CHAPTER 1

Introduction

Forest has been defined as a minimum area of land of 0.05–1.0 ha with tree crown cover, or equivalent stocking level, of more than 10–30% and containing trees with the potential to reach a minimum height of 2–5 m at maturity (UNFCC, 2001). The Global Forest Resources Assessment (GFRA) (FAO, 2010) was the most comprehensive assessment to date. GFRA (2010) reported that the world's total forest area was just over 4 billion ha, corresponding to 31 percent of the total land area. Forests are important socially, economically and environmentally. Forests provide a wide range of goods and services in addition to their role in maintaining the ecological balance (Berlyn and Ashton, 1996). Forests are the renewable natural and ecological resources of earth. They occupy an unique position among the various natural resources as they support life on the earth in many ways (Jaykumar et al., 2002). Forest ecosystems cover large parts of terrestrial land surface and are major component of terrestrial carbon cycle (Lal, 2004). The world's forests store an enormous amount of carbon – more than all the carbon present in the atmosphere (FAO, 2010). Forests play a crucial role in climate change mitigation and adaptation. Forests can play an important role in capturing and storing carbon from the atmosphere, thereby mitigating CO_2 emissions (Watson, 2000; Houghton, 2005). Forest industries have the opportunity to maximize energy efficiency, spur innovation, create a reliable fiber supply and contribute to local economies (FAO, 2010). Forests are increasingly valued for their potential to contribute to the local economy through production, both timber and non-timber, 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 and O'Leary, 2002). The world's forests are prominent sites to study climate change, not only in terms of total net carbon emissions but also in terms of global carbon storage capacity, important for climatic regulation.

The structure, composition and functioning of forests are undergoing rapid changes because of anthropogenic activities. Due to the increase in human and cattle population and widespread rural poverty, forests are subjected to enormous pressure resulting in deforestation and degradation (Panigrahy et al., 2010). This is leading to significant loss of forest cover at an alarming rate. Depletion of forests affects many ecological, social and economic consequences leading to loss of biodiversity, soil erosion, global warming and loss in income to forest dwellers (Panigrahy et al., 2010). The forest ecosystems can be optimally managed if timely information on their structure and function is available. An accurate and continuously updated resource data are a prerequisite for the present day forest ecosystem management. Assessing the health and function of forest ecosystems requires a long term inventory and monitoring effort (Brendeis and Rozo, 2005). Forest cover is an important natural resource which should be conserved on priority basis for sustainable environmental management (Panigrahy et al., 2010). The net change in forest area in the period of 2000–2010 was estimated at ≈5.2 million hectares per year, down from≈8.3 million hectares per year in the period of 1990–2000 (FAO, 2010). However, most of the loss of forest continued to take place in countries and areas in the tropical regions (FAO, 2010).

1.1 Tropical forest cover

Tropical and subtropical dry forests occur in areas where the mean annual temperature is above 17°C, annual mean precipitation ranges from 250 to 2,000 mm, and potential evaporation is greater than precipitation for a significant part of the year (Holdridge, 1967; Murphy and Lugo, 1986). Tropical ecosystems are among the world's hotspots of species richness and endemism (Myers et al., 2000). Tropical forest ecosystems are one of the richest terrestrial ecosystems storing approximately half of the world living terrestrial carbon. They play an important role in global carbon cycle and regulation of biospheric climate (Brown and lugo, 1982). The tropics strongly affect climate and atmospheric composition. These forest ecosystems also support a variety of life forms and maintain huge global biodiversity (Shi and Singh, 2002).Tropical forests are often called the "lungs" of the world, for their gas exchange (Malhi and Grace, 2000; Foley et al., 2007). With increasing threats of forest degradation in the tropics, biodiversity loss and the loss of environmental services, there has been an escalating need for in depth studies into forest dynamics and biophysical characteristics. This supports sustainable resource development and achieves environmental protection goals (Daily et al., 1997; Sanchez-Azofeifa et al., 2003, 2005). Rapid strides in the economy of developing countries such as India are putting tremendous pressure on tropical forests. Knowledge of the structure and chemistry of a tropical forest canopy would provide key insights into ecosystem function and ecological processes (Chambers et al., 2007).

1.2 Forest cover of India

The five countries with the largest forested area (China, Australia, Indonesia, India and Myanmar) accounted for 74 percent of the forests in the Asia and the Pacific region. India, one of the 17 mega diversity countries in the world, harbors a high level of biodiversity. This biodiversity is also unique: four of the 34 global hotspots of biodiversity are located within the country (Bawa, 2006). Based on figures supplied in FAO (2010), some 25 percent of India's land area was covered by forests, other wooded land or other land with tree cover. However, the pressure on existing forest resources is immense in India (Rawat et al., 2008). 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 conditions resulting in diversity of habitats. As a result, India represents two major realms (Palaearctic and Indo-Malayan) and three biomes (Tropical Humid Forests, Tropical Dry Deciduous Forests and warm and semi deserts) which includes 12 bio-geographical regions (MoEF, 2009). Biotic pressure and widespread economic growth are altering the natural vegetation cover and putting tremendous pressure on the sustenance of the few leftover tropical forest covers in India (Christian and Krishnayya, 2009). Indian forestry is in a phase of dismal scenario due to heavy pressure of burgeoning human population on land, growing demand of timber, fuel wood, fodder, grazing, encroachment, shifting cultivation, urbanization, industrialization and improper land management (Datta and Singh, 2007). There is a need to reassess the climate change mitigation opportunities in India in the context of sustainable and commercial forestry strategies. Therefore it is extremely essential to monitor natural resources like forests in developing countries such as India. An accurate and continuously updated resource data is a prerequisite for the present-day forest ecosystem management in India. Moreover, assessing the health and function of forest ecosystems requires a long-term inventory and monitoring effort. By means of remote sensing one can easily achieve requirements of continuously updated resource data and long term inventory and monitoring.

