Chapter 1

Introduction

1.1 Brief description of forest cover

A forest represents a complex ecosystem primarily dominated by trees and other woody vegetation, forming a closed canopy and containing a diverse range of flora and fauna. Forest cover is defined as any land larger than one hectare with a tree canopy density exceeding 10% (FSI, 2021). Forests are distributed across four main climatic regions: boreal, temperate, subtropical, and tropical. These forests, constituting renewable and invaluable ecological resources, cover approximately 31 percent (4.06 billion hectares) of the Earth's land surface, as reported by the United Nations Food and Agriculture Organization (FAO, 2020). Around 10% of the global forests are specifically designated for biodiversity conservation.

The estimation of biodiversity on Earth involves three primary methods: assessing the number of species, the extent of evolutionary history, and the biomass quantity (Díaz & Malhi, 2022). Among these, the method most frequently employed is estimating the number of species. Earth hosts around 2 million eukaryotic species (https://www.catalogueoflife.org/). This diverse array includes roughly half as insects, one-fifth as vascular plants, predominantly flowering plants, and the remainder encompassing various eukaryotic life forms, with fungi comprising about 7% and vertebrates accounting for merely 4% of known species (Purvis et al., 2019; Willis, 2017; Willis, 2018). Collectively, all living entities are often referred to as the "fabric of life," a product woven by natural processes over millions of years, collaboratively with human influence for hundreds of thousands of years (Díaz et al., 2019).

In recent years, the pace of biodiversity loss has escalated significantly, coinciding with major shifts in globalization and economic practices (Moore, 2017). This acceleration has led to a reduction in the size and integrity of natural ecosystems, the uniqueness of local communities, the size and distribution of plant and animal populations, the number of species, and the intraspecific genetic diversity of wild and domesticated organisms (Díaz et al., 2019; Purvis et al., 2019). This decline has occurred alongside two global phenomena: biotic homogeneity (Olden et al., 2004) and contemporary evolution (Hendry, 2017; Palumbi, 2001).

There are other various factors contributing to the decline in nature and are categorized as direct and indirect drivers. Direct drivers exert immediate physical effects on nature and can be either natural (e.g., volcanic eruptions, earthquakes, weather events) or human-induced (e.g., deforestation, hunting, pollution, anthropogenic climate change). Some instances involve a combination of both, such as the El Niño–Southern Oscillation phenomena and zoonotic diseases intensified by anthropogenic climate change. In contrast, indirect drivers, are entirely human-induced, encompassing social, economic, demographic, cultural, institutional, and political factors with social values and narratives at their core (Brondízio et al., 2019). These drivers collectively have rapid impacts on forest cover.

Forests are facing various threats, primarily arising from direct drivers attributed to human activities. Biodiversity loss, climate change, and the emergence of new diseases are consequences of environmental degradation. The overall forest area is diminishing, as highlighted by FAO, (2020), which reported deforestation of 420 million hectares between 1990 and 2020, with an ongoing rate of approximately 10 million hectares per year (or roughly 0.25 percent per year) from 2015 to 2020. Ongoing research actively explores the evolving nature of these changes, scrutinizing patterns at increasingly finer scales, ranging from individual plots to entire landscapes.

Natural processes as well as human and livestock interventions can lead to alterations in the structure, composition, and functioning of forests (Bhat et al., 2000). Recognizing the urgency of the situation, it becomes increasingly evident that restoring, sustaining, and managing natural ecosystems in a sustainable manner is imperative. The narrowing window for effective action, coupled with population growth and escalating aspirations, places new demands on physical resources. Preserving these invaluable ecosystems for future generations requires concerted efforts in conservation, sustainable forest management practices, and the protection of forested areas. Global initiatives such as

Global Forest Observations Initiative (GFOI, https://www.fao.org/gfoi) and Global Forest Watch (GFW, https://www.globalforestwatch.org/) are underway to monitor and address deforestation, promote sustainable forestry practices, and enhance reforestation and afforestation efforts.

1.2 Tropical forest cover

The tropical forest, situated between the Tropics of Cancer and Capricorn, characterized by high temperatures and high annual rainfall, encompasses approximately 45% of the world's forests, surpassing the boreal, temperate, and subtropical domains as shown in Figure 1.1 (FAO, 2020; Saha, 2021). Tropical forests, often referred to as rainforests, are not uniformly moist and are primarily found in regions like the Amazon in northern South America, Central Africa, and Southeast Asia, characterized by high temperatures (Landsberg & Waring, 2014). Despite covering approximately 10% of the land surface, tropical forests harbor more than half of all plant and animal species (Corlett, 2014). These forests are rich in biodiversity because they define the horizontal and vertical substrate, food resources, and gradients of light, moisture, and temperature. Renowned for their lush greenery, intricate structure, and remarkable biodiversity, tropical forest ecosystems remain enigmatic regarding the functionality and interactions of their diverse species (Clark et al., 2005; Leigh et al., 2004).

