EXPLORING THE UTILITY OF MODERATE RESOLUTION
TIME SERIES REMOTELY SENSED DATA FOR LAND
USE/Cover CLASSIFICATION

by

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This is to certify that the work contained in this thesis, “Exploring the utility of moderate resolution time series remotely sensed data for land use/cover classification”, by Sudhir Gupta (Roll no: 200707034), has been carried out under my supervision and the work has not been submitted elsewhere for a degree.

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ABSTRACT

Monitoring or surveillance by machines has become very popular nowadays because of the advantages that it provides over monitoring by human beings. Remote sensing has a huge potential to monitor the events on a large scale that millions of cameras put together on the surface of earth cannot monitor. Remote sensing data analysis involves examining the data using various viewing and interpretation devices to analyze the remotely sensed digital data. Reference data about the resources being studied are used when and where available to assist in the data analysis. Results of data analysis are then compiled generally in the form of hardcopy maps and tables or as computer files that can be merged with other ‘layers’ of information in a geographic information system (GIS). Finally, the information is presented to users who apply it to their decision making process.

Image classification is one of the most widely used techniques on remote sensing data. The overall objective of image classification procedures is to automatically categorize all pixels in an image into land cover classes or themes. Land cover can be defined as the physical material at the surface of the earth. The range of projects, programs and organizations that use land cover maps to meet their planning, management, development and assessment objectives is expanding every day and the remote sensing community has been challenged to produce regional- to global-scale data sets on a repetitive basis that characterize ‘current’ Land Use Land Cover (LULC) patterns and also document all the LULC changes, however large or small they be.

Spectral pattern recognition refers to the family of classification procedures that utilize the pixel-by-pixel spectral information as the basis for automated land cover classification. That is, different feature types manifest different combinations of digital numbers based on their inherent spectral reflectance and emittance properties. Spatial pattern recognition involves the categorization of image pixels on the basis of their spatial relationship with pixels surrounding them.

Temporal pattern recognition uses time as an aid in feature identification. The multi-temporal data that is now available because of better revisit times of the satellites allows us to characterize objects based on their dynamic processes rather than static properties like color, shape, etc and this is being successfully demonstrated in this research for a few classes.

In case of multi-temporal studies, atmospheric influences and sensor malfunctioning leads to data gaps and data anomalies that have to be corrected for and is usually a pre-processing stage in all time series studies. This research has adopted a technique called local maximum fitting to smooth the noisy time series. Local maximum fitting combines temporal window operation and harmonic series fitting to provide a faithful representation of the ground process.

We have viewed the classification of the pixel-time trajectories as a curve matching problem comparing the unknown time series of a pixel to the temporal signatures
available in the library derived from the training samples obtained either through our proposed automatic method or any other method. An important part of curve matching problem is the definition of similarity measure. We have used various similarity measures and concluded that constrained dynamic time warping is best suited for classifying enhanced vegetation index (EVI) time series. Conventional classification methods inherently use Euclidean distance as a similarity measure even for time series classification. Through our empirical experiments, we have concluded that a Sakoe-chiba radius of 4 (equivalent to 2 months) for constraining DTW (Dynamic Time Warping) provides the best classification accuracy which is reasonable as there can be a maximum shift of this period in growing practices. The classification accuracy for Dharwad district was 86.57% with Euclidean distance as compared to 90.89% with constrained dynamic time warping distance measure for the moderate resolution imaging spectroradiometer (MODIS) dataset. The results obtained though the proposed classification procedure were also being compared with the conventional kNN and SVM classifiers. kNN classifier with k = 5 provided a classification accuracy of 79.75% and SVM classifier, an accuracy of 83.89%. The low classification accuracy of these classifiers for time series satellite image classification can be attributed to the use of Euclidean distance in the feature space.

Whereas the actual supervised classification of satellite image is a highly automated process, assembling the training data needed for such classification is anything but automatic. In many ways, the training data needed for land cover classification is both an art and a science. It requires close interaction between the image analyst and the image data thus making the classification results very subjective. Our research has focused on developing a method to extract the training samples for some classes automatically from the data itself by analyzing the discrete fourier transform of the temporal signatures of every class. The training samples obtained as point data using the proposed method were validated by overlaying them on relatively high resolution LISS-3 (Linear Imaging Self Scanning Sensor) color composite. A visual interpretation was then being performed by an expert. The training samples were also validated against the land cover dataset provided by NRSC (National Remote Sensing Centre) and the results were very promising with an accuracy of 100% at 0% false alarm rate for different geographical regions. Since the trainings samples are point data, they can be used not only with temporal classifiers but even with contextual and spectral classifiers. Contextual and spectral classifiers work on single date images and thus to demonstrate the utility of the training samples obtained using the proposed method, an expert was being asked to provide the training samples for classifying single date LISS-3 image. The expert derived training samples and automatically derived training samples were then used with the same classifier (Maximum likelihood) and the results compared. An average of 68% pixels matched. An important observation that was made is that most of the misclassifications or contradictions with expert classification occurred in water. To demonstrate the utility of the obtained training samples for time series classification, they were used to train a k nearest neighbour (kNN) and a support vector machine (SVM) classifier.

Multi temporal data for vegetation can provide phenology parameters like start of season, senescence, end of season, etc. These phenology parameters characterize the crop or vegetation. We have derived phenological parameters from EVI time series and used unsupervised classification (density based clustering) to find structures in this data which has provided a season calendar which describes the start date (sowing), senescence (harvest) and end date (post harvest) of major crops grown in a particular
geographic area without naming the crop. This is one step short of a crop calendar which can be derived by knowing the labels of at least one sample in the clusters resulting from unsupervised classification assuming non overlapping clusters.

The phenological parameters derived from EVI time series also helps us to know the cropping practices of a region. This has been demonstrated by producing what is being christened as cropping practice variability map by mapping various similar phenologies which have different absolute values of start date, senescence and end dates. The number of phenologies or seasons obtained per pixel also allows us to label every crop pixel as single or multi cropping area. Such a classification is important in many policy decisions one of which is Special Economic Zone (SEZ) Act, 2002 which prohibits from using multi cropping lands for setting up special economic zones.
ACKNOWLEDGMENTS

This thesis is a combined result of many factors though it started with a problem being defined by me for solving a problem of 'How to save agricultural lands from being occupied by industries without both agriculture and industries getting effected?'. Many people are instrumental in the culmination of this thesis which is the beginning of a new chapter in my life.

I earnestly thank my parents and brothers who stood by my decision to pursue higher studies in India.

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I also thank all the great minds who have built this wonderful institute and the great minds running it efficiently. Let IIIT, Hyderabad scale new heights every day.
The author wishes to dedicate this dissertation to his parents, brothers and his faculty advisor.
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CHAPTER 1 : INTRODUCTION

1.1 LAND COVER

Land cover is the physical material at the surface of the earth. It includes grass, asphalt, trees, bare ground, water, etc. It can be defined more formally as observed (bio) physical cover on the earth’s surface. In a pure and strict sense, it should be confined to the description of vegetation and manmade features. It is also disputable whether water surfaces are real land cover. However, in practice, the scientific community usually includes these features within the term land cover. [LAND COVER].

There are two primary methods of capturing information on land cover: field survey and through analysis of remotely sensed imagery. In India, the former method is practiced largely which is the main reason for delay in obtaining information on land cover at the right time. While efforts are on to create a national land use/land cover map by the national remote sensing agency, we are still a long way in using remotely sensed imagery in real time applications. There is a high demand for improved land cover data sets and researching new methods for classifying remotely sensed imagery has gained priority because of the vast array of utilities that such a classification can provide. They are needed to support science and policy decisions, for environmental modeling and for natural resource management. The range of projects, programs and organizations that use land cover maps to meet their planning, management, development and assessment objectives is expanding every day.

1.2 REMOTE SENSING OF LAND COVER

Remote sensing technology is concerned with the determination of characteristics of physical objects through the analysis of measurements taken at a distance from these objects. One important problem in remote sensing is the characterization and classification of spectral and temporal measurements. This problem falls into the general problem of pattern recognition. While much research is being done in classification through spectral measurements, a lot more remains to be exploited using temporal measurements. Each of them has its own advantages. For uniquely identifying an object, hyperspectral data may be the best choice but remote sensing image forming devices do not record activity directly. The remote sensor acquires a response which is based on many characteristics of the land surface including natural or artificial cover. Thus, temporal measurements and their analysis become important (For e.g. vegetation growth as a process) to understand the process and thus the object. Satellite image classification provides an answer to the question “Where is what on the surface of the earth?” Different materials provide a unique response to various wavelengths which is the main concept behind spectral classification of a single scene of a given time step. It depends on the availability and knowledge of scene area being analyzed and is largely based on cloud free images. However, the major drawback of single scene classification is that many land cover classes provide similar spectral responses leading to similar tone and texture in the
resulting image. This makes it difficult to distinguish between these classes. As shown in figure 1.1, the spectral response obtained by imaging in the wavelength band 0.9-1.1 micrometers will result in similar values for both vegetation and soil.

There are some materials which behave differently over time also; particularly vegetation and depending on their temporal behavior, one can label such temporal patterns with some prior information or some other automatic method. In this research, an attempt is made to extract information from temporal data to aid in classification and also to derive certain other products that are of a great utility. Processes can be analyzed using time series [Colditz] and temporal information can be an efficient aid for land cover classification as different classes behave differently with time. Every class is characterized by a process. The main question investigated in this research is whether pixel time trajectories can be used to identify the land cover type. Suitable algorithms were built for recognizing these temporal patterns and many products derived from the resulting land cover map. The focus was on crop pixels to devise better algorithms for monitoring agriculture using time series of remotely sensed data. A major contribution of this research is the remote sensing based season calendar which is one step short of a crop calendar for Indian districts.

Figure 1.2 illustrates the utility of EVI time series. An ideal EVI curve shows a perfect correlation with the crop/vegetation growth on ground. Analysis of these time series and extracting information that has utility in the real world is the focus of this research.

1.3 QUESTIONS INVESTIGATED IN THIS RESEARCH

1. Can high temporal resolution be used to improve the accuracy of land cover classification?

We have devised a classification procedure for EVI time series that outperforms single scene classification and conventional classifiers.

2. Can time series of vegetation indices be looked as curves and can a method similar to spectral matching or spectral clustering be employed?
We have devised a classification scheme that views the time series classification as a curve matching problem. The unknown time series is being compared with the time series library created from the automatically extracted training samples and the majority best match is being reported as the class of the unknown time series.

3. What is the best similarity measure for time series matching intended to be done in previous question?

Many different similarity measures were being tested and as per our intuition, constrained dynamic time warping has been successful in comparing the time series well.

4. Can we extract the training samples for supervised classification of remotely sensed data from the data itself?

We have extracted training samples from the data itself by exploring the discrete fourier transform of the pixel-time trajectories. These training samples have been found to represent the classes well and have been validated through different techniques.

5. Can we derive phenological parameters from time series data to produce season/crop calendar, single/double crop maps?

We have derived the conventional phenological parameters from the pixel-time trajectories which were then being used to construct season calendar and single-double crop maps for Indian districts.

![Figure 1.2: Ideal EVI Time Series](image)
6. Can we use pixel-time trajectories of crop pixels for finding the spatial variability of cropping practices across a given geographic region?

The phenology parameters were also being analyzed to map their variability spatially which produced the cropping practice variability map.

1.4 OBJECTIVES OF THIS RESEARCH

1. To use time series of MODIS moderate resolution remotely sensed data at 250-meter spatial resolution composited every 16 days for classification of land cover and validate it.

2. Building of a temporal library similar to a spectral library for classifying time series satellite imagery and posing the classification problem as a curve matching problem.

3. To extract appropriate training samples using systemic phonological response captured by the time series data.

4. To extract the vegetation growth parameters over the growth period of crops and to describe their phenology.

5. To understand the cropping patterns and build a pixel-specific crop calendar.

1.5 THESIS OUTLINE

Figure 1.3 provides a snapshot of the entire work which form the solutions provided to the questions posed in section 1.4. The following paragraphs describe the various steps and point to the corresponding chapter in the thesis where detailed information about these steps is provided.

CHAPTER TWO reviews the techniques and research in the remote sensing community for land cover classification and various outcomes of time series analysis.

CHAPTER THREE describes the data sets used in this research including those used for validation. Besides the satellite imagery from MODIS sensor, Advanced Wide Field (AWiFS) sensor, LISS-3 sensor and other vegetation index products, this chapter also introduces the study sites used in this thesis.

CHAPTER FOUR describes the filtering of time series data as a pre processing step. Once the time series for various pixels are generated, these have to be pre processed to fill data gaps and correct data anomalies. While naming some of the techniques used for such filtering, this chapter provides a detailed description of a method called local maximum fitting which is adopted in this research.

CHAPTER FIVE proposes a method for automatic extraction of training samples for land cover classification using time series of remotely sensed data. The raw time series and the smoothed time series are then analyzed to find training samples for three broad land cover classes namely crop, forest and water.
CHAPTER SIX describes a novel classification procedure that has been designed in this research for supervised classification of these time series patterns. The applicability is demonstrated and compared with the classification results of a conventional kNN and SVM classifier.

CHAPTER SEVEN demonstrates one of the important utility of EVI time series which is to derive phenological parameters that quantify the vegetation growth process. Such phenological parameters were extracted and used to derive a season calendar which is one step short of producing a crop calendar for Indian districts.

