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**An Intelligent Classification System for Land Use and  
Land Cover Mapping Using Spaceborne  
Remote Sensing and GIS**

**A thesis submitted to the Middlesex University  
In partial fulfilment of the requirement of the degree of  
Doctor of Philosophy**

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## Abstract

The objectives of this study were to experiment with and extend current methods of Synthetic Aperture Radar (SAR) image classification, and to design and implement a prototype intelligent remote sensing image processing and classification system for land use and land cover mapping in wet season conditions in Bangladesh, which incorporates SAR images and other geodata. To meet these objectives, the problem of classifying the spaceborne SAR images, and integrating Geographic Information System (GIS) data and ground truth data was studied first. In this phase of the study, an extension to traditional techniques was made by applying a Self-Organizing feature Map (SOM) to include GIS data with the remote sensing data during image segmentation. The experimental results were compared with those of traditional statistical classifiers, such as Maximum Likelihood, Mahalanobis Distance, and Minimum Distance classifiers. The performances of the classifiers were evaluated in terms of the classification accuracy with respect to the collected real-time ground truth data. The SOM neural network provided the highest overall accuracy when a GIS layer of land type classification (with respect to the period of inundation by regular flooding) was used in the network. Using this method, the overall accuracy was around 15% higher than the previously mentioned traditional classifiers. It also achieved higher accuracies for more classes in comparison to the other classifiers. However, it was also observed that different classifiers produced better accuracy for different classes. Therefore, the investigation was extended to consider Multiple Classifier Combination (MCC) techniques, which is a recently emerging research area in pattern recognition. The study has tested some of these techniques to improve the classification accuracy by harnessing the goodness of the constituent classifiers. A Rule-based Contention Resolution method of combination was developed, which exhibited an improvement in the overall accuracy of about 2% in comparison to its best constituent (SOM) classifier.

The next phase of the study involved the design of an architecture for an intelligent image processing and classification system (named ISRIPaC) that could integrate the extended methodologies mentioned above. Finally, the architecture was implemented in a prototype and its viability was evaluated using a set of real data. The originality of the ISRIPaC architecture lies in the realisation of the concept of a complete system that can intelligently cover all the steps of image processing and

classification and utilise standardised metadata in addition to a knowledge base in determining the appropriate methods and course of action for the given task. The implemented prototype of the ISRIPaC architecture is a federated system that integrates the CLIPS expert system shell, the IDRISI Kilimanjaro image processing and GIS software, and the domain experts' knowledge via a control agent written in Visual C++. It starts with data assessment and pre-processing and ends up with image classification and accuracy assessment. The system is designed to run automatically, where the user merely provides the initial information regarding the intended task and the source of available data. The system itself acquires necessary information about the data from metadata files in order to make decisions and perform tasks. The test and evaluation of the prototype demonstrates the viability of the proposed architecture and the possibility of extending the system to perform other image processing tasks and to use different sources of data. The system design presented in this study thus suggests some directions for the development of the next generation of remote sensing image processing and classification systems.

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# Table of Contents

<b>Abstract</b> .....	<b>i</b>
<b>Acknowledgements</b> .....	<b>iii</b>
<b>Table of Contents</b> .....	<b>iv</b>
<b>List of Figures</b> .....	<b>vi</b>
<b>List of Tables</b> .....	<b>vii</b>
<b>1. Introduction</b> .....	<b>1</b>
1.1 <i>BACKGROUND AND MOTIVATION</i> .....	1
1.1.1    The Importance Of Land Use And Land Cover Mapping.....	2
1.1.2    The Potential Of Remote Sensing.....	3
1.1.3    Problems In The Use Of Remote Sensing.....	4
1.1.4    Potential Alternative Methods Of Image Processing .....	7
1.1.5    Present Requirements.....	9
1.2 <i>RESEARCH GOAL AND OBJECTIVES</i> .....	10
1.2.1    Objectives.....	11
1.3 <i>SCOPE OF THE WORK</i> .....	11
1.4 <i>THESIS OUTLINE</i> .....	12
<b>2. Review of Previous Research</b> .....	<b>13</b>
2.1 <i>INTRODUCTION</i> .....	13
2.2 <i>REMOTE SENSING FOR LAND USE AND LAND COVER MAPPING</i> .....	13
2.2.1    Remote Sensing.....	13
2.2.2    Land Use And Land Cover.....	14
2.2.3    Applications Of Remote Sensing For Land Use And Land Cover .....	14
2.2.4    Potentials And Limitations Of Remote Sensing.....	16
2.3 <i>SYNTHETIC APERTURE RADAR (SAR) REMOTE SENSING</i> .....	18
2.3.1    Synthetic Aperture Radar (SAR).....	19
2.3.2    Radar Interaction With Vegetation/Agriculture .....	21
2.4 <i>IMAGE PROCESSING AND CLASSIFICATION</i> .....	24
2.4.1    Image Processing Steps.....	25
2.4.2    Traditional Classification Techniques And Limitations .....	26
2.4.3    Advanced Methods Of Image Classification.....	29
2.4.4    The Integration Of GIS For Image Processing.....	34
2.5 <i>MULTIPLE CLASSIFIER SYSTEMS</i> .....	37
2.5.1    Methods Of Combining Multiple Classifiers .....	37
2.5.2    Combination Methods Used In Remote Sensing .....	42
2.6 <i>INTELLIGENT SYSTEMS AND REMOTE SENSING</i> .....	43
2.6.1    Intelligent Systems .....	44
2.6.2    Expert Systems (ES) .....	46
2.6.3    The Use Of Intelligent Systems In Remote Sensing .....	53
2.7 <i>METADATA AND POTENTIAL USES IN IMAGE PROCESSING AND CLASSIFICATION</i> ..	59
2.7.1    FGDC Standard.....	61
2.8 <i>CONCLUSIONS</i> .....	63
<b>3. The Case Study</b> .....	<b>67</b>
3.1 <i>INTRODUCTION</i> .....	67
3.2 <i>STUDY AREA</i> .....	67
3.3 <i>GENERAL LAND USE AND LAND COVER IN THE STUDY AREA</i> .....	69

3.3.1	General Landscape .....	69
3.3.2	Agricultural Land Use.....	70
<b>3.4</b>	<b>METHODOLOGY.....</b>	<b>73</b>
3.4.1	SAR Images And Pre-Processing.....	75
3.4.2	GIS Data.....	78
3.4.3	Field Data Collection And Organization.....	79
3.4.4	Analysis Of Training Data .....	81
3.4.5	Accuracy Assessment.....	86
3.4.6	Image Classification.....	88
3.4.7	Software Used.....	90
3.4.8	Combination Of Multiple Classifiers .....	91
3.4.9	Design And Architecture Of An Intelligent System .....	92
3.4.10	Prototype Development And Evaluation.....	92
<b>3.5</b>	<b>CONCLUSIONS .....</b>	<b>93</b>
<b>4.</b>	<b>Comparison of Different Classifiers .....</b>	<b>94</b>
4.1	INTRODUCTION.....	94
4.2	RESULTS OF CLASSIFICATIONS .....	94
4.2.1	Visual Analysis Of Classified Images.....	95
4.2.2	The Accuracy Of The Classified Images .....	97
4.2.3	Comparison Of Classification Methods .....	100
4.3	COMBINING MULTIPLE CLASSIFIERS .....	102
4.3.1	Classifiers Combinations And Results.....	103
4.3.2	Analysis Of Classifier Combination Results.....	107
4.4	CONCLUSION .....	108
<b>5.</b>	<b>Architecture of Intelligent Image Processing and Classification System.....</b>	<b>110</b>
5.1	INTRODUCTION.....	110
5.2	REQUIREMENTS ANALYSIS .....	111
5.2.1	Need Assessment .....	111
5.2.2	Limitations Of The Present Systems .....	117
5.2.3	The Potentials Of Artificial Intelligence .....	118
5.2.4	Summary Of Requirements.....	119
5.3	ANALYSIS AND DESIGN.....	120
5.3.1	Physical Framework.....	120
5.3.2	The Logical Framework Of The System.....	125
5.3.3	Architecture Of The System.....	128
5.4	CONCLUSION .....	129
<b>6.</b>	<b>Implementation and Evaluation of Prototype .....</b>	<b>130</b>
6.1	INTRODUCTION.....	130
6.2	OVERVIEW OF THE PROTOTYPE .....	130
6.3	SYSTEM COMPONENTS OF THE PROTOTYPE .....	131
6.3.1	Expert System Shell .....	132
6.3.2	Image Processing Software .....	134
6.3.3	The Control Agent.....	135
6.3.4	Metadata For The Prototype.....	137
6.3.5	The Knowledge Base .....	137
6.4	EVALUATION OF THE PROTOTYPE .....	143
6.4.1	Testing The Functional Capability Of The Prototype.....	143
6.4.2	Evaluation Of The Prototype From An Expert And Novice Point Of View... ..	148
6.4.3	Analysis Of Viability Of The System .....	150
6.5	CONCLUSION .....	153

<b>7. Conclusions And Future Work.....</b>	<b>154</b>
7.1 INTRODUCTION.....	154
7.2 OVERVIEW OF THE WORK.....	154
7.3 CONTRIBUTION TO KNOWLEDGE .....	156
7.4 FUTURE WORK .....	157
<b>Bibliography .....</b>	<b>159</b>
<b>Appendix A: Publication .....</b>	<b>177</b>
<b>Appendix B: Field Data Collection Form.....</b>	<b>189</b>
<b>Appendix C: The Knowledge Base Of The Prototype .....</b>	<b>192</b>
<b>Appendix D: Metadata .....</b>	<b>206</b>

## List of Figures

Figure 2.1	Different platform of remote sensing and properties	.....	15
Figure 2.2	The requirement of spatial and temporal resolution of remote sensing for agriculture in compare with other applications	.....	17
Figure 2.3	Different band of electromagnetic energy and the Microwave bands used in SAR systems	.....	19
Figure 2.4	Horizontal and vertical polarisation in radar transmission	.....	20
Figure 2.5	Visual impression of RADARSAT SAR raw image compare to a multi-spectral in false colour composite image	.....	22
Figure 2.6	Multiple neural network system	.....	41
Figure 2.7	Expert system shell in compare to the expert system	.....	49
Figure 2.8	Basic architecture of a knowledge based expert system	.....	52
Figure 2.9	Number of literatures on intelligent systems in remote sensing image processing and classification	.....	54
Figure 2.10	Overview of the ARKTOS intelligent sea ice image classifier	.....	57
Figure 2.11	Main content of the geospatial metadata	.....	62
Figure 3.1	Study area	.....	68
Figure 3.2	Crop calendar in relation to seasonal flooding	.....	73
Figure 3.3	Activity flowchart of the case study	.....	74
Figure 3.4	Distribution of GCPs	.....	76
Figure 3.5	Georeferenced radar images displayed in RGB combination	.....	77
Figure 3.6	Histogram of the images of different dates	.....	78
Figure 3.7	Distribution of the surveyed field polygons (land-parcels)	.....	80
Figure 3.8	Changes in current field condition on different imaging dates	.....	82
Figure 3.9	Land cover classes in the multi-temporal image	.....	83
Figure 3.10	An example of confusion matrix composed of four information classes	.....	87
Figure 3.11	SOM process in SOM_PAK	.....	90
Figure 3.12	Functionality of the developed tools for image classification in SOM networks	.....	91
Figure 4.1	Visual impression of land use and land cover in multi-temporal SAR image before classification	.....	95
Figure 4.2	Results of classification by different classifier	.....	96
Figure 4.3	Mean Backscattering plot from different classes over time	.....	102
Figure 4.4	Graphical presentation of the difference between the maximum conditional kappa (Max-single) among the single classifiers and	.....	108



	same of classifier combining (Max-combi) methods		
Figure 5.1	Basic organizational scenario of the required system	.....	112
Figure 5.2	Example of experts' involvements in image processing and classification steps	.....	114
Figure 5.3	Major steps of image processing and classification	.....	116
Figure 5.4	Major tasks in different steps of the image processing and classification	.....	127
Figure 5.5	Proposed system architecture	.....	128
Figure 6.1	Functional plan for the prototype ISRIPaC	.....	131
Figure 6.2	Example of an IDRISI Kilimanjaro .iml file written for the prototype	.....	135
Figure 6.3	Main interface of the ISRIPaC prototype showing the menus for stepping through some of the Knowledge Handler processing stages	.....	136
Figure 6.4	Knowledge base building process for the prototype	.....	138
Figure 6.5	An example of the rules written for the prototype	.....	143
Figure 6.6	An example of the facts written for the prototype	.....	144
Figure 6.7	Classified image and error matrix produced using the prototype	.....	148

## List of Tables

Table 2.1	A comparison of techniques in passive and active remote sensing (mainly space borne) system compiled from different sources	.....	16
Table 2.2	Summarisation of the reviewed literature on the basis of main tasks and used AI method	.....	55
Table 3.1	Land types defined on the basis of flood depth (derived from MPO, 1987)	.....	71
Table 3.2	Basic statistics of the images after pre-processing		77
Table 3.3	Statistics from the training samples	.....	86
Table 3.4	Classification quality associated to the kappa coefficient values	.....	88
Table 4.1	Confusion matrix calculated with respect to field data		98
Table 4.2	Accuracy and Kappa coefficients of classifiers	.....	99
Table 4.3	User's and Producer's accuracies	.....	100
Table 4.4	Overall accuracy and Kappa coefficients of the multiple classifier combination methods	.....	105
Table 4.5	Accuracies of different combination methods with the Best Possible Accuracy (BPA) and the SOM5 (a, b, and c)	.....	106
Table 6.1	Part of Condition-Action table as example of the knowledge identification step	.....	139
Table 6.2	Conceptualisation of the knowledge	.....	140
Table 6.3	Formalization of the identified knowledge	.....	141
Table 6.4	Comparison of the remote sensing image processing and classification scenario with and without the prototype system	.....	150

# Chapter 1

## 1. Introduction

This thesis examines ways in which various intelligent techniques may be incorporated into an automated remote sensing image processing system. In operation, the study is limited to the investigation of a particular case study: the classification of satellite-based Synthetic Aperture Radar (SAR) images to classify land use and land cover in a particular area of southwest Bangladesh. Through this process, it is expected that generic recommendations can be made concerning how future automated tools could be made more intelligent, more automated, and easier to use. In order to set out the background to the work, this chapter discusses the development and potential of remote sensing and the importance of land use and land cover information for policy makers. In addition, it includes the author's experience of using remote sensing data in practice and the problems that were observed. The research goals and objectives are then outlined.

### 1.1 Background and Motivation

Satellite based remote sensing has made considerable progress over the last three decades. Through research and development it has proven its usefulness for earth surface resource mapping, planning, monitoring, and management. It has become a powerful tool for the assessment of land use and land cover in terms of localisation, quantification, change detection, vegetation, and crop health assessment. It has also become important for monitoring the occurrences of catastrophic events such as fires, storms, droughts, floods, and pest outbreaks (Ghosh 2004). Moreover, the use of advanced image processing techniques has made remote sensing a precision level tool for agriculture and forestry, providing information about growth, yield, damage, and environmental impact assessment. Nonetheless, the extraction of information from remotely sensed images often requires highly qualified remote sensing experts (Lück, 2004). The processing of the images, from the condition in which they are available from the vendor to the final product, is extremely labour intensive. Even with commonly used advanced techniques, the results remain inconsistent and are not sufficiently accurate to make them adaptable to the relevant agencies in developing countries. In many developing countries, such as Bangladesh, the traditional field based

survey system cannot be replaced yet due to both economical and technical limitations. More particularly, remote sensing is not as widely used for natural resource management as was predicted 20 years ago or as was often claimed by the field's experts and data providers (Blaschke, et. al. 2000). In this context, the current state of the art will be discussed further in the following sections.

### **1.1.1 The importance of land use and land cover mapping**

One of the initial steps in dealing with important physical and environmental planning, development and management issues is to produce relevant up-to-date and accurate spatial information (Moller-Jensen, 1997), especially for those sectors where the problems are in some way related to the spatial distribution of earth surface phenomena. Such spatial information can be presented suitably in a land use and land cover map, which can provide a better understanding of the problems and form the basis for the identification of suitable strategies for sustainable planning, development, monitoring, and management. Land use and land cover is already an input parameter for a number of agricultural, hydrological and other environmental models (e.g. EGIS, 2000) and is a fundamental variable that impacts on and links many parts of the human and physical environments. Foody (2000) pointed out that despite the great significance of land cover, our knowledge of this area and its related dynamics remains poor. We know that the world is changing quickly and changes in land use and land cover are not separate issues. One example will illustrate the motivation:

*In three districts of southwest Bangladesh, the total agricultural area is about 4300 km<sup>2</sup>. The change in shrimp cultivated area was from 1410 km<sup>2</sup> to 1740 km<sup>2</sup> during 3 years from 1995 to 1998 (EGIS, 2001). The change in land use is massive and that has a significant impact on the economic, social, and cultural life of the people in that area. This signifies the importance of knowing about such changes for resource management and planning purposes.*

However, understanding the significance of land use and land cover change is particularly limited by the scarcity of accurate and timely data. Such data, especially in the form of maps, is not usually readily available, whereas, the speed and flexibility with which the data can be produced and analysed is clearly an important factor. The direct field survey based traditional systems for such mappings are time-consuming

processes and the data is outdated by the time it is ready for use. These methods are particularly inefficient and impractical for real-time applications. In comparison, remote sensing and digital image processing are highly suitable tools for mapping land use and land cover.

### **1.1.2 The potential of remote sensing**

The production of thematic maps, such as those depicting land use or land cover, using image classification is one of the most common applications of remote sensing (Foody, 2002). Briefly, remote sensing refers to any technique whereby information about objects and their environment is obtained from a distance, without direct contact. This study is concerned with remote sensing systems that are engaged in gathering information about features of the earth's surface. Today a wide range of remote sensing systems are used to collect data from both aerial and spaceborne platforms. These systems include everything from aerial cameras to earth orbiting shuttle missions or satellite based multispectral sensors, and imaging radar systems. The discussion of this study is focused on remote sensing via satellite-based imaging systems.

Images from the satellite-based remote sensing system, due to their synoptic view of the earth, map-like format, and repetitive coverage, are a valuable source of timely land use and land cover information. In the last decade, significant technological developments have occurred in this area. The literature shows a number of new satellite systems have become operational in recent years. These include the introduction of satellite based SAR imaging systems (RADARSAT, ERS, ENVISAT), high spatial resolution imaging systems (IRS, IKONOS), hyperspectral imaging system (ASTER), and high temporal frequency satellite systems (MODIS). Beside these new advanced systems, in order to maintain the continuation of data supply, several improved versions of the old systems, near retirement, have been launched (RADARSAT II, ERS II, Landsat 7). The types of imaging systems (optical and radar) and the spatial (pixel size), temporal, and spectral (number of spectral bands) resolutions of the images acquired by these satellite systems have also removed many technical barriers. These have significantly reduced the costs of the images and made those more readily available. Nowadays, users may select the type of images as required for their intended applications. They enjoy the flexibility to acquire the images relating to the dates they require. For example, despite the difficulties of data interpretation (Woodhouse, 2000),

the availability of the spaceborne Synthetic Aperture Radar (SAR) data, which is considered in this study, has provided the scope for mapping crops even in the wet season where cloudy conditions are common (Shao et al., 2001). The possibility of all weather, day-and-night operation, and the ability to penetrate through clouds and other features, gives SAR some advantages over the optical systems (Hara et al., 1994). Synthetic aperture radar (SAR) is an active imaging system using microwave bands of electromagnetic spectrum to generate images through the coherent processing of the scattering signals. Therefore, SAR data is considered suitable for detecting the changes in land use even in wet season conditions, especially in a tropical region like Bangladesh where much of the time cloud cover limits the use of optical remote sensing (EGIS and SPARRSO, 2001). One of the other special properties of SAR systems is that they are active systems; that is, they both transmit and receive their own signals (FAO, 1993). Therefore, these can operate as easily at night as during the day. Further technical details concerning SAR data will be discussed in Chapter 2.

### **1.1.3 Problems in the use of remote sensing**

Although remote sensing image processing techniques have been used successfully in a range of land uses and land cover mapping with a variety of spatial and temporal scales, their full potential as a source of information has not yet been fully realized due to several reasons (Wilkinson, 1996a). One of the most frequently stated reasons for this is the lack of expertise among the users in extracting the information available from the remotely sensed imagery to support their endeavours (Skidmore, 1999). This causes concern to the various space agencies and the industry when considering the emerging markets for image data as predicted for fields such as agriculture, insurance, intergovernmental agencies and international treaties (Blaschke, et. al., 2000). Because of the lack of expertise, reducing the cost of the data may not reduce the overall cost of utilizing remote sensing techniques. Along with the scarcity of expertise, the accuracy and the complexity of the data processing techniques have also been blamed. The available data, tools, and techniques are too complex for most users, unless they devote a considerable amount of time to obtaining the relevant “technical” background. Users are faced with the problems of viewing a mass of data, applying appropriate methods, evaluating the results, and handling the specific computer platform (Moller-Jensen, 1997). The development of the data acquisition technology is clearly ahead of the data processing techniques currently available, and experts and skills remains inadequate to

exploit the full potential of the recently available data. Despite the potential mentioned above, due to the speckle noise in SAR data, conventional image processing methods are not suitable for segmentation and consequent classification of images (Woodhouse, 2000). As is the case with other types of digital data, a human expert can accomplish the classification of a SAR image, where the process is strongly dependent on the skill, experience, and knowledge of the field condition during image acquisition. A computer using a quantitative approach can also accomplish this, however, speckle noise in SAR data drastically reduces the ability to distinguish and classify the features of SAR images automatically (Chen et al., 1996). In order to illustrate these problems, the author's experience of working with remote sensing data in Bangladesh over a period of ten years will be briefly reviewed. Among the problems encountered, the questions related to the accuracy of image classification and the re-applicability of the whole procedure followed for image processing and reaching the end products significantly influence the adaptation of this technology for land use and land cover mapping and monitoring.

The author worked in the Remote Sensing (RS) and Geographic Information System (GIS) Support Cluster of "Environment and GIS Support Project for Water Sector Planning (EGIS)" under the Ministry of Water Resources in Bangladesh, currently known as the Centre for Environment and GIS (CEGIS). Particularly, in the three years before embarking on the current research, the author worked exclusively with Remote Sensing data from acquisition and procurement to the production of the final product for different clients. During this period, dealing with the accuracy of the products was one of the main concerns for every project. Two types of accuracy were of concern: positional accuracy and thematic accuracy. Positional accuracy answers the question: "How accurate it is in terms of where it should be?" Thematic accuracy answers the question: "How accurate is it in terms of what it should be?" The problem of positional accuracy is tackled using Differential Global Positioning System (DGPS) supported Ground Control Points (GCPs) for Geo-referencing the images. Thematic accuracy was also improved to some extent by using DGPS supported ground truth information for the image classification. However, overall thematic accuracy of the classified image was still generally less than 80%, unless it is manually edited in the light of the knowledge of subject matter specialists. It was also observed that the accuracy provided by the various traditional methods of classification, such as,

Maximum Likelihood (MLH), Minimum Distance (MND), and Mahalanobis Distance (MHD) was not always acceptable. In addition, none of these methods could be accepted as being superior to the others. The degree of accuracy varied over the data quality (noise level) and type (optical, radar), the number of output classes, and the physical and spectral properties of the land cover classes. Moreover, these difficulties increased with the satellite based SAR data as observed over the period. To improve the accuracy of the ultimate product, which was usually a map showing different land cover and land use classes, specialists usually analysed the initial classification result against the field data and ground knowledge with the support of colleagues with relevant expertise and other GIS and tabular data. The success of such efforts depends on the skill and expertise of the person involved in that post classification stage and is difficult to replicate. It is also the case that, from the beginning of the process, remote sensing image processing and classification is labour intensive. For example, one of the many initial tasks of a remote sensing image is to perform geometric correction through geo-referencing. In the geo-referencing process, the quality and time in terms of selection of GCPs is operator dependent. Although quality can be improved through checking the parameters, ultimately, the dependency of the operator's knowledge and skills in performing that, decides the cost of the value adding. Similarly, for noise reduction, currently available software may provide a number of filtering methods. Which filtering method will be used depends upon the knowledge and skills of the operator. Therefore, the whole procedure cannot be replicated further unless all of the individual's skills and knowledge can be accumulated into a system.

On the other hand, it is also the case that currently available various commercial image processing software packages provide collection of tools for contemplating different image processing tasks, such as tools for image enhancing, image resizing and conversion, image registration and geo-referencing, and classification. Some software packages provide several methodologies for performing the same task, which are even more puzzling for a user without adequate knowledge of the subject, and make the software package more expensive. Recently, some vendors have added expert system capabilities to their software for rule-based classification, although only a domain expert is likely to be able to use such facilities. Overall then, remote sensing and image processing are highly expert dependent, and are a combination of both quantitative and

qualitative processes. However, the qualitative methods are still in favour and dominate many processing steps, and so, consequently results are not replicable.

Moreover, in a country like Bangladesh, there are probably not more than 15 highly experienced remote sensing experts in the country and there are no formal under graduate or postgraduate degrees in remote sensing. Therefore, despite the great potential of remote sensing techniques, they cannot yet replace the traditional surveying systems. This means that an alternative improved technique is required to make the remote sensing image classification process replicable through providing consistent results. One potential solution to this problem is to develop an intelligent image processing system that reduces the need for technical expertise from the analyst.

#### **1.1.4 Potential alternative methods of image processing**

Research and development into new techniques for remote sensing image processing are in progress. There are well-regarded and widely practised techniques of data processing and classification, which are providing efficient results with higher accuracy in other domains, many of which could be applicable to the processing of remote sensing data. Alternative methods of SAR classification to reduce the given effort and loss of information content in data by the speckle-reduction operations have been investigated by many researchers. Various properties of SAR imaging systems have also been used in classification. Oliver and Quegan (1998) described the classification and segmentation methods based on statistics relating to radar cross-section and polarimetric data, and textures of the SAR images. Kahny and Wiesbeck (1991) studied the influences of the input parameters on the classification of the polarimetric SAR data for land cover classification. These suggest that some form of additional information in the classification process could be useful in reducing the impact of the noise of the data in the classification process. It has been long acknowledged that GIS data can be used as auxiliary information to improve remote sensing image classification as mentioned by Deren et al. (2000).

In recent years, the successful use of the neural network approach for pattern recognition has led to its application in remote sensing image classification. Many researchers also compared the capability of different neural network algorithms with commonly used classification algorithms by the remote sensing community (Foody



1995a, Hara et al. 1994). These studies revealed that a neural network could be used to classify remote sensing image data at least as accurately, and indeed often more accurately, than conventional classification approaches. The literature suggests that unlike many conventional statistical classifiers, neural networks do not rely on the nature and distribution of the input vectors (Foody, 1999). This indicates the potential for using additional discriminatory information with the image layers in neural networks. From the literature, it is found that GIS layers are usually used in post classification refining activities for increasing the classification accuracy of remote sensing images. The use of GIS data as further discriminating information during image segmentation may provide the classification with higher accuracy and the speckle and noise reduction effort for SAR data could be kept to a minimum using the neural network methods, although this needs to be tested. Neural networks, therefore, have considerable potential for accurate land cover mapping and the potential for spaceborne SAR remote sensing as a source of land use, land cover and other thematic data should be realized.

A promising and recent direction in other domains suggested that a number of classifiers could be combined to tackle the limitation of one system over another. This has the advantage that the features of the classification procedures of different types of classifiers can be used simultaneously or sequentially and then the results can be combined to complement one another and improve the overall accuracy of recognition. The common understanding is that such a combination may generate more accurate classification than each of the constituent classifiers would. The combination of classifiers' output was first developed for the improvement of handwritten character recognition (Xu et al., 1992; Ho et al., 1994). Since then, many applications have benefited from the idea of Multiple Classifier Combination (MCC). This technique has also been adopted recently in several studies of remote-sensing image classification (Benediktsson, et. al., 2003; Briem, et. al., 2002; Debeir, et. al., 2001), which shows that there is scope for further work with remote sensing data, such as satellite based synthetic aperture radar (SAR) data.

The above discussion indicates that there are methods for image classification in other domains that could be examined for utilization in remote sensing image processing. Any advanced technique requires experts and skills, which are not readily available in the developing countries. Probably that is why expert system methodologies are becoming popular in many areas of science and technology. Expert systems are

computer programmes that perform in a similar way to a human operator, in some limited area of expertise, and that make use of stored representation of knowledge as a means of providing solutions and explanations (CSS, 1989). The basic idea behind the Expert System is the transferring of human expertise in a domain to a computer system so that it can solve a problem in a similar way to a human consultant of that domain (Turban and Aronson, 2001). Therefore, the advanced techniques and the experts' knowledge of remote sensing image processing can be integrated into an expert system for remote sensing image processing and classification.

While considering the expert system, another promising idea could be the utilization of metadata in the system. Human remote sensing image processing experts utilise different knowledge about the data during image processing when deciding the methods and steps. Some information about the data, such as the spatial resolution and extent, projection system, and the accuracy achieved in previous processing activities, can provide vital information in many subsequent processing techniques. Recently, preparation of such descriptions of data (which is also called metadata) is frequently proposed and awareness is growing in the spatial data (remote sensing images, GIS layers) handling community. As a source of this information, metadata could play an important role in automatic expert reasoning. Metadata usually includes information about the intellectual content, digital representation, accuracy and security or rights management information of the actual dataset (FGDC, 2002). Spatial Metadata is information that describes spatial datasets such as images and GIS layers. The literature on metadata suggests that the main objectives for developing the metadata are data sharing, preventing the duplicity or redundancy of given effort for data generation and processing. However, another potential use of metadata could be its utilization in expert systems, as a source of the basic information required for image processing.

### **1.1.5 Present requirements**

The potential of identifying earth surface phenomena from satellite based SAR images, even in difficult weather and irrespective of daylight condition, is continually inspiring research into improving the classification and interpretation techniques. The discussion above suggests that improved methods and an appropriate system are greatly required for the extraction of accurate information from these data. There are several potential methods in other domains and their usability in remote sensing image processing and

classification needs to be explored. By automating the remote sensing image processing and classification methodologies incorporating the intelligent techniques, current obstacles to the operational use of these tools could be overcome. A system is required that will perform the image processing and classification requiring a minimum level of domain experts' input. Such a system could be used by a less experienced analyst and even by an expert from another domain. For example, a fisheries expert may need a current land use map for identifying the fishponds and planning the fish fry distribution strategy. The map can be derived from a current or recent set of remote sensing images and so the fisheries expert does not need to be an image-processing expert, but rather requires a DIY type tool for deriving the land use map from the collected image(s).

In this context, this study intended to investigate an image processing system that should be less dependent on the expert's skills and knowledge. Thus, the improvement in technical efficiency and the decrease in the dependency on the expertise and skills of the human operator for deriving useful information from the remote sensing data through accurate and consistent classification and interpretation will certainly increase the economic viability of competing with the traditional methods.

## **1.2 Research Goal and Objectives**

The goal of the study is to reduce the need for trained and experienced remote sensing experts by designing an intelligent system for image processing and the classification of remote sensing data. This system should be less dependent on high-level image processing expertise by automatically completing the tasks of image processing and classification with the added knowledge of experts and appropriate methods in the system. A working hypothesis is that the integration of the other information from GIS during the image segmentation, especially when SAR images are concerned, will provide the classification with higher accuracy. The concept behind this approach is that the use of the GIS layer as additional discriminating information for image segmentation may provide the classification with higher accuracy and it may also require very limited ground truth data and speckle reduction activities in SAR images. However, traditional methods of segmentation frequently show their limitations in such integration and an advanced methodology is required. In this context, in order to achieve this goal this study attempted to fulfil the objectives given below.

### **1.2.1 Objectives**

The overall objectives of the study are:

1. To evaluate and extend as necessary the techniques of using GIS for satellite based SAR image segmentation and classification
2. To design an intelligent system architecture for reducing the dependencies on expertise and skills of the human operator in image processing and classification
3. To develop a prototype and evaluate the system for the identification of land use and land cover using SAR image processing and classification

### **1.3 Scope of the Work**

To fulfil the objectives of the study, it is intended to undertake a case study of the processing and classification of satellite-based remote sensing images to identify appropriate methods and derive knowledge for the development of an intelligent system architecture.

In particular, the case study will classify SAR images integrating a GIS layer using neural networks and will compare the results with those of certain traditional classification methods. This section of the work is intended to provide the basis of the argument outlined above that the inclusion of a GIS layer during image segmentation using neural networks may also improve the classification accuracy.

Next, the study will review the currently practiced methods for the combination of multiple classifiers techniques, which is a not yet a well explored area for the remote sensing domain, and proposes a method aimed at improving the classification accuracy.

Then, the study will design an intelligent system architecture for remote sensing image processing and classification to incorporate these advanced methodologies of image classification with the existing methods. The system should start with a list of available resources and information about the expected output from the analyst and does the work by calling in functions and methods as necessary.

Finally, the study will implement a prototype of the proposed architecture and evaluate the system.

## 1.4 Thesis Outline

The current chapter of the thesis provides the background, motivation, objective, and scope of the research.

Chapter 2 contains the literature review of issues related to the current research. It may be relevant to mention here that this study is focused on researching the technological aspects of Earth Science and Geography. In this case remote sensing image processing techniques and methodology are part of Computing Science, whereas the application to the land use and land cover mapping is part of Earth Science and Geography. Therefore, the literature review addresses issues from both subject areas. The initial sections of the chapter review land cover and land use systems and their responses to the remote sensing SAR data and the technicality of SAR data. The remaining sections of the chapter review the advanced methodologies for image processing and classification that have potential for remote sensing. 1

Chapter 3 describes the research methodology, and includes the background of the study area; the field data collection methodology; the analysis and manipulation of data for determining land use and land cover classes; the preparation of the training and evaluation data; and other methods employed with the aim of achieving the study objectives.

Chapter 4 largely addresses the first objective of this study. This chapter first presents the results of the various classifications and provides a comparison of those results. It then discusses the methods and results of experiments using multiple classifier combinations.

Chapters 5 and 6 fulfil mainly the second and third objectives. Chapter 5 presents the proposed architecture of the intelligent image classification system, and chapter 6 discusses the implementation of the prototype and its evaluation.

Chapter 7 concludes the study with recommendation for future work.

## Chapter 2

### 2. Review of Previous Research

#### 2.1 Introduction

The ultimate goal of the study is to achieve an intelligent system for remote sensing image processing and classification that maximises the accuracy of the results and can be run by a user with limited knowledge. To achieve this goal, a relevant case will be studied in order to evaluate advanced methodologies, such as neural networks and multiple classifier systems, and so design the architecture of an intelligent system. The case study will use relatively new satellite based remote sensing SAR images as case data for land use and land cover mapping. Accordingly, in this chapter, it is necessary to introduce the topics of remote sensing and the characteristics of case data with respect to the application domain. Subsequently, remote sensing image classification techniques will be reviewed with the focus on the neural network approaches. Then a recently emerging area of computer science, which is the use of multiple classifier systems, will be reviewed in relation to their use or applicability in the field of remote sensing. Finally, the applications and architectures of intelligent systems will be examined in order to determine how they may be developed in the domain of remote sensing.

#### 2.2 Remote Sensing for Land use and Land cover mapping

##### 2.2.1 Remote sensing

Remote sensing can be defined as a technology that is employed to acquire information about an object by detecting the energy reflected or emitted by that object when the distance between the object and the sensor is far greater than any linear dimension of the sensor (Teillet et al., 2002). However, remote sensing has been described in various ways by numerous authors, e.g. Campbell (1996), Lillesand and Kiffer (1994), Sabins (1997). Campbell's definition is of most relevance to this study:

*Remote sensing is the practice of deriving information about the earth's land and water surfaces using images acquired from an overhead perspective,*

*using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the earth's surface.*

In this study the phrase "remote-sensing" is synonymous with aerial or satellite photography/imagery, which is the use of electromagnetic waves (light, infrared radiation, microwave and radio waves) from satellite and airborne sensors for observing the earth's surface and its atmosphere. In this sense, remote sensing is used in a similar way to our own senses, to provide information that may be difficult or expensive to obtain by direct measurements. In this context, remote sensing is an alternative means of mapping, measuring and monitoring the changes in the earth's resources phenomenon.

### **2.2.2 Land use and land cover**

When we consider earth surface mapping in general, land use and land cover go side by side. Land cover is a generic term for expressing the cover of the earth surface seen in a remote sensing image, whereas, land use is specific to the land cover that is created by human activities. While these two terms go together, land cover is closer to the natural conditions, while land use refers to the pattern of human activities over the land (Lodha, 1992). Seas, rivers, deserts, and natural forests are examples of land covers. On the other hand, housing areas, agriculture, special infrastructures, or in a further detail classification levels, different crop types, categories of water bodies, categories of housing areas, are examples of land uses. Land use may also follow seasonal patterns. The case study employed in this research is particularly focused on examining the methods of classification for wet season agricultural land use in the study-area using remote sensing. Further details of the study area are given in Chapter 3.

### **2.2.3 Applications of remote sensing for land use and land cover**

Remote sensing techniques have been used for land cover mapping activities for over 30 years, even before the term was coined, and they played an important role in many developments that we enjoy today. "Mapping forest vegetation from aerial photographs was first attempted in the 1850s using a camera carried aloft in a hot air balloon" (Ulaby et al. 1981) and has been used for the identification and monitoring of agricultural land use targets since the late 19<sup>th</sup> century (Brisco and Brown, 1998). The spatial context,

large aerial or scale dependent synoptic view, frequency of temporal coverage as well as the continuous improvement of resolutions (spatial, temporal and electromagnetic) in remotely sensed data are becoming an integral part of recent land use land cover assessment, monitoring and planning over time. Remote sensing techniques can be applied to data from different types of observation platform and each platform, mobile or stationary, has its own characteristics. In a broader sense, there are three types of platform for remote sensing; ground, airborne and spaceborne observation platform (Figure 2.1). Each type of platform has its own particular advantages, disadvantages, and uses. This study is particularly concerned about the spaceborne orbiting satellite based remote sensing. The figure also shows some of the properties of remote sensing systems with their height above the earth's surface.

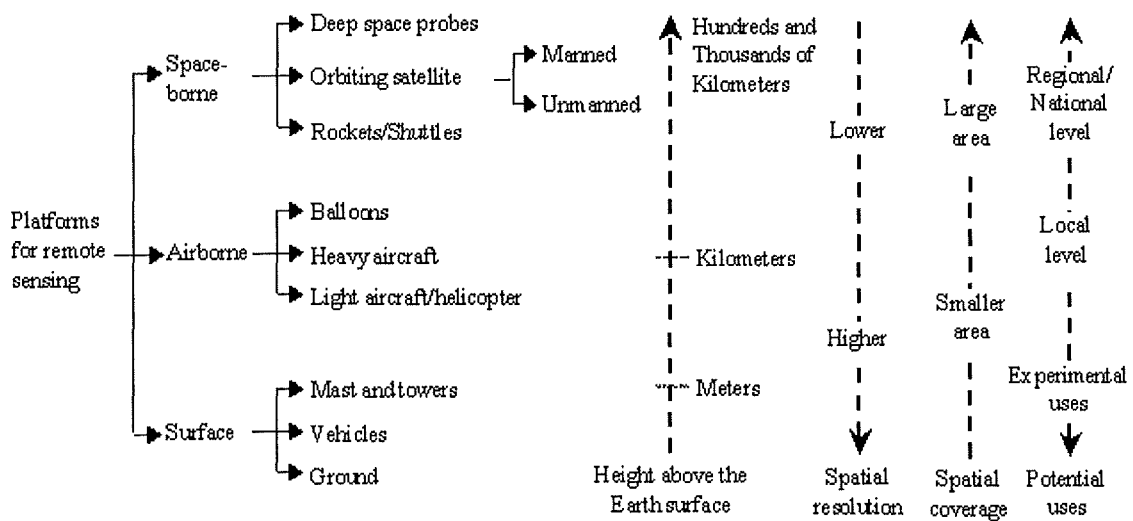


Figure 2.1: Different platform for remote sensing and properties (Modified from Barrett and Curties, 1992)

There are two broad categories of sensor systems, passive and active, that are used for remote sensing (Barret and Curtis, 1992). Passive systems use mainly the visual and infrared portion of electromagnetic web bands reflected or emitted from the earth's surface objects. Active systems mainly use the microwave portion of the electromagnetic spectrum bands used in RADAR systems. Moreover, both systems have particular advantages and disadvantages depending upon the application. Table 2.1 provides a comparison of passive (visible and infrared) and active (microwave) remote sensing systems.



Table 2.1: A comparison of techniques in passive and active remote sensing systems compiled from various sources

Context		Passive (V+IR)	Active (microwave)
Broad	Specific		
General	Detection	Reflected sunlight	Radar backscatter
	Interaction	Chemical/molecular	Geometric/dielectric
	Wavelength	0.3-3 $\mu\text{m}$	2-70 cm
	Frequency	1000-100 THz	15-0.43 GHz
	Resolution	1-1000 metre	1- 1000 metre
	Swath width	60 – 3000 km	15 – 5000 km
	Geometry	Vertical looking	Side-looking
Penetration	Soil	None	Yes (variable)
	Vegetation	None	Yes (variable)
	Water	Yes (variable)	Negligible
Information	Soil	Surface	Surface & volume
	Vegetation	Surface	Surface & volume
	Water	Volume (variable)	Surface
	Urban	Surface	Surface structural
Independence	Cloud cover	No	Yes
	Haze	No	Yes
	Rainfall	No	Variable
	Sunlight	No (except Thermal bands)	Yes
Data presentation	Stereo	Yes	Yes
	Interferometry	No	Yes
	Multi-spectral	Yes	Yes
	Multi-temporal	Yes	Yes
	Multi-polarization	No	Yes
	Available since	70s	90s
General Difficulties	Acquisition	Cloud cover	Limited ground station
	Interpretation	Intuitive	Non-intuitive
	Illumination	Variable	Constant
	Distortions	Limited	Topographic layover, foreshortening & shadows
	Noise	Limited	Highly speckled

### 2.2.4 Potentials and limitations of remote sensing

Satellite based remote sensing imagery has been available in the public domain since 1972 with the launching of the Landsat platform. Since then, it has opened up a wide scope of research and application potential to scientific and land resource management professionals. According to Cracknell (1999), remote sensing systems are now operational. The term “operational” means firstly, that they are providing data on a regular basis. Secondly, back-up systems can be brought into service if one of these

satellites should fail and thirdly, as a longer-term response to the failure of a system in space, a new replacement system is already in existence on the ground waiting to be launched to provide a continuation of the service. Therefore, users can obtain data at more regularly and closer to the required frequency and spatial coverage. Before the introduction of remote sensing imagery, the professionals had to be happy with the topographic, soil, geological or land use maps for their information requirements for analysing spatial phenomenon for their applications. Those maps were usually available in the scales ranging from 1:250000 to 1:10000 and were never produced more frequently than once in every five years (Alan, 1990), while the study of certain spatial phenomena (e.g. landuse changes) requires higher temporal and/or spatial resolutions. Figure 2.2 based on Alan (1990), outlines the requirements of different applications with respect to the spatial and temporal resolution of remote sensing systems. It is clear from the figure that

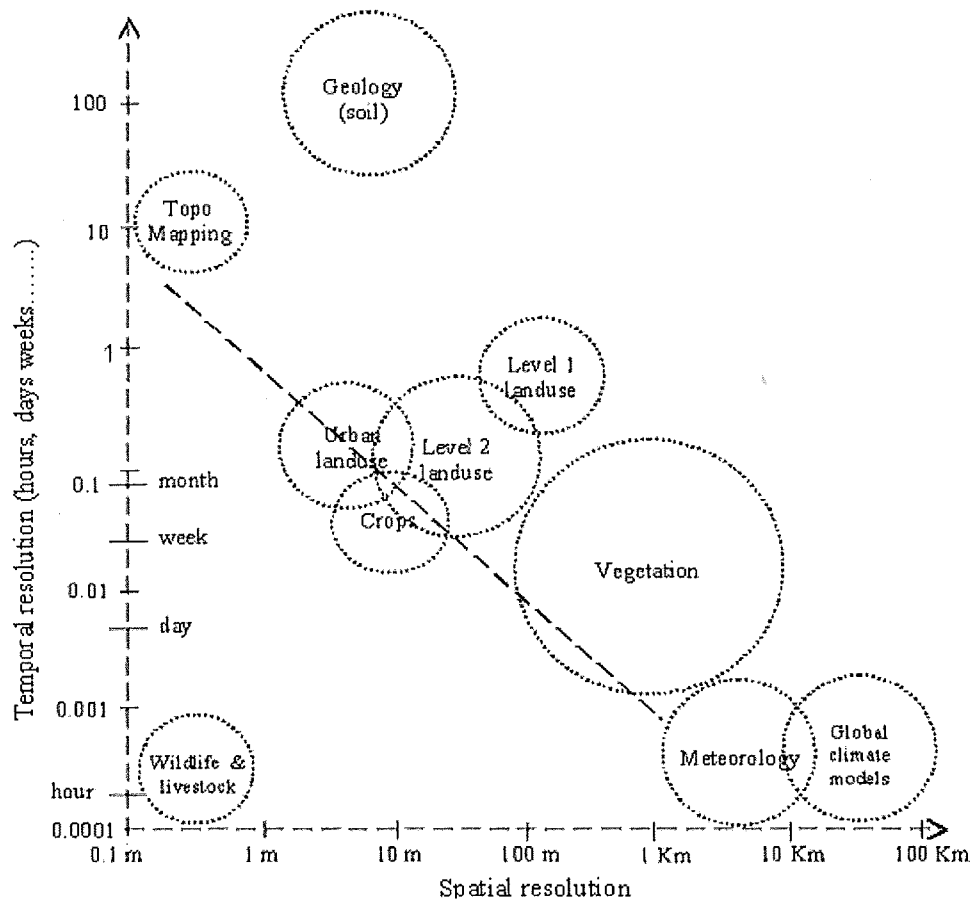


Figure 2.2: The requirement of spatial and temporal resolution of remote sensing for different applications

the land use and agricultural applications cannot be well addressed by traditional mapping systems. Currently, satellite images are available from several kilometres to a

few metres in terms of spatial resolution and one month to a few hours in terms of temporal resolution, which are further widening the application potentials.

One of the aims of remote sensing application is to provide information that can help to improve the management of resources (agriculture, forest, fisheries, etc.). The usability of remote sensing images from different systems is dependent on the region, season, and type of land use and land cover under consideration (Alan, 1990). Particularly, while considering agriculture, the type of crops, the growing season, and the size of land parcels are important factors related to the use of remote sensing in monitoring crop areas, conditions, estimations of yield, etc. Furthermore, it also varies depending on whether the platform of the sensor, such as remote sensing is carried out from a vehicle in the field or is satellite based remote sensing. There are differences in parcel size, the seasonal and spatial patterns of cropping, climatic conditions, and other geophysical phenomena in different regions of the world. These differences also limit the selection of remote sensing sources. In a tropical climate like that of Bangladesh, there is cloud-cover for over half of the year and so optical sensors are unsuitable for year-round applications (Toan et al., 1997). The interference of cloud limits the acquisition of timely and comprehensive information in optical image acquired using the visible and infrared bands, whereas, the methodologies for such images have long been studied, well researched and documented. In an area of this kind, while there is cloud, microwave bands using active sensors may have potential for inventorying and monitoring agricultural crops with other land use and land cover. The backscatter signature from each crop in a microwave image using active sensors varies according to the target's characteristics, such as leaf moisture, plant separation and number of leaves per square metre or canopy over the ground (Aschbacher et al., 1995). The crop growth models predict the characteristics of different crops at given times, and provide inputs to the radar models, which estimate the backscatter from each crop of interest. In this context, the use of microwave images may be an alternative to direct field measurement when many of the fields become inaccessible due to the wet season conditions.

### **2.3 Synthetic Aperture RADAR (SAR) Remote Sensing**

This study is using SAR data for its case study. Therefore, it will be relevant to understand the basics of this data that are useful for deriving the knowledge for

processing and classification. The following discussion also highlights the advantages of this over optical and NIR remote sensing data in certain applications.

### 2.3.1 Synthetic Aperture Radar (SAR)

This section will review the SAR imaging process and explore how it differs from the other form of remote sensing data. Radar remote sensing has a different imaging-mechanics from the other forms of remote sensing. SAR data provides more information than optical data, although it is more difficult to interpret the image. It requires advanced technology to process the images (Zhang et al, 1999). Radar is an acronym for Radio Detection and Ranging. The basic idea of radar is that, by sending out short pulses of microwaves and measuring the echoes, information about the distance (range) and properties of different objects can be obtained. Woodhouse (2000) provides a useful conceptual model of different aspects of radar remote sensing. SAR relies on the fact that radar is an active system; that is, the system both transmits, and receives, its own signals. The frequency of the used microwave spectral band in SAR imaging is one of the system parameters that influence the magnitude of radar backscatter from the targets. It also defines how deeply into the object the SAR image can penetrate. Figure 2.3 shows the microwave bands used in SAR imaging systems in comparison with other bands of the electromagnetic spectrum.

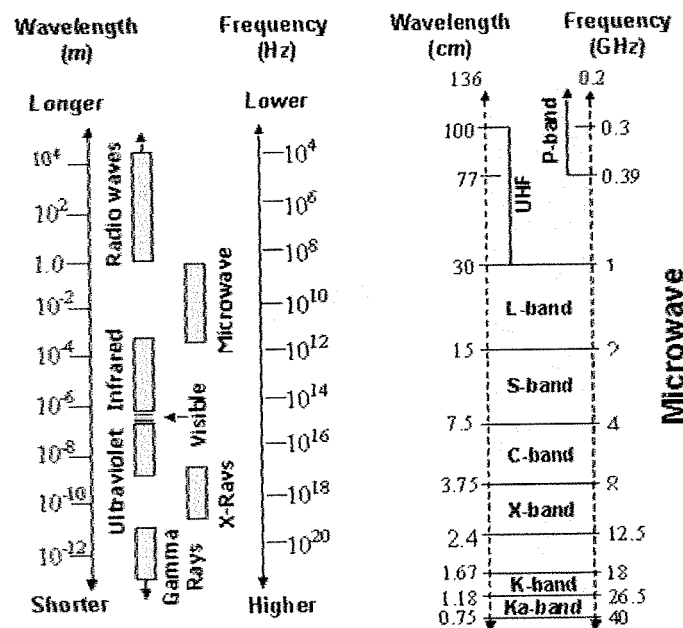


Figure 2.3: Different band of electromagnetic energy and the Microwave bands used in SAR systems figured from the table in Henderson and Lewis (1998)

Another consequence of SAR is that the microwave may be given a well-defined polarisation. This allows the use of polarimetric SAR data for discriminating the target feature (Hara et al., 1995). The transmission or backscattering that is parallel to the earth's surface is the 'horizontal' polarisation and perpendicular to this direction is 'vertical' polarisation. Figure 2.4 illustrates the polarisation in radar transmissions. In this manner, it is possible to measure the scattering from either polarisation to the other in terms of amplitude and phase, and thus measure the full polarimetric scattering matrix of the target. The scattering matrix can be used to derive information about the shape and orientation of the scattering object. However, this property cannot be used in this case study, as it does not exist for the used data set.

