	Wheat	Wheat	-	-	-
3	Wheat	Wheat	Wheat	Wheat	Wheat	Wheat
4	Wheat	Wheat	-	-	Wheat	Wheat
5	Wheat	Wheat	Wheat	-	-	Vetch
6	-	-	-	-	Wheat	Wheat
7	Corn	Corn	Corn	Corn	Wheat	Wheat
8	Vetch	Vetch	-	-	-	-
9	Clover	Clover	Clover	Clover	Clover	Clover
10	Meadow	Meadow	Meadow	Meadow	Meadow	Meadow

For the classification, as a first step, class definitions for each level were made. The features or feature combinations that define the classes are shown in Table 6.19 (for level 1), 6.20 (for level 2) and 6.21 (for level 3) with the membership functions and values selected to represent the most suitable distributions. Some classes (such as bright areas in level 2) were defined only by inheritance (no additional criteria used).

Not many features other than spectral properties were used since the dataset well represent the temporal changes of crops in time, allowing discrimination well. Hence, shape and texture properties were used for only urban and river classes.

The classification process was applied step by step in the order of extracting the bigger objects in size in low level classification and then classification of the smaller objects in higher levels.

A three step classification process was applied to classify crop fields. First similar field types according to their spectral properties were extracted as groups, and then they were discriminated according to the crop regimes.

Table 6.19 : The features defined in the classes for level 1.

Classes	Subclasses	Features	Membership Function	Values
Bright 60		Brightness	Full Range	15.6 - 200

Table 6.20 : The features defined in the classes for level 2.

Classes	Subclasses	Features	Membership Function	Values
Urban 30		Average length of edges	Full Range	4.6 - 4.8 m.
		Brightness	Singleton	0 – 60

Table 6.21 : The features defined in the classes for level 3.

Classes	Subclasses	Features	Membership Function	Values
River 20		Brightness	Singleton	0 - 34
		GLCM homogeneity for layer 3	Full Range	0.018 – 0.037
		Rectangular fit	Full Range	0 - 0.85
Group 1		Mean for layer 1	Full Range	23 - 33, 13 - 24
		Mean for layer 2	Full Range	23 - 48, 12 - 18
	Field 1	Mean for layer 1	Full Range	8.93 - 20.64
		Mean for layer 3	Full Range	9.97 - 14.47
		Mean for layer 6	Full Range	10.19 - 13.83
	Field 6	Mean for layer 1	Full Range	9.3 - 9.4
		Mean for Layer 3	Full Range	9.2 - 9.3
		Mean for layer 6	Full Range	12 – 12.2
Group 3		Mean for layer 1	Full Range	12 - 18
		Mean for layer 2	Full Range	11 - 18
		Mean for layer 3	Full Range	15 - 39
		Mean for layer 4	Full Range	11 - 13
	Field 7	Mean for layer 1	Full Range	14 -15
		Mean for layer 3	Full Range	16 - 17
		Mean for layer 6	Full Range	14 - 15
Group 4		Mean for layer 1	Full Range	8 - 20
		Mean for layer 2	Full Range	6 - 11
		Mean for layer 3	Full Range	7 - 14
		Mean for layer 4	Full Range	6 - 10
		Mean for layer 5	Full Range	7 – 13
		Mean for layer 6	Full Range	5 – 10
	Field 9	Mean for layer 1	Full Range	10.25 - 15.63
		Mean for layer 3	Full Range	9.73 – 11.36
		Mean for layer 6	Full Range	7.57 - 9.5

Table 6.21 (contd.) : The features defined in the classes for level 3.

