“ROBUST CHANGE DETECTION OF FORESTS: A CASE STUDY OF MOUNTAIN RANGE FROM GHATGHAR TO WASHERE IN AKOLE TAHSIL, AHMEDNAGAR DISTRICT (M.S.)”

A DISSERTATION SUBMITTED BY

MR. KISHOR RAMDAS SONAWANE

UNDER THE GUIDANCE OF

DR. VIJAY S. BHAGAT

ASSISTANT PROFESSOR, POST GRADUATE RESEARCH CENTRE IN GEOGRAPHY, AGASTI ARTS, COMMERCE AND DADASAHEB RUPWATE SCIENCE COLLEGE, AKOLE, TAHSIL – AKOLE, DISTRICT – AHMEDNAGAR (M.S.)

FOR THE DEGREE OF

MASTER OF PHILOSOPHY (M. Phil)

IN

GEOGRAPHY

TO

TILAK MAHARASHTRA VIDYAPEETH, PUNE

JUNE 2015

FORM A

DECLARATION BY THE RESEARCH STUDENT

I hereby declare that the dissertation entitled **"ROBUST CHANGE DETECTION OF FORESTS: A CASE STUDY OF MOUNTAIN RANGE FROM GHATGHAR TO WASHERE IN AKOLE TAHSIL, AHMEDNAGAR DISTRICT (M.S.)"** completed and written by me has not previously formed the basis for the award of any degree or similar title of this or any other university or examining body.

Place: Akole **Signature of the Research Student**

Date: **(Mr. Kishor Ramdas Sonawane)**

FORM B

CERTIFICATE

This is to certify that the dissertation entitled **"ROBUST CHANGE DETECTION OF FORESTS: A CASE STUDY OF MOUNTAIN RANGE FROM GHATGHAR TO WASHERE IN AKOLE TAHSIL, AHMEDNAGAR DISTRICT (M.S.)"** which is being submitted here with for the award of the **Master of Philosophy (M.Phil.)** in **Geography of Tilak Maharashtra Vidyapeeth, Pune** is the result of original research work completed by **Mr. Kishor Ramdas Sonawane** under my supervision and guidance. To the best of my knowledge and belief the work incorporated in this dissertation has not formed the basis for the award of any degree or similar title of this or any other university or examining body upon him.

Place: Akole **Signature of the Research Guide**

Date: **(Dr. Vijay Shivaji Bhagat)**

ACKNOWLEDGEMENTS

I would like to express my very sincere gratitude to my research guide, Dr. Vijay S. Bhagat, Post Graduate Research Centre in Geography, Agasti Arts, Commerce and Dadasaheb Rupwate Science College, Akole, Dist.-Ahmednagar (M.S.), for not only his valuable support and guidance for the research work including field work, data analyses, preparation of final report but also his constant encouragement during the course.

I would like to express my sincere thanks to ITC, Netherlands for ILWIS 3.4 Academic, as well as Leica Geosystem United States for ERDAS Imagine making available of GIS software and IBM United States for SPSS. USGS (United States of Geological Survey) Earth Explorer, USA for providing Landsat-5 TM and Landsat-7 ETM+ datasets free of charge for downloading, 'Taylor and Francis Online' for free article access under STAR [Special Terms for Authors and Researchers] support. The various departments of the government of Maharashtra have provided necessary data for the research viz. Tahsil office and forest department of the Akole Tahsil. The people from the study area have participated in discussions and communication during the research work. The author records thanks to these persons for their co-operation.

I thank to Dr. S. N. Karlekar, Dean, Moral and Social Sciences Faculty and Dr. B. M. Yargop, Head, Department of Earth Sciences, Tilak Maharashtra Vidyapeeth, Pune for making available required infrastructure for this research work. I also thank to Asst. Prof. Rajendra Zolekar and Asst. Prof. Surendra Wawale, Mr. Sudhir Fargade and Mr. Sagar Kudale for supporting me for this research work. I express my thanks to my friends for their great help in preparing my research work. I also thank my parents for their selfless love for my overall development. At length, I appreciate Mrs. Kalpana Bhagat and her daughter, Gatha and my wife Mrs. Minal as well as all the family members for their great help, support and endurance during the completion of my research project. The researcher is thankful to all those who have directly or indirectly helped in completing the present study.

Kishor Ramdas Sonawane

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

A forest is a community of living organisms. Organisms interact mutually with the physical environment. A forest usually covers approximately 9.4% of the earths' surface with highest degree of complexities and self-regenerating capacities. They are habitat of wild life, regulate different cycles like hydrological, nutrient, atmospheric, conserve soils, etc. It is a backbone support to create a balance in temperature, climatic conditions, active elements of soil, source of organic carbon and shelter for all kind of living species, bacteria, increasing scenic beauty, etc. Interactions and unlimited use of forest resource from population has increasing with tremendous rate. The forests are degrading in some last decades at alarming rate which show need of conservation. Therefore, planning, management and conservation of forest demands in-depth investigation and analyses. This demand of analytical data about forest covers is increased in recent years. The analysts have stated increasing uses of modern sophisticated technology like remote sensing data, geographic information system, global positioning system along with mathematics, multivariate statistics, etc. Therefore, modified forest change detection technique has been designed based on field data and statistical analyses to get more precise results.

The major objectives of the study are to detect and delineate the changes in forest using post-classification change detection techniques and to suggest improved sophisticated model for robust forest change detection. The physiographic and socio-economic set-up of the study area has reviewed. The landsat-5 TM and Landsat-7 ETM+ datasets have used to achieve the set objectives with the help of GIS software. The distribution of area under forest classes using post-classification of NDVI has used to estimate the forest change based on traditional methods. The correlations

between NDVI, GREENNESS and other different spectral indices have been estimated by using correlation technique in SPSS software.

TM and ETM+ datasets are potentially capable to detect and classify various forest types at good accuracy level. Calculated NDVI images for the years 2002 and 2009 have been classified and merged similar classes into different groups using crossing operations in GIS software. These images are compared to detect the changes in forest cover. Overall forest change has been detected positive for 58.59% of reviewed area, no change for 33.69% and negative change for 7.72% during the years 2002 and 2009 with overall accuracy 77.84%. However, these results of forest change detection are lesser than required accuracy for applications.

The digital numbers of pixels in satellite images show illusional exaggerated reflectance which may lead false results. Therefore, improved forest change detection technique was designed based on field data and statistical analyses to improve results up to the acceptable accuracy. Ground reference digital number triangle (GRDNT) and Mechanical Error Estimation (MEE) techniques have been performed for modification of conventional post-classification technique. Greenness based forest classification has been used for robust forest change detection. Overall change show positive for 23.59 % area, no change for 70.08% and negative change for only 6.33%. The comparison of the results of previous analyses and the results of new technique show illusional exaggeration in class positive about 35% of area. The overall accuracy this estimation calculated about 95.21% and acceptable of applications.

The suggested technique for forest change detection is useful for researcher, planners, scholars, NGO, governmental organisations working in the field of land management spatially for forests. The findings of this study are helpful to navigate, map and plan the forest resources for better future.

CONTENTS

****

CHAPTER I
INTRODUCTION

1.0 General

A forest is a community of living organisms. Organisms interact mutually with the physical environment. A forest usually covers approximately 9.4% of the earth's surface with highest degree complexities and self-regenerating capacities. They are habitat of wild life, regulate different cycles like hydrological, nutrient, atmospheric, etc., conserve soils, etc. (Southworth 2004). Forests are combination of canopy and understory. The understory again divided into several layers i.e. the moss layer, soil microbes, herb layer and the shrub layer. Forests are source of organic carbon, help to maintaining the planetary climate, fresh water, biodiversity and useful to manage hazards like soil erosion, landslides, floods, etc. However, human activities like agriculture, forest cuttings, industrial projects, and natural hazard like forest fire, avalanche, landslides etc. are reducing the area under forests and its qualities (Lannom *et al.* 2001). Therefore, the first step towards conservation of forests through to projection and replantation help for protecting them from desertification.

Natural forest land is estimated about 33.36 million km^2 (WRI) to 39.88 million km^2 (WCMC) excluding marine resources. However, from last some decades world-wide forest destruction and land grabbing increasing due to the impingement of manmade activities (Turker and Derenyi 2000). Government agencies like ISFR (2009) and FSI (2011) reported that the forest lands in India declining to 23.41% of TGA due to imbalance in climatic conditions, soil degradation, deforestation, desertification and water stress in drought prone areas. India has been endowed with an immense variety of forest resources (Southworth 2004). However, with continuing pressures of an exploding population and the subsequent growing needs of industries, food, fuel wood, fodder, small timber etc., depletion and degradation of forests and subsequent adverse changes in ecosystem are taking place. As a result, there are significant losses of forest cover at an alarming rate (Pant *et al.* 2000). The impacts of deforestation in tropical biodiversity hotspots like Western Ghats are of particular concern because these regions are house of rich biodiversity and the high concentration of globally endemic species (Fang and Xu 2000). Though, it is widely believed that the natural vegetation in the tropical regions is experiencing loss of biodiversity at unprecedented rates (Panigrahy *et al.* 2010). Around, 275 million rural people (27%) in India is depending on forests for their subsistence and livelihoods, earned from trade in fuel wood, fodder, bamboo, and a range of non-timber forest products. One thing is notable that 17% of India's rural population depends on fuel wood which is obtained from forest to meet their domestic energy needs.

The Forest Conservation Act (FCA) was enacted to provide priority to conservation of forests over extracting economic resources by regulating the diversion of forest land for non-forest activities. The National Forest Policy (1952) amended in 1988 with focus on conservation of floral and faunal diversity. Scheduled Tribes and Other Traditional Forest Dwellers (Recognition of Forest Rights) Act 2006 was result of the struggle by the marginal and tribal communities to assert their rights over the forestland who are traditionally dependent. Thus, these acts and policies are helping for protecting forest resources against forest destruction and land grabbing. Many Non-Governmental Organizations (NGO), Governmental acts and regulations, Social Agencies are emphasize to reserve natural species with the help of modern technologies, deep case studies and sophisticated mechanism. Monitoring of forest land is a challenging task. Various satellite data with different spatial resolutions useful for analysis of land use-land cover elements, sustainable land management in urban, forestry with environmental impact assessment, flood mapping, agricultural development, urbanization, etc. Amarsaikhan *et al.* (2009) was studied coatings of geographic information systems and remote sensing data for urban land use and land cover change studies in Mongolia. He compared changes within the urban land use and land cover classes.

The present study deals with detection and delineation forest change based on satellite data. This satellite data is compiled, processed and analysed in GIS software for detection of changes in forest cover. The ability to predict future states of forest cover over micro to macro scale is required detailed knowledge about existing forest cover (Martin and Turner 1993, Hansen *et al.* 2000). Spatial information on existing land uses is important for the analysis of environmental conditions and predictions. Therefore, an accurate and continuously updated forest cover data is a prerequisite for forest ecosystem analyses and management. The synoptic and repetitive data acquired using satellite-based sensors has potential to detect, identify and map canopy changes. Variation in the electromagnetic radiation generates unique identical information. This information recorded as per land characteristics associated with an alteration in reflective and emissive spectral properties of land. Therefore, many scholars, scientist and technicians have used remote sensing data with the help of GIS software for forest studies like patterns, change detection, land use-land cover analyses, potential forest growth, etc.

1.1 Statement of problems

Many parts of this study area are covered by ancient forest. However, these forests are degraded for agricultural activities, forest cuttings for domestic and industrial purpose. On the other hand, different governmental and non-governmental agencies are involved in conservation of forests from some decades. A change detection analysis has provided access to generate analytical data about forest degradation and achievements of investments in the area. These changes in forest lands can be broadly grouped into different types: i) forest cover increased, ii) no change in forest cover, and iii) forest cover decreased, etc. Satellite image processing techniques give satisfactorily reliable results to solve the problems in estimations of forests in remote areas. However, reliable change detections forest lands using remote sensing data is challenge task.

Different satellite datasets like Landsat series (RBV, MSS, TM, ETM+), IRS (LISS II, III, IV), Cartosat, Quick Bird, etc. have used for forest change detection (Grant 1985, Gausman *et al.* 1969). Techniques of forest change detection i.e. Principal Component Analysis (Dhakal *et al*. 2002), Spectral classification (Stow *et al*. 2004), Support vector analysis (Mountrakis *et al*. 2010), Fusion techniques (Cano *et al*. 2006), etc. have used to generate information of forest class, forest cover, identify and detect different vegetation species, etc. These techniques have reported optimal results in different regions. Existing forest change detection approaches and techniques are used in different spatial and temporal satellite data. Satellite data have atmospheric noise, diffusion in recorded reflectance, etc. This kind of noise full change detection can be generating results and conclusions which become a reason of misguidance for further planning and development. However, reported approaches have insufficient ability to reach up to reliable and exact conclusion for worldwide problems. Therefore, present study is including optimal resolution with improved forest change detection technique.

1.2 Applications of remote sensing in forest analysis

The scholars from fields like environment sciences, geology, resource management, weather forecasting, land planners, geographer, etc have used remote sensing data along with GIS and statistical techniques efficiently. Remotely sensed data has an efficient quality, real time applicability as well as cost effective application with reliable results (Dymond *et al.* 1996, Nagendra and Gadgil 1999, Knudsen and Olsen 2006) especially of remote areas (Apan 1997). These results and conclusions are useful source for planning, management and monitoring the forest at local to global scales (Nagendra 2001, Zomer *et al.* 2002, Gong *et al.* 2004). It would be helpful to save the money, manpower and time of several non-governmental and governmental organizations (Bhagat 2009).

The spatial and temporal resolution satellite datasets are varied from Landsat MSS to Quick bird. However, Landsat TM and ETM+ datasets have been used for analyses like classification, estimations, etc. of forests cover with optimal accuracy and applicability (Ramsey 2004). Further, different enhancement techniques i.e. histogram equalisation (Tanriverdi 2010), band ratio (Davis et al. 2010), support vector analysis (Mountrakis *et al*. 2010), trend neural networks (Pu *et al*. 2008), etc. have been used for these forest analyses. NDVI is one of the band ratio techniques useful to study the vegetation cover. Roy *et al.* (1996) has been used NDVI along with Greenness index of Landsat ETM+ satellite data for three way crown density model for their classifications. NDVI composites are used by Alonso *et al.* (2004) for forest biomass estimations. The relationship between soil moisture and NDVI has been stated by Adegoke and Carleton (2002). Wang *et al.* (2004) have crucially used NDVI to estimate temperature vegetation dryness index. Bhagat (2009) has used NDVI and soil wetness index for the detection of potential areas for afforestation.

Identify and map the forest land in Mexico using Greenness of high resolution satellite datasets has been studied by Lanoom *et al.* (2001). These both indicators have very strong correlation to identify the vegetation cover. Lu and Weng (2007) have been studied a survey of image classification methods and techniques for improving classification performance. Therefore, Landsat-5 TM and Ladsat-7 ETM+ datasets year 2002 and 2009 have been used for the detection and delineation of forest change in this study.

1.2.1 Spectral properties of plants

The interaction between plants, plant leaves and radiation is exceedingly complex. All general components in this interaction have been studied but among them many micro level features are remain unexplained. Gates *et al.* (1965) have been studied spectral characteristics of leaf absorption transmission and reflection. Understanding the mechanisms of plants optical properties have been further studied by Wooley (1971) and Allen *et al.* (1970), Gausman and Allen (1973). Reflectance parameter of the individual plant, group of plant, cluster of plant, their parts, canopy organization and type, age of plant has different influence according to structure, texture, nature and state of canopies (Figure 1.1).

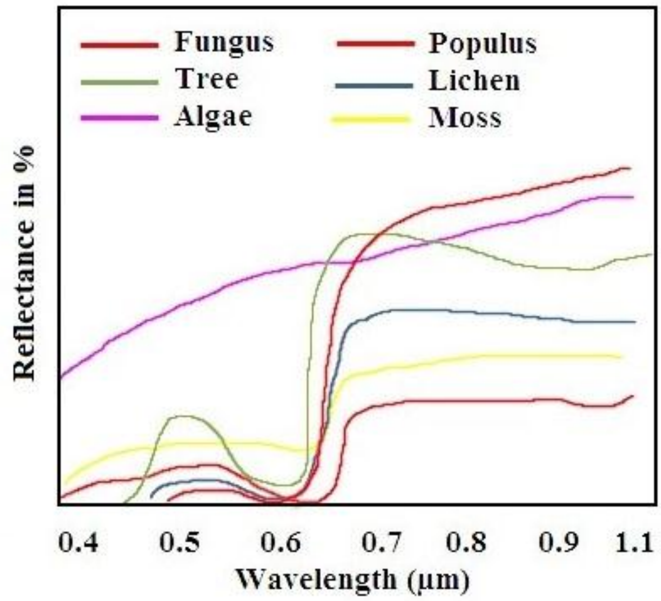


Figure 1.1 Spectral properties of plants

Nature of plant leaves response with energy in the form of reflectance and absorption. The interaction of energy with forest cover is in specific range of electromagnetic spectrum like visible (0.4 to 0.7 µm), near infrared (0.7 to 1.35 µm), etc. (Figure 1.2). This reflected back scattered energy further recorded in satellite data which have used for study of forest change detection.

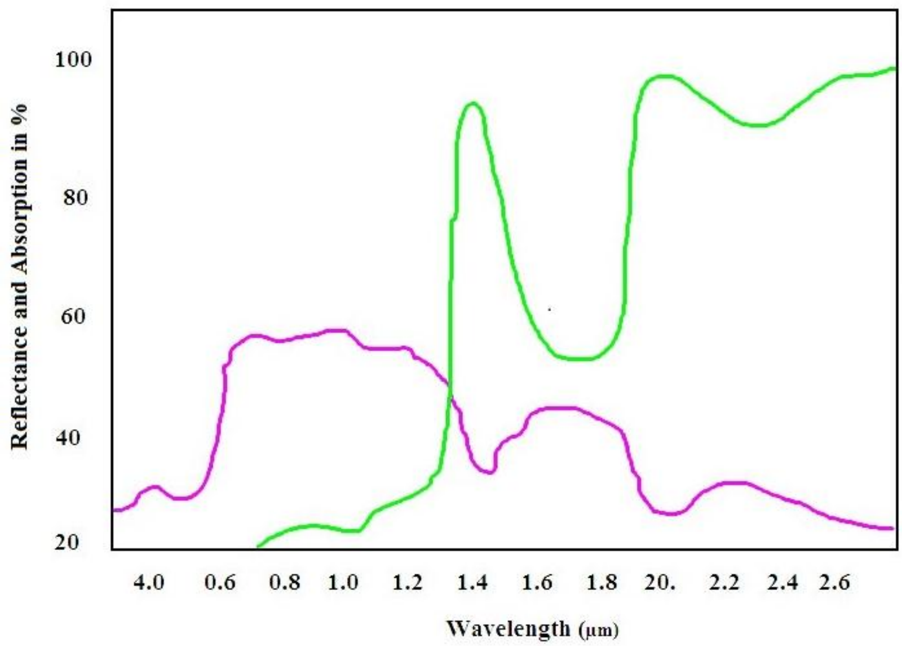


Figure 1.2 Comparison between reflectance and absorption

The spectral curves (Figure 1.2) of plant reflectance can be discussed into three spectacular zones i.e. Hydric zone, Pigment absorption zone and Multi dioptric reflectance zone, etc. The hydric zone indicates the pattern of spectral reflectance with water specific absorption. Water in a leaf causes strong absorption throughout middle infrared region (Gates *et al.* 1965, Wooley 1971). Pigment absorption zone indicates the chlorophyll, xanthophyll and carotenoids absorb energy strongly in ultraviolet blue and red regions of the EMR (Allen *et al.* 1970). Third one is multi dioptric reflectance zone where the reflectance is high, while the absorbance remains weak (Abbas *et al.* 1974). Multi dioptric reflectance zone is correlated with structural characteristics of the leaves (Gates *et al.* 1965). All the unabsorbed energy (30 to 70% varies with types of plant) is transmitted into reflectance (Gausman and Allen 1973). The reflectance is essential due to the internal structure of the leaf and the radiation is able to penetrate (Abbas *et al.* 1974). The reflectance from internal structure of vegetation is related to physical properties more than chemical nature (Thomas *et al.* 1966, Wooley 1971). This information is useful to prefer and apply different vegetation indices for the study of forest change detection.

1.2.2 Vegetation indices

Radiant energy interrupted by canopy is primarily scattered from leaves. The scattered radiation again divided into three stages i.e. reflection, transmission and absorption. This deviation in radiance energy mainly depend on the chemical properties and mechanism available in the leaf cellular structures (Kfipling 1970, Woolley 1971, Gates *et al.* 1965), leaf roughness (Gausman 1977), morphology of leaf (Gausman *et al.* 1969, Gausman *et al.* 1970, Gausman and Allen 1973) and leaf surface characteristics (Grant 1985, Breece and Hommes 1971).

Vegetation and forest canopy leaves have diffused and secular characteristics. This is indicating a non-lambertian distribution. Typical reflectance and transmittance spectrum of an individual plant leaf indicate three distinct wavelength regions in interaction: visible (0.4-0.7 μm), near infrared (NIR) (0.7-1.35 μm) and mid infrared (mid IR) (1.35-2.7 μm) (Kfipling 1970, Gausman *et al.* 1969, Grant 1985). This core information about forest canopy has been used to calculate difference vegetation indices like Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Transformed Vegetation Index (TVI), etc. These indices are capable of handling variation in the scene due to atmosphere, sensor and vegetation background influence in low vegetation cover areas. Digital image processing of satellite data have involved many processes like georeferencing, enhancement and classification. Where, in the recorded backscattered EM radiation from atmosphere, landforms, water bodies, etc. are useful to extract information of forest further used in change detection. The most common strategy relating remote sensing data with vegetation canopies through correlation technique using vegetation indices, vegetation structure and functional variables. This simple empirical approach yields substantial understanding of the structure and dynamics of vegetation at wide scales (Grant 1985).

The capacity to assess and monitor the structure of terrestrial vegetation using spectral properties recorded by remote sensing is important because structure can be related to functioning of ecosystem processes. This process is ultimately aggregated up to the functioning of the local-regional-global level of ecosystem. The categorizations of the various spectral indices are into approximately five types i.e. ratio indices, vegetation indices, orthogonal based indices, perpendicular vegetation indices and tasseled cap transformation, etc. (Gausman *et al.* 1969, Grant 1985). Remote sensing of forest and grassland involves the measurement of reflected energy of component in the presence of each other. The development and usefulness of vegetation indices are dependent upon the degree to which the spectral contribution of non-vegetation component can be isolated from the measured canopy response (Gates *et al.* 1965, Wooley 1971). Although, vegetation indices have been widely recognized valuable tools in the measurement and interpretation of 'vegetation condition' with several identified limitations. However, these indices show relationship with soil brightness effect and soil spectral deviations. The use of site specific soil lines reduces soil background influence. The vegetation indices are simplified methods to extract information about vegetation parameter from multispectral data. Therefore, their use in spectral modeling needs to be studied in context of spectral dynamics of earth surface components.

1.3 Hypothesis

The study area is a natural mountain range between River Pravara and River Mula Basin in Akole Tahsil, District Ahmednagar. This is covered by forest and Tribes lives in villages at foothill zones are dependent on forest for their domestic needs. The slopes of the mountain are covered by dense and medium forest at west part. Many of the studies have analysed and classified forests into different classes based on different indices based on medium regulation data e.g. TM and ETM+ datasets. However, conventional post classification based forest change detection techniques have shown exaggerated results with less accuracy. That accuracy can be improved with the help of statistical analysis based robust techniques. Therefore, hypothesis for this study can be outlined as "modified robust forest change detection techniques can improve the results of post classification forest change detection."

1.4 Objectives

The selected mountain range is covered by natural forest shows spatiao-temporal changes according to variations in availability of soil moisture as well as human activities. Change in forest cover has strong influence on ecosystem and socio-economic setup of the people. Therefore, this study is focused on forest change detection using conventional post-classification change detection technique and to formulate the robust forest change detection for detection of optimal changes in forests. Following objectives are outlined for the present study:

1. To detect and delineate the changes in forest using post-classification change detection techniques.
2. To suggest improved sophisticated model for robust forest change detection.

1.5 Study area

The study area (13858.83 ha) is a mountain range between River Pravara and River Mula Basin. This is started from western boarder (Ghatghar) to eastern border (Washere) in Akole tahsil, district Ahmendagar of Maharashtra state. The extent of the area is 19° 35' 06.86" to 19° 30' 13.08" N latitude and 73° 37' 00.03" to 74° 04' 24.65" E longitude. The depth and water-holding capacity of the soils are varied according to variations in slopes. The slope of the area is decreasing from NW to SE respectively and the height varies from 560 m to 1646 meters above mean sea level. The forest cover varies with slopes, height, soil qualities, rainfall, etc. in the region. Foothill zones in western parts of the study area have dense forest than the eastern parts and hilltops with thin soils and less rainfall.

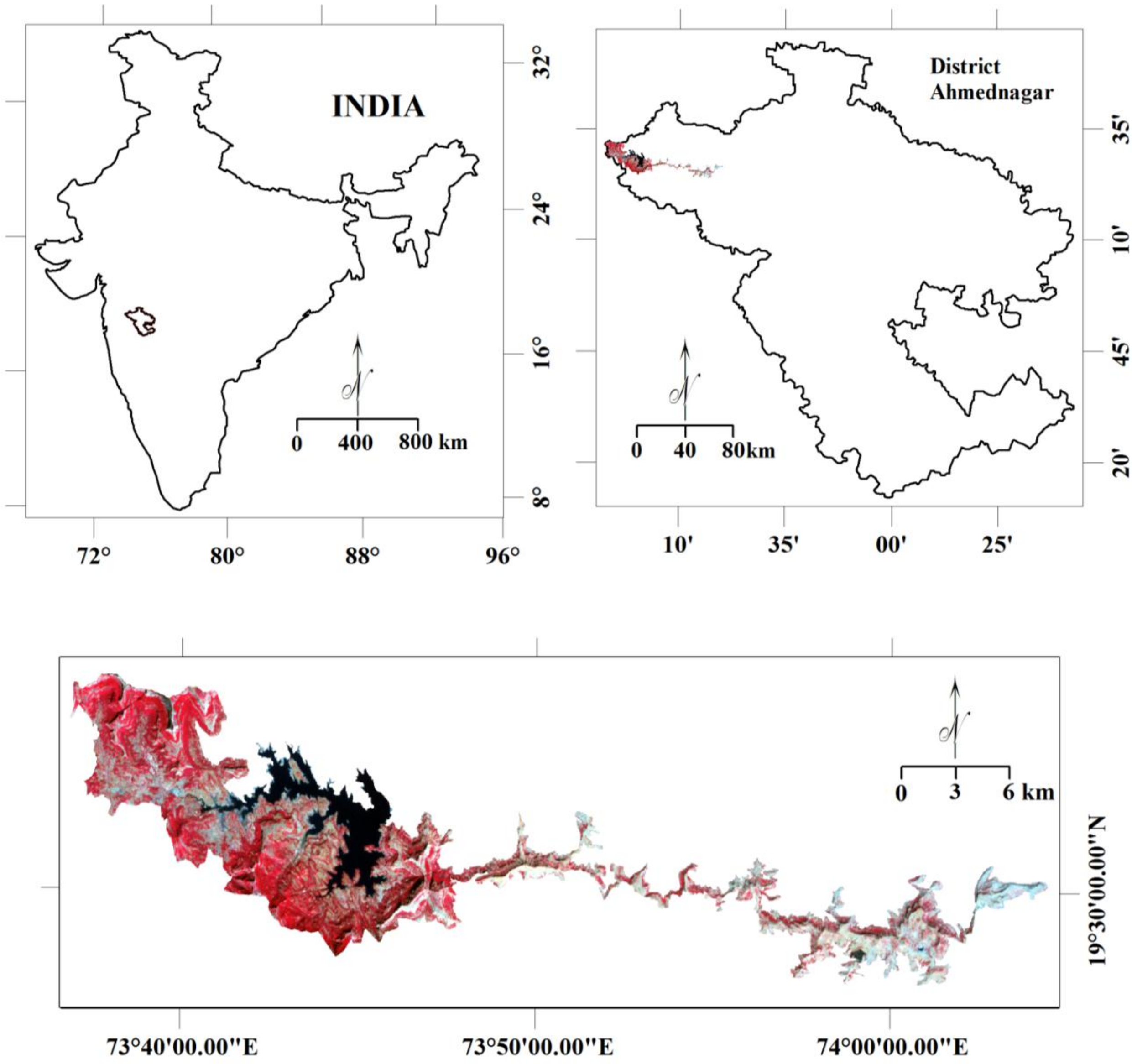


Figure 1.3 Location map

The study area is eastern offshoot from Sahyadri Mountain in the Maharashtra state. Geologically, this area formed by basaltic rock which prevents water percolation in to underlying zone. The soils are very shallow at the top of the range and depth increasing to the foothill zones. Very shallow loamy, shallow clayey soil found on the moderate (1°- 3°) and stiff (3°- 6°) slope. Soil moisture shows impact on distribution of vegetation cover. Therefore, North West and South zone have maximum vegetation cover compare to other land in the study area. It receives average annual rainfall above 440.4 mm. The mean annual maximum and minimum temperatures are 39.80° C and 8.70° C, respectively. Local tribal people are engaged in agricultural activities on land reclaimed from forests dependant on forests for domestic needs.