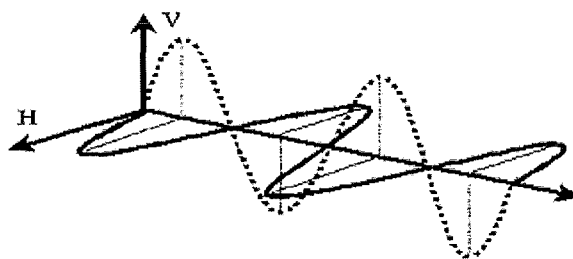


Figure 2.4: Horizontal and Vertical polarization in radar transmission

In order to produce an image, firstly, the waves must propagate from the sensor to the target, then a sufficient proportion must be reflected back towards the sensor, and finally the energy must be received and measured (FAO, 1993). In a SAR image, the digital number in each pixel position is determined by the strength of the radar signal reflected from the corresponding location in the scene. Both of the system parameters (wavelength, polarization, incidence angle, resolution) and the object parameters (complex dielectric properties, surface roughness, terrain geometry and surface and volume scattering) are responsible for radar backscattering from which the images are derived. From the SAR perspective, land cover can be viewed as a multi-scale collection of scatters. This means that features like the settlements, leaves, twigs, branches and trunks of trees and crops, soil and water exposed and/or underneath the vegetation and crops, etc. represent a spectrum of different dimensions, which have different spatial distributions (Brisco and Brown, 1998). An undulated or rough surface, such as a rocky surface or ploughed dried land, is more likely to have higher backscattering, which results in a brighter signature on the image. On the other hand, a smooth surface reflects the energy in the opposite direction which will produce potentially less scattering towards the sensor and the signature will be darker, such as

the surface of a relatively calm water-body like a lake or a river. If there are any obstacles next to the smooth surface, then most of the reflected energy potentially bounces back to the sensor and creates a very bright signature in the image. Such a corner effect is common in urban areas and the SAR images show a very bright tone. The multiple bouncing from the volume of vegetation or soil creates grey signatures depending on the loss of energy due to scattering in other directions. The comparatively longer wavelengths of the 'microwave' portion of the electromagnetic spectrum are used in a SAR imaging system, which can get through the cloud and atmospheric obstacles with less interruption to and from the target. The increasing frequency or decreasing in wavelength reduces the radar signal penetration into the crops canopy and/or in underlying soil (Wooding, 1995).

Figure 2.5 provides a visual impression of a raw SAR image from the RADARSAT satellite system and an optical multi-spectral (bands 4,3&2) image from the Landsat Thematic Mapper system, displayed in false colour composite.

### **2.3.2 Radar interaction with vegetation/agriculture**

The case study of this research will classify SAR images for land use and land cover mapping where vegetation, primarily in agricultural land use, is the most dynamic part of the area. In this context, this section will review the understanding of the potential impression of those features in the image to be used.

Radar RS image data also gives the impression of volume characteristics where optical RS gives mainly the surface characteristics of the target, as described in Zhang et al. (1999). Different crops have unique roughness and moisture levels. Radar is sensitive to differences in these parameters resulting in contrasting backscatter patterns. In the case of vegetation, there might be a contribution of volume scattering in the vegetation layer and surface scattering by the underlying ground (Ulaby et al., 1981). The relative importance of these two contributions depends on several factors, including the radar penetration depth, the height of the canopy, microwave wavelength, incident angle etc. In the case of crop identification, the major target parameters are the geometrical and dielectric characteristics of crops. Depending upon the crop canopy and the height of the crop, the underlying soil influences the interaction of the microwaves with the agricultural targets (Ulaby, 1975). For any crop, the structure of the individual

plants (stalk, leaves, fruit, etc.) and the moisture content of the plant may be unique (FAO, 1993). It is the differences in the structure and the moisture content, which result in the differential volume and surface scattering at various microwave frequencies, allowing the differentiation between various crop types. Visually and from a radar standpoint, the crops are dynamic as their structure and moisture is continually changing during different growth stages.

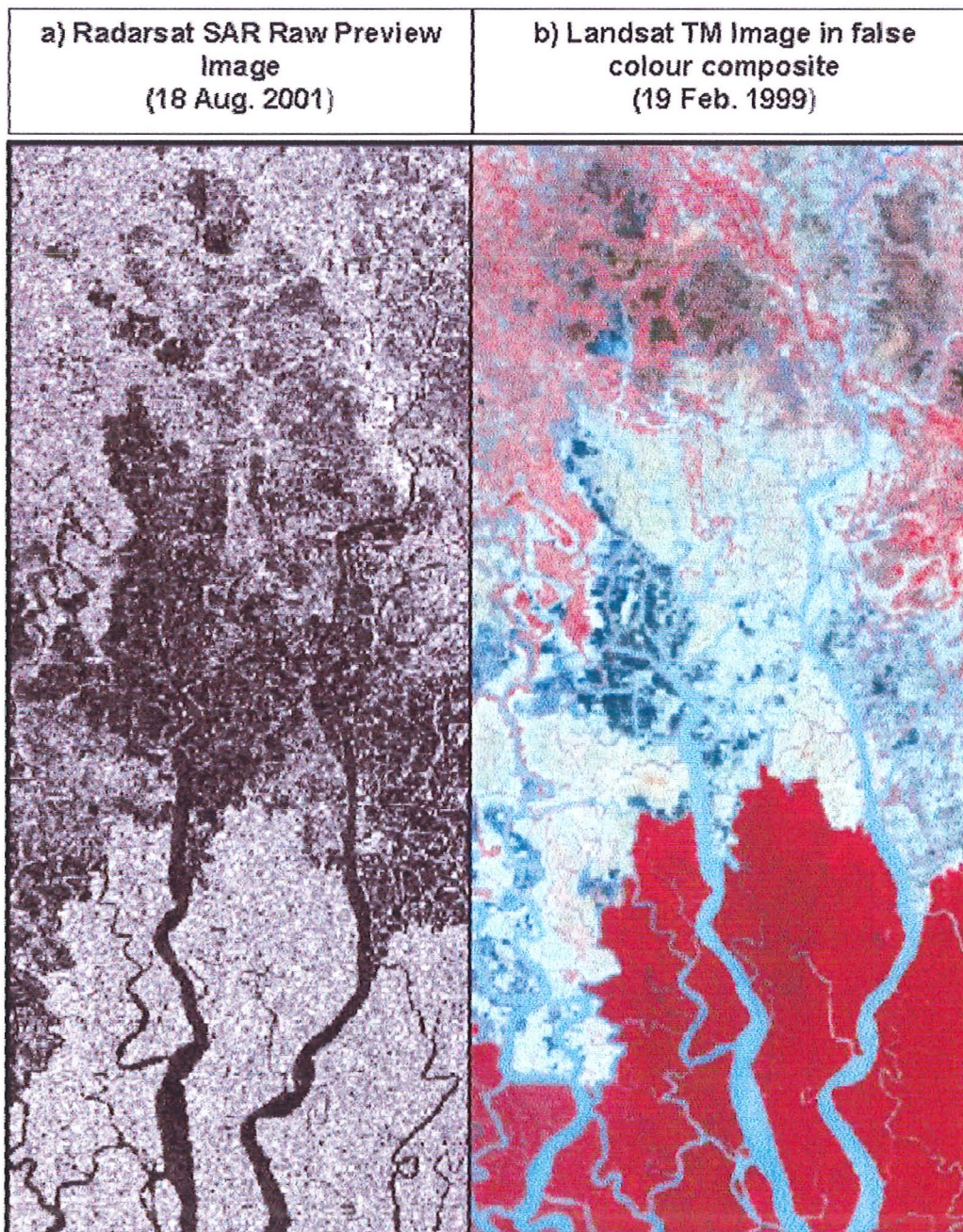


Figure 2.5: Visual impression of a SAR image compared to a multispectral optical image

Due to the mechanism of the SAR interaction with the target and the imaging of the target, the identification of features in the image becomes more difficult when the target feature is agriculture. The features of a SAR image result from radar backscattering rather than the reflection of sunlight. During interpretation, one needs to be careful about this difference between the SAR and optical systems. The analysis of SAR imagery deals with the analysis of the tone, texture, shape, size, pattern, etc. of the image with respect to the ground information. Intensive studies on radar remote sensing for various agricultural applications have been going on for more than 3 decades as reported in Brisco and Brown (1998). Scientists have become more interested in radar remote sensing for agricultural application since the ERS-1, JERS-1, RADARSAT, and Almaz-1 single-channel SAR imaging satellites become operational during the 90s (JoBea and Smith, 1991; Wooding, 1995; Aschbacher et al., 1995). The understanding of radar interaction with vegetation has also developed greatly since the simple “cloud” model of Attema and Ulaby (1978). The literature reveals that, in the last decade the acquisition, study and the knowledge of radar data for agricultural applications have significantly increased. Despite the potential of SAR imagery for agriculture land use, it is a more indirect approach for crop applications in comparison to optical remote sensing (Brisco and Brown, 1998). In a multispectral optical image, the interpreter can easily identify the vegetation from the visible and infrared wave bands. This is not the case for radar imagery and the success of identification depends on the incorporation of appropriate ground information.

Nonetheless, until recently, it has been difficult to extract useful information from SAR images on a routine basis because of the problems in dealing with ‘speckle’, a noise-like phenomenon that renders standard optical image processing algorithms ineffective (Brisco and Brown, 1998). The noise or ‘speckle’ in SAR imagery is a common phenomenon for several reasons and it is not possible to eliminate ‘speckle’ at the image formation stage. ‘Speckle’ in the image complicates the interpretation and reduces the effectiveness of image segmentation, classification, and other information extraction procedures. Several studies (Zhenghao and Fung, 1994, Lee 1986) indicate that there is always a trade-off between these two requirements, i.e. the requirement of speckle reduction and preserving the information contents when parameters of different filters usually affect the performance of the results. There are various types of existing filters for reducing the level of noise or speckle in an image (Shi and Fung, 1994). By



mathematically modelling the noise or speckle, it is possible to develop a suitable filter for the image and that should reduce the noise or speckle while preserving the useful information contained in the image (Lopes et al., 1993).

A single SAR image may contain useful information for crop classification but low accuracy is typically obtained unless the region under consideration is characterised by just a few crop types, which are significantly different with respect to their microwave signatures (Brisco and Brown, 1998). These authors cited several examples of using multiples SAR images of different dates for better crop identification since, as the crops grow and their canopy, structures, etc. change, and accordingly their backscatter characteristics change. Further, such change may be different from crop to crop, which is also useful information in time series radar data. Therefore, this study is also using four SAR images of different dates over the crop-growing period to distinguish different crops.

## **2.4 Image Processing and Classification**

This section initially reviews the steps involved in remote sensing image processing. Then it reviews the commonly used methods and techniques for remote sensing image processing and classification to determine the current limitations and the points to be addressed. The section also reviews some advanced techniques of image processing and classification that have potential applications in the remote sensing domain.

Remote sensing image classification involves the grouping of all or selected land cover features into summary categories that allow the interpretation of the earth's surface imaged by the imaging sensor. In remote sensing image classification, techniques are most generally applied to the spectral data of a single-date image or to the varying spectral data of a series of multi-spectral or multi-date images (Wilkinson, 1996a). The complexity of image classification techniques can range from the use of a simple threshold value for a single spectral band to complex decision rules that operate on multivariate data. Numerous classification approaches have been used with varying degrees of success. Despite the considerable recent developments, the accuracy with which thematic maps may be derived from remotely sensed data is still often judged too low for operational use (Townshend, 1992).

## 2.4.1 Image processing steps

Image processing is an aspect of the computer vision area that involves two steps: low-level and high level as described in Rao and Jain (1988). Low-level vision is based on the extraction of features, resulting in a segmented image with labelled different regions, where the shapes, spatial interrelationships, and surfaces of objects may be described. The high-level vision consistently attempts to interpret the labels obtained from low-level processing using a priori information about the scene's domain. Thus, they considered the two main steps in image processing: segmentation and interpretation. The basic steps involved in general image processing are also discussed in Gonzalez and Wood (1992) as acquisition (capturing image), pre-processing (quality improvement), segmentation, and interpretation.

Image acquisition phase is where an image is acquired through means of a sensor producing a two-dimensional image. So far, among remote sensing image processing experts, the acquisition stage of the images had been of less concern beyond establishing any information that is necessary for image processing. The image acquisition stage is mainly handled by the space technologists. The recent vision in the remote sensing image processing community jointly with the space technologists is to introduce satellite systems that are more intelligent, where subsequent processing steps can be performed in space, during and immediately after the acquisition. As a result, users would directly access data in a manner similar to selecting a TV Channel according to their choice. More and more users want the imagery provider to provide the 'value-added' content, so that users need to employ processing expertise at a minimum level. Although many corrections of the pre-processing level (radiometric and atmospheric corrections) are frequently adopted at the acquisition level, due to the technical complexities most parts of the image processing are still left to the users. In this context, it may be relevant to mention the recent work of Zhou et al. (2004), who propose a concept design of future intelligent earth observing satellites. However, the current study is not concerned with the acquisition step of remote sensing image processing, it is interested in the other steps starting with the pre-processing.

The pre-processing step aims to improve the quality of the image by enhancing the contrast, removing noise caused by the sensor, or physical and environmental elements in between the scanner and the objects, and by minimising geometric errors.

The third step in image processing and classification is the segmentation of the image, whereby it is partitioned into its constituent parts or regions. Data can be represented as boundaries or regions. Boundary representation concerns external shape characteristics, while regional representation focuses on internal characteristics such as the homogeneous spectral properties of the objects that are captured in the image. For land use and landcover mapping, regional representation is more appropriate. The description of feature selection involves feature extraction, allowing for the highlighting of the features of interest. Recognition labels an object from the descriptors in the final step of image processing, which involves assigning the meaning to the recognised objects. This step is also known as interpretation and is essential in remote sensing image processing unlike many other types of image processing. In supervised approaches, segmentation and interpretation is performed simultaneously based on the training data fed into the system earlier and in remote sensing image processing these two steps are commonly referred to as classification. However, one further step, which is frequently practiced by the remote-sensing experts to increase the ultimate accuracy and to make the classes more meaningful, is the post-classification refining or post-classification interpretation, reclassification or regrouping. This step is when expertise is required beyond just image processing.

## **2.4.2 Traditional classification techniques and limitations**

### **2.4.2.1 Conventional practice**

Conventional practice for remote sensing image classification is usually based on classical statistical methods and decision theory, such as, the Maximum likelihood (MLH), Mahalanobis distance (MHD) and Minimum distance (MND) classification methods described details in Tso and Mather (2001), etc., which are commonly used methods in the remote sensing community. These methods are usually described in the supervised category and required ground reference information as training data for image classification. Among these, the most frequently used MLH classifier relies upon the assumption that the populations, from which the training samples are derived, are normally distributed. This is not always the case with remote sensing data (Collet, 1999), especially, when it is SAR data. Image pixel values are discrete and have a lower and upper limit of value depending upon the type of remote sensing, whereas the normal distribution usually relates to the continuously measured and unbounded data sets,

though the probabilities at the extremes may be so small that they are meaningless. The maximum likelihood classification is by far the most popular type of classification for multispectral images. The decision rule of this method is based on the probability a pixel belongs to a particular class. The basic equation assumes that the input bands (image layers) have normal distributions. The equation first determines the distributions of pixel values in each band for each class. Each unknown pixel is then assigned to a class based upon the probability. For minimum distance classifier, the decision rule calculates the spectral distance (Euclidian distance) between the measurement vector for the candidate pixel and the mean vector for each signature class. It assigns candidate pixels to a class whose means are most similar to the value of the candidate pixel. The Mahalanobis distance classifier decision rule uses the covariance matrix in the equation of measuring the distance of the candidate pixel from the signature class mean. Variance and covariance are calculated so that the clusters that are highly varied will lead to similarly varied classes, and *vice versa*. There is ample literature that evaluates these traditional classifiers for various type of image classification (Tso and Mather, 2001; Xue-Hua et al, 2002; Benediktsson et al., 1990; Roli et al. 1997; Foody, 1999).

#### **2.4.2.2 Limitations**

Although results from MLH classification may lead to claims of an overall accuracy of 80% or more, its reliance on normally distributed data is suggested widely as a reason for its abandonment (Mather, 1999). Foody (1999) noted that the conventional statistical classification techniques may not always be appropriate for mapping from remotely sensed data and it is more complex when multi-source data is used (Benediktsson et al., 1990).

Conventional parametric classifiers consider the distribution of data in the calculation and many of them (e.g. MLH) assumes that the data are normally distributed. This often may not be the case and there may be significant inter-class differences in the distributions. Moreover, if the distributions of two classes are same then the method fails to distinguish the classes. In statistical supervised methods, typically a large training sample is required to define a representative sample that would be the source of descriptive statistics (e.g. mean, covariance) for the classifier. However, as Mather (1987) recommended, the minimum training set size is some 10-30 times the number of discriminating variables (such as number of wavebands or number of images in a time

series) per class. Mather (1987) asserts that, firstly, a very large training set is required for mapping from multi-spectral or multi-temporal remotely sensed images. This situation runs contrary to the major goal of remote sensing, which involves extrapolation over a large area from limited ground data. Therefore, in cases of high dimensional datasets, additional effort is required for the identification of optimal numbers of bands for the classification. The statistical methods commonly are based on assumption that all data layers used as stacked input vectors are modelled in the same way (Benediktsson et al., 1990). However, in the case of multi-source datasets they are most likely to be in different measurement scales and therefore may require to be normalized using the same measurement scale for some of the classification method (Tso and Mather, 2001). Foody (1995; 1999) also mentioned that parametric classifiers like MLH can only make direct use of data acquired at a high level of measurements and cannot accommodate low-level data like soil map or other land properties such as land use, or land type data to increase the classification accuracy. The MHD takes in to account the shape of the frequency distribution (assumed to be Gaussian) for a given cluster in feature space, resulting in ellipsoidal clusters (Tso and Mather, 2001). The equation here used the variance-covariance matrix in the distance measurement equation and in case of equal distance between the pixel under consideration and two of the class-centres are same, the pixel will be assigned to cluster that has higher value in the variance-covariance measurement. The MND uses the Euclidean distance that assumes equal variances and a correlation of 0.0 between the features, giving circular clusters. In this method, in case of equal distance between the pixel under consideration and two of the class-centres are same, then the decision to place the pixel in clusters become ambiguous. All these conditions limit the use of multi-source data as image and GIS data together for classification using commonly used statistical method like MLH, MHD and MND, although there may be useful discriminatory information available in GIS data and inclusion of those data in the classification may increase the discrimination between the classes. Some of the classical statistical techniques such as Bays, and weight of evidence reasoning such as Dempster Shaeffer allow the other data such as a GIS layer to be incorporated into these classification techniques, however, not included in the scope of this study.

### **2.4.3 Advanced methods of image classification**

Since the mid-eighties, applications of Artificial Neural Networks (ANNs), also widely known as Neural Networks (NNs), have gained attention as providing rather promising results in both supervised and unsupervised classifications. In fact, the advanced methods of artificial neural classifiers have been consistently and convincingly shown to be outperformed the traditional classifiers, such as the maximum likelihood method in the area of remote sensing (Mokken, 1995). Several other researchers also provide similar evidence as discussed below. In this context, this case study also intended to investigate one of these advanced techniques for the classification of SAR images and compare it with the conventional methods. Therefore, this section will review the neural networks and their application in remote sensing in detail.

#### **2.4.3.1 Artificial Neural Networks (ANN)**

Artificial Neural Networks (ANNs) are powerful tools that use a machine learning approach to quantify and model complex behaviour and patterns. ANNs are a collection of mathematical models that emulate some of the observed properties of biological nervous systems and employ the analogies of adaptive biological learning. According to Gurney (1997), a neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the inter-unit connection strengths or weights obtained by a process of adaptation to, or learning from, a set of training patterns.

This review reveals that although ANNs have been around since the late 1950's, they were not sophisticated enough for use in general applications until the mid-1980s. Today, ANNs are being applied to an increasing number of real-world problems of considerable complexity. Literature suggest that they are often good at solving problems that are too complex for conventional technologies, such as the problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. From the review of the relevant literature identifying pattern association, pattern classification, regularity detection, image processing, speech analysis, optimisation problems, robot steering, processing of inaccurate or incomplete inputs, quality assurance, stock market forecasting, and simulation are the common problem domains

where ANNs are found to be used. From the review, a number of network structures are also found. Some of the ANNs' structures are classified as feedforward and recurrent or feedback depending on how the data is processed through the network. ANNs are also categorised by the method of their learning or training as supervised and unsupervised networks. Multilayer perceptron (MLP), Hopfield network, Kohonen's Self-Organizing feature Map (SOM), ART, Learning Vector Quantization (LVQ), and techniques based on adaptive resonance theory (ARTMAP) are different types of ANNs that are commonly found to be used, especially for image classification.

#### **2.4.3.2 The use of neural networks in the field of remote sensing**

One of the most recent advances in the field of remote sensing has been the adaptation of Artificial Neural Networks (ANN) in a wide range of applications and image analysis and the number of reported application has been steadily increasing. The literature shows that the use of different types of neural networks has been found for various applications of remote sensing data. The most commonly encountered ANNs in remote sensing are Multilayer perceptron (MLP) type. Among others, applications are found employing the SOM, LVQ, and Hopfield neural networks methods for the classification of remote sensing images. Several researchers also compared the results from neural networks with the results from different conventional classifiers.

In the field of remote sensing, one of the main applications of neural networks is the image classification, including: supervised classification (Benediktsson et al., 1990; Kanellopoulos et al., 1992); unsupervised classification (Baraldi and Parmiggiani, 1995; Hara et al., 1994, 1995); and image segmentation (Austin, 1997; Clastres et al., 1897; Visa and Peura, 1997). Some of other uses of neural networks in remote sensing are also found, such as in geometric correction and image compression (Walker et al., 1994; Gaganis et al., 1997) etc.

Different types of neural networks have been used on a variety of remotely sensed data including optical high (Landsat TM, SPOT) and low (NOAA-AVHRR) resolution multi-spectral imagery, data from Imaging Spectrometers (AVIRIS) and SAR data (ERS-1, RADARSAT). Although early experiments made use of single source data, recent research has demonstrated the flexibility of neural networks in the fusion of multi-source data for improved land use and land cover classification.

#### **2.4.3.2.1 ANNs for multispectral image classification**

Several researchers described the use of neural networks for classifying multispectral images. Downey et al. (1992) used an MLP neural networks classifier for classifying multispectral images from a Landsat Thematic Mapper (TM) satellite system. They also used MLH and MND statistical classifiers to classify the same image into thirteen vegetation types and compared the result with those produced by MLP. The experiments showed that the neural network was much better in classifying natural vegetation and gave the most accurate representation of the actual ground cover observed during a post-classification field inspection. A similar result was observed by Bischof et al. (1992), who compared MLP and a Bayesian (maximum likelihood) classifier for the classification of Landsat TM images into four land cover classes. The overall classification accuracy achieved by the neural network was higher. However, the maximum likelihood (MLH) was able to better separate one category, the agricultural class. They also examined the integration of textural features of the multi-spectral data into the neural network classifier. With the added texture, the network was able to classify the agricultural area more accurately, resulting in a greater overall accuracy even than that provided by the MLH classifier. They also performed a post-classification smoothing operation and that was performed also using a two-layer neural network. In Dejhani et al. (2000) a flooded area assessment was achieved via texture feature analysis of multispectral data classified by an MLP neural network based on a back propagation (BP) algorithm. They added two kinds of texture content into the last two input nodes of the network to increase the classification accuracy. Promcharoen et al. (1999) compared the result of an MLP neural network with a fuzzy logic approach for Landsat TM image classification, and the result showed an improvement in performance. Kanellopoulos et al. (1992) used a four-layer neural network for classifying multi-temporal SPOT multi-spectral imagery into twenty land cover classes. They had to use such relatively large neural network architecture owing to the complexity of the classification into so many classes and observed that the computation time required for the network was quite long in order to obtain a high standard of generalization. However, the experiment resulted in much higher classification accuracy compared to a maximum likelihood classifier. Mereny et al. (1996) compared Kohonen's Self-organisation Neural Network with several traditionally used sequential classification methods such as MLH, MND, and MHD, using hyperspectral remote



sensing data. They recommend SOM due to the relatively ease in training, compared to the most frequently used back propagation network, and suggested SOM for high dimensional data as used in hyperspectral image classification, especially for its capability of making accurate predictions based on only a small training sample.

#### **2.4.3.2.2 ANNs for SAR image classification**

An early attempt to apply an MLP neural network to the classification of remote sensing data was described by Decatur (1989), as mentioned in Roli et al. (1997). He used MLP for the classification of terrain using radar images and compared the performance with a Bayesian classifier. He found significant improvements obtained by the MLP classifier over the Bayesian classifier in the case of radar images. Xiao et al. (1998) also used the MLP for the classification and fusion of interferometric SAR data and multispectral images and found promising results. Hara et al. (1994) demonstrated a two-step method: in the first step, they automatically classified polarimetric SAR images using an unsupervised neural network, Learning Vector Quantization (LVQ). They then used an iterative algorithm, where the classified image was re-classified using the maximum likelihood classifier to improve the performance.

#### **2.4.3.2.3 Use of ancillary data in ANNs for RS image classification**

Probably the first attempt at using ancillary data in neural networks for classification of remote sensing images was made by Benediktsson et al. (1990). They used MLP neural networks classifiers for the classification of multi-source data, i.e., four bands of Landsat Multispectral Scanner (MSS) and three types of ancillary topographic data. The topographic data were elevation (10 m contour interval), slope ( $0^{\circ}$ - $90^{\circ}$  in  $1^{\circ}$  increments), and aspect ( $0^{\circ}$ - $180^{\circ}$  in  $1^{\circ}$  increments). The output classes were ten ground-cover classes. They also used MLH, MND and MHD statistical classifiers for the same set of data. Comparing the results, they showed that although the additional data increased the accuracy in the statistical classifiers, the accuracy of the neural network was superior. Moreover, the statistical classifier could not identify several classes. They also tested with different weights for individual data layers while combining the multi-source data in the statistical classifiers. They found that the full weight for Landsat data and 40% weight for all ancillary data provided the best result among the weight combinations they tested, but concluded that it is problematic to find optimal weight combination. Another attempt used a soil map with multi-temporal SAR images in a feed-forward

artificial neural network (Foody 1995a) and produced similar results. Rangsneri et al. (1998) compared the result of multispectral (JERS-1) image classification result from the MLP and MLH algorithms and demonstrated a better result from the MLP. They did not do so but suggested the potential of using additional layers of spatial and temporal information in MLP neural networks.

#### **2.4.3.2.4 *The comparative advantages of ANNs***

Each type of network is very different from the others and consequently they may vary in their appropriateness for different applications. Different types of artificial neural networks may be superior for different types of data and given tasks. Although there has been no clear research into this issue, some indications can be drawn from the literatures, such as, feedforward networks have been used widely for supervised image classification (Kanellopoulos et al., 1992). Hopfield networks have been used in studies involving stereo matching and feature tracking (Lee et al., 1994; Cote and Tatnall, 1995; Lewis et al., 1995). Kohonen networks (Kohonen, 1995) are self-organising and so are particularly attractive for unsupervised and semi-supervised classification. Pham and Bayro-Corrochano (1994) also suggested that Kohonen's Self Organising feature Map (SOM) as an alternative to supervised techniques for remote sensing image classification as well. Petersen et al. (2002) also experienced the same in their review of image processing using neural networks. Better results from SOM for multi-temporal satellite image classification in comparison to some other neural networks has already been demonstrated by several studies (Tso and Mather, 2001; Torma, 1993; Luo and Tseng, 2000; Lewis et al., 1992). Merenyi (1999) found that, in supervised environment, training a SOM network is much easier than training a back propagation (BP) network, and it produces more accurate classification results based on a smaller amount of training spectra than would be required for the training of BP.

#### **2.4.3.3 *Some other advantages and limitations of ANNs***

In a number of studies, ANNs produced higher classification accuracies than conventional statistical classifier, although this is not guaranteed to be the case in all circumstances (Atkinson and Tate, 1999). In general ANNs methods are not statistically rigorous and cannot produce maps showing classification uncertainty. One of the useful outputs of a MLH classifier could be the probability maps which represents the reliability of a pixel belongs to a certain class, which cannot be obtained from an ANNs.

Mather (1999) further mentioned that, while the use of ANNs may improve land cover classification accuracy by a small percent, they do not represent a breakthrough in terms of raising overall accuracy of classification much beyond 80%. However, according to the literature, it is undoubtedly the case that the designing and training of an artificial neural network is time-consuming, although it is equally true that, once the network is trained, it is computationally faster than the statistical classifiers. An artificial neural network usually comprises a large number of simple processing units linked by weighted connections according to a specified architecture. All of the long-term knowledge of the network is effectively stored in the strength of the weighted connections between the units. As such, networks may learn and generalise, and typically are massively parallel in nature (Aleksander and Morton, 1990; Bishop, 1995). Moreover, ANNs are able to handle any kind of numerical data and do not depend of the distribution of input vector like many statistical classifiers. Therefore, a large sample may not be required to estimate the properties of the classes. Nonetheless, a representative training set is still required to provide an adequate description of the classes and the training set properties require careful selection in relation to the classes and the network in use, as noted in Foody (1995b). A neural network also learns the underlying relationships in the data and effectively weights the importance of the discriminating variables. This feature of a network provides no limitation to the data dimensionality, which reduces the need for the exercise of finding optimal band combination.

#### **2.4.4 The integration of GIS for image processing**

Traditionally, RS and GIS researchers have worked separately (Atkinson and Tate, 1999). According to them, these techniques may be loosely described as 'spectral' and 'spatial' respectively. In this sense, the classification of remote sensing data is the conversion of spectral information into spatial information. However, it has been increasingly recognised that existing spatial information can play an important role in the spectral analysis of remote sensing image classification. In particular, the land use and the agricultural system of an area are largely dependent on the properties of the soil, land type, water availability, climatic condition, and other geo-physical characteristics of the area. In remote sensing images, different types of crops may have similar or minor differences in terms of their spectral responses. Therefore, it is an emerging idea

that RS is not only a source of information for a GIS, but rather that GIS may be integrated with RS for the purpose of image analysis and classification (Dijk and Bos, 2001; Apisit 2000, King and Meyer, 1990).

Hence, the question is how to integrate the GIS. Many spatial phenomena cannot be represented properly using conventional classification techniques. Therefore, expert or knowledge based systems, fuzzy logic, and neural networks have recently been used for multispectral remote sensing image classification (Chen 1999). A recent study suggested the integration of vector GIS data for image classification in a fuzzy system for a forestry application (Hinton, 1999). Wilkinson (1996b) identified three types of integrations of remote sensing and GIS technologies: (i) remote sensing can be used as a tool for gathering datasets for use in GIS, (ii) GIS datasets can be used as ancillary information to improve products derived from remote sensing, and (iii) remote sensing data and GIS data can be used together in environmental analysis.

In the second approach of integration as mentioned above in which remote sensing and GIS technologies are complementary to each other, while using pre-existing GIS data sets in the interpretation of remote-sensing data. However, such an approach can be two ways: (a) the use of GIS data as secondary input vector, where GIS is used for refining the image classification result, which is the most common way of integration or vice versa where the preliminary classification (e.g. land use layer) is updated by the remote sensing data; (b) the use of GIS data as one of the primary input vectors with the images in the process of segmentation and classification. Although the huge potential of this second approach has been pointed out by many researchers, its full potential is yet to be realised. It may be mentioned here that GIS layers can be continuous (e.g. DEM, Slope, Aspect) or categorical (e.g. landuse, land type, geological type) as suggested by Strahler (1981). Two approaches are commonly found to be used for combination of spectral images and different GIS data. One is the use as prior probabilities and the other is the use of the logical channel approach (Tso and Mather, 2001).

In the use of the prior probabilities approach the basic idea is that if the information about an area shows the preferences of certain classes for particular locations in the terrain, then this information can be expressed in terms of prior probabilities of occurrence for each class and this information can be incorporated into

the classification process. The methods based on the Bayes' Theorem are mostly used in this type of integration approach. This method is commonly applied in remote sensing when thematic information provides a priori probabilities of a pixel containing a given class type and then image spectral information is used to revise these probabilities, resulting in improved land cover classification accuracy (Strahler et al., 1978; Richards et al., 1982; Pereira and Itami, 1991). Bayes, theorem is the foundation of the commonly used MLH method, however, in a review on current practice, Eastman (2003) found that little use is made of the ability to incorporate prior knowledge into the procedure and no assumptions about the relative likelihood of finding the land cover classes of interest is made before considering the evidence, and it thus assumes that each class is equally likely. The major difficulty involved in this approach is to define a suitable function of prior probability relating to each class in terms of achieving optimal results (Tso and Mather, 2001). Therefore, despite the considerable interest, progress has been somewhat slow, largely because of the inability to specify prior probabilities in a spatial manner Eastman (2003).

In the logical channel (also known as 'stacked vector') approach, the GIS layer(s) is added as an additional feature vector with the spectral images, so that the pixel vector is extended by the addition of this external information. Although this method is easier to apply, several issues require attention: the scale of measurement in each feature vector; the computational cost due to the number of layers in the stack; and the issue of the reliability (or uncertainty) of data layers in the stack. The first two issues have already been pointed out in earlier sections and limitations of the traditional methods and advantages of neural network methods over these issues are discussed. The advantages of neural network methods includes (Paola and Schowengerdt, 1995; Skidmore et al., 1997; Openshaw and Openshaw, 1997) cited in Liu et al. (2002): nonparametric nature; arbitrary decision boundary capabilities to manage nonlinear modeling tasks; easy adaptation to different types of data and input structures; capability of identifying subtle patterns in training data; good generalization of the input data; and capability to process noisy data. So far, several studies have experimented with the inclusion of GIS data with remote sensing images for information extraction using neural networks (Wilkinson, 1996b) and promising results were obtained by, for example, Benediktsson et al. (1990) and Foody (1995a), as discussed in Sections (2.4.3.2). However, no research is found that used relatively low-level (categorical) data

layer(s) as additional information for image classification using neural networks. Therefore, this study intends to evaluate a method for the integration of low-level GIS data in remote sensing image classification using a neural network.

## 2.5 Multiple Classifier Systems

Classifier combination is an advanced pattern recognition technique that is gaining increasing attention in the recent literature. Many disciplines have already benefited from this. While a variety of multiple classifier systems were studied in the 1950s (Ghosh, 2002), this area came in focus again in the 1990s and its applications and theoretical development was boosted when Hansen and Salomon (1990) presented a technique for exploiting the different characteristics of a neural network ensemble. The method was first developed for handwritten character recognition where combination generated a more accurate classification compared to each of the constituent classifiers (Xu et al., 1992; Ho et al., 1994). Several studies already used this technique in various areas of applications and observed promising results. The examples are: the problem of text-independent speaker identification (Chen et al., 1997); visual object detection (Jaimes and Chang, 2000); Medical problems diagnosis (Parmanto et al. 1996; Bovis and Shingh, 2002); Drug Designing (Buxton et al. 2001); Magnetic Resonance spectra recognition (Zhilkin and Somorjai, 1996); independent person verification (Kittler et al., 1998); and earthquake risk prediction (Giacinto et al., 1997). A few applications of the technique are also found in the area of different types of image classification. This study will further investigate the suitability of the technique for SAR data classification. Therefore, a detail of review has been presented in this section.

### 2.5.1 Methods of combining multiple classifiers

During the last decade, various schemes of classifier combination were devised in different areas of applications. By this time, it has become an established research area under different names as identified by Kuncheva et al. (2001) as follows;

*Combination of multiple classifiers; classifier fusion; mixture of expert; committees of neural networks; consensus aggregation; voting pool of classifiers; dynamic classifier selection; composite classifier system; classifier ensembles, etc.*

The paradigms of these models differ in terms of the assumptions about classifier dependencies; type of classifier outputs; aggregation strategy (global or local);

aggregation procedure (a function, a neural network) etc. The idea behind all these is not to rely on the results of single classifiers. Instead, designing a scheme for combining the results of several classifiers would potentially improve the classification accuracy by harnessing the goodness of the constituent classifiers. Several recent works proposed various methods of multiple classifier combinations through deeper theoretical investigation of the issue (Huang and Suen, 1995; Huang and Suen, 1994; Lam and Suen, 1997; Ji and Ma, 1997). Different authors have also tried to group these methods in different ways. For example, Tso and Mather (2001) summarised these combination frameworks into four groups; voting rules, statistical methods like Bayesian formalism, evidential reasoning, and multiple Neural Networks. DiLecce et al. (2000) investigated the role of the *a priori* knowledge in the process of classifier combination and identified classifier combination methods of three major categories; abstract-level, ranked-level and measurement-level. Abstract-level combination methods use the top candidate provided by each classifier, ranked-level combination methods use the entire ranked list of candidates and measurement-level combination method use the measured confidence value of each candidate in the ranked list. They considered 'majority voting method' (MV) as a form of the first category, the evidential reasoning such as the Dempster-Shafer (D-S) method as in the second category and the Behavioural Knowledge Space Method (BKS) was proposed in the third category. The study also observed that *a priori* knowledge is not necessary to achieve high-performance from the classifier combination process when combining the weakly correlated classifiers using majority-voting method. Conversely, as the correlation increases, the *a priori* knowledge becomes the key aspect for classifier combination. The study also observed that, as the classifiers become more correlated the D-S method becomes very effective and when the correlation is very strong (i.e. very close to 1), while BKS provides the best performance. Another study conducted by David et al. (2000), identified three types of combination schemes from their review. Firstly, each classifier outputs a single class label and these labels have to be combined. The second type is when the classifiers output sets of class labels ranked in the order of likelihood, and the third type involves the combination of real valued outputs for each class by the respective classifiers. However, the literature review suggested that the most commonly used methods of multiple classifier combination can be discussed, as in the following categories: Combination by Voting Rules; Bayesian Formalism; Evidential reasoning; Behaviour

Knowledge Space (BKS); Multiple Neural Network Systems; and Methods of Manipulating the Training Sample.

Voting rules are quite simple and are one of the first combination strategies presented in the literature. These are also known as committees, ensembles, or linear opinion pools (Alimoglu and Alpayin, 2001). The commonly used voting principle is majority voting (MV), where the labels output by a number of classifiers for a given pixel are collected, and the majority label is selected. However, several other variations in decision-making principles have been found in the literature. In the 'Unanimity' method the output class label of the data patterns should be accepted by all the classifiers, i.e., the combined classifier decides on an input pattern 'x' as the class *C* if and only if all the classifiers decide that 'x' is the pattern of class *C*. In the 'Modified Unanimity' method, the combined classifier decides that the pattern 'x' as the class *C* if some classifiers support that 'x' belongs to *C* and no other classifier supports that 'x' belongs to any other class. A modified majority vote principle, also known as 'Threshold plurality/majority' is used in some literature where the combined classifier decides that the pattern 'x' belongs to class label *C* if the number of classifiers that support it is considerably bigger than the number of classifiers that support any other class label (Bahler and Navarro, 2000). The simplicity of combining the classifiers by voting is that it does not require any kind of *a priori* knowledge about the combination of classifiers nor does it require any complex methodology to decide.

Xu et al. (1992) demonstrated a method based on the Bayesian formalism for integrating predictions from classifiers to be combined. Using this method, the authors used the classifiers that output a probability (or probability-like) estimate of the likelihood of pixel 'a' belonging to class 'C'. The final classification is made according to the Bayesian criterion (discussed in detail in Tso and Mather, 2001) that the input pattern is assigned to the data class for which the probability is the maximum. The probabilities of a pixel for each possible class by the different classifier are accumulated, and the winner is that pixel that has the greatest accumulated probability.

The mathematical theory of evidence is a field in which a number of data sources can be combined to generate joint inference concerning pixel labelling. In brief, the Dempster-Shafer Method (D-S) method uses the performance of each classifier as *a priori* knowledge. The theory was first developed by Dempster in the 1960s and later



extended by Shafer (Shafer, 1979; Shafer and Logan, 1987). Shafer provided further details for the development of the evidential theory, which has therefore become known as the Dempster-Shafer (D-S) theory of aggregating evidential knowledge. The method associates a degree of belief with each source of information, and a formal system of rules is used in order to manipulate the belief function. In the context of pattern recognition, this method is useful in handling multiple sources of data of different kinds and with different levels of accuracy as described by Tso and Mather (2001). It can also be used to assess the plausibility of labels assigned to a given pixel by different classifiers.

The BKS method uses the behaviour of the whole set of classifiers as *a priori* knowledge extracted in a suitable “learning” procedure. The method is described in detail in DiLecce et al. (2000). BKS is based on two processing phases: the “learning” phase and the “operation” phase. The learning allows the filling of a suitable K-dimensional space. Each dimension of this space corresponds to the decision of a specific classifier. The K-tuple of decisions provided by the K classifiers defines a “Focal Unit”. When a “Focal Unit” is addressed by the vector of recognition responses, the index  $I(j)$  corresponds to the class  $\omega_j$  for which the input pattern is incremented. This index counts the number of times in which a pattern belonging to the class  $\omega_j$  generates the specific K-tuple of decisions. In the operational phase, when a “Focal Unit” is addressed by the K-tuple of decisions, the result of the combined classifier is the class label  $\omega_j$  for which the corresponding index is the maximum, i.e.  $I(\omega_j) = \text{Max} \{ I(\omega_i), i = 1, 2, \dots, m \}$ . Ensembles using BKS do not assume that the decisions of the classifiers are independent.

One of the initial works on the ensemble of artificial neural networks is presented by Hansen and Salamon (1990), where each of the networks have been trained on the same database to classify a given input pattern by obtaining a classification for each of the networks. Then they used a consensus scheme to decide the collective classification by vote. Similarly, Wilkinson *et al.* (1995) fed the output from several classifiers into an artificial neural net, which is trained to produce a single class label as output from several different possible labels output by the multiple classifiers. Wan and Fraser (2000) proposed a concept of multiple maps in Self-Organizing Feature Map (SOM) in which several smaller maps are used and then fused in various ways to explicitly represent a class or cluster regions for their statistical

distributions. They named the proposed framework as the Multiple Self-Organizing Map (MSOM). They have tested the proposed framework with both simulated and real optical remote sensing data classification and observed the great potential of the proposed MSOM approach for remote sensing classification tasks. Kanellopoulos and Wilkinson (1997) tested two strategies. Firstly, they experimented with multiple neural network followed by the majority voting approach of Hansen and Salamon (1990). The second technique they used to take combinations of more than one type of classifier and used a neural network to decide the disputed classes, as shown in the Figure 2.6.

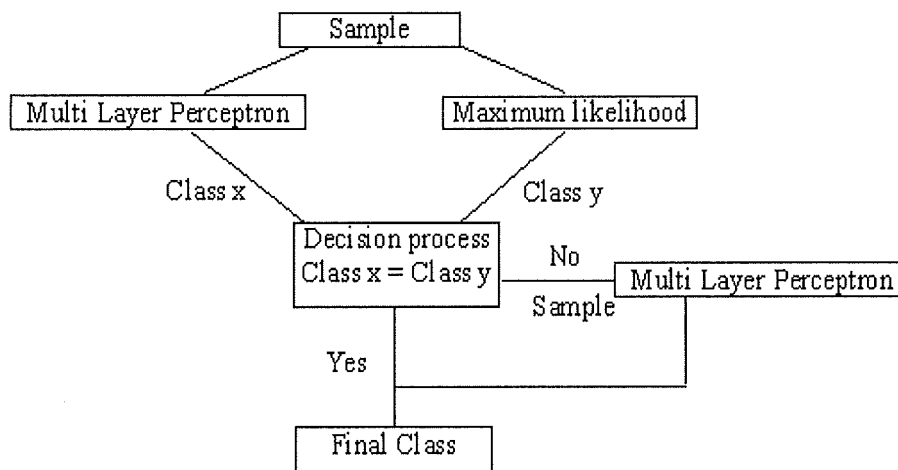


Figure 2.6: Multiple Neural Network System after Kanellopoulos and Wilkinson (1997)

Other combination methods are found mainly based on the manipulation of training samples in the learning processes of a data classification method, where 'Bagging' and 'Boosting' have drawn attention of the researchers recently. The learning algorithms in these methods run several times, each time with a different partition of the training samples. Bagging and Boosting were initially designed for decision trees, however, they were found to perform well for other classification methods such as, neural networks, linear classifiers, and k-nearest neighbour classifier (Skurichina et al., 2002). Several researchers discussed in detail bagging and boosting, such as Skurichina et al. (2002), Breiman (1996), Schapire (1990), and Freund and Schapire (1996). Several others have compared boosting and bagging with other methods and demonstrated their superiority (Bauer and Kohavi, 1999; Diettrich, 2000; Quinlan, 1996; Benediktsson et al. 2003).

## 2.5.2 Combination methods used in remote sensing

Almost all the methods of multiple classifier combination discussed above were have been used on remote sensing data. However, the common consensus was that the methods avoiding the independent errors are more satisfactory compared to the others (Giacinto and Roli, 1997; Roli et al., 1997; Giacinto et al., 2000; Debeir et al. 2001; Santos et al., 2001; Smith, 2001; Briem et al., 2002; Paclik et al. 2001). Possibly that is the reason that there was more work found using some sort of neural network ensemble. For example, in their study Giacinto and Roli (1997) found 85.99%, 85.45% and 85.60% overall accuracy in the Voting rule, Bayesian and Belief Function methods respectively, which is about 2-3% more than that of the individual classifiers, whereas, the method they proposed, which is a combination of neural networks, provided 87.98% accuracy. While working with image data, Hansen and Salamon, (1990) found that if the constituent classifiers have an error less than 50%, then ensemble using the voting rule will improve the accuracy. However, this proof is restricted to the situation when all of the classifiers perform independently and have similar error rate. Ali and Pazzani (1995), cited in Alpaydin (1998), show that, while using voting rule, there is a substantial correlation between the amount of error reduction due to the use of multiple classifier models and the degree to which the errors made by individual models are correlated. However, for spatial data, Matan (1996) has shown that, the majority-voting rule may perform worse than that of each member of the ensemble. The simplicity of the voting rules suffers from certain drawbacks. For example, these methods are solely based on the output label provided by the constituent classifiers, and the expertise or accuracy of the individual classifiers is not considered. Experimenting with the Bayesian formalism method, Kuncheva et al. (2001) observed that the assumption-based classifier combination schemes, based on Bayes' theorem or probabilistic approach, do not always achieve the performance of the other methods. The D-S theory also assumes the independence in the decision of members of the ensemble and there is a similar limitation as with the Bayesian formalism. In the D-S method, the classifiers using the same function to decide the class of each observation are unlikely to behave independently and the calculations involved are relatively complex (Bahler and Navarro, 2000; Kuncheva et al. 2001). In their experiment, Kuncheva et al. (2001) observed that the BKS method is prone to over training and its lookup table needs large data sets in order to be properly calculated. The authors found that KBS always provides a best

training set but not the best result. Similar experience was also reported by Bahler and Navarro (2000).

However, from the review, it is shown that in remote sensing image classification, a combination of classifiers can be a promising alternative to the development of a new classification algorithm that may be more complex than the existing one. Nonetheless, the existing works are not based on different types of remote sensing data, moreover especially, none of the works used satellite based SAR data. Therefore, considering a new promising area of research, this study also aims to experiment with classifier combination methods for satellite based SAR data classification as an advanced technique of image classification.

## **2.6 Intelligent Systems and Remote Sensing**

The methods most often used for remote sensing image classification are the basic algorithms of supervised and unsupervised techniques of digital image classification. The outputs from these methods rarely meet the accuracy requirements for operational uses of remote sensing images. One of the drawbacks of these basic methods is the use of only the information contained in the image itself in the form of one or more layers. The information content in remote sensing imagery depends upon various factors, such as spatial and radiometric resolutions, spatial scale, and the canopy of the features to be imaged, the radiometric contrast between different target types, and the type and amount of noise present in the imagery. Moreover, the current ground and climatic conditions affects most of these factors. Therefore, to achieve the expected accuracy, the outputs of these methods often require vigorous input from human experts, based on personal field experience, common sense, and other available information such as maps, reports, and knowledge of the natural conditions of the targets at imaging time. Remote sensing image classification needs expert decisions and inputs at every step from the data selection and quality assessment to achieving the expected accuracy and finally accepting the output for further uses. However, human domain specialists take many years to develop the knowledge and reliable experience and skills. Access to an expert for an organization, such as an Agricultural Department in a developing or underdeveloped country, is not always easy. This limitation becomes acute when they need classified images on a regular basis in order to assist with managing and monitoring the agriculture of the country. In such cases, a computer-implemented

intelligent system can work continually and consistently with the given knowledge of experts in the field of application. Therefore, this study aims to find an intelligent system that will integrate the existing advanced methods and the experts' knowledge for remote sensing image processing and classification. In this context, this section will review the intelligent systems, particularly the expert system methodologies, to achieve a suitable architecture for an intelligent system.

### **2.6.1 Intelligent systems**

An intelligent system is a computerised system that utilizes artificially added human intelligence in the course of actions and may acquire further knowledge during the process for maximizing the probability of success and minimizing the probability of failure. Meystel and Albus (2000) defined such intelligence as the ability to act appropriately in an uncertain environment where an appropriate action is one that increases the probability of success where success is the achievement of behavioural sub-goals that support the system's ultimate goal. Such intelligent coupling of software and hardware should perform intelligent actions like a human. For example, it can solve a variety of problems, learn from experience, understand language, interpret visual scenes, and, in general, behave in a way that could be considered intelligent if observed by a human. Therefore, the development of intelligent systems lies within the discipline of artificial intelligence. One of the early and well-regarded definitions of AI is given by Barr and Feigenbaum (1981) as "that concerned with designing intelligent computer systems, that is, systems that exhibit the characteristics we associate with intelligence in human behaviour-understanding language, learning, reasoning, solving problems, and so on". However, Kelly (1993) summarised three somewhat different emphases among protagonists of AI and identified three distinct definitions of AI resulting from different motivations or backgrounds as follows:

- Making the machines smarter;  
this group of people defined AI as moving computers into the space occupied by intelligent beings.
  
- Modelling the activities of human intelligence;  
this group defined AI as simulating human behaviour and cognitive processes on a computer system. And

- Studying the nature of the whole space of the mind;  
this third group of people offer a bit broader in their sense as exploring the position of computation in the space of any possible intelligent entities.

This study is concerned with a system, that is more aligned to the second group of people above and that can perform as an expert when used by a relatively novice technician in the field.

