Neighbourhood Correlation Image Analysis Technique for Change Detection in Forest Landscape

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by

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Abstract

Climatic changes, drought, flood, loss of habitat, biodiversity, livelihood etc are some of the consequences of depletion of forest cover which has far reaching effect on survival of human kind. It is in this context monitoring of forest cover is very crucial. In recent times advancement in RS technology and development of new mathematical algorithm has opened the door for new possibilities for change detection analysis.

Neighbourhood Correlation Analysis technique is such new technique which uses contextual information of Correlation, Slope, and Intercept in the neighbourhood of a central pixel between two date images to get detail change detection. The origin of the concept of using contextual information of Correlation in neighbourhood of a pixel is the simple geo-statistical fact that the same geographical area (neighbourhood window) on two dates of imagery will tend to be highly correlated if no or little change has occurred and uncorrelated when change occurs. The usability of this technique in detecting change in urban area using very high-resolution imagery has already been established. The main objective of this study is to investigate the usability of this technique for change detection in forest landscape with the use of medium spatial resolution satellite data and decision tree classification approach.

For the purpose of this study four neighbourhood window of sizes 1, 2, 3 and 4 pixel radius were considered for NCI generation. Reference data for training and testing the decision tree classifier is generated by visual inspection of FCC images of two dates along with NDVI information of the randomly selected pixels. Canopy density is considered to categorize forest cover into forest, open forest and non forest as no change classes and five other change classes i.e. forest to non forest, forest to open forest, open forest to forest, open forest to non-forest and non-forest to open -forest. Data mining software SEE5 is used to generate decision tree classifier. Knowledge base so developed then is used to generate the detail change detection map through ERDAS knowledge classifier. It is analysed whether contextual information of correlation, slope and intercept improves the over all change detection process.

This research has came to the conclusion that the NCI analysis technique does provide change information but it requires bigger windows for NCI information to become useful when medium resolution imagery is used for change detection in forest. Contrary to the expectation it is observed that small neighbourhood window of pixel 1, 2, and 3 pixel radiuses are not able to improve the result. In general the correlation coefficient in even no change area is found to be too low. The factors responsible for low correlation are investigated.
Acknowledgements

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1. Introduction

More than two thousands years ago the Greek sage Heraclitus claimed that “it is impossible to step in the same river twice”. About 1600 years ago, the Chinese Taoist, Gehong noted that “the sea changes into mulberry fields, while the mulberry fields changes into seas.” We do not know exactly how Gehong observed or detected those landscape changes nor do we know exactly if Heraclitus meant changes in the content of the river or changes in its morphology but it can be said with certainty that mankind have been always aware of changes in their living environment since thousands of year (Yuan et al., 1999).

1.1. Background

Change is a continuous phenomenon. Mankind has always been in sincere endeavour to understand the process of environmental change. But even with many scientific advances in twentieth century that have improved our understanding of ecosystem processes, we are still unable to detect and predict with an acceptable degree of certainty about what awaits humanity in the coming decades. Important scientific question which require future research to answer are: How will we know if, when and where predicted environmental impacts will occur? What ecosystems are most vulnerable to anthropogenic and natural stresses? Which ecosystem has the best potential for sustaining important ecological function critical to maintain global ecosystem processes? Will it be possible to identify the onset of predicted changes early enough to act pre-emptively to either avoid or minimize the potential of catastrophic consequences (Lunetta and Elvidge, 1999)? The answer of all these questions can only be given when accurate and precise detection of change along with its dynamics is known.

1.2. Change

Detection of change and learning about the process of change like change itself is a continuous process. It is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, it involves the ability to quantify temporal effects using multi-temporal data (Singh, 1989). Change is also defined as “an alteration in the surface components of the vegetation cover” or as "a spectral/spatial movement of a vegetation entity over time"(Coppin et al., 2004). Changes may be due to anthropogenic or natural reasons. The manifestation of such changes may reflect in the form of land-use and land-cover (LULC) change, forest or vegetation change, wetland change, landscape change, urban change, environmental change, changes due to flood, desertification, changes in crop cultivation, glacial mass balance change etc (Lu et al., 2004). Detection of such changes and their assessment is necessary for planning and management of natural resources. It also provides important information about resources at risk. Timely and accurate change detection is extremely important to understand the relationship and interaction between human and natural phenomena in order to facilitate better decision making. Of all the above enumerated form of changes, forest vegetation change detection and its monitoring is one of the most important fields of study in the present milieu. It is because the stresses on the forests are increasing with increasing human developmental activities and lately but rightly, the realization of existence of intricate relation between human and natural world with forest has been felt. The increasing Carbon content in the
atmosphere and the concern of world community about this, expressed through Kyoto Protocol further emphasizes the importance of change detection in forest landscape (Rosenqvist et al., 2003).

1.2.1. Changes in forest landscape

The important issues of change in forest landscape are (i) the qualitative and quantitative aspect of change (ii) factors of change and (iii) the rate of change. Besides this, it is also important to know the perspective at which change is being considered.

In terms of qualitative and quantitative change in forest cover, change has negative as well as positive aspects. On the negative side of change there is deforestation and degradation of natural forests and on the positive side, aforestation and reforestation can take place, either naturally or by planting. The quality of forest cover in terms of its density may improve due to various silvicultural operations and conservation measures and at the same time with increase in biotic pressure the aerial extent as well as density of forest cover may decrease. Dense forests may get converted into open forests and at the same time non forest area may get converted into open forest.

The negative causative factors for forest cover change are conversion of forest land to pasture, population growth, over dependency on forest for livelihood, forest fire, pest attack, disease, urban development, construction of dams, reservoir, mining etc. The positive causative factors are mainly silvicultural operations, protection and plantation.

Forests world wide cover some 3.9 billion hectares Though vast, this wooded area is only half the size of forested land at the dawn of agriculture some 11,000 years ago (FAO, 2005). Most forests have changed in composition and quality. Most of this depletion of forest has mainly occurred in last few decades. This implies that the rate of change in forest cover has been too fast in the recent past. This rate of change can be dramatic and/or abrupt, as exemplified by large-scale tree logging, or subtle and/or gradual, such as regeneration and growth of standing volume (Coppin et al., 2004). Hence time interval at which any change study is done is very important to understand the rate of change.

1.2.2. Global scenario

According to FAOs Global Forest Resource Assessment Report 2005, total global forest area in 2005 is estimated to be just under 4 billion hectares (ha) or 30 percent of total land area. This corresponds to an average of 0.62 ha of forest per capita (FAO, 2005).

Deforestation, mainly due to conversion of forests to agricultural land, continues at an alarmingly high rate – some 13 million hectares per year. At the same time, forest planting, landscape restoration and natural expansion of forests have significantly reduced the net loss of forest area.

The total net change in forest area in the period 1990–2000 is estimated at -8.9 million hectares per year – equivalent to a loss of 0.22 percent of the remaining forest area each year during this period.

The total net change in forest area in the period 2000–2005 is estimated at -7.3 million hectares per year – an area the size of Panama or Sierra Leone – or equivalent to a loss of 200 sq. km of forest per day. Compared to the 1990s, the current annual net loss is 18 percent lower and equals a loss of 0.18 percent of the remaining forest area each year during this period (FAO, 2005).

In summary, deforestation continues at an alarming rate – but the rate of net loss is decreasing due to aforestation and natural expansion of forests in some countries and regions.
1.2.3. Indian scenario

India is seventh largest and second most populated country of the world. Vastness of the country reflects in the form of diversity in its land-form, people, climate and vegetation. Her forests are one of the most treasured repositories of biodiversity of the world. But the ever increasing human and cattle population has created immense biotic pressure on the forest. As the country is progressing on the path of development, the various types of stresses on forest landscape is increasing. This is leading to qualitative and quantitative decrease in density and area of forest. Various governmental initiatives have been successful in slowing down this process but still a lot is required to be done. Policy makers and forest manager require more detail and accurate assessment of changes in forest landscape to formulate appropriate initiatives for conservation and management of forest.

Forest survey of India (FSI) is the official agency of government of India to map and monitor the forest resources of the country. According to its latest report of 2003, the total forest cover of India is 6,783,333sq.km. The forest cover under dense, open and scrub forests classes are 390,564sq.km, 287,769sq.km and 40,269sq.km respectively (F.S.I., 2003). The qualitative and quantitative change in forest cover over a period of 1999 to 2003 is explained in Table 1.

<table>
<thead>
<tr>
<th>Year</th>
<th>Dense forest</th>
<th>Open forest</th>
<th>Scrub</th>
<th>Total forest cover</th>
<th>Percent of geog. Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>377358</td>
<td>255064</td>
<td>51896</td>
<td>632422</td>
<td>19.39</td>
</tr>
<tr>
<td>2001</td>
<td>416809</td>
<td>258729</td>
<td>47318</td>
<td>675538</td>
<td>20.55</td>
</tr>
<tr>
<td>2003</td>
<td>390564</td>
<td>287769</td>
<td>40269</td>
<td>678333</td>
<td>20.64</td>
</tr>
</tbody>
</table>


The analysis of the forests cover change shows that net forest cover during 1999 to 2003 has increased by 45,911sq.km. In qualitative terms net area under dense and open forest has increased by 13,206sq.km and 32705sq.km respectively where as area under scrub has decreased by 11,627sq.km. The net change here is a non spatial entity denoted only by extent of its area. Even if net change is nil it does not mean that there has been no change in forest cover classes. It is through the analysis of “from to” change matrix this information can be obtained.

Still from the above trend an interpretation can be made that huge investment in plantation activities in last few decades has started to show some positive result but since last two years there has been a decreasing trend in density of forest cover.

1.2.4. Need of Change detection

Timely and accurate change detection of Earth’s surface features provides the foundation for better understanding relationships and interactions between human and natural phenomena to better manage and use resources. Also the requirements of sustainability in present-day ecosystem management need continuous, accurate and up-to-date resource data. Some of the important field of forest management for which there is need for change detection in forest landscape are as follows:-

• Identify areas of deforestation/reforestation
• Monitor growth of urban or rural populations near forest fringes
• Predict future change based on past change
• Provide data for climate or carbon budget models
• Monitor changes in species habitat
• Monitor changes in biodiversity

In general, change detection based on remotely sensed multi-spectral images has developed into an important technique for a multitude of fields (Richards, 1999; Singh, 1989). It supports research and monitoring in virtually all geosciences, as well as in cadastre, land use management and urban planning.

1.3. Motivation

The motivation for doing this study in forest landscape through remote sensing using innovative change detection technique are firstly, the interest in the field of forest vegetation change detection and its monitoring is growing rapidly because the existence of human and natural world depends on forest. The increasing Carbon content in the atmosphere and the concern of world community about this, expressed through Kyoto Protocol further emphasizes the importance of change detection in forest landscape (Rosenqvist et al., 2003).

Secondly, remotely sensed data, because of the advantages of repetitive data acquisition, its synoptic view and digital format suitable for computer processing have become the major data source for forest change detection. Remote sensing technique coupled with the power of GIS as analytic tool for digital data processing offers an outstanding opportunity to monitor forest ecosystems that are undergoing rapid changes.

Thirdly, in the recent past, the constant endeavour to solve combination of real world problems and to understand complexity of natural phenomena has led to quantum jump in advancement of RS technology. There are now wide varieties of sensors available like Multi-spectral scanner Thermal, Radar, Lidar, Hyper-spectral with different spatial, spectral and radiometric resolution. Besides that there is further advancement in mathematical data processing algorithms. This has further opened the door for new possibilities. To explore these possibilities there has always been a need to develop and use new techniques to compare multi-spectral/multi-temporal image data for the purpose of change detection in different landscape.

1.4. Problem identification

1.4.1. Instrument for change detection

Inventorization of biophysical processes is one of the most important pre-requisite for change detection (Jensen, 1996). Remote sensing technique is a tool which not only provides the means of digital inventorization of such processes but that too at frequent interval. It is a tool for monitoring large scale spatial extents, providing detail information, limited only by the spatial and spectral resolution of the sensors being used. LANDSAT sensors (MSS, TM and TM+) are particularly well suited to monitor regional deforestation due to their moderately high spatial resolution (15m to 120m), spectral resolution (4 to 8 bands) and wide spatial extent (185km swath) as well as image data availability dating back to 1972 (Greenberg et al., 2005). Recent innovation in Hyper-spectral, Radar, Lidar and Very high spatial resolution imaging offers promising technique to monitor forest change to the extent of individual tree and species level (Skidmore et al., 1997).
1.4.2. Context of change

The detection of change is a function of the "from" and "to" classes, the spatial extent, and the context of change. As far as context of change is concerned, there are different perspectives from which the variability in the change event has been approached and its classifications in forest ecosystems have been proposed. These are thematic, hierarchical, mechanistic, ecological and spatial (Coppin et al., 2004). The proper understanding of the nature of the change and the context at which it is to be observed along with the principles that enable its detection is very important for any change detection analysis to be successful. The hierarchal classification of forest cover on the basis of forest cover density is the context in which the present study proposes to analyse the change.

1.4.3. Change detection techniques

There are four important aspects of change detection for monitoring natural resources (i) Detecting if a change has occurred (ii) Identifying the nature of change (iii) Measuring the aerial extent of change and (iv) Assessing the spatial pattern of change (Macleod and Congalton, 1998). In recent past many change detection techniques have been developed which attempted to focus on either or all of the above aspects with varying success. Different sensors with different change detection algorithm for different applications were used for this purpose but the question of best suitability of the technique for a specific study area remains unanswered which implies that no single method is suitable for all cases. It is for this reason different change detection technique are often tested and compared to provide a best result based on the accuracy assessment or qualitative assessment and this is also one of the purposes of this study.

Various remote sensing change detection algorithms which have been developed in the process of addressing above mentioned four aspects of change detection, can be grouped into two categories (i) Binary change/no change or Image enhancement method like Image differencing Image ratioing, Vegetation index differencing and PCA. These algorithms provide information on the existence and magnitude of change but do not identify the nature of change (ii) Information on the nature of change extraction method i.e. Post classification comparison, CVA and hybrid change detection method. These algorithms provide detailed information about the type of land cover change but it requires accurate thematic classification of the images. There is also an ample possibility of classification error propagation into final output (Jungho and Jensen, 2005) (Chan et al., 2001; Lu et al., 2004).

Most of the above traditional algorithm has been used to identify change using coarse to medium resolution images (Hayes and Sader, 2001; Lyon et al., 1998). They do not function successfully in high and very high resolution domain especially in the highly heterogeneous urban areas because high resolution images exhibit high frequency component details such as buildings, land parcel, roads, commercial/industrial services and shadow (Al-Khudhairy et al., 2005).

To overcome this problem, instead of pixel based change detection technique (traditional methods) object oriented image segmentation change detection approach has been adopted (Niemeyer and Canty, 2003). Use of knowledge based expert system ANN (Gopal and Woodcock, 1996), Fuzzy-logic and Genetic algorithm (Zhou and Civco, 1996) were made for automation of classification for change detection.
1.4.4. Neighbourhood Correlation Image

An entirely different approach to this change detection problem for high resolution image is a technique which is still pixel based but dependent on contextual information of a pixel on first image and its associated neighbouring pixels on second image. This technique has been tried on urban landscape using very high resolution imagery (Digital-globe 0.7X0.7mts)(Jungho and Jensen, 2005). The study is based on the fact that the same geographical area (pixel window) on two dates of imagery will tend to be highly correlated when no change occurs and less correlated when change occurs. The contextual information of “correlation” between two dataset provides information about location and numeric value of change. It has also been found that a high correlation between pixels under consideration and corresponding neighbour is not always associated with “no change” and such information of change associated with even high correlation can be derived from other two contextual images of Slope and Intercept. To explore this, regression analysis of sample point having high correlation can be done to compare intercept and slope value associated with those sample points.

In this approach a new three channel Neighbourhood Correlation Image (NCI) that contains three different types of information about (i) Correlation (ii) Slope and (iii) Intercept is generated to derive the information of change (Jungho and Jensen, 2005). Correlation image derived from a specific neighbourhood of pixels (2x2, 3x3, 4x4,) contains valuable change information associated with central pixel and its neighbouring pixels of two images. The other two images “Slope” and "Intercept" provides change related information which facilitates the process of accurate change detection through “Correlation” image. The value of slope and intercept associated with central pixel under consideration is obtained from the brightness value of neighbouring pixels on images of two dates. When combined with Decision tree classification technique the extent of correlation, slope and intercept can be used to produce detailed “from to” change information.

The above approach has been tested by using multi-temporal image of 0.7x0.7mts spatial resolution on urban area of Edisto Beach (Jungho and Jensen, 2005). Altogether 5 unchanged classes, namely Developed (D), Barren (B), Tree (T), Grass (G), Shadow (S) and 8 change classes i.e.; B to D, T to D, T to B, G to B, T to G, T to S and change in G were considered for detecting change. The result of overall accuracy of that analysis was found to be more than 97% and Kappa more than 0.94, which is a very high accuracy and probably more than other traditional change detection techniques which I have gone through.

1.4.5. NCI for change detection in forest landscape

Interpretation of term “low spatial resolution and high spatial resolution” is subjective and is largely dependent on the field of application. For the change detection application in forest where the feature of interest is individual tree crown, the use of high resolution ~1m may be essential, but in the forest landscape the most sought after and common area of interest is, to detect change in aerial extent of forest cover for example, from Non forest to Forest, Dense forest to Non forest and vice versa. The physical and biological processes of forestation and deforestation and change in forest cover and its density over a period of 2-5 years in Indian context normally occurs at the scale of 0.25 to 5.0 ha. Hence minimum mapping unit (MMU) can be taken as 50x50mts. For detection of such processes of change, use of very high resolution image of the order of~1mt is not required. A spatial resolution of the order of 30mts is sufficient for this purpose.
The Neighbourhood Correlation Image (NCI) Analysis Technique was found to be a powerful tool in detecting changes in the urban area with high accuracy but by using very high resolution imagery of ~1m spatial resolution. The problem for research is that high resolution images for change detection purpose in forest landscape cannot be used always because of the following reasons:
- Huge cost of very high resolution imagery.
- Retrospective or historical data may not be always available for comparison.