1.6 Previous literature

The previous studies have thoroughly been examined and explained the role of forest cover in environmental and socio-economic issues across the rapid changes in land-cover over large areas (Hayes and Sader 2001). Remote sensing technology is an essential tool for monitoring tropical forest conditions. The remote and inaccessible nature of many tropical forest regions limits the feasibility of ground based inventory and monitoring methods for extensive land areas. Initiatives to monitor land-cover and land-use change are increasingly reliant on information derived from remotely sensed data. Such information provides the data link to other techniques designed to understand the human processes behind deforestation (Strahler 1994, Rindfuss and Stern 1998). Pant *et al.* (2000) examined the forest and land-use change detection with its impact assessment in part of western Himalaya. He has been worked to understand the changes in forest land with respect to the types of the trees, local impact, natural damages, etc. Panigrahy *et al.* (2010) worked on forest change at result loss of dense forest at an annual rate of 0.72% and that of open forest at 0.49% in area of the Western Ghats of Maharashtra. Robbins (2001) explained the remote sensing technique for forest classifications and land cover analysis in Rajasthan (India). He stated that importance of remote sensing techniques in forest mapping for development planning is increasing rapidly. Virk and King (2006) investigated on the potentials of remote sensing techniques in forest change monitoring in the state of Karnataka, India.

Process flow of forest change detection generally analysed based on Image Co-registration and Georeference approach, satellite image noise correction and enhancement improving the strength of the analysis. Toutin (2008) has been reviewed the ASTER DEMs for geomatic and geoscientific applications. He explained the most geoscientific applications using georeferenced cartographic/geospatial data require good knowledge and visualization of the topography of the earth's surface. Kelly and Liu (2004) studied the mapping diseased Oak trees using RADAR Imagery. They have investigated the ability of high resolution 4-band imagery to discern moisture stress in trees affected by Sudden Oak Death. Image Classification approach depicting the accurate identification of land cover and land usage elements detection by this approach. Narayanan and Zhang (2002) have been explained the utilization of various land cover classification algorithms using Shuttle Imaging Radar (SIR-C) SAR data. They have been distinguished the Minimum Distance Classification (MDC) and Maximum a posteriori Probability (MAP) Classification processes to get good results. Retalis and Nikitopoulou (2006) worked on the use of Earth Observation (EO) data from different sources (NOAA, AQUA, TERRA, TOMS) for the detection and mapping of the intense Saharan dust event. Amarsaikhan (2010) discussed the two objectives of the study to compare the performances of different data fusion techniques for the enhancement of urban features and subsequently to improve urban land cover types classification using a refined Bayesian classification. Saxena and Nautiyal (1997) examined the deforestation on a factor by factor level, using linear and static approaches that ignored the feedback mechanisms. Object specific analysis required precise methodologies to gain reliable results and conclusion to resolve the root of the problems. Different spectral indices maneuver a vital role in this approach. Kerr *et al.* (2003) applied the procedure to assume the Leaf Area Index using remotely sensed data and BRDF models in a semiarid region. Soudani *et al.* (2006) have been explained comparative analysis of IKONOS, SPOT, and ETM+ data for leaf area index estimation in temperate coniferous and deciduous forest stands. Huang *et al.* (2000) established the derivation of a Tasseled Cap Transformation based on Landsat 7 at satellite reflectance developed. Mallick *et al.* (2008) have been worked on the estimation of land surface temperature index over Delhi using Landsat-7 ETM+. Bhagat (2009) has discussed the use of Landsat ETM+ data for detection of potential areas for afforestation. He has been used Normalized Difference Vegetation Index and Soil Wetness Index. Bhagat and More (2013) have explained the Normalized Difference Vegetation Index, Soil Wetness Index and Normalized Differential Salinity Index to detection of Prosopis Juliflora in irrigated zones using Landsat ETM+ data.

Effective and trusted results of various fields in remote sensing required qualitative and quantitative satellite data. Landsat datasets are very useful in change monitoring and classification of forests at regional and local level. Allen (2000) discussed on the topographic normalization of Landsat TM data in three mountain Environments. He has been used the method of comparative analysis is presented for empirical topographic normalization of Landsat TM data in varied forest and topographic settings. Wolter *et al.* (1995) have used improved spatial, spectral and radiometric properties of Landsat Thematic Mapper (TM) satellite imagery for precise forest classification. Chander and Markham (2003) discussed the revised Landsat-5 TM radiometric calibration procedures and post-calibration dynamic ranges. Rahman and Saha (2008) compared the remotely sensed data for the studies of multi-resolution segmentation for object-based land use and land cover classification at good level of accuracy. Yagoub and Kolan (2006) stated the Landsat satellite data for monitoring land use and land cover changes in the coastal zones of Abu Dhabi. Propastin (2011) explained the multi-scale analysis of the relationship between topography and aboveground biomass in the tropical rainforests of Sulawesi, Indonesia. Deshpande and Karia (1999) investigated bounds for the hazard gradients in the competing risks set up. Gaikwad (2004) has been pointed that the remote sensing technique can effectively and efficiently be used for the change detection in terms of land use and land cover around Pune city. Kushwaha (1990) analysed the change in forest cover through visual interpretation of satellite data. Igbokwe (1999) discussed the Multi-sensors and Multi-temporal satellite images for digital analysis and interpretations for studies of change analysis. Huang *et al.* (2002) applied the procedure to develop a tasselled cap transformed derivatives for Landsat-7 ETM+ data at-satellite reflectance. Jiang *et al.* (2004) have estimated the relationship between vegetation and hydrological processes. Healy *et al. (*2006) established the Landsat data for the application of two regression-based methods to estimate the effects of partial harvest on forest structure. They have used normalized difference vegetation index (NDVI) and normalized difference moisture index (NDMI). Kulawardhana *et al.* (2007) have attempted to contribute to the evaluation of the wetland mapping methods by using Landsat ETM+ and SRTM data. Thus, remotely sensed data has been widely used in land use/land cover analyses, change detection studies and estimations of potentials of different environmental elements.

Therefore, the previous studies have proved the important role of the forest cover and the different forest change detection techniques in analysis of natural as well as socio-economic resources. The present study is focused on to improve the conventional forest change detection techniques based on Landsat-5 TM and Landsat-7 ETM+ data.

1.7 Methodology

The analyses in the present study are based on remotely sensed data, statistical models and field checks. The satellite data Landsat-7 ETM+ year 2002 and Landsat-5 TM year 2009 (01 January 2012 is data access date) has been used for the detection of the forest cover and it is based on distribution of NDVI and Greenness. Field checks have been undertaken to verify the inferences of the analyses. The remotely sensed dataset has complied, merged and loaded in the GIS image processing software, ILWIS 3.4 Academic, ArcGIS 9.3 and ERDAS Imagine 9.2. The Survey of Indian topographical maps at 1:50000 scale (SOI, 47 E/10, 47 E/11, 47 E/14, 47 E/15 and 47 I/2, 47 I/3) have been used for topographic and drainage mapping. GPS (Global Positioning System) has been used to gather the information for ground verification. The Geological map and the soil maps have been used to understand the relationship between nature of forest and the change in the soil structure with respect to slope. Forest change detection has analysed based on the traditional classification techniques to obtain the base information about forest cover. Corrections in the forest classification made using several band ratios and indices and filter out with statistical models to achieve final reclassified forest changes. The information about permanent land cover was collected and compiled to build the data base for further analyses.

Some well-established forest change detection approaches i.e. spectral data fusion, spectral classification, change vector analysis and regression analysis, etc. have been used for forest change detection (Kulawardhana *et al.* 2007). Among them most popular and widely used post-classification based forest change detection approach is useful to estimate change in forest cover (Yagoub and Kolan 2006). However, accurate estimations of forest change depending upon correct georeference and image classification techniques (Kelly and Liu 2004). The quality of results and conclusions are dependent on the correctness and completeness of the satellite data (Ramsey 2004). Mainly row satellite data rich with noises, some of them many noised already corrected at preliminarily stage by satellite data centres (Lannom *et al.* 2001). Illusional exaggeration in satellite image leads exaggerations in change detection estimations, results and conclusions which can misguide the forest conservation plans and management. Present study is focused on modification of change detection techniques for normalization of illusional exaggeration in satellite image. It is useful to improve the accuracy of post-classification based forest change detection technique.

1.8 Arrangement of the text

This study is discussed in five chapters. The first chapter deals with the introduction of the study. The review of previous literature has been made to highlight the forest land detection and delineation using different change detection techniques. The hypothesis, objectives, spectral properties of forest and methodology used in the study are also been explained in this chapter. The physiographic characteristics of the study area are discussed in the second chapter. The detailed methodology of post classification based on forest change detection and its results with accuracy assessment is explained in the third chapter. The fourth chapter deals with the modification in post-classification based forest classification and robust forest change detection technique. Ground Reference Digital Number Triangle (GRDNT) with different geographical elements i.e. forest, rocky land, water, etc. and its implementation and Mechanical Error Estimation (MEE) has been explained in this chapter. Findings and conclusions have been given in the last chapter. The relevant references and appendices have also been given at the end of the dissertation.

1.9 Resume`

Forest cover is an important natural resource for the environment and socio-economic setup. It can bridge the gap between nature and human made conflicts. Changes in the forest land are increase the imbalance in the ecosystem, climatic conditions, temperature, land degradation, drought prone zones, soil erosion, and dependent manmade activities, etc. The tribal peoples in the mountain region are dependent on forest for their domestic needs. Therefore, the objectives of detection and delineation of the forest land by using post classification methods have been outlined in the present study. The Landsat-5 TM and Landsat-7 ETM+ dataset has suggested as a source of information to achieve the objectives of the study. The detailed study of spectral properties of the forest and physiographic elements of the study area has proposed for the second chapter to make information base for image analysis and interpretation in the next chapters.

****

CHAPTER II
STUDY AREA PROFILE

2.0 General

Forest change detection requires the information about bio-physical elements i.e. geology, relief, slope, drainage, soil qualities, climatic conditions, forest canopy, plant species, etc. This study provides the impact of bio-physical parameters on forest change detection using different spatio-temporal techniques. Several researchers have been used post classification, principal components analysis, change vector analysis, regression approach, etc. using bio-physical parameters for change detection analysis for different fields. Therefore, present study has carried out these parameters for understanding physical characteristics of the study area for forest change detection analysis. The distribution of forests in the study region has varies from north-west to south-west. The implementation of forest change detection techniques are depend on the amount and the distribution of forest canopy. Total TGA of the study area is 13858.83 ha.

2.1 Geology

Study area is a part Deccan trap and it formed by basaltic rocks, amygdaloidal basalts form the bedrock. Overlying weathered and fractured rocks are rested on hard massive basalt (Subbarao and Hooper 1988). The basalts are nearly horizontal, separated by thin layers of ancient soil and volcanic ash (red bole). The basalt flows are nearly flat-lying with regional southerly deep of 0.5-1° and mainly belong to the Thakurvadi Formation of the Kalsubai Subgroup (Gareeau *et al*. 2009).

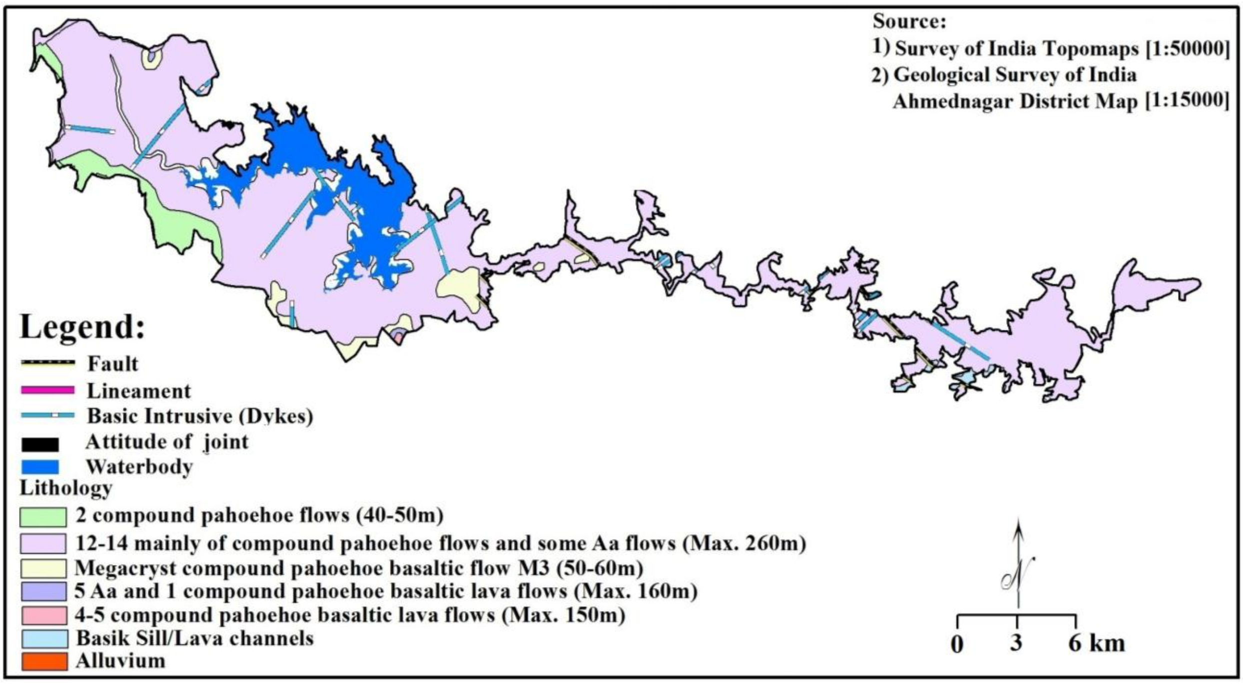


Figure 2.1 Geological map

The geological map shows that about 77.17% area is covered by 12-14 compound pahoehoe flows and some Aa flows (Max. 206m). Around 4.53% by 2 compound pahoehoe flows (40-50m) and 3.26% by Megacryst compound pahoehoe basaltic flow M3 (50-60m). Reaming 0.89% area is covered by 5 Aa and 1 compound pahoehoe basaltic lava flows (Max. 160m), 4-5 compound pahoehoe basaltic lava flows (Max. 150m), Basik Sill/Lava channels, respectively. The regional stratigraphy of the Deccan basalts has been described by Beane *et al. (*1989), Gareeau *et al.* (2009), and Subbarao and Hooper (1988). Structural indices are indicate the part of basic intrusive (dykes) in the part of north-west and south-east. About 13 dykes and one fault line cross at the middle part of the study area.

2.2 Relief

Study area situated at the middle of the tahsil Akole and water divide between Mula and Pravara rivers. The altitude varies from 640 meter to 1646 meter. The variation in soil qualities, soil moisture and vegetation are varies with changes in the relief of the region. Kalasubai (1646m) and Harishchandragarh (1422m) are the highest peaks located in the study region.

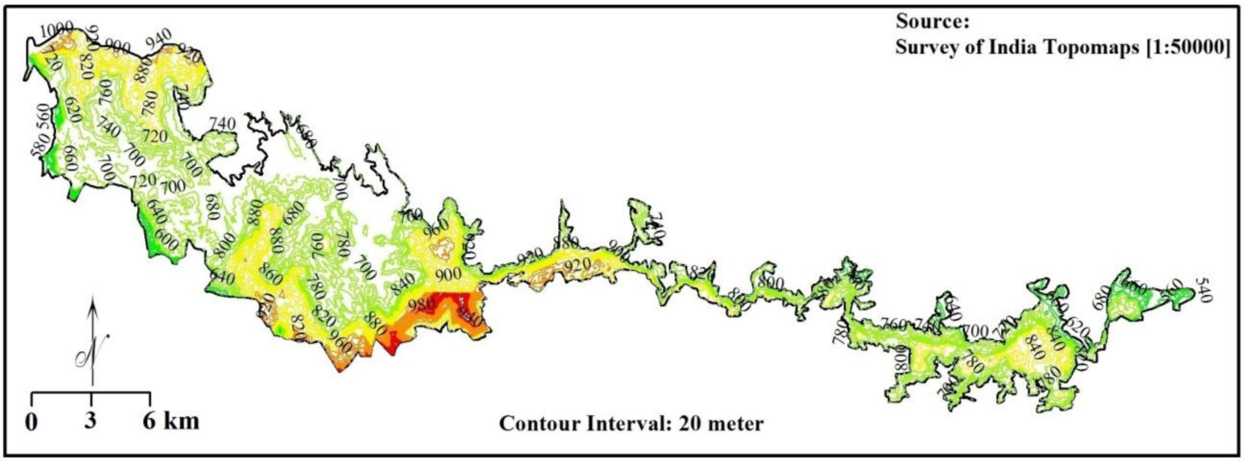


Figure 2.2 Contour map

2.3 Slope

Geo-physical parameters like soil, water, groundwater, vegetation are varies with variations in slopes. Slope of the study area calculated in degree (0° to 90°) on the basis of contours. The slopes of the area are classified into 5 classes. Gentle slope has covered about 6% area distributed near to water reserve, Bhandardhara. About 66.39% area is covered by steep to precipitous slope at the top hill and cliffs. Foothill slopes i.e. moderate to steep covered 33.61% area with dense forest cover in north-west and south-west. Eroded materials on the top hills are transported to the foothill slopes (Karia *et al.* 2001). Therefore, good soil moisture, soil depth and vegetation cover are found in foot hill zone.

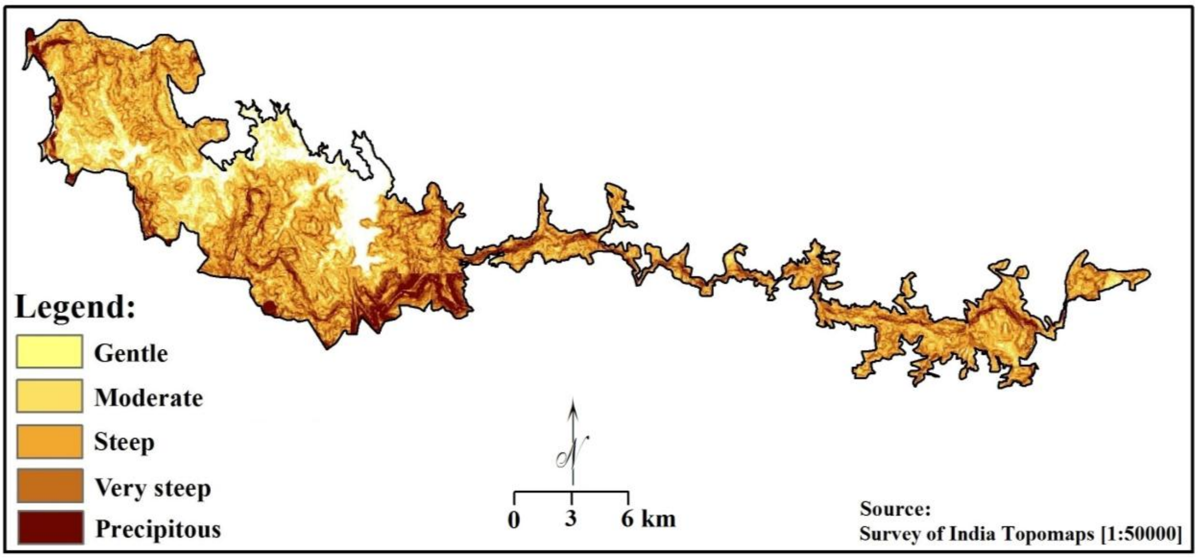


Figure 2.3 Slope map

2.4 Drainage

Relief controls the drainage network including flow, structure, etc. The streams eroded surface and convert into different landforms. Relief and streams have strong correlation. Pravara river is originated from Ratangarh. River Pravara flows from north-west to south-east. Some major and minor dams are observed in the basin. Bhandardara is main dam situated on river Pravara, which is one of the important land-cover in study area and play an important role for identify no change digital numbers in further forest change detection. Soil moisture depends upon drainage network and water reservoirs which made difference variations in vegetation cover.

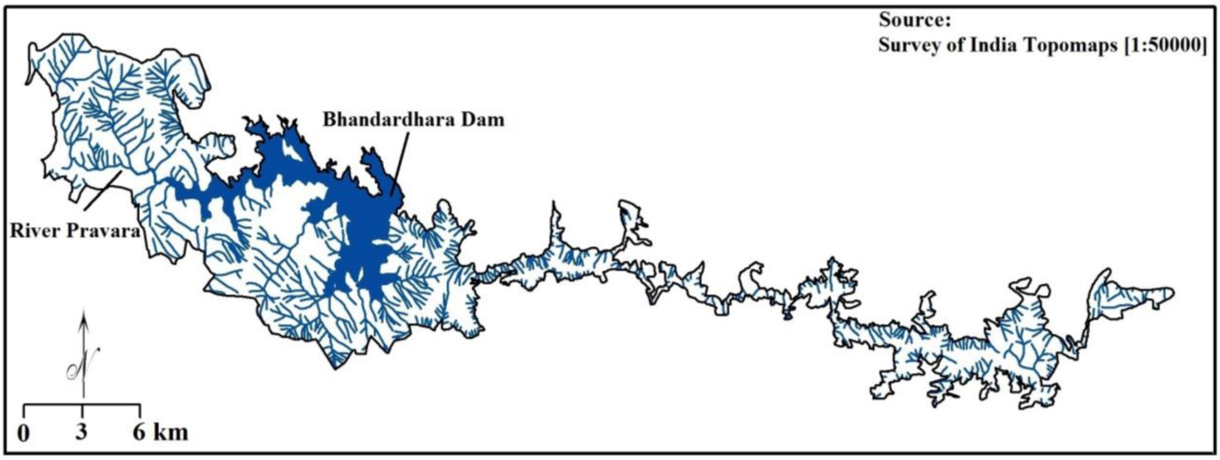


Figure 2.4 Drainage system

2.5 Vegetation cover

Top of the hilly area vegetation cover is less due to the high degree of slopes like steep to precipitous. Hilly area is covered by thin grasses and bushes. Foothill zones are covered with dense to very dense forest. Weathered and eroded suspended material has potentials to convert into fertile soils (Zomer *et al.* 2002). Huge amount of soil moisture and natural compost as compared to top hill is suitable for soil formation and well growing land for forest canopy. Though, the maximum amount of ancient forest observed in north-west parts. The maximum forest canopies have distributed around the major water reservoir i.e. Bhandardhara dam and foothills. Middle part of study area covered with sparse vegetation. Moderate and gentle slopes are covered with the mixture of sparse as well as thin grasses and bushes at south-east.

2.6 Climate

The climate is fundamental natural change factor in the interface and scenic beauty of forests. Change in climatic factors like rainfall, temperature, air moisture, wind velocity, etc. directly affecting on the growth and density of forest canopy (Pandit and Thampan 1988). The climate of the study area is hot in summer and generally dry except monsoon season. Average annual rainfall is above 440 mm. Rainfall is decreasing from west to east part of the tahsil Akole. About 70% rainfall received in rainiest month. This type of favourable rainfall helps to improve the growth and density of forest cover. Seasonal variation in temperature is impacting soil moisture conditions. The mean annual maximum and minimum temperatures are 39.80° C and 8.70° C, respectively. The growth and distribution of forest canopy depends on the climatic conditions (Sommer *et al*. 2011).

2.7 Soils

Soil element is one of the most important biophysical parameters. Soil gives good information towards the knowledge of nutrient cycle and bio-chemical cycle in the soil–plant ecosystem (Pandit and Thampan 1988). The growth and reproduction of forest cannot understand without the least basic knowledge of soil. The soil and vegetation have a complex interrelation because they are developed together over a long period of time. The vegetation covers are influencing the chemical properties of soils. The absorption of various nutrients like carbon, nitrogen, phosphorus, potash, iron, zinc, etc. by different trees and return some of them into soils has changed the fertility and soils properties (Singh *et al.* 1986). Soil formations are depend on geology, topography, climatic conditions, organic and inorganic factors and time span, etc. Forests have a greater influence on soil conditions than other parameters with well-developed ‘O’ horizon, moderating temperature, and humidity at the soil surface, input of litter with high lignin content, high total net primary production and high water and nutrient demand (Binkley and Giardina 1998).