Group 5		Mean for layer 3	Full Range	10 – 12
		Mean for layer 4	Full Range	17 – 21
		Mean for layer 5	Full Range	11 – 18
		Mean for layer 6	Full Range	14 – 23
	Field 8	Mean for layer 1	Full Range	10.63 - 10.79
		Mean for layer 3	Full Range	10.82 -122.33
		Mean for layer 6	Full Range	20.96 - 22.14
Group 6		Mean for layer 3	Full Range	9.5 - 11.5
		Mean for layer 4	Full Range	9 – 11
	Field 10	Mean for layer 1	Full Range	11 – 12
		Mean for layer 3	Full Range	10 – 11
		Mean for layer 6	Full Range	8 – 9
Group 2	Field 2	Mean for layer 1	Full Range	10.05 - 13.11
		Mean for layer 3	Full Range	9.27 - 12.96
		Mean for layer 6	Full Range	9.57 - 19.03
	Field 3	Mean for layer 1	Full Range	8.74 - 13.66
		Mean for layer 3	Full Range	9.1 - 16.57
		Mean for layer 6	Full Range	10.19 - 23.71
	Field 4	Mean for layer 1	Full Range	8.93 - 11.1
		Mean for layer 3	Full Range	9.1 - 13.83
		Mean for layer 6	Full Range	10.19 - 17.76
	Field 5	Mean for layer 1	Full Range	8.53 - 13
		Mean for layer 3	Full Range	10.01 - 14.32
		Mean for layer 6	Full Range	9.62 – 23

The classification results of each level are given in Figure 6.19.

One of the reasons to use full ranges for features, was the tests can be made only for one year’s dataset. These values were going to be improved by distribution functions if any other datasets were available to suggest the best distribution function. An observation of the region i.e. for a ten year period would provide good data to determine the distribution approach.

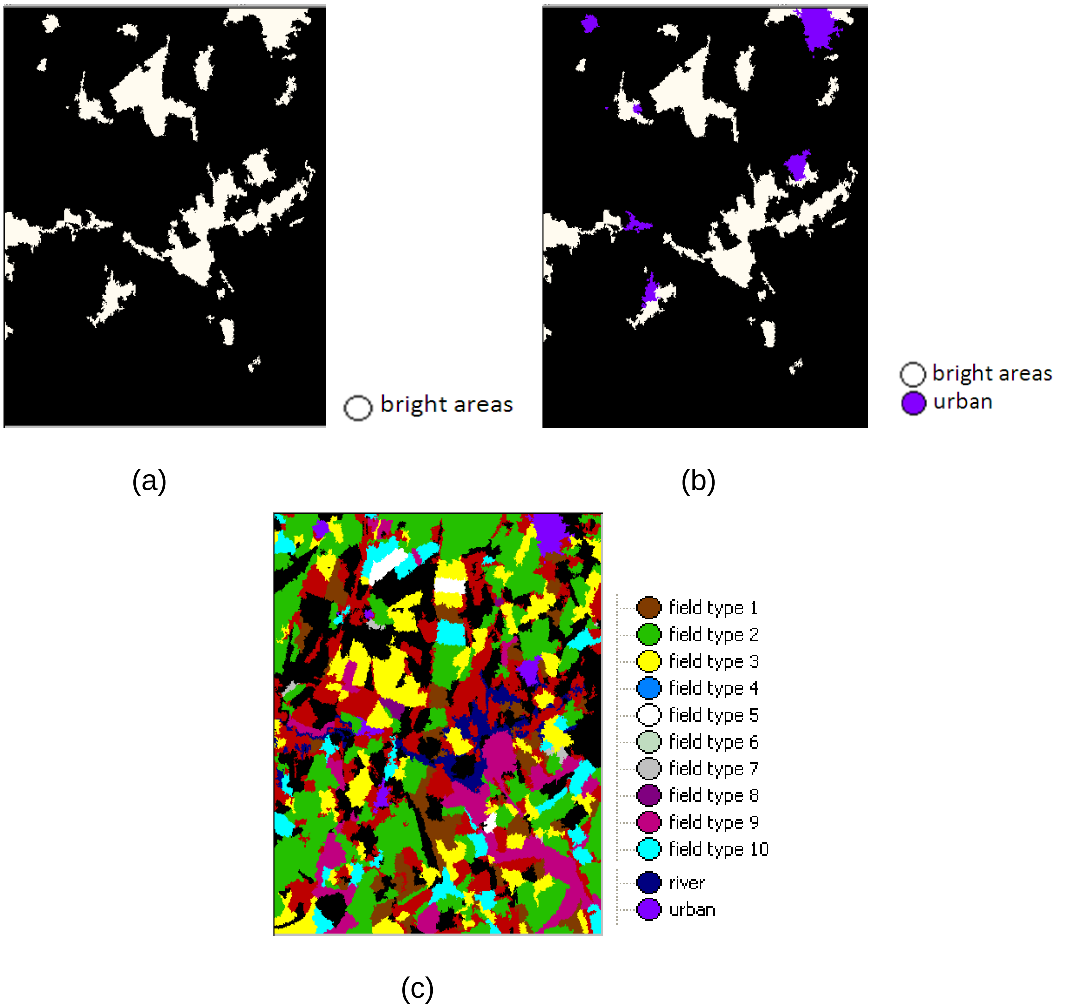


Figure 6.19 : Classification images with legends at (a) level 1, (b) level 2, (c) level 3.

