Modelling Land Cover Change: A Fuzzy Approach

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by

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Signed

ಹಾರ್ದಿಕ ಧನ್ಯವಾದಗಳೊಂದಿಗೆ,

ಮನೆಯವರೆಲ್ಲರಿಗೂ……

With sincere gratitude,

To my family members……

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Abstract

This research is concerned with land cover changes occurred in the Shimla district of Himachal Pradesh in India between 1987 and 1999. The LANDSAT – TM of 1987 and the IRS – 1D of 1999 satellite images are used as sources of information about the area. Supervised and unsupervised image classifications are common techniques used for land cover mapping from satellite data. They both assume that land cover classes have crisp boundaries. Vagueness in the boundaries of land cover classes is one the major problems of image classification. This study is an investigation of supervised classification of a satellite image in which most of the land cover classes are vaguely defined. It proposes a fuzzy supervised approach, which is based on fuzzy set theory. The fuzzy supervised classification proposed in this study consists of two major steps – first defining the parameters of a fuzzy membership function based on both field knowledge of the analyst and statistics of the training sets; second measuring the uncertainty arising from vagueness in transitional areas. The results show that the accuracy of a fuzzy classification is better than a crisp classification. To model land cover change, a fuzzy post-classification comparison approach is used, which uses the data of fuzzy classified images as information. This work explores the use of fuzzy operators in identifying and quantifying changes, nature and direction of changes occurring in land cover.

Key words: Supervised classification; post classification comparison; fuzzy logic; membership function; uncertainty; defuzzification

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1. Introduction

“So far as the laws of mathematics refer to reality, they are not certain. And so far as they are certain, they do not refer to reality”.

--Albert Einstein

Human intervention and natural phenomena cause change in land cover day by day. Availability of accurate land cover information is essential for many applications like natural resource management, planning and monitoring programs. Land cover change is important information for a number of applications like agriculture, hydrology, forestry and ecology etc. For example in an aforestation programme, we need to know which are the areas where forest is degrading or areas with less forest and suitable for planting etc.

Land cover change has become a central component in current strategies for managing natural resources and monitoring environmental change. Because of the rapid development in the field of vegetation mapping, there is an increase in studies of land cover change worldwide. Providing an accurate assessment of the extent and health of the world’s forest, grassland, and agricultural resources has become an important priority.

For studying land cover classes, some of the information sources are field survey, existing maps, statistical data, existing documents or available literature and remote sensing images. Traditional methods of land cover mapping have been limited to field surveys, which are time-consuming and uneconomical. This will give the printed maps without any statistics or only statistics without any map. But printed maps have not attracted as much attention as statistics among the people because of its limited applications (Himiyama, 2002). Remotely sensed data, like aerial photographs and satellite imageries are undoubtedly the most ideal data for extracting land cover change information.

Satellite images are the most economical way of getting data for different times. The multitude of existing software helps getting information from satellite images also in manipulating the information. The approach used in this study to classify satellite images and change detection based on fuzzy logic approach.

Change detection is a major task in digital image processing. This task helps in many applications as mentioned above. Change detection is done digitally using two satellite images. If the images are classified and compared for the change, it is called Post Classification Comparison (PCC) (Singh, 1989). If this is done before classification, using only geo-referenced images, it is called pre-classification change detection. This is purely based on the digital number of a pixel in different bands. But simple methods of classification of images and change detection suffer from poor accuracy (Deer and Eklund, 2001). To detect the change accurately, we need the accurate classification. Results of traditional classification methods assign crisp boundaries to classes. Crisp class assignment is often inappropriate in geographical and Remote Sensing sciences (Burrough and McDonnel, 1998). This is because of the uncertainties present in the geographical objects. To quantify uncertainties, it is advisable to use fuzzy approach.

The past few years have witnessed a rapid growth in the number and variety of applications of fuzzy logic. The applications range from consumer products such as cameras, washing machines, and microwave ovens to industrial process control, medical instrumentation, decision-support systems, and in remote sensing of course.

There are several methods to extract the information about the earth. But efficient and economical method is through satellite data. Important thing to be mentioned here that *data* from satellite image is converted into *information* of the earth surface. Using satellite data we can extract the information in all scales ranging from local to global scale. It is very easy for frequent updating the existing information using satellite data. There are many techniques like visual interpretation of satellite image, multi-spectral image classification, band rationing etc. to extract information from satellite data. Out of which, multi-spectral image classification is most commonly used.

The overall objective of classification is to automatically categorize all pixels of an image into land cover classes. There are mainly two approaches in traditional methods of classification. They are unsupervised and supervised classification, which are often called *hard classification*. Also there exist *soft classification* like sub-pixel classification and *fuzzy classification*.

We can distinguish two kinds of uncertainty while classifying an image. First, in most of the cases there is no fixed boundary between two land cover classes. Second, there may be chances of more than one class in a pixel. These uncertainties cannot be classified using Boolean approach of classification as it calculates and assigns a single class per pixel. This problem has lead to the concepts *soft classification* techniques like *fuzzy classification, sub-pixel classification.*

As human and natural forces modify the landscape, resource agencies find it increasingly important to monitor and assess these alterations. Change in vegetation affect wildlife habitat, fire conditions, aesthetic and historical values and ambient air quality. These change, in turn, influence management and policy decisions. Methods for monitoring vegetation change range from intensive field sampling with plot inventories to extensive analysis of remotely sensed data. While aerial photography can detect change over relatively small areas at reasonable cost, satellite imagery has proven more cost effective for both global scale and local scale.

Change detection is a technique that is used to highlight conversion of land from one use to another within a given time frame (Karanja, 2002). In this study, the focus is on change per pixel in different images of the same area using a fuzzy logic approach, which uses the concepts of fuzzy sets in which elements are having a partial degree of belongingness to that set.

1.1. Motivation

Land cover classes like forest, agriculture, barren lands, water body etc. usually do not have any distinct boundaries in the geographic space and it is imprecise. A fuzzy approach can measure the uncertainty between class boundaries.

The study area being a hilly region, will not be having crisp classes like in plane areas. In plane areas, we may find some classes with crisp boundaries like agricultural fields, some settlement areas etc. Because of the undulated terrain, the boundaries between two or more classes are very vague. In a hilly terrain there are very few areas with homogeneous classes. Except some area under forest and barren land, all other land cover classes are very small which cannot be easily identified by coarser resolution satellite images. So there is lot of mixed pixels in images. These mixed pixels can be identified by fuzzy classification approach. By considering these points, fuzzy based supervised classification approach is opted for classifying the area.

In the post classification comparison, more the classification accuracy better is the change detection accuracy. A supervised approach uses the prior knowledge about the field and thus it is very useful in getting better results than an unsupervised classification.

In hilly regions there will not be drastic change as we find in plane areas. It is a slow and continuous process. That is why the images with at least 8- 10 years difference are chosen for change detection. A linear approach to detect change does not give the best results as it gives only "change" or "no-change" information. But in the fuzzy approach, it is possible to describe change as a degree. By keeping all the above points in mind, a fuzzy approach is chosen for classification and change detection of major land cover classes.

Results of this research can be utilized as a temporal land-use change model for a region to quantify the extent and nature of change, and aid in future prediction studies, which helps in planning agencies to develop sustainable land-use practices.

This research looks into the applications of remotely sensed image in land cover classification and change detection, and come out with a methodology for classification and change detection using fuzzy logic approach.

1.2. Research Objectives

- To perform a supervised fuzzy classification of remotely sensed imagery of an area in India to identify land cover types.
  - to define fuzzy membership functions for classification based on field data and expert knowledge,
  - to quantify classification uncertainty,
  - to assess the accuracy of the fuzzy classification result.
- To model fuzzy land cover change between two dates using post classification comparison.
  - to quantify the changes occurred between two dates,
  - to identify the nature of changes between any two selected class,
  - to identify the direction of change per pixel.

1.3. Research Questions

For the fulfillment of the objectives, this research should answer to the following questions.

- How to decide the parameters in a fuzzy membership function based on user's field knowledge and training sets?
- How to identify and quantify the change in a land cover along with its direction using a fuzzy based post classification comparison?
- What are the advantages of a fuzzy supervised approach in classification and a fuzzy approach in change detection, compared to other approaches?
- How to assess accuracy of a supervised fuzzy classification?

1.4. Structure of the Thesis

This research work is explained in six chapters. Chapter 1 dealt with introduction, motivation for fuzzy approach, objectives of this research and research questions. Chapter 2 makes the survey of some literature related to this work along with a brief explanation of fuzzy logic, classification and change detection. Chapter 3 shows the chosen study area. It also gives an explanation about the data used for this work. Chapter 4 illustrates in detail the methodologies used and developed for this research, advantages of each of them and the expected results from each approach. Chapter 5 discusses the analysis and results. In the end, Chapter 6 concludes the research work with some recommendations for future line of work in this field.

2. Literature Review

2.1. Fuzzy logic

In this world, we are having lot of uncertain information, which are used to estimate and understand many complex problems. Specially in representing a geographical object it is very difficult, as in most of the cases they do not have well defined boundaries. We, the human beings know how vague they are. But to represent them as a map is very difficult because computers or processors cannot understand what we perceive. To make these devices compatible with our thinking, we need to represent these uncertain information mathematically. For this purpose, to handle the concept of "partial truth", Dr. Lofti Zadeh in 1965 proposed a new theory called "Fuzzy Sets" (Zadeh, 1965). The logical processing using fuzzy sets, is known as "Fuzzy Logic" (Klein, 1999).

Fuzzy set theory provides useful concepts and methods to deal with uncertain information. The boundaries between any two classes are not well defined in all the cases. They are simply a subjective interpretation of where between-class variation is greater than within-class variation. Meaning that the hard classification procedure may not interpret the boundaries in an appropriate manner, where as the fuzzy approach, in general, gives the vagueness in the boundaries between classes.

Fuzzy logic has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multi-valued logic. But in a wider sense, it is a theory that relates to classes of objects with continuous boundaries in which membership values are degree of belongingness. Fuzzy logic starts with the concept of *a fuzzy set*, which is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership.

Fuzzy set theory provides useful concepts and methods to deal with uncertain information. The set associated with a membership function and each element in this set has its own membership value towards that particular set. The membership values range between 0 and 1. If the membership value of an element is 0, it means that, it does not belong to that set and if it is 1, then it belongs completely. But, in crisp sets, the membership value is either 1 or 0.

Fuzzy memberships differ from probabilities interpretation. A fuzzy set is defined by a *membership function,* which defines how each point in the input set is mapped to a membership value (or degree of belongingness) between 0 and 1. In probability theory only one class or set is present and expresses the degree to which its presence is likely as a probability. The class with highest probability is interpreted as actual class. Fuzzy set theory accepts that multiple classes or sets can be present at one place or at one time, and expresses the possibility to which each class or set is present as a membership value (Brown, 1998) or belongingness value. Using fuzzy set theory, we can determine and reason with the grade of membership of a particular pixel in a number of classes (Zadeh, 1965).

A *fuzzy classification* is a *soft classification*, which is used to find out uncertainty in the boundary between classes and to extract the mixed pixel information. This is achieved by applying a function called "membership function" on remotely sensed images. Using "hard" classification methods, we cannot measure the uncertainty in an image where as in a fuzzy classification technique; we can get more information from the data. For a geo-scientist, extraction of information is important than representation of that information.

The fuzzy approach plays an important role in the whole classification procedure, as these clusters are required to form classes of the given data set such that the degree of association is strong for data within the blocks of class and weak for data in different blocks (Klir and Yuan, 1995). Fuzzy logic is an attempt to address imprecise thinking by using a precise mathematical concept.

For crisp classification, if a pixel P belongs to a class C, then membership function MF [P, C] = 1, else MF [P, C] = 0. If the classes have no definite boundaries, then the assignment of the pixel to a class is uncertain, which is expressed by fuzzy class membership function (Cheng, 1999). It takes value between 0 and 1, such that CLASS (P)={C/M [P, C]>0}

2.2. Mapping

Land cover mapping is one of the most important and typical applications of remote sensing data. Land cover corresponds to the physical condition of the ground surface, for example, forest, grassland, concrete pavement etc., while land use reflects human activities such as industrial zones, residential zones etc. Initially land cover classification system should be established, which is usually defined as levels and classes (Remote Sensing Notes, 1999). Level and class should be designed in consideration of the purpose of use (national, regional or local), the spatial and spectral resolution of the remote sensing data, user's request and so on.

For instance land cover change is a major component of the global carbon cycle and a significant control on biodiversity. Although the significance of land cover is recognized our knowledge on its precise effects is limited by the poor quality of land cover data.

The only feasible method to acquire land cover data at such scales is through satellite remote Sensing. Remote Sensing, one of the most important and frequently used technologies to map an area. Image classification is a widely accepted and used approach of mapping using satellite images. There are many reasons behind this like it is quick; less cost is involved when compared to other methods etc. The maps prepared or the information extracted from these satellite images is the good source of data in GIS fields.

Remotely sensed images are not the maps. However the information extracted from images is to be integrated with the maps in GIS environment to present consumers in a map-like form (Mather, 1999). “A map is defined as a graphic representation on a plane surface of the earth’s surface or part of it, showing its geographical features. These are positioned according to pre-established geodetic control, grids, projections and scales” (Steigler, 1978).

There are many ways to prepare thematic maps from remotely sensed data. Visual interpretation, automatic image classification are some of the examples. Image classification is considered as one of the important aspects of preparing maps. A thematic map is a set of points, lines and polygons that are defined both by their location in space and by their non-spatial attributes about single theme (Wang, 1990). At present the linkage between the spatial entities and non-spatial attributes are based on the membership concepts of classical set theory – an entity either has an attribute or not at all. No other situation is possible.

The scale of the maps prepared using satellite images mainly depend on the pixel size of images (Williams, 1995). The general rule of thumb is that the pixel size should equate that of 0.3 mm in the final hard copy (Colvocoresses, 1986).

As per the Steigler's definition, map has to be positioned according to pre-established geodetic control, grids, projections and scales. In the digital image processing procedure, image will be geo-referenced to a projection and datum. Important steps in map making using satellite images are,

- Transform images to match a map projection,
- Bring adjacent images into registration, (to mosaic two or more images to get the full scene of the study area)
- Overlay temporal sequences of images of the same area (to detect the change in two temporal images).
- Locate points of interest on map and images, (to train the system for classification)

2.3. Classification

The aim of computer-assisted classification of an image is to automatically categorize all pixels in an image into land cover classes. This is the conversion of image data into information. Two main types of image classification are *supervised* and *unsupervised* classification.

The process of multi-spectral mapping of the landscape consists of drawing boundaries around geographically located classes that are homogeneous and the description of those classes and their attributes and relations in a consistent and logical manner (Robinove, 1981). The Earth's landscape has an extremely large number of attributes that may be used for classification and description, depending upon the purpose of the classification and the needs of the classifier.

Unsupervised classification procedure is more automated than supervised classification (Jensen, 1996). Clustering is one of the fundamental issues in an unsupervised image classification. The crux of clustering is to find several clusters that can properly categorize the relevant classes of given data set. There exist many approaches of clustering pixels into different groups, which are called classification methods in Remote Sensing.

Supervised classification is more controlled by the user than unsupervised classification. It requires experience by the user about field and more input, but it can produce better results than unsupervised classification. The approach is to identify homogenous, representative samples of the different land cover types of interest. These samples are called *training areas*. The spectral information in all spectral bands for the pixels comprising these training areas are used to "train" the computer to recognize spectrally similar areas for each class (Fundamentals of Remote Sensing, 1999). The computer uses a special algorithm to determine the *spectral signatures* for each training class. In supervised training, it is important to have a set of predefined classes, and then create the appropriate signatures from the data. There are a number of different algorithms available for performing supervised classification.

Classical (crisp) clustering algorithms generate classes in which each pixel is assigned to exactly one of the clusters or classes. But in practice, the separation of classes is a fuzzy notion. This is especially in case of land cover classes. Benedikt and Nishiwaki (2003) reported that, the concept of fuzzy sets has the advantages over classical clustering, by allowing algorithm to assign to each pixel a partial or distributed membership to each class. We can call this uncertainty or inexactness. We can see two kinds of inexactnesses in Remote Sensing and GIS context:

- *Attribute ambiguity*: In this case we cannot assign membership of a given location to a single class.
- *Spatial ambiguity*: Boundaries drawn between two sets as mapped in space are not located with 100% certainty.