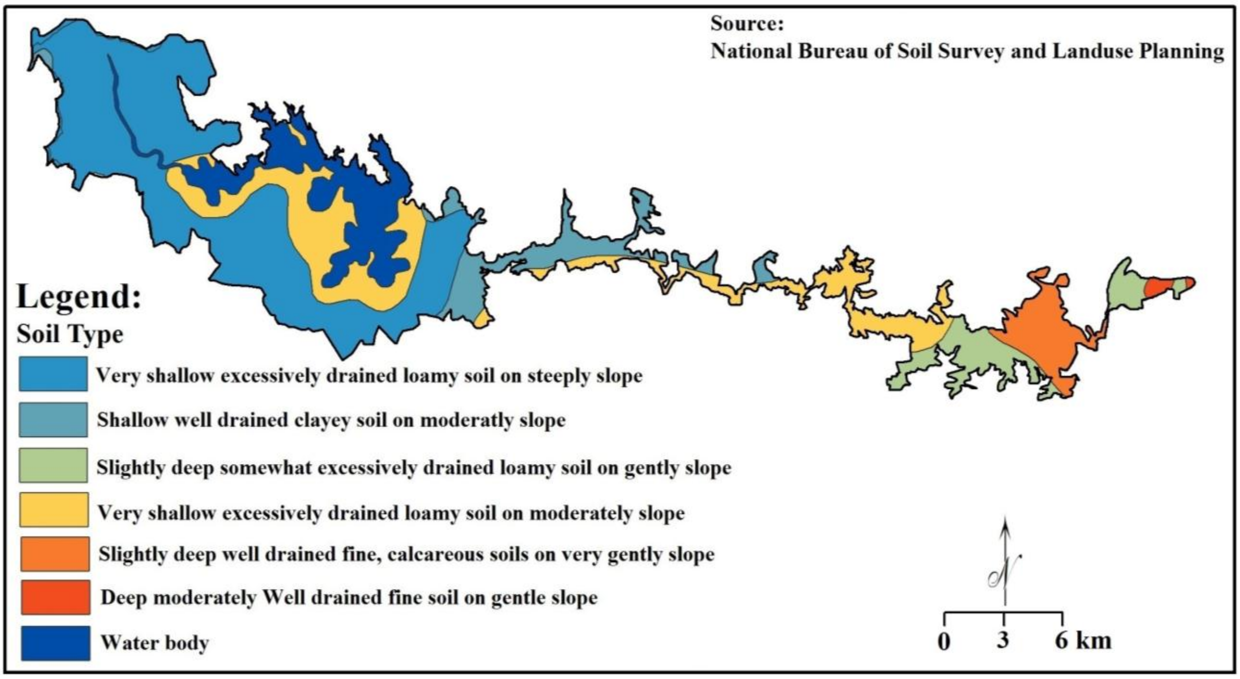


Figure 2.5 Soil map

Study area is a hilly zone and soils are very shallow at the top-hills. Excessively drained loamy soil 43.38% found at steep slopes north-west direction. Shallow well drained clayey soil and slightly deep excessively drained loamy soil (8.57%) found over moderate to gentle slope, respectively (Table 2.1). Clay soils, are made up of very fine microscopic particles.

Table 2.1 Soil distribution

Sr. No.	Soil Type	Area %
1	Very shallow excessively drained loamy soil on steeply slope	43.38
2	Shallow well drained clayey soil on moderately slope	8.57
3	Slightly deep somewhat excessively drained loamy soil on gently slope	6.83
4	Very shallow excessively drained loamy soil on moderately slope	20.59
5	Slightly deep well drained fine, calcareous soils on very gently slope	5.96
6	Deep moderately Well drained fine soil on gentle slope	0.53
7	Water Bodies	14.14

These tiny particles fit together tightly, resulting in tiny pore spaces between them. The tiny pore spaces allow water to move through them, but at much slower pace than in sandy soils. Clay soils drain quite slowly and hold more water than sandy soils. Loams soil capacity of maximum water holding (MWHC) approximately 0.18 inches of water per inch of soil depth and clays hold up to 0.17 inches of water per inch of soil depth. However, soil types, soil elements, soil depth depend on the geology of the study area, explained in next point.

2.8 Population and economic activities

Every region dominated by human activities. This region has partial dependency on natural resources. This dependency fulfil without the interaction of human being with surrounding areas (Singh 1996). The total population of Akole tahsil is 291950 as per census 2011. About 40 villages observed near to the study area and they depend on these forest lands for primary needs. Population of these villages is 59109 (20.25%). ST population is 57.23% (11.59%). They are engaged in primary economical activities like cultivation, animal husbandry, fishery, etc. Forest material i.e. food, fruits, black berries, honey, tree leaves, small scrubs lands, timber, naturally available grass land, etc. are using for domestic use (Turker and Derenyi 2000).

2.9 Resume`

Forest cover is an important natural resource for the environment and socio-eco setup. It can bridge the gap between nature and human conflicts. Changes in the forest land increase the imbalance in the ecosystem, climatic conditions, temperature, land degradation, drought prone zones, soil erosion, depending manmade activities, etc. The tribes in the mountain region are dependent on forests for their domestic needs. Therefore, the objectives of detection and delineation of the forest land using conventional post classification techniques processed in the present study. The methodology of change detection is outlined and discussed in next chapter.

****

CHAPTER III

FOREST CHANGE DETECTION

3.0 General

Surface of the earth is all-inclusive phenomenon which includes the information of various lands and water resources, vegetation covers, deserts, swamp, marsh lands, etc. (Bai *et al.* 2008). Accumulation of surface information by using space technology than the field survey of large area is quite suitable and less time consuming with better conclusion. Digital change detection (DCD) technique is measured the difference between two or more satellite images at the same location but different time. Satellite image is a registered back scattered radiance from different land structure with temporal, spatial and radiometric resolution (Puissant and Weber 2002). This data has recorded information about vegetation, changes in vegetation phenology, reclaimed land from sea, desertification, snow cover, hazardous conditions, land degradation, day and night thermal characteristics variation, near surface climatic structure, transport network and urbanization, etc. Digital change detection results regarding particular target depends on 1) Methodology used for change detection, 2) Satellite data with good resolution and accuracy, 3) Time interval, 4) Sample selection and 5) Ground verifications, etc.

Several researchers and studies have attempted successfully using satellite data to demarcate digital change of the earth surface (Bhojvaid *et al.* 1996, Singh 1996, Felkar *et al.* 1981, Gessing *et al.* 2000, Pasiecznik *et al.* 2004, Mwangi and Swallow 2008). Number of DCD procedures have proposed which can be tending an upgrade in existing resource inventories. Measurement of the difference in backscattered radiance values give capacity to understand the change in land classes

(Sing 1989). Change in surface radiance controlled by earth's atmosphere and vegetation cover with balancing land and water temperature at day and night. Factors are responsible for this radiance change like difference in atmospheric condition, difference in sun angle, difference in air and soil moisture condition, difference in emission from various surface objects, etc. Methods of DCD includes multiband satellite data classification, image ratio, tasselled cap coefficient indexing, spectral vegetation indices differencing, principal component analysis, change vector methods, threshold based classification, post classification comparison, univariate image differencing, simultaneous analysis of multi temporal data, fusion approach, spectral classification, algebraic methods, regression approach, and hybrid approach, etc. Among these several methods no existing methods are ideally suitable, reliable and applicable to all surface change conditions (Du *et al.* 2002, Bhagat 2012). These surface conditions binding with lot of environmental, natural and manmade hazardous problems i.e. fire, nuclear blasts, war, chemical and oil leak, etc. and still awaiting for their resolutions (Coppin and Bauer 1996). The present study can provide a primary solution in the demarcation of digital change detection approach.

Change detection analysis provides a thematic view to understand the natural and artificial behaviour of change in land phenomena (Sommer *et al.* 2011). Detection and demarcation of digital change is useful for land changes in the form of increase and decrease excluding no change area, assessment of sessional change in forests, flood mapping, snow cover melting assessments, cost line changes, oceanic water level monitoring, landslides, volcanic eruptions, corral rifts segmentation, wild animals, birds as well as seasonal migration of sea species, changes in near surface atmospheric conditions like snow fall, rainfall, thermal change, cloud monitoring, fog, storms, human activities like military actions, observation, planning and management for reinforcement in war areas, coal mining, etc. (Lunetta *et al.* 2006). When problems are observed using real time information and situations, it interpreted and understood by scholars and researches in several specialized targeted areas then DCD technique made realistic, easiest and reliable way to generate a suitable models, solutions for the same instated of using old techniques like field visits, report generation, etc. DCD methods have applicability for planning, management, assessment and providing resolution regarding problem oriented areas in environment, geography, geology, climatology, geomorphology, defence, transportation, population and economic activities, deserter management, etc. (Jenson 1983).

Satellite imageries are widely used for digital change detection analysis. Recorded radiance data from surface objects has converted in to reflected grey scale digital numbers as per their spectral band width at the time of image acquisition (Michener and Houhoulis 1997). These digital numbers represent in the form of pixel value in image data. All images in primary stage have row, crude form and purely unprocessed. However, noise in the multi temporal imagery created by variation in atmospheric condition, satellite sensor performance and sun rays radiation (Tang *et al.* 2010). Therefore, these noise correction need to be fixed or reduced before performing digital change detection analysis using multi-temporal imagery data. Many researches, space engineers and scholars have suggested the number of techniques for radiometric normalization like radiometric calibration using absolute, multi-temporal, inter band and inter sensor, simple radiometric rectification techniques, pseudo invariant features and regression model, automatic scatter gram controlled regression, intensity normalization, illumination modelling, linear transformation of intensity, radiometric corrections algorithm, etc. Present study used satellite data already normalised by Earth Explorer United State Geological Survey

(USGS) research data centre. Selection of satellite data is also a difficult and challenging task while performing digital change detection analysis (Macleod and Congalton 1998).

3.0.1 Data used

Satellites loaded with several sensors at different spatial, spectral radiometric and temporal resolution are launched by different leading countries in space technology through earth observation program. Based on surface features, research objectives satellite imageries need to be decided before beginning core analysis (Chen *et al.* 2012). Problem oriented requirement of satellite imageries made difference in change detection analysis.

Table No. 3.1 Operational earth observation satellites

EUROPE		**MIDDLE EAST**	**NORTH AMERICA**			**ASIA**	
France	ESA		USA		Canada	India	Japan
SPOT1-86 10m			**LANDSAT5-85 30m**				
SPOT2-90 10m	ERS1-92/00 Radar		LANDSAT6-93 30m				
SPOT3-93/96	ERS2-95 Radar		EARLYBIRD-98	IKONOS1-99 1m	RADARSAT-95	IRS1C-95 6m	
SPOT4-98 10m	ENVISAT-2001 Radar		**LANDSAT7-99 15m**	IKONOS2-99 1m		IRS1D-97 6m	
		EROS A/1-00 2m	QUICKBIRD-01 0.6m	ORBVIEW-01 1m		IRS P6-2003 5.8m	
SPOT5-02 3m+hrs10		EROS B/1-02 1m		ORBVIEW-02 1m	RADARSAT-03	CARTOSAT-1&2 2.5m/80cm	ALOS-03 2.5m
			LANDSAT8-13 15m				
Distributors							
SPOT IMAGING	Miscellaneous	Imagesat	SI-EOSAT, Earthwatch, Orbimage, USGS		RADARSAT	NRSC-EOSAT	Java
Source: ITC's database of Satellites and Sensors							

Satellite imageries selected for this study are useful to prove the objectives with satisfactory result. Coarse resolution satellite data is useful larger area like Landsat MSS (79m), IRS LISS-I (72.5m), etc. The research area to be covered is small or medium then reasonably use of data with medium and fine resolution data like SPOT multispectral data (20m), Landsat TM as well as ETM+ data (30m), IRS LISS-II (36.25m), LISS-III (23.5m), LISS-IV (5.8m), etc. Cloud free satellite data have been selected and downed from Earth Explorer USGS departments for present study.

Required data has obtained from primary as well as secondary sources. The government records, SOI topo-maps and satellite imageries have been taken from online sources. The ground verifications and sample data have collected from field checks. Referenced or base image has been used for analysis of data acquired by Landsat-7 Enhanced Thematic Mapper Plus (ETM+ path-147 row-047 from http://earthexplorer.usgs.gov/) dated 06th Nov. 2002 and targeted image is Landsat-5 Thematic Mapper (TM path-147 row-047 from http://earthexplorer.usgs.gov/) dated 01st Nov. 2009 (01 January 2012 is data access date). Same month, same season and same spatial resolution of these imageries helpful to obtained for better results. After monsoon season in Indian peninsula forests and vegetation covers growing rapidly and representing a higher amount of greenery, which is useful to study the change and it increase the quality of vegetation classes. Samples selection and ground verifications done by Global Positioning System (GPS) for good accuracy.

Remotely sensed data is available in different resolution forms (Simmonds *et al*. 2004). Spectral or radiometric resolution is related to the radiance band width, temporal resolution related to time factor and spatial resolution which related to the size of an each pixel within satellite imagery (Hadeel *et al.* 2011). All satellite images acquired by the converted radiance, which has been recorded as a digital numbers (DN). These digital numbers are depicted by pixels. Satellite image is nothing but a table of array which created with the combination of rows (represent latitude) and columns (represent longitude). This combination forms a pixel containing converted digital numbers (Blackett and Wooster 2011). Smaller the size of pixel surface information is more accurate and reliable for the analysis. This high resolution image covers small area as per the limitation of sensor coverage. Acquiring high resolution satellite imageries to achieve more precise results of change detection is still a challenge for researches. Landsat-5 TM and Landsat-7 ETM+ Image datasets having a good enough spatial resolution for the study of forest changes in study area (Sepehry and Liu 2006).

Table No. 3.2 Characteristics of Landsat-5 and Landsat-7 satellite

Sensor	Spectral Resolution (µm)	Spatial Resolution (m)	Scan-width (km)	Time interval Equator	Orbital altitude (km)	Mission and Operational Period
TM	Band 1: 0.45 - 0.52 Band 2: 0.52 - 0.60 Band 3: 0.63 - 0.69 Band 4: 0.76 - 0.90 Band 5: 1.55 - 1.75 Band 6: 10.40 - 12.50 Band 7: 2.08 - 2.35	30 x 30 30 x 30 30 x 30 30 x 30 30 x 30 120 x 120 30 x 30	185	16 days	710	Landsat 5 01/03/1984 to 05/06/2013
ETM+	Band 1: 0.45 - 0.52 Band 2: 0.52 - 0.60 Band 3: 0.63 - 0.69 Band 4: 0.76 - 0.90 Band 5: 1.55 - 1.75 Band 6L: 10.40 - 12.50 Band 6H: 10.40 - 12.50 Band 7: 2.08 - 2.35 PAN 0.50 to 0.90	30 x 30 30 x 30 30 x 30 30 x 30 30 x 30 60 x 60 60 x 60 30 x 30 15 x 15	185	16 days	705	Landsat 7 15/04/1999

Source: Landsat-7 Data User Handbook, NASA

3.0.2 Field data

Accuracy assessment is an important parameter to assess and control the qualitative output of satellite image classifications as well as verifications. Image classification accuracy has been checked through Garmin device of Global Positioning System (GPS) and high resolution (1x1 meter) Google Earth Pro images for ground verification of vegetation, water resources, mountains, etc. surface characteristics.

3.0.3 Software used

In this study, Earth Resource Data Analysis System (ERDAS) Imagine 9.2 and Integrated Land Water Information System (ILWIS 3.4, ITC, RSG/ GSD, January 2004, www.52north.org/) Remote Sensing and Geographic Information System (RS & GIS) softwars have been used to perform the digital image processing analysis. ERDAS is a raster based geo-processing software used for GIS, image processing and photogrammetry purpose and developed by Leica Geosystems, USA. ILWIS software is an integrated Remote Sensing and GIS open source software developed by International Institute for Geo-Information science and Earth observation (ITC), Netherland. MS-Excel developed by Microsoft and Statistical Packages for the Social Sciences (SPSS 15.0) have been used for tabulation and statistical analyses. SPSS developed by IBM, USA.

3.1 Methodology

Research work flow of the present study has designed and implemented as per the requirement for robust change detection analysis. TM and ETM+ multispectral band data has been used to detect forest cover change (Figure 3.1) and it follows by the following step by step digital image processing analysis.

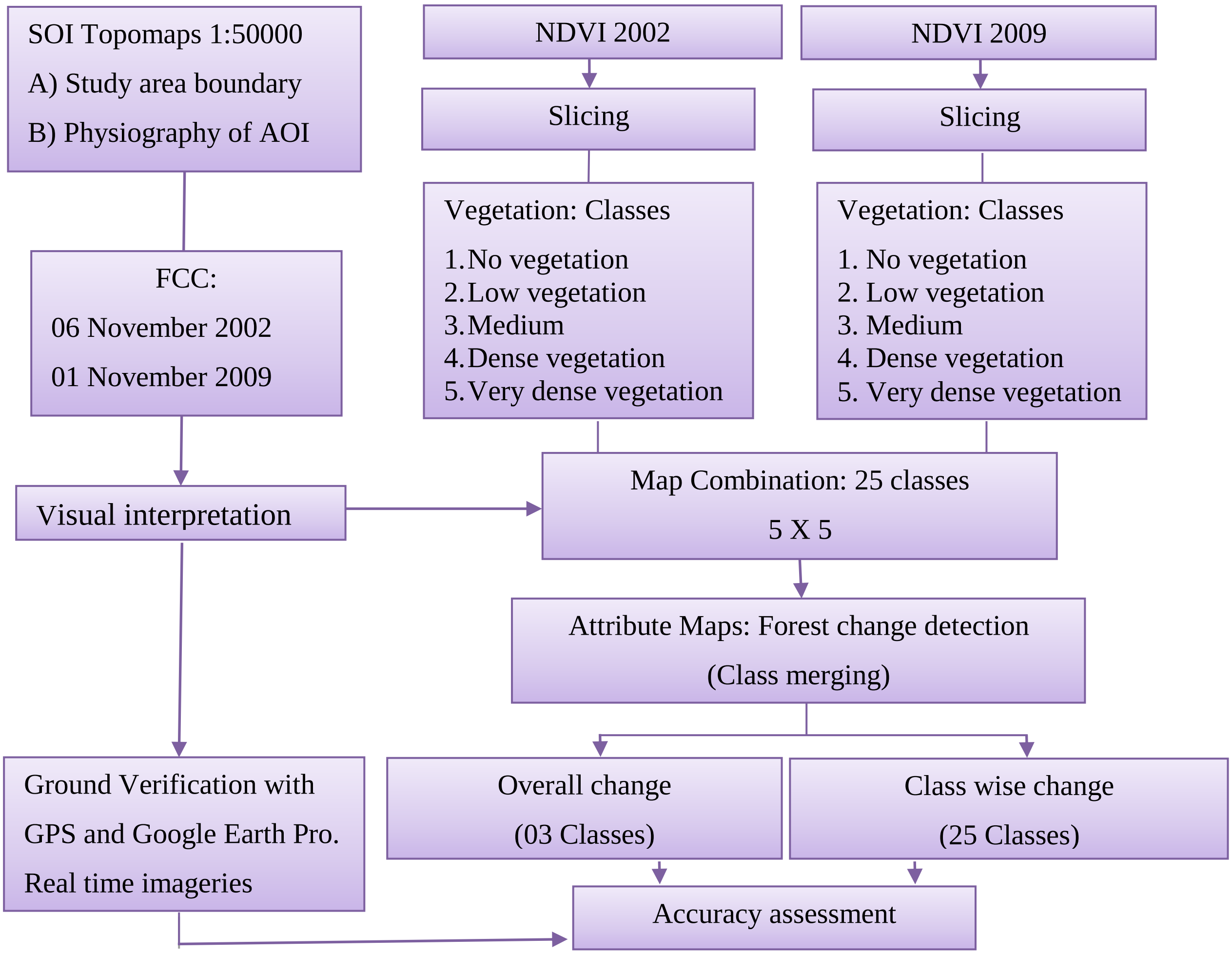


Figure 3.1 Schematic preparation of image processing

3.1.1 Co-registration

Requirement of researchers area of interest and objectives, co-registration or geo-referencing of multi-temporal satellite images used for different purposes. Integrated information from multiband images, matching spatial resolution and different conditions have been used for change detection, accurate mosaicking and overlay purpose, etc. Matching of multi-temporal images of different time periods is a critical but prerequisite process before beginning a core analysis. Co-registration gives lesser accurate in result due to a first pixel of mis-registration (Pajares *et al.* 2012). This task is quite difficult to achieve a precise accuracy because less numbers of Ground Controlling Points (GCP) taken from the multi-temporal images. Same surface features identification, equalizing, transformation process and resampling have involved in co-registration of images with different time span (Burnicki *et al.* 2010). This method many time used in remote sensing, photogrammetry, image fusion, etc. Anonymous (1999) and Singh *et al.* (2006) have suggested automatic tie point registration, pixel to pixel matching, ground control point registration, semi-automotive registration, etc. to obtained reliable and authenticate change detection results (Julien *et al.* 2011).

In the present study ERDAS Imagine software has been used to generate precise co-registered the Survey of India (SOI) topographic sheet 47 E/ 10, 11, 14, 15; 47 I/ 2, 3 to create a study area outline. Using Ground Truth verification with Garmin GPS device for GCP's registration of these both multi-temporal images i.e. Landsat ETM+ (t_1) and TM (t_2) have been pixel to pixel match in ERDAS Imagine environment for the further change detection analysis.

3.1.2 Image enhancement

Enhancement of the co-registered multi-temporal and multi-spectral imageries play an important role in change detection analysis. Image enhancement improves the quality of information without generating new data (Clifton 2003). This technique is highlighting, depicting and modelling the image spectral surface information by using colour composite such as 1) True Colour Composite (TCC) with combining blue, green and red bands and 2) False Colour Composite (FCC) images generated with the combination of green, red and near infrared band to eliminate the noise of image interpretation, histogram equalization, filter operation such as noise correction, edge enhancement using high pass filter or low pass filter, band ratio, trend surface analysis, principal component analysis, spectral indices such as Leaf Area Indices (LAI), Normalised Differenced Vegetation Indices (NDVI), Normalised Difference Water Indices (NDWI), Land Surface Temperature Indices (LST), Tasselled Cap Coefficient Transformation (TCCT), Normalised Difference Salinity Indices (NDSI), etc. suggested and successfully applied by researchers to obtained change detection results (Petit and Lambin 2001).

After reliable co-registration of Landsat ETM+ and TM imageries have loaded into Integrated Land Water Information System (ILWIS 3.4) environment for enhancement and classification purpose. FCC (Figure 3.2) and NDVI (Figure 3.3) successfully calculated and generated using image enhancement band ratio method of both imagery datasets to get more information of forest change in the study area.

3.1.2.1 Preparation of FCC

False Colour Composite (FCC) is used in many digital images processing analysis (Theiler and Perkins 2011). It helps to improve image interpretation and surface characteristics visualization. Spectral band combination processes used in the FCC (Figure 3.2) preparation. Whereas band 2^{nd}, 3^{rd} and 4^{th} have used to represent the DN of green, red and near infrared, etc. (Hara *et al*. 2012). Green and Red are visible bands. Near Infrared has use to identified and characterise the vegetation. FCC of both time periods has been prepared to identify the surface features such as land, water bodies, vegetation, agricultural land, settlements, etc. It has mainly useful the meaningful image classification of above mentioned surface features (Lippitt *et al.* 2011).

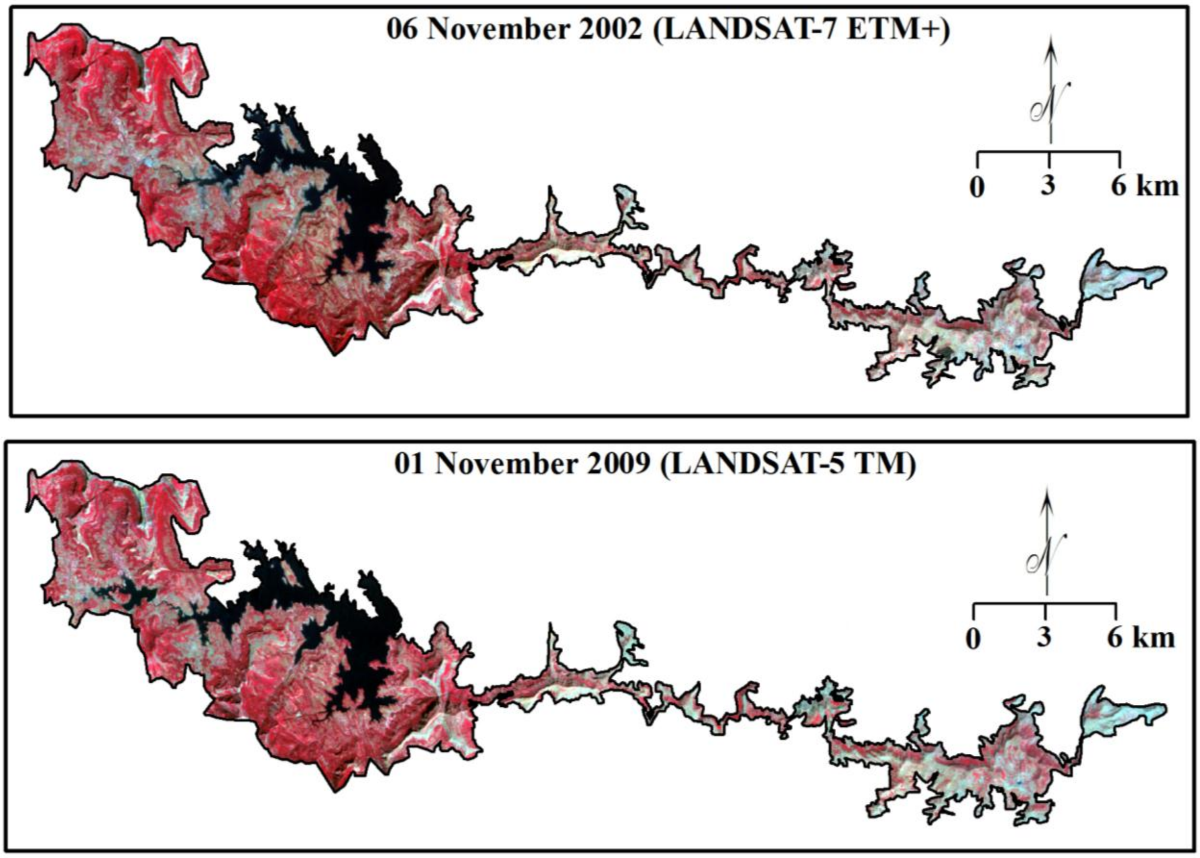


Figure 3.2 False Colour Composite (FCC)

3.1.2.2 Preparation of NDVI

An extraordinary extend occurs in scientific understanding and application of behaviour and functioning of the vegetation landscape using remotely sensed recorded spectral, radiometric, temporal and spatial resolution satellite data and geographic information system science last two decades (Balschke 2010). Ratio images are having or demonstrating ability to recognize or draw fine distinctions. It has been applied to eliminate the effects of environmental factors (Ghent *et al*. 2011). Ratio gives unique information which cannot be obtained from single band. Normalised Difference Vegetation Index (NDVI) has enough potential to discriminate the spectral variation in different vegetation cover and species (Kloer 2011).

$$NDVI = \left(\frac{(NIR - RED)}{(NIR + RED)}\right) \quad \text{(Eq. 3.1)}$$

NDVI has been calculated by using Near Infrared (Band 4) and Red (Band 3) of sensor ETM+ and TM, respectively (Bhagat and Sonawane 2011).