### **2.6.1.1 Different areas of intelligent systems**

AI made its debut in the academic community in 1950, which is the year that Alan Turing published his classic writings 'Computer Machinery and Intelligence' (Ringle, 1979) and McCarthy coined the phrase "Artificial Intelligence" (Shapiro, 1987, Turban and Frenzel, 1992). Graham and Barrett (1996) described AI as an area of a number of sub disciplines, such as, Game Playing, Machine Learning, Natural Language Processing, Vision, Robotics and Parallel Distributed Processing (PDP), as well as Expert or Knowledge-Based Systems. This list is by no means exhaustive and may vary among the protagonists of AI. Such a grouping is termed as the field of AI in Turban and Frenzel (1992).

However, the development of an intelligent system frequently involves overlap between these groups. Building computer programmes that play intellectual games is one of the problems that have traditionally fallen within the range of AI. Computer programmes for playing chequers and chess at a high level of skill are perhaps the earliest interests of AI, and Arthur Samuel developed a chequers-playing programme in the early 1960's (Kelly, 1993). The research and development of expertise in the automated gathering of knowledge by a computerised system falls under the general rubric of machine learning activities. Natural language processing for understanding by a computer system investigates the methods of allowing the system to comprehend instructions given in ordinary English so that the computer can understand the people easily and accurately. SHRDLU is an example of an early intelligent system for understanding natural language, which was written by Terry Winograd in 1972 (Barr and Feigenbaum, 1981). The system answers questions, executes commands, and accepts information in an interactive English dialogue. The system contains a parser, a recognition grammar of English, programmes for semantic analysis, and a general problem solving system. The system can remember and discuss its plans and actions as

well as carrying them out. Knowledge in the system is represented in the form of procedures. The "Put-that-there" system can combine natural interaction modes, such as speaking and gesturing together in a media room (Bolt, 1980) or iRoom (Harada et al., 2003) environment. The system responds in a "natural" way based on how a person might respond to similar behaviour. Artificial vision is related to the area of AI, and deals with making computer systems see objects like those that humans do, although it is still crude compared to actual human sight. However, it covers the area of computer systems for vision process that includes image acquisition, image processing, image analysis, and image understanding. Robotics is the most complete and complex part of AI that accumulates almost all the parts of AI into a system for substituting humans for doing work. Many different AI techniques are involved in the science of robotics. In defining robotics, the most commonly given examples of robots are R2D2 in the movie *Star War* and HAL 9000 in movie *2001*. Therefore, robotics is the area of AI that deals with the development of machines (robots) that utilize human intelligence to perform physical work like humans and intelligence that comes from the utilization of vision or scene recognition, the understanding of voice and natural language or machine learning, etcetera.

Among all the above, so far, Expert Systems (ES) are used and applied more than any other areas of AI (Turban et al 2001) and that is one of the areas of interest in this study.

### **2.6.2 Expert Systems (ES)**

AI came to be largely synonymous with "expert systems" during the 1980s (Engelmore, 1993). Expert Systems (ES) deal with a small area of human expertise that can be converted from human intelligence to AI (Levine et al, 1986). However, it is also called Knowledge-Based Systems (KBS), Knowledge-based Expert System, or simply Knowledge Systems (KS) (Turban and Frenzel, 1992). Nevertheless, Johnson (1990) attempted to distinguish the expert system as a knowledge-based system through an evaluated level of performance close to that of an expert as cited in Graham and Barrett (1996). Expert systems may be composed of two major parts: the development environment and the consultation environment (Turban and Frenzel, 1992). The ES builder uses the development environment to build the components and to introduce knowledge into the knowledge base. A non-expert uses the consultation environment.

The interest of this study is in the system that can be used by a novice-engineer or technician to perform the job at an expert level.

### **2.6.2.1 The development and architecture of different ES**

Expert systems were developed in the AI community in the mid 1960s. During that period, a few laws of reasoning coupled with computers were believed to have produced an expert system. One such attempt was the development of a “General-purpose Problem Solver” by Newell and Simon (Turban and Frenzel, 1992; Kelly, 1993). This was an attempt to create an intelligent computer and was regarded as the predecessor of expert systems. However, the shift from such general-purpose to special-purpose programmes occurred very soon with the introduction of DENDRAL by Feigenbaum at Stanford University. DENDRAL began as an effort to explore the mechanization of scientific reasoning and the formalization of scientific knowledge by working within a specific domain of science, organic chemistry. DENDRAL infers the molecular structure of unknown compounds from mass spectral and nuclear magnetic resonance data. It uses an algorithm to enumerate systematically all possible molecular structures. It uses chemical expertise to prune the list of possibilities to a manageable size. DENDRAL was an invention of a new problem solving architecture called plan-generate-test and in many ways is similar to the chess-playing programme of Newell and Simon’s (Feigenbaum, 1992). Knowledge in DENDRAL is represented as a procedural code i.e. a block of statements, which makes up the process. The recasting of DENDRAL’s knowledge into a separate knowledge base of production rules marks the invention of production rules as a representation of knowledge for knowledge based system (Feigenbaum, 1992).

DENDRAL marked the beginning in the organic chemical domain, and by the end of the 1970s expert systems were operating in the medical, chemical, educational, natural resources, and science domains (Prasad, et. al. 2003). Several other expert systems also became prominent during that period. PROSPECTOR is a natural resources system of that period that evaluates geographic sites for potential mineral deposits of commercial interest. MYCIN is an interactive programme that diagnoses certain infectious diseases for prescribing the therapy, and can explain its reasoning in detail. PROSPECTOR and MYCIN systems are discussed in detail by Alty and Coombs (1984). The architecture of both systems is based upon a production system approach.



This means that they have: a collection of facts; a set of production rules; inference engine and a reasoning mechanism, and a knowledge structure that enables the control structure to decide which candidate rules should take part in the inference mechanism. They also have a mechanism for drawing inferences from uncertain evidence.

The period up to 1991 is called “the first era” of expert systems. This era includes the major academic experiments in technological development, and then the first wave of industrial adopters, now numbering in the thousands of companies (Feigenbaum, 1992). The success of the above systems inspired the expert system technology to spread to commercial ventures and prominent systems of that period are XCON, CATS-1, XSEL. XCON is one of the successful commercial ES of the Digital Equipment Corp (DEC) of that period that was used for configuring minicomputer system. XSELL is an associated system of XCON that was also developed by the DEC for checking the customer orders for consistency, such as ensuring that the power supplies match the requirement of the other parts of the equipment being shipped. General Electric (GE) used the CATS-1 for locomotive’s troubleshooting, also known as DELTA. Different expert system programming tools commonly called expert systems shells (discussed below) also appeared during that period, such as, EMYCIN, EXPERT, META-DENDRAL, EURISKO etc.

Feigenbaum (1992) considered the period onwards 1991 as the “second era” of the expert systems and pointed that the “*thrusts of the second era research are the concepts of large knowledge bases, knowledge sharing, and the interoperability of knowledge bases that are geographically distributed*”. A typical expert system of first era is hardly based on more than a few hundred of facts and rules. In a large knowledge base of the second era, the volume of represented knowledge would require a huge effort of knowledge acquisition and engineering. The knowledge sharing indicated not just the sharing of the knowledge of several experts, but also the federated sharing of the existing systems for utilizing the expertise of many sub-domains.

#### **2.6.2.2 Expert System Shells (ESS)**

Expert System Shells (ESSs) are the integrated packages that consist of all the components of ES except the Knowledge Base, and can be used for building a new expert system adding the knowledge of the intended specific domain. EMYCIN, for example, is the skeleton of MYCIN that contains the rest of the components except the

knowledge base. Keravnou and Johnson (1986) describe the ESS as “a generalisation of an ES, made by deleting the domain specific knowledge from the knowledge base and adding the facilities necessary for instantiating the knowledge base for some other domain”. At the end of the 1980s, a substantial effort was made to develop such tools for speeding up the construction of ES. Figure 2.7 shows the difference between the ES and the ESS, as outlined in Turban and Frenzel (1992). The authors state that the bottom five subsystems shown in the pyramid (Figure 2.7) are the common components of an ESS and that the sixth component added at the top of the pyramid completes the ES. The literature suggests that, by using the shell approach, the ES can be built much faster.

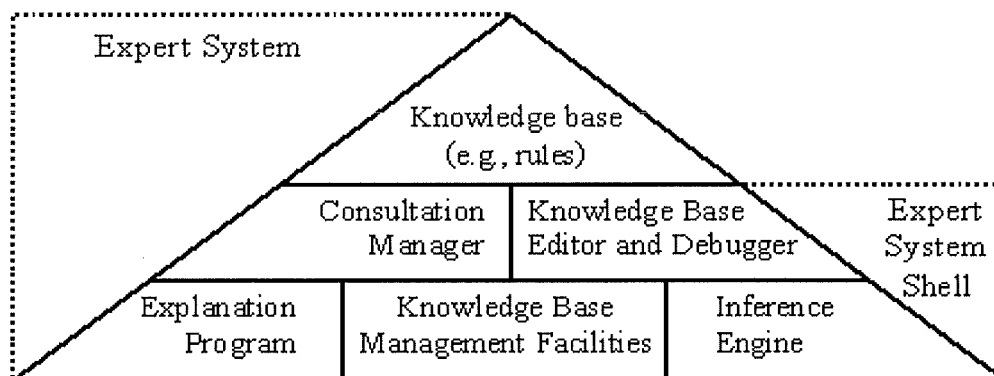


Figure 2.7: Expert System Shell in compare to the Expert System (Turban and Frenzel, 1992)

It is also not always necessary to programme the bottom five subsystems of the shell for every application and so much lower programming skill is required. All of these factors together reduce the cost of building an ES. However, the inflexibility of the chosen shell may lead to certain difficulties. These are: the proliferation (the use of multiple shells), which may cause costly training and maintenance, problems of interfacing or interpretation due to the different programming languages, platforms, poor documentations, and other factors caused by the single reasoning mechanism (restricted to forward or backward chaining), weak security, and improper maintenance.

### 2.6.2.3 Expert system methodologies

ESs are distinguished from conventional computer programmes in two essential ways (Barr, et al. 1989); firstly, ESs reason with domain-specific knowledge that is symbolic as well as numerical; and, secondly, ESs use domain-specific methods that are heuristic as well as algorithmic. ESs provide powerful and flexible means for obtaining solutions to a variety of problems that often cannot be dealt with by other, more traditional and orthodox methods (Liao, 2005). Liao undertook a detailed literature review on expert

systems dated from 1995 to 2004, and grouped the methodologies of the systems into rule-based systems, knowledge-based systems, neural networks, Fuzzy Expert Systems, object-oriented methodologies, case-based reasoning (CBR), modelling, intelligent agent systems, and ontology.

In this review, the author (Liao, 2005) defined all of these categories together with their application for different research and problem domains. In rule-based systems, experts' knowledge is represented in the simple form of rules, such as IF-THEN, and, they use these rules to perform operations on the data in order to reach appropriate conclusions. Liao (2005) referred to Dhaliwal and Benbasat's (1996) work in distinguishing four components of a knowledge-based system (KBS): a knowledge base, an inference engine, a knowledge engineering tool, and a specific user interface, where the knowledge base is made up of facts and rules. Neural networks are another AI methodology that is used in many expert systems and integrated with the knowledge base or rule base. Fuzzy Expert Systems deal with uncertainty using the method of fuzzy logic. The systems use the mathematical theory of fuzzy sets, and simulate the process of normal human reasoning by allowing the computer to behave less precisely and logically than conventional systems. This approach is used in some systems because decision-making may not always be a matter of straight 'yes or no' or 'true or false' and often lies in the grey area between the two extremes. An object-oriented methodology is used for frame base knowledge representation in many of the systems cited by Liao. A frame is a large block of knowledge about a particular object, event, location, situation, or other element. The frames are usually used to represent knowledge built on well-known characteristics and experiences. The idea of case-based reasoning (CBR) involves adapting the solutions that were used to solve previous problems and use them to solve similar new problems. The expert system using such a methodology searches for stored cases with problem characteristics similar to the new one, finds the closest fit, and applies the solutions of the old case to the new one. Modelling methodology based systems are structured around a model that is used to build formal relationships based on knowledge towards solving a problem. Intelligent agents are actually computer programmes that are intended to help users with routine tasks. These are also called software agent or wizards (Turban and Aronson, 2001) and are used in expert systems for coordinating or controlling the flow of information among the components of expert systems. Ontology is a system of vocabulary also used by some ESs as a communication basis between domain experts and knowledge engineers.

#### **2.6.2.4 Expert system architectures**

The architecture of an expert system describes the components of the system, the logical or mathematical relationship of the components, and how the system is going to be implemented. In his review, Liao (2005) found that the architecture of ESs describes the general capabilities of the system, the users' interface, system functions, system information flow, system management, database management systems (DBMS), necessary protocol and specific programming language and software, and things like the blackboard architecture, etc.

##### **2.6.2.4.1 Common components of ES**

Graham and Barrett (1996) provided the basic architecture of a knowledge-based or expert system as shown in Figure 2.8. The figure shows the common components of such a system. Two main components of the system are the knowledge base and the inference engine. The knowledge base represents the expert's knowledge of a particular domain. It is the assembly of all of the information and knowledge relating to a specific area of interest and is organized in the form of facts, rules, and procedures into a schema. The inference engine is responsible for the process of drawing a conclusion from the evidence derived from the knowledge base. This component of the system is a computer programme that provides the methodology for reasoning, organizing and controlling the steps taken to solve the problems by developing the agenda. Among others, current or working memory, and user interface are common in most of the expert systems. The working memory, which is explained as a blackboard or workplace in Turban and Frenzel (1992), contains conclusions specific to the ongoing session, elicited from the user or as specified by the input data. This information is known as inferred knowledge, and is not part of the overall knowledge base (Graham and Barrett, 1996). It also records intermediate hypothesis and decisions. Three types of decision are usually recorded in this so-called blackboard or working memory: a) plan – how to address the problem; b) agenda – the potential actions awaiting execution and c) solution – the candidate hypotheses and alternative courses of action. The use of this blackboard is especially common when several experts team up to solve one problem. The architecture of such systems is commonly known as a blackboard architecture. Such systems are relatively open and can accept any type of knowledge. This can also be used for complex problems that can be divided into smaller problems (Turban and Frenzel, 1992, Barr et al., 1989). The main purposes of such "blackboard" systems are that they

can be used for sharing or inheriting information that is already known between different components and can be used in the problem-solving process as a control mechanism.

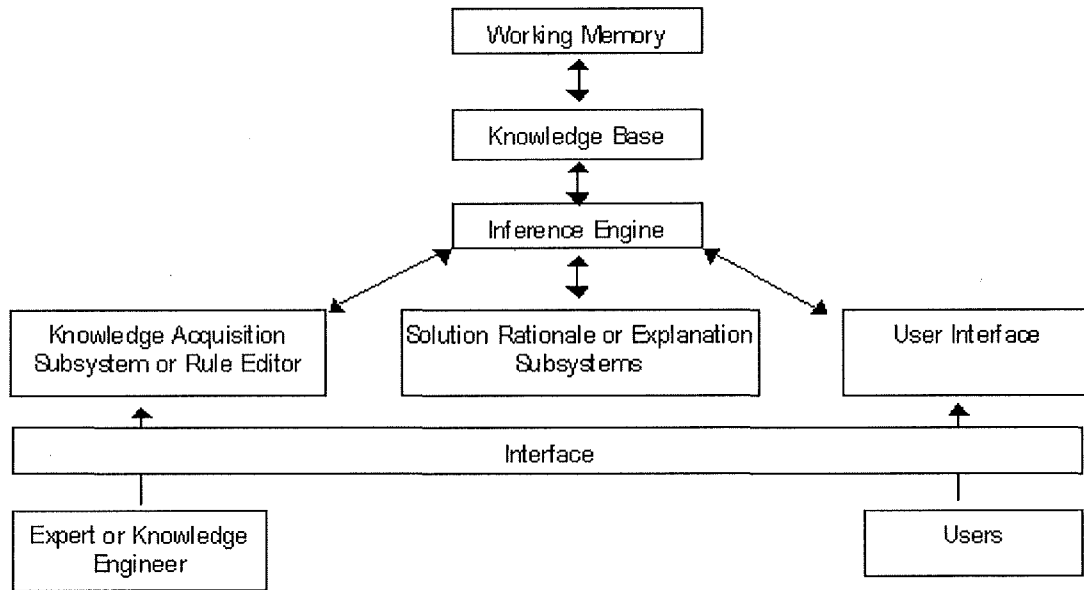


Figure 2.8: Basic Architecture of a Knowledge Base or Expert System  
(Graham and Barret, 1996)

#### 2.6.2.4.2 Topology of ES

The topology of an expert system describes the physical and logical layout of the system components. The components can be laid and connected in a parallel, serial, tree-type pattern, a network, or even mixed pattern. Logical connections show the information flow pattern between the components and this can be in one way or two ways. In the blackboard architecture, the blackboard becomes the centre of the system components and the control part of the blackboard system determines what will be placed on the blackboard (Turban and Frenzel, 1992). The information flow is the flow of knowledge, data, function instructions, and action feedback between the components that are managed by the control of the system. The user interface part of the system varies widely from system to system, from a menu driven text based interface to a graphical user interface (GUI) or even an interface via speech recognition. In a typical knowledge-based or rule-based expert system, users interact with the system through the user interface, which may use menus, natural language, or any other style of interaction. Then the inference engine is used to reason with both the expert knowledge that exists as the knowledge base and the data that is specific to the particular problem

being solved. The expert knowledge in a system is typically in the form of sets of facts and rules. The facts could be a description of data and the task and rules could be in the form of IF-THEN rules. The case specific data includes both data provided by the user and partial conclusions (along with certainty measures if these options are included, usually in fuzzy system) based on the given data. The interpretation stage of the inference engine executes the chosen agenda items by applying the corresponding knowledge based rules. In a simple forward chaining rule-based system, the case specific data may be the elements in working memory. Many expert systems also have an explanation subsystem, which allows the programme to explain its reasoning to the user. Some systems also have a knowledgebase editor, which helps the expert or knowledge engineer to update easily and check the knowledge base easily.

### **2.6.3 The use of intelligent systems in remote sensing**

Intelligent systems in remote sensing image processing involve the convergence of two fields: image processing and artificial intelligence (AI). Recently, ESs have become widespread and deeply embedded, as the techniques have matured into standard information technology. The most important recent trend is the increasing integration of AI methods with conventional information processing, such as data processing or management information systems (Engelmore, 1993). Due to the high level of data rates and information flow of remote sensing systems, in the early 1970s, there were calls for the implementation of automatic interpretation technique in exploiting the full information content of remote sensing image data (Bodechtel, 1972). However, only limited work has been done using expert systems for remote sensing image processing and classification compared to the volume of research associated with remote sensing.

From the review, sixty-four works were found that discuss some sort of intelligent methodology for remote sensing image processing and classification. These date from 1983 to 2004 (Table 2.2). Figure 2.9 provides the scenario of how AI obtained the attention of the remote sensing community. At the end of 1980s, the use of AI in remote sensing image processing came further into focus when several authors (Matsuyama 1987; Wang and Newkirk, 1988; Smyrniotis and Dutta, 1988; Kaufmann, et al., 1988; Wharton and Newcomer, 1989) strongly recommended its use with knowledge-based systems. Wharton and Newcomer (1989) argued for the use of expert

systems for remote sensing image segmentation, target recognition, and target description based on the following goals:

- to reduce the level of human interaction required on a scene-by-scene basis to perform repetitive image processing tasks
- to allow the user to experiment with *ad hoc* rules and procedures for the extraction, description, and identification of the features of interest
- to provide methods that are not necessarily limited to the image(s) from which they were derived (i.e., image-independent rules and procedures)

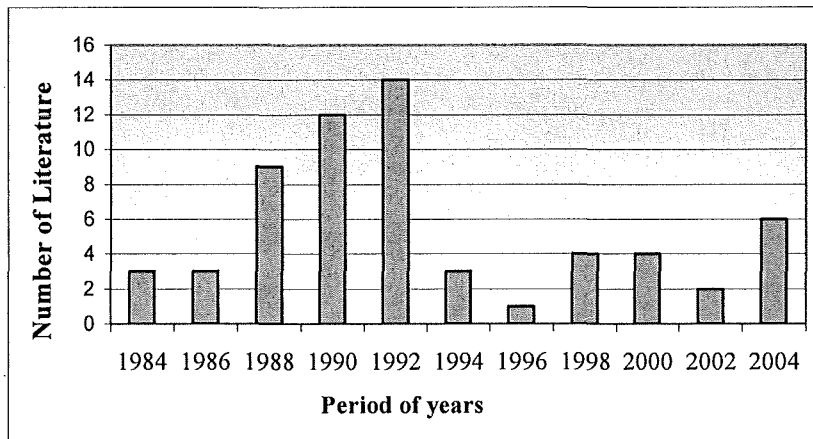


Figure 2.9: Number of study on intelligent systems in remote sensing image processing and classification

Nonetheless, the interest of the community quickly declined. Two reasons behind this were pointed out by Tsatsoulis (1993). One reason could be that the data used in remote sensing is usually numerical and has very low granularity, whereas, expert systems prefer data and information on a higher symbolic level. The second reason could be that the remote sensing community has concentrated on using the traditional classification and analysis techniques. Recently, as the shortcomings of the traditional and practiced methods became apparent, researchers have looked for new approaches as is evident from Figure 2.9. From the review, it is evident that the common AI components used in these systems are rule-based, knowledge-based, neural networks, and fuzzy algorithms. Common areas of applications are forestry, sea-ice classification, and land use-land cover mapping mainly for agricultural applications. Table 2.2 provides a summary of the reviewed literature based on the main tasks and the use of AI methods.

The 'classification' task in the table refers to the systems used to classify the remote sensing image directly using rules-based, knowledge-based, or fuzzy rule-based

methods, where different contextual knowledge was used. For example, the use of the spectral signature of the features in different bands in RS image in terms of colour, shape, size, and texture of features in the hardcopy aerial photo or image. The “interpretation” task in the table refers to the systems where images are first segmented using different traditional classifiers (e.g. MLH, threshold of pixel values), and then the segmented image is interpreted using rules-based, knowledge-based, or fuzzy rule-based methods. The “segmentation and interpretation” task group in the table represents the systems that mainly used neural network for image segmentation and then mainly performed the rule-based interpretation.

Table 2.2: Summarisation of the reviewed literature on the basis of main tasks and used AI method

Tasks	AI method(s)	References
Classification	Rule based systems	Carlotto et al., 1984; McKeown, et al., 1985; Wyatt et al., 1988; McAvoy and Krakowski, 1989; Jayasinghe and Miller, 1989; Clarkson and Strome, 1989; Tjahjadi and Henson, 1989; Kontoes et al., 1991; Charlebois et al., 1991; Xiao and Raafat, 1992; Comber et al., 2004; Ghosh, 2004; Dufour et al, 2004
	Knowledge based system	Matsuyama, 1987; Wang and Newkirk, 1988; Gegg et al., 1990; Clement et al., 1992; Kruse et al. 1993.
	Rule based fuzzy systems	Wang, 1989; Wang, 1990; Curlander and Kober, 1992; Onsi, 2003; Ronei, 2004
Interpretation	Rule based systems	Goldberg et al., 1985; Lybanon et al., 1986; Wharton, 1987; Skidmore, 1989; Schowengerdt and Wang, 1989; Johnsson and Kanonier, 1991; Mori and Kosoli 1991; Haverkamp and Tsatsoulis, 1992; Nazif and Aboelenine, 1992; Warner et al., 1994; Gineris et al., 2000; Soh and Tsatsoulis, 2002; Soh, et al, 2004; Cohen and Shoshany, 2002
	Knowledge based system	Yee 1987; Nicolin and Gabler, 1987; Srinivasan and Richards, 1990; Venkatachalam and Murty 1991; McNoleg, 1996; Deren, et al., 2000; Prasad et al. 2003
	Rule based fuzzy systems	Zhou, 1989; Wilkinson, et al, 1992; Metternicht, 2001
Segmentation and Interpretation	Neural network and rule based systems	Crompt and Cook, 1991; Short, 1991; Zhang et al., 2000; Lui et al. 2002

Some of the above systems also used additional information, such as, GIS data, and agricultural information, in the classification and interpretation processes. Although the subsequent success of image processing is largely influenced by the processing performed in the pre-processing step for correcting the spectral errors in the image, only a few works were found in the literature search in which some sort of pre-processing



tasks are addressed. For example, the rule based spectral band selection from multi-spectral images (Millette, 1990), intelligent interfacing for the selection of appropriate images for the given task (Noack et al., 1987), rule based image enhancement (Lefevre et al., 1993), and a rule-based system for searching ground control points in SAR imagery for geometric corrections (Plöbnig et al., 1989). There are also some studies found in which the system assists in deciding the appropriate algorithm for the image processing based on the image metadata and target application (Smyrniotis and Dutta, 1988; Tjahjadi and Henson, 1989; Charlebois et al. 1991). Pakiarajah, et al. (2000) investigated the conflict resolution techniques for expert systems used to classify remote sensing images.

The review shows that the techniques from AI and ES have been used with increased frequency in recent years. Common applications of expert systems are found in the creation of “smart” user interfaces for assistance with the interpretation of remotely sensed data. Most of them are concentrated on simple classification tasks based on hard copy images. So far, almost all of the current expert systems have been applied to solve some very small portion of the image processing and classification steps discussed earlier. Moreover, from the review, two systems are found to be used at the operational level while most of the others are experimental. One of those is the ARKTOS and the other is SEIDAM, as described below.

### **2.6.3.1 The ARKTOS system**

The ARKTOS (Advance Reasoning Using Knowledge for Typing of Sea Ice) is a recent fully automated intelligent sea ice classification system developed and used at the U.S. National Ice Center (NIC) for the daily operation of mapping the ice covered oceans (Gineris, et al, 2000, Soh and Tsatsoulis, 2003, and Soh, et al, 2004). The underlying methodology of ARKTOS is to perform an analysis of sea ice images and classify them into different classes of sea ice thickness by mimicking the reasoning process of sea ice experts and photo-interpreters. With this system, the reasoning process is designed and implemented to incorporate components including image processing, rule-based classification, multi- source data fusion, and GUI-based knowledge engineering and evaluation. Figure 2.10 shows the system flowchart as provided by Soh et al. (2004). The system incorporates ancillary data, and knowledge based rules to

interpret the images. ARKTOS computes a host of descriptors for a feature and then applies expert rules to classify the floe into one of several ice classes.

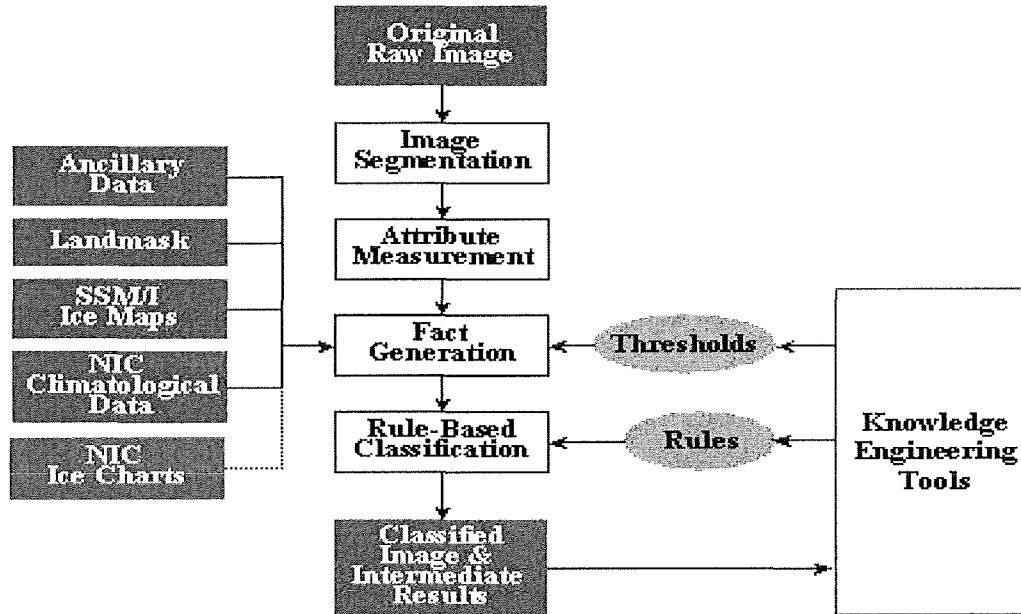


Figure 2.10: Overview of the ARKTOS intelligent sea ice image classifier (Soh et al. 2004)

The main AI component in ARKTOS is the knowledge base. It also generates facts from the measurements and integrates ancillary data into the post segmentation interpretation stage, such as masking land cover. It performs relatively extended tasks of image processing and classification (including pre-processing, segmentation, interpretation, attribute measurements, and fact generation) compared to other systems. However, the pre-processing stage performs a filter for removing the noise of the image and uses a single classification method, giving no alternative, where its intelligence is limited. It does not include any data assessment or post classification evaluation. It is not a generalized system for image processing and classification. The system is task specific, includes only rules and methods specific to sea ice classification, but shows the possibility of a more generalized image processing and classification system that could perform all of the steps of image processing and classification.

### 2.6.3.2 The SEIDAM system

SEIDAM (Experts for Intelligent Data Management) was developed for managing the terabytes of remotely sensed data used in a national system for monitoring the forests of

Canada. SEIDAM responds to queries or to the product requests in order to select the appropriate mix of sensors, data processing methods, and GISs to provide the answers. A natural language processing interface is introduced into SEIDAM as one of the modes by which queries can be asked. The other intelligent components included in its architecture are the use of case-based reasoning, software agents, machine learning, and planning methods with previously captured domain expertise. It uses the extended version of standardised metadata (USGS-FGDC) for managing large amounts of remotely sensed and GIS data, and processes information for intelligent forest management and inventory updates (Goodenough et al., 1994; Goodenough et al., 1995; Goodenough et al., 1999). The extensions to the USGS-FGDC standard were made to support an object-oriented metadata system. At the top level is the catalogue metadata. The catalogue level provides information about the spatial and temporal mission together with general characteristics. The next level, the granule level, provides details of the image, sensor, and platform. For the spatial data, the most important attributes for the catalogue level are the geographical bounding coordinates appropriate to the site of interest, followed by the sensor name and the time frame of acquisition. All of these metadata files for the system are usually verified by parsing with the FGDC "mp" tool for syntax checking as well as manually. The "mp" tool is configured for use with the syntax of the extensions of this system.

SEIDAM is capable of operating on several different computers networked together so that it can be updated for the current resource inventories. Specifically the GIS files have to be updated with the changes in forests (e.g. due to fires, logging), and also be able to respond to the queries by dynamically selecting remote sensing data sources in a distributed system of geographic information systems, databases, and models. Internally, SEIDAM is organized as a blackboard architecture with a multitude of software agents (Bulitko, 2000). Although the SEIDAM system is not exactly developed for image processing, the system is interesting for its realistic use of an agreed standard of metadata for selecting the appropriate mix of sensors, data processing methods, and GIS for forestry application.

## 2.7 Metadata and Potential Uses in Image Processing and Classification

In an intelligent system, metadata can play a vital role in automatic expert reasoning as appears in the case of a SEIDAM system. However, it is necessary to use a standardized metadata structure. In this context, this section reviews the currently available standards and discusses the potential use in the remote sensing image processing and classification. Metadata is the data that provides information or documentation about the other data managed within an application or environment. It usually includes information about the intellectual content, digital representation, accuracy and security or rights management information of the actual dataset. Spatial Metadata is information that describes spatial datasets. This provides a consistent approach to allow the storage and retrieval of information about a particular dataset. An analogy may be the labelling of an item on supermarket shelves or historical information about a motor vehicle in a second-hand car yard. In Caplan's (1995) words

*"Metadata really is nothing more than data about data; a catalogue record is metadata; we could call it cataloguing, but for some people that term carries excess baggage. So to some extent this is a "you call it corn, we call it maize" situation, but metadata is a good neutral term that covers all the bases."*

One of the necessities for data sharing is metadata. A recent requirement for a metadata set is that it needs to be machine understandable information, so that it can be accessed using database and Internet technologies that automate search and retrieval capabilities. To ensure that all dataset descriptions are of a consistent type, it requires agreed standards for defining the metadata elements and their order, structure, rules, and relationships. It is not necessarily has to be exhaustive but is intended to convey the basic information in plain language that will be contained in the metadata (Crompton and Crook, 1991). In general, metadata should respond to questions, such as: what does the data set describe; who produced the data set; why was the data set created; how was the data set created; how reliable is the data; what problems remain in the data set; how can someone get a copy of the data set; who wrote the metadata; etc. In the case of geospatial data these standards may specify methods, tools and services for data management (including definition and description), acquiring, processing, analysing, accuracy, accessing, presenting and transferring such data in digital/electronic form

between different users, systems and locations. As with any other metadata, the purpose of geospatial standards is to facilitate data sharing and increase interoperability among automated geospatial information systems. Moreover, it would also facilitate automatic expert reasoning. Every organization invests in the data acquisition, conversion, processing, and manipulation of data for spatial analysis in different projects. A standardised documentation could provide data reusability for their further projects. An agreed standard document could facilitate the sharing of data among the organizations, which will definitely save the investment behind the data. However, the standardised documentation needs to be precise to avoid jargons, however, detailed enough to provide the necessary information to the interested data re-user.

Having these objectives, the efforts of concerned world communities towards harmonizing the standards have intensified in recent years. The current urge of the community is to create metadata based on any suitable standard. The idea is that if metadata exists then it can be converted into the international standard that is expected to be released in the near future under International Standardization Organization (ISO) and this was echoed in a recent workshop on metadata standard for remote sensing data in early 2004 at Cambridge University (the author of this dissertation attended the workshop)([http://www.niees.ac.uk/events/metadata\\_remote\\_sensing/index.html](http://www.niees.ac.uk/events/metadata_remote_sensing/index.html)). Several metadata standards have already been developed for describing geospatial data and many more are underway. Examples of popular metadata standard include: DCMI-Dublin Core; USMARC; Federal Geographic Data Committee (FGDC); Global/Government Information Locator Service (GILS); Directory Interchange Format (DIF); Inter-University Consortium for Political and Social Research (ICPSR); Survey Design and Statistical Methodology (SDSM); Consortium for the Computer Interchange of Museum Information (CIMI); and the Information Resource Dictionary System (IRDS); Content Model Standard; and ANZMETA. There are many other national or regional standards. However, most of the standards do not contain the data quality information, such as accuracy, dimensions, projections, etc. The International Standardization Organization defines standards as "documented agreements containing technical specifications or other precise criteria to be used consistently as rules, guidelines, or definitions of characteristics, to ensure that materials, products, procedures, and services are fit for their purpose". One of the standards that the ISO Technical Committee for Geographic information/Geomatics (ISO/TC 211) is working

on is a standard on metadata known as ISO 19115 (the International Standard for Metadata). It defines the schema required for describing geographic information and services. It provides information about the identification, extent, quality, spatial and temporal schema, spatial references, and the distribution of digital geographic data. This International Standard is currently being published. From the review it is evident that the most widely accepted and used standards that contains almost all of the data attributes, as the defined by the ISO, is the FGDC standard. Therefore, a further review has been done on the FGDC standard to understand the structure and applicability in an intelligent system.

### **2.7.1 FGDC standard**

The FGDC standard set by the US Federal Geographic Data Committee is intended to be useable by all levels of the US government and the private sector to support the collection and processing of geospatial metadata. The standard was developed from the perspective of defining the information required by a prospective user to determine the availability of a set of geospatial data; to determine the fitness of the set of geospatial data for an intended use; to determine the means of accessing the set of geospatial data; and to transfer successfully the set of geospatial data. The information included in the standard is selected based on four basic rules that metadata should follow, as mentioned in the Content Standard for Digital Geospatial Metadata (CSDGM) and its extension for remote sensing data:

- Availability: data needed to determine the sets of data that exist for a geographic location
- Fitness for use: data needed to determine if a set of data meets a specific need
- Access: data needed to acquire an identified set of data
- Transfer: data needed to process and use a set of data

As the US Federal Geographic Data Committee (FGDC) standard for geospatial metadata (FGDC-STD-001-1998) is found, so far, most commonly regarded and most relevant to the GIS-Remote Sensing community, it will be the ideal standard for use in an intelligent image processing and classification system. The details of the Geospatial Metadata are available in the FCDC documentation “Content Standard for Digital

Geospatial Metadata (CSDGC)” (FGDC, 1999). The major group of data elements content of a Geospatial Metadata are as shown in Figure 2.11.

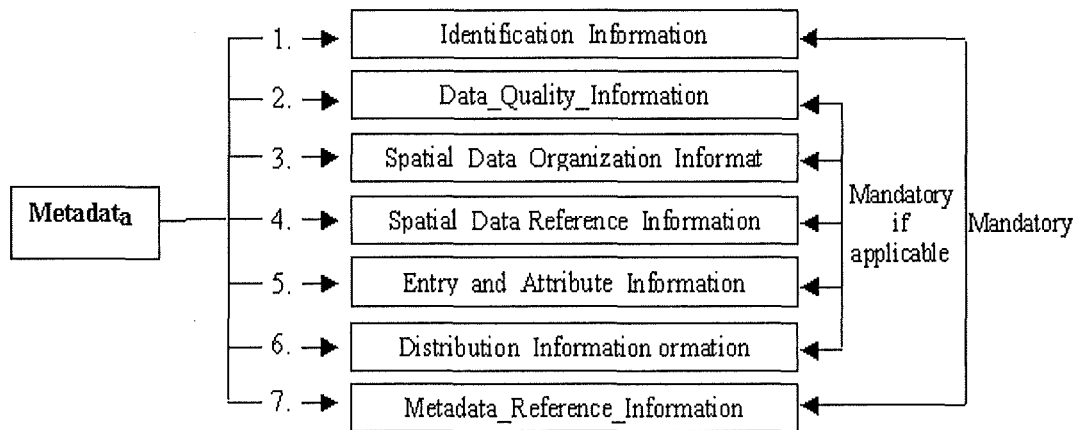


Figure 2.11: Main content of a Geospatial Metadata

The FGDC Metadata Content Standard was developed to identify and define the metadata elements used to document digital geospatial datasets. The Extensions for Remote Sensing Metadata (FGDC, 2002) of the document defines content standards for additional elements, which are not defined in the Metadata Content Standard and are needed to describe the data obtained from remote sensing. These Remote Sensing Extensions follow the rules for extended elements specified in the FGDC Metadata Content Standard. The combination of the base standard and these Remote Sensing Extensions serve all the purposes of the base standard but expand it to support the data from remote sensing. They include the elements describing the sensor, the platform, the method, and the process of deriving geospatial information from the raw telemetry, and the information needed to determine the geographical location of the remotely sensed data. The main content groups of the remote sensing metadata are as follows, with two additional items at the end:

$$\begin{aligned}
 \text{Metadata} = & \text{Identification Information} + 0\{\text{Data Quality Information}\}1+ \\
 & 0\{\text{Spatial\_Data\_Organization\_Information}\}1+ \\
 & 0\{\text{Spatial\_Data Reference\_Information}\}1+ \\
 & 0\{\text{Entry\_and\_Attribute\_Information}\}1+ \\
 & 0\{\text{Distribution\_Information}\}1+ \\
 & \text{Metadata\_Reference\_Information}+ \\
 & \mathbf{0\{\text{Platform\_and\_Mission\_Information}\}1+} \\
 & \mathbf{0\{\text{Instrument\_Information}\}n}
 \end{aligned}$$

The production rules and the syntax are described in detail in the Content Standard for Digital Geospatial Metadata Workbook (FGDC 2000). In brief, the production rules describe the section in terms of lower-level component elements. Each production rule has an identifier (left side) and an expression (right side) connected by the symbol "=", meaning that the term on the left side is replaced by or produces the term on the right side. Each section is composed of data elements, either directly or using intermediate elements. The composition of intermediate elements also is provided in the production rules.

The format for the exchange of metadata is the Standard Generalized Markup Language (SGML) conforming to the FGDC Document Type Declaration. This is not generally something one may want to create by hand. The most expedient way to create such a file is to use "mp," a compiler for formal metadata. That tool takes as its input an ASCII file in which the element names are spelled out explicitly and the hierarchical structure of the metadata are expressed using consistent indentation. Therefore, it might be relevant to use the ASCII Text file format for the data, following the FGDC Geospatial Metadata Standard structure. The file could be a valuable source for basic information about the GIS, image, and other spatial data to be used in the image processing and classification using an automatic system.

## 2.8 Conclusions

To build up the theoretical basis and motivation for this study, a wide range of literature was reviewed. The importance of remote sensing for land use and land cover mapping, and the usefulness and difficulties of the SAR data were reviewed in this chapter. The limitations of the traditional image classification methods and potentials of AI methodology are also reviewed. From the review, several conclusions can be outlined as follows:

1. Timely and accurate land use and landcover map is an important tool for resource planning, monitoring, and management. The recent development of remote sensing technology has raised the potential for regular mapping activities. The traditional methods of remote sensing image processing and classification have become unsuitable for exploiting the full potentials.



2. The review of neural networks suggests the suitability of the methods for remote sensing image processing and classification, although several issues remain to be answered and further research is required. Wilkinson (1997) suggested several open questions for further research, of which very little have been realised. One of the questions he raised is that, since Multi Layer Perceptron type networks are commonly used, is there a need for new or less common neural networks model architectures to be explored for use in remote sensing? That question remains unanswered and only a few works has been found that used other neural networks in the field of remote sensing. Among others, SOM is found to be very promising for several reasons, as found in the review (Mereny et al. 1996; Kohonen, 1998). These are as follows:

- a. A SOM may be suitable for both the unsupervised and semi-supervised techniques
- b. The better results observed from a SOM for multi-temporal SAR image classification compared to other neural networks
- c. SOM networks are relatively ease to train compared to the most frequently used backpropagation networks
- d. It is suggested for high dimensional image classification, especially, for its capability to make good predictions based on only a small training sample

One of the most significant potentials of neural networks is the capability to use ancillary and GIS data in the process. There are some works that use GIS layers, such as DEM, slope data in degree of slope direction in degree, etc. (Benediktsson at al., 1990; Foody, 1995a), but these are higher level data compared to the few classes of slope (e.g. high, low, medium slope) or land type based on flood inundation level (e.g. high, medium and low flooding). Ancillary data or GIS layers are low-level data, which can be valuable input to image classification using neural networks, and no evidence has been found for the use of such data in a neural network. Therefore, it will be relevant and timely to experiment with integrating ancillary data in a SOM network for classifying the RADARSAT SAR data.

3. The review of multiple classifier combination methods suggests that there is still inadequate understanding about why some combination schemes are better than

others and in what circumstances (Kittler et al., 1998; Chen, et al. 1997) and why the accuracy is not always higher (Hansen and Salomon 1990). Further research may develop a method of deriving the results of multiple classifiers that will be always better than the constituent classifier.

4. Methods like neural networks or multiple classifier combinations are useful and could become part of the standard toolbox for remote sensing image processing. The question remains how they can become more user-friendly, so that they can be used less experienced remote sensing image analyst, for example, by environmental scientists, or even a novice with a minimum knowledge of their inner functionality.

The review of intelligent systems shows that much effort has been devoted to the development of expert systems that attempt to solve a specific problem, such as image classification or interpretation or a few pre-processing tasks. Although "SHRDLU" (Barr & Feignbaum, 1981) and "Put-that-there" (Bolt, 1980) are very early systems and were not designed for image processing purposes, they provide the vision of next generation remote sensing image processing software, where, users will be able to tell the system about what they have and what they want as output. The system will decide what tools need to be used, what method has to be followed, what parameters have to be used, etc. The system should incorporate intelligent tools and methods with the given knowledge of domain experts so that it can decide the appropriate method to provide the optimum accuracy of the output. It should be intelligent enough to acquire additional information from other sources, such as metadata.

5. The ultimate goal of designing a classification system for remote sensing images is to achieve the best possible classification performance for the identification of the earth surface features that is close to the real distribution of the objects at the time concerned. This objective traditionally led to the development of different classification schemes for any task in hand. The different schemes are often viewed as alternative methods, and many researchers compared the various procedures in order to demonstrate that one is 'better' than the other in some way. It appears that many of the methods are complementary; some are 'better' in terms of resolving one aspect of the labelling problem, while another method may be

superior in another respect. It had also been observed that, although one of the schemes would yield the best performance, the sets of classes misclassified by the different classifiers would not necessarily overlap. This understanding is not new and is also echoed in Kanal (1974) and cited further in Ghosh (2002):

*“No single model exists for all pattern recognition problem and no single technique is applicable to all problems rather what we have a bag of tools and a bag of problems”.*

All of the above issues inspired the idea of an integrated intelligent system that will be a federation of appropriate tools for solving the domain's problems. This system should be intelligent enough to work as a domain expert to produce the output with optimum accuracy for the given problem solving.

## Chapter 3

### 3. The Case Study

#### 3.1 Introduction

The aim of this study is to develop an intelligent system for image processing and classification of remote sensing data. To achieve this aim, the study was organized into two phases. During the first phase, a particular case study was undertaken in classification in order to determine to what extent the aim could be achieved. In the second phase, the outcomes of the case study will be extended to other tasks related to remote sensing image processing and classification. Accordingly, this chapter discusses the case study and methodologies that have been followed to achieve the stated objectives. In particular, this chapter describe the case study area, together with the data collection and processing and analysis procedures used to prepare for experimentation with the classification methodologies. The comparison of the classification methodologies and multiple classifier systems will be discussed in the following chapter.

#### 3.2 Study Area

The study area lies within the southwest coastal region of Bangladesh (Figure 3.1). This figure shows the boundary of Bangladesh over a Landsat TM image mosaic pointed from the map of South Asia. The image is displayed as band 4 (infrared), 3 (red), and 2 (green) in the RGB combination to make a false colour composite; therefore, the intensity of red in the image represents the greenness of vegetation. The cyan and deep blue area in the south shows the presence of the Bay of Bengal in the image. The middle image in the figure shows an enlargement into the area of which the remote sensing SAR images were collected for this case study and considered as the “study area”. The details of the four SAR images of different dates acquired by the RADARSAT satellite system used in the case study will be discussed later in this chapter. The image in the far right most part of Figure 3.1 shows the multi-temporal SAR images for 29 October, 11 September, and 18<sup>th</sup> August (2001) displayed as in the RGB channels respectively.

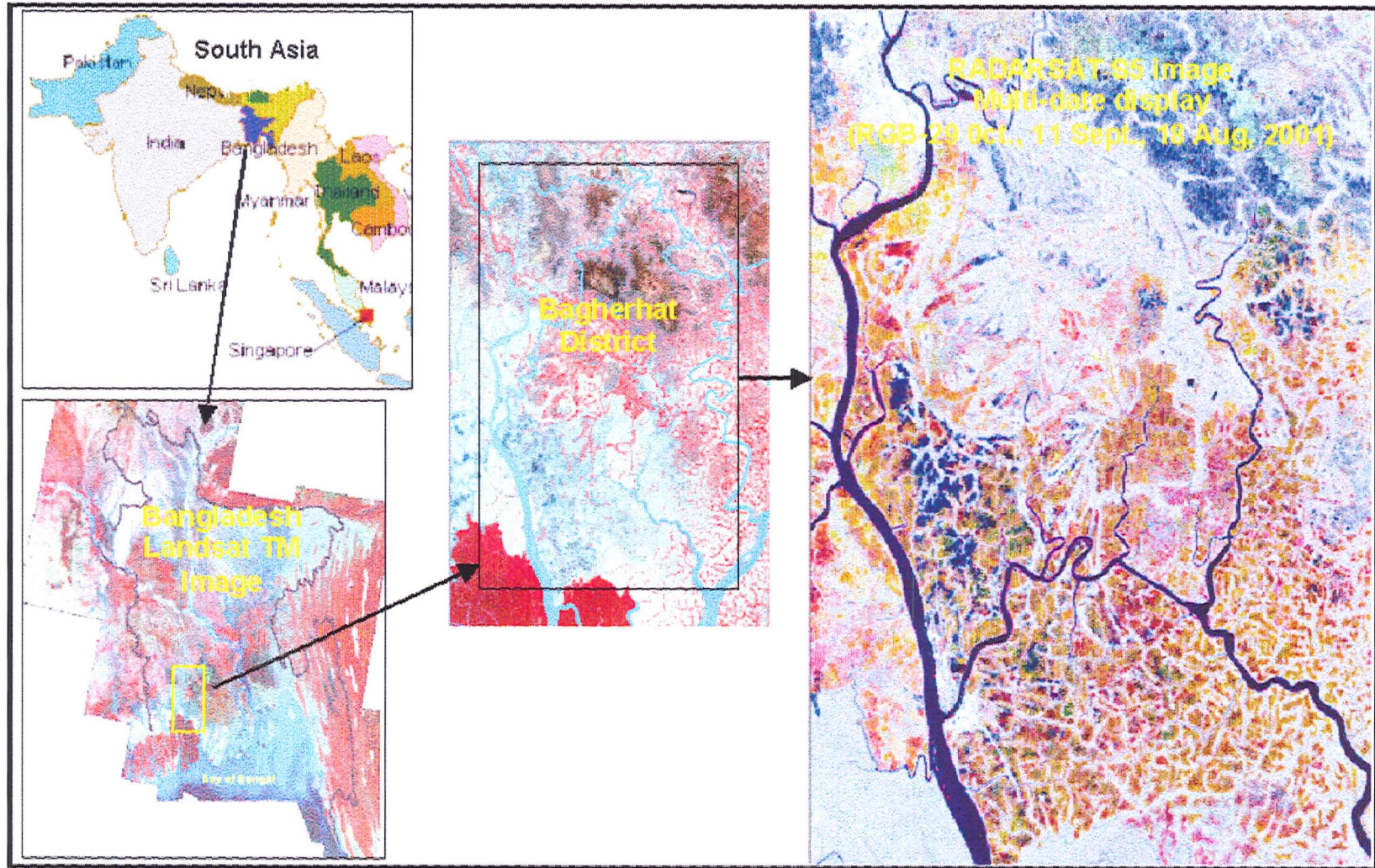


Figure 3.1: Case study area

In the RADARSAT SAR image shown in the Figure above, the grey colours apparently show the signature of vegetations, and the dark colours show the signature of the water-bodies. The tiny white patches in the image are signatures of the high backscattering that denotes the urban infrastructures in the study area. Signature refers the colour, tone, and texture in an image that distinguish different features. The study area is centred on  $22^{\circ} 38' 07''$  N and  $89^{\circ} 40' 39'$  E geographical coordinates. Among the perennial land cover in the study area, there are mangrove, rural and urban settlements, and water-bodies like rivers and ponds. The southwest part of the study-area is mainly covered by the coastal mangrove forest "Sundarban", that shows also a grey signature in the multi-temporal radar image. A significant amount of the area is settlements that can be seen as a linear patchy signature pattern and they are very distinct in all the images of the Figure and exist all over the study area.

### **3.3 General Land Use and Land Cover in the Study Area**

This section provides a brief description of the different phenomena related to the land use and land cover in Bangladesh, with particular reference to the study area, which also influences the application potential of remote sensing.