CHAPTER EIGHT concludes the thesis with the major research conclusions and also deliberates on the future scope of various objectives that were levied on this research.
CHAPTER 2: RELATED WORK

2.1 SATELLITE IMAGE CLASSIFICATION

Two broad approaches namely spectral and contextual image classification techniques are in vogue in the field of remote sensing. Spectral techniques are based on the spectral response pattern of a pixel. These spectral bands are snapshots of the same area imaged at different wavelengths and thus capturing different information. Generally, the spectral response of a ground object forms a unique spectral signature of the reflectance or radiance, and can be regarded as a spectral curve in spectral space. Theoretically, each class of ground object has its own shape and variances of the spectral curve. Based on these important properties, spectral matching methods can distinguish an unknown spectral curve by comparing with a series of pre-labeled spectral curves. The contextual classifiers consider the spatial context of the pixel in the image and are generally applied on satellite data when a large variety of spectral responses are observed in the same field.

Numerous classification algorithms have been developed since the first Landsat image was acquired in early 1970s. The most commonly used classification methodologies for satellite image classification are Iterative Self Organizing Data Analysis (ISODATA), k-means and maximum likelihood classifier. Most of the classification techniques published in the area of pattern recognition have been applied on satellite images including decision trees, ensemble learning etc. Duda and Canty (2002) consider several unsupervised classification (clustering) algorithms and evaluate their ability to reproduce the same results as with ground observational data but their work greatly depends on in-situ observations. Wilkinson (2005) presents a study of 15 years of satellite image classification experiments. Nair (2008) presents a system for pattern recognition and pattern summarization in multi-band satellite images. All supervised classification algorithms depend on expert knowledge or reference maps for obtaining training samples. Thus, the performance of the classification procedures using these trainings samples vary extensively across images and the kind of homogenous or heterogeneous landscapes that are being studied. Most of these methods are fine tuned every time they are applied to the area of interest and hence are not robust enough. This fine tuning requires a large human intervention and has limited applications for scalability of the approaches and to monitor large regions, the latter being one of the primary reasons for opting satellite based natural resource monitoring and management. A general observation that is made during the literature survey is that only a limited work is done on deriving appropriate features or indices for land cover classification. In most cases, spectral reflectances are directly used as features for classification algorithms without much emphasis on developing new features that are more relevant for the classification. In case of spectral methods, the choice of different similarity metrics is not explored.

The supervised and non supervised classification methodologies generally used by remote sensing scientists [CCRS] for land cover classification are described below.
2.1.1 Supervised Classification Techniques

Supervised classification is the procedure most often used for quantitative analysis of remote sensing image data. It rests upon using suitable algorithms to label the pixels in an image as representing particular ground cover types, or classes. A variety of algorithms is available for this, ranging from those based upon probability distribution models for the classes of interest to those in which the multispectral space is partitioned into class-specific regions using optimally located surfaces. Irrespective of the particular method chosen, the essential practical steps usually include:

1. Decide the set of ground cover types into which the image is to be segmented. These are the information classes like water, urban regions, croplands, rangelands, etc.
2. Choose representative or prototype pixels from each of the desired set of classes. These pixels are said to form training data. Training sets for each class can be established using site visits, maps, air photographs or even photointerpretation of a colour composite product formed from the image data. Often the training pixels for a given class will lie in a common region enclosed by a border. That region is then often called a training field.
3. Use the training data to estimate the parameters of the particular classifier algorithm to be used; these parameters will be the properties of the probability model used or will be equations that define partitions in the multispectral space. The set of parameters for a given class is sometimes called the signature of that class.
4. Using the trained classifier, label or classify every pixel in the image into one of the desired ground cover types (information classes). Here the whole image segment of interest is typically classified. Whereas training in Step 2 may have required the user to identify perhaps 1% of the image pixels by other means, the computer will label the rest by classification.
5. Produce tabular summaries or thematic (class) maps which summarise the results of the classification.
6. Assess the accuracy of the final product using a labelled testing data set.

Supervised classification techniques can further be classified as parametric and non-parametric supervised classification techniques

A parametric decision rule is one which takes into account the functional form of the conditional probability distribution of the patterns given the categories. Some of the parametric classification techniques used are

**Maximum likelihood classification:** A statistical decision rule that examines the probability function of a pixel for each of the classes, and assigns the pixel to the class with the highest probability. The classifier assumes that the training statistics for each class have a normal or 'Gaussian' distribution. However many are not, radar statistics in particular. Training statistics with bi- or tri-modal histograms are not suitable as they indicate non-homogeneity within classes and are non-'Gaussian'. The classifier then uses the training statistics to compute a probability value of whether it belongs to a particular land cover category class. This allows for within-class spectral variance. The image analyst can use a-priori knowledge to weight the probability function. (G) MLC usually provides the highest classification accuracies. Accordingly, it has a high computational requirement because of the large number of calculations needed to classify each pixel.

**Minimum distance classification:** A Minimum Distance to the Mean classifier uses the mean values for each of the land cover classes calculated from the training areas. Each
pixel within the image is then examined to determine the mean value that it is closest to. Whichever mean value that pixel is closest to, based on Euclidian Distance, is the class to which that pixel will be assigned.

**Parallelepiped classification:** The Parallelepiped classifier uses a mean vector as opposed to a single mean value. The vector contains an upper and lower threshold, which dictates which class a pixel will be assigned to. If a pixel is above the lower threshold and below the upper threshold, then it is assigned to that class. If the pixel does not lie within the thresholds of any mean vectors, then it is assigned to a unclassified or null category.

**Table look up classification:** Since the set of discrete brightness values that can be taken by a pixel in each spectral band is limited, there is a finite, although large, number of pixel vectors in any particular image. For a given class in that image the number of distinct pixel vectors may not be very extensive. Consequently a viable classification scheme is to note the set of pixel vectors corresponding to a given class, using representative training data, and then use those to classify the image by comparing unknown image pixels with each pixel in the training data until a match is found. No arithmetic operations are required and, notwithstanding the number of comparisons that might be necessary to determine a match, it is a fast classifier. It is referred to as a look up table approach since the pixel brightnesses are stored in tables that point to the corresponding classes. An obvious drawback with this approach is that the chosen training data must contain one of every possible pixel vector for each class. Should some be missed then the corresponding pixels in the image will be left unclassified.

**k nearest neighbor classification:** A classifier that is particularly simple in concept, but can be time consuming to apply, is the $k$-Nearest Neighbour classifier. It assumes that pixels close to each other in feature space are likely to belong to the same class. In its simplest form an unknown pixel is labelled by examining the available training pixels in multispectral space and choosing the class most represented among a pre-specified number of nearest neighbours. The comparison essentially requires the distances from the unknown pixel to all training pixels to be computed.

**Context classification:** Classification methods that take into account the labelling of neighbours when seeking to determine the most appropriate class for a pixel are said to be context sensitive, or simply context classifiers. They attempt to develop a thematic map that is consistent both spectrally and spatially. In general terms, context classification techniques usually warrant consideration when processing higher resolution imagery.

A nonparametric classification rule is one which makes no assumptions about the functional form of the conditional probability distributions of the patterns given the categories. Some of the nonparametric classification techniques used are

**Linear discrimination:** A discriminant function that is a linear combination of the components of the feature vector is called a linear discriminant function. These functions have a variety of pleasant analytical properties. They can be optimal if the underlying distributions are cooperative, such as Gaussians having equal covariance, as might be obtained through an intelligent choice of feature detectors. Even when they are not optimal, we might be willing to sacrifice some performance in order to gain the advantage of their simplicity. Linear discriminant functions are relatively easy to compute and in the absence of information suggesting otherwise, linear classifiers are attractive candidates
for initial, trial classifiers. The problem of finding a linear discriminant function will be formulated as a problem of minimizing a criterion function. The obvious criterion function for classification purposes is the sample risk, or training error—the average loss incurred in classifying the set of training samples. It is difficult to derive the minimum-risk linear discriminant, and for that reason it will be suitable to investigate several related criterion functions that are analytically more tractable. Much of our attention will be devoted to studying the convergence properties and computational complexities of various gradient descent procedures for minimizing criterion functions. The similarities between many of the procedures sometimes make it difficult to keep the differences between them clear.

**Neural networks:** A computer architecture that achieves its performance from massive parallelism and a dense interconnection of simple computational elements. It is based on our understanding of the biological nervous system. Neural Networks are being developed and researched for their ability to classify image data in a 'human-like' decision process. The main advantage of ANNs, in terms of image classification, is that the input data does not need to be normally distributed. Instead, ANNs develop a decision-rule based on a model approach that is dependent on the input data. This is particularly important for radar data, as it is seldom normally distributed.

**2.1.2 UNSUPERVISED CLASSIFICATION TECHNIQUES**

Categorization of digital image data by computer processing based solely on the image statistics without availability of training samples or a-priori knowledge of the area. Multivariate statistical technique which separates image data into groups such that the between-group variance of the specified number of groups is maximized.

**Iterative optimization clustering algorithm:** The iterative optimization clustering procedure, also called the migrating means technique, is essentially the isodata algorithm presented by Ball and Hall (1965). It is based upon estimating some reasonable assignment of the pixel vectors into candidate clusters and then moving them from one cluster to another in such a way that the sum of square error measure of the preceding clustering is reduced.

**Agglomerative hierarchical clustering:** Another clustering technique that does not require the user to specify the number of classes beforehand is hierarchical clustering. In fact this method produces an output that allows the user to decide the set of natural groupings into which the data falls. The procedure commences by assuming all pixels are individual clusters, it then systematically merges neighbouring clusters by checking distances between means. This is continued until all pixels appear in a single, larger cluster.

**Clustering by histogram peak selection:** A multidimensional histogram of a segment of image data may exhibit peaks at the locations of spectral classes or clusters. Consequently, a further clustering technique adopted with remote sensing data is to construct such a histogram and then search it to find the location of its peaks. Pixels are then associated with the nearest peak to produce the clusters. This method has been described by Letts (1978).
The remote sensing community has been challenged to produce regional- to global-scale data sets on a repetitive basis that characterize current land use land cover (LULC) patterns, document major LULC changes, and include a stronger land use component [Turner; NRC; NASA]. In many countries, production forecasting of certain crops, crop yield modeling and crop stress detection are done using remote sensing data [Das]. To do so, the first step is to detect the cropping regions.

2.2 TIME SERIES ANALYSIS

Although the value of satellite time series data for classification has been firmly established, only a limited number of methods for exploring such data series have been developed [Malingreau]. Time series analysis of satellite data such as standardized principal component analysis [Eastman and Fulk] or Fourier analysis [Andres et al., Azzali and Menenti] have been used to obtain the information of seasonal vegetation changes characterized by phenology. Jakubauskas (2001) used the harmonic analysis to characterize seasonal changes for natural and agricultural land use/land cover. Sawada (1998) have devised a process called local maximum fitting to fit time series satellite data that can reduce the influences of noise such as cloud, haze and system noise. Further, they have taken forward this concept to fit Advanced Very High Resolution Radiometer (AVHRR) time series normalized difference vegetation index (NDVI) data to obtain the agricultural map of Asian region [Sawada et al, 2002]. Eklundh and Jonnson (2004) have developed a tool for analyzing time series of satellite data. Their analysis is restricted to extracting seasonal parameters which are then used with conventional classification techniques for classification. In our work, we have chosen the time series of a quantity called Enhanced vegetation Index which quantifies the amount of vegetation for every pixel.

Crop monitoring is generally done using field visits that are time consuming and do not provide the required results in due time. Frequent revisit time of satellites that can range as less as half a day allows us to monitor the processes on the surface of the earth in a more efficient manner though they have to be supplemented with a limited amount of ground based studies. In this thesis, some products that can aid crop monitoring are being developed and their utility demonstrated.

Of the various conventional methods available for deriving crop calendar, a remote sensing based approach has been found to be a cost- and time-effective solution, providing near-real-time information. In the Indian context, researchers have mostly used crop calendar as an input to crop classification systems [NRSC]. Some work is done to derive crop calendar using satellite imagery for particular crops and particular regions [Murthy et al.; Panigrahy et al.]. The feasibility of using MODIS data for remotely determining the phenological stages of paddy rice in Japan has been demonstrated [Toshihiro et al.]. Multi temporal vegetation indices have already been used for crop mapping [Wardlow et al.; Galford et al.]
CHAPTER 3: DATA AND STUDY AREA

3.1 MODIS

MODIS (or Moderate Resolution Imaging Spectroradiometer) is a key instrument aboard the Terra (EOS AM) and Aqua (EOS PM) satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands, or groups of wavelengths. These data have improved our understanding of global dynamics and processes occurring on the land, in the oceans, and in the lower atmosphere. MODIS is playing a vital role in the development of validated, global, interactive Earth system models that may be able to predict global change accurately enough to assist policy makers in making sound decisions including the protection of our environment [GSFC].

The Moderate Resolution Imaging Spectroradiometer (MODIS) provides a global, repetitive coverage of multi-spectral, multi-resolution imagery and a suite of higher-level science quality products in support of global environmental change research. The MODIS 250-m Vegetation Index (VI) product (MOD13Q1), which consists of NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index) data composited at 16-day intervals, holds considerable promise for regional-scale crop mapping given its resolutions, large area coverage, and cost free status. VIs represent dimensionless radiometric measures of green vegetation amount/condition and are well correlated with biophysical parameters such as biomass and leaf area index (LAI). As a result, time-series (or multitemporal) VI data have been widely used for classifying land cover types based on their seasonal spectral differences and to characterize major phenological events.