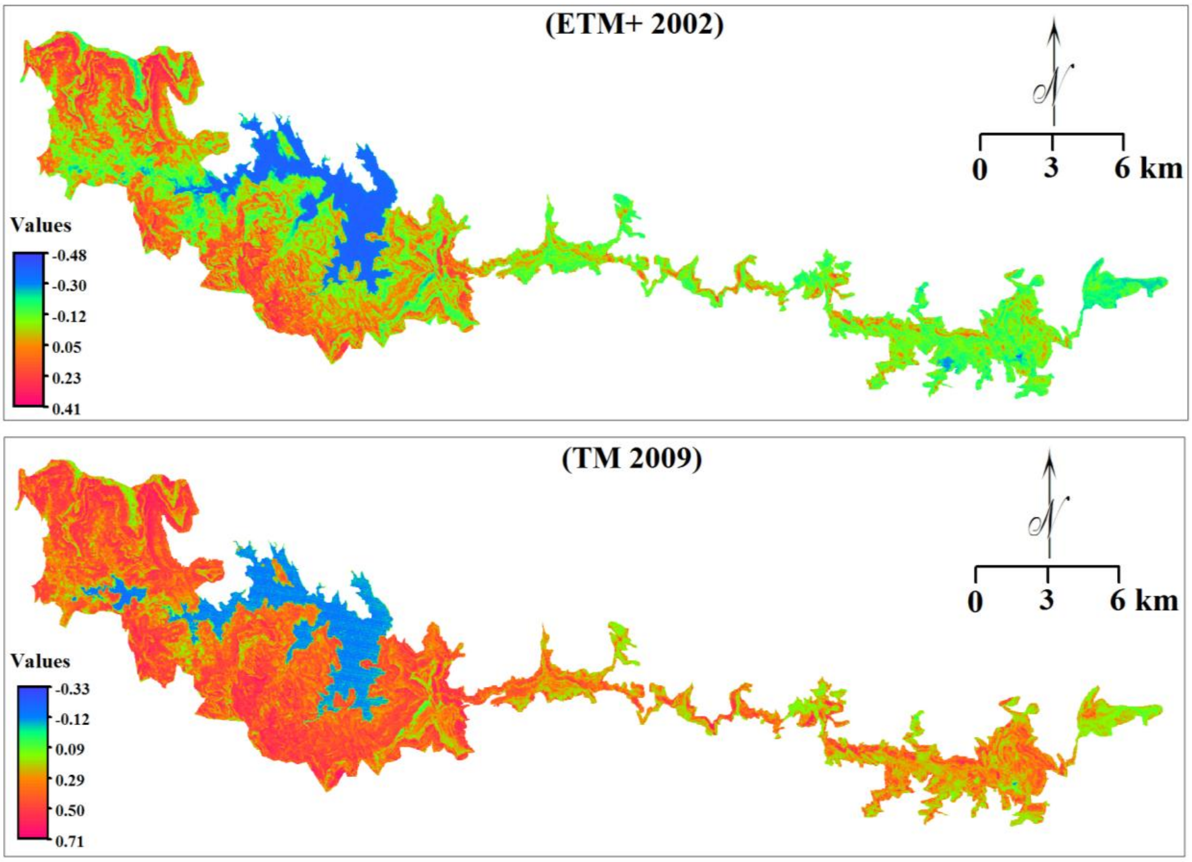


Figure 3.3 Normalized Difference Vegetation Index (NDVI)

It is a ratio of subtraction and addition of these two bands. These ratio values have been distributed between -1 to +1 depending on absolute and relative values in the Near Infrared and Red band. In both images high value of NDVI indicating high vegetation covers and low NDVI value represents absence of vegetation covers. These estimated values have been grouped into differenced classes by using natural breaks or threshold found in the resulted NDVI 2002 and NDVI 2009. These groups have been used in further classification to understand the density of different vegetation cover which have been used to detect and delineate forest change detection analysis.

3.1.3 Classification

Satellite image selection for image enhancement processes highly prerequisite to arrive in image classification stage (Ehlers *et al*. 2010). Satellite image classification initiated and led up into meaningful information associated with surface features (Chowdhury *et al.* 2005). Mainly two traditional classification methods used for classification purpose for any kind of image analysis including forest change detection i.e. unsupervised classification and supervised classification. Some prior knowledge required about the land features in the imagery for supervised image classification whereas unsupervised does not required. Prior knowledge given as set of training samples for classifier usages in supervised classification (Weng *et al.* 2009). Adegoke and Carleton (2002) have been made an innovative contribution to use different hybrid image classification techniques to forest change detection analysis.

Table No. 3.3 NDVI domain classes of ground truth

NDVI ETM+ 2002		**NDVI TM 2009**	
Classes	**Index values**	**Classes**	**Index values**
No vegetation	Below -0.16	No vegetation	Below 0.20
Low to medium	-0.16 to -0.02	Low to medium	0.20 to 0.23
Medium	-0.02 to 0.01	Medium	0.23 to 0.36
Medium to dense	0.01 to 0.16	Medium to dense	0.36 to 0.45
Dense to very dense	0.16 to 0.45	Dense to very dense	0.45 to 0.75

NDVI has been used to extract the spectral variation between ETM+ 2002 and TM 2009 for forest change in the study area. The maximum value (0.41) in base/ referenced image (t_1) indicating the highest vegetation cover (Table 3.3) whereas minimum (-0.48) depicts no vegetation cover land including water body with 0.05 mean and 0.16 standard deviation in NDVI 2002.

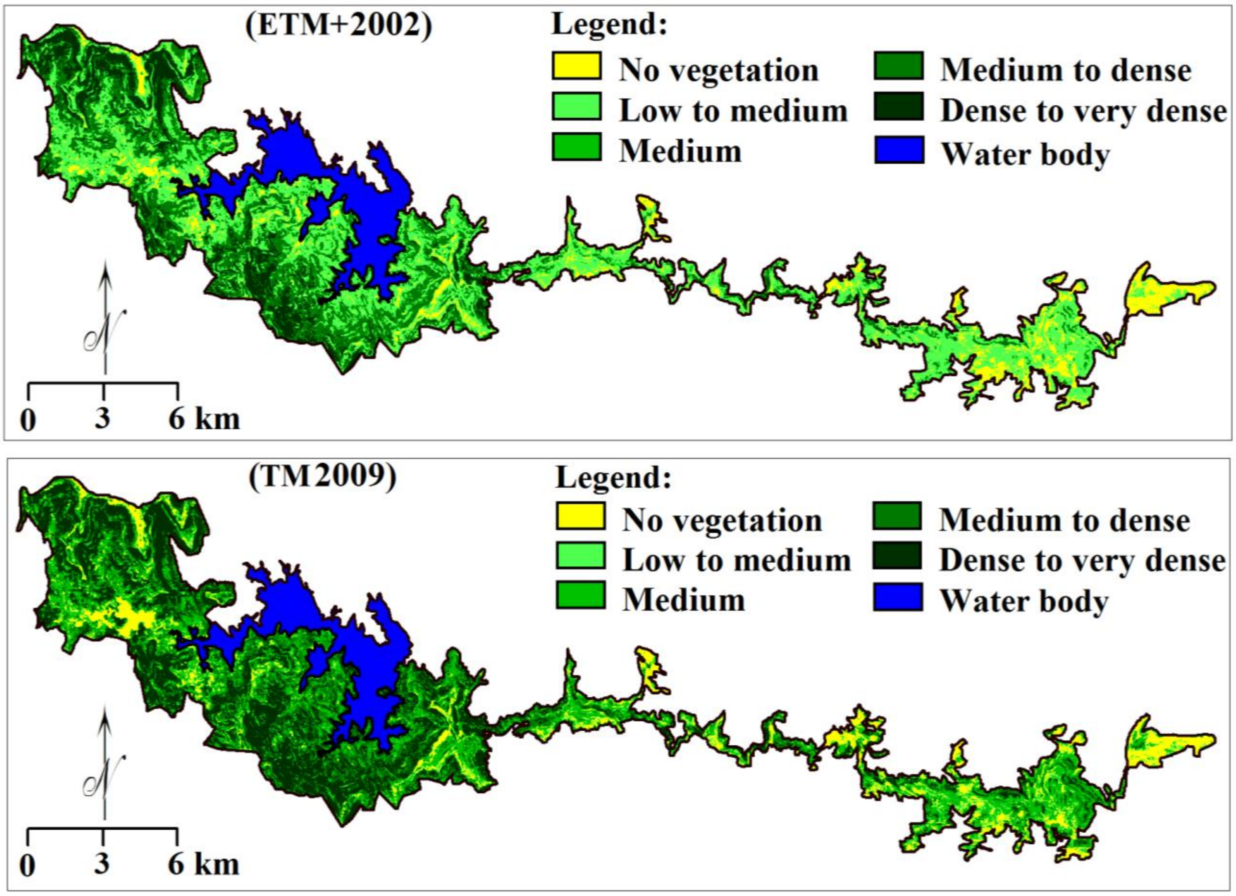


Figure 3.4 Distribution of forest

Whereas in targeted image, (t_2) the maximum value (0.71) indicates the high vegetation and decreasing up to the minimum (-0.33) in areas on no vegetation with 0.31 mean and 0.16 standard deviation in NDVI 2009. Domain classes have generated by using repetitive field checks. These images have been classified into five classes (Table 3.3) i.e. no vegetation, low to medium, medium, medium to dense, dense to very dense and water body (river, major and minor dams, streams, etc.), respectively in forest cover declining manner using ‘slicing’ operation in Ilwis 3.4.

Class ‘no-vegetation’ includes rocky and barren lands which are mainly located land at higher level (> 1100 m) of mountain as well as deep water bodies. Ground verifications of this classes (Figure 3.4) have been done by using Google earth Pro high resolution imageries, FCC as well as number of intensifier and insistent field checks using trial and error correction method.

3.2 Detection of forest change

Measurement of the difference in recorded radiance at base image (t_1) and targeted image (t_2) is called as digital change detection. The causes in radiance difference mainly occurred due to real change in surface features (natural and manmade), deviation in atmospheric conditions, deviation in censor calibration, minimum to maximum error in Route Mean Square (RMS) at the time of georeferencing, deviation in illumination and difference in soil moisture conditions, etc. Image enhancement and classification are the basic part of digital image processing. In advanced processes includes change detection model making based on classified images at different time span using 'cross' operation in ILWIS. Thus, overall forest change and class wise forest change have been estimated to get final results.

3.2.1 Overall change

Crossing operation generates new 25 classes in matrix using classified (5 classes) reference image NDVI (2002) and targeted classified (5 classes) images NDVI (2009). These classes need to rename with new meaning which associated with real surface features as per study objective, scope and the methodology indicating in process flow. Some classes have been merged (Table 3.4) using tool 'merging the classes' in Ilwis. These merged classes broadly divided in to three new criteria i.e. no change in vegetation, forest cover increase and forest cover decline (Figure 3.5).

Table 3.4 Class merging scheme for forest change detection

NDVI Class ETM+ 2002	NDVI Class TM 2009				
	No vegetation	**Low to medium**	**Medium**	**Medium to dense**	**Dense to very dense**
No vegetation	No Change	Positive Change	Positive Change	Positive Change	Positive Change
Low to medium	Negative Change	No Change	Positive Change	Positive Change	Positive Change
Medium	Negative Change	Negative Change	No Change	Positive Change	Positive Change
Medium to dense	Negative Change	Negative Change	Negative Change	No Change	Positive Change
Dense to very dense	Negative Change	Negative Change	Negative Change	Negative Change	No Change

Finally, at wide view the forest changes have been identified by using density vegetation classes of images acquired in 2002 and 2009.

3.2.2 Class wise change

Overall change in forest cover was detected successfully (Figure 3.5), however, the question remain and rises that in 2002 to 2009 forest classes changing their identity and behaviour with respect to natural, climatic and manmade changes with time scale (Table 3.5). At micro level, class wise changes in forest cover have successfully delineating (Figure 3.5) in class wise forest change detection.

Table 3.5 Class wise forest change detection

NDVI Class ETM+ 2002	NDVI Class TM 2009				
	No vegetation	**Low to medium**	**Medium**	**Medium to dense**	**Dense to very dense**
No vegetation	NVNoC	NVPL	NVPM	NVPD	NVPVD
Low to medium	LNNV	LNoC	LPM	LPD	LPVD
Medium	MNNV	MNL	MNoC	MPD	MPVD
Medium to dense	DNNV	DNL	DNM	DNoC	DPVD
Dense to very dense	VDNNV	VDNL	VDNM	VDND	VDNoC

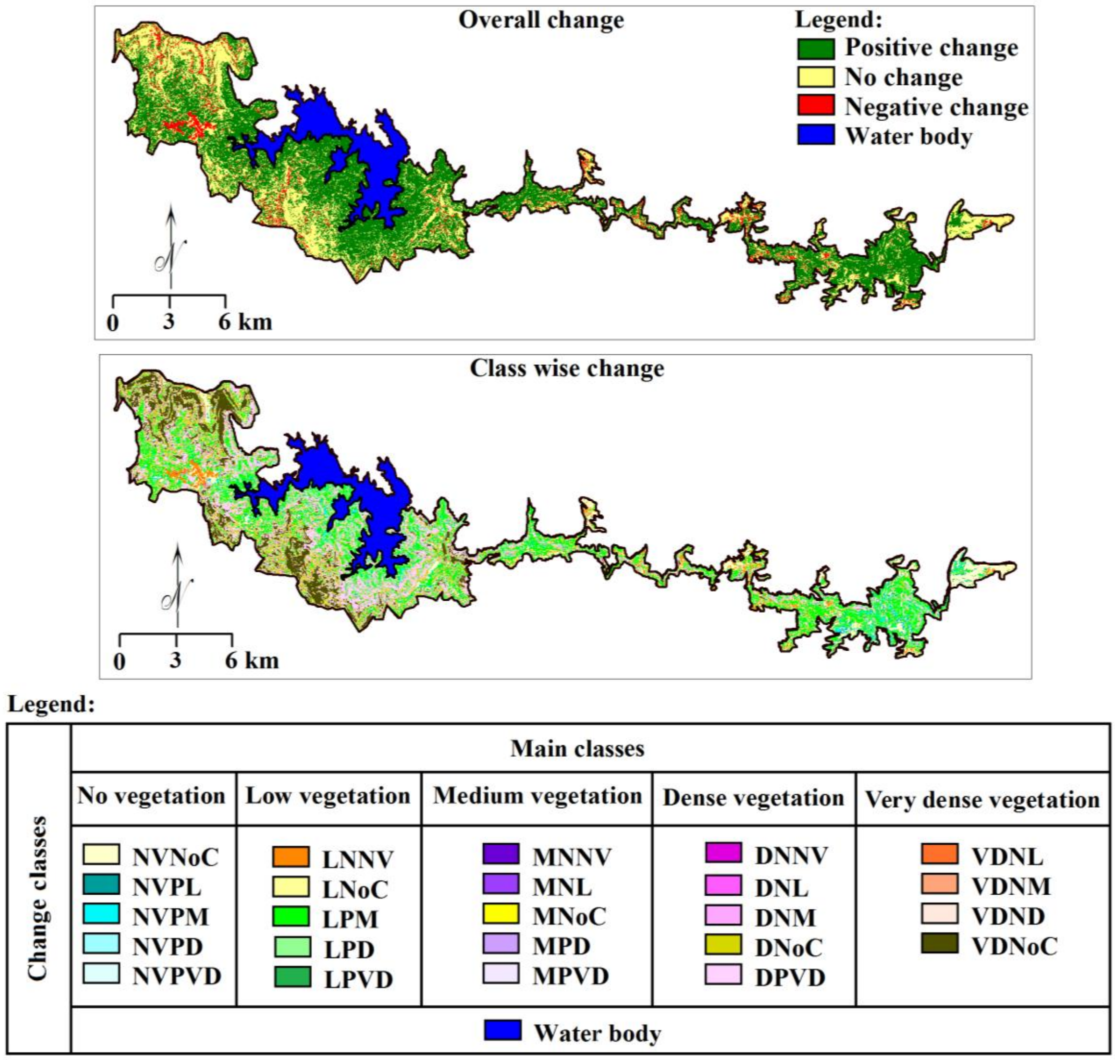


Figure 3.5 Class wise change in forest

Detailed explanation of codes of forest change classes are given in the table 3.8.

3.3 Results and discussion

This distribution of change in forest cover has been detected based on NDVI estimated for both imageries and classified into vegetation classes. The forest change detection map using post-classification methods (Figure 3.5) has been prepared to know the overall forest change and at micro level from class to class. The total geographical study area is 13858.83 ha (Table 3.6), except water body of major dam (1905.34 ha, Bhandardhara) the area is 11953.49 ha.

3.3.1 Overall forest change

The change in forest area within period of images acquired has been detected and successfully demarcated. About 58.59% of reviewed area shows forests with increasing trends, 33.69% area shows no change and the land which losing forest estimated in 7.72% lands. These changes in targeted image have estimated increase in forest cover i.e. low to medium 36.32 %, medium 22.42 % and dense to very dense around 16.8%. Slightly change has been depicted in no vegetation 0.13% and medium to dense 2.81% (Figure 3.6).

Table 3.6 Class wise changes in area under forest

Classes	2002 Area in ha	2002 Area in %	2009 Area in ha	2009 Area in %	Change in %
No vegetation	1713.51	12.36	1695.96	12.24	0.12
Low to medium	5840.46	42.14	806.76	5.82	36.32
Medium	968.4	6.99	4075.11	29.4	-22.41
Medium to dense	3706.65	26.75	3317.76	23.94	2.81
Dense to very dense	1629.81	11.76	3963.24	28.6	-16.84
Total Area	13858.83	100	13858.83	100	

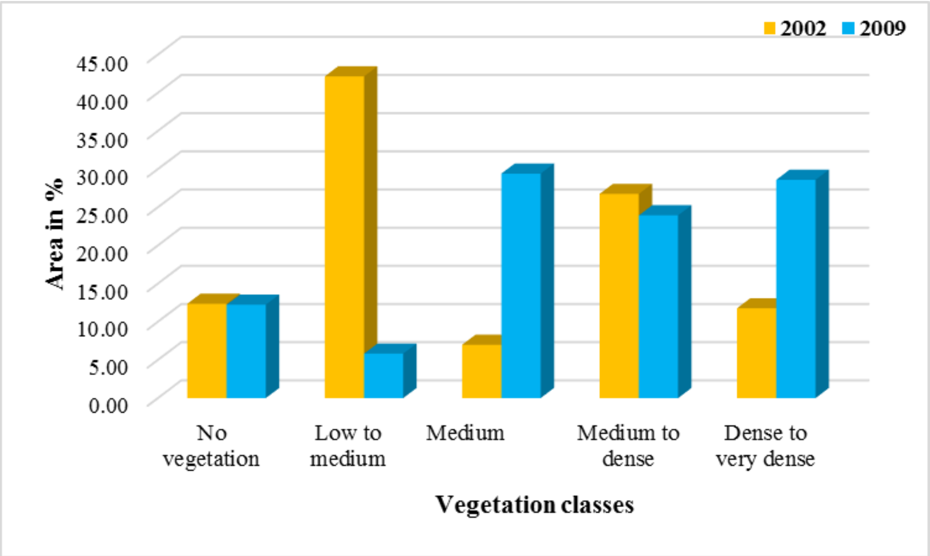


Figure 3.6 Class wise changes in area under forest

Overall change in estimated area increased to 8119.98 ha, no change to 4669.29 ha and decreasing to 1069.56 ha. The area of forest and vegetation cover changes means that amount of forest land rising. This process is occurring within existing area neither new area affecting nor interrupt.

3.3.2 Class wise forest change

Forest classes (Table 3.7) are moving from one class to another due to several natural and manmade activities. Surface forest cover is increasing from low forest cover to medium 22.68% and dense vegetation cover to very dense cover 15.02%. This forest change estimations show maximum area in very dense vegetation with no change 10.89%. Forest cover is decreasing with high changes found in low vegetation to no vegetation cover estimated around 4.30 %. In this way, the class wise forest change area has been detected. Accuracy assessment has been performed to check reliabilities of the estimations (Table 3.8).

Table 3.7 Class wise forest area distribution

Class Code	Full form of class code	Area in ha	Area in %
NVNoC	No Vegetation No Change	1083.96	7.8214
NVPL	No Vegetation Positive change to Low vegetation	259.92	1.8755
NVPM	No Vegetation Positive change to Medium vegetation	347.31	2.5061
NVPD	No Vegetation Positive change to Dense vegetation	21.24	0.1533
NVPVD	No Vegetation Positive change to Very Dense vegetation	1.08	0.0078
LNNV	Low vegetation Negative change to No Vegetation	597.24	4.3095
LNoC	Low vegetation No Change	531.09	3.8321
LPM	Low vegetation Positive change to Medium vegetation	3143.34	22.6811
LPD	Low vegetation Positive change to Dense vegetation	1393.38	10.0541
LPVD	Low vegetation Positive change to Very Dense vegetation	175.41	1.2657
MNNV	Medium Vegetation Negative change to No Vegetation	9.54	0.0688
MNL	Medium Vegetation Negative change to Low vegetation	8.19	0.0591
MNoC	Medium Vegetation No Change	253.98	1.8326
MPD	Medium Vegetation Positive change to Dense vegetation	500.94	3.6146
MPVD	Medium Vegetation Positive change to Very Dense vegetation	195.75	1.4125
DNNV	Dense vegetation Negative change to No Vegetation	5.22	0.0377

DNL	Dense vegetation Negative change to Low vegetation	7.47	0.0539
DNM	Dense vegetation Negative change to Medium	321.48	2.3197
DNoC	Dense vegetation No Change	1290.87	9.3144
DPVD	Dense vegetation Positive change to Very Dense vegetation	2081.61	15.0201
VDNNV	Very dense vegetation Negative change to No Vegetation	0.02	0.0002
VDNL	Very dense vegetation Negative change to Low vegetation	0.07	0.0004
VDNM	Very dense vegetation Negative change to Medium vegetation	9	0.0649
VDND	Very dense vegetation Negative change to Dense vegetation	111.33	0.8033
VDNoC	Very dense vegetation No Change	1509.39	10.8912
Total Area		**13858.83**	**100**

3.4 Accuracy assessment

Accuracy assessment is a quality assurance procedure which decide the analysis calibre based on different parameters i.e. user’s accuracy, producer’s accuracy and overall accuracy. Therefore, all the classes used in this study has assessed with help of error matrix. Rahman and Saha (2008) have suggested that the sample size should take minimum 30 for each class to estimate accuracy at 90%. This assessment process includes the comparison between the classes of references (t_1) classified images and targeted (t_2) classified images. The sample and ground truth have been taken for the accuracy assessment based on GPS points and Google earth high resolution imageries as well as field checks.

Table 3.8 Error Matrix

Classified Data	**Reference Data**					
	Positive change	**No change**	**Negative change**	**Water**	**Row total**	**User’s accuracy in %**
Positive change	**19**	6	4	4	33	**58**
No change	5	**31**	5	3	44	**70**
Negative change	2	3	**32**	3	40	**80**
Water	1	0	1	**48**	50	**96**
Column total	27	40	42	58	**167**	
Producer's accuracy in %	**70**	**78**	**76**	**83**		**77.84%**

Overall accuracy = 77.84%

In the present study, ground verification data have been compared with ETM+ 2002 NDVI classes and TM 2009 NDVI classes for accuracy assessments. This process gives combine results of user's, producer's and overall accuracy to get final quality of forest change detection. Error matrix is an array of table with combination of row (producer's) and column (user's) accuracy. Number of sample pixels compared with user and producers accuracy. 167 samples have been collected and distributed in all categories of error matrix reference and targeted image classes i.e. no change, low to medium, medium, medium to dense, dense to very dense, and water body etc.

User's accuracy was estimated about 58% for positive change, 70% for no change and 80% for negative change, 96% for water. On the other hand producer's accuracy estimated about 70% for positive change, 78% for no change, 76% for negative change and 83% for water. Overall accuracy estimated around 77.84%. This assessment indicates the forest land increased in the period of 2002 to 2009. This is an estimation of forest change detection by using post classification forest change detection techniques. However, overall accuracy of the assessments suggests the reclassifications and detections of changes in forest cover in the region for better applications of the results.

3.5 Limitation of forest change detection using post classification techniques

Post classification based forest change detection show some limitations. Many researchers, scholars and technicians have been used this method from last two decades with limitations. Based on primary digital image processing techniques i.e. image rectification and image enhancement next process of image classification has competed with ground truth verification or visual interpretation of FCC imageries.

These results have been prepared and published with this kind of post classification. Satellite image depicts number of pixels including digital numbers of reflectance. These pixels represent illusional exaggerated reflectance in digital numbers. This illusional exaggeration may generates false positive results of any research and become a false guideline for researchers, planner and monitors. Therefore, revised method for forest change detection is suggested in next chapter.

3.6 Resume`

This chapter has performed for discussion of conventional forest change detection technique i.e. post classification based technique. The Landsat ETM+ 2002 and TM 2009 satellite data has been analysed and classified with the help of ERDAS Imagine and Ilwis 3.4 RS and GIS software. The combination of classified NDVI 2002 and 2009 maps are capable to detect forest change. The overall forest change has estimated in positive change around 58.59%, no change of existing land around 33.69% and 7.72% negative change in 13858.83 ha (TGA) with 77.84% overall accuracy which is not meets optimum level. Class wise forest change has been estimated to understand the internal change within the classes. Revised improves forest change detection technique based on statistical analyses is discussed in next chapter.

****

CHAPTER IV

IMPROVED FOREST CHANGE DETECTION TECHNIQUE

4.0 General

Post classification based forest change detection technique has been used and discussed in previous chapter. However, the results of the accuracy assessments show the need of improved forest detection techniques. The favourable soils distribute on foothill slopes are suitable for forest growth (Anonymous 1976) and tribal population is dependent on this forest for their domestic needs. Therefore, it is an important to understand the behaviour and characteristics of forest cover change at reliable confidence.

4.1 Theoretical background

The algorithm of robust forest change detection analysis has been modified number of time. Newer, enthusiastic, innovative approaches have used to get refine results than the older methods (Singh 1996, Felkar *et al.* 1981). The present study described simple but very unique process flow to obtain realistic and reliable results of forest change detection (Figure 4.1) and provide solutions for the real world problems. Though, recorded, rectified and enhanced satellite data of land classes have unique identity and important i.e. forest covers, rocky lands, water bodies, and barren lands, etc. (Gessing *et al.* 2000). Therefore, each land class depends on each other and have equal importance. Selection of samples of each land class is based on Ground Reference Digital Number Triangle (GRDNT) method. This unique method is used to collect samples of each land class like water, forest, rocky land, barren land, etc. for this study work.

