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Component-I (B) - Description of Module

Items	Description of Module
Subject Name	Geography
Paper Name	**Remote Sensing, GIS, GPS**
Module Name/Title	**Hyperspectral remote Sensing**
Module Id	**RS/GIS 13**
Pre-requisites	
Objectives	
Keywords	

HYPERSPECTRAL REMOTE SENSING

Learning Outcome

- Student will get to know the need of Hyper spectral data.
- Student will acquire skill for processing required in hyper spectral data.
- Student will be equipped with knowledge to study further about applications of hyper spectral data.

Outline

- Hyperspectral remote sensing and the atmosphere.
- Information extraction from optical image data.
- Elements of Hyperspectral sensing
- Hyperspectral remote sensing application in:
    - Agricultural applications.
    - Environmental applications.
    - Flood detection and monitoring
    - Wetland mapping.
- Snow and glacier studies.

INTRODUCTION

Imaging spectroscopy is of growing interest as a new approach to Earth Remote Sensing. With the advent of hyperspectral remote sensors, both airborne and space-borne, along with the high storage capacity of the fast computing systems and advanced software to store and process the hyperspectral data, it is now possible to detect and quantify various earth resource materials (Goetz, 2009). The original definition for imaging spectrometry proposed by the author and others (Goetz et al., 1985) was given as “the acquisition of images in hundreds of contiguous, registered, spectral bands such that for each pixel a radiance spectrum can be derived." Hyperspectral sensors or imaging spectrometers collect unique data that are both a set of spatially contiguous spectra and spectrally contiguous images (Goetz *et al.* 1985) Fig. 1. One of the earliest applications of hyperspectral remote sensing identified was geological mapping and its commercial role in mineral exploration.

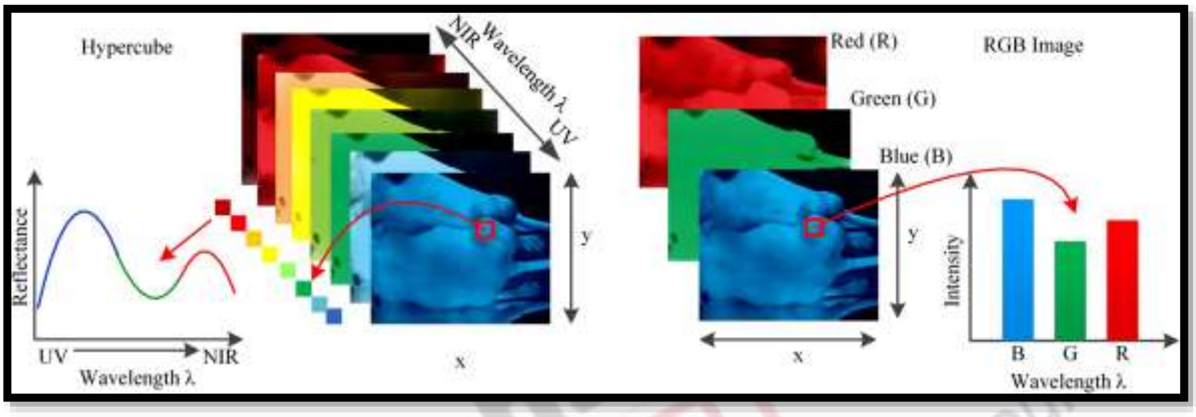

Fig. 1 Hyperspectral vs Multispectral imagery

Source: http://biomedicaloptics.spiedigitallibrary.org/article.aspx?articleid=1816617

One of the most important thrust of remote sensing technology is the study and monitoring of Earth's vegetation. The EM radiation when incident over the surface, either gets reflected, absorbed, re-radiated or transmitted through the material depending upon the nature of the object and the wavelength of the incident radiation which, thus forms the signature of that object. When vegetation is observed/imaged from the space, the integrated effect of plant/tree as a whole is recorded. This includes leaves, stems, branches, flowers etc. as well as the background, which in many cases is soil. Nonetheless, the major contribution is from the leaves only which form the higher surface area in comparison to the other parts of the plant/tree. With varying shapes, sizes and internal characteristics of the leaves, the spectral characteristics of the plants also change. In earth observation, over more than a decade, efforts have been made to investigate the applicability of multi spectral data and to improve geometric resolutions of optical sensors down to one meter. There is a need to have accurate, quantitative information of land surface parameters to understand the biogeophysical processes in terrestrial ecosystems. This calls for quantification of many parameters as well as inventory of a very different kind based upon spectral response in various wavelength regions. In this context, hyperspectral and ultra spectral remote sensing data has a crucial role to play. The comparison between hyperspectral and multispectral techniques is given in Table 1.

Table 1: The comparison between hyperspectral and multispectral techniques

Details	**Hyperspectral**	**Multispectral**
Bands	Contiguous each other	Discrete each other
Analysis objectives	Discriminate material among various earth surface features	Categorize features
Signal-to-noise ratio	Lower (i.e. tendency of more noise)	Higher
Atmospheric interference	More susceptible	Less susceptible
Analysis methods	More reliance on physical and biophysical models	More reliance on statistical techniques (ex. maximum likelihood classification)

The development of terrestrial imaging spectroscopy, as documented by Staenz, 2009, started in the late seventies by NASA's Jet Propulsion Laboratory (JPL) and a government of Canada/private partnership (Department of Fisheries and Ocean/Moniteq) leading to the Airborne Imaging Spectrometer (AIS; Vane and Goetz, 1988) in the U.S.A. and the Fluorescence Line Imager (FLI; Gower et al., 1987) in Canada with first data acquisitions in 1983 and 1984, respectively. These activities led in 1987 to the first visible and near-infrared (VNIR) and short-wave infrared (SWIR) sensor, JPL's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS; Green et al., 1998; Vane et al., 1993) and in 1988 to the first commercial instrument, Itres' Compact Airborne Spectrographic Imager (casi; Anger et al., 1990). Many more airborne systems have been developed since that time (e.g., Buckingham, 2008; Birk and McCord, 1994).

The first successfully launched civilian hyperspectral satellite sensor, NASA's Hyperion on EO-1, has been in orbit since 2000 (Pearlman, 2003). A year later, the Compact High Resolution Imaging Spectrometer (CHRIS) on board ESA's Project for On-Board Autonomy (PROBA) platform was launched (Barnsley et al., 2004). Both systems are still operating today, providing imagery in the VNIR (CHRIS) and VNIR/SWIR (Hyperion). With the current launches of ISRO's VNIR Hyperspectral Imager (HySI) on board the Indian Microsatellite 1 (IMS-1) and the Chinese VNIR HJ-1A satellite sensor in 2008, new opportunities will arise for the use of hyperspectral data in various application areas due to the larger ground sampling distance (GSD) (≥100 m) combined with a larger swath width (≥ 50 km) of these sensors (Goetz, 2009; Staenz, 2009).