6.5.2.3 Process Sequence

All the steps to reach the final output were done by following the process tree coded for the application.

Process sequence has 5 main steps.

Step 1: Segmentation and classification at level 1. In this level bright areas were extracted (Figure 6.20).

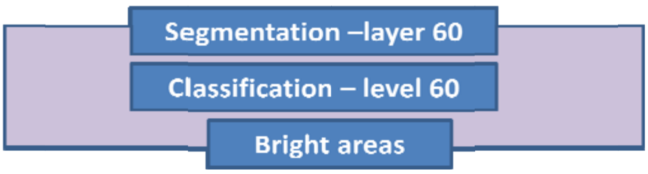


Figure 6.20 : Segmentation and classification at level 1.

Step 2: Segmentation and classification at level 2. In this level urban class was extracted (Figure 6.21).

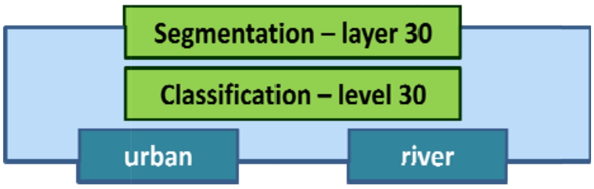


Figure 6.21 : Segmentation and classification at level 2.

Step 3: Segmentation and classification at level 3. First river class was defined as not being urban class of the bright areas of the superlevel. Level 3 was used as the main layer for crop mapping over the area. First planting groups and then the crop regime classes were determined (Figure 6.22).

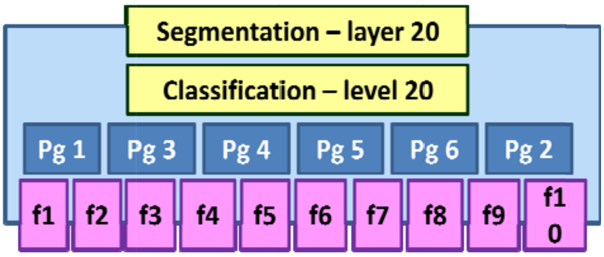


Figure 6.22 : Segmentation and classification at level 3.

Step 4: This level was designed to combine the best classification results from the related level to form the final classification.

Step 5: This level was for the automatic production of the outputs (Figure 6.23).

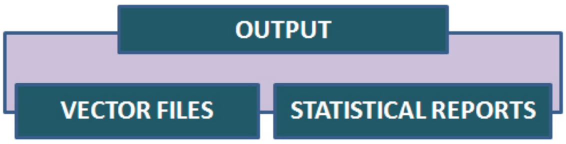


Figure 6.23 : Step for the production of outputs.

Result of the crop regime classification of radar image dataset is given by Figure 6.24.

Level 3 classification is the final one, since the image objects on this segmentation level has the most suitable image object sizes for the fields of study area, and also for the final classification is organized on this level.

Türkgeldi SPF region boundaries were not used in the presentation of the result, since it was still not a rectified image.