#### **3.3.1 General landscape**

In brief, three major physiographic units dominate the landscape of Bangladesh: hill areas, terrace area, and floodplain. The major portion of the country is the old, new, and coastal floodplains, where agriculture is the most important activity. There is a broad range of agro-ecological environments in Bangladesh because of the differences in climate, physiography, soil, and hydrology (MPO, 1987). In addition to regional diversity, there are local variations with respect to the land type and soil properties that make the land suitable for different crops and cropping patterns under irrigated and rain-fed conditions. Based on the hydro-morphology regime, the country is divided into five main regions: northwest, northeast, southeast, south central, and southwest. For the purposes of this study, the case study-area is chosen in the southwest (SW) region of Bangladesh mainly due to the availability of data.

The major land use and land cover in the SW region are agriculture, settlements, water bodies, and coastal mangrove forest. If we look at any remote sensing image of

Bangladesh, agricultural land use is the dominating signature in the image, unless it is acquired at a time of deep flooding. Therefore, knowledge about the agricultural system is essential for the application of remote sensing in land use and land cover mapping. Another dominating feature's signature in an image is for the settlement area that can also be understood by the population density of the country, which is among the highest in the world. However, the settlements are unlike that in any developed country, where the roofs of houses are distinct in a remote sensing image. In Bangladesh, especially in rural areas, homestead vegetations keep the dominating signature in the image instead of the roofing of houses. A contributing factor for such a signature is the canopy of the homestead vegetation over the small houses, which is highly contrasted to the signature of surrounding agricultural features. Another property that makes the settlements distinguishable even in a small-scale image display (as we may be seen in Figure 3.1) is the linear pattern due to the concentration along the riverbanks or floodplain levee areas. The mangrove forest lies in the southwest corner of the study area and keeps quite a distinguishable signature in an image, as those are relatively large patches of vegetation shaped by the river networks through and around the area. However, the backscattering signature of mangrove in SAR images is very close to that of the vegetation of settlements and cause difficulties for in digital classification.

### **3.3.2 Agricultural land use**

The use of land in Bangladesh for specific crops and cropping patterns is largely determined by hydrologic, physiographic and soil conditions. According to MPO (1987), the most important factors affecting the agricultural land utilisations of an area are:

- Flood depth and duration during the monsoon season
- Rainfall pattern and intensity
- Soil moisture storage capacity, particularly during the dry season
- Capillary rise of groundwater to the soil profile
- Local relief, soil texture, permeability, and erodability
- Frequency of sudden rise of flood water, flash flooding and storm surge
- Salinity, toxicity, and dry-season drainage

Since depth of flooding is a key factor in crop selection, the land resources of Bangladesh have been classified into five land types by flooding depth (Table 3.1). Each land type is associated with a specific land use in terms of main crop rotation.

Table 3.1: Land types defined on the basis of flood depth (MPO, 1987)

Land type	Description	Flood depth	Flood type	Common land cover and agricultural practices
F0	High land	0-30 cm	Intermittent	Settlements, Land suited to HYV rice in wet season
F1	Medium highland	30-90 cm	Seasonal	Land suited to local varieties of <i>Aus</i> and <i>T. Aman</i> in monsoon season, shrimp,
F2	Medium lowlands	90-180 cm	Seasonal	Land suited to <i>B. Aman</i> in wet season, deep water shrimp
F3	Low lands	>180	Seasonal	Land on which <i>B. Aman</i> can be grown in wet season
F4	Low to very lowlands	>180	Perennial	Land on which either the depth or rate or timing of flooding do not permit growing of <i>B. Aman</i> in wet season

There are two distinct cropping seasons a year in Bangladesh: *kharif* and *rabi*. *kharif* is the main cropping season that starts in March and ends in October. The *Kharif* season is characterised by the monsoon climate, with high rainfall and high temperatures. Based on crop adaptability and crop culture, the *Kharif* season has been further divided into *Kharif I* (March - June) and *Kharif II* (July - October). The crop environment during this season is not favourable to high yields because of the uneven distribution of rainfall, variable flooding depths, low solar radiation, high temperatures, and high humidity. Due to the high soil moisture, or the submergence of the soil, during the *Kharif* season, rice is the predominant crop and most other crops that are suitable for a high temperature regime suffer from excessive soil moisture. Among the different groups of rice, *T. Aus* grows during the *Kharif I* season and the *T. Aman* grows during the *Kharif II* season. *B. Aman* requires both *Kharif* seasons to mature. Jute, summer vegetables, and fruits are also grown during the *Kharif* season. This study deals with the crops of the *Kharif II* season.

*Rabi* is the short dry season, which covers the period from November to February and is characterised by scanty or no rainfall, low temperatures and clear skies. The crop environment during this season is very favourable for higher yields per unit area because of the high solar radiation, low humidity, and wide variations between day and night. Major crops, like rice, pulse, oilseeds, spices, and vegetables are commonly grown in all areas of Bangladesh. These crops have their specific position in the annual cropping systems in the different land types. Of these crops, rice is grown in all three cropping seasons during the year, although not necessarily in the same area. The position of rice in the annual cropping system varies with different land properties that are also named differently such as *Boro*, *Aus*, *Aman*. *Aus* and *Aman* rice, which are also



categorised *B. Aus* and *B. Aman*, *T. Aus* and *T. Aman*, according to the plantation methods. *B* is for the category that is directly broadcast in the field, which is a local low-yielding variety of rice. *T* is for the category of rice that is first grown in seedbed and then the seedlings are transplanted to the fields, which is usually a short duration high yielding variety. Jute is an important crop in Bangladesh and is grown under conditions where broadcast *Aus* is grown. Thus, Jute competes with broadcast *Aus* for land. However, none of these two crops grows in the study area. Figure 3.2 provides a generalised scenario of the major crop growing period with respect to the crop season, land type (see Table 3.1) and seasonal flooding. Crop type suitability is also influenced by the favourable soil-plant water conditions, and again, this is mainly subject to seasonal flooding. Seasonally flood prone land is suitable for rice cultivation, but the HYV rice of the *kharif* season is limited in the relatively shallower flood depth area in L0 and L1 type lands. The lands with deep flooding for longer periods during the *kharif* season are mainly used for low-yielding and deep-water rice crop. The internal drainage of the soils, soil moisture status and storage capacity significantly control the crop choices especially during the pre-monsoon and *rabi* seasons. For instance, broadcast *Aus* is mainly grown in high to medium high lands (F0-F1) that are usually not flooded deeper than 90 cm before the harvest in July/August. *T. Aman* is planted in poorly drained F0-F1 lands where flooding depth does not exceed 30 cm at the time of transplantation during July - September. *B. Aman* is the main crop in medium low to lowlands (F2-F3) lands where the flood depth may rise up to 180 cm or more during peak flood periods (August - September).

Agricultural land use in the coastal areas, which constitute the major portion of the study area, is limited to wet season cropping because of the high dry season soil salinity. Therefore, a significant amount of the area of F1 and F2 type lands is occupied by saline water Shrimp cultivation during the dry season. Saline water shrimps are cultivated mainly in the F1 type lands. The transplantation of the next crop (*T. Aman*) is delayed up to the middle of September due to the high salinity. During that time, the land salinity is reduced to a suitable level by the monsoon rain and artificial flushing using less saline river water (bringing in the river water at the time of high tide and draining out during low tide by controlling the sluice gates of the dikes). Fresh water Shrimp are cultivated mainly in the F2 lands of the area and that continues throughout the rainy season.

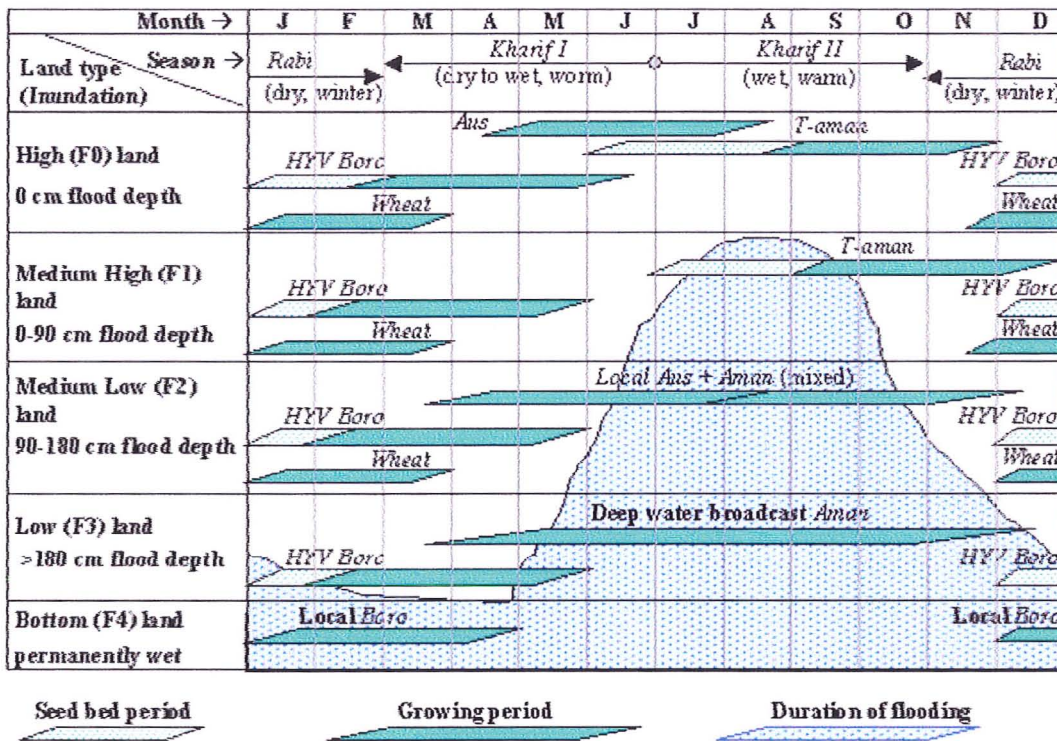


Figure 3.2: Crop calendar in relation to seasonal flooding (Brammer et al, 1988)

### 3.4 Methodology

The challenges and potentials of SAR data and the advantages of GIS integration for remote sensing image classification were discussed in Chapter 2. The literature review also revealed that there are advanced methods, such as neural networks and multiple classifier systems that are appreciated in many other types of data processing and classifications that have great potential for remote sensing image processing and classification. From the review in Chapter 2, it is also evident that the potential of AI has not been fully realised in the currently available systems in this domain. Recent developments in remote sensing technology, especially satellite-based SAR data inherit the complexity in data processing and classification in addition to its merits. In many cases, simple systems are incapable of completely exploiting merit of this technological advancement. Therefore, an advanced system is required. In order to achieve this, some well-regarded advanced methods of image data processing and classification have been tested along with several other commonly used methods of remote sensing image classification. The results were compared in the case study. Figure 3.3 includes the activities and steps followed in the case study.

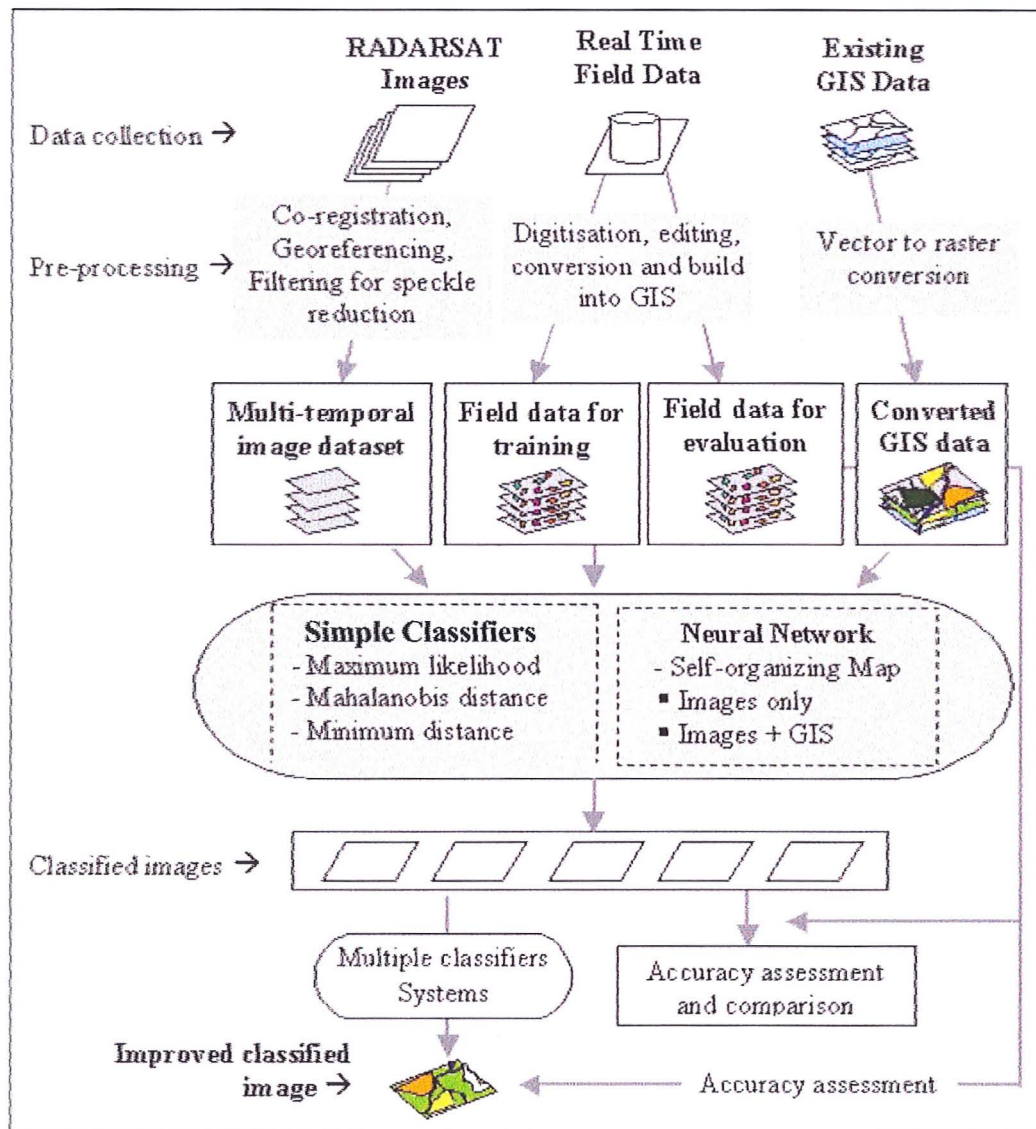


Figure 3.3: Activity flowchart of the case study

For the case study, a set of SAR images was collected, which was acquired by the Canadian RADARSAT1 satellite system. The major activities of the case study were the data collection, the pre-processing of the data, the execution of a number of single classifiers, accuracy assessment and comparison, and the combination of the classifications' results using multiple classifier methods. Three commonly used supervised classification methods by the remote sensing community (MLH, MHD, and MND discussed in Chapter 2) are used in the case study to classify the multi-temporal SAR images. A GIS layer was used only in Kohonen's Self-Organizing Map (SOM) neural network as an additional input vector for evaluating the potential for such image classification. Field data were collected for use as training data for the classifications and as evaluation data for post classification evaluation. The results of these classifiers

are evaluated against field data and compared. Finally, several methods of combining multiple classifiers are evaluated to assess the potential in this domain. The details are discussed in the subsequent sections.

### 3.4.1 SAR images and pre-processing

The study used four SAR images from four dates in the wet season crop growing period. SAR images were acquired for the study from the Centre for Environmental and Geographic Information Services (CEGIS) in Bangladesh. The images were acquired by the RADARSAT 1 satellite system, and were pre-processed for calibration by the RADARSAT and supplied to CEGIS as Path Image Product. RADARSAT-1 provides horizontal-transmit and horizontal-received (HH) data only. The dates of the images are: 18 August, 11 September, 05 October, and 29 October 2001. The images were acquired in standard beam mode (S5). The nominal resolution is 25 meters. The image incidence angles are between  $36^{\circ}$ - $42^{\circ}$  and the aerial extent is  $100 \times 100$  km.

The images were obtained in dB (decibel) format. The subsequent processing steps for the images were co-registration, georeferencing, and filtering for noise reduction. The images were filtered using the Gamma-MAP filter (Kuan *et al.*, 1987). It has been reported that in Bangladesh, the Gamma-MAP filter is best suited for SAR imagery (FAP19/ISPAN, 1995 and EGIS, 1997) and it is commonly used by the CEGIS. The co-registration among the images was done using the control point method. Upon collecting the control points for each pair of images, the images were co-registered using the neighbourhood re-sampling technique to retain the integrity of the datasets. Then the images were compared with each other to check the spatial error (the root mean square (RMS) errors were within 0.25 pixels).

The images were georeferenced so they could be used with GIS layers subsequently. Similar co-registration techniques were used for georeferencing the images. The control points were taken from a set of georeferenced  $6 \times 6$  meter resolution panchromatic images. The panchromatic images were acquired from the Indian Remote Sensing (IRS) satellite system and georeferenced using the Differential Global Positioning System (DGPS) corrected Ground Control Points (GCPs). The figure 3.4 shows the distribution of the GCPs over the image acquired on 18 August 2001 before geocorrection. In may be mention here that there is methods of incorporating Digital

Elevation Model (DEM) for accurate image geocorrection, however, due to the flat terrain condition of the study area simple neighbourhood re-sampling technique were used.

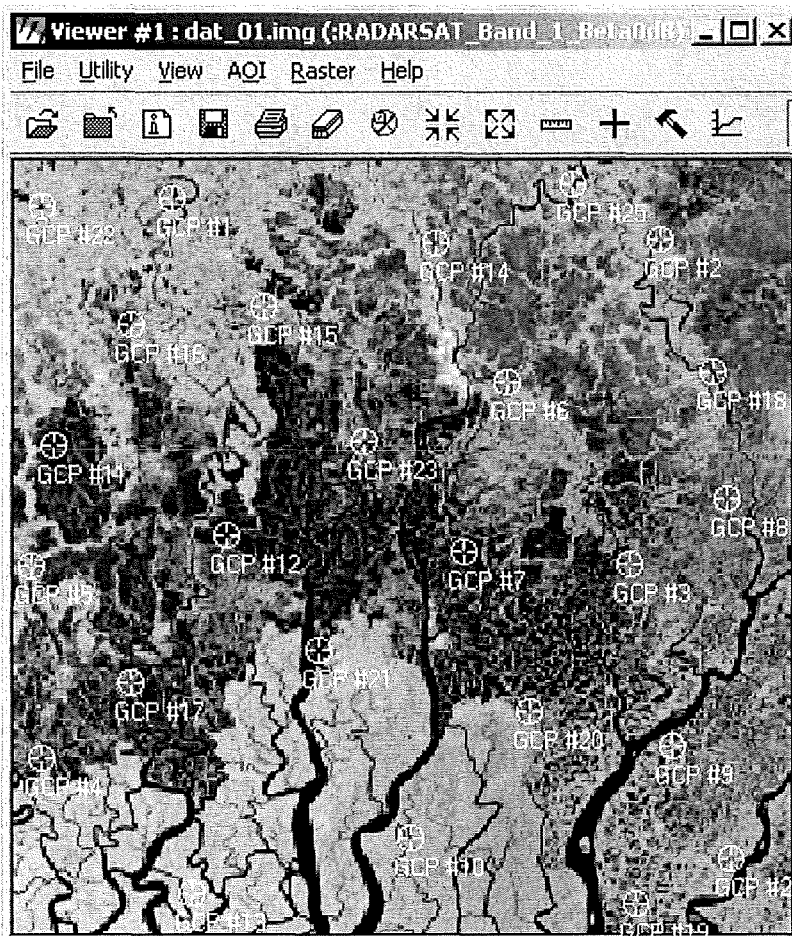


Figure 3.4: Distribution of GCPs

After taking the control points for the first image, the same set of control points was used for all other images to maintain consistency in the georeferencing accuracy. Figure 3.5 provides a view of pre-processed images displayed in Red Green and Blue channel for 4<sup>th</sup>, 2<sup>nd</sup>, and 1<sup>st</sup> dates respectively. The images were all projected to the Bangladesh Transverse Mercator (BTM) system (FAP19/ISPAN, 1993). The BTM is a modified Transverse Mercator projection system adopted for Bangladesh where main parameters are used as follows:

Spheroid Name:	Everest
Datum Name:	Everest
Scale factor at central Meridian:	0.999600
Longitude of central meridian:	90:00:00.000000 E
Latitude of origin of projection:	0:00:00.000000 N
False easting:	500000.000000 meters
False northing:	-2000000.000000 meters

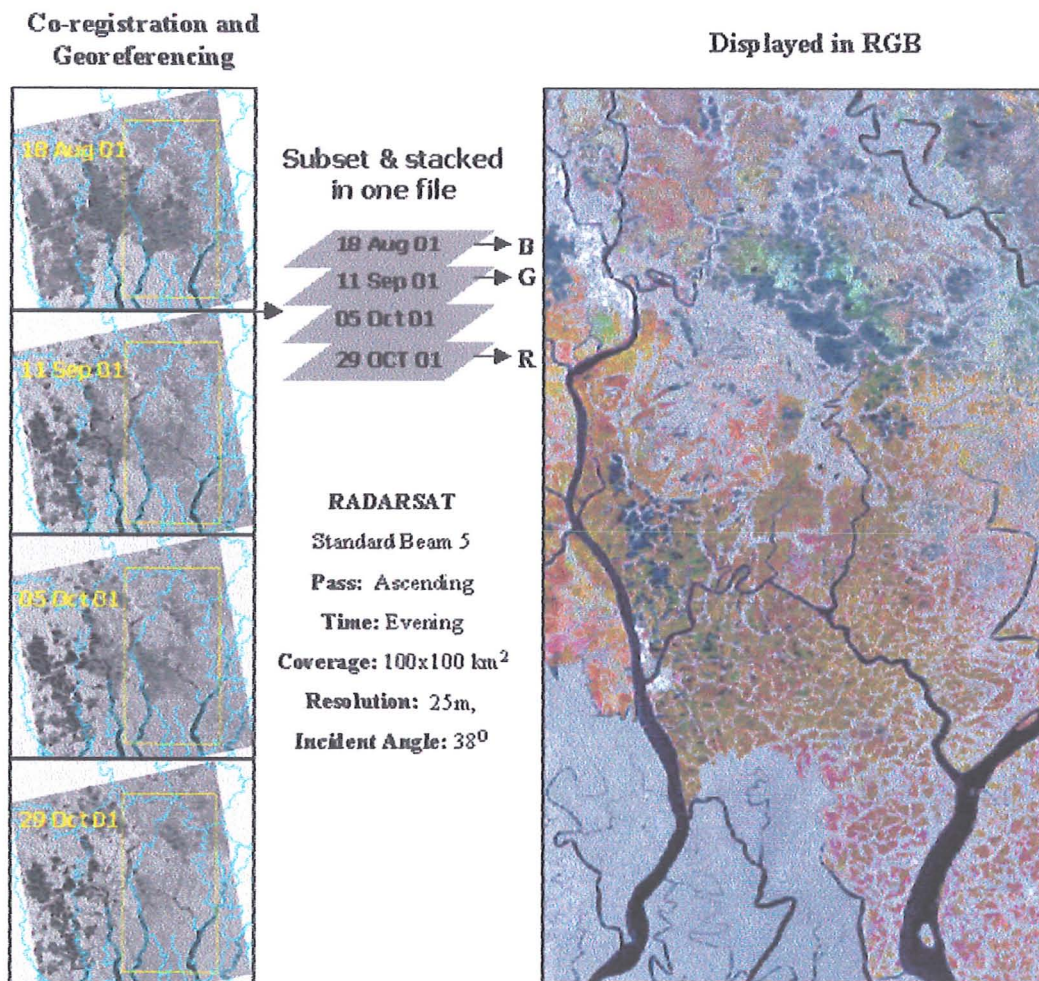
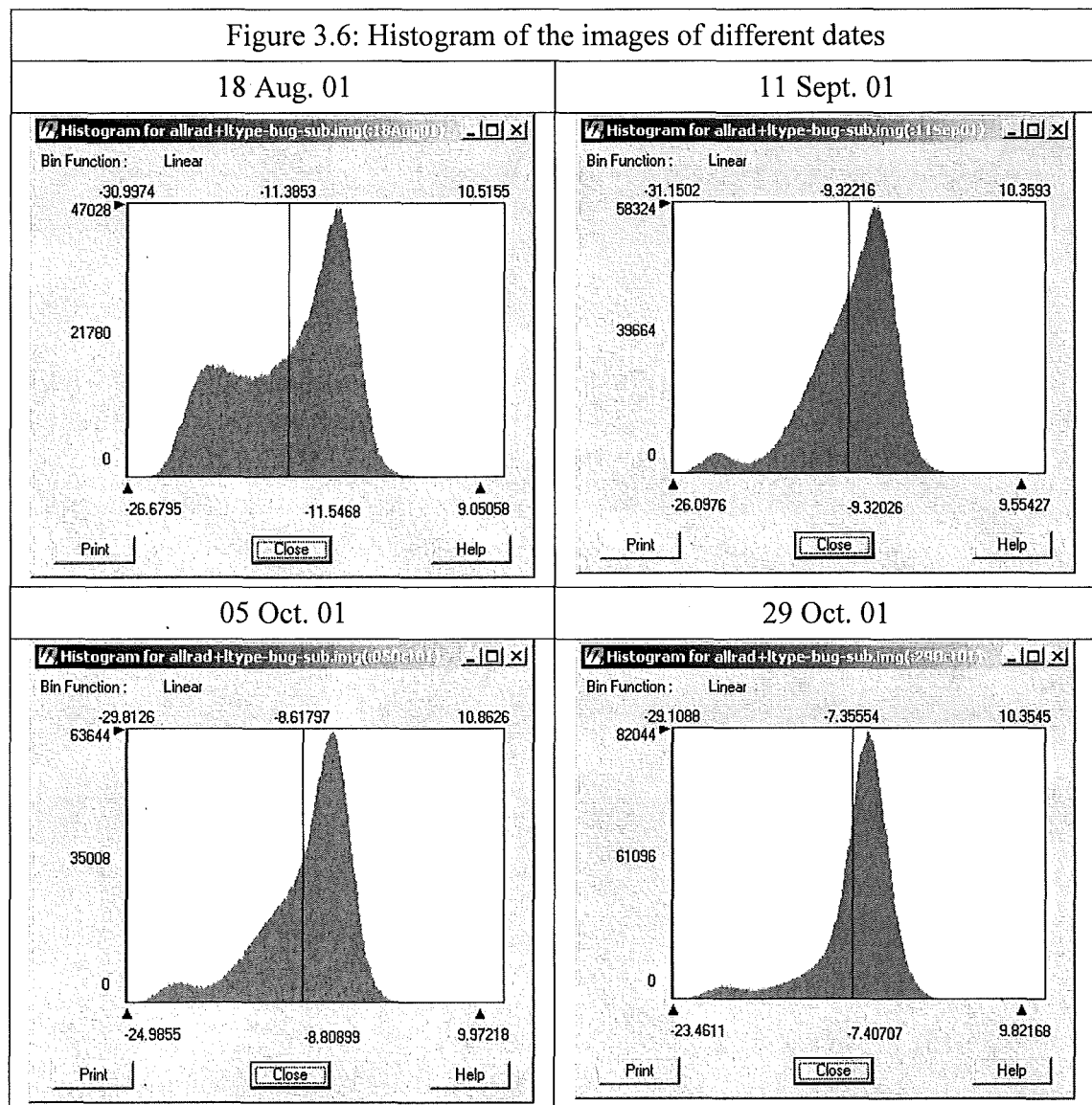


Figure 3.5: Georeferenced SAR images displayed in RGB combination

Table 3.2 provides the basic statistics of the images after pre-processing and Figure 3.6 shows the histograms. The table shows that although the minimum and maximum pixel values of the images are similar, the mean, median, and mode values are gradually increasing over the time series from 18 August 01 to 29 October 01. The minimum value in the image indicates the reflectance of water while maximum value indicates the same of from built-up areas. The gradually increasing mean, median, and mode indicate the increasing vegetation canopies over the land, especially in the crop fields. The figure showing histogram of the data also indicates the same.

Table 3.2: Basic statistics of the images after pre-processing (in dB)

Images	Min	Max	Mean	Median	Mode	Std. Dev.
18 Aug. 01	-30.99	10.52	-11.39	-10.32	-7.14	5.37
11 Sept. 01	-31.15	10.36	-9.32	-8.55	-6.73	4.37
05 Oct. 01	-29.81	10.86	-8.61	-7.51	-6.14	4.36
29 Oct. 01	-29.11	10.36	-7.36	-6.56	-6.30	3.77



### 3.4.2 GIS data

A GIS layer “Inundation Land Type” (Land-type) was also collected from the CEGIS for the study area. The Land-type (ISPAN, 1995) data is the combined information of land level, inundation date, and duration. Details about the land-type were given in an earlier section (3.3). The inundation land type layer has only been used in the self-organizing feature map (SOM) neural network for the classification of the SAR image set, as it is probably the most significant GIS layer that influences the vegetation and agricultural land cover (MPO, 1987).

### 3.4.3 Field data collection and organization

When using remote sensing data one of the sources of errors may result from ground data collection and the actual method of ground data collection, also referred to as 'ground truthing'. Ground data is used both for calibration and for subsequent accuracy assessment of classified image. Many researchers (Hord and Brooner, 1976; Hay, 1979; Justice and Townshend, 1996, Curran and Williamson, 1985, Zhou and Pilesjö, 1996) have presented various methods of ground data collection and indicated that inappropriate ground data collection easily may result in "Ground lies" as seen in Brogaard and Ólafsdóttir (1997). However, the methods and scale of effort in collecting ground truth data are frequently influenced by several factors like geo-physical and seasonal condition of the area that limits accessibility, the aerial extent of the area, and the available resources and even the type of images to be used. For example to achieve better accuracy in the SAR data classification the field conditions need to be known at the time when the satellite is imaging the area.

In this study, field information was collected in real time (i.e. during the image acquisition) for all the imaging dates. The CEGIS field team, including the author (during first two dates) was equipped with a Global Positioning System (GPS) receiver, field map, camera, and other necessary instruments. The team collected information about the existing land cover condition for a number of land parcels in the study area. Figure 3.7 shows the locations of the land-parcels (the field polygons) for which information were collected. The field team was split into four groups (three persons in a group) to cover the four quadrant of the image acquisition extent. The main consideration was to cover all variety of land use and land cover within the day and one day before and after the image acquisition date. Due to the inaccessibility caused by the geo-physical and seasonal condition and the limitation of road communication network of the area, any statistical approach of sample selection was avoided in the selection of land parcel. For collecting the field information for the first imaging date (18 August 2001), each group drove through the major roads in their area to observe the field conditions both side of the road, which is also known as a peering over hedges survey. They randomly stopped to collect necessary information whenever they found a homogenous type of land use or land cover parcel with estimated size of about 5x5 pixels of the images (image pixel size 25x25). Justice and Townshend (1981) provided a formula to calculate the size of each sample site, in relation to the pixel size and the



geometric accuracy of the imagery. According to the formula, if an image resolution is 25x25 meters and the georeferencing accuracy is 0.5 pixels then the minimum size of a ground truth parcel needs to be 5x5 pixel size of the image. For collecting ground truth information, a pre-designed field data collection form (Appendix B) was used. The contents of the form were focused on the current land use or land cover. For instance, in the case of vegetation or crops, information concerning the current height, canopy, growth stage, presence of water and depth of water, height of plant over water, plantation time of crop and tentative harvesting time of crop, etc. was collected. Two to four point coordinates were recorded in GPS for each parcel.

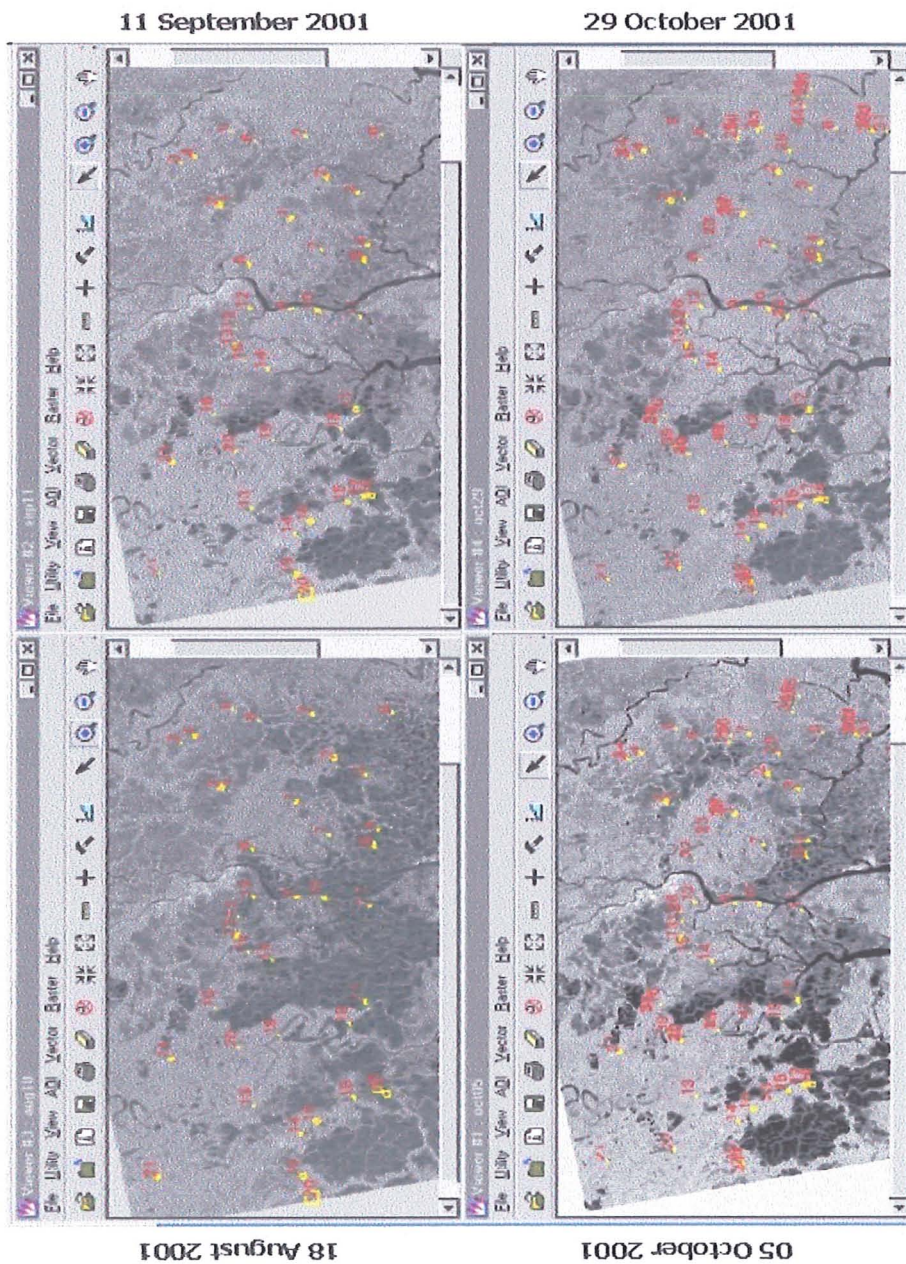


Figure 3.7: Distribution of the surveyed field polygons (land-parcels)

After the first field trip, the land-parcels were identified on the GIS map using the location coordinates collected with GPS to create polygon coverage. The collected information was converted and linked with the polygon coverage in GIS. All collected field data were carefully examined alongside photographs taken in the field to identify different land use and land cover types and to select for further field operation during the other imaging dates. Figure 3.8 demonstrates the changes in current field condition on different imaging dates. 3.8a shows the zoom in a field polygon on different dates. Figure 3.8b shows the photographs of the polygon in 3.8b on different dates showing the current field situation and Figure 5.8c shows the collected information organised in a database, linked with the GIS file of field polygons.

Usually the training data set makes up the first part of the collected ground data, whereas the remaining part is used for accuracy assessment of the classified image (Brogaard and Ólafsdóttir 1997). Accordingly, the collected information for about half of the parcels was used as training data in the image segmentation process and the rest was used as reference data for the evaluation of the results. The total numbers of training pixels was 0.58% and the total numbers of reference pixel was 0.47% of the total pixels in an image for extent used in the case study. The same set of training pixels was used as training or calibration data for all classifiers. Similarly, the same set of reference pixels was used for the evaluation of the result for all classification methods used in the case study.

#### **3.4.4 Analysis of training data**

The supervised approach in image classification requires the user to select representative training data for each predefined class. Classification performance is highly dependent on how well the training data is distributed in relation to the target class distribution. A supervised classification can be carried out using the following steps (Tso and Mather, 2001):

- 1) Define the number and nature of the information classes from the field knowledge and collect sufficient and representative training data for each class
- 2) Estimate the required statistical parameters from the training data and
- 3) Use an appropriate decision rule for segmenting the given whole data set on the basis of the estimated parameters

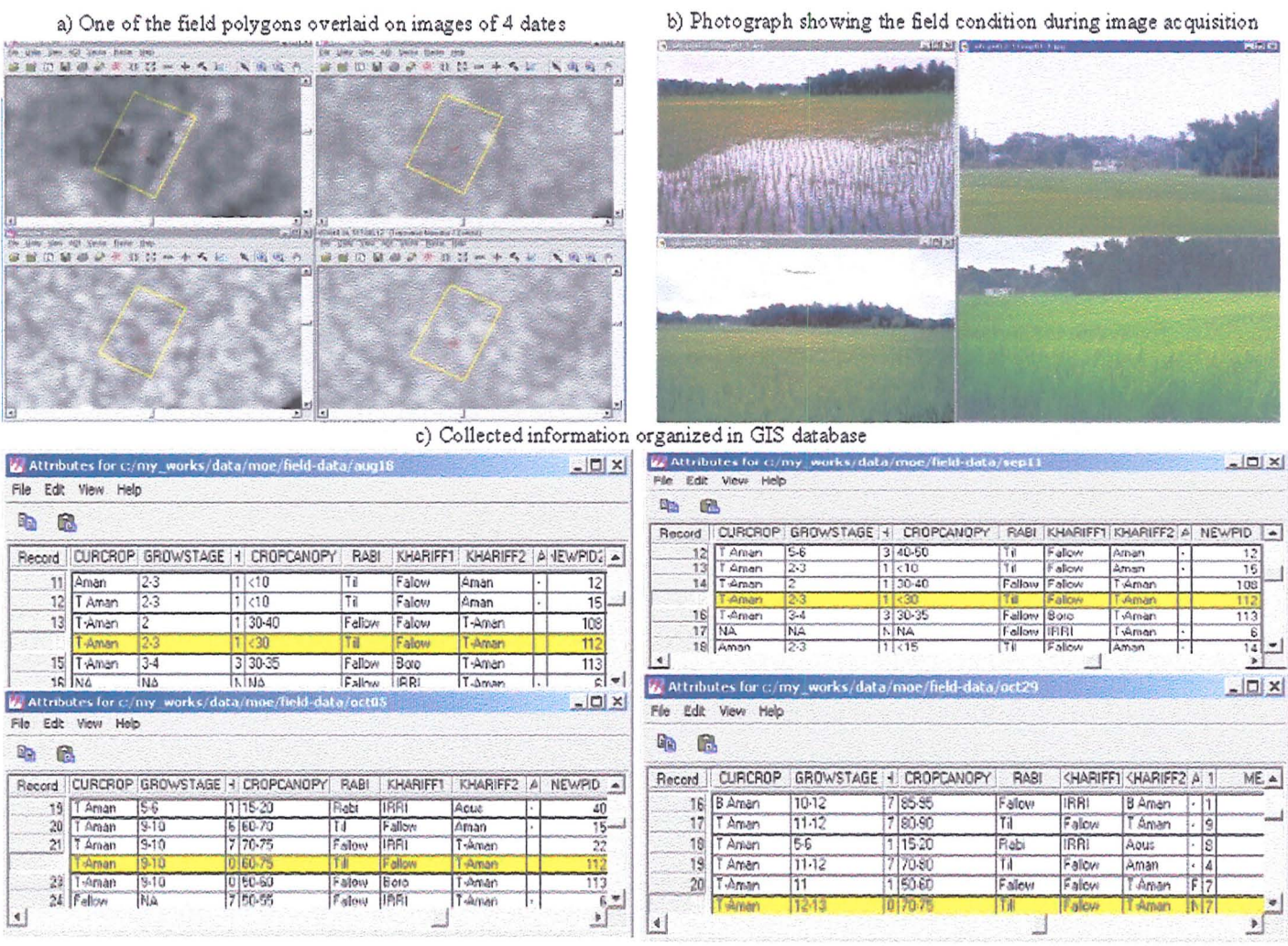


Figure 3.8: Changes in current field condition on different imaging dates

### 3.4.4.1 Defining the information classes

According to the first step, from the analysis of collected field information, ten classes were selected for classification: Water, Grass, *B. Aman*, Rural settlements, Shrimp cultivation, Shrimp-*T. Aman*, *T. Aman*, Mangrove, Built-up area and the Unknown class.

Figure 3.9 shows examples of these classes in which the images of the first, second and the fourth date are displayed in the Blue, Green and Red channels (RGB) respectively.

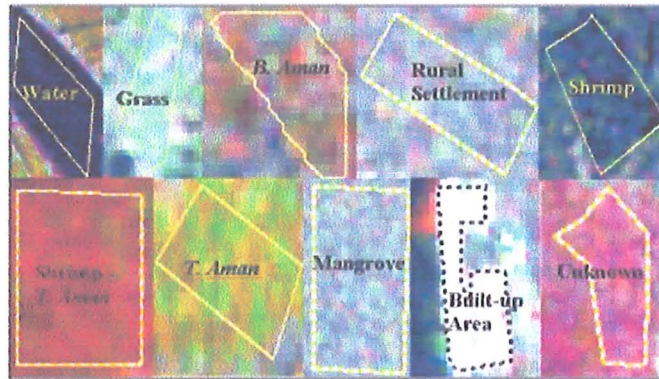


Figure 3.9: Land cover classes in the multi-temporal image

- The water class includes the field polygons containing clear water such as rivers, wetlands, and other water bodies. This provides dark signature in the images for all dates.
- Grass mainly grows in very low lands that become inundated at the beginning of the wet season. HYV rice is cultivated only once per year during the dry season in similar type of land clearing the grass if the lands dries out sufficiently. This class appeared as greenish in the display, since grass had higher backscattering on the second dated image than on the first and fourth dates.
- The *B. Aman* (*Broadcast Aman*) is a local deep-water variety of rice. This rice grows in the low area and usually broadcast in the field at the beginning of the wet season. It grows with the increase of water over time during the wet season. This gradual growth and the increase of canopy over time are responsible for the relatively reddish signature in the display for this class.
- The rural settlements include homesteads associated vegetation, and clearly identifiable patches in the satellite images. In this multi-temporal image display, this class appears as a mixed texture signature of grey, blue, and other colours when zoomed in. As seen in Figure 3.9, this class is clearer and more easily identifiable due to the linear pattern in grey colour.
- The shrimp class includes both saline (*Bagda*) and non-saline deep- water shrimp (*Galda*). *Galda* areas lie mainly in the lower lands and mostly close to the *B. Aman* and grass areas. *Bagda* fields are in the relatively higher lands and

close to the coast. Part of the *Bagda* shrimp areas, which are under year round cultivation, are included in this class. This class shows a dark signature in the display, but not similar to the water class as the average backscattering is higher in all dates of images than that in case of the open water.

- There are some areas, where *Bagda* are cultivated only in the dry season, and *T. Aman* rice is the following crop in wet season. These areas are grouped into the Shrimp & *T. Aman* class. The *T. Aman* is transplanted rice, which is usually HYV. In the wet season, this rice is transplanted into the field after growing the broadcasted seedlings in seedbeds. In the Shrimp & *T. Aman* areas the transplantation of *T. Aman* rice is late due to the soil salinity caused by the cultivation of saline water *Bagda* shrimp during the previous season. Therefore, *T. Aman* does not produce a significant canopy to produce its signature in SAR images until the end of September. Thus, the tone in the images is far darker for the first and the second dates than the fourth date and had a reddish appearance in the display.
- The *T. Aman* class includes areas where rice is transplanted from the beginning of the season (July-August). Therefore, these areas are characterized by a brighter signature for the second and the fourth dates and have a yellowish appearance in the display.
- The Mangrove class is concentrated in the southernmost part of the study area. Like the rural settlements class, this class shows the mixed signature.
- The built-up areas mainly include the urban-centres and industrial zones. This class has very bright white tones (high backscatters) for all the images dates due to the corner reflection of the physical structures.
- The last class is the unknown class, which had a very distinct signature in multi-temporal display, and was observed in some small pockets over the study area. This class was not covered in the field data.

#### **3.4.4.2 Statistical parameters of the information classes**

According to the second step of supervised classification, field polygons for different classes were uploaded from the GIS in the signature analyser module of the ERDAS

Imagine image processing software (discussed in section 3.4.7) with the multi-layer stack of all the radar images to derive the statistical parameters. Three statistical classifiers (MLH, MHD, and MND) were applied in this case. Table 3.3 provides the statistical parameters analysed from the class field polygons of the training samples overlying over the images of different dates. The imaging dates are 18 August (1), 11 September (2), 05 October (3), and the 29 October (4).

Two classes, water and built-up areas, can be identified very distinctly from the above table. The water class provides consistently the lowest backscattering in all images whereas the built-up areas provide the highest values. Backscattering from the year round shrimp area is slightly higher than the clear water bodies of rivers and lakes, and does not have much variation over the period. The “Shrimp-*T. Aman*” class has a similar response to the radar as the ‘Shrimp’ class at the beginning, then increases due to the transplantation of *T. Aman* rice in between the second and third imaging dates. Although backscattering from the *T. Aman* class is steadily rising over the first three dates, it shows a fall on the fourth date. This may be due to the maturity of the crop and the proximity to the harvesting stage when both the crop and fields were relatively dry. The “Mangrove” and “Rural Settlement” classes show very similar backscattering for all dates, because both are dominated by the scattering properties of trees. A similar complexity is also seen between the Grass and the *B. Aman* rice. These two classes are not so distinct from each other in the backscattering pattern of the images. It is also remarkable that the backscattering values are similar for *B. Aman*, Grass, Rural Settlement, and the Mangrove classes for different dates. The “Unknown” class is comparatively distinct as the pixel value falls clearly on the second date and rises again steadily from then on. This indicates that there might be a crop in these fields, that might have been harvested after the first imaging date and different crops were planted afterwards, which probably continued to grow steadily.

This analysis suggests that further discriminating information is required in addition to the images for identifying the different land use classes by remote sensing. In this case, the land-type GIS data seems to be most significant as it is characterized by the elevation of the land and inundation depth and duration. Land type signifies that the pieces of land have the potential for the type of land use or land cover. For example, Rural Settlement, Mangrove, or *B. Aman* do not usually exist for similar land types. Therefore, the land-type GIS data was considered for use with the images as an

additional layer for discriminating between the classes. The land-type dataset was resampled to the image pixel size (25x25 meters) to use with the images in the SOM network (SOM5). The same set of training polygons were used to extract the new training data set for SOM5 where land-type was the additional input vector with the images. The following section presents the comparisons among the results obtained from different classifiers used to classify the imagery.

Table 3.3: Statistics from the training samples

Class Name	No. of Training Pixels	Mean of all pixel value in decibel (dB)				Std. Deviation			
		Image Date 1	Image Date 2	Image Date 3	Image Date 4	Image Date 1	Image Date 2	Image Date 3	Image Date 4
<b>Water</b>	<b>1178</b>	<b>-18.6804</b>	<b>-21.5121</b>	<b>-20.2809</b>	<b>-18.3711</b>	<b>1.42</b>	<b>1.31</b>	<b>1.27</b>	<b>1.22</b>
Grass	676	-5.2247	-3.2297	-4.1725	-8.2190	2.63	2.54	2.64	2.80
B.Aman	1541	-8.8364	-6.4624	-5.8413	-5.8171	1.80	1.47	1.40	1.38
Rural Settlement	936	-6.4196	-6.1223	-5.7884	-5.9377	1.53	1.39	1.47	1.56
Shrimp	552	-15.2359	-15.5768	-15.8516	-14.4017	2.08	2.63	2.56	1.95
Shrimp-T.Aman	969	-18.7976	-14.7640	-10.1728	-5.2418	1.67	1.82	1.85	1.57
T.Aman	1122	-16.4821	-5.9115	-5.2275	-6.0744	3.49	1.39	1.36	1.88
Mangrove	3760	-6.2509	-5.8056	-6.0275	-6.1254	1.28	1.32	1.28	1.25
<b>Built-up</b>	<b>115</b>	<b>5.4886</b>	<b>6.0943</b>	<b>5.6025</b>	<b>5.6426</b>	<b>3.15</b>	<b>3.30</b>	<b>3.53</b>	<b>3.44</b>
Unknown	1077	-7.5241	-12.1026	-6.5246	-3.5945	2.27	2.15	1.80	1.49

### 3.4.5 Accuracy assessment

Accuracy of the classifications is assessed based on the analysis of a confusion matrix. A confusion matrix is a square array of  $n \times n$  dimensions where  $n$  is the number of classes under consideration. Usually the columns of the matrix represent the class label of evaluation data, while rows represent the class label assigned by the classifier. Commonly used classification accuracies are the overall accuracy, the user's and producer's accuracies and the Kappa coefficient and conditional Kappa. These indices are calculated from the confusion matrix (details of the accuracy indices are given in TSO and Mather, 2001). Figure 3.10 shows an example involving four land use information classes: namely, water, grass, paddy, and shrimp. In this figure, the column totals (92, 81, 83, and 73) are the numbers of evaluation data for each class that gives 329 evaluation pixels in total. The row totals of the matrix show that the total numbers of pixels correspond to the evaluation pixels in each class labelled by the classifier. This means that, in the classified image out of 329 pixels (in the same location as the evaluation pixels), 85 are classified as water, 82 as grass, 86 as paddy, and 76 as shrimp

class. The principal diagonal (downwards-diagonal) entries of the matrix represent the number of correctly classified pixels that are given the same class identification by the classified image and the evaluation data. According to the matrix out of 85 pixels labelled as water class, 78 are correctly classified. Similarly, 68, 71, and 85 pixels are correctly classified with respect to the 82, 86, and 76 pixels labelled by the classifier as grass, paddy and shrimp classes.

The “overall accuracy” provides the probability of the correctness in the classified image. This is obtained by dividing the sum of the correctly classified pixels (principal diagonal entries of the matrix) by the total number of evaluation pixels. In the example, the overall accuracy is 84%  $(78+68+71+85)/329$ , which can be interpreted as: 84% of the image area is correctly classified.