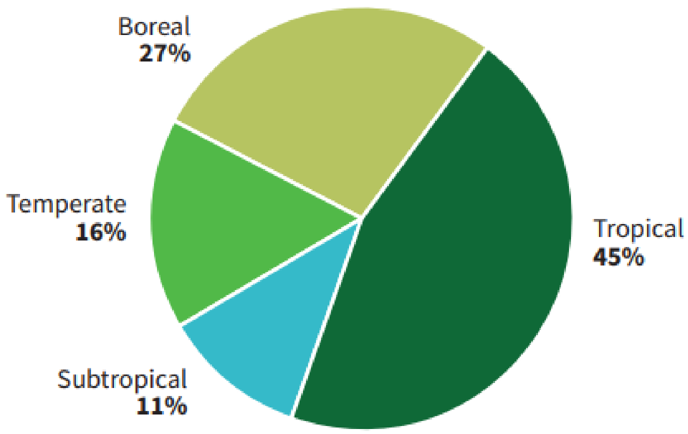

Figure 1.1| Proportion of global forest area by main climatic domain (Source: FAO, 2020)

Critical to climate management and the global carbon cycle, tropical forests annually sequester 2.2-2.7 Gt of carbon (Pan et al., 2011). Climate management refers to the efforts and strategies aimed at mitigating climate change by reducing greenhouse gas emissions and enhancing carbon sequestration. At the same time, these vital ecosystems are facing a decline, releasing more carbon than they absorb. Forest degradation, attributed to activities such as agriculture expansion, logging, and fuelwood gathering, is anticipated to contribute up to 3% of yearly emissions from human activities (Baccini et al., 2017). Fire, a common disturbance in the tropics, poses a significant threat, with over 98 million hectares of forest destroyed by fire in 2015, primarily within the tropical domain, where fire affected almost 4% of the total forest area (FAO, 2020).

The rapid development of tropical countries is exerting immense pressure on natural resources, particularly forests (Foody, 2003). Over recent decades, tropical forests have been adversely impacted by rapid land use changes (Achard et al., 2002). Warmer global temperatures, linked to greenhouse gas emissions, may alter tree growth rates, recruitment, and mortality, potentially resulting in novel tree assemblages as temperatures rise (Clark et al., 2003; Laurance et al., 2004). The continuous disappearance of forests at an alarming rate is a matter of grave concern. For sustained yield from forests, they must be managed scientifically, which would require up-to-date statistics on their extent and type.

1.3 Forest cover of India

India, situated in South Asia between 08º04′-37º06′N and 68º07′-97º25′E, is positioned north of the equator. Bounded by the Indian Ocean to the south, the Arabian Sea to the west, the Bay of Bengal to the east, and the Himalayas to the north, India is the seventh-largest country by land area in the world and the second largest in Asia. Covering a geographical area of 329 million hectares, the country's predominant climate is tropical and subtropical, with vegetation growth primarily influenced by temperature and precipitation (Tripathi, 2015).

The forest cover in India covers an area of 713,789 sq. km, accounting for 21.71% of the country's geographical area, with an increase of 1540 sq. km (FSI, 2021). Madhya Pradesh possesses the largest forest cover in the country followed by Arunachal

Pradesh, Chhattisgarh, Odisha, and Maharashtra. Classifying the forests based on physiognomy and climatic conditions, Champion & Seth, (1968) identified five major groups, 16 type groups, and 221 forest types. Tropical dry deciduous forests occupy 34.80%, followed by tropical moist deciduous forests (33.19%), tropical semi-evergreen forests (7.72%), tropical wet evergreen forests (7.54%), and miscellaneous types comprising the rest (Reddy et al., 2015).

The Indian forests represent a unique assemblage that lies at the junction of the three major biogeographic realms, namely the Indo-Malayan, the Eurasian, and the Afro-tropical (Reddy et al., 2015). The country's diverse climatic variations contribute to its rich flora and fauna, earning it the status of a 'mega biodiversity country' with 8% of the total species worldwide (Tripathi, 2015). The Botanical Survey of India and the Zoological Survey of India have recorded around 47,000 plant species and 81,000 animal species, respectively (Roy & Roy, 2015). Approximately 33% of the reported plant species in Indian forests are endemic. Despite this biodiversity wealth, around 10% of India's recorded wild flora and potentially more of its fauna are under threat, with many species on the verge of extinction. Given the loss of natural habitats, forest conservation has become synonymous with biodiversity conservation (Singh & Kushwaha, 2008). Four of the world's identified hotspots (Western Ghats, Himalaya, Indo-Burma, and Sundaland) are located in India (Tripathi, 2015). These hotspots are determined based on the number of endemic species and the degree of threat to the ecosystem, guiding *in situ* conservation efforts.

However, rapid industrialization has heightened pressure on India's forests, leading to a significant reduction in the area under closed forests. Another concern is the escalating demand for timber, projected to increase from ~68,857 m tonnes in 1980 to an estimated 181,270 m tonnes by 2025 (Navalgund et al., 2007). Bhat et al. (2000) observed considerable regional and temporal variations in species richness, composition, and productivity, suggesting that the ecological status and production capability of these forests are struggling to keep pace with the exponential growth rate of the human population. Considering the resource richness and emerging challenges, there is a critical need to monitor the rate and extent of changes in tropical forest cover of countries like India for sustainable development.