One of the major problems in remote sensing is that, land cover may vary more frequently than the sampling interval between pixels in the imagery. Therefore a single pixel may represent mixture of land cover classes. Such pixels are called mixed pixels or mixels. For example, a pixel may contain 20% cultivated land, 20% forest and 60% water. This is a typical example where we can use fuzzy set theory and apply fuzzy logic. In this case it is not appropriate to assign the pixel into class water, as 40% of the pixel is not water. In these circumstances, a traditional hard spectral classifier is inappropriate - as it assigns the pixel to class water - and should be replaced by a fuzzy classifier where we can assign one pixel to many classes in varying proportions (Foody and Atkinson, 2002).

One of the crisp classification method used in this study is maximum likelihood classification. This is carried out to compare the accuracies of both “hard” and “soft” classification. The maximum likelihood classification method assumes that the data in input bands have normal distribution. It assigns the pixel to a class where the probability is high.

In the satellite remote sensing, Digital Number (DN) of pixel represents the reflected energy of earth’s surface. In multi-spectral image, different DN is recorded for different bands. In general, the *n*DN, where *n* is the number of bands, are used in the multivariate image classification product to assign a land cover class to each pixel (Fisher and Pathirana, 1990), i.e. land cover is the function of DN of all the bands. It can be represented as, $LC_{ij} = f(DN_{1ij}, DN_{2ij}, DN3_{ij} \ldots DN_{nij})$, where LC_{ij} is the land cover class of pixel i^{th} row and j^{th} column. This is a typical Boolean approach of classification. It assumes that i) A pixel represents a single class and ii) All the classes generate a distinctive signature.

But this is very rare in the field conditions. When we compare the image with field observation, it is clear that DN of pixel is the function of all different classes,

i.e. $DN_{nij} = f(LC1, LC2 \ldots LCk)$, where k is the number of classes defined.

Zadeh states “the development of fuzzy set theory was motivated in large measure by problems in pattern classification and cluster analysis”. According to Bezdek and Pal (1992), “feature vectors should be allowed to have degrees of membership in more than one class”. This statement strongly supports the fuzzy classification of a multi-spectral image.

The literature gives many successful and unsuccessful attempts of classifying an image based on different fuzzy membership functions. We can see both unsupervised and supervised fuzzy classification methods in the literature. But supervised method of classification is much faster (30 – 40 times) than the unsupervised classification method (Key *et al*, 1989) as it requires only one pass through the data set. Also supervised classification technique uses prior knowledge about the field, which is very much helpful in getting better classification results.

To perform a fuzzy unsupervised classification, fuzzy *c*-means (FCM) clustering algorithm was proposed by Cannon *et al* (1986). They have applied this technique on a LANDSAT – TM image and fuzzy sets are used to represent the intermediate results, which cannot be represented by a classical unsupervised classification of images. A fuzzy *c*-means clustering algorithm may be used to subdivide an image into *c*-clusters. It has a non-hierarchical clustering technique. It starts by randomly assigning the pixels to classes and then, iteratively, moves pixels to other classes with the aim of minimizing the generalized least-squared error (Foody, 1996). The FCM algorithm is one of a family of clustering algorithms that have been developed within the field of pattern recognition (Hoppner *et al.* 2000). But unsupervised approach does not allow us to incorporate our field knowledge.

In this research we use fuzzy supervised approach to classify the satellite images. This is a useful approach as it helps in representing the geographical information, in quantifying the change, in measuring the uncertainty between the boundaries of two or more classes or the uncertainty in a pixel because of mixed classes. Unlike the above-mentioned works, this approach takes into consideration fuzzy membership values right from classification to the preparation of magnitude of change, direction of change and likelihood of change maps.

2.4. Accuracy assessment

Accuracy assessment of classified image is a complex subject and a fairly immature one. Readers with specific interests in accuracy assessment are directed to Congalton and Green's book, "*Assessing the Accuracy of Remotely Sensed Data-Principles and Practices*".

The purpose of accuracy assessment is to allow the user to determine the map's "fitness for use" for their application. Map accuracy assessment is not a standardized procedure. Many research questions are still being explored relating to field methods over large geographic areas and to statistical techniques and measures (Stoms *et al.*, 1994).

We can see many kinds of accuracies in GIS and Remote Sensing context, like spatial accuracy, thematic accuracy, topological accuracy and temporal accuracy. Spatial accuracy assessment is the determination of positional accuracy of objects (points, lines, polygons, and / or pixels) relative to known locations. Thematic accuracy concerns the measure of errors in the attributes associated with objects. By comparing the reported values to a standard or other well-documented data set, the thematic accuracy is assessed. Topological accuracy measurement, which is also called logical consistency, is measuring the errors associated more with the processed data than interpretation. Temporal accuracy assessment has not much importance as in large scale map preparation; very negligible change may occur in between the field observation and map preparation.

2.4.1. Sources of Errors

But from where do the errors arise? What are all the sources of errors? These can be listed as follows.

- Image Acquisition: This depends on the position of satellite, environmental conditions during the time image acquisition, sun angle etc. which will lead to geometric and radiometric erros.
- Image Processing: There are chances of errors to occur during geometric and radiometric corrections.
- Analysis: If the analyst gives the wrong input data, and uses the wrong methodology then there may be chances of errors in the output.
- Data Conversion: Due to data definition problem, errors can occur. This may happen when data is converted from one format to another.

2.4.2. General constraints in the accuracy assessment work

- *Technological Constraint*: This category of constraints includes all forms of potential measurement error relating to observation of "ground truth". The first of these sources of uncertainty in the observation dataset is determining the true location of the sample plot in the field. Identifying one's location on a topographic map or satellite image can sometimes be difficult in hilly terrain like this study area or far from known locations. GPS technology has improved this situation, providing precision at the 10-20 m level for quick readings. Much greater precision is available at the expense of longer recording time or the cost of using differential GPS. Even GPS has limited utility in some environments, particularly densely forested landscapes, where the receiver can detect few satellites. Fortunately, a small amount of uncertainty in locating the sampling unit in the field is not seriously detrimental to statistical inference in accuracy assessment (Stoms *et al.*, 1994). It is just a part of measurement error in the test data.

- *Logistical Constraints*: Some locations are simply too far from existing roads to be visited without incurring extravagant expense, such as using a helicopter. The landowner or manager may deny access as well. Safety considerations may also preclude access to locations where the route is too dangerous (e.g., crossing rivers, landslides). If sampling measurements cannot be made from some remote sensing platform, then these sites may need to be dropped from the sampling scheme and either replaced with a more accessible one or reported as a non-response in the assessment. This is just a fact-of-life that should be acknowledged when reporting the assessment.

- *Financial Constraints*: This is not an important constraint in a research, but of course, has some concern in few cases or projects in particular.

In general the assessment method should be

- Scientifically sound
- Economically feasible
- Universally applicable

It is very difficult to make the map of previous years using satellite images of that particular time. For this one has to go for ground data collection. Even though many sampling methods are available, there are no standard sampling methods for this purpose. Congalton and Green (1999) explained in detail about different kinds of sampling designs for remotely sensed data.

Cluster sampling method has to be used very intelligently. A proper prior knowledge of area is needed for this method. This method is mostly used for industrial applications. In stratified random sampling method, the area is divided into different groups or strata, and then each stratum is randomly sampled. The advantage of this method is that all land cover type will be included in the sampling. By keeping the advantages of the method in mind, stratified random sampling method is used in this research work for accuracy assessment of classified images.

Maps may be compared on the basis of several accuracy measures. For example, the map comparison can be based on user's accuracy and producer's accuracy for different land cover classes. Sometimes, map comparison involves a single accuracy measure because of convenience or because of large number of comparisons (Stehman, 1998). In this study, classified outputs are compared based on both user's and producer's accuracy.

In general, the results of the accuracy assessment are summerised as an error matrix (also called confusion matrix or contingency table). The error matrix summerises the comparisons between the maps and reference data collected for pixels. Kappa coefficient can be derived using error matrix, which is a measure of how accurate the map is. It considers omission, commission and overall accuracy simultaneously. Frequently reported in the literature and used as a common way to compare maps.

2.5. Change detection

Classification has many uses, out of which land cover change detection is an important one. There are many models available at present to model land cover change like Markov Chain Model, Evidential Weighted Approach, Global X Model, CLUE-CR Model, LUGEC Basic Model, Lambin's Model, and Grid Map Prediction Model.

In Global X Model, CLUE-CR Model and LUGEC Basic Model, remote sensing data are not at all used. The basic input data used in Global X model are social and physical aspects. Data used in CLUE-CR model are census data on population and agriculture. In LUGEC basic model, the municipal statistical data are used. Using these models, the causes of change are understood vaguely and the outcomings are too general to predict the future change (Himiyama, 2002). As the land cover is described spatially, it is advisable to use geo-spatial approach rather than statistical methods.

The traditional methods of detecting change using remote sensing data can be broadly divided into two main types: pre-classification and post-classification change detection. Jensen (1996) states that post classification comparison is the most commonly used method for quantitative analysis.

Even though SPOT satellite images were used as basic input data in Lambin's model, the classification and change detection were done linearly (Himiyama, 2002). This gives either "change" or "no change" information. The changes in land cover classes are non-linear in nature. It has the intermediate stages ranging from “absolutely changed” to “not at all changed”. Hence a linear approach to detect change will not give good results. It is very difficult to predict the future and hence difficult to take decisions. Importance of fuzzy approach comes into picture here. Fuzzy operation helps to produce maps of *magnitude of change*, *nature or direction of change* and *likelihood of change* (Metternicht, 2001). There are several types of fuzzy operations like AND, OR which can be used for preparing the above-mentioned maps.

The map of *magnitude of change* tells the change quantitatively. It may be in terms of percentage, membership values etc. The map of the *nature of change* tells how land cover is changing. This is a comparison between any two classes. These kinds of comparison using fuzzy operators are further used for preparing the *direction of change* map. Based upon the magnitude of change, direction of change along with some other ancillary data like slope, aspect, wetness index, socio-economic data, the *likelihood of change* map is prepared using fuzzy rule based system. The map of *likelihood of change* aids in prediction of land cover change in the future. Based upon these maps one can go for the development of predictive model of land cover change (Metternicht, 2001).

In the Markov Chain method, a first order equation is used, which assumes that to predict land cover change, the state of land cover at the previous time is needed along with the transition matrix. Transition matrix summarizes the probability of a cell belonging to a particular class to be changed from one type to another type. Main disadvantage of this system is that, it has several assumptions. One basic assumption is to regard land cover change as a stochastic process. It is also assumed that, land cover change is stationary. As land cover change reflects the dynamics and interplay of economic, social, and biophysical factors over time, stationarity in land cover will not be expected. To overcome this problem fuzzy knowledge based rules can be applied (Weng, 2002).

In the evidential weighted approach, (Jeganathan and Chauniyal, 2000) the probabilities obtained are used as the evidential weightage for the class; otherwise there would be a bias in determining the higher probable contributing elements. In this method, the weightage given itself is the ranking but there are no membership values to the classes. It results in crisp classification. Jeganathan and Chauniyal (2002) used the evidential weighted approach in landslide hazard zonation. Landslides are phenomena, which can be predicted using probabilities. But land cover change is an indeterminist continuous phenomenon. Hence the prediction has to be done using fuzzy approach. According to the results of their study, land-use and land cover seems to be fuzzy in nature

In this research, the fuzzy approach is used to detect the change. It is an approach of change detection, which consists of three primary elements. They are fuzzy sets, membership functions and fuzzy production rules (Klein, 1999). The fuzzy rule based system allows the user to combine and process both subjective information obtained from an expert and objective observations and measurements (Bock and Salski, 1998). This can be successfully implemented for Post Classification Comparison (PCC).

Fuzzy rule based system consists of a set of rules to get a single output from *n*-dimensional input (Zeng, 2001). It has three main stages. They are Fuzzification of input data, Fuzzy inference system for analysis and Defuzzification stage.

2.5.1. Why fuzzy logic approach for change detection?

- *Fuzzy rule based system can be developed based on the experience of experts.*
  In contrast to artificial neural network, which considers training data and generates unclear, hidden models, fuzzy logic allows user to depend on the experience of people who already understand the system.
- *Fuzzy set theory is like natural language.*
  The language used for communication purpose is very vague and it can be easily converted into mathematical form using fuzzy rule based system.
- *Fuzzy logic system is flexible.*
  This system can be used for many applications and in many situations.
- *Fuzzy sets are easy to understand.*
  The mathematical concepts behind fuzzy reasoning like *minimum, maximum* etc. are very simple. These concepts have the "naturalness" in their approach.

Fuzzy rule based modeling is important particularly where the relations between the components of the system are not exactly known, if there is insufficient statistical data for analysis (Salski *et al.*, 1996) and if the data is uncertain about a particular thing, which the user needs. The rule based system can be developed using many linguistic rules, which can be formulated with "IF – THEN – ELSE" along with some fuzzy mathematical operators.

3. Study Area and Data

3.1. Study Area

Simla, the capital of Himachal Pradesh state, is one of the most famous tourist places of India. Simla district is famous for its natural beauties like hills, thick forest, snow peaks etc. The study area is located in the southern part of Himachal Pradesh, which is on the border of the Middle Himalayas. Simla district has a geographical extent of 30 45’ 50.54”N to 31 43’ 11.93”N and 76 59’ 33.92”E to 78 18’ 53.84”E.

The topography of Simla is very distinctive with altitude ranging from 397 meters to 2922 meters above mean sea level. The area is charecterised by a mixture of hills and valleys with slopes varying from a minimum of around 25 % to a maximum of around 75 – 80 %. Very few flat areas can be seen as more than 80 % of the whole study area having slopes of more than 65%.

Rainfall season is during June to September with an average of 1190 mm per annum (Source: - Directorate Economics & Statistics Department). This is the main source of water for agriculture and horticulture, which are the main sources of income of the district. Other sources of water for this area are the rivers like Sutluj, Giri, and Toans etc. Because of the aspect influence, we can see the vegetation on the northern side of hills. As southern slopes receive a high intensity of sunlight, there is less moisture when compared to northern slopes. It leads to barren land formation on the southern slopes.

The soil type is mostly acidic because of leaching caused by high rainfall. High amount of humus is found as a result of high forest coverage. There are two main catchments in this area – Sutluj basin and Yamuna basin. Water of Sutluj basin enters the Arabian Sea, whereas Yamuna basin water flows to the Bay of Bengal.

Economy is mainly depending on horticulture, agriculture, hydroelectric power generation and tourism. Regular and accurate information about the changes happening in this area is required to development authorities for the better administration and management.

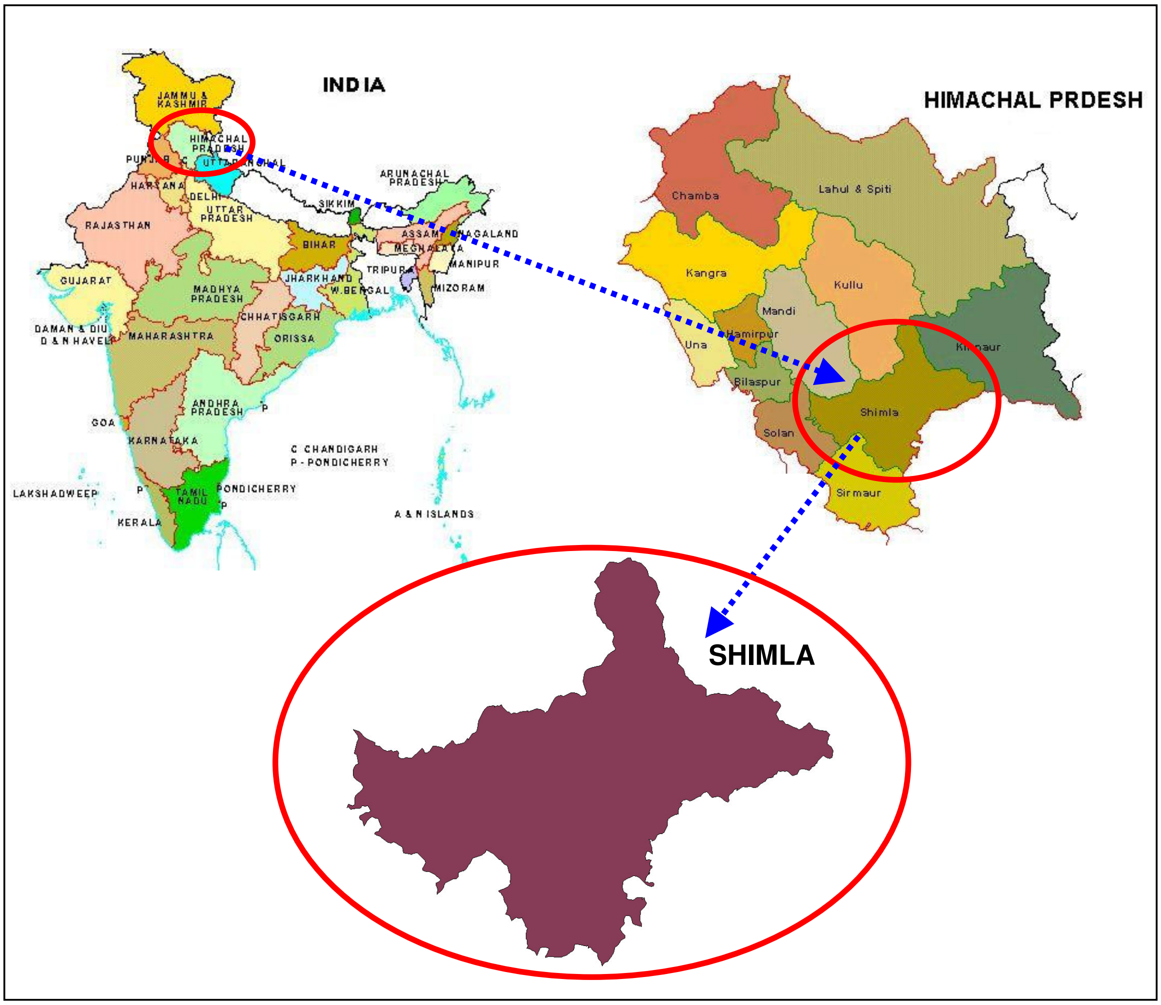


Figure 3-1 Study Area

3.2. Data

Two scenes of the LANDSAT – 5 TM satellite acquired in 1987 and the IRS-1D LISS-III satellite acquired in 1999 are used for this study. Both images are geo-referenced in Lambert Conformal Conic (LCC) projection system and Everest spheroid using ERDAS IMAGINE image processing software. First the IRS – 1D satellite image is geo-referenced with the help of 63 well-distributed points from Geo-coded hardcopy of the satellite images along with GPS readings. Image to image registration is done to geo-reference the LANDSAT – TM satellite image.