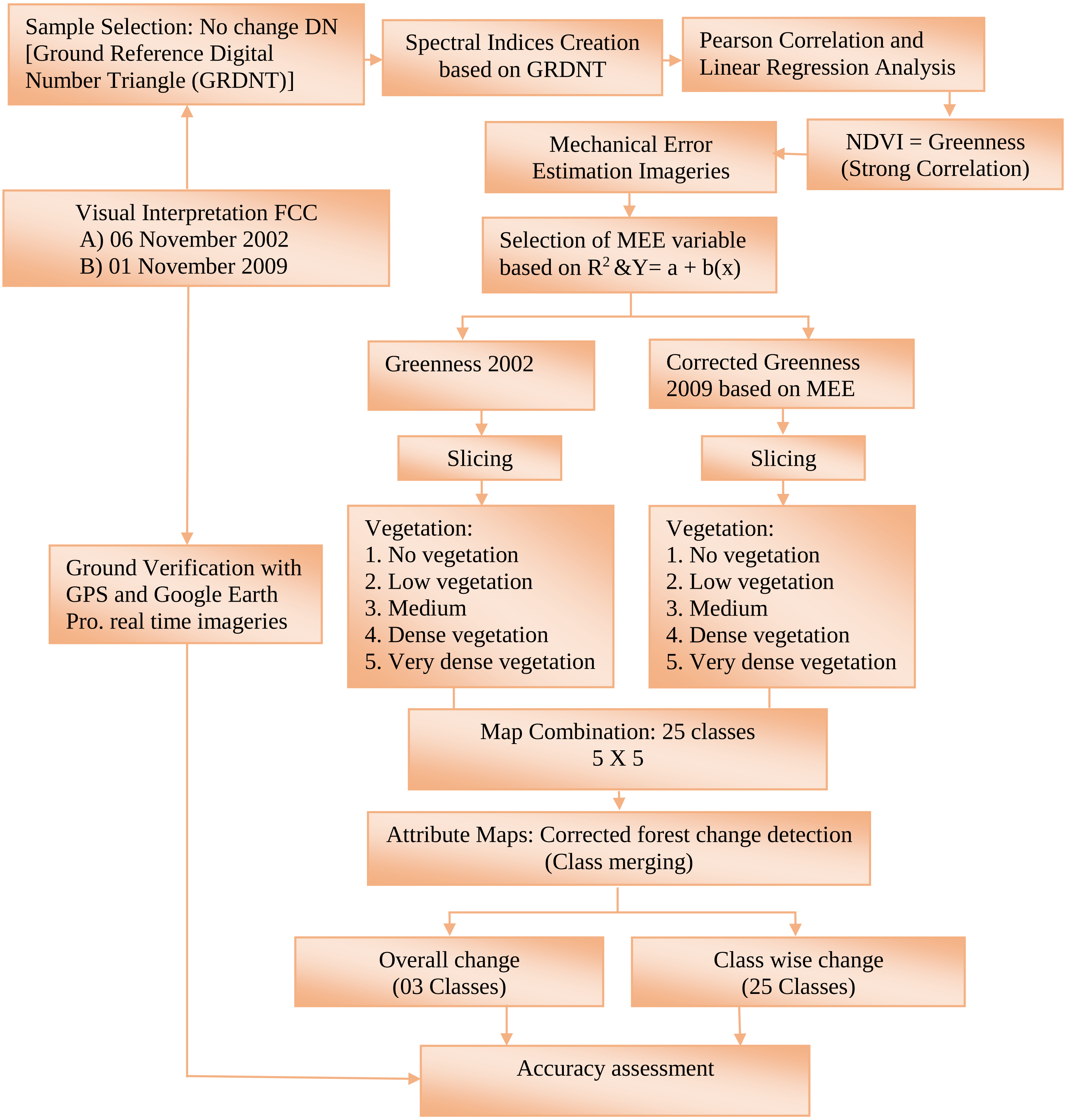


Figure 4.1 Schematic preparation of robust forest change detection image processing

4.1.1 Sample selection

Many researches have been successfully reported using single band, single ratio indices as well as single time domain, etc. unable to generate proper and precise solution for any kind of object detection and demarcation (Anonymous 1976). Although, the study area have combination of number of land surface classes, i.e. forest, water, barren land, rocky land, snow cover, marsh land, desert area, etc. These land phenomenon regulates surface radiance as per their unique identity (Benchalli and Prajapti 1998). Therefore, radiance, surface temperature response is change due to soil moisture and vegetation cover. Since last decade many researcher and scholars have been successfully reported different land object change results base on fusion or combination of more than two approaches. Such as near infrared, thermal infrared, middle infrared combined with vegetation indices to generate an effective technique for DCD. Vegetation indices like NDVI, LAI, Greenness, TVI, etc. have been combined with surface temperature. Though, Soil Wetness Index (SWI), NDSI, Brightness have been used to estimate the energy balanced, evapotranspiration, etc.

Every region is presumed as an assortment of water body, forest land, bare soil and rocky land, etc. (Figure 4.2). EM radiation interacts with surface elements (Carlson *et al.* 1990). Although, surface temperature indicated with the help of thermal band data and vegetation can detected with the help of near infrared band in satellite data (Tanriverdi 2010). Therefore, soil moisture, evaporation, and surface temperature, etc. have been estimated with the help of combination approach known as ‘Triangle approach’ includes vegetation indices, soil moisture indices and thermal indices (Weng 2009, Moran *et al.* 1994). The combination approach provides object oriented estimated information more reliable and accurate than single band. Thus, the all elements of surface have equal importance while estimating forest change detection (Owen *et al.* 1998).

Sample selection method GRDNT has developed to understand the nature and characteristics of No Change Digital Number (NCDN) is depicting in t_2 image pixels with different time scale and space. Samples are chosen based on no change radiance value with reference to naturally stable land classes. Total 170 NCDN pixels samples have taken for forest CD. Among them 31.18% are collected from forest cover, 27.65% from rocky land, 29.41% from water body and 11.76% from barren land for further process. Each land class is responsible to other class and controlling them for their existence purpose (Figure 4.2).

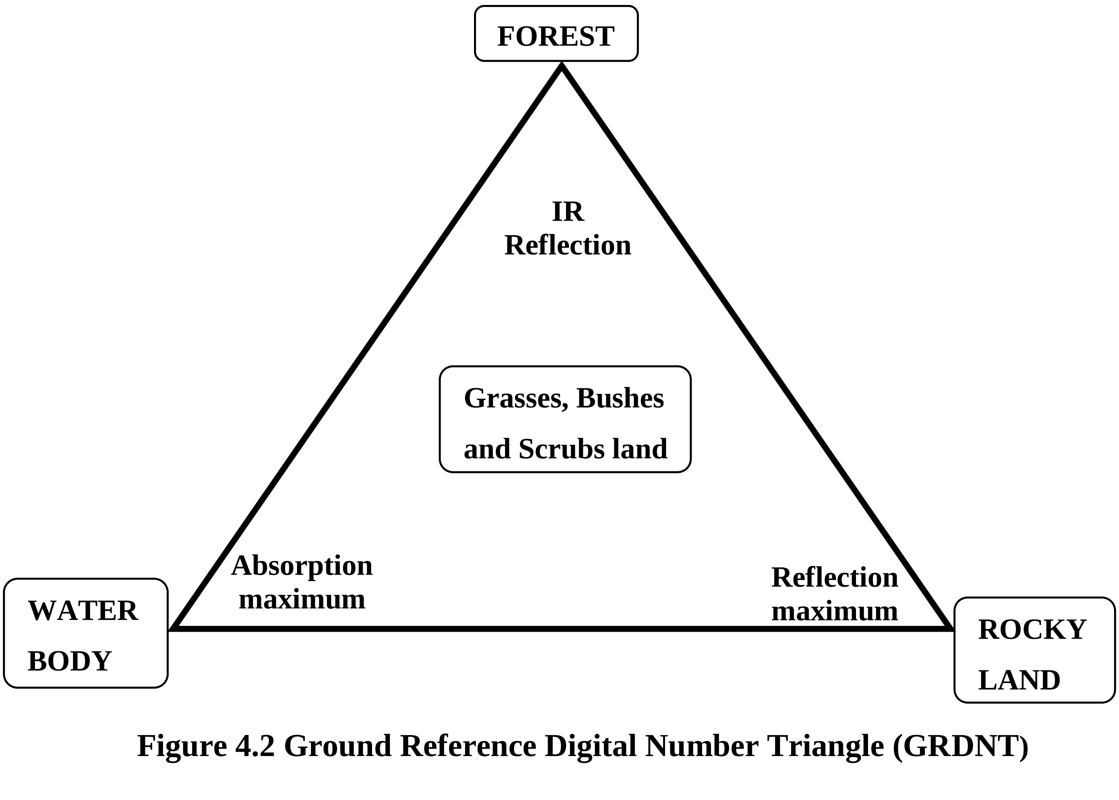


Figure 4.2 Ground Reference Digital Number Triangle (GRDNT)

Water body absorbs maximum amount of radiation and emit very little energy. Forest cover reflects maximum amount of Green and Near Infrared (NIR) waves and a good absorber of Blue and Red band. Chemical component existing in tree leaves known as 'chlorophyll' effectively absorb radiation from the blue and red band. The inner structure of these leaves response as good emission of NIR wavelength. On the other hand, visible and NIR radiation absorb more in the form of longer wavelength from water body and less from shorter wavelength. Thus, water appears blue-green or blue due to maximum reflectance of shorter wavelength and viewed dark because reflectance of red and near infrared depending on the suspended sediments amount in water. Rocky lands are purely dry and rarely covered by thin grass and algae in wet seasons. However, rocky lands absorb very low amount of visible as well as NIR and reflect maximum as compare to other classes. Among the all classes barren land play an important role to make balance in between these land classes. Samples for no change (GRDNT) land have been collected for each spectral band of ETM+ 2002 and TM 2009, respectively. These all DN values have used to generate different spectral indices i.e. NDVI, SWI, LAI, TAO, LSTI, Tasselled Cap Coefficient Transformation (TCCT) for the correlation and regression analysis.

4.1.2 Spectral indices

Usage of single band, single ratio or any single spectral index to accumulate the information about forest change detection, rather the number of bands, spectral indices and their difference become suitable and helpful to create a meaningful and logical, finer than earlier results and more reliable output of forest change analysis. Some indices have generated for both ETM+ 2002 and TM 2009 band data using NCDN samples.

4.1.2.1 Normalized Difference Vegetation Index (NDVI)

$$NDVI = \left(\frac{(NIR - RED)}{(NIR + RED)}\right) \quad \text{(Eq. 4.1)}$$

whereas,

NIR is Near Infrared band 4
RED is Visible band 3

NDVI calculated to understand the identical change in vegetation cover or forest. It is helpful as relative indicator of greenness, biomass, healthy vegetation, etc.

4.1.2.2 Leaf Area Index (LAI)

$$LAI = 4.222 * (NDVI + 1.176) \quad \text{(Eq. 4.2)}$$

whereas,

NDVI is a Normalized Difference Vegetation Index
4.222 and 1.176 are the constant

LAI also one of the important vegetation index parameter used to identify and delineate lite interception, gross productivity, soil moisture and transpiration as a key point in various kind of vegetation covers and types.

4.1.2.3 Land Surface Temperature Index (LSTI)

Top of Atmospheric Radiance: $L_{\lambda} = (L_{max} - L_{min}) * \left(\frac{QCAL}{255}\right) + L_{min}$

(Eq. 4.3.1)

whereas,

L_λ is a spectral radiance in W/ (m2 in μm)

L_{max} is a maximum spectral radiance in (W/m2 in μm) at QCAL equal 0 DN

L_{min} is a minimum spectral radiance in (W/m2 in μm) at QCAL equal 255 DN

$QCAL$ are the quantized calibrated pixel values in DN

This is a one part of the calculation of land surface temperature index which further added as a spectral radiance L_λ into main equation. This equation extract top of atmospheric radiation values in to spectral radiance.

$$\textbf{LST}\ (T) = \frac{k_2}{In\left(\frac{k_1}{L_{\lambda+1}}\right)} \qquad \text{(Eq. 4.3.2)}$$

whereas,

T is an effective at-satellite temperature in k (kelvin)

L_λ is a spectral radiance in W/(m2 in μm)

$k_1\ and\ k_1$ are pre-launch calibration constant (for ETM+ and TM by NASA)

Land surface temperature index has been calculated to understand the behaviour of energy change between earth surface and environment. This equation has been calculated using thermal band 6 radiance values in ETM+ and TM sensors. This equation introduce by Plank also known as Plank's function.

4.1.2.4 Tasselled Cap Coefficient Transformation (TCCT)

This approach is useful to compare number of spectral band with land surface characteristics. It has enough potential to derive forest attribute and different regional applications where, atmospheric noise correction not executable. The applicability of this transformation approach oriented to the study of soil and vegetation. This data transformation is simply reduced the number of radiance noise density and provide high association in single response and physiographical process on the ground. Therefore, this approach extract, visualised the precise data and exact types of usable information as per targeted regions.

Table 4.1 Tasseled cap coefficient for Landsat 7 ETM+ at satellite reflectance

Index	Band1	Band2	Band3	Band4	Band5	Band7
Brightness	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596
Greenness	-0.3344	-0.3544	-0.4556	0.6966	-0.0242	-0.2630
Wetness	0.2626	0.2141	0.0926	0.0656	-0.7629	-0.5388
Fourth	0.0805	-0.0498	0.1950	-0.1327	0.5752	-0.7775
Fifth	-7252	-0.0202	0.6683	0.0631	-0.1494	-0.0274
Sixth	0.4000	-0.8172	0.3832	0.0602	-0.1095	0.0985

Source: Huang *et al*. 2002

Table 4.2 Landsat-5 TM Tasseled cap coefficient at satellite reflectance

Index	Band1	Band2	Band3	Band4	Band5	Band7
Brightness	0.2909	0.2493	0.4806	0.5568	0.4438	0.1706
Greenness	-0.2728	-0.2174	-0.5508	0.7221	0.0733	-0.1648
Wetness	0.1446	0.1761	0.3322	0.3396	-0.6210	-0.4186
Fourth	0.8461	-0.0731	-0.4640	-0.0032	-0.0492	0.0119
Fifth	0.0549	-0.0232	0.0339	-0.1937	0.4162	-0.7823
Sixth	0.1186	-0.8069	0.4094	0.0571	-0.0228	0.0220

Source: Crist *et al.* 1986

All transformed indices calculated for statistical analyses for selection of index for improve forest change detection technique in this study i.e. brightness, greenness, wetness, fourth, fifth and sixth for both ETM+ (Table 4.1) and TM (Table 4.2), respectively.

4.2 Statistical approach

All required basic parameters have collected, compiled, arranged and calculated for statistical analysis i.e. no change pixel samples collection, indices calculations, difference calculation within indices, etc. These basic parameters have been used to calculate correlation and linear regression. Mechanical Error Estimation (MEE) technique has generated using the estimations and results of regression analysis. MEE is further used to correct magnified radiance values in the targeted image. This amplification of radiance value in the recorded satellite image is depicting huge change in surface landform covers and characteristics.

4.2.1 Correlation analysis

All no change pixel samples from ETM+ and TM spectral bands, above all spectral indices and their differences are correlated by using Karl Pearson correlation technique in SPSS software. This relation is also known as Pearsonion Coefficient of Correlation and indicated by ‘*r*’ as mention below.

$$r_{xy} = \frac{COV\ (\bar{x},\bar{y})}{\sigma_x . \sigma_y} \qquad \text{(Eq. 4.4)}$$

whereas,

r_{xy} is correlation between the x and y variables (criteria)

$COV\ (x, y)$ is the covariation between mean of the x and y variables

σ_x and σ_y are the square root of the mean of the squared deviation from the arithmetic mean

If the correlation between two variable is r = +1 then it’s a strong positive correlation, if r = -1 then strong negative and r = 0 that means no relationship between two variables. The relation between NDVI (Eq. 4.1) and Greenness (Eq. 4.5 & 4.6) depicts the strong positive correlation. Both criterions have equal weightage and used for vegetation analysis. However, TCCT (Huang *et al*. 2002, Crist *et al.* 1986) are finer for the particular object based vegetation analysis. Thus, instate of NDVI index for further analysis Greenness index used and calculated (Eq. 4.5 and 4.6) as equation mention below. Multi-spectral bands of ETM+ and TM (Figure 4.3) data are used to estimate for forest change detection in the study area.

Greenness (ETM+) = ((Band1 * (-0.3344)) + (Band2 * (-0.3544)) +
(Band3 * (-0.4556)) + (Band4 * (0.6966)) +
(Band5 * (-0.0242)) + (Band7 * -0.2630))) (Eq. 4.5)

Greenness (TM) = ((Band1 * (-0.2728)) + (Band2 * (-0.2174)) +
(Band3 * (-0.5508)) + (Band4 * (0.7221)) +
(Band5 * (0.0733)) + (Band7 * -0.1648))) (Eq. 4.6)

The correlation between NDVI 2002 and Greenness 2009 indices r = 0.976 indicates positive relationship and NDVI 2009 and Greenness 2009 indicates r = 0.976. These two criterion have estimated strong correlation (Table 4.3, Figure 4.4). Vegetation characteristics, identical thermal emission, healthiness of vegetation are more clearly and digitally enhanced numbers obtained using multi-spectral and object specific indices using tasseled cap coefficient.

Table 4.3 Correlations between NDVI and Greenness

		GREEN02	**GREEN09**
NDVI02	Pearson Correlation	0.684**	**0.976****
	Sig. (2-tailed)	.000	.000
	N	170	170
NDVI09	Pearson Correlation	0.571**	**0.975****
	Sig. (2-tailed)	.000	.000
	N	170	170

****. Significance at the 0.01 level (2-tailed).**

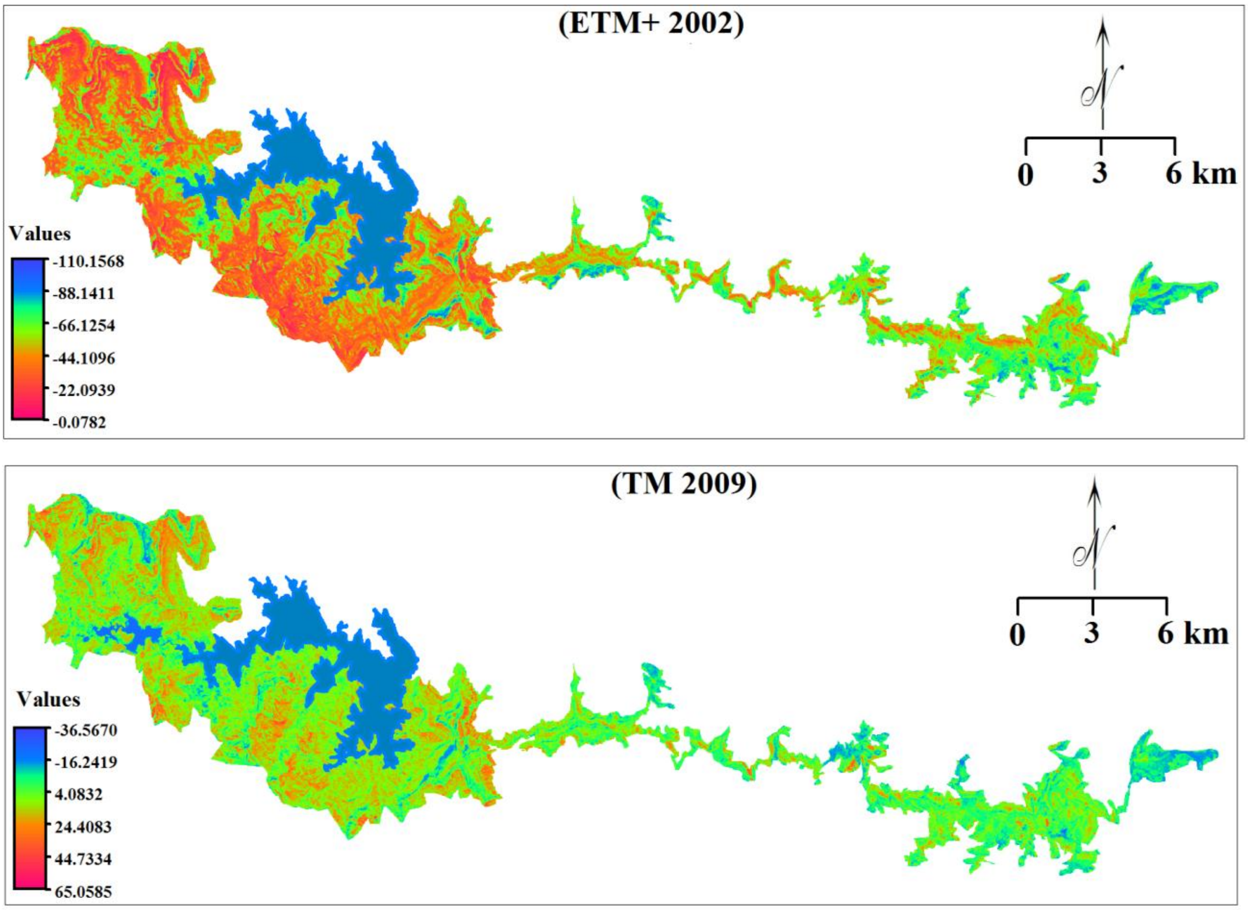


Figure 4.3 Greenness Index

The raster maps (Figure 4.3) are depicting Greenness index based on TCCT (Table 4.1, 4.2). The maximum (-00.08) value in Greenness 2002 and (65.06) value in Greenness 2009 have been observed for vegetation which is a forest cover land in study area. Minimum, -110.16 value estimated for Greenness 2002 and -36.57 for Greenness 2009 for no vegetation cover i.e. water, rocky land, shadow, etc. This two map has used for forest classification and further analysis to obtained robust forest change.

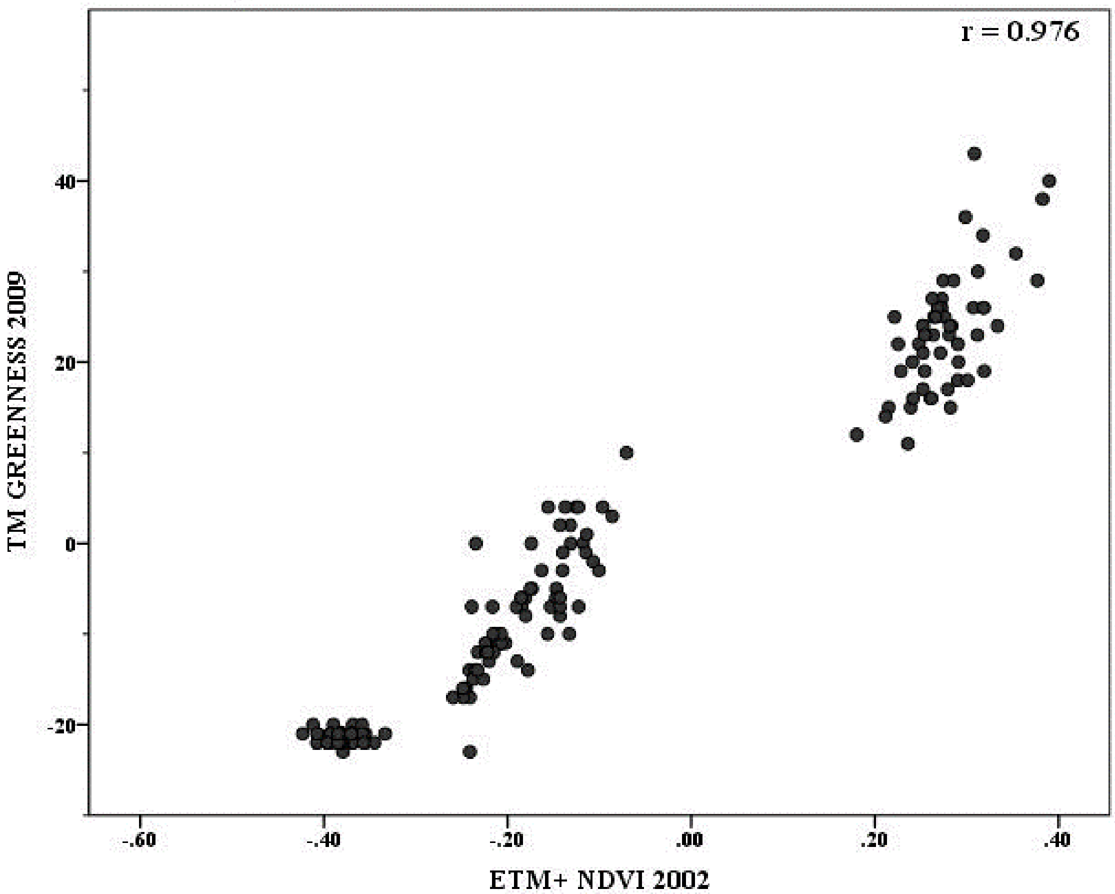


Figure 4.4 Scatterplot of NDVI and Greenness

This scatterplot (Figure 4.4) of NDVI and Greenness are indicated the concentration of clusters designating different vegetation reflectance categories. The same relationship between other criterion i.e. SWI, LAI, TAO, LSTI, Brightness, Fifth, Sixth, their differences, etc. have been estimated. Among these all criterion some are selective i.e. Band7 of ETM+2002, SWI of ETM+2002, Band7 of TM2009, Band5 of ETM+2002, Brightness of ETM+2002, difference in SWI, difference in Fifth, etc. correlated with the difference in Greenness. Some strong positively and negatively correlated criterion are separated for further linear regression analysis (Table 4.4). Samples from all land surface types i.e. forest land, rocky land, water, barren land, etc. (Figure 4.2) are required for this analysis. Eliminate any one land class from this process cause to decrease the correlation result.

Table 4.4 Correlation values of selected criterion

Y and X variable		B7_02	SWI02	B7_09	B5_02	BRIGH02	DSWI	DFifth
Difference Greenness	Pearson Correlation	0.983**	-0.964**	0.960**	0.960**	0.949**	0.934**	-0.933**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	170	170	170	170	170	170	170
****. Significance at the 0.01 level (2-tailed).**								

Regression analysis helps to modulate MEE values to correct the exaggerated values in target images and to reduce the errors in estimations of forest changes.

4.2.2 Regression analysis

This approach is the next step towards robust forest change detection. Satellite data based image regression approach has pure mathematical foundation. It described the fit between two different multi-spectral imageries acquired at different time for same area. Whereas algorithmic rule portrays a pixel at t_2 targeted imagery is linearly related to the same pixel at t_1 referenced imagery. The position of residual is an indicator of at what location change occurred. Among all samples which pixel value close to the regression line represent the no variation between two time span in the same area.

$$\boldsymbol{Y = a + b(x)} \qquad \text{(Eq. 4.7)}$$

whereas,

Y is an estimated variable (dependent variable)

$a\ and\ b$ are constant (a is intercept and b is rate of change in slope)

x is independent variable

Many researcher and scholars have been reported the highest change detection accuracy by using regression approach. This technique described in equation.

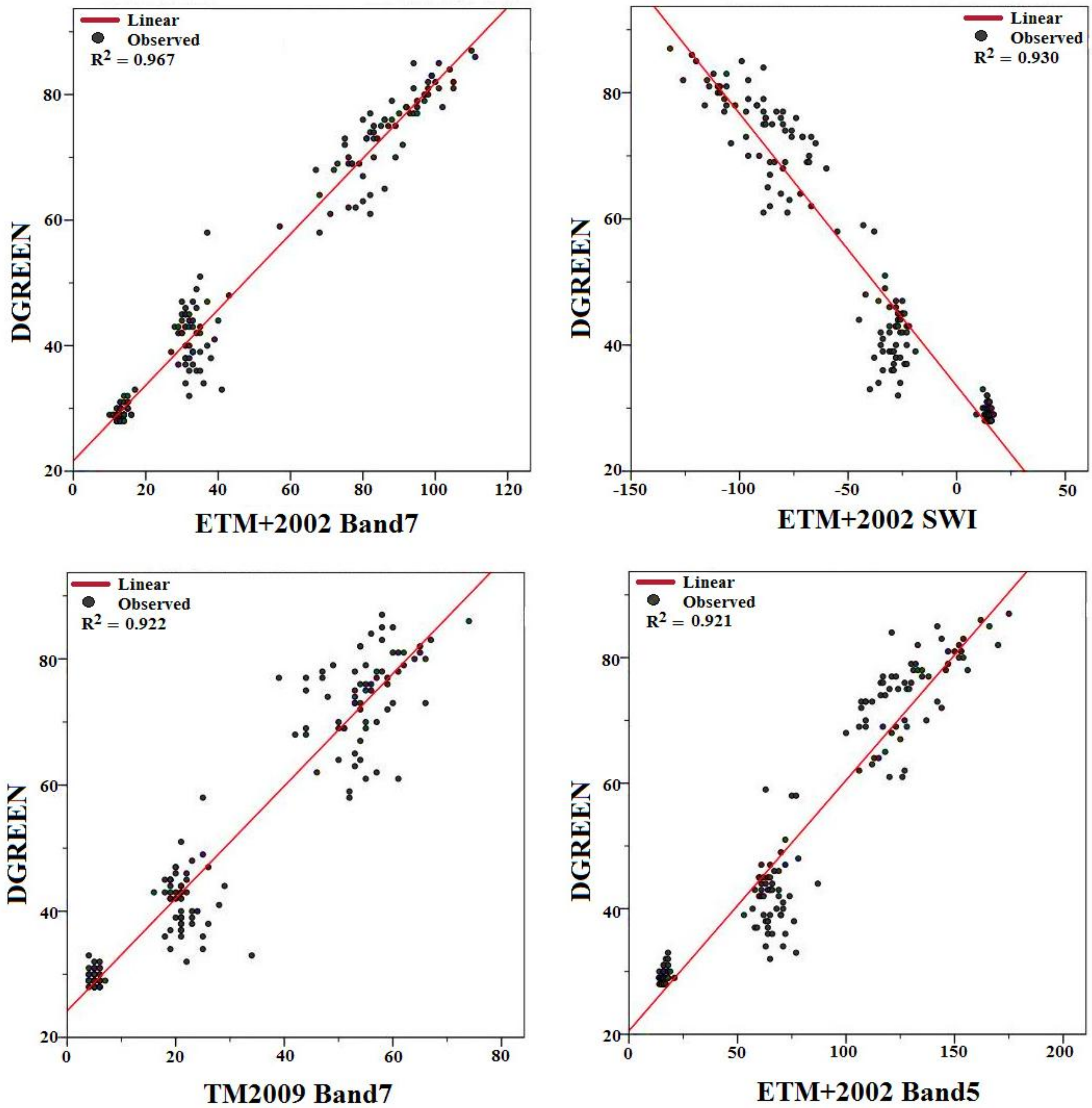


Figure 4.5 Regression analysis of selected criterion

The linear regression analyses depicts (Figure 4.5) the fit between differences in Greenness and band 7 of ETM+ 2002 which is very high R^2= 0.967 and correlation among them also higher as compare to other criteria. All samples are closer to linear regression line. Accordance in spectral wavelength of the different surface types their reflectance concentrating in cluster format. Whereas, the values closer to zero on x-axis related to water component, then next cluster related with forest cover and at last far from the zero, the clusters combination of barren as well as rocky land. Spectral band 5 (Mid NIR) and band 7 (Mid IR) are the band in both ETM+ and TM satellite datasets having higher sensitivity to acquire finer reflection from soil and vegetation cover. Also SWI and difference of Fith index has calculated based on the TCCT (Hung *et al*. 2002 and Crist *et al.* 1986) to gain qualitative classification of vegetation cover and soil moisture both are strongly correlated to each other.