So if with same high accuracy this technique is able to detect change in forest landscape using medium resolution imagery than it can be established that this technology can be used and applied successfully using both medium as well as high resolution satellite data.

### 1.4.6. Research objective and question

#### 1.4.6.1. Research objective

The main objective of the proposed study is to investigate the usability of NCI analysis and Decision tree classification technique in forest landscape with the use of medium spatial resolution satellite data.

#### 1.4.6.2. Research questions

The research question which has to be answered by this study is:-

1. Is the NCI technique suitable for medium resolution data?
   - (a) What is the threshold of correlation coefficient for no change?
   - (b) Does a high correlation always imply no change?
   - (c) What is the accuracy percentage of change detection with and without NCI?

2. If so, what is the most suitable configuration of NCI for this purpose?
   - (a) How does the configuration of the neighbourhood window affect the total area under various change and no change classes?
   - (b) How is the interpretability of the Change map affected by NCI configurations?

### 1.5. Research utility

The present research may serve as an input in the endeavours of an organization like Forest Survey of India, which is engaged in mapping forest and presenting an authentic report on the status of Forests in India biannually. The use of proposed new technique to detect change in quantity and quality of forest cover will further able to detect it with more accuracy. It may also help Madhya Pradesh Forest department in the long run in formulating appropriate policies, assessing the success of sustainability of various conservation plans such as joint forest management, protected area conservation initiative, social forestry and wasteland development.

### 1.6. Structure of the thesis

The present research is elaborated in six chapters. Chapter 1 deals with the back ground and basic reasons behind this research, its objective and research questions. Chapter 2 explores existing literatures related to the various components associated with the Change Detection for the purpose of ecosystem monitoring. Chapter 3 introduces the study area chosen and reason for that and the various data sets used in the study. Chapter 4 describes in brief about the methods employed in achieving the
objective and addressing the research questions. Chapter 5 presents the various outputs and their analysis. Chapter 6, the final chapter of the thesis summarizes the work, draws conclusion and provides few suggestions and recommendations.
2. Literature review

The world's forest ecosystems are in a state of permanent flux at a variety of spatial and temporal scales. Monitoring techniques based on multi-spectral satellite-acquired data have demonstrated potential as a means to detect, identify and map changes in forest cover. Change detection is a central task for all kinds of monitoring purposes. It uses multi-temporal image data sets in order to detect land cover changes caused by natural or anthropogenic agents of change. Property of Spectral variation in image due to variation in spectral characteristics of the vegetation in a given location over time is utilized to detect change (Hoffer, 1978). Change detection has been described as a process that observes the differences of an object or phenomenon at different times (Singh, 1989). In general, change detection involves the application of multi-temporal datasets to quantitatively analyse the temporal effects of the phenomenon.

Digital change detection encompasses the quantification of temporal phenomena from multi-date imagery that is most commonly acquired by satellite-based multi-spectral sensors.

The various important stages of development of any digital change detection analysis are:-
1. Defining the objective of analysis
2. Requirement of data
3. Data acquisition and pre-processing
4. Geometric correction
5. Radiometric correction
6. Selection and application of appropriate change detection analysis technique
7. Accuracy assessment
8. Representation of output in the form of table or maps.

2.1. Objective of study

For executing any change detection analysis it is very important to define the objective of the whole exercise and set a goal and standard for final output. For this it is required to lay down the level of details and threshold of accuracy of the output desired. Greater is the level of detail, higher the probability of a successful outcome. Knowledge of R.S. and GIS capability and its use in various past and present applications is also helpful for defining the realistic goal of the study. Remote sensed digital data has a wide range of application in the field of environmental monitoring. Past application have focused mainly on mapping environmental conditions or characterization of forest ecosystem at “one point of time” to establish baseline condition. These applications were capable only for monitoring ecosystem processes at the level of coarse scale (Lunetta and Elvidge, 1999). These analysis included land cover characterization and classification (Townshend et al., 1987), forest conversion monitoring and biomass estimation (Vogelmann, 1988), habitat condition mapping, forest biomass estimation etc.

Current applications focus on application of R.S. data for forest ecosystem characterization, dynamics and processes. It includes various applications such as deforestation and carbon budget dynamics and processes (Prins and Menzel, 1992), tropical forest deforestation documentation (Mayaux and Lambin, 1995), forest succession dynamics (Song and Woodcock, 2002), forest fire monitoring (Kiran Chand...
et al., 2006) etc. Beside these, other applications are in the field of habitat evaluation, biodiversity assessment, arid ecosystem changes, forest biomass and productivity monitoring and LCLU change detection.

The above enumerated past and present environmental studies done with the use of R.S. data were as per the need and the availability of R.S. and GIS technology at that point of time. The present day requirement may be quite different but still the knowledge of earlier work done helps immensely to precisely define the objective of the study.

2.2. Requirement of data

Natural and anthropogenic processes at the Earth’s surface operate at a range of spatial and temporal scales. Different scales of observation are required to match the spatial scales of the processes under observation. At the same time, the temporal sampling rate of the observing systems must be reconciled with the dynamics of the processes observed (Aplin, 2006). For change detection analysis there are three important criteria’s on which the data requirement is finalized. They are (i) spectral resolution (ii) spatial resolution and (iii) temporal resolution.

Spectral resolution requires the definition of specific portion of electromagnetic spectrum to be detected and the bandwidth to be sampled. Both of these components can be decided only after through understanding of the interaction of surface of interest with incident electromagnetic radiation (solar radiation). In the case of vegetation or forest, those wave lengths which correspond to chlorophyll absorption minima and reflectance maxima is considered as suitable for the study. NIR range of E.M. spectrum is most suitable for vegetation observation. But the observation of forest in totality includes the observation of interaction of E.M. wave also with moisture and soil hence band 2 (green) and band 3 (red) are also taken along with NIR band as these two bands are suitable for observation of soil and water. For the present study three LISS III Bands i.e.; band2-0.52-0.59 µm, band3-0.62-0.68 µm and band4-0.77-0.86 µm have been included.

Spatial resolution (pixel size) decides the scale to which the data may be useful for forest ecosystem analysis. A general rule of thumb is that the pixel size of the remotely sensed data should be less than the minimum spatial size of event of interest (minimum mapping unit- MMU) (Skidmore et al., 1997). To derive the MMU, the analysis of spatial scale at which the biophysical processes of interest occurs in the forest ecosystem should be thoroughly done. In the present study biophysical process specific to the area of study are encroachments in forest area for agricultural purpose, regeneration and rehabilitation of degraded forest since last 7-10 years due to Joint Forest Management (JFM) initiatives and clear felling of forest area for construction of Narmada Valley Dam. All these processes occur over a spatial extent of more than two to five hectare. The MMU in these cases are more than 100mts. The spatial resolution of the LISS III (23.5 Meters) is suitable for the purpose of study as it is higher than MMU of the biophysical process of interest.

Temporal resolution is the minimum time interval at which any change in forest due to different biophysical process can be detected by remotely sensed data and which is of interest of study. Further, understanding of annual phonological cycles of vegetation which includes green up, growth and maturation cycles and leaf fall is very important for deciding temporal resolution. Besides this the temporal nature of physical processes like thinning, felling, forest fire, encroachment, water submergence etc is also required to be analysed for finally deciding the temporal resolution of the
data. In this study temporal resolution of six years has been taken as these processes of change become appreciable during this time interval and can be detected.

2.3. Data acquisition and pre-processing

There are some very important initial pre-processing steps which are required to be done before data analysis in any change detection process. This includes assembling complete data mosaics of study area, sub setting and masking. The sole purpose of doing this initial pre-process is to reduce data dimensionality associated with the scene to optimise the performance of change detection algorithm. One of the biggest problems in preparing data for analysis is presence of cloud over the scene. Availability of overlap areas between scene and flight lines provides a means of avoiding cloud. In order to solve the cloud cover problem effectively, the mosaic approach offers a wide variety of possibilities in connection with other fusion techniques. Apart from creating simple or complex mosaics there are other techniques such as Optimal Resolution Approach (C. Pohl J. L. Van, 1998), IHS and others to fuse the data for the purpose of filling the gaps. The problem of cloud was recently addressed by developing “image fusion methodology” in which a 1-D Pseudo-Wigner distribution (PWD) transformation is applied to the source images and on the pixel-wise cloud model (Gabarda and Cristobal).

In another study, by analysing the unique spectral characteristics of cloud having consistently high reflectivity in all visible and NIR wavebands, most of the clouds was separated by applying suitable threshold in the developed algorithm for cloud removal in Blue band and visible bands (Prasad et al., 2004)

2.4. Geometric correction

Of the various aspects of pre-processing for change detection, there are two essential requirements: multi-date image registration and radiometric calibration.

It should be evident that accurate spatial registration of the multi-date imagery is absolutely essential to digital change detection. The importance of accurate spatial registration of multi-temporal imagery is obvious because largely spurious results of change detection will be produced if there is mis-registration. In a study on the impact of mis-registration on change detection simulations of MODIS data run with spatially degraded Landsat MSS images, Townshend et al clearly demonstrated the need to achieve high values of registration accuracy if there is to be reliable monitoring of change (Townshend et al., 1992). Their results showed that for spatial resolutions of 250 and 500 meters, errors of more than 50% of actual differences in the NDVI were caused by misregistration of one pixel. To achieve errors of only 10%, registration accuracies of 0.2 or less were required. The same conclusion was drawn by Xiaolong and Khorram on the study of the effects of image mis-registration on the accuracy of remotely sensed change detection using Landsat TM imagery (Xiaolong and Khorram, 1998). However, change detection capabilities are intrinsically limited by the spatial resolution of the digital imagery. Further, residual mis-registration at the below-pixel level commonly degrades the aerial assessment of the change events somewhat, specifically at the change/no change boundaries. This within-pixel shift is inherent to any digital change detection technique (Coppin et al., 2004).
2.5. Radiometric correction

For the purpose of accuracy and meaningfulness of the change detection study there is always a need to separate interesting change from uninteresting change. In a multi-temporal imagery analysis the uninteresting changes arise due to radiometric inconsistency in multi temporal images. The reasons for this inconsistency are:

- Phenological changes
- Sun angle effects
- Atmospheric effects
- Sensor view angle

Radiometric corrections are often performed on multi-temporal imagery to reduce any or all of the above influences and increase sensitivity to landscape change (Chavez and Mackinnon, 1994; Coppin et al., 2004; Song et al., 2001). Changes arising due to phenology are normally mitigated by acquiring datasets of nearly same dates whereas, sun angle, view angle and atmospheric effects can be minimized only by proper radiometric correction. Radiometric correction is primarily aimed at making the two input images similar with respect to radiometric qualities. In other words, it is an attempt to simulate the same illumination and atmospheric conditions that occurred when the two images were acquired. But this has often been difficult to accomplish. There are two primary reasons for this. The first is that it is difficult to accurately create two normalized images. This is largely because the variations caused by illumination and atmospheric effects are rarely homogeneous across an image, and simple and reliable methods to normalize imagery are still being perfected. The second issue is that there is often a change in the state of the land cover between the two dates due to senescence, green-up, disease, or different growing conditions, such as growing days, water availability, and so on. The assumption, therefore, that similar land cover types will look the same on both images is often invalid. It should be noted that radiometric normalization is not always necessary for multi-temporal satellite image inter-comparison. For example, it is not necessary to perform normalizations if the land cover classification method for multiple images is based on the spectral signals from each individual image (Song et al., 2001).

Two types of radiometric corrections, absolute correction and relative correction, are commonly employed to normalize remotely sensed images for time-series inter-comparison (Cohen and Goward, 2004; Coppin et al., 2004; Lu et al., 2004).

2.5.1. Absolute radiometric correction

Absolute radiometric correction is aimed towards extracting the absolute reflectance of scene targets at the surface of the earth. This method requires the input of simultaneous atmospheric properties and sensor calibration, which are difficult to acquire in many cases, especially in historic data (Chavez and Mackinnon, 1994; Lu et al., 2004; Song et al., 2001). Absolute radiometric correction is a two-step process. The first step is to convert the digital number (DN) of the sensor measurements to spectral radiance measured by satellite sensors. The second step is to transfer the sensor-detected radiance into ground surface reflectance. Absolute radiometric models use in-situ measurements or reasonable estimation of atmospheric optical depth, solar zenith angle and satellite status to input parameters for calculating the ground surface reflectance (Chavez, 1996).
2.5.2. Relative radiometric correction

Relative radiometric correction is aimed towards reducing atmospheric and other unexpected variation among multiple images by adjusting the radiometric properties of target images to match a base image (Hall et al., 1991). Most relative methods assume that radiometric relationships between the target image and the base image are linear (Lu et al., 2002; Song et al., 2001). The relative radiometric correction method normalizes images of the same area and different dates by using landscape elements (pixels) whose reflectance values are nearly constant over time. This procedure assumes that the pixels sampled at Time 2 are linearly related to the pixels, of the same locations, sampled at Time 1, and that the spectral reflectance properties of the sampled pixels have not changed during the time interval. The limitation of this kind of approach is that the landscape elements are normally selected by visual inspection, which could result in a subjective radiometric normalization (Paolini et al., 2006). There are three important methods for relative radiometric correction (i) Dark Object Subtraction (DOS) method, (ii) Pseudo invariant Features (PIF) methods and (iii) Ridge method.

2.5.2.1. Dark Object Subtraction (DOS) method

In the Dark Object Subtraction (DOS) method, it is assumed that any radiance received at the sensor for a dark object pixel is due to atmospheric path radiance (Chavez, 1996). Thus, for dark objects, the pixels containing the lowest DN values are selected from the image and their representative value is subtracted from the DN values across the whole scene to reduce scattering influences. Clear water bodies and dark vegetation under shadows are traditionally selected as dark objects (Song et al., 2001). This method can correct atmospheric scattering (additive) effects but it cannot correct for (multiplicative) differential atmospheric transmittance (Chavez, 1996).

2.5.2.2. Pseudo invariant Features (PIF) method

Schott et al. developed a relative radiometric normalization method using spectrally pseudo-invariant features, such as impervious roads, roof tops and parking lots, to allow inter-comparisons between a target image and a base image by calculating an image-based linear regression. Shortcomings of this method include the fact that moisture changes in PIF can influence the accuracy of the approach and the accuracy of isolating the pseudo-invariant features depends on the user's ability and knowledge (Schott et al., 1988). Elvidge et al. also created a relative radiometric normalization method using an Automatic Scattergram Controlled Regression (ASCR) algorithm to identify invariant regions and compute regression lines for radiometric correction. Large areas of land and water features containing significant reflectance differences in near infrared bands are required to apply this method (Elvidge et al., 1995). Du et al. also developed an improved method for PIF selection. With this method, PIFs are selected via principal component analysis (PCA) using the scatter plots of two images. A linear regression function for relative radiometric normalization is created by objective statistics calculation based on the PIFs (Du et al., 2002).

2.5.2.3. Ridge method

Song et al. were first to describe and apply ridge method (Song et al., 2001). This method uses a density plot of all pixels collocated in two images acquired on different dates to identify the linear normalization function. The axes of the density map represent the DN values of collocated pixels in the respective images. In the density plot, the invariant pixels in two images cluster together to form a high density ridge that is used to calculate a linear regression function to normalize the target image. The accuracy of this simple method is comparable to that of some complex absolute normalization
methods, and as a result has seen much recent use (Andrefouet et al., 2001; Song et al., 2001). The shortcoming of this method is that the identification of a regression function is based on the visual observation of the density ridge. If most of the collocated pixels contain subtle and systemic changes due to factors such as phenological responses to different growth seasons, the density ridge may contain biased distortions and the regression function may be difficult to identify or will contain bias errors (Chen et al., 2005).

PIF method of radiometric normalization has been used in this study as it allows inter-comparisons between year 1999 image and a base image 2005 by calculating an image based linear regression taking into account of entire range of brightness values of the scene. This is also the requirement of the study.

2.6. Selection and application of appropriate change detection analysis technique

There are four important aspects of change detection for monitoring natural resources (i) Detecting if a change has occurred (ii) Identifying the nature of change (iii) Measuring the aerial extent of change and (iv) Assessing the spatial pattern of change (Macleod and Congalton, 1998). In recent past many change detection techniques have been developed which attempted to focus on either or all of the above aspects with varying success. Different sensors with different change detection algorithm for different applications were used for this purpose but the question of best suitability of the technique for a specific study area remains unanswered which implies that no single method is suitable for all cases. It is for this reason different change detection technique are often tested and compared to provide a best result based on the accuracy assessment or qualitative assessment and this is also one of the purposes of this study.

Depending upon the methodology, complexity and suitability for different change detection application various remote sensing change detection algorithms have been developed. Each one of them has tried to address above mentioned four aspects of change detection into different way. All these algorithms can be grouped into six categories (i) algebra (ii) transformation (iii) classification (iv) advance model (v) GIS based and (vi) visual analysis (Lu et al., 2004; Yuan et al., 1999).

2.6.1. Algebra

It includes Image differencing, Image regression, Image ratioing, Vegetation index differencing and Change Vector Analysis (CVA). In this category two aspects are critical for change detection result (a) selecting suitable band combinations or vegetation indices and (b) selecting suitable thresholds to identify the changed areas. Selecting thresholds is one of the difficulties in this technique. Attempt has also been made towards automatic selection of threshold based on clustering, statistics, moments and entropy (Rosin and Hervas, 2005). Further results vary depending upon characteristic of study area and image data used.

2.6.1.1. Image differencing

Image differencing is probably the most widely applied change detection algorithm for a variety of geographical environments (Singh, 1989). It involves subtracting one date of imagery from a second date that has been precisely registered to the first. With "perfect" data, this would result in a data set in which positive and negative values represent areas of change and zero values represent no change. These methods (excluding CVA) are relatively simple, straightforward, easy to implement and interpret(Lu et al., 2004). Chavez and Mackinnon indicated that red band image differencing provided better vegetation change detection results than using Normalized Difference Vegetation Index(Chavez
and Mackinnon, 1994). Lyon et al. compared seven vegetation indices from three different dates of MSS data for land cover change detection and concluded that NDVI differencing technique demonstrated the best vegetation change detection (Lyon et al., 1998).