	Water	Grass	Paddy	Shrimp	Row Total
Water	78	0	0	7	85
Grass	1	68	11	2	82
Paddy	0	9	71	6	86
Shrimp	13	4	1	58	76
Column Total	92	81	83	73	329

Figure 3.10: An example of confusion matrix composed of four information classes

The user’s and the producer’s accuracy provide impressions of the commission and omission errors respectively for each of the classes in the classified image. User’s accuracy is the ratio of correctly classified pixels of the class and the total number of pixels classified by the classifier for that class (row total of the confusion matrix). The producer’s accuracy is the ratio of the correctly classified pixel of the class and the total number of evaluation pixels for that class (column total). In the example, these accuracies are as below:

	User’s accuracy:	Producer’s accuracy
Water:	$78 / 85 = 91.76\%$	$78 / 92 = 84.78\%$
Grass:	$68 / 82 = 82.93\%$	$68 / 81 = 83.95\%$
Paddy	$71 / 86 = 82.56\%$	$71 / 83 = 85.54\%$
Shrimp	$58 / 76 = 76.32\%$	$58 / 73 = 79.45\%$

The overall accuracy, user’s accuracy, and producer’s accuracy are quite simple to calculate; however, as a single index none of this represents the whole information from the confusion matrix. As we see above, they are based on either of the principal diagonal, rows, and columns of the matrix. The kappa coefficient uses all of the information of the confusion matrix in its equation (Foody, 2000). The objective of the



kappa coefficient is to evaluate the degree of similarity between the classified image and the evaluation data. The equation is:

$$k = \frac{\{N * \sum X_{ii} - \sum (X_r X_c)\}}{(N^2 - \sum X_r X_c)} \dots\dots\dots(3.1)$$

In the equation, *k* is the kappa coefficient, *X<sub>ii</sub>* is the correctly classified pixels of classes (entries in the principal diagonal), *X<sub>r</sub>* and *X<sub>c</sub>* are the row total and column total of the respective classes, and *N* is the total number of evaluation pixels in all classes. From the equation, the kappa coefficient varies from “-1” to “+1” and the higher the value, the better the classification. The table 3.4 provides the classification quality associated with the Kappa coefficient value (Ortiz et al., 1997). In the above example (Figure 3.10), using the equation 3.1, the kappa is 0.78, which represents the quality of the classification as “very good”, according to the Table 3.3.

Table 3.4: Classification quality associated with the kappa coefficient values

Kappa Value	Quality
<0.00	Worst
0.00 – 0.20	Poor
0.20 – 0.40	Reasonable
0.40 – 0.60	Good
0.60 – 0.80	Very Good
0.80 – 1.00	Excellent

While the kappa coefficient is the reflection of the general accuracy of the classification, the conditional kappa coefficient indicates the same for individual classes (TSO and Mather, 2001). The equation of the conditional kappa (*k<sub>conditional</sub>*) is:

$$k_{conditional} = \frac{(NX_i - X_r X_c)}{(NX_r - X_r X_c)} \dots\dots\dots(3.2)$$

In the equation *N*, *X<sub>ii</sub>*, *X<sub>r</sub>*, and *X<sub>c</sub>* denote the same as the above equation (3.1). The calculated value of the conditional kappa also varies from “-1” to “+1” and the higher the value, the better the classification for that respective class. In the example (Figure 3.6), using the equation 3.2, the conditional kappa coefficients for each of the classes are: Water- 0.89, Grass- 0.77, Paddy- 0.77, and Shrimp- 0.70.

### 3.4.6 Image classification

Image processing software (ERDAS Imagine) was used for pre-processing and performing the classification methods Maximum likelihood (MLH), Mahalanobis distance (MHD), and Minimum distance (MND). Initially, a portion of the field data

was used to create the signature file from the multi-temporal SAR images. The signature file (discussed in Section 3.4.4.2) was used as the training/calibration data for all classifiers. The maximum likelihood decision rule is based on the probability that a pixel belongs to a particular class. The equation assumes that these *a priori* probabilities are equal for all classes, and that the input bands have normal distributions. The Mahalanobis distance decision rule is based on the maximum variance between classes. Variance and covariance are figured so that clusters that are highly varied will lead to similarly varied classes, and *vice versa*. The minimum distance decision rule used the minimum Euclidian distance between the measurement vector for the candidate pixel and the mean vector for each class signature. A routine was written within the Imagine modeller to generate the confusion matrix (Section 3.4.5), comparing the classified images and the evaluation data (Section 3.4.3).

The Self-organizing feature map (SOM) neural network developed by Kohonen (1995) was tested as an extended procedure for integrating GIS. The advantage of the SOM network has already been discussed in Section 2.4.3.2.4. The review suggests that the capability of the automatic detection of relationships within the set of input patterns is useful in terms of the problem of image mapping from higher dimensions to a two dimensional feature space. The SOM\_PAK software from the Helsinki University of Technology was used for the SOM network classifications. Figure 3.11 shows the SOM network process using the SOM\_PAK software. The set of field data that was used for preparing the class signatures for the statistical classifiers was used as the calibration data in SOM\_PAK. Unlike most of the other neural networks, a SOM has no hidden layer but is composed of one input and one output layer.

The number of neurones in the input and output layer defines the SOM network. The number of input neurones is equal to the number of input vectors. In this study, the SOM network is tested for the classification of the mentioned multi-temporal SAR images both with and without the GIS layer. For the network used without GIS layer, there were four input neurones for four images and the result is referred to SOM4 for future discussion. When the GIS layer was used in the network, then the input neurones were 5, that is 4 neurones for four images and one is for the GIS layer. This output is referred to as the SOM4 GIS layer. However, there are no clear rules about the specification of the number of output neurones. The training and calibration data were also prepared accordingly. Several random combinations of number of output neurones,

iteration, and other parameters were tested. Finally, a 10\*12 output map was accepted with 100,000 iterations and hexagonal topology.

### 3.4.7 Software used

The image processing software “ERDAS Imagine” was used in the first phase of the study, up to the evaluation of classification methodologies. The software license for the ERDAS Imagine expired in June 2003. Image-processing software was required for the second phase of the study, which involved implementing the prototype of the proposed intelligent system for image processing and classification. The recent version of IDRISI software, IDRISI Kilimanjaro provides an image-processing suite with its previous GIS functionalities and this was found adequate for the prototype. Therefore, IDRISI Kilimanjaro software was acquired and was employed for the rest of the study. In the prototype development, the CLIPS expert system shell is used. CLIPS was developed by NASA at the Johnson Space Centre and is freely downloadable from their website. Further details about CLIPS are discussed in Chapter 6. Metadata is one of the concerns in this study, as discussed in the Chapters 1 and 2. “MP” is a tool for writing geospatial metadata according to the USGS-FGDC standard and is used in this study for developing the metadata for the SAR and Land-type GIS data. “MP” is also freely available software from the USGS website.

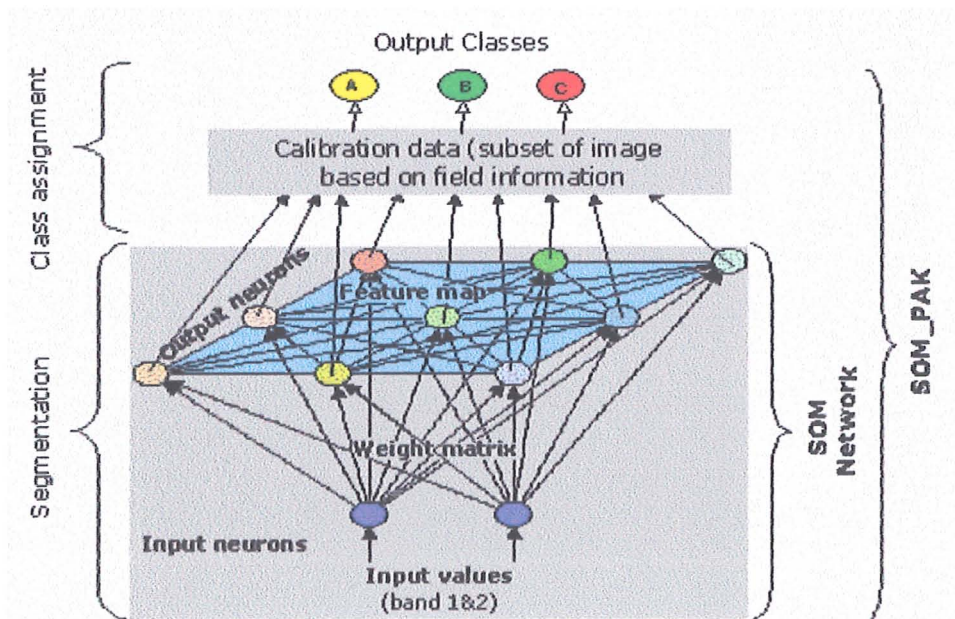


Figure 3.11: SOM process in SOM\_PAK

However, during the first part of the study, the software “SOM\_PAK” that was used for the SOM classification was unable to read the images and GIS data directly. Therefore, a conversion tool was developed using Visual C++ for bi-directional data conversion between ERDAS Imagine and SOM\_PAK. ARCVIEW GIS software was used to prepare and convert the GIS field data for use as calibration data in SOM\_PAK. Figure 3.12 illustrates the functionality of the SOM operation using SOM\_PAK, the conversion tool, ERDAS Imagine, and the ARCVIEW GIS software.

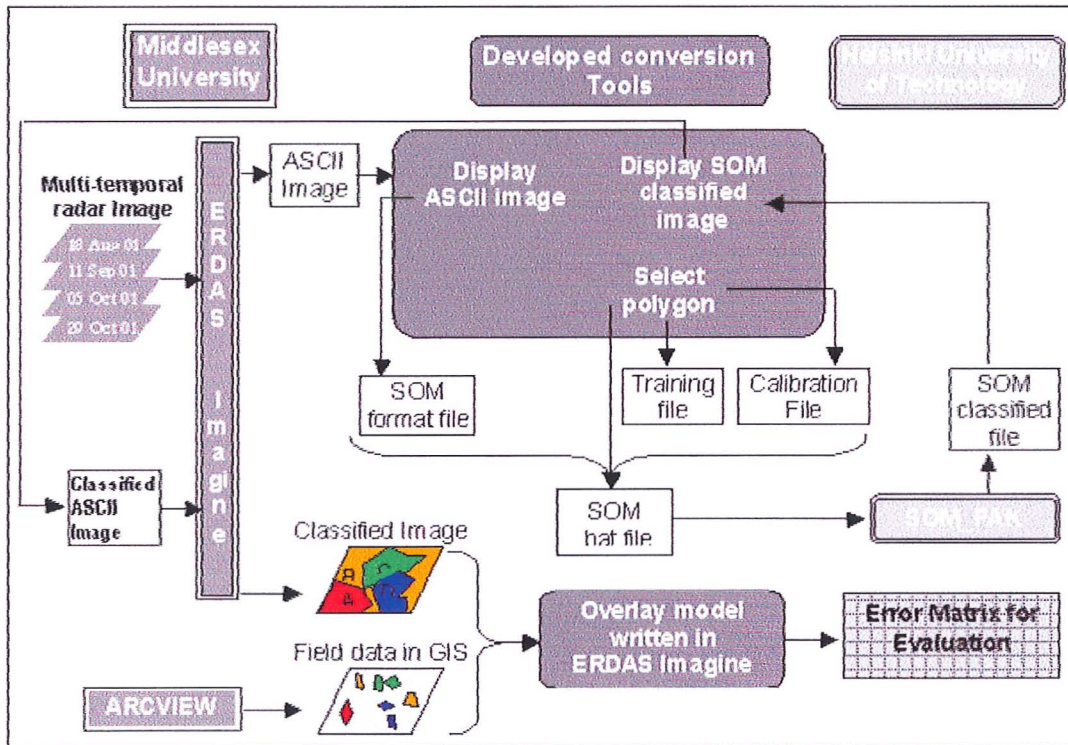


Figure 3.12: Functionality of the conversion tool developed for classification

### 3.4.8 Combination of multiple classifiers

Several methods of combining the results obtained from the classifiers were tested. This study mainly examined the Majority Voting Rule (MVR) method discussed in Chapter 2. Tested modified MVR methods include: the Maximization of Average of User’s and Producer’s accuracy (MAUP), and Conditional Kappa Maximization (CKM). Two new methods of combination Weighted Contention Resolution (WCR), and the Rule based Contention Resolution (RCR) are also examined in this study. The RCR method provided the highest accuracy. The procedures involved with each of these methods are discussed in Chapter 4.

### **3.4.9 Design and architecture of an intelligent system**

The goal of the study is to devise an intelligent system for remote sensing image processing and classification. The requirements of the system were derived from the case study as well as several years of experience in remote sensing image processing and classification in diverse applications. Accordingly, the analysis was undertaken to define the components and finalize the architecture of the required system. Details of the design and architecture are provided in Chapter 5.

### **3.4.10 Prototype development and evaluation**

Prototyping is a traditionally practised and well-regarded method of exploring and expressing designs for interactive computerised artefacts (Houde and Hill, 1997). It is usual practice to build prototypes in order to represent different states of evolving design and evaluation. There are two doctrines found in the literature for describing prototypes. One group of scholars describes prototypes in terms of “role,” “look,” “feel,” and implementation (Houde and Hill, 1997). “Role” refers to questions about the function it serves i.e. the way in which it is useful to them. “Look and feel” denotes questions about the concrete sensory experience of the user while using the prototype. “Implementation” refers to questions about the techniques and components through which it performs its functions that is the nuts and bolts of how it actually works. The other group of scholars’ description of prototypes are centred on the attributes of the prototypes, such as what tool was used to create them, and how refined the look or behavior (Buskirk and Moroney, 2003). These attributes can have varying coverage, resolution, and fidelity. The coverage or resolution represents the amount of detail and fidelity to denote the closeness to the eventual design. The coverage scales goes towards either the Horizontal or Vertical and the fidelity scale varies from “low-fidelity” to “high-fidelity” with respect to the original system. A Horizontal prototype covers a large breadth of features and functions; however, most of it may not be in working condition. Vertical prototyping covers only a narrow portion of features and functions. “Low-fidelity” represents the prototype at pencil and paper level, whereas, High-fidelity prototypes reflect the system in a precise manner. However, the main benefit of prototyping is providing a model that reveals the features of the actual product and ensures a productive and safe environment for the discussions and refinements of a proposed system.

Therefore, this study attempts to implement a prototype of the proposed architecture and discusses in Chapter 6 for representation of the system, exhibiting its functions and initiating understanding of its interaction among the components. The knowledge of the prototype intelligent system is derived from the case study as well as experience and informal discussion with colleagues and friends working in the domain. The procedural knowledge is represented in the form of *rules* in the system and the declarative knowledge will be represented and added in the system as *facts*. The expert system shell CLIPS is used in the reasoning process. The image processing software IDRISI is used to perform the necessary image processing and GIS functions. A controlling agent was programmed using Visual C++ to control and run the whole system. Further details of the prototype are discussed in Chapter 6.

### **3.5 Conclusions**

Based on the objectives there were two phases in this study. The first phase seeks to explore the suitable methods that can improve the classification accuracy of remote sensing data, utilizing GIS data in the process. The second phase works towards an intelligent system that will improve the accuracy of remote sensing image processing and classification as well as provide a complete system that can be used by non-specialist analysts. After the completion of the first phase of the study, a paper was presented to the annual conference (2003) of the Remote Sensing and Photogrametric Society (RSPSoc), (see Appendix A). The evaluation of the advanced classification method is discussed in Chapter 4 and the detailed work in developing the intelligent system is described in Chapter 5 and 6.

## Chapter 4

### 4. Comparison of Different Classifiers

#### 4.1 Introduction

The limitations of traditionally used statistical classification methods were discussed in Chapter 2. In brief these are: the most popular MLH method is based on the assumption of normally distributed data; the complexity of using low level (categorical) GIS data and the requirement of large training samples for defining a representative source of descriptive statistics used in the equations of the commonly used MLH, MND or MHD methods. However, SAR data are not usually normally distributed. Moreover, for the interpretation of SAR data, real time field data is required (Section 3.4.3). Gathering a large amount of real time field information for a training sample is unrealistic. For better accuracy of SAR data classification, the significance of ancillary data as an input in the processing is discussed in Chapter 2. To address this issue, Kohonen's Self-Organizing Feature Map (SOM), discussed in Chapter 3, is considered. Two combinations of data sets are used for SOM classification; the results are referred to as SOM4, and SOM5 as discussed in Section 3.4.6. The performed traditional classifiers are Maximum Likelihood (MLH), Mahalanobis Distance (MHD), and Minimum Distance (MND) using multi-temporal SAR images. Several methods of combining multiple classifiers are also tested. This chapter first analyses and compares the results of the performed classifications, and then discusses the results of the tested methods of combination of multiple classifiers.

#### 4.2 Results of Classifications

According to the analysis of training data discussed in Chapter 3, ten classes of land use and land cover were identified: Water, Grass, *B. Aman*, Rural Settlement, Shrimp, Shrimp & *T. Aman*, *T. Aman*, Mangrove, Built-up Area, and Unknown class. Five different methods are used for classification: MLH, MHD, MND, SOM4 and the SOM5. The results of the classification are examined and described here by visual analysis and an analysis of the different accuracy assessment indexes discussed in chapter 3.

### 4.2.1 Visual analysis of classified images

Figure 4.1 provides a visual impression of land use and land cover in a multi-temporal SAR image display before classification. In the figure, the SAR images for 29<sup>th</sup> October, 11<sup>th</sup> September, and 18<sup>th</sup> August are displayed as in the RGB channels respectively. According to the field-knowledge, the “Mangrove” area should be concentrated in the lower-left corner of the image shown in grey in the figure. The “*B. Aman*” and “Grass” should be concentrated in the upper-right corner of the image. The “Shrimp”, “Shrimp-*T.aman*”, and the “*T-Aman*” are mainly spread out in the middle part of the image. The “Rural-Settlement” class referred to also as “Settlements” spreads all over the image except in the mangrove area. The “Unknown” class areas should lie in tiny patches above the mangrove.

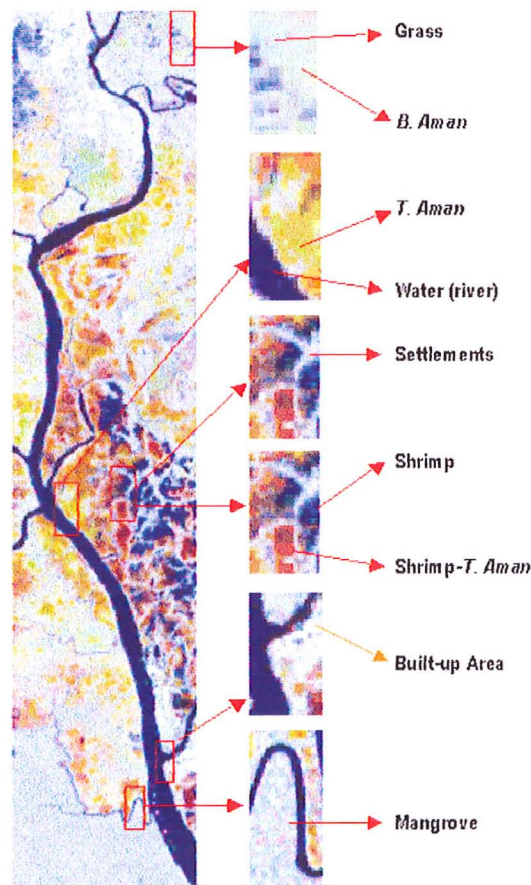


Figure 4.1: Visual impression of land use and land cover in multi-temporal SAR image before classification

Given the above description of field knowledge and the visual impression of different land use and land cover classes in Figure 4.1, Figure 4.2 shows the results of classification by different classifiers (omitting SOM4).



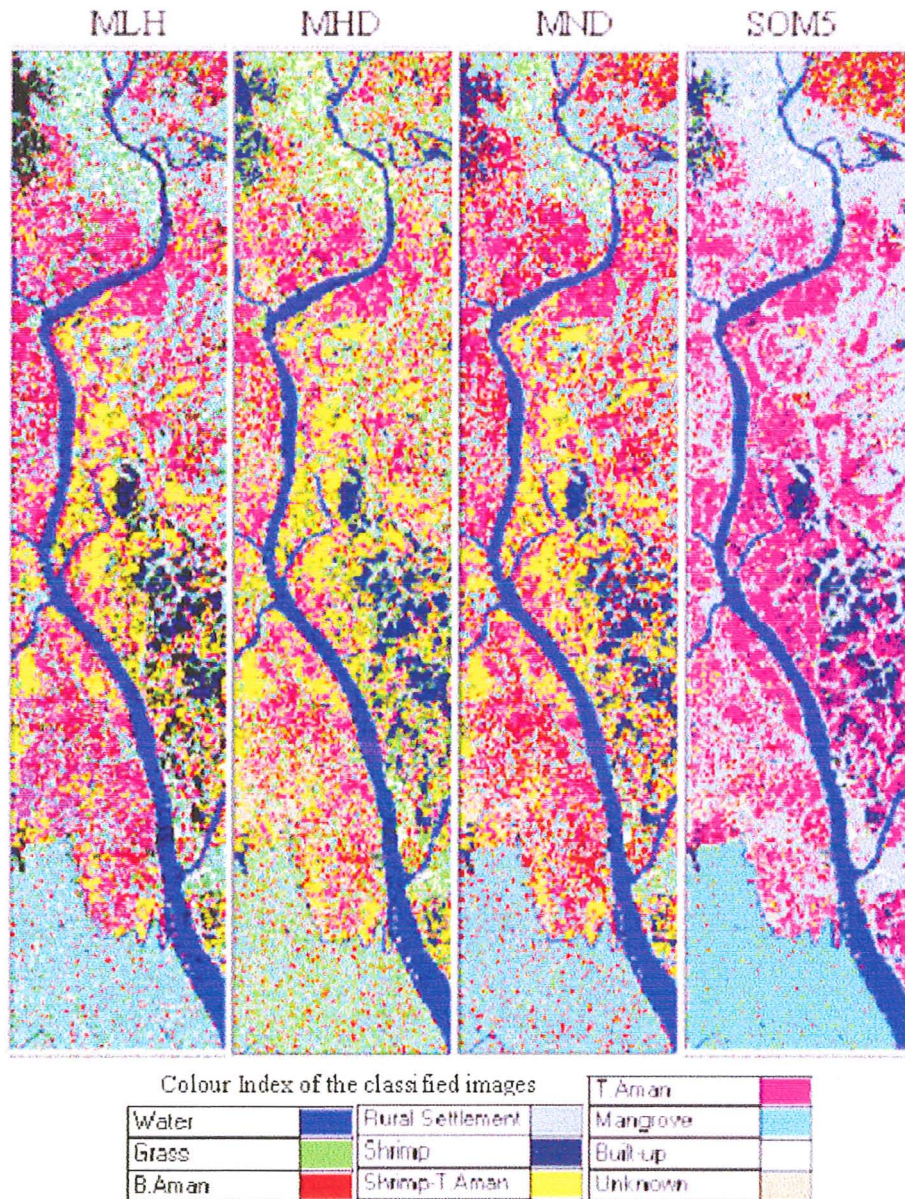


Figure 4.2: Results of classifications by different classifiers

A visual inspection of the Figure 4.2 suggests that in the MLH image, the Mangrove (shown in cyan) and the Settlements (shown in grey) are mixed-up and the Settlements areas are misclassified as Mangrove all over the image. In the MHD image, the Mangrove, Settlements, and the Grass (shown in green) classes are mixed-up and the Grass is dominating in this mix. In the MND image the condition of the Mangrove and the Settlements classes are similar to the MLH image. The Grass and the *B. Aman* classes are identified more accurately in the MND image and far more accurately in the SOM5 image, lying in the upper-right corner, which is the correct location according to the field knowledge discussed above. The Settlement and the mangrove classes are

clearly identifiable in SOM5. The “Unknown” class also appears more clearly in the SOM5 image, as lying above the Mangrove area on the left hand side of the image. However, in terms of visual impression, the ‘*T. Aman*’ class appears to be overestimated in SOM5 and to have pirated the area of ‘Shrimp-*T.Aman*’ class in comparison to the other methods. The Water, Built-up and Shrimp appear to be consistent in all of the classified images.

#### 4.2.2 The accuracy of the classified images

Classified images are compared with the evaluation data to derive the confusion matrixes. A part of the collected field data is used as evaluation data as discussed in Chapter 3 (section 3.3.4). Table 4.1 provides the confusion matrixes containing information about actual (according to the field data) and the predicted classifications done by the different classification methods use in the study. The rows labelled as “Column Total” in the table also represents the total number of the pixels available as evaluation data for each of the classes. From the table it can be observed that the Water is the most distinguishable class by all the methods used in the study as in most remote sensing image classification. The Built-up area is also well identified by all the methods except the SOM4. In the SOM4 method most of the Built-up and Settlements classes are misclassified as Mangrove. The Grass, *B. Aman*, Settlements, and the Mangrove classes are always showing mixed up in all the methods except the SOM5. However, there is misclassification between the *B. Aman* and the Grass classes in the SOM5 method. This two classes share the same land type and very close spectral pattern in time series SAR, can be seen in Figure 4.3, and perhaps that could be the reason that even with the additional land type GIS layer in SOM5 method these classes were not identified well. The Shrimp class was showing mixed up with the Water and Shrimp-*T. Aman* classes in MLH, MND, MHD, and SOM4. In SOM5 method, it seems that a number of misclassified Shrimp pixels are recovered from the Water and Shrimp-*T. Aman* classes, however, it shows many pixels misclassified as *T. Aman* class. The *T. Aman* class shows high omission in all the methods and is largely misclassified as Settlements, and *B. Aman*. The reason could be that although *B. Aman* was broadcasted in the fields long before than the first date of used SAR image and transplantation of *T. Aman*, from the second date of the images the spectral pattern is very similar for both *B. Aman* and *T. Aman*. The Settlements and *T. Aman* share the same land type in many locations in the area.

Table 4.1: Confusion matrix calculated with respect to field data

Method	Land use and land cover category	Water	Grass	B. Aman	Rural Settlement	Shrimp	Shrimp & T. Aman	T. Aman	Mangrove	Built-up Area	Unknown Class	Row Total
Maximum likelihood	Water	6001	1	0	0	192	0	0	0	0	0	6194
	Grass	0	384	12	38	7	0	79	56	0	0	576
	B. Aman	0	246	187	236	1	7	605	113	0	4	1399
	Rural Settlement	0	126	18	430	0	0	163	187	0	2	926
	Shrimp	125	73	25	0	404	164	57	0	0	0	848
	Shrimp & T. Aman	0	0	69	0	138	298	1097	0	0	0	1602
	T. Aman	0	24	62	2	10	18	987	0	0	0	1103
	Mangrove	0	141	6	544	0	0	100	626	0	0	1417
	Built-up Area	1	0	0	0	0	0	0	0	313	0	314
	Unknown class	0	6	81	18	0	0	579	3	0	337	1024
	Column Total		6127	1001	460	1268	752	487	3667	985	313	343
Mahalanobis distance	Water	5782	0	0	0	153	0	0	0	0	0	5935
	Grass	0	616	48	282	15	0	257	311	0	0	1529
	B. Aman	0	182	128	236	1	5	424	112	0	2	1090
	Rural Settlement	0	82	11	579	0	0	135	361	0	2	1170
	Shrimp	344	62	20	0	439	165	49	0	0	0	1079
	Shrimp & T. Aman	0	0	65	0	134	295	1049	0	0	0	1543
	T. Aman	0	23	83	3	10	22	1076	0	0	0	1217
	Mangrove	0	28	1	134	0	0	27	193	0	0	383
	Built-up Area	1	0	0	0	0	0	0	0	313	0	314
	Unknown class	0	8	104	34	0	0	650	8	0	339	1143
	Column Total		6127	1001	460	1268	752	487	3667	985	313	343
Minimum Distance	Water	6113	1	0	0	270	3	0	0	0	0	6387
	Grass	0	293	0	40	0	0	26	61	12	0	432
	B. Aman	0	380	224	301	12	7	784	135	0	14	1857
	Rural Settlement	0	121	7	492	0	0	122	269	0	8	1019
	Shrimp	14	41	6	0	320	156	15	0	0	0	552
	Shrimp & T. Aman	0	2	57	0	133	301	941	0	0	0	1434
	T. Aman	0	18	110	0	13	20	1226	0	0	0	1387
	Mangrove	0	141	5	431	1	0	83	519	0	0	1180
	Built-up Area	0	0	0	0	0	0	0	0	301	0	301
	Unknown class	0	4	51	4	3	0	470	1	0	321	854
	Column Total		6127	1001	460	1268	752	487	3667	985	313	343
SOM4	Water	6125	2	0	0	313	18	0	0	0	0	6458
	Grass	0	43	17	0	8	0	17	0	0	0	85
	B. Aman	0	252	130	201	5	4	470	137	0	32	1231
	Rural Settlement	0	0	0	0	0	0	0	0	0	0	0
	Shrimp	2	30	5	0	257	131	16	0	0	0	441
	Shrimp & T. Aman	0	4	73	0	157	314	1204	0	0	3	1755
	T. Aman	0	10	132	3	1	20	1124	0	0	0	1290
	Mangrove	0	632	32	1033	0	0	324	839	313	177	3350
	Built-up Area	0	0	0	0	0	0	0	0	0	0	0
	Unknown class	0	28	71	31	11	0	512	9	0	131	793
	Column Total		6127	1001	460	1268	752	487	3667	985	313	343

Table 4.1: Confusion matrix calculated with respect to field data

Method	Land use and land cover category	Water	Grass	B. Aman	Rural Settlement	Shrimp	Shrimp & T. Aman	T. Aman	Mangrove	Built-up Area	Unknown Class	Row Total
SOM5	Water	6113	1	0	0	156	0	0	0	0	0	6270
	Grass	0	476	44	0	9	0	32	70	7	0	638
	B. Aman	0	264	320	0	6	4	485	65	0	16	1160
	Rural Settlement	0	4	0	1220	0	0	348	0	0	29	1601
	Shrimp	14	52	9	0	328	105	50	0	0	0	558
	Shrimp & T. Aman	0	0	0	0	0	91	113	0	0	1	205
	T. Aman	0	3	72	9	253	287	2256	0	0	0	2880
	Mangrove	0	197	15	0	0	0	19	850	1	0	1082
	Built-up Area	0	1	0	0	0	0	0	0	305	0	306
	Unknown class	0	3	0	39	0	0	364	0	0	297	703
	Column Total		6127	1001	460	1268	752	487	3667	985	313	343

From the confusion matrixes, the overall accuracy and kappa coefficients are calculated for all classified images. The user's and producer's accuracies and conditional kappa coefficients for all classes are also calculated for all classified images. In brief, the overall accuracy provides an indication of the correctness of the classified image, where the user's and the producer's accuracy provide impressions of the commission and omission errors respectively for each of the classes in the classified image. Kappa is the reflection of accuracy of the classification in general where conditional kappa indicates the same for individual classes. The overall accuracies and kappa coefficients for all of the classifications are shown in Table 4.2. The table shows that inclusion of the GIS layer (land-type) as additional input to the SOM neural network (SOM5) significantly improved the overall accuracy and kappa coefficient. In the absence of GIS data in the SOM network (SOM4), the overall accuracy and Kappa coefficient were the lowest.

Table 4.2 Accuracy and Kappa coefficients of classifiers

Classifier	Only multi-temporal SAR images				Images and Land-type
	MLH	MHD	MND	SOM4	SOM5
Overall Accuracy	64.71	63.36	65.64	58.19	79.57
Kappa coefficient	0.57	0.55	0.57	0.47	0.74

Table 4.3 provides the user's and producer's accuracy for all the methods. The user's accuracy represents the commission error, which is that the percentage of pixels from the other classes labelled as the current class by the classification method. This means the higher the user's accuracy, the lower the commission error. The producer's

accuracy represents the omission error, which is the percentage of the pixels labelled as other classes by the method according to the evaluation data. That means that the higher the producer's accuracy, the lower the omission error. The table shows that the Shrimp class was not well identified in any of the images. It also suggests that none of the classifiers could maximise the user's and producer's accuracy for all of the classes achieved by the different classification methods. However, it can also be observed that SOM4 methods provided worst results and none of the evaluation pixels in Settlements and Built-up area are correctly classified by this method. Considering the lowest accuracy, the SOM4 method is ignored in further discussion.

Table 4.3 User's and producer's accuracy

User's accuracy (%)					Classes	Producer's accuracy (%)				
MLH	MHD	MND	SOM4	SOM5		MLH	MHD	MND	SOM4	SOM5
97.9	94.4	99.8	94.84	99.8	Water	96.9	97.4	95.7	99.97	97.5
38.4	61.5	29.3	50.59	47.6	Grass	66.7	40.3	67.8	4.30	74.6
40.7	27.8	48.7	10.56	69.6	B. Aman	13.4	11.7	12.1	28.26	27.6
33.9	45.7	38.8	0.00	96.2	Rural Settlements	46.4	49.5	48.3	0.00	76.2
53.7	58.4	42.6	58.28	43.6	Shrimp	47.6	40.7	58	34.18	58.8
61.2	60.6	61.8	17.89	18.7	Shrimp & <i>T. Aman</i>	18.6	19.1	21	64.48	44.4
26.9	29.3	33.4	87.13	61.5	<i>T. Aman</i>	89.5	88.4	88.4	30.65	78.3
63.6	19.6	52.7	25.04	86.3	Mangrove	44.2	50.4	44	85.18	78.6
100	100	96.2	0.00	97.4	Built-up Area	99.7	99.7	100	0.00	99.7
98.3	98.8	93.6	16.52	86.6	Unknown	32.9	29.7	37.6	38.19	42.2

According to the Table 4.3, the *T. Aman* class achieved the highest user's accuracy by MLH but the highest producer's accuracy by SOM5. The Shrimp & *T. Aman* class achieved the highest user's accuracy by SOM5 but the highest producer's accuracy by MND. However, the user's and producer's accuracy of most of the classes were improved by SOM5 classifier. Table 4.3 also shows that for some of the classes the user's and producer's accuracies are very high (e.g. 97.9% for water by MLH classifier), whereas, for the others they are low (e.g. only 18.7% for Shrimp & *T. Aman* with the SOM5 classifier). Given these results, the following section compares the performance of different classifiers.

### 4.2.3 Comparison of classification methods

The results shows that the inclusion of a land-type GIS layer with the multi-temporal SAR image and a discriminating input vector in the SOM network (SOM5) increased the overall accuracy to about 15% over the other statistical classifiers. If the SOM4

method is ignored then Table 4.3 shows that with the SOM5 method, the user's and producer's accuracy increased for four and five classes respectively, and for seven classes, both the user's and producer's accuracies increased in SOM5 compared to the used statistical classifiers. None of the other classifiers could achieve the highest user's and producer's accuracy for any particular class, as was the case with SOM5. It may be concluded that the inclusion of the land-type GIS layer in the SOM network with multi-temporal RADARSAT SAR imagery increased the accuracy of the classification. It may be recalled from the previous chapter that, for all of these classifications, the training data covers only 0.53% of the total image. Therefore, it may also be suggested that SOM neural networks with an additional GIS layer show a substantial improvement in terms of classification accuracy, even with a small amount of training data.

Table 4.3, however, also shows that, for some of the classes, the user's and producer's accuracy was very low, even in SOM5. Figure 4.3 provides the SAR mean backscattering from different information classes on different imaging dates derived from the analysis of the training data. Considering the mean SAR backscattering over the imaging dates with respect to the field information, it is fairly clear that the Water and the Built-up areas are very distinct classes that lie at the two extremes of the backscattering range in the imagery. These two classes were well identified by all classifiers (Table 4.3). The Rural Settlement, Mangrove and *B. Aman* classes had similar backscattering for all dates. The inclusion of land-type information in the SOM5 improved the classification accuracy of these three classes but *B. Aman* still had very low user's accuracy. Figure 3.6 in Chapter 3 (Section 3.4.4.1) indicates that the field polygon for *B. Aman* rice provides a very mixed signature, which indicates the limitation of the field data in this case. Moreover, *B. Aman* rice shares the same land-type (lowlands) as grass as discussed earlier. Similarly, the Shrimp (*Bagda*), Shrimp & *T. Aman*, *T. Aman* and the Unknown classes share the same land-type class. Therefore, it may be concluded that the added knowledge of land-type in the SOM network was insufficient to increase the individual class accuracy significantly for these classes. In this case, the addition of other GIS layers, such as soil properties, might provide results that are more accurate, however, this requires investigation.

From the above, it is clear that different classifiers performed differently for different classes. This indicates the possibility of maximising the accuracy by exploiting the goodness of the results of the various classifiers. In this context, this case study

attempts to combine the results of the performed classifiers in order to maximise accuracy, as will be discussed in the next sections.

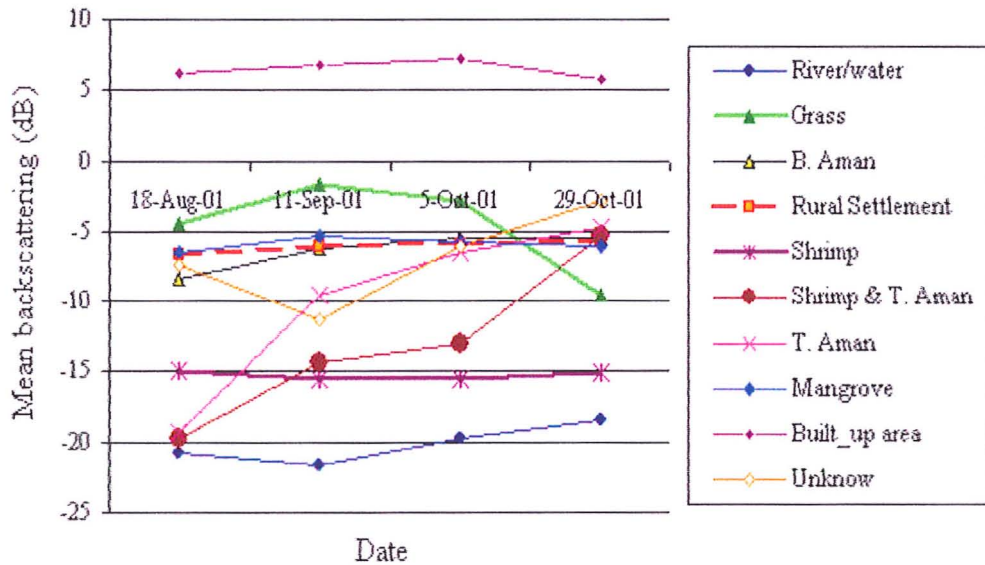


Figure 4.3: Mean backscattering plot from different classes over time

### 4.3 Combining Multiple Classifiers

Experimental comparisons between neural network and statistical classifiers, reported in the remote sensing literature, suggest that no single classification algorithm could be regarded as a “panacea” (Giacinto and Roli, 1997). A significant amount of recent research into the classification of remotely sensed data focuses on the development of new statistical and neural network classification algorithms. The literature related to multiple classifier systems suggests that some pattern recognition problems cannot be solved by a single classification rule. This happens when the data sets are high dimensional, have small training sample sizes compared to the data dimensionality, and/or when the data distribution is very complex. To address this issue, in the past few years, significant efforts have been devoted to the development of useful techniques for combining different types of classifier in order to take advantage of the complementary information that they provide in different application domains (Ghosh, 2002). However, limited investigation has been conducted into applying these techniques in the context of remote sensing problems (Bruzzone et al., 2000). The experiment above clearly shows that none of the methods achieved the best accuracy for all of the land use and land cover classes. This indicates that the superiority of one algorithm over the other strongly depends on many parameters: the nature and quality of the data used, the

reliability of ground-truth information, and, especially, the effort devoted to the design phase of the classifier (when considering a neural network). In addition, any algorithm may reach a certain level of classification accuracy through vigorous effort, but further improvements often require an increasingly expensive design phase (Bruzzone et al. 1997). Considering these issues, the evaluation of combining different classification algorithms for the classification of remotely sensed data is justified. Therefore, attempts are made to combine the results obtained from different traditional classifiers and neural network classifiers that accommodate useful GIS layers to maximize the accuracy in image classification. This section of the report presents the work on combining different classifiers for the given dataset and classifications.

### 4.3.1 Classifiers combinations and results

#### 4.3.1.1 Methods used for multiple classifier combinations

The potential of multiple classifier combination and different methods of combination is discussed in Chapter 2. According to Dilecce et al. (2000) as stated in Chapter 2, *a-priori* knowledge is not necessary to achieve high-performance from the classifier combination process when combining the weakly correlated classifiers, and that the majority voting rule works very well in such a case. Moreover, assumption-based classifier combination schemes, such as, D-S or BKS methods do not always achieve the performance and the calculation involved is relatively complex (Bahler and Navarro, 2000; Kuncheva et al. 2001). In this study, five non-conventional approaches, however, three of them, in principle, are same as the majority-voting rule method, are used to combine the results of the performed single classifiers, as follows:

- a) Majority Voting Rule (MVR)
- b) Maximization of Average of User's and Producer's accuracy (MAUP)
- c) Conditional Kappa Maximization (CKM)
- d) Weighted Contention Resolution (WCR)
- e) Rule-based Contention Resolution (RCR)

The MVR, MAUP and the CKM methods can be described as an *abstract-level* combination approach, the WCR method as *ranked-level* and the RCR as the *measurement-level*. It may be mentioned here that the abstract-level combination methods described in Dilecce et al. (2000) use the top candidate provided by each classifier. The ranked-level combination methods use the entire ranked list of candidates



and the measurement-level combination method uses the measured confidence value or each candidate in the ranked list.

The MVR method is a purely majority voting method as it picked up the class label that appears the maximum time for a given pixel in the GIS overlay of all classified images by the different classification methods. In cases of equal number of different class labels by the different classifiers, the overall accuracy of the constituent classifiers are considered for selecting the winning class label.

In the MAUP approach, the winner label of a pixel in the output image is taken as the label assigned by the classifier that has achieved the maximum average of user's and producer's accuracy for that pixel. Similarly, in the Conditional Kappa Maximization approach the winner label of a pixel in the output image is taken as the label assigned by the classifier that has achieved the maximum kappa conditional for that pixel.

The WCR was developed to assign weight to the contending classifications. A weighted index was derived from the conditional kappa value of the assigned class by a classifier and the maximum conditional kappa value achieved for that class by the different classifiers. For example, if we consider a pixel to be labelled as class 1, 2, and 3 by the classifiers A, B, and C respectively.  $A_{k1}$ ,  $A_{k2}$ , and  $A_{k3}$  are the conditional kappa of class 1, 2 and 3 in classifier 'A', and  $K1_{max}$ ,  $K2_{max}$  and  $K3_{max}$  are the maximum accuracy of class 1, 2, and 3 from all the classifiers. In this case, the weighted index (WI) of that pixel in classifiers 'A' is calculated as:

$$WI_a = A_{k1} / ((A_{k1}/K1_{max}) + (A_{k2}/K2_{max}) + (A_{k3}/K3_{max}))$$

Similarly,

$$WI_b = B_{k2} / ((B_{k2}/K2_{max}) + (B_{k1}/K1_{max}) + (B_{k3}/K3_{max}))$$

$$WI_c = C_{k3} / ((C_{k3}/K3_{max}) + (C_{k1}/K1_{max}) + (C_{k2}/K2_{max}))$$

And the 'winner' classifier 'Wc' is:

$$Wc = \text{Max} (WI_a, WI_b, WI_c)$$

Finally, the Rule-based Contention Resolution method was developed to consider to what extent rules could be developed to optimise the accuracy achievable for a specific dataset where the training and evaluation data are the same, due to the unavailability of alternative training or test data. The method was developed to consider systematically whether each of the contenders are allowed in turn from a particular

contention pattern to ‘win’ improved overall accuracy, leading to a set of rules for particular contention patterns. In the classification if a rule existed for a contention pattern, it was used; otherwise, the WCR approach was used to classify individual pixels.

#### 4.3.1.2 Results of classifier combination methods

The results of the four classification methods (MLH, MHD, MND, and SOM5) are used in the methods of multiple classifier combination (MCC). For evaluating the used methods of multiple classifier combination, the results are compared with the field based evaluation data, which was also used for evaluating the individual classification methods. The overall accuracy, the user’s and producer’s accuracy, the kappa coefficient, and the conditional kappa are calculated from the confusion matrixes. Table 4.4 provides the overall accuracies and the kappa coefficients achieved by the different methods of combination with the same of SOM5 classifier. The table shows that the Rule-based Contention Resolution (RCR) method provided the highest level of overall accuracy and the kappa coefficient, which are 81.33% and 0.76 respectively. This is a marginal improvement in comparison to the result of the best constituent classifier (SOM5), where the overall accuracy and the kappa coefficient are 79.57% and 0.74 respectively.

Table 4.4: Overall accuracy and Kappa coefficients of the multiple classifier combination methods						
Multiple classifier combination methods -->	MVR	MAUP	CKM	WCR	RCR	SOM5
Overall Accuracy	70.62%	78.55%	72.58%	78.30%	81.33%	79.57%
Kappa coefficient	0.63	0.72	0.65	0.68	0.76	0.74

To evaluate the results of the multiple classifier combination methods, an attempt is made to find out how the best overall accuracy can be achieved from the combination of the given results by the constituent single classification methods. This maximum “overall” accuracy is termed the “best possible accuracy” or BPA. This is calculated by checking for each ground truth pixel whether it was correctly classified by any of the constituent method or not. The user’s and producer’s accuracy, and kappa coefficient and conditional kappa were also calculated for the output image that providing the BPA. The BPA and the kappa coefficient achieved from that image are 84.94 % and 0.81 respectively. Table 4.5 demonstrates the conditional kappa and the user’s and producer’s accuracies of the individual classes achieved by different methods

of multiple classifier combination. The conditional kappa and the user's and producer's accuracies by the BPA and the SOM5 are also added in the table for the purpose of comparison.

Table 4.5: Accuracies of different combination methods with the BPA and the SOM5

Table 4.5.a: Conditional Kappa

Classes	BPA	RCR	WCR	CKM	MAUP	MVR	SOM5
Water	0.97	0.96	0.95	0.93	0.93	0.95	0.96
Grass	0.92	0.68	0.69	0.83	0.69	0.64	0.73
<i>B. Aman</i>	0.28	0.28	0.25	0.22	0.22	0.13	0.25
Rural Settlements	0.85	0.75	0.74	0.71	0.74	0.64	0.74
Shrimp	0.69	0.59	0.47	0.48	0.46	0.53	0.57
Shrimp & <i>T. Aman</i>	0.49	0.44	0.19	0.19	0.45	0.19	0.43
<i>T. Aman</i>	0.97	0.78	0.93	0.78	0.68	0.89	0.72
Mangrove	0.86	0.81	0.77	0.75	0.74	0.59	0.77
Built Up Area	1.00	1.00	0.99	0.99	0.99	1.00	1.00
Unknown	0.46	0.43	0.40	0.27	0.28	0.34	0.41

Table 4.5.b: User's accuracy

Classes	BPA	RCR	WCR	CKM	MAUP	MVR	SOM5
Water	98.11	97.50	97.13	95.72	95.72	96.89	97.50
Grass	92.47	69.71	71.13	84.54	71.14	66.22	74.61
<i>B. Aman</i>	30.21	29.76	26.91	24.65	24.02	15.16	27.59
Rural Settlements	86.27	77.18	76.20	73.23	76.20	66.61	76.20
Shrimp	70.04	61.45	50.00	50.98	48.96	55.31	58.78
Shrimp & <i>T. Aman</i>	50.83	46.19	21.59	21.24	47.15	21.26	44.39
<i>T. Aman</i>	97.40	83.03	94.75	83.42	75.93	91.52	78.33
Mangrove	86.67	81.87	78.83	76.20	75.98	61.84	78.56
Built Up Area	100.00	99.68	99.36	99.37	99.37	100.00	99.67
Unknown	46.84	44.63	40.88	28.44	30.02	35.72	42.25

Table 4.5.c: Producer's accuracy

Classes	BPA	RCR	WCR	CKM	MAUP	MVR	SOM5
Water	99.90	99.77	97.94	99.90	99.90	99.64	99.77
Grass	65.03	57.24	47.25	32.77	51.95	48.95	47.55
<i>B. Aman</i>	80.00	60.43	66.74	54.13	25.43	46.74	69.57
Rural Settlements	97.16	97.08	94.95	94.72	96.21	59.78	96.21
Shrimp	68.09	62.10	55.32	27.79	28.19	52.66	43.62
Shrimp & <i>T. Aman</i>	63.24	18.69	60.37	61.81	18.69	60.16	18.69
<i>T. Aman</i>	64.36	63.13	39.41	34.44	63.73	35.01	61.52
Mangrove	89.14	84.37	86.19	86.80	86.70	67.61	86.29
Built Up Area	100.00	100.00	99.68	100.00	100.00	99.36	97.44
Unknown	99.42	92.13	86.88	98.83	91.55	95.92	86.59

The table shows that most of the individual class accuracies are less than the BPA, using any of the classifier combinations methods. It also shows that the RCR method provided accuracies fairly closed to the BPA for most of the individual classes.

However, there are other combination methods where some of the classes achieved the closest accuracies to the BPA. For example, in Tables 4.5.a and 4.5.b, the class of Grass from CKM and *T. Aman* from WCR achieved the higher conditional kappa and user's accuracy than the RCR method. In Table 4.5.b the "Shrimp & *T. Aman*" class from MAUP and the Build-up area from MVR, and in Table 4.5.c, the Shrimp, *T. Aman*, Mangrove, and the Unknown class, achieved higher accuracy than the RCR method. The conditional kappa coefficient for Grass is higher from SOM5 than that from any of the multiple classifier combination methods

### 4.3.2 Analysis of classifier combination results

Three basic criteria are usually used to evaluate a classifier ensemble (Skalak, 1997), which includes accuracy, efficiency, and diversity. Accuracy is the top priority of these three factors. This study only considered the accuracy criteria for evaluation. Among the tested five classifiers' combination approaches, only the Rule Based Contention Resolution (RCR) method provided about 0.02 higher kappa coefficients and less than 2% higher overall accuracy with respect to that of the best constituent classifier (SOM5). However, it is still less than the maximum achievable overall accuracy (BPA) and kappa coefficient. It may also be noted that the use of the evaluation data for deciding the contention resolution rules in the RCR method due to the unavailability of alternative training data, may be considered as a weakness of the method in this case study.

Figure 4.4 shows that there is very high (0.99) correlation between the maximum conditional kappa achieved from any of the single classifiers, referred to as max-single and the same from the multiple classifier combining methods referred to as max-combi. The figure reveals that a significant improvement of classifier combination is highly dependent on the accuracy of the constituent classifier.

This investigation reveals that not all methods of classifier combination may provide superior results in terms of classification than the best constituent classifiers; however, some of the methods do, such as the RCR method employed in this study. The literature review suggests that the best combination of a set of classifiers depends on the application and on the classifiers to be combined. No single combination scheme of a multiple classifier system and the individual constituent classifiers was found to be superior. This study introduced two new methods of multiple classifiers, which are the

Weighted Contention Resolution (WCR) and the Rule-based Contention Resolution (RCR). The RCR method showed its superiority over the others and could be applicable only with a limited number of single classifiers. In cases of unlimited numbers of single classifiers, RCR would become a computationally hard np-complete type of problem.

