# CHAPTER 1: INTRODUCTION

## 1.1 REMOTE SENSING: FUNDAMENTALS

Remote sensing is a phenomenon which gathers information of any far object without coming into physical contact with target. The acquisition of information involves detecting the scattered and emitted radiations from a distance to sense changes in the surrounding field caused by the object, whether electromagnetic, acoustic, or potential.

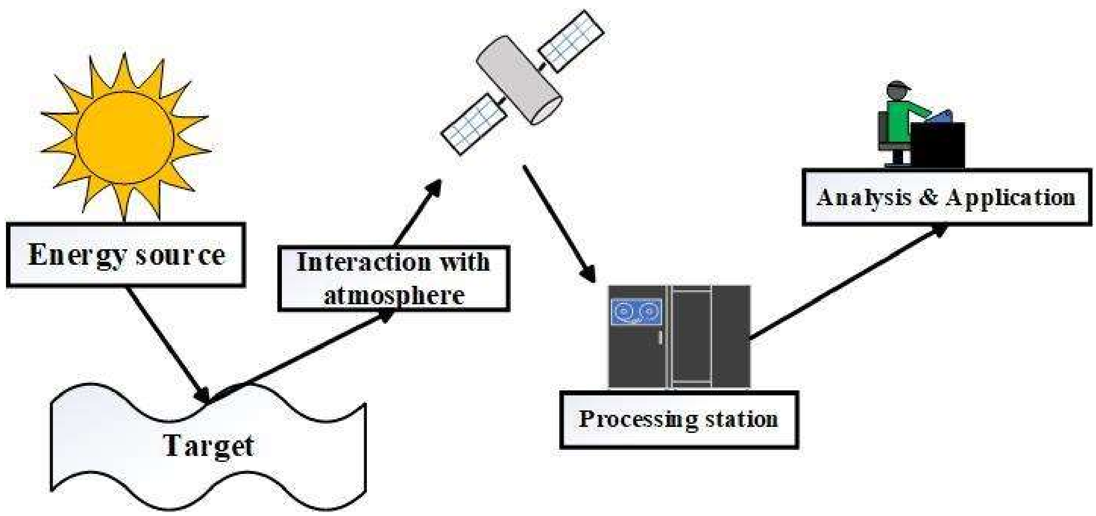


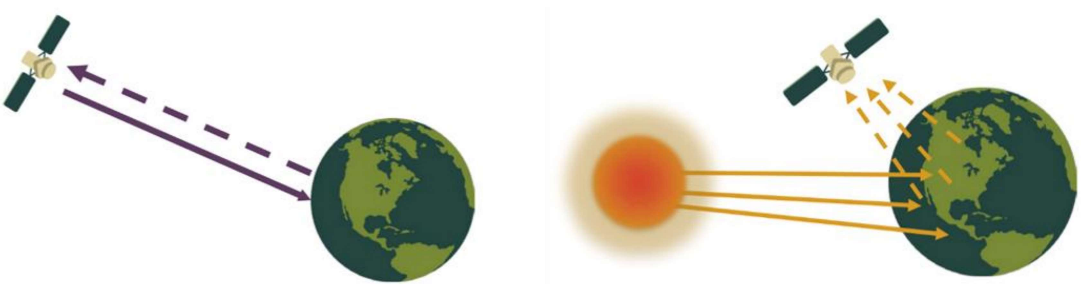

**Figure 1.1.** Remote sensing process

Figure 1.1 shows a typical remote sensing process, a target is illuminated by an energy source and interacts with it, the radiation is captured by a sensor which send the signal to a processing station, where it is corrected and further sent to application centre for further use. The sensors are mounted on different platforms such as satellite, aircraft, UAV, etc.

The most basic and marvellous example of a remote sensor is human eyes, which sees any object's reflection illuminated by any light source in visible range. In remote sensing process, usually Electromagnetic radiation (EMR) is employed as an information carrier from the target to the sensor.

## 1.2 TYPES OF REMOTE SENSING

Based on energy source used to illuminate the target, it can be differentiated into two types, namely, active and passive remote sensing.



**(a)** **(b)**

**Figure 1.2. (a)** Active Remote Sensing; **(b)** Passive Remote Sensing

(Source: https://www.earthdata.nasa.gov/learn/backgrounders)

### 1.2.1 Active Remote sensing

The act of remote sensing, where the sensors emit their own source of radiation to illuminate the target as shown in Figure 1.2 (a). A regulated beam of energy is emitted by an active sensor towards the target to be investigated. The energy reflected or backscattered from the target is then measured by the sensor. The primary benefits of active sensor systems are that they can work at any time throughout the day and night and in different weather situations. Sensors such as RADAR, SONAR, LiDAR, etc. fall under the examples of active remote sensor.

### 1.2.2 Passive remote sensing

Sensors which depend on natural energy source of radiation to illuminate the target are called passive remote sensors and this process is called passive remote sensing, illustrated in Figure 1.2 (b). Profound examples are optical satellites such as MODIS, Sentinel-2, LANDSAT-8, etc., these satellites depend on the sun, to illuminate the target on the earth surface. These sensor measures natural radiation emitted from the target present on earth's surface. Although, there is a certain limitation with passive remote sensing, such as it mostly works with sunlight, so during night these sensors do not acquire any information. However, natural energy (such as thermal infrared) may be sensed at any time of day or night. Passive remote sensing is affected with the sun's fluctuating lighting conditions, which are heavily influenced by atmospheric variables.