Data handling and correction of sensor artifacts dominated software development in the early phases of imaging spectroscopy, followed by an intense period of algorithm development (AVIRIS, 2007). Innovative procedures, such as atmospheric correction and spectral linear unmixing, were developed (Staenz and Williams, 1997; Neville et al. 2008). These procedures together with the capability to handle hyperspectral data were incorporated into several hyperspectral image analysis systems by government and academic institutions and, ultimately, resulted in the release of the first commercial system, ENVI, in 1994 (Boardman et al., 2006). With the availability of ENVI, the development of applications increased significantly, making imaging spectroscopy an important tool in areas such as climate change, resource management, and environmental monitoring and assessment as, for example, shown in the AVIRIS Workshop proceedings (AVIRIS, 2007). Additional hyperspectral image analysis systems have emerged, such as the hyperspectral packages in ERDAS Imagine and in PCI Geomatica (Goetz, 2009; Staenz, 2009). The hyperspectral absorption features and indices are given below in Table 2:

Table 2: Spectral Vegetation Indices

Index	Computation	Reference
Structural indices		
NDVI (Normalized Difference Vegetation Index)	(ρn – ρr)/(ρn + ρr)	Rouse et al. (1973)
SR (Simple Ratio)	ρn / ρr	Birth and McVey (1968)
SAVI (Soil Adjusted Vegetation Index)	(ρn – ρr) (1+L) / (ρn + ρr + L), L=0.5	Huete (1988)
MSAVI2 (Modified SAVI)	ρn + 0.5 – ((ρn + 0.5)2 – 2 (ρn – ρr))0.5	Qi et al. (1994)
OSAVI (Optimized SAVI)	(1+0.16) (ρ800 – ρ670)/(ρ800 + ρ670 + 0.16)	Rondeaux et al. (1996)
MSR (Modified SR)	MSR = ((R800 – R670)-1) / ((R800 + R670) 0.5 + 1)	Chen (1996)
RDVI (Renormalized Difference Vegetation Index)	RDVI = (R800 – R670) / (R800 + R670)0.5	Roujean and Breon (1995)
EVI (Enhanced Vegetation Index)	EVI=2.5*((Rn-Rr)/(Rn+6Rr-7.5Rblue+1))	Huete et al. (1997)
ARVI (Atmospherically Resistant Vegetation Index)	ARVI=(Rn-(2Rr-Rblue)/(Rnir+(2Rred-Rblue))	Kaufman and Tanre (1996)

	Greenness/pigment related indices	
MCARI (Modified CARI)	MCARI = [(R700 – R670)-0.2(R700 – R550)] (R700/R670)	Daughtry et al. (2000)
TCARI (Transformed CARI)	TCARI = 3 [(R700 – R670)-0.2(R700 – R550) (R700/R670)]	Haboudane et al. (2002)
TVI (Triangular vegetation index)	TVI = 0.5 [120 (R750 – R550) – 200 (R670 – R550)]	Broge and Leblanc (2000)
SIPI (Structural insensitive pigment index)	SIPI = (R800 – R445)/(R800 + R680)	Penuelas et al. (1995)
NPCI (Normalized Pigment Chlorophyll Index)	NPCI = (R680 – R430) / (R680 + R430)	Penuelas et al. (1995)
PRI (Photochemical Reflectance Index)	PRI=(ρ531 – ρ570)/(ρ531 + ρ570)	Penuelas et al. (1994)
RGR (Red Green Ratio Index)	RGR=Rg/Rred	Gamon and Surfus (1999)
Red Edge Normalized Difference Vegetation Index	RedNDVI=(R750-R705)/(R750+R705)	Gitelson and Merzylak (1994), Sims and Gamon (2002)
mSR (Modified Red Edge Simple Ratio Index)	mSR=(R750-R445)/(R705-R445)	Sims and Gamon (2002)
Modified Red Edge Normalized Difference Vegetation Index	(R750-R705)/(R750+R705-2R445)	Sims and Gamon (2002), Datt et al. (1999)
Vogelmann Red Edge Index 1	VOG1=R740/R720	Vogelmann et al. (1993)
Vogelmann Red Edge Index 2	VOG2=(R734-R747)/(R715-R726)	Vogelmann et al. (1993)

Vogelmann Red Edge Index 3	VOG3=(R734-R747)/(R715-R720)	Vogelmann et al. (1993)
Red Edge Position Index	Between 690 and 740nm	Curran et al. (1995)
CRI1 (Carotenoid Reflectance Index 1)	CRI1=(1/R510-1/R550)	Gitelson et al. (2002)
CRI2 (Carotenoid Reflectance Index 2)	CRI2=(1/R510-1/R700)	Gitelson et al. (2002)
ARI1 (Anthocyanin Reflectance Index 1)	ARI1=(1/R550-1/R700)	Gitelson et al. (2001)
ARI2 (Anthocyanin Reflectance Index 2)	ARI2=R800(1/R550-1/R700)	Gitelson et al. (2001)
Other indices		
Red edge 750~700	R750 – R700	Gitelson and Merzylak (1997)
Red edge 740~720	R740 – R720	Vogelmann et al. (1993)
ZTM (Zarco Tejada and Miller)	ZTM = (R750 / R710)	Zarco Tejada et al. (2001)
NDNI (Normalized Difference Nitrogen Index)	NDNI= (log(1/R1510)-log(1/R1680))/(log(1/R1510)+log(1/R1680))	Serrano et al. (2002), Fourty et al. (1996)
NDLI (Normalized Difference Lignin Index)	NDLI= (log(1/R1754)-log(1/R1680))/(log(1/R1754)+log(1/R1680))	Serrano et al. (2002), Fourty et al. (1996), Melillo et al. (1982)

CAI (Cellulose Absorption Index)	CAI=0.5(R2000+R2200)-R2100	Daughtry (2001), Daughtry et al. (2004)
PSRI (Plant Senescence Reflectance Index)	PSRI=(R680-R500)/R750	Merzlyak et al. (1999)
WBI (Water Band Index)	WBI=R900/R970	Penuelas et al. (1995) and Champagne et al. (2001)
NDII (Normalized Difference Infrared Index)	NDII=(R819-R1649)/(R819+R1649)	Hardisky et al. (1983) and Jackson et al. (2004)
NDWI (Normalized Difference Water Index)	NDWI=(R857-R1241)/(R857+R1241)	Gao (1995)
MSI (Moisture Stress Index)	MSI=R1599/R819	Ceccato et al. (2001)
MCARI1	MCARI1 = 1.2 [2.5 (R800 – R670) - 1.3 (R800 – R550)]	Haboudane et al. (2004)
MCARI2	MCARI2 = 1.5 [2.5 (R800 – R670) - 1.3 (R800 – R550)]/ [(2 R800 + 1)2 – (6R800 –5 (R670)0.5) – 0.5]	Haboudane et al. (2004)