During pixel-by-pixel change detection process, it is important, that both the images should have same spatial resolution. The IRS-1D LISS-III image is resampled to 30 meters from its original resolution of 23 meters. The purpose of this step is to match the spatial resolution of the two images.

Only three bands in each satellite image are taken for the case study. This is because to make it easy to apply this methodology. But any number of bands can be taken for analysis.

With the wide range of spatial resolution and spectral bands, the IRS – 1D satellites can be used for a wide variety of applications. In the IRS – 1D satellite image 3rd, 2nd and 1st bands are taken into consideration for this work. The 3rd band is a near IR band with a wavelength of 0.77 – 0.86 μ. 2nd band is a red band and 1st is a green band with wavelengths 0.62 – 0.68 μ and 0.52 – 0.59 μ respectively. The 4th band, which is a short-wave infrared, having a very coarser resolution when compared to other three bands and hence it is not considered for classification.

In the LANDSAT – TM image, 5th, 4th and 3rd bands are used for classification, where 5th band is mid-IR with a wavelength of 1.55 – 1.74 μ. This band is sensitive to the amount of water in plants, which is useful in crop drought studies and in plant health analyses. Band 4 is a near IR band with 0.76 – 0.90 μ wavelength. This is responsive to determine different vegetation types, delineating water body and soil moisture discrimination. 3rd band is a visible red band with the wavelength of 0.63 – 0.69μ. This is very much useful in discriminating between many plant species. It is also useful for determining soil boundary and geological boundary delineations as well as cultural features (Lillesand and Kiefer, 1994).

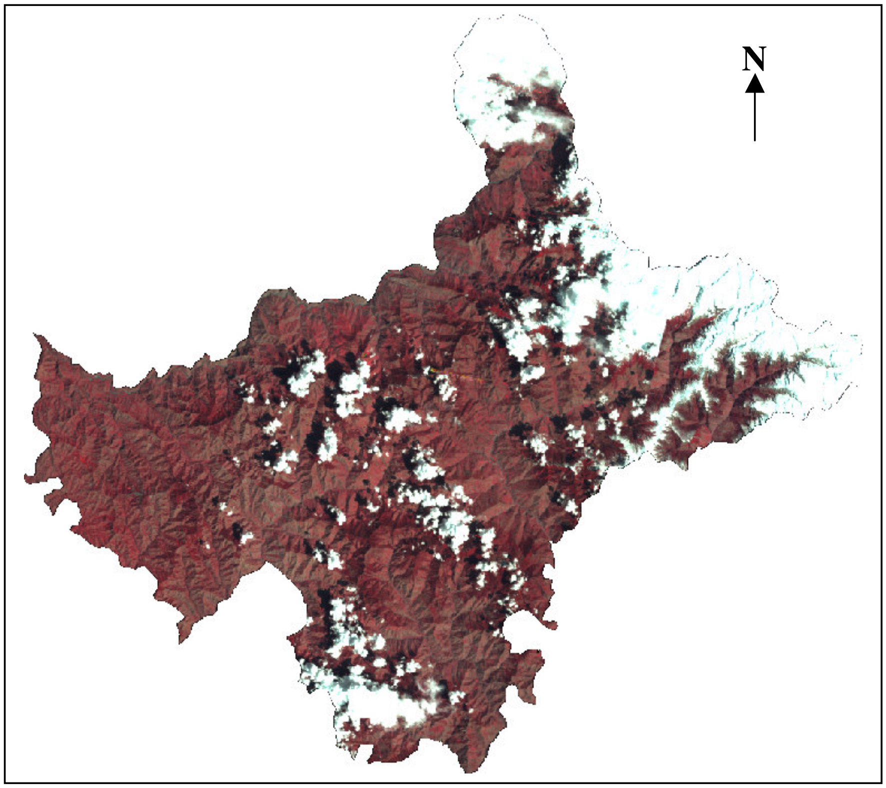


Figure 3-2 LANDSAT - TM Satellite Image

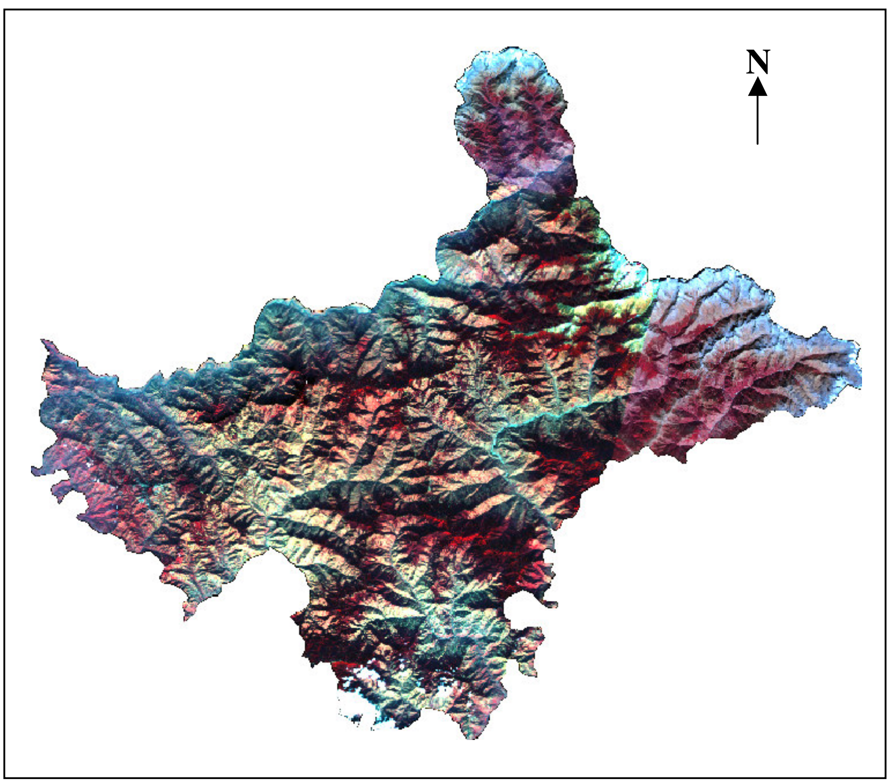


Figure 3-3 IRS - 1D Satellite Image

4. Methodology

The LANDSAT – TM image and the IRS –1D LISS –III images are used as image 1 and image 2 as shown in the figure 4.1. Three bands of LANDSAT – TM (5,4,3) and three bands of IRS – 1D LISS – III (3,2,1) images are taken into consideration for classification purpose. However, any number of bands can be taken in this approach and more number of bands will give better results.

Following flowchart (Figure 4-1) briefly shows the methodology of this research. Two images of the same area acquired on different dates are geo-referenced. On these images fuzzy membership functions are applied to get the classified maps. By using some fuzzy operators on these two images, change map is derived, which gives the information about magnitude, nature and direction of changes. Likelihood of changes is also proposed, but it needs more satellite image data sets as well as more ancillary data.

4.1. Geo-referencing

After obtaining the satellite images in digital format, images are geo-referenced and mosaiced using ERDAS IMAGINE image processing software. Geo-referencing attaches real world coordinates to the image so that it can be co-registered with any other imagery or spatial data that overlies the same area. Geo-referencing also enables warping an image to correct for topographic displacement.

Real worlds Ground Control Points (GCP), obtained with a GPS, are used for geo-referencing along with well-distributed points from geo-coded hard copy of the image. This method also attaches real world coordinates to pixels within an image. The number of reference points required depends on the complexity of topography and instrumental displacement or distortion within the image. As the study area is a hilly region, the number of GCPs used is high in this study.

Mosaicing is the method by which individual images are pieced together to form a single layer. Images were arranged according to their real world GCPs and by picking control points in overlapping areas. Most image processing software offer edge matching options such as averaging, feathering, mixing, maximum, minimum, etc, although these change data values to some extent. Averaging function is used in this study.

With the help of geo-coded hard copy of IRS – 1D satellite image and GPS readings of the study area are used for geo-referencing. Geo-referencing is done on Lambert Conformal Conic (LCC) projection, Everest spheroid and an undefined datum. LCC projection is used for zones extending mostly in an east – west direction. Lambert Conformal Conic projection system is developed by Lambert in 1772 and commonly used in mapping of the United States by the U.S. Geological Survey. While some distortion is inherent in all map projections, a characteristic of the Lambert conformal conic projection is that shape distortion is minimized (GIS Rule Definition, 2001). It is used mainly for mapping mid-latitude zones.

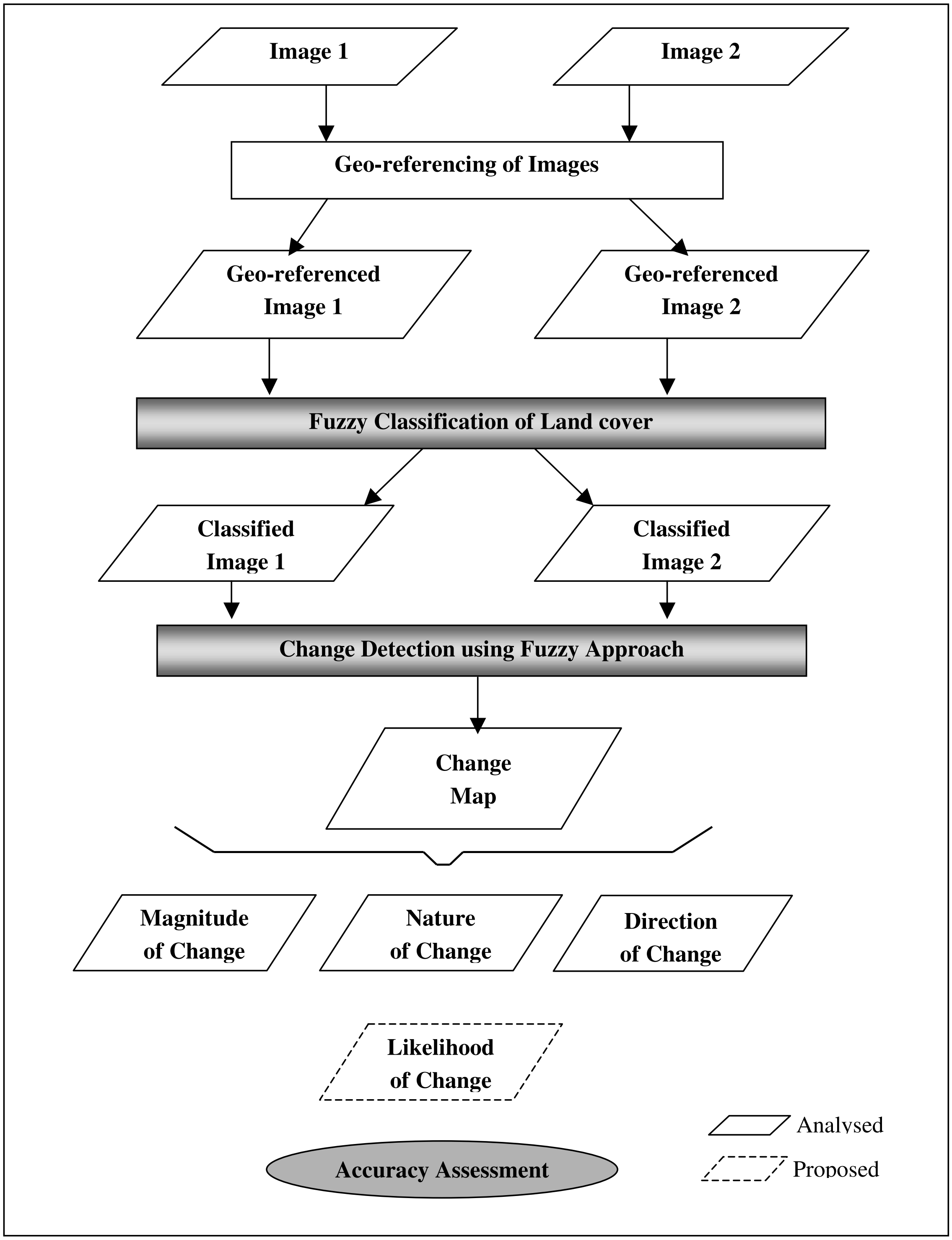


Figure 4-1 Flowchart of methodology

4.2. Fuzzy Classification

The approach used in this study to classify the images is based on Semantic Import Model (SIM) in which a prior knowledge of about the field is used. In this case, a fuzzy membership function is used to represent the prior knowledge.

There are many membership functions that can be used for land cover classification using a fuzzy approach. Example of fuzzy membership function shapes are Boolean, bell-shaped, triangular, trapezoidal etc. A Boolean function will result in a crisp classification without any fuzziness. The classification training set contains a range of pixels. A triangular function is not suitable to describe the data in the training set. It has only peak value, at which membership equals to 1. The bell-shaped function gives rise to a similar problem, where only one peak value is there along with many values nearer to the peak. So, this does not hold good for supervised classification.

A trapezoidal function or a function that results in a fuzzy set with a central core region and upper and lower transition zones with different widths can be successfully used for fuzzy supervised classification. The width of transition zone can be user defined based on field experience and on the extent of mixed pixels or mixels present in the image. In this study, the transition widths are defined both by the user based on field experience and statistics based on the training sets given for classification.

The transition width may be equally broad on either side of function or unequal, (Burrough and McDonnel, 1998) based on user requirement. If it is equal, it is called symmetric membership function otherwise it is asymmetric membership function.