## 1.3 ELECTROMAGNETIC RADIATION (EMR) IN REMOTE SENSING

In order to observe earth surface passively or actively, choice of part of EMR is important, based on the choice, it could either be microwave remote sensing or optical remote sensing.

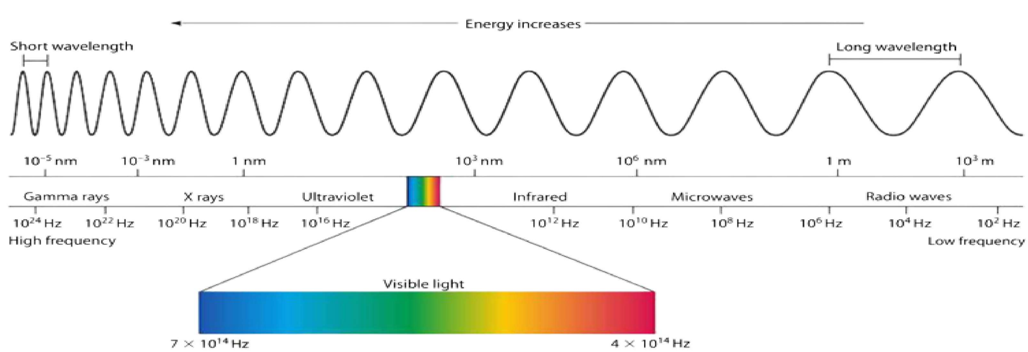



**Figure 1.3.** Electromagnetic radiation

(Source: https://www.miniphysics.com/electromagnetic-spectrum_25.html)

The part of electromagnetic spectrum is covered by remote sensing methods, starting with low-frequency radio waves and moving through the microwave, far IR, NIR, visible, UV, x-ray, and gamma-ray as shown in Figure 1.3.

The optical region of the electromagnetic spectrum, which ranges from 0.4 µm to 0.7µm, is generally referred to as visible light. The infrared (IR) part of the electromagnetic spectrum is also of great importance, spanning roughly 0.7 µm - 100µm. It is more than a hundred times larger than the visible section. Based on its radiation qualities, the IR area may be divided into two types: reflected IR and emitted or thermal IR. The radiation in the reflected infrared zone, which extends from 0.7 µm to 3.0µm, is quite comparable to that in the visible range. The thermal IR range, which extends from 3.0 µm -100µm, offers information on the heat radiated from the Earth's surface. The microwave range, extending from around 1mm to 1m, is the most recent area of interest in the spectrum. The microwave area has the longest wavelength employed in remote sensing and may offer surface information such as roughness, water content, and so on.

The advancement of satellite sensors helps us allow the acquisition of global information about the Earth and its environment. Different sensors mounted on Earth orbiting satellites provide global information about cloud cover, vegetation or ocean cover on earth surface and its variation throughout a timeline.

## 1.4 DIFFERENT INTERACTION BETWEEN THE ATMOSPHERE AND EMR

While traveling from the source to the target EMR must go through the earth atmosphere, and during the process it goes through different types of interaction, such as absorption, scattering, and transmission.

The EMR is scattered and absorbed by the atmosphere's gas and particle elements. The atmospheric impacts are determined by radiation parameters such as amplitude and wavelength, and variants in the path length. Further, the transmitted EMR through the atmosphere is subsequently either reflected or absorbed by the target.

### 1.4.1 Scattering

When an EMR passes through the atmosphere, it interacts with gaseous particles, aerosols, which diverts its initial path. This diversion is based on the size difference between the size of scatterers and wavelength of the radiation. This is known as scattering and it can be further divided into three parts.

#### 1.4.1.1 Rayleigh scattering

Discovered by Rayleigh in 1971, this type of scattering occurs whenever the size of the scatterers is smaller than the radiation's wavelength and the scattering is inversely proportional to the fourth power of wavelength.

#### 1.4.1.2 Mie scattering

Mie scattering happens if the scatterers' size and radiation' wavelength are comparable. Aerosols such as water vapours, dust, and smoke particles are Mie scatterers, they affect radiation of larger wavelength compared to Rayleigh scatterers.

#### 1.4.1.3 Non-selective scattering

When the diameter of the air scatterer is substantially greater than the radiation wavelength being measured, non-selective scattering takes place. Non-selective scattering is caused by the air scatterer, which includes water droplets, ice crystals, and volcanic ash.

### 1.4.2 Absorption

In comparison to the scattering, the electromagnetic signal is effectively lost due to the absorption of atmospheric elements by the atmosphere. Certain gases in atmosphere absorb particular bands of the EM spectrum such as $H_2O$, $CO_2$, and $O_3$ are the three components of the atmosphere that are most able to take in and store energy. $O_3$ absorbs the harmful UV radiation from sun, whereas $CO_2$ absorbs strongly in IR region, it is also known as greenhouse gas. As a direct result of this, they have a substantial influence on the overall design of any remote sensing system. The parts of the electromagnetic spectrum in which the atmosphere has a relatively high level of transparency are referred to as "atmospheric windows."

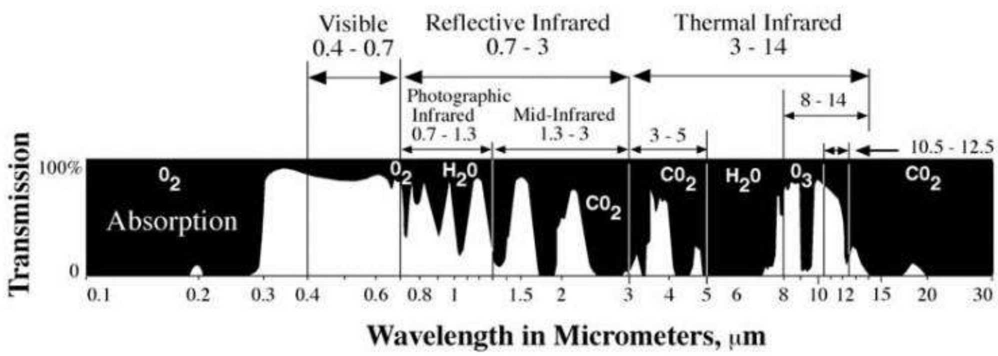



**Figure 1.4**. Atmospheric window in Remote sensing [1]

Figure 1.4 illustrates the atmospheric window of the electromagnetic spectrum that is helpful in remote sensing to decide the spectra range to be used. The usable window for optical remote sensing lies between 0.4 μm and 2μm and include both the visible and reflected infrared portions. In the thermal infrared part, a third window with a reasonably large range of around 8 μm –14 μm can be beneficial for thermal remote sensing. This window is located between two rather narrow windows measuring about

3 µm and 5 µm. The microwave region is connected to the vast atmospheric window that occurs at wavelengths longer than one millimetre.

## 1.5 INTERACTION BETWEEN THE EARTH SURFACE AND THE EMR

The electromagnetic radiation (EMR) that has not been absorbed or scattered in the atmosphere can travel to the surface of the Earth, where it can interact with the characteristics of the land surface. There are three possible forms of interaction that might take place when radiation encounters a surface. A, T, and Rf stand for absorption, transmission, and reflection, respectively.

When the EMR (energy) is absorbed by the target, the process known as absorption (A) takes place. As an EMR travels through the target, this phenomenon is known as transmission (T). The phenomenon known as reflection (Rf) takes place when the EMR "bounces" off the target and is then directed in a different direction. In remote sensing, only the radiation that is reflected off the surface is of any important significance since it can provide information about the surface's features. Specular and diffuse reflections are the two forms of reflections that may be seen when looking at the manner that energy is reflected off an object.

(a) When the surface is smooth, then specular reflection (mirror-like reflection) occurs and the energy is directed from the target it in a single direction.

(b) In case of rough surface, the reflection occurs in different direction, that is called diffused reflection.

## 1.6 SPECTRAL RESPONSE/SIGNATURE CURVE

There are many different kinds of target materials that make up the surface of the Earth. The majority of the targets, sadly, exhibit behaviour that falls somewhere in the middle of that of fully specular and perfectly diffuse reflectors. The problem of identifying a target based purely on the data of its reflectance is a difficult one. The relationship between reflectance and wavelength can be plotted to produce a spectral reflectance curve, which is also known as spectral signature. It is a description of the degree to which the energy is emitted by the objects in various parts of the electromagnetic spectrum. Every object present in the universe has a unique spectral response, based on that the identification of the target is done.

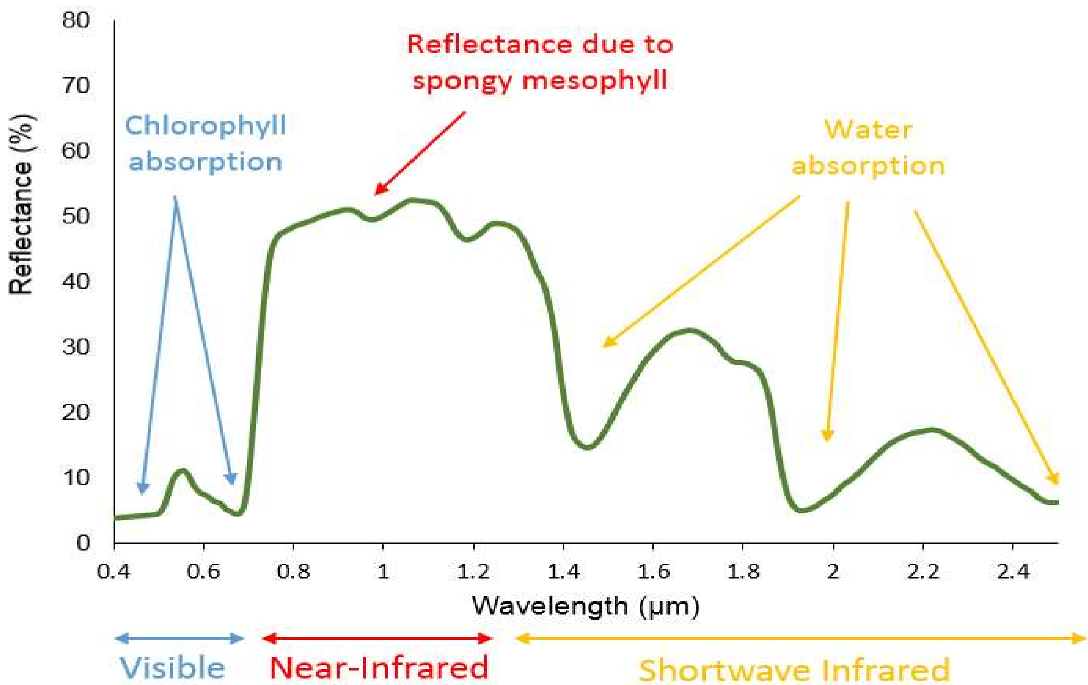



**Figure 1.5**. Typical vegetation spectra [2]

Figure 1.5 shows a typical vegetation spectral response, the spectra can be divided into three parts, response in visible, near infrared, and shortwave infrared

(a) In visible region (400-700nm), there is a strong absorption in blue and red region, radiation from these two regions are required in photosynthetic process, and reflects strongly in green region which is the reason for green colour of vegetation. This portion comprises of 10-15% of the reflection.

(b) When Near Infra-Red (NIR) penetrates the leaf cells, it becomes transparent to the chlorophyll cells, and it is reflected strongly by mesophylls present inside the leaf cells. This region is responsible for 50-60% of reflection. The dips present at 1000nm and 1200nm occurs due to presence of cellulose lignin, starch etc.

(c) In Short Wave Infra-Red (SWIR) region, there are major dips at 1450nm, 1965nm, and 2500nm, these are water absorption bands and it happens due to different type of transitions in the water molecule. These bands are quite important for vegetation because it gives the information about water content inside the leaf.

## 1.7 DIFFERENT TYPES OF RESOLUTION IN REMOTE SENSING

The quality of a remotely sensed images is judged on the basis of resolution of the sensors on board the satellites. A satellite image contains information about the electromagnetic radiation coming from a target, and it saves the information in a "pixel" which refers to an acronym for "picture element," which describes the little, uniformly sized and shaped portions that make up each image. The recorded readings of the detected energy are referred to as "DN values," which stands for discrete digital number.

In remote sensing there are four types of resolutions; Spectral, Spatial, Temporal, and Radiometric resolutions.

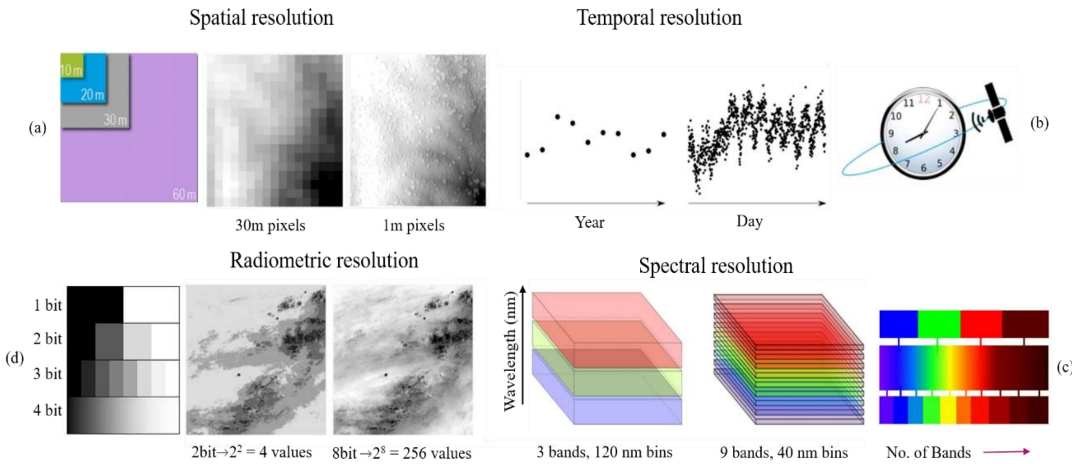



**Figure 1.6**. Different types of resolutions: **(a)** Spatial resolution; **(b)** Temporal resolution; **(c)** Spectral resolution; **(d)** Radiometric resolution [3]

### 1.7.1 Spatial resolution

The smallest area that can be detected by the sensor is known as the spatial resolution of any sensor. It establishes how finely a picture can preserve the spatial detail of the target and, therefore, it is expressed in the terms of pixel. Figure 1.6 (a) shows an example image with spatial resolution of pixel size 10m, 20m, 30m, and 60m along with a comparative higher and lower spatial resolution image. It is clear from the figure that a 1m pixel resolution image has much more detailing than a 30m pixel dimension image.

### 1.7.2 Temporal resolution

The time elapse between two consecutive image acquisitions of the same region on Earth is referred to as the temporal resolution of the image. The number of days is typically used when referring to the revisit time of a satellite sensor. When the revisit time is short, the temporal resolution is much better, illustrated by Figure 1.6 (b). The higher temporal resolution is favourable when we have to study about, climate change, vegetation change of the earth surface. The actual temporal resolution is determined by a number of different parameters, such as the capability of the satellites and sensors, the amount of swath overlap, and the latitude.

### 1.7.3 Spectral resolution

The capacity of a sensor to specify narrow wavelength intervals or to resolve the energy received in a spectrum wavelength range is what is meant by the term "spectral resolution." This enables the sensor to characterize various components of the earth's surface. When the spectral resolution is increased, the precision of wavelength range corresponding to a certain band increase. Figure 1.6 (c) shows a comparison between higher and lower spectral resolution images, for a three bands image much more energy information is lost as compared to 9 bands image. As we increase the number of bands the spectral information becomes continuous (e.g., hyperspectral information) from being discrete (e.g., multispectral information) (Figure 1.7).

### 1.7.4 Radiometric resolution

The ability of a sensor to differentiate between extremely minute variations in the electromagnetic field is called "radiometric resolution", it is measured in terms of greyscale. The sensitivity of any sensor to detect even minute variations in the amount of energy reflected or emitted enriches proportionately with the level of radiometric resolution it possesses. The number of bits, often known as binary numbers, determines the number of different greyscale values. Figure 1.6 (d) shows a comparison between a 2 bit and 8 bits images with greyscale values of 4 and 256 respectively.

## 1.8 HYPERSPECTRAL REMOTE SENSING

Hyperspectral imaging (HSI) also known as imaging spectroscopy captures an image in a large number of contiguous, narrow spectral bands which has the order of hundreds of bands with spectral resolution as high as 5-10nm. While multispectral images give information only in 5-10 bands, with poor spectral resolution. HSI breaks the information into numbers of spectral bands, shown in Figure 1.7. Table 1.1 shows various hyperspectral sensors along with their basic specifications.

This technique enables researchers and scientists to acquire non-invasive information regarding the material composition and physical properties of any object. An HSI contains, three-dimensional image cube in which every pixel contains spectral information that is recorded in numerous spectral bands with narrow bandwidth (spectral resolution). The spectral dimension is one of the dimensions among three, the other two dimensions denote the spatial resolution representing the image or scene (Figure 1.7).

These techniques are useful for analysing the invisible characteristics in the form of spectra of targets, such as the chemical composition of a material or the presence of specific compounds. In addition, hyperspectral techniques offer increased precision when detecting and quantifying the presence of substances or materials.

The ability to distinguish and identify various materials and objects within an image is one of the primary advantages of hyperspectral techniques. This is achieved by analysing the distinct spectral signatures or characteristics of materials, which can be used to distinguish one substance from another. Compared to multispectral, RGB, or panchromatic data, HSI gives information with higher spectral detail about the target.

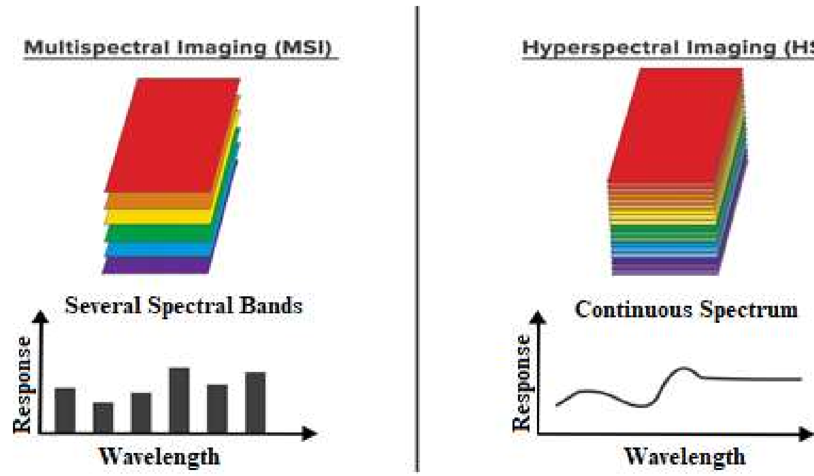



**Figure 1.7.** Multispectral imaging (MSI) Vs Hyperspectral imaging (HSI)

(Source: https://sensing.konicaminolta.asia/understanding-hyperspectral-imaging-hsi/)

**Table 1.1**. Various known hyperspectral sensors along with their resolution details

| **Sensors** | **No. of spectral bands** | **Spectral resolution/bandwidth** | **Spatial resolution** | **Launch Year** |
|---|---|---|---|---|
| AVIRIS | 224 | 10nm/360-2450nm | 20m | 1993 |
| AVIRIS-NG | 425 | 5nm/380-2510nm | ~5m | 2013 |
| PRISMA | 237 | 5nm/400-2505nm | 30m | 2019 |
| HYPERION | 220 | 10nm/400-2500nm | 30m | 2000 |
| CASI | 144 | 2.4nm/360-1050nm | 2.5m | 2007 |
| EnMAP | 228 | 5.25-12.5nm/420-2400nm | 10m | 2022 |
| HysIS | 316 | 10nm/400-2500nm | 30m | 2018 |

### 1.8.1 Applications of hyperspectral remote sensing

This extensive sampling of the EM spectrum offers a significant increase in the amount of spectral information that can be put to use in a variety of fields, including agriculture, mineral identification, urban planning, geography, geology, monitoring environment, surveillance, classification, and target detection of the data that has been acquired.

(a) Environment modelling: The use of hyperspectral imaging to monitor shifts in the surrounding environment is gaining significant traction. It is widely used to understand surface $CO_2$ emissions, mapping of hydrological formations, tracking level of pollution, and in a variety of other applications as well.

(b) Crop monitoring: Hyperspectral information finds it immense application in crop monitoring field to give detailed information about health, nutrient, and stress of the crop. Apart from these, it also informs agronomists about detection of diseases, increasing crop yield, detecting weed, irrigation, and fertilizers treatment.

(c) Plant Phenomics: Various HSI techniques can now be used to determine how plants react to their surroundings. In order to collect data in a lab, glasshouse, or field scenario, HSI has emerged as a viable method to quantify features using a wide variety of wavebands simultaneously in 3D. To optimize crop management, HSI has been used to determine abiotic, biotic, and qualitative parameters.

(d) Precision agriculture (PA): PA is the science of using high-tech sensor and analysis systems to improve agricultural yields and help management decisions. The development of technically advanced agricultural tools is critical to assisting farmers in making crop health and resource management decisions. The effective use of HSI in precision farming not only helps farmers use resources such as herbicides and pesticides more efficiently, but it also provides information into crop development and health at the current stage.

(e) Mineral exploration: HSI also find its application in mineral exploration, to provide geologists with comprehensive information about the composition and distribution of rocks and soils. It finds it use in mineral identification and mapping, exploring target. This information come in handy whenever informed judgments is required regarding where to focus their efforts, resulting in more successful mineral discoveries.

(f) Food industry: The food industry makes extensive use of hyperspectral imaging technology. It is utilized in several areas of the food business, including the identification of bruises in fruits, the evaluation of the freshness of seafood, the examination of citrus fruit, the classification of melons and potatoes, and the distribution of sugar in melons.

(g) Medical diagnosis: The early identification of sickness and the prevention of disease are both extremely crucial for maintaining a healthy body. The technology of HSI can be used to detect early stages of a variety of cancers as well as diseases that affect the retina.

(h) Forensic science: Studying questioned document analysis, investigating arson, seeing bloodstain evidence, comparing fibers, visualizing gun powder residue, etc.

(i) Defence: Hyperspectral images have shown to be an excellent tool for a broad variety of military and defence applications, including target detection and surveillance, identifying camouflage hiding in plain sight, as well as other matters pertaining to security.

These examples are just few among many fields where HSI find its applications.

### 1.9 UNMANNED AERIAL VEHICLE (UAV)

UAV enables monitoring of local-scale environmental that provide a timely and cost-effective method for data collecting in some applications. A variety of multispectral and hyperspectral imaging sensors can be installed on UAV, and they can be flown at various temporal frequencies to produce images with high spatial resolution. UAV offer the chance to collect data during various environmental conditions. However, these new opportunities greatly expand our ability to detect and measure the impacts of hazards, monitor environmental conditions, track species propagation, and monitor changes in surface conditions. For instance, UAV data collection will take place under diverse environmental conditions, at various times of day, and with different flying altitudes, all of which will have a significant impact on the UAV remotely sensed imagery. In comparison to satellite images, UAV images have better spatial resolution because they are airborne but when it comes to cover large area satellite image acquires larger areas. While taking an image from a UAV based camera, to minimize variations in solar angle, flights are conducted close to solar noon (around 12PM), this type of variation is rectified in a satellite image.

### 1.10 REVIEW OF LITERATURE

Leaves are the important eco-physiological parts of the vegetation that interacts with the atmosphere, because they absorb and assimilate $CO_2$, intercept sunlight that is used in chemical process such as photosynthesis, and release $O_2$ as a by-product of photosynthesis. This chemical process determines the growth and yield of any vegetation. Further, being the direct link between atmosphere and plant, due to evapotranspiration, which releases water vapour and increases pressure so that groundwater from the soil can be absorbed. The reflectance from a canopy depends on both biochemical and biophysical vegetation parameters. Studying biophysical/biochemical parameters of plants, such as Leaf Chlorophyll Content (LCC) and leaf area index (LAI) is now possible with the widespread usage of hyperspectral remote sensing data, due to its spectral resolution richness. These parameters are of immense importance in agricultural studies due to their contribution in photosynthesis and plant functioning.

These two parameters are very important in crop monitoring purposes, with their hyperspectral information it is easier to detect any minute change in the health of a vegetation caused by biotic/abiotic stresses. This can be achieved by comparing spectra of healthy and diseased vegetation, and hence identifying affected areas and take precautionary measures to help prevent any further damage. Apart from identifying stress, HSI can also provide ample information on the status of nutrient of the crops, which help to quantify the amount of fertilizers to be given. Based on the information about vegetation health and nutrient it becomes convenient to take contingent measures and predict crop yield.

HSI can also be used to monitor soil moisture levels in the agricultural field and determine the optimal amount of irrigation. Farmers can detect area that are under stress due to water constraint by studying the reflectance of plants in various spectral bands.

Furthermore, if we already have the spectra of different agricultural species, this can be used to distinguish between crops and weed that grows around it. With this information farmers can recognize weed infestations and take the necessary steps to control them.

### 1.10.1 Importance of LAI and LCC

- LAI can be mathematically represented as ratio of the leaf area per unit ground area ($m^2/m^2$). It is a metric that may be utilized on a worldwide scale to monitor the growing status of vegetation and predict agricultural yields. In addition to this, it is a very essential input parameter for a wide variety of climate and land-atmosphere [4,5, and 6]. There are several ways for the estimation of LAI, most traditional one is by forming the empirical relationship between LAI and Vegetation Indices (VI) [7, 8]. In order to calculate LAI from the reflectance of NIR, visible, and other bands based on VIs, many algorithms were developed. Regional and worldwide maps of LAI, as well as associated products were generated with varying accuracy. [9-11].
- LCC, a vegetation biochemical parameter, is essential for photosynthesis and the conversion of carbon dioxide into glucose in vegetation. About 85% of visible solar energy is absorbed by pigments to power up photosynthesis, 10% is reflected, 2% is released as fluorescence, and the remaining is transmitted [12]. Accurate measurements of this parameter over various geographical and temporal scales are required for monitoring vegetation stress and productivity, that is beneficial in precision agriculture. The capability of leaves to absorb photosynthetically active radiation is predominantly determined byfoliar concentrations of photosynthetic pigments, which influences $CO_2$ absorption and primary production [13]. As a result, LCC is an important component of water, energy, and carbon cycles, as well as a component that is gaining importance in carbon modelling at local and global scales [14]. Inspecting LCC of vegetation in response to changing environmental and climatic conditions is also essential for comprehending and modelling ecosystem reactions. Two of the most popular techniques for analysing LCC are a destructive laboratory procedure based on in vitro spectrophotometric techniques

and a non-destructive method based on in-situ observations collected by chlorophyll meters, such as SPAD system [15, 16]. Nonetheless, despite the great precision of the laboratory method and the portability of hand-held devices, both methods have limits when analysing vast research regions.

Couple of researches have been conducted on physical models incorporating complicated mathematical calculation for retrieving vegetation parameters using VIs. [17, 18]

The energy-matter interaction hypothesis serves as the foundation for spectroradiometry. It is a technique for determining the state of a plant's health through the examination of its spectral fingerprint. It has been put to use in a variety of fields, including the classification of species, the analysis of changes in pigment levels, the evaluation of the water content of canopies, the diagnosis of diseases in plants, and the differentiation of weeds from agricultural plants [19]. The statistical technique involves developing regression models using ground truth data to connect the parameter(s) of interest to the spectral data. Most studies employ spectral vegetation indices to reduce topography, soil background, and atmospheric impacts. [20-22].

Statistical models provide several benefits, which have contributed to the proliferation of their usage. For instance, several of the statistical models are simple to put into practice, as appropriate software is easily accessible [23, 24]. It is a common knowledge, on the other hand, that produced models might lack the capacity to be transferred to other locations with distinct vegetation, as well as the ability to be transferred to various types of images or acquisition settings [5]. Furthermore, for statistical models, they must be fed with data collected locally, and the resilience of these models is contingent on the characteristics of the data they are given. Given the often-high costs associated with the collecting of ground truth data, it would be instructive to conduct a comprehensive analysis of the implications of sample size.

Radiative transfer models (RTM) are utilized as part of the physical approach in order to reduce the amount of reliance placed on ground data. These models, which are based on physical principles, characterize the spectrum variation of canopy reflectance as a function of various parameters such as viewing and lighting geometry, canopy, and soil background parameters. RTM provide an explicit link between the vegetation parameters characteristics of the plant and the canopy reflectance as determined by a sensor [25]. This makes it possible to simultaneously employ all of the spectrum bands that satellite sensors have acquired. To overcome the mathematical complication of RTMs, several machine learning algorithms such as PLSR, SVR, etc., with vegetation indices as input parameters are used extensively in agriculture for classification and estimation. [26, 27].

This observation is summarized by Verrelst et al [23, 28] that there are usually four methods for parameters retrieval parametric, non-parametric, physically based, and hybrid models. When a machine learning algorithm and a physically based model are used in combination, hybrid models are created, which are composites of the previous three methods.

## 1.11 RESEARCH OBJECTIVES

The methods that have been mentioned in the last section have given inexplicable results, although when it comes to the availability of hyperspectral imageries, working sensors are very few, and, they are not freely available. So, there is need to work with algorithms that simulates such image with higher spectral resolution. Apart from image simulation, there is further need to check the validity of the generated image about its utility for parameter retrieval or for classifying different objects present in it.

In the present studies, the Universal Pattern Decomposition Method (UPDM) technique is used, which is combined with couple of multispectral images. It is a linear unmixing method that decomposes the reflectance of pixels reflectance into its constituents' classes. UPDM also possess sensor independent property, based on the fact that class percentage will remain same in multi as well as hyperspectral images. Thus, we get an image with spectral info similar to a hyperspectral image and spatial resolution similar to multispectral image. This method is very useful whenever we require a hyperspectral image is not feasible or viable owing to restrictions in imaging technology or data storage capacity.

Moreover, use of filters to remove noise from a spectrum from image is also required to increase the accuracy of estimation of vegetation parameters such as Fourier or Wavelet transform. Although, the satellite images used are usually atmospherically corrected, but to remove redundant bands and obtain even more smooth spectra, filtering is required. Fourier filters works in the frequency domain, it works on the basis that noise signals present in the main signal is usually high frequency signal, whereas important features present in the image are low frequency information. Thus, these noises can be removed by applying a high frequency filter.