HYPERSPECTRAL SENSORS

- **Airborne**
- CASI (Canadian Technology)
- HyMAP (Australian Technology)
- AVIRIS (American NASA Technology)
- HYDICE (US Naval Research Lab)
- DAIS (European Technology)

- AIMS (Indian Technology)
- AHySI (Indian Technology)

- **<u>Spaceborne</u>**
- MODIS
- MERIS
- Hyperion
- CHRIS

- **<u>Ground based</u>**
- Spectro-radiometer

INFORMATION EXTRACTION FROM OPTICAL IMAGE DATA

In hyperspectral remote sensing, the ability to derive information from spectral data is the key to any successful collection. The vast amount of spectral data must be culled to define the spectral signature of interest for the material under consideration. In spectral terms, the pure spectral signature of a feature is called an endmember. One method of collecting pure end members is from a laboratory spectroradiometer that is focused on a single surface or material. These signatures are then used in the spectral sensor, and detection algorithms are used to define and refine the spectral scene collected so a material or materials with similar characteristics can be defined. However, when the material of interest is not available for laboratory measurements, it must be defined within the spectral scene collected. Data can be collected at pixel level as well as object level (Fig.3).

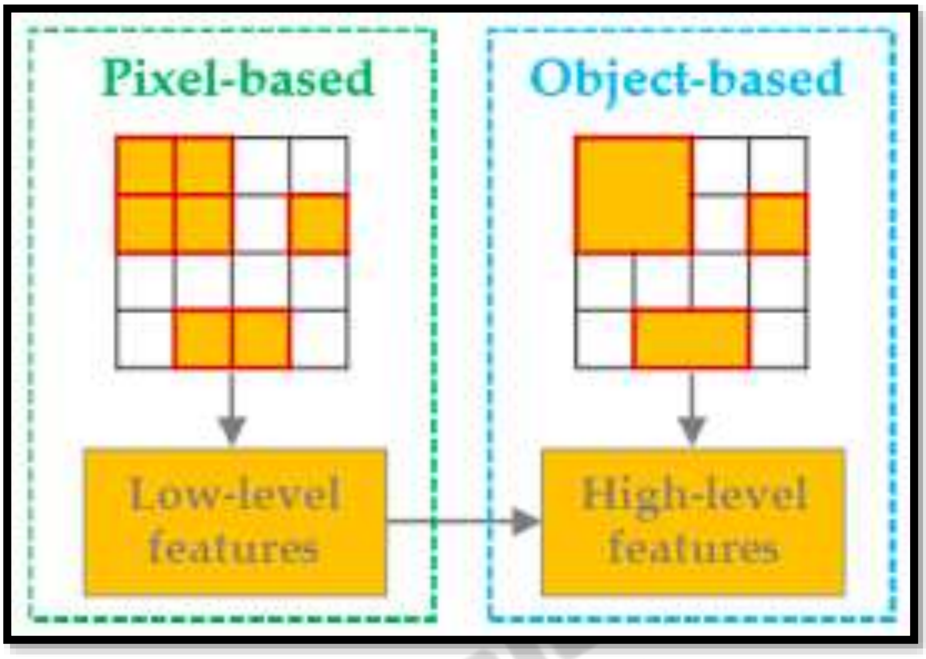

Fig. 3 Pixel based and Object based data collection

Source: http://www.mdpi.com/2072-4292/8/8/689

Even though current remote sensors and data collection systems often create extremely large data sets that are difficult to work with, the information contained in these data sets can be valuable. As a result, software has been developed to aid with the visualization and classification. One option for the image classification process is feature extraction. This option reduces the spectral or spatial characteristics with spectral transformations or spatial filters so data sets can be easily processed and exploited. Feature extraction can also be accomplished by selecting a subset of bands based on the characteristics of certain items of interest.

One method for isolating spectral features is called Spectral Mixture Analysis (SMA). SMA is a structured approach that addresses the mixed-pixel problem and other factors that contribute to the image quality, such as calibration and light conditions.

The SMA equation for each band is:

$$Rb = \sum_{em=1}^{Nk} Fem\, Rem, b + Eb$$

where Rb is the spectral radiance at band b, Fem is the fraction coefficient of each end member, Rem, and their weight factor at band b, while Eb is the error for any other sources of radiance in band b. Each endmember is selected based on its distinct material and its contribution to the overall spectral scene. This method works best when spectral diversity and content of the scene are not complex and the spectral features of interest are very minor in the scene. Other methods of feature extraction include the first difference Partial Least Squares (PLS) regression, which uses a Singular Value Decomposition (SVD) of the entire spectrum within the scene, and Hierarchical Foreground/Background Analysis (HFBA), which divides the spectral scene into two groups, foreground and background, that contain the spectral signature of he feature or features of interest.

ELEMENTS OF HYPERSPECTRAL SENSING

The important element of hyperspectral sensing includes:

a) Material Spectroscopy b) Radiative transfer c) Imaging spectrometry d) Hyperspectral data processing.

a) Material spectroscopy:

Material spectroscopy talks about interaction of electromagnetic radiation with matter, particularly with respect to the wavelength dependence of observable material features, and provides the physical basis of hyperspectral sensing in terms of the direct relationship between observable (or apparent) material spectral features and the inherent compositional characteristics. Spectroscopy relates to electromagnetic interaction at the atomic and molecular level and behaves strictly like quantum mechanics. Such behavior provides great insight into the origins of observable spectral features that are the foundation for the information extracted from a hyperspectral sensor.
Let's take simple example of Quartz. Quartz is a crystalline or amorphous form of SiO_2 molecules that are extremely common in silicate-based soils prevalent all over the world. A physical chemist would recognize SiO_2 as a tri-atomic molecule, with three vibrational degrees of freedom and three corresponding resonant absorptions of electromagnetic radiation: symmetric and asymmetric stretch resonances that roughly

coincide, and a bending resonance that occurs at a lower electromagnetic frequency. As is typical for such materials, these resonances correspond to frequencies in the LWIR spectral region and are responsible for the intrinsic spectral properties of crystalline or amorphous quartz. Intrinsic spectral properties describe how the material interacts with electromagnetic radiation of different wavelengths. These intrinsic spectral properties are captured by the spectral nature of the real and imaginary parts of the complex index of refraction n(ƛ) and k(ƛ). The intrinsic spectral properties are unique to a material and therefore can be considered to provide a signature from which the material type can be determined.