In this case study, asymmetric membership functions are used. There is no standard set of rules for choosing a transition width for a membership function, but as explained by Burrough and McDonnel, it is meaningful if the transition width is related to what is known about the precision of measurement of the attribute of an object. As the land cover classes have diffused boundaries in geographic space, the transition width could be defined using expert knowledge from terrain. (Burrough and McDonnel, 1998)

In multi-spectral images, pixel values are considered as vectors in a feature space. Class clusters are formed by pixels showing similar spectral characteristics, which represent different user defined land cover classes. These groups are called *spectral classes* while the land cover classes are called *information classes*. (Wang, 1990)

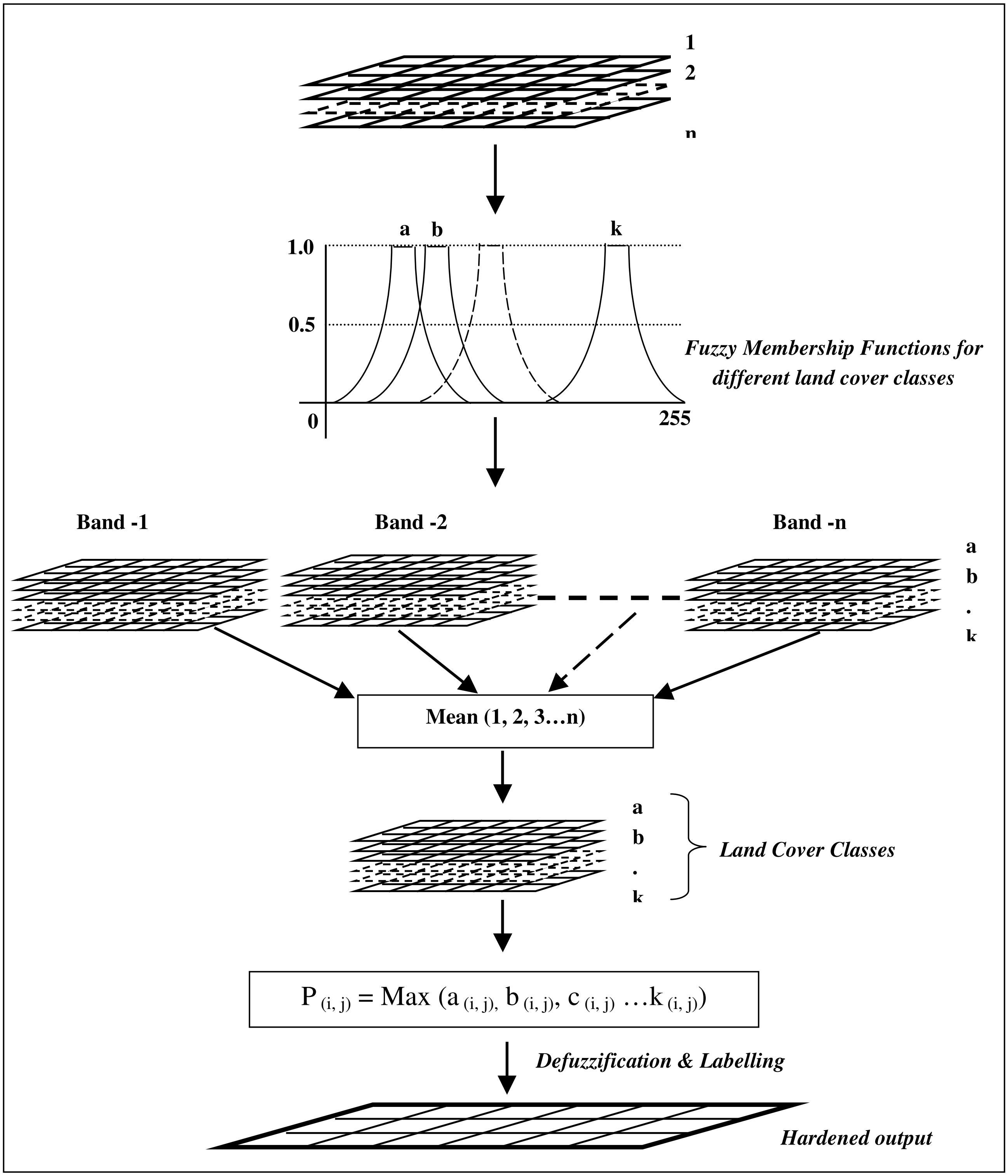


Figure 4-2 Fuzzy classification process

4.2.1. Fuzzy Membership Functions

We can see many kinds of membership functions to classify the images. As discussed in section 4.2, it may be triangular, trapezoidal, Gaussian, bell shaped or a function with a central core region and upper and lower transition zones with different widths.

Case – 1: Classification using statistically calculated transition width

In this case, transition width is calculated statistically using the following function.

$$\begin{aligned}\mathbf{TW(L)} &= (\text{mean} - \text{SD}) - \text{min} \\ \mathbf{TW(R)} &= \text{max} - (\text{mean} + \text{SD})\end{aligned} \qquad \textbf{Eq. 4.1}$$

Where TW(L) = Left transition width

TW(R) = Right transition width.

The fuzzy membership function used in this study is given below.

$$\boldsymbol{\mu}\,\mathbf{(x)} = \begin{cases} e^{\{x-(\text{min}-\text{SD})\}} & \forall x \in (\text{Min}) \text{ to } (\text{Mean} - \text{SD}) \\ 1 & \forall x \in (\text{Mean} - \text{SD}) \text{ to } (\text{Mean} + \text{SD}) \\ e^{\{(\text{max}+\text{SD})-x\}} & \forall x \in (\text{Mean} + \text{SD}) \text{ to } \text{Max} \\ 0 & \text{otherwise} \end{cases} \qquad \textbf{Eq. 4.2}$$

Where Min – minimum pixel value of the training set

Max – maximum pixel value of the training set

SD – standard deviation

If a training set consists of very heterogeneous pixels, then the standard deviation (SD) is more. In that case, in the above equation (Eq. 4.2) maximum membership value range is high and chances of overlapping of functions is also high. If the training sets are pure i.e. consisting of homogeneous pixels then the classified output is also accurate. But every time it may not be possible for a user to train the system with homogeneous training set. In that situation, a fuzzy algorithm gives good results as it can handle the overlapping functions better than crisp classification.

For example, in the Shimla district, agriculture is carried out along with horticulture. This area is confused with agriculture and forest. If we take this area as training set for agriculture, heterogeneity is high. This leads to high SD. At the same time, this area is similar to forest also; it assigns a high membership value to class forest also. Because of this reason, there is an overlapping of functions. In this while hardening the output map, some ancillary data can be incorporated and overlapping problem can be resolved.

Equation 4.2 gives the following membership functions (Figure 4-3) for different classes for different bands. Exponential functions are used here.

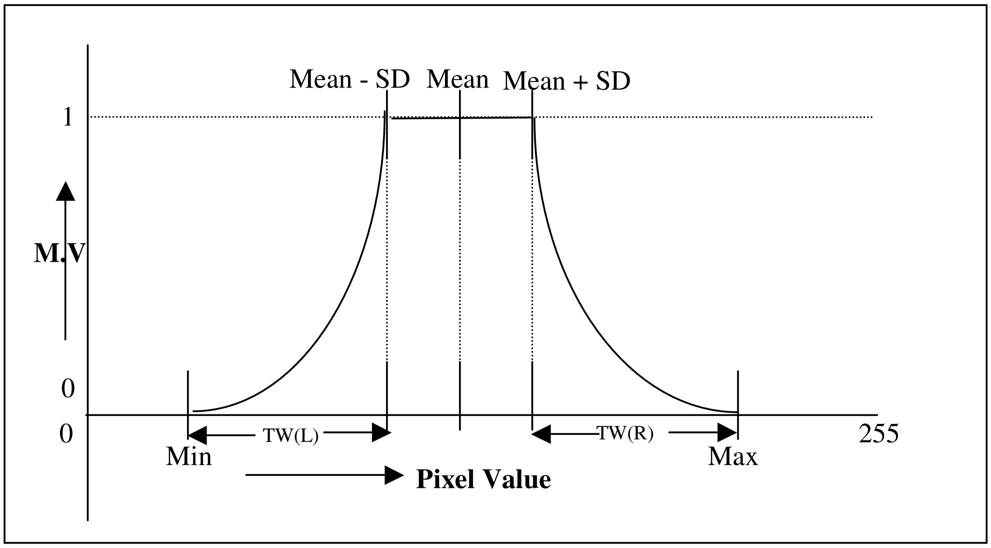


Figure 4-3 Membership function for statistically calculated transition width

Case – 2: Classification using user defined transition width

However based on user's requirements and application membership functions can be changed accordingly.

The function used for user defined transition width is as following.

$$\mu(x) = \begin{cases} e^{(x - Min)} & \forall x \in (Min - a) \text{ to } (Min) \\ 1 & \forall x \in (Min) \text{ to } (Max) \\ e^{(Max - x)} & \forall x \in (Max) \text{ to } (Max + b) \\ 0 & \text{otherwise} \end{cases} \qquad \textbf{Eq. 4.3}$$

Where *a* and *b* are the user defined transition widths
Min – minimum pixel value of the training set
Max – maximum pixel value of the training set

In this case, user is defining the transition width based on the field knowledge. If he feels that the terrain is having too vague boundaries between the classes, based upon his knowledge he can alter the transition width. But the main requirement here is that user has to train the system with pure seed pixels as it assigns the maximum membership value to the training set. Based on the transition widths defined by the user, the membership value increases or decreases exponentially.

This function will give the following kind of curve as in the previous case.

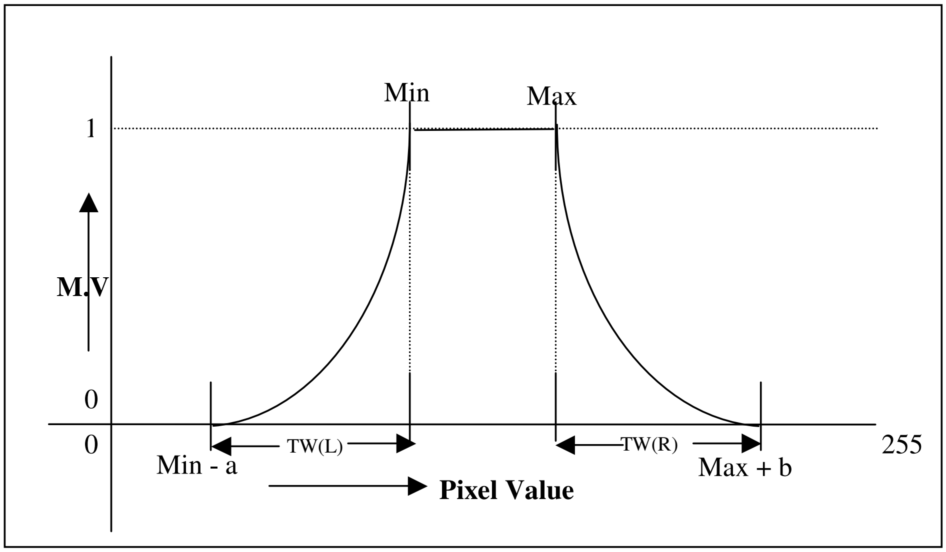


Figure 4-4 Membership function for user defined transition width

There will be overlapping of class curves because of vagueness in the boundary between two classes and mixed pixels. Because of these reasons, the reflectance of two classes is the same. This results in overlapping membership functions. But the amount of overlap differs from band to band in a multi-spectral image.

4.2.2. Fuzzy land cover classes

Application of these functions on the multi-spectral image with *n* spectral bands for *k* number of classes, results in (*n* x *k*) number of output images. Fuzzy representation of geographical classes in a layer with each pixel having its own membership value gives rise to following kind of *fuzzy partition matrix*.

$$\begin{pmatrix} f\mathrm{F}_{1(}x_{1)} & f\mathrm{F}_{1(}x_{2)} & \ldots\ldots & f\mathrm{F}_{1(}x_{p)} \\ f\mathrm{F}_{2(}x_{1)} & f\mathrm{F}_{2(}x_{2)} & \ldots\ldots & f\mathrm{F}_{2(}x_{p)} \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ f\mathrm{F}_{k(}x_{1)} & f\mathrm{F}_{k(}x_{2)} & \ldots\ldots & f\mathrm{F}_{k(}x_{p)} \end{pmatrix}$$

(Source: Wang, 1990)

Where *p* is the number of pixels, *k* is the number of predefined classes and $f\mathrm{F}_j$ is the membership function of the fuzzy set $\mathrm{F}_{j.}$

The mean of all the bands is calculated to normalize the membership value from 0 to 1. The mean function results in the output image with number of layers equal to the number of user defined classes (*k*) with each pixel in each layer has its own membership value of all classes.

Because of overlap in the spectral signatures of two or more classes, there will be overlap of the membership functions. (Figure 4.6.)

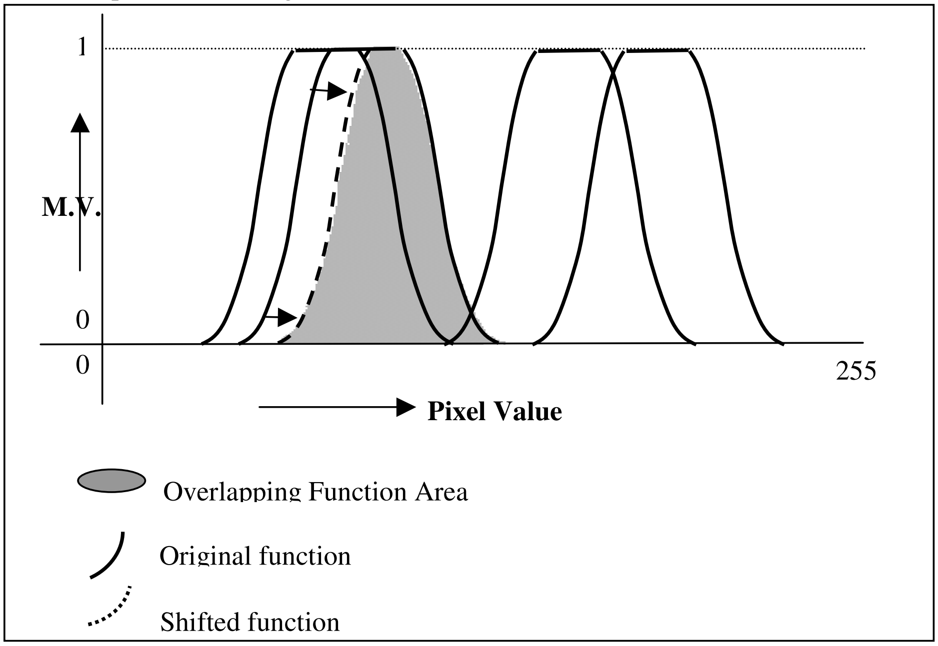


Figure 4-5 Overlap of Membership Function

Overlap may not be the same in all the bands. It differs based on the reflected energy in different wavelengths. Even after taking the mean of all the bands, there may be chance of overlapping between the classes. In that case it will be removed by shifting the over lapped peak value to a single class using ancillary data in a fuzzy rule based system. Ancillary data may be field knowledge, slope, aspect, Digital Elevation Model (DEM), etc.

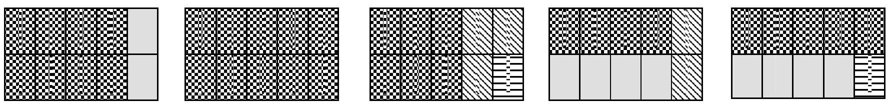
It can be explained by taking an example as following. After taking the mean, if grassland has its peak values as that of agriculture, then slope can be taken into consideration. If the slope is more than 60 %, then it can be classified into grassland because possibilities of agriculture is very less on the area with slope more than 60%. However it is subjected to the field conditions.

4.2.3. Defuzzification

To represent the output, it is necessary to harden the image. This can be done using standard defuzzification process. For defuzzification, *MAXIMUM* function is used here. Taking the maximum membership value of each pixel, hardening image is done. But at this stage one cannot determine from which layer the maximum value has came from. Also, if two or more classes are having the same membership value, then to which class the pixel has to be assigned? To solve these, labeling of classes is achieved using knowledge engineer of ERDAS IMAGINE.

The defuzzification using maximum function is explained with an example here (Source: Arnot, 2003). By taking five sample pixels with different composition of membership values of different classes.

Pixel	Class				Maximum Membership Class	CI
	A	B	C	D		
1	0.8	0.2	0.0	0.0	**A**	0.25
2	1.0	0.0	0.0	0.0	**A**	0
3	0.6	0.0	0.3	0.1	**A**	0.5
4	0.4	0.4	0.2	0.0	**A** *	1
5	0.5	0.4	0.0	0.1	**A**	0.8



1 **2** **3** **4** **5**

* Even though class 'A' and class 'B' are having the same membership value, it is assigned to class 'A' based on the ancillary data used in defuzzification.

Figure 4-6 Hardening a pixel maximum membership values

Five pixels are shown here with different proportion of membership values. Class A has the greatest membership value than any other classes. So, all five pixels are assigned as class A. Confusion index (CI) is calculated in all the cases using the equation 4.4. Greater the value of CI, less the certainty of that class. For example in pixel 4 in the above figure, both class A and B are having the same membership values, hence more is the CI. Thus CI indicates the pixels of high classification uncertainty. While hardening the image, classifier attempts to assign the pixel to a class with the maximum membership value, which will cause the resulting uncertainty.

4.2.4. Uncertainty measure

Uncertainty present in a land cover class can be measured by calculating the confusion index. The confusion index (CI) is the ratio of the second highest class membership value to the highest. More the CI, more is the uncertainty. The confusion index values are scaled between 0-1,

$$\boxed{CI = \frac{P_{2(i)}}{P_{1(i)}}} \qquad \textbf{Eq. 4.4}$$

Where P2 = Second maximum membership value,

P1 = Maximum membership value

i = Pixel index

This is one of the measures of uncertainty in a classified image. If the values of two classes are similar, then CI is close to one, meaning that there is a high confusion about class membership. If a pixel is a pure pixel, it will have a maximum value of membership value to that class and other classes will have lower membership value. Then CI will be close or equal to 0.