3.2 MODIS TIME SERIES EVI DATA CHARACTERISTICS

The Land Processes Distributed Active Archive Center (LP DAAC) was established as part of NASA's Earth Observing System (EOS) Data and Information System (EOSDIS) initiative to process, archive, and distribute land-related data collected by EOS sensors, thereby promoting the inter-disciplinary study and understanding of the integrated Earth system. The role of the LP DAAC includes the higher-level processing and distribution of ASTER data, and the distribution of MODIS land products derived from data acquired by the Terra and Aqua satellites.


The MODIS data used in this study were ordered through the EOS data gateway using warehouse inventory search tool at

https://wist.echo.nasa.gov/~wist/api/imswelcome/
Sensor: MODIS
Dataset: MODIS/Terra Vegetation Indices 16-Day L3 Global 250m
Granule short name: MOD13Q1
Temporal Extent: 2000-02-24 to present

**Data Set Characteristics**

Area ~ 10° x 10° lat/long
Image Dimensions 4800x4800 row/column
Resolution 250 meters
Projection: Sinusoidal
Data Format HDF-EOS

Figure 3.1: MODIS Tiles

Free availability, quick delivery, efficient service, and good archive were the influencing factors in selecting the data and in this sense MODIS was the only sensor that qualified. EVI has been chosen due to its ability to better avoid atmospheric and soil disturbances. It is also more sensitive than NDVI in areas of high vegetation density [Huete et al.]. While for experiments with AWiFS data, NDVI was derived.

### 3.3 DATASETS USED

The MODerate-resolution Imaging Spectroradiometer (MODIS) Vegetation Indices products use, as input, MODIS Terra surface reflectances (MOD09) corrected for molecular scattering, ozone absorption, and aerosols. Two vegetation index (VI) algorithms are produced globally for land. One is the standard normalized difference vegetation index (NDVI), which is referred to as the "continuity index" to the existing NOAA-AVHRR derived NDVI. The other is an 'enhanced' vegetation index (EVI) with improved sensitivity into high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences. The two VIs complement each other in global vegetation studies and improve
upon the extraction of canopy biophysical parameters. A new compositing scheme that reduces angular, sun-target-sensor variations with an option to use BRDF models utilized in EVI. The gridded vegetation indices dataset include quality assurance (QA) flags with statistical data that indicate the quality of the VI product and input data [ATBD].

3.3.1 VEGETATION INDEX

Vegetation Index is a simple numerical indicator that can be used to analyze remote sensing measurements and assess whether the target being observed contains live green vegetation or not. Healthy vegetation absorbs red light (to power photosynthesis). Low red means high chlorophyll. Leaf cell walls reflect near infrared light (NIR 700-900 nm). High NIR means lots of leaf cells. A large difference between NIR and red is a unique signature of vegetation. Thus, NDVI (Normalized Difference Vegetation Index) is being defined as

\[
NDVI = \frac{NIR - RED}{NIR + RED}
\]

Figure 3.2 explains the rationale behind NDVI calculation. Healthy vegetation (left) absorbs most of the visible light that hits it, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation (right) reflects more visible light and less near-infrared light. The digital reflectance values or numbers (DN) captured by the satellite sensors as shown in figure 3.2 are representative of actual values, but real vegetation is much more varied and the DN is a complex outcome of the spatial, spectral and radiometric resolution of the objects, either single or multiple, that are present in the area imaged. [EOS NASA]

The EVI was developed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring while correcting for canopy background signals reducing atmospheric influences. The equation takes the form,

\[
EVI = \frac{r_{NIR} - r_{red}}{r_{NIR} + C_1 r_{red} - C_2 r_{blue} + L} X G
\]

where \( r \) values are atmospherically-corrected (Rayleigh and ozone absorption) surface reflectance, \( L \) is the canopy background adjustment term, and \( C_1, C_2 \) are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the EVI algorithm are, \( L = 1, C_1 = 6, C_2 = 7.5, \) and \( G \) (gain factor) = 2.5.
Figure 3.3 shows an example of EVI and NDVI images from MOD13Q1 product. These images use a pseudo color map that is being shown beside the images.

3.3.2 DATASET IMAGES

Time series of EVI images for cropping seasons 2003-04, 2004-05 and 2005-06 were constructed for all the districts of Karnataka. These districts together have an area of 191,791 square kilometers. To summarize, the enhanced vegetation index images with a spatial resolution of 250 meters and temporal resolution of sixteen days is being used. AWiFS NDVI series of spatial resolution 56 meters and temporal resolution of 5 days was also used for some experiments.

Figure 3.4 shows an example EVI image (values 0-1 scaled to 0 -255 for display) of Dharwad district. Bright regions correspond to high vegetation regions. Figure 3.5 shows an example of LISS-3 data with a spatial resolution of 24 meters that was being used in validating the work in this research. The image is a false colour composite (FCC) with red, green and blue mapped to bands 3,2 and 1 respectively.

Figure 3.6 shows an example of AWiFS image. The color mapping used is Red: MIR, Green: NIR, Blue: Red. NDVI was being derived from this data.

Figure 3.7 shows an example of the land use land cover dataset of Dharwad district derived from AWiFS sensor that was used for validation in most of the studies. Source: National Remote Sensing Centre (NRSC), ISRO, India
Figure 3.4: Example LISS-3 FCC Image of Dharwad district

Figure 3.5: Example EVI Image of Dharwad district

Figure 3.6: Example AWiFS image of Atmakur
3.4 STUDY AREA

All the research experiments – from hypothesis testing to validation described in detail in the respective chapters of this thesis are conducted on some districts of Karnataka state and on one taluk in Andhra Pradesh state, India. Table 3.1 lists the research work and their corresponding study areas. Table 3.2 lists the spatial extent of the study areas.

<table>
<thead>
<tr>
<th>Name of the experiment</th>
<th>Thesis Chapter</th>
<th>Study Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Novel classification procedure for time series remotely sensed data</td>
<td>Chapter 5</td>
<td><strong>Karnataka State:</strong> Dharwad district, <strong>Andhra Pradesh State:</strong> Atmakur Taluk</td>
</tr>
<tr>
<td>Automatic extraction of training samples for supervised classification of time series remotely sensed data</td>
<td>Chapter 6</td>
<td><strong>Karnataka State:</strong> Dharwad, Hassan, Chamrajnagar</td>
</tr>
<tr>
<td>Remote sensing based season calendar</td>
<td>Chapter 7</td>
<td><strong>Karnataka State:</strong> Dharwad, Hassan, Chamrajnagar, Bidar</td>
</tr>
</tbody>
</table>

Figure 3.7: Example NRSC LULC 2005 dataset for Dharwad district

<table>
<thead>
<tr>
<th>Symbol</th>
<th>LU/LC Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Built up land</td>
</tr>
<tr>
<td>2</td>
<td>Kharif crop land</td>
</tr>
<tr>
<td>3</td>
<td>Rabi crop land</td>
</tr>
<tr>
<td>4</td>
<td>Zaid crop land</td>
</tr>
<tr>
<td>5</td>
<td>Double / Triple crop land</td>
</tr>
<tr>
<td>6</td>
<td>Currently fallow</td>
</tr>
<tr>
<td>7</td>
<td>Plantation / orchard</td>
</tr>
<tr>
<td>8</td>
<td>Evergreen / Semi-evergreen</td>
</tr>
<tr>
<td>9</td>
<td>Deciduous Forest</td>
</tr>
<tr>
<td>10</td>
<td>Shrub / degraded forest</td>
</tr>
<tr>
<td>11</td>
<td>Littoral / Swamp / Mangrove</td>
</tr>
<tr>
<td>12</td>
<td>Grassland &amp; grazing land</td>
</tr>
<tr>
<td>13</td>
<td>Other wasteland</td>
</tr>
<tr>
<td>14</td>
<td>Gullied / Ravines</td>
</tr>
<tr>
<td>15</td>
<td>Scrubland</td>
</tr>
<tr>
<td>16</td>
<td>Waterbodies</td>
</tr>
<tr>
<td>17</td>
<td>Snow covered</td>
</tr>
<tr>
<td>18</td>
<td>Shifting Cultivation</td>
</tr>
<tr>
<td>Study Area</td>
<td>Geographic area in square kilometers</td>
</tr>
<tr>
<td>------------------</td>
<td>--------------------------------------</td>
</tr>
<tr>
<td>Bidar</td>
<td>5448</td>
</tr>
<tr>
<td>Chamarajanagar</td>
<td>5101</td>
</tr>
<tr>
<td>Dharwad</td>
<td>4265</td>
</tr>
<tr>
<td>Hassan</td>
<td>6826</td>
</tr>
<tr>
<td>Kolar</td>
<td>8225</td>
</tr>
<tr>
<td>Udupi</td>
<td>3575</td>
</tr>
</tbody>
</table>

Table 3.1: Study Areas

Table 3.2: Spatial Extent of Study Areas
CHAPTER 4: TIME SERIES DATA PROCESSING

Sensing the earth surface is not trivial as the electromagnetic radiation which carries the information about the surface is scattered and absorbed by earth atmosphere. In addition, clouds may partially or fully obstruct the field of view of the sensor. Altogether these perturbations lead to EVI signals which are in most of the cases far lower of what would have been observed under ideal measurement conditions. To eliminate the strongest perturbations, the daily imagery is atmospherically corrected and generally analyzed as X-day maximum value composite (MVC) imagery [Tarpley]. In this simple pre-processing step, for a given pixel location, only the highest EVI value is retained for each X-day period thus minimizing the mentioned perturbations. For the dataset used in this research, X is equal to 16 days. Nevertheless, even such composites still contain perturbations and missing data. Sharp edge lines may appear in regions where insufficient registrations were available for the compositing process. Missing values occur for example at higher latitudes during polar nights. Clouds and/or atmospheric conditions with high aerosol load may persist longer than X-days leading to sub optimal MVC outputs which are easily recognized as irregular dips [Holben].

One of the important steps in analysis of any time series is to pre process the time series by filling data gaps and correcting for data anomalies. A data anomaly is defined as sudden increase or decrease in the value whereas data gaps are formed due to missing values. The techniques of deriving EVI could also have led to data anomalies. Data anomalies and gaps can make the resulting time series no longer reflect the ground process and can distort the analysis of such data leading to wrong information being extracted. An illustration of how data gaps and data anomalies can distort the time series is shown in figure 4.1. Thus, algorithms for filling the data gaps and removing data anomalies are required. Such a pre processing step is also called as construction of time series and various methods have been proposed to construct the time series to match the ground process. [Colditz et.al.; Jonsson et.al.2002,2004]. Popularly used techniques include minmax filtering or temporal window operation, savitzky golay filtering, fourier series fitting, gaussian model fitting and logistic function fitting. Damien(2008) provides a comparison of some smoothing algorithms on multi temporal EVI profiles. In this work, Local Maximum Fitting (LMF) is used and is discussed in this chapter for smoothing the time series data curves.

4.1 LOCAL MAXIMUM FITTING

We have used local maximum fitting devised by Sawada et.al., (2005) which combines temporal window operation and fourier series fitting. The feature of the LMF processing is to be able to remove effects due to clouds, and to be able to capture the seasonal variation of the natural vegetation. Smoothing may improve the classification results considerably but the extent of improvement depends largely on the classification algorithm in question. The potential of LMF to aid classification is proved by Gupta et al. (2008).
Local Maximum Fitting is a time series model filter and is composed of a linear combination of cyclic functions controlled by time-dependent coefficients. LMF consists of three steps,
1. Revision of data
2. Fitting the time series model by a combination of cyclic functions
3. Automatically determine the optimum combination of cyclic functions.

4.1.1 REVISION

Revision of data is necessary before fitting of the cyclic functions especially in cases where noise has a strong influence on the data or if there are some periods without observations. Also, the value of a vegetation index or of thermal infrared radiation decreases with clouds and hazes. In that case, time series filter processing is applied, extracting the local maximum value. The equation below describes the time series filter

$$d'_i = \min[\max(d_{i-w+1}, d_{i-w+2}, \ldots, d_i), \max(d_i, d_{i+1}, \ldots, d_{i+w-1})]$$

This filter does not affect the values if it is maximum at time ‘t’ or if it has a monotonous change in the window ‘w’. The data value ‘d’ is replaced only if it locally decreases at time ‘t’.
4.1.2 FITTING WITH CYCLIC FUNCTIONS

The cyclic functions were introduced to model seasonal changes over a year for a given pixel that is imaged all through the period creating a time-series of satellite data. The functions used in this study are

\[
f(t) = c_0 + c_1 t + \sum_{l=1}^{N} \left[ c_{2l} \sin \left( \frac{2\pi k_l t}{M} \right) + c_{2l+1} \cos \left( \frac{2\pi k_l t}{M} \right) \right] \quad \ldots \ldots (4.2)
\]

where \( c_j \) is a coefficient, \( t \) is time (the interval unit), \( N \) is the pair number of the cyclic function, \( M \) is the data number in a period and \( k_i \) is the periodicity of each cyclic function in a period, where \( k_i = 1, 2, 3, 4, 6, \) and \( 12 \), (meaning one year, a half year, 4 months, 3 months, 2 months and 1 month periods, respectively). The first and second terms indicate the mean value and the trend of the function respectively. The other trigonometric function terms show the periodicity. By repeating the fitting when determining coefficients \( c_j \), the optimal coefficients are obtained by the least squares method. To begin with, the difference between the fitting result of the model and the original data is calculated. If the difference is bigger than a threshold value, the processes described by equations 4.1 and 4.2 are repeated by removing contaminated data from the original one. By this processing, the influence of clouds and other noise sources are removed from the data set, and the time series model is established. The resulting time series more accurately reflects the surface changes.