2.6.1.2. Image regression

In this technique, relationship between bi-temporal images are established. On the basis of this relationship the pixel value of second date image is estimated by regression function. The change is detected by subtracting regressed image from the first date image. It reduces the impact of atmosphere, sensor and environmental differences between two date images. This technique requires development of accurate regression function for selected bands. It has been shown by Myeong et al. that this technique is simple and cost effective. They have used image regression method based on the satellite image time series for urban forest carbon storage mapping. Satellite imagery collected in different decades was used to develop a regression equation to predict the urban forest carbon storage from the Normalized Difference Vegetation Index (NDVI) computed from a time sequence (1985-1999) of Landsat image data. The total carbon storage estimates based on the NDVI data agree closely with the field-based model estimates (Myeong et al., 2006). Liu et al. while comparing image differencing, image ratioing, image regression, and principal component analysis (PCA) from a mathematical perspective found that image regression and standardized PCA (SPCA) achieved the best performance for change detection (Liu et al., 2004).

2.6.1.3. Image ratioing

In the image ratioing technique the ratio of registered images of two dates are determined band by band. The areas of no-change get a value near unity, while areas that have undergone changes acquire values less than or greater than one, as the case may be. These technique assumes the Gaussian distribution of DN values and requires appropriate selection of bands to be ratioed and the threshold of the final ratioed values at which the change is assumed to have occurred. On comparative analysis of various change detection technique it was found that the ratio images give a slight overestimation in results compared to image differencing technique (Prakash and Gupta, 1998).

2.6.1.4. CVA

Change vector analysis (CVA) is a radiometric technique, the primary utility of which is the detection of all changes present in the input multi-spectral data. It is also flexible enough to be effective when using diverse types of sensor data and radiometric change approaches. Change vector-based procedures have also been employed to data having high temporal dimensionality (Lambin and Strahlers, 1994). This technique generates two outputs (1) the spectral change vectors which describe the direction and magnitude of change from first to the second date and (2) the total change magnitude per pixel which is computed by determining the Euclidean distance between end points through n-dimensional change space (Jensen, 1996).

The potential advantages of CVA over some other methods include: (1) capability to concurrently process and analyse change in all multi-spectral input data layers (as opposed to selected bands), (2) avoidance of compounding of spatial-spectral errors often inherent in multi-date classifications, (3) the capability to detect changes both in land cover and condition and (4) computation and separation of multidimensional change vector components, and composition of change images that retain this information and facilitate change interpretation and labelling (R. D. Johnson E. S, 1998).
Sohl reviewed and evaluated five methods: univariate image differencing, an ‘enhanced’ image differencing, vegetation index differencing, post-classification differencing and CVA, and concluded that CVA excelled at providing rich qualitative details about the nature of a change (Sohl, 1999).

### 2.6.1.5. Vegetation index Differencing

Development of vegetation indices from Red and IR multi-spectral values is based on the differential absorption and reflectance of solar energy by chlorophyll present in green vegetation. Various vegetation indices have been formulated either based on ratio or differences of these bands. In change detection, the derived vegetation indices for two dates are subtracted to generate a band of vegetation index differences. It emphasizes the difference in spectral response of different features and reduces impacts of topographic effects and illumination. It requires the suitable identification of vegetation index and thresholds of change.

Nelson examined the utility of image differencing, image ratioing and vegetation index differencing in detecting gypsy moth defoliation and found that a difference of the MSS7/MSS5 ratio was more useful in delineation of defoliated area than any single band-pair difference or ratio (Nelson, 1983). Lyon, Yuan et al compared seven vegetation indices for their value in vegetation and land-cover change detection in part of the State of Chiapas, Mexico using different dates of Landsat Multi-spectral Scanner (MSS) data. It was concluded that the NDVI was least affected by topographic factors and NDVI difference technique demonstrated the best vegetation change detection as judged by laboratory and field results (Lyon et al., 1998).

### 2.6.2. Transformation

This includes PCA, Tasseled cap (KT), Gramm –Schmidt (GS) and Chi-square transformation. Principal component analysis is performed on the image data of each data of each date. The derived PCA are again analyzed by other change detection methods. It can be performed on original or standardized data. In KT, the reflectance bands are transformed into three orthogonal indices called brightness, greenness and wetness and the analysis for change detection is done on one or combination of these indices (Healey et al., 2005).

Advantage in transformation method is in reducing data redundancy between bands and availability of different information in derived components. However they cannot provide detailed change matrices. It also requires selection of thresholds and labelling of change information. PCA and KT are most often used for change detection analysis where as GS and Chi-Square methods are relatively less frequently used in practice due to their relative complexity compared to PCA and KT methods (Lu et al., 2004). KT transform has advantage over PCA as it is independent of the image scenes while PCA is dependent on image scenes.

Fung examined image differencing, PCA and KT transformation for land-cover change detection and found that images associated with changes in the near-infrared reflectance or greenness could detect crop type change and changes between vegetative and non vegetative features (Fung, 1990). Collins and woodcock used linear change detection techniques for mapping forest mortality using Landsat TM data and found that PCA and multi-temporal KT transformation were better than the GS orthogonalization process and that changes in KT wetness were the most reliable single indicators of forest change (Collins and Woodcock, 1996).
2.6.3. Classification

Classification category technique includes Post classification comparison (Delta classification), Spectral-Temporal combined analysis, Un-supervised and Hybrid change detection and ANN. These methods are based on the classified images. Though, they provide a matrix of change information but selecting numerous high quality training sample sets for image classification is time consuming and difficult. In these change detection techniques, impact of atmospheric and environmental differences between the multi-temporal images get reduced but at the same time there is multiplicative error propagation of classification which may give erroneous result (Singh, 1989).

In post classification comparison technique, multi-temporal images are separately classified into thematic maps and then comparison of classified image is done pixel by pixel.

In spectral temporal combined analysis, multi-temporal data are kept into a single file and then the combined dataset is classified and change labelled. But there is difficulty in identifying and labelling the change. Complete matrix of change info is also not obtained (Lu et al., 2004).

Unsupervised change detection is a first level automation of change detection process. In this technique, spectrally similar group of pixels are selected in date 1 image then spectrally similar group of pixels in date2 image clustered and labelled. Finally, changes are identified.

Hybrid change detection technique combines the advantages of the threshold and classification methods. It uses an overlay enhancement from selected image to isolate changed pixel, then a supervised classification is performed. A binary change mask is constructed from the result which further sieves out the change themes from the LULC maps produced for each date. This method excludes unchanged pixel from classification to reduce classification error but require threshold to identify change no-change mask. This technique is complex, requiring a number of steps, and the final outcome is dependent on the quality of change/no-change binary mask (Jensen, 1996).

J.F.Mas compared six change detection procedures using Landsat Multi-Spectral Scanner (MSS) images for detecting areas of change. The change detection techniques considered were Image differencing, Vegetative index differencing, Selective principal components analysis (SPCA), Direct multi-date unsupervised classification, Post-classification change differencing and a combination of image enhancement and post-classification comparison. It was found that Post-classification comparison was less sensitive to the spectral variations due to differences in soil moisture and in vegetation phenology between both scenes (Mas, 1999).

All the above discussed techniques of change detection assume that the relationship among spectral data and forest attributes are linear and not complex. But plant biophysical characteristic often do not confirm to this criteria (Jensen et al., 1999). For this reason nonparametric statistical method was adopted to describe this complex nonlinear relationship. Artificial Neural Network is one of such method. It makes no priori assumption about data. In classification of remotely sensed image, the ANN system learn by predicting output data from patterns learned from set of input training data. For change detection analysis spectral data for the period of change is used as input. A back propagation algorithm is often used to train the multi layer perceptron neural network model. Although in various studies this technique was found to be more accurate then other parametric techniques but the main disadvantage with this is, it requires a long training time and is sensitive to training data used.

ANN has been used for land-cover change (Dai and Khorram, 1999), forest change (Woodcock et al., 2001) and urban change. Liu and Lathrop applied the ANN approach to detect urban change using multi-temporal TM data and found that the ANN-based method improved accuracy about 20–30% compared to post classification comparison (Liu and Lathrop, 2002). In the study done by Dai and
Khorram, ANN based change detection was able to provide complete categorical information about the nature of changes and detect land-cover changes with an overall accuracy of 95.6 percent for a four-class (i.e., 16 change classes) classification scheme. In comparison, a maximum-likelihood supervised classification produced an accuracy of 86.5 percent, while using the same training data (Dai and Khorram, 1999).

### 2.6.4. Advanced model

This category includes Li-Strahler reflectance model, Spectral mixture model and Biophysical parameter estimation model. In these methods reflectance value are often converted to physically based parameters through linear or non-linear models. This helps in better interpretation. But these methods are time consuming and there is difficulty in development of suitable models for conversion of image reflectance values to biophysical parameter (Lu et al., 2004).

In this category, Linear Spectral Mixture Analysis (LSMA) is the most often used approach for detection of land-cover change (Roberts et al., 1998) and vegetation change (Rogan et al., 2002). It uses spectral mixture analysis to derive fraction images. End members are selected from training areas on the image or from spectra of materials occurring in the study area or from relevant spectra library. Changes are detected by comparing the ‘before’ and ‘after’ fraction images of each end member. The quantitative changes can be measured by classifying images based on the end member fractions (Lu et al., 2004).

Rogan et al. compared multi-temporal KT and LSMA methods for vegetation change detection using TM images in southern California and found that the LSMA approach provided about 5% higher change detection accuracy than the KT approach. A key step in implementing LSMA for change detection is to select suitable end members for development of high-quality fraction images and to find proportional compositions of each land-cover class. The big advantage of this approach is its stable, reliable and repeatable extraction of quantitative sub-pixel information that provides the potential to accurately detect land-cover change (Rogan et al., 2002). Li-Strahler and Biophysical parameter estimation model are useful for vegetation change detection only when sufficient field vegetation measurement data is available but both the methods are complex and requires more time.

### 2.6.5. GIS based category

When change detection involves long period intervals associated with multiple data source then GIS based techniques have been found useful for change detection analysis. This category includes Integrated GIS and R.S. method and Pure GIS method. It has the ability to incorporate different source data into change detection application. It integrates past and current maps of land use with topographic and geological data. The images over laying and binary masking techniques are useful in revealing quantitatively the change dynamics in each category. But the result is often dependent on data accuracy and format of different source data.

Hamisai Hamandawana et al illustrated how with the integrated use of GIS and Remote sensing, archival, historical and remotely sensed data can be used to complement each other for long-term environmental monitoring. With a database covering over 150 years between 1849 and 2001, their study (1) outline how modern remotely sensed data (i.e., CORONA and Landsat) can be complemented by historical in situ observations (i.e., travellers records and archival maps) to extend
temporal coverage into the historical past, (2) illustrate that different forms of declassified Cold War intelligence data (i.e., CORONA) can be constructively exploited to further scientific understanding and (3) provide a conceptual framework for collating and disseminating data at regional and international levels through electronic media (Hamandawana et al., 2005).

2.6.6. Visual analysis

It includes visual interpretation of multi-temporal image composite and on screen digitising of changed area. It is totally dependent on analyst experience, skill and knowledge. It is also highly time consuming and unsuitable for large area change detection. Further identification of nature of change is difficult to extract. Digitised high resolution aerial photography displayed on screen can be easily interpreted using standard photo interpretation techniques such as size, shape, shadow and texture (Jensen, 1996).

2.6.7. Recent advancement

In recent times with advancement of sensor technology, high sub meter range spatial resolution remotely sensed data is available. Most of the above traditional algorithm has been used to identify change using coarse to medium resolution images (Hayes and Sader, 2001; Lyon et al., 1998). They do not function successfully in high and very high resolution domain especially in the highly heterogeneous scene because high resolution images exhibit high frequency component details such as buildings, land parcel, roads, commercial/industrial services and shadow (Al-Khudhairy et al., 2005). Further there is problem of shadow.

To overcome these problems, instead of pixel based change detection technique (traditional methods) object oriented image segmentation change detection approach has been adopted (Niemeyer and Canty, 2003; Walter, 2004).

An object-based approach in high resolution image has been applied by Zhan et al. to identify shadow areas as objects instead of pixels so that adjacency relationships with surrounding areas can be derived (Zhan et al., 2005). It was concluded that per-object comparison between shadow areas and their corresponding surroundings is much more robust as compared with per-pixel approach. A shadow correction model is proposed that is based on quantitative comparison of different sites with different configurations. The experimental results show that local setting and configuration have to play an important role in shadow correction due to complexity of shadow effects.

Jungho and Jensen proposed a unique model of “Neighbourhood Correlation Image” analysis technique in which contextual information of correlation, slope and intercept associated with central pixel in its neighbourhood is made to derive detail “from to” change detection map using very high resolution image (0.7 x 0.7 mts) in urban set up (Jungho and Jensen, 2005). The overall accuracy obtained with 13 change and no change class with different neighbourhood configuration is more than 97%. Being a pixel based technique, its uniqueness lies in its usability in high resolution dataset and high accuracy of change detection. The present study is being done to analyse this technique in forest landscape using medium resolution remotely sensed dataset.

In the recent past use of knowledge based expert system, Artificial Neural Network (ANN), Fuzzy-logic and Genetic algorithm (Zhou and Civco, 1996) has been made for automation of classification for change detection.

Recently, the use of machine-learning algorithms, among which artificial neural networks and decision tree classifiers, has gained considerable attention as an alternative to conventional approaches such as the maximum likelihood classification (Huang and Jensen, 1997). Increased classification
accuracy is often cited as the primary reason for developing and applying these techniques. Machine-learning algorithms in the change detection environment are Multi-layer Perceptrons (MLP) (Gopal and Woodcock, 1996), Learning Vector Quantization (LVQ) (Chan et al., 2001) and Decision Tree Classifiers (DTC) such as, Quinlan’s See5.0. While perceptron procedures were reported as the most difficult to replicate, tree classifiers were found the easiest to use, and learning vector quantization the best performer when it concerned change detection accuracy (Chan et al., 2001).

In the present study Decision tree classification approach for change detection analysis is being taken due to some of its inherent advantages. Firstly, it is a non parametric classification method and makes no assumption about data distribution and independency. Secondly, the knowledge base created can be easily interpreted by storing it in rule based format. Thirdly, it is one of the most efficient forms of expert systems and suited for remotely sensed data sets with relatively small number of training samples (Jungho and Jensen, 2005; Quinlan, 2003).

In general, change detection algorithms discussed above from (i) to (vi) can be grouped into two categories (i) Binary change/no change or Image enhancement method like Image differencing Image ratioing, Vegetation index differencing and PCA. These algorithms provide information on the existence and magnitude of change but do not identify the nature of change (ii) Information on the nature of change extraction method i.e. Post classification comparison, CVA and Hybrid change detection method. These algorithms provide detailed information about the type of land cover change but it requires accurate thematic classification of the images. But there is also an ample possibility of classification error propagation into final output (Jungho and Jensen, 2005) (Chan et al., 2001; Lu et al., 2004).

2.6.8. Accuracy assessment

Assessing the accuracy of a change map is comparatively more difficult than accuracy assessment of simple thematic map because the number of change classes is the square of the number of thematic map classes and also many of the “from-to” classes are infrequent and rare (Biging et al., 1999). Change detection maps usually contain significant errors depending upon classification scheme employed, classification and rectification errors, remote sensor system characteristics, environmental conditions and the technique of change detection adopted (Biging et al., 1999). The three basic components of accuracy assessment are: 1) the sampling design used to select the reference sample; 2) the response design used to obtain the reference land-cover classification for each sampling unit; and 3) the estimation and analysis procedures (Stehman and Czaplewski, 1998). The sampling design is the protocol by which the reference sample units are selected. Sampling design also requires defining a sampling frame, along with the sampling unit (point and aerial) that forms the basis of the accuracy assessment. The response design is the protocol for determining the reference land-cover classification of a sampling unit. The reference classification must have high accuracy for a valid assessment (Congalton, 1991). The analysis and estimation protocols applied to the reference sample data constitute the third main component of an accuracy assessment.

Although there are many methods of accuracy assessment but the most widely promoted and used, is a confusion or error matrix. An error matrix effectively summarizes the key information obtained from the sampling and response design. The error matrix represents a contingency table in which the diagonal entries represent correct classifications, or agreement between the map and reference data, and the off-diagonal entries represent misclassifications, or lack of agreement between the map and the reference data.
It is used to provide a site-specific assessment of the correspondence between the image classification and ground conditions. The confusion matrix may, for example, be used to summarize the nature of the class allocations made by a classification and is the basis of many quantitative metrics of classification accuracy. However, there are many problems with accuracy assessment. A key concern is that the basic assumptions underlying the assessment of classification accuracy may not be satisfied. Rarely, for instance, will the data used be truly site-specific due to problems of mixed pixels and misregistration of the ground and remotely sensed data sets. The classes defined are also typically a generalization that may often be problematic. Moreover, rarely are the ground data an accurate representation of the ground conditions or the necessary information on the sampling design used in their acquisition provided. Obtaining a reliable confusion matrix is, therefore, a weak link in the accuracy assessment chain, yet it remains central to most accuracy assessment and reporting (Foody, 2001).
3. Study Area and Data Used

3.1. Location of study area

The area of study chosen for the current research is Kannod Forest Subdivision of Dewas district. The area is located in the central Indian province of Madhya Pradesh. Kannod Forest Sub-Division which is a part of Dewas Forest Division has a total geographical area of 1374.32 Sq.k.m. Out of this area, 622.62 Sq.k.m is under forest area which constitute 45.26% of total geographical area. The boundary of the study area lies between the latitude of 22° 15’ N and 22° 50’ N and longitude of 76°00’E and 77°10’ E (Fig. 3.1). Narmada River, which is one of the most important rivers of central India, makes the southern boundary and her tributary Khari river makes the western boundary of the study area. District of Sehore makes the eastern boundary and part of Dewas district makes the northern boundary. The whole area lies in the catchments area of Narmada River.