4.2.5. Maximum likelihood classification

Both the LANDSAT – TM and IRS – 1D satellite images classified using Maximum likelihood classification method. The same training sets used for fuzzy classification is used for classification in this case also. This is carried out just to compare the results and accuracies of both crisp and fuzzy classification.

4.2.6. Accuracy Assessment

The land cover displays continuous variation in class composition at all scales. Segmenting the earth's surface into map units with relatively homogeneous composition of different class, at a particular observational scale, is a useful, but a hectic, activity.

Accuracy assessment is one of the toughest works because of the technological constraints and logistical constraints. Because of the hilly terrain, it is very difficult to get the precise GPS readings. Especially in the valleys and in dense forest, the receiver is not able to detect the satellites. This is one of the technological constraints where as the logistical constraints are like many places are not easily reachable because of too difficult roads (landslides, hilly terrain), far away from existing roads and access is denied by the owners (some apple orchards and potato fields).

Error matrix is calculated for both images and for both kinds of classification viz. user defined transition width and statistically calculated transition width. More than 200 points are identified on the ground and with the help of a hand held GPS, ground truthing is done for the accuracy assessment purpose.

4.3. Change Detection Using Fuzzy Approach

4.3.1. Magnitude of Change (MC)

To quantify the occurred change, we need to calculate the magnitude of change. It is calculated using the principle used in spectral change vector analysis.

The difference between two fuzzy classified images is calculated using the fuzzy difference operator. This is the summation of absolute difference between membership functions of each class in two different times.

The function used to calculate magnitude of change is given below.

$$\boxed{\mathbf{MC}_{(i)} = \sum_{c=1}^{k} | \mu^{1}{}_{c(i)} - \mu^{2}{}_{c(i)} | / k} \qquad \textbf{Eq. 4.5}$$

Where $\mu^1{}_{c(i)}$ and $\mu^2{}_{c(i)}$ are membership functions of pixel i of class k at date 1 and date 2 respectively.

4.3.2. Nature of Change (NC)

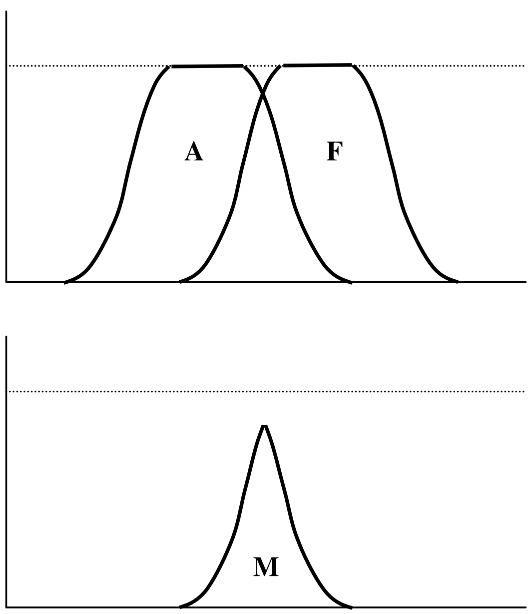
In the nature of change, every pixel of both the images is compared for user-interested classes. Fuzzy operators can be successfully used to know the nature of change.

For example, the analysis like "which pixels of class *F* in time *t1* have changed to class *A* in time *t2*" etc. this can be explained as follows.

A pixel *i* belongs to class *F* at time *t1* to the extent of $\mu^1{}_{F\,(i)}$ and at time *t2* belongs to class *A* to the extent of $\mu^2{}_{A\,(i)}$. The membership value of change class *F* and *A* is

$$\boxed{\mathbf{NC}_{\mathbf{F,\,A(i)}} = \min[\ \mu^1 F(i),\ \mu^2 A(i)\ ]} \qquad \textbf{Eq. 4.6}$$

The *minimum* operator is used here as it gives the least upper bound on the chosen class. Additionally this operator provides highest reasonable estimate of membership of that particular change class, i.e. class *F* to *A*. ((Deer and Eklund, 2001). The *minimum* operator in fuzzy sets is analogous to the intersection of two sets in classical set theory. It is also called fuzzy *AND* operator. It can be shown as in the following figure.



A and F are the continuous classes, Agriculture (A) and Forest (F) respectively.

M is the change class (A, F) using equation 4.6

Figure 4-7 Intersection of two fuzzy sets

4.3.3. Direction of Change (DC)

It is nothing but *maximum* of all the comparisons made in the *nature of change*. If there are *k* predefined classes, total comparisons will be k^2. The *maximum* of all these comparisons is taken as the *direction of change*. The *maximum* function acts as a defuzzifier.

$$\mathbf{DC(i)} = \max\{ NC_{c1,c2}(i) / c1, c2 \in 1,2...k \} \qquad \textbf{Eq. 4.7}$$

Where NC = Nature of changes

c1 = class at date – 1

c2 = class at date – 2

k = No. of classes

Even though there are more changes in a single pixel, to represent a change the image has to be hardened. This tells that whether a pixel is changing to a class from another class or it is not. The result of direction of change analysis can be used in future change prediction model as this result includes magnitude information also.

4.3.4. Proposed model of Likelihood of Change (LC)

Likelihood of change can be analysed by developing a rule-based system that uses the fuzzy approach. It has different components as maps like magnitude of change, direction of change, ancillary data like slope, wetness index, socio-economic data etc. To get more accurate results, it is advised to use more data as the components of this system.

The system uses the magnitude of change map, direction of change map and ancillary data in degrees as the fuzzy input. In the second step, i.e. fuzzy inference system for analysis, the rules are developed using "IF – THEN – ELSE" and some fuzzy operator are used.

Fuzzy Knowledge Based System for likelihood of change

This is a Post Classification Comparison (PCC) using fuzzy rule based approach. This system is developed based on different functions on fuzzy sets like fuzzy intersection (fuzzy AND operator), fuzzy union (fuzzy OR operator), fuzzy implication operator (*IF, THEN, ELSE* rules) etc. The fuzzy knowledge based system should have the following three important stages.

1. *Fuzzification of input data:* In this stage the crisp input is transformed into fuzzy set, which can be used in the fuzzy inference. In the satellite images, the DN values for a particular class is a crisp set and is fuzzified by applying the membership functions on both the satellite images to classify those into different classes.

2. *Fuzzy inference for analysis:* The fuzzy rules are generated in this stage. By applying the fuzzy implications operators like IF, THEN, ELSE rules, on both the fuzzy classified images, the change detection analysis is done.

3. *Defuzzification of fuzzy output:* This process converts the fuzzy values back to crisp values. Once the analysis is over, it has to be presented as crisp values. The map has to be "hardened" to represent the output classes as one cannot represent two or more classes for a pixel in a single output map. Hardening is done by the defuzzification process using fuzzy operators like *MAXIMUM, MINIMUM* etc.

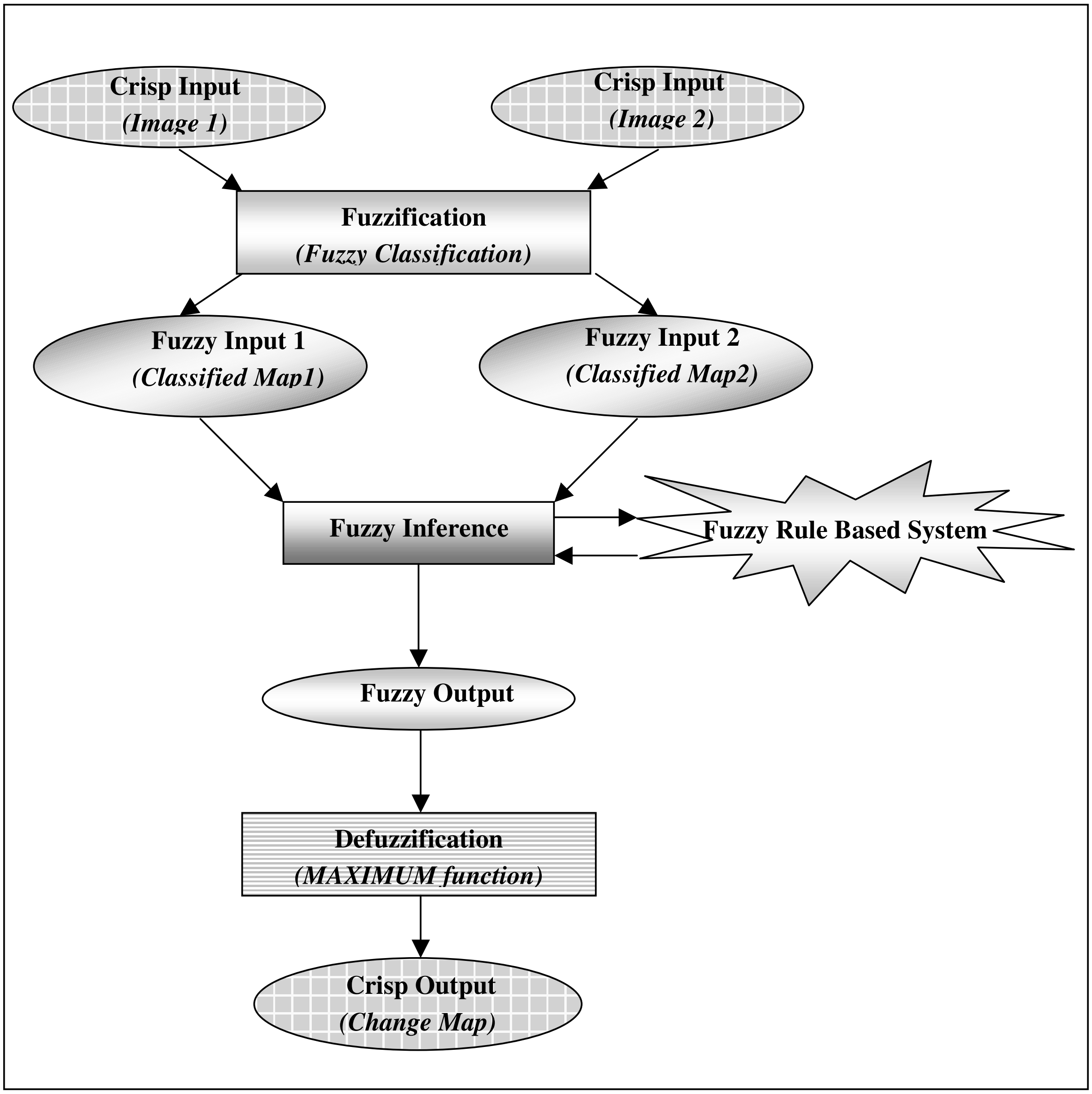


Figure 4-8 Fuzzy Rule Based System

5. Results and Discussions

5.1. Classification of fuzzy land cover classes

Out of four bands available in IRS – 1D satellite image 3rd, 2nd and 1st bands and 5th, 4th and 3rd bands of LANDSAT – TM satellite image are taken into consideration. This is just to make the analysis work easier. As discussed in the Chapter 4, the fuzzy classification of an image results in different fuzzy files for different classes. There are totally six predefined classes for three bands in each image. It results in three images for each class and thus the total number of fuzzy files is 18 (i.e.6 x 3) each in date – 1 (1987) and date – 2 (1999). The mean of the above three images are taken for all the classes and the resultant is only one fuzzy image for each class.

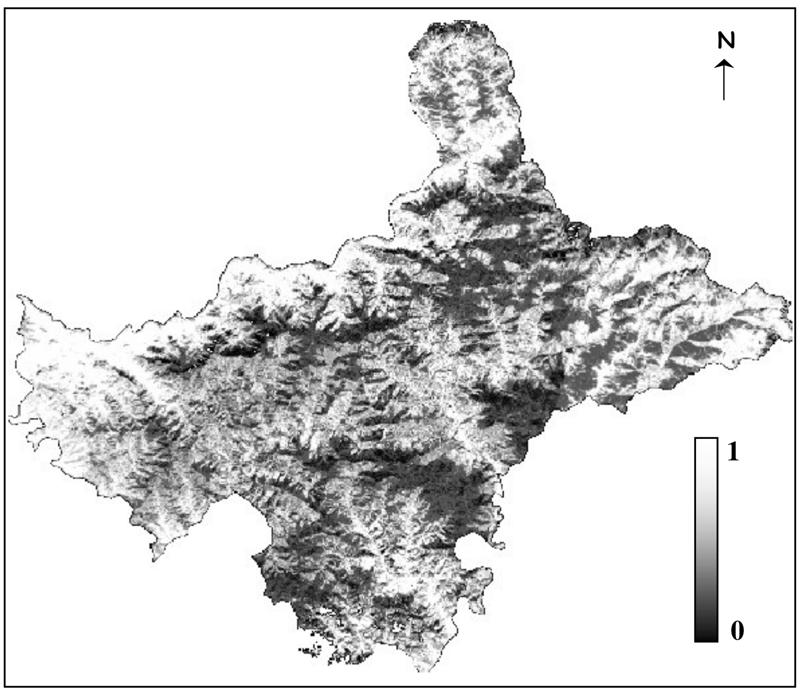


Figure 5-1 Fuzzy classified output of Agriculture in IRS – 1D satellite image

One of the examples is taken here i.e. class AGRICULTURE, from the IRS – 1D satellite image of year 1999. In figure 5-1, more the brightness value higher is the membership value. The field survey clearly showed that these results are true to the satisfactory extent. In the Shimla district, agriculture is predominant on the banks of rivers like Sutlej, Giri, and Toans etc. and in the valleys as small patches. The above figure clearly shows that more brightness value (in turn it is membership values) can be seen on the riversides and in some valleys. In this district, usually agriculture is mixed with horticulture like apple, apricot etc. This leads to mixed pixels of agriculture and horticulture and hence reduces the membership value for agriculture in a particular pixel.

In the same way all six other classes i.e. FOREST, WATER BODY, BARREN LAND, SETTLEMENT and SNOW COVERED LAND are classified. All these are stacked one on the other and *MIXIMUM* function is applied for the defuzzification purpose. At the same time labeling is also done to identify the class. Slope is taken into consideration as ancillary data while defuzzifying the image. For example, if a pixel is having the maximum value to two classes – agriculture and grass land – and if the slope is more than 60 %, then that class is assigned to grass land, as on a land with more than 60 % slope, one cannot expect agriculture.

5.1.1. Fuzzy Classification of LANDSAT-TM image based on user defined transition width

Overall accuracy of fuzzy classified LANDSAT – TM Image using a fuzzy membership function with user defined transition width is 70.35 %. Study area is having a lot of hills and valleys, which results in more shadows in the satellite images. These shadows resulted in misclassification.

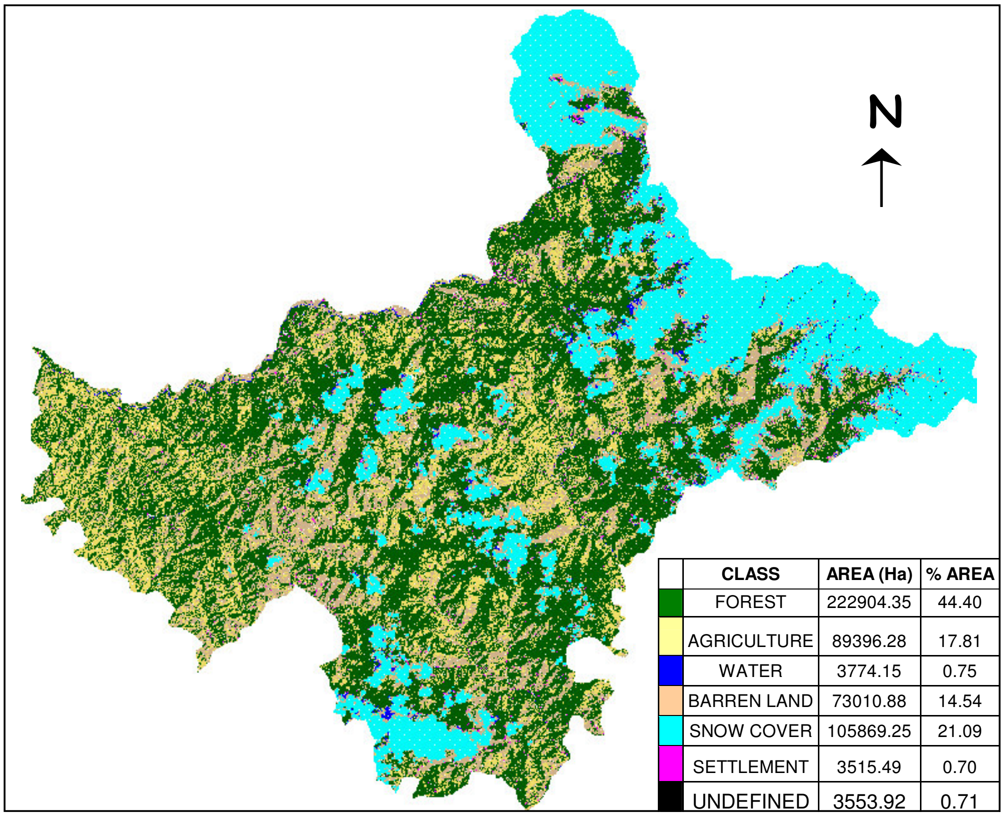
Only 59.09 % and 46.67 % of accuracies are obtained in agriculture and barren land respectively. This is mainly because both classes are having the same reflectance value. User's accuracy is very poor in case of settlement. This is because of the same signatures between settlement and some barren land where we can find lot of hard rocks. Also the some riverbed areas are giving the same reflectance value as that of settlement.