1.4 Monitoring of forest cover

Forests play a crucial role as ecosystems, offering numerous benefits such as biodiversity conservation, climate regulation, and resources for human populations. They contribute to ecological equilibrium by ensuring environmental stability, carbon sequestration, soil moisture retention, and conservation, all essential for sustaining life-support systems on Earth. According to United Nations, (2019) reports, 1.6 billion people throughout the world rely on forests as a source of fuel, construction materials, medicine, and food, and have an impact on the quantity and quality of freshwater (Marion et al., 2014). In the current global context of heightened concern regarding greenhouse gas emissions, forests are recognized as a vital biome for the health of the planet. They serve as a significant carbon reservoir, storing approximately 45% of the world's terrestrial carbon (Bonan, 2008). This not only makes them instrumental in mitigating climate change but also enhances ecological and societal resilience.

Unfortunately, despite these invaluable benefits, forests are under increasing threats, experiencing a decline. Forest degradation, often linked to activities such as agriculture expansion, deforestation and logging, contributes to this concerning trend. Deforestation rates are increasing, driven by commodities like soy, palm, and timber (40%), local subsistence agriculture (33%), and mining and infrastructure (17%) (Hosonuma et al., 2012). The intricate link between development and deforestation poses considerable challenges, necessitating effective monitoring of forest changes to address these threats.

Monitoring methods, including landscape assessment, change detection, and trend analysis (Figure 1.2), address diverse needs through system design trade-offs (Tabor & Connell, 2019). Satellite-based Forest monitoring, a "top-down" approach, provides a historical record and real-time alerts through stable and reliable satellite observations. Advances in processing and open-source data policies from United States (US) and Europe (EU) make satellite monitoring globally accessible (Tabor & Hewson, 2018), aiding transparency in forest cover changes due to development or conservation. Satellite remote sensing is crucial not just for monitoring and reporting forest cover but also for managing emerging threats (Musinsky et al., 2018; Tabor & Hewson, 2018). According to the Indian Space Policy – 2023 (IN-SPACe- Indian National Space

Promotion & Authorization Centre), authorizations are required for various space activities. IN-SPACe authorization is necessary for disseminating high-resolution satellite-based remote sensing data due to national security concerns (https://www.isro.gov.in/media_isro/pdf/IndianSpacePolicy2023.pdf). Web-based Early Warning Systems are becoming widespread, utilizing near real-time satellite capabilities to detect deforestation, fires, and degradation. These systems aid in making informed policy and land management decisions (Palomino et al., 2017).

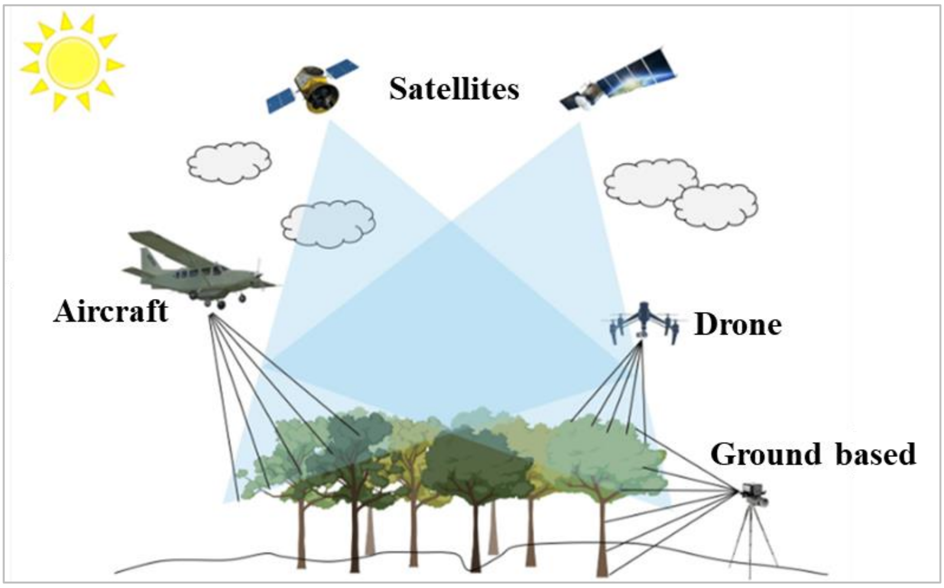

Figure 1.2| Different forest monitoring approaches: Top-down uses satellite and aircraft data; bottom-up involves ground-based observations; integrated combines in-situ sensors, satellites, and drones (Source: Tabor & Connell, 2019; Tian et al., 2023).

In a complementary "bottom-up" approach, monitoring techniques report forest cover changes through field observations. Local community monitoring emerges as a cost-effective strategy, fostering collaboration between communities and organizations (Balderas Torres, 2014; Fry, 2011; Pratihast et al., 2016). Integrated monitoring combines ground observations with satellite data, acoustic sensors, and camera traps for a more comprehensive monitoring system (Bustamante et al., 2016; Tabor & Hewson, 2018; Wright et al., 2018).

Forest monitoring is essential for climate change mitigation, biodiversity conservation, sustainable resource management, early warning systems, land use planning, and forest health assessment. It facilitates informed decision-making, proactive measures, and ensures the long-term sustainability of forests and their valuable services. As technology, artificial intelligence, and social networking become more affordable, emerging methods of monitoring forests will fulfill a wide range of applications. Traditional monitoring techniques are inefficient and costly, making remote sensing an increasingly practical and cost-effective means for studying forest cover changes globally.