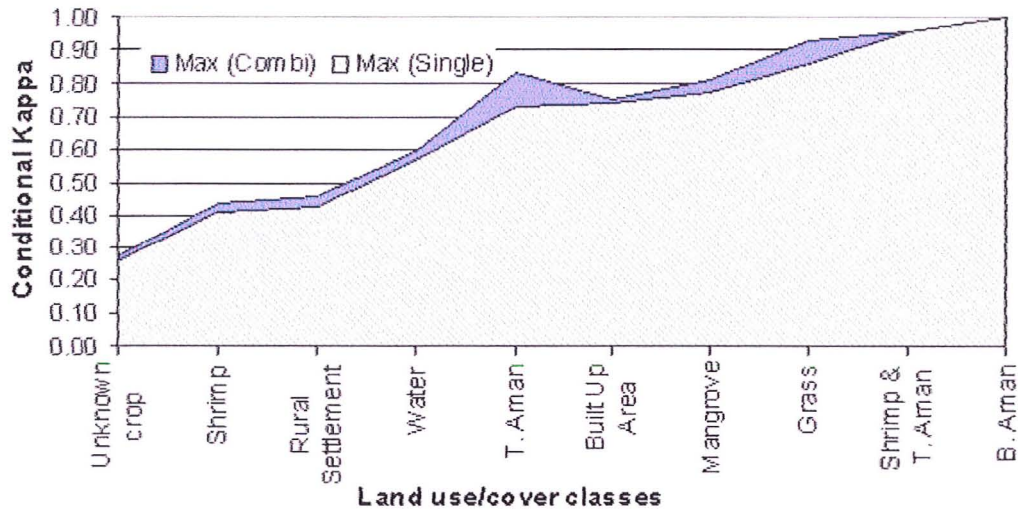


Figure 4.4: Graphical presentation of the difference between the maximum conditional kappa (Max-single) among the single classifiers and that of classifier combining (Max-combi) methods.

However, in image classification, there is room for further investigation involving multiple classifier combination. There are several related questions yet to be answered regarding this area of application. The current study, for example, used four classifiers in combination methods. Investigations are required to determine the suitable numbers of single classifiers to be combined, to find out whether the types (statistical, neural networks and others) of classifiers in the combination sets matter or not and whether repetitive combination process could be considered.

#### 4.4 Conclusion

In this chapter, two important aspects of remote-sensing image classifications were discussed. Firstly, the possibility of using neural networks for the integration of GIS data in the segmentation of multi-temporal SAR images has been explored. Secondly, several methods of classifier combination were evaluated which is an emerging research area in the field of data classification and even newer in terms of remote sensing image classification. From the investigations of this study, three important messages emerge as follows:

Firstly, no classifier can provide acceptable accuracy for all the target classes, i.e. it is observed that one classifier gives better accuracy for some of the classes while another classifier may provide higher accuracy for others.

Secondly, the experiments with the classifier combination methods increased the accuracy, but never achieved the best possible accuracy (BPA). Moreover, the combination of classifiers may not always provide higher accuracy than the individual constituent classifiers.

The third observation may not be generalized yet, as it may merely be the case with this exercise. The observation is that the marginal improvement in accuracy diminishes with the efforts made towards classification. This means that, although the accuracy increased as results of the GIS integration in neural networks and further by the combination of results of the classifiers, the increments in the improvements in accuracy gradually dropped. Whilst the RCR method is not generally valid due to the use of same set of data for both training and evaluation it does allow us to conclude that even if we 'cheat' in this way the overall gain may be very small. This effect can be described as the "law of diminishing marginal improvement."

Moreover, the exercise of the best possible accuracy (BPA) shows that, with the results from the individual classifiers, the achievable BPA is only about 85% and may not be acceptable by the target users: the executive decision makers and planners. Therefore, the conclusion is that further work is needed to improve the method of image classification.

## Chapter 5

# 5. Architecture of Intelligent Image Processing and Classification System

### 5.1 Introduction

A review of the remote sensing technology for earth resources mapping and monitoring reveals that digital image processing algorithms have been widely adopted since the images become available from the LANDSAT mission in the early 1970s. Before that time, mainly aerial photo interpretation techniques were researched. A review of intelligent systems in remote sensing image processing shows that the adaptation of AI components in the field began in the early 1980s (Tsatoulis, 1993). In the 1990s, the remote sensing community's research interest was mainly oriented towards new and diversified sources of remote sensing data, such as high-resolution imaging, SAR imaging, and hyper-spectral satellite imagery. Consequently, considerable effort was devoted to designing advanced imaging satellites, refining digitisation techniques, deriving digital data sets (e.g. a vegetation index), and integration with GIS.

The industry is now facing a new challenge. Spatial data users can now log onto the Internet and obtain a huge amount of off-the-shelf satellite images, digital elevation models (DEMs), pre-packaged vector and raster GIS files, and other geographic data and their metadata all in digital formats. Simultaneously, the size of the user community is increasing rapidly. More and more, environmental, forestry, disaster management, water resource, infrastructure, urban development, and other agencies in both developed and developing countries are setting up systems for using remote sensing data in resource planning, monitoring and mitigation activities. These initiatives are increasing the frequency and volume of image processing and classification. At the same time remote sensing data have become diverse and more complex, and the techniques of processing are laborious, dominated by the time-consuming qualitative analyses engaged in by skilled and experienced remote sensing scientists, which are largely unreplicable (Moller-Jensen, 1997, Luck, 2004) in terms of image processing capability. Thus, there is a real scarcity of domain experts to support the growing demand.

Therefore, there is a major need for an intelligent image processing and classification system that can minimise the increasing gap between the availability of experts and the demand for capability. From the review and the case study, it can be seen that there are advanced methods of coping with recent trends in remote sensing data. However a system is required that can integrate the methods in a way that is less dependent on the domain expert. In this context, this chapter presents the requirements and analysis for an intelligent system, and proposes a design for such a system. In chapter 6, a prototype is described and its operation evaluated.

## 5.2 Requirements Analysis

Based on the review, experience, and the experiment and analysis of the case study, this section analyse the detailed physical and functional requirements of the system to be designed. The detailed requirements of a new system can be analysed through three points of discussion: the need assessment, the limitations of current systems, and the potentials of the methodologies in hand. Then the requirement will be summarised.

### 5.2.1 Need assessment

It is understood that despite the scope for further improvement, there are many advanced image processing and GIS techniques, and many of them have come within the reach of the mass user through the spread of commercially available software. However, image-processing software may have several algorithms for performing the same task (e.g. image classification). Deciding which one is the most appropriate and preparing the data accordingly requires a certain skill and knowledge which is not readily available. Therefore, a system is required that matches the understanding of Kelly's (1993) second group of protagonists (section 2.6), which is the modelling of the activities of human intelligence. A system is required that is sufficiently intelligent to decide and perform the necessary task of image processing and classification using the necessary functions off the shelf, with the given knowledge of the domain experts, to produce the best possible results using the given data and information by even a non-expert user. This requirement provides the basic scenario of an intelligent human-machine system as shown in Figure 5.1. The figure illustrates all of the physical and functional requirements of the system. The system should have non-expert *Users*; the



intelligence and capability of a *Domain Expert*; an *Input* subsystem; advanced functions of *Image Processing*; and an *Output* subsystem.

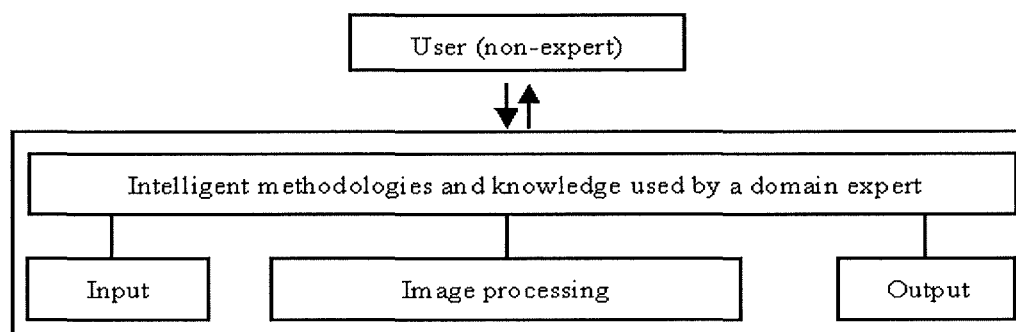


Figure 5.1: Basic organizational scenario of the required system

According to the Figure 5.1, the system will acquire appropriate input information from the user in the same way as an expert would ask and prompt the user about the intended task and available resources. The system will then assess, analyse, and process the input data and other information just as an expert would using the appropriate tools and intelligent techniques. Finally, it will provide the best possible result with the given resources. Details of these system components are discussed below.

### 5.2.1.1 User of the system

The understanding of the perception, learning, reasoning and operation process of the potential human operator (user) is very important when designing a system. Therefore, this section defines the intended users of the proposed system.

It is already understood from the earlier discussion that a system is required for cases where the human operator is a non-expert, i.e. a novice engineer or technician. Even the users could be the decision maker or experts in another field, with very little knowledge of image processing, but with the desire to use the output of remote sensing for their model. A novice engineer could be a fresh graduate who has recently started working in the field, who has a fresh and recent theoretical background in the field of remote sensing and GIS applications. Such users tend not to have many skills in terms of hardware, software, techniques, and technology in the field. A technician may have been working in the field for a relatively longer period and have gathered some skills in terms of hardware, software, techniques, and technology. They may also have acquired some theoretical knowledge, although this may not be as detailed as that of an expert.

In general novices usually work through the given instructions or user guide in a step-by-step manner. Novices lack confidence, are hesitant about attempting to model their problem, are uncertain concerning the best action or strategy, and look for the supervision of an expert. Novices or technicians lack the level of *decision*, *analysis*, *assessment*, or *processing* skills of the experts. Decision skills refer to the skills of deciding about what to do and when to do it. Analytical skills refer to the analytical capabilities of an expert, such as calculation, measurements, etc. Assessing skills refer to the assessment capability, such as whether the given data are adequate or not. Processing skills refer to the processing efficiency that answers the questions like how accurate are the results. However, novices or technicians gradually become experts over time, acquiring the skills and knowledge of experts.

#### **5.2.1.2 Domain experts**

This section discusses the domain experts' knowledge and skills that are used in the decisions concerning and selection of appropriate tasks, tools, and techniques that have to be added to the system. In fact, the proposed system will be working like a domain expert with the given knowledge, not the human operator.

Commonly, experts have an adequate theoretical background, much longer working experience, and gather a high level of expertise in a specific area within the domain. Unlike a novice, an expert can easily model a strategy for solving the problem, using their acquired knowledge and skills. They even utilise other relevant sources of knowledge, if necessary, that are already known to them from their long work experience in the domain. Experts have large amounts of information beyond the instructions or guidance. When a novice presents a problem to an expert, the expert does not assume that the novice has the clear understanding of the problem. Therefore, experts assist novices to obtain a clear idea about the problem. Experts may also anticipate some aspects of the problem through looking into the task and already gathered information through their assessment skills. They can perform many tests and measurements using their analytical skills to support the assessment; they can perform the processing accurately and quickly using an appropriate algorithm. Experts acquire these skills over the period during which they have worked in the domain. Therefore, a system is required that adopts these cognitive and operational processes of experts in the domain.

Figure 5.2 provides an example of the experts' involvements in the various steps of remote sensing image processing and classification. For example, experts need to decide upon appropriate images and GIS data depending upon the application; they decide on necessary tests and corrections for data compatibility and suitability, while using multiple images from different timings or sources, or integrate the images with the GIS data; they need to decide the necessary analysis and manipulation of GIS and other data. If the task in hand is the classification of vegetation from the remote sensing image, for example, and they want to use information from the digital elevation model (DEM) for improving the accuracy, the DEM may need to be converted into slope or elevation classes according to the potential impact on the land cover. Experts decide, which classification algorithm should be used; the achieved accuracy is acceptable or not depending upon the accuracy of the source data, and so on. All of this expert knowledge need to be incorporated into the knowledge based intelligent system.

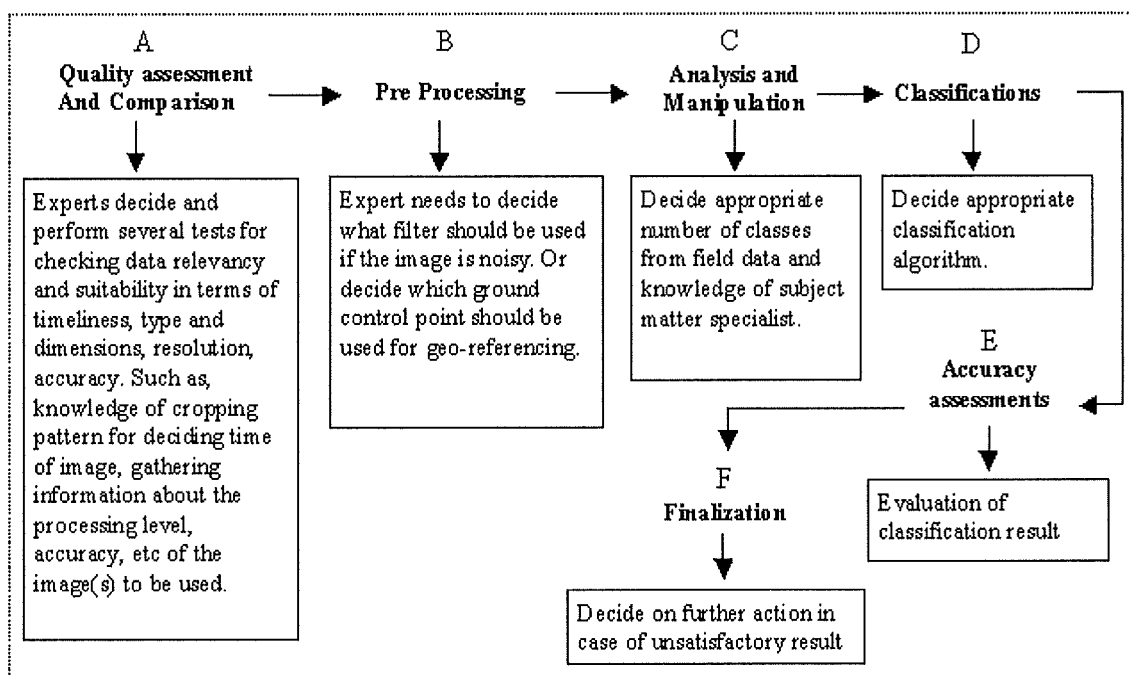


Figure 5.2: Example of expert's involvements in major image processing and classification steps

### 5.2.1.3 Human-machine functional relationship

The cognitive and operational processes of the users of the system and the domain experts must be transferred into the system as discussed above. Before proceeding to a discussion of the further requirements of the system, it is important to understand the anticipated role of the system in the human-machine environment. The role of the system can be well perceived from the modified example, which was originally cited in

Boy (1991): in an aircraft cockpit, a human co-pilot shares the work with the captain. The ultimate responsibility remains with the captain, who is the master on-board. The captain may consult with the co-pilot and delegates the task to be executed. In addition, the captain may choose to stop the execution running by the co-pilot at any time if s/he judges this to be necessary. However, the co-pilot may have personal initiatives, such as testing parameters, remaining current with the evaluation situation, predicting deducible faults, and so on. In the case of remote sensing image processing and classification, the system should perform the role of the co-pilot and the captain's controlling power will be given to the human operator (the user).

In such a human-machine system environment, the conditions of association between humans and machines are diverse. Boy (1991) grouped these conditions into three principal schematic types. The first group is where the operator is a monitor. The system functions in an automatic mode, as long as this mode is not deactivated by human intervention. The second group is where the operator is a supervisor. In this case, the system functions in an automatic mode, but the operator can take control at any moment. The other group is where the operator is in command. This group of systems are built to operate with strong interaction from the operator who commands it and is always in control of it. Unlike flying aircraft, in image processing and classification, the decision concerning actions is not so life threatening or deadly and the course of action nor straightforward as going from place "A" to "B". Moreover, in the case of the intended system, the ultimate goal is that the novice users of the image processing and classification system gradually become expert over time. Therefore, it will be justified to build a system, where the human-machine association will be similar to the second group of systems mentioned by Boy (1991).

#### **5.2.1.4 Inputs of the system**

Experts always gather appropriate input information from the user to perform the job and try to avoid unnecessary information. To be specific about the data and information, experts ask and prompt the user in the process of gathering inputs, for example, about the intended task and available resources. Experts use these inputs as necessary and may look for additional information as required for processing the task. Even in the middle of the processing, based on any intermediate measurement, the expert may decide to add some more input information. Therefore, the system requires an input interface that will

maintain a two-way linkage between the system and the user and that will be intelligent enough to prompt the user when gathering the problem specific input, as an expert does. The interface should use appropriate tools and intelligent techniques. The design of the interface should adopt the cognitive and operational process of experts in acquiring inputs from the user.

### 5.2.1.5 Image processing and classification

The intended task of the system is image processing and classification. Image processing refers to the acts of the digital analysis and manipulation of the input images and the preparation for the classification. Classification refers to the ultimate part of the act of the segmentation and interpretation of the processed image, where segments are assigned with appropriate names for representing the underlying characteristics. Having inputs from the user, image-processing experts first assess the data before embarking on the processing steps. The assessment may suggest that some pre-processing or additional information may be required. Therefore, following the cognitive and operational process of experts, as discussed earlier, the system needs to be extended for data assessment and pre-processing. Figure 5.3 illustrate the major processing steps that should be required for such a system.

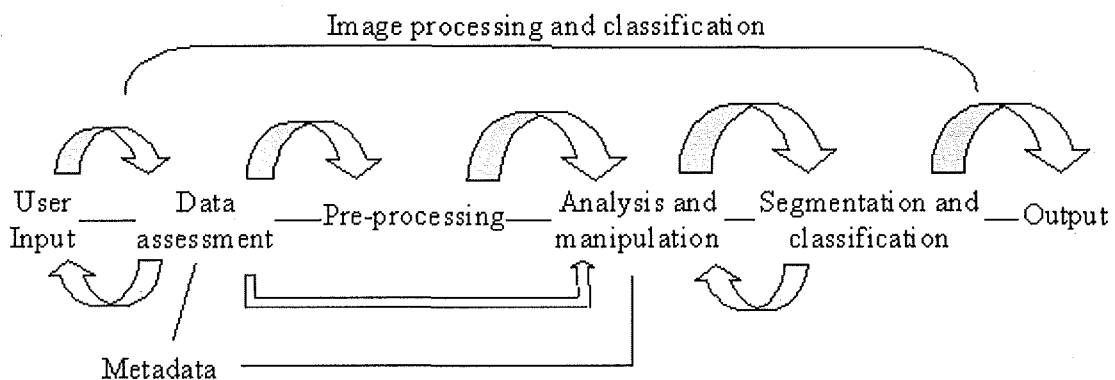


Figure 5.3: Major steps of image processing and classification

The system should have the necessary pre-processing functionality, as will be discussed below. However, users do not need to run this function, since it is considered that they do not have the adequate knowledge and skill to do that. For example, the user may not have the knowledge about which filter is suitable for reducing the noise in the given data and the application. Therefore, the system should perform some sort of test to find out what filter will be most suitable and then will itself run the required functions with the given experts' knowledge in the system. Similarly, the analysis,

manipulation, and the classification steps will also be selected and run by the system as required for the job. The system should use advanced techniques for processing and classification, such as neural networks and multiple classifier systems. The system should perform an accuracy assessment of the classifications and compare the accuracy with that of the source data or use it as an accuracy target set by the user initially to justify the result.

#### **5.2.1.6 Output of the system**

The output of the system will be a classified image showing different land use and land cover with the accuracy reporting. This could be a digital and hard copy map with other relevant features, such as road networks and the location of special infrastructures from the GIS, overlaid on the classified image.

### **5.2.2 Limitations of the present systems**

An intelligent system in remote sensing image processing involves the convergence of two fields: image processing and artificial intelligence (AI). These are mainly the systems that integrate AI methodologies, such as neural networks, the experts' knowledge, multi-source information integration, rule-based hard or fuzzy reasoning processes, etc. in the system with the image processing methods. A common objective is that the system can assist an expert to perform the work consistently and efficiently. Most of the currently available systems have been applied to solve a very specific portion of the whole process of remote sensing image processing and classification. A major portion of the whole process, such as the assessment of data quality and the necessary pre-processing, selection of classification algorithm(s) and accuracy assessments, are mostly done by the human operator. Moreover, the area of AI is mostly applied to the image understanding and interpretation part. Most of the current systems in this domain are designed to provide some sort of user assistance for classification, image fusion, GIS integration for classification, or some level of processing problem. Considering the knowledge components, commonly, the attention of the present systems is directed towards the use of expert's knowledge or mining knowledge from the data itself in a knowledge-based or rule-based interpretation or post-processing tasks, whereas, an accurate image processing and classification task requires experts' knowledge from a diverse background depending upon the application. It is impossible

to obtain high accuracy in terms of the classification of remote sensing images without vigorous input from the remote sensing image-processing expert with the relevant and adequate ground knowledge. The requirements of a wide area of expert's knowledge for remote sensing image processing can be appraised from the words of Dana Parker's at the First Symposium on Remote Sensing of the Environment in 1962:

*“Since these sensors are radiation detectors, we need to know something about the radiation properties of the source in the spectral region concerned; we need to know something about the medium through which radiation is propagated; and we also need to know something about the detector and the method of displaying the detected radiation.”*

More words can be added to the above when discussing SAR remote sensing where knowledge regarding the properties of the state of the target at the time of imaging is vital for the purpose of classification.

The interaction with the experts' knowledge occurs in the steps of image processing due to a perceived prior knowledge about what will be the action or result. Some of the steps use the knowledge of methods for processing the images, while others, especially, the interpretation, require domain relevant concepts to be represented in the knowledge. Local knowledge is the most difficult part in terms of the availability of experts. This expertise has no limits in its dimensions. Dimensions can range from knowledge of the soil to the atmosphere, social history to the economic and administrative policy. In some research (Graham and Barrett, 1996), such knowledge is categorised as the knowledge in general aspects and in local aspects. Mangrove forest, for example, exists only in coastal environments, and forest do not exist over 3,000 metres above sea level. These are examples of general aspects of knowledge about an object. In Bangladesh HYV rice cannot exist on land with a deep-water condition, or, if it is shrimp cultivation in lowlands, this will be sweet water shrimp. These are examples of local knowledge about an object. However, hardly any system uses every source of knowledge that is appropriate to all of the major image-processing steps.

### **5.2.3 The potentials of artificial intelligence**

The methods of AI have great potential for image processing and the classification of remotely sensed imagery far beyond the current uses, as seen from the review in Chapter 2. As seen from the earlier sections and from the review, artificial neural

networks can provide better accuracy. Moreover, they are also suitable for integrating other sources of nominal data, such as the GIS layer, in the process of image classification. Multiple classifier systems can give the best results by exploiting the good portions of the constituent classifiers. An expert system with the given knowledge of domain experts can be used for integrating all of these intelligent methodologies to produce accurate results and offer the potential for the use even by a non-expert user. Moreover, although the development of metadata is not really aimed for use in expert systems, it may be used by them.

#### **5.2.4 Summary of requirements**

Considering the above discussions, a system is required that can be run by a user with very little knowledge about the methods of remote sensing image processing and classification. More specifically the requirements can be listed as below:

1. The system should have the domain experts' knowledge and reasoning capability for deciding and performing appropriate tasks relating to remote sensing image processing.
2. The system needs a user interface to get the user's input about the intended task and source (file name, location path) of available data and metadata, and associated information, and to provide necessary feedback and output to the user.
3. It should also be able to suggest to the user the requirement of additional GIS or additional information based on the intended task.
4. The system should perform all of the steps of remote sensing image processing and classification and use advanced techniques of image processing.
5. The system should handle GIS and tabular data.
6. The system should be intelligent enough to gather the additional information from the metadata.
7. It should assess the accuracy of the results and suggest further steps. Finally,
8. It should be able to produce a digital or hardcopy map, overlaying other relevant GIS layers over the classified image.

Based on these system requirements, the following section will provide further analysis and the design of a remote sensing image processing and classification system.



## 5.3 Analysis and Design

This study aims to produce a unique architecture for an intelligent image processing and classification system to fulfil the above aspiration. This section analyses the *physical* and *logical* framework of the system that led to the design of the architecture. The physical framework discusses the physical components of the system, while the logical framework will consider the process among the components to achieve the aspiration.

### 5.3.1 Physical framework

Figure 5.1 shows the physical components of the system. In a common computer system, the major components are the input subsystem, processing subsystem, and the output subsystem. In a more intelligent computer system, the intelligent components are added to all of these components, which are the expert's knowledge and the intelligent techniques. A large portion of the input and output subsystem, for example, is the communication between the user part and the machine part of the human-machine system which is done by a user interface. An intelligent processing subsystem contains the intelligent techniques for doing the job. On top of that, there is a need for an experts' knowledge-based control subsystem, especially when there is a non-expert user of the system. The intelligent processing system should be capable of processing data and knowledge, and it uses the processed knowledge for further processing. Thus, the processing subsystem consists of the data processing part and the knowledge processing part. These then bring in the types of data it processes and how the knowledge is represented for processing in the subsystems and what tools are used for processing. Thus, the components of the system should be the *user interface*; the *knowledge base*; the *data and metadata*; *processing tools* for the data, metadata and the knowledge; and a *control agent* for running of these components of the system; they are discussed below.

#### 5.3.1.1 The user interface

Since the users of the system are considered as non-experts in the remote sensing image processing, an intelligent interface is required for communication between the user and the system. Much work has been done regarding making the user interface easier, more efficient in terms of time and ultimately more user friendly. The user interface could be of a different type, with its merits and demerits, such as being a menu-based interaction,

form-based 'fill in the blanks', language based command line input, object oriented manipulation based, or even question and answer based. A comparative table of merits and demerits is given in Turban and Frenzel (1992) for all types of user interface. A suitable one can be adopted from these types. It may be mentioned here that this study will not cover this area further.

### **5.3.1.2 Knowledge and knowledge representation**

The intelligent behaviour of a system is based on the knowledge it contains. In this case, this must be derived from remote sensing experts. Remote sensing experts have knowledge of remote sensing technology and image processing, as well as contextual knowledge. This knowledge of remote sensing and image processing provides them with the procedures, and the contextual or declarative knowledge. To make a system intelligent, the procedures have to be fed into the system, and that can be done in the form of rules. However, when running the system, contextual knowledge is required at every step and has to be provided to the system to do the work. This contextual knowledge can be given to the system in the form of facts. For example, the knowledge is that noise reduction is required before the classification of an image if the image is noisy. The representation of this knowledge in the form of a rule is that "*if the image is noisy, then do noise reduction*" and the knowledge of the context or the fact could be that the "*image is noisy*".

#### **5.3.1.2.1 The rules base of the system**

The rules of the system have to be acquired through consultations with experts and the literature review. The knowledge can be expressed by different types of rules, such as deduction rules, transformation rules, integrity content, and the event-condition-action (ECA) rules. The deduction rules are simple rules that express the knowledge that, if one set of statements are true, then some other set of statements must be true. Sometimes this type of rules is called a logical implication, a material conditional, or a Horn clause (<http://www.w3.org/2000/10/swap/doc/rule-systems>). For example, if SAR images are dark on all the dates of the time series then those must be the Water class. The transformation rules are those whereby each rule relates truth in one knowledge base to the truth in another. For example, a rule could be that if the pixel values are greater than 5 in a multi-temporal RADARSAT SAR S5 db image then these are the Bright pixels and the Bright pixels indicate an Urban/Built up area if the cluster of

pixels on the image is greater than 8 pixels, or say 0.5 hectare. The integrity constraints rule can be emulated with derivation rules like "if it is not true that ... then we-have-an-error" and do a check for "we-have-an-error". For example, if the expected output scale of the map is larger than 1:10000 and the image pixel size is greater than 10x10 metres then the rule is to provide an error message to the system user. The ECA type rules are the notions of action, i.e. a set of rules brings up a knowledge that suggests a new action. In some cases, the rules could be a combination of different types, such as in the example of an Urban/built-up area, an action needs to be suggested as: "perform grouping function to get the clusters of more than 8 pixels". Therefore, in this case the rule is a combination of ECA and Transformation type of rules. This type of combination may be called as meta-rule.

#### **5.3.1.2.2 *Facts for the system***

The fact can be given to the system by the user and can be generated by the system. The system will be more intelligent when it can produce the facts for feeding the rules. For example, for feeding the rule in the above example about noise reduction, the fact about whether or not the image is noisy can be determined in two ways - either by the system itself (by doing some calculation and measurements), or by the user (the user will do the calculation and present the measurement vector to the system). If the user of the system is considered a non-expert then the first option is preferable. Nonetheless, the facts will be initialised from the initial user's inputs and acquired through the interface into the system. The facts will keep growing and changing until the end of the processing. For instance, after reducing the noise of the image, the new fact is that the image is noise free and that fact leads to firing a rule for a new action concerning the image processing, which will produce a new fact.

#### **5.3.1.2.3 *Organization of the rules and facts***

In general, a rule base is a list of rules. If the rule base or knowledge base becomes larger, it is better to structure it into subsets or so-called knowledge islands (Boy, 1991). Boy highlighted two problems with a large list of rules base: the exploration of the rule base is difficult, and the speed of execution is low. On the other hand, the advantage of a structured rule base is that a subset of the rules base will be used in a certain context of inference. Similarly, the initial facts can also be grouped, as not all of the information provided by the user may be used at the same stage of the processing. In the proposed

system, the rules and facts can be structured by following the image processing steps shown in Figure 5.3: the data assessment, pre-processing, analysis and manipulation, and the segmentation and classification.

### **5.3.1.3 Data and data processing**

The data components can be of two types for the system: the existing data, and the run-time data. Remote sensing image files, GIS layers, field data, met-office data, and ground control points (GCP) data are examples of the existing data. This data can be stored in the local workspace or in the distributed computer system. In a more ambitious system these data could even be somewhere in the World Wide Web networks.

The run-time data will be the data generated while running the system for processing, such as the signature table that defines the descriptive statistics of the training sample, especially for the statistical classifier, will be generated through the analysis of the images against the field data. These statistical properties will subsequently be used as facts for the image classification rules. Data from the evaluation of the classification accuracy may also be an example of run-time data and that might be used for multiple classifier combination.

The data files should also follow an agreed structure and format. As example of this is that a Met-office data file will keep the information regarding the seasons' start and end dates, rain fall and wind information following the met-office data standard. GIS and images should also be in a suitable format. For instance, a tabular file entitled "major crops" could contain information on major crops with respect to the region, season, or other land properties. As there might be different types of file formats for different types of data, the employed expert system shell should have the capability of reading different types of file formats. After any processing, the new name of the data will bear the previous name and the executed function name. For example, if the name of a given GIS data set is 'Landtype.gis', after clipping, a portion of the area of interest could be termed 'Landtype-clp.gis'.

### **5.3.1.4 Metadata**

The metadata are mainly the archive documents that describe the content, quality, condition, and other characteristics about the spatial data in use, and the details of this

were discussed in Chapter 2. These could be grouped as related to images and GISs or even for the tabular data. Standardized metadata can be an additional and important source of data quality, authenticity, and timeliness, and much more information can be used in an intelligent system. In Chapter 2, a detailed description of different metadata data standards was presented. The proposed system is intended to use an agreed standard structure of metadata, such as USGS-FGDC. The system could be able to access a metadata file that can be located locally, in a distributed computer network system, or even in the World Wide Web network. The utilization of metadata in decision-making is also a significant aspect of the system. Moreover, the system should also be able to write metadata for its final product.

### **5.3.1.5 Processing tools**

Three major processing tools for running the system will be the control agent, the expert system shell and the image and GIS processing software. These are discussed below.

#### **5.3.1.5.1 Control agent**

The control agent will be the backbone of the system. In delegating the responsibility for processing the knowledge using an expert system shell and processing of data using a suitable image processing software, the control system will play the role of coordinator. For instance, its role will be: the acquisition of facts from user inputs to organize them accordingly; initialising the facts; loading the appropriate set of rules and asserting the facts to the knowledge processing tools; acquiring the instance from the fired rule and calling for necessary image processing function(s), pull-in the data and metadata; and providing feedback to the user. It will also assert information about the completion of a function execution in the form of a new fact. This agent must be written in a suitable language, as it needs to be communicating with the used expert system shell and the image processing software.

#### **5.3.1.5.2 Expert system shell**

For processing the knowledge of the system, a suitable expert system shell should be employed. The review in Chapter 2 demonstrated that using the shell approach expert system can be easy to build and far faster, as it is unnecessary to programme all of the subsystems of an expert system. The expert system shell will be responsible for the

reasoning process. It should have a conflict resolution strategy, as this is necessary when several rules fire at the same time. Various strategies are possible for resolving the conflicts of which one should get priority in the agenda. Some possible strategies are the first rule encountered; the rule with highest priority; the most specific rule that pertains to a certain criterion; the rule that refers to the most recently added fact in the fact base; a rule chosen by chance; or all rules are applicable in parallel (Boy, 1991). However, this list may not be exhaustive and several strategies may be needed in a system for different circumstances.

#### **5.3.1.5.3 *Image processing and GIS software***

The image and GIS processing software will be responsible for performing the processing functions, as instructed by the control agent. These are mainly the executable programmes required for different stages of the system. For example, a rule could be "*if appropriate GIS layer(s) is available then perform SOM classifier*". In this case, the programme for performing the SOM classification is a classification function. The functions can be grouped for easy handling as Data assessment, Pre-processing, Data analysis, Classifications Accuracy assessment, and Multiple Classifier Combination (MCC) methods. For instance, for a classification task, a classifier will be selected based on the facts relating to the task in hand, the assessment of the data, and the rules derived from the knowledge of image processing. If the task is to derive a flood extent map or a classification of two or three classes of land cover such as "land, sand and water," MCC may not be required, if the accuracy provided by a single classifier satisfies the user's expectation. In the function library, a different type of statistical or neural network classifier should exist. However, commercially available image processing and GIS software may not possess all of these functions. If any specific classifier requires special processing of the data, then the relevant function must be added to the function library and in that case, relevant rules must be added to the rule base of the system.

### **5.3.2 The logical framework of the system**

This section describes the logical connections of the system components and their functional process. Initially, the user will input the information about his intended work and the available data to the system through the user interface. Examples of the

information about the intended work could be the type of application, the number of output classes, the expected output map scale and accuracy, etc. Examples of information about the data could be the list of data file names, image acquisition date(s), the extent of the area of interests, and the metadata file name and location path. The control agent will convert all of this information into the acceptable form of facts for the expert system shell (ESS) and build up the initial set of facts. Then the control agent will load the existing initial set of rules and the initial set of facts into the ESS and run the process for reasoning. Based on the loaded facts, relevant rules will be fired. The fired rule may come up with any or all of the instances, such as asserting a new set of facts suggesting an image processing action, a feedback message to the user, requesting further information from the sources, retracting an existing fact, or loading a new set of rules. The control agent will read the instance of the fired rule and act accordingly. If the instance is an image processing action, then the agent will call for the relevant function for execution. The functions could be for any of the tasks of the data assessment, pre-processing, analysis, classification, accuracy assessment, or other image processing steps shown in Figure 5.4. This figure shows that, in terms of quality and compatibility checking, the system will mainly deal with the initial facts derived from the user input and metadata. The system should be linked to the aforementioned metafiles and checked for spatial extent, resolution, projection system, accuracy report and other necessary information, prepare a list of required pre-processing and prompt a report for the user. The pre-processing could be the field data editing, conversion of the field data into "Table" and GIS with appropriate projection, re-sampling, re-scaling, re-projection, or sub-setting the input data for compatibility.

Examples of the analysis and manipulation stages are shown in Figure 5.4. These are: extracting land use and land cover classes from the analysis of the field data; analysing the training data to find the spectral patterns for each of the classes; or signature analysis, and the calculation of the statistical parameters of the images with respect to the target classes, etc. The next step is the classification of images using one or multiple classifiers as required. The classifiers will be selected using the knowledge-based rules given in the system and the facts gathered from the analysis of the data and metadata. From the classifications, a new set of data will be produced, which are the classified files produced by different classifiers. The accuracy analysis involves evaluating the classified images with respect to the evaluation data. The assessed

accuracies will be analysed to decide which classifiers will be used for the combination of classifiers. The next step will be the combination of the results from the classifiers using a suitable methodology based on rules if this is required by the intended task. Finally, the system will evaluate the accuracy of the combination result with respect to the evaluation data.

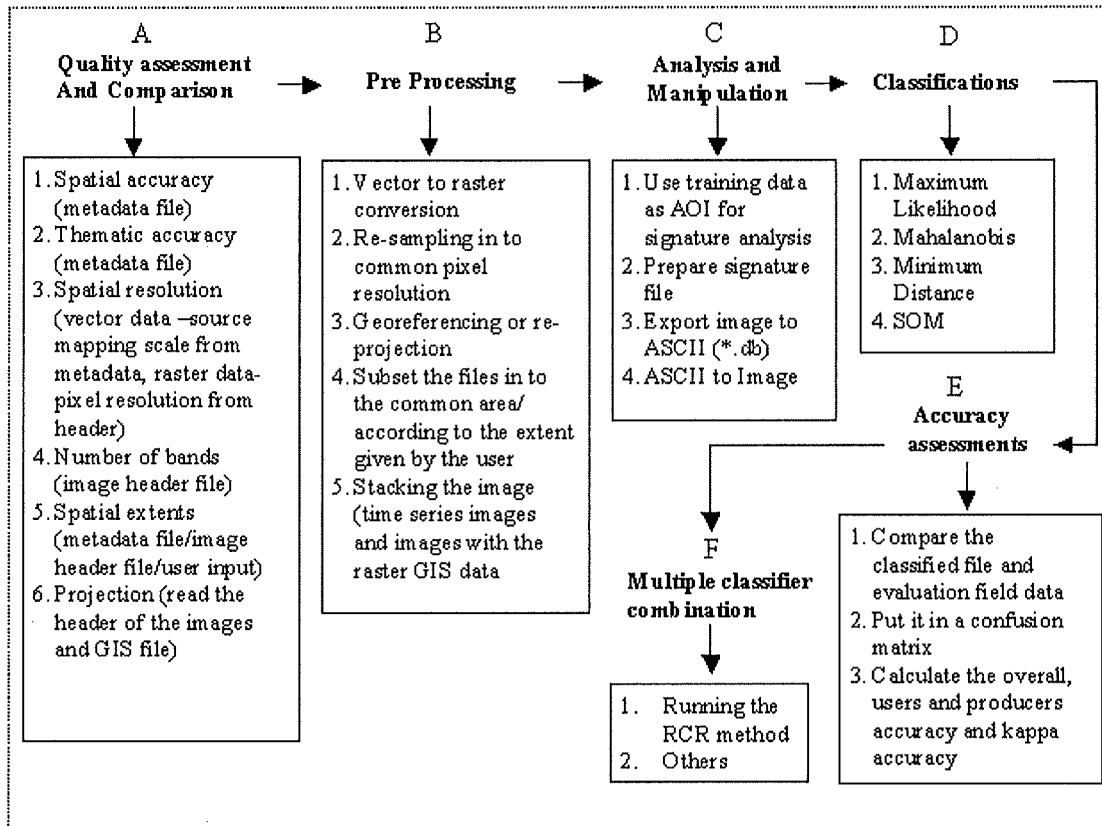


Figure 5.4: Major tasks in different steps of the image processing and classification

The control agent will acquire the completion report of the function-execution and assert new facts in the ESS. It may retract any existing fact from the memory of the ESS. In this way, the facts keep changing throughout the process. The system will present different classification algorithms based on the facts derived from the measurements of the pre-processed data, user input, and/or metadata. After performing the different classifiers and analysing the achieved accuracies, the system will perform the assessments, and propose and perform the multiple classifiers combination process. If the fired rule indicates the action as the search for further information or an error message then the agent should seek an executive decision from the user through the user interface. In this context, the system is called an Intelligent System for Remote Sensing Image Processing and Classification (ISRIPaC)



### 5.3.3 Architecture of the System

From the analysis of the requirements and the subsequent discussion of a suitable physical and logical framework for an intelligent system, the basic architecture of the proposed ISRIPaC system is given in Figure 5.5. The figure shows the physical and logical layout of the components of the system. Users will interact with the system using the user interface. The control agent is the coordinating centre of the system. Rules and facts are organized in the knowledge base of the system. All the necessary images and GIS processing functions will be available in the function library of the system. An expert system shell will be used for the logical reasoning using the facts and rules of the system, coordinated by the control agent. The arrows and the associated numbers (1, 2, 3...) in the figure indicate the flow of information from one component to another in the system. In the figure, the lines inside the box showing the control agent are symbolic to express its communication with the other components. The information flow arrows number 10 and 11 pass directly through the control agent box, because the agent does not take part in the processing of the data (images, GISs, and tables). The control agent only passes the name and the location path data to the relevant processing function.

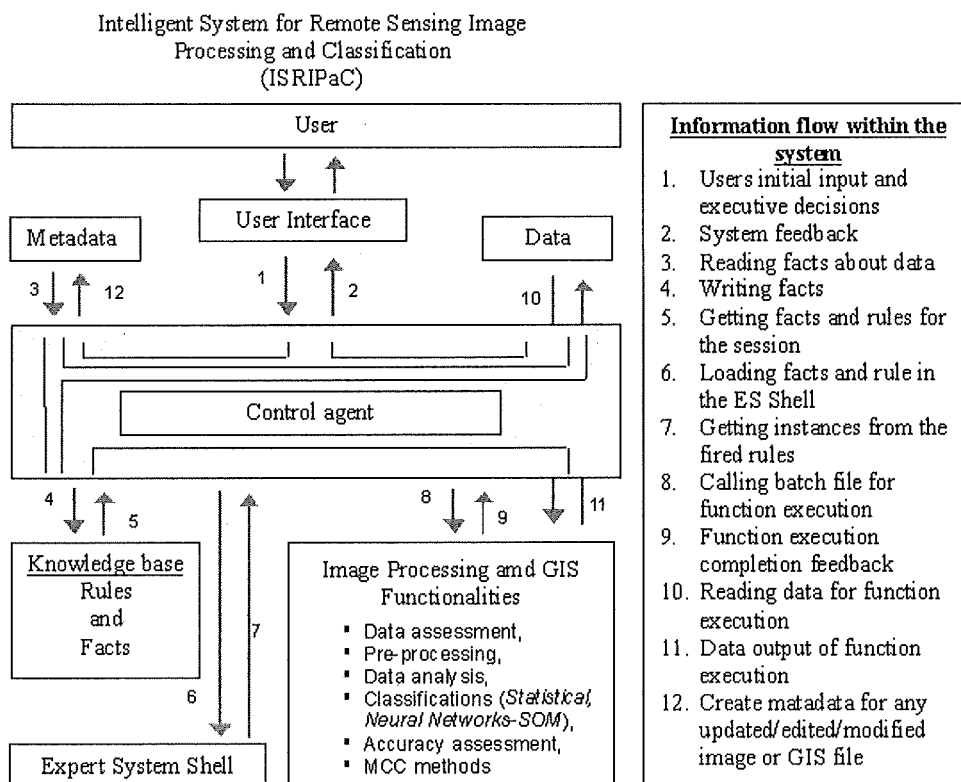


Figure 5.5: Proposed architecture of the system

## 5.4 Conclusion

The proposed system, ISRIPaC, is not only a knowledge based image classification or interpretation system, but also a complete system for image processing and classification. Beside the experts' knowledge base, other AI methodologies considered for the system are neural networks, and multiple classifier combination (MCC). The system will compare and combine the suitable results to provide higher accuracy outputs to the user. In between, the system will acquire necessary information from other sources, such as ancillary data and metadata; perform an assessment for the required pre-processing, and perform necessary pre-processing, classification, and accuracy assessment using various methods as necessary. It will be a federated system of existing methodologies of AI and image processing software, although the utilization of these are in a different context to their usual use. Moreover, it is an open system architecture, which is capable of accommodating new functionality in its image processing function library, and new rules in the rule base as needed. The system will contain the necessary image and GIS processing functionality and the expert system shell. Therefore, it can be useable for any sort of image processing and classification by adding an appropriate set of rule base and processing functions. Thus, it is justified to say that the proposed architecture of the system is quite generic, in the sense of image processing and classification.

## Chapter 6

### 6. Implementation and Evaluation of Prototype

#### 6.1 Introduction

The requirements of an ideal remote sensing image processing and classification system were discussed in Chapter 5. The discussion of the requirements led to the design of the system and ultimately to an intelligent system architecture named ISRIPaC. This chapter describes a prototype implementation of the proposed ISRIPaC architecture that sufficiently represents the features of the proposed system and provides a basis for evaluating the proposed system.

#### 6.2 Overview of the Prototype

The basic principle that was considered in prototyping the system is that the advanced methods and tools for image processing and classification and the domain experts' knowledge have to be combined in such a way that the system can perform the given tasks in an intelligent manner, thus depending less on its user for instructions. It has been designed to work according to the image processing steps outlined in Figure 5.4. In this chapter, Figure 6.1 shows the planned functional process of the prototype. Major stages of the prototype implementation were: the selection of the expert system shell; the acquisition of relevant knowledge and development of rule base; the generation of metadata files; the selection of image processing software; the development of the control agent; and the testing of the interfaces. In the prototype, the CLIPS expert system shell is used with the IDRISI Kilimanjaro software for image and GIS processing.

According to the functional plan, the control agent is the coordinator of the system. A task is initialised from the user input and then the rest of the processes are controlled and coordinated by the control agent until the end of the task. The control agent will convert this information into a readable code for the expert system shell (ESS) for knowledge processing. The experts' knowledge will be available in the system base. The agent loads the facts and the relevant set of rules into the ESS and runs it for

reasoning. Then from the rule fired in ESS, the agent gets the information about ‘what to do next’. If a fired rule seeks additional information then the control agent will acquire that information from the metadata files, convert all of the information into readable code of facts, and load these facts into the expert system shell. If the fired rule asks for data processing, then the control agent prepares a command line code adding the data file names (input and output) and the relevant parameters to call and run the relevant image-processing function. It passes the code to the image processing software to perform the processing task. The access path for the input data and the metadata will already have been provided by the users as part of the initial information. When the image processing software has performed the processing task, it provides a completion report to the control system. The control agent loads the completion report into the ESS in the form of a new fact and runs the ESS for further reasoning in order to proceed with the next task.

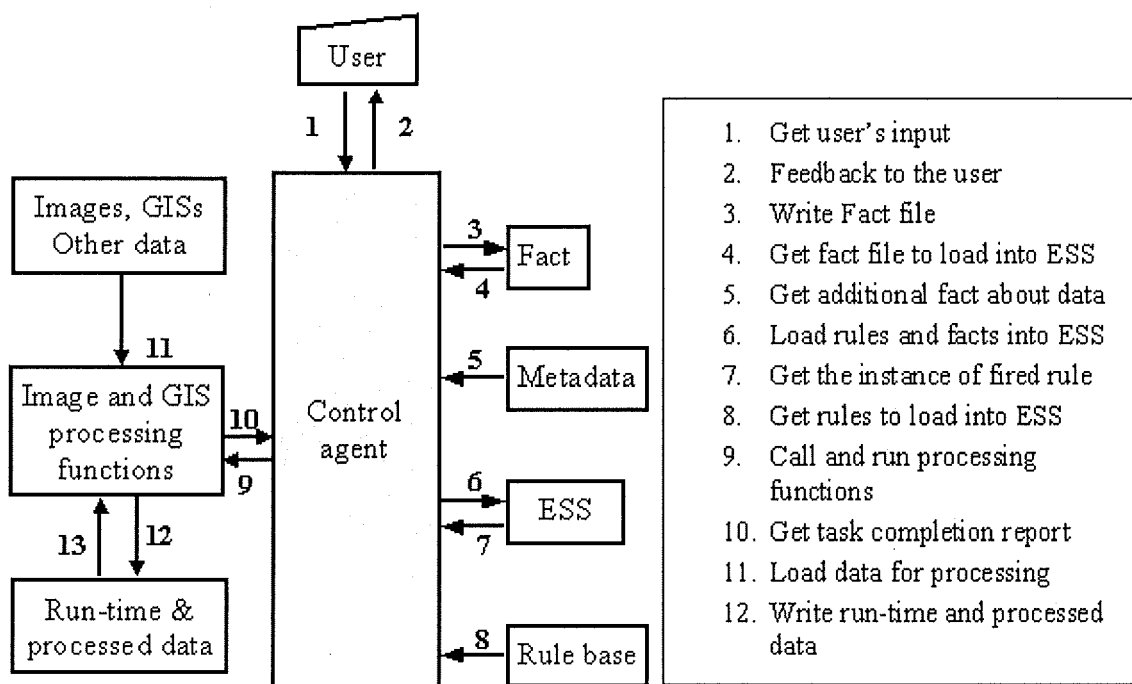


Figure 6.1: Functional plan for the prototype ISRIPaC

### 6.3 System Components of the Prototype

The prototype has been implemented as a simplified representation of the proposed architecture. It is a task-based implementation of the architecture, in which the expert system shell, the image processing software, the control agent, the knowledge base, and metadata are the main components. The knowledge base of the expert system has to be

coded according to the requirement of the expert system shell and the control agent was programmed to communicate with the shell, the image-processing software and the user input. Therefore, a suitable expert system shell and image-processing software had to be selected and acquired. The control agent is written using the Visual C++ programming language. To keep the prototype simple, the user interface component is replaced with an ASCII text file containing the necessary information that represents the user input.

### 6.3.1 Expert System Shell

The expert system shell (ESS) is one of the intelligent components of the proposed system, as it processes the experts' knowledge for running the system. A list of precise requirements was drawn up to select a suitable ESS for the prototype. These are:

- The expert system shell needs to be based on Windows operating system, as most users are likely to be familiar with that.
- The system has to be designed for full integration with other languages.
- The shell should preferably have a reasoning mechanism with conflict resolution strategies for tackling the situation when several rules can be fired at the same time, as discussed in the Chapter 5.
- The shell should be callable from a programming language, perform its function, and then return control to the caller program. This was necessary as the main control of the system lies with the control agent, which has to communicate with both the ESS and the image processing functions.
- Finally, it should preferably be free or inexpensive.