1.3 Introduction to 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 and Kiefer, 2000). Although coarse-spatial resolution meteorological satellite data have been available since the 1960s, civilian remote sensing of the Earth's surface from space at medium spatial resolutions (i.e. ,250 m) only began in 1972 with the launch of the first of a series of Earth Resource Satellites (i.e. Landsat) (Rogan and Chen, 2004). The last few years have seen a proliferation of satellite platforms with a large number of sensors (e.g. Terra,ENVISAT, Indian remote sensing Satellites) and increasing spatial resolutions (e.g. IKONOS, Quickbird and Cartosat). Indeed, the ever-expanding constellation of satellite platforms has acquired thousands of trillions of bytes of data invaluable for planning and land management applications (Jensen, 2000). Furthermore, high-resolution airborne data acquisition technology has developed rapidly in recent years. As a result, there is a large selection of remote sensing data of the Earth's surface with respect to spatial, spectral and temporal sampling. Remote sensing technology is being increasingly used for the measurement of necessary attributes in the crop land monitoring for the purpose of precision farming and also in forestry. Remote sensing technology is offering tremendous opportunities especially for monitoring of forest ecosystems where large scale monitoring is vital.

Remote sensing deals with the detection of electromagnetic energy from hand held instruments and aircraft or spacecrafts. The electromagnetic spectrum can be divided into wavelength regions known as 'optical' and 'microwave' **(Figure 1.1)**. Optical remote sensing targets energy reflected and emitted by the Earth, typically at wavelengths between 400 and 2500 nm. Remote sensing sensors record the intensity of a signal within a wavelength interval, known as a 'band' or 'channel', of specified width within the electromagnetic spectrum. Data are often distributed to remote-sensing practitioners in a matrix of square picture elements (or pixels). The size of these pixels corresponds to the 'spatial resolution' of the sensor, which determines the smallest object detectable. So, '30 m data' would refer to data in matrix of 30 × 30 m pixels. The matrix of pixels is often called a' scene'. Data describing energy reflected or emitted from the surface of the Earth are statistically or visually analyzed to identify objects. The width of the bands of the electromagnetic spectrum detected by a sensor determines its ability to detect spectral differences and as such constitute the spectral resolution of that instrument. All objects have spectral signature based upon how they reflect, absorb and emit electromagnetic radiation. Spectral bands of narrower width allow researchers to find more unique features within the spectral signature of an object that distinguish it from other objects. Temporal resolution, or 'revisit time', refers to the time period between repeat passes over an object being remotely sensed. For example, Landsat satellites pass over the same point on the surface of the Earth every 16 days. Thus, they have a 16-day revisit or repeat time. Systems that image wider areas might pass over the same point everyday but must usually sacrifice spatial resolution to do so (i.e. they can only detect much larger objects). Temporal resolution is especially important when one is trying to obtain a clear view of areas frequently obscured by clouds (or other atmospheric phenomena) because optical sensors cannot view through clouds.

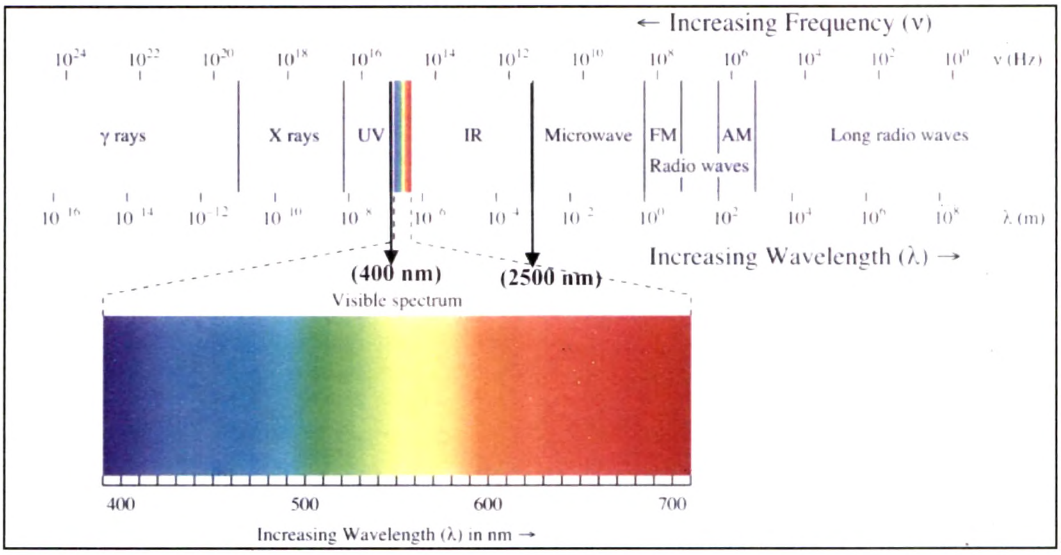

Figure 1.1 Electromagnetic Spectrum (Shippert, 2002)