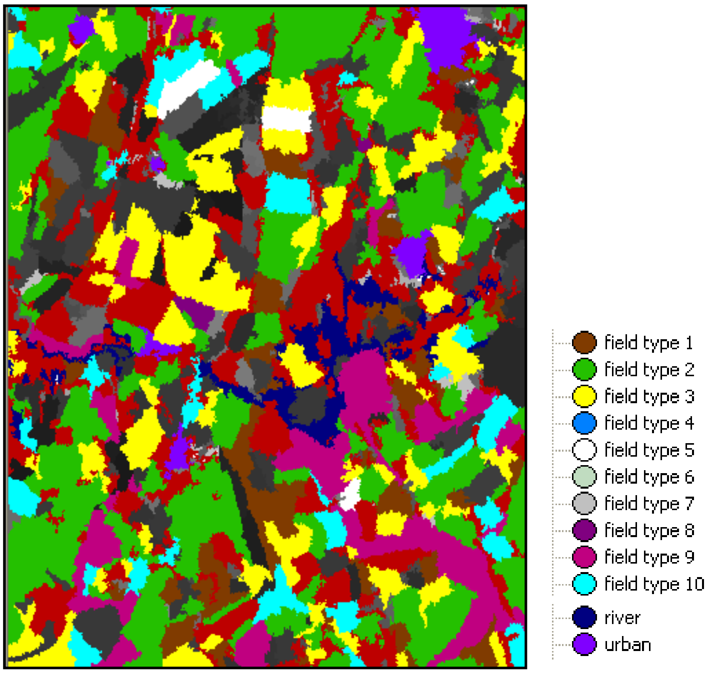


Figure 6.24 : Classified image of the radar image dataset.

6.5.2.4 Accuracy Assessment

The error matrix method based on selected sample image objects from manual inputs was applied for accuracy assessment. In Figure 6.25, the samples selected as a control set for accuracy assessment is shown. As in optical dataset, the limitations such as the use of restricted samples for the crops planted in few fields and no availability of random sample selection were also valid for this dataset.

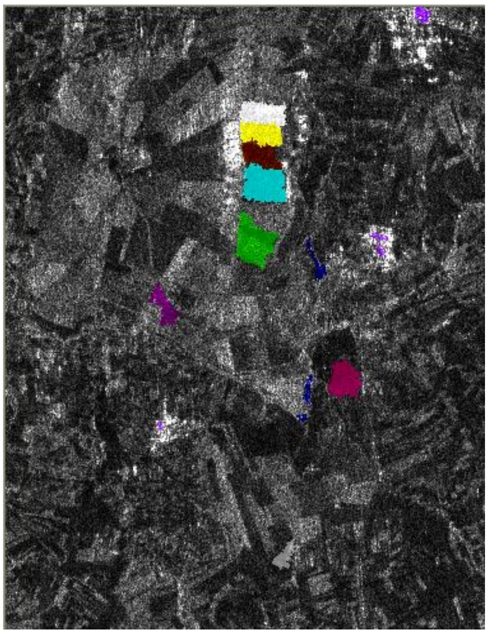


Figure 6.25 : Image objects selected as a control set for accuracy assessment.

The match between the sample objects and the classification is expressed by error matrix given in Table 6.21.

Table 6.22 : Error matrix of the radar dataset classification.

Error Matrix based on Samples

User Class \ Sample	tarla 1	tarla 2	tarla 3	tarla 5	tarla 7	tarla 8	tarla 9	tarla 10	nehir	yerlesim 20	Sum
Confusion Matrix											
tarla 1	1	0	0	0	0	0	0	0	0	0	1
tarla 2	0	1	0	0	1	0	0	0	0	0	2
tarla 3	0	0	1	0	0	1	0	0	0	0	2
tarla 5	0	0	0	1	0	0	0	0	0	0	1
tarla 7	0	0	0	0	0	0	0	0	0	0	0
tarla 8	0	0	0	0	0	0	0	0	0	0	0
tarla 9	0	0	0	0	0	0	1	0	0	0	1
tarla 10	0	0	0	0	0	0	0	1	0	0	1
nehir	0	0	0	0	0	0	0	0	3	0	3
yerlesim 20	0	0	0	0	0	0	0	0	0	3	3
unclassified	0	0	0	0	0	0	1	0	0	0	1
Sum	1	1	1	1	1	1	2	1	3	3	
Accuracy											
Producer	1	1	1	1	0	0	0.5	1	1	1	
User	1	0.5	0.5	1	undefined	undefined	1	1	1	1	
Hellden	1	0.6667	0.6667	1	0	0	0.6667	1	1	1	
Short	1	0.5	0.5	1	0	0	0.5	1	1	1	
KIA Per Class	1	1	1	1	0	0	0.4643	1	1	1	
Totals											
Overall Accuracy	**0.8**										
KIA	**0.7727**										

reduce expand Close

Accuracy assessment result of error matrix based on samples showed that the overall accuracy is 80 %.