Evaluating the system based on these criteria, the CLIPS (C Language Integrated Production System) expert system shell was found to be suitable for the system. CLIPS is developed and made publicly available by the Software Technology Branch (STB) and the NASA/Lyndon B. Johnson Space Center and can be downloaded from the website [www.ghg.net/clips](http://www.ghg.net/clips). In addition to the expert system shell, the most recent version (CLIPS 6.20) provides a complete environment for developing expert systems (further details about CLIPS can be obtained from NASA website). This version (6.20) also provides the ability to interface with Windows 2000/XP. It is well-documented and well-maintained software and it available free. The design of CLIPS

permits integration with other languages including C++. In addition to being used as a stand-alone tool, CLIPS can be called from a procedural language, perform its functions, and then return control to the calling programme. In CLIPS, knowledge is represented in one of three ways: Rules, which are primarily intended for heuristic knowledge based on experience; generic functions and *deffunctions* (for defining additional functions), which are primarily intended for procedural knowledge; and object-oriented programming. CLIPS provides a global memory for facts and an inference engine for reasoning. Facts are the data that stimulate the execution via the inference engine. The inference engine decides which rules should be executed and when. When the conditions for multiple rules are satisfied, a conflict resolution strategy (discussed in Section 5.3.1.5.2) is required for prioritising the execution. CLIPS offers seven different modes of conflict resolution strategy: depth, breadth, simplicity, complexity, lex, mea, and random (details can be found in Giarratano, 2002). Rules, facts, and CLIPS objects form an integrated system since rules can pattern-match on facts and objects. The process of reasoning in CLIPS is data driven, i.e. it employs forward chaining.

Although CLIPS provides all the necessary tools for expert system development, in the prototype only the portion that performs inference and reasoning, which is termed the 'Shell', is used. Rules in the CLIPS Shell represent the domain experts' knowledge. Facts represent the information and this is the fundamental unit of data used by the rules. Each fact represents a piece of information that needs to be placed in the current list of facts in the Shell. As usual, a rule in CLIPS is composed of an antecedent and a consequent. These can be referred to as the "if portion" or left-hand side (LHS) of the rule, and the "then portion" or right-hand side (RHS) of the rule respectively. The antecedent of the rule is a set of conditions that has to be satisfied for firing the rule. The conditions can be satisfied based on the existence of certain facts in the Shell. The consequent of a fired rule is the set of actions to be executed. The actions are executed when the CLIPS inference engine is instructed to begin the execution of the fired rule. If more than one rule is satisfied by the given facts, the inference engine uses a conflict resolution strategy where the sequence of the rules to be fired is determined by the salience level of the rules.

### 6.3.2 Image Processing Software

This system component is responsible for providing the necessary image processing functions. It should be mentioned here that the ERDAS Imagine image-processing software was used for the earlier part of the study. However, because the license for the software expired before the implementation of the prototype, alternative image-processing software had to be acquired. A set of criteria was drawn up for selecting a suitable one. These are:

- The software should possess the necessary image processing functions, as discussed in Chapter 5.
- It should preferably have the ability to handle GIS data.
- It must be callable from a procedural language to perform its functions and then return control to the calling programme.
- It should preferably be free, or at least inexpensive.

In this context, IDRISI Kilimanjaro was found to be the most suitable image-processing software package to adopt for the prototype. IDRISI Kilimanjaro is a product of Clark Labs of Clark University, USA. It provides facilities for the input, display, and analysis of geographic and remotely sensed data. Although IDRISI is adept at the input and display both of raster and vector layers, the analysis is primarily oriented towards the use of raster layers. The recent version of IDRISI (IDRISI Kilimanjaro) offers many other functions for the processing of remotely sensed image data. Besides the traditional methods, IDRISI provides a method for the classification of imagery through artificial neural networks using the back propagation (BP) algorithm. However, it does not provide the Self-Organizing feature Map (SOM) or other advanced techniques like multiple classifiers systems. IDRISI can be integrated with programming languages such as Delphi, Visual C++, Visual Basic, or Visual Basic for Applications (VBA) as macro languages for controlling its operation. This feature of IDRISI indicates the possibility of adding further image processing and classification functions into it as necessary. IDRISI can be called from a procedural language and then return control to the calling programme. It has a built-in facility for writing macro languages to run any functions from the command line or from an external program. Figure 6.2 shows an

example of a macro file that was written for the prototype, and which was used to subset the images for the test area.

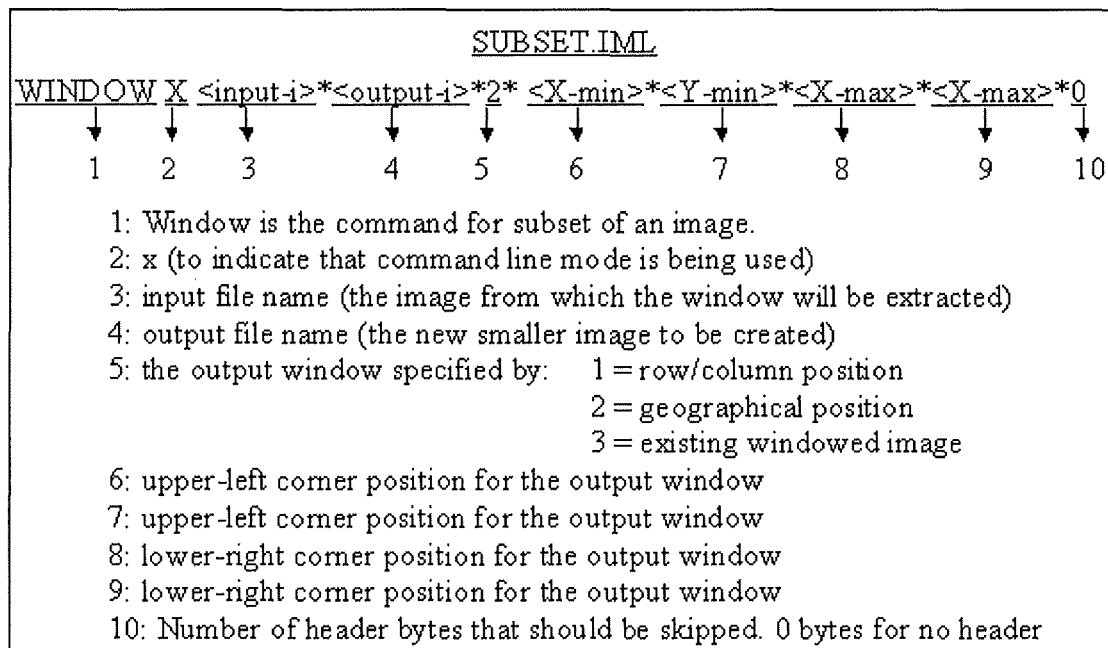


Figure 6.2: Example of an IDRISI Kilimanjaro .iml file written for the prototype

Macro Language files may be created in any text editor, using the appropriate syntax and saved in ASCII format with an '.iml' (IDRISI Macro Language) extension. The syntax includes the function name (termed a module in IDRISI), input and output file names, and all of the parameters necessary to run the function in the required order. Macro files are written for all the functions used in the prototype. Nearly every IDRISI module may be run in this mode. The macro file needs to be stored in the working data directory and the directory path must be declared while running the function.

### 6.3.3 The Control Agent

The control agent is the main interface programme of the whole system and significant efforts were devoted to developing the programme in Visual C++. This system is essentially a one-button system, but for the purpose of development and testing, the stages in processing can be stepped through via various menu controls. For example, Figure 6.3 shows the main interface of the prototype: a 'knowledge handler' menu links with the CLIPS expert system shell; and 'image processing' and 'GIS' menu links to the IDRISI Kilimanjaro functionalities and additional image processing functions. A 'Metadata' menu can also be linked to the metadata parser 'MP', which is a tool for



writing geospatial metadata according to the USGS-FGDC standard, as discussed in Chapter 3, and further in the next section.

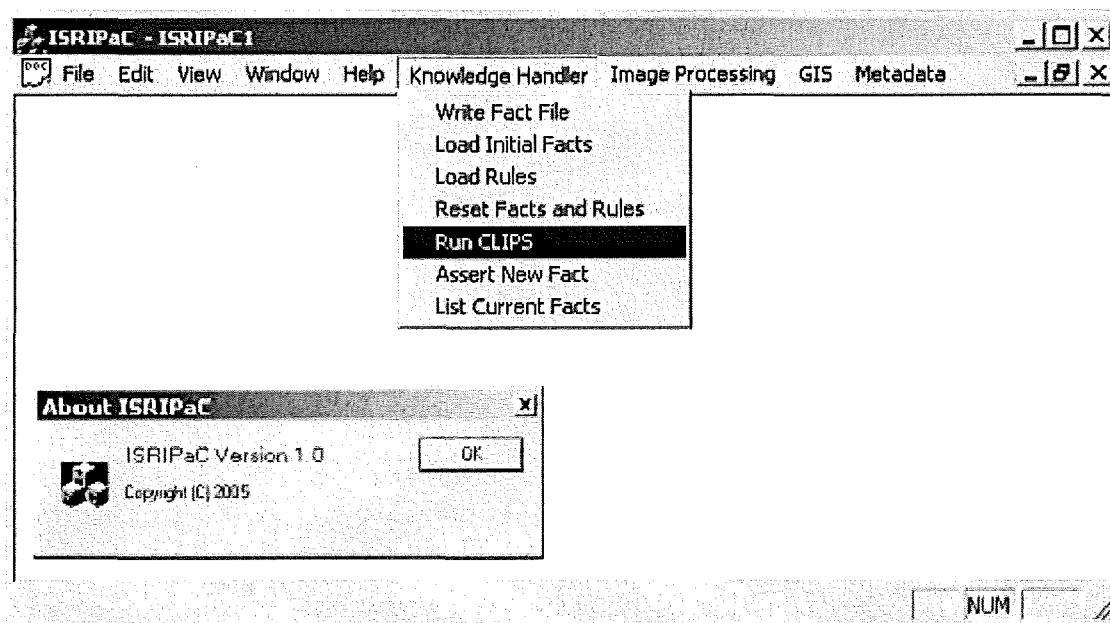


Figure 6.3: Main interface of the ISRIPaC prototype showing the menus for stepping through some of the Knowledge Handler processing stages

The 'Knowledge Handler' is the main functional menu of the system, and is used for acquiring the user information, loading the rules and initial facts into the expert system shell (CLIPS), initialising the Shell, and starting the job. In the main interface of the control agent, the 'Write Initial Fact' function gathers the user input from a text file and writes the initial facts into a command file, so that it can be read by the CLIPS code. The 'Load Initial Facts' and 'Load Rules' options are used for loading the initial facts and the rule base into the CLIPS Shell. After loading the facts and rules, CLIPS needs to be initialised using the 'Reset Facts and Rules' function for setting the current focus. This function prepares the agenda in CLIPS, which is the list of the rules including their execution sequence which have their conditions satisfied by the given facts. 'Run CLIPS' will start the execution. The fired rule may be a new fact like 'Subset images to the AOI', which means that the images need to be a subset according to the extent of the study area. The control agent obtains the fact immediately and interprets the fact in order to decide what to do next. Accordingly, the agent writes the '.iml' file and saves it in the temporary folder. To write the '.iml' file, the agent uses the existing template file that is already given in the function library (see the example in Figure 6.2). The agent picks appropriate parameters (e.g. the name and location path of the images and the extents of the study area) from the initial facts that were written from the user input.

Then it will activate IDRISI to run the function. After executing the .iml file, IDRISI will pass a completion message to the control agent, which in turn passes the information to CLIPS. Having received that, CLIPS fires the next rule in the agenda. If the outcome of a new fired rule is a new image image-processing task or a simple message such as 'Assessment of Data - done', then CLIPS will move on to the next rule on the agenda. If there is no rule on the agenda then CLIPS will wait for the control agent to load a new fact or a set of rules according to the last outcome of the fired rule.

While building the prototype, several other functions and menus were added in the main interface to maintain control over the processes and check their consistency. For example, 'Assert New Fact' option in the 'Knowledge Handler' menu is used to assert a new fact to CLIPS, and the 'List Current Facts' option is used to check the list of facts in the CLIPS memory.

### **6.3.4 Metadata for the Prototype**

Use of metadata is part of the functional process of the system as discussed in Chapter 5. However, metadata is not always readily available. This prototype is designed to utilise the USGS-FGDC geospatial metadata standard and identified the Metadata Parser (MP) as the tool for writing according to that standard (chapter 3). Details about the USGS-FGDC geospatial metadata standard are given in Chapter 2. A screen view of 'MP' and further description also is given in section D1 of Appendix D. 'MP' is also used to prepare the metadata for the images and GIS data for testing the prototype.

### **6.3.5 The Knowledge Base**

The knowledge base for the prototype is derived from several sources: the case study; the author's experience of remote sensing image processing and classification; and informal discussions with colleagues working in the domain. The knowledge building process followed for the prototype is shown in Figure 6.4, and was developed based on the discussions in Turban and Frenzel (1992).

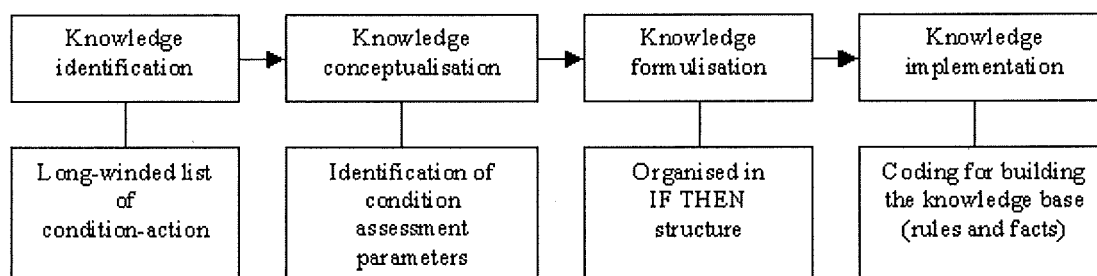


Figure 6.4: Knowledge base building process for the prototype

### 6.3.5.1 Knowledge identification

In the knowledge identification phase, initially, a long-winded list of condition-action/assertions was prepared based on the methodology followed in the case study and extended further based on the experience of remote sensing applications. The list was then organised and broken down into various levels (assessment, pre-processing, analysis and manipulation, and segmentation and classification) according to the discussion in Chapter 5. Then the list was refined and shortened for adoption in the prototype. Table 6.1 provides a part of the organized condition-action list as an example of the knowledge identification effort. The conditions are given a serial number prefixed with the letter A, P, M, and C to denote the Assessment, Pre-processing, analysis and Manipulation, and segmentation and Classification levels respectively.

The assessment knowledge is used for checking the appropriateness of the data in terms of application, season, type, and dates. This is the knowledge about the suitability of the type of the data or the resolution of the data in order to complete the intended task. For example, for rainy season crop assessment, SAR data is more suitable than the optical images; or for damage assessment in case of a Tsunami type disaster, either data may be suitable depending upon the season and cloud coverage in the image.

The pre-processing level knowledge includes the knowledge of checking the accuracy of the individual data and compatibility of the image, GIS and other data in terms of accuracy, noise level, projection, extent, and resolution, etc. and preparing the data for subsequent image processing steps. Based on this knowledge the system will perform all the necessary actions, such as subset the spatial dataset according to the study area, and perform geo-referencing for geo-rectification. Example of analysis and manipulation level knowledge is the knowledge of image signature based on field data, grouping of field data for training and evaluation, analysis of the confusion matrix for

multiple classifier systems. Finally, in the segmentation and classification stage, the choice of single or multiple classifiers or the type of classifier to be used is based on the overall knowledge that was gathered at all the previous stages.

Table 6.1: Part of Condition-Action table as example of the knowledge identification step

Sl.	Condition	Action/Assertion
Assessment level		
A1	Image classification is targeted for vegetation (crop, natural vegetation) identification	Use multiple image (Multi-temporal/ multi-spectral/ multi-polarization)
A2	Wet season image classification and interested in more than 3 classes	Use multiple SAR images
A3	Client interested in wet season and interested in crops classification	Use multi-temporal SAR images acquired on well distributed dates over the crop's growing period (planting-growing-maturing and harvesting)
Pre-processing level		
P1	Image extent is larger than the study area	Crop the image
P2	Using GIS layer in image classification	Use georeferenced image
P3	Image resolution is not equal to the GIS resolution	Resample GIS layer to image resolution
Analysis and Manipulation		
M1	Field data available	Generate training (signature file) and evaluation data
M2	Training data available	Overlay with image to generate statistics
M3	Classification done	Overlay output with the evaluation data to generate confusion matrix
Classification		
C1	Using single SAR image for less than 3 output classes	Use simple threshold method
C2	Using multi-temporal SAR image for wet season crop classification	Use multiple classifier systems

### 6.3.5.2 Conceptualisation of knowledge

Obtaining the organized list of the identified knowledge relevant to the different image processing and classification steps described above, the subsequent context of each of the conditions is conceptualised. For instance, which information is to be used for the action, how the information can be gathered, how the task could be implemented, and what will be the rules for performing the task? Such questions were answered in this step for each of the conditions and actions. Table 6.2 provides an example of the conceptualisation of conditions.

For the condition A1, the action/assertion (Table 6.1) is the use of multiple image layers. The conceptualisation stage (Table 6.2) was to look for the answers for the questions such as: from where and how the system will know about the type of intended application, and the number of images will be used, etc. In this condition, the system has to obtain the application type from the user inputs. If the user provides more than one image file name then the system can get the number of images from the user's input. If the user provides a single image file name then the system will look for the image metadata file (the name should be given by the user) to check how many layers are available in the image file. Similarly, in the case of the P1 condition, to compare the extent of the study area and the extent of the images, the coordinates of the Upper-Left (UL) and Lower-Right (LR) corners are compared. The UL and LR of the study area (SUL & SLR) must be established from the user input and the same information for the image (IUL & ILR) should be gathered from the image metadata file.

Table 6.2: Conceptualisation of the knowledge

SI.	Condition	Conceptualisation
Quality and Compatibility assessment		
A1	Image classification is targeted for vegetation (crop, natural vegetation) identification	Check user inputs for application type. Check user inputs and/or metadata for number of images
A2	Wet season image classification and interested in more than 3 classes	Check imaging date in metadata & season table (additional data), and compare Check metadata for image type Check user inputs and/or metadata for number of image
Pre-processing		
P1	Image extent is larger than the study area	Check user inputs for upper-left (SUL) and lower right (SLR) coordinate of the study area Check metadata for image extent (IUL and ILR) Compare the coordinates of the extents
P2	Using GIS layer in image classification	Check user inputs for GIS data in use or not. Check the projection of image. Compare the projection system

### 6.3.5.3 Formalisation of knowledge

After the conceptualisation of the knowledge, the statements are converted into simple rules. Table 6.3 provide an example of the formalisation process. For instance, in case of the condition A1, the system gathers the information from the relevant sources (e.g. user input, metadata), and if it finds that the application type is Vegetation then it will test for the number of image file names provided by the user. If the number is greater

than 1 then the system will proceed to the next condition, otherwise it will issue a message requesting more image file names to be provided for the classification.

Table 6.3: Formalization of the identified knowledge

Sl.	Condition	Formalisation
Quality and Compatibility assessment		
A1	Image classification is targeted for vegetation (crop, natural vegetation) identification	If application is Vegetation And image layer is equal to 1 Then prompt to the user "Multi-layer/Multiple images is required for your intended application"
Pre-processing		
P1	Image extent is larger than the study area	If $SUL \neq IUL$ And $SLR \neq ILR$ Then call Crop the image data set using SUL and SLR coordinates

### 6.3.5.4 Implementation of knowledge

The list of conditions and associated formalized knowledge were coded according to the CLIPS requirements. Knowledge in CLIPS is represented in the form of Rules and Facts, as discussed earlier in this chapter. The coding of the formulated knowledge in the form CLIPS rules and facts will now be discussed.

#### 6.3.5.4.1 Rules in CLIPS

Figure 6.4 provides an example of the coding of formalized knowledge into rules for CLIPS. In the figure, the term 'defrule' begins the rule definition and 'Check\_Proj\_of\_images' is the name of this rule. The line '(declare (salience 95))' is used to set the execution priority level among the activated rules in the agenda. The sign '=>' distinguishes between the left hand side (LHS) and right hand side (RHS) of the rule. Above the sign is the 'if' portion and below the sign is the 'then' portion of the rule. The text after ';' is a comment. One limitation of the current rule base is that the rules are not completely generic as they are prepared keeping the evaluation data in mind. For example, the projection is checked against the Bangladesh Transverse Mercator (BTM) projection (figure 6.5), because the projection of the evaluation data is the same. However, this type of limitation can be removed by adding the relevant rules, for example, for checking other projections. The complete coded rule-base of the prototype is given in section C1 of the Appendix C.

```

===== Check_Proj_of_images =====

(defrule Check_Proj_of_images
  (declare (salience 95))
  (requirement_asses?d)
  (test (eq ?d done))
  (Number_of_Images: ?N_imgs)
  (assessment_of_images: ?assess_imgs)
  ?f <-(Image_info (Image_muber: ?img_no)(Image_name: ?img_name)(assessment: required))
  (Image_Map_Projection: ?img1_proj_type $?)
  =>
  (if (eq ?assess_imgs not_ok)
    then
      (while (<= ?img_no ?N_imgs)
        (if (neq ?img1_proj_type Transverse_Mercator) ;;check projection of images
          then (printout t "Reproject required for " ?img_name crlf)
                (assert (reproject ?img_name))
                (modify ?f (assessment: not_complete))
          else (printout t ?img_name " --> Projection is OK" crlf)
                (modify ?f (assessment: not_complete))
        )
        (bind ?img_no (+ ?img_no ?N_imgs))
      )
    )
  (assert (Projection is OK))
  (assert (Check_Proj_of_images Done))
)

```

Figure 6.5: An example of rules written for the prototype

#### 6.3.5.4.2 Facts in CLIPS

The facts for the system are initialised from the user's input. The control agent codes user input into the form of facts for CLIPS. The current prototype uses an ASCII text file (Appendix C section C2), which has been written containing the user inputs. The control agent reads the text file and then writes the information into CLIPS fact file. Figure 6.6 provides an example of the coding of user input by the control agent into CLIPS readable format. In this example, the term 'deffacts' defines the portion of the facts that are named as 'General\_info'. In the next line, 'Data\_path:' is the name of a 'slot' and 'd:/kamal/work-2005/clips\_work' is the value. 'Application:', 'Landuse-landcover' and others follow a similar pattern. The slots of the fact base are determined according to the rules base of the system and these will not be changed unless the rules are changed. However, the values will be task specific.

```

=====Initial Facts=====
;
;
;1. ***** General_info*****

(deffacts General_info
  (Data_path: d:/karnal/work-2005/clips_work) (Application: Landuse-landcover)
  (Output_Scale: 30000) (No_of_Output_Classes: 7)
  (Season_Concerned: Wet_season)
)

```

Figure 6.6: An example of facts written for prototype

## 6.4 Evaluation of the Prototype

The proposed architecture in this study provides a complete environment for the processing and classification of remote sensing data. However, the focus of the prototype development was to provide proof-of-concept to illustrate and instantiate the idea of such a system through targeting the task of SAR data classification integrating with a GIS layer. Therefore, the evaluation of the prototype focussed on proving the concept of such a system rather than the completeness of the prototype. In order to evaluate the prototype the following criteria were chosen:

1. Testing the functional capability of the prototype with a real set of remote sensing images, GIS data and metadata
2. Evaluation of the prototype from the point of view of a domain expert and novices.
3. Analysis of the viability of the system in relation to the requirements outlined in Chapter 5.

### 6.4.1 Testing the functional capability of the prototype

#### 6.4.1.1 The test data

The functional capability of the prototype was tested using a small subset of the data collected for extracting the current land use and land cover. The test area extent was selected to cover the maximum number of land use and land cover classes and four images for four dates and a GIS layer of inundation land type were selected (a detailed description of the data is presented in Chapter 3). Images were already pre-processed for



noise reduction and georeferencing during the case study. Therefore, the remaining pre-processing tasks were to subset all of the images for the extent of the test area. GIS data was used in its original resolution, which was different from the image resolution, so the data assessment phase involved a pre-processing task, which was the re-sampling of the GIS data to make it the same resolution as the images. Two metadata files, one for the images and the other for the GIS layer, were created using the 'MP' tool according to the USGA-FGDC standard as mentioned above. Details of the metadata and the 'MP' tool are given in Appendix D. The rule base of the system, already prepared for the prototype, as shown in Appendix C, was also used for the testing.

#### **6.4.1.2 The process of the test operation**

The system started the processing with the loading of an initial facts file, which is derived from the user input text file (section C2 of Appendix C). Section C3 of Appendix C shows the initial facts file generated by the control agent from the user input text file and metadata files. The control agent acquires the name of the image, GIS, and metadata files from the user input, and reads the metadata files to capture additional information for the initial facts. When the control agent loads the knowledge base (in the form of rules) and relevant data (in the form of facts) into the CLIPS expert system shell and resets it, the system becomes ready to apply the knowledge (rules and facts) for reasoning process. A list of satisfied rules becomes prepared as the agenda. The first group of focused rules was for quality assessment and compatibility checking from the assessment level and then the pre-processing level. These include checking for the appropriateness of the image and other data, the extent of the image and the GIS layer against the extents of the test area, and the resolution and projection compatibility of the image and GIS data. As soon as the agent asks CLIPS to run, the execution cycle starts and includes the following processes:

- a) Rules keep firing as they match the facts. When there is no current focus (the rule in the agenda is ready to be fired) and the agenda is empty, execution is halted and CLIPS wait for the new fact or rule to be loaded by the control agent. Otherwise, the rules on the agenda are selected according to the order from top to bottom for execution.
- b) The execution of any rule from the agenda comes up with a relevant proposition. For example: Subset the images according to the study area;

Resample the GIS to match image resolution; Projections of image and GIS data are compatible; Assert 'Subset of Images done' when the clipping of the image is complete; Assert 'Resample of GIS is done' when the re-sampling of GIS is complete.

- c) When all rules on the agenda have been fired, the execution is halted, and CLIPS waits for a new assertion by the control agent, otherwise step 'a' is executed again.
- d) The control agent prepares the 'Subset.iml' file (Figure 6.2) with the actual input and output file names, and extent parameters (x-min, y-min, x-max and y max), and saves the file with the new name as 'Subset\_tmp.iml'. However, instead of one line as in Figure 6.2 there are four lines for four images in this new IDRISI modeller file. It should be noted that the control agent acquires the names of the images from the initial fact file.
- e) Subsequently, the control agent calls IDRISI for the execution of the 'Subset' command and the new images are saved with their new names, which are added '\_sub' with the previous name. For example, '18Aug01\_radarsat.ras' obtains new name as '18Aug01\_radarsat\_sub.ras'. At the end of this process the control agent deletes the 'Subset\_tmp.iml'.
- f) A similar process runs for the 're-sample' procedure. The control agent updates the 'Resample.iml' file and saves that as 'Resample\_tmp.iml'. At the end of the processing the control agent deletes the '\*\_tmp.ini' files.
- g) After the completion of the pre-processing tasks, the control agent asserts new facts ('Subset of Images done' and 'Resample of GIS is done') into CLIPS. Then the current focus in CLIPS changes to the next phase of the rules and lists a new agenda.
- h) For the current prototype, the signature file (training data) for use in the statistical classifier was prepared manually and the name of the file was given to the system to perform only the Maximum Likelihood classification and draw an accuracy report.
- i) After the quality assessment has been done, the control agent prepares the

'Maxlike\_tmp.iml' file for classification and 'display\_tmp.iml' files for displaying the image after classification. Then runs the IDRISI to classify the images and display the classified file.

- j) Subsequently, the control agent prepares the 'Erromat\_rmp.iml' file and runs that to provide the error matrix comparing the image file with the evaluation data. The system uses the IDRISI Kilimanjaro viewer for displaying these results.

### 6.4.1.3 Results

The above processes indicate the functional capability of the current prototype. The current prototype can accommodate experts' knowledge in the form of a rule base; it can generate relevant data for satisfying the rules during processing; and it can decide the appropriate course of action. It can also acquire necessary information from the metadata, and it provides the expected output from the image processing system.

In the current prototype, the processes end with a MLH classification and display of the classified image and the accuracy assessments on screen. The system also provides the accuracy assessment of the classification comparing the classified image with the evaluation data. Figure 6.7 shows a screen shot of the produced classified image using the maximum likelihood classifier and the associated accuracy assessment. The accuracy assessment output includes the confusion matrix with column and row marginal totals, errors of omission and commission, an overall error measure, confidence intervals for that figure, and a Kappa Index of Agreement (KIA). It may be mentioned that the IDRISI function (ERRMAT) is used in the system to perform the accuracy assessment. This IDRISI function provides the overall error percentage instead of the overall accuracy percentage discussed in Chapter 3. The KIA, as termed in IDRISI, includes the conditional kappa and the kappa coefficient; however, the kappa coefficient discussed in Chapter 3 is termed in IDRISI as overall kappa in the output.

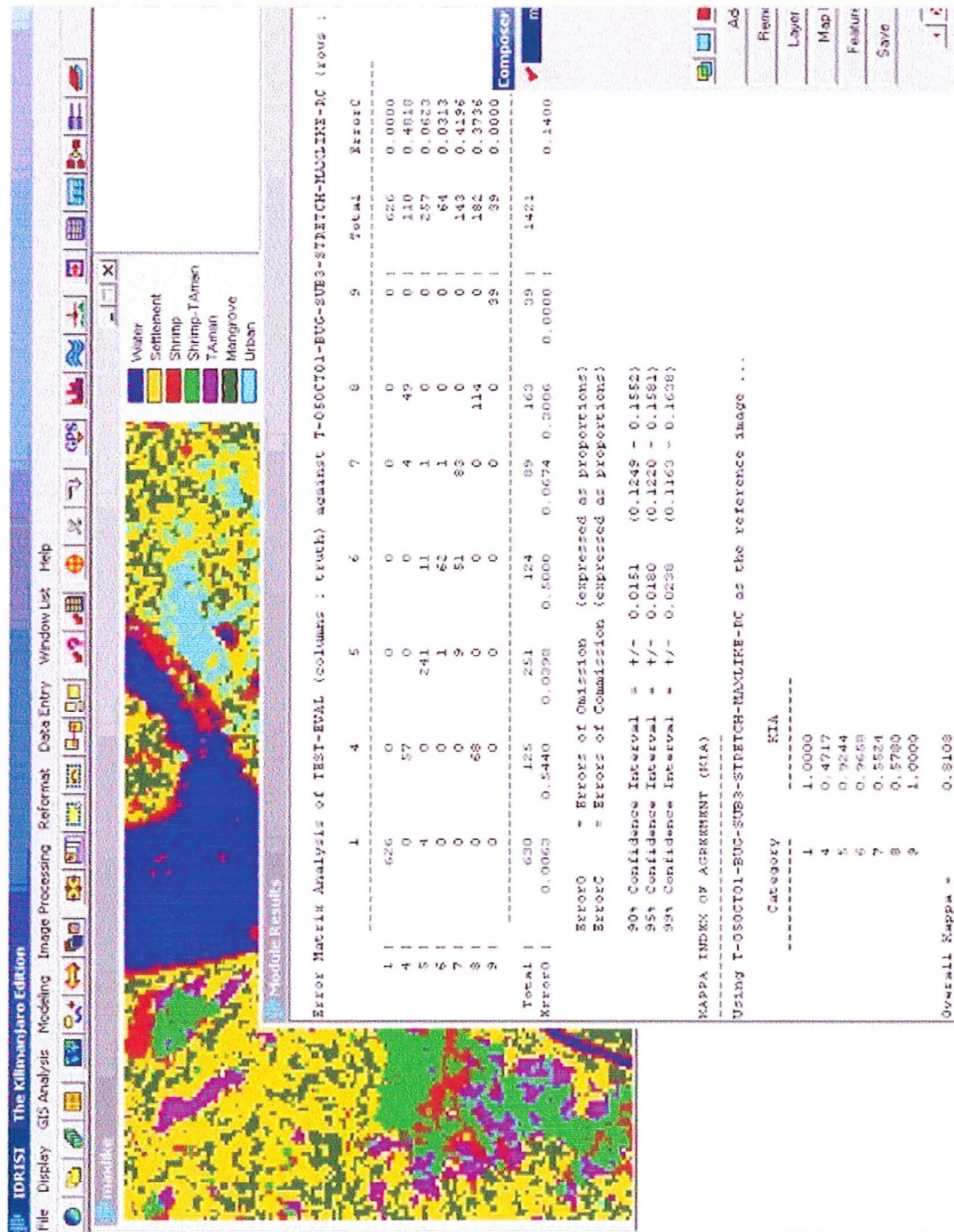


Figure 6.7: Classified image and error matrix produced using the prototype

The results show that the system is working. All of the functional capabilities of the prototype satisfy the system requirements drawn in Chapter 5. The capability of the CLIPS expert system shell and the IDRISI Kilimanjaro GIS and image processing software for this system is discussed in Section 6.3 and found satisfying the requirements. Through this test using a real set of data it can be concluded that,

although the system performs limited tasks in several stages of remote sensing image processing, it is enough to show the viability of the proposed intelligent system.

## **6.4.2 Evaluation of the prototype from an expert and novice point of view**

The cognitive and operational processes of experts and novices in terms of remote sensing image processing and classification are discussed in detail in Chapter 5. This section compares the efforts required in using the prototype by a domain expert and a novice with the efforts required to undertake the same tasks without the system.

### **6.4.2.1 Evaluation of the prototype from experts point of view**

The testing of the prototype with a set of real data exhibit that several tasks of the image processing and classification steps, as discussed in Chapter 5, are performed automatically by the system. An image-processing expert needs to complete the rest of the processing task manually. When a processing step is done ‘automatically’, this indicates that the system does the processing by itself with the given experts’ knowledge based rules and the image processing functional capabilities. On the other hand, ‘manually’ indicates that an expert uses appropriate tools (software) and methods with their knowledge and experience to complete the same processing task. For instance, obtaining the understanding about the task in hand, and the available data, in manual processing, experts would first undertake a data assessment. They would use the various sources in search of the necessary information and appropriate methods and software for these tasks. For example, an expert needs to open the metadata file using suitable software, find out the extent or projection information of the data, and compare the information for the data compatibility assessments. On the other hand, using the prototype, the user only needs to provide some information about the intended task and the available data to the system for it to completing the task. Thus, the system reduces the time and efforts of domain experts. From this discussion, a comparison can be drawn between the expert’s efforts with and without using the system in order to perform a task like the above testing with a set of real data. Table 6.4 provides such a comparison for the major image processing operations.

Table 6.4: Comparison of the remote sensing image processing and classification scenario with and without the prototype system

<b>Image Processing Task</b>	<b>Using the system</b>	<b>Without the system</b>
<i>Quality assessment</i>		
1. Spatial accuracy (read metadata file)	Automatically	Manually
2. Thematic accuracy (read metadata file)	Automatically	Manually
3. Spatial resolution (read metadata file)	Automatically	Manually
4. Number of bands (read metadata file)	Automatically	Manually
5. Spatial extents (read metadata file)	Automatically	Manually
6. Projection (read metadata file)	Automatically	Manually
<i>Pre Processing</i>		
1. Vector to raster conversion	Automatically	Manually
2. Re-sampling into common pixel resolution	Manually	Manually
3. Georeferencing or re-projection	Manually	Manually
4. Subset the files in to the common area/ according to the extent given by the user	Automatically	Manually
5. Staking the image (time series images and images with the raster GIS data)	Not required	Manually
<i>Initial Analysis</i>		
1. Use training data as AOI for signature analysis	Manually	Manually
2. Prepare signature file	Manually	Manually
3. Export image to ASCII	Automatically	Manually
<i>Classifications</i>		
1. Maximum Likelihood	Automatically	Manually
2. Mahalanobis	Automatically	Manually
3. Minimum Distance	Automatically	Manually
4. SOM	Manually	Manually
<i>Accuracy assessments</i>		
1. Compare classified file and evaluation data	Manually	Manually
2. Put it in a confusion matrix	Automatically	Manually
3. Calculation accuracy indexes	Automatically	Manually
<i>Multiple classifier</i>		
1. Running the RCR method	Manually	Manually
2. Others	Manually	Manually

From the table it can be observed that some of the tasks of the image processing steps considered in earlier discussion need to be completed by an expert manually while using the current prototype. However, several tasks (more than 60% of the list) are already automatically undertaken by the system, which reduces the dependency on the knowledge and skills of the user, and thus, the system can save effort and time of experts. By performing these tasks automatically, the prototype demonstrates that a fully developed system would save more time and effort for domain experts.

### 6.4.2.2 Evaluation of the prototype from a novice point of view

An aim of this study was to design an intelligent system architecture for reducing the dependencies on expertise and skills of a human operator in image processing and classification. Therefore, the issues related to the suitability of the system for a novice or non-expert user is discussed. However, no novice was employed to test the system, instead, a summary table showing the number of tasks that have been automated in the system (thus making it easier for a novice to use) is given in Table 6.4. From the Table 6.4 it is seen that several tasks are undertaken by the system automatically, which indicates the substitution for experts and the suitability for novice users. One of the strengths of the system can be determined by the acquisition of domain experts' knowledge used in the system's rule base. In this context, the current prototype uses only a small portion of experts' knowledge that is required for processing the data used for the test, this is sufficient to show the feasibility of such a system. The utilisation of metadata in the system also reduces the effort of an operator, where the operator needs to utilise knowledge, skills, and appropriate tools for gathering the data about the data necessary for the image processing and classification. In addition, the collection of advanced image processing functions, the processing of expert knowledge using the expert system shell for reasoning, and deciding subsequent tasks are also significant considering the cognitive and operational processes of a novice.

Some of the tasks, such as the analysis of accuracy assessment results for further actions, multiple classifier systems, and SOM network classifier, have not been added to the current prototype, which can be seen as problem of the current system in terms of its suitability for novice users. A novice may not be knowledgeable enough to analyse the accuracy assessment report produced by the current prototype to decide further actions as an expert could. However, relevant rules to cover experts reasoning and decision-making could be introduced in the future to overcome this limitation. The same also applies to the use of SOM and MCC systems and the addition of these capabilities to the system will make the system complete and thus, more suitable for novice users.

### 6.4.3 Analysis of viability of the system

The proposed architecture is a functional integration of computer-based methods and techniques in a loosely coupled system. The implemented prototype is a representation

of the architecture to demonstrate the viability of such an integrated system for remote sensing image processing and classification. In this part of the evaluation, the system components of the prototype are evaluated in terms of the requirements, what is currently done, and what can be done in a fully developed system.

#### **6.4.3.1 Functional capability of the prototype**

The detailed requirements of the system are discussed earlier in chapter 5. Currently, the prototype performs tasks of the image processing and classification specific to the SAR image using a single GIS layer, because only that portion of the domain experts' knowledge is added to the knowledge base of the system. The system is also programmed for only those image processing functions that are necessary for performing the intended tasks through the control system which runs the expert system shell and the image processing software and use metadata for relevant information. Through interfaces among the components, it can switch from one task to the next and then back again based on the information provided by the user regarding the intended task and the data source, and subsequent assessment of the performed tasks. One of the important properties of the prototype is that it effectively demonstrates a combination of the existing tools and methods that can be used to build up an intelligent system for remote sensing image processing and classification.

#### **6.4.3.2 Viability of the integrated software**

The discussion about the CLIPS expert system shell and the IDRISI Kilimanjaro GIS and image processing software shows that both run in the Windows system and integrate with other programming languages. Moreover, both are well-documented software. These were the part of requirements set out in the earlier sections. These features of the components have given the openness of the system in terms of adding the knowledge of other tasks of different steps of image processing and extending the programmes for other functions. Thus, new image processing techniques can be added into the image processing subsystem along with the associated knowledge into the knowledge base for a complete system for remote sensing image processing and classification. Another requirement discussed in Chapter 5, which is the user interface, is not included in the current prototype. Adding such a component will be another step toward the completeness of the system according to the proposed architecture.



### **6.4.3.3 The challenge of using metadata**

A frequently raised issue by colleagues while talking about this system is related to the use of the metadata in the system. The questions were about the availability of metadata and capability of a novice in producing the metadata. The answer to this question is that the data producer, provider or the party involved in adding value to the data are responsible for producing the metadata, which is a current motivation of the user community and that has to be done following an agreed standard, as discussed in Chapter 2. In this consideration, a currently well-accepted standard of metadata is proposed and adopted in the current system, which is the USGS-FGDC geospatial metadata standard. Moreover, metadata has to be updated following any complete processing cycle, so that the information can be used in any subsequent processing cycle. Therefore, incorporation of a tool for updating the metadata is also proposed for the fully developed system. The tool could be used to rewrite the used metadata adding all the relevant processing, accuracy, and procedural information according to the standard for the newly produced data by the system.

### **6.4.3.4 The challenge in building the knowledge base**

Building an extensive knowledge base is the bottleneck of a system involving an expert system as one of its components. Feigenbaum (1992) considered the period from 1991 as the “second era” of expert systems, when a typical knowledge base is huge and that is the main challenge (discussed further in Chapter 2). The required knowledge for remote sensing image processing and classification is usually not just from the sharing of the knowledge of several experts of the domain, but also the expertise of many sub-domains. This is also the case for the proposed system. The acquisition of experts’ knowledge in the form of rules and conditions, and extracting the appropriate variables will be the biggest challenge for such a system. However, once the basic structure is completed, the proposed system will be a valuable tool for a large user community. Moreover, in the areas of image processing and classification, many rules, procedures, and functions are common. For example, many methods of image registrations, noise reductions, and segmentation and the associated rules are common in remote sensing image processing, medical image processing, and in face recognition. The differences of these application areas are: the types, scale, dimensions, and formats of the images; knowledge about the target features and their environment; and the required accuracy of the outputs. These

differences usually form the basis of the knowledge, procedures, and functions of the image processing and classification systems in these subject areas. Therefore, such a system, keeping the common portion of the knowledge and altering or extending the appropriate knowledge base and the necessary image processing methods and functions as appropriate could be usable in other areas of image processing.

## **6.5 Conclusion**

The prototype implemented and described above should be seen as an initial step towards developing a complete remote sensing image processing and classification system according to the ISRIPaC architecture proposed in the previous chapter. It represents the features and functions of the proposed architecture. In addition to the basis for evaluating the proposed system, the implementation of the prototype also provided new points for the further refinement of the proposed architecture, such as the potential for incorporating the metadata editing tools for writing metadata for newly produced or modified data by the system during its operation. Although a number of compromises and limitations may be noted in the prototype, it demonstrates the viability of the proposed system architecture and generally satisfies the requirements as given in Section 5.

## Chapter 7

### 7. Conclusions and Future Work

#### 7.1 Introduction

Remote sensing and digital image processing are highly suitable tools for mapping land use and land cover. The recent development of remote sensing technology has raised the potential for regular mapping activities. Simultaneously, the size of the user community is increasing rapidly. At the same time, remote sensing data has become diverse and more complex. The traditional methods of remote sensing image processing and classification are showing limitations when dealing with advanced data like SAR. Currently used techniques are labour intensive, dominated by the time-consuming qualitative analyses engaged in by skilled and experienced remote sensing scientists. Product accuracies are also unsatisfactory. Given this background, the goal of the current study was to achieve a system of remote sensing image processing and classification, particularly for SAR data, that will improve accuracy, and reduce the need for trained and experienced remote sensing experts.

#### 7.2 Overview of the Work

To achieve the objectives of the study, a review of the relevant areas of knowledge was undertaken to acquire the technical and theoretical basis for the work. Essentially, the review explored the state of currently practised methods as well as several advanced methods of image processing and classification such as neural networks and multiple classifier combination systems. The limitations of the traditional image classification methods and the potential of advanced methods for remote sensing image processing and classification were also discussed in the review. It also examined the existing systems used for remote sensing image processing and classification. Subsequently, a case study was used to explore suitable methods that can improve the classification accuracy of spaceborne SAR images integrated with Geographic Information System (GIS) data. In this case study, promising results were observed by applying the Self-Organizing feature Map (SOM) to include a GIS layer of land type classification with the remote sensing data during image segmentation. The results were compared with

those of traditional statistical classifiers, such as Maximum likelihood, Mahalanobis distance and Minimum distance classifiers. The performance of the classifiers was evaluated in terms of the classification accuracy with respect to the collected near real-time ground truth data. The SOM neural network method without the GIS layer was the poorest performing classifier; however, incorporating the GIS layer provided the highest accuracy. The use of GIS layer with the images in the SOM neural network classification (SOM5 method) improved the kappa index of agreement from 0.47 to 0.74 for the SOM method; a significant improvement. It also achieved higher accuracies for more classes in comparison to the other methods. In addition, during the experiments it was observed that different classifiers produced better accuracy for different classes. The investigation was extended to consider some of the Multiple Classifier Combination (MCC) techniques, to improve the classification. A rule-based contention resolution method of combination was developed in the case study. This combination method exhibited further improvement in the overall accuracy of about 3% in comparison to its best constituent (SOM) classifier.

Thus, from the case study, the requirements of an intelligent remote sensing image processing and classification system were identified. Through the analysis of the requirements, a system architecture (called ISRIPaC) was designed to integrate the advanced methods as mentioned above and used in the case study. Finally, the system components according to the proposed architecture were assembled and programmed to implement a prototype. The implemented prototype is a representation of the proposed ISRIPaC architecture, in which the expert system shell, the image processing software, the control agent, the knowledge base and metadata are the main components. In the prototype, the CLIPS expert system shell was used with the IDRISI Kilimanjaro image and GIS processing software. The control agent of the system was written using the Visual C++ programming language. The knowledge base for the prototype was derived from several sources: the case study, the author's experience of remote sensing image processing and classification, and from discussions with colleagues working in the domain. The implemented prototype is programmed to utilise geospatial metadata, which is one of the important components of the proposed architecture, which was written according to USGS-FGDC standards. The prototype was tested using a set of test data and the evaluation showed the viability of the proposed architecture.

### 7.3 Contribution to Knowledge

It is recognized that the AI methods used and evaluated in this study and considered for the proposed intelligent system are not new to image processing. However, the demonstrated way of adapting these methods for remote sensing image processing and classification (especially, for RADARSAT SAR images classification) is an extension of knowledge in this domain.

To meet the objectives of the study, an initial step was to test the traditional techniques most commonly used, and to compare the results with a SOM neural network method. At this stage, five classification methods (Maximum likelihood, Minimum Distance, SOM neural network with and without a GIS layer) were tested and evaluated (Chapter 4). Although the use of neural network systems is not new in remote sensing image classification, as discussed in Chapter 2, the use of a low level GIS layer like Landtype classes as an input vector, in addition to the multi-dimensional SAR image layers in the SOM networks, is a new approach. In order to achieve this, a C++ programme was developed to enable the SOM networks to read images from the ASCII file format and convert it into the usable file format for running in the SOM\_PAK programme (discussed in Chapter 3). One of the findings of this research is that the use of even a low level GIS dataset with the image layers for classification has proved superior to other methods and provides the highest level of accuracy for the data used in the case study. However, this approach did not achieve the highest individual class accuracy for all of the classes.

In the above experiment, where individual class accuracy was a concern, it was also found that different classifiers provided better individual accuracy for different classes. These findings led to the second stage of the work, which involved the use and evaluation of methods of multiple classifiers combination (MCC). Several methods for combining the results obtained from the aforementioned classifiers were tested in this study. Among these, the novel Rule based Contention Resolution (RCR) method, which is implemented and tested in this study, provided the best result in comparison to the other methods used, however MCC techniques did not improve accuracy significantly.

The next stage of the research involved the design of an architecture for an intelligent system for the classification of remote sensing data to meet the second

objective. The design and architecture of the proposed ISRIPaC system is described in detail in Chapter 5 and includes the integration of a number of advanced and AI techniques, including SOM, MCC, an expert system shell, the utilization of domain experts' knowledge and metadata in automatic decision making, and mediation via a control agent for image processing and classification.

The next stage was the implementation of the proposed architecture in a prototype and evaluating the viability of the system to meet the third objective as described in Chapter 6. The implementation and evaluation of the prototype demonstrates that a federated system of advanced techniques and existing tools coupled with the domain experts' knowledge can work successfully for the remote sensing image classification for land use and land cover mapping with SAR imagery. Besides the demonstration of the viability of the proposed architecture, the acquisition of the domain experts' knowledge relevant to the classification of SAR and development of the rule base for the prototype may be considered as a contribution of this study.

## **7.4 Future Work**

Despite the above significant achievements, a number of compromises and limitations may be noted from the research and those can be addressed in future. The current system is based on a single set of data; not all the advanced methods like other neural networks or multiple classifiers systems, fuzzy techniques, and others measures of accuracy assessment are tested and incorporated; and the knowledge base is also limited to the specific data used in the case study and evaluation of prototype. However, the work undertaken for this study has opened up several interesting windows for further research. Certainly, future work should be targeted towards extending the prototype intelligent system to a generic system for remote sensing image processing and classification. Some of the very specific and immediate work is outlined as follows:

1. A major effort is required to extend the system's knowledge base. In order to do this a more systematic method of knowledge acquisition, such as interviewing the domain and sub-domain experts, could be adopted to identify the appropriate conditions, rules and variables to be measured, and alternative methods for measurements and solutions for all the steps of remote sensing image processing and classification tasks.

2. An intelligent and user-friendly interface has to be developed to provide the initial information to the system. An explanation component for the system would also enrich its viability. This could convey the information to the user as to how the result was achieved or how to reach a solution.
3. The experiments in the case study suggest that there is room for further investigation involving multiple classifier combination. This study used four classifiers in combination. Further investigations are required to determine the suitable number of single classifiers to be combined and to determine whether the type of the constituent classifiers in the combination sets matters in achieving the required accuracy.
4. The case study demonstrates that the integration of the Land-type GIS layer in the SOM networks improves individual class accuracies for some of the classes. This approach needs to be attempted with other GIS data (e.g. soil type) as well as other neural networks, methods based on Bayesian theorem, and nonparametric statistical method like MND in order to identify the suitability of such integration for further improving the classification accuracy. At the same time, the suitability of other types of neural networks in such operations needs to be investigated.
5. In this study, the method and techniques were applied only over a set of RADARSAT SAR data. Further experimentation is necessary to employ the system for classifying other remote sensing SAR or optical data for generalising the conclusion of the study to a greater extent.
6. A further issue that may be addressed is to explore whether analysts are best served by having the system on their own desktop or whether it is better to access this functionality online by extending the proposed architecture using the Service Oriented Architecture model.

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## Appendix B: Field Data Collection Form

### B.1 Sample of a form used for field data collection

B1. First page of the form used for collecting the descriptive information of a homogenous polygon of the feature under consideration.