1.5 Remote sensing techniques

Over the past few decades, the science of remote sensing has emerged as one of the most fascinating subjects. Remote sensing is a technique that uses airborne or space-borne sensors to acquire information about the Earth’s surface and atmosphere without making physical contact with it (Lillesand et al., 2015). This technique enables capturing images of the Earth’s surface at various wavelengths within the electromagnetic spectrum (EMS). Key wavelengths include ultraviolet (UV), visible (VIS), near-infrared (NIR), short-wave infrared (SWIR), mid-infrared (MIR), thermal infrared (TIR), and microwave. From a remote sensing perspective, the VIS, IR, and microwave regions of the electromagnetic spectrum are particularly significant, with NIR being especially suitable for vegetation, as healthy green vegetation reflects more in NIR than in VIS. Remote sensing of the Earth's surface relies on the distinct spectral responses of its features. Each object displays a unique reflectance/emittance pattern, commonly known as a spectral reflectance signature or spectral fingerprint, at different wavelengths. This uniqueness enables the identification and discrimination of objects.

Data acquisition and analysis are the two fundamental steps in remote sensing (Lillesand et al., 2015). The data acquisition process includes sources of energy, energy propagation through the atmosphere, energy interaction with Earth’s surface features, energy retransmission via the atmosphere, collection of radiation by airborne or spaceborne sensors, and the generation of sensor data in graphical and/or digital form. Conversely, the data analysis process involves examining the collected data using a variety of viewing and interpreting tools.

1.5.1 Types of sensors

Sensors are devices designed to record responses from objects based on the electromagnetic spectrum. Examples of sensors include cameras and scanners. Remote sensing technology has significantly advanced with the deployment of specialized sensors, enhancing the precision and scope of data acquisition.

Airborne and Spaceborne sensors

Airborne sensors are mounted on helicopters, balloons, drones, and low to medium-altitude aircraft, offering a flexible and dynamic means of data acquisition. These sensors are capable of capturing high-resolution imagery and collecting data over specific regions of interest with agility.

On the other hand, spaceborne sensors are positioned on satellites orbiting the Earth, providing a broader perspective and global coverage. These sensors enable systematic data collection on a large scale, contributing to various applications such as environmental monitoring, agriculture, and disaster management.

Passive and Active sensors

Depending on the source of energy there are passive and active sensors (Jensen, 2009). Passive sensors detect natural radiations, either emitted or reflected from the Earth. They utilize the sun's energy as a natural power source to detect objects, capturing reflected radiation during the presence of sunlight. Operating in the visible, infrared, microwave, and thermal infrared regions of the electromagnetic spectrum, passive sensors observe objects exclusively in the presence of light. Examples of passive sensors include accelerometers, hyperspectral radiometers, and spectrometers. These sensors find applications in agriculture, biodiversity monitoring, climate change studies, forest monitoring, urban growth analysis, disaster management, and various other fields.

In contrast, active sensors generate their own energy to observe objects. Primarily using microwaves in the electromagnetic spectrum, active sensors emit radiation to illuminate objects or scenes and then receive the reflected or backscattered energy. Active sensors can operate day and night, providing the advantage of obtaining measurements at any time. Examples of active sensors include Lidar (Light Detection and Ranging), Radar (Radio Detection and Ranging), and Scatterometer. Active sensors play crucial roles in topographical monitoring, groundwater monitoring, soil moisture and vegetation monitoring, weather forecasting, coal mining activities, and more.

Broadband (Multispectral Imaging) and narrow band (Hyperspectral imaging) sensors

Broadband sensors, often represented by multispectral sensors, capture a range of wavelengths across the electromagnetic spectrum. They use a multichannel detector with a few spectral bands covering the visible to middle-infrared regions (Figure 1.3a). Historically, Earth Observation Satellites carried broadband sensors have played a crucial role in providing a general overview of large areas. Examples of such sensors include the advanced spaceborne thermal emission and reflection radiometer (ASTER), moderate resolution imaging spectroradiometer (MODIS), Landsat-7 enhanced thematic mapper plus (ETM+), Multispectral Scanner (MSS), Satellite Pour l' Observation de la Terre (SPOT), high resolution visible (HRv), and the Indian Remote Sensing (IRS) Linear Imaging Self-scanning (LISS). The resulting output of these sensors is a multilayer image, referred to as a multispectral image, containing both brightness and spectral information about the observed targets (Lillesand et al., 2015).