Table 4.5 Regression analysis of difference in greenness with selected criterion

Y	x	**Correlation (*r*)**	a	b	R^2	**Trend**
Difference Greenness	B7_02	0.983	21.664	0.602	0.967	+'ve
	SWI02	-0.964	33.511	-0.432	0.930	-'ve
	B7_09	0.96	24.208	0.891	0.922	+'ve
	B5_02	0.96	20.554	0.399	0.921	+'ve
	BRIGH02	0.949	-2.307	0.370	0.901	+'ve
	DSWI	0.934	30.447	0.769	0.871	+'ve
	DFIFTH	-0.933	90.231	-2.110	0.871	-'ve

Pearson's correlation has been separated strongly correlated components (Table 4.4) and linear regression equation has been estimated (Table 4.5) the constants related to the same components to generate MEE.

4.3 Improved forest change detection

The deviation in reflected radiation from land surface objectives has been recorded as a digital numbers in satellite data as per spectral and radiometric resolution. This recorded digital numbers are exaggerated due to the atmospheric impact as well as distortion in sensor properties. The result of an image depicts false positive measurements of surface characteristics, i.e. water resources, forest cover, barren land, rocky land, urbanize area, agriculture, snow land, swamp-marshes land, desert area, etc. Therefore, statistical modelling and digital image processing analysis has been used in the present study to eliminate exaggeration of satellite data and used corrected resultant imageries to understand and delineate improved change detection in forest land.

4.3.1 Mechanical Error Estimation (MEE)

This analysis has been used to eliminate the noise of exaggeration from targeted t_2 imageries (Figure 4.3). The correlation and linear regression analysis ETM+ Band7 2002 have been used for made a correction in Greenness 2009 Index imagery. MEE corrected Greenness of targeted image has been calculated based on the following equation.

$$\boldsymbol{MEE\ Band7\ 2002} = a + b * (Band7\ 2002) \qquad \text{(Eq. 4.8)}$$

$$\boldsymbol{CORRECTED\ Greenness\ 2009} = Greenness\ 2009 - (MEE\ Band7\ 2002)$$

whereas,

$\mathrm{MEE\ Band7\ 2002}$ is an estimated variable based on linear regression

a & b are constant, a intercept and b is rate of change in slope

$Band7\ 2002$ is independent variable i.e. original radiometric normalized imagery

The histograms for resultant imageries have been prepared in SPSS environment and compared with original referenced histograms for t_1 and targeted t_2 Greenness imageries to clear the effect of MEE and robust forest change analysis (Figure 4.6). In the ETM+2002 Greenness histogram, the frequency of digital numbers distribution is minimum (-110.1568) and maximum (-0.0782), in TM2009 Greenness. This frequency distribution extends up to minimum (-36.5670) and maximum (65.0585). It indicates the highest increase in vegetation. Applying MEE techniques in corrected Greenness 2009 (Eq.4.8) based on MME Band7 digital numbers frequency distribution is minimum (-108.6296) and maximum (17.5085).

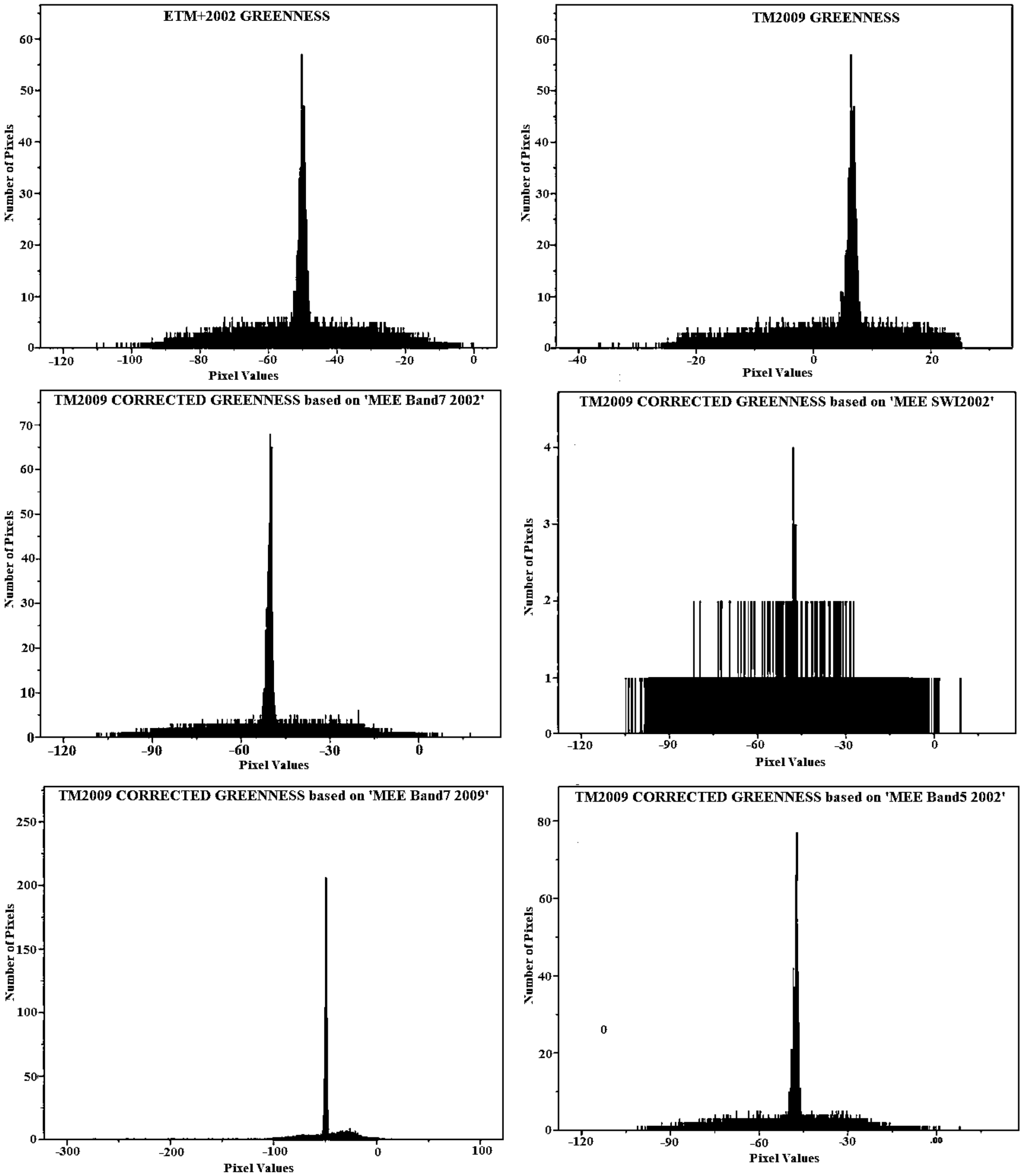


Figure 4.6 Histogram of corrected Greenness 2009

Same results obtained by applying MEE for rest of the closely correlated components i.e. SWI 2002, Band7 2009 and Band5 2002. These components are also show the same result as MEE Band7 2002.

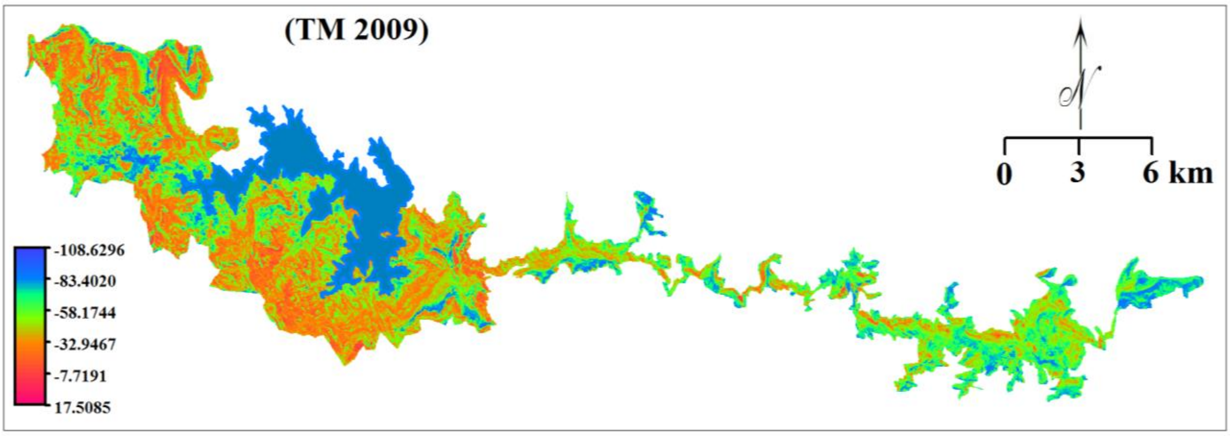
4.3.2 Corrected forest change detection

Normalisation of illusional exaggerated reflectance recorded in pixels of satellite imageries has removed using MEE. Corrected Greenness index of TM2009 proceed for further classification and detection of forest change. The maximum (-00.08) value in Greenness 2002 and (17.51) value in corrected Greenness 2009 have been observed for vegetation which is forest covered land in study area. Minimum (-110.16) value in Greenness 2002, the class 'no vegetation' -108.63 value is estimated for no vegetation lands i.e. water, rocky land, shadow, etc. in corrected Greeness2009 (Figure 4.7).

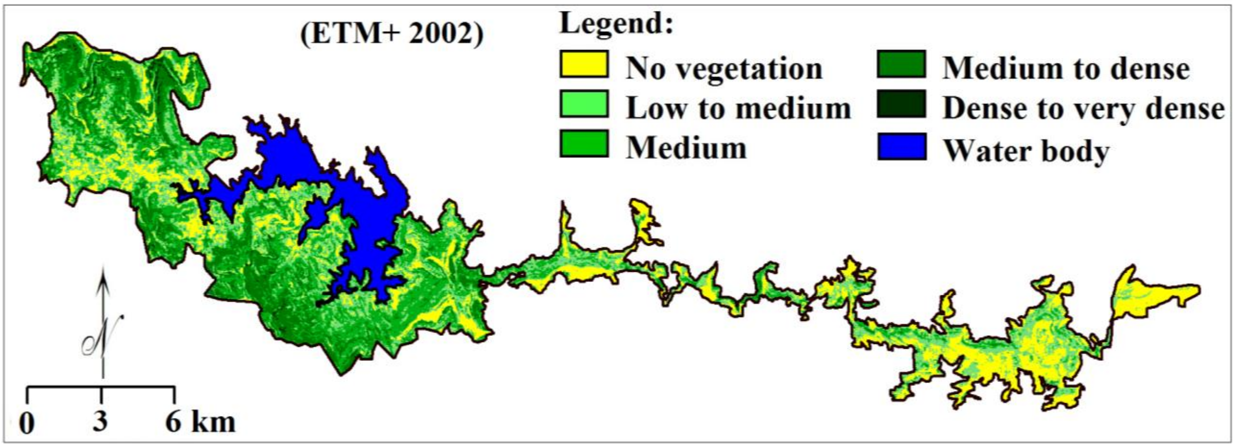
Table No. 4.6 Greenness domain classes of ground truth

Greenness ETM+ 2002		Corrected Greenness TM 2009	
Classes	**Index value**	**Classes**	**Index value**
No vegetation	Below -64	No vegetation	Below -64
Low to medium	-64 to -48	Low to medium	-64 to -48
Medium	-48 to -32	Medium	-48 to -32
Medium to dense	-32 to -16	Medium to dense	-32 to -16
Dense to very dense	-16 to50	Dense to very dense	-16 to50

Reference (t_1) as well as corrected target (t_2) imageries of Greenness index have been classified into five classes (Figure 4.7) using domain group values (Table 4.6). This domain class has been prepared on the basis of ground verification for both imageries. Image classes have been decided to keep same as NDVI classes in previous chapter to maintain similarities in this analysis. Robust forest change has been calculated using Eq. 4.9 which is subtraction of corrected and classified (t_2) imagery from reference (t_1) imagery.



Corrected Greenness Index 2009 based on MEE Band7 of 2002



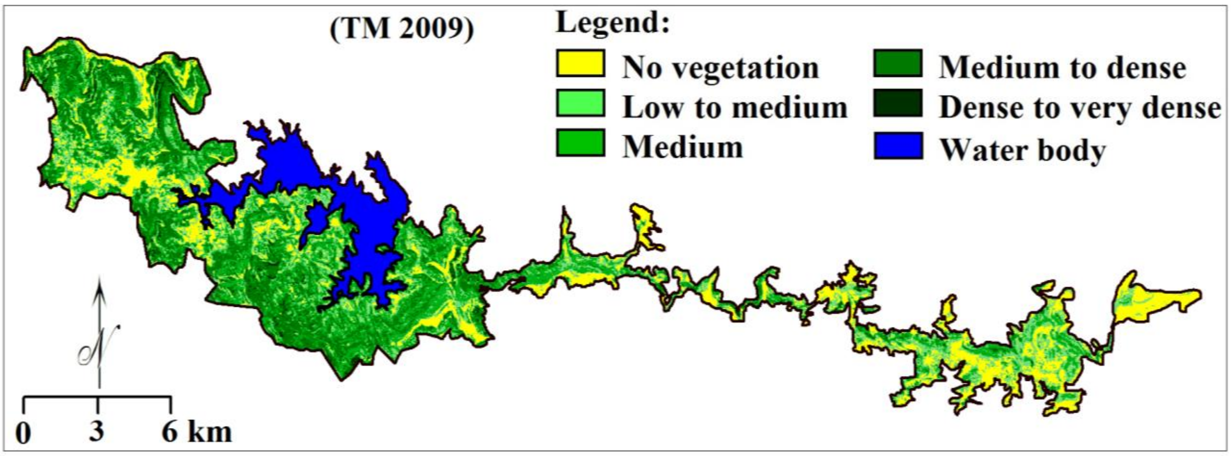


Figure 4.7 Corrected Greenness 2009 and distribution of forests based on Greenness Index

$$\textit{Robust Forest Change} = \textit{Greenness } 2002 - \textit{Corrected Greenness } 2009$$

(Eq.4.9)

whereas,

Greenness 2002 *and Corrected Greenness* 2009 both are superwised classified

This equation has been performed with the help of cross operation in Ilwis. New 25 classes merged into meaningful criteria (Table 4.7). Those classes and features are available on ground surface. The class 'no change' has been re-classed into 'no change' in new estimations. Those pixels transformed from the class 'no vegetation' to next vegetation classes show positive change in new classifications and those transformed in reverse direction shows 'negative changes' in overall forest change detection (Table 4.7).

Table 4.7 Class merging scheme for forest change detection

Greenness Class ETM+ 2002	**Corrected Greenness Class TM 2009**				
	No vegetation	**Low to medium**	**Medium**	**Medium to dense**	**Dense to very dense**
No vegetation	No change	Positive change	Positive change	Positive change	Positive change
Low to medium	Negative change	No change	Positive change	Positive change	Positive change
Medium	Negative change	Negative change	No change	Positive change	Positive change
Medium to dense	Negative change	Negative change	Negative change	No change	Positive change
Dense to very dense	Negative change	Negative change	Negative change	Negative change	No change

In the second stage of change detection, class wise changes have been estimated to know the transformations from one class to another. Class types changes are shown in table (4.8) i.e. positive change, no change and negative change, etc. These classes arrange in the form of symmetric matrix. Upper triangle indicates the positive change and lower triangle indicating negative changes. Diagonal pixels of this tables (4.7, 4.8) indicating 'no change' in vegetation.

Table 4.8 Class wise forest change detection

Greenness Class ETM+ 2002	Corrected Greenness Class TM 2009				
	No vegetation	Low to medium	Medium	Medium to dense	Dense to very dense
No vegetation	NVNoC	NVPL	NVPM	NVPD	NVPVD
Low to medium	LNNV	LNoC	LPM	LPD	LPVD
Medium	MNNV	MNL	MNoC	MPD	MPVD
Medium to dense	DNNV	DNL	DNM	DNoC	DPVD
Dense to very dense	VDNNV	VDNL	VDNM	VDND	VDNoC

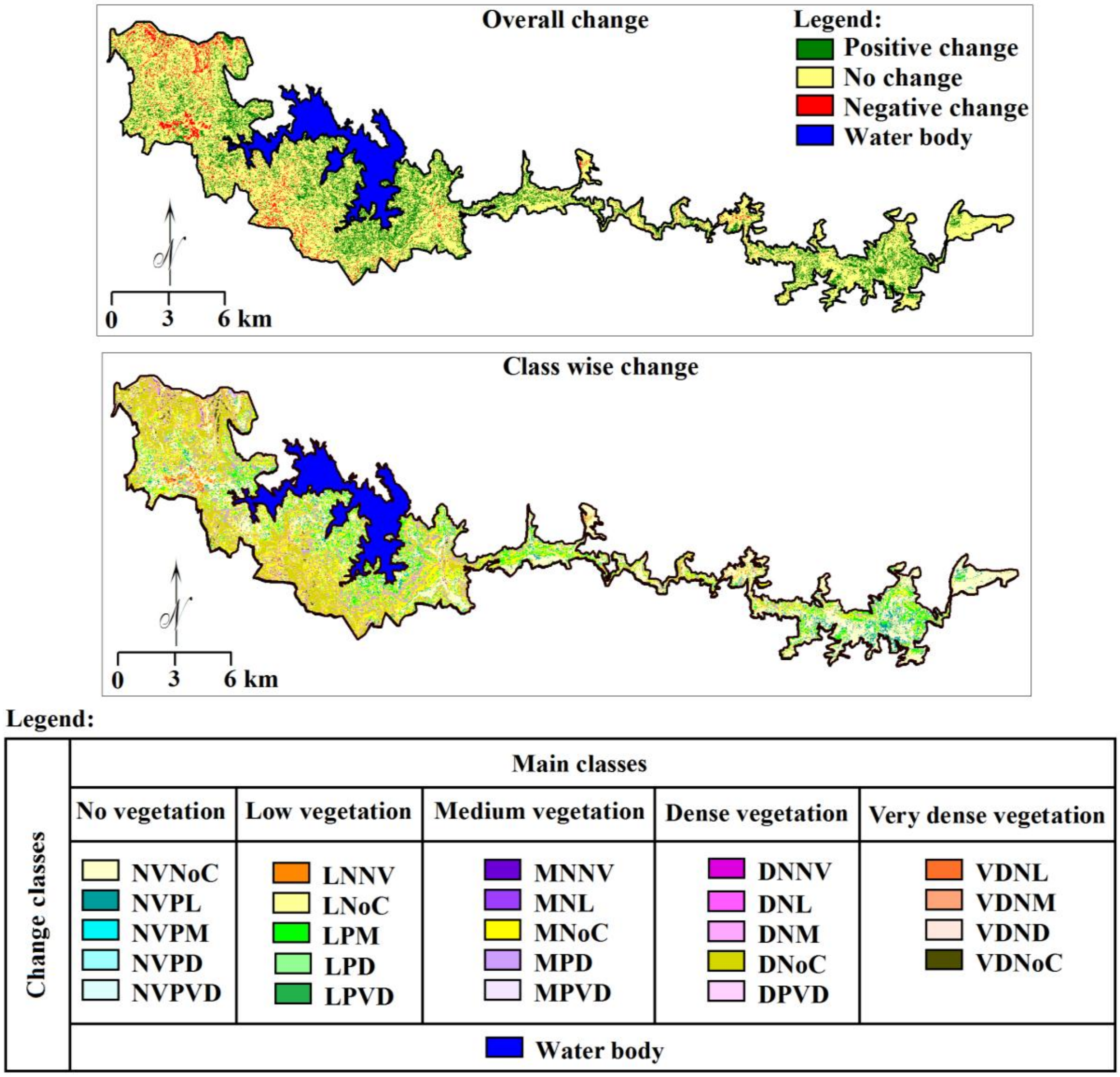


Figure 4.8 Improved forest change detection

Improved change detection technique is totally oriented to find out the actual change in the form of land, forest cover, agricultural land, urban land growth, etc. Exaggeration in satellite images normalized with MEE and then reliable forest change has been estimated (Figure 4.8). MEE is based on sample selection mode and it has been generated scientifically using GRDNT (Figure 4.2).

4.4 Results and discussion

Improved forest change detection has been calculated using sophisticated methodologies and techniques. These changes are discussed into two parts. One is overall change and another is class-wise. Overall change has been estimated on the basis of class merging (Table 4.7, 4.8) scheme. About 23.59 % 13858.83 ha TGA shows positive change, 70.8 % shows no change and only 6.33 % shows negative change. This change shows more realistic results compared to post classification based change detection. The land in the class 'no change vegetation' is classified into low to medium vegetation in new map (Table 4.9). Medium to dense and dense to very dense vegetation shows positive change.

Forest growth is very slow process. However, previous method shows faster growth expansions in forest cover within short period, i.e. 7 years. It is nothing but illusional exaggeration make confusion to the researchers, planners and stood unreliable. Class wise changes in different classes also been estimated for micro level analyses (Table 4.10).

Table 4.9 Class wise changes in forests

Classes	Greenness 2002 Area in ha	Greenness 2002 Area in %	Corr. Greenness 2009 Area in ha	Corr. Greenness 2009 Area in %	Change in %
No vegetation	3310.2	23.89	2975.22	21.47	2.42
Low to medium	4228.47	30.51	3505.68	25.3	5.21

Medium	4115.97	29.7	4251.24	30.68	-0.98
Medium to dense	2083.95	15.04	2908.71	20.99	-5.95
Dense to very dense	120.24	0.87	217.98	1.57	-0.7
Total Area	13858.83	100	13858.83	100	

The classes like 'no vegetation', 'low vegetation', 'medium vegetation' and 'dense vegetation' show no change in forest cover and estimated about 16.33%, 13.27%, 13.94% and 10.90%, respectively. The classes like 'low vegetation' show positive change with about 13.85% area.

Table 3.7 Class wise forest area distribution

Class Code	Full forms of class code	Area in ha	Area in %
NVNoC	No Vegetation No Change	1931.31	13.94
NVPL	No Vegetation Positive change to Low vegetation	1176.48	8.49
NVPM	No Vegetation Positive change to Medium vegetation	196.02	1.41
NVPD	No Vegetation Positive change to Dense vegetation	6.3	0.05
NVPVD	No Vegetation Positive change to Very Dense vegetation	0.09	0.01
LNNV	Low vegetation Negative change to No Vegetation	338.67	2.44
LNoC	Low vegetation No Change	1838.99	13.27
LPM	Low vegetation Positive change to Medium vegetation	1919.72	13.85
LPD	Low vegetation Positive change to Dense vegetation	168.75	1.22
LPVD	Low vegetation Positive change to Very Dense vegetation	2.34	0.02
MNNV	Medium Vegetation Negative change to No Vegetation	8.73	0.06
MNL	Medium Vegetation Negative change to Low vegetation	317.43	2.29
MNoC	Medium Vegetation No Change	2262.79	16.33
MPD	Medium Vegetation Positive change to Dense vegetation	1511.28	10.9
MPVD	Medium Vegetation Positive change to Very Dense vegetation	27.73	0.2
DNNV	Dense vegetation Negative change to No Vegetation	0.34	0.01
DNL	Dense vegetation Negative change to Low vegetation	16.54	0.12
DNM	Dense vegetation Negative change to Medium	401.13	2.89
DNoC	Dense vegetation No Change	1466.17	10.58
DPVD	Dense vegetation Positive change to Very Dense vegetation	98.73	0.71
VDNNV	Very dense vegetation Negative change to No Vegetation	0.17	0.01
VDNL	Very dense vegetation Negative change to Low vegetation	6.94	0.05
VDNM	Very dense vegetation Negative change to Medium vegetation	73.92	0.53
VDND	Very dense vegetation Negative change to Dense vegetation	31	0.22
VDNoC	Very dense vegetation No Change	57.26	0.41
Total Area		**13858.83**	**100**

The improved forest change detection technique is simple and successfully implemented.

4.5 Accuracy assessment

Accuracy assessment has been performed for forest change detection using new method. Same information regarding sample points and ground truth and similar method used in accuracy assessments in last chapter has been used for this analysis.

Table 4.11 Error Matrix

Classified Data	Reference Data					
	Positive change	**No change**	**Negative change**	**Water**	**Row total**	**User's accuracy in %**
Positive change	**32**	0	0	1	33	**97**
No change	1	**42**	1	0	44	**95**
Negative change	1	1	**37**	1	40	**93**
Water	1	0	1	**48**	50	**96**
Column total	35	43	39	50	**167**	
Producer's accuracy in %	**91**	**98**	**95**	**96**		**95.21%**

Overall accuracy = 95.21%

The user's accuracy has been estimated about 97% for positive change, 95% for no change, 93% for negative change and 96% for water whereas producer's accuracy estimated about 91% for positive change, 98% for no change, 95% for negative change and 96% water. Overall accuracy estimated to 95.21%. It is greater than the accuracy estimated for previous method. This assessment indicates that the forest land increasing but not at higher rate as estimated using post classification method discussed in previous chapter. Therefore, improved normalised post classification forest change detection technique is useful to detect changes forests.

4.6 Resume`

Robust forest change has been successfully estimated using this new method with higher confidence of accuracy. Normalized post classification forest change technique has developed with the help of MEE and GRDNT. These methods have been developed on the basis of Pearson's correlation and linear regression statistical analysis in SPSS software. More sophisticated and reliable spectral index i.e. Greenness of TCCT has been calculated in ILWIS for vegetation detection and classification. The positive forest change has been estimated for 23.59% land, no change for 70.08% land and negative change for 6.33% of 13858.83 ha TGA with 98.56% overall accuracy. Class wise changes have also been estimated and plotted on the map. The technique has been stood applicable for forest change detection with higher accuracy and applicability. The major findings, conclusions, limitations, etc. are given in the next chapter.