Mixed pixel information shows that around 18 % area with very high, and 6 % area with high uncertainty. This is very difficult to assign those classes to a single class, as it is not possible to represent all the classes in a single pixel as a map, though the information can be shown. But while assessing accuracy, all the classes of a single pixel is not taken into consideration as reference to that pixel. That's why the results of the hardened output are of less accurate.

Table 5-1 Accuracy assessment of classified LANDSAT – TM Image based on user defined transition width

Class	Reference	Classified	No. Correct	Producer's Accuracy	User's Accuracy
Forest	43	48	38	88.37	79.17
Agriculture	44	37	26	59.09	70.27
Water	8	10	8	100.00	80.00
Barren Land	60	36	28	46.67	77.78
Snow Cover	35	39	33	94.29	84.62
Settlement	9	21	7	77.78	33.33
Undefined	0	8	0	0.00	0.00
TOTAL	**199**	**199**	**140**		

Overall classification accuracy: **70.35%**
Overall Kappa statistics = **0.6344**



CLASS	AREA (Ha)	% AREA
FOREST	222904.35	44.40
AGRICULTURE	89396.28	17.81
WATER	3774.15	0.75
BARREN LAND	73010.88	14.54
SNOW COVER	105869.25	21.09
SETTLEMENT	3515.49	0.70
UNDEFINED	3553.92	0.71

Figure 5-2 Defuzzified output of classified LANDSAT – TM Image based on user defined transition width

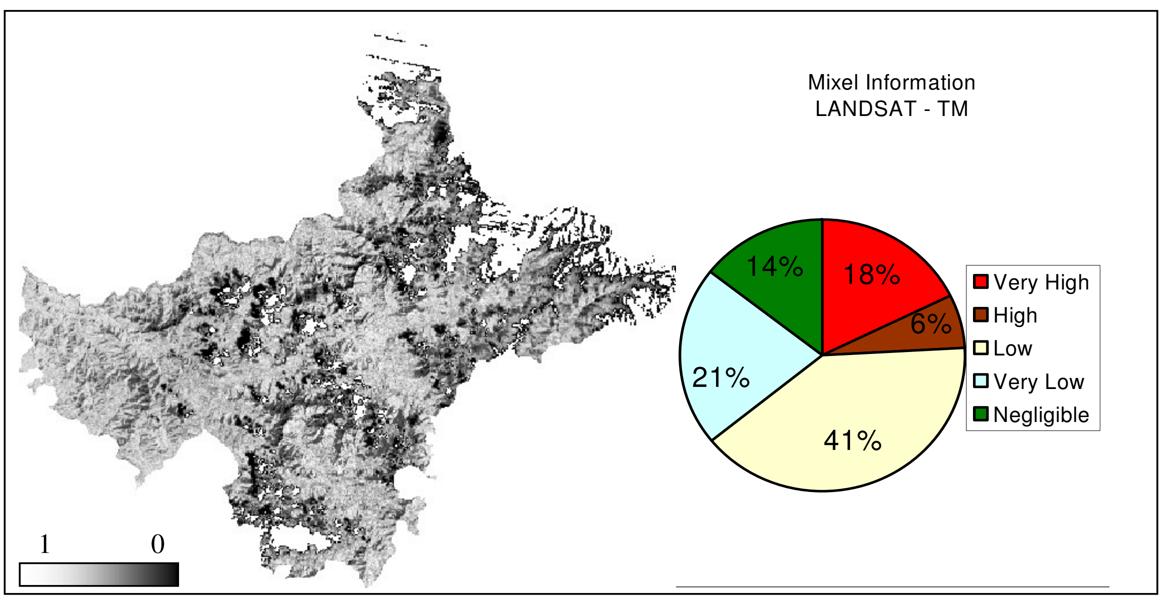


Figure 5-3 Confusion Index for LANDSAT - TM image based on user defined transition width

5.1.2. Fuzzy Classification of LANDSAT-TM image based on statistically calculated transition width

By examining the confusion matrix individually, it can be seen that in both cases, classification accuracy of agriculture is lower. Seasonal variation between data acquisition and ground data collection has a lot of influence on the results. Agriculture is mainly dependent on season here. During March – April, many flat fields are covered by snow, but the same area is under agriculture during October. These issues lead to a lot of confusion during accuracy assessment.

The accuracy of class agriculture and barren land are comparatively low in both membership functions because of the similarity in the reflectance of both the classes. Agriculture lands are kept fallow during summer and satellite data is acquired in the same period. These areas are classified into class barren land. This is one of the main reasons of misclassification.

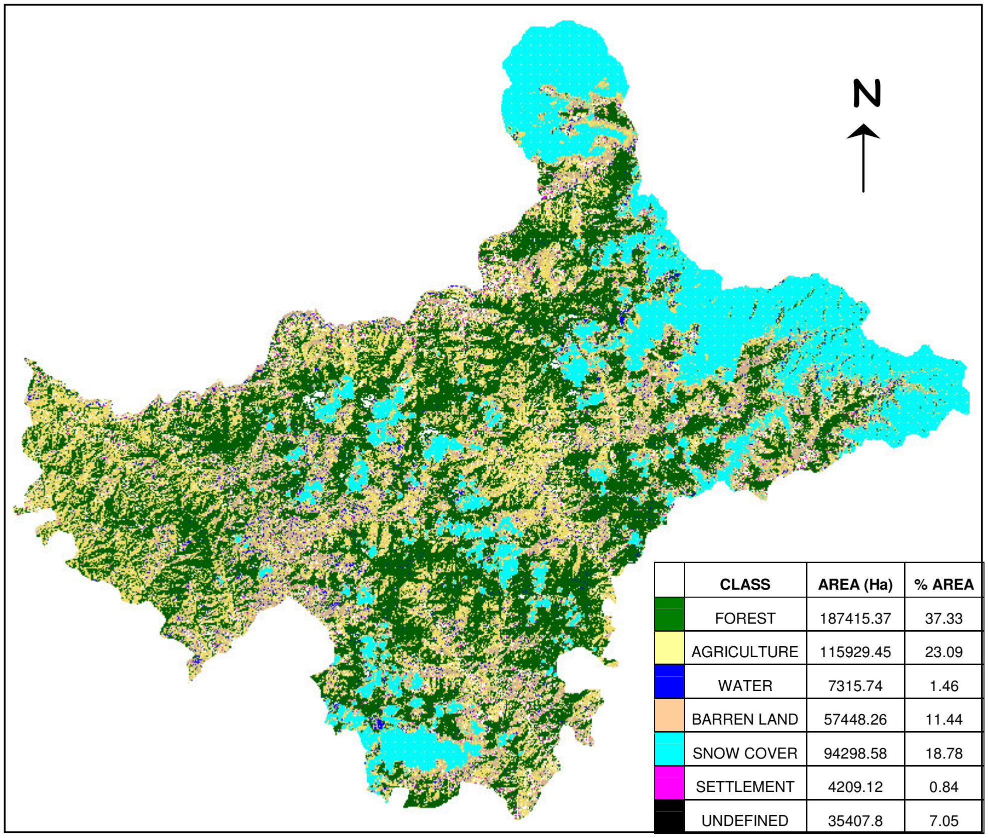
As this study is carried out to test the methodology, only three bands are taken into consideration. The omission of other four bands could be one of the reasons for loosing information from the satellite image.

Table 5-2 Accuracy assessment of classified LANDSAT – TM Image based on statistically calculated transition width

Class	Reference	Classified	No. Correct	Producer's Accuracy	User's Accuracy
Forest	47	57	35	74.47	61.40
Agriculture	40	43	30	75.00	69.77
Water	9	12	8	88.89	66.67
Barren Land	61	52	42	68.85	80.77
Snow Cover	31	9	7	22.58	77.78
Settlement	11	13	7	63.64	53.85
Undefined	0	13	0	0.00	0.00
TOTAL	199	199	129		

Overall classification accuracy: **64.82%**

Overall Kappa statistics = **0.5632**



	CLASS	AREA (Ha)	% AREA
	FOREST	187415.37	37.33
	AGRICULTURE	115929.45	23.09
	WATER	7315.74	1.46
	BARREN LAND	57448.26	11.44
	SNOW COVER	94298.58	18.78
	SETTLEMENT	4209.12	0.84
	UNDEFINED	35407.8	7.05

Figure 5-4 Defuzzified output of classified LANDSAT – TM Image based on statistically calculated transition width

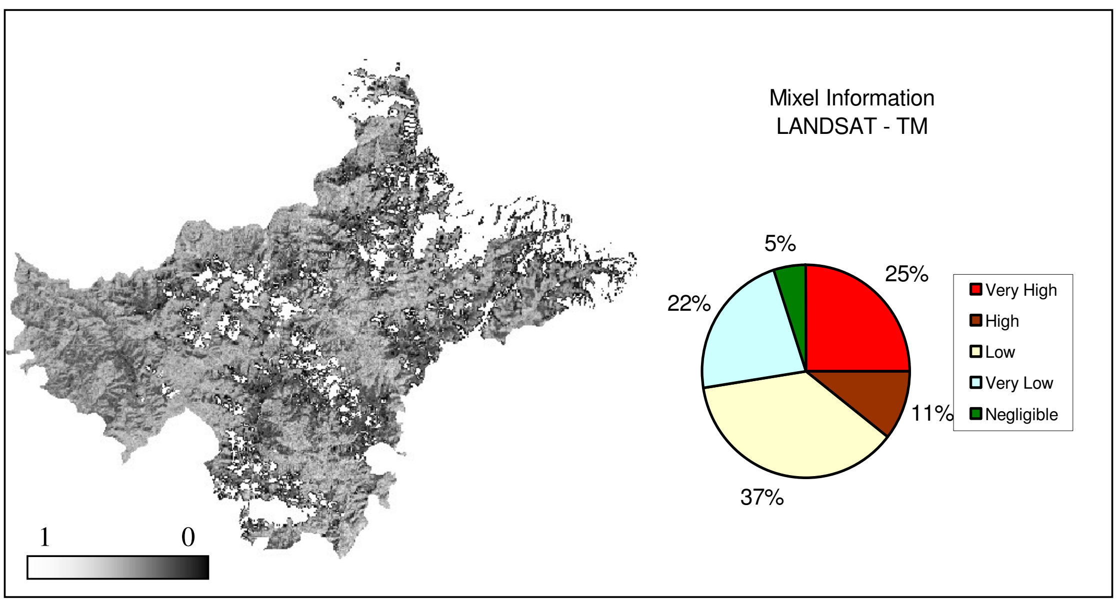


Figure 5-5 Confusion index for LANDSAT - TM image based on statistically calculated transition width

5.1.3. Fuzzy Classification of IRS-1D image based on user defined transition width

In this case low user's accuracies can be seen in forest and water, 73.58 % and 53.33 % respectively. This is because of shadow effects. As the whole study area is under hilly terrain, maximum forest area is under shadow. This leads to misclassification with water.

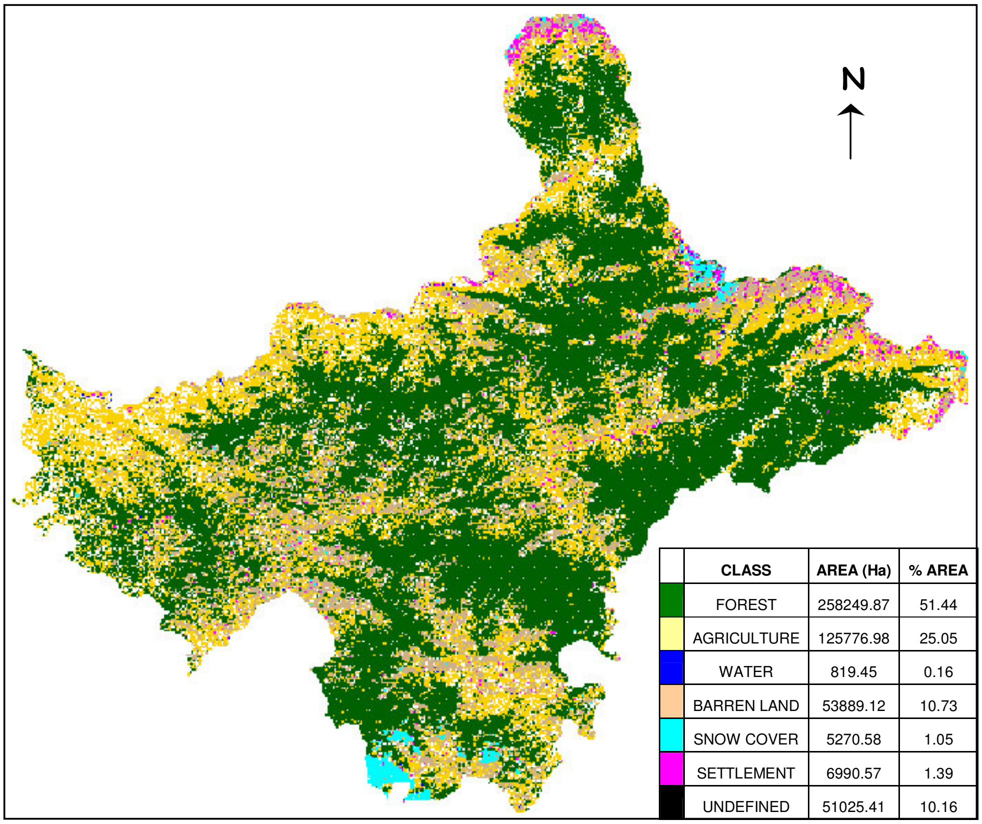
Producer's accuracy of snow is very poor i.e. 16.13 %, because of the seasonal gap between ground data collection and satellite data acquisition. This is one of the major drawbacks of accuracy assessment, which is called temporal accuracy.

In case of settlement, user's accuracy is very less because many of the barren land areas are classified as settlement. This is because of the same digital number in the satellite data. Even though, overlapping functions are resolved, it is not possible to overcome this problem completely.