b) Radiative transfer

Radiative transfer is the science of the propagation of electromagnetic radiation from various sources to a sensor, including interactions with objects and their environment, as well as the atmospheric. Radiative transfer is another critical factor that must be carefully understood because it provides the physical relationship between the measured spectrum, typically in the form of a spectral radiance measurement at the sensor location, to the apparent material characteristic, such as its reflectance distribution. Because of intervening atmosphere the illumination actually includes two components: the direct solar illumination reduced by the atmospheric attenuation, and an indirect component due to energy scattered by atmospheric constituents such as aerosols, clouds, and surrounding objects. Under some approximations, it is sufficient to describe the diffuse downwelling illumination in terms of its surface irradiance integrated over the hemisphere above the surface:

$$E_d(\lambda) = \int_0^{2\pi} \int_0^{\pi/2} Ld(\lambda, \Theta, \Psi)\ sin\Theta\ cos\Theta\ d\Theta\ d\Psi$$

where we define $Ld(\lambda, \Theta, \Psi)$ as the indirect spectral radiance, a radiometric quantity that maintains the angular dependence of propagating radiation, and $Ed(\lambda)$ as the integrated spectral irradiance. This diffuse illumination can be influenced by light scattered either directly or indirectly from adjacent objects in the scene.

c) Imaging spectrometry

Imaging spectrometry refers to the art and science of designing, fabricating, evaluating, and applying instrumentation capable of simultaneously capturing spatial and spectral attributes of a scene with enough fidelity to preserve the fundamental spectral features that provide for object detection, classification, identification, and/or characterization. A variety of optical techniques can be employed to develop a sensor capable of capturing hyperspectral imagery, including dispersive prism or grating spectrometers, Michelson Fourier transform spectrometers, spatial Fourier transform spectrometers, scanning Fabry–Perot etalons, acousto-optic tunable filters, and dielectric filters.

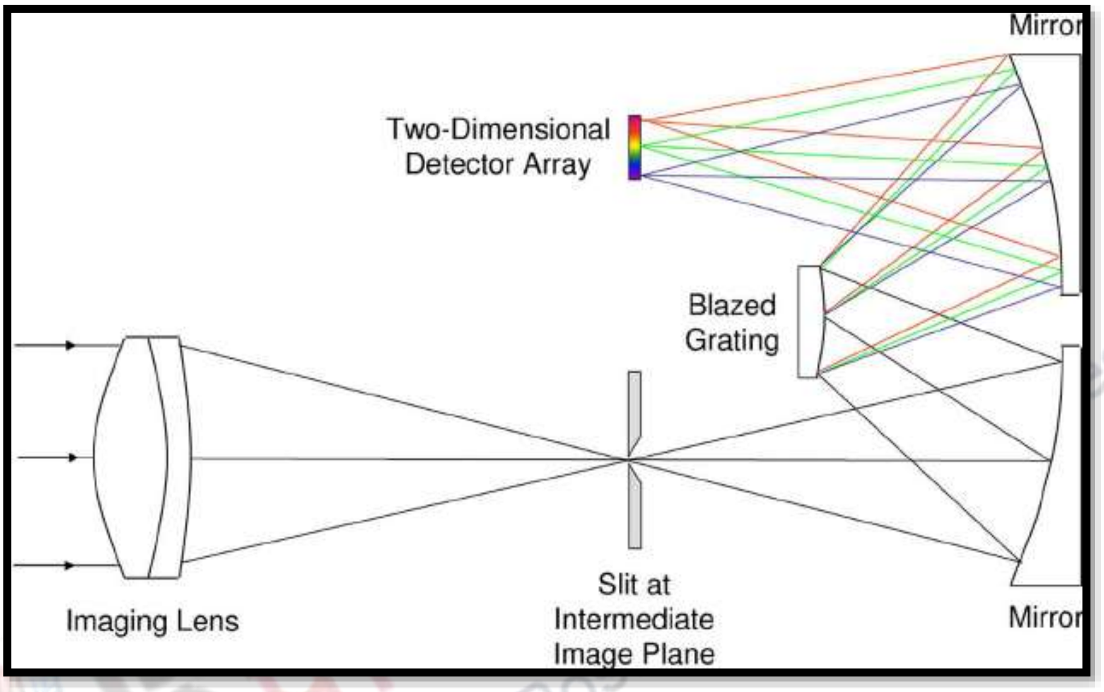

Fig. 4   Basic layout of Imaging grating spectrometer

Source:
https://www.researchgate.net/figure/224453518_fig2_Fig-2-Basic-layout-of-an-imaging-grating-spectrometer

Light entering the grating spectrometer from a remote location (from the left in the figure) is first focused by an imaging lens assembly to form an image on the slit plane. The slit is an opaque surface that blocks all light except for a rectangular area one pixel high (in the dimension shown) and many pixels wide (in the orthogonal direction). This surface is reimaged by the three spectrometer mirrors onto the 2D detector array, so that the slit height nominally matches the detector element size and the slit width matches the detector array width. If there are no other elements, the 2D detector array simply produces a line image of the portion of the scene that passes through the slit. However, the spectrometer also includes a periodic blazed grating on the surface of the middle mirror of the reimaging optics that disperses light across the detector array dimension shown. Thus, the arrangement forms an optical spectrum for each spatial location in the entrance slit across this dimension of the array shown in Figure 4.

d) Hyperspectral Data Processing

After hyperspectral data have been calibrated, the question becomes how to extract and utilize the information content within the data. Two general approaches are taken toward such processing: physical modeling and statistical signal processing. Typical methods employ a linear mixing model for the radiance spectra and a sophisticated radiation transport code such as MODTRAN to capture the atmospheric transmission, radiation, and scattering processes. These methods are often focused beyond the detection and classification of materials to a more quantitative estimation of constituent material abundances and physical properties.

ORBITAL DYNAMICS:

Orbit types are:
Low Earth Orbit (LEO) – Typically ~300-1500km altitude

• Medium Earth Orbit (MEO) – ~1500-35800km altitude

• Geostationary/Geosynchronous Orbits (GEO) – 35800km altitude, circular (orbital period matched with earth 24hrs)

• Highly Elliptical Orbit (HEO) – Typically

a) Satellite ground trace- LEO

LEO satellites are typically placed at altitudes of 500 Kilometers or higher. LEO offers the advantage of short delays (typically 1 to 4 milliseconds), but the disadvantage that the orbit of a satellite does not match the rotation of the earth. Thus, from an observer's point of view on the earth, an LEO satellite appears to move across the sky, which means a ground station must have an antenna that can rotate to track the satellite (Figure. 5). Tracking is difficult because satellites move rapidly. The lowest altitude LEO satellites orbit the earth in approximately 90 minutes; higher LEO satellites require several hours. The general technique used with LEO satellites is known as clustering or array deployment. A large group of LEO satellites are designed to work together. In addition to communicating with ground stations, a satellite in the group can also communicate with other satellites in the group