The accuracy of classification is directly dependent to the accuracy of segmentation. However, the segmentation and the classification effects in classification accuracy cannot be quantified.

7. CONCLUSION

Agricultural management is very important for the countries such as Turkey, whose mainstay of economy is agriculture. Besides, agricultural activities that manage the main source of food production for human needs have effects on both regional and global scale. Technological developments such as remote sensing technology improve the agricultural applications in many ways.

In this thesis, considering the automation trend in many fields of information extraction methods, a process-based system for image analyze was developed for crop mapping.

For an automated system, process tree design that would apply a step by step crop mapping of an agricultural area in the Turkgeldi State Production Farm was performed.

In the process based system, object based image analysing method was applied and the process steps and the method used were described dependent to the algorithms of the Definiens software used. In the literature, much of the work also referred to as “Object Based Image Analysis” originated around the software known as “Definiens” (which was previously known as “eCognition”) [104-107]. In the object-based approach, since supervision would require human interaction to define the samples, nearest neighbor classification (supervised method) was not preferred and condition-based approach (unsupervised method) was thought to be more convenient for the application.

In this thesis, an optical dataset of SPOT 4 and a radar dataset of JERS, belonging to 2007 and 1997 years, respectively, were used. Two seperate process trees were developed for these different kinds of image datasets. The purpose of using different datasets was to evaluate their efficiency and advantages/disadvantages.

The problems of datasets according to their sensing principles faced, can be outlined as the cloud and speckling effect for optical and radar datasets, respectively. In this study, only one of the images in optical dataset had some little cloud problem. For radar dataset, inherent speckle problem existed. This problem was minimized by using object-based analysis, due to the use of image object mean values instead of pixels overcomes the problem. This advantage of object based image analysis has been mentioned in the literature by other researchers [100, 133].

The application were realized in two main steps. As a first step, the image datasets were segmented, and then image objects were classified according to the steps outlined in the following.

In segmentation step of the process for optical dataset, the cloud effects were observed in field boundaries due to having one cloudy image. To overcome this problem, weight of this image's layers were changed to zero.

For radar dataset there was no problem in segmentation. The weight of the layers were arranged in order to provide the most suitable extraction of field boundaries.

In classification step of the process, different strategies were applied for two datasets. For optical dataset, the classification was applied in three levels. The hierarchical structure brought flexibility about making the classification in the convenient image object layer for the desired classes. The first level was created to classify the features like urban and river. The second level was the suitable one for the crop mapping of Turkgeldi area. The third level was created to meet the classification for the whole image level, so the smaller agricultural fields other than Türkgeldi region were taken into account.

For radar dataset's classification, planting calendar was used as an additional information source and the dataset was classified according to the planting regime. For this dataset, the first and second levels were created for detecting and classifying relatively big sized features like river and urban. In the third level crop discrimination was performed and the final classification map was produced.

For the class descriptions, the spectral and other properties of objects were used in both datasets. In the literature it has shown that, use of textural properties in addition to spectral properties increase the classification accuracy by up to 7% and use of shape properties in addition to spectral properties enhance the classification accuracy between 8% and 11% [97, 134]. For optical dataset, shape and texture properties were used to distinguish crop classes similar in spectral properties (such as wheat and vetch) effectively. In this study, the texture analysis was more efficient for optical dataset although it was expected more for the radar dataset. The reason of it was that the dates were suitable to make good discriminations, and textural and shape properties were used mainly for the extraction of river and urban classes.

After class descriptions were defined, class assignments were performed according to the membership value that the image objects took. This process was based on fuzzy logic, and fuzzy classification has provided flexibility, by allowing and considering the image objects took membership values for more than one class. This was also an improving tool for the analyst to evaluate the approach during the processing procedure.

All the segmentation was done in three layers, and classification was performed in three levels. The network structure used in classifications of both datasets has shown the benefit of using inheritance property between classes.

After image classifications were performed, the accuracies were obtained for both datasets and found to be approximately % 80. These accuracies were not only about the classification success but also it is directly dependent to the accuracy of segmentation in object based classifications. However, segmentation and classification effects in the resultant accuracy cannot be quantified.