****

CHAPTER V

OVERVIEWS AND CONCLUSIONS

5.0 General

The review of previous literature shows many approaches and techniques used for forest change detection. They have used RS and GIS techniques, successfully for change detection studies for planning and management of environmental issues from last two decades. However, existing conventional approaches are not applicable for all cases, many analysis done on the basis of satellite data which used without normalization of recorded reflectance at difference spectral, radiometric, temporal and special resolution. The results of these analyses may misguide the users. Therefore, the major objectives of the study are to detect and delineate the forest land and to suggest improved sophisticated methods for robust forest change detection. The physiographic profile and its relation with population of the study area have been discussed in the second chapter. The Landsat7 ETM+ 2002 and Landsat5 TM 2009 datasets have been used for forest change detection using RS and GIS (ERDAS Imagine, Ilwis, and Google Earth Pro.), statistical (MS Excel and SPSS) software. The conventional post classification based forest change detection technique has been performed and discussed with results in third chapter. The forth chapter has been dedicated to new sophisticated improved post classification technique for robust forest change detection with good result and accuracy. Therefore, the study has reached to the final stage with overviews and conclusions. The post classification technique of forest change detection affects by illusional exaggeration and show cause for false positive results. Therefore, normalised post classification based robust forest change detection technique has been preformed to get reliable results at optimal level of accuracy.

Table 5.1 Comparison of forest change detection techniques

New Criterion Classes	**Post classification based forest change**		**Normalized post classification based on robust forest change**	
	Area in hectare	Area in %	Area in hectare	Area in %
Positive change	8119.98	58.59%	3269.25	23.59%
No change	4669.29	33.69%	9712.89	70.08%
Negative Change	1069.56	7.72%	876.69	6.33%
Total Area	**13858.83**	**100%**	**13858.83**	**100%**

Post classification based forest change depicts (Figure 5.1) the positive change in 58.59% of reviewed area whereas ‘no change’ area show only 33.69% lands with negative changes in 7.72% area. However, new technique based on normalised post-classification for robust forest change detection show (Table 5.1) positive changes in forest on only 23.59% of reviewed area. No change in land cover estimated for 70.08% area and negative change for 6.33% lands. Thus, normalised image data using statistical techniques removes illusional exaggeration of reflectance values and gives reliable results of forest change detection. This innovative technique can become useful to researcher, scholars, environmental planners and managements for forest change detection and environmental analyses.

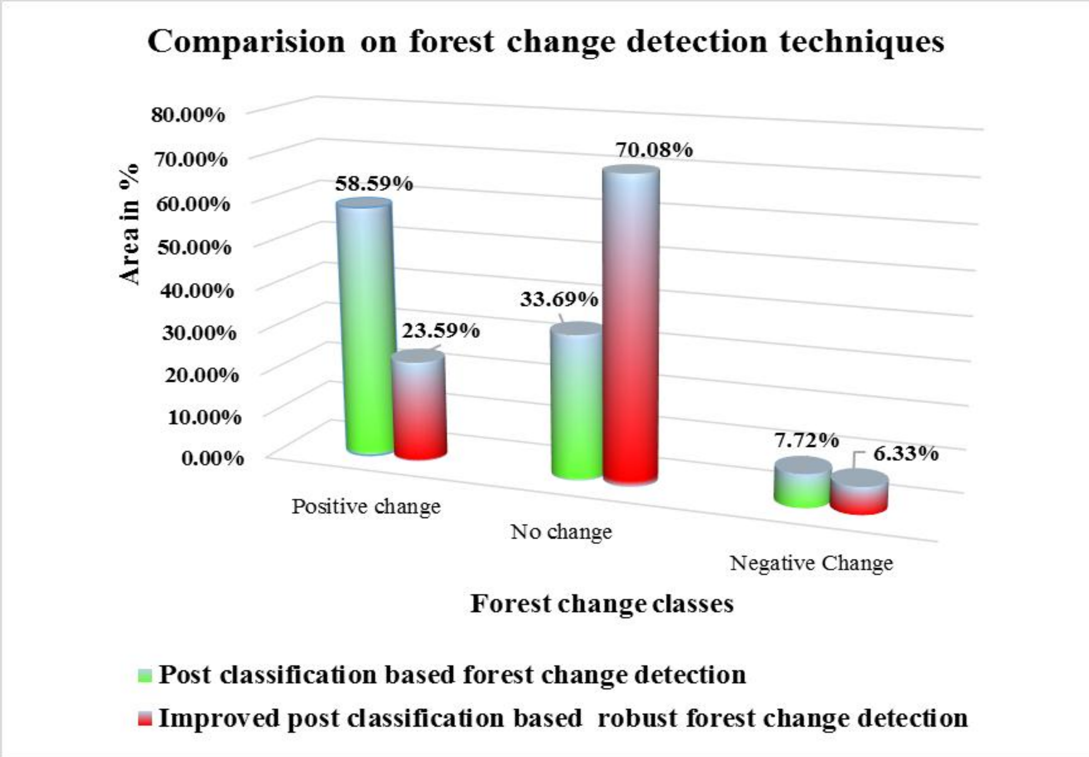


Figure 5.1 Comparison of forest change detection techniques

5.1 Overviews

1. The forest cover is important natural resource for environmental parameters as well as human activities.
2. It is a backbone support to achieve balance in different cycles like atmospheric cycles, nutrient cycles, water cycles, etc., biodiversity, scenic beauty, etc.
3. The human being across the world using forest products for domestic, industrial and commercial needs, i.e. food, shelters, timber, medicines, tools, row materials, etc.
4. In some last decades, human activities have negatively affects on natural forests and qualities and area under forests decreasing at alarming rate.
5. Therefore, change detection of forest is become very essential activity to analyses of changes and make plants to protect and conserve the forests.

6. RS data at different spatial, radiometric, spectral and temporal resolution has been used for change detection in forest lands from some decades.
7. Datasets of Landsat-5 and 7 are useful for forest change detection with acceptable accuracy.
8. NDVI has been calculated for ETM satellite image acquired in 2002 and ETM+ image captured in 2009 for change detection in forest cover using congenital post classification technique.
9. Post classification based change in forest has been detected to estimate the overall change and class wise transformations.
10. About 58.59% of reviewed area shows positive change in overall change detection, 33.69 % area shows ‘no change’ and 7.72% area shows negative changes.
11. In class wise change, the class of low vegetation is positively transformed to medium vegetation on about 22.68% area, dense forest positively transform to very dense 15.02%, low vegetation positively transform in dense forest on 10.05% area.
12. No change was estimated for the class very dense vegetation (10.89%), dense vegetation (9.31%) and no vegetation (7.82%).
13. The negative changes were observed in classes, low vegetation and dense vegetation. The class, low vegetation negatively transformed into class no vegetation (4.31%) and dense vegetation to medium vegetation (2.32%).
14. Overall accuracy of the post classification based forest change detection has been calculated about 77.84%.
15. The accuracy assessment performed for change detection show least acceptance for planning and management of forests in the study area.

Therefore, improves robust change detection technique designed based on statistical analyses to achieve reliable results.

16. Samples for normalization have been collected from areas of no-change in land characteristics for robust forest change detection. The mechanical errors in chaptered data have been eliminated using Pearson's Correlation and Linear Regression statistical methods.
17. Object oriented Greenness index has been used for robust forest change detection analysis in the present study.
18. Normalized post classification based robust forest change has been calculated again to detect overall and class wise changes using method for earlier analyses.
19. Overall change analysis shows positive change in forest cover on 23.59% of TGA, no change on 70.08% and negative change on 6.33% area.
20. The comparison of these results shows illusional exaggeration in the class 'positive change' is convectional change detection by 35% land.
21. Class wise change detection for the class, 'low vegetation' is positively transform in 'medium vegetation' on 13.85% lands, class, 'medium vegetation' positively transform to dense on 10.90% lands.
22. No change was estimated for 'medium vegetation' on 16.33% land, 'no vegetation' on 13.94% land, 'low vegetation' on 13.27% and 'dense vegetation' on 10.58% lands.
23. Negative changes have been estimated for class, 'dense vegetation', medium vegetation and low vegetation. The class, 'dense vegetation' negatively transform to 'medium vegetation' on 2.89% lands, 'medium vegetation'

transform to 'low vegetation' on 2.29% lands and 'low vegetation' to 'no vegetation' for 2.44% lands.

24. Overall accuracy this improved post-classification based forest change detection calculated about 95.21% and acceptable for applications.
25. The methodology formulated in this study can be useful for researchers, planners, governmental and non-governmental agencies (NGO) for environmental management.

5.2 Applicability of the study

The technique and methodology of forest change detection used in this study and findings are applicable for research, development, planning and management in forest management. The techniques give more precise results for forest change detection importance in planning and monitoring the protected forests. The findings of the study are useful for planner working the study area like lands with 'no vegetation' is barren lands. Some of them are distributed in foothill which is potential lands for afforestation. Old forest need to conserve through protection and plantation. The study shows more realistic applications of RS data along with statistical techniques and GIS in forest change detections. This technique may be useful for detection of other land parameters including water, agriculture, settlement, etc.

5.3 Limitations of the study

The researcher is cognisant about the limitations and drawbacks of the present study.

1. The satellite data used in this study has captured in the year of 2002 and 2009 for the robust forest change detection. Normally, 15-20 years are required to

have changes in forest cover therefore, this time span of these images is not enough for realistic change detection in forest area.

2. The spatial resolution of used satellite imageries is medium i.e. 30x30m which may not match to fine resolution images. High resolution imageries would be more helpful to separate lands other than forest area with merged and similar reflectance surface characteristics of land.

5.4 Conclusions

Landsat-7 ETM+ and Landsat-5 TM datasets have been used for detection of forest changes in the study region. GIS software ERDAS Imagine, Ilwis as well as MS Excel and SPSS statistical software are useful for change detection studies. Results of improved post-classification based forest change detection techniques designed using statistical analyses based on field data are stood useful to element illusional exaggeration in results of conventional change detection techniques at good accuracy and satisfactory results. Therefore, the hypothesis of the study is accepted and objectives are proved on the basis of present analyses.

****

LIST OF ABBREVIATIONS

AOI	Area Of Interest
ASTER	Advanced Space Borne Thermal Emission and Reflection Radiometer
BRDF	Bidirectional Reflectance Distribution Function
DCD	Digital Change Detection
DEM	Digital Elevation Model
DN	Digital Numbers
DNL	Dense vegetation Negative change to Low vegetation
DNM	Dense vegetation Negative change to Medium
DNNV	Dense Vegetation Negative change to No Vegetation
DNoC	Dense vegetation No Change
DPVD	Dense vegetation Positive change to Very Dense vegetation
EE	Environmental Ecosystem
EMR	Electro Magnetic Radiation
EO	Earth Observation
Eq	Equation
ERDAS	Earth Resource Data Analysis System
ETM+	Enhanced Thematic Mapper Plus
FCA	Forest Conservation Act FCA
FCC	False Colour Composite
FSI	Forest Survey of India
GCP	Ground Controlling Points
GIS	Geographical Information System
GPS	Global Positioning System
GRDNT	Ground reference digital number triangle
IBM	International Business Machines
ILWIS	Integrated Land Water Information System
IR	Infrared
IRS	Indian Remote Sensing
ISFR	India State of Forest Report
LAI	Leaf Area Indices

LISS	Linear Imaging Self Scanning Sensor
LNNV	Low vegetation Negative change to No Vegetation
LNoC	Low vegetation No Change
LPD	Low vegetation Positive change to Dense vegetation
LPM	Low vegetation Positive change to Medium vegetation
LPVD	Low vegetation Positive change to Very Dense vegetation
LSTI	Land Surface Temperature Index
LULCC	Land Use Land Cover Change
MAP	Maximum a posteriori Probability
MDC	Minimum Distance Classification
MEE	Mechanical Error Estimation
MNL	Medium vegetation Negative change to Low vegetation
MNNV	Medium vegetation Negative change to No Vegetation
MNoC	Medium vegetation No Change
MOTA	Ministry of Tribal Affairs
MPD	Medium vegetation Positive change to Dense vegetation
MPVD	Medium vegetation Positive change to Very Dense vegetation
MS	Microsoft
MSS	Multi Spectral Scanner
MWHC	Maximum Water Holding Capacity
NCDN	No Change Digital number
NDMI	Normalized Difference Moisture Index
NDSI	Normalised Difference Salinity Indices
NDVI	Normalized Difference Vegetation Index
NDWI	Normalised Difference Water Indices
NGO	Non-Governmental Organizations
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
NVNoC	No Vegetation No Change
NVPD	No Vegetation Positive change to Dense vegetation
NVPL	No Vegetation Positive change to Low vegetation
NVPM	No Vegetation Positive change to Medium vegetation
NVPVD	No Vegetation Positive change to Very Dense vegetation

NW	North-West
RADAR	Radio Detection And Ranging
RMS	Route Mean Square
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SE	South-East
SOI	Survey of India
SPOT	Système Pour l'Observation de la Terre
SPSS	Statistical Packages for the Social Sciences
SRTM	Shuttle Radar Topography Mission
TAO	Top of Atmospheric Radiance
TCC	True Colour Composite
TCCT	Tasselled Cap Coefficient Transformation
TERRA	Latin word for Earth
TGA	Total Geographical Area
TM	Thematic Mapper
TOMS	Total Ozone Mapping Spectrometer
TVI	Transformed Vegetation Index
USGS	United State Geological Survey
VDND	Very Dense vegetation Negative change to Dense vegetation
VDNL	Very Dense vegetation Negative change to Low vegetation
VDNM	Very Dense vegetation Negative change to Medium vegetation
VDNNV	Very Dense vegetation Negative change to No Vegetation
VDNoC	Very Dense vegetation No Change
WCMC	World Conservation Monitoring Centre
WRI	World Resources Institute

****

REFERENCES

Abbas AH, Hall JD, Crane FL and Baumgardner MF 1974, Spectral of normal and nutrient deficient maize leaves, Agronomy Journal, 66, PGS. 16-20.

Adegoke JO and Carletion AM 2002, Relations between soil moisture and satellite vegetation indices in the U.S. Corn Belt, Journal of Hydrometeorology, 3 PGS. 395-405.

Allen RG 2000 , Using the FAO-56 dual crop coefficient method over an irrigated region as part of an evapotranspiration intercompari- son study, Journal of Hydrology, 229, PGS. 27-41.

Allen WA, Gausman HW and Richardson AJ 1970, Mean effective optical contents of cotton leaves. Jr. Opt. Soc. Amer, 60, 542-547.

Alonso F, Romo A, Cuevas JM 2004 , Spanish vegetation monitoring during the period 1987–2001 using NOAA-AVHRR images, International Journal of Remote Sensing, 25, PGS. 3-6.

Amarsaikhan D, Blotevogel HH, Ganzorig M and Moon TH 2009, Applications of remote sensing and geographic information systems for urban land-cover change studies in Mongolia, Geocarto International, 24, PGS. 257-271.

Amarsaikhan D, Blotevogel HH, Genderen JL, Ganzorig M, Gantuya R and Nergui B 2010, Fusing high-resolution SAR and optical imagery for improved urban land cover study and classification, International Journal of Image and Data Fusion, 1, PGS. 83-97.

Anonymous 1976, National Forest Policy, National commission on agriculture, Ministry of Agriculture and Co-operation, New Delhi.

Anonymous 1999, State of Forest Report, Forest Survey of India, Deharadun.

Apan AA 1997, Land-cover mapping for tropical forest rehabilitation planning using remotely sensed data, International Journal of Remote Sensing, 18, PGS. 1029-1049.

Bai JO, Hua B, Cui Q, Wang 2008, Changes in landscape pattern of alpine wetlands on the Zoige Plateau in the past four decades, Acta Ecologica Sinica, 28, PGS. 2245-2252.

Bean JE, Turner CA, Hooper PR, Subbarao KV, Walsh JN 1986 , Stratigraphy, composition and form of Deccan Basalts, Western Ghats, India, Bull Volcano,48, PGS. 61-83.

Benchalli SS and Prajapati RC 1998, Modelling for forest growing stock satellite data-A Case Study, 26, PGS. 15-21.

Bhagat VS 2009, Use of LANDSAT ETM+ data for detection of potential areas for afforestation, International Journal of Remote Sensing, 30, PGS. 2607-2617, DOI: 10.1080/01431160802552793.

Bhagat VS and More RK 2013 , Use of LANDSAT ETM + Data for Detection of *Prosopis juliflora* in irrigated zones, Journal of Remote Sensing and GIS, 4, PGS. 36-47.

Bhagat VS and Sonawane KR 2010 , Use of LANDSAT ETM+ Data for delineation of water bodies in hilly zones, Journal of Hydroinformatics, 13, PGS. 661-671, DOI: 10.2166/hydro.2010.018.

Bhojvaid PP, Timmer VR and SINGH G 1996, Reclaiming sodic soils for wheat production by Prosopis juliflora (Swartz) DC afforestation in India, Agroforestry Systems, 34, PGS. 139-150.

Binkley D, Giardina C 1998, Why do tree species affect soils? The warp and woof of tree soil interactions, Biogeochem, 42, PGS. 89-106, DOI: 10.1023/A:1005948126251.

Blackett M and Wooster MJ 2011 , Evaluation of SWIR-based methods for quantifying active volcano radiant emissions using NASA EOS-ASTER data, Geomatics Natural Hazards and Risk, 2, PGS. 51-78.

Blaschke T 2010, Object based image analysis for remote sensing, International Journal of Photogrammetry and Remote Sensing, 65, PGS. 2-16.

Breece HT and Holmes RA 1971, Bi-directional scattering characteristic of healthy green soybean and corn leaves in vivo, Applyed Optics, 10, PGS. 119-127.

Burnicki AC, Brown DG and Goovaerts P 2010, Propagating error in land-cover-change analyses: impact of temporal dependence under increased thematic complexity, International Journal of Geographical Information Science, 24, PGS. 1043-1060.

Clifton C. 2003, Change detection in overhead imagery using Neural Networks, Applied Intelligence, 18, PGS. 215-234.

Cano F, Cerrillo RMN, Ferrer AG, De La Orden MS 2006, Detection of forest decline using IKONOS sensor for Cork Oak woods in South Spain, Geocarto International, 21, PGS. 13-18.

Carlson TN, Perry EM and Schmugge TJ 1990, Remote estimation of soil moisture availability and fractional vegetation cover for agricultural fields, Agriculture for Meteorololy, 52, PGS. 45-69.

Chander G and Markham BL 2003, Revised Landsat 5 TM radiometric calibration procedures and post-calibration dynamic ranges, IEEE transactions on geoscience and remote sensing, 41, PGS. 2674-2677.

Chen G, Hay GJ, Luis MTC and Wulder MA 2012, Object-based change detection, International Journal of Remote Sensing, 33, PGS. 4434-4457.

Chowdhury AB, Paul CJ, Martyn GF and Geoff KF 2005, The role of cuticular waxes and surface roughness in determining the insecticidal efficacy of deltamethrin and dimethoate applied as emulsifiable concentrates to leaf surfaces, International Journal of Pest Management, 51, PGS. 253-263.

Coppin P and Bauer M 1996, Digital change detection in forest ecosystems with remote sensing imagery, Remote Sensing Reviews, 13, PGS. 207- 234.

Crist EP and Kauth RJ 1986, The tasseled cap de-mystified, Photogrammetric Engineering & Remote Sensing, 52, PGS. 81-86.

Liverman D, Moran E, Rindfuss R, Stern P 1998 , People and Pixels, Linking Remote Sensing and Social Science, National Academy Press, Washington D.C.

Davis CH, Claywell BC, Keller JM, Klaric MN, Scott JG, Shyu CR 2010, Detecting geographic-area change using highresolution remote sensing imagery, US 2010/00998342.

Deshpande JV and Karia S 1999, Bounds for the hazard gradients in the competing risks set up, Journal of Statistical Planning and Inference, 75, PGS. 363-377.

Dhakal AS, Amada T, Aniya M and Sharm RR 2002, Detection of areas associated with flood and erosion caused by a heavy rainfall using multitemporal Landsat TM data, Photogrametry Engineering and Remote Sens, 68, PGS. 233-239.

Du Y, Teillet PM and Cihlar J 2002 , Radiometric normalization of multitemporal high-resolution satellite images with quality control for land cover change detection, Remote Sensing Environmrnt, 82, PGS. 123-134.

Dymond JR, Page MJ and Brown LJ 1996, Large area vegetation mapping in the Gisborne district, New Zealand, from Landsat TM, International Journal of Remote Sensing, 17, PGS. 263-275.

Ehlers M, Klonus S, Astrand PJ and Rosso P 2010 , Multi- sensor image fusion for pansharpening in remote sensing, International Journal of Image and Data Fusion, 1, PGS. 25-45.

Felkar P, Cannell GH and Clark PR 1981, Variation in growth among 13 Prosopis (mesquite) species, Experimental Agriculture, 28, PGS. 209-218.

Gaikwad S 2004 , Land Use/Land cover analysis using remote sensing technique and potentialu of land resources: A case study of the villaqge Ranjane, Tahsil: Velhe, District Pune (Maharashtra), Maharashtra Bhugolshastra Sanshodhan Patrika, XVIII, 2, 3PGS. 7-49.

Gareeau RM, Gutierrez M, Ham T, Nemethy J and Hackett J 2009, Geospatial image change detecting system and associated method, US 7528938 B2.

Gates DM, Keegan HJ, Schleter JC and Weidner VR 1965, Spectral properties of plants, Applied Optics, 4, PGS. 11–20.

Gausman HW 1977, Reflectance of leave component, Remote Sensing Environment, 6, PGS. 1-9.

Gausman HW, Allen WA 1973, Optical parameters of leaves of 30 plant species, Plant Physio., 52, PGS. 57-62.

Gausman HW, Allen WA and Cardenas R 1969, Reflectance of cotton leaves and their structure, Remote Sensing of Environment, 1, PGS. 19-32.

Gausman HW, Allen WA, Cardenas R and Richardson AJ 1970, Relation of light reflectance to histological and physical evaluation of cotton leaf maturity, Applied Optics, 7, PGS. 545-552.

Geesing D, Felker P and Bingham RL 2000, Influence of mesquite on soil nitrogen and carbon development: Implications for agro forestry and global carbon sequestration, Journal of Arid Environments, 46, PGS. 157-180.

Ghent D, Kaduk J, Remedios J and Balzter H 2011, Data assimilation into land surface models: the implications for climate feedbacks, International Journal of Remote Sensing, 32, PGS. 617-632.

Gong P, Miao X, Tate K, Battaglia C and Biging GS 2004 , Water table level in relation to EO-1 AL.I and ETM+ data over a mountainous meadow in California, Canadian Journal of Remote Sensing, 30, PGS. 691-696.

Hadeel AS, Mushtak TJ and Chen X 2011 , Remote sensing and GIS application in the detection of environmental degradation indicators, Geo-spatial Information Science, 14, PGS. 39-47.

Hansen HO 2000, An AIDS model with reproduction with an application based on data from Uganda, Mathematical Population Studies, 8, PGS. 175-203.

Hara GC, Cheriyadat A, Seo S and Vijayaraj V 2012, Change Analyst, US 8160296 B2

Hayes D and Sader SA 2001 , Change detection techniques for monitoring forest clearing and regrowth in a tropical moist forest, Photogrammetric Engineering and Remote Sensing, 67, PGS. 1067-1075.

Healey PS, Yang Z, Cchen WB, Pierce DJ 2006 , Application of two regression-based methods to estimate the effects of partial harvest on forest structure using Landsat data, Remote Sensing of Environment, 101, PGS.115-126.

Hongliang Fang and Jun Xu 2000, Land cover and vegetation change in the Yellow river delta nature reserve analysed with Landsat Thematic Mapper data, Geocarto International, 15, PGS. 43-50.

http://earthexplorer.usgs.gov/

Huang C, Wylie B, Yang L, Homar C and Zylstra G 2002, Derivation of a tasselled cap transformation based on Landsat-7 at-satellite reflectance, International Journal of Remote Sensing, 23, PGS. 1741-1748.

Hung M and Ridd MK 2002 , A subpixel classifier for urban land-cover mapping based on a maximum-likelihood approach and expert system rules, Photogrammetric Engineering and Remote Sensing, 68, PGS. 1173-1180.

Igbokwn JJ 1999, Geometrical processing of multi-sensor, multi-temporal satellite images for change detection studies, International Journal of Remote Sensing, 20, PGS. 1141-1148.

Jenson JR 1983, Urbanlsuburban land use analysis, Manual of Remote Sensing, 2, PGS. 1571-1666.

Jiang H, Strittholt JR, Frost PA and Slosser NC 2004 , The classification of late serial forests in the Pacific Northwest USA using Landsat ETM+ imagery, Remote Sensing of Environment, 91, PGS. 320-331.

Julien Y, Sobrino JA, Mattar C, Ruescas B, Jimenez-mun JA, Sorai G,Hidalgo V, Atitar M,Franch B and Cuenca J 2011 , Temporal analysis of normalized difference vegetation index (NDVI) and land surface temperature (LST) parameters to detect changes in the Iberian land cover between 1981 and 2001, International Journal of Remote Sensing, 32, PGS. 2057-2068.

Kerr S, Newell RG and Sanchirico JN 2003 , Evaluating the New Zealand Individual Transferable Quota Market for Fisheries Management, Paper presented at a Workshop on Ex-post Tradable Permit Evaluation for the National Policies Division, Environment Directorate, Paris, OECD.

Kloer DP, Welsch R, Beyer P, Schulz GE 2006 , Structure and reaction geometry of geranylgeranyl diphosphate synthase from Sinapis alba, Biochemistry, 45, PGS. 15197-15204.

Knipling EB 1970, Physical and physiological basis for the reflectance of visible and near infrared radiation from vegetation, Remote Sensing Environment, 1, PGS. 55-159.

Knudsen T and Olsen BP 2006, Automated change detection for updates of digital map data bases, Photogram. Eng. Remote Sens., 69, PGS. 1289-1296.

Kulwardhana RW, Thenkabail PS, Vithanage J, Biradar C, Islam MA, Gunashinghe S, Alankar R 2007 , Evaluation of the wetland mapping methods using Landsat ETM+ and SRTM data. Journal of Spatial Hydrology, l.7, PGS. 62-96.

Kushwaha SPS 1990, Forest type mapping and change detection from satellite imagery, ISPRS Journal of Photogrammetry and Remote Sensing, 45, PGS. 175-181.

L. Grant 1985 , Polarized and nonpolarised component of Leaf reflectance, Ph. D. Thesis, Prude University, West Lafayette Indiana, USA.

Lannom KB, Evans DL and Cooke WH 2001, Forest mapping of Central America and Mexico with AVHRR data, Geocarto International, 16, PGS. 45-53.

Lippitt CD, Coulter LL, Freeman M, Lamantia J, Pang W and Stow DA 2011, The effect of input data transformations on object based image analysis, Remote Sensnsing Letters, 3, PGS. 21-29.

LP Simmonds, C Antolin, JC Calvet 2004, Soil moisture retrieval by a future space-borne Earth observation mission, Europian Space Agency Study Report, 14662 / 00 / NL, UK.

Lu D and Weng Q 2007, A survey of image classification methods and techniques for improving classification performance, International Journal of Remote Sensing, 28, PGS. 823-870.