4.1.3 DETERMINING THE OPTIMUM NUMBER OF CYCLIC FUNCTIONS

If the number of functions (i.e. \( N \)) for fitting through a time series is increased, the residual decreases and the fitting result tend to be unstable. It is well known that the optimum number of functions for these models is obtained when the Akaike's Information Criteria (AIC) is at its minimum \([AIC]\). The AIC is given by the following equation as the residuals are assumed to have a Gaussian distribution.

\[
AIC = D \left[ \log(2\pi\sigma + 1) + 2(j + 1) \right] \quad \ldots \ldots (4.3)
\]

where \( D \) is the number of data points, \( j \) is a number of functions used and \( \sigma \) is the standard deviation of the residual. The combination of functions for which the AIC is minimized is automatically selected so that model functions for a pixel are determined. The time series model (called the LMF model) for each pixel is generated by this procedure and the image at time \( t \) (called the LMF model image) is reproduced on the basis of the pixel models. Figure 4.2 shows a sample time series and the effect of local maximum fitting on that time series.

Figure 4.2: Effect of Local Maximum
CHAPTER 5: TIME SERIES CLASSIFICATION

Land cover classification is an important remote sensing technique and the remote sensing community has been challenged to produce land cover data sets at various scales on a repetitive basis [DeFries and Belward]. The range of clientele that use land cover datasets is expanding every day. Spectral and contextual supervised classification schemes with manual delineation of training samples remain the preferred choice of remote sensing scientists [Wilkinson]. The most commonly used classification methodologies for satellite image classification are decision tree, ISODATA, k-means and maximum likelihood classification. However, the multi-temporal data that is now available because of better revisit times of the satellites allow us to characterize objects based on their dynamic processes rather than static properties like color, shape, etc and this is being successfully demonstrated in this work. An important requirement for such a study is the definition or use of a variable whose time series can describe the process on the basis of which we would like to arrive at the classification. We have used time series of vegetation index to classify forest, crop and water. Although the value of satellite time series data for classification has been firmly established, only a limited number of methods for exploring such data series have been developed [Malingreau].

Till date, features derived from temporal and spectral response patterns of spatial locations have been used with conventional classification techniques for classifying satellite imagery [Jonsson and Eklundh] but the time series itself has not been used as an inherent class identifier. We have viewed the classification of the pixel-time trajectories as a time series signature (curve) matching problem comparing the unknown time series of a pixel to the temporal signatures available in the library of the training samples. An important part of such a curve matching problem is the definition of similarity measure. The conventional classification techniques typically measure closeness in Euclidean space. This leads to an anomaly that two similar classes of vegetation having an identical vegetation index profile with different growing practices (sowing, senescence, harvest, etc) appear as points separated by a large distance leading to different class labels. This chapter demonstrates the application of novel similarity measures to compare temporal signatures of various land cover classes.

One common measure for curve matching is the Hausdorff distance which simply takes the minimum distance between any two points, one from each curve. While the Hausdorff metric does measure closeness in space, it does not take into account the flow of the curves which is an important property to be considered in case of vegetation profile changes – a clue for land cover classification and hence this distance measure is rejected. Of the various other curve matching measures, a measure based on dynamic time warping distance and its variants and a measure based on fast marching method seemed to be promising and have been investigated for the problem in hand.
5.1 PROPOSED CLASSIFICATION PROCEDURE

Figure 5.1 shows the block diagram of the proposed classification procedure. The basic assumption on which the classification procedure is based is that the EVI of a target monitored over a growth period forms a temporal signature of that target which can be used to classify the target. Instances of such temporal signatures along with the corresponding labels are stored in a library which can act as templates for labeling unlabeled EVI time series. This is similar to classification of multispectral or hyperspectral data in which a spectral library comprising of unique spectral response curves is stored and classification of unlabeled samples is done based on the results of the matching between the unlabeled spectral curves and labeled spectral curves present in the spectral library. However, the same approach cannot be used to classify temporal signatures. One of the problems with temporal signature matching is that there can be variability in the growth pattern of similar vegetation based on the geographical area which conventional distance measures like Euclidean distance capture as belonging to different classes though the patterns belong to the same class.
In other words, the conventional distance measures do not take temporal shifts and small variations in ordinate (EVI values in this case) into account. We have tried various distance metrics as discussed in the next sub section and have proposed a distance metric that can be used for matching temporal signatures that can overcome misclassifications due to temporal shifts and small variations in EVI values. Figure 5.2 shows temporal signatures for fifty crop pixels. If all the fifty crops exhibited similar temporal responses, then they would have lined up on the time axis but this is not the case. Some variation in the responses can be seen that is not captured as intra class variation by conventional distance metrics like Euclidean distance because these distance measures compare the value of input pattern at time ‘t’ to that of the template pattern at time ‘t’.

The first step in the proposed classification procedure is to stack the vegetation index images to construct a time series. Knowledge of location of some representative samples for each class is used to construct a temporal library that consists of EVI patterns and the corresponding class labels. These are the training patterns or reference patterns. Thus the training phase of the proposed classification scheme consists of creating a temporal library unlike the conventional training phases that include determining certain classifier parameters. The classification of unlabeled EVI time series is a two step process. First, the distance between the unlabeled EVI pattern and all the reference patterns in the temporal library is found using a specified distance metric. In the second step, these distances are sorted in ascending order and ‘k’ most similar patterns are found. The label that occurs more frequently in these ‘k’ patterns is the label that is provided to the unlabeled EVI pattern and thus the name k nearest neighbor classification.

5.1.1 PROPOSED ALGORITHM

The proposed classification scheme can be formulated as follows

\[ \{(y_1, \theta_i), (y_2, \theta_i), \ldots, (y_n, \theta_i)\} \] is the training dataset
\[ \theta_i \in \{A, B, C, \ldots\} \quad \forall i \]
A,B,C,........ are the class labels
Given an unclassified feature vector \( x \), find its distances to the feature vectors \( y \) in the temporal library

Let \( D_n = \{d(x, y_1), d(x, y_2), d(x, y_3), \ldots, d(x, y_n)\} \) be these distances

Assuming, indices of the label feature vectors in \( D_n \) are permuted to satisfy

\[
d(x, y_1) \leq d(x, y_2) \leq \ldots \leq d(x, y_k)\]

\[
d(x, y_j) \geq d(x, y_k)\]

for \( j = k + 1, \ldots, n \)

The \( k \) nearest neighbours are

\[
\{Y_1, Y_2, Y_3, \ldots, Y_k\}\]

where \( Y_i = (y_i, \theta_i)\)

The \( k \) nearest neighbor classification rule then becomes

\[
\theta(x) = \max(n_A, n_B, n_C, \ldots)
\]

where \( n_A = |\{i | \theta_i = A\}|; \quad n_B = |\{i | \theta_i = B\}|; \quad n_C = |\{i | \theta_i = C\}| \) and so on

\( d \) is the distance metric or similarity measure. Experiments were performed with the various distance metrics described in section 5.2.

---

**Algorithm : EVI time series classification**

**Require:** Training patterns \( \text{train\_pat}[\ ] \) in which each row consists of a sequence of EVI values followed by the class label; \( \text{train\_pat}[\ ] = \text{train\_pat[EVI values; label]} \)

Unlabeled feature vector \( X \)

Function for calculating the distance metric \( D \)

**Output:** Label for the feature vector \( X \)

**Ensure:**

\[
n = \text{size}(\text{train\_pat}[\ ])
\]

for \( i = 1 \) to \( n \)

Calculate \( d[i] = D(X, \text{train\_pat}[i]) \)  

// \( D \) is the distance function

end for

permute \( \text{train\_pat}[\ ] \) such that

\[
d[i] > d[j]\]

for \( i = 1 \) to \( k \)

\( \text{cls\_labels}[\ ] = \text{label( train\_pat[1 : k])} \)

// Store the labels of the \( k \) nearest

// patterns

end for

\( x\_\text{label} = \text{majority( cls\_labels[\ ])} \)

// Function majority find the maximum

// occurrences of labels

---

**Pseudo code for EVI time series classification**

We have run experiments using many distance metrics. Best results have been obtained for a distance measure called constrained dynamic time warping which has been suggested as part of the proposed classifier in this research. Results for euclidean and other distance metrics have been provided as a comparison. These distance metrics are being discussed in the following section.
5.1.2 SIMILARITY MEASURES

EUCLIDEAN DISTANCE

The simplest time-domain algorithm for computing a similarity metric between time series is the Euclidean distance between two discrete time series \( x[n] \) and \( y[n] \) where the distance between the two series is defined as:

\[
D(x, y) = \sqrt{\sum_{n=0}^{M} (x[n] - y[n])^2}
\]

where \( M \) is the length of the time series.

DYNAMIC TIME WARPING (DTW)

Suppose we have two time series \( X \) and \( Y \) of length \( n \) and \( m \) respectively, where

\[
X = x_1, x_2, x_3, \ldots, x_n \quad \text{and} \quad Y = y_1, y_2, y_3, \ldots, y_m
\]

To align two sequences using DTW, an \( n \)-by-\( m \) matrix is constructed whose element at \((i,j)\) position contains the distance \( d(x_i, y_j) \) between the two points \( x_i \) and \( y_j \) (Typically the Euclidean distance is used). This is illustrated in Figure 5.3. A warping path \( W \) is a contiguous (in the sense stated below) set of matrix elements that defines a mapping between \( X \) and \( Y \). The \( k^{th} \) element of \( W \) is defined as \( w_k = (i, j)_k \), so we have:

\[
W = w_1, w_2, w_3, \ldots, w_K \quad \text{where} \quad \max(m,n) \leq K < m + n - 1
\]

The warping path is typically subject to several constraints,

1) Boundary conditions: \( w_1 = (1,1) \) and \( w_K = (m,n) \), simply stated, this requires the warping path to start and finish in diagonally opposite corner cells of the matrix.
2) Continuity: Given \( w_k = (a, b) \) then \( w_{k-1} = (a', b') \) where \( a - a' \leq 1 \) and \( b - b' \leq 1 \). This restricts the allowable steps in the warping path to diagonally adjacent cells.

3) Monotonicity: Given \( w_k = (a, b) \) then \( w_{k-1} = (a', b') \) where \( a - a' \geq 0 \) and \( b - b' \geq 0 \). This forces the points in \( W \) to be monotonically spaced in time.

There are exponentially many warping paths that satisfy the above conditions, however the path which minimizes the warping cost is of interest:

\[
\text{DTW}(X, Y) = \min \left( \sum_{k=1}^{K} \frac{w_k}{K} \right)
\]

The \( K \) in the denominator is used to compensate for the fact that warping paths may have different lengths. This path can be found very efficiently using dynamic programming.

**DERIVATIVE DYNAMIC TIME WARping (DDTW)**

An additional problem with DTW is that the algorithm may fail to find obvious, natural alignments in two sequences simply because a feature (i.e. peak, valley, inflection point, plateau etc.) in one sequence is slightly higher or lower than its corresponding feature in the other sequence.

With DDTW the distance measure \( d(x_i, y_j) \) is not Euclidean but rather the square of the difference of the estimated derivatives of \( x_i \) and \( y_j \).

\[
D_x[x] = \left[ (x_i - x_{i-1}) + \left( (x_{i+1} - x_{i-1}) / 2 \right) \right] / 2
\]

Similarly, the other sequence is also processed and then DTW of these sequences is calculated.

**CONSTRAINED DYNAMIC TIME WARping (CDTW)**

Although DTW has been successfully used in many domains, it can produce pathological results. The crucial observation is that the algorithm may try to explain variability in the Y-axis by warping the X-axis. This can lead to unintuitive alignments where a single point on one time series maps onto a large subsection of another time series. Such examples are called singularities. A variety of ad-hoc measures have been proposed to deal with singularities. All of these approaches essentially constrain the possible warpings allowed. However they suffer from the drawback that they may prevent the "correct" warping from being found.

Of the many solutions proposed to overcome the singularities, we have used the windowing method [Sakoe and Chiba]. Allowable elements of the matrix can be restricted to those that fall into a warping window, \(|i-(n(mfj))| < R\), where \( R \) is a positive integer window width. This effectively means that the corners of the matrix are pruned from consideration, as shown by the dashed lines in figure 5.3. This is also known as Sakoe Chiba band.

Euclidean distance can be treated as a limiting case of CDTW with \( R = 0 \). Detailed explanation of the above metrics is provided by Keogh and Pazzani.
CURVATURE BASED DISSIMILARITY USING FAST MARCHING METHOD (FMM)

Given a pair of curves
\[ C_1(t) = (x_1(t), y_1(t)), t \in [0, m] \]
\[ C_2(t) = (x_2(s), y_2(s)), s \in [0, n] \]

Where \( s \) and \( t \) are arc-length parameters and \( m \) and \( n \) are the lengths of the curves. Assuming that the end points of the input curves match, and given some local dissimilarity measure \( F \), we are interested in a path \( C \) through \( t,s \)-space from \((0,0)\) to \((m,n)\) such that

\[ T(m,n) = \min_c \int_c F(C(\tau)) d\tau \]

For such a path, distance between \( C_1 \) and \( C_2 \) is defined as

\[ d(C_1, C_2) = T(m,n) - \lambda \sqrt{m^2 + n^2} + |1 - (\min(m,n) / \max(m,n))| \]

\( \lambda \) is a smoothing constant such that \( \lambda > 0 \). Thus, dissimilarity between \( C_1 \) and \( C_2 \) is defined as the minimal sum of local dissimilarities between individual pair of curve points. The second term is needed for normalization and the third term penalizes global stretching of the curves.