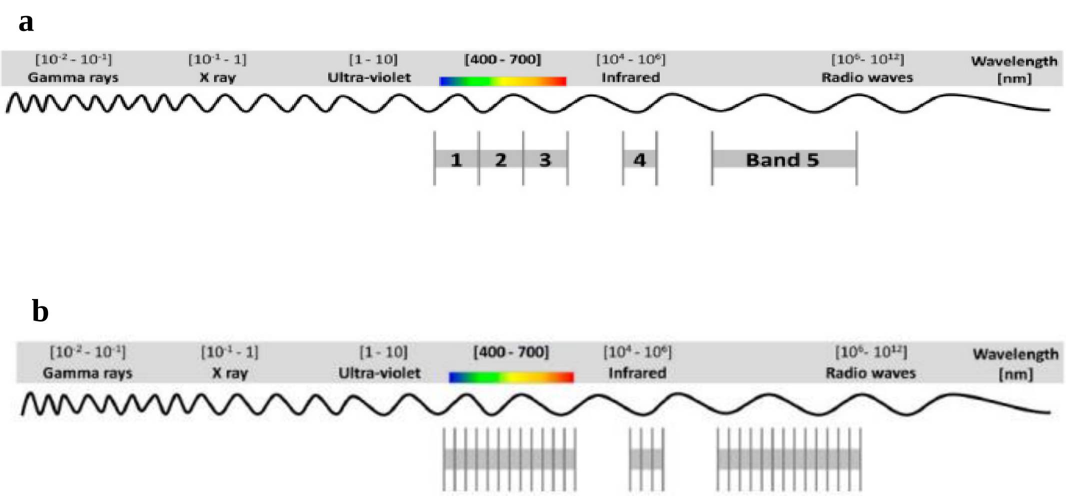

Figure 1.3| (a) Multispectral imagery with limited bands, comprising blue (Band 1), green (Band 2), red (Band 3), near-infrared (Band 4), and short-wave infrared (Band 5), and (b) Hyperspectral imagery with numerous narrow bands (Source: Adão et al., 2017).

While multispectral images are valuable for certain applications, their limited spectral resolution can be a constraint in scenarios where finer details and precise material discrimination are critical. In response to this limitation, there has been a growing interest in narrowband sensors, typified by hyperspectral sensors. These sensors operate within a more confined range of wavelengths. Hyperspectral sensors detect hundreds of very narrow and contiguous spectral bands across the visible, near-infrared, and mid-infrared portions of the electromagnetic spectrum as shown in Figure 1.3b (Hati et al., 2021; Hycza et al., 2018). This finer resolution allows narrowband sensors to provide highly detailed information on the reflectance properties of various materials in the scene.

The choice between broadband and narrowband sensors depends on the objectives of the remote sensing study. In the past two decades, hyperspectral remote sensing technology has undergone significant advancements, also known as “imaging spectrometer”. Hyperspectral images enable detailed land use/cover (LULC) classification, especially for vegetation and water bodies. In these images, each pixel represents the reflectance values for a specific location across all spectral bands (Figure 1.4). The contiguous bands and narrow spectral ranges enhance the capability for improved characterization and identification of targets. Description and examples of hyperspectral sensors are given in Table 1.1.

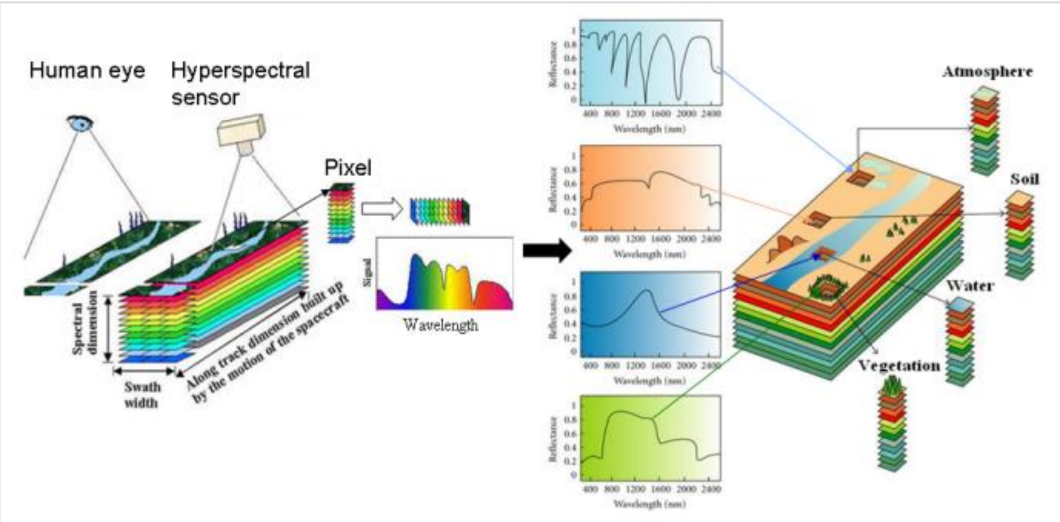

Figure 1.4| Hyperspectral remote sensing of the Earth’s surface, with each pixel containing a continuous spectrum for material identification (Source: Liao, 2012).

Table 1.1| Overview of hyperspectral and commercially available sensors with technical specifications.

Sensor name	Platform/ Mission	Launch date	Temporal Resolution (days)	Number of bands	Band width (nm)	Wavelength region (nm)	Spatial resolution (m)
Hyper-spectral sensors (satellites) Launched							
Hyperion	EO-1	2002	On demand	242	10	400-2500 nm	30
FAHI	EO-1	2000	On demand	512	3	400-1000	-
CHRIS	PROBA-1	2001	On demand	18-37-62	5-11	400-1050	17 or 34
PRISMA	ASI	2019	29	250	>12	400-2500	30
EnMap	DLR	2022	27	242	6.5-10	420-2450	30
HyspIRI	NASA	2013	5-19	-	10	380-2500	60
HISUI	ISS	2019	60	185	10-10.5	400-2500	30
HySIS	IMS-2	2018	On demand	256	10	400-2400	30
Hyper-spectral sensors (satellites) To be Launched							
HYPXIM	CNES	between 2023 and 2025	0.5-3	210	10-200	400-12000	10-20-100
FLORIS	FLEX	approved	2	-	0.3-3.0	500-780	300
SBG	NASA's Earth System Observatory	2027	16-3	-	-	400-2500	-
Hyper-spectral sensors (air-borne and cameras)							
AVIRIS	NASA	1998	On demand	224	10	380-2500	4-20
AVIRIS-NG	NASA-ISRO joint collaboration	2015	On demand	425	5	380-2500	3-4
HYDICE	NASA	1995	On demand	210	10	400-2500	1
APEX	ESA	2009	On demand	300-500	1.5	380-1000 1000-2500	2-5
Commercial hyperspectral sensors (airborne)							
CASI	Itres	1994	On demand	288	3	400-946	2-4
HyMap	HyVista	1998	On demand	128	15-20	450-1350	3-10
HySpex	ODIN	1995	On demand	427	3.0-6.1	400-2500	-
AISA-Fenix	Specim	2014	On demand	620	3.5-12	380-2500	1
Hyperspec	Headwall		On demand	67-370	1.9-9.6	360-2500	-

Source: **(Sanchez-Azofeifa et al., 2017)**

1.5.2 Characteristics of remote sensing images

Remote sensing images exhibit diverse characteristics influenced by the sensors used in capturing satellite imagery. The smallest unit within these images is a pixel, constituting the smallest area in a digital image and typically assuming a square shape. Resolution represents the quantity and quality of information in imagery, conveyed through pixels, colors, and wavelengths captured over a specific period. More pixels, colors, and wavelengths enhance information and visual clarity, while fewer diminish them. The remote sensing images have different types of resolutions (Jensen, 2009; Jr & Ellis, 2020):

Spatial resolution

Spatial resolution denotes the smallest angular or linear separation between two discernible objects in a remote sensing system. It refers to the clarity of features on the Earth's surface, representing the ability of the sensor to differentiate between diverse objects. Spatial resolution is the ratio of pixel size to the area it represents, with more pixels enhancing image resolution. Higher spatial resolution yields finer details, facilitating the differentiation of minute features in digital images. Conversely, lower resolutions may lead to a single pixel representing multiple Earth objects, impacting object extraction and identification processes.

Spectral resolution

Spectral resolution pertains to the bandwidth of a wavelength and encompasses the number and size of specific wavelength intervals (bands or channels) to which a remote sensing instrument is sensitive. Higher spectral resolution is achieved when narrower bands of different wavelengths are available in the sensor. This enables discrimination between land cover classes based on their spectral signatures.

Radiometric resolution

Radiometric resolution refers to a sensor's ability to capture the minute differences in the radiated energy from the Earth's surface. It is expressed in bits and defines the number of discernable signal levels. Radiometric resolution depends on Signal-to-Noise Ratio (SNR) and Saturation Radiance. The number of bits used to represent energy recorded by each pixel determines the radiometric resolution. A higher bit count enables better discrimination between intensities and reflectance.

Temporal resolution

The temporal resolution indicates how often a sensor captures imagery of a specific area, representing the revisit time of a satellite over a region. It is crucial for understanding the direction and extent of changes in the study area over time.

1.6 Role of remote sensing in biodiversity estimation

Field-based biodiversity estimates are widely utilized to measure species richness and abundance (Lengyel et al., 2008). However, these methods can be costly, time-intensive, and challenging to scale up for larger spatial extents. Remote sensing provides a faster and more cost-effective alternative for collecting information across larger spatial scales than field sampling (Lengyel et al., 2008; Nagendra, 2001). Integrating field and remote sensing metrics enhances estimates of species, as well as spatial and temporal distributions of biodiversity, fostering collaboration between ecological and remote sensing communities (Wang & Gamon, 2019; Zhang et al., 2006). Wide area mapping through remote sensing (Schepaschenko et al., 2019) presents an alternative approach to traditional field sampling for monitoring biodiversity.

Researchers have actively engaged to find a relationship between species richness and diversity and spectral reflectance values coming from remote sensing (Gillespie et al., 2008). Numerous studies have highlighted a significant positive correlation between plant species diversity, obtained from plot data, and NDVI in tropical ecosystems (Bawa et al., 2002; Cayuela et al., 2006; Foody & Cutler, 2003; Gillespie, 2005; Turner et al., 2003). Additionally, other studies have successfully estimated species diversity and chemical diversity using remotely sensed data (Asner & Martin, 2008, 2011; Féret & Asner, 2014), including variability in spectral features associated with pigments. Estimating species diversity can be achieved by analyzing variations in spectral features, encompassing those linked to pigments (Asner & Martin, 2008; Rocchini et al., 2010).

Hyperspectral remote sensing, exemplified by sensors like Airborne Visible InfraRed Imaging Spectrometer (AVIRIS) and AVIRIS Next Generation (AVIRIS-NG), holds promise for investigating inter- and intra-species variability (Schweiger et al., 2018; Wang et al., 2019). Spectral characteristics in remotely sensed images, including spectral heterogeneity, indicate species richness (Palmer et al., 1999, 2002). The observed spectral heterogeneity serves as a proxy for species diversity, influencing plant community assemblages (Oldeland et al., 2010; Rocchini et al., 2004) and environmental gradients (Asner & Martin, 2016). Various spectral diversity metrics are used such as convex hull volume (CHV), that quantifies the volume of trait space occupied by species within a community, irrespective of distribution shape, and serves as the multivariate equivalent of range (Cornwell et al., 2006). For instance, Dahlin, (2016) demonstrated that the CHV calculated from the first three principal components of AVIRIS-NG spectral data can unveil crucial insights into the relative significance of drivers influencing community assembly, even in the absence of additional data on functional traits of plants. Thus, CHV not only reduces the dimensionality of spectral data through principal component analysis (PCA) but also serves as a metric for spectral diversity (Gholizadeh et al., 2018).

Earlier studies have established a correlation between ecological diversity indices (Shannon Diversity Index and Simpson’s Index) and spectral diversity metrics such as Standard Deviation (SD), Coefficient of Variation (CV) (Aneece et al., 2017; Wang et al., 2018). Similarly, Rocchini et al., (2017) applied Rao's Q to remotely sensed data for biodiversity estimation. Gholizadeh et al., (2018) examined five spectral diversity metrics, including CV, CHV, spectral angle mapper (SAM), spectral information divergence (SID), and convex hull area (CHA). The current study draws inspiration from these findings.

1.7 Role of hyperspectral data in tree species discrimination

Due to their extended lifespan, trees possess the capacity to adjust to spatio-temporal variation in environmental conditions (Knapp et al., 2017). Furthermore, they play a crucial role in shaping ecosystem structure and function, making substantial contributions to biomass (Babst et al., 2013). This significance is particularly pronounced in tropical forests, where diversity is more extensive; however, there remains a notable gap in the understanding of the mechanisms governing ecosystem structure and distributions (Kapos, 2017; Poorter et al., 2008). Accurate discrimination between tree species is crucial for revealing their composition and distribution using remotely sensed data. Recent advancements in remote sensing technology, particularly hyperspectral sensors with high spatial and spectral resolutions, offer significant potential for mapping tree species' spatiotemporal distribution and attributes across extensive areas (Fassnacht et al., 2016).

Traditionally, species discrimination for vegetation mapping required exhaustive and time-consuming fieldwork, involving taxonomical information and the visual estimation of percentage cover for each species (Kent, 2011). The emergence of hyperspectral sensors has elevated expectations regarding the spectral discrimination of species and allows for the exploration of spectral variation as a direct estimate of canopy diversity (Clark et al., 2005; Cochrane, 2000; Schmidt & Skidmore, 2003). Some species are spectrally similar and difficult to discriminate, while other species are easily differentiable (Féret & Asner, 2014).

The optimal hyperspectral narrow bands (OHNBs) provides optical information for species classification (Thenkabail et al., 2021; Thenkabail & Lyon, 2016). Spectral bands associated with leaf chemistry prove helpful in species discrimination (Alonzo et al., 2014; Peerbhay et al., 2013). These distinctive bands include those related to photosynthetic pigments (Chlorophyll) in the VIS region, water absorption in the NIR at 970, 1100, and 1200 nm, nitrogen in the near SWIR region at 1500 and 1700 nm, as well as carbon, cellulose, and lignin in the far SWIR region at 2020, 2150, and 2350 nm, respectively, that drive the separability of trees (Figure 1.5) (Asner & Martin, 2015; Paz-Kagan et al., 2017; Paz-Kagan & Asner, 2017). The considered spectral regions significantly impact the ability to estimate species diversity through spectral diversity (Aneece et al., 2017).

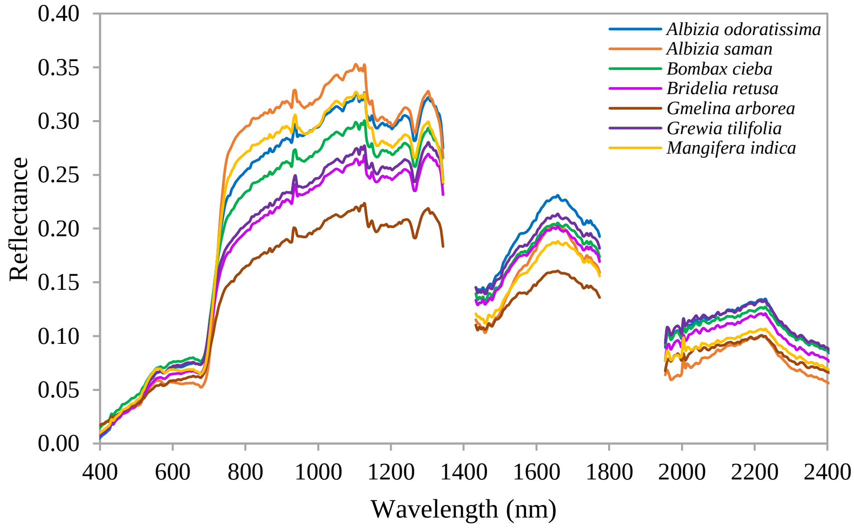

Figure 1.5| Spectra of different species across the entire spectral region (Authors own work).