Lunetta RS, Knight JF, Ediriwickrema J, Lyon JG and Worthy LD 2006, Land-cover change detection using multi-temporal MODIS NDVI data, Remote Sensing Environment, 105, PGS. 142- 154.

Macleod RD and Congalton RG 1998, A quantitative comparison of change-detection algorithms for monitoring eelgrass from remotely sensed data, Photogram Engineering Remote Sensing, 64, PGS. 207-216.

Maggi K and Desheng L 2004, Mapping Diseased Oak Trees Using ADAR Imagery, Geocarto International, 19, PGS. 57-64.

Mallick J, Kant Y, Bharath BD 2008, Estimation of land surface temperature over Delhi using Landsat-7 ETM +, Journal of Indian Geophisics Union, 12, PGS. 131-140.

Martin FJ and Turner RW 1993, SAR speckle reduction by weighted filtering, International Journal of Remote Sensing, 14, PGS. 1759-1774.

Michener WK and Houhoulis PF 1997, Detection of vegetation changes associated with extensive flooding in forested ecosystem, Photogram Engineering Remote Sensing, 63, PGS. 1363-1374.

Moran MS, Clarke TR, Inoue Y and Vidal A 1994, Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index, Remote Sensing Environment, 49, PGS. 246-263.

Mountrakis G, Im J and Ogole C, Support vector machines in remote sensing: A review, ISPRS Journal of Photogrammetry Remote Sensing, doi:10.1016/j.isprsjprs.2010.11.001.

Mwangi S and Swallow B 2008 , Prsopis juliflora invasion and livelihoods in the Lake Baringo area of Kenya, Conservation and Society, 6, PGS. 130-140.

Nagendra H 2001, Using Remote Sensing to assess biodiversity, International Journal of Remote Sensing, 22, PGS 2377-2400.

Nagendra H and Gadgil M 1999, Satellite imagery as a tool for monitoring species diversity: an assessment, Journal of Applied Ecology, 36, PGS. 388-397.

Narayanan RM and Zhang J 2002, Land Cover Classification Models Using Shuttle Imaging Radar (SIR-C) Data: A Case Study in New Hampshire, U.S.A., Geocarto International, 17, PGS. 59-68.

NM Pasiecznik, PJ Harris and SJ Smith 2004 , Identifying tropical Prosopis Species: A Field Guide, HDRA, Coventry, UK.

Owen TW, Carlson TN and Gillies RR 1998, An assessment of satellite remotely-sensed land cover parameters in quantitatively describing the climatic effect of urbanization, International Journal of Remote Sensing, 19, PGS. 1663 -1681.

Pajares G, Alonso C, Cruz JM and Moreno V 2002, Shade identification in urban areas through the bayesian classifier, Proc. European Symposium on Intelligent Technologies, PGS. 476-481.

Pandit BR, Thampan S 1988 , Total concentration of P, Ca, Mg, N & C in the soils of reserve forest near Bhavnagar (Gujarat State), Indian Journal of Forest, 11, PGS. 98-100.

Panigrahy S, Anitha D, Kimothi MM and Singh SP 2010 , Timberline change detection using topographic map and satellite imagery, Tropical Ecology, 51, PGS. 87-91.

Pant T, Singh D and Srivastava T 2010, The potential application of fractal approach for surface roughness retrieval: A study for simulated surfaces, Geomatics Natural Hazards and Risk, 1, PGS. 243-257.

Pavel Propastin 2011 , Multiscale analysis of the relationship between topography and aboveground biomass in the tropical rainforests of Sulawesi, Indonesia, International Journal of Geographical Information Science, 25, PGS. 455-472.

Petit CC and Lambin EF 2001, Integration of multi-source remote sensing data for land cover change detection, International Journal of Geographical Information Science, 15, PGS. 785-803.

Pu R, Gong P, Tian Y, Miao X, CarruthersI RI and Anderson GL 2008, Invasive species change detection using artificial neural networks and CASI hyperspectral imagery, Environ Monitoring Assessment, 140, PGS. 5–32, DOI 10.1007/s10661-007-9843-7.

Puissant A and Weber C 2002, The Utility of very high spatial resolution images to identify urban objects, Geocarto International, 17, PGS. 33-44.

Rahman R and SAHA SK 2008, Multi-resolution segmentation for object-based classification and accuracy assessment of land Use /land cover classification using remotely sensed data. Journal of the Indian Society of Remote Sensing, 36, PGS. 189-201.

Ramsay R, Douglas W, Dennis L and Mcginty C 2004, Evaluating the use of Landsat 30m enhanced thematic mapper to monitor vegetation cover in shrub-steppe environments, Geocarto International, 19, PGS. 39-47.

Retalis A and Nikitopoulou T 2006 , Use of satellite remote sensing for studying the intense Saharan dust event of April 17, 2005, Geocarto International, 21, PGS. 29-35.

Roy PS, Sharma KP, Jain A 1996 , Stratification of density in dry deciduous forest using satellite remote sensing digital data-An approach based on spectral indices, Journal of Bioscience, 21, PGS. 723-734.

Rpbbins P 2001, Fixed categories in a portable landscape: the causes and consequences of land-cover categorization, Environment and Planning, 33, PGS. 161-179.

Saxena AK and Nautiyal JC 1997, Analyzing Deforestation, Journal of Sustainable Forestry, 5, PGS. 51-80.

Sepehry A and Liu GJ 2006 , Flood induced land cover change detection using multitemporal ETM+ imagery, 2nd Workshop of the EARSeL SIG on

Land Use and Land Cover, Center for Remote Sensing of Land Surfaces, PGS.28- 30.

Sinch A 1986 , Change detection in the tropical forest environment of northeastern India using Landsat, International Remote Sensing and Tropical LandManagement, PGS. 237-254.

Singh A 1989, Digital change detection techniques using remotelysensed data, Internation Journal of Remote Sensing, 10, PGS. 989-1003.

Singh G 1996, Effect of site preparation techniques on Prosopis juliflora in an alkali soil, Forest Ecology and Management, 80, PGS. 267-278.

Sommer S, Zucca C, Grainger A, Cherlet M, Zougmore R, Sokona Y, Hill J, Della R, Peruta JR and Wang G 2011 , Application of indicator systems for monitoring and assessment of Desertification from National to Global scales, Land Degradation Development, 22, PGS. 184-197.

Soudani K, François C, Le V, Dufrêne E 2006, Comparative analysis of IKONOS , SPOT , and ETM + data for leaf area index estimation in temperate coniferous and deciduous forest stands, Remote Sensing of Environment, 102, PGS. 161-175.

Southworth J, Munroe D and Nagendra H 2004, Land cover change and landscape fragmentation-comparing the utility of continuous and discrete analyses for a Western Honduras region, Agriculture Ecosystems and Environment, 101, PGS. 185-205.

Stow DA, Hope A, McGuireb D, Verbyla D, Gamon J, Huemmrich F, Houston S, Racine C, Sturm M, Tape K, Hinzman L, Yoshikawa K, Tweedie C, Noyle B, Silapaswan C, Douglas D, Griffith B, Jia G, Epstein H, Walker D, Daeschner S,Petersen A, Zhou L and Myneni R 2004, Remote sensing of vegetation and land-cover change in Arctic Tundra Ecosystems, Remote Sensing Environment, 89, PGS. 281–308.

Strahler AH, Moody A and Lambin E 1994, MODIS land cover product algorithm technical basis document, 11, PGS. 2669-2671. Washington DC NASA.

Subbarao KV and Hooper PR 1988, Reconnaissance map of the Deccan basalt group in the Western Ghats, India. In: Subbarao KV (ed) Deccan flood basalts, Geological Society of India.

Tang Y, Huang X, Muramatsu K and Zhang L 2010 , Object-oriented change detection for high-resolution imagery using a genetic algorithm”, Remote Sensing Spatial Information Sciences, 38, PGS. 769-774.

Tanriverdi C 2010, Improved agricultural management using remote sensing to estimate water stress indices, Application in Remote Sensing Journal, 1, PGS. 19-24.

Tewari VP and Singh B 2006, Total and Merchantable Wood Volume Equations for Eucalyptus hybrid Trees in Gujarat State, India, Arid Land Research and Management, 20, PGS. 147-159.

Theiler JP and Perkins JS 2011, Anomalous change detection in imagery, US 7953280 B2.

Thomas JR, Myers VT, Heilman MD and Wiegand CL 1966, Factors affecting light reflectance of cotton. Proc. Ivth Int. Symp. on Remote Sensing of Environment, Ann Arbor, Michigan, PGS. 305-312.

Toutin T 2008, ASTER DEMs for geomatic and geoscientific applications: a review Author, International Journal of Remote Sensing, 29, PGS. 1855-1875.

Turker M and Derenyi E 2000, GIS assisted change detection using remote sensing, Geocarto International, 15, PGS. 51-56.

Virk R and King D 2006 , Comparison of techniques for forest change mapping using Landsat data in Karnataka, India, Geocarto International, 21, PGS. 49-57.

Wang CQ, Shuhua NZ and Wang J 2004, Evaluating soil moisture status in China using the temperature-vegetation dryness index, TVDI, Canedian Journal of Remote Sensing, 30, PGS. 671-679.

Weng Q 2009, Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends, Journal of Photogrammetry Remote Sensing, 64, PGS. 335-344.

Wolter PT, Mladenoff DJ, Host GE and Crow TR 1995, Improved forest classification in the northern lake states using multi-temporal Landsat imagery, Photogrammetric Engineering and Remote Sensing, 61, PGS. 1129-1143.

Wooley JT 1971, Reflectance and transmittance of light by leaves, Journal of Plant Physiology, 47, PGS. 556-662.

www.52north.org/

Yagoub MM and Kolan GR 2006, Monitoring coastal zone land use and land cover changes of Abu Dhabi using Remote Sensing. Photonirvachak, Journal of the Indian Society of Remote Sensing, 34, PGS. 57-68.

Zomer RJ, Ustin SL andIves JD 2002, Using satellite remote sensing for DEM extraction in complex mountainous terrain: landscape analysis of the Makalu Barun National Park of Eastern Nepal, International Journal of Remote sensing, 23, PGS. 125-143.

****

Appendix 1

Sample data: No change digital number of Landsat-7 ETM+

Land Classes	Landsat-7 ETM+ Nov.2002								
	B1_02	B2_02	B3_02	B4_02	B5_02	B61_02	B62_02	B7_02	B8_02
Forest	69	57	47	91	77	133	153	41	64
Forest	70	52	44	75	66	133	153	34	53
Forest	68	54	44	80	70	131	151	35	59
Forest	69	52	42	75	71	131	149	36	58
Forest	72	56	48	84	78	138	162	43	59
Forest	71	54	44	80	72	136	157	35	56
Forest	71	52	43	72	63	133	153	31	52
Forest	71	53	46	79	66	135	156	31	58
Forest	69	55	42	80	71	129	146	37	61
Forest	70	53	44	73	61	132	153	33	56
Forest	69	52	43	70	64	133	153	33	53
Forest	67	50	42	65	62	131	149	33	51
Forest	71	55	44	77	64	134	156	30	56
Forest	69	51	42	74	58	131	150	29	53
Forest	68	50	41	59	53	131	149	27	45
Forest	70	52	41	63	57	131	150	31	46
Forest	69	51	43	82	61	132	151	28	58
Forest	70	54	42	94	66	133	154	30	69
Forest	69	55	43	90	74	134	155	34	62
Forest	71	55	43	95	76	133	154	38	64
Forest	73	55	45	87	68	133	154	32	60
Forest	72	55	46	77	65	134	153	32	57
Forest	73	56	47	79	71	141	168	39	57
Forest	71	56	44	83	69	136	159	35	58
Forest	72	54	43	77	65	135	157	31	58
Forest	71	53	44	70	65	134	156	32	53
Forest	71	52	43	72	60	134	156	31	51
Forest	72	55	45	78	67	135	158	31	58
Forest	70	55	47	76	65	135	157	32	56
Forest	73	57	47	107	87	141	168	40	75
Forest	70	52	44	72	64	135	156	32	50
Forest	71	53	45	79	65	136	158	33	57
Forest	71	54	45	81	69	135	157	34	59
Forest	71	53	45	87	70	135	157	33	60
Forest	70	52	43	68	60	134	156	31	51
Forest	68	51	43	75	64	133	153	31	54
Forest	69	50	40	71	64	132	151	32	55
Forest	69	51	41	73	62	132	151	30	49
Forest	70	54	43	80	63	133	152	31	54
Forest	68	52	41	70	59	131	149	31	52
Forest	71	51	42	72	63	133	153	32	52
Forest	68	52	39	78	65	132	153	33	56
Forest	69	51	41	67	61	134	154	30	49
Forest	68	51	40	69	62	131	151	31	52
Forest	70	52	45	77	72	136	158	37	54
Forest	71	55	46	82	69	434	156	35	57
Forest	70	53	43	83	70	134	155	34	57

Forest	71	55	46	87	77	136	158	37	62
Forest	68	51	44	69	61	132	152	30	51
Forest	67	50	39	71	58	125	139	29	54
Forest	70	56	47	87	72	134	155	35	61
Forest	68	52	44	74	60	132	151	29	54
Forest	69	54	43	72	64	129	147	33	55
Rocky Land	93	89	113	83	153	153	190	105	78
Rocky Land	89	77	93	76	127	153	189	89	71
Rocky Land	70	51	50	31	63	148	181	57	32
Rocky Land	74	54	57	35	75	150	183	68	37
Rocky Land	84	72	84	63	113	146	177	82	61
Rocky Land	82	73	85	62	118	152	187	86	60
Rocky Land	97	90	108	66	121	159	200	104	68
Rocky Land	89	84	108	75	132	151	185	95	73
Rocky Land	87	82	108	89	146	155	193	95	78
Rocky Land	91	84	116	89	154	152	187	99	82
Rocky Land	94	91	122	92	150	155	192	98	87
Rocky Land	94	91	121	90	154	153	191	98	82
Rocky Land	89	85	109	86	147	150	185	97	77
Rocky Land	93	90	125	86	162	151	186	111	81
Rocky Land	90	86	113	84	156	150	184	102	72
Rocky Land	90	86	125	96	170	158	197	105	90
Rocky Land	91	87	132	99	166	155	193	101	85
Rocky Land	90	86	130	101	175	152	188	110	85
Rocky Land	84	76	101	85	137	157	196	83	71
Rocky Land	93	84	108	71	130	158	199	86	71
Rocky Land	94	86	106	66	116	162	206	80	68
Rocky Land	93	82	104	68	120	159	200	83	66
Rocky Land	92	82	97	60	112	158	198	84	64
Rocky Land	94	87	110	70	130	162	206	88	70
Rocky Land	95	83	99	61	109	163	206	81	62
Rocky Land	92	81	101	64	117	162	205	86	63
Rocky Land	94	87	108	69	131	166	213	92	70
Rocky Land	93	85	111	70	128	164	209	89	67
Rocky Land	92	64	103	63	112	161	205	80	67
Rocky Land	96	85	104	63	107	158	197	75	62
Rocky Land	93	83	104	63	109	163	207	76	63
Rocky Land	92	83	103	62	109	163	206	76	65
Rocky Land	90	82	100	68	107	150	185	75	67
Rocky Land	94	85	104	69	117	151	185	95	68
Rocky Land	93	83	104	66	127	164	208	88	69
Rocky Land	93	83	107	70	135	163	207	94	67
Rocky Land	92	83	105	69	124	162	207	87	67
Rocky Land	90	84	103	63	106	156	195	76	64
Rocky Land	94	87	113	73	133	155	192	92	71
Rocky Land	96	87	118	76	142	159	200	94	76
Rocky Land	93	85	106	66	116	159	201	83	66
Rocky Land	94	84	103	62	109	161	203	81	62
Rocky Land	90	81	108	75	142	157	197	83	71
Rocky Land	92	85	114	86	153	149	183	94	77
Rocky Land	91	84	115	81	152	151	186	97	76
Rocky Land	89	80	104	78	144	155	194	91	74

Rocky Land	99	91	113	77	121	157	196	90	77
Water	72	49	42	20	19	131	149	15	25
Water	69	50	40	20	21	132	150	16	25
Water	74	51	42	20	18	131	149	13	27
Water	72	51	39	17	16	131	149	13	24
Water	73	52	41	18	18	132	150	17	24
Water	74	51	40	18	17	131	150	15	24
Water	73	50	41	18	18	132	151	14	25
Water	71	52	40	18	16	131	151	14	25
Water	72	50	39	18	18	132	151	15	22
Water	71	51	40	19	18	132	152	14	26
Water	72	49	38	17	16	131	149	13	24
Water	71	49	37	16	16	131	150	12	24
Water	71	49	36	16	15	131	148	12	24
Water	72	48	38	17	15	132	151	13	23
Water	73	50	38	17	16	132	152	15	23
Water	76	51	42	19	18	132	152	15	25
Water	73	49	38	17	16	131	149	10	21
Water	71	49	38	17	16	131	150	13	26
Water	69	49	38	16	16	131	149	13	24
Water	71	48	37	17	15	131	150	12	23
Water	71	48	38	16	16	131	149	13	23
Water	72	50	39	17	16	132	151	13	22
Water	72	49	38	17	18	132	151	13	22
Water	72	48	39	17	18	132	150	14	24
Water	72	51	40	18	16	132	151	14	23
Water	75	51	40	18	18	133	153	15	23
Water	72	50	39	18	16	132	150	14	20
Water	73	49	39	18	16	131	150	13	24
Water	74	49	39	19	16	133	153	16	25
Water	72	50	40	18	16	132	151	13	26
Water	71	48	38	17	15	130	149	14	24
Water	72	48	38	17	16	131	150	12	25
Water	72	50	38	17	17	131	149	14	25
Water	71	50	39	17	16	132	150	12	26
Water	70	48	38	16	15	131	149	13	23
Water	71	48	36	16	15	131	149	12	21
Water	72	48	37	16	15	131	149	14	23
Water	72	47	36	15	14	131	150	12	23
Water	69	47	37	15	14	131	148	14	21
Water	70	48	37	17	14	131	150	13	23
Water	71	47	36	16	15	130	148	13	23
Water	71	48	36	16	14	131	149	12	26
Water	73	48	37	17	15	130	149	14	23
Water	70	49	36	17	15	131	149	11	22
Water	69	48	36	17	17	131	149	12	24
Water	73	48	37	17	15	131	151	11	23
Water	70	47	38	16	14	130	148	13	20
Water	71	48	37	17	16	131	149	12	22
Water	70	48	37	17	16	131	149	13	22
Water	72	48	38	18	15	131	150	13	22
Barren Land	80	67	91	79	123	152	187	73	67

Barren Land	88	79	105	82	152	159	200	100	74
Barren Land	83	74	91	64	135	155	193	92	62
Barren Land	83	70	89	65	123	154	190	82	60
Barren Land	81	69	87	66	138	154	190	93	61
Barren Land	84	73	96	67	126	157	195	82	63
Barren Land	90	83	109	75	147	159	199	101	69
Barren Land	93	83	107	77	144	159	200	99	73
Barren Land	86	76	96	72	125	150	185	80	65
Barren Land	87	77	98	75	127	153	189	78	66
Barren Land	88	77	97	77	128	151	185	77	68
Barren Land	85	76	93	75	115	148	181	68	68
Barren Land	84	74	93	74	121	148	179	72	67
Barren Land	84	75	96	75	120	148	180	71	69
Barren Land	89	80	104	73	129	149	180	85	71
Barren Land	86	77	96	66	100	149	182	67	62
Barren Land	87	75	99	65	117	147	179	79	64
Barren Land	95	86	107	69	133	161	204	98	67
Barren Land	92	82	102	65	118	158	198	82	62
Barren Land	91	79	102	60	106	156	195	77	60

Appendix 2

Sample data: No change digital number of Landsat-5 TM

Land Classes	Landsat-5 TM Nov.2009						
	B1_09	B2_09	B3_09	B4_09	B5_09	B6_09	B7_09
Forest	62	31	31	83	88	152	34
Forest	57	24	20	66	61	145	21
Forest	58	25	21	75	68	142	23
Forest	55	24	19	63	64	142	25
Forest	60	26	22	84	70	150	23
Forest	59	25	23	72	70	147	25
Forest	60	25	21	69	59	141	21
Forest	58	25	21	79	62	145	20
Forest	58	24	20	76	65	136	24
Forest	55	25	20	74	58	139	21
Forest	57	23	19	63	58	139	21
Forest	56	23	20	64	58	138	21
Forest	58	26	21	81	58	142	19
Forest	60	25	21	80	56	138	16
Forest	56	24	20	61	53	137	21
Forest	57	24	19	63	55	136	21
Forest	57	23	19	84	57	138	18
Forest	58	26	20	97	67	141	21
Forest	58	24	20	87	63	138	19
Forest	59	26	22	87	75	146	26
Forest	59	27	22	83	67	143	23
Forest	57	25	21	78	60	142	19
Forest	62	28	24	76	73	152	28
Forest	58	25	21	81	63	145	19
Forest	59	25	21	79	62	142	21
Forest	57	25	20	70	62	144	21
Forest	58	24	19	76	58	141	19
Forest	59	26	21	82	64	147	22
Forest	59	25	22	62	57	144	22
Forest	62	29	23	105	79	150	29
Forest	59	25	22	69	64	145	23
Forest	59	26	21	85	64	140	20
Forest	61	25	22	86	64	143	20
Forest	61	27	22	83	66	144	21
Forest	56	24	20	73	55	141	18
Forest	55	24	19	71	57	140	21
Forest	55	23	19	65	54	139	18
Forest	56	24	19	75	58	138	20
Forest	56	25	20	68	59	138	19
Forest	56	24	21	67	54	137	21
Forest	57	25	20	76	57	138	19
Forest	57	24	20	76	63	139	20
Forest	60	26	20	73	60	138	21
Forest	55	25	21	78	62	136	22
Forest	58	28	23	85	74	139	26
Forest	58	25	21	78	59	142	21
Forest	60	28	23	95	74	140	25

Forest	58	29	24	107	76	142	25
Forest	56	24	20	77	62	139	20
Forest	54	23	20	70	50	129	19
Forest	59	28	22	96	65	143	21
Forest	58	24	20	76	61	140	19
Forest	59	27	22	76	62	135	22
Rocky Land	80	44	56	79	124	159	61
Rocky Land	73	38	43	70	113	159	55
Rocky Land	69	37	52	78	112	146	52
Rocky Land	70	37	49	67	105	147	52
Rocky Land	69	34	38	57	98	158	54
Rocky Land	71	34	39	56	102	154	53
Rocky Land	78	41	46	61	107	166	56
Rocky Land	73	38	45	67	99	160	49
Rocky Land	75	39	49	85	116	165	53
Rocky Land	78	42	54	88	128	158	58
Rocky Land	81	45	60	87	138	168	65
Rocky Land	79	43	57	81	137	162	66
Rocky Land	76	41	55	85	133	155	62
Rocky Land	82	45	63	85	153	163	74
Rocky Land	79	41	55	77	131	158	61
Rocky Land	77	41	56	85	142	164	65
Rocky Land	77	42	61	92	140	168	60
Rocky Land	77	42	61	94	137	159	58
Rocky Land	78	41	56	89	133	170	57
Rocky Land	81	41	55	72	126	178	59
Rocky Land	80	42	53	69	110	176	55
Rocky Land	81	41	53	71	117	167	53
Rocky Land	85	41	50	65	111	178	53
Rocky Land	83	42	55	73	116	177	55
Rocky Land	82	42	53	66	110	180	54
Rocky Land	81	42	53	71	110	181	54
Rocky Land	83	43	56	70	127	177	58
Rocky Land	82	43	55	68	114	182	56
Rocky Land	83	43	56	66	107	178	53
Rocky Land	84	42	55	67	107	172	54
Rocky Land	85	42	55	66	105	181	50
Rocky Land	82	43	55	64	106	178	51
Rocky Land	87	47	60	86	128	165	66
Rocky Land	79	41	48	66	88	163	47
Rocky Land	82	41	53	69	120	180	56
Rocky Land	79	40	51	68	118	177	59
Rocky Land	78	40	52	68	113	176	55
Rocky Land	82	42	52	54	83	174	46
Rocky Land	77	41	52	67	114	170	57
Rocky Land	79	40	55	76	121	176	58
Rocky Land	80	40	54	66	105	174	53
Rocky Land	81	41	51	62	103	170	53
Rocky Land	80	40	55	74	130	171	60
Rocky Land	80	42	57	86	142	161	62
Rocky Land	83	45	61	85	143	160	64
Rocky Land	80	43	57	79	129	170	59

Rocky Land	83	44	56	73	108	163	57
Water	56	22	18	13	10	133	5
Water	56	22	17	13	10	134	6
Water	58	22	17	12	8	132	5
Water	56	21	16	12	9	133	5
Water	58	22	15	12	9	133	4
Water	56	22	15	12	9	134	6
Water	57	21	15	12	11	135	5
Water	56	22	15	12	9	133	6
Water	58	22	17	13	7	135	5
Water	59	21	16	12	8	134	4
Water	59	21	15	12	9	134	6
Water	60	22	15	12	10	134	6
Water	60	22	14	11	6	135	5
Water	57	22	15	12	7	135	5
Water	58	21	16	12	8	134	5
Water	59	22	18	13	8	135	5
Water	56	22	16	12	7	135	4
Water	57	21	14	11	7	135	4
Water	58	21	15	12	8	134	6
Water	58	21	15	12	8	135	5
Water	58	21	16	12	9	135	6
Water	59	21	16	13	8	135	4
Water	58	22	17	13	8	135	4
Water	60	22	18	14	9	135	6
Water	60	23	18	13	10	135	7
Water	59	23	17	13	10	135	6
Water	58	21	17	12	9	135	5
Water	59	21	15	13	9	136	5
Water	61	22	17	13	11	134	5
Water	58	21	16	12	9	135	6
Water	59	21	16	12	7	135	5
Water	57	22	17	12	8	135	5
Water	58	22	17	12	8	135	5
Water	58	22	17	13	10	135	5
Water	58	22	16	11	10	134	5
Water	58	22	16	12	7	135	5
Water	59	21	16	11	9	135	5
Water	55	21	15	12	7	135	4
Water	57	20	15	11	9	135	4
Water	58	21	15	12	8	135	6
Water	59	21	16	12	9	135	6
Water	58	22	16	13	8	134	5
Water	57	21	15	11	9	135	6
Water	57	21	14	12	9	135	5
Water	57	21	16	13	8	136	6
Water	57	21	15	12	8	135	5
Water	56	21	14	11	8	134	5
Water	57	20	15	11	8	135	5
Water	58	21	16	13	8	135	6
Water	59	22	17	13	8	135	4
Barren Land	72	37	51	91	113	159	44

Barren Land	72	39	51	84	123	167	54
Barren Land	69	33	41	68	109	162	47
Barren Land	69	32	38	71	92	154	39
Barren Land	66	31	40	70	108	156	44
Barren Land	79	39	51	64	116	168	61
Barren Land	75	38	49	70	127	174	60
Barren Land	79	42	58	85	143	163	67
Barren Land	74	36	44	66	108	164	54
Barren Land	76	37	47	64	113	167	57
Barren Land	71	36	45	71	115	161	51
Barren Land	76	39	51	77	116	161	50
Barren Land	70	36	47	74	109	160	42
Barren Land	78	40	52	73	117	168	55
Barren Land	72	34	42	64	98	161	44
Barren Land	75	39	48	70	94	162	44
Barren Land	76	39	51	67	117	162	55
Barren Land	80	40	52	69	117	169	54
Barren Land	80	42	53	68	108	172	48
Barren Land	81	39	51	60	100	174	50

****