Table 5-3 Accuracy assessment of classified IRS - 1D Image based on user defined transition width

Class	Reference	Classified	No. Correct	Producer's Accuracy	User's Accuracy
Forest	43	53	39	90.70	73.58
Agriculture	46	42	37	80.43	88.10
Water	10	15	8	80.00	53.33
Barren Land	60	49	42	70.00	85.71
Snow Cover	31	6	5	16.13	83.33
Settlement	9	26	8	88.89	30.77
Undefined	0	8	0	0.00	0.00
TOTAL	**199**	**199**	**139**		

Overall classification accuracy: **69.85 %**
Overall Kappa statistics = **0.6254**



	CLASS	AREA (Ha)	% AREA
	FOREST	258249.87	51.44
	AGRICULTURE	125776.98	25.05
	WATER	819.45	0.16
	BARREN LAND	53889.12	10.73
	SNOW COVER	5270.58	1.05
	SETTLEMENT	6990.57	1.39
	UNDEFINED	51025.41	10.16

Figure 5-6 Defuzzified output of classified IRS – 1D Image based on user defined transition width

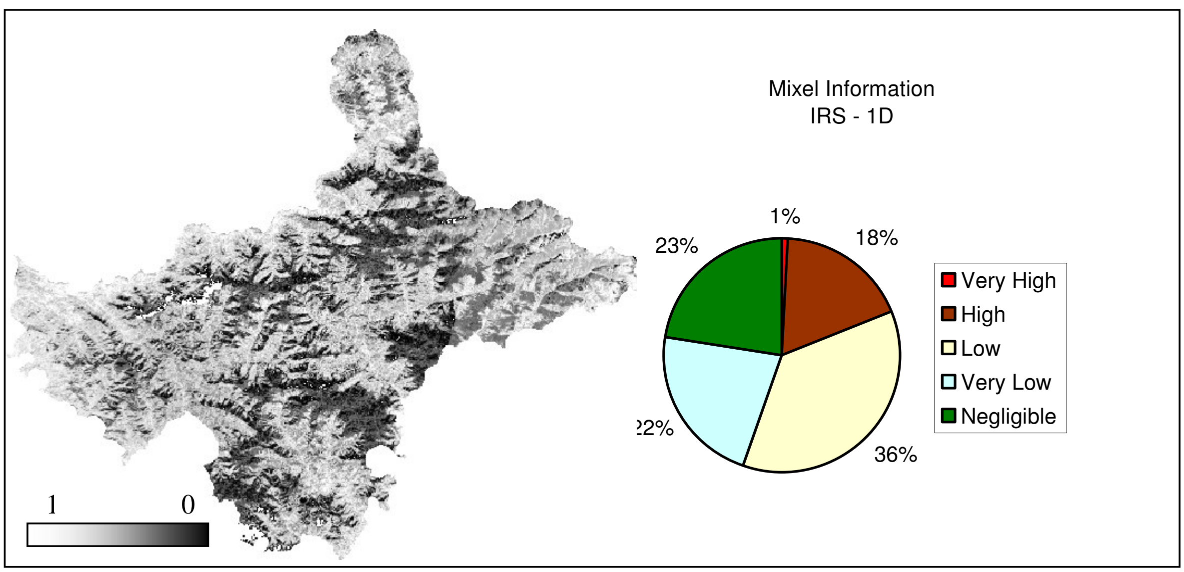


Figure 5-7 Confusion index for IRS - 1D image based on user defined transition width

5.1.4. Fuzzy Classification of IRS-1D image based on statistically calculated transition width

In IRS – 1D classified output water and settlement are giving low user's accuracy in both the cases. Low user's accuracy of water is because of shadow effects. Because of the shadows, some of the areas are giving the same reflectance value as that of water. This is the main reason for misclassification of water.

For the change detection purpose, both images should have the same spatial resolution. To achieve this pixel resolution of the IRS – 1D is resampled to 30 meters. The original resolution of this image is 23 meters. This leads to loss of information. This could also be one of the reasons for lower accuracy.

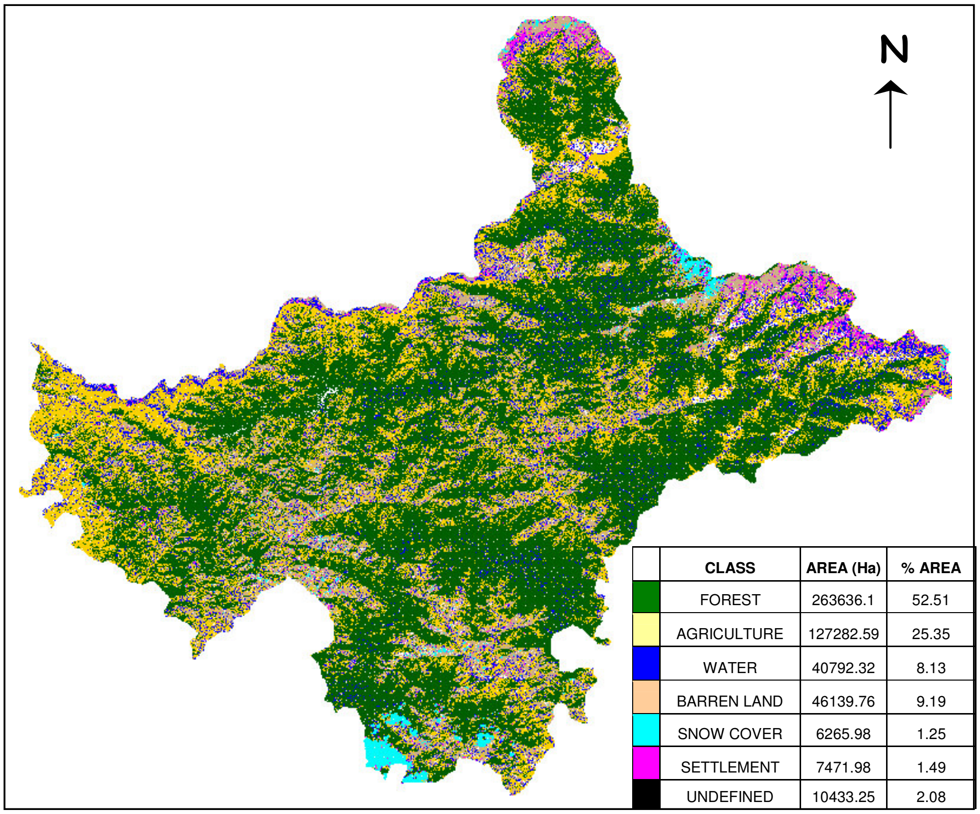
By the above results it is clear that, accuracy in case where transition width defined by the user is giving good results. This is mainly because of the knowledge about the field. An extensive fieldwork is done to give the training set for classifier. All the major classes are identified before going to field and stratified random sampling method is adapted for sampling. Samples are collected for mixed classes also as it is very much important in defining transition widths of a fuzzy membership function, which in tern responsible for a successful classification. Hence accuracy is better in the first case than in case where transition width is calculated statistically.

Table 5-4 Accuracy assessment of classified IRD – 1D Image based on statistically calculated transition width

Class	Reference	Classified	No. Correct	Producer's Accuracy	User's Accuracy
Forest	44	59	39	88.64	66.10
Agriculture	45	52	39	86.67	75.00
Water	9	13	8	88.89	61.54
Barren Land	60	43	36	60.00	83.72
Snow Cover	31	3	3	9.68	100.00
Settlement	10	14	8	80.00	57.14
Undefined	0	15	0	0.00	0.00
TOTAL	**199**	**199**	**133**		

Overall classification accuracy: **68.83 %**

Overall Kappa statistics = **0.5861**



	CLASS	AREA (Ha)	% AREA
	FOREST	263636.1	52.51
	AGRICULTURE	127282.59	25.35
	WATER	40792.32	8.13
	BARREN LAND	46139.76	9.19
	SNOW COVER	6265.98	1.25
	SETTLEMENT	7471.98	1.49
	UNDEFINED	10433.25	2.08

Figure 5-8 Defuzzified output of classified IRS – 1D Image based on statistically calculated transition width

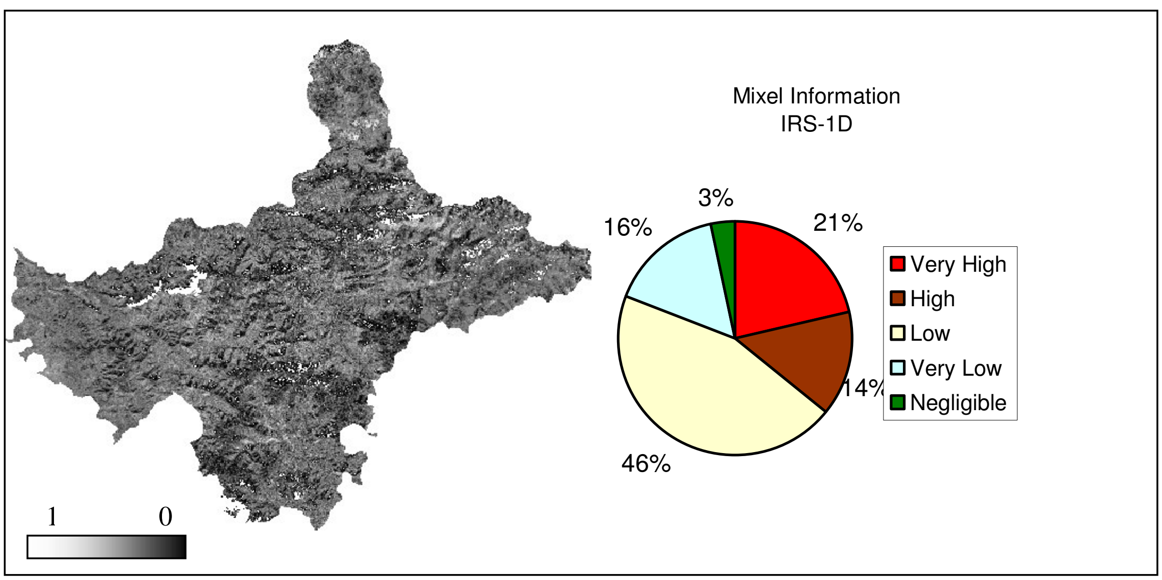


Figure 5-9 Confusion index for IRS – 1D image based statistically calculated transition width

5.1.5. Comparison between Supervised Fuzzy Classification and Maximum Likelihood Classification

Both images are classifies based on maximum likelihood classification method using the same training sets used for supervised fuzzy classification. The maximum likelihood decision rule is based on the probability that a pixel belongs to a particular class. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions.

In both the images, settlement is having very low user's accuracy. Also this has low accuracy when compared to supervised fuzzy classification proposed in this study. This is because; maximum likelihood classification is crisp classification process, which cannot resolve the overlapping function as that of a fuzzy classifier.

Table 5-5Accuracy assessment of LANDSAT – TM Image based on maximum likelihood classification

Class	Reference	Classified	No. Correct	Producer's Accuracy	User's Accuracy
Forest	44	54	35	79.55	64.81
Agriculture	45	56	36	80.00	64.29
Water	9	13	8	88.89	61.54
Barren Land	60	48	33	55.00	68.75
Snow Cover	31	5	4	12.90	80.00
Settlement	10	23	9	90.00	39.13
Undefined	0	0	0	0.00	0.00
TOTAL	**199**	**199**	**125**		

Overall classification accuracy: **62.81 %**
Overall Kappa statistics = **0.5298**

Table 5-6 Accuracy assessment of IRS - 1D Image based on maximum likelihood classification

Class	Reference	Classified	No. Correct	Producer's Accuracy	User's Accuracy
Forest	44	57	39	88.64	68.42
Agriculture	45	50	33	73.33	66.00
Water	9	15	8	88.89	53.33
Barren Land	60	46	31	51.67	67.39
Snow Cover	31	6	4	12.90	66.67
Settlement	10	25	8	80.00	32.00
Undefined	0	0	0	0.00	0.00
TOTAL	**199**	**199**	**123**		

Overall classification accuracy: **61.81 %**
Overall Kappa statistics = **0.5200**

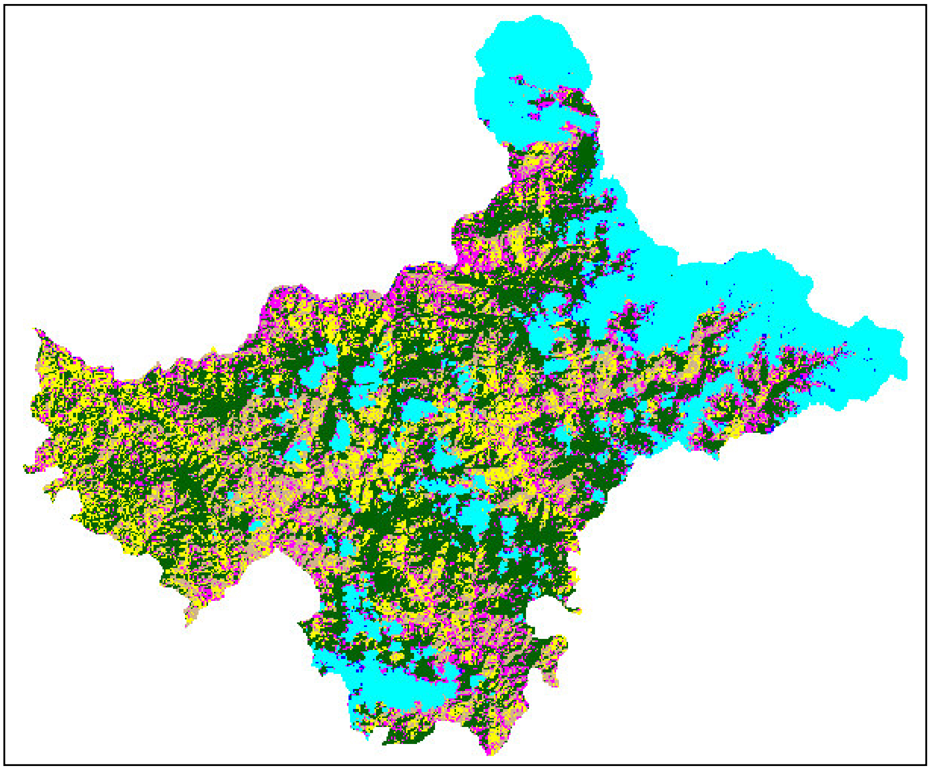


Figure 5-10 Maximum likelihood classification of LANDSAT - TM image

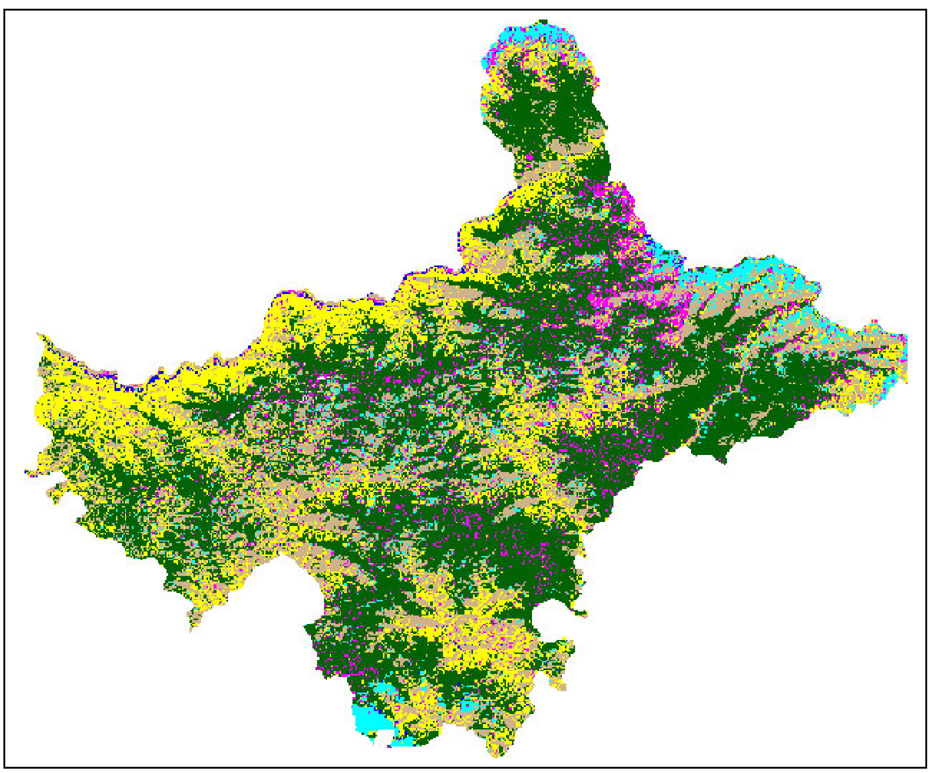


Figure 5-11 Maximum likelihood classification of IRS - 1D image

Figure 5-12 and 5-13 show the comparison of accuracies between three different methods of classification. In most of the cases, accuracy of crisp classification is lesser than the other two methods of fuzzy classification. Maximum likelihood classification assigns a pixel to a class based on maximum probability. But in reality, there may be a possibility that, that particular pixel belongs to more than one class. This is because of vagueness in the boundary between the classes. This can be identified in the results of fuzzy classification. This is one of the reasons of better accuracy with fuzzy classification.

