

Chapter 1

Introduction

1.1 Definition of Remote Sensing

Remote sensing serves as a pivotal tool for observing and monitoring Earth and studying celestial bodies. In its broadest sense, remote sensing involves gathering information from a distance. However, for the purpose of this Ph.D. Thesis, it is necessary to refine this definition to narrow the focus to specific topics. This refinement excludes certain concepts, methodologies, and technologies that fall under broader definitions, such as sensing the Earth's magnetic field, atmosphere, or human body temperature. In this Ph.D. Thesis, we adopt the more specific definition provided by J. B. Campbell (Campbell and Wynne, 2011).

"Remote sensing involves extracting information about the Earth's land and water surfaces through the utilization of images captured from an aerial viewpoint. This process relies on the utilization of electromagnetic radiation within one or multiple segments of the electromagnetic spectrum, which is either reflected or emitted from the Earth's surface."

Within this definition, remote sensing encompasses a series of techniques and approaches designed to collect data about the Earth's surface by using the transmission and reception of Electromagnetic (EM) waves. The chosen frequency range has significant implications

for both the required hardware and the types of information that can be gathered, ultimately influencing the various applications of remote sensing systems. For instance, radar remote sensing predominantly employs microwave and millimeter wave frequencies, optical sensors rely on the propagation of light, and lidar remote sensing is centered around the emission and reflection of laser pulses within the near-infrared, visible, and ultraviolet segments of the EM spectrum. Remote sensing is intrinsically tied to the propagation, reflection, and scattering of EM waves by both natural and man-made surfaces. This connection brings us into the realm of intricate interactions between radiation and matter. However, electromagnetic theory provides analytical solutions only in a limited number of standard scenarios, where a deterministic framework can yield closed-form expressions for the scattered field. When it comes to working with remote sensing data, these idealized cases are rarely sufficient. To illustrate, when evaluating scattering, we might approximate large ice sheets or exceptionally calm seas as infinite planes, which is an oversimplification. In most real-world situations, the reflecting interface needs to be characterized as a random, uneven surface, introducing unpredictable fluctuations in the received signal. In these instances, the actual measurements of the signal cannot be precisely forecasted, and valuable insights about the illuminated surface are gleaned from statistical analysis of the signal's behavior.

1.2 Concept and basis of Remote Sensing

Remote sensing is a dynamic and interdisciplinary field that revolutionizes our understanding of the Earth and its surroundings. At its core, remote sensing involves the non-contact acquisition of information about objects or phenomena through the detection and interpretation of electromagnetic radiation. This remarkable science and technology enable us to explore and analyze remote, often inaccessible areas with great precision. The concept of remote sensing is rooted in the idea that the electromagnetic spectrum, which encompasses

visible light, infrared, microwave, and more, as shown in Figure 1.1, holds a wealth of data about our environment.

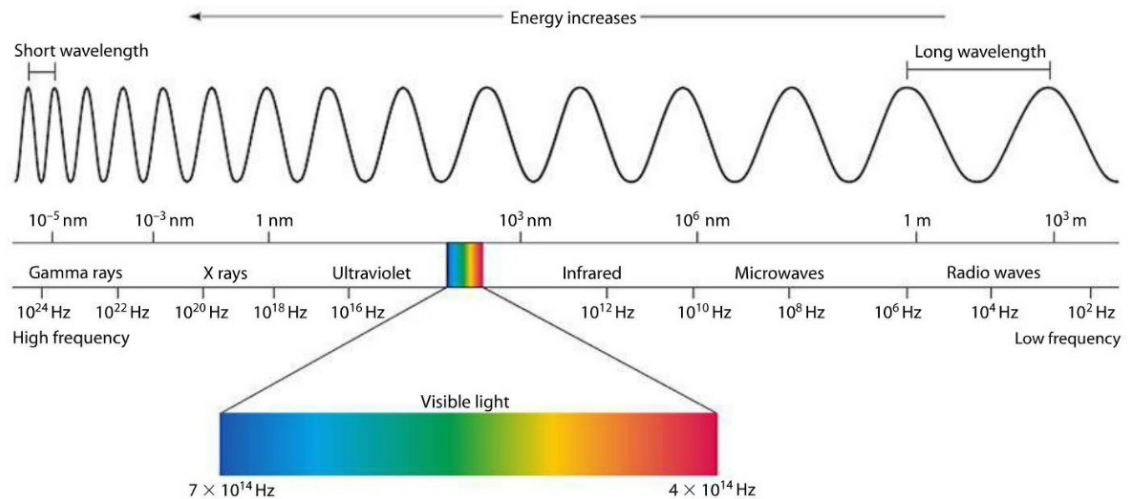


Figure 1.1 The electromagnetic spectrum.