![Figure 3-1 Location of study area](image)

3.2. Reason for selection of particular study area

This research is mainly focusing on methodology development hence it can be applicable to any study area. But for the initial development we have to have a test site where various biophysical processes are active in forest landscape so that change associated with those processes in forest are detected well. As discussed earlier (Section 1.2.1) change in forest cover is either positive or negative.
Processes of plantation, regeneration and participatory forest protection and its conservation leads to positive change in forest cover whereas logging, thinning, illicit felling, illicit mining, forest fire and encroachment on forest land for agriculture purpose contributes towards negative change in forest. A test site was required where all these type of processes are active. Kannod subdivision forest of Dewas forest division was found fulfilling this criteria hence it was selected as area for this study.

Importantly as the study area is located in catchments of Narmada River. The existence of forest cover has a very significant impact on water recharge of Narmada River, which is the lifeline of central India. Hence information obtained regarding change in forest cover in the study area as a result of this study later could be used for assessment of water security for the region.

Another reason for selection of Kannod forest of Dewas district for this study was the information obtained regarding forest cover change from Forest Survey of India (FSI). FSI, which monitors the status of forest in India every two years, has suggested four districts of Madhya Pradesh, where appreciable change in forest cover during past four years has been detected. District of Dewas was one of them, the other three districts were Khandwa, Shivpuri and Burhanpur.

Here a special mention of construction of multipurpose dam on Narmada River would be pertinent. The construction of this dam involves a submergence of approximately 4000 ha of forest area. It was during the period of 2000 to 2005, extensive clear felling operation in the prospective submergence area was carried out. The dam was finally closed for water storage in 2005. This has led to appreciable change in forest cover which evokes special interest for the research.

Lastly one of the most important reasons for selection of this study area was my professional background of forestry and local knowledge of study area. Since I am a forest official of Madhya Pradesh Forest department and have ample experience of working in the study area, I had the important advantage of knowing ground level information related with various type of changes and the factors responsible for these changes in the forest of study area.

3.3. Factors determining forest characteristics

Interpretation of remote sensed imagery is a primary requirement for any change detection analysis to begin with. To analyse change in forest landscape a deep understanding of phenological characteristic of forest is a necessary requirement. Phenological characteristics of forests in turn are dependent on, topography, climate, temperature, rainfall, geology and soil of the area besides other micro climatic parameters.

3.3.1. Topography

The northern half of the area lies on the Malwa plateau. The average elevation of the plateau is 400 meters above the mean sea level. The land is undulation with a few scattered flat topped hills roughly aligned between the valleys from south to north. The general slope is towards the north. The valleys are covered with black cotton soil of varying thickness, mostly adapted for cultivation. Below the Malwa plateau in the south lays the narrow valley of the Narmada. It occupies the southern part of the area. The width of the valley is 15 to 30 kilometres. The elevation varies from 275 to 150. Proceeding westwards the valley is studded with hills alternatively cut up by numerous streams which join the Narmada along the southern boundary of the district. The result is that there are few stretches and pockets of alluvium along the streams.
3.3.2. Soil
The soil is predominantly Black Cotton soil which is very fertile, but at the same time, it does not allow rain water to percolate down owing to its impervious character. Since the topography of the district is rolling terrain, most of the rain water drains away into the rivers and flows out of the district. The soil is derived mainly from basaltic rocks more commonly known as Deccan trap. The soil of study area can be broadly classified as under:
- Black Cotton Soil: 85%
- Lateritic Soil: 8%
- Alluvial Soil: 3%
- Others (Loam, sandy loam, clay, rocky etc.): 4%

3.3.3. Climate
The climatic condition is generally warm to very warm during summer and moderate winter with rainy season in between. The rainy season starts with onset of monsoon showers in June and continues till September. The cold season begins in November and last up to beginning of February. Except monsoon season the general climatic condition throughout the year is dry.

3.3.4. Temperature
The maximum temperature fluctuates between 35°C to 43°C and minimum temperature from 12°C to 19°C. The hottest months are from March to June and the coldest months are from December to January.

3.3.5. Precipitation
Kannod forest sub-division receives southwest monsoon, which sets in by June and lasts up to September. The annual rainfall varies from 900 mm to 1209 mm. Out of total annual rainfall, 90% percent of rainfall is received during the months of June to September. The pattern of rainfall has an important effect on the phenological characteristics of the forest. The annual rainfall in Kannod in the year 1999 was 794 mm and 982 mm in 2005. Average rainy days were 47 days in 1999 and 39 days in 2005.

3.4. Forest profile of study area
Forest Type of Study area as per Champion and Seth classification is (Champion and Seth, 1968)
1. Type 3B/C-1-c: South Indian Moist Deciduous Slightly Moist Teak Forests (about 5% of total forests)
2. Type 5A/C1-b: Southern tropical Dry Deciduous Teak Forests (about 85% of total forests)
3. Type 5A/C-3: Southern Tropical Dry Deciduous Mixed Forests (about 10% of total Forests)
The main characteristic of forests of Kannod subdivision is that they are composed of a large number of dry species. It is usually predominated by the teak (Tectona grandis) except on the hills under limestones and quartz, or on hard lateritic and shallow soils, where the conditions are suitable for the predominance of Salai (Boswelia serrata) and Anjan (Hardwickia binata), respectively.

The top canopy of forest vegetation which have the predominant influence on reflectance recorded by sensor mainly constitute of Teak (Tectona grandis), Saj (Terminalia tomentosa), Dhwada (Anogeissus latifolia), Haldhu (Adina cordifolia), Landia (Lagerstroemia parviflora), Bija (Plerocarpus marsupium), Shisum (Dalbergia latifolia), and Kalam (Mitragyna parviflora). The scrubs, herbs and
grasses abound where the top canopy and the middle canopy are open due to adverse growing condition or biotic pressure.

### 3.5. Dynamics of forest change

The growing period of forest vegetation of the study area begins with the onset of monsoon and continues till one month after the rainy season i.e. from June to October. For forest vegetation monitoring of the area, period of October to November is the most suitable months as from December onwards *Tectona grandis* tree leaves, which is the dominant species in top canopy, is totally eaten away by an insect attack. After this attack whole of the teak leaf is devoid of chlorophyll and only skeleton of the leaf is left attached with branches. It is why this process is called as attack of skeletonizor (*Hablya purea, Hapailya maikarlis*). This is due to this reason second week of November was chosen for satellite data acquisition.

There are three major change processes, which have contributed towards forest cover change in the study area during the period of 1999 to 2005. During this period altogether 4000 ha of dense or open forest was cleared felled in the study area, which was coming under submergence of a multipurpose dam that is being constructed on Narmada River. The second major process was unreported decrease in density of forest due to increasing biotic pressure in the form of encroachments, fire and grazing. Lastly, during the aforesaid period sincere efforts has also been made to reverse the process of depletion of forest cover by taking up plantation and regeneration activities and adopting participative protection practices to conserve the forest. According to the official record provided by Divisional forest office the total area effected due to above activities are given below:

<table>
<thead>
<tr>
<th>Activities</th>
<th>Area in Hectare</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i) Plantation and regeneration activities</td>
<td>2655ha</td>
</tr>
<tr>
<td>(ii) Encroachment</td>
<td>772.985 ha</td>
</tr>
<tr>
<td>(iii) Clear felling in Submergence area</td>
<td>3977.29 ha</td>
</tr>
<tr>
<td><strong>Total Change in forest area of Kannod</strong></td>
<td><strong>7405.275 ha</strong></td>
</tr>
</tbody>
</table>

### 3.6. Agricultural practices

The knowledge of agricultural cropping pattern for visual interpretation of remote sensed data for forest vegetation monitoring is very important. In the study area agriculture is mostly rain fed. The major crops are Soybean, Cotton, Wheat and Gram. Wheat is sown in November and harvested in March where cotton is sown in July and harvested in December. Soybean, which is an oil seed crop is sown in July and harvested in October. Thus Cotton is the main agricultural crop whose spectrum can overlap with forest spectrum as the data used is of the month of November.

### 3.7. Socio economic profile

Increasing human and cattle population leads to increase in biotic pressure on forest. This is one of the major causes of perpetual depletion of forest cover. According to 1991 and 2001 census, total human population of Kannod subdivision was 165,915 and 206,711 respectively (Census of India report 1991, 2001). Thus 21% growth in population is observed during a period of ten years. The main economic activity of the people is agriculture. Almost 83% of rural energy need in the form of fuel wood is met by forest of the area. The ever-increasing demand of fuel wood besides other forest produce has been a major reason of forest depletion. Further the agricultural productivity of the area is
low hence with increasing population there is always an urge of local people to increase their land holding to maximise agricultural production. This economic scenario leads to encroachment in forest area and depletion of forest cover.

3.8. Remotely sensed and ancillary data

3.8.1. Remotely sensed data

The study proposes to detect change in forest landscape of the study area between year 1999 and 2005 using medium spatial resolution multi spectral remote sensed data. Satellite of Landsat, SPOT and IRS series usually provides medium resolution multi spectral data. The spatial resolution of 23.5 meters of IRS-1D and IRS-P6 LISS-III multi spectral sensor due to it’s readily availability in Indian context is considered suitable for this study. IRS ID and IRS P6 carry a medium resolution Linear Imaging Self Scanner (LISS-III) camera operating in three visible spectral bands (B2, B3, B4) suitable for vegetation monitoring. Besides these bands, it has fourth band (B5) as SWIR which is not considered due to its unsuitability for the purpose of the study. The spectral bands available are

- B2: 0.52-0.59 μm
- B3: 0.62-0.68 μm
- B4: 0.77-0.86 μm
- B5: 1.55-1.70 μm

For the purpose of this research it was required that bi-temporal data should be of near anniversary dates so that seasonal variation in phenological character of the vegetation under observation is kept at minimum. The remotely sensed data of second week of November was considered suitable for this study. The details of RS data acquired and used in this study are given in Table 3.1.

<table>
<thead>
<tr>
<th>Satellite ID</th>
<th>Sensor Type</th>
<th>No. of Bands</th>
<th>Spectral Range (micron)</th>
<th>Resolution (meters)</th>
<th>Swath Width (km)</th>
<th>Revisit Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>IRS-ID</td>
<td>LISS-III</td>
<td>Multi-spectral</td>
<td>3 VNIR 1 SWIR</td>
<td>0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70</td>
<td>23.5 70.5</td>
<td>141 148</td>
</tr>
<tr>
<td>IRS-P6</td>
<td>LISS-III</td>
<td>Multi-spectral</td>
<td>3 VNIR 1 SWIR</td>
<td>0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70</td>
<td>23.5 70.5</td>
<td>141 148</td>
</tr>
</tbody>
</table>
Table 3-2 Details of the Satellite data procured from NRSA

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Sensor</th>
<th>Path</th>
<th>Row</th>
<th>Data type</th>
<th>Lat</th>
<th>Long</th>
<th>Date of pass</th>
</tr>
</thead>
<tbody>
<tr>
<td>IRS-ID</td>
<td>LISS-3</td>
<td>097</td>
<td>056</td>
<td>BIL</td>
<td>22°10’N To 23°38’N</td>
<td>76°09’E-77°68’E</td>
<td>10-11-1999</td>
</tr>
<tr>
<td>IRS-P6</td>
<td>LISS-3</td>
<td>097</td>
<td>056</td>
<td>BIL</td>
<td>22°10’N To 23°38’N</td>
<td>76°09’E-77°68’E</td>
<td>13-11-2005</td>
</tr>
</tbody>
</table>

Working on LISS-III image acquired on near anniversary dates of 10NOV 1999 and 13 NOV 2005 of the study area, gives good opportunity to explore the usability of this sensor for Change Detection in forest landscape based on the Neighbourhood Correlation Image analysis technique with Decision tree classification approach.

3.8.2. Survey of India map sheets

Survey of India is the national mapping organization of India. All the map sheets either in the form of hard or soft copy is prepared by SOI. For this study SOI Map sheets of study area on 1:50000 scales were used for map to image geo-referencing. Also as digital forest boundary map of study area was not available with forest department of Madhya Pradesh hence these map sheets were used for generation of forest boundary map of the study area through digitization process. The hard copy map sheets were scanned, geo-referenced mosaiced and re-projected for further use. The details of map sheets used are given in Table 3.3

Table 3-3 Details of map sheets used

<table>
<thead>
<tr>
<th>S.No</th>
<th>Map sheet No</th>
<th>Scale</th>
<th>Projection</th>
<th>Year of publication</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>55B/6</td>
<td>1:50000</td>
<td>Polyconic</td>
<td>1970</td>
</tr>
<tr>
<td>2</td>
<td>55B/7</td>
<td>1:50000</td>
<td>Polyconic</td>
<td>1976</td>
</tr>
<tr>
<td>3</td>
<td>55B/9</td>
<td>1:50000</td>
<td>Polyconic</td>
<td>1971</td>
</tr>
<tr>
<td>4</td>
<td>55B/10 to 55B/15</td>
<td>1:50000</td>
<td>Polyconic</td>
<td>1973</td>
</tr>
<tr>
<td>9</td>
<td>55F/1</td>
<td>1:50000</td>
<td>Polyconic</td>
<td>1970</td>
</tr>
<tr>
<td>10</td>
<td>55F/2</td>
<td>1:50000</td>
<td>Polyconic</td>
<td>1970</td>
</tr>
</tbody>
</table>

3.8.3. Forest Survey of India “SFR” Report

Forest Survey of India biannual “State of Forest Report” which provides the information about the district wise extent of forest cover was utilized to determine the suitable study area where appreciable change in forest cover has occurred during last six years. Dewas district is one of the four district of Madhya Pradesh where most of the change in forest cover has been reported. The detail of forest cover of Dewas districts during the year 1999, 2001 and 2003 is explained below in Table 3.4
Table 3-4 Details of change in forest cover of Dewas district.

<table>
<thead>
<tr>
<th>Assessment Year</th>
<th>Total area of Dewas district (Sq.Km.)</th>
<th>Area under Dense forest (Sq.Km.)</th>
<th>Area under Open Forest (Sq.Km.)</th>
<th>Total Forest area (Sq.Km.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>7020</td>
<td>1108</td>
<td>536</td>
<td>1644</td>
</tr>
<tr>
<td>2001</td>
<td>7020</td>
<td>1157</td>
<td>560</td>
<td>1717</td>
</tr>
<tr>
<td>2003</td>
<td>7020</td>
<td>1027</td>
<td>776</td>
<td>1803</td>
</tr>
</tbody>
</table>

Although total forest area under observation has increased during the period of 1999 and 2003 but it is apparent that there is a total change of -81 sq km in area under dense forest and +240 sq km in area under open forest.

3.8.4. Working plan of Dewas Forest Division

Forest Working plan is one of the most authentic official reports on the status of forest of the Forest Division concerned. During working plan preparation detail assessment of the forest is done on the basis of existing growing stock, annual mean increment in forest stock and the previous management practices it was subjected to. This assessment becomes the basis for allotment of different forest area into various Working Circles. A comprehensive management prescription is then given for each type of working circles. During this exercise, growing stock of each of the forest block or forest compartment is recorded and mapped. It is updated every ten years. Thus management map, growing stock record prepared during working plan preparation and compartment history maintained subsequently becomes the source of information about the status of forest and the forestry activities taken in a particular forest compartment during any year.

In change detection analysis, since real time validation of change, no change class at any location is not possible as either or both of temporal R.S. data is historical hence such information can only be obtained through ancillary data or historical records. Working plan, management map, compartment history are the official records from which the information of status of forest or any change thereof can be well obtained.

In this study the status of forest and occurrence of any change at predetermined sample points in year 1999 and 2005 was obtained from existing compartment history, management map and stock map which are available on the scale of 1:50000 and 1:15000. Other relevant information about the quality and quantum of change in the study area was obtained from current working plan and other official information provided by Divisional Forest Officer, Dewas which in turn are utilized for comparison of results obtained from study.

3.8.5. Field data

Field verification of 51 randomly selected points which were earlier used for generation of reference data for training and testing the knowledge classifier was done with the use of GPS. At each and every point reached the present condition of forest was observed and historical information about condition of forest in 1999 and 2005 was assessed on the basis of stock map, compartment history and local knowledge. This information was later utilized to assess the accuracy of change classification done by visual interpretation of both date images.
4. Methods and analysis

4.1. Introduction

Considering the research questions and the objective aimed at, the research approach for change detection based on Neighbourhood Correlation Image analysis using Decision tree classification technique is phased out into five major stages. They are pre-processing of data, which includes geometric correction, image-to-image co-registration and radiometric normalization. Second stage is band wise Correlation, Intercept and Slope image generation. The third stage is generation of reference data for training and testing the knowledge based classifier and classifier generation. Next step is assessment of accuracy of classifier so developed and the final step is interpretation of result of classification and generation of change detection map. At every stage there is an utmost requirement of exactness of execution of processing and validation of result as any error at any stage may finally result into spurious change detection information. In this chapter techniques involved at each processing stage are discussed in details.

4.2. Classification Scheme for change and no change

Before initiating any change detection analysis it is very important to first define all those phenomena of change which are of interest. This study focuses to observe change in forest landscape. It is in this context understanding of forest cover classification is utmost requirement for defining those phenomena of change in forest landscape.