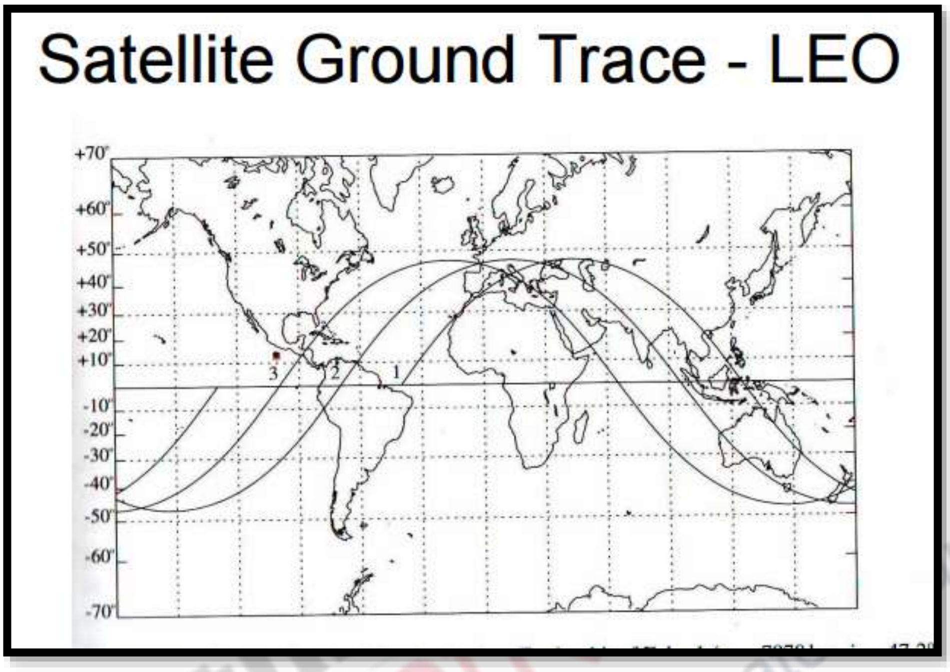

Fig 5. Sample ground track of circular low earth orbit (a=7978km, i=47.2°, T=118.3)

b) Satellite ground trace- Polar orbit

Due to the rotation of the Earth, it is possible to combine the advantages of low-altitude orbits with global coverage, using near-polar orbiting satellites, which have an orbital plane crossing the poles (Figure. 6). These satellites, termed Polar Orbiting Environmental Satellites (POES) are launched into orbits at high inclinations to the Earth's rotation (at low angles with longitude lines), such that they pass across high latitudes near the poles. Most POES orbits are circular to slightly elliptical at distances ranging from 700 to 1700 km (435 - 1056 mi) from the geoid. At different altitudes they travel at different speeds."High inclination" means that the sub satellite point moves north or south along the surface projection of the earth's axis. If the orbit is designed correctly, the sub satellite point can be largely in the day side (or night side) of the planet during the entire orbit. Such an orbit is termed "sun-synchronous" and more details on that are given below. Obviously, in order for this to happen, the orbital speed of the satellite (and its orbital altitude) would have to be phased with the rotation of the earth. The result is that the orbit of the satellite can be phased so that the satellite maximizes its coverage of the the day side of the plane.

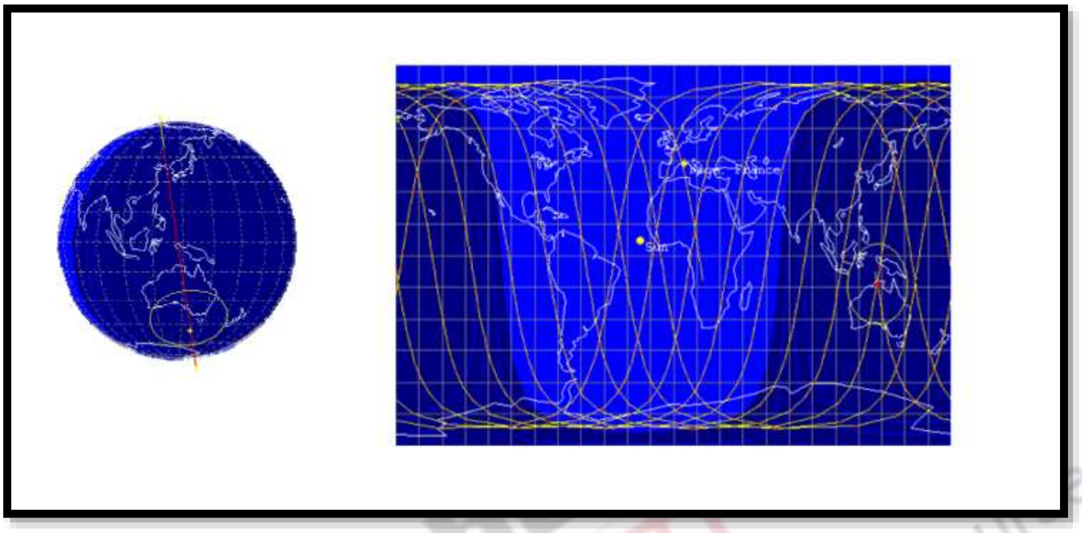

Fig 6: Polar orbit trace- greater coverage near the poles
Source:
http://web.aeromech.usyd.edu.au//AERO4701/Course_Documents/AERO4701_week2.pdf

c) Geostationary orbit

Geostationary orbits of 36,000km from the Earth's equator are best known for the many satellites used for various forms of telecommunication, including television. Signals from these satellites can be sent all the way round the world. Telecommunication needs to "see" their satellite all time and hence it must remain stationary in the same positions relative to the Earth's surface. A stationary satellite provides the advantage for remote sensing that it always views the Earth from the same perspective, which means that it can record the same image at brief intervals. This arrangement is particularly useful for observations of weather conditions shown in Figure. 7. One disadvantage of geostationary orbits is the great distance to the Earth, which reduces the achievable spatial resolution.