\( F \) is a local dissimilarity function based on curvature

\[ F(t,s) = |\kappa_1(t) - \kappa_2(s)| + \lambda \]

\( \kappa_1 \) and \( \kappa_2 \) are curvatures of \( C_1 \) and \( C_2 \) respectively, and \( \lambda > 0 \). This distance metric satisfies the property of identity, uniqueness and symmetry. Detailed explanation of curve matching using fast marching method is provided by Frenkel and Basri.

5.1.3 TRAINING SAMPLES

Approximately, 1% of the total pixels to be classified are deemed sufficient for training. Since the proposed classification procedure matches the query EVI patterns with the template patterns in the temporal library, it is necessary that the temporal library and thus the training samples be selected carefully so that the patterns in the temporal library are truly representative of the classes to be classified. Training samples are being identified automatically using the techniques described in chapter 6. However it is not necessary to use the automatic method with this classification. Training sample locations obtained through any other method can also be used with the proposed classification procedure.

5.2 RESULTS

Classification results were compared with 56-m resolution classified image obtained from National Remote Sensing Centre. This image had 16 classes which were merged to obtain the required three classes. After appropriate scaling, it was compared with the derived map. Accuracy results are reported using several definitions of agreement between the map and primary or alternate reference land cover labels. Pixel-to-pixel comparison is the most restrictive protocol for defining agreement. It reflects a 'conservative bias' [Verbyla
and Hammond, 1995] due to the confounding of true classification error with errors attributable to misregistration or inability to confidently photo-interpret a sample unit. The second definition of agreement allows a match between the photo-interpreted label of a sample pixel and the most common class within a 3 by 3 pixel block centered on the sample pixel. This comparison takes into consideration that, for many applications, a certain level of spatial generalization from the original full resolution land cover data is appropriate. Yet another set of accuracy estimates are derived using a subset of the original samples, i.e., the sample pixel is located within a homogeneous area in which only one land cover type exists within the 3x3 pixel block. The estimates based on this comparison likely have an 'optimistic bias' [Hammond and Verbyla, 1996] because of the restriction to areas where land cover is homogeneous and generally is easily identified. The latter method is used for validation of the land use map in this study as the reference map used has a resolution of 56-m.

5.2.1 MODIS DATASET RESULTS

MODIS time series data for the cropping years 2003-04, 2004-05 and 2005-06 were constructed and used as input with the proposed classifier. A value of k=5 for k-nearest neighbor classification in case of MODIS dataset was found optimal.

<table>
<thead>
<tr>
<th>Our Method</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>3540</td>
</tr>
<tr>
<td>Crop</td>
<td>408</td>
</tr>
<tr>
<td>Water</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Producer's Accuracy:</th>
<th>User's Accuracy:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest 89.64295</td>
<td>Forest 49.3655</td>
</tr>
<tr>
<td>Crop 86.47967</td>
<td>Crop 98.57627</td>
</tr>
<tr>
<td>Water 57.59717</td>
<td>Water 7.345651</td>
</tr>
</tbody>
</table>

Overall % correct = 86.573003

Table 5.1: Confusion Matrix for Classification Using Euclidean distance

<table>
<thead>
<tr>
<th>Our Method</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>3208</td>
</tr>
<tr>
<td>Crop</td>
<td>740</td>
</tr>
<tr>
<td>Water</td>
<td>1</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Producer's Accuracy:</th>
<th>User's Accuracy:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest 81.23576</td>
<td>Forest 58.64717</td>
</tr>
<tr>
<td>Crop 88.3187</td>
<td>Crop 97.74098</td>
</tr>
<tr>
<td>Water 56.89046</td>
<td>Water 5.721393</td>
</tr>
</tbody>
</table>

Overall % correct = 87.521885

Table 5.2: Confusion Matrix for Classification Using DTW Distance
Tables 5.1, 5.2, 5.3, 5.4 and 5.5 show the confusion matrix, producer’s accuracy and user’s accuracy for proposed classifier with Euclidean, DTW, DDTW, CDTW and Curvature based similarity measure respectively.
Figure 5.4a shows the ground truth for the area under study and Figure 5.4b shows the classified map with CDTW as the distance measure used with proposed classification scheme and Sakoe Chiba radius of 4.

Figure 5.4: a) Ground Truth   b) Classified Map

5.2.2 AWIFS DATASET RESULTS

To demonstrate sensor independence, the proposed classification procedure was also run on NDVI time series constructed from AWiFS data which has a spatial resolution of 56m and temporal resolution of 5 days. Classification results using the proposed classification method and CDTW as similarity measure for AWiFS data is quantified by the confusion matrix in table 5.6. Since the ground truth was also at a resolution of 56 meters, a pixel to pixel comparison was done to obtain this confusion matrix.

<table>
<thead>
<tr>
<th></th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Forest</td>
</tr>
<tr>
<td>Our Method</td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>224949</td>
</tr>
<tr>
<td>Crop</td>
<td>7110</td>
</tr>
<tr>
<td>Water</td>
<td>1485</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Producer's Accuracy:</th>
<th>User's Accuracy:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>96.32</td>
<td>Forest 87.07</td>
</tr>
<tr>
<td>Crop</td>
<td>54.89</td>
<td>Crop 82.46</td>
</tr>
<tr>
<td>Water</td>
<td>89.96</td>
<td>Water 83.51</td>
</tr>
</tbody>
</table>

Overall % correct = 86.0716

Table 5.6: Confusion Matrix for Classification Using CDTW Distance for AWiFS data
5.3 OBSERVATIONS

It can be observed that the classifier using CDTW as distance measure performs better than classifier using Euclidean distance as similarity measure. Thus, the basic assumption that was made about Euclidean distance not being able to capture temporal shifts in growth patterns as intra class variation holds true. Also, derivate dynamic time warping distance measure based classifier does not perform well as this works on the derivatives and not the absolute values of EVI which are important for characterizing the vegetation classes. Curvature based similarity measure is not being able to provide good user accuracies for forest and water as curvature in these patterns is a characteristic of only crops. From figure 5.4(b), it can be observed that a lot of misclassifications happen with water. This is largely due to the inaccurate training samples. Also vegetation index is not a proper descriptor for characterizing water. The error may also be due to the way time series is constructed using compositing in which the highest value during the compositing period is used in the time series. The performance of classifier using CDTW as distance metric is around 4% higher as compared to the classifier using Euclidean distance metric which is not phenomenal but the gap between these accuracies will increase as large spatial areas are used as input for classification. Since the input used for the results shown in the previous section was a district, the variation in the vegetation growth patterns may not have been significant. As the area used for classification increases, the probability of variations in vegetation growth patterns increases and thus the ability of the Euclidean distance to capture these variations decreases. This is where the proposed classification procedure using CDTW as the distance metric is the best way of classifying temporal signatures.

To evaluate the performance of the proposed algorithm in comparison with some commonly used classification techniques, we used the same training set to train a k-NN classifier with k=5 using LNKNET and support vector machine classifier using SVM multiclass whose results are shown in figure 5.5 and 5.6 respectively. The results of these experiments are tabulated in table 5.7 and table 5.8 respectively. The low classification accuracy of these classifiers for time series satellite image classification can be attributed to the use of Euclidean distance in the feature space.

<table>
<thead>
<tr>
<th>Our Method</th>
<th>Reference</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Forest</td>
<td>Crop</td>
<td>Water</td>
</tr>
<tr>
<td>Forest</td>
<td>3126</td>
<td>8308</td>
<td>24</td>
</tr>
<tr>
<td>Crop</td>
<td>820</td>
<td>33641</td>
<td>127</td>
</tr>
<tr>
<td>Water</td>
<td>3</td>
<td>84</td>
<td>132</td>
</tr>
</tbody>
</table>

**Producer's Accuracy:**

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>79.159</td>
<td></td>
</tr>
<tr>
<td>Crop</td>
<td>80.035</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>46.643</td>
<td></td>
</tr>
</tbody>
</table>

**Overall % correct = 79.75**

**Table 5.7: Confusion Matrix for Classification Results of the kNN Classifier (LNKNET)**

Figure 5.5: kNN classified map
5.4 EFFECT OF CONSTRAINING THE TIME WARP

The classifier using CDTW as distance measure was further tested with different values of Sakoe-Chiba radius and the classification accuracies noted. Figure 5.7 shows the result of this experiment. It is observed that the maximum classification accuracy is obtained at radius equal to 4 (equivalent to 60 days) for MODIS dataset and at radius equal to 5 (equivalent to 25 days) for AWiFS dataset. Further observations that can be made from this plot are that CDTW performed better than Euclidian distance (radius = 0) and DTW (radius = 69) because CDTW is able to capture temporal shifts from pixel to pixel based on the geographic location as intra class variation. The classification accuracies saturate to a constant value after radius equal to 23 for MODIS dataset. Since there are 23 images per year, this also shows that most of the vegetation phenological patterns repeat during the subsequent years. The reduction in classification accuracy from maximum to this constant value can be attributed to the patterns that do not repeat during the subsequent years.

Table 5.8: Confusion Matrix for Classification
Results of the SVM Classifier

<table>
<thead>
<tr>
<th>Reference</th>
<th>Forest</th>
<th>Crop</th>
<th>Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>3196</td>
<td>6254</td>
<td>16</td>
</tr>
<tr>
<td>Crop</td>
<td>647</td>
<td>35477</td>
<td>127</td>
</tr>
<tr>
<td>Water</td>
<td>106</td>
<td>302</td>
<td>140</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Producer's Accuracy:</th>
<th>User's Accuracy:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>80.932</td>
</tr>
<tr>
<td>Crop</td>
<td>84.403</td>
</tr>
<tr>
<td>Water</td>
<td>49.47</td>
</tr>
</tbody>
</table>

Overall % correct = 83.89

Figure 5.6: SVM classified map

Figure 5.7: Plot of Classification Accuracies Vs Sakoe Chiba Radius
CHAPTER 6 : AUTOMATIC EXTRACTION OF TRAINING SAMPLES FOR SUPERVISED LAND COVER CLASSIFICATION

Whereas the actual supervised classification of satellite image is a highly automated process, assembling the training data needed for such classification is anything but automatic. The behavior of certain classes in the temporal dimension can be unique that can be exploited to find training samples from the time series data itself. Such an approach allows us to obtain land cover land use classification automatically given just the time series EVI data which can reduce the time taken for land cover classification considerably. A rule based training sample detection technique used with a time series classification scheme such as that proposed in chapter 5 can provide land cover land use classification given time series EVI as input.

6.1 TRAINING SAMPLES

Training samples are the representative or prototype pixels from each of the desired set of classes. These can be obtained using site visits, maps, aerial photographs or even a photointerpretation of a colour composite product formed from the satellite image data. Training data helps find certain parameters of the classifier and the trained classifier is then used to classify unknown samples. Supervised classification with manual delineation of training samples continues to be the preferred technique for land cover classification. Supervised classification is preferred over unsupervised classification as imagery will have variations in tone, colour, spectral and radiometric characteristics due to the changes in the vegetation and other land cover responses in changing natural environments. Field visits and manual delineation of training samples are imperative/cannot be dispensed with in supervised classification. Ripley (1996) defines classification as “Given some examples of complex signals and the correct decisions for them, make decisions automatically for a stream of future samples”. This definition makes it clear that correct decision of the training sites plays an important role in supervised classification technique. In general, classification accuracy is a function of training sample selection.

6.1.1 CHARACTERISTICS OF TRAINING SAMPLES

A good training set has the following characteristics [Marf et al.]:

1) It should contain samples describing all classes;
2) It should have a sufficient number of independent samples for each class;
3) It should be made up of samples that completely describe the intra-class variability.

6.1.2 NEED FOR AUTOMATIC EXTRACTION OF TRAINING SAMPLES

The choice of training samples relies on the cognition and skills of the image specialist who can identify conventional or meaningful classes from his knowledge base. This
‘apriori’ knowledge can be in the form of personal experience, or based on the region in which the scene is located, or based on thematic maps, or based on personal field visits. These methods are tedious and time consuming, thus becoming a bottleneck for creating products like land use/land cover maps in the least possible time. Another problem is that most of the field visits cannot be timed to be undertaken exactly at the time of the satellite overpass. This leads to proxy ground control points that are used as training samples. Also, field visits of a particular date are nothing more than of archival value in regions of rapid land use/land cover change. Thus, the current practices are highly demanding on both resources and time, with limited utility.

6.2 PROPOSED METHOD

Figure 6.1 shows the block diagram of the proposed algorithm for automatic extraction of the training samples for land cover classification.

Time series of EVI images for cropping seasons 2003-04, 2004-05 and 2005-06 were constructed for Dharwad, Hassan and Chamrajnagar districts of Karnataka state, India located in different agro climatic zones. These districts together cover an area of 16,784 square kilometers.