The high spectral resolution has not only improved the accuracy of conventional classifiers but has also enabled the use of sub-pixel-level spectral unmixing algorithms, identifying the relative abundance of endmembers within a pixel (Adam et al., 2010). The pioneering work by Martin et al., (1998) marked the beginning of tree species detection using hyperspectral images, and recent spectral innovations have increased their prevalence in studies focusing on tree species detection (Ferreira et al., 2020; Grabska et al., 2020). Studies examined by Yel & Tunc Gormus, (2023) suggest that hyperspectral images are more commonly used for individual tree detection. The unique chemical composition of trees results in distinct reflections in different bands, enabling the discrimination of individual tree crowns. Sensor selection is tailored to utility aspects, with a greater spectral resolution sensor being necessary to discriminate between two tree species with highly similar spectral reflections (Richter et al., 2016).

1.8 Image classification methods

In the past two decades, there has been a notable shift in forest monitoring and inventory systems from traditional field surveys to methods based on remote sensing. Hyperspectral image classification, particularly, has emerged as a dynamic area of research in recent years (Landgrebe, 2003). The primary goal of classification is to assign distinct labels to each pixel in a hyperspectral image, defining it as a specific class within a set of observations. Four methods are commonly employed for classification: unsupervised, supervised, semi-supervised and hybrid (Al-Doski et al., 2013; Bioucas-Dias et al., 2013). Currently, there is a growing focus on supervised classification using machine learning algorithms owing to their high accuracy. These algorithms predict the class of input data by utilizing specific methods embedded within them, which are learned from training data. The integration of machine learning algorithms with hyperspectral data presents novel opportunities for addressing complex issues, such as tree species classification (Ba et al., 2020).

Machine learning algorithms can be broadly categorized into three types: classification tree methods like decision trees and Random Forest (RF), grouping and separability methods such as Support Vector Machine (SVM) and k-nearest neighbors (kNN), and rule creation and application methods like Convolutional Neural Network (CNN) (Ba et al., 2020; Brodrick et al., 2019). These classifiers have found application in various ecosystems, including subtropical wet and dry forests (Ferreira et al., 2016; Shen & Cao, 2017), temperate and boreal forests (Ballanti et al., 2016; Dalponte et al., 2014; Maschler et al., 2018), plantations and agroforestry (Ghosh et al., 2014; Graves et al., 2016) and urban forests (Alonzo et al., 2014; Pu, 2009). The synergy of machine learning, deep learning, newly developed algorithms, and plant indices with remotely sensed data has significantly improved classification accuracy (Xi et al., 2021; Yang et al., 2022).

The field of remote sensing-based species classification has advanced with methodological improvements in statistical learning. Two additional methods for mapping land cover and detecting tree cover include pixel-based approaches and object-based image analysis (Ballanti et al., 2016). In pixel-based approaches, a classifier operates on a per-pixel basis, while in object-based methods, pixels are grouped based on local spectral similarity, and subsequent classification is performed on these objects. The selection of an appropriate classification method depends on various factors, such as the type and characteristics of remote sensing data, the diversity of tree species, the complexity of the classification task, and the desired accuracy level.

1.9 Importance of this study

Over the past 35 years, the importance of studies on tree species classification has consistently increased, driven by the growing availability of hyperspectral data (Fassnacht et al., 2016). Airborne hyperspectral imagery has demonstrated considerable potential for classifying tree species, particularly in boreal and temperate ecosystems (Jones et al., 2010; Maschler et al., 2018; Mäyrä et al., 2021), However, challenges persist in tropical regions due to the complexity of tropical forest ecosystems (Asner & Martin, 2009; Baldeck et al., 2015).

Apart from classification, current research is directed towards integrating field and airborne datasets for the assessment of land surface characteristics (Chadwick et al., 2020). Numerous studies highlighted an interesting correlation between species diversity and spectral diversity derived from remote sensing (Aguirre-Gutiérrez et al., 2020; Aneece et al., 2017; Wang et al., 2018). However, such studies are relatively limited in the tropics, especially in regions like India characterized by high heterogeneity and significant anthropogenic pressure. This gap suggests that there is a need for more comprehensive studies focusing on the relationship between species diversity and spectral diversity using remote sensing techniques, particularly in tropical ecosystems. Additionally, there is a lack of understanding of how anthropogenic pressures impact this relationship in regions like India. Therefore, further research is needed to bridge this gap and improve our understanding of the complexities of tropical forest ecosystems and their response to environmental changes.

As a part of the collaborative initiative between the Indian Space Research Organization (ISRO) and NASA, the AVIRIS-NG sensor was utilized to facilitate the acquisition of airborne data for some of the forest covers of India (Bhattacharya et al., 2019). AVIRIS-NG data were utilized over some of the forest cover in India to map dominant species and diversity metrics at a community level (Jha et al., 2019). Airborne imagery, known for its high spatial and spectral resolution, proves more effective in discriminating individual tree crowns (Wang & Gamon, 2019). Acknowledging this as a substantial opportunity, this study investigates the utility of AVIRIS-NG data by establishing connections between field observations and diversity metrics, aiming to achieve the following objectives.

1.10 Objectives of the study

- To develop tree species map of selected forest covers of India.
- To estimate how tree species diversity is correlated with spectral diversity in different spectral regions of AVIRIS-NG spectra.