Source:<https://www.gistraverse.in/electromagnetic-spectrum//>

When this spectrum interacts with the Earth's surface, it provides valuable insights into the properties, composition, and changes in natural and artificial features. Remote sensing is not confined to optical data from cameras; it embraces a wide spectrum of sensors and platforms, including satellites, aircraft, drones, and ground-based instruments. This diversity of tools allows researchers and practitioners to address a myriad of challenges, from mapping land cover changes and monitoring atmospheric conditions to studying the Earth's ecosystems and aiding in disaster management.

The basis of remote sensing is the utilization of EM radiation as a medium for acquiring data about objects and phenomena. EM radiation, which includes visible light, infrared, microwave, and other wavelengths, is used because it interacts uniquely with different materials and surfaces. This interaction is the foundation for understanding and characterizing objects and environmental conditions from a distance. When delving into the realm of electromagnetic energy, there are several critical factors that demand careful consideration. Initially, the atmosphere exerts a significant influence on the energy signals

as they traverse it. It is imperative to recognize that certain frequency bands may experience complete absorption by the atmosphere, necessitating prudent selection and avoidance. Secondly, a comprehensive understanding of the interaction between EM energy and the Earth's surface is essential. This necessitates a comprehensive examination of the dynamic interplay between these energies and their consequential impact on surface properties and characteristics. When EM radiation impinges upon an object or a surface, it is either absorbed, reflected, or transmitted. The manner in which these interactions occur depends on the properties of the object, such as its composition, texture, and shape. Remote sensing devices, often referred to as sensors, are designed to capture this interaction by measuring EM radiation at specific wavelengths or frequency bands. The choice of sensor and wavelength is tailored to the specific application. For example, thermal infrared sensors can detect temperature variations, while multispectral optical sensors are excellent for vegetation analysis. Sensors are classified as active or passive systems based on whether they provide their own energy source. Active sensors, like radars, emit energy to illuminate the object or area under investigation and subsequently measure the response. In contrast, passive sensors detect naturally available energy, such as sunlight, which can be either emitted or reflected. Once the data is collected, it is processed and analyzed to extract meaningful information, revealing the characteristics and changes in the observed objects or environments.

In essence, remote sensing is about expanding our perspective, transcending geographic barriers, and harnessing the power of EM radiation to gain a comprehensive view of our planet. It plays a vital role in fields such as environmental science, geology, agriculture, urban planning, and beyond, driving innovation and enhancing our capacity to address complex global challenges.

1.3 Microwave Remote Sensing

Radar sensors, due to their extended wavelengths ranging from 1 millimeter to 1 meter (Barton, 2004), possess the unique ability to penetrate through clouds and even atmospheric moisture, as well as the upper layers of vegetation within a forest canopy (Steele-Dunne et al., 2017; Waring et al., 1995). These waves interact with leaves, branches, twigs, and stems, allowing for the capture of objects in the form of digital images. Emitting electromagnetic radiation towards the Earth's surface, the radar sensor receives back a portion of the scattered radiation upon hitting an object. This received signal, known as radar backscatter, offers insights into the structure, and size of the canopy, and vital information about the growing stock and biomass. Typically, longer radar antennas and narrower beam widths, as observed in studies (Handbook, 2007; Skolnik, 1962), yield higher azimuth resolution, providing more detailed information about specific objects. However, deploying large satellite antennas in space proves to be financially challenging. Hence, an alternative technique utilizing satellite motion and Doppler principles synthesizes a longer antenna from a shorter one, enabling fine resolution in the azimuth direction. Achieving a constant and enhanced resolution in radar relies on the application of the Doppler frequency shift concept. This principle involves analyzing the change in wave frequency of the received signal, which indicates the relative movement of the target concerning the platform. When a target is positioned ahead of the antenna, it causes an upshift in frequency, whereas targets behind the antenna result in a downshift in frequency. This shift in wave frequency is utilized to discern and identify targets located precisely within a narrow beam aligned with the antenna. The technology that synthesizes a lengthy antenna from a moving shorter one is called the Synthetic Aperture Radar (SAR) system. The radar return, which constitutes the energy reflected from the terrain back to the radar antenna, is contingent upon several key parameters. These parameters significantly impact the nature and strength of the returned signal. They include:

1.3.1 Wavelength/Frequency

The interaction of radar with diverse terrains is notably influenced by its frequency. Different surface structures, such as rough, smooth, or textured surfaces, respond uniquely to radar signals, impacting the characteristics of the energy reflected back and shaping the radar return. In the realm of mapping and monitoring Earth's surface, the SAR system employs distinct frequency bands classified as X-band, C-band, L-band, and P-band (Lucas et al., 2012; Spies, 2016). These bands offer varying penetration capabilities and resolutions, enabling versatile applications in remote sensing, environmental monitoring, and disaster management. For instance, while X-band radars possess higher resolution suitable for urban monitoring, L-band and P-band radars penetrate foliage better, making them apt for forest mapping and biomass estimation. This diversification of frequency bands in SAR systems enables a wide array of applications, including environmental monitoring, disaster response, agriculture, and land cover classification, contributing significantly to our understanding and management of the Earth's surface dynamics. The Table 1.1 provides the letter codes corresponding to the standard bandwidths commonly used:

Table 1.1 Frequency bands, Frequency range, and Application examples

Frequency bands	Frequency range	Application example
VHF	300 KHz - 300 MHz	Foliage, Ground penetration, biomass
P-Band 2	300 MHz - 1 GHz	Biomass, soil moisture, penetration
L-Band	1 GHz - 2 GHz	Agriculture, forestry, soil moisture
C-Band	4 GHz - 8 GHz	Ocean, agriculture
X-Band	8 GHz - 12 GHz	Agriculture, Ocean, high resolution radar
Ku-Band	14 GHz - 18 GHz	Glaciology (snow cover mapping)
Ka-Band	27 GHz - 47 GHz	High resolution radar

The diagram illustrates a conceptual overview of how the sensor wavelength λ impacts signal penetration across different surface types. Generally, radar signals penetrate more deeply with longer sensor wavelengths. Within Figure 1.2, a comparison depicts penetration depths in the X-band, C-band, and L-band, respectively. While X-band radar

waves merely interact with the canopy's top layer, the L-band radar penetrates through to the ground. Utilizing a longer-wavelength L-band radar becomes essential for effectively reaching through dense vegetation down to the ground level, allowing for measurements of its vertical structure. Additionally, longer-wavelength radar signals offer a crucial advantage in significantly improved temporal coherence. This coherence proves vital in accurately measuring surface deformation and glacial motion over time.