1.4 Applications and significance of remote sensing

Remote sensing data applications have evolved as very useful tool in the characterization of the state of the biosphere at regional and global scales (Madugundu et al., 2008). Owing to its fast, non-destructive and relatively cheap characterization of land surfaces, remote sensing has been recognized as a reliable method for estimating various biophysical and biochemical vegetation variables (Cohen et al., 2003; Curran et al., 2001; Hansen and Schjoerring, 2003; Hinzman et al., 1986; Mc-Murtrey et al., 1994; Weiss and Baret, 1999). Remote sensing is a key tool for assessing vegetation periodically over larger areas, offering the possibility to analyze ecological issues at a wide range of spatial scales (Kokaly et al., 2003). Remote sensing plays an important role in meeting the needs of forest management, providing information on the extent, biophysical state, and structure of forests. Forest characteristics extracted from remotely sensed data are important for global atmosphere–biosphere models (i.e. water, energy and carbon dioxide flux) (Schlerf et al., 2005), the creation of environmental policies and conservation areas (Pfaff et al., 2000; Pfaff and Sanchez-Azofeifa, 2004) and secondary forest characterization (Arroyo-Mora et al., 2005). Remote sensing is very useful tool especially for tropical regions where it is very difficult to measure forest biochemical and biophysical attributes at large scale due to high species diversity and inaccessibility. In the last three decades, the technologies and methods of remote sensing have evolved dramatically to include a suite of sensors operating at a wide range of imaging scales with potential interest and importance to planners and land managers (Rogan and Chen, 2004). A range of optical airborne and space-borne sensors has acquired remote sensing data, with the number of sensors and their diversity of capability increasing over time. Today a large number of satellite sensors observe the Earth at wavelengths ranging from visible to microwave, at spatial resolutions ranging from sub-meter to kilometers and temporal frequencies ranging from 30 min to weeks or months. In addition, archives of remotely sensed data are increasing and provide a unique, but not complete, chronology of the Earth during this time period. New sensors are continually being launched and existing sensors are often replaced to ensure continuity in the data record (Rosenqvist et al., 2003). A number of optical remote sensing systems are available for researchers. Amongst all optical remote sensing systems two major ones are (1) Multispectral remote sensing system (MSS) and (2) Hyperspectral remote sensing system (HSS). MSS such as Landset TM ,SPOT, Indian Remote sensing systems (IRS) sample the information content by making only few measurements in spectral bands up to several hundred nanometres wide (Jensen, 1996). This type of sensors is non contiguous type. MSS providing systematic observations at the regional/global level and at coarse (≥1 km) spatial resolution include the NOAA advanced very high resolution radiometer (AVHRR) and SPOT VEGETATION. At finer spatial resolution (10–30 m), Landsat sensor (currently the Enhanced Thematic Mapper Plus or ETM+) and SPOT sensor (currently the high resolution visible infrared or HRVIR) data can be combined to provide regional and even continental level observations. HSS such as Hyperion, AVIRIS sample information in the form of number of measurements in spectral bands up to 10-20 nm wide (Jensen, 1996). These types of sensors are of contiguous type. A summary of the key characteristics of selected satellite sensors is presented in **Table1.1**.

Table 1.1. Characteristics of selected remote sensing sensors

Sensor mission	Organization	Spatial resolution (m)	Spectral coverage (μm)	Number of bands
Multispectral sensors				
AWiFS	ISRO,India	56 to70	0.52-1.70	4
AVHRR(NOAA 6-15)	NASA,USA	1100	0.58-11.50	5
TM (Landset 4,5)	NASA,USA	30	0.45-2.35	7
HRV (SPOT1,2,3)	(SPOT) image, France	10(PAN) 20(MS)	0.50-0.89	3
LISS-I (IRS-1A)	ISRO,India	72.5	0.45-0.86	4
LISS-II (IRS-1B)	ISRO,India	36.25	0.45-0.86	4
SAR,OPS(JERS-1)	NASDA,Japan	18	0.43-1.70	7
LISS-III (IRS-1C,1D)	ISRO,India	23	0.52-1.70	4
Panchromatic LISS-IV (IRS-1D)	ISRO,India	5.8	0.50-0.75	1
SPOT 4,5	(SPOT) image, France	1150	0.43-1.75	5
MODIS (EOS)	NASA,USA	250(PAN) 500(NIR)1000(SWIR)	0.620-2.155	36
ETM+ (Landset 7)	NASA,USA	15(PAN) 30(MS)	0.45-2.35,10.4-12.50	7
Cartosat	ISRO,India	<1	0.5-0.85	1
IKONOS	Space imaging ,USA	1(PAN) 4(MS)	0.45-0.90	4
Quick Bird	Digital globe,USA	0.82(PAN) 3.2(MS)	0.45-0.90	4
Air borne hyperspectral sensors				
HYDICE	Naval research lab,USA	20	0.40-2.50	210
AVIRIS	JPL,USA	20	0.40-2.5	224
Space borne hyperspectral sensors				
Hyperion (EO-1)	NASA,USA	30	0.40-2.50	242
CHRIS (PROBA)	ESA	18-36	0.40-1.05	19-63
HySi (Chandrayan - 1)	ISRO,India	80	0.40-0.95	64
PRISMA (2012)	ASI, Italy	30	0.40-2.5	200
EnMAP (2013)	DLR and OHB systems	30	0.42-2.45	200