This research exploits the cyclic nature of the LMF processed data to automatically extract the training samples that have the characteristics described in 6.1.1. Since the variation in the amount of vegetation in forest areas is marginal, only subtle variation in EVI is observed. The LMF procedure characterizes this behavior by fitting very few
cyclic functions to forest EVI patterns. On the other hand, multiple cyclic functions are fitted to crop EVI patterns to capture the variation. When transformed to the Fourier domain, usage of less number of cyclic functions for forest data translates into strong first harmonic as shown in Figure 6.3(c), while for the crop pixels, the energy will be distributed in multiple harmonics as shown in figure 6.2(c). We used this cue to extract possible training samples for forest and crop classes. EVI values for water bodies are negative or close to zero. Even clouds have this characteristic but since clouds occur only for a part of the year, we were able to discriminate between low EVI values due to clouds and those due to the presence of water bodies. Our method examines the time series EVI profile to look for a large number of negative or zero values and tags such pixels as possible training samples for water. This leads to an initial classification.

Figure 6.2: a) Unprocessed EVI Time Series Pattern for a Crop pixel b) Corresponding LMF Fitted Pattern for that pixel c) Corresponding DFT

Figure 6.3: a) Unprocessed EVI Time Series Pattern for a Forest pixel b) Corresponding LMF Fitted Pattern for that pixel c) Corresponding DFT

Figure 6.2 a, b, and c show an unprocessed EVI time series pattern for a single crop pixel, corresponding LMF fitted pattern and its discrete fourier transform (DFT) respectively while figure 6.3 a, b and c show the same for a single forest pixel. To further refine the training samples, we deployed an outlier detection algorithm described by Leroy and Rousseeuw (1987). The principle of the algorithm is illustrated in Figure 6.4. This refinement helps to find a smaller subset of representative samples and does not lead to any loss of information with respect to the template patterns.

Figure 6.4: Principle of Outlier Detection.
6.2.1 IDENTIFICATION OF PURE PIXELS

Pixels along the boundaries of water bodies are prone to misclassification as they are interspersed with vegetation. Similarly, pixels in the boundaries of forest and agricultural areas tend to exhibit mixed responses. Thus, it can be safely assumed that the innermost pixels of such class patches would represent the pure pixels of a given class. These innermost pixels are identified by using a combination of connected component analysis and Euclidean distance transform. In summary, the training samples were labeled based on the temporal characteristics of the EVI curve and were further pruned to find homogeneous training samples that are truly representative of the classes of interest by using spatial information. The above reasoning follows Tobler’s law in Geography.

6.2.2 PROPOSED ALGORITHM

Given a EVI time series
\[ X = \{x_1, x_2, \ldots, x_n\} \]
\[ Y = \text{mag}(DFT(X)) \]
is the magnitude spectrum of the discrete fourier transform of \( X \)
\[ Y = \{y_1, y_2, \ldots, y_n\} \]
Where \( y_1 \) is the dc component
\( y_2, y_3, \ldots \) are first, second harmonics and so on.
Let forest Ts[], crop Ts[] and water Ts[] be the structures holding the training samples for forests, crops and water respectively.

\[
\text{if (} y_2 / y_3 > Th_1 \text{)} \\
\text{forest Ts[] } \leftarrow X \\
\text{else if} \\
\text{n } = 0; \\
\text{n } = \text{n } + \sum I\{x_i\} \quad \text{where} \quad I\{x_i\} = 1 \quad \text{if} \quad x_i < 0 \quad 0 \quad \text{otherwise} \\
\text{if (n } > Th_2 \text{)} \\
\text{water Ts[] } \leftarrow X \\
\text{else if (} Th_3 > y_2 / y_3 > Th_4 \text{)} \\
\text{crop Ts[] } \leftarrow X \\
\]
The values of \( Th_1, Th_2, Th_3 \) and \( Th_4 \) were obtained by visual inspection of some representative temporal profiles. Each of forest Ts[], crop Ts[] and water Ts[] is now scanned for removing outliers.

Let \( p_i \) be the time series reference patterns (training patterns) belonging to a particular class obtained by methods described previously. Majority of them form a cluster. First, the central point \( p_c \) of the cluster is found as the point whose median distance from all other points is minimal as shown by the equation below,
\[
d_{med}(i) > d_{med}(c) \quad \forall i \neq c \\
d_{med}(i) = \text{median}_{j \neq i} D_{dist}(p_i, p_j)
\]
The distance measure used for the experiment in question between patterns $p_i$ and $p_j$ is $D_{dist}(p_i, p_j)$. Choice and calculation of these distance metrics is dependent on the classification technique used. The distance metric that is found to perform well for land cover classification using multitemporal values is described in Chapter 5. By the radius $r_i$ of a pattern $p_i$, we mean its distance from $p_c$. A pattern $p_k$ is then selected as an outlier if its radius exceeds a threshold $r_{max}$. In our experiments, we have set $r_{max} = 2 \times r_{mean}$, where $r_{mean}$ is the mean radius of the cluster. This completes the creation of a truly representative training set. Once the outliers in forest_ts[], crop_ts[] and water_ts[] are removed, the final training set is obtained.

---

**Algorithm: Automatic extraction of training samples**

**Require:** $m \times n \times p$ EVI image $img$ where $m$ and $n$ are spatial dimensions and $p$ is in the temporal dimension.

Values of the thresholds $Th_1$, $Th_2$, $Th_3$ and $Th_4$

**Output:** Initial training sample set

**Ensure:**

```plaintext
crop_ts = [ ]; // arrays to hold training samples
forest_ts = [ ];
water_ts = [ ];
```

```plaintext
for i = 1 to m
    for j = 1 : n
        X = img(i, j, 1 : n)
        Y = magnitude(DFT(X)) // discrete fourier transform magnitude
        if $h_1/h_2 > Th_1$ then  # h1 and h2 are first and second harmonics
            forest_ts[ ] = X // include X in forest training samples
        else
            count = 0;
            for t = 1 : n
                if $X(t) \approx 0$ then
                    Increment count
                end if
            end for
            if count > $Th_2$ then
                water_ts[ ] = X // include X in water training samples
            else if $Th_3 < (h_1/h_2) < Th_4$ then
                if $Th_3 < (h_1/h_2) < Th_4$ then
                    crop_ts[ ] = X
                end if
            end if
        end if
    end for
end for
```

```plaintext
forest_ts[ ] = detect_outliers(forest_ts[ ])
crop_ts[ ] = detect_outliers(crop_ts[ ])
water_ts[ ] = detect_outliers(water_ts[ ])
```

---

Pseudocode for automatic extraction of training samples
Function: Outlier detection (detect_outliers)

Require: Training samples identified for a particular class, say ts[ ] (forest, crop or water) These training samples form a cluster

Output: Revised final training sample set

Ensure:

\[ t = \text{size}(ts[ ]) \]
\[ \text{find } p[c] \text{ such that } \]
\[ \text{dmed}(i) > \text{dmed}(c) \quad \text{for all } i \neq c \quad \text{// dmed calculates the median distance} \]

where
\[ \text{dmed}(i) = \text{median}( D(p[i], p[j]) ; \quad i \neq j \quad \text{// } D \text{ is the distance measure and } p[i] \text{ is } i^{th} \text{ row of } ts[ ] \]

for \( x = 1 \) to \( t \)
\[ r(x) = D(p[x], p[c]) \]
end for

\[ r_{\text{mean}} = \text{mean}(r[ ]) \quad \text{// Function mean returns the mean of the input array} \]

if \( D(p[x], p[c]) > (2 * r_{\text{mean}}) \) then
Remove \( p[x] \) from ts[ ]
end if

Figure 6.5: a) Representative EVI Patterns for Land Use Classes b) Time Series Patterns for Forest. c) Time Series Patterns for Crop. d) Time Series Patterns for Water.
6.3 RESULTS

The training set derived from the method described in the above section contained 1.27% of total forest patterns, 0.09% of total crop patterns and 1.18% of total water pixels. These numbers can be modified by changing the limits imposed on the maximum number of training samples to be chosen. Figure 6.6 shows the locations of the extracted training samples overlaid on the NRSC land use land cover dataset. The red boxes in the figure correspond to the locations of the extracted training samples.

![Figure 6.6: Extracted training sample locations for Dharwad district](image)

6.3.1 VALIDATION I

The training data obtained by methods described above was validated using the 56-m AWiFS derived land use/land cover map provided by National Remote Sensing Centre (NRSC) of India. This image had sixteen classes which were merged to obtain the required three classes. After appropriate scaling, it was compared with the derived map. Figure 6.6 shows this land cover map for Dharwad district. The results are promising with an accuracy of 100%. This high accuracy is not just the result of the heuristics used but also the conditions levied on a pixel to be considered as a training sample. Table 6.1 shows the confusion matrix for training set obtained for Dharwad district labeled through our method versus the LULC map of NRSC.

<table>
<thead>
<tr>
<th></th>
<th>Reference</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Forest</td>
<td>Crop</td>
<td>Water</td>
</tr>
<tr>
<td>Forest</td>
<td>50</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Crop</td>
<td>0</td>
<td>41</td>
<td>0</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>25</td>
</tr>
</tbody>
</table>

Overall % correct = 100

Table 6.1: Training Set Validation with NRSC LULC
6.3.2 Validation II

Claims of 100% accuracy needed to be evaluated more and thus we decided to do a visual inspection of the extracted training samples. The training samples for various classes were overlaid on 24 meter spatial resolution LISS-3 data for the year 2005 provided by NRSC, India. Figure 6.7, 6.8 and 6.9 show the training sample locations for Dharwad, Hassan and Chamrajnagar districts respectively with some training samples zoomed in. Visual inspection of these locations proves that they have been picked from the right places as intended. Polygons were drawn around the training samples and only area within these polygons was being interpreted by an expert. The classified polygons provided by the expert were then overlaid on the training samples to supplement the visual inspection and were found to correlate well.

Figure 6.7: Training samples derived for Dharwad District
Figure 6.8: Training samples derived for Hassan District

Figure 6.9: Training samples derived for Chamarajanagar District
6.4 UTILITY OF EXTRACTED TRAINING SAMPLES IN CLASSIFICATION

The training samples obtained automatically were used to classify a single scene of LISS-3 data and a time series MODIS EVI data to demonstrate their utility. This thesis has described the use of the automatically extracted training sample with the time series classification procedure described in chapter 5. This is not necessary and the obtained training samples which are point data can be used for classification of various satellite data with different characteristics with any valid classification procedure.

6.4.1 CLASSIFICATION OF SINGLE SCENE LISS-3 DATA

The training samples obtained were used to classify a single scene of LISS-3 image for the study districts using maximum likelihood (ML) classification technique. An expert was also asked to mark the training samples as is done conventionally. The training samples marked by the expert were used with the same classification technique. The results of the above mentioned classification were compared on a pixel to pixel basis which is then quantified using a confusion matrix. Figure 6.10a and 6.11a shows the ML classification obtained by training samples provided by expert for Dharwad and Chamarajanagar district respectively while figure 6.10b and 6.11b show the ML classification obtained by using automatically derived training samples for Dharwad and Chamarajanagar respectively. Water pixels are highly misclassified as seen in figure 6.10b and 6.11b, using the automatically derived training samples in this single scene classification as the automatically derived training samples are based on the vegetation response and any low or nil vegetation cover areas are being classified as water, though it might be largely fallow lands or barren soil. The expert is better able to differentiate this, but might be misclassifying these as crop lands.

![Figure 6.10](image1.png) ![Figure 6.11](image2.png)

(a) ML Classification using a) Expert provided training samples b) automatically derived training samples for Dharwad

(a) ML Classification using a) Expert provided training samples b) automatically derived training samples for Chamarajanagar
ANALYSIS

Table 6.2 and table 6.3 quantify the comparisons between the classification obtained with expert provided training samples and classification obtained by automatically derived training samples for Chamarajanagar and Dharwad districts respectively. The entries in the tables are in hundreds of hectares. The corresponding numbers as estimated from the NRSC LULC dataset are provided as a benchmark to compare the performance of classification done using automatically derived training samples and that done using manually marked training samples.

<table>
<thead>
<tr>
<th>Automatic Training</th>
<th>Expert Derived Training</th>
<th>NRSC dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>1017.75</td>
<td>2395.35</td>
</tr>
<tr>
<td>Crop</td>
<td>621.52</td>
<td>2256.59</td>
</tr>
<tr>
<td>Water</td>
<td>12.51</td>
<td>36.27</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Manual Method Accuracy:</th>
<th>Automatic Method Accuracy:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>61.62</td>
</tr>
<tr>
<td>Crop</td>
<td>65.91</td>
</tr>
<tr>
<td>Water</td>
<td>100</td>
</tr>
</tbody>
</table>

Overall % correct = 64.8923

Table 6.2: Confusion Matrix for validating automatically derived training samples for Chamarajangar district

<table>
<thead>
<tr>
<th>Automatic Training</th>
<th>Expert Derived Training</th>
<th>NRSC dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>217.09</td>
<td>253.79</td>
</tr>
<tr>
<td>Crop</td>
<td>545.04</td>
<td>3004.52</td>
</tr>
<tr>
<td>Water</td>
<td>0.035</td>
<td>14.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Manual Method Accuracy:</th>
<th>Automatic Method Accuracy:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>28.48</td>
</tr>
<tr>
<td>Crop</td>
<td>83.51</td>
</tr>
<tr>
<td>Water</td>
<td>94.2</td>
</tr>
</tbody>
</table>

Overall % correct = 70.4876

Table 6.3: Confusion Matrix for validating automatically derived training samples for Dharwad district

6.4.2 CLASSIFICATION OF TIME SERIES MODIS DATA

To demonstrate the utility of the training samples derived by the proposed method, we used the derived training set to perform classification on MODIS time series data for 2005-06. Time series classification was done by training a k-NN classifier with k=5 using LNKNET and support vector machine classifier using SVM multiclass whose results are shown in figure 6.12 and 6.13 respectively.
A N A L Y S I S
The results of MODIS time series classification using the automatically derived training samples used with k-NN and SVM classifiers are tabulated in table 6.4 and table 6.5 respectively. The reference data is from the LULC map of NRSC for the same region. The classification results reported are deemed satisfactory based on expert opinion and are comparable with the results obtained using conventional techniques of manual demarcation of training samples or samples obtained through field visits.