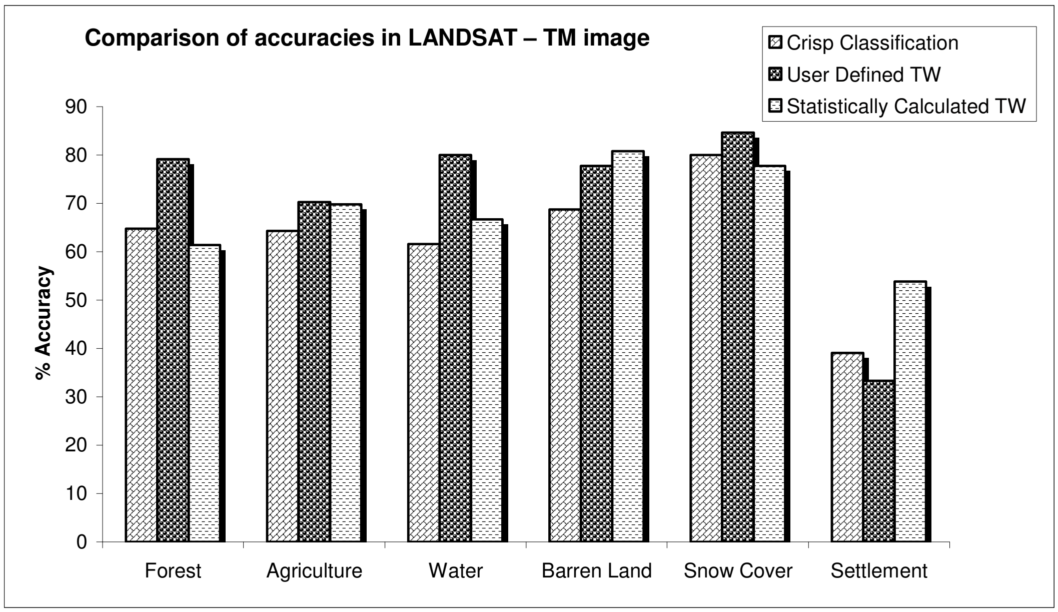


Figure 5-12 Comparison of accuracies in LANDSAT – TM image

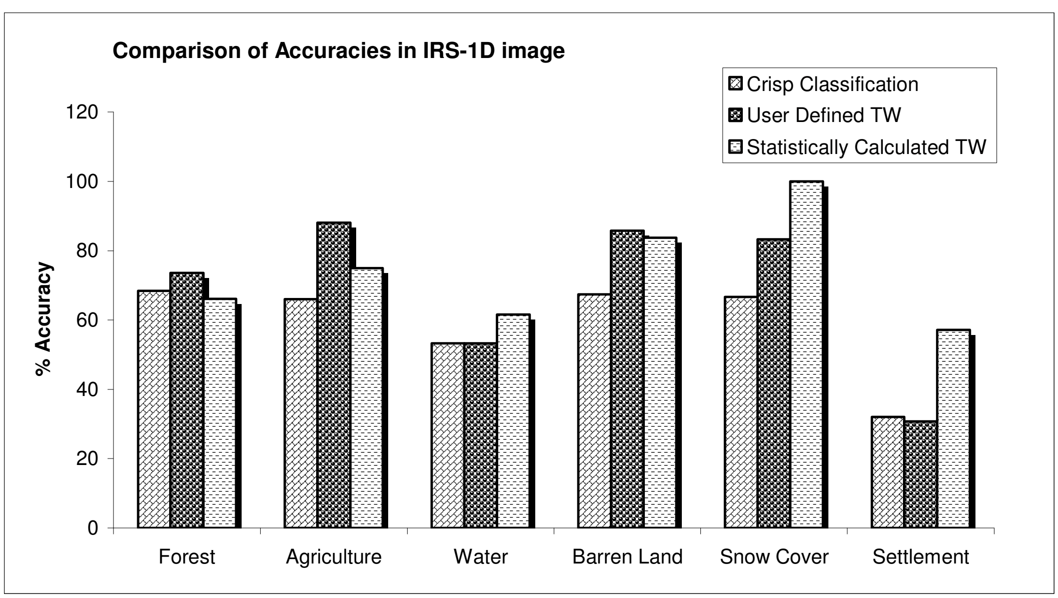


Figure 5-13 Comparison of Accuracies in IRS-1D image

5.2. Change Detection

5.2.1. Magnitude of Change

As discussed in the previous chapter, magnitude of change was calculated by taking the fuzzy difference of two fuzzy classified maps. It produces the following type of output. In this figure, wherever the brightness value is high, it tells that the magnitude of change is high in that pixel.

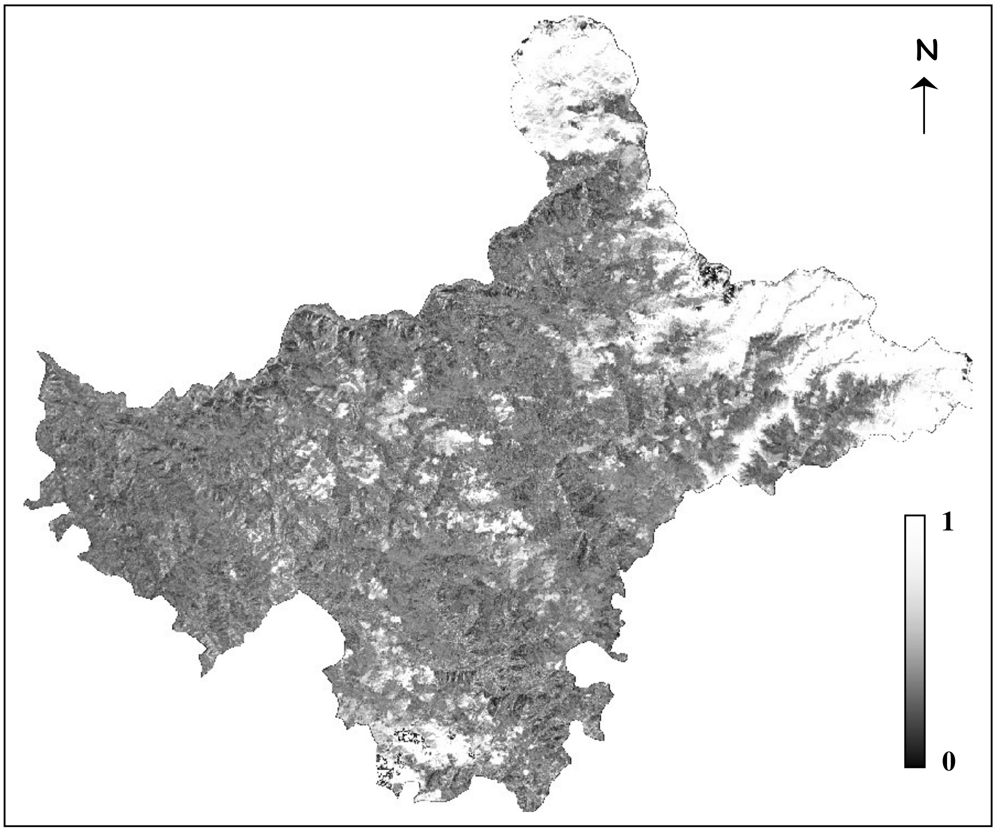


Figure 5-14 Magnitude of change

The above figure clearly shows the change. In the first image more snow-covered area is present than in the second. So, wherever there is snowmelt, there the brightness value is more.

Magnitude of change is categorized in five parts as very high, high, less, very less and no change based on both field observation and expert opinion. Figure 5-15 shows that around 7 % area has very high changes. Also 7 % area is under high changes. In hilly terrains, changes are very minute when compared to flat regions. Results also prove this as around 74 % area is under no change and very less change categories.

To assess the accuracy of magnitude of change, extensive ground truthing is required along with a lot of field knowledge. To achieve this, first we have to quantify the change in field. For this we have to identify and measure the area exactly of a pixel of a satellite image, which is practically very difficult. After that quantify the change based on the data of previous date, it can be compared with the output. An error matrix can be prepared based on this. For example, if the whole area is forest in date 1 and now it is agriculture fully. Then change is 1. If number of classes is more in a pixel, it is very tedious work to quantify the change in field.

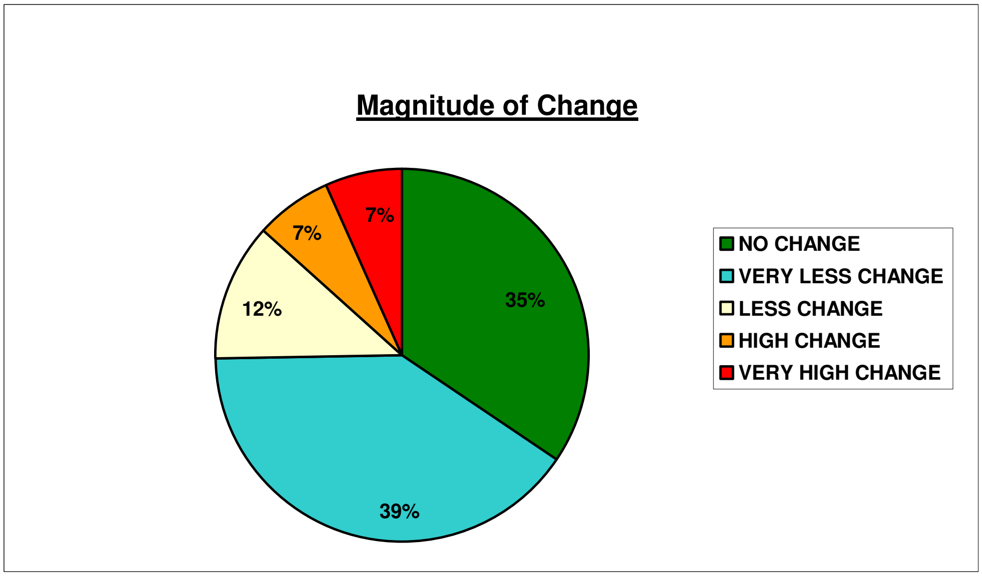


Figure 5-15 Overall change during 1987 to 1999

5.2.2. Nature of Change

By comparing all the classes with each other, nature of change is determined between any of the two classes. All possible layers of different nature of change are stacked and the *maximum* function is applied on that. The nature of change is determined as this is a pre-requisite for direction of change. In this research, there are six predefined classes and thus the total number of comparisons is 36 (i.e. 6 x 6). One of the comparisons is taken as an example here.

A pixel belongs to class Forest in 1987 to the extent of $\mu^1_{F(i)}$ and in 1999 belongs to class Agriculture to the extent of $\mu^2_{A(i)}$. These kinds of queries are helpful specially when the users need specific information. For example, an agriculture scientist needs information about increasing area in agriculture from barren land to develop a verity or a hybrid, which suits to that kind of area. In this situation, a specific query has to be done like above.

5.2.3. Direction of Change

The result of this analysis gives the direction of change occurring in a pixel. Following graph shows the percent area under different direction of change. Direction of changes is having some value along with the direction label. This is useful information, which can be an important input for prediction of change study in future.

Around 27 % of study area is changing from forest to agriculture. Agriculture area besides forest is growing and encroaching forest area, which is clearly reflected by this study. At the same time results show that 26 % area is changing in the other way, i.e. from agriculture to forest. This is because of increasing in horticulture – especially apple orchards – that has the same reflectance of a forest area. Because of the Government's strict and good policy, forest cover is increasing. The results are also showing the same. Around 3 % barren land is changing towards forest.

Satellite image acquired in 1987 has more snow covered area that the satellite image of 1999. Hence, result is showing around 20 % area as snowmelt. The result shows that 9 % area is converting from barren land to agriculture. Some of the agriculture fields are kept fallow land during summer and these lands are classified as barren land in date 1 satellite image. This leads to misclassification and hence this result.

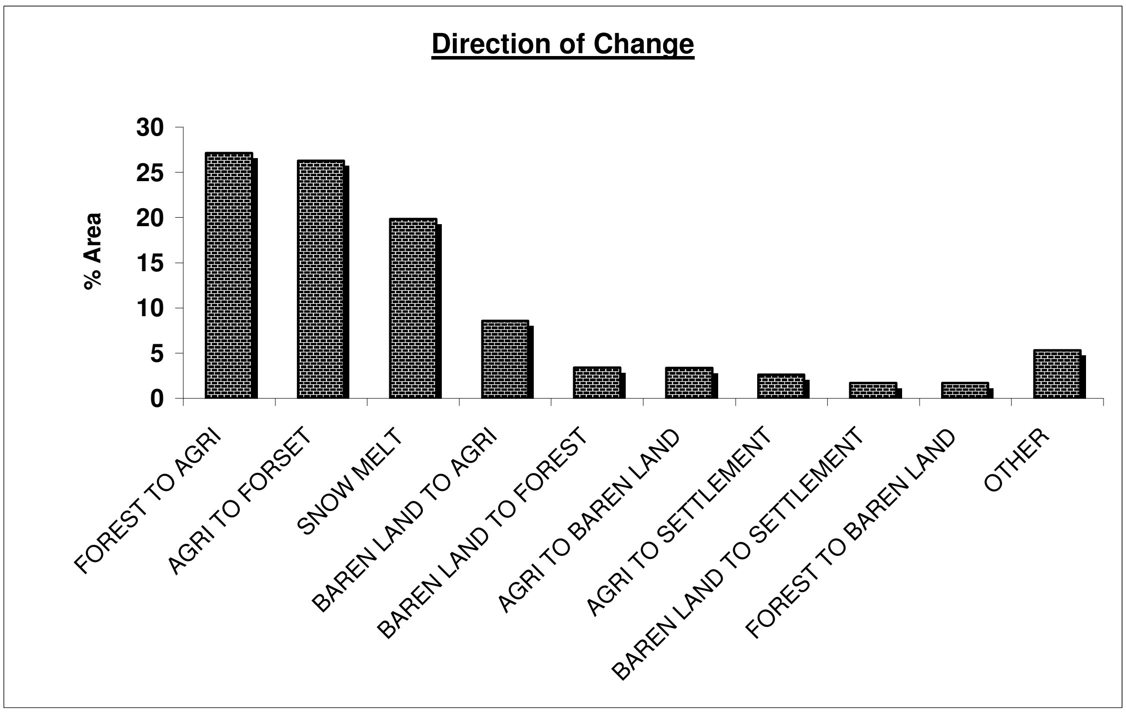


Figure 5-16 Percentage area under different directions of change from 1987 to 1999

6. Conclusions and Recommendations

6.1. Conclusions

This study shows that using fuzzy approach we can get better results than a crisp classification of a satellite image to map land cover classes. The main reason is that fuzzy operators can resolve overlapping problems better than crisp operators. A pixel is no longer considered as indecomposable and information in a pixel can be derived and processed further for many applications like change detection. The results also show that output of a crisp classification method is of poor quality in the boundary zones, e.g.- in differentiating settlement and barren land. The fuzzy approach proposed in this study is giving good classification results because it allows overlapping classes, as opposed to classical set theory.

Image classification using a fuzzy membership function in which the user defines the transition width, needs expert field knowledge to train the system. When the transition width is statistically calculated from the training set, there is no need for other expertise in training the system. The purer the training set, the more accurate the result will be.

Supervised classification of two satellite images using a fuzzy classification method shows different land cover classes like forest, agriculture, water bodies, barren lands, snow covered areas and settlement areas prevailing in two dates i.e. 1987 and in 1999. The whole study reveals the importance of fuzzy sets and fuzzy logic in image classification and change detection process. Both classification and change detection processes are important applications of digital image processing. The fuzzy classification method described in this study has proven many advantages. In hilly terrain, it is very difficult to distinguish between a small settlement area and barren lands using a coarser resolution satellite image. A fuzzy classification is a good approach for resolving the overlapping functions, which are derived because of the same reflectance values

More than the accuracy, the main advantage of a fuzzy classifier is the extraction and representation of the information. Vagueness can be extracted successfully and can be represented with different membership values. This approach is simple and user friendly. It is observed that this approach is less prone to the errors occurred because of the same reflectance of value of two or more classes.

Remote sensing change detection is the process of identifying changes through detecting differences between two or more set of images of the same area at different dates. However to apply a technique, it requires expertise, skill, fieldwork and considerable time. Even then it may not be possible to identify the change very accurately. This is one of the limitations of change detection using remote sensing.

Change is quantified by taking the difference of two classified images, using fuzzy operators. This gives more accurate results than a simple difference approach, as it takes into consideration of all the class membership values of a pixel because a pixel is a mixture of many classes. This gives the overall magnitude of change occurred in a pixel.

Results also show that post classification comparison, can also be done not only using Boolean, but also using fuzzy operators. Also it is a simple powerful and intuitive approach to make queries related to change in two or more classes in two dates.

6.2. Recommendations

For likelihood of changes, more ancillary data should be used in a fuzzy rule based system. Also other ancillary data like socio-economic data, soil physical and chemical data, wetness index etc. can be used in future to develop fuzzy rule based system for change detection and future prediction.

In the accuracy assessment part, more intensive ground data should be collected. Especially in fuzzy classification procedure, where the output is with more than one class per pixel, analyst must be very careful in selecting the reference points. This has to be observed in the field and accordingly error matrix has to be derived. In this case, the error matrix has to be plotted separately for different classes. This needs a lot of field expertise or field data along with precise GPS measurements to identify the pixels with mixed classes. The training sets in a classification – especially in a fuzzy classification – are very subjective; it should not be used for accuracy assessment. Because of this reason, accuracy should be assessed by comparing a sample of classification results with reference data.

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