1.5 Broadband Remote sensing systems

Multispectral remote sensing systems use parallel sensor arrays that detect radiation in a small number of broad wavelength bands. According to Smith (2001), most multispectral satellite systems measure between three and six spectral bands within the visible to middle infrared region of the electromagnetic spectrum. This is due to their (a) broad band widths (100-200nm) and (b) fewer wavebands (4-7 bands) which cover the visible, near and middle infrared regions of the electromagnetic spectrum (Jakubauskas and Price, 1997). The new technology showed that although the information produced by broadband sensors was useful in many applications, still it had limitations. Data acquired from broadband multispectral sensors proved to be less accurate because of coarse spectral resolution (Ellis et al., 2006). That is, because of the limited number of bands and their relatively wide width, large amount of information about vegetation will be lost during averaging. Traditional broad band sensors not proved robust in providing more detailed species level maps because they average the reflectance over a wide range and so the narrow spectral features are lost or masked by other stronger features surrounding them. This greatly reduces the ability of the broad band sensor to spectrally discriminate between two objects on the ground. Too little spectral information, insufficient spatial resolution and soil brightness interference variability are cited as the dominant limitations with traditional sensors to improve surface biophysical mapping (Verstraete et al., 1996; Smith et al., 1990). Most of the natural features have special spectral signals that occur in a very narrow region of the electromagnetic spectrum. Consequently, for identification and recognition of these signals, narrow band sensors are needed. Many materials have diagnostic absorption features that are only 20-40 nm wide, the broad band sensors which have relatively large band width, may not be able to resolve these spectral differences (Jensen, 1996). Hyperspectral sensors produce data with sufficient spectral resolution for direct identification of those materials with diagnostic spectral features. Therefore, hyperspectral remote sensing would be a better option for remote sensing of vegetation parameters. In terms of opportunities, hyperspectral data have provided new options for assessing biological diversity and contributed to assessments of dead and live carbon, measures of forest health, and understanding of ecosystem processes(e.g., through retrieval of foliar biochemicals) (Lucas et al., 2008).

1.6 Hyperspectral remote sensing systems

Imaging spectroscopy (Goetz et al., 1985), also known as hyperspectral imaging, is concerned with the measurement, analysis, and interpretation of spectra acquired from a given scene (or specific object) at a short, medium or long distance by an airborne or satellite sensor. The concept of imaging spectroscopy originated in the 1980's, when A. F. H. Goetz and his colleagues at NASA's Jet Propulsion Laboratory began a revolution in remote sensing by developing new instruments such as the Airborne Imaging Spectrometer (AIS), then called AVIRIS, for Airborne Visible Infra-Red Imaging Spectrometer (Green, 1998). This system is now able to cover the wavelength region from 400-2500 nm using more than two hundred spectral channels, at nominal spectral resolution of 10 nm. This is a major advancement over multispectral systems as they record earth surface information up to 10 spectral bands with 100nm bandwidth. The data produced by the Hyperspectral sensors is different from that of the multispectral instruments with regard to the number of wavebands in which data is recorded. Hyperspectral remote sensing data can provide a significant enhancement of spectral measurement capabilities over conventional remote sensor systems that can be useful for the identification and subsequent modeling of terrestrial ecosystem characteristics (Kumar et al., 2001; Thenkabail et al., 2004). Spaceborne / Airborne hyperspectral remote sensing technology, with its inherent high spectral resolving properties, has been applied in a variety of research fields in forestry, such as forest biochemistry (Grossman et al. 1996, Jacquemoud et al., 1996; Johnson and Billow, 1996; Zagolski et al., 1996; Martin and Aber, 1997; Kokaly and Clark, 1999) and stand structure characterization (Kalacska et al., 2007). With the advent of airborne (e.g. Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) and

HyMap) and, more recently, experimental space borne imaging spectrometers [e.g. Compact High Resolution Imaging Spectrometer (CHRIS) and Hyperion], with high spectral and radiometric resolutions and signal: noise ratios, there have been opportunities to acquire vegetation reflectance spectra and test methods for imaging plant pigment concentrations (Blackburn, 2006).

The forests of the tropics and subtropics represent a diversity of habitats that vary both spatially and temporally. A large proportion of forests is also secondary and exists at varying stages of degradation or regeneration. For remote sensing scientists, this spatial and temporal variation represents both an opportunity and a challenge for the use of hyperspectral data. The latest and significant breakthrough in passive optical remote sensing has been the development of hyperspectral sensors on spaceborne platforms (e.g. EO-1 Hyperion, CHRIS/PROBA) providing continuous narrow bands and high resolution in the visible and infrared spectral region (Stagakis et al., 2010).

1.7 Challenges associated with spaceborne Hyperspectral remote sensing systems

Great power comes with great responsibility. This is true with Hyperspectral data. Although the information content in hyperspectral images is more as compared to multispectral images, there are some challenges to the image analysis. Hyperspectral imagery requires a more detailed image analysis. So, conventional image processing techniques of multispectral data cannot be applied. New image processing techniques are necessary for retrieval of the information from the Hyperspectral images. Following are the Challenges associated with spaceborne Hyperspectral remote sensing systems.

1.7.1 Data Volume: Tremendous increase in the data volume of hyperspectral remote sensing needs suitable data compression techniques for archival or transmission purposes. Following is the comparison of data volume of MSS and HSS data.

Name of the sensor	Type of sensor	Number of Bands	Radiometric resolution
LISS 3	MSS	4	7
Landsat Thematic Mapper	MSS	7	8
AVIRIS	HSS	224	10
Hyperion (EO-1)	HSS	242	12

1.7.2 Redundancy: Data redundancy is a major concern in Hyperspectral data. The increase in the data volume by 40 times seems to contain 40 times more information but that is not the case. Much of the information is redundant due to overlap between adjacent bands. Spectral redundancy means that the information content of one band can be fully or partly predicted from the other bands in the data.

1.7.3 The Need for Calibration (Atmospheric Correction): Hyperspectral data shows atmospheric absorption features which get mixed up with absorption features of land cover. These absorption features of the atmosphere are to be removed to identify important land cover features.

1.8 Addressing Challenges associated with spaceborne Hyperspectral remote sensing systems

Data handling become easier with the increase in storage and processing power of recent computational systems. Conventional statistical techniques cannot be applied to reduce redundancy problem of Hyperspectral data. Many new statistical techniques have been developed and applied to spectra for obtaining relevant wavelengths easily from highly overlapping wavelengths of hyperspectral reflectance spectra. Commonly tested techniques are the Minimum noise fraction (MNF), Linear discriminant analysis, Principle component analysis, Wavelet analysis, Multiple linear regression, Partial least square regression. FLAASH and ACORN are two most commen software modules available for correction of atomospheric effects on reflectance spectra of target materials.