Basis of classification of forest cover adopted by “Forest Survey of India” is crown density. A crown density of 1 signifies totally dense forest and density of 0 as non forest. Forest cover classification done on the basis of crown density is:-

1. Dense forest  
   (i) Very Dense forest  
   (ii) Moderately Dense forest
2. Open forest
3. Non-forest/scrub

<table>
<thead>
<tr>
<th>Category</th>
<th>Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dense forest</td>
<td>Density more than 0.4</td>
</tr>
<tr>
<td>Very Dense forest</td>
<td>Density 0.7 to 1.0</td>
</tr>
<tr>
<td>Moderately Dense forest</td>
<td>Density 0.4 to 0.7</td>
</tr>
<tr>
<td>Open forest</td>
<td>Density 0.1 to 0.4</td>
</tr>
<tr>
<td>Non-forest/scrub</td>
<td>Density less than 0.1</td>
</tr>
</tbody>
</table>

The category Non-forest includes all lands without forest cover such as agricultural croplands, scrub, water bodies, riverbeds, and built up areas. For the purpose of this study three major forest cover class are considered. They are dense forest, open forest and non-forest. They will be classified as no change if no change occurs. The change classes associated with these classes are “Forest to Non forest”, “Forest to open forest”, “Open forest to Dense forest”, “Open forest to Non forest” and “Non-forest to Open forest”. Change class from Non forest to Dense forest was excluded as it is most improbable for non forest area to change into dense forest in a period of six years. A separate class for water was also considered in the study considering its unique spectral distinctiveness. Thus there are four no change classes and five change classes which is of interest and this study seeks to detect these classes using LISS-III image of 1999 and 2005 and test the usability of Neighbourhood Correlation Image analysis
technique of change detection in doing so. The notations used in this study for these classes are F-F, OF-OF, NF-NF and WW for no change classes of dense forest, open forest non-forest and water respectively. Similarly for change classes F-NF, F-OF, OF-F, OF-NF and NF-OF are used for dense forest to non-forest, dense forest to open forest, open forest to dense forest, open forest to non forest and non forest to open forest respectively.

4.3. Neighborhood correlation image analysis

NCI analysis technique uses contextual information of a pixel on first image associated with its neighbourhood and corresponding pixels on second image to determine the location and characteristics of change. The contextual information used is correlation coefficient, slope and intercept. The study is based on the fact that the same geographical area (pixel window) on two dates of imagery will tend to be highly correlated when no change occurs and less correlated when change occurs. The contextual information of “correlation” between two dataset provides information about change at a particular location. This analysis is based on the change magnitude and direction of brightness value by bands in a specific neighbourhood between two multi-spectral datasets. If the spectral change of the pixel within a specified neighbourhood is significant, the correlation coefficient between the two data sets in the neighbourhood falls to a lower value. The value of other two contextual information of slope and intercept will increase or decrease depending upon the magnitude and direction of change (Jungho and Jensen, 2005).

4.4. Decision tree classification approach

Decision tree is one of the inductive learning algorithms that generate a classification tree to classify the data. It is based on the “divide and conquer” strategy. The classification tree is made by recursive partitioning of the feature space, based on a training set. At each branching, a specific decision rule is implemented, which may involve one or more combinations of the attribute inputs or features (Quinlan, 2003).

In the present study Decision tree classification approach for change detection analysis is being taken due to some of its inherent advantages. Firstly, it is a non parametric classification method and makes no assumption about data distribution and independency (Chan et al., 2001; Quinlan, 2003). Secondly, the knowledge base created can be easily interpreted by storing it in rule based format. Thirdly, it is one of the most efficient forms of expert systems and suited for remotely sensed data sets with relatively small number of training samples. Lastly, it can handle non-categorical and categorical data equally well. (Jungho and Jensen, 2005; Quinlan, 2003).

The advantages of decision tree classifier over traditional statistical classifier include its simplicity, ability to handle missing and noisy data, and non-parametric nature i.e., decision trees are not constrained by any lack of knowledge of the class distributions.

4.5. Methods

The entire process of change detection using NCI analysis technique is explained by a conceptual flow chart given in Figure 4.1.
4.5.1. Pre-processing

For any change detection analysis it is important that the images which are being used for the analysis is free from cloud and if it is there a corrective step is required to annul the effect of cloud by masking or mosaicing with the use of overlapping images. Secondly if there is any presence of haze then its reduction process should also be employed. For this study the LISSIII data that was used is free from cloud and haze hence no such corrective processing was done.

4.5.2. Geometric correction

4.5.2.1. Image to map registration

Map sheets of study area prepared by Surveys of India (SOI) were used as reference data for image to map geo-correction. Permanent features like road crossings, bridges, railway lines, islands, reservoir and dams which were easy to locate both on map and image of year 1999 were used as GCPs for geometric correction. Theoretically three GCPs are required for this but other 16 GCPs well-distributed over the study area were taken for final geo-correction (Jensen, 1996). The Root Mean Square error on geo-correction was 0.676 Pixels. The transformation projection selected for the geometric correction was Transverse Mercator whose projection parameters are given below.
## Table 4-1 Projection Parameters

<table>
<thead>
<tr>
<th>S.NO</th>
<th>PROJECTION PARAMETERS</th>
<th>PARAMETERS DETAILS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Projection type</td>
<td>Transverse Mercator</td>
</tr>
<tr>
<td>2</td>
<td>Spheroid name</td>
<td>WGS 84</td>
</tr>
<tr>
<td>3</td>
<td>Datum Name</td>
<td>WGS84</td>
</tr>
<tr>
<td>4</td>
<td>Scale factor at central meridian</td>
<td>0.999444</td>
</tr>
<tr>
<td>5</td>
<td>Longitude of Central Meridian</td>
<td>24:57.6</td>
</tr>
<tr>
<td>6</td>
<td>Latitude of Origin of projection</td>
<td>24:00:00 N</td>
</tr>
<tr>
<td>7</td>
<td>False Northing</td>
<td>500000 meters</td>
</tr>
<tr>
<td>8</td>
<td>False Easting</td>
<td>500000 meters</td>
</tr>
</tbody>
</table>

### 4.5.2.2. Image to image registration

Change detection analysis requires that the co-registration of two images should be below sub-pixel level (Lu et al., 2004). The geo-referenced 1999 image was used to co-register the image of 2005. The root mean square error (RMSE) on final image to image co-registration achieved was 0.267 pixels. During this process special care was taken in selecting well distributed GCPs as any mis-registration at this stage could give erroneous change information result. Through visual inspection of geo-linked distinct pixel on both the images the geo-registration was ascertained to be within sub pixel level. The correctness of geo-registration was further cross verified by swiping and flickering in ERDAS IMAGINE 8.7 software.

### 4.5.3. Radiometric normalization

On preliminary inspection and analysis of DN values of features like deep water body on both the images it was found that radiometric normalization is required on any one of the two images to bring that image at near same radiometric level as of second image. The need of this normalization was also important because later, reference data generation for training and testing the knowledge base classifier was to be done on visual inspection of the two images. Pseudo invariant feature (PIF) radiometric correction method was used to bring image 1999 at radiometric level of image 2005. For this normalization process, features which have high, medium and low range of brightness values on the scene were considered for reference so that the normalization takes care of entire range of DN values of the scene. Feature like Barren soil or sand was considered as these pixels show high brightness values, Deep-water pixels were considered due to their lowest brightness values and healthy vegetation was considered as its pixels shows brightness values of medium range. All together 10 Pixels of Deep water, 7 pixels of Barren soil and 9 Pixels of Healthy vegetation were carefully selected which were found to be invariant feature on the both the images, for determining band wise correlation between the DN values of these features in the two images. The DN values of such PIFs observed in different bands in year 1999 and 2005 is given in Table No 4.2

### Table 4-2 Band wise DN values of Pseudo Invariant Features on Image 1999 and 2005

<table>
<thead>
<tr>
<th>S.N O</th>
<th>Features</th>
<th>IMAGE 1999</th>
<th>IMAGE 2005</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>X</td>
<td>Y</td>
</tr>
<tr>
<td>1</td>
<td>Water</td>
<td>335238</td>
<td>377818</td>
</tr>
<tr>
<td>2</td>
<td>Water</td>
<td>321580</td>
<td>408645</td>
</tr>
<tr>
<td>3</td>
<td>Water</td>
<td>321769</td>
<td>408481</td>
</tr>
<tr>
<td>4</td>
<td>Water</td>
<td>313337</td>
<td>371964</td>
</tr>
<tr>
<td>5</td>
<td>Water</td>
<td>315206</td>
<td>375528</td>
</tr>
</tbody>
</table>
A linear regression analysis was done between each pair of bands keeping DN values of 1999 as dependent variable. Gain and Intercept value of best-fit linear regression equation was determined to normalize the dependent variable (DN values of 1999).

The output of regression analysis obtained between band-2 pair is given in Figure 4.2. Value of gain (X Variable 1) and Intercept obtained was 1.2685 and 2.2549 respectively.

Figure 4.2 Regression output of band 1

For band 3 pair, value of gain and intercept obtained is 1.101 and 2.1218 respectively. Output of regression analysis is given below in figure 4.3.
For band 4 pair, value of gain and intercept obtained are 1.0336 and 4.8239 respectively. Output of regression is given below in Figure 4.4

Post normalization, DN values of PIFs for the year 1999 are given in Annexure 4.1. Gain and intercept value obtained on regression above is further applied to respective bands of entire image of 1999 using ERDAS IMAGINE 8.7 modeller to finally get radio-metrically normalized 1999 image bands for next stage processing and NCI image generation.

4.6. Neighborhood configurations

For generation of meaningful contextual information between the two images in the form of Correlation, Slope and Intercept images, circular neighbourhood (kernel) instead of rectangular neighbourhood is considered. There has been earlier study in which it has been found that there is not much difference in output of circular or rectangular kernel, rather circular kernel reduces the redundancy (Jungho and Jensen, 2005). For identification of most suitable NCI configuration appropriate for forests change detection, four neighbourhood configuration of sizes 1, 2, 3 and 4 pixel radius were considered for generation of Correlation, Slope and Intercept images (NCI). Neighbourhood configuration of different sizes considered in this study are shown in Figures 4.5.
NEIGHBOURHOOD CORRELATION IMAGE ANALYSIS TECHNIQUE FOR CHANGE DETECTION IN FOREST LANDSCAPE

Figure 4-5 Circular windows considered
At spatial resolution (pixel size) of 23.5 meters, window size of radius 1 to 4 pixel will be equivalent to an area of 0.49 ha to 4.47 ha respectively on ground. In the usual stock mapping of forest, change in area only of greater than 5 ha is observed and recorded on a scale of 1:50000 and it is also the minimum observational area of interest. Since ground extent equivalent to maximum window size of four-pixel radius is less than 5 ha hence it is considered as maximum window size for observation.

4.7. Generation of Correlation coefficient, Slope and Intercept Images
For generation of Correlation, Slope and Intercept images the FCC image of both the year were unstacked into respective band 2, band 3 and band 4 components. For a given neighbourhood configuration having \( n \) number of pixel around the central pixel, Correlation coefficient \( r \), slope \( a \) and intercept \( b \) is given by the following equation (Jungho and Jensen, 2005)

\[
\begin{align*}
    r &= \frac{\text{cov}_{12}}{s_1 s_2} \\
    \text{cov}_{12} &= \frac{\sum (BV_{i1} - \mu_1) (BV_{i2} - \mu_2)}{n-1} \\
    a &= \frac{\text{cov}_{12}}{s_1^2} \\
    b &= \frac{\sum_{i=1}^{n} BV_{i2} - a\sum_{i=1}^{n} BV_{i1}}{n}
\end{align*}
\]

Where, \( r \)= Pearson correlation coefficient.
\( \text{cov}_{12} \)=covariance between brightness values found in all bands of the two date data sets in the neighbourhood.
\( s_1, s_2 \)=standard deviations of the brightness values found in all bands of two date datasets in the neighbourhood.
\( BV_{i1}, BV_{i2} \)=brightness value of \( i^{th} \) pixel in all bands of image 1 and 2 respectively.
\( n \)= total number of pixels in the neighbourhood.
Value of \( n \) for neighbourhood of configuration of 1, 2, 3 and 4 pixel radius is 5, 13, 29 and 49 respectively.

\( \mu_1 \) and \( \mu_2 \) are the means of brightness values in the neighbourhood in image1 and image2 respectively.

For generating above contextual images all the bands of both date images were converted into grid format from img format so that geo-statistical operation on the images could be done in ARC GIS. An AML code was written to generate moving window covariance using above algorithm. The above code is given in Annexure 4.2. Using the above covariance image, Correlation coefficient, Slope and Intercept image was derived using focal statistics function of Arc map and applying above given formula.

### 4.8. Composites preparation

Total no of bands in consideration in this study are three each in Image1 (I_1) and Image2 (I_2). For each pair of band one Correlation, one Slope and one Intercept image was generated. Thus for three pair of bands, altogether three Correlation (C_1,C_2,C_3), three Slope (S_1,S_2,S_3) and three Intercept (I_n1,I_n2,I_n3) images were generated for a particular Neighbourhood configuration. A composite image was prepared by stacking three bands of image 1999, three bands of image 2005 and nine NCIs so generated as explained above. The schematic diagram of preparation of composite image is explained in Figure 4.6

![Schematic diagram showing preparation of NCI composites](image)

Thus each composite constituted of 15 layers. Such composites were prepared for each neighbourhood configuration. The composites so prepared were used as input for creation of knowledge base for training knowledge classifier by the use of Data mining SEE 5 software.

A raw composite having no NCI and consisting only of three bands each of image 1999 and 2005 was also made to study the utility of using NCI in change detection process through Decision Tree Classification approach, which is also one of the objective of this study.
4.9. Framework data generation for training and testing decision tree classifier

For training and testing of Decision Tree Classifier, reference data is required in the terms of pixel values of each layers (attributes) for which change/no change class is known. Such knowledge base is required to be generated for sufficient number of points randomly distributed over the entire area of study.

4.9.1. Random point generation

An earlier work of Mahesh Pal et al was referred for determining the total no of reference data required for training of Decision Tree Classifier in SEE5. The study recommends 250 to 300 cases per class as sufficient for training and testing the Decision Tree Classifier (Pal and Mather, 2003). In this study there are total nine “Change and No change” classes. When two points per square kilometres was taken as criteria for generating total no of random points with the help of random point generator in Arc View then total 2043 points are generated. This also approximately fulfils the above recommendation. A random point application was downloaded from [www.jennessent.com](http://www.jennessent.com) and installed in Arc View for this purpose. The point shape file of generated random points was then used further for assigning change no change classes to each point. It was also used to extract pixel values from each layer of NCI composites in ASCII format through “Pixel to ASCII” operation in ERDAS IMAGINE 8.7. The combined information of both this operation was later used as input in SEE5. The flow diagram showing the creation of ASCII output is given in Figure 4.7.

![Figure 4-7 Flow diagram for ASCII output generation](image)

4.9.2. Visual inspection and class assignment

“Change, No-Change” class assignment to each of the random point generated was done on visual inspection. The point layer was overlaid on geo-linked FCC image of 1999 and 2005. On visual comparison of the pixel, corresponding to a particular point on both the images, one of the nine appropriate “Change or No-Change” class was assigned to that point. Besides using my background local knowledge of forest landscape for assignment of class to random points, NDVI values associated with the pixel under consideration was also used to further facilitate this classification process. The final reference data for each random point is kept in ASCII format.
4.9.3. Division of points into training and testing sample

Out of total 2043 random points whose class assignment has earlier been done, 60% of points were used for training and 40% of points were kept aside for testing the accuracy of classification. The class wise details of no of points used for training and testing the classifier is given below in Table 4.3

<table>
<thead>
<tr>
<th>S.No</th>
<th>Class</th>
<th>Class Code</th>
<th>Total points</th>
<th>Points for Training</th>
<th>Points for Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Forest to Forest</td>
<td>1</td>
<td>509</td>
<td>308</td>
<td>201</td>
</tr>
<tr>
<td>2</td>
<td>Forest to Non forest</td>
<td>2</td>
<td>21</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>Forest to Open forest</td>
<td>3</td>
<td>302</td>
<td>192</td>
<td>110</td>
</tr>
<tr>
<td>4</td>
<td>Non forest to Non forest</td>
<td>4</td>
<td>159</td>
<td>158</td>
<td>101</td>
</tr>
<tr>
<td>5</td>
<td>Non forest to Open forest</td>
<td>5</td>
<td>24</td>
<td>16</td>
<td>8</td>
</tr>
<tr>
<td>6</td>
<td>Open forest to Forest</td>
<td>6</td>
<td>120</td>
<td>75</td>
<td>45</td>
</tr>
<tr>
<td>7</td>
<td>Open forest to Non forest</td>
<td>7</td>
<td>274</td>
<td>166</td>
<td>108</td>
</tr>
<tr>
<td>8</td>
<td>Open forest to Open forest</td>
<td>8</td>
<td>504</td>
<td>304</td>
<td>200</td>
</tr>
<tr>
<td>9</td>
<td>Water</td>
<td>9</td>
<td>30</td>
<td>21</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>2043</td>
<td>1251</td>
<td>792</td>
</tr>
</tbody>
</table>

4.10. What is SEE 5?

See5 is a data mining system that extracts informative patterns from data. Its job is to find how to predict a case's class from the values of the other attributes. See5 does this by constructing a classifier expressed as decision trees or as sets of rules that makes this prediction. See5 algorithm is the latest version of the ID3 and C4.5 algorithms (Quinlan, 2003). The criterion employed in See5 algorithm to carry out the partitions is based on concepts of Information Theory. It defines a statistical property called information gain that measures how well a given attribute separates the training samples according to their target classification. The main idea shared with this algorithm is to choose a variable that provides more information to realize the appropriate partition in each branch in order to classify the training set.

4.10.1. Data preparation for Decision tree classifier software SEE 5

Every See5 application has a short name called a filestem. All files read or written by See5 for an application have names of the form filestem.extension, where filestem identifies the application and extension describes the contents of the file. The filestem name for this research project is NCI.

Three files are essential for See5 applications. The first essential file is the names file (e.g. NCI.names) that describes the data type of attributes and classes. The second essential file is the application's data file (NCI.data) that provides information on the training cases from which See5 will extract patterns. The entry for each case consists of one or more lines that give the values for all explicitly-defined attributes in csv format. If the classes are listed in the first line of the names file, the attribute values are followed by the case's class value.