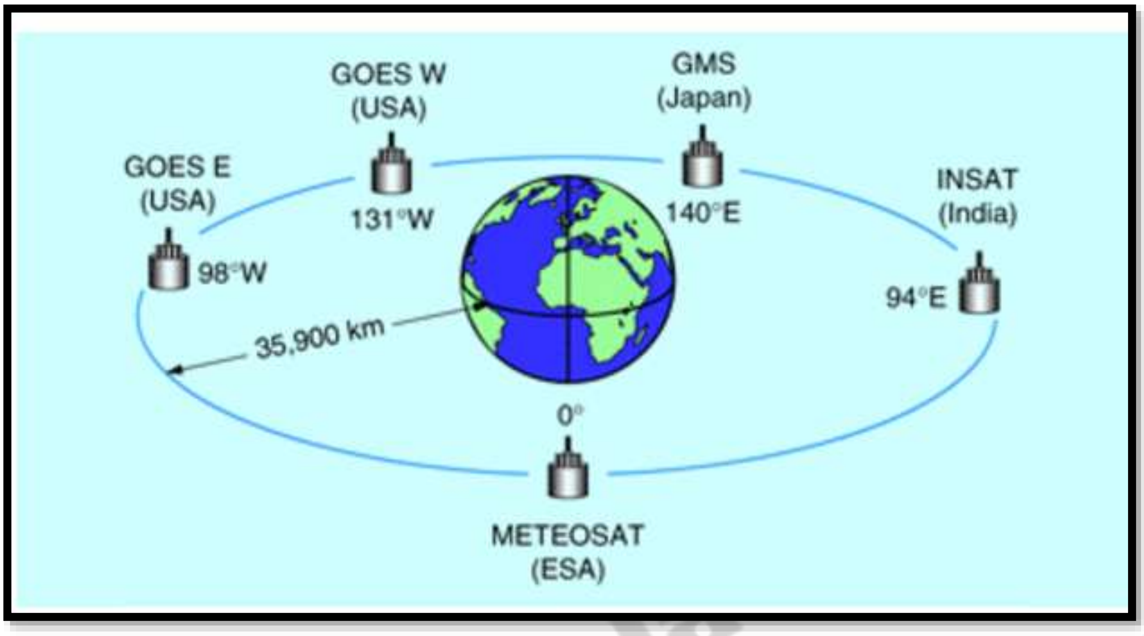

Fig 7. Metosat and other satellites in Geostationary orbit

Source: http://www.esa.int/Education/3._The_geostationary_orbit

HYPERSPECTRAL REMOTE SENSING SENSORS

Various air borne and space borne sensors developed by national and some international agencies are as follows.

Table 3 Air borne Hyperspectral sensor

Sensor	Spectral coverage (nm)	No. of Bands	Band width (nm)	Spatial Resolution (m)	Image tech	Country	Launched /developer
GERIS(Geophysical Environment Research Imaging Spectrometer II)	400 - 1000 1400 - 1800 2000 - 2500	24 7 32	25.4 120.0 16.5	1-10	Whisk broom	USA	1987/GRE corp.
AVIRIS(Airborne visible infrared imaging spectrometer)	380-2500	220	10	5-20	Whisk broom	USA	1987/JPL
CASI(Compact Airborne Imaging Spectrometer)	400-800	288	1.8	30	Pushbroom	Canada	1988/ITRES research Ltd
DAIS (Digital Airborne Imaging Spectrometer)	400-1200 1500-1800 2000-2500	72	15-30 45 20	1-10	Pushbroom	Europe	1995/GRE corp.

HYDICE(Hyperspectral Data Image Collection Experiment)	400 - 2500	10.2	210	3	Whisk broom	USA	1996/Naval research lab
HyMAP	400 - 2500	16	125	3-5	Whisk broom	Australia	HyVista Corp
AisaEAGLE	400 - 970	5	200	<1			Spectir Corp

Table2:Spaceborne Hyperspectral sensors

Sensor	Spectral coverage (nm)	No. of Bands	Band width (nm)	Spatial Resolution (m)	Swath (km)	launch Year	Agency
Moderate Resolution Imaging Spectrometer (MODIS)- AQUA MODIS- TERA	400 - 800 800 - 1455	32 36		250-1000 250-1000	1500 2300	May 2002 Dec 1999	NASA
MERIS (Medium Resolution Imaging Spectrometer)	410to1050	15	10	Ocean: 1040x 1200, Land & coast: 260 x 300	1150		ESA
Hyperion on EO-1	400-2500	220	10	3	7.5	Nov 2000	NASA
CHRIS (Compact High Resolution Imaging Spectrometer on PROBA-1)	438 -1035	18-64	1.25-11	18-36	14-18	Oct 2001	ESA
HySI(Hyperspectral Imager) on IMS-1	400 - 950	64	<15	550	128	Apr 2008	ISRO
Extraterrestrial hyperspectral sensors							
Chandrayaan-1 HySI	400 - 920	64	15	80	20	2008	ISRO
Chandrayaan-1 M3 (Moon Mineralogy Mapper)	400 - 3000	86	10-40	70-140	40	2008	ISRO
OMEGA(Observatoire pour la Mineralogie, l'Eau, le Glace e l'Activite)	360 to5100		7-20	300-4000	8.8		NASA
CRISM (Compact Reconnaissance Imaging Spectrometer for Mars)	362-3920	545	6.55	15.7 to 19.7	9.4 - 11.9		NASA

HYPERSPECTRAL REMOTE SENSING IN GLOBAL SCENARIO

The term "hyperspectral imaging" was first coined by Goetz et al. (1985) in a paper discussing the early results of the technique of imaging spectrometry. Hyperspectral imaging has enabled applications in a wide variety of Earth studies (Goetz, 2009). The prime motivation for the development of imaging spectrometry was mineralogical mapping of surface soils and outcrops (Abrams et al., 1977; Goetz et al., 1985). The reflectance spectra of minerals are rich in electronic as well as overtone and combination vibrational features that characterize surfaces that are relatively vegetation-free (Clark et al., 1990). Only approximately 30% of the land surface is relatively devoid of vegetation and the remaining 70% is covered by vegetation to the extent that the substrate is rendered inaccessible to remote sensing identification (Siegal and Goetz, 1977). However, the vegetation cover, its type, health, vigor and expression of environmental conditions including the substrate are the subject of many ongoing studies (Goetz, 2009).

Wessman et al. (1988) identified tree species for the first time based on nitrogen and lignin content in the foliage. They used statistical regression techniques also known to spectroscopists as chemometrics (Mark, 1989) and built a prediction model based on known occurrences of broadleaf and evergreen species on Blackhawk Island, WI. As follow-on to the HIRIS project, NASA funded the Accelerated Canopy Chemistry Program in which chemometrics techniques were used successfully on AVIRIS data acquired over the Harvard Forest, MA (Aber & Martin, 1995; Martin and Aber, 1997) (Source: Goetz, 2009). Other diverse studies of species and canopy health, water content as well as relative abundances of photosynthetic (PV) and non-photosynthetic (NPV) vegetation in a pixel can be found in papers by Gamon et al. (1992, 1993), Ustin et al. (1992, 1998), Roberts et al. (1993, 1998), and Asner and Lobell (2000) (Source: Goetz, 2009).