1.9 Reflectance spectra of vegetation

Hyperspectral sensors collect and provide unique reflectance spectra of vegetation. It is necessary to know that how different vegetation characteristics (biochemical and biophysical) affecting reflectance spectra of vegetation. Leaves represent the main surfaces of plant canopies where energy and gas are exchanged. Hence, knowledge of their optical properties is essential to understand the transport of photons within vegetation (Despan and Jacquemoud, 2004). The general shape of reflectance curves for green leaves is similar for all species **(Figure 1.2).** It is controlled by absorption features of specific molecules and the cellular structure of the leaf tissue (Ustin et al., 1998). Three spectral domains can be distinguished. In the visible domain (400-700 nm) absorption by leaf pigments is the most important process leading to low reflectance and transmittance values. The main light absorbing pigments are chlorophyll a and b, carotenoids, xanthophylls, and polyphenols. Chlorophyll a is the major pigment of higher plants and together with chlorophyll b account for 65 percent of the total pigments (Cunningham and Schiff, 1986). Chlorophyll a and b have absorption bands in the blue at around 430-450 nm and in the red domain at around 660-640 nm (Schlerf, 2005). These strong absorption bands induce a reflectance peak in the green domain at about 550 nm. Carotenoids and xanthophylls absorb mainly in the blue and are responsible for the colour of flowers, fruits, and the yellow colour of leaves in autumn (Mlodzinska, 2009). Polyphenols (brown pigments) absorb with decreasing intensity from the blue to the red and appear when the leaf is dead (Verdebout et al., 1994). In the near-infrared domain (near-IR: 700-1300 nm) leaf pigments and cellulose are almost transparent, so that absorption is very low and reflectance and transmittance reach their maximum values (Schlerf, 2005). The level of reflectance on the near-IR plateau increases with increasing number of intercellular spaces, cell layers, and cell size. Scattering occurs mainly due to multiple refractions and reflections at the boundary between hydrated cellular walls and air spaces (Guyot, 1990).In the mid-infrared domain (shortwave IR: 1300-2500 nm), also called shortwave-infrared (SWIR), leaf optical properties are mainly affected by water and other foliar constituents. The major water absorption bands occur at 1450, 1940, and secondary features at 960, 1120, 1540, 1670, and 2200 nm (Ustin et al., 1998). Water largely influences the overall reflectance in the mid-IR domain and also has an indirect effect on the visible and near-IR reflectance. Protein, cellulose, lignin, and starch also influence leaf reflectance in the SWIR. However, the absorption peaks of those organic substances are rather weak as they result from overtones or combinations related to fundamental molecular absorptions in the region of 500 to 800 nm (Curran, 1989). The molecular absorptions are associated with certain chemical bonds, such as C-H, N-H, C-O, and O-H. In fresh leaves, spectral features related to organic substances are masked by the leaf water, so that estimation of leaf constituents is difficult (Verdebout et al., 1994). The optical properties of a vegetation canopy depend mainly on the optical properties of the canopy chemical constituents and on the canopy structure. The most important canopy elements are the leaves and the underlying soil. When a plant canopy grows, the contribution of the soil to the observed total signal progressively decreases as the reflectance spectrum of the bare soil is gradually replaced by that of the plant. When the amount of vegetation increases during growth, the canopy reflectance can reach saturation levels, the canopy structure is primarily defined by leaf area index (LAI) and leaf angle distribution (LAD) (Barton et al., 2001). As a consequence, during growth the visible and middle-infrared (mid-IR) reflectance decreases and the near-infrared (near-IR) reflectance increases the reverse phenomenon is observed during senescence or selective cutting of trees (Guyot, 1990).