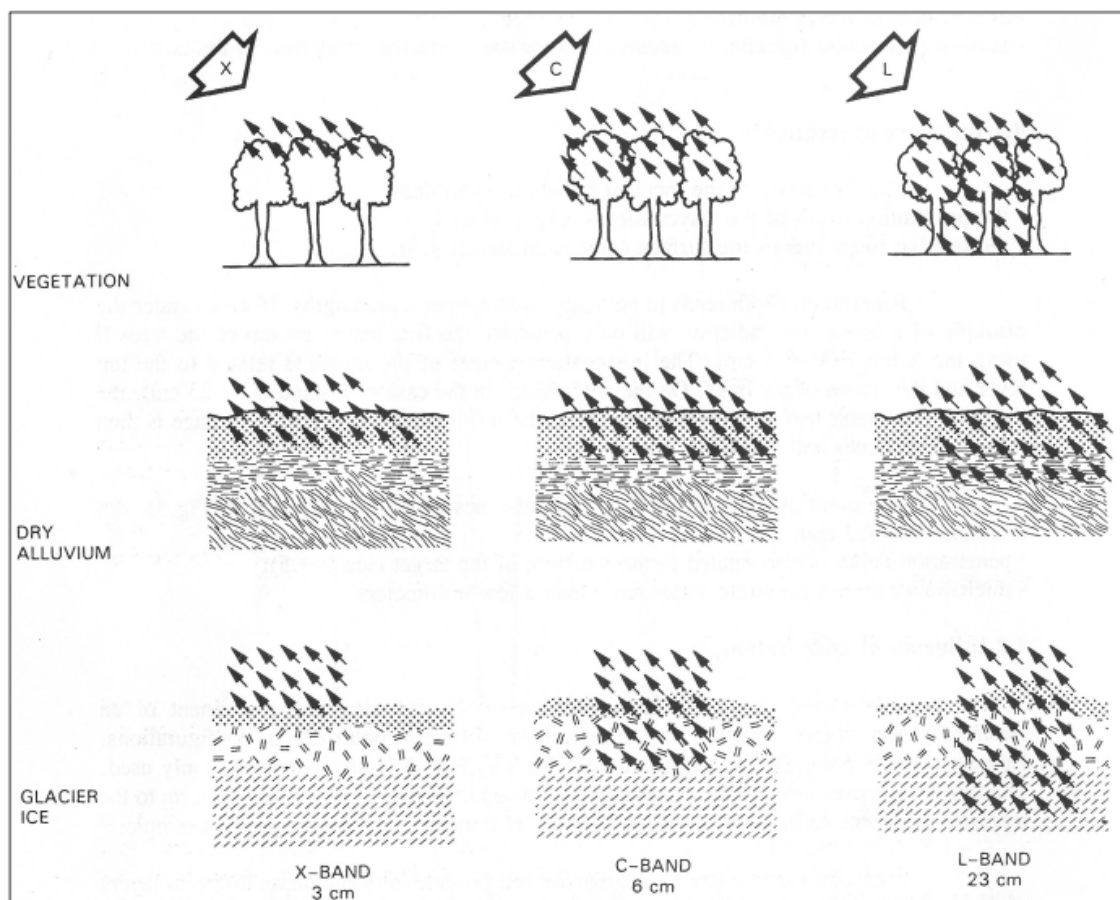


Figure 1.2 The impact of the SAR frequency spectrum on the ability to penetrate different surfaces. Greater wavelengths result in increased penetration in different kinds of terrain.

Source: servirglobal.net/resources/sar-handbook

1.3.2 Polarization

When we explore how microwave energy moves and scatters, one essential aspect is the polarization of the radiation. Simply put polarization in this context refers to the direction of the electric field in relation to the wave's path. It's like the path traced by the tip of the electric field vector, perpendicular to the direction the wave is traveling, Figure 1.3. In terms of understanding the electric field's strength, which is akin to the voltage in an EM wave, it's possible for this wave to have a predictable pattern (polarized) or a random one (unpolarized). Sometimes, waves can exhibit a mix of predictability and randomness. In such cases, the degree of polarization indicates the ratio of power in the wave that is predictable to the total power it carries. For instance, a fully polarized wave could resemble a simple, consistent sine wave, with a stable amplitude and a single, unchanging frequency.

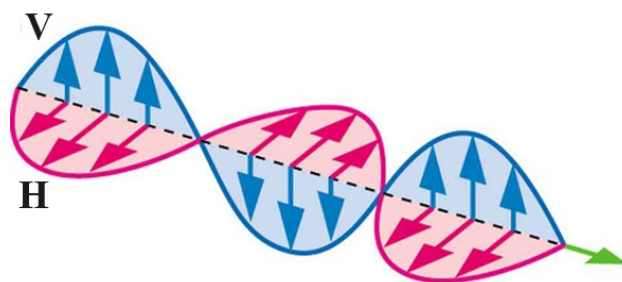


Figure 1.3 Representations of horizontal and vertical polarizations of a plane electromagnetic wave.

Source: pressbooks.bccampus.ca/collegephysics/wp-content/uploads/sites/29/2016/04/

Many radar systems are designed to send out microwave radiation with either horizontal (H) or vertical (V) polarization. When a wave of either polarization is emitted, it can bounce back in various polarizations. The study of these combinations of transmitting and receiving polarizations forms the basis of radar polarimetry. Using a mix of horizontal (H) and vertical (V) components, any polarization during transmission or reception can be created, maintaining a clear relationship between them. Because of this, radar systems

that can both transmit and receive these linear polarizations are widely used. These radar systems allow for four different combinations of transmitted and received polarizations which are:

- **HH**: Transmitted in horizontal as well as received in a horizontal channel.
- **VV**: Transmitted in vertical as well as received in vertical channel.
- **HV**: Transmitted in horizontal but received in vertical channel.
- **VH**: Transmitted in vertical but received in horizontal channel.