The value of predictive patterns lies in their ability to make accurate predictions. It is difficult to judge the accuracy of a classifier by measuring how well it does on the cases used in its construction; the performance of the classifier on new cases is much more informative. Hence to test the accuracy of predictive patterns, data of test cases are further loaded as input by a third type of file. This third type of file consists of new test cases (e.g. NCI.test) on which the classifier can be evaluated. This has
exactly the same format as the data file. A snapshot of print screen of data file for NCI2 is shown in Figure 4.8. Each row signifies one case (training or test point). The entry 1, 2 and 3 in first column shows the class code of change and no change class as explained in Table 4.3. Entries in other columns are the value of attributes. There are 15 such attributes for each case as explained in section 4.8 above.

Figure 4-8 Snapshot of Data file

For creation of names, data and test file a user interface developed by Mr. Ravi Kumar of National Remote Sensing Agency (NRSA) was used. The simultaneous running of ERDAS and SEE5 in background is required for this interface to work. The print screen view of the user interface is given below in Figure 4.9

Figure 4-9 Print screen view of the user interface

On inputting the ASCII file generated as explained in section 1.9.1 and 1.9.2, sought by the interface, names, data and test file is automatically gets generated. These files are then recalled by SEE5 to finally generate classifier and rule sets. The output is in the form of rule sets and result of application of classifier on the test file in the form of confusion matrix.

On generation of classifier another file with same filestem name and .out extension is created (NCI.out). This file is then used by the interface to generate knowledge base file with extension ckb (NCI.ckb).
4.11. **Change detection map generation**

The knowledge base file NCI.ckb file generated above is recalled in knowledge base classifier of ERDAS IMAGINE 8.7 to generate final classified change detection map for further interpretation.

4.12. **Accuracy assessment**

Accuracy assessment is performed by comparing two sources of information (Jensen, 1996)
- Remote-sensing derived classification data and
- Reference test data

In this study classified data is the data derived from Decision tree classifier application on different composites and reference test data are the classification information of 792 point reserved for this purpose as explained in section 4.9.3

The relationship of these two sets is summarized in an error matrix where columns represent the reference data while rows represent the classified data. An error matrix is a square array of numbers laid out in rows and columns that expresses the number of sample units assigns to a particular category relative to the actual verified category reserved as test reference data. From the error matrix various accuracies is derived.

4.12.1. **Overall Accuracy**

The overall accuracy is weighted by the number of samples (pixels) in each class, i.e. the sum of all samples on the diagonal divided by the total number of samples. However, as a single measure of accuracy, the overall accuracy (or percentage classified correctly) gives no insight into how well the classifier is performing for each of the different classes. In particular, a classifier might perform well for a class that accounts for a large proportion of the test data and this will bias the overall accuracy, despite low class accuracies for other classes. Therefore error matrix itself is not a sufficient way to predict the accuracy of the classified image.

4.12.2. **User’s and Producer’s Accuracy**

Producer’s accuracy (or Error of omission) represents an error from including a pixel to a particular class, which is actually not a part of the class. User’s accuracy (or Commission error) represents that a pixel, which should be part of a particular class but is not included.

4.12.3. **The Kappa Statistic**

The Kappa statistic was derived to include measures of class accuracy within an overall measurement of classifier accuracy (Congalton, 1991). It provides a better measure of the accuracy of a classifier than the overall accuracy, since it considers inter-class agreement. KAPPA analysis yields a Khat statistics that is a measure of agreement or accuracy.

A detailed analysis of the result of accuracy assessment is done to understand the whole process of NCI based change detection process.
5. Results and discussion

Introduction

This chapter analyses the results of change detection on the basis of accuracy assessment derived from error matrices as discussed in Section 4.12. Accuracy of change classification done through decision tree classification approach, considering contextual information in the form of NCI, is compared with the accuracy result when no NCI is taken into consideration. It is further analyzed by comparing the results obtained with different neighbourhood configuration. It is found that there is not much difference in accuracy result obtained between two scenarios i.e. when NCI is considered and NCI is not considered. In comparison of non NCI accuracy, the accuracy is higher only in the case of NCI-4 configuration. This result is further analyzed and discussed in context of correlation coefficient. Contrary to the expectation that no change classes will have higher correlation values, the values observed in these classes are generally low. Reasons for low correlation coefficient even in no change classes are most probably, sensor parameters, local climatic condition at the time of data capture, geo-correction accuracy and window size which is investigated in this chapter.

5.1. Accuracy assessment

The result of change detection in general is done on the basis of overall accuracy assessment and kappa coefficient. Whereas the class wise analysis is done on the basis of user and producer accuracy results. The confusion in classification between some classes is possible to understand on the analysis of these two results. Here classification result of single image for forest, open forest and non forest classes further helps in understanding this confusion.

5.1.1. Forest cover classification

Forest cover classification for the no change classes of dense forest, open forest and non forest is done on the FCC image of 1999 using decision tree classification approach. The error matrix of the classification is given in table 5.1 and the forest cover classification map is shown in figure 5.1.

<table>
<thead>
<tr>
<th>Forest cover class</th>
<th>Forest</th>
<th>Non Forest</th>
<th>Open Forest</th>
<th>Row Total</th>
<th>User accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>313</td>
<td>0</td>
<td>3</td>
<td>316</td>
<td>0.9905</td>
</tr>
<tr>
<td>Non Forest</td>
<td>0</td>
<td>94</td>
<td>7</td>
<td>101</td>
<td>0.9307</td>
</tr>
<tr>
<td>Open Forest</td>
<td>9</td>
<td>15</td>
<td>342</td>
<td>366</td>
<td>0.9344</td>
</tr>
<tr>
<td>Reference Total</td>
<td>322</td>
<td>109</td>
<td>352</td>
<td>783</td>
<td></td>
</tr>
<tr>
<td>Producer Accuracy</td>
<td>0.9720</td>
<td>0.8624</td>
<td>0.9716</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

From the error matrix it appears that there is a confusion between open forest and non forest as 15 cases of open forest are wrongly classified as non forest and 7 cases of non forest is wrongly classified as open forest.
5.1.2. Overall accuracy

The assessment of accuracy of change detection classification is done on the basis of error matrix. For testing the classification, 792 reference data were considered as explained in Section 4.9.3. The error matrices of classification done by decision tree classifier from knowledge base consisting only of six initial bands of two date images (without NCI), and with NCIs derived from different neighbourhood configuration of 1, 2, 3 and 4 pixel radius are given in Table 5.1 to 5.5. Table 5.1 gives the error matrix of classification when no NCI was used where Tables 5.2 to 5.5 explains the error matrices when NCI configuration of 1, 2, 3 and 4 pixel radius were considered. From the analysis of all the five error matrices it is found that overall accuracy i.e. with and without NCI, is within a narrow range of 82 to 84 percent. When NCI-1, NCI-2 and NCI-3 are considered the overall accuracy goes down below the overall accuracy of without NCI. The decrease is most in the case of NCI-3. But in the case of NCI-4 overall accuracy is higher than overall accuracy of all cases either with or without NCI. This shows that decision tree classifier utilizing NCI-4 knowledge base is most efficient in this case though the difference is not significant.

5.1.3. Kappa coefficient

Kappa coefficient, which is a more realistic indicator of classification accuracy, is also calculated for each case. On the analysis of Kappa similar trend is observed as was in overall accuracy. The Kappa coefficient in all the cases is found within a narrow range of 0.79 to 0.80. Kappa coefficients of NCI-1, NCI-2 and NCI-3 are below the Kappa coefficient of the case when no NCI is used. It is lowest in the case of NCI-3. Only in the case of NCI-4 it is higher than that of without NCI.
Table 5-2 Error matrix of change classification without NC1

<table>
<thead>
<tr>
<th>Without NC1</th>
<th>ACCURACY ASSESSMENT WITHOUT NCI</th>
<th>Row Total</th>
<th>User Acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F-F</td>
<td>FNF</td>
<td>FOF</td>
</tr>
<tr>
<td>F-F</td>
<td>180</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>F-NF</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F-OF</td>
<td>15</td>
<td>3</td>
<td>98</td>
</tr>
<tr>
<td>NF-NF</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>NF-OF</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>OF-F</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>OF-NF</td>
<td>0</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>OF-OF</td>
<td>3</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>WW</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Ref.Total</td>
<td>201</td>
<td>10</td>
<td>110</td>
</tr>
<tr>
<td>Pro. Acc.</td>
<td>0.9</td>
<td>0.89</td>
<td>0.852</td>
</tr>
</tbody>
</table>

OVERALL ACCURACY = 83.71                KHATT = 0.7987

For class description see section 4.2

Table 5-3 Error matrix of classification with NC1-1

<table>
<thead>
<tr>
<th>NCI-1</th>
<th>ACCURACY ASSESSMENT WITH NCI 1</th>
<th>Row Total</th>
<th>User Acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F-F</td>
<td>FNF</td>
<td>FOF</td>
</tr>
<tr>
<td>F-F</td>
<td>183</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>F-NF</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>F-OF</td>
<td>14</td>
<td>1</td>
<td>96</td>
</tr>
<tr>
<td>NF-NF</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>NF-OF</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>OF-F</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>OF-NF</td>
<td>0</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>OF-OF</td>
<td>1</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>WW</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Ref.Total</td>
<td>201</td>
<td>10</td>
<td>110</td>
</tr>
<tr>
<td>Pr Acc.</td>
<td>0.9</td>
<td>0.2</td>
<td>0.87</td>
</tr>
</tbody>
</table>

OVERALL ACCURACY = 83.08                KHATT = 0.7912

Table 5-4 Error matrix of classification with NC1-2

<table>
<thead>
<tr>
<th>NCI-2</th>
<th>ACCURACY ASSESSMENT WITH NCI 2</th>
<th>Row Total</th>
<th>User Acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F-F</td>
<td>F-NF</td>
<td>F-OF</td>
</tr>
<tr>
<td>F-F</td>
<td>179</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>F-NF</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>F-OF</td>
<td>12</td>
<td>1</td>
<td>98</td>
</tr>
<tr>
<td>NF-NF</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>NF-OF</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>OF-F</td>
<td>8</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>OF-NF</td>
<td>0</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>OF-OF</td>
<td>2</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>WW</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Ref.Total</td>
<td>201</td>
<td>10</td>
<td>110</td>
</tr>
<tr>
<td>Prod.Acc</td>
<td>0.9</td>
<td>0.1</td>
<td>0.89</td>
</tr>
</tbody>
</table>

OVERALL ACCURACY = 83.46                KHATT = 0.7962
Table 5-5 Error matrix of classification with NC1-3

<table>
<thead>
<tr>
<th>NCI-3</th>
<th>ACCURACY ASSESSMENT WITH NCI 3</th>
<th>Row Total</th>
<th>User Acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-F</td>
<td>189 0 10 0 0 0 11 0 4 0 214 0.883</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-NF</td>
<td>0 0 0 0 0 0 0 0 0 0 0 DIV/0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-OF</td>
<td>8 2 92 0 0 1 0 11 0 114 0.807</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NF-NF</td>
<td>0 0 81 0 0 15 1 3 100 0.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NF-OF</td>
<td>0 0 0 1 4 0 0 1 0 6 0.667</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OF-F</td>
<td>3 0 0 0 0 22 0 2 0 27 0.815</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OF-NF</td>
<td>0 8 14 0 0 6 0 0 0 111 0.748</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OF-OF</td>
<td>1 0 8 3 4 11 10 175 0 212 0.826</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WW</td>
<td>0 0 0 2 0 0 0 0 6 0.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ref.Total</td>
<td>201 10 110 101 8 45 108 200 9 792</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prod.Acc</td>
<td>0.9 0.84 0.802 0.5 0.49 0.769 0.875 0.67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OVERALL ACCURACY = 82.32</td>
<td>KHATT = 0.7808</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5-6 Error matrix of with NC1-4

<table>
<thead>
<tr>
<th>NCI4</th>
<th>ACCURACY ASSESSMENT WITH NCI 4</th>
<th>Row Total</th>
<th>User Acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-F</td>
<td>186 0 7 0 0 11 0 1 0 205 0.907</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-NF</td>
<td>0 3 0 0 0 0 0 0 3 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-OF</td>
<td>12 2 95 0 0 2 0 11 0 122 0.779</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NF-NF</td>
<td>0 0 89 3 0 11 0 2 105 0.848</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NF-OF</td>
<td>0 0 1 1 0 0 0 0 2 0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OF-F</td>
<td>1 0 0 1 24 0 4 0 30 0.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OF-NF</td>
<td>0 4 1 9 0 88 8 0 110 0.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OF-OF</td>
<td>2 1 7 2 3 8 9 176 0 208 0.846</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WW</td>
<td>0 0 0 0 0 0 0 7 7 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ref.Total</td>
<td>201 10 110 101 8 45 108 200 9 792</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prod.Acc</td>
<td>0.9 0.3 0.86 0.881 0.125 0.53 0.815 0.88 0.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OVERALL ACCURACY = 84.47</td>
<td>KHATT = 0.8078</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5-2 Overall Accuracy and Kappa Coefficient

A graphical representation of both “Overall accuracy” and “Kappa” is given in Figure 5.1 which clearly shows that NCI-4 configuration gives the best accuracy results.
5.1.4. User accuracy

User accuracy gives the probability that a pixel classified on the map actually represent that category on the ground. A graphical representation of user accuracy of different change and no-change classes with respect to NCI size including accuracy obtained without NCI (NCI-0) is given in Figures 5.2. From the analysis of user accuracy it is found that it is in general higher in no-change classes than in change classes in all NCI cases. For no-change classes (F-F, OF-OF, NF-NF) its value is approximately higher than 0.80 whereas it is lower than the value of 0.80 for change classes. It is highest for F-F (Forest to Forest) class and lowest for NF-NF (Non forest to Non forest) class. All the change classes have the highest value of user accuracy in NCI-4 except F-F. In this class it is highest when no NCI is used. One of the interesting observations made is regarding unpredictable trend of change in user accuracy of any of the change or no-change classes, which involves a non-forest class such as NF-NF, OF-NF and F-NF. It seems that it is due to the fact that class NF consists of varied features like barren land, riverbed, agricultural crop and built-up area of different shape and sizes. The confusion between non-forest and open forest is also very much evident in forest cover classification result in section 5.1.1.

Figure 5-3 User Accuracy in Change and No-Change classes

5.1.5. Producer Accuracy

Producer accuracy signifies probability of a reference pixel being correctly classified. The trend of change of producer accuracy with respect to NCI configurations inclusive of its value in the case when no NCI (NCI 0) is considered is graphically represented in Figure 5.3. Producer accuracy of no-change classes (F-F, NF-NF, OF-OF) and producer accuracy of change classes (F-OF, NF-OF, OF-F, and OF-NF) are shown separately. From the analysis of the producer accuracy of all classes across all the NCIs, it is observed that producer accuracy is in general higher in no-change classes and lower in change classes. The highest producer accuracy value for change classes is 0.89 for F-OF when no NCI is considered. In the case of no-change classes this value is 0.94 in NCI-3. Producer accuracy is highest for F-F in all NCI cases. In change classes it is the F-OF class which shows higher value in all NCIs. Similar to user accuracy result, NF-NF, F-NF and NF-OF have relatively lower value of producer accuracy. The producer accuracy of these classes also shows more sensitiveness towards the variation in NCI size which may be due to the different shape and size and spectral variability of features included in NF class.

From the above analysis it is very much clear that neighbourhood configuration of 4 pixel radius in general gives better user as well as producer accuracy result for all classes. Amongst no-change classes F-F and F-OF amongst change class shows better user and producer accuracy. It is also observed that though producer accuracy for F-OF is better but same is not true for reverse process of
change i.e. OF-F but in the case of user accuracy, these two classes have approximately equal accuracy.

![Producer Accuracy in Change and No-Change classes](image)

Taking user and producer accuracy together it can be concluded that within no change classes of F-F, OF-OF and NF-NF, all the classifiers are able to classify these classes efficiently in the same order. In the case of change classes F-OF and OF-F are most efficiently classified by all classifiers.

### 5.2. Map Output

The FCC image of forest area within the Kannod Sub-division of year 1999 and 2005 is given in Figure 5.4.

![FCC Images of 1999 and 2005 of Forest area of Kannod Sub-division - Dewas district](image)

The change detection map derived without using NCI is shown in Figure 5.6 where as the change detection map derived from using NCI-1, NCI-2, NCI-3 and NCI-4 is shown in Figures from 5.5 and 5.6.
Figure 5-6 Change detection map with and without using NCI information
5.2.1. Area Analysis

From the change detection map generated total area of each change and no change classes is evaluated which is given in Table 5.6. On the analysis of this area table it is found that all the classifiers either with NCI or without NCI are giving approximately similar area in no change classes (F-F, NF-NF, OF-OF and WW). Within change classes area detected in OF-NF, OF-F classes are similar but there is too much variation in detection of F-NF and NF-OF classes. This may be due to lesser no of training pixels in these classes. Considering the average area of all classes for all NCI configurations it is found that forest cover of 28962 ha is degrading (high crown density class to low density class) and 7932 ha is getting restocked in terms of density.

<table>
<thead>
<tr>
<th>CLASS</th>
<th>FF</th>
<th>FNF</th>
<th>FOF</th>
<th>NNF</th>
<th>NFOF</th>
<th>OFF</th>
<th>OFNF</th>
<th>OFOF</th>
<th>WW</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCI-0</td>
<td>31499.40</td>
<td>355.70</td>
<td>17956.08</td>
<td>15825.28</td>
<td>1583.96</td>
<td>5589.32</td>
<td>9710.38</td>
<td>27740.68</td>
<td>831.30</td>
</tr>
<tr>
<td>NCI-1</td>
<td>27572.41</td>
<td>10.49</td>
<td>16765.04</td>
<td>15185.22</td>
<td>4112.33</td>
<td>5382.89</td>
<td>12987.48</td>
<td>27992.56</td>
<td>1083.68</td>
</tr>
<tr>
<td>NCI-2</td>
<td>28861.58</td>
<td>480.62</td>
<td>15544.95</td>
<td>14875.41</td>
<td>2160.62</td>
<td>5307.56</td>
<td>11771.87</td>
<td>31099.74</td>
<td>989.74</td>
</tr>
<tr>
<td>NCI-3</td>
<td>28783.71</td>
<td>0.00</td>
<td>16030.71</td>
<td>16185.84</td>
<td>336.71</td>
<td>4883.16</td>
<td>13146.42</td>
<td>30850.78</td>
<td>874.76</td>
</tr>
<tr>
<td>NCI-4</td>
<td>28497.65</td>
<td>58.76</td>
<td>17127.21</td>
<td>15447.04</td>
<td>6523.01</td>
<td>3781.59</td>
<td>12865.00</td>
<td>25916.43</td>
<td>875.43</td>
</tr>
</tbody>
</table>

5.3. Analysis of Contextual Information

Contextual information of Correlation, Intercept and Slope was expected to add valuable knowledge base for decision tree classifier to increase its efficiency in detecting magnitude and characteristics of change. As discussed above, results of overall accuracy and Kappa coefficient shows that it is only
with NCI-4 the efficiency of the classifier increases over without NCI classifier. But this increase is not as significant as it is higher only by two percent. This result gives ample reason to investigate the pattern of contextual information to find out the causes of its being not so contributive in building the knowledge base.

