Monitoring of forest cover in India: imaging spectroscopy perspective

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Tropical forests are the most diverse and complex terrestrial systems. India is one of the mega diverse countries supporting rich floral diversity coming from diverse climatic conditions spread across the length and breadth of the country. Unique characteristics of these forest covers coupled with immense pressure of human activities make their monitoring essential so as to ensure their long-term sustainability. More reliable evaluation of forest cover can give better inputs to the National Mission for a Green India. Imaging spectroscopy is an appropriate technique to address some of these vital issues. This technique has seen an exponential growth in the past two decades, addressing various forestry applications such as tree species identification, invasive species mapping, monitoring phenology, biophysical and biochemical characterization, to name a few. Data acquisition through imaging spectroscopy can be done across different spatial and spectral ranges according to the needs of the user. The review highlights important measures to be taken in using imaging spectroscopy for forestry studies, specifically in the Indian context. It emphasizes future outlook of the technology for a sustained assessment of tropical forest cover.

Keywords: Forest cover, imaging spectroscopy, parameter estimation, sustained assessment.

Assessment of forest cover

TROPICAL forests are the most diverse and ecologically complex land community, storing approximately 50% of the world's living terrestrial carbon[1]. They cover less than 10% of the land area, representing the largest terrestrial reservoir of biological diversity[2]. They also hold 18 of the world's 25 biodiversity hotspots[3]. India is one of the 12 mega diversity countries in the world and comprises two biodiversity hotspots in the north-eastern states and the Western Ghats[4]. The country's rich vegetation, wealth and diversity is undoubtedly due to the immense variety of climatic and altitudinal variations[5]. Over the past few decades, rapid land-use changes in these regions showed great impact on biodiversity reduction[6]. These changes are severely influencing the normal functioning of the systems. Deforestation at large and more specifically of tropical forests (coupled with climate change and loss of biodiversity) is contributing to an increase in global CO_2 emissions[7]. This ever-increasing pressure on an important natural land cover like the tropical forest has made close monitoring mandatory. Our ability to measure and predict the functioning of tropical forests lags behind many other biomes[8]. Forest and tree cover of India constitutes nearly 789,164 sq. km, which is 24.01% of the geographical area of the country[9]. Over the past few decades, forest composition has undergone changes due to mining, hydropower plants and biotic pressure[10]. This has resulted in altering the structure, composition and function of these forests rapidly. Unique characteristics of our forest covers and immense human pressure make their monitoring essential in implementing remedial measures for ensuring their long-term sustainability.

Traditional methods to monitor forest cover are less effective, time-consuming and often too expensive. Remote sensing offers a practical and economical means to study forest cover changes over space and time. Broadband multispectral and multi-temporal data allow monitoring forest attributes more quickly and effectively. Newer techniques in advanced data processing help develop better maps of forest cover enabling their successful monitoring. The Forest Survey of India (FSI) periodically monitors and reports the state of forests biennially using broadband multispectral remote sensing data with varying levels of success[11]. Traditional multispectral broadband sensor data have known limitations of sensor saturation. Their coarse spectral and spatial resolution leads to significant errors in estimating different forest attributes[12]. Many recent reports[7] about the status of forests in our country indicate that there is an overestimation compared to actual spread because of the classification mechanisms adopted. Rapid land-use land-cover changes occurring in

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our country and the biennial statistics of FSI about our forest cover are not congruent. Previous reports share the fear about India's forest cover estimation and that an over-reliance on inadequate imaging by coarse-resolution satellite system is making destructions (illegal felling and logging) easy to overlook[13]. Thus there is an urgent task to chart and protect the remaining forest covers using advanced remote sensing sensors. Advances in the development of sensor technology such as imaging spectroscopy have overcome a major limitation of broadband sensors, i.e. its spectral resolution.

Imaging spectroscopy measures continuously in the visible and infrared regions of the electromagnetic spectrum (400–2500 nm) using dozens to hundreds of narrow spectral bands[14] and offers considerable potential to discriminate earth surface materials. It is well suited for vegetation studies since reflectance/absorption features in the spectral signature of single species as well as mixed species communities are better differentiated using narrower spectral bands[15]. With the advent of imaging spectroscopy, significant advancement was achieved in monitoring quantitative characteristics of forest ecosystems[16]. There are many reports mentioning the use of imaging spectroscopy in species discrimination[17–19]. The utility of high spectral resolution imagery (HYDICE) to discriminate seven tropical tree species was explored and achieved accuracies were on the order of 90% (ref. 18). Crown-scale hyperspectral data of tropical rainforest were used to discriminate 11 tree species[20]. Many institutes of our country (CSIR Institute of Himalayan Bioresource Technology (IHBT), Palampur; Indian Institute of Remote Sensing (IIRS), Dehradun; Indian Institute of Space Science and Technology (IIST), Thiruvananthapuram; M.S. University, Vadodara; National Remote Sensing Centre (NRSC), Hyderabad; Space Applications Centre (SAC), Ahmedabad; Department of Natural Resources, TERI University, New Delhi)) are actively utilizing imaging spectroscopy for monitoring forest covers[21–25]. However, discrimination of species in high-resolution imagery continues to be a major challenge. Tropical vegetation has unique features compared to temperate vegetation. Species diversity, structure and functional composition of communities and phenological variations are some of the major hurdles in their classification. This makes the application of imaging spectroscopy more challenging in developing countries like India. Precision evaluation of forest cover would significantly add greater inputs to a decade-long plan taken up by the National Mission for a Green India to improve 10 m ha of forest cover. Imaging spectroscopy is an appropriate tool to address such plans.

Imaging spectroscopy

In the literature, the terms imaging spectroscopy, imaging spectrometry, hyperspectral imaging and occasionally ultraspectral imaging are often used interchangeably. A common framework for defining them is the simultaneous acquisition of images in many narrow spectrally contiguous bands (400–2500 nm) with narrow bandwidth (5–10 nm), measured in calibrated radiance units, from a remotely operated platform[26]. The imaging spectroscopy era began in the late 1970s and early 1980s. A number of studies have reported the potential utility of field, airborne and spaceborne imaging spectroscopy in different applications such as geology[27], agriculture[28,29], mangroves[30] and forestry applications[18,21,24,31].

The first portable field reflectance spectrometer (PFRS) was capable of measuring in the visible, near infrared and shortwave infrared regions[32]. Development in the science of field spectroscopy has been reviewed by Mitton *et al.*[33]. Field spectroscopy supports the vicarious calibration of airborne and spaceborne sensors and provides a means of scaling-up measurements from leaves (Figure 1 *a*) to vegetation canopies (Figure 1 *b*) and ultimately to pixels. Analytical spectral devices (ASD Inc.) is the leading manufacturer of field spectroradiometers (www.fieldspectroscopy.com). Handheld spectroradiometers generally measure a much smaller area and hence how to sample the surface of interest becomes an impediment. In the field environment, susceptibility to temperature and poor signal-to-noise (SNR) characteristics are often a problem for highly portable and miniaturized systems.

Researchers at the Jet Propulsion Laboratory (JPL), NASA proposed an advanced airborne sensor, the airborne visible/infrared imaging spectrometer (AVIRIS)[14]. Concurrent with advances in imaging spectroscopy applications, the airborne instruments have improved substantially and have become more readily available. Some of the widely used sensors include the HyMap Imaging spectrometer[34] (Integrated Spectronics Corporation, Australia) and the Compact Airborne Spectrographic Imager (CASI, ITRES Research Limited, Alberta, Canada). An effort was undertaken to develop fully integrated imaging spectroscopy (400–2500 nm) and wLiDAR technologies in a system called the Carnegie Airborne Observatory (CAO;

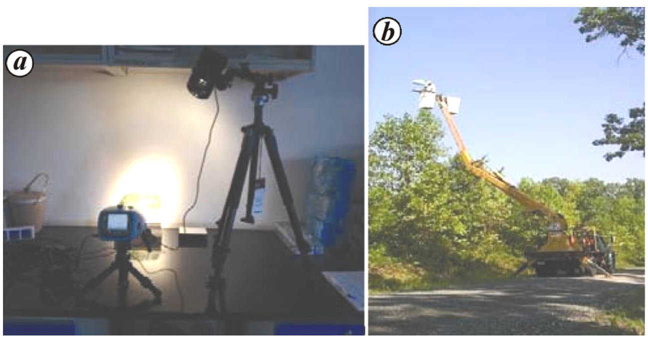

Figure 1. Lab-based leaf scale (***a***) and field-based canopy scale (***b***) studies using spectroradiometer for forestry applications. Sources: (***a***) M.S. University, Vadodara and (***b***) J. A. Van Aardt[101].

http://cao.standford.edu)[35]. CAO was developed to measure a suite of ecosystem structural and biochemical properties in a way that can rapidly advance regional ecological research for conservation, management and resource policy development (http://cao.ciw.edu/?page=videos). Similarly, the National Ecological Observatory Network's (NEON, USA) Airborne Observation Platform (AOP) will include imaging spectroscopy to quantify plant species identity and function (http://www.neoninc.org/science/aop). However, airborne hyperspectral sensors are expensive. They cover smaller area and require multiple flight lines for larger spatial coverage. Hyperspectral analyses of phenological variations in vegetation have been limited due to the restricted abilities of aerial platforms to repeatedly sample larger areas[36].

Larger area coverage at repeated intervals with consistent quality is the major advantage of spaceborne sensors. Spaceborne imaging spectroscopic era began in 2000 with the launch of Earth Observation One (EO-1) satellite from NASA. It was launched with an estimated one-year lifespan. Based on high interest of remote sensing research and scientific communities, EO-1 mission has evolved through several stages in its more than 13 years of service (January 2001 to February 2014). Researchers have clearly described different phases of EO-1 lifetime and anticipated that so long as the solar array charge degradation remains nominal and is sufficient to maintain altitude, EO-1 will continue to acquire images throughout 2015 and possibly longer[37]. EO-1 carries two unique spectral instruments – the Hyperion and the Advanced Land Imager (ALI). The Hyperion sensor acquires high spectral (242 band, wavelength ranging from 400 to 2500 nm) and high spatial (30 m) resolution data. Today, Hyperion remains the only spaceborne continuous source of full-range hyperspectral data. However, it is more sensitive to the atmospheric effects than the airborne sensors and one has to wait for a good quality image due to cloud coverage.

EO-1 data availability and quality

EO-1 datasets are easily accessible. Hyperion data products are available for search and download through Earth Explorer (http://earthexplorer.usgs.gov/) or Glovis (http://www.glovis.usgs.gov/) free of cost. The United States Geological Survey (USGS) reports that 20 times more EO-1 data have been distributed since it became cost free (in 2009), compared with all previous years (2002–2008)[37]. Unlike LANDSAT, IRS, SPOT series, EO-1 is a tasking satellite; it collects data only when requested. Therefore, it may not have coverage area of one's interest as default. To obtain imagery of an area, one can submit a data acquisition request (DAR) (https://eo1.usgs.gov/dar). The same can be downloaded from more than 48,000 images of targets all over the globe that have been archived (Figure 2). Hyperion is still acquiring cloud-free data from different parts of the world.

The stability of the Hyperion measurements is within ± 1.5%, which is considered to be 'moderate fidelity'. Hyperion data have a variable SNR (~150 : 1, 0.4–1.0 μm; ~60 : 1, 1.0–2.5 μm). Moderate fidelity measurements and poor SNR performance limit the stability of Hyperion. These specifications come from the data released during the launch of EO-1 way back in 2000. For any kind of on-board instrumentation, inherent temporal changes are inevitable. Currently, the satellite is more than 13 years old and is still acquiring data. To look for the plausible variations (coming from aging of the instrument therein) in the spectral datasets, a simple exercise was carried out. Hyperion datasets for three different days of year (DOY) of the same region (Shoolpaneshwar Wildlife Sanctuary (SWS), 21.7017N; 73.735E, Gujarat, India) were obtained. Datasets were acquired on 3 April 2006 (93/2006), 21 October 2006 (294/2006) and 22 January 2011 (22/2011). These represent three seasonal datasets with a time lapse of five years. SNR was calculated using mean/standard deviation method[38] for 179 bands (after removing uncalibrated and water-absorptive bands) before atmospheric correction (Figure 3). Three different homogenous objects (vegetation, water and barren land) were selected. Ground control points (GCPs) of homogenous objects from 3 × 3 pixel window for comparison were kept the same across three datasets. SNR values of marked pixels across the three images ranged from 0 to 325 for 294/2006, 0 to 347 for 93/2006, and 0 to 137 for 22/2011 (Figure 3). SNR was highest in VIS/NIR region for all three datasets at 752 nm (294/2006) and 783 nm (93/2006 and 22/2011). From Figure 3 it can be observed that signal values have decreased in the VIS/NIR region from 2006 to 2011 for the selected homogenous areas. The estimated SNRs for three Hyperion datasets are in good agreement with the

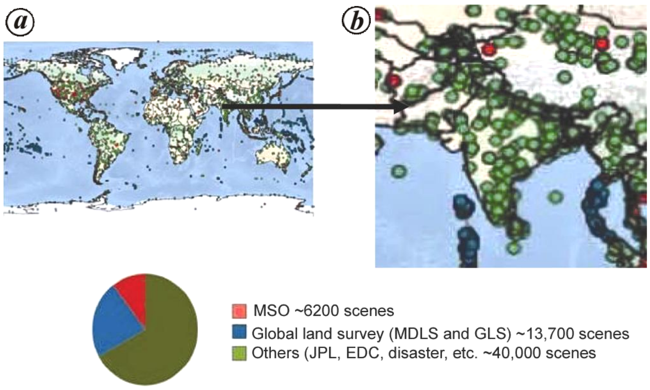

Figure 2. Global map (***a***) showing locations of EO-1 scene collections from 2000 to 2012, (***b***) enlarged view of India. Acquisitions are divided into three types: those requested by the EO-1 Mission Science Office (MSO) for science activities (red circles); those acquired in support of the two global land surveys (blue circles), and other scenes acquired for disaster monitoring and requests from the general public (green circles)[37].

predicted SNR for Hyperion instrument[39]. Results of this exercise indicate that Hyperion data obtained in the recent past or tasked data can be utilized for earth observation.

Data analysis

Hyperspectral data user community follows standard pre-processing and post-processing steps to analyse the EO-1 Hyperion data. A schematic flowchart is given in Figure 4, marking important steps in data processing widely used for forest application. Pre-processing steps facilitate to the removal of instrumental distortion, gaseous interference and geometric alterations. Raw Hyperion data contain bad bands, bad pixels, striping artefacts and spectral smile which need to be removed prior to atmospheric correction. This helps users to remove Hyperion instrumental distortions from the data for further analysis. Atmospheric correction of satellite data is a major step in the retrieval of surface reflective properties. It involves removal of the effect of gaseous absorption as well as correcting for the effect of path radiance. Atmospheric correction models are available in ready-to-use software, such as ACORN, FLAASH, ATREM and HATCH. Many recent studies have used ACORN and FLAASH codes for tropical[17,19,25] and temperate Himalayan[24] regions of India. Researchers have explained ACORN processing for the Indian tropics[21]. The user community can refer to these published articles to understand the nuances in Hyperion data-processing.

Imaging spectroscopy and forest applications

Imaging spectroscopy has shown exponential growth over the past two decades in terms of referenced publications and associated citations[40]. It has highlighted successful applicability in modelling and mapping of specific forest vegetation characteristics, such as (a) biophysical and biochemical properties[8,25,40–44], (b) tree species identification and discrimination[17,19–21,24,36,45], (c) invasive species mapping[46], (d) biodiversity studies[47], (e) phenological variability[48], (f) stress detection[49,50], (g) litter characteristics and forest fire[22] and (h) above-ground biomass[51] with varying levels of success.

At the same time, overcoming Hughes' phenomenon[52] or curse of dimensionality of data and data redundancy is of great importance to make rapid advances in the much wider utilization of hyperspectral data. This is because, for focused applications a large number of hyperspectral

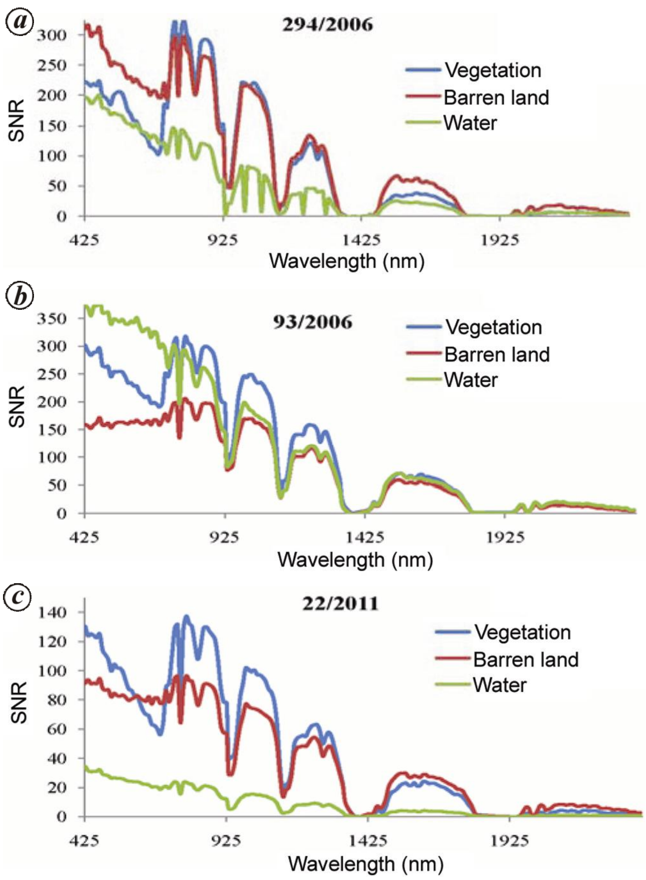

Figure 3. Calculated signal-to-noise ratio for EO-1 Hyperion datasets: ***a***, 294/2006; ***b***, 93/2006; ***c***, 22/2011, acquired for Shoolpaneshwar Wildlife Sanctuary, Gujarat, India.

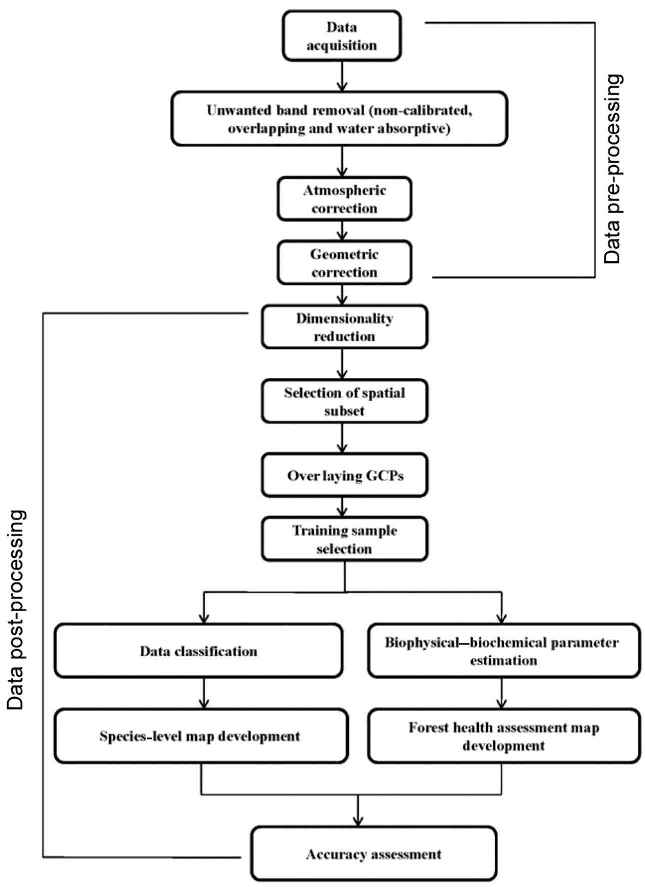

Figure 4. Schematic representation for data analysis.

bands are redundant[53]. Selecting the relevant bands will require the use of data mining[54] to identify optimal bands. A dimensionality reduction method is usually adopted before addressing a targeted application[55]. In recent years, many efforts have been put forward to reduce the large data volume through (i) feature selection (such as minimum noise fraction (MNF) transformation, principal component analysis (PCA), independent component analysis (ICA) and kernel-principal component analysis (k-PCA))[17,19,55], (ii) stepwise discriminant analysis (SDA)[24,31] and (iii) partial least square regression (PLSR)[25]. These methods help to maximize the efficiency of the data and reduce unnecessary computing. The user community can explore various ways and means available in the published literature to address planned issues.

Tree cover classification

Imaging spectrometers are powerful instruments for addressing classification problems in complex forest scenarios. Due to their hyperspectral sampling, they provide detailed information on tree canopies and this enables better classification[18,56]. During recent years, extensive research has been devoted to the use of imaging spectroscopy for tree species classification and it has shown good performance in different types of forest environment from tropical[57] to boreal[56]. Past studies have proved that these data can be used to classify individual tree species in combination with plant chemical and structural components[18]. The relationship between foliar chemistry and species identification was developed using maximum likelihood classifier (MLC) to demonstrate the applicability of imaging spectroscopy to classify 11 tree species at the Harvard Forest[58]. The consequence of the hyperspectral measurements in the visible and near-infrared wavelength regions was demonstrated by showing good spectral differentiation among the six coniferous species using *in situ* hyperspectral measurements taken with a field spectroradiometer[59]. A past study achieved reasonable discrimination of 11 tropical tree species using simulated branch and crown-scale hyperspectral data and suggested that best separation occurred near the red edge and in the NIR regions[20].

In the past few decades many advanced classification techniques, both parametric and nonparametric, have been developed and are used for species-level classification such as spectral angle mapper (SAM)[51], MLC[45], linear discriminant analysis (LDA)[51], Decision tree classifier[60], random forest (RF)[61], artificial neural networks (ANN)[62] and support vector machine (SVM)[56,63]. These techniques have been used to obtain the most sensitive information on species-level discrimination using laboratory spectra[64], airborne spectra[65] and spaceborne spectra[66]. The age composition of coniferous stands was studied in the western part of Germany with a combination of spectral and textural characteristics[45]. The authors achieved 66% OAA using SAM classifier and MNF 1–5 components (HyMap dataset). They were also able to achieve an accuracy of 75% using AVIRIS airborne datasets. In a study carried out at SWS (India), five tropical tree species were discriminated with 60% OAA[17]. MLC also was used to discriminate tropical dry deciduous forest covers of Gujarat[29]. The best classification accuracies were achieved using k-PCA through MLC for the monsoon season with overall accuracy of 83–100% for single species, 74–81% for two species, and 72% for three species. The performance of ANN over highly diverse tropical forest vegetation utilizing EO-1 Hyperion data has been evaluated[45]. The study showed 81% OAA (22 bands) using ANN for the mapping of eight tropical tree species. The effectiveness of SVM has been pointed out to analyse hyperspectral data directly in the hyperdimensional feature space, without the need of any feature reduction procedure[67]. The advantage of SVM in classifying heterogeneous tropical data was also mentioned for which only few training samples are available for each identified class. SVM functions well with only ten training pixels per class and more than 90% accuracy can be achieved[63]. Recently, SVM was used in the Indian context to classify tree species of Western Himalayas and dry deciduous forests of Gujarat using EO-1 Hyperion data[24,31].

In the classification of trees for Indian forest cover, heterogeneity in climate leads to enormous diversity in tree species occurrence and distribution. These features pose major hurdles in the classification.

Biophysical–biochemical parameter estimation

Forest biophysical parameters provide data on the productivity, structure and better estimates of forest resources. Leaf area index (LAI) is considered to be a key biophysical parameter of ecosystem processes[68]. Various ecophysiological processes of a forest ecosystem such as interception of light[69], precipitation[70] and transpiration[71] are controlled by LAI. Imaging spectroscopy has been efficiently utilized to derive LAI for tree species[44,72]. LAI estimations from spectral reflectance measurements can be derived using two types of techniques: (i) deterministic or stochastic canopy radiation models (PROSPECT, SAIL)[73] and (ii) empirical spectral indices[72]. Analytical techniques model the radiative transfer process between the land surface and the sensor to invert reflectance measurements to a particular physical parameter[74]. Radiative transfer models rarely simulate forest heterogeneity or generally require input data for parameterization at resolutions that are difficult to obtain[75]. Hence majority of the studies to estimate biophysical variables from remotely sensed data have used empirical techniques. It is suggested that simple transformations of band reflectance are more closely correlated with plant biophysical qualities[76]. These can help in improvizing accuracy level of estimates of biophysical parameters (such as LAI, canopy spread, standing biomass). Partial least square (PLS) regression model was tested for the estimation of LAI (teak and bamboo)[44]. Precise spectral bands were identified to develop the normalized difference ratio (ND 1457/1084) for the prediction of LAI.

Investigators have been using imaging spectroscopy to estimate pigment[41] and non-pigment[42] biochemical constituents of vegetation, such as chlorophyll, water, nitrogen, cellulose and lignin. This interest is because of the important role these substances play in physiological processes such as tree productivity, photosynthesis, their relationships with ecosystem processes such as litter decomposition and nutrient cycling, and their use in identifying key plant species and functional groups[77]. These quantifications have been made across different scales, from leaf[78] to whole plant reflectance measurements made in the field[79], and to vegetation canopy and community reflectance spectra measured by airborne and spaceborne imaging spectrometers[16]. It is generally based on the idea that reflectance spectra from vegetation canopies exhibit characteristic absorption features mostly governed by biochemical constituents of trees. Characteristic absorptive features of various canopy constituents are shown in Table 1 (ref. 80). Wavelengths, specifically of different biochemical parameters can be explored for their canopy scale quantification[81].

To relate hyperspectral data with canopy biochemical composition, several spectral transformation methods have been proposed. These are first difference reflectance (FDR) spectra, stepwise multiple linear regression (SMLR) and PLSR analysis[43,81]. Investigators have also tested spectral matching algorithms[82], Radiative transfer models[83] and reflectance indices[43] to estimate biochemical components. More details can be obtained from the comprehensive reviews for chlorophyll indices[84], plant stress and cell wall constituents[29]. Another focus has been on the detailed examination of leaf and canopy spectra in wavelength regions where biochemical constituents of interest display strong absorption features. Based on band depth analysis of continuum-removed reflectance spectra coupled with stepwise regression, good predictions were obtained for nitrogen, lignin, and cellulose contents on dried and ground leaves[81]. The concentration of 12 foliar biochemical constituents was estimated with high accuracy[85]. A strong nonlinear relationship was found typically either as power or exponential fit at leaf and canopy scales[41].

Earlier attempts focused on estimating the content of photosynthetic pigments using ratios of different spectral bands or the normalized difference vegetation indices. Subsequently, simple transforms of band combinations were developed as practical methods of analysis. PLS regression model was tested for the estimation of chlorophyll; 600–750 nm was identified as a sensitive spectral region and the simple ratio (SR 743/692) was developed for the prediction of chlorophyll contents of teak and bamboo covers[44]. A strong relationship was reported between Hyperion reflectance spectra and PLSR model developed for nitrogen, lignin and cellulose contents of teak and bamboo covers[25]. These studies indicate the importance and practical applicability of Hyperspectral data in assessing biochemical constituents of forest covers.

Forest floor cover studies

Forest fires are influenced by the type and chemical characteristics of litter, its moisture content, above-ground thickness of fallen litter, stand history and disturbance regime[86]. The FSI reports that 50% of forest area in the country is fire-prone and most forest fires occur between February and June (dry summer months). Many trees shed their leaves and the dry leaf cover of the forest floor is prone to forest fire. Imaging spectroscopy demonstrates the capability of separating spectral signals from bare soil and fallen dry plant litter. The potential of Hyperion data was highlighted in deciphering floor cover characteristics in the dry season using continuum removal spectra[22]. This helps in demarcating forest covers based on quantitative and qualitative characteristics of litter. It can assist the Forest Department officials to take precautionary measures in time, to avoid damage because of forest fire.

Invasive species mapping

Invasive species are harmful both ecologically and economically. It is necessary to monitor invasive species accurately to enable timely control of their unwanted spread. The spectral resolution available from imaging spectrometers is optimal to distinguish invasive species from native vegetation by the differences in growth form, stand structure, timing of phenological activity and physiological characteristics[87]. The Airborne Imaging Spectroradiometer (AISA) data were used to map salt cedar in the Lake Meredith Recreational Area, Texas, with an accuracy of 83% (ref. 88). Past studies have accurately identified several riparian and aquatic weeds in northern California, USA using HyMAP (GSI $\leq$ 3.5 m) sensor[89]. To measure and compare the structural, biochemical and physiological characteristics of the highly invasive and common native tree canopies in Hawaiian Montana rainforests, a time series of Hyperion hyperspectral metrics was computed and combined with field measurements[90]. Accurate invasive species maps were also developed from spaceborne Hyperion data with 86% OAA in southern Taiwan[55]. These studies can be considered to assess invasive species of Indian forest covers.

Table 1. Absorption features of different biochemical constituents[81]

Wavelength (nm)	Cause of absorption	Chemicals
430, 460, 640, 660	Electron transition	Chlorophyll *a*, chlorophyll *b*
910, 1020, 1510, 1690, 1940, 1980, 2060, 2130, 2150, 2180, 2240, 2300, 2350	C–H stretch, N–H stretch, O–H stretch, H–H asymmetry, H–H stretch, C–OP, C–N stretch	Protein, nitrogen
1690, 1940, 2350,	C–H stretch, O–H stretch, O–H deformation, C–H deformation	Lignin, starch, water, cellulose

Biodiversity studies

Biological diversity is a central determinant of ecosystem function and a key contributor to the portfolio of services provided by ecosystems to humans[91]. Mapping biological diversity is a major goal to the global conservation community[92]. Imaging spectroscopy has potential applicability to detect canopy-level diversity in complex, multi-layered forested areas of our country. AVIRIS data were used to map plant species richness in the tropical systems of Hawaii[91]. Density and diversity variations seen in the forest covers of our country can be assessed using hyperspectral data. These studies can help in monitoring changes in the diversity status of our forest covers and in developing effective management plans for better forest cover protection.

Above-ground biomass

Estimation of above-ground biomass in forests is critical for carbon cycle modelling and climate change mitigation programmes. Hyperspectral data record canopy spectral information that is potentially related to forest biomass. Few studies have attempted to improve biomass estimates in boreal, temperate and tropical forests by combining hyperspectral imagery with lidar data[51]. Biomass of African rainforest was assessed by combining lidar footprint metrics and airborne hyperspectral data[93]. Fusion of datasets helps in improvizing the quality of biomass estimates. Such studies can help in quantifying biomass of Indian forest covers, enabling their utility in harvesting forest produce and carbon stock evaluation.

Mangrove forests

Mangrove forests are found in the intertidal zones of tropical and subtropical coastlines[94] and exist as an ecosystem, comprising estuaries, lagoons, creeks and intertidal mudflats. Information on the floristic composition of the mangroves using remote sensing data is still at feasibility stage. Broadband multispectral remote sensing has been found to be inadequate to discriminate the mangrove classes at genus or species level[95]. In this context, hyperspectral remote sensing plays a significant role; many studies have been carried out using airborne and satellite hyperspectral data[96]. Use of J–M distance indices for separation of leaves of some mangroves species has been reported. A genetic search algorithm-based selector was used for selecting a subset of bands that maintained spectral separability between mangrove species classes of Sawi Bay, Chumporn Province, Thailand[97]. Discrimination of four mangrove species and one mangrove associate from Tok Bali, Malaysia, using hyperspectral leaf reflectance measurements was carried out[98]. A similar experiment was conducted[99] for discerning three mangrove species from the Caribbean coast of Panama. The authors also used some ratio indices for detecting stress in these mangroves. Leaves of four mangrove species of Indian Sundarbans and Gulf of Kachchh, were discriminated using different statistical protocols[100]. All these studies clearly demonstrated the use of foliar hyperspectral measurements. The potential of *in situ* hyperspectral data for discriminating mangrove canopies of 17 species and for discerning mudflat classes of Sundarbans (India) was studied[30].

Future outlook

Globally, imaging spectroscopy has come of age in the past 15 years. Germany's EnMap mission (http://enmap.org) having hyperspectral sensors is on the anvil in 2015–2016. NASA is coming up with HyspIRI (http://hyspiri.jpl.nasa.gov/). ISRO is planning to launch a hyperspectral sensor by 2018. Additionally, better technical features and superior cost–benefit ratios are making the use of unmanned aerial vehicles (UAVs) as platforms for carrying miniaturized sensors (optical and hyperspectral cameras) more user-friendly. This offers additional benefits in obtaining repetitive data of a site with finer temporal variations. These advancements offer a broad range of solutions for different applications. They are more suitable as other forms of airborne data acquisition (aircraft-based ones) are highly expensive. Newer hyperspectral sensors are coming up with higher SNRs (nearly 2–3 times better than the present operational ones). These developments clearly indicate the advancements and immense potential associated with this technology. This is principally due to its precision monitoring of natural systems of our earth. The scientific community across the world is working on several long-term research programmes associated with this technology. In India, ISRO and the Department of Science and Technology, Government of India are having dedicated programmes to utilize hyperspectral remote sensing for evaluating natural systems of our country. Substantial challenges are to be addressed in data processing, algorithm development, data interpretation and inference-making. All these developments help researchers, foresters and policy makers in sustained monitoring and assessment of forest covers of India with higher levels of precision.

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