In addition to the quantative evaluation, the classification results were also evaluated by visual analysis. It was seen that the results were more compact than the pixel based classification results done in previous studies. There were not much salt and pepper effect both for the optical and the radar dataset. This advantage was more obvious for radar image classification. This property has accepted as an advantage of object-based classification, moreover this advantage has significant importance for agricultural applications since as Ehlers et al. indicated (2003) “pixel is not closely related to vegetation physiognomy as a whole and vegetation always shows heterogeneity as a result of irregular shadow or shade” [135]. Because of that, object-based image analysis provide the flexibility of being able to overcome various kinds of ‘within-patch heterogeneity’ [136]. Therefore, a field based crop map is considered to be more useful than a pixel based one for agricultural authorities,.

The misclassifications of optical dataset were found in between two types of wheat (guadalupe and flamura) classes; corn and sunflower classes; and river and linearity (roads, ways and railways) classes. If the process was written for a specific region, the river and roads could be input to the system as a thematic layer to avoid misclassifications. For the crop types, other object properties may be tested to increase the discrimination success in further studies.

The advantage of a having classification results at different levels was significant. For the resultant classification, the most suitable level was chosen for each thematic class. For example river class was defined in level 2 of optical dataset and this was directly used in the final classification. Also the sub and super class relations was used effectively to make the crop discriminations step by step in a process tree.

The use of textural, shape or neighbor type of properties in addition to spectral properties had provided great advantage in class discriminations. For example, corn2 class in optical dataset was discriminated from wheat class easily by using the shape property since the shape of these fields do not have uniform geometry since corn2 was planted along the river.

The % 80 accuracy obtained for both datasets were compared with the accuracy results of previous studies applied on optical and radar datasets of the same region. The supervised pixel-based classification accuracy obtained in “Crop Yield Forecast By Using Remote Sensing Methods” research done by Sunar et al., 1996 for the same region by Landsat data for 1993 was found to be 88 % [137]. The classification accuracy in “Crop Type Mapping with Multitemporal JERS Radar Data: A Case Study in the Türkgeldi Agricultural Administration Area, Thrace Region, Turkey” research done by Sunar et.al., 2004, which was performed with supervised pixel-based classification, for the same region by JERS data for 1997 was found to be 87 %, besides, the classification accuracy was obtained as 73 % by ANN [138]. When compared, these results, the accuracy of this study seemed to be less than the traditional classification methods. However, the reason for this was that the process tree was not written specifically for the present dataset. Instead of this, it was designed for a general classification that will also be used for other datasets. For example the actual field boundaries were not input to the system as a thematic layer although it would increase the segmentation process accuracy considerably, however it was thought that it could change over time. Another reason could be that no image enhacement was applied to the raw images, since the success of an automatic process on raw data was the main aim of this study. (Registration was used as the only required initial processing step.)

The accuracy could be higher if the aim was not focusing on writing a general process tree to be applicable for many cases, for different regions etc. If the best result for a unique case was planned, then together with the use of thematic layers, more spectral bands and ground based spectral measurements as additional data would increase the success.

Although the accuracy results could be acceptable for only one dataset, the use of a new dataset for the same region would also improve the accuracy. In this thesis, due to time and data access limitations, only one year’s dataset have been used.

Hence, a process tree formed was tested on one dataset since the main aim was a process-based application. However, another dataset belonging to any other year should be reinterpreted to improve the process tree. The advantage of using a ready process tree will probably be the saving of time, i. e. new dataset will not take time as for the first one, since it will only require to change some values for the next applications. Therefore future study will be done with the new dataset having nearly same dates of acquisition and running the process to see how accurate classification results will be obtained. It cannot be claimed that the written process is the final one, however, it can be accepted as the main step to write a suitable process tree; and it is thought that, the more parameter value that can remain stable for any year’s dataset, the more efficient and accurate results from the process tree will be obtained. The process-based system can also be developed in time, to define and use its own crop spectral and textural signatures, however it would require many datasets belonging to different years.

For future studies, inclusion of an improved preprocessing step (as atmospheric correction) in the process would be a discussion. For example, in this study, the cloudy data was not used in the segmentation step, however if every or most of the data was partial cloudy in different parts of the images, a segmentation operation that considers different layers for image parts would have to be used and that would require an additional complex processing step.