Studies of the coastal zone are better served by hyperspectral imaging, which makes it possible to unmix the bottom and several in-column constituents (Carder et al., 1993; Lee et al., 1994). Hyperspectral imaging is equally applicable to the solid water phase which makes it possible to study the properties of ice and snow, in particular grain size (Nolin & Dozier, 1993; Painter et al., 1998). Environmental studies using hyperspectral imaging are yielding results that would be impossible to obtain or would be prohibitive in cost or time spent with standard techniques. One example that has been documented to have saved millions of dollars is in the cleanup of the Leadville, CO Superfund Site in which AVIRIS images combined with field spectral measurements identified the waste piles with the greatest potential for leaching heavy metals into streams and groundwater (Swayze et al., 2000). Asbestiform minerals have also been identified in situ from AVIRIS data (Swayze et al., 2005). Maps of expansive soils, important in construction engineering, can also be identified in AVIRIS images (Chabrillat et al., 2002) (Source: Goetz, 2009).

HYPERSPECTRAL REMOTE SENSING INDIAN SCENARIO AND CURRENT STATUS

Indian researchers are actively engaged in making use of the potential of hyperspectral data since late 1990’s and early 2000’s in various fields of applications such as agriculture, precision firming, pest and disease, forestry, coastal applications and geological and mineral exploration and spectral library related activities.

Land applications include vegetation studies (species identification, plant stress, productivity, leaf water content, and canopy chemistry), soil science (type mapping and fertility status), geology (mineral identification and mapping) and hydrology (snow grain size, liquid/solid water differentiation). Lake, river and ocean applications include biochemical studies (photoplankton mapping, activity), water quality (particulate and sediment mapping) and bathymetry. Atmospheric applications include parameter measurement (water vapor, ozone, and aerosols) and cloud characteristics (optical thickness, cirrus detection, particle size). All these work were carried out in collaboration with various state and national agencies relevant in respective fields and the study sites also were spread over various parts over India. Few studies also been carried out for wetland ecosystem and the results showed that different wetland plats have similar spectra curves while they still possible to be distinguished in some visible and NIR in hyperspectral data. Many applications with hyperspectral data were carried out for mineral exploration, and snow studies in the Himalayan region. These studies showed the capability of hyperspectral data for identifying and quantifying minerals and rocks as well as mapping the indicators for mineral exploration; and for studying the effect of contamination and grain size variability on snow. These studies also derived the optimum hyperspectral bands for these studies.

HYPERSPECTRAL REMOTE SENSING AND ITS APPLICATIONS

- **Agricultural Applications**

Agriculture forms important field for hyperspectral studies owing to diversity in the crop growing conditions and management practices. These complexities get compounded to variety of factors such as soil, water, management and crop varieties etc. In the field of crop science major works carried out are - Pulse crop discrimination, Crop stage discrimination and analysis of angular effect, Crop biophysical parameter retrieval, Tea crop discrimination studies and crop residue studies. These studies identified important narrow bands required for pulse crop discrimination, important view angle and hyperspectral indices for crop stage discrimination, identified hyperspectral indices for LAI and plant nitrogen estimation, Optimum bands for tea crop identification, optimum bands as well as important indices for crop residue studies.

For soil science, hyperspectral data were used for Soil fertility parameter retrieval and mapping, Soil variability mapping and fertility zonation, Estimation of Soil parameters like bulk density, EC, nitrogen, phosphorus etc. These studies concluded that several soil properties, namely, surface condition, particle size, organic matter, soil color, moisture content, iron and iron oxide content and mineralogy can be mapped through imaging spectroscopy and that hyperspectral data can be effectively used for generating soil variability and fertility zonation. Crop stage discrimination using IMS-1 HySI has also been carried out. Works have carried out to develop Spectral signature bank and prototype spectral library of vegetation; develop Software for Reflectance Spectra Analysis and PROSAIL Model Inversion.

- **Snow and Glacier Applications**

Reflectance characteristics (in the form of spectral library), hyperspectral analysis (continuum depth, asymmetry, first derivative, peak shift), image processing tools and statistical methods along with better availability of temporal satellite based hyperspectral data can address the hydrological and climatological applications (like contamination, grain size etc.) for better understanding of climate in snow covered area of the Himalayan region. Analysis of field and Hyperion data have shown that hyperspectral remote sensing plays a crucial role to understand the effect of contamination and grain size variation on snow for wavelength ranging from 350 to 2500 nm. HySI data has limited spectral coverage upto 350-960 nm which restricts its utility in snow applications. HySI temporal data may provide information on different snow types due to metamorphism processes. The difficulty which can be seen using HySI data will be coarser resolution which imposes a restriction over end members selection, snow/cloud discrimination as data is available only in visible/NIR regions and saturation over snow surface. At present, the limitation of hyperspectral imaging data over Himalayan terrain along with complete spectral coverage (350-2500 nm) impose a constraint for various snow and glacier applications. Hyperspectral data with improved spatial and spectral resolution will provide better insight of retrieval of snow physical properties, albedo, fractional snow cover, climate radiative forcing and many more, however at the same time, developing tools for advance data processing techniques for Himalayan terrain will be another area to research to further exploit the imaging spectroscopy for snow and glacier applications.

- **Environmental application**

Hyperspectral remote sensing can be used to study the state of our environment and track changes that occur over time. This technology has been particularly successful in monitoring water bodies of all sizes from ponds to oceans and brooks to rivers.

a) Classifying lake water quality

The main advantage of using remote sensing instead of the traditional lake monitoring method based on water sample collection is its good spatial and temporal coverage. Monitoring can be carried out several times per year, and lakes too small or inaccessible to be included in the traditional sampling can be also monitored. In the 2002 Koponen et al. study, the researchers classified the water quality using the parameters Secchi depth, turbidity, and chl-a. They obtained the class limits from two operational classification standards and discovered that using a combination of them was the most suitable when remote sensing data is used. Because the classification was possible even without concurrent ground truth data, they discovered that operational classification with remote sensing data is possible. Their classification accuracy ranged from 76% to 90%. The airborne water quality classification system was able to classify the target lakes with good accuracy despite different measurement configurations and lake types. This indicates that remote sensing is a useful tool for water quality classification. However, airborne remote sensing is quite expensive and its use will be limited to operational monitoring of large areas.

- **Flood Detection and Monitoring**

Flood detection and monitoring are constrained by the inability to obtain timely information of water conditions from ground measurements and airborne observations at sufficient temporal and spatial resolutions. Satellite remote sensing allows for timely investigation of areas of large regional extent and provides frequent imaging of the region of interest (Felipe et al., 2006). Until recently, near real-time flood detection was not possible, but with sensors such as Hyperion on board the EO-1 satellite this has been vastly improved (Felipe et al., 2006). According to research conducted by Felipe et al. (2006) automated spacecraft technology reduced the time to detect and react to flood events to a few hours. Advances in remote sensing, have resulted in the investigation of early warning systems with potential global applications. Most recent studies from NASA and the US Geological Survey are utilizing satellite observations of rainfall, rivers and surface topography into early warning systems. Specifically, scientists are now employing satellite microwave sensors to gauge discharge from rivers by measuring changes in river widths and satellite based estimates of rainfall to improve warning systems (Brakenridge et al., 2006). Procedure for the detection of flooded areas with satellite data were also investigated by Glaber and Reinartz (2002). Moisture classes in flood plain areas in relation to high water changes, the accumulation of sediments and silts for different land-use classes and erosive impacts of floods were investigated (Glaber and Reinartz, 2002). The estimation of discharge and flood hydrographs from hydraulic information obtained from remotely sensed data was assessed by Roux and Dartus (2006). Remote sensed images as used to estimate the hydraulic characteristics which are then applied in routing modules to generate a flood wave in a synthetic river channel. Optimization methods are used to minimize discrepancies between simulations and observations of flood extent fields to estimate river discharge (Roux and Dartus, 2006)

- **Wetland mapping**

Wetland mapping has gained increased recognition for the ability to improve quality of ecosystems (Schmidt and Skidmore, 2003). Sustainable management of any ecosystem requires, among other information, a thorough understanding of vegetation species distribution. Hyperspectral imagery has been used to remotely delineate wetland areas and classify hydrophytic vegetation characteristics of these ecosystems (Schmidt and Skidmore, 2003; Becker et al., 2005). Research undertaken by Schmidt and Skidmore (2003) promoted the use of high spatial and spectral resolution data for improved mapping of salt marsh vegetation of similar structure. The hyperspectral analysis identified key regions of the electromagnetic spectrum which provided detailed information for discriminating between and identifying different wetland species (Schmidt and Skidmore, 2003). Becker et al. (2005) performed a similar study based oncoastal wetland plant communities which are spatially complex and heterogeneous. This study also emphasized the importance of hyperspectral imagery for identifying and differentiating vegetation spectral properties from narrow spectral bands focusing on the visible and near-infrared regions (Becker et al., 2005). A number of studies have investigated the potential of providing timely data for mapping and monitoring submerged aquatic vegetation which has been identified as one of the most important aspects of ecosystem restoration and reconstruction (Lin and Liquan, 2006). Such species have been termed ecological engineering species and the quantification of their coverage and spectral reflectance properties is currently being researched (Lin and Liquan, 2006).

- **Forests Ecosystems**

Forest covers more than one fifth of geographical area of the country. It constitutes a large part of natural resources. Additionally forest serves as major regulator of earth's environment. Remote sensing based forestry applications related to optical remote sensing are in matured state. In order to enhance the application of RS data for forestry, hyperspectral sensing can be used for discrimination at species level and community level using the potential of narrow band data. A primary advantage of hyperspectral remote sensing is its ability to provide measurements of forest chemistry. Major elements of chemistry area: chlorophyll a, b, leaf water, cellulose, pigments, lignin canopy chemistry can be used to estimate new and old foliage, detect damage, identify trees under stress or diseased, and map chemical distributions in the forest. This property will enable the forest researchers in applications related to forest health, stress, detection of diseases, and assessment of nitrogen and heavy elements. The concentration of nitrogen in foliage is strongly related to rates of net photosynthesis, and hence carbon uptake across a large number of species. This represents a strong meaningful link between terrestrial cycle of nitrogen and carbon (Field et al, 1986, Reich et al, 1999, Wessman et al, 1988). These variables or vegetation indices will be useful for coming out with plant functional types, which is still nascent area of research through remote sensing. More insights to ecosystem function, such as biochemical fluxes and processing will require advanced vegetation indices. These indices may give elucidation of bio-chemical fluxes in terrestrial ecosystem functions relevant to the nitrogen and carbon cycle components.

With the advent of sensors capable of collecting high-spectral-resolution radiance data between 380-2510 nm with about 7 nm spectral resolution and at 30 m spatial resolution the expectation is that, if measurements are made with sufficient signal to noise ratio to avoid spectral mixing, most types of vegetations could be remotely identifiable. However, despite the creation of spectral libraries for various plant species, the unique identification of many species has proven difficult due to the numerous problems present in real-world measurements, such as angle of view, atmospheric properties, spectral mixture, moisture content and illumination angle, to mention just a few. Furthermore, Price (1994) has suggested that several species may actually have quantitatively similar spectra due to the spectral signature variation present within a species. In short, spectral signatures may not be unique. The spectral separability of vegetation provides special difficulties because its spectral behavior is described by a small number of independent variables (Price, 1992). Specifically, the response of vegetation reflectance spectra in visible wavelengths (400 – 700 nm) is primarily determined by the composition and concentration of chlorophyll a, chlorophyll b and the carotenoids (Tucker and Garrett 1977). Furthermore, the response of reflectance spectra in the near-infrared wavelengths (700–1300 nm) is a function of the number and configuration of the air spaces that form the internal leaf structure (Danson 1995). In summary, the reflectance of vegetation from different species is highly correlated due to their common chemical composition (Portigal et al. 1997). It will be interesting to combine and use the response of other biochemical properties from 1300 – 2510 nm and complex indices can be attempted for species level classification of forests. With the availability of narrow bands within 380-2510 nm wavelength from airborne/space platforms, research in this area will become more intensive and new techniques and indices of assessment of the data will be explored.

Biomass burning is another area where hyperspectral remote sensing will be of immense use. Hyper spectral sensor would be able to provide sub pixel burnt scar. To model the fire risk potential, the dry or senescent carbon indices designed to provide an estimate of the amount of carbon in dry states of lignin and cellulose can be used to know the state of forests. Lignin is a carbon-based molecule used by plants for structural components; cellulose is primarily used in the construction of cell walls in plant tissues. Dry carbon molecules are present in large amounts in woody materials and senescent, dead, or dormant vegetation. These materials are highly flammable when dry. Increases in these materials can indicate when vegetation is undergoing senescence. Vegetation indices can be used and developed for fire fuel analysis and detection of surface litter based on the pure spectra of lignin, cellulose and water content. The Cellulose Absorption Index is one such vegetation index which indicates exposed surfaces containing dried plant material. Absorptions in the 2000 nm to 2200 nm range are sensitive to cellulose. Applications also include crop residue monitoring, plant canopy senescence, fire fuel conditions in ecosystems, and grassland grazing management. The Moisture Stress Index (MSI) is a reflectance measurement that is sensitive to increasing leaf water content. As the water content of leaves in vegetation canopies increases, the strength of the absorption around 1599 nm increases. Absorption at 819 nm is nearly unaffected by changing water content, so it is used as the reference. Applications include canopy stress analysis, productivity prediction and modeling, fire hazard condition analysis, and studies of ecosystem physiology. The MSI is inverted relative to the other water VIs; higher values indicate greater water stress and less water content.

The hyperspectral data also provides scope for research related to pre-processing, atmospheric correction, reducing redundancy, classification techniques, parameter retrieval algorithms and modelling.