![Figure 6.13: kNN classified map](image1)

![Figure 6.13: SVM classified map](image2)

<table>
<thead>
<tr>
<th>Our Method</th>
<th>Reference</th>
<th>Forest</th>
<th>Crop</th>
<th>Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>3126</td>
<td>8308</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>Crop</td>
<td>820</td>
<td>33641</td>
<td>127</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>3</td>
<td>84</td>
<td>132</td>
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</table>

Producer's Accuracy

<table>
<thead>
<tr>
<th>Reference</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>79.159</td>
</tr>
<tr>
<td>Crop</td>
<td>80.035</td>
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<tr>
<td>Water</td>
<td>46.643</td>
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</tbody>
</table>

Overall % correct = 79.75

Table 6.4: Confusion Matrix for Classification Results of the kNN Classifier (LNKNET)

<table>
<thead>
<tr>
<th>Our Method</th>
<th>Reference</th>
<th>Forest</th>
<th>Crop</th>
<th>Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
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<td>6254</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>Crop</td>
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<td>35477</td>
<td>127</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>106</td>
<td>302</td>
<td>140</td>
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</tbody>
</table>

Producer's Accuracy

<table>
<thead>
<tr>
<th>Reference</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>80.932</td>
</tr>
<tr>
<td>Crop</td>
<td>84.403</td>
</tr>
<tr>
<td>Water</td>
<td>49.47</td>
</tr>
</tbody>
</table>

Overall % correct = 83.89

Table 6.5: Confusion Matrix for Classification Results of the SVM Classifier (SVM_Multiclass)
CHAPTER 7: SPATIAL MAPPING OF CROPPING PRACTICES

The land cover information obtained by methods described in chapter 5 and chapter 6 together with the time series EVI input data were being used to create some products that are of a great utility in Indian context. Seasonal characteristics and crop growth information is of great utility for crop management. The primary occupation in India being agriculture, it is important to devise quick and reliable methods that will help in making decisions affecting agricultural practices at a macro level more efficiently. We have devised an algorithm to derive a seasonal calendar from the time series data of a moderate resolution satellite, MODIS, which is one step short of producing a crop calendar.

Data sets available from a variety of satellites have opened up tremendous possibilities for extracting a variety of features. Remote sensing can be a valuable tool for agricultural statistics that could save precious resources like time and money and provide real time information for farmers, policy makers, etc. The use of remote sensing data for estimating crop acreage estimation has reached a near operational level. Studies carried out for estimating acreage under different crops in many countries show a near 90 percent accuracy level. In many countries, production forecasting of certain crops, crop yield modeling and crop stress detection are done using remote sensing data [Das]. To do so, the first step is to detect the cropping regions and the cropping practices – single and multi-cropping. We have used the phenology parameters derived from time series EVI to map the single and double cropping regions of five districts of Karnataka State, India namely Bidar, Chamrajnagar, Dharwad, Hassan, Kolar and Udupi which are located in different agro-climatic zones.

Trend analysis is a useful tool for forecasting. It also helps in providing useful advisory. As in a stock market where portfolio managers analyze the trend of financial instruments from their desktop, a remote sensing based analysis of the cropping practices in a particular geographical area will definitely provide useful insights to a wide range of users ranging from farmers to policy makers. Remote sensing can play a vital role in monitoring the fields and provide a snapshot of the outcome of the field practices which can then be processed to aid the agricultural scientist to make meaningful conclusions. Global coverage and repeated temporal sampling provided by satellites have significant potential for monitoring vegetation dynamics at regional to global scales. In many parts of India, multiple varieties – traditional, high yielding (HYV) and short high yielding (SHYV) varieties of crops are grown in the same region like, Annapoorna, IR-64, KMP-1 (Mandya-vani) [DACNET], based on weather and other local conditions including labour availability leading to different sowing/harvest dates. To effectively estimate crop production, it is required to estimate these cropping varieties and cropping practices. In addition, this lack of knowledge of cropping varieties and cropping practices across regions is a major deterrent in effectively understanding the response or modelling of these crops for climate and other input changes over time, thus limiting the adaptation potential of the region. This chapter elucidates the work done to map the cropping practices of a particular geographic area using time series data of MODIS EVI. Crops or vegetation in general follow a systematic pattern of growth. Growth is a process and this
process can provide valuable insights into the crop type/variety, cropping pattern, irrigation practices etc. Information about such a process cannot be deciphered from single date imagery. With the advent of moderate resolution earth observing satellites that have revisit time as small as one day, the growth process can be monitored at a much more finer temporal resolution. In the Indian context, studies have been carried out using high temporal resolution data for analyzing the trends in cropping practices of particular crops over particular geographic area [R. K. Panigrahy et.al.]. The main objective of this work is to demonstrate that time series satellite imagery can aid the agricultural experts for better monitoring.

7.1 DERIVING PHENOLOGY PARAMETERS

Time series EVI data allows us to extract crop phenology which provides valuable information for crop management. The smoothed time series obtained as a result of local maximum fitting, as explained in Chapter 4 was analyzed for finding critical points (maxima and minima) with some set of constraints on their values that are well established by various studies. For every triplet of left minima, maxima and right minima, four phenological parameters were derived as follows.

1) Time for the start of the season: datestamp at which there is a rise of 20% above left minimum level.
2) Time for the end of the season: datestamp at which the right edge is 20% above the right minimum level.
3) Time for the mid of the season: computed as the mean value of the times for which, respectively, the left edge has increased to its 80% level and the right edge has decreased to the 80% level. and
4) Seasonal amplitude: difference between the maximal value and the base level

These parameters are illustrated in figure 7.1. Some of the empirical constraints levied on the values are mentioned here. The value of the maxima cannot be greater than 0.6 for

![Figure 7.1: Illustration of Phenology Parameters](image-url)
crops. Similarly, minima greater than 0.5 were discarded. This work identifies only the major seasons and hence phenologies with length of growing period (LGP) less than two months were being discarded.

7.2 DERIVING SEASON CALENDAR

Crop calendar provides the schedule of the maturing and harvesting of seasonal crops. Time series EVI data can be used to find start of the season, senescence and harvest of crops. A schedule in which the type of crop is not known can be called as a season calendar as it provides information about the major seasons of a particular geographic area.

7.2.1 CLUSTERING PHENOLOGY PARAMETERS

Phenology patterns for every crop pixel are known and it is interesting to understand and extract the unique seasonal patterns among the phenologies of all the crop pixels present in a given geographic area. Once the phenology parameters are obtained, they are clustered using a density based clustering method called Density Based Spatial Clustering of Applications with Noise (DBSCAN). Density based approaches apply a local cluster criterion. Clusters are regarded as regions in the data space in which the objects are dense. These regions may have an arbitrary shape and the points inside a region may be arbitrarily distributed. The useful properties that the clustering method should provide for are 1) number of clusters is determined by the algorithm itself 2) ability to identify a dense set of points, that form a cloud of irregular, non-spherical shape as a cluster. DBSCAN algorithm satisfied these properties that helped to make the process of deriving season calendar fully automatic without requiring any field visit or manual intervention.

7.2.2 POST CLUSTERING PROCESSING

This algorithm also categorizes points as those belonging to the core of the cluster, those belonging to the border of the clusters and outliers. In this study, only points of the first kind have been processed further to avoid outlier bias. The cluster centers are found as the mean of these cluster points and these are output as identified seasons.

7.2.3 RESULTS

<table>
<thead>
<tr>
<th>Type</th>
<th>Start</th>
<th>End</th>
<th>Mid</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12-Jul</td>
<td>15-Oct</td>
<td>14-Sep</td>
</tr>
<tr>
<td>2</td>
<td>1-Nov</td>
<td>4-Mar</td>
<td>1-Jan</td>
</tr>
<tr>
<td>3</td>
<td>15-Oct</td>
<td>18-Feb</td>
<td>19-Dec</td>
</tr>
<tr>
<td>4</td>
<td>15-Oct</td>
<td>17-Jan</td>
<td>3-Dec</td>
</tr>
<tr>
<td>5</td>
<td>30-Sep</td>
<td>1-Jan</td>
<td>17-Nov</td>
</tr>
</tbody>
</table>

Figure 7.2: Derived season calendar for Chamrajanagar District
Seasons thus obtained for different districts are expressed in the form of Gantt Charts. Figure 7.2 shows one such Gantt chart for Chamrajanagar District. Figure 7.3 shows the season calendar derived for Hassan district. The green color represents the dates when the crop is fully grown where maximum EVI value was observed. The color scale before the green tab represents the length of growing period and the extreme right end of the color scale represents the end of season. The season calendar derived here represents the major cropping practices in the respective districts. For Hassan district, we find that there are many clusters, while for Chamrajnagar district, there are two clear Kharif and Rabi seasons because majority of the cropping area is irrigated allowing well defined cropping patterns. The large set of clusters for Hassan can be attributed to the mixed cropping that is prevalent in the region and to connect these clusters to a specific or a group of crops requires corresponding field correlation. Also, the temporal spread of the data (one value for 15 days) brings in another set of challenges that need to be addressed for a better resolution of the clusters. Some of this will be addressed by building an expert system that will combine the knowledge of the experts/agronomists with the cluster characteristics to identify the crop with an intention of deriving a crop calendar. It is anticipated that with one labeled point per cluster in case of non overlapping clusters or two or more unambiguous labeled points in case of overlapping clusters, same labels can diffuse throughout the cluster thus allowing us to create crop calendar and crop maps. Season calendar for all districts of Karnataka state India was derived.

7.3 MAPPING SINGLE AND DOUBLE CROPPING REGIONS

The number of phenology parameters also indicates whether the crop pixel in question is a single or double cropping area. A single cropped area refers to a land area or parcel, where only one crop is grown, generally in the Kharif (rainy) season while, a double
cropped area is one where crops are grown in both Kharif and Rabi (winter) seasons. This was mapped for the six districts under study as shown in figure 7.4. Yellow coloured regions refer to single crop areas and green coloured regions refer to double crop areas.

7.4 MAPPING SPATIAL VARIABILITY OF CROPPING PRACTICES

Cropping varieties can be estimated from cropping practices and hence it is imperative to identify the spatial variability of the cropping practices. We have used the time series EVI data to find structures in the feature space (comprising of values observed temporally) that correspond to different cropping practices.

If the phenologies are similar, the growth process is assumed to be similar and is hence clustered to form a single vegetation class (crop type). The clustering is manually improvised to merge the similar clusters that may have been separated by the parameters but could be an artefact of the data, like all the parameters show a shift by a fortnight (16-days, here) as seen in group typed 4 and 5 of figure 7.2 above. While at the same time, neighbouring clusters may show a large variation – like one may show a double seasonal cropping area (pixels) while the adjacent cluster may have a annual crop. These clusters are representative of the differing cropping practices in the region.

The pixel locations of these clusters are marked with different colors to map the variability in the cropping practices to produce the cropping practice variability map. The identified seasons were then classified as Kharif, Rabi and Zaid and as Annual crops manually. Pixel locations for the various combinations of Kharif, rabi and zaid were mapped spatially to produce the cropping season map. The cropping practice variability maps derived are shown here. Each color represents a unique cropping practice. A sample set of the results are reported here, while the original result set has many more variations. The variations are in sowing, senescence or end of season dates/fortnights.
Figure 7.5 and 7.7 show the variability in the cropping practices of a Kharif crop which grows for around 150 days and 120 days respectively. 7.6 shows the variability in cropping practice of a rabi crop. Figure 7.8 shows the same for a zaid crop.

<table>
<thead>
<tr>
<th>Season</th>
<th>Start</th>
<th>Mid</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10-Jun</td>
<td>3-Dec</td>
<td>9-May</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>30-Sep</td>
<td>23-Apr</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>17-Nov</td>
<td>7-Apr</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>30-Sep</td>
<td>7-Apr</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>1-Nov</td>
<td>7-Apr</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>30-Sep</td>
<td>22-Mar</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>17-Nov</td>
<td>22-Mar</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>1-Nov</td>
<td>22-Mar</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>30-Sep</td>
<td>6-Mar</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>1-Nov</td>
<td>6-Mar</td>
</tr>
<tr>
<td></td>
<td>10-Jun</td>
<td>17-Nov</td>
<td>6-Mar</td>
</tr>
</tbody>
</table>

Figure 7.5: Kharif cropping practice variability map for a 150 day crop.