To develop the process tree for the regions that are not well managed agricultural areas such as Turkgeldi SPF, different parts within a field such as less irrigated or unhealthy regions must be considered carefully. In this case, since they were not homogeneous and compact, some of the definitions would be meaningless or had to cover a wide interval of values for feature definitions that cause misclassifications. If the region have these kind of problems, then to overcome the problem, the process should have steps to extract these parts separately and then combine in a latter step.

Radar data are being used in many fields of remote sensing, and this active system data is always a good choice especially for the regions which might have cloudy weather almost all of the year. However, if the optical and radar datasets were nearly same dated images of the same year, then it would be able to make interpretations on which dataset was more convenient to use in this kind of study or whether both datasets were needed together with their advantages and disadvantages.

For a further study, the process can also be extended for a wide region to improve the whole process and also to validate the output crop map. The process may also be tested how accurate it is for any other year (i.e. for the discrimination of same kind of crops in another region), wheather it can be generalised for all of the country, or how it can be more specialised for a region.

It should be mentioned that the accuracy obtained was regarded to the object based classification applied through the process. However, the accuracy or success of the process tree written was not evaluated. To do so, any other year's dataset must be used for improving the process tree and the values used, and also for testing the success of the process tree written.

The process tree was written by considering the repeatibility requirement. However the flexibility in limits of values used for class definitions and the repeatibility of the system have to be tested. With the experience to be obtained from the process tree for other datasets, other distribution functions that will better present the classes' behaviors instead of the used full range distribution functions will be derived. Besides, if other sensors (bands, resolution) integrated to the system for future applications, sub processes could need to be written regarding to the sensor type.

The process trees can also be enhanced for GIS integration. Object based image analysis is seen to be more suitable for GIS approach than traditional methods as "linking the pixel world and the vector world" and convenient to develop geographic-based intelligence [139].

As a conclusion, it can be stated that the process-based image analysis seems to be a promising method regarding to the importance of automation need in today's world. Automated information extraction systems will be a need in an information age since more and more data will be available to be evaluated, and also the results will be needed in a short time. Related to the periodic environmental changes in time, agricultural activities are more suitable for the improvement of process based systems. With this improved system, agricultural applications can get benefit and the fast and accurate information can be obtained from automated image extraction systems for wide regions.

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APPENDIX A: Texture After Haralick

The Gray Level Co-occurrence Matrix (GLCM) is a tabulation of how often different combinations of pixel gray levels occur in an image. A different co-occurrence matrix exists for each spatial relationship. To receive directional invariance, all 4 directions (0°, 45°, 90°, 135°) are summed before texture calculation. Its formula is given in Eq. A1.

Formula is: $P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}}$ **(A.1)**

Here, $V_{i,j}$: the value in the cell i,j of the matrix.

The normalized GLCM is symmetrical. The diagonal elements represent pixel pairs with no gray level difference. Cells, which are one cell away from the diagonal, represent pixel pairs with a difference of only one gray level. Similarly, values in cells, which are two pixels away from the diagonal, show how many pixels have 2 gray levels and so forth. The more distant to the diagonal, the greater the difference between the pixels' gray levels is. Summing-up the values of these parallel diagonals, gives the probability for each pixel to be 0, 1, 2 or 3 etc. different to its neighbor pixels. (Figure A.1)

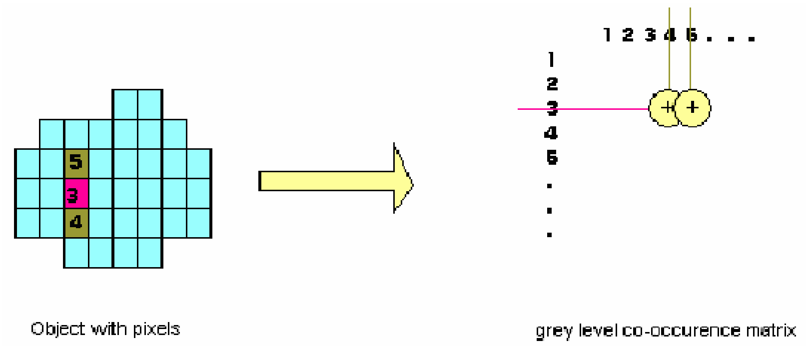

Figure A.1 : The calculation of grey level co-occurrence matrix.

This appendix is prepared from Definiens Reference Guide.

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