The first two polarization channel combinations are termed "like-polarized" since both the transmitted and received polarizations are similar. The latter pair of combinations are termed "cross-polarized" because the transmitted and received polarizations are perpendicular or orthogonal to each other.

1.3.3 Incidence angle

The angle of incidence refers to the angle formed between the radar beam and a line perpendicular to the surface. On the other hand, the look angle is the angle between the vertical line and the illuminated path at the antenna. The complementary angle to the look angle is referred to as the nadir or due look angle. When the terrain is flat, the incidence angle is equivalent to the look angle. Radar returns from rough surfaces tend to be fairly consistent regardless of the angle of incidence. However, smooth surfaces typically result in a more pronounced return at steep depression angles, particularly close to the vertical, while minimal to no return is observed at shallower depression angles.

1.4 Optical Remote Sensing

Optical remote sensing is a pivotal technology in the field of Earth observation, leveraging visible, near-infrared, and short-wave infrared sensors to capture detailed images of the planet's surface. By harnessing solar radiation reflected from ground targets, these systems enable the differentiation of various materials based on their unique spectral reflectance signatures. This multifaceted approach to imaging facilitates a deeper understanding of Earth's complex and dynamic landscapes. The classification of optical remote sensing systems is based on the number of spectral bands utilized during the imaging process. These systems are primarily categorized into the following types: panchromatic, multispectral, and hyperspectral sensors. Each category serves distinct purposes, contributing to a comprehensive understanding of the Earth's surface and its intricate features.

- **Panchromatic imaging system:** Panchromatic sensors, commonly used in high-resolution satellite imagery, capture data in a single broad spectral band, often in the visible spectrum. Although these sensors provide high-resolution images, their ability to differentiate between various surface materials is limited due to the absence of specific spectral bands.
- **Multispectral imaging system:** These sensors incorporate multiple spectral bands, and offer improved discrimination capabilities. By capturing data across specific portions of the electromagnetic spectrum, these sensors enable the identification of different surface materials based on their unique reflectance properties. This enhanced spectral resolution facilitates the detailed analysis of vegetation health, land use, and various environmental phenomena.
- **Superspectral imaging :** This system encompasses an advanced sensor technology that surpasses the capabilities of multispectral sensors by offering a significantly higher number of spectral channels, often exceeding 10 channels. The key dif-

ferentiator lies in the narrower bandwidths of these channels, which enable the sensor to capture even the most intricate spectral characteristics of the targets under observation.

- **hyperspectral sensors:** Operating at even finer spectral resolutions, this type of sensor captures data across numerous narrow and contiguous spectral bands. This advanced technology enables the identification of subtle differences in surface materials, leading to the precise classification of land cover types and the detection of specific substances or pollutants. Hyperspectral imaging plays a crucial role in environmental monitoring, mineral exploration, and agricultural assessment, providing invaluable insights into the Earth's diverse ecosystems and their intricate dynamics.

1.4.1 Solar Irradiation

Optical remote sensing relies exclusively on solar illumination, with the solar irradiation spectrum above the Earth's atmosphere modeled as a black body radiation spectrum with a source temperature of 5900 K shown in Figure 1.4. The peak irradiation is typically situated around the 500 nm wavelength. Ground-based and spaceborne sensors have been utilized to physically measure solar irradiance. Upon entering the Earth's atmosphere, the solar irradiation spectrum undergoes modulation due to atmospheric transmission windows. Notably, substantial energy is preserved within the wavelength range spanning approximately 0.25 to 3 μm .