To investigate this, the information of correlation coefficient, intercept and slope for all the pixels (1251) in all bands used to train the classifier is extracted from various NCI configurations. The number of pixels in each class for which this information is extracted is given in Table 5.8.

Table 5-8 Training pixels in different classes

<table>
<thead>
<tr>
<th>Class</th>
<th>F-F</th>
<th>F-OF</th>
<th>F-NF</th>
<th>NF-NF</th>
<th>NF-OF</th>
<th>OF-F</th>
<th>OF-NF</th>
<th>OFOF</th>
<th>WW</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Points</td>
<td>308</td>
<td>11</td>
<td>192</td>
<td>158</td>
<td>16</td>
<td>75</td>
<td>166</td>
<td>304</td>
<td>21</td>
<td>1251</td>
</tr>
</tbody>
</table>

For statistical analysis of these information, mean of correlation, intercept and slope for all pixels was calculated for each class. To compare the result between change and no-change classes these classes are further grouped into “No-change and “Change” group. NCI wise detail information of these values is given in Annexure 5.2.

On the analysis of values of correlation coefficient it is evident that the average correlation coefficient of all the classes in all bands for all NCI is generally low. Correlation coefficients of No-change classes are though higher than average correlation coefficient of Change classes but it is still far below than what it should be. In ideal case of No-change class of “Forest to Forest” or “Non forest to Non forest” or “Open forest to Open forest” the value of correlation coefficient should be one or near one. Across all the four NCI configurations in band 2, its value ranges only from minimum mean value of 0.224 for class NF-NF in NCI-1 to maximum mean value of 0.539 for class F-F in NCI-4. It is the pattern of correlation coefficient in the other two bands also. Separate graphical plot was drawn for all classes in Change and No-change classes for each band between correlation coefficient and NCI size, which is shown in Figure 5.11 to Figure 5.13.

![Correlation Coefficient of Change and No-Change classes in Band 2](image-url)

Figure 5-8 Correlation Coefficient of Change and No-Change classes in Band 2
Figure 5-9 Correlation Coefficient of Change and No-Change classes in Band 3

Figure 5-10 Correlation Coefficient of Change and No-Change classes in Band 4

From the study of graphs it is evident that correlation coefficient tends to increase with increase in neighbourhood size with only exception of WW (Water) in Band 4.

In some cases the mean correlation value of no-change class is even lower than its value in change class as is evident from its value in band 3 when NCI-1 is considered. Here the mean value of change class is 0.275692, which is lower than the corresponding value in change class which is 0.312231. Such comparison can be made within the individual class and even at pixel level. This implies that high correlation coefficient do not always signify a no-change class.

It is here the other two information of intercept and slope comes into play to determine correct class. Though it is the correlation coefficient, which requires detail analysis to understand the process, but an observation regarding intercept and slope can also be made by comparing their values in different classes with respective correlation values in that class. From the analysis of intercept and slope values for NCI4 in Annexure5.2 it is observed that when correlation value is lowest for any class within change and no-change group then intercept value is highest and slope value is lowest for that class. For example in NCI-4 when correlation value of NF-NF in Band 3 is 0.3953 which is minimum in no-change class group then its corresponding intercept value is 51.73 which is highest in that group. Similarly slope value of 0.4626 is lowest in the group. From this an inference can be made that intercept and slope may facilitate correlation coefficient to determine the true nature of change.

From the above discussion on the nature of contextual information obtained when different Change or No-change classes are considered under various NCI configurations, it can be concluded that
correlation coefficients for No-change classes are too low and the reason for such low values should be investigated.

5.4. Reasons for Low correlation coefficient

The reason or low correlation coefficient for even No-change classes may be due to the following reasons, which need to be investigated.

- Sensor characteristics
- Mis-registration of two date image
- True Radiometric correction
- Climatic condition during data acquisition
- Training of pixels for classification
- Effect of Window size

5.4.1. Sensor characteristics

The images used in the study have been taken from two different platforms as described in Chapter 3. From the header file of the data it is found that satellite-heading angle for IRS 1D and IRS P6 is 192.878 and 193.967 respectively. The sun elevation at the time of data capture for IRS 1D and IRS P6 was 48.954 and 46.566 respectively. The difference in sun elevation here is not so significant but there may be some possibility of change of scene characteristics due to this difference.

5.4.2. Mis registration of images

As previously discussed in 4.5.2, image-to-image registration plays a very important role in change detection result. To rule out this possibility images co-registration were again checked carefully and it was found to be within sub pixel level. Hence this possibility can be safely ignored.

5.4.3. True radiometric correction

It is a well-established fact that ideally two images can never be brought to same radiometric level but this radiometric difference can be minimized. It is possible that discrepancy in correlation between two images may arise due to incorrect normalization technique employed. To rule out this possibility it was investigated as how the radiometric normalization has affected the value of correlation for any pixel. To check this, un-normalized image of 1999 was taken and correlation coefficient of a pixel in homogeneous forest area within a specified neighbourhood on both images was manually calculated and compared with the correlation value of the same pixel which was obtained when radiometric normalization has been previously done. It was found that correlation value obtained with non-normalized image is lower than the value obtained when normalized image was used. It can be inferred that radiometric normalization has no reducing effect on correlation value. Hence this possibility can also be safely ignored.

5.4.4. Climatic condition

Variation in phenological characteristics of the vegetation cover of the scene may also contribute to overall spectral change of the scene in image 2005 with respect to image 1999. Since the phenological characteristics depends on the climatic condition prevalent at the scene during the time period in which the image was captured hence it is important to further look into the climatic condition of the study area during month of November of year 1999 and 2005.

Table 5-9 Climatic parameters at the time of Data capture
Climatic parameters | Annual rainfall | Total Rainy days | Average monthly temperature in Nov. | Rainfall in Oct. and Nov |
--- | --- | --- | --- | --- |
1999 | 794 | 47 | 17.3 | 110 |
2005 | 982 | 39 | 19.2 | 00 |

From the comparison of climatic condition prevalent in year 1999 and 2005 it is observed that total annual rainfall in year 2005 was 188 mm. more than rainfall in year 1999. Rainfall during the months of October and November was 110 mm in 1999 but no rainfall was recorded in 2005 during this period. There is also a difference of 8 rainy days between two years. Average monthly temperature in November shows not much difference. From the above climatic data it is found that in 1999 though annual rainfall was less than of 2005 but it continued till October-November. This might have extended the growth period of forest vegetation in year 1999. Thus it can be inferred that above variation in climatic condition might have contributed towards overall shift in phenological characteristics of vegetation.

5.4.5. Training of pixels for classification

Assignment of forest class to training pixels into forest, open forest and non forest classes through visual inspection of FCC images is a subjective process. The classification done is totally based upon visual analysis of colour, texture, brightness and location of the pixel. Here the knowledge of expert who is doing the exercise becomes an important factor. It is assumed that my background knowledge of study area to some extent might have helped in correct classification of the pixel. To further reduce the subjectivity in classification, NDVI value of the pixel was also considered before assignment of a particular class to the pixel. But besides taking all preventive measures for getting correct classification, it is fairly possible that final classification is not as accurate as required. This may cause ambiguity in generation of decision tree for classification. As a result of which final result may not be as per expectation. In this context number of pixels (reference data) for training the classifier is also an important factor, which may have given this result.

5.4.6. Effect of window size

From the formula of correlation coefficient given in section 4.7, it is evident that correlation coefficient is directly dependent on covariance between the value of pixels on both images in a specified neighbourhood. Covariance in turn is directly proportional to variance of pixel values in that neighbourhood. The low value of correlation coefficient needs an investigation of value of variance as a function of neighbourhood size.

To investigate this fact, spectral values of all pixels within in a bigger square neighbourhood windows of sizes 17x17, 15x15, 13x13, 11x11 along with already considered 9x9, 7x7, 5x5 and 3x3 (equivalent to circular windows of radius 8.7.6.5.4.3.2 and 1 pixel) was taken in a homogeneous forest area of one image. The DN values of pixels in these windows for band2 are shown in Figure 5.14. Similar representation for band 3 and band 4 is given in Annexure 5.3. Variance in spectral values of all pixels considered for each window size was calculated for each band, which is summarized in Table 5.9.
coefficient of no change area may increase accordingly and similarly for change area it may further

hence it appears that if bigger windows size 15x15 or 17x17 are considered correlation

Figure 5-11 DN values in window sizes considered for variance calculation in Band 2

Figure 5-12 Change of variance with different window sizes

The trend of change of variance with respect to window sizes is graphically shown in Figure 5.11. From the analysis of these values it is found that with increase in window size variance increases for the considered homogeneous forest. The increase is sudden at window size 13x13 with maximum at 17x17 size. Hence it appears that if bigger windows size 15x15 or 17x17 are considered correlation coefficient of no change area may increase accordingly and similarly for change area it may further

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<tbody>
<tr>
<td></td>
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<tr>
<td>BAND 2</td>
<td>2.0278</td>
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<td>BAND 3</td>
<td>1.5278</td>
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VARIANCE of BAND1 DENSE FOREST

<table>
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<td>88</td>
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<tr>
<td>84</td>
</tr>
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</table>
decrease. The difference of correlation coefficient between classes of no change area and change area is expected to be significant. This significant difference in correlation coefficient will add required knowledge in the form of attribute which will then facilitate the decision tree to develop better classifier, which may be more accurate.

5.5. Testing with bigger neighborhood configuration

On the above analysis of factors responsible for low correlation coefficient it is decided to test the effect of still bigger neighbourhood on the utility of NCI information for increasing overall accuracy of classification. To test this, for simplicity, square neighbourhood of 11x11, 15x15 and 17x17 pixel was considered and applied on a small subset of 2222x5555 pixels of the two images. For training and testing the classifier total 554 random points were generated. Change no-change was assigned to these points in the similar way as was earlier done. Class wise details of training and testing pixels are given in Table 5.10.

<table>
<thead>
<tr>
<th>Class</th>
<th>F-F</th>
<th>F-OF</th>
<th>NF-NF</th>
<th>OF-NF</th>
<th>OF-F</th>
<th>OF-OF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>250</td>
<td>40</td>
<td>6</td>
<td>11</td>
<td>15</td>
<td>35</td>
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<tr>
<td>Testing</td>
<td>150</td>
<td>18</td>
<td>3</td>
<td>6</td>
<td>6</td>
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<tr>
<td>Total</td>
<td>400</td>
<td>58</td>
<td>9</td>
<td>17</td>
<td>21</td>
<td>49</td>
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</tbody>
</table>

Since the subset was small hence all the earlier classes of change and no-change were not present. Thus classifier was tested on six available classes only. Classifier so generated in SEE5 was applied on NCI-11, NCI-15 and NCI-15. It was also applied on without NCI (NCI-0) composite of same image subset for comparison of results. The Overall accuracy and Khat obtained from the error matrices of these classifications for above NCIs are given in Table 5.11

<table>
<thead>
<tr>
<th>NCI Configuration</th>
<th>NCI-0</th>
<th>NCI-11</th>
<th>NCI-15</th>
<th>NCI-17</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Accuracy</td>
<td>88.832</td>
<td>90.355</td>
<td>90.862</td>
<td>89.847</td>
</tr>
<tr>
<td>Khat</td>
<td>0.7208</td>
<td>0.7569</td>
<td>0.7653</td>
<td>0.7391</td>
</tr>
</tbody>
</table>
The detail error matrices of the above change detection classification are given in Annexure 5.4. From the above result it is very much evident that NCI plays an important role in increasing the efficiency of classifier as accuracy with NCIs configuration is greater than the accuracy when no NCI is considered. It is also observed that the Overall accuracy and Khat is highest in NCI configuration of 15x15 pixels. The overall higher accuracies compare to accuracy of NCI-1, NCI-2, NCI-3 and NCI4-4 earlier evaluated is due to the reason of lesser number of Change and No-change classes considered here. The classified change detection maps of subset is given in Figure 5.7. From the NCI-15 and NCI-17 change detection map it is observed that these two configurations are able to detect OF-NF class more accurately than others NCIs, NCI-15 being the most efficient of all.

5.6. Inference

From the above discussion it can be inferred that for forest change detection with medium resolution remote sensed imagery, “Neighbourhood Correlation Image Analysis Technique” requires bigger neighbourhood so that contextual information of correlation, intercept and slope derived from the neighbourhood may add valuable knowledge to decision tree classifier. The detail conclusion is given in chapter 6.
6. Conclusions and recommendations

The main objective of this study was to investigate the usability of NCI analysis technique for change detection in forest landscape with the use of medium spatial resolution satellite data and Decision tree classification approach. The origin of the concept of using contextual information of Correlation in neighbourhood of a pixel in this study was the simple geo-statistical fact that the same geographical area (neighbourhood window) on two dates of imagery will tend to be highly correlated if no or little change has occurred and uncorrelated when change occurs. The other two derived information such as Intercept and Slope were expected to facilitate the correlation information in further determining direction and magnitude of change when used with knowledge base decision tree classification approach. The three most important considerations of this study was the use of contextual information, medium resolution imagery and knowledge based (machine learning) classification. This research has tried to find out interrelationship among them in detecting change in forest landscape.

6.1. General Conclusion

The result of this study is contrary to the expectation that correlation between pixel values of the same unchanged areas on the two different images would always be high. It can be concluded that NCI information obtained with a smaller window size of one, two or three pixel radius does not provide this change information rather it tends to degrade the detection process. But when a window size of four pixel radius is considered it is found that NCI provides change information as a result the accuracy achieved by NCI-4 is found better than the other NCIs. A test study done with much bigger sizes of window have been able to establish the fact that bigger window may give more accurate results (section 5.1). Some of the other parameters besides the window size which might have affected in getting useful contextual information vis-à-vis accuracy of change detection in forest landscape are sub pixel level geo-correction of images, radiometric normalization, phenological characteristic of vegetation, climatic condition at the time of data capture, sensor characteristics and window size. In this study these parameters were kept under manageable limit by using anniversary date dataset from same type of sensor.

The outcome of this research can be summarized by concluding that the NCI analysis technique does provide change information but it requires bigger windows for NCI information to become useful when medium resolution imagery is used for change detection in forest. The earlier study done by Jungho and Jensen using very high resolution imagery (0.7x0.7mts) in urban area has found that NCI size of 3 pixel radius is most suitable but same is not found applicable in this study (Jungho and Jensen, 2005). The detail conclusion of the research in the background of research questions are discussed below.

6.1.1. Is the NCI technique suitable for medium resolution data?

At first instance it appears that this technique is not usable for medium resolution dataset when only small neighbourhood is considered but at the same time on consideration of larger window sizes it is found that it is helpful in enhancing the accuracy result. This implies that NCI does provide information of change. It is only on the suitable selection of neighbourhood size this technique can be
used for medium resolution dataset in forest landscape. From the accuracy results it can also be concluded that though there is an increase in efficiency of classifier when neighbourhood size equal to four pixel or may be more than this size is considered but it is only able to increase the accuracy by small amount in comparison of when NCI is not used. This may be due to other influencing factors like overall phenological difference of vegetation during two dates, difference in sensor characteristics, geo-correction of images, training of pixels for decision tree classifier and interclass overlapping of spectral characteristic of forest vegetation under observation. The overlapping of spectral characteristics between classes is clearly evident from the result of classification of forest cover on single image, which shows that there is confusion between open forest and non-forest classes (section 5.1).

In comparison earlier work, which establishes the suitability of this technique in urban area using high-resolution imagery, the result of this study can also be seen in the context of type of land cover in urban and forest area. In urban area features are more man made where in forest it is all natural features. Forest features are more dynamic than urban feature.

6.1.2. **What is the threshold of correlation coefficient for no change?**

Ideally a no or little change area should have correlation coefficient near the value of one. In this study, for no change classes the correlation coefficient in general was found to be low in all bands. The highest average value of it is found in NCI-4 .The maximum mean value of correlation in no change area is 0.61 for F-F (Forest to forest) in NC14. In many cases its value is even below the value of correlation of change area. Hence the study finds it difficult to arrive at any threshold of correlation coefficient for no change area.

6.1.3. **Does a high correlation always imply no change?**

On the analysis of correlation values of change and no change classes it has been found that a relatively higher correlation values are associated with no change classes but wise versa is not true as discussed in section 5.3. A closer look into the correlation values in different change and no change classes given in annexure 5.2 shows that higher correlation value for no change class in comparison of change class hold only true when the class in consideration does not involve non forest class.

6.1.4. **What is the accuracy percentage of change detection with and without NCI?**

On detail assessment of accuracy of change detection it can be concluded that when small neighbourhood configuration of 1-3 pixel radius is considered the accuracy is below the accuracy achieved when no NCI is used. But the accuracy increases when four pixel radius NCI is considered but this increase is not significant. Hence in clear cut terms it can not be concluded that accuracy with NCI is better than the accuracy without NCI.