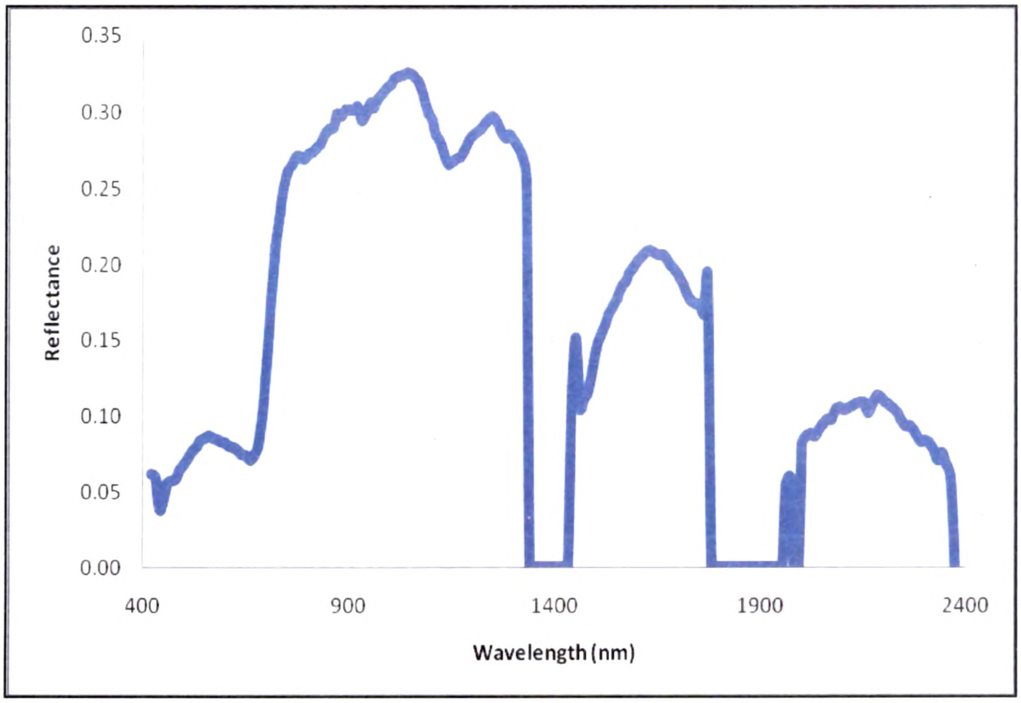

Figure 1.2. The general shape of reflectance curves for green vegetation

1.10 Vegetation biophysical and biochemical attributes

Knowledge of the structure and chemistry of a tropical forest canopy would provide key insights into ecosystem function and ecological processes (Chambers et al., 2007). Many fundamental questions in tropical ecology revolve around the biochemistry, physiology, and biodiversity of forest canopies (Asner, 2008). Because canopies are a locus of biogeochemical processes in an ecosystem, canopy chemistry is core to understanding the spatial and temporal variability of carbon, nutrient, and hydrological cycling (Asner, 2008). Canopy physiology, which controls gross and net primary production, is also mediated by canopy biochemistry (Asner, 2008). In all, the biochemistry, physiology, and biophysical structure of the tree canopies are intimately linked and cannot be easily studied without acknowledging these linkages. Therefore, estimations of biochemical and biophysical attributes at canopy scale are useful inputs for understanding functioning of natural systems. Biochemical attributes such as Leaf pigments, Water, Nitrogen, Lignin, and Cellulose are vital for understanding the physiology and functional role of trees dominant at natural systems. Remote sensing is an important tool for assessing vegetation condition over large areas, offering the possibility to analyzing ecological issues at a wide range of spatial scales (Ustin et al., 1991; Hope, 1995). Many important biochemical attributes can be easily quantified and analyzed for their role in canopy scale dynamics by utilizing this tool. Each attribute has an important role. Leaf pigments are fundamental determinants of light capture and utilization. They provide protection against the harmful effects of high radiation, which is common in the tropics (Björkman and Demmig-Adams, 1995; Evans et al., 2004). Leaf water is another important factor regulating canopy temperature and moisture stress, both of which are particularly acute in tropical forest canopies (Williamson et al., 2000; Nepstad et al., 2002). Foliar nitrogen regulates physiological processes such as photosynthesis and leaf respiration (Field and Mooney, 1986; Reich et al., 1998, 2006). Nitrogen is also related to canopy and stand-level traits such as light use efficiency, wood growth and net primary production (Smith et al., 2002; Green et al., 2003; Ollinger and Smith, 2005). It is an important indicator of photosynthetic rate and overall nutritional status (Curran, 1989; Field and Mooney, 1986). Structural components like cellulose and lignin indicate about the quality and quantity of wood. Lignin plays a key role in both terrestrial and oceanic carbon cycles (Opsahl et al., 1997). Estimates of these constituents can also help in looking at different kinds of inputs to litter decomposition. Developing estimates to all these listed characteristics helps in the overall assessment of the functioning of tropical ecosystems. .

Vegetation biophysical parameters such as the size, distribution of trees in a tropical forest conveys much information about site-to-site differences in growth and mortality rates stem density, canopy architecture and forest structure (Chambers et al., 2007). There is greater need for accurate and detailed information about their biophysical characteristics along different stages of ecological succession (Kalacska et al., 2004). Above ground biomass (AGB) is an important biophysical parameter to be estimated for forest covers. This helps in monitoring the harvest time, carbon cycle studies (Ponzani et al., 2010). Information about forest stand structure and aboveground biomass (AGB) is used to assess forest ecosystem productivity, determine carbon (C) budgets, and support studies of the role of forests in the global carbon cycle (Kurz and Apps, 1999; Cihlar et al., 2002; Lu et al., 2005; Palacios-Orueta et al., 2004; Zeng et al., 2004). It is critical to understand the role canopy species play in determining tropical forest responses to climate change (Clark, 2004). Leaf Area Index (LAI) is considered to be a key vegetation biophysical parameter (Asner, 2008). Various eco-physiological processes of a forest ecosystem such as interception of light (Vargas et al., 2002), precipitation (Van dijk and Bruijnzeel, 2001), and transpiration (Granier et al., 2000) are controlled by LAI. Canopy spread and LAI are two important biophysical attributes in assessing forest production.

1.11 Contribution of Hyperspectral remote sensing in estimation of vegetation biochemical and biophysical attributes

Many researchers have shown the significance of hyperspectral data for the estimation of chlorophyll (Curran et al., 1991; Vogelmann et al., 1993; Gitelson and Merzlyak, 1994; Datt, 1998; Gitelson and Merzlyak, 1997; Blackburn, 1998; Broge and Leblanc 2001; Sims and Gamon 2002; le Maire et al., 2004; Haboudane et al. 2008). All these studies were performed using laboratory spectra. Recently researchers have estimated chlorophyll with the help of pixel level (Air borne or Space borne) hyperspectral reflectance spectra (Jago et al., 1999; Asner and Martin 2008; Darvishzadeh et al., 2008; le Marie et al., 2008; Schlerf et al., 2010; Stagakis et al., 2010). Asner et al. (2005, 2006) used Hyperion (EO-1) satellite sensor to estimate spatial variation in upper-canopy pigments across substrate age and precipitation gradients, and among native and invasive tree species in Hawaiian forests. Foliar Nitrogen for temperate vegetation was estimated by Smith et al. (2002, 2003) using air borne hyperspectral data. Schlerf et al. (2010) estimated foliar nitrogen from coniferous tree species using leaf level hyperspectral data. Martin et al., (2008) have estimated foliar nitrogen from temperate and tropical vegetation using space borne hyperspectral data. Earlier, Huang et al.