1.4.2 Spectral Reflectance Signature

When solar radiation encounters a surface, it can either pass through, get absorbed, or bounce back as a reflection. Various materials exhibit distinct behaviors in terms of absorption and reflection at different wavelengths. The reflectance spectrum of a material

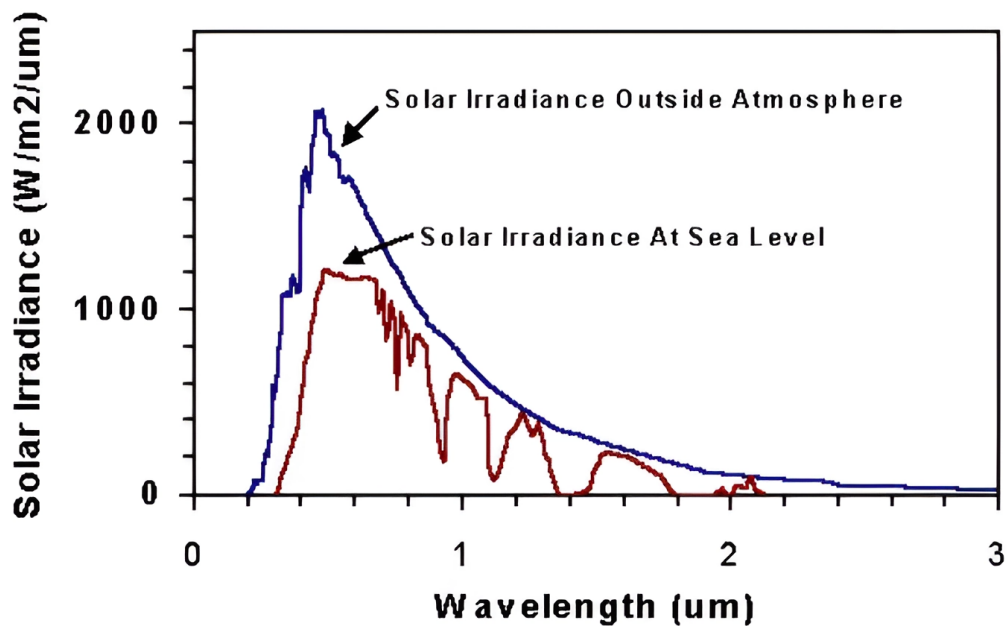


Figure 1.4 Solar Irradiance Spectra: Above the Atmosphere and at Sea Level

Source: <https://crisp.nus.edu.sg/research/tutorial/optical.htm>

represents the proportion of radiation reflected with respect to the incident wavelength, functioning as a distinctive identifier for that material. Effectively, if the sensing system possesses adequate spectral resolution to differentiate between different spectra, it can theoretically identify a material based on its unique spectral reflectance signature. This fundamental concept forms the foundation for multispectral remote sensing techniques. Figure 1.5 illustrates the standard reflectance spectra of five materials, including clear water, turbid water, bare soil, and two variations of vegetation. Clearwater has low reflectance, peaking in the blue spectrum and diminishing as the wavelength increases, giving it a dark bluish appearance. Turbid water, containing suspended sediment, reflects more in the red spectrum, resulting in a brownish look. Bare soil reflects differently depending on composition, typically showing an increasing trend with wavelength, leading to a yellowish-red appearance.

Vegetation possesses a unique spectral signature, making it distinguishable from other land covers in optical and near-infrared images. It exhibits low reflectance in the blue and