On the other hand, wavelet filters operate in both the time as well as frequency domains. The image is decomposed down into a collection of wavelet coefficients of various sizes and orientations. The signal that contains noise is removed and remaining signals are added back to give denoised signals. Wavelets filters preserve the edges and textures of an image better than Fourier filter. Furthermore, the choice of filters to be used in noise removal is described in more details in Chapter 5.

In addition, numerous machine learning techniques are utilized in the process of choosing significant absorption bands among huge dataset that are important to vegetation parameters. These bands can then be used to construct various vegetation indices, which in turn is used to form models that estimate LCC and LAI. Feature selection refers to the process of selecting, from a very large dataset, the characteristics that are significant to the parameters being studied. The accuracy of LAI and LCC estimations derived from remote sensing data can be improved by the utilizing Feature Selection Methods (FSM) and machine learning algorithms, which in turn enables improved decision-making across a variety of application.

Given the importance of LAI and LCC, and keeping in mind the importance and limitations of availability of HSIs, objectives of the present work have been formulated to estimate these important biophysical/biochemical parameters with simulated and denoised hyperspectral images, and models that have been produced by various types of learning methods.

- Hyperspectral image simulation
    - LCC Mapping on generated image (SRF of Sentinel-2 and AVIRIS-NG, using UPDM)
    - Classification on the simulated image
    - Validation from in-situ LCC
- Improving the Ground Sampling Distance (GSD) of the simulated image
    - LCC and LAI mapping on simulated image (SRF of RedEdge-MX and AVIRIS-NG, using UPDM)

- Validation from in-situ LCC and LAI

- Denoising vegetation spectra for vegetation parameters estimation
    - Use of Wavelet analysis to denoise the vegetation spectra
    - FSM to select absorption bands
    - Formulate indices for the parameter retrievals
    - Linearize model, generate map, and validate from in-situ data
- Use of learning algorithms to generate parameters retrieval model using VIs as input and validate them using in-situ data, to find out the best model.

## 1.12 CONTENT OF THE THESIS

The work completed between December 2017 and December 2022 has been presented in the thesis, and divided into seven chapters. Detailed information on each chapter is provided in the following paragraphs.

**Chapter 1:** It is introductory part, that gives fundamentals about remote sensing along with-it various aspects, hyperspectral remote sensing and its application. Literature survey about the progress of research in the field of vegetation parameters retrieval, followed by research objectives, that briefly talks about the research gap, which led to the motivation and objectives of study.

**Chapter 2:** In this chapter, there is detailed information about the satellite, airborne images used in the study, along with the different study sites covered during the research period. This chapter also shines light on working of sensors and devices to be used in the research in brief.

**Chapter 3**

In this work, there is an evaluation of a simulated hyperspectral image equivalent to AVIRIS-NG for the LCC estimation, this image was generated using a spectral reconstruction technique called UPDM, and Spectral Response Functions (SRF) of AVIRIS-NG and Sentinel-2, a multispectral image. The simulated image has spectra resolution and no. of bands like the original AVIRIS-NG and spatial resolution of the Sentinel-2. From the generated image, LCC was estimated and compared to in-situ LCC. Furthermore, the image was also classified using Spectral Angle Mapper (SAM). The output of the work i.e., LCC estimation and classification from the simulated image give very agreeable results, which has been discussed in Section 3.5.

**Chapter 4**

The image simulated using Sentinel-2 and AVIRIS-NG, has a spatial resolution of Sentinel-2, which is 10m, but the Ground Sampling Distance (GSD) of AVIRIS-NG image is around 5m. Thus, in order to get an image with better GSD, a multispectral image mounted on a drone was used with very high GSD, resulting in an image simulated with high spectral and spatial resolution and improving the accuracy in estimation of LCC. The GSD of MSI used was ~5cm, therefore the generated pseudo hyperspectral image has the resolution of 5cm and 5nm. The image generated was further used to map LAI and LCC for the study site and validated using ground truth data.

**Chapter 5**

In this chapter an AVIRIS-NG was denoised using Discrete Wavelet Transform (DWT), different types of wavelets were run over vegetation spectra extracted from the image, and the approximated signal (denoised) was further used for the estimation of LCC. Feature Selection Methods (FSMs) were used to select relevant bands for

LCC and then those bands were used to formulate vegetation indices (VIs) to generate models, these models were further validated using in-situ LCC. Conclusively, it was found that the accuracy of estimation was very much improved using wavelet transform filter and choosing absorption bands by implementing FSM, the details are provided in the chapter’s conclusion.

**Chapter 6**

Different enhanced learning algorithms were scrutinized for modelling LCC and LAI of various agricultural species under different irrigation and fertilizer treatments. Twenty-five VIs sensitive to LCC and seven VIs sensitive to LAI were calculated from spectroradiometer data of the species. These indices were given as input parameter to SVR, RFR, HyFIS, and PLSR, each model was validated using in-situ LCC and LAI. Among all these algorithms, model generated from SVR with radial kernel gave the best estimation under different treatments for LCC and LAI. Detailed method, VIs selection process and results have been discussed in this chapter.

**Chapter 7**

In the last chapter, conclusion of overall work has been discussed, and further plans is also mentioned in brief.

*********