(2004) have used air borne hyperspectral data for estimation of nitrogen. Similarly, Asner and Martin (2008) have estimated foliar nitrogen using air borne hyperspectral data with high accuracy. Foliar nitrogen is yet to be estimated with high accuracy using space borne hyperspectral data for tropical forests. Many studies were found for estimation of foliar water content through air borne or space borne hyperspectral data (Gao, 1996; Huete et al, 1997; Peneules et al., 1997; Serrano et al., 2000; Ustin et al., 2004; Cheng et al., 2006). However, accuracy of these studies across wide range of ecological condition is uncertain. Leaf level Hyperspectral studies (Serrano et al., 2002 and Kokaly et al., 2009) for estimation of lignin and cellulose were carried out. No study has been carried out for estimation of lignin and cellulose using canopy level hyperspectral data for tropical regions.

Many studies have investigated the ability of remote sensing data to estimate forest biomass, many problems have been encountered, including the generalization constrains due to the lack of methodological uniformity and the availability of reliable radiometric and biophysical data (Foody et al., 2003). Quantifying AGB in tropical forest cover becomes difficult owing to the variations in canopy spread and its architecture. This increases the levels of uncertainty and errors in estimates. Availability of remote sensing data during leaf shedding season (deciduous period) is likely to give reasonable estimates. The greatest uncertainty in understanding the role of tropical forests in the carbon cycle is associated with AGB estimation (Houghton et al. 2000; Keller et al., 2001). Prediction of AGB estimates in tropical ecosystems gains importance because of the sudden spurt seen in land use land cover changes across these regions. Recently Cho et al. (2007) estimated biomass of tropical herbaceous vegetation with high accuracy. Such types of studies were not conducted for tropical tree covers. A Number of Hyperspectral studies have been found out for estimation of LAI for agricultural crops (Spanner et al., 1990; Elvidge and Chen, 1995; Broge and Leblanc, 2001;Broge and Mortensen 2002; Zhao et al., 2007). Few studies were found in which researchers have estimated LAI of tree species using pixel level hyperspectral data (le Marie et al., 2008; Darvishzadeh et al., 2008; Delaieux et al., 2009).

Taken as a whole, number of Hyperspectral studies have been applied to quantify biochemical and biophysical attributes such as leaf pigments, water, nitrogen, lignin, cellulose, biomass, LAI. Data from imaging spectrometers have been applied to quantify various vegetation biochemical and biophysical parameters at leaf level (summarized by Sims and Gamon, 2002; Ustin et al., 2004 and Ollinger, 2011; Martin and Aber, 1997; Ustin et al., 1998; Kokaly and Clark, 1999; Haboudane et al., 2008). Researchers have also tried to estimate different biochemical and biophysical parameters of tropical vegetation using air borne and space borne hyperspectral data (Thenkabail et al., 2004; Zhang et al., 2006; Cho et al., 2007; Kalacska et al., 2007; Martin et al., 2008; Asner and Martin, 2008). However, canopy-level hyperspectral measurements are frequently lower in precision and accuracy compared to those of leaf-level studies (Asner and Martin, 2008). Scaling issue is a major concern in these studies. A number of hyperspectral studies are available for detecting changes in canopy biochemical concentration at the pixel level in temperate forests, but it has proven difficult on tropical ecosystems characterized by greater structural variability. Cross application of generated data is an important task and many a times generated models do not work across. The validity of the models may be limited to the local environmental conditions (Asner et al., 2003). Tropical forest canopies are yet to be explored for retrieval of diverse biochemical and biophysical attributes using space borne hyperspectral reflectance spectra. Strong linkages between ecological, remote sensing and human influence on tropical dry forest research are necessary to achieve sound sustainable development policies (Bawa et al., 2006). It becomes imperative to have a focused study for evaluating attributes of tropical vegetation covers. Hyperspectral remote sensing has been recognized as a reliable method for estimating biochemical and biophysical attributes of vegetation.

1.12 Algorithms for estimation of vegetation attribute

Algorithms are used for calculation, data processing, and automated reasoning. Algorithm is a step by step procedure for calculations. Many algorithms were developed for estimation of biochemical and biophysical attributes of vegetation using hyperspectral data. Diverse statistical techniques are used to develop algorithms. Two important approaches are,

1. Univariate analysis (Computation of Vegetation indices)
2. Multivariate analysis (Stepwise linear regression/Partial least square regression)