6.1.5. **What is the most suitable configuration of NCI for this purpose?**

The study considered only four neighbourhood sizes for analysis of this technique. From the accuracy assessment of all the four cases it can be concluded that neighbourhood configuration of four pixel is the most suitable for the purpose of change detection in forest landscape using medium resolution dataset but its results are not significantly better than without NCI. On the analysis of reasons for low correlation it is found that one of the most probable reasons for this is the neighbourhood window size. To further investigate it, a trial with rectangular neighbourhood size of 11x11, 15x15 and 17x17 was done on small subset of image with only six change and no change classes and it is found that
15x15 window is most suitable for this technique which requires further trial on entire image for all classes to establish it firmly.

6.1.6. How does the configuration of the neighbourhood window affect the total area under various change and no change classes?

Total area of observation under this study was 111,092 ha. The study focuses on three unchanged classes i.e. forest (F-F), open forest (OF-OF), non forest (NF-NF) and five change classes forest to non forest (F-NF), forest to open forest (F-OF), open forest to forest (OF-F), open forest to non forest (OF-NF) and non forest to open forest (NF-OF). On close scrutiny of area classified under these classes by different classifier with and without NCI it is found that area predicted in all the no change classes shows least variation from the mean of the area of that class in all NCIs (Annexure 6.1). Same is true with F-OF, OF-F and OF-NF. But in the case of F-NF and NF-OF there is large variation in area predicted by different NCI classifier. It is observed that NCI-3 is not able to identify F-NF class where NCI-4 prediction of area is more nearer to mean value. NCI-2 tends to over estimate the area. But the same is not true in NF-OF class where it is the NCI-1 and NCI-2, which seems to be closer than the mean value. This anomaly of classification in these two change classes may be attributed to lesser number of training pixels considered (Table 5.7) due to infrequent occurrence of these two processes or due to presence of varied type of features like agricultural crop, barren land, built up area etc. in non-forest class.

The patch size of different forest cover class with respect to window size is also an important factor in detection of change and no change area. The minimum patch size of all the three classes is 0.04 hectare and mean area of patches of forest, open forest and non-forest is 2.5, 1.3 and 0.83 hectare respectively. This implies that with bigger size window smaller patches may smoothen with its surrounding class. Hence the optimum size of window will depend on the scale at which the monitoring is required as discussed in section 4.6.

6.2. Relevance of this study for forest managers

Forest managers are mostly interested to know the overall depletion and restocking of forest, which has taken place between two points of time. They would also like to know the exact location of these changes. Area obtained under various classes from the change detection map of all five classifier (with and without NCI) shows that out of total 111,092 ha of total forest area, 36894 ha (mean of area of change class in all NCI) of has gone under some type of positive or negative change which is 33.21 percent of total forest area. There is a depletion of 28962 ha (26.07%) and restocking of 7932 ha (7.14%) of forest area (Annexure 6.1). The depletion of such a large extent of forest during a period of six years is a cause of concern for forest managers. The reason of this depletion may be due to the increasing human population pressure on the forests. According to census of India report human population of Kannod subdivision has increased by 19% during the period of 1999 and 2005. Demand of forest produce in the form of fuel wood, fodder and small timber has increased with increasing population, which has mainly resulted into depletion of forest. This study will help forest policy maker to formulate such policy so that dependency of local people on forest is reduced.

6.3. Accuracy of output map

The positional accuracy of the output map depends upon the accuracy with which map to image geo-correction has been done and thematic accuracy depends on input knowledge of the expert utilized in generation of reference data through visual inspection of images. The building of training set is a tedious job because one has to pick the training data pixel by pixel that takes too much time. In
contrast, the learning process is fast and takes very little time to build a classifier from the training samples in SEE5.

To validate the accuracy of output, field verification of fifty sample points were done using hand held GPS. As discussed in section 3.9.4 information regarding present and past status of forest at those points were collected from ancillary data which is given in Annexure 6.2. From the information so gathered it has been found that in almost 78% of cases the thematic information obtained from the field is in accordance with on screen generation of reference data for the NCI-4. It is felt that a hybrid approach of onscreen classification and field data input can improve the overall output as it will lead to qualitative improvement in training pixel. But since for training, numbers of pixels required are in thousands and it is not practical to reach each and every point hence the number of points for which field information can be used in the hybrid approach would depend upon the time constraint and requirement of project.

6.4. Recommendations

Some of the important recommendations that emerge from this research work are discussed below.

- On the basis of trial classification done using bigger window sizes of 11x11, 15x15 and 17x17, it is found that 15x15 window shows promising result. It is recommended that detail analysis is done using this window size. It would also be pertinent to analyse the ability of bigger size window in detecting small areas of change.

- It has been found in this study that window size is a crucial factor for this technique to work efficiently. The spectral variance between pixels within the window is also a function of phenological character of the forest vegetation, which is usually different for different forest type and class. Thus it is possible that working with same resolution imagery, window size would be different for different forest type and class. Hence it is recommended that further study may focus on investigating suitability of size of window for different type of forests.

- The role of total number of pixels considered and its distribution over the scene is very important factor in development of a correct decision tree classifier. It is expected that the classification accuracy may increase with the increase in the size of the training set but up to a certain limit. Number of training samples depends on the complexity of the study area. If study area is simple and it consists of well-defined crisp classes then less number of pixels can also give better accuracy but this is not the case with forest. Hence it is recommended that further study can focus on this aspect so that an optimum number of training set is determined for different forest type at landscape level.

- A further validation of usability of this technique in forest landscape can be done by using the result of this study with similar study done on same area with high and coarse resolution imagery.

- One of the important aspects of this study was the use of contextual information in the form of Correlation, Slope and Intercept. Future study can in corporate other contextual information such as entropy.

- Another aspect of the study is selection of bands. Though the three bands selected for this study are most commonly used for vegetation monitoring but other information layer like DEM and soil type can also be considered for knowledge base creation as forests vegetation is dependent on these variables.
7. References


Annexure 4.1

Post radiometric normalization DN values of image 1999 in three bands

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<th>IMAGE 2005</th>
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</table>
Annexure 4.2

AML Code for generation of covariance image between band-1 of 1999 and 2005 image for
neighbourhood configuration of 3 pixel radius

<p>| | | | | |</p>
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</table>

Above figure shows the neighbouring pixels considered in a 3 pixel radius circular window. The pixel
address w.r.t central pixel is mentioned in the cell. This cell address is referred in AML code given
below.

T1=band 1 of image 1999 in grid format
T2= band 1 of image 2005 in grid format
Covar_bn1= output covariance image

&type 'PLEASE SELECT THE 1ST GRID'
&sv .t1 = [getgrid]
&type 'PLEASE SELECT THE 2nd GRID'
&sv .t2 = [getgrid]
%t1%mean = focalmean(%t1%,irregular,kernal3.txt)
%t2%mean = focalmean(%t2%,irregular,kernal3.txt)

DOCELL
a1 := ( %.t1%(0,-1) - %.t1%mean(0,0)) * ( %.t2%(0,-1) - %.t2%mean(0,0))
a2 := ( %.t1%(1,0) - %.t1%mean(0,0)) * ( %.t2%(1,0) - %.t2%mean(0,0))
a3 := ( %.t1%(0,1) - %.t1%mean(0,0)) * ( %.t2%(0,1) - %.t2%mean(0,0))
a4 := ( %.t1%(-1,0) - %.t1%mean(0,0)) * ( %.t2%(-1,0) - %.t2%mean(0,0))
a5 := ( %.t1%(0,0) - %.t1%mean(0,0)) * ( %.t2%(0,0) - %.t2%mean(0,0))
a6 := ( %.t1%(2,0) - %.t1%mean(0,0)) * ( %.t2%(2,0) - %.t2%mean(0,0))
a7 := ( %.t1%(1,-1) - %.t1%mean(0,0)) * ( %.t2%(1,-1) - %.t2%mean(0,0))
a8 := ( %.t1%(0,-2) - %.t1%mean(0,0)) * ( %.t2%(0,-2) - %.t2%mean(0,0))
a9 := ( %.t1%(-1,-1) - %.t1%mean(0,0)) * ( %.t2%(-1,-1) - %.t2%mean(0,0))
a10 := ( %.t1%(-2,0) - %.t1%mean(0,0)) * ( %.t2%(-2,0) - %.t2%mean(0,0))
a11 := ( %.t1%(-1,1) - %.t1%mean(0,0)) * ( %.t2%(-1,1) - %.t2%mean(0,0))
a12 := ( %.t1%(0,2) - %.t1%mean(0,0)) * ( %.t2%(0,2) - %.t2%mean(0,0))
a13 := ( %.t1%(1,1) - %.t1%mean(0,0)) * ( %.t2%(1,1) - %.t2%mean(0,0))
a14 := ( %.t1%(3,0) - %.t1%mean(0,0)) * ( %.t2%(3,0) - %.t2%mean(0,0))
a15 := ( %.t1%(2,-1) - %.t1%mean(0,0)) * ( %.t2%(2,-1) - %.t2%mean(0,0))
a16 := ( %.t1%(2,-2) - %.t1%mean(0,0)) * ( %.t2%(2,-2) - %.t2%mean(0,0))
a17 := ( %.t1%(1,-2) - %.t1%mean(0,0)) * ( %.t2%(1,-2) - %.t2%mean(0,0))
a18 := ( %.t1%(0,-3) - %.t1%mean(0,0)) * ( %.t2%(0,-3) - %.t2%mean(0,0))
a19 := ( %.t1%(-1,-2) - %.t1%mean(0,0)) * ( %.t2%(-1,-2) - %.t2%mean(0,0))
a20 := ( %.t1%(-2,-2) - %.t1%mean(0,0)) * ( %.t2%(-2,-2) - %.t2%mean(0,0))
a21 := ( %.t1%(-2,-1) - %.t1%mean(0,0)) * ( %.t2%(-2,-1) - %.t2%mean(0,0))
a22 := ( %.t1%(-3,0) - %.t1%mean(0,0)) * ( %.t2%(-3,0) - %.t2%mean(0,0))
a23 := ( %.t1%(-2,1) - %.t1%mean(0,0)) * ( %.t2%(-2,1) - %.t2%mean(0,0))
a24 := ( %.t1%(-2,2) - %.t1%mean(0,0)) * ( %.t2%(-2,2) - %.t2%mean(0,0))
a25 := ( %.t1%(-1,2) - %.t1%mean(0,0)) * ( %.t2%(-1,2) - %.t2%mean(0,0))
a26 := ( %.t1%(0,3) - %.t1%mean(0,0)) * ( %.t2%(0,3) - %.t2%mean(0,0))
a27 := ( %.t1%(1,2) - %.t1%mean(0,0)) * ( %.t2%(1,2) - %.t2%mean(0,0))
a28 := ( %.t1%(2,2) - %.t1%mean(0,0)) * ( %.t2%(2,2) - %.t2%mean(0,0))
a29 := ( %.t1%(2,1) - %.t1%mean(0,0)) * ( %.t2%(2,1) - %.t2%mean(0,0))

cover_bn1 = ( a1 + a2 + a3 + a4 + a5 + a6 + a7 + a8 + a9 + a10 + a11 + a12 + a13 + a14 + a15 + a16 + a17 + a18 + a19 + a20 + a21 + a22 + a23 + a24 + a25 + a26 + a27 + a28 + a29 ) / 28

end

&type 'PROCESS OVER'
&return
Annexure 5.1

Band wise Correlation, Intercept and Slope images using neighbourhood configuration of four pixels radius
Annexure 5.2

**SUMMARY OF CLASS WISE MEAN VALUE OF CORRELATION COEFFICIENT, INTERCEPT AND SLOPE IN ALL BANDS FOR DIFFERENT NCI CONFIGURATIONS**

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<th>INTERCEPT</th>
<th>SLOPE</th>
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CC = Correlation coefficient; IN = Intercept; SL = Slope; B1, B2, B3 = Three Bands
F = Forest; OF = Open Forest; NF = Non Forest; WW = Water
## Summary of Class Wise Mean Value of Correlation Coefficient, Intercept and Slope in Three Bands in NCI-2 Composite

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## Summary of Class Wise Mean Value of Correlation Coefficient, Intercept and Slope in Three Bands in NCI-3 Composite

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Annexure 5.3
DN values of pixels in band3 and band4 in a rectangular window of 17x17 considered in Dense Forest

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### Band 4
**Annexure 5.4**

Error Matrix of change detection classification done on small Image subset without using NCI.

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<tr>
<th>NO-NCI</th>
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<th>Row Total</th>
<th>User Acc.</th>
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**OVERALL ACCURACY = 88.83249**  **KHAT = 0.72080**

Error Matrix of change detection classification done on small Image subset using 11x11 pixel rectangular window NCI.

<table>
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<th>NC I-11</th>
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**OVERALL ACCURACY = 90.3553**  **KHAT = 0.75698**
Error Matrix of change detection classification done on small Image subset using 15x15 pixel rectangular window NCI.

<table>
<thead>
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<th>NCI-15</th>
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<td>NF-NF</td>
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<td>OF-F</td>
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OVERALL ACCURACY = 90.8629 KIHAT = 0.77653

Error Matrix of change detection classification done on small Image subset using 17x17 pixel rectangular window NCI.

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<th>NCI-17</th>
<th>Accuracy Assessment with NCI - 17</th>
<th>Row Total</th>
<th>User Acc.</th>
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<td>NF-NF</td>
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<td>F-F</td>
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<td>F-OF</td>
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<td>NF-NF</td>
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<tr>
<td>OF-F</td>
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<tr>
<td>OF-NF</td>
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<td>OF-OF</td>
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<td>2</td>
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<tr>
<td>Ref.Total</td>
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<td>3</td>
</tr>
<tr>
<td>Prod.Acc</td>
<td>0.9800</td>
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<td>0.3333</td>
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OVERALL ACCURACY = 89.8477 KIHAT = 0.73910
### Annexure 6.1

**AREA STATEMENT TABLE SHOWING DETAILS OF AREA CLASSIFIED UNDER VARIOUS CLASSES BY DIFFERENT CLASSIFIER**

<table>
<thead>
<tr>
<th>CLASS</th>
<th>F-F</th>
<th>OF-OF</th>
<th>NF-NF</th>
<th>WW</th>
<th>F-NF</th>
<th>F-OF</th>
<th>NF-OF</th>
<th>OF-NF</th>
<th>OF-F</th>
<th>Total Area</th>
</tr>
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<tbody>
<tr>
<td>NCI-O</td>
<td>31499.4</td>
<td>27740.68</td>
<td>15825.28</td>
<td>831.3</td>
<td>355.7</td>
<td>17956.08</td>
<td>1583.96</td>
<td>9710.38</td>
<td>5589.32</td>
<td>111091</td>
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<tr>
<td>NCI-1</td>
<td>27572.4</td>
<td>27992.56</td>
<td>15185.22</td>
<td>1083.7</td>
<td>10.49</td>
<td>16765.04</td>
<td>4112.33</td>
<td>12987.5</td>
<td>5382.89</td>
<td>111091</td>
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<tr>
<td>NCI-2</td>
<td>28861.6</td>
<td>31099.74</td>
<td>14875.41</td>
<td>989.74</td>
<td>480.62</td>
<td>15544.95</td>
<td>2160.62</td>
<td>11771.9</td>
<td>5307.56</td>
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<tr>
<td>NCI-3</td>
<td>28783.7</td>
<td>30850.78</td>
<td>16185.84</td>
<td>874.76</td>
<td>0</td>
<td>16030.71</td>
<td>336.71</td>
<td>13146.4</td>
<td>4883.16</td>
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<td>NCI-4</td>
<td>28497.7</td>
<td>25916.43</td>
<td>15447.04</td>
<td>875.43</td>
<td>58.76</td>
<td>17127.21</td>
<td>6523.01</td>
<td>12865</td>
<td>3781.59</td>
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<tr>
<td>Mean</td>
<td>29042.95</td>
<td>28720.04</td>
<td>15503.76</td>
<td>930.98</td>
<td>181.11</td>
<td>16684.80</td>
<td>2943.33</td>
<td>12096.23</td>
<td>4988.90</td>
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</tbody>
</table>

|                   | Total area under positive change | 7932.23 | 7.14 percent |
|                   | Total area under negative change | 28962.14| 26.07 percent|
|                   | Total area under change          | 36894.37| 33.21 percent|

---
Annexure 6.2 Table showing agreement/disagreement between field verification and digital interpretation of classes

<table>
<thead>
<tr>
<th>Point Id</th>
<th>Forest Range</th>
<th>Present Forest status/density/class</th>
<th>Forestry operation during last one year (2005-2006)</th>
<th>Status in 2005</th>
<th>Status in 1999 as per stock map density/class</th>
<th>Forestry operation during 1999-2005 as per compartment history</th>
<th>Status of forest as per local knowledge</th>
<th>Status in 1999</th>
<th>Chang e Class as per ground verification</th>
<th>Change Class as per visual interpretation</th>
<th>Agreement/Disagreement</th>
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<tr>
<td>771 Satwas</td>
<td>0.3/OF None</td>
<td>OF</td>
<td>None</td>
<td>OF</td>
<td>0.2/OF</td>
<td>None</td>
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<td>None</td>
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<td>0.2/OF</td>
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<td>OF</td>
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<td>None</td>
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<td>CBO in 2005</td>
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<td>0.4/OF</td>
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<td>0.4/OF</td>
<td>CBO in 2003</td>
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CBO = Cut back operation; ANR = Assisted natural regeneration
### Neighbourhood Correlation Image Analysis Technique for Change Detection in Forest Landscape

Total agreement = 39; Total= Disagreement = 11; Over all accuracy = 78%

<table>
<thead>
<tr>
<th>Point Id</th>
<th>Forest Range</th>
<th>Present Forest status density/class</th>
<th>Forest operation during last one year (2005-2006)</th>
<th>Status in 2005</th>
<th>Status in 1999 as per stock map density/class</th>
<th>Forestry operation during 1999-2005 as per compartment history</th>
<th>Status of forest as per local knowledge</th>
<th>Status in 1999</th>
<th>Change Class as per ground verification</th>
<th>Change Class as per visual interpretation</th>
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