#### General Information

Filled by: <u>AZH/ISS</u>	Date Filled: <u>18/08/01</u>		
Overpass No: <u>01</u>	Polygon No: <u>01</u>	Map/Image No: _____	Land Type: <u>Fc-Fi</u>
Location:			
District: <u>Bagerhat</u>	Thana: <u>Bagerhat</u>	Village: <u>Korali</u>	

#### Water Bodies

Type: <input type="checkbox"/> Permanent/Seasonal River <input type="checkbox"/> Beels <input type="checkbox"/> Transitional <input type="checkbox"/> Shrimp farms
Current Water Depth (cm): Max: _____ Min: _____ Avg: _____
If Vegetation Cover Exist: Types: _____ Canopy (%): _____ Height (cm): _____
Source, Duration, Direction of Water Movement:
Others Comments:

#### Agricultural Conditions

Water Condition of the ground: <input type="checkbox"/> Dry <input type="checkbox"/> Moist <input checked="" type="checkbox"/> Wet
If Wet, Current Water / Flood Depth (cm): 1. _____ 2. _____ 3. _____ 4. _____ 5. _____ (Measured in gauge)
Field Condition: <input checked="" type="checkbox"/> With Crop <input type="checkbox"/> Current fallow
If with Crop Current Crop Type (s): <u>T. Aman (Seed bed)</u>
Stage of Growth (in weeks): <u>0-1</u> Canopy (%) _____ Height (cm) _____
If with Veg. Types: _____ Canopy (%) <u>30</u> Height (cm) <u>2-20</u>
Source, Duration, Direction of Water Movement:
<u>Rainwater &amp; Jaikhab River</u>

#### Annual Cropping Pattern

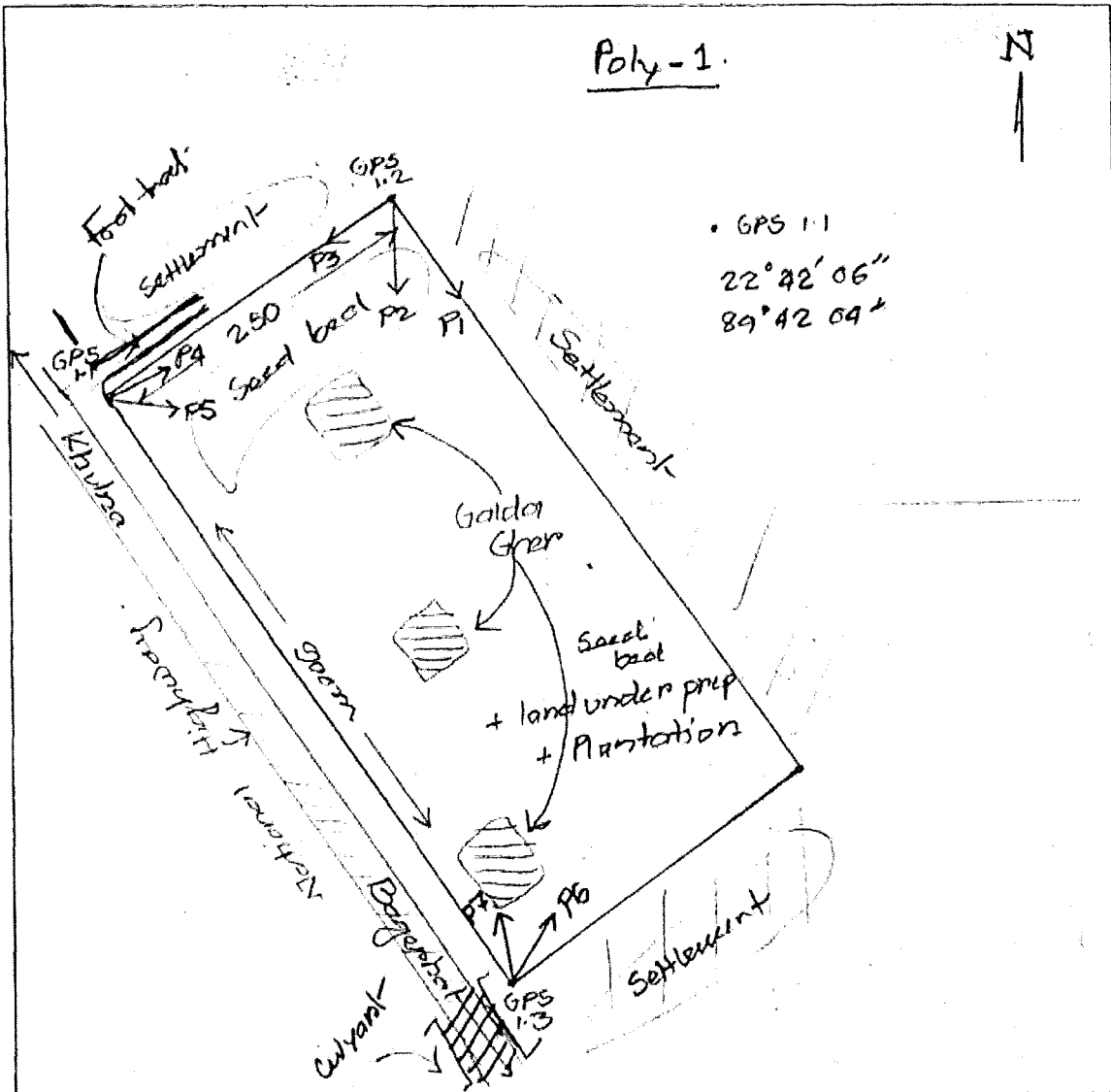
	Rabi (November - February)	Kharif - I (March - June)	Kharif - II (July - October)
Crop Type:	<input checked="" type="checkbox"/> Boro	<input checked="" type="checkbox"/>	<u>T. Aman</u>
Plant Time:			
Harvest Time:			

#### GPS Reading

Point #1	Latitude _____ N	Longitude _____ E	PDOP _____
Point #2	Latitude _____ N	Longitude _____ E	PDOP _____
Point #3	Latitude _____ N	Longitude _____ E	PDOP _____

B2. Second page of the form for sketching the locational aspects of the plot considered as the field polygon.

Detailed sketch of the polygon and surrounding with location of GPS points and Photographs



Details of Photographs

Photo No: P1-P7

Processing Roll No: 1

Remarks

Nature of Landuse in the polygon is: land under preparation + plantation + Seed bed + Current Follow.

B3. Some of the photographs taken from different direction of the polygon considered in the B1.



## Appendix C: The Knowledge Base of the Prototype

### C1. The rule base used in the prototype

Formulated knowledge from the case study and the experiences in the remote sensing image processing is coded into the CLIPS readable form of

Rules as below:

```
*****File Name:KB_Rules.clp*****
;;;...Developing work for this file started on 24th April 2004
;;;...combining the rules_requirement.clp, Revise_image_assess.clp And rules_data.clp

.....
;;; Requirement level rules ***** rules_requirement.clp *****
.....
(defrule requirements
  (declare (salience 1000))
  ?r <-(requirement_asses req)
  (not (requirement_asses done))
  (Application: ?appl_type)
  (No_of_Output_Classes: ?N_classes)
  (Images_dimension: ?img_dim)
  (Season_Concerned: ?season)
  (Image_Type: ?img_type)
  (Output_Scale: ?out_scale)
  (Image_Spatial_resolution: Abscissa_Resolution: ?x_res Ordinate_Resolution: ?y_res Planar_Distance_Units: meter)
  (No_of_GIS_layer: ?N_GISs)
  =>
  (if (or (eq ?appl_type Landuse-landcover)
          (eq ?appl_type Agriculture)
          (eq ?appl_type Forestry)
          (> ?N_classes 3))
      then
      (if (or (eq ?img_dim Multi-temporal) .....***** Requirement level rule 9, 8, & 5 *****
              (eq ?img_dim Multi-spectral))
```

```

then
(if (or (and (eq ?season Wet_season) ;;;;;;**** Requirement level rule 6 & 8 *****
            (eq ?img_type Radar))
        (and (eq ?season dry)
            (or (eq ?img_type Optical)
                (eq ?img_type Radar))))
    then
    (if (or (and (<= ?out_scale 10000) ;;;;;;**** Requirement level rule 1, 2, & 3 *****
                (<= ?x_res 15)
                (<= ?y_res 15))
        (and (<= ?out_scale 50000)
            (<= ?x_res 50)
            (<= ?y_res 50))
        (and (> ?out_scale 50000)
            (>= ?x_res 50)
            (>= ?y_res 50))
        )
    then
    (if (and (eq ?img_type Radar) ;;;;;;**** Requirement level rule 10 *****
            (> ?N_classes 3))
        then
        (if (> ?N_GISs 0)
            then (printout t "Rule satisfied....." crlf)
                (printout t "Please Assert requirement_asses done" crlf)
                (retract ?r)
                (assert (requirement_asses done)) ;;;;;; ADDED IN THE KB_RULE_3a.clp
                (printout t " " crlf)
            else (printout t "It will be good to use GIS Layers" crlf)
                )
        else (printout t "Rule satisfied" crlf)
            (printout t "Please Assert requirement_asses done" crlf)
            (retract ?r)
            (assert (requirement_asses done)) ;;;;;; ADDED IN THE KB_RULE_3a.clp
            (printout t " " crlf)
        )
    else (printout t "Sorry! Illegal Images resolution for " ?appl_type " Application" crlf)
        )
    else (printout t "Sorry! Illegal Images type for " ?appl_type " Application" crlf)

```

```

    )
  else (printout t "Sorry! Illegal Image Dimension for " ?appl_type " Application" crlf)
)
)
;=====
;; REVISING --> THE ASSESSMENT OF THE IMAGES 1Oct04
;;REVISING --> Data Level Rule, 27-April-05
;=====
;===== Check_Proj_of_images =====

(defrule Check_Proj_of_images
  (declare (salience 95))
  (requirement_asses ?d)
  (test (eq ?d done))
  (Number_of_Images: ?N_imgs)
  (assessment_of_images: ?assess_imgs)
  ?f <-(Image_info (Image_muber: ?img_no)(Image_name: ?img_name)(assessment: required))
  (Image_Map_Projection: ?lmg1_proj_type $?)
  =>
  (if (eq ?assess_imgs not_ok)
    then
      (while (<= ?img_no ?N_imgs)
        (if (neq ?lmg1_proj_type Transverse_Mercator:) ;;check projection of images
          then (printout t "Reproject required for " ?img_name crlf)
                (assert (reproject ?img_name))
                (modify ?f (assessment: not_complete))
          else (printout t ?img_name " --> Projection is OK" crlf)
                (modify ?f (assessment: not_complete))
        )
        (bind ?img_no (+ ?img_no ?N_imgs))
      )
  )
  (assert (Projection is OK))
  (assert (Check_Proj_of_images Done)) ;;;; ADDED IN THE KB_RULE_3a.clp
)
;===== "Please assert Check_Proj_of_images Done" (Temporary Portion) =====
;===== This section switched off in IN THE KB_RULE_3a.clp =====

```

```

;(defrule temporary-1
;  (declare (salience 90))
;  (Projection is ?ok)
;  ?f <-(Image_info (Image_muber: ?img_no) (Image_name: ?img_name)(assessment: ?temp))
;  =>
;    (if (or (eq ?temp not_complete)
;           (eq ?ok OK))
;        then (printout t "Please assert Check_Proj_of_images Done" crlf)
;    )
;)
;===== Check_extent_of_images =====

(defrule Check_extent_of_images
  (declare (salience 85))
  (Check_Proj_of_images ?d)
  (Number_of_Images: ?N_imgs)
  ?f1 <-(assessment_of_images: not_ok)
  ?f <-(Image_info (Image_muber: ?img_no) (Image_name: ?img_name)(assessment: ?temp))
  (EOI Bounding_Coordinates: $?EOI_bound)
  (Image Bounding_Coordinates: $?Img_bound)
  =>
  (if (and (eq ?temp not_complete)
           (eq ?d done))
      then
        (while (<= ?img_no ?N_imgs)
              (if (neq $?Img_bound $?EOI_bound)
                  then (printout t ?img_name " needs Subsetting to EOI" crlf)
                      (assert (subset ?img_name))
                      (modify ?f (assessment: subset_req))
                      (printout t "Please assert assessment_of_images ok" crlf)
                  else (modify ?f (assessment: complete))
              )
          (bind ?img_no (+ ?img_no ?N_imgs))
        )
      else (printout t "Extent of images are OK" crlf)
          (retract ?f1)
          (printout t " " crlf)
          (printout t "Please-- assert assessment_of_images ok --" crlf)
  )

```



```

)
(assert (assessment_of_images ok)          ;;: ADDED IN THE KB_RULE_3a.clp
)
;===== seems up to this point ok---28/04/05=====
;=====
; REVISING THE ASSESSMENT OF THE GISs 1Oct04 -----not done
; Revised the assessment of the GISs 29April05-----Done
; Revised on 29-05-05 -----
;=====
(defrule assessment_of_GISs
  (declare (salience 80))
  (assessment_of_images ?y)
  (test (eq ?y ok))
  (GIS_info (GIS_layer_no: ?GIS_no)(GIS_name: ?GISname))
  (No_of_GIS_layer: ?N_GISs)
  (EOI Bounding_Coordinates: $?EOI_bound)
  (bdItype Bounding_Coordinates: $?GIS1_bound)
  (bdItype Spatial_resolution: $?GIS1_res)
  (Image Spatial_resolution: $?Img1_res)
  (bdItype Map_Projection: $?GIS1_proj)
  (Image Map_Projection: ?Img1_proj_type $?)
  (Image Map_Projection: $?Img1_proj)
  =>

  (while (<= ?GIS_no ?N_GISs )

    (if (neq $?GIS1_bound $?EOI_bound) ;;:=== Checking Extent Compatibility ===
      then (assert (Subset ?GISname))
            (printout t " " crlf)
            (printout t " -----" crlf)
            (printout t "Subset " ?GISname crlf)
            (printout t " -----" crlf)
            (printout t "Please -- assert GIS Extent is OK -- after subsetting " ?GISname crlf)
            else (printout t ?GISname " Extent is OK" crlf)
                 (assert (Extent of ?GISname is OK))
    )
    (if (neq $?GIS1_res $?Img1_res) ;;:=== Checking Rexolution Compatibility ===

```

```

then (assert (Resample ?GISname))
      (printout t " " crlf)
      (printout t "-----" crlf)
      (printout t "Resample " ?GISname crlf)
      (printout t "-----" crlf)
      (printout t "Please -- assert GIS Resolution is OK -- after resampling " ?GISname crlf)
else (printout t ?GISname " Resolution is OK" crlf)
      (assert (Resolution of ?GISname is OK))
)
)
(if (and (eq ?img1_proj_type Transverse_Mercator:)
        (neq $?GIS1_proj $?img1_proj)) ;;;==== Checking Projection Compatibility ====
    then (assert (Reproject ?GISname))
          (printout t "Reproject " ?GISname crlf)
          (printout t "Please -- assert GIS Projection is OK -- after reprojecting " ?GISname crlf)
    else (printout t " " crlf)
          (printout t "Projection of " ?GISname " is OK " crlf)
          (assert (Projection of ?GISname is OK))
    )
)
(bind ?GIS_no (+ ?GIS_no ?N_GISs))
)
(printout t "Please -- assert gis_assessment done -- If" crlf)
(printout t "Extent, Resolution, and Projection of GISs are OK" crlf)
)
;=====data assessment and processing done (Temporary Portion) =====

(defrule assess_process_done
  (declare (salience 75))
  (gis_assessment ?a)
  (test (eq ?a done))
  ?c2 <- (data_assessment req)
  ?d3 <- (data_preProcess req)
  ?e4 <- (classification req)
  =>
  (retract ?c2 ?d3 ?e4)
  (assert (requirement_asses done)(data_assessment done)
          (data_preProcess done))
  (printout t "PLEASE ENTER assert classification go IF " crlf)
  (printout t "  PRE-PROCESSING COMPLETED"      crlf)
)

```

```

)
;=====Classification Go ===== not done
(defrule Classifications_go
  (declare (salience 65))
  (classification ?d_cls)
  (test (eq ?d_cls go))
  (No_of_GIS_layer: ?N_GISs)
  (Number_of_Images: ?N_imgs)
  (No_of_Output_Classes: ?N_classes)
  (Images_dimention: ?img_dim)
  =>
  (if (> ?N_imgs 1)
    then
      (if (and (eq ?img_dim Multi-temporal)
                (> ?N_classes 3))
        then
          (if (> ?N_GISs 0)
            then
              (printout t "Do Maximum Likelihood Classification" crlf)
              (printout t "Do Minimum Distance Classification" crlf)
              (printout t "Do Mahalanobis Distance Classification" crlf)
              (printout t "Do SOM Classification" crlf)
              (assert(classification not_done)(Maximum_Likelihood Classification)
                (Minimum_Distance Classification)(Mahalanobis_Distance Classification)
                (SOM Classification))
              (printout t "Please -- assert classification done -- after performing all Classifications" crlf)
            else (printout t "Do Maximum Likelihood Classification" crlf)
              (printout t "Do Minimum Distance Classification" crlf)
              (printout t "Do Mahalanobis Distance Classification" crlf)
              (assert (classification not_done)(Maximum_Likelihood Classification)
                (Minimum_Distance Classification)(Mahalanobis_Distance Classification)
                (SOM Classification))
              (printout t "Please -- assert classification done -- after performing all Classifications" crlf)
            )
          )
        )
      )
    else (printout t "Data is suitable for thresh-holding" crlf)
  )
)

```

===== Accuracy Assessment Classification Result =====

=====Multiple Classifier System (MCS) =====

===== Accuracy Assessment of MCS Result =====

=====Output Level Rules=====

## **C2. User's input used for the prototype for initialisation of the fact for the prototype**

### General Info

Application: Landuse\_land\_cover  
Output\_Scale: 1:30000  
Number\_of\_Output\_Classes: 7  
Season\_Concerned: Wet\_Season  
Extent\_of\_Interest:  
West\_Bounding\_Coordinate: 455766.0000  
East\_Bounding\_Coordinate: 461066.0000  
North\_Bounding\_Coordinate: 485258.0000  
South\_Bounding\_Coordinate: 481008.0000

### Image\_Layers

Images: Multi-temporal  
Image\_Type: Radar  
Number\_of\_Images: 4  
Image\_Dates: 18 August, 11 September, 05 October, 29 October  
Images\_Info:  
radarsat-18aug01-test.ras  
Metadata\_File\_Name: metadata-MOE-radarsat.met  
Image\_Data\_Type: raster\_digital\_data  
radarsat-11sep01-test.ras  
Metadata\_File\_Name: metadata-MOE-radarsat.met  
Image\_Data\_Type: raster\_digital\_data  
radarsat-05sep01-test.ras  
Metadata\_File\_Name: metadata-MOE-radarsat.met  
Image\_Data\_Type: raster\_digital\_data  
radarsat-29sep01-test.ras  
Image\_Data\_Type: raster\_digital\_data

Metadata\_File\_Name: metadata-MOE-radarsat.met [SEE APPENDIX D]  
Image\_Data\_Type: raster\_digital\_data

GIS Layers

Number\_of\_GIS\_Layers: 1  
bdltype  
Metadata\_File\_Name: metadata-FAP19-bdltype.met

Training Data

Raster\_Layer\_Name: dum-field-train.ras  
AOI\_Layer\_Name: dum-field-train.aoi  
ASCII\_File\_Name: dum-field-train.asc

Evaluation Data

Raster\_Layer\_Name: dum-field-eval.ras  
AOI\_Layer\_Name: dum-field-eval.aoi  
ASCII\_File\_Name: dum-field-eval.asc

Meta Files

Crop\_Calendar\_File: Crop\_Calendar.txt

### C3. The initial fact base prepared from the user's input by the control agent

```
.....:File Name Fact_1c.clp:.....  
:.....:Initial Facts:.....  
(defacts Ini_facts  
  (requirement_asses req)  
  (data_assessment req)  
  (data_preProcess req)  
  (classification req)  
  (MCS req)  
)  
;1. ....: * General_info*  
  
(defacts General_info  
  (Data_path: d:/kamal/work-2005/clips_work)  
  (Application: Landuse-landcover) (Output_Scale: 30000)  
  (No_of_Output_Classes: 7) (Season_Concerned: Wet_season)  
)  
;2. ....: * Extent_of_Interest*
```

```

(deffacts Extent_of_Interest
  (EOI Bounding_Coordinates:
    West_Bounding_Coordinate: 455766.0000
    East_Bounding_Coordinate: 461066.0000
    North_Bounding_Coordinate: 485258.0000
    South_Bounding_Coordinate: 481008.0000
  )
)
;3. ....* Image_layers*
(deffacts Image_layers
  (Images_dimension: Multi-temporal)
  (Image_Type: Radar) (Number_of_Images: 4)
  (assessment_of_images: not_ok)
)
;4. ....* image_season*
(deftemplate image_season
  (slot im_month1)
  (slot im_month2)
  (slot im_month3)
  (slot im_month4)
)
;5. ....* image_Dates*
(deffacts image_Dates
  (image_season(im_month1 August) (im_month2 September)
    (im_month3 October)(im_month4 October)
  )
)
;6. ....* Image_info*
(deftemplate Image_info
  (slot Image_muber: )
  (slot Image_name:)
  (slot Image_Data_Type:)
  (slot ImgMetadataFile:)
  (slot assessment: (default required))
)
;7. ....* Image_details*
;;;added (Image_muber: 1)for loop and get sequence during stacking

```

```

(deffacts Image_details
  (Image_info (Image_muber: 1)(Image_name: radarsat-18aug01-test.ras)
    (Image_Data_Type: raster)
    (ImgMetadataFile: metadata_MOE_radarsat.met)
  )
  (Image_info (Image_muber: 2)(Image_name: radarsat-11Sept01-test.ras)
    (Image_Data_Type: raster)
    (ImgMetadataFile: metadata_MOE_radarsat.met )
  )
  (Image_info (Image_muber: 3)(Image_name: radarsat-05Oct01-test.ras)
    (Image_Data_Type: raster)
    (ImgMetadataFile: metadata_MOE_radarsat.met )
  )
  (Image_info (Image_muber: 4)(Image_name: radarsat-29Oct01-test.ras)
    (Image_Data_Type: raster)
    (ImgMetadataFile: metadata_MOE_radarsat.met)
  )
)
;8. ....* GIS_info*
(deftemplate GIS_info
  (slot GIS_layer_no: ) ;;;;;; Added on 29-05-05
  (slot GIS_name:)
  (slot GIS_Data_Type:)
  (slot GISMetadataFile:)
)
;9. ....* GIS_details*
(deffacts GIS_info
  (No_of_GIS_layer: 1)
)
(deffacts GIS_details
  (GIS_info (GIS_layer_no: 1) ;;;;;; Added on 29-05-05
    (GIS_name: BDLTYPE)
    (GIS_Data_Type: raster)
    (GISMetadataFile: metadata-FAP19-bdltype.met)
  )
)
;10. ....* Train_Data *

```

[SEE APPENDIX D]

```

(deffacts Train_Data
  (Raster_train: dum-field-train.ras)
  (AOI_train: dum-field-train.aoi)
  (ASCII_train: dum-field-train.txt)
)
;11. ....* Eval_Data *

(deffacts Eval_Data
  (Raster_eval: dum-field-eval.ras)
  (AOI_eval: dum-field-eval.aoi)
  (ASCII_eval: dum-field-eval.txt)
)
;12. ....* Meta_Files *
(deffacts Meta_Files
  (Crop_Calendar_File: Crop_Calendar.txt)
)
;13. ....* bdltype_extent*
(deffacts bdltype_extent
  (bdtype Bounding_Coordinates:
    West_Bounding_Coordinate: 299400.0000
    East_Bounding_Coordinate: 772500.0000
    North_Bounding_Coordinate: 946500.0000
    South_Bounding_Coordinate: 283800.00
  )
)
;14. ....* bdltype_projection*
(deffacts bdltype_projection
  (bdtype Map_Projection:
    Transverse_Mercator:
      Scale_Factor_at_Central_Meridian: 0.9996
      Longitude_of_Central_Meridian: +90.0000
      Latitude_of_Projection_Origin: 0.0000
      False_Easting: 500000
      False_Northing: -2000000
  )
)
;15. ....* bdltype_resolution*
(deffacts bdltype_resolution

```



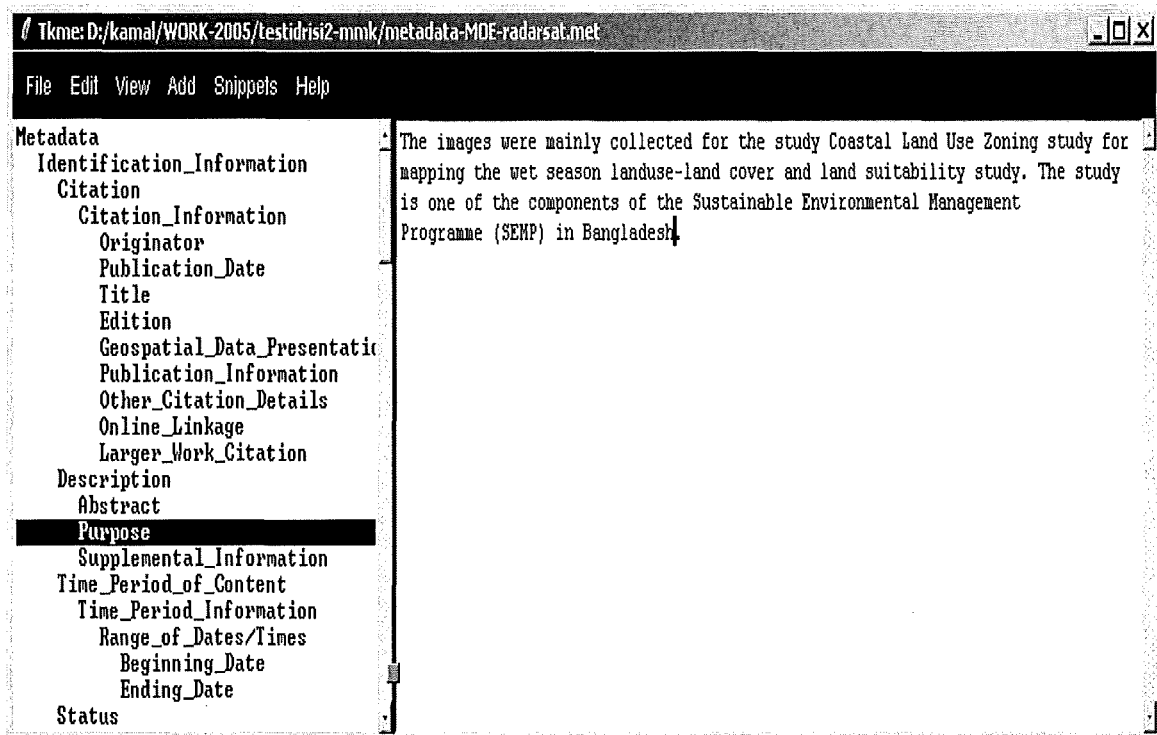
```
(bdftype Spatial_resolution:
  Abscissa_Resolution: 300.0000
  Ordinate_Resolution: 300.0000
  Planar_Distance_Units: meter)
)
;16. ....* Image_extents*
(deffacts Image_extents
  (Image Bounding_Coordinates:
    West_Bounding_Coordinate: 449591.0000
    East_Bounding_Coordinate: 487966.0000
    North_Bounding_Coordinate: 528483.0000
    South_Bounding_Coordinate: 475233.0000
  )
)
;17. ....* Image_Projection*
(deffacts Image_Projection
  (Image Map_Projection:
    Transverse_Mercator:
      Scale_Factor_at_Central_Meridian: 0.9996
      Longitude_of_Central_Meridian: +90.0000
      Latitude_of_Projection_Origin: 0.0000
      False_Easting: 500000
      False_Northing: -2000000
    )
)
;18. ....* Image_resolution*
(deffacts Image_resolution
  (Image Spatial_resolution:
    Abscissa_Resolution: 25.0000
    Ordinate_Resolution: 25.0000
    Planar_Distance_Units: meter)
)
;19. ....* Wet_season*
(deftemplate Wet_season
  (slot se_month1)
  (slot se_month2)
  (slot se_month3)
  (slot se_month4)
```

```
)  
;20 .....* Season_months*  
(defacts Season_months  
  (Wet_season (se_month1 July)(se_month2 August)  
    (se_month3 September)(se_month4 October)  
  )  
) .....end.....
```

## Appendix D: Metadata

### D1. Metadata Parser (MP) for writing metadata in USGS-FGDC standard

“MP” is a tool for writing geospatial metadata according to the USGS-FGDC standard and used in this study for developing the metadata for the used SAR and Land-type GIS data. “MP” is a freely available software from the USGS website (<http://geology.usgs.gov/peter/>). “MP” runs from the "MS-DOS" command prompt. The following figure shows the opening menu of “MP”: the left hand side of the window provides the USGS-FGDC metadata elements as described in chapter 2; the write hand side of the window provides space for adding the description of each element.



### D2. Metadata for the images in USGS-FGDC standard

This section provides the metadata prepared for the RADARSAT SAR images and used in the prototype. The metadata is prepared using the “MP” software following the USGS-FGDC standard

File name: metadata-MOE-radarsat.met

Identification\_Information:

Citation:

Citation\_Information:

Originator:

A Ministry of Environment Project, Conducted by the Environmental and GIS Support Project for Water Sector Planning (EGIS II).

EGIS Project Code: MOE001

Publication\_Date: Not yet Published

Title: RADARSAT Images For MOE001

Edition: 1

Geospatial\_Data\_Presentation\_Form: remote-sensing image

Publication\_Information:

Other\_Citation\_Details: None

Online\_Linkage: [www.cegisbd.com](http://www.cegisbd.com)

Larger\_Work\_Citation:

Description:

Abstract:

SAR images were collected by the Environmental and GIS Support Project for Water Sector Planning (EGIS II) in Bangladesh for its "Coastal Land Use Zoning" study. The study is one of the components of the Sustainable Environmental Management Programme (SEMP). Four images were acquired by the RADARSAT 1 satellite system on four different dates in the wet season cropping period (18 August, 11 September, 05 October and 29 October of 2001). The images were acquired in standard beam mode (S5). The nominal resolution is 25 meter. Image incidence angles are between 360- 420 and aerial extent is 100\*100 km. The images were pre-processed for calibration by the RADARSAT International (RSI) and supplied to CEGIS as "Path Image Product" (processing level). Path Image processing aligns the scene parallel to the satellite's orbit path. Latitude and longitude positional information has been added to the data. All the images were acquired in ascending pass that was at around 6:00 pm local time. The images were downloaded in dB (decibel) format. The subsequent processing steps for the images were co-registration, filtering, georeferencing and finally the images were filtered using the Gamma-MAP filter (Kuan et al., 1987). It has been reported that in Bangladesh the Gamma-MAP filter is best suited for SAR Imagery and commonly used by the CEGIS. The co-registration among the images was done using the ground control points (GCPs) method. Upon collecting the GCPs, the images had been co-registered using the neighbourhood re-sampling technique to retain the integrity of the datasets. The co-registered radar images had been compared with each other and less than 0.25 pixel root mean square (RMS) error was obtained. The images were georeferenced in order to be used with GIS layers afterwards. Similar techniques as co-registration were used for georeferencing the images where the GCPs were taken from the DGPS corrected 6x6 meters resolution Pan chromatic image of the Indian Remote Sensing (IRS). After taking the GCPs for the first image, same set of GCP was used for all other images to keep the consistency in georeferencing accuracy. The images were projected to Bangladesh Transverse Mercator (BTM) system (FAP19/ISPAN, 1993).

Purpose:

The images were mainly collected for the study Coastal Land Use Zoning study for mapping the wet season landuse-land cover and land suitability study. The study is one of the components of the Sustainable Environmental Management Programme (SEMP).

Supplemental\_Information:

Satellite\_System\_Name: RADARSAT-1

Sensor\_Type: Synthetic Aperture Radar (SAR)

Homepage\_URL:

<http://www.rsi.ca/products/sensor/radarsat/radarsat1.asp>

[http://www.rsi.ca/products/sensor/radarsat/rsiug98\\_499.pdf](http://www.rsi.ca/products/sensor/radarsat/rsiug98_499.pdf)

Sensor\_Platform: Satellite Sensor

Antenna\_Type: Stearable antenna

Orbit\_Type: Near-polar, Sun-synchronous, Near-circular  
Sensor Revisit Frequency: 24 days  
Launch\_Date: 19951104  
Microwave\_Band: C  
Transmission\_Polarization: H  
Receiving\_Polarization: H  
Imaging\_Beam\_Mode: Standard 5  
Nominal Resolution: 25  
Resolution\_Unit: Meter  
Swath\_Width: 100  
Swath\_Width\_Units: Kilometers  
Flight\_Pass: Ascending  
Incidence\_Angle:  
High\_Beam\_Incidence\_Angle: 36.00000  
Low\_Beam\_Incidence\_Angle: 42.00000

Beam\_Mode\_Description:

The radar transmitter and receiver operate through a steerable antenna that directs the transmitted energy in a narrow beam normal to the satellite track. The elevation angle and profile of the beam (beam positions) can be adjusted so that the beam intercepts the earth's surface over the desired range of incidence angles. This capability is important because image characteristics vary with the incidence angle associated with each beam mode.

Time\_Period\_of\_Content:

Time\_Period\_Information:

Range\_of\_Dates/Times:

Beginning\_Date: 20010818

Ending\_Date: 20011029

Status:

Spatial\_Domain:

Bounding\_Coordinates:

West\_Bounding\_Coordinate: 449591.0000

East\_Bounding\_Coordinate: 487966.0000

North\_Bounding\_Coordinate: 528483.0000

South\_Bounding\_Coordinate: 475233.0000

Keywords:

Theme:

Theme\_Keyword: radar

Place:

Place\_Keyword: Khulna, Satkhira, Bugherhat

Stratum:

Temporal:

Temporal\_Keyword: August, September, October, wet season

Access\_Constraints: Need aproaval of MOE / WARPO / CEGIS

Use\_Constraints: Non Commercial

Point\_of\_Contact:

Contact\_Information:

Contact\_Organization\_Primary:

Contact\_Organization: CEGIS or WARPO

Contact\_Address:

Address\_Type: Mailing and physical address

Address: House # 6, Road # 23/C, Gulshan - 1,

City: Dhaka

State\_or\_Province:

Postal\_Code: 1212

Country: Bangladesh.

Contact\_Instructions:

Browse\_Graphic:

Data\_Set\_Credit: less noisi radar image

Native\_Data\_Set\_Environment: ERDAS Imagine 8.4, Microsoft Windows NT,

Data\_Quality\_Information:

Logical\_Consistency\_Report: None

Completeness\_Report: None

Positional\_Accuracy:

Horizontal\_Positional\_Accuracy:

Horizontal\_Positional\_Accuracy\_Report: None

Quantitative\_Horizontal\_Positional\_Accuracy\_Assessment:

Horizontal\_Positional\_Accuracy\_Value: 10

Horizontal\_Positional\_Accuracy\_Explanation: meter

Lineage:

Cloud\_Cover: none

Spatial\_Data\_Organization\_Information:

Direct\_Spatial\_Reference\_Method: raster

Point\_and\_Vector\_Object\_Information:

Raster\_Object\_Information:

Raster\_Object\_Type: pixel

Row\_Count:

Column\_Count:

Spatial\_Reference\_Information:

Horizontal\_Coordinate\_System\_Definition:

Planar:

Map\_Projection:

Transverse\_Mercator:

Scale\_Factor\_at\_Central\_Meridian: 0.9996

Longitude\_of\_Central\_Meridian: +90.0000

Latitude\_of\_Projection\_Origin: 0.0000

False\_Easting: 500000

False\_Northing: -2000000

Planar\_Coordinate\_Information:

Planar\_Coordinate\_Encoding\_Method: row and column

Coordinate\_Representation:

Abscissa\_Resolution: 25.0000

Ordinate\_Resolution: 25.0000

Planar\_Distance\_Units: meter

Entity\_and\_Attribute\_Information:

Distribution\_Information:

Metadata\_Reference\_Information:

Metadata\_Date: 20040514

Metadata\_Review\_Date: None

Metadata\_Future\_Review\_Date: None

Metadata\_Contact:

Metadata\_Standard\_Name: FGDC Content Standards for Digital Geospatial

Metadata\_Standard\_Version: FGDC-STD-001-1998

Metadata\_Time\_Convention: local time

Metadata\_Access\_Constraints: Grant access to all users

Metadata\_Use\_Constraints: None

Metadata\_Security\_Information:

Metadata\_Security\_Classification\_System: None

Metadata\_Extensions:

Online\_Linkage:

Profile\_Name:

Metadata\_Language: English

### C3 Metadata for the GIS in USGS-FGDC Standard

This section provides the metadata prepared for the Land-type GIS layer and used in the prototype. The metadata is prepared using the “MP” software following the USGS-FGDC standard

File name: metadata-FAP19-bdltype.met

Identification\_Information:

Citation:

Citation\_Information:

Originator: Bangladesh Flood Action Plan -19

Publication\_Date: 1995

Publication\_Time:

Title: BDLTYPE- Raster Map (Inundation land type data for Bangladesh

Edition: 1

Geospatial\_Data\_Presentation\_Form: raster digital data

Series\_Information:

Series\_Name: Technical Note

Issue\_Identification: 8

Publication\_Information:

Publication\_Place: Dhaka, Bangladesh

Publisher:

Bangladesh Flood Action Plan 19

Irrigation Support Project for Asia and the Near East (ISPAN)

Bangladesh Flood Plan Coordination organization (FPCO)

Ministry of Water Resources

Government of Bangladesh

Other\_Citation\_Details:

Technical Note on

Soil & Agriculture Data of NWRD

Online\_Linkage:

Larger\_Work\_Citation:

Citation\_Information:

Description:

Abstract:

BDLTYPE GIS layer is a combined product of information on the land inundation extent and duration and Digital elevation model (DEM) GIS layer. Land inundation information is taken from the Agro-ecological zone (AEZ) map where information was in the form of percentage of area flooded in a zone during normal flood and remain flooded for how many days, however, it was not pointed exactly which location is flood prone. DEM was used to find the location of the flood prone area in the AEZ polygons. It is an 8-bit colour raster data in ERDAS 7.x (.GIS) file. An associated colour palette (.TRL) file ensures the uniform colours throughout a particular land type class. The pixel values in the data layer represents as follows; 1- Background, 2-F0 Land, 3-F0+F1 Land, 4-F1 Land, 5-F1+F2 Land, 6-F2 Land, 7-F2+F3+F4 Land, 8-F3F4 Land, 9-Mixed, 10-Reserved Forest, 11-Water/River, 12-Urban, 13-No Data, 14-Sand.

Purpose:

It has a variety of useful application, especially in the design of flood control structures, input information for agronomic and environmental studies, agricultural and landuse planning.

Supplemental\_Information:

Metadata for Digital Elevation Model

Agri-ecological Zone

Soil Map

Time\_Period\_of\_Content:

Time\_Period\_Information:

Single\_Date/Time:

Multiple\_Dates/Times:  
Range\_of\_Dates/Times:  
  Beginning\_Date: 1985  
  Beginning\_Time:  
  Ending\_Date: 1995  
  Ending\_Time:  
Currentness\_Reference: Publication Date  
Status:  
  Progress: Complete  
  Maintenance\_and\_Update\_Frequency: Not Planned  
Spatial\_Domain:  
  Bounding\_Coordinates:  
    West\_Bounding\_Coordinate: 299400.0000  
    East\_Bounding\_Coordinate: 772500.0000  
    North\_Bounding\_Coordinate: 946500.0000  
    South\_Bounding\_Coordinate: 283800.00  
Keywords:  
  Theme:  
    Theme\_Keyword\_Thesaurus: None  
    Theme\_Keyword: Digital Raster Data  
    Theme\_Keyword: Land Type  
    Theme\_Keyword: Digital Land Type data for Bangladesh  
    Theme\_Keyword: GIS Database  
    Theme\_Keyword: Majore Cities  
    Theme\_Keyword: Majore River Network  
    Theme\_Keyword: Large water bodies  
  Place:  
    Place\_Keyword\_Thesaurus: None  
    Place\_Keyword: Bangladesh National Coverage  
  Stratum:  
    Stratum\_Keyword\_Thesaurus:  
    Stratum\_Keyword:  
  Temporal:  
    Temporal\_Keyword\_Thesaurus:  
    Temporal\_Keyword: Latest Information  
Access\_Constraints: None  
Use\_Constraints: Acknowledgment of the WARPO would be appreciated  
Point\_of\_Contact:  
  Contact\_Information:  
    Contact\_Person\_Primary:  
    Contact\_Organization\_Primary:  
      Contact\_Organization:  
        National Water Resources Database (NWRD)  
        Water Resources Planning Organization (WARPO) Bangladesh  
    Contact\_Person:  
    Contact\_Position:  
    Contact\_Address:  
      Address\_Type: Mailing and physical address  
      Address: Simon Tower, Gulshan 1,  
      City: Dhaka  
      State\_or\_Province:  
      Postal\_Code:  
      Country: Bangladesh  
    Contact\_Voice\_Telephone:  
    Contact\_TDD/TTY\_Telephone:  
    Contact\_Facsimile\_Telephone:  
    Contact\_Electronic\_Mail\_Address:  
    Hours\_of\_Service:  
    Contact\_Instructions:  
Browse\_Graphic:  
  Browse\_Graphic\_File\_Name:



Browse\_Graphic\_File\_Description:  
Browse\_Graphic\_File\_Type:  
Data\_Set\_Credit:  
Security\_Information:  
  Security\_Classification\_System:  
  Security\_Classification:  
  Security\_Handling\_Description:  
Native\_Data\_Set\_Environment:  
Cross\_Reference:  
  Citation\_Information:  
Data\_Quality\_Information:  
  Attribute\_Accuracy:  
    Attribute\_Accuracy\_Report:  
      Flood depth supplied by the maps are based on  
      general soil association map units digitised  
      from 1:250000 scale AEZ map and represent only  
      average depths which occur during normal flood  
      years. No formal effort was undertaken to develop  
      a quantitative attribute accuracy statement.  
    Quantitative\_Attribute\_Accuracy\_Assessment:  
    Attribute\_Accuracy\_Value:  
      No formal effort was undertaken to develop a  
      quantitative attribute accuracy statement.  
    Attribute\_Accuracy\_Explanation:  
  Logical\_Consistency\_Report:  
  Completeness\_Report:  
  Positional\_Accuracy:  
    Horizontal\_Positional\_Accuracy:  
    Horizontal\_Positional\_Accuracy\_Report:  
      No formal effort was undertaken to develop a  
      quantitative attribute accuracy statement.  
    Quantitative\_Horizontal\_Positional\_Accuracy\_Assessment:  
    Horizontal\_Positional\_Accuracy\_Value:  
    Horizontal\_Positional\_Accuracy\_Explanation:  
    Vertical\_Positional\_Accuracy:  
    Vertical\_Positional\_Accuracy\_Report:  
      No formal effort was undertaken to develop a  
      quantitative attribute accuracy statement.  
    Quantitative\_Vertical\_Positional\_Accuracy\_Assessment:  
    Vertical\_Positional\_Accuracy\_Value:  
    Vertical\_Positional\_Accuracy\_Explanation:  
Lineage:  
  Source\_Information:  
  Source\_Citation:  
  Citation\_Information:  
    Originator:  
      Environment And GIS Support Project for Water Sector Planning (EGIS-II)  
      National Water Resources Database (NWRD)  
      Water Resources Planning Organization (WARPO)  
      Ministry of Water Resources  
    Publication\_Date: 200008  
    Publication\_Time:  
    Title:  
      Technical Note on  
      Soil & Agriculture Data of NWRD  
    Edition: Draft  
  Geospatial\_Data\_Presentation\_Form:  
  Series\_Information:  
    Series\_Name: Technical Note  
  Issue\_Identification:  
  Publication\_Information:

Publication\_Place: Dhaka  
Publisher: Environment And GIS Support Project for Water Sector Planning (EGIS-II)  
Other\_Citation\_Details:  
Online\_Linkage:  
Larger\_Work\_Citation:  
Source\_Scale\_Denominator: 250000  
Type\_of\_Source\_Media: Paper Map  
Source\_Time\_Period\_of\_Content:  
Time\_Period\_Information:  
Single\_Date/Time:  
Calendar\_Date: 1987  
Time\_of\_Day:  
Multiple\_Dates/Times:  
Range\_of\_Dates/Times:  
Source\_Currentness\_Reference:  
Source\_Citation\_Abbreviation:  
Source\_Contribution:  
Process\_Step:  
Process\_Description:  
Detail description can be obtained from the report  
"Bangladesh National Level GIS Database, May 1995"  
as referred before. The algorithm for delineating  
the land type classes is as follows:  
1. Obtain percentage of each land type (F0-F4) in  
the digital Soil association map that was derived  
from the AEZ data.  
2. Overlay the soil map with DEM layer to locate the  
DEM pixels that geographically correspond to the  
same polygon.  
3. Sort the DEM pixels by elevation in descending order.  
4. Allocate the sorted pixels high-low) to land type  
classes (F0-F4) based on the percentages obtained  
in step 1, i.e. the highest pixels are allocated to  
high land area (F0) using the appropriate percentage,  
and so on down to lowland (F4) which is allotted the  
lowest elevation pixels.  
5. Repeat steps 1 to 4 until all soil association  
polygons on the map are classified.  
Source\_Used\_Citation\_Abbreviation:  
Process\_Date: 199505  
Process\_Time:  
Source\_Produced\_Citation\_Abbreviation:  
Process\_Contact:  
Contact\_Information:  
Contact\_Person\_Primary:  
Contact\_Person:  
Contact\_Organization: Water Resources and Planning Organization (WARPO)  
  
Contact\_Position:  
Contact\_Address:  
Address\_Type: mailing and physical address  
Address: Simon Tower  
City: Gulshan #1  
State\_or\_Province: Dhaka  
Postal\_Code:  
Country: Bangladesh  
Contact\_Voice\_Telephone:  
Contact\_TDD/TTY\_Telephone:  
Contact\_Facsimile\_Telephone:  
Contact\_Electronic\_Mail\_Address:  
Hours\_of\_Service:

Contact\_Instructions:  
Cloud\_Cover: None  
Spatial\_Data\_Organization\_Information:  
Indirect\_Spatial\_Reference:  
Direct\_Spatial\_Reference\_Method: Method  
Point\_and\_Vector\_Object\_Information:  
SDTS\_Terms\_Description:  
SDTS\_Point\_and\_Vector\_Object\_Type:  
Point\_and\_Vector\_Object\_Count:  
VPF\_Terms\_Description:  
VPF\_Topology\_Level:  
VPF\_Point\_and\_Vector\_Object\_Information:  
Raster\_Object\_Information:  
Raster\_Object\_Type: Pixel  
Row\_Count: 2210  
Column\_Count: 1578  
Vertical\_Count:  
Indirect\_Spatial\_Reference:  
Direct\_Spatial\_Reference\_Method:  
Point\_and\_Vector\_Object\_Information:  
Raster\_Object\_Information:  
Spatial\_Reference\_Information:  
Horizontal\_Coordinate\_System\_Definition:  
Geographic:  
Latitude\_Resolution:  
Longitude\_Resolution:  
Geographic\_Coordinate\_Units:  
Planar:  
Map\_Projection:  
Transverse\_Mercator:  
Scale\_Factor\_at\_Central\_Meridian: 0.9996  
Longitude\_of\_Central\_Meridian: +90.0000  
Latitude\_of\_Projection\_Origin: 0.0000  
False\_Easting: 500000  
False\_Northing: -2000000  
Grid\_Coordinate\_System:  
Local\_Planar:  
Planar\_Coordinate\_Information:  
Planar\_Coordinate\_Encoding\_Method: row and column  
Coordinate\_Representation:  
Abscissa\_Resolution: 300.0000  
Ordinate\_Resolution: 300.0000  
Planar\_Distance\_Units: meter  
Local:  
Geodetic\_Model:  
Horizontal\_Datum\_Name:  
Ellipsoid\_Name:  
Semi-major\_Axis:  
Denominator\_of\_Flattening\_Ratio:  
Geodetic\_Model:  
Horizontal\_Datum\_Name: WGS84  
Ellipsoid\_Name:  
  
Semi-major\_Axis:  
  
Denominator\_of\_Flattening\_Ratio:  
Vertical\_Coordinate\_System\_Definition:  
Horizontal\_Coordinate\_System\_Definition:  
Vertical\_Coordinate\_System\_Definition:  
Entity\_and\_Attribute\_Information:  
Detailed\_Description:

Entity\_Type:

Entity\_Type\_Label: Integer

Attribute:

Attribute\_Label: Inundation Land Type Information

Attribute\_Definition:

The pixel values in the data layer represents as follows

Pixel Class

Value Name

1 Background

2 F0 Land

3 F0+F1 Land

4 F1 Land

5 F1+F2 Land

6 F2 Land

7 7-F2+F3+F4 Land

8 8-F3F4 Land

9 Mixed

10 Reserved Forest

11 Water/River

12 Urban

13 No Data

14 Sand

Attribute\_Definition\_Source: Bangladesh National Level GIS Database report

Attribute\_Domain\_Values:

Beginning\_Date\_of\_Attribute\_Values:

Ending\_Date\_of\_Attribute\_Values:

Attribute\_Value\_Accuracy\_Information:

Attribute\_Measurement\_Frequency:

Overview\_Description:

Entity\_and\_Attribute\_Overview:

Entity\_and\_Attribute\_Detail\_Citation:

Distribution\_Information:

Distributor:

Contact\_Information:

Contact\_Organization\_Primary:

Contact\_Organization:

Water Resource and

Planning Organization (WARPO)

Contact\_Person:

Contact\_Position:

Contact\_Address:

Address\_Type: mailing and physical address

Address: Simon Tower

City: Gulshan #1

State\_or\_Province: Dhaka

Postal\_Code:

Country: Bangladesh

Contact\_Voice\_Telephone:

Contact\_TDD/TTY\_Telephone:

Contact\_Facsimile\_Telephone:

Contact\_Electronic\_Mail\_Address:

Hours\_of\_Service:

Contact\_Instructions:

Resource\_Description: National Water Resources database

Distribution\_Liability:

Standard\_Order\_Process:

Non-digital\_Form: None

Digital\_Form:

Digital\_Transfer\_Information:

Format\_Name: Erdas 7.x GIS file formate

Format\_Version\_Number:  
Format\_Version\_Date:  
Format\_Specification:  
Format\_Information\_Content:  
File\_Decompression\_Technique: WinZip  
Transfer\_Size:  
Digital\_Transfer\_Option:  
Online\_Option:  
Offline\_Option:  
Offline\_Media: CD  
Recording\_Capacity:  
Recording\_Density:  
Recording\_Density\_Units:  
Recording\_Format:  
Compatibility\_Information:  
Fees: Unknown  
Ordering\_Instructions: Contact WARPO  
Turnaround:  
Custom\_Order\_Process:  
Technical\_Prerequisites:  
Available\_Time\_Period:  
Time\_Period\_Information:  
Single\_Date/Time:  
Multiple\_Dates/Times:  
Range\_of\_Dates/Times:  
Metadata\_Reference\_Information:  
Metadata\_Date:  
Metadata\_Review\_Date:  
Metadata\_Future\_Review\_Date:  
Metadata\_Contact:  
Contact\_Information:  
Contact\_Organization\_Primary:  
Contact\_Organization: WARPO  
Metadata\_Standard\_Name:  
Federal Geographic Data Committee (FGDC)  
Content Standard for Digital Geospatial  
Metadata  
Metadata\_Standard\_Version: FGDC-STD-001 June 1998  
Metadata\_Time\_Convention:  
Metadata\_Access\_Constraints:  
Metadata\_Use\_Constraints:  
Metadata\_Security\_Information:  
Metadata\_Extensions:  
Metadata\_Language: English