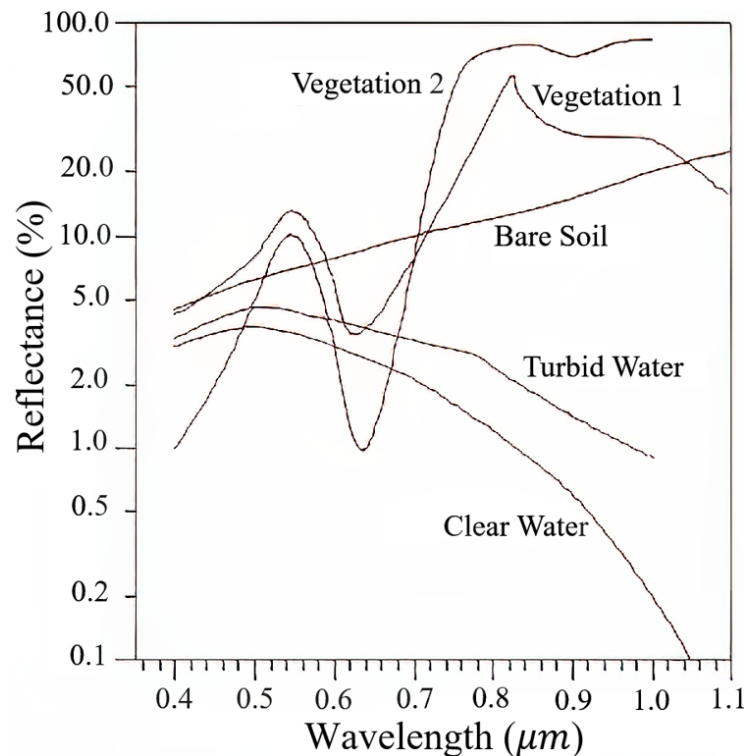


Figure 1.5 Reflectance Spectrum of Five Land Cover Types.

Source: <https://crisp.nus.edu.sg/research/tutorial/optical.htm>

red spectrum regions due to chlorophyll absorption for photosynthesis, while peaking in the green region, resulting in its green color. Moreover, in the near-infrared (NIR) region, the reflectance is notably higher than in the visible band, primarily due to the cellular structure in leaves as shown in the figure 1.6. This property has historically been leveraged in early reconnaissance missions for camouflage detection during wartime. The shape of the reflectance spectrum aids in identifying different vegetation types. For instance, while vegetation 1 and 2 in Figure 1.5 may share the general characteristics of high NIR and low visible reflectances, they can be distinguished based on their specific reflectance profiles. Additionally, the reflectance spectrum of vegetation is influenced by factors such as leaf moisture content and overall plant health. Figure 1.6 shows in the shortwave infrared (SWIR) region, the reflectance of vegetation varies, contingent upon plant types and water content. Water's absorption bands around 1.45, 1.95, and 2.50 μm play a significant role,

while reflectance outside these bands tends to increase with decreasing leaf liquid water content. SWIR data can be utilized to detect plant drought stress, delineate burnt areas, and identify fire-affected vegetation. Furthermore, the SWIR band's sensitivity to thermal radiation emitted by intense fires allows for the detection of active fires, especially at night when the interference from reflected sunlight in the SWIR is absent.

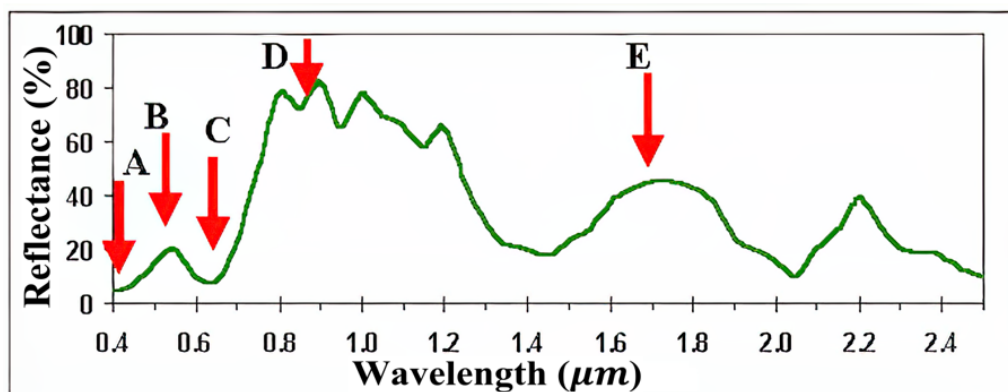


Figure 1.6 Standard Vegetation Reflectance Spectrum. Labeled arrows denote key wavelength bands utilized in optical remote sensing of vegetation: A: blue band, B: green band; C: red band; D: near IR band; E: short-wave IR band.

Source: <https://crisp.nus.edu.sg/research/tutorial/optical.htm>

1.5 Theory and models of electromagnetic backscattering:

The exploration of electromagnetic wave scattering from rough surfaces has remained a prominent area of study for more than two centuries, initially pioneered by J. W. Strutt Rayleigh's (Strutt et al., 2005) investigations into light reflection and dispersion from randomly distributed particles. This intricate phenomenon has drawn significant attention, with researchers striving to comprehend EM wave scattering patterns arising from irregular surfaces. The study of EM scattering directly intertwines with Maxwell's equations, