INTRODUCTION

Globally, forests cover ~4.1 billion hectares (30%) of the Earth's land surface (Mygatt, 2006). Ecologically, forest is said to be the plant community dominated by trees and other woody vegetation with a closed canopy and their species composition varying in different parts of the world. Forests, one of the most important features in natural resources are fundamental to the healthy functioning of the biosphere and the main depositors of biodiversity. They are renewable, natural and valuable ecological resources of earth (Jaykumar et al., 2002). Forests are increasingly valued for their potential to contribute to the local economy through production of both timber and non-timber products and provision for attractive recreation and tourism facilities, to create an attractive environment for living and working, to maintain biodiversity and protect natural resources, and to preserve and enhance characteristics of rural landscapes and related cultural heritage (Elands et al., 2002). Forests maintain ecological balance by providing environmental stability, carbon sequestration, soil moisture and conservation which is vital for preserving life supporting system of the globe. In an era of global concern about the sources and sinks of greenhouse gases, forests are seen as an important biome in the health of the planet. Forests are an important repository of carbon, an attribute that can be determined from knowledge of forest biomass. Dixon and Turner (1991) had reported that the world's forests contain up to 80% of all above ground C and ~ 40% of all below-ground (soils, litter, and roots) terrestrial C. Thus multiple-use of forestry is aimed at achieving an appropriate balance between the various needs of society. Any interruption to this ecological balance brings the unimaginable miseries to life on earth.

Based on extensive ecological research it is now clear that the flora and fauna on the surface of the Earth are rapidly changing (McCarty, 2001; Hughes, 2000). Driving these biological changes are global climate change (Nemani et al., 2003; Parmesan & Yohe, 2003) and human activity (Turner et al., 1990). With regard to climate change, increases in global temperature and global land precipitation have been documented (Kerr, 2006; Hansen et al., 1999; Hulme et al., 1998), both of which are expressed in spatial and temporal variations (Doherty et al., 1999, Hansen et al., 1999). Climate change is likely to cause increasing forest damage and tree mortality from direct and indirect causes. It has been estimated that the composition of one-third of the planet's forests could be altered markedly due to climate changes (Melillo, 1999; Shriner & Street, 1998). Additionally warming trend due to the increasing concentrations of carbon dioxide (CO_2) and other greenhouse gases in the Earth's atmosphere would cause major changes in all living systems, including forests. Concerning human activity, land cover has been changing rapidly throughout the twentieth century and at the start of the twenty-first century (Foley et al., 2005). In particular, many regions have experienced forest cover decline and desertification while other areas have experienced reforestation, intensification and/or expansion of agriculture (Xiao and Moody, 2004). Hence, the structure, composition and functioning of forests undergo changes as a result of natural processes or on account of human and livestock intervention (Bhatt et al., 2000). It is reported that over the last five years, the world suffered a net loss of some 37 million hectares (91 million acres) of forest, according to data from the United Nations Food and Agriculture Organization. Nowadays conservation of forests is one of the prime objectives among the environmentalists, as forests are being depleted at an unprecedented and alarming rate due to current global climate warming, loss of biodiversity, environmental degradation, and increased need for forest products.

1.1 Tropical forests – Global scenario

Among different types of forests, tropical forests constitute about half of the world's forests (Rahman et al., 2004) and which are mostly occurring in developing country like India, Brazil, Burma, and Srilanka. Tropical forests have the intrinsic property of being extremely rich in terms of species richness, density (Clark et al., 2005; Leigh et al., 2004; Wright, 2002; Hubbell, 1997; 2001) & high standing biomass (Ravindranath, 1997). Tropical forests cover approximately 17% of the terrestrial biosphere, yet they account for an essential 43% of global net primary productivity (NPP) and 27% of the carbon stored in forest soils (Melillo et al., 1993). Tropical forests are exceptionally rich in biodiversity. Almost half of all vertebrates, 60 percent of known plant species and possibly 90 percent of world's total species are found in tropical forest. At individual crown to landscape scales, tropical trees have a dominant role in maintaining rich biota because they define the horizontal and vertical substrate, food resources, and gradients of light, moisture and temperature. Furthermore, these forests are major players in the world's carbon cycle. Tropical tree biomass represents major pool of terrestrial carbon (Clark et al., 2003; Dixon et al., 1994; Lugo & Brown, 1992). They harbor globally significant amounts of carbon both in the vegetation and in the soil (Dixon et al. 1994), and they annually process vast amounts of carbon in photosynthesis and respiration (Field et al., 1998; Melillo et al., 1993). Changes in tropical forest carbon cycling can therefore affect the pace of climate change (Clark, 2004a).

Countries within the tropics are developing rapidly and inevitably this often places great pressure on natural resources, perhaps most noticeable on forests (Foody, 2003). Over the past few decades tropical forests are suffering because of rapid land use changes (Achard et al., 2002). Recent studies have suggested that land use changes are likely to have a greater impact on biodiversity reduction. Moreover, Geist & Lambin (2002) reported that agricultural expansion, commercial logging, plantation development, mining, industry, urbanization and road building are all causing deforestation in tropical regions. Uncontrolled deforestation processes threaten the large biodiversity resources present in tropics and remove the protective shield of earth. Currently tropical forests are experiencing high rates of deforestation and play an important role in determining the atmospheric concentration of carbon dioxide (Malhi and Grace, 2000; Myers et al., 2000). Global ecosystem-process models based on current understanding (White et al., 2000; Cramer et al., 2001; Fung et al., 2005) have projected declining productivity for the world's tropical forests as warming proceeds, in spite of physiological benefits from increasing atmospheric CO_2 (Clark, 2007). Scientists have reported that warmer global temperatures are linked to greenhouse gas emissions which may alter tree growth rates, recruitment and mortality, thereby creating new assemblages of trees as global temperatures increase (Laurance et al., 2004; Clark et al., 2003). It is expected that biodiversity will decline if these altered tree communities fail to sustain the complex interactions among trees, pollinators, seed dispersers, herbivores, symbiotic fungi and other species that are common in tropical forests (Laurance et al., 2004). It is reported that tropical forest is being destroyed at the rate of 40,000 square miles per year at global level which is due to slash-and-burn agriculture in areas of high population growth (Srivastava, 2004) The rate is about 10,000 times as high as the rate prior to the existence of human being. One recent global scale study concluded that climate-change effects on tropical forests over the next 50 years may pose as much risk to species survival as deforestation (Thomas et al., 2004). Hence there is a growing interest in quantifying habitat characteristics such as forest structure, floristic composition and plant species richness in intact and degraded forest fragments and forest landscapes (Myers et al., 2000; Laurance and Bierrengaard, 1997; Bierregaard et al., 1992).

1.2 Indian forests – a fast changing landscape

India is the second most populous and the seventh largest country in the world with an existing forest cover of 678,333 km^2 which is 20.64% of the geographical area of the country (FSI, 2003). India having only 2.5% of the world's geographic area is at present supporting 16% of the world's population and 18% of the cattle population (Singh et al., 2002). But the per capita forestland available is just 0.08 ha, which is the lowest in the world. India is rich in biodiversity which possesses a rich flora of flowering plants (17,000 species) with a high degree of endemics (33.5%). India is one of the 12 mega diversity countries of the world. 12% of the world's recorded flora and about 7.3% of the world's recorded faunal species are in the Indian subcontinent. The vegetation in Indian sub-continent is distributed mainly in four geographically distinct mountain ranges viz. Himalayas, Vindhyans, Western and Eastern Ghats (Srivastava, 2004). India's immense biological diversity encompasses ecosystems, populations, species and their genetic make up. This diversity can be attributed to the vast variety in physiography and climatic situations. India represents two major realms (Palaearctic and Indo-Malayan) and three biomes (Tropical Humid Forests, Tropical Dry Deciduous Forests and warm desert and semi deserts) which includes 12 bio-geographical regions (MOEF, 1994). India, with a large forest cover contains a variety of climatic zones such as tropical evergreen forests, alpine forests, semi-evergreen forests, dry-moist deciduous forests, and sub tropical to temperate forests (Bahuguna, 1999).

In India luxuriant vegetation compositions have undergone changes over the past few decades due to introduction of agriculture, commercial forestry, mining, hydropower plants and other biotic pressures inside the forest ecosystem (Srivastava, 2004). After independence, rapid industrialization led to increased pressure on India's forests. Due to large human population, cattle population and widespread rural poverty, the forest of the country is subject to enormous pressure resulting in deforestation and degradation. Land degradation impacts on critical environmental issues such as food security, loss of biodiversity, and global climate change. The major factors contributing to this phenomenon are large scale timber extraction, over-grazing, over-exploitation for fuelwood, forest fire, shifting cultivation, diversion of forest land by encroachment and infra structure development. As a result the structure, composition and functioning of these forests is undergoing rapid changes. Biotic pressure, wide-spread economic growth are altering natural vegetal cover and putting tremendous pressure on the sustenance of few leftover tropical forest covers in India. It is reported that the area under closed forest category is presently half of what it was about fifty years ago and only 11.73% of India's land area has reasonably good forests (FSI, 1996). In addition to this the increasing requirements of timber, estimated at 68,857 m tonnes in 1980, would rise to 181,270 m tonnes by 2025, is yet another area of concern (Navalgund et al., 2007). Bhatt et al. (2000) have also reported a lot of spatial and temporal variation in the values of species richness, composition and productivity. Hence the ecological status and the production capacity of these forests could not keep pace with exponential growth rate of human and livestock population and their requirements.

Fire is a significant and an important contributory factor for the degradation of forests in our country. Forest Survey of India reported that 50% of forest areas in the country are fire prone and most of the forest fires occur between February and June (dry summer months). According to an assessment of the Forest Protection Division of the Ministry of Environment and Forests, Government of India, fires affect annually 3.73 million ha of forests. Forest fires are mainly of anthropogenic origin on account of rampant biotic pressure. The majority of the forest fires (99%) in the country are caused by humans. Bahuguna (1999) reported that the ecological and socio-economic consequences of wildland fires include: loss of timber, loss of bio-diversity, loss of wildlife habitat, global warming, soil erosion, loss of fuel wood and fodder, damage to water and other natural resources, loss of natural regeneration.

Considering resource richness and the mounting problems, there is a pressing need to monitor the rate and extent of changes in tropical forest cover of countries like India for sustainable development. Monitoring changes in forest cover for efficient management has become an important aspect for forest department. Sustainable planning and management of forests requires vital information about forest resources, mapping and monitoring of existing natural resources and forecasting the future scenarios.

1.3 Forest monitoring – Need of the hour

Since 1970s it has been realized that forest monitoring is required not only at national but also at regional and global levels as forests are the major contributors to the flora and fauna which preserves the bio-diversity of the planet. The need for global data has further increased in the context of environmental conventions (e.g. Convention on Biological Diversity) and of growing interest in global climate modeling. As tropical deforestation is considered a major environmental problem, many studies have aimed at measuring the extent of the phenomenon and modeling the drivers of change (Geist & Lambin, 2002). In recent years developed countries have maintained an abiding interest in the extent, quality and management of tropical forest resources (Fuller, 2006). It becomes even more important in view of the fact that the increasing human and cattle population is far greater than the available forest resources. In this context, Singh et al. (2002) reported that the vegetation maps are the key for any planning, such as protected area management, sustainable development, social forestry, agroforestry, development without destruction, ecodevelopment, etc. This data can be obtained through monitoring, although access limitations may make the cost of direct monitoring prohibitive (Rosso et al., 2005). Added to this our understanding for monitoring, conservation and management of tropical forests is greatly hindered by a lack of spatially and temporally extensive information of tree floristic composition, species richness and structure. There is an urgent need to develop a reliable database for forest cover of India.

Traditionally, forest cover maps were developed mainly by foresters who used field and aerial surveys and scaled these figures to reflect the extent of national forest cover as a whole. These national figures were then transmitted to international agencies, which compiles global estimates of forest cover every 10 years (Zhu & Waller, 2003). In most cases sampling methods and standards adopted by different national agencies change and forest monitoring was never harmonized. Due to prohibitive costs and inaccessibility, most of the available data comes from relatively small field plots with infrequent re-sampling intervals. It is difficult to generalize such field data to the landscape, regional and global scales which is needed for understanding the important processes affecting biodiversity (Foody et al., 2003; Tuomisto et al., 2003). Another critical constraint for field survey and photointerpretation is the requirement for intensive human involvement. De Fries & Townshend (1999) further reported large discrepancies among widely used global cover maps and emphasized the need for a more consistent use of remote sensing technology. International efforts to establish remotely sensed forest monitoring have emerged recently such as Global Observation of Forest Cover and Land Cover Dynamics (GOFC-GOLD), which aims at to provide ongoing space based and *in situ* observations of forests to assist the sustainable management of terrestrial resources. Largely due to the launch of earth-observation sensors in the 1970s, operational satellite sensors have supplanted the traditional estimation of forest cover from field samples and aerial surveys, and more routine application of satellite imagery suggest that the traditional approach is no longer the most efficient or accurate means to map forest cover at regular intervals. However traditional field ecological data do not translate readily to regional or global extents, and models derived purely from such local data are unlikely to predict the global consequences of human activities. Therefore, ecologists and conservation biologists are turning to rapidly developing discipline of remote sensing to provide the techniques and data sources necessary to prepare scientific responses to environmental change. With remote sensing technology, one can produce independent and up to date estimates of both forest cover and cover change (Mayaux et al., 2005).

Remote sensing is a key tool for assessing vegetation condition periodically over larger areas, offering the possibility to analyze ecological issues at a wide range of spatial scales (Kokaly et al., 2003; Ustin et al., 1991). Remotely sensed data also can be used as inputs in ecosystem models that are used to assess functional changes brought by climate variability and land use change (Scholes & Archer, 1997). In addition to change measurements, remote sensing observations can be useful in revealing gradients in vegetation cover that can be further shown in relation to precipitation, groundwater, or edaphic factors across the landscape (Smith et al., 1990). Likewise there is considerable interest in the use of remote sensing to estimate variables affecting the rate of operation of forest ecosystem processes, such as evapotranspiration, photosynthesis and nutrient cycling (Running et al., 1989), and those affecting the state of the forest ecosystem such as leaf area index (LAI) and foliar chemistry (Wessman et al., 1988; Peterson et al., 1988, 1987). Remote sensing of the earth can potentially provide a wide array of information not easily acquired from ground surveys. For example, remote sensing can be used to investigate vegetation for leaf water, chlorophyll, cellulose, and leaf structure (Green et al., 1998). Ecological remote sensing now encompasses a wide range of applications including vegetation mapping, land-cover change detection, disturbance monitoring, and the estimation of biophysical and biochemical attributes of ecosystems (Asner et al., 1998a). Hence remote sensing is widely viewed as time and cost effective way to map vegetation which is one of the important motivations for its utilization in land use planning with large scale monitoring (Kokaly et al., 2003). Scientific management of tropical forests needs a large amount of reliable information that can only be obtained in a time and cost effective way as fieldwork is difficult or impossible at scales useful for management (Tueller, 1987). Currently concerns over global land use and land cover change are rising as we strive to understand the impact of human activities on our planet. Remote sensing has been widely used to monitor land cover changes such as those associated with deforestation. The ability to map land cover and infer its properties was shown to be important in a number of key scientific areas, such as biodiversity conservation and carbon cycling (Foody, 2003). Indeed, remote sensing techniques and technologies are likely to afford the best opportunities to proceed with regional-or global-scale environmental change detection.

1.4 The technique of remote sensing

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation (Lillesand & Kiefer, 2000). Such measurements would require medium for interaction. Remote sensing deals with electro-magnetic radiation (sunlight) as a medium of-interaction which refers to the identification of earth features by detecting the characteristics of electro-magnetic radiation that is emitted/reflected by earth's surface. Every object reflects/scatters a portion of the electro-magnetic radiation incident on it depending on its physical properties. Remote sensing of Earth resources is based on the principle of characteristic spectral response of the Earth's surface features. Reflectance/emittance pattern at different wavelengths for each object is different which enables identification and discrimination of objects possible.

Remote sensing usually refers to the technology of acquiring information about the earth's surface and atmosphere, using airborne (aircraft, balloons) or space-borne (satellites, space shuttle) sensors. Remote sensing employs passive and active sensors. Sensors which sense natural radiations, either emitted or reflected from the Earth, are called passive sensors. It is also possible to produce electromagnetic radiation of a specific wavelength or band of wavelengths and illuminate a terrain on the Earth's surface. The interaction of this radiation with the target could be then studied by sensing the scattered radiation from the targets. Such sensors which produce their own electromagnetic radiation are called active sensors.

1.5 Evolution of remote sensing - An international scenario

The detection of electromagnetic radiation can be done either electronically or by photography. Balloons were the first 'elevated platforms' used for photography in 1858, especially during the American civil war. Aerial platforms were used for reconnaissance and imaging for strategic plan during World War I & II. After the war scientists developed ingenious use of such imaging from 'heights' – especially for surveying and mapping-thus giving rise to modern aerial photography and its applications (Kasturirangan, 2004). But aerial photography did not receive much emphasis during the ensuing decades because the process was cumbersome and risky and the results uncertain (Lillesand & Kiefer, 2000). With the advent of satellites, space-based imaging became an essential tool to look at Earth in its totality and address issues of environment, disasters, global change, and natural resources management and many other applications of day-to day relevance. So the application of satellite imagery for forest mapping has increased greatly over the past decade (Fearnside & Barbosa, 2004) owing to their own characteristics such as being able to cover large areas, their revisit frequency, their constant spatial resolution and finally their possibility of automatic analysis. Indications are that estimates of tropical forest cover may be converging with more routine application of satellite imagery (Zhu & Waller, 2003; Hansen & Reed, 2000; Skole et al., 1994). However, global land cover maps derived from satellite imagery may disagree substantially as to the extent and distribution of tropical forest. For example, Giri et al. (2005) found important differences in forest distribution between two prominent land cover products, namely the Global Land Cover-2000 (available at http://www.gvm.jrc.it/glc2000) and MODIS (Moderate Resolution Imaging Spectrometer) land cover prepared by a researcher at Boston University. At regional to national scales, the adoption and application of satellite technology lags in certain countries in the tropics that are faced with scarcities of technology, funding and human capital.

Since 1960s, Images from space were available with various levels of detail (low resolution) and often at oblique angles. Since the advent of the Landsat satellite program in the 1970s and SPOT satellite programme in 1980s, near vertical images with resolutions useful for earth resources mapping have become available. Launch of earth-observation sensors in the 1970s have supplanted the traditional estimation of forest cover from field samples and aerial surveys. Routine application of satellite imagery currently suggests that the traditional approach is no longer the most efficient or accurate means to map forest cover at regular intervals. According to Barrett &

Curtis (1999), the most important satellite family is the Landsat family. There are many other equally important satellite series as well.

In the studies of tropical forest, the literature suggests that Landsat imagery has been the most commonly applied one. Since the launch of the first earth-observing civilian Landsat satellite in 1972, satellite remote sensing has been used for gathering synoptic information on forest (Iverson, 1989). The Landsat satellite platforms have carried three main sensors: the MSS (Multispectral Scanner), TM (Thematic Mapper) and ETM+ (Enhanced Thematic Mapper Plus). These imageries are inexpensive and have permitted mapping of general forest cover classes for calculating the rate and extent of regional deforestation and forest fragmentation (Roberts et al., 2002; Steininger et al., 2001; Cochrane et al., 1999; Skole & Tucker, 1993). Thus, remote sensing applications in the tropics have relied upon medium spatial resolution imagery from multispectral space-borne sensors (Landsat Thematic Mapper with 30-m resolution, 6 optical bands).

Several factors explain the widespread use of ETM+ imagery including its moderate cost relative to previous Landsat imagery, improved online search (Arvidson et al., 2001), a spatial resolution (30m) appropriate for the detection of change in canopy condition and land use around forested areas (Fuller, 2006). In recent years, several Landsat data archives have greatly improved the availability of imagery over tropical areas to the user community, including the Global Land cover Facility (http://glcf.umiacs.umd.edu/index.shtml) at the University of Maryland. Such increased availability of inexpensive Landsat imagery has stimulated a number of change detection studies that have helped identify drivers of land cover change in the tropics (Dennis & Colfer, 2006; Pereira et al., 2002). Landsat imagery generally provides a clear delineation between forest and non-forest cover type (Townshend et al., 1995). They also have their limitations. Owing to their coarser resolutions, they are unable to go for finer level details of forest attributes. Another principal limitation of the use of Landsat and other optical imaging systems is that these technologies cannot penetrate clouds which persist over many parts of the tropics. This effectively reduces the number of Landsat passes that researchers may use to map and monitor tropical forest as months or years may transpire before cloud-free Landsat imagery becomes available for certain cloudy locations (Trigg et al., 2006). Thus low temporal coverage over cloudy regions can render Landsat and similar polar-orbiting systems virtually useless for periodic forest monitoring. Researchers have therefore turned increasingly to cloud penetrating radar imagery provided by such satellite platforms as the Japanese Earth Resources Satellite (JERS -1) and the European Remote Sensing Satellite (ERS) as an alternative to study tropical forest cover. Sgrenzaroli et al. (2002) have reported that JERS-1 mosaics provide a robust measure of canopy texture and allow detection of forest vegetation at 100 m spatial resolution. Although such radar imagery generally do not provide as much spatial detail on land use and cover as cloud-free Landsat imagery. Despite the all weather capability of radar imagery, moderate to fine resolution optical imagery is still more frequently used in studies of tropical forests than space-borne radar. Reasons for this include the greater spatial detail on land cover type; numerous image classification algorithms and software that apply to optical imagery, and its greater availability in image archives. However, some sources of optical imagery are clearly more suitable than others for tropical forest classification. For example, Thenkabail et al. (2004) evaluated four optical sensors – Hyperion, IKONOS, ALI (Advanced Land Imager) and ETM+ for classifying complex moist forest vegetation such as young fallow, old fallow, secondary forest and primary forest in the Congo Basin. The 30m Hyperion sensor, which consists of 220 individual narrow spectral bands, performed best and was able to distinguish nine different vegetation classes with an overall accuracy of 96.1% when 23 to 157 usable bands were employed in a discriminate model. The other three sensors, including the 4m multispectral IKONOS imagery, performed relatively poor and were able to distinguish the same classes with overall accuracies of 42-51%. These results underscore the limited information content of multispectral (usually less than eight broad spectral bands) relative to hyperspectral imagery.

Additionally, in the tropical forest domain, AVHRR (Advanced Very High Resolution Radiometer) 1.1 km data were also used for producing pan-tropical forest maps, with classification techniques adapted to the ecological conditions (Achard et al., 2001; Mayaux et al., 1998). But the AVHRR dataset had shown its radiometric and geometric limitations for land-cover mapping at 1 km resolution and was not appropriate to national or continental studies.

1.6 Indian imaging system: the technology evolution

In view of the vast potential of space technology in the development of the country, Department of Space, Government of India, launched the ambitious programme to harness the benefit of space technology for the betterment of the fellow countrymen in the year 1962. The main thrust of the progrmme was to design and develop the sensors and satellites and associated technology and also to demonstrate the utility of satellite data in management of natural resources of the country. Starting from Bhaskara, the first experimental EO (Earth Observation) satellite launched in 1979, to the recently launched Cartosat-2 in 2007, a range of spatial resolution ability from 1 km to better than 1m has been achieved and operationalized. The evolution of the Indian EO satellites can be classified into three broad categories, viz. first generation of experimental satellites (Bhaskara-1 and 2), second generation of operational satellites (IRS series) and present generation of theme specific satellites (Oceansat-1, Resourcesat-1, Cartosat-1 and 2). The first Earth Observation Satellite of India (BHASKARA-I) was launched in 1979. This was followed by BHASKARA-II in 1981. The spatial resolution of the image from the Bhaskara satellite was about 1 km and the data was used for specific applications in geology, forestry, land use etc. India entered operational remote sensing arena by launching indigenously built satellite IRS-1A in 1989 and the second follow-up was IRS-1B in the year of 1991, having two payloads employing Linear Imaging Self Scanner (LISS) sensors. The second generation India satellite (IRS-IC & ID), launched in 1995 and 1997 carried the panchromatic camera, multispectral camera and a wide-field-of-view (WiFS) sensors. The new generation satellite, such as Resourcesat-I launched in the year of 2003, carried three different sensors (LISS-III, LISS-IV & AWiFS). ISRO's Polar Satellite Launch Vehicle-C6 (PSLV-C6) successfully launched CARTOSAT-1 and HAMSAT satellites in the year of 2005. CARTOSAT 1 and newly launched CARTOSAT-2 satellites are state-of – the-art remote sensing satellites intended for cartographic applications. The present IRS systems discussed so far, gave an idea of application-driven development of imaging technology, within a span of two and half decades (Navalgund et al., 2007). In addition to the present EO missions, there are specific remote sensing satellites planned in future to address issues of monitoring disasters, ocean observations, atmospheric profiles and global change. The planned EO missions include Oceansat-2, INSAT-3D, RISAT, Megha-Tropiques and resourcesat-2.

Indian Earth Observation (EO) programme has been application-driven and national development has been its prime motivation. From Bhaskara to Cartosat, India's EO capability has increased manifold. Today, India is one of the major providers of the earth observation data in the world in a variety of spatial, spectral and temporal resolutions, meeting the needs of many applications of relevance to national development (Navalgund, 2006). Some of the major operational application themes, in which India has extensively used remote sensing data are agriculture, forestry, water resources, land use, urban sprawl, geology, environment, coastal zone, marine resources, snow and glacier, disaster monitoring and mitigation, infrastructure development etc (Navalgund et al., 2007).

1.7 Broadband sensors & forest cover assessment

Globally satellite remote sensing has been used extensively to map forests of the tropics where up to date data about spatial distribution are absent or lacking. A number of studies have used sensors such as the Landsat Thematic Mapper (TM) and Multispectral scanner (MSS), the airborne Thematic Mapper Simulator (TMS), SPOT HRV, and the AVHRR for land cover identification and to classify forest type with varying degrees of success (Schriever & Congalton, 1995; White et al., 1995; Franklin, 1994; Frank, 1988). Landsat Thematic Mapper (TM) and SPOT-HRV have been widely used to estimate percent canopy cover, canopy height, tree volume and tree biomass using empirical approaches. Indices such as spectral vegetation index, simple ratio, and normalized difference vegetation index (NDVI), obtained from satellite data have been shown to be useful predictors of leaf area index (LAI), biomass and productivity in grasslands and forests (Steininger, 2000; Jakubauskas, 1996). Earlier many efforts also have been made to develop the fuel map using multispectral data (de Vasconcelos et al, 1998; Jain et al., 1996; Quigley et al., 1996; Mark et al., 1995; Ottmar et al., 1994).

In India use of aerial photographs in working plans for stock mapping was started during seventies (Tiwari 1978; Tomar 1976; Maslekar 1974). However, aerial photographs could not become popular due to difficulty in their procurement. For a subcontinent like India, survey of mapping vegetation and other land cover using conventional techniques is too complex and demands a huge amount of human resource and time. Satellite remote sensing has played an important role in generating information about forest cover, vegetation type and the land use changes (Roy, 1993; Malingreau, 1991; Botkin et al., 1984; Houghton & Woodwell 1981). Several studies have been done for Indian tropical forests using broad band multispectral instruments like Indian Remote sensing satellite (IRS) 1C/1D, LISS III, Wifs, Multispectral Scanner (MSS), Thematic Mapper (TM), ETM+, SPOT, etc. with varying degrees of success (Goparaju et al., 2005; Sudhakar et al., 2004;

Balaguru et al., 2003; Singh et al., 2002; Bhat et al., 2000; Murli et al., 1998). It can be said that the remote sensing with broad band multi-spectral and multi-temporal data collection systems allows one to perform the work for different forest attributes more quickly and effectively. Multispectral imagery has demonstrated its strength in discriminating and mapping physical vegetation variables (biomass, LAI, cover) and in monitoring vegetation condition which has opened up new opportunities for conservation and sustainable use of forest resources.

1.9 Limitations of broad band sensors

A major limitation of traditional broadband remote sensing products is that they use average spectral information over broadband widths resulting in loss of critical information available in specific narrowbands (Thenkabail et al., 2000; Blackburn, 1998). In this process, narrow spectral features are lost or masked by other stronger features surrounding them (Koger et al., 2004; Schmidt & Skidmore, 2003). This makes them unable to explain a large proportion of the variability present in spectral reflectance of vegetation. For example, the spectral shift of the red-edge (670-780nm) slope associated with leaf chlorophyll content, phenological state and vegetation stress, is not accessible with broadband sensors (Horler et al., 1983). This is owing to their (a) broad band widths (100-200nm) and (b) fewer bands (4 - 7 bands) covering the visible, near and middle infrared regions of the electromagnetic spectrum (Jakubauskas & Price, 1997). This greatly reduces the ability of broad band sensor to spectrally discriminate between two objects on the ground. Too little spectral information, insufficient spatial resolution and soil brightness interference are cited as the dominant limitations with traditional sensors (Smith et al., 1990). Addition to this sensor saturation is a problem with the older generation of sensors (Thenkabail, 1999; Curran et al., 1997; Foody et al., 1996; Steininger, 1996; Moran et al., 1994; Sader et al., 1994) and is still present in the new generation broadband sensors such as IKONOS and ETM+, and to a lesser extent in the ALI (Advanced Land Imager) sensor (Thenkabail et al., 2004). It is reported that the earlier generation sensors have these known limitations with respect to their suitability for studying complex biophysical and biochemical characteristics of vegetation (Salas et al., 2002; Sampson et al., 2001; De Jong et al., 2000; Steininger, 2000). Equally sustainable ecosystem management requires the comprehensive understanding of species composition and distribution (Nagendra, 2002). In this context, proper discrimination between species is necessary to map and monitor the spatial distribution of certain species, but this is not possible using traditional multispectral images of moderate spectral resolution and hence there is a need to evaluate the new generation of sensors.

1.10 Species discrimination – an increasingly crucial task

Plant species is the main building block of almost all ecosystems, and sustainable management of any ecosystem requires a comprehensive understanding of species composition and distribution (Nagendra, 2002). Characterizing the spatial distribution of tree species in forest ecosystems is central to a wide range of scientific and land management issues. State of the art monitoring systems aimed at forest tree species identification are potentially key tools for the development of sustainable development policies (Sanchez-Azofeifa et al., 2003). Moreover, accurately defining the spatial distribution of species and species groups is fundamental to the management of any conservation area. In this context, Plourde et al. (2007) reported that the effective and reliable methods for characterizing the spatial distribution of tree species through remote sensing would represent an important step towards better understanding of changes in biodiversity, habitat quality, climate, and nutrient cycling. To reveal species composition and distribution by using remotely sensed data, species-level discrimination of plants is essential, which in turn can make it viable to recognize the succession process of the ecosystem. Tree species mapping has long been of interest to managers concerned with biodiversity and habitat quality (Chokkalingam & White, 2001; Puttock et al., 1998; Spetich et al., 1997), and some of our most pressing present-day environmental concerns stem from the loss of native species, the spread of exotics, or shifts in distribution brought about by climate change (Allison & Vitousek, 2004; Drohan et al., 2002; Iverson et al., 1997). In order to develop a sustainable protection strategy, research has also been undertaken to discriminate invasive species from the native vegetation (Hunt et al., 2004; Parker-Williams & Hunt, 2004; Hunt et al., 2003; Lass et al., 2002). In tropical forests tree species identification has also become important due to their dominant role in maintaining rich biota. Tree species identification, their spread, forest produce and biogeochemistry have become important in the application of forestry to understand different processes.

A number of studies have made important progress on this general topic of species level discrimination (Leckie et al., 2003; Gilabert et al., 2000; Woodcock et al., 1994). Traditionally, species discrimination for floristic mapping has involved exhaustive and time-consuming fieldwork, including taxonomical information and the visual estimation of the percentage cover for each species (Kent & Coker, 1992).Given the importance of species-specific ecological interactions and potential consequences of changes in species distributions, reliable methods for remote sensing of forest composition at the species level would be a significant advancement towards understanding present dynamics. Given the additional spectral detail provided by imaging spectrometers, hyperspectral remote sensing has emerged as a potentially useful approach for distinguishing composition at the species level (Kokaly et al., 2003; Ustin & Xiao 2001; Roberts et al., 1998; Martin et al., 1998; Gong et al., 1997).

1.11 What is Hyperspectral imaging/ Imaging spectroscopy?

Hyperspectral imaging/Imaging spectroscopy is the study of the interaction between radiation and matter. In the remote sensing community, the term "imaging spectroscopy" has many synonyms, such as imaging spectrometry and hyperspectral or ultraspectral imaging (Clark, 1999). Hyperspectral imaging/Imaging spectroscopy can best be described as a system that collects and provides a unique reflectance signature of many materials reflecting electromagnetic energy from the surface of the Earth in hundreds of bands with 10nm bandwidth. It is reported that the Hyperspectral images are spectrally over determined (Jacobsen, 2000; Shippert, 2002; Boardman et al., 1995) and so they provide ample spectral information to identify and distinguish spectrally unique materials. Hyperspectral sensors (also referred as imaging spectrometers) are instruments that acquire images in many very narrow, contiguous spectral bands throughout the Visible, Near-IR, and Short Wave IR portions (400-2500nm) of the spectrum (Figure 1). This is a major advancement over multispectral systems as they record earth surface information up to 10 spectral bands with 100nm bandwidth. Furthermore, hyperspectral sensors can discriminate among earth surface feature that have diagnostic absorption and reflection characteristics over narrow wavelength intervals that are "lost" within the relatively coarse bandwidths of the various bands of conventional multispectral scanners (Lillesand & Kiefer, 2000) such as those acquired from Landsat ETM+ which has 8 broad spectral bands (Figure 2).

Hyperspectral imaging is a technology based on the phenomenon of electromagnetic spectrum and its underlying principles. It studies light as a function of wavelength that has been absorbed, reflected or scattered from a solid, liquid or gas. Atoms and molecules are constantly communicating messages and signing their name with specific spectral signatures. The reflectance behavior of the surface as a function of wavelength throughout the optical portion of the spectrum is commonly referred as a spectral reflectance signature or spectral fingerprint. Most natural objects have unique spectral signatures that distinguish them from others and many of these signatures occur in a very narrow wavelength region. The concept of Hyperspectral remote sensing has been used to detect and map a wide variety of materials having characteristic reflectance spectra (Shaw & Bruke, 2003) (Figure 3). These systems typically collect 200 or more bands of data, which enables the construction of an effectively continuous reflectance spectrum for every pixel in the scene (Figure 4) (Shaw & Bruke, 2003). This can be compared directly to laboratory or field collected spectra (Shippert, 2002). Hyperspectral data have details and accuracy that permit investigation of phenomena and concepts that greatly extend the scope of remote sensors. The Hyperspectral images are normally visualized in a 3-dimensional data set with two spatial and one spectral dimension. This data set is referred to as an image cube (Figure 4). During the past decade, though, hyperspectral image analysis has matured into one of the most powerful and fastest-growing technologies in the field of remote sensing.

The hyperspectral era began with airborne mineral mapping in the late 1970s and early 1980s. In 1989, a major advancement occurred with the arrival of the NASA/JPL Airborne Visible/IR Imaging Spectrometer (AVIRIS) (Green et al., 1992). It collects imagery in 224 spectral bands over the spectral range from 400 to 2500nm. Spurred by the success of this instrument, other hyperspectral instruments came into being. Some other examples of hyperspectral sensors in operation are HYDICE (NRL), AISA (Specim ltd.), CASI (Itres Research, Canada), DAIS (GER), AIS (JPL), MISI (RIT), Probe-1 (ESSI), TRW Hyperion (EO-1), Mightysat II and many others. Detailed description for these sensors is given in table-1.

1.12 Use of Hyperspectral data in different applications

The principles of spectroscopy employed in hyperspectral image data collection and processing are well known and have been used for many years (Goetz et al. 1985). Spectroscopy measures the electromagnetic radiation from objects as a spectrum, with different materials having different characteristic spectra based on their chemical composition. Relative to the broadband sensors, finer levels of details and more subtle changes in the landscape are captured by the Hyperspectral sensor (Thenkabail et al., 2004) which offers considerable potential for discriminating earth surface (Lewis et al., 2000). High spectral resolution reflectance spectra collected by imaging spectrometers allow direct identification of individual materials based upon their reflectance characteristics which successfully applied in many fields (Aspinall et al., 2002) including minerals (Clark & Swayze, 1995; Boardman & Kruse, 1994; Kruse et al., 1993; Boardman, 1993; Crowley, 1993), atmospheric constituent gases (Carrere & Conel, 1993; Gao & Goetz, 1990), Vegetation (Ustin et al., 1999; Gamon et al., 1993; Roberts et al., 1993), Snow and Ice (Clark & Swayze, 1995; Nolin & Dozier, 1993), soils (Palacios-Oreuta & Ustin, 1996), Geobotanical studies (Ustin et al., 1999) and dissolved and suspended constituents in lakes and other water bodies (Hamilton et al., 1993; Cardner et al., 1993) with great potential and bright prospects (Lewis et al., 2000). Hyperspectral data is also used for monitoring the quality of water (Kallio et al., 2001). Vegetation analysts are using hyperspectral imagery to identify species (Clark & Swayze, 1995), to study plant canopy chemistry (Martin & Aber, 1997) and to detect vegetation stress (Merton, 1992). Additionally, hyperspectral images have a definite advantage over the conventional systems as they are capable of separating bare soil surfaces from senescent vegetation (De Jong, 2000). They can also analyse biophysical and chemical information that is directly related to the quality of wildfire fuels, including fuel type, fuel moisture, green live biomass and fuel condition (Roberts et al., 2003). They have also been used to estimate more permanent fuel properties, such as fuel load and fuel structure, commonly through the classification of fuel types (Roberts et al., 1997; Wilson et al., 1994).

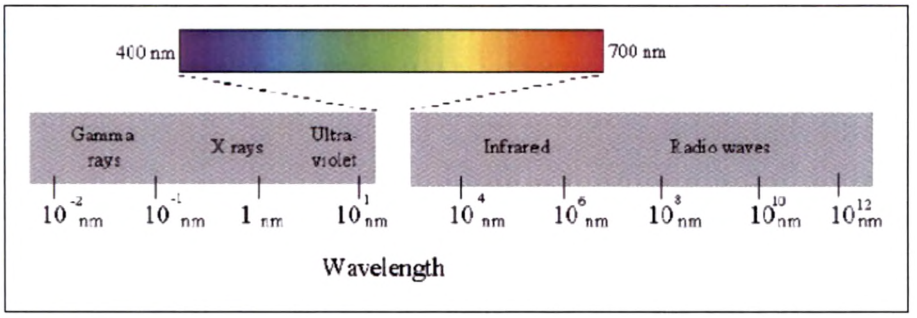

Figure 1: Electromagnetic spectrum Example, visible light has wavelengths between 400 and 700 nm, while radio waves have wavelengths greater than about 30 cm (Shippert, 2002)

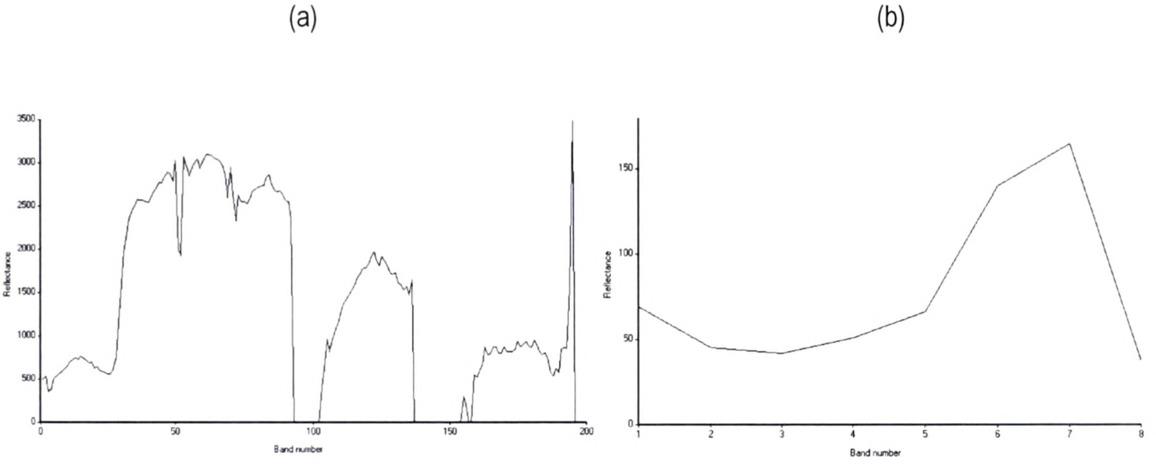

Figure 2: (A) Contiguous spectrum of healthy green vegetation using Spaceborne EO-1 Hyperion data and (B) the same spectrum re-sampled to 8 bands of Landsat ETM+ imagery

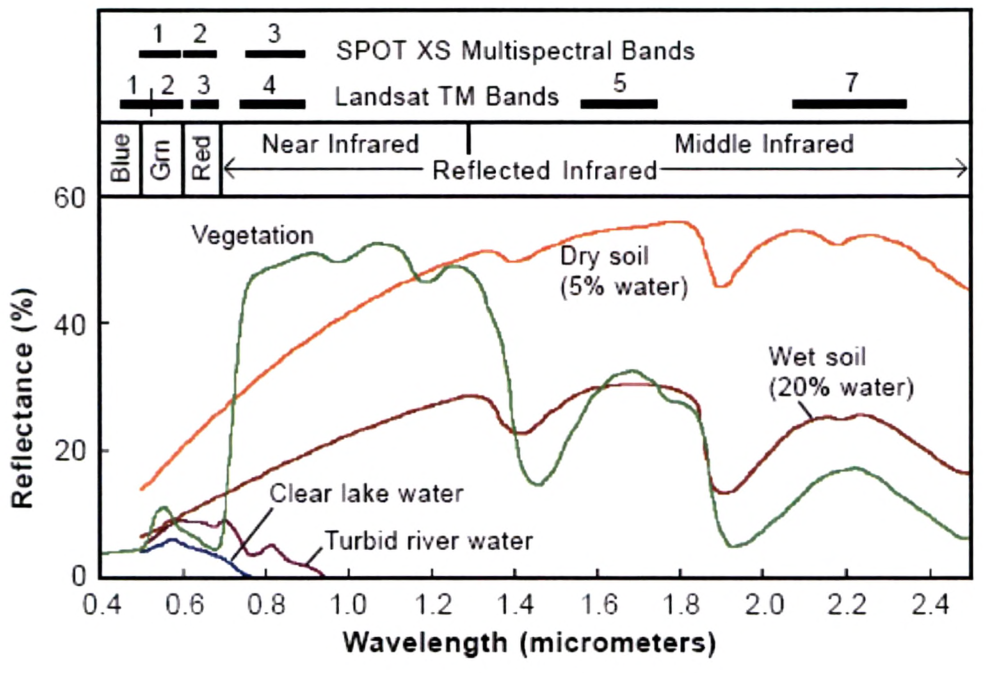

Figure 3: Representative spectral reflectance curves for several common Earth surface materials over the visible light to reflected infrared spectral range. The spectral bands used in several multispectral satellite remote sensors are shown at the top for comparison. Reflectance is expressed as a percentage, as in this graph. When spectral measurements of a test material are made in the field or laboratory, values of incident energy are also required to calculate the materials reflectance. These values are either measured directly or derived from measurements of light reflected (under the same illumination conditions as the test material) from a standard reference material with known spectral reflectance

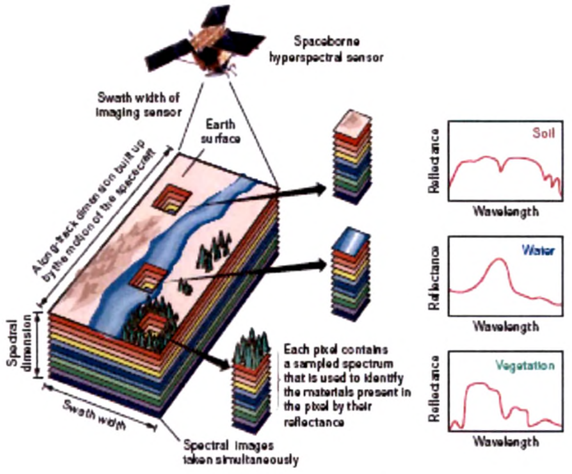

Figure 4: The concept of imaging spectroscopy: An airborne or spaceborne imaging sensor simultaneously samples multiple spectral wavebands over a large area in a ground-based scene. After appropriate processing, each pixel in the resulting image cube contains a sampled spectral measurement of reflectance, which can be interpreted to identify the material present in the scene. The graphs in the figure illustrate the spectral variation in reflectance for soil, water, and vegetation. A visual representation of the scene at varying wavelengths can be constructed from this spectral information (Shaw & Burke, 2003)

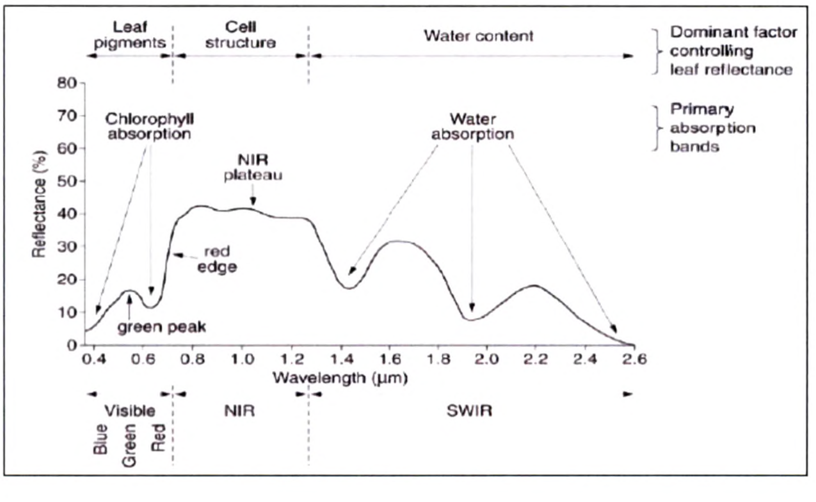

Figure 5: Reflectance spectra of green vegetation. Different portions of the spectral curves for green vegetation are shaped by different plant components, as shown at the top

Table 1: Current and Recent Hyperspectral Sensors, manufactures, with the number of bands and Spectral Range of the sensors.

Sensors	**Manufacturer**	**Number of Bands**	**Spectral Range**
FTHSI on MightySat II	Air Force Research Lab	256	0.35 to 1.05 mm
Hyperion on EO-1	NASA Goddard Space Flight Center	220	0.4 to 2.5 mm
AVIRIS (Airborne Visible Infrared Imaging Spectrometer)	NASA Jet Propulsion Lab	224	0.4 to 2.5 mm
HYDICE (Hyperspectral Digital Imagery Collection Experiment)	Naval Research Lab	210	0.4 to 2.5 mm
PROBE-1	Earth Search Sciences Inc.	128	0.4 to 2.5 mm
CASI (Compact Airborne Spectrographic Imager)	ITRES Research Limited	228	0.4 to 1.0 mm
HyMap	Integrated Spectronics	100 - 200	Visible to thermal infrared
EPS-H (Environmental Protection System)	GER Corporation	76 (VIS/NIR), 32 (SWIR1), 32 (SWIR2), 12 (TIR)	VIS/NIR (.43 to 1.05 mm), SWIR1 (1.5 to 1.8 mm), SWIR2 (2.0 to 2.5 mm), and TIR (8 to 12.5 mm)
DAIS 7915 (Digital Airborne Imaging Spectrometer)	GER Corporation	32 (VIS/NIR), 8 (SWIR1), 32 (SWIR2), 1 (MIR), 6 (TIR)	VIS/NIR (0.43 to 1.05 mm), SWIR1 (1.5 to 1.8 mm), SWIR2 (2.0 to 2.5 mm), MIR (3.0 to 5.0 mm), TIR (8.7 to 12.3 mm)
DAIS 21115 (Digital Airborne Imaging Spectrometer)	GER Corporation	76 (VIS/NIR), 64 (SWIR1), 64 (SWIR2), 1 (MIR), 6 (TIR)	VIS/NIR (0.40 to 1.0 mm), SWIR1 (1.0 to 1.8 mm), SWIR2 (2.0 to 2.5 mm), MIR (3.0 to 5.0 mm), TIR (8.0 to 12.0 mm)
AISA (Airborne Imaging Spectrometer	Spectral Imaging	< 288	0.43 to 1.0 mm

1.13 Limitations of imaging spectroscopy

These sensors also have their disadvantages as well, including an increase in the data to be processed, relatively poor signal-to-noise ratio and an increased susceptibility to the effects of unwanted atmospheric interference. The high spectral resolution of hyperspectral data, which is the key feature and is essential for capturing and discriminating subtle differences in the targets, also contains redundant information at band level (Bajwa et al., 2004). The increase of band number and decrease of bandwidth mean that the spectral resolution of hyperspectral data is very high. The information increases greatly with the increase of band number. However, the number of image channels is not simply equal to the number of information dimensions because of the existence of band correlation and data redundancy (Dai & Lei, 1989). This high data dimensionality makes computation difficult for classification and discrimination. Therefore dimensionality reduction is necessary to remove Hughes Phenomena during classification procedure.

1.14 Leaf optical properties: A state of the art

The optical properties of leaves have been shown to be correlated with their photosynthetic performance (Vogelmann, 1993) and thermal energy budgets. Moreover, an understanding of the leaf structural components that influence leaf reflectance is important for interpreting remotely sensed data, such as in the identification of plant functional types (Knipling, 1970). Vegetation reflectance spectra are often quite informative, containing information in the visible region, NIR (Near Infra Red) region, and in the MIR (Middle Infra Red) region of the electromagnetic spectrum. Detailed leaf reflectance properties are shown in Ill 5. Leaf – scale reflectance spectra are controlled by 1) leaf biochemical properties (water, photosynthetic pigments, structural carbohydrates), which create wavelength specific absorption features, and 2) leaf morphology (cell-wall thickness, air spaces, cuticle wax), which affects photon scattering (Roberts et al., 2004; Asner, 1998). VIS spectral variability among species is low due to strong absorption by chlorophyll (Cochrane, 2000; Poorter et al., 1995). High NIR transmittance and reflectance result from photon scattering within leaf air-cell wall interfaces, such as in spongy mesophyll (Grant, 1987; Gausman, 1985). At the transition from red to NIR wavelengths, leaf reflectance greatly increases, producing a distinct spectral feature referred to as the red edge. The positioning of this edge has been correlated to chlorophyll content, plant phenological stages, as well as plant stress (Gitelson et al., 1996; Carter, 1993). In SWIR 1 (Short Wave Infra Red-I) and SWIR 2 (Short Wave Infra Red-II) water absorption tends to obscure other absorption features produced by biochemical constituents (lignin and cellulose) (Asner, 1998; Gausman, 1985). These properties can help to identify tree species if these characteristics can be determined for each species of interest and so the challenge lies in being able to spectrally distinguish tree species from each other. Active research into the use of hyperspectral sensors includes vegetation structure and dynamics (Miller et al., 1991), vegetation biochemical composition (Kumar et al., 2001; Wessman et al., 1989), stress detection (Merton, 1998) and species identification (Cochrane et al., 2000; Kokaly et al., 1998).

1.15 Vegetation spectroscopy

With the introduction of imaging spectroscopy both quantitative and qualitative remote sensing of vegetation improved significantly. Hyperspectral imagery has great potential for monitoring vegetation type and vigor. As ecological studies require the quantification of biochemical and biophysical attributes (Asner, 1998), the high spectral resolution of hyperspectral data is vital for yielding quality information about vegetation health, biomass and other physico-chemical properties (Zarco-Tejada et al., 2005; Mutanga & Skidmore, 2004; Mutanga et al., 2004; Mutanga et al., 2003; Zarco- Tejada et al., 2003; Soukupová et al., 2002; Asner et al., 2000; Kokaly & Clark, 1999; Todd et al., 1998; Green et al., 1998; Peñuelas et al., 1997; Curran et al., 1992). Moreover, hyperspectral data have made it possible to measure more accurately both the quantity and particularly the quality of the vegetation.

Measuring vegetation quantity (or biomass) at field level is a difficult and destructive process (Gower et al., 1999). In addition, it is expensive and can rarely be extended to cover large areas (Scurlock & Prince, 1993). With the arrival of remote sensing, quantifying biomass became a reality (Daughtry et al., 1992; Elvidge, 1990). Various vegetation indices (i.e., NDVI, SR, TVI, SAVI) had been developed and successfully used to measure vegetation quantity and leaf area index (LAI). In spite of these successes, vegetation indices can be unstable, owing to the underlying soil color, canopy and leaf properties, and atmospheric conditions (Todd et al., 1998). However, most of these problems have been tackled or at least reduced since the appearance of hyperspectral sensors. New indices such as red-edge position (REP) are able to measure biomass much more accurately than NDVI (Cho & Skidmore, 2006; Curran et al., 1995).

Measuring the biochemical parameters necessary for uncovering vegetation quality is more difficult than remote sensing of biomass or LAI (Johnson et al., 1994; Curran, 1989). In plant tissue, the absorption of energy from radiation has been attributed to the energy transition of the molecular vibration in C-H, N-H, O-H, C-N and C-C bonds, which are the building blocks of all organic compounds (Elvidge, 1990). Hence any reflection from a plant at a specific wavelength is a function of the chemical composition of that plant (Foley et al., 1998). However after the introduction of spectrometry, a whole new branch of science started to develop. Scientists began to measure in plant materials the contents of various chemicals, including nitrogen and phosphorus, which are directly related to such plant qualities as pigment concentration, plant health, stress and damage (Ferwerda et al., 2006; Ferwerda et al., 2005; Mutanga et al., 2004; Gamon & Surfus, 1999; Kraft et al., 1996; Peñuelas et al., 1995).

1.16 Contribution of Hyperspectral data in species discrimination

Traditionally, species discrimination for floristic mapping involved exhaustive and time-consuming fieldwork, including taxonomical information and the visual estimation of percentage cover for each species (Kent & Coker, 1992). Other studies that have attempted tree species classification have found and outlined tree crown radii using aerial photography and high resolution multispectral videography. This delineation uses different types of pattern recognition to separate the images into individual tree crowns. The species can either be determined by the tree crown shape and size, or the crown can be classified using the digital counts of its spectral reflectance to determine which species it is (Brandtberg, 1999; Pinz, 1998). Yet all these methods usually require manual delineation or verification of automatic edges. Such work could be just as time consuming as having the tree studies on the ground, thus nullifying its usefulness as an aid (Sphere, 2005). Technological advancement and the advent of hyperspectral sensors with both high spectral and spatial resolutions have raised new expectations about the species level discrimination (Clark et al., 2005; Schmidt & Skidmore, 2003; Cochrane, 2000).

In past studies importance of spectral reflectance characteristics for species discrimination and its alteration due to the influence of biochemical and biophysical parameters, plant stress, disease, moisture level etc. is well documented (Van Aardt & Wynne, 2001; Cochrane, 2000; Demarez et al., 1999). Researchers have been able to discriminate and classify species based on their leaf reflectance (Vaiphasa et al., 2005; Schmidt & Skidmore, 2001; Cochrane, 2000; Knapp & Carter, 1998; Kumar & Skidmore, 1998; Gong et al., 1997), canopy reflectance (Schmidt & Skidmore, 2003; Yamano et al., 2003; Peñuelas et al., 1993a) and hyperspectral imagery (Clark et al., 2005; Thenkabail et al., 2004; Silvestri et al., 2003; Bajjouk et al., 1996). However, even after successful applications of reflectance spectra for discriminating between species, some researchers claim that the leaf reflectances of different species are highly correlated because of their similar chemical composition (Portigal et al., 1997). Many studies reported within species and among species variability (Cochrane, 2000, Price, 1994) due to difference in the pigment concentration, microclimates, soil characteristics, topography (Portigal et al., 1997), stress factors such as air pollution, drought (Westman & Price, 1987), foliage age (Roberts et al., 1998; Gausman, 1985) and canopy position (Danson, 1995).

1.16.1 Species discrimination among conifer species using Hyperspectral data

Hyperspectral approaches have been applied to various forestry related research questions, but to a far lesser degree than was done in agriculture and mining (mineralogical) applications. Hyperspectral technology, with its inherent resolving properties, does appear to be ideally suited to a task as difficult as species separation on a spectral basis. The use of hyperspectral data collected with a spectroradiometer for conifer species recognition has been explored to a certain extent. Studies done by Gong et al., (1997) had showed very good spectral differentiation for the six coniferous species such as sugar pine (*Pinus lambertiana*), ponderosa pine (*Pinus ponderosa*), white fir (*Abies concolor*), Douglas fir (*Pseudotsuga menziesii*), incense cedar (*Calocedrus decurrens*), giant sequoia (*Sequoiadendron giganteum*), and one hardwood species, California black oak (*Quercus keloggii*). The data were collected using a ground-based spectroradiometer with a wavelength range of 250-1050 nm and spectral resolution of 2.6 nm. The analysis methods consisted of two approaches, namely an artificial neural network algorithm and a discriminant analysis, after initial pre-processing (smoothing and derivative analysis) was done on the data. In some cases, an accuracy of greater than 91% was obtained using sunlit samples alone. The effects of site background and illumination changes on species' spectra were found to be large (influenced by conditions as well as leaf properties). Their study also found that the visible bands had higher discriminating power than near-infrared bands (blue-green the best followed by the red-edge). Lawrence et al. (1993) found distinct visual differences between coniferous and deciduous vegetation using AVIRIS imagery acquired over hemlock-spruce-fir (*Tsuga* spp., *Picea* spp. and *Abies* spp.) hemlock-hardwood (*Tsuga* spp. and hardwoods) and aspen-birch (*Populus.* spp and *Betula* spp.) mixed stands. Although no quantitative result is given, the possibilities of linear mixture modeling and distinct spectral differences (especially in the near infrared region of the spectrum) are mentioned. A classification of AVIRIS data into 11 different forest cover types, including red maple (*Acer rubrum*), red oak (*Quercus rubra*), white pine (*Pinus strobus*), red pine (Pin*us resinosa*), Norway spruce (*Picea abies*), and pure hemlock (*Tsuga canadensis*), as well as mixtures there of, has been attempted and also yielded very promising results (Martin et al., 1998). This approach implemented a maximum likelihood classifier and was based on 11 AVIRIS bands previously used to derive relationships between foliar chemistry (nitrogen and lignin concentration) and hyperspectral data. It was shown that both nitrogen and lignin information were important for species discrimination. The bands corresponding to these chemicals are 620 - 820 nm, 1640 - 1740 nm, and 2140 - 2280 nm. The overall classification accuracy was 75% (Martin et al., 1998). Van Aardt & Wynne (2001) investigated the inherent canopy spectral separability among three southern pine species, namely loblolly pine (*Pinus taeda*), Virginia pine (*Pinus virginiana*), and shortleaf pine (*Pinus echinata*), using high spectral resolution spectroradiometer reflectance data (350–2500 nm). Discriminant techniques were used to reduce data dimensionality and test spectral separability among species. They had also shown that the VIS, NIR SWIR-I regions are useful for discriminating species of temperate forest conifer and hardwood species when using *in situ* crown scale hyperspectral data (sunlit sides of crown). Spectral derivatives provided the best overall classification accuracies, which were 85% for conifer species and 93% for hardwood species. A study by Wulder et al. (2004) used local maxima filtering for the identification of individual trees on 1m spatial resolution IKONOS satellite images with 67% overall accuracy.

1.16.2 Species discrimination among tropical species using Hyperspectral data

Little is known about the potential for identifying tropical tree species using hyperspectral data. Some of the earlier reports on tropical vegetation used either lab spectra or airborne data. Clark et al. (2005) have opted for 7 tree species classification using field spectrometer and airborne hyperspectral data. They have used SAM, linear discriminate analysis and maximum likelihood classification. The study represents an important breakthrough for identifying tropical tree species. They could obtain an overall classification accuracy of 92% for 7 species using 30 reflectance bands optimally-selected by linear discriminant analysis. Different levels of accuracy also were reported at pixel scale. They have reported importance of near infrared and short wave infrared spectral region for the discrimination of tree species. Importance of the spectral angle between two spectra also was reported to quantify the similarity between spectra from different tree species. Cochrane (2000) provides the investigation of Tropical Rain Forest (TRF) crown-scale hyperspectral data for automated species recognition (350-1050nm). The study used laboratory spectra for 11 tree species to simulate branch and crown scale. It is anticipated that the classification of tropical species may be possible with Hyperspectral imagery that is fine enough to resolve objects and measure pertinent discriminatory spectral features from 400 to 2500nm. Fung et al. (1999) used a spectroradiometer with range 210-1050 nm, but only used the portion of the spectrum between 400-900 nm. A hyperspectral database was constructed for the species being studied by collecting spectral samples from each species during all four seasons. These species included slash pine (*Pinus elliottii*), baldcypress (*Taxodium distichum*), tallowtree (*Sapium sebiferum*), punktree (*Melaleuca quinquenervia*) and bottletree (*Firmiana simplex*). The first and second derivatives of the spectra were used in a linear discriminant analysis. An overall accuracy was 84% where producer's accuracy varied from 56-91%. The original spectra tended to produce better results than the first and second derivatives. Summer and spring accuracies were found to be significantly lower than those obtained for winter and autumn, which can be attributed to leaf color changes and hence lower reflectance in the green and near-infrared reflectance for the latter two seasons. More importantly, little research to date has been conducted on the identification of tropical tree species at the crown level using airborne hyperspectral imagery, a problem that is compounded by the strong control of canopy structure in addition to leaf-level spectral reflectance on canopy level information (Asner, 1998). However this has remained untested with spaceborne Hyperspectral sensor in tropical forests of India.

1.17 Drawbacks of airborne sensor over space-borne sensor

Most hyperspectral sensors are airborne, with two exceptions: NASA's Hyperion sensor on board the EO-1 satellite with 242 bands (Goodenough et al., 2003) and the U.S. Air Force Research Lab's FTHSI sensor on board the Mightysat II satellite with 256 bands (Shippert, 1992). Imaging spectroscopy has evolved substantially during the past two decades (Rock et al., 1994; Vane & Goetz, 1988) and today the highest performance instruments, such as the Airborne Visible/Infrared

Imaging Spectrometer (AVIRIS), have stability and *S/N* capabilities approaching laboratory spectrometers (Green et al., 1998). Airborne imaging spectroscopy has been successfully applied to map vegetation cover (Martin et al., 1998; Roberts et al., 1998). But Wulder et al. (2004) have reported the disadvantages of aerial photos and airborne data due to inherent geometric artifacts of the camera or sensor optics along with the relatively small area of the ground they typically cover. Airborne hyperspectral sensors are clearly disadvantaged by the limited spatial coverage they can provide. Unlike airborne sensors, space-based sensors are able to provide near global coverage repeated at regular intervals with consistent quality and provides suitable information for both visual and digital analysis. Moreover, hyperspectral analyses of seasonal changes in vegetation have been limited due to the restricted abilities of aerial platforms to repeatedly sample larger areas (Gracia & Ustin, 2001; Merton, 1998; Roberts et al., 1997; Elvidge & Portigal, 1990). Aplin et al. (1997) described the potential of satellite sensors to negate some of the common problems associated with airborne data and to facilitate the detailed information on forest attributes over larger areas.

Hyperion is a major advancement in space-based hyperspectal instruments. It was designed as a technology demonstration to build and maintain a science grade instrument for validating push broom performance and to initiate hypespectral application on a global scale (Pearlman et al., 2003). However, it is also true that hyperspectral sensor data requires more sophisticated data analysis procedures (Landgrebe, 1999).

1.18 Analysis of Hyperspectral data

Almost all studies utilizing hyperspectral data require some form of data analysis techniques which are as follows:

- Reduction of data dimensionality
- Class separability
- Types of classifier/matching algorithm

The reduction of data dimensionality makes valid statistical inferences possible, as the ratio of variables and sample size is usually very large in the case of hyperspectral data and has to be reduced (Hoffbeck & Landgrebe, 1996). To reduce redundancy or dimensionality, various univariate and multivariate band reduction techniques have been developed, such as multiple stepwise and partial least square regressions, discriminant analysis, principal component analysis, Minimum Noise Fraction transformation (MNF) and artificial neural network.

Derivative analysis is a common tool used to suppress the effects of background and brightness differences and enhance subtle spectral difference amongst spectra (Fung et al., 1999; Martin et al., 1998; Shaw et al., 1998; Bubier et al., 1997; Gong et al., 1997; Martin & Aber, 1997b; Niemann, 1995). The main reason for this is that derivatives of spectral data should be relatively insensitive to variations in illumination intensity caused by sun angle, cloud cover and topography (Tsai & Philpot, 1998). The effect of band separation on second order derivatives has also been studied (Tsai & Philpot, 1998) and it was concluded that derivatives extract different information from spectra at different wavelength scales. Some studies in vegetation analysis have focused on the use of a subset of channels using continuum removal spectra which corresponds to the principal absorption features of vegetation (Kokaly, 2001; King et al., 2000; Kokaly & Clark, 1999; Kokaly et al., 1998) that offers the greatest separability between materials (Asner & Lobell, 2000). Another way of matching curve shape and not differences in reflectance magnitude is by normalizing spectra. Many studies utilize ratios between known key-feature points in vegetation spectra, such as the red-edge inflection point, the chlorophyll absorption well, the green reflectance peak, or vegetation indices such as the normalized difference vegetation index or NDVI (Ray et al., 2006; Pu et al., 2003). Some of these curve features (e.g., the red-edge position) show variations with different vegetation ages (Niemann, 1995).

Numerous approaches have been taken to compare remotely sensed hyperspectral image data to known reference spectra. In matching algorithm, statistical approaches include one-way analyses of variance (Luther & Carroll, 1999), correlation analyses (Shaw et al., 1998), linear discriminant analysis (Fung et al., 1999; Gong et al., 1997; Niemann, 1995) and canonical discriminant analysis (Palacios-Orueta & Ustin, 1996). Other ways of matching different spectra include distance functions, which calculate the relative fit of one spectrum vs. a reference spectrum (Drake et al., 1999), K-means clustering (unsupervised classification), and maximum likelihood classifiers (Supervised classification) (Martin et al., 1998; Volden et al., 1998; Hoffbeck & Landgrebe, 1996). Correspondingly classification algorithms such as ML (Maximum Likelihood), SAM (Spectral Angle

Mapper), SCM (Spectral Correlation Mapper) and LDA (Linear Discriminant Analysis) have been optimized for distinguishing trees in temperate forests (Buddenbaum et al., 2005, Kokaly et al., 2003) and also in tropical forests (Zhang et al., 2006; Clark et al., 2005) using airborne hyperspectral data. It is unclear that how these algorithms will perform on a complex scene of tropical forest collected by spaceborne hyperspectral data (EO-1, Hyperion). Every method has its particular prerequisites, strengths, and weaknesses.

1.19 Importance of this study

Understanding the Earth system, in all of its fascinating complexity, is the most important scientific adventure of our time. We should get on with it, as free as possible from our preconceptions of the way the world ought to work (Kirchner, 2002).

Given the key roles of the tropical forest biome in the global carbon cycle and in terms of biodiversity and environmental services, intensified research is urgently needed to establish what is currently happening to these forests and to provide the process-level understanding needed to project their likely future (Clark, 2004a). In a developing country like India, biotic pressure, widespread economic growth are altering these landscapes and putting tremendous pressure on the sustenance of leftover tropical forest cover. Consequently, there is a pressing need to monitor the rate and extent of changes in forest cover for efficient planning and management leading to sustainable development at both large and small scales. To date, advances in tropical remote sensing research have focused primarily on developing sound methods to quantify large-scale tropical deforestation (Sanchez-Azofeifa et al., 2001; Skole & Tucker, 1993). While there have been major advances in remote sensing research of boreal and temperate ecosystems, research on tropical systems currently is lacking the fundamental scientific understanding and potential for routine applications observed in other parts of the globe. This gap is due in part to the complexity of tropical forest ecosystems. Tropical vegetation has unique features as compared to temperate vegetation. Besides having larger diversity, the vegetal cover is not as uniform as is normally seen in temperate region. This makes the discrimination process more challenging. However this has remained untested with space-borne Hyperspectral sensor in tropical forests of many parts of the world. In recent years, advances have been made in spectral reflectance characteristics using red-edge, derivative spectra, continuum removal and , narrow band indices but no one knows what the applicability of such techniques will be in a complex scene such as the one presented by a tropical forest. Doing this exercise for Hyperion data becomes more difficult. It is also unclear that how classification algorithms such as ML (Maximum likelihood) and SAM (Spectral Angle Mapper) will perform on a complex scene of tropical forest. Spaceborne sensors are cost effective. Consequently, they are more appropriate for vegetal cover monitoring in countries like India. Keeping all these in view the current study was undertaken to look into the utility aspect of space-borne hyper data for spectral reflectance characteristics and species level classification of trees growing in a sanctuary in Gujarat, India.

1.20 Objectives

To achieve the overall objective of this study, specific objectives were addressed are:

1. To develop spectral signatures for selected/dominant tree species
2. To describe distinct absorption pattern in the vegetation spectra of dry and wet season imagery by applying continuum removal spectra
3. To look at within-species variation based on size and topography
4. To look at the importance of uniformity/homogeneity in patch size & phenology of vegetal cover in affective accuracy assessment for wet and dry season data.
5. To highlight the potential of Hyperion data in deciphering floor cover characteristics from soil in dry season.