Vegetation indices are computationally fast and require little expertise (Haboudane et al. 2008). Originally, the purpose of spectral vegetation indices was to minimize variability due to external factors such as illumination and atmospheric condition and internal factors such as underlying soil and leaf angle distribution (Darvischzadeh, 2008). Researchers have shown that narrow band vegetation indices can be crucial in providing essential information for quantifying the biochemical (Broge and Leblanc, 2001; Ferwerda and Jones.,2005; Gamon et al., 1992; Gitelson and Merzlyak, 1997; Sims and Gamon, 2002; Mutanga et al., 2005; Haboudane et al., 2008) and biophysical characteristics of vegetation (Blackburn, 1998; Elvidge and Chen,1995; Gong and Miller., 1992; Lee et al., 2004; Mutanga and Skidmore, 2004; Schlerf et al., 2005; Zhao et al., 2007). For development of vegetation indices a limited number of spectral wavelengths from the massive spectral contents of hyperspectral data are used. In contrast, several studies have addressed statistical techniques such as Discriminant Analysis (DA), step wise multiple linear regression (SML) and partial least square regression (PLS) that integrate spectral information of several spectral wavelengths for discrimination of vegetation and for estimation of vegetation biochemical biophysical properties (Curran, 1989; Kokly and Clark, 1999; Curran et al., 2001; De jong et al., 2003; Hansen and Schjoerring, 2003; Huang et al., 2004; Atzberger et al. 2003; Cho et al., 2007; Asner and Martin, 2008). Several studies have also focused on statistical techniques such as stepwise multiple linear regression (SMLR) which make use of the spectral information of several spectral wavelengths to estimate vegetation biochemical properties (Curran ,1989; Curran et al., 2001; Grossman et al.,1996; Huang et al., 2004; Kokaly and Clark 1999; Darvishzadeh et al. 2008) and biophysical properties (Atzberger et al., 2003; De Jong et al., 2003; Darvishzadeh et al., 2008). PLS regression analysis has proven to be one of the most successful empirical approaches for deriving different foliar characteristics from canopy spectral data (Ollinger et al. 2002; Smith et al. 2003, 2002; Cho et al., 2007; Martin et al., 2008; Darvishzadeh et al., 2008; Asner and Martin, 2008). Huang et al. (2004) stated that PLS regression method reduces the effects of background and avoids the potential of over fitting problem typically associated with stepwise regression analysis. PLS regression technique can extract the relevant part of the information from very large data matrices and produce the most reliable models compared to others (Thomas and Haaland, 1990). Atzberger et al., (2003) has stated that PLS regression is known to be suitable for analyzing multi-collinear spectral data. Carrascal and Gordo. (2009) have stated that PLS regression is especially useful when the number of predictor variables is similar to or higher than the number of observations (i.e. overfitting) and/or predictors are highly correlated (i.e. there is strong collinearity). PLS regression produces more stable results with regard to the identification of the relevant variables and their magnitudes of influence independent of the sample size in the analyses, a situation in which other regression approaches fail (Carrascal et al., 2009). PLS regression uses the entire spectrum as a single measurement rather than a band-by-band analysis. Values generated by PLS calculation relate the features of the spectra to the constituents analyzed (Haaland and Thomas, 1988).

1.13 Significance of present study

Given the key role 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 et al., 2004). In developing countries like India rapid economic development and increase in population is creating tremendous pressure on natural resources like forests. Gujarat is one of the most rapidly developing states of India. Gujarat has a territory of 196,024 km^2 and is endowed with a great diversity of natural ecosystem ranging from desert, semi-arid, mangroves, coral reef-rich coast and forests with dry deciduous, moist deciduous and evergreen trees. The angiosperm flora of Gujarat is mostly varied in extent and composition. There are 2198 species of higher plants belonging to 902 genera and 155 families which represent 12.91 per cent of the flora of the India (Singh et al., 2007). Some of the dominant and economically important species are planted at large scale in the state of Gujarat. Accurate estimates of canopy biochemical and biophysical properties of these important species of these regions can help in evaluating the healthy status of these vegetation covers. Teak *(Tectona grandis* Linn.) belongs to family Verbenaceae and Bamboo (*Dendrocalamus strictus* Nees.) belongs to family Poaceae are two important species of tropical regions. Teak and Bamboo are spread across (both naturally and through human intervention) larger areas in tropics. Both are important because of their commercial and conservation values. At many regions both species are being planted under social forestry programme. Both the species are known for their commercial and conservation values. Wider distribution and larger utility value of both these species makes it necessary to monitor them at larger spatial scales. Keeping the importance of these two species in mind the present study has carried out.

Teak is a fine quality timber-yielding deciduous species, suitable for rapid production of large volume of timber, poles and fuel wood (Kaul et al., 2010).Teak timber is of high value, and the species is easily established in plantations. This makes teak one of the most promising species for plantations in the tropics (Keogh, 1996). Today it is widely planted in South East Asia, and as exotic species in Africa, South and Central America (Ball et al., 1999). Tree improvement activities have been initiated in several countries, e.g. Tanzania (Madoffé and Chamshama, 1989), Thailand (Kaosa-ard, 1993; Kaosa-ard et al., 1998),India (Kumaravelu, 1993; Subramanian et al., 1994), Indonesia (Harahap and Soerianegara, 1977; Indonesia Forest

State Enterprise, 1993), Myanmar (Htun and Kaufmann, 1980), Bangladesh (Banik, 1993),Papua New Guinea (Cameron, 1968), Sri Lanka (Maddugoda, 1993), China (Bingchao and Shuzhen, 1993) and Costa Rica (Gamboa and Montoya, 1992). Teak is an obvious choice for intensive domestication activities, because it is used as timber on a large scale in many countries. Teak easily establishes in plantations. In tropical countries like India Teak occurs across the region (Kaul et al., 2010).

Bamboo occurs in many types of forests in this continent. Bamboo is a member of Poaceae growing as a large woody grass. Bamboo species is widely distributed in dry deciduous forests and grows rapidly in all climatic conditions across India (Reddy, 2006). Bamboo, popularly known as giant grass, with more than 1575 species in 111 genera in the world, occurring in a great variety of soil and climatic conditions, plays important role in providing livelihood, ecological and food security of man kind (Bystriakova, 2003). Bamboo has a wide spread distribution in other countries of Asia such as China. It provides natural habitat to giant Panda. India is second to china in bamboo resources with 23 genera and 128 species (Nimachow et al., 2010). India has a vast bamboo cover of about 100,000 km^2 which constitutes about12.8% of the country's forest area (Nimachow et al., 2010). Bamboo has its own unique economic importance. Tribes utilize bamboo stem for making their homes as well as for making baskets and carry boxes etc. A few species of bamboo are edible and are also of medicinal value. Keeping this as a background this study has been carried out to address the following **objective.**

- To examine the utility of space borne Hyperspectral remote sensing data (EO-1 Hyperion) for developing algorithms for accurate prediction of biophysical and biochemical characteristics of teak and bamboo.