<table>
<thead>
<tr>
<th>Season</th>
<th>Start</th>
<th>Mid</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>28-Jul</td>
<td>30-Sep</td>
<td>7-Apr</td>
</tr>
<tr>
<td></td>
<td>28-Jul</td>
<td>17-Nov</td>
<td>7-Apr</td>
</tr>
<tr>
<td></td>
<td>28-Jul</td>
<td>1-Nov</td>
<td>7-Apr</td>
</tr>
<tr>
<td></td>
<td>14-Sep</td>
<td>17-Nov</td>
<td>22-Mar</td>
</tr>
<tr>
<td></td>
<td>14-Sep</td>
<td>1-Nov</td>
<td>22-Mar</td>
</tr>
<tr>
<td></td>
<td>14-Sep</td>
<td>1-Jan</td>
<td>22-Mar</td>
</tr>
</tbody>
</table>

Figure 7.6: Rabi cropping practice variability map
<table>
<thead>
<tr>
<th>Season</th>
<th>Start</th>
<th>Mid</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kharif</td>
<td>28-Jul</td>
<td>30-Sep</td>
<td>7-Apr</td>
</tr>
<tr>
<td>Kharif</td>
<td>28-Jul</td>
<td>17-Nov</td>
<td>7-Apr</td>
</tr>
<tr>
<td>Kharif</td>
<td>28-Jul</td>
<td>1-Nov</td>
<td>7-Apr</td>
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</table>

Figure 7.8: Kharif cropping practice variability map for 120 day crop.

<table>
<thead>
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<th>Season</th>
<th>Start</th>
<th>Mid</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zaid</td>
<td>17-Jan</td>
<td>6-Mar</td>
<td>25-May</td>
</tr>
<tr>
<td>Zaid</td>
<td>17-Jan</td>
<td>7-Apr</td>
<td>25-May</td>
</tr>
<tr>
<td>Zaid</td>
<td>2-Feb</td>
<td>7-Apr</td>
<td>25-May</td>
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<tr>
<td>Zaid</td>
<td>19-Dec</td>
<td>18-Feb</td>
<td>7-Apr</td>
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<tr>
<td>Zaid</td>
<td>19-Dec</td>
<td>22-Mar</td>
<td>9-May</td>
</tr>
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<td>Zaid</td>
<td>18-Feb</td>
<td>7-Apr</td>
<td>25-May</td>
</tr>
<tr>
<td>Zaid</td>
<td>17-Jan</td>
<td>6-Mar</td>
<td>23-Apr</td>
</tr>
<tr>
<td>Zaid</td>
<td>19-Dec</td>
<td>2-Feb</td>
<td>22-Mar</td>
</tr>
</tbody>
</table>

Figure 7.7: Zaid cropping practice variability map

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<thead>
<tr>
<th>Season</th>
<th>Start</th>
<th>Mid</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kharif + Rebi + Zaid</td>
<td>17-Jan</td>
<td>6-Mar</td>
<td>25-May</td>
</tr>
<tr>
<td>Kharif + Rebi</td>
<td>17-Jan</td>
<td>7-Apr</td>
<td>25-May</td>
</tr>
<tr>
<td>Kharif + Zaid</td>
<td>19-Dec</td>
<td>18-Feb</td>
<td>7-Apr</td>
</tr>
<tr>
<td>Kharif only</td>
<td>19-Dec</td>
<td>22-Mar</td>
<td>9-May</td>
</tr>
<tr>
<td>Rebi + Zaid</td>
<td>18-Feb</td>
<td>7-Apr</td>
<td>25-May</td>
</tr>
<tr>
<td>Rebi only</td>
<td>17-Jan</td>
<td>6-Mar</td>
<td>23-Apr</td>
</tr>
<tr>
<td>Zaid only</td>
<td>19-Dec</td>
<td>2-Feb</td>
<td>22-Mar</td>
</tr>
</tbody>
</table>

Figure 7.9: Cropping season map
The cropping season map for Hassan District, obtained by plotting combinations of Kharif, Rabi and Zaid is shown in figure 7.9. This categorisation into Kharif, rabi and zaid was done manually and important combinations of the cropping seasons were plotted spatially. Such maps can be helpful in extracting other information like irrigated areas, etc. At regional and larger scales, variation in community, climate regime, soils, land management, progress of monsoon, distribution of seeds and fertilizers results in complex spatio temporal variation in phenology. The cropping practice variability maps are able to capture this variation which can then be analysed along with other spatial data that influence cropping practices by the agricultural expert to better understand the cropping practices. It was also found that there was a correlation between the directions of increasing sowing dates to the progress of the south west monsoon for all the districts under study.

7.5 NET SOWN AREA

Net sown area represents the area sown with crops at least once in any of the crop season of the year, counting area sown more than once in the same year, only once.

The net sown area reported in statistics is 3,96,487 hectares while the net sown area estimated from our analysis of Kharif, rabi, zaid and annual crops from the cropping season map is 4,12,716 hectares which is an error of 4% and well within acceptable errors for such regional studies. The sown area during Kharif and Rabi for Hassan district was also compared with that available from statistics, the results of which are tabulated in table 7.1.

<table>
<thead>
<tr>
<th></th>
<th>Statistics hectares</th>
<th>Our results hectares</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kharif</td>
<td>393481</td>
<td>367010</td>
</tr>
<tr>
<td>Rabi</td>
<td>66244</td>
<td>40756</td>
</tr>
</tbody>
</table>

Table 7.1: Comparison with statistics for Hassan district.

Since rabi and zaid crops can only grow in this district with irrigation support, it would be safe to conclude that areas which show cropping during non monsoon period are irrigated areas. However, such an assumption still needs to be evaluated. An important observation that was made was the absence of triple cropping lands in this area. Pixel-time trajectories of pixels that showed the combination of rabi and zaid (Red pixels in figure 7.9) were being analyzed and we found that the phenological curve in the Kharif season had a very small length of growing period of around 30 days. Since, our algorithm was designed to discard such phenologies, they did not appear in the final list of phenologies. Whether this short length of senescence is because of data compositing process or indeed a ground process is yet to be known. Nevertheless, to achieve the best results and to investigate this discrepancy, we have to revert to the daily EVI data.

Since, Kharif season is covered by clouds for majority of the time, optical sensors provide limited information that may not reflect the ground situation properly. The spatial resolution of 250 meters provide by MODIS for such studies in Indian context can be very high owing to fragmented landholdings. Thus, the same study if done at a better spatial resolution, say 56 meters using AWiFS sensor on board Resourcesat-I, an Indian satellite, may provide more insights and explain some of these observations.
CHAPTER 8 : CONCLUSIONS

This research was focused on understanding both spatially and temporally the vegetation growth parameters, especially for the agricultural land cover regions, using time-series satellite imagery. The work has demonstrated the viability and utility of a system for automatic information extraction from remotely sensed data that can help a large group of users. This system has different hierarchical levels and each level uses appropriate spatial and temporal resolution images to produce outputs that aid the process in the subsequent levels.

We have successfully presented an automated way of extracting training samples for satellite image classification, exploiting the frequent revisit capabilities and the time series data that it generates. Though the validation done using the land use land cover data has shown good promise, field based ground truth collection and validation can further reinforce the performance of such techniques before such a system can be made operational as part of a regional agricultural monitoring system. The objective of this study being to demonstrate the utility of time series data for land use classification, the number of classes were less in this initial investigation but an attempt is being made to build a hierarchical system and define appropriate algorithms and input data at each hierarchy. In such a hierarchical system, the classifier developed in this algorithm with MODIS 250m data as input will be the first level. By improving the spatial resolution of the input data, training samples that are much more representative of the classes can be obtained. In the Indian context, use of AWiFS data with 56m spatial resolution seems to be a good choice. When the spatial resolution of the input satellite imagery increases, so does the number of training samples extracted. The question of optimum number of training samples required for classification remains an open area of research in pattern recognition though different techniques have been proposed. In the context of this work, an optimum method for fixing the maximum number of training samples per training class is to be found as the present work uses previous land use information and fixes a constant percentage of training samples to be the maximum number of training samples allowed per class.

We have demonstrated the utility of using constrained derivative dynamic time warping as a distance metric for classifying time series in a framework similar to that of supervised spectral classification. The type of patterns that can be classified using curve matching are limited but this depends on the feature or physical parameter selected for time series patterns. This is only the beginning of an investigation into looking at these patterns as curves and applying curve matching in the time space instead of clustering in the feature space. The possibility of using other distance metrics or finding one that is suitable for this application can be further investigated in future works. In the recent past, there has been advancement in the nearest neighbor algorithms which remain to be experimented. A value of k=4 for the Sakoe-Chiba Band for constraining the warping path producing the highest classification accuracy makes sense as there can be variations in sowing practices which can differ regionally by a maximum of one to two months at maximum.
One may wonder if the technique used for deriving training samples itself can be used to classify the whole image. This is not possible because the training samples or the representative curves are obtained as ideal representations of the classes in question by levying a number of constraints on the location of these samples spatially. The same technique cannot be applied for pixels which exhibit mixed response whose temporal response will vary around the ideal representations and to classify these variations into their appropriate classes, a next level of classification is required. Moreover, the heuristics used for the discrete fourier transform of various classes in question do not hold for mixed pixels. Recent research has emphasized that the training data should be selected on the basis of the classifier being used. Foody and Mathur (2006) support this by using mixed pixels for training a SVM classifier since this classifier inherently uses samples lying near the hyper plane separating classes as support vectors. While this reasoning may be true for SVM, for all other classifiers, training with pure pixels is found to produce good classification results. Even in cases where mixed pixels are required as training samples, the proposed method for extracting training samples can be modified to retain pixels at the boundary of classes which have presently been ignored.

We have successfully devised a system for automatic extraction of season calendar from time series of satellite images. In the Indian context, such a season calendar can prove to be of great utility for crop management. As there are many different agro climatic zones and diverse and multiple cropping practices in India, such an automated system helps in getting information at the right time. The results show that remote sensing can be successfully used to derive season calendar at the district level for Indian districts with moderate resolution satellite imagery. Expert knowledge like that of an agronomist or a published crop calendar can be used to correlate the seasonal calendar to particular crops for crop mapping. This will lead to automatic crop classification which is an important input to a satellite data based crop management system. Average landholdings in India are of a very small order as there are a lot of fragmented cropping areas. Crops grown in adjacent fields may not be the same always which leads to mixed spectral response at a spatial resolution of 250 meters. To overcome this problem, either the spectral response has to be unmixed or satellite imagery with high spatial resolution that can fully resolve the small landholdings is to be used. Wavelet transform retains time components when transforming time series data and can reproduce seasonal changes of vegetation without losing the temporal information. Although studies have shown that there is not a large difference between phenological parameters obtained after Fourier smoothing to that of wavelet smoothing, it remains to be implemented and compared. In conclusion, this study has demonstrated the feasibility of using multi temporal remotely sensed data to describe vegetation dynamics, mapping phenological variation and understand the cropping practices over a given geographic area.

The work has also demonstrated that remote sensing data can be successfully used to derive single and double crop regions at the district level for the whole nation. This study has not used any ancillary inputs which can improve the classification accuracy.

The outcomes of this research can be summarized as follows

1. Demonstrated the utility of time series information by deriving land use classification, phenology parameters extraction, deriving season calendar.
2. The work demonstrates that dynamic time warping is best suited distance measure for classifying crops based on multi temporal data because there can be shifts in the growing seasons based on climatic factors.

3. The results based on constrained dynamic time warping show maximum accuracies for a constraint distance of 5 which is around 2 months that can be the maximum variability in the sowing practices.

4. Discrete fourier transform of the time series helps in automatic extraction of the training samples.

5. Phenomenological features extracted from the time series helps to create season calendar automatically which can be converted to a crop calendar with a minimum of field information.

6. Single and Double cropping areas for Karnataka were mapped using time series information.

7. Time series information and curve matching also enable to detect land use changes across different periods of time.
CHAPTER 9 : FUTURE WORK

The following are the extensions of the proposed research that are possible

1. A fully operational system that uses various components of this research to provide real time high level information can be built.

2. A new set of algorithms can be built for classification at the next level of hierarchy that uses better resolution (spatial, temporal and spectral) remotely sensed data.

3. Quality assessment flags associated with remote sensing data can be used in filtering/pre processing.

4. An extensive field study for validating the results obtained in this research is essential to build an operational system.

5. Spatio-temporal and spectral-temporal features can be used for classification. Every pixel will be represented by a surface with such features.

6. Dynamic time warping can match variable length sequences which can be a very useful property to compare EVI time series data obtained from different sensors.
APPENDIX A: ABBREVIATIONS

AIC  Akaike's Information Criterion
AVHRR  Advanced Very High Resolution Radiometer
AWiFS  Advanced Wide Field Sensor
CDTW  Constrained Dynamic Time Warping
DDTW  Derivative Dynamic Time Warping
DFT  Discrete Fourier Transform
DTW  Dynamic Time Warping
EOS  Earth Observing Satellites
EVI  Enhanced Vegetation Index
FMM  Fast Marching Method
ISODATA  Iterative Self Organizing Data Analysis
kNN  k Nearest Neighbour Classification
LAI  Leaf Area Index
LISS-3  Linear Imaging Self Scanning Sensor
LMF  Local Maximum Fitting
LP DAAC  Land Processes Distribution and Archive Centre
LULC  Land Use Land Cover
ML  Maximum Likelihood Classification
MODIS  Moderate Resolution Imaging Spectroradiometer
MVC  Maximum Value Compositing
NDVI  Normalized Difference Vegetation Index
NIR  Near Infra Red
NRSC  National Remote Sensing Centre
SHYV  Short High Yield Variety
SVM  Support Vector Machines
VI  Vegetation Index
BIBLIOGRAPHY


AIC – Akaike Information Criterion. [http://www.modelselection.org/aic/](http://www.modelselection.org/aic/)


EOS NASA 


LAND COVER http://en.wikipedia.org/wiki/Land_cover


SVM light software for multiclass, Available:  
http://svmlight.joachims.org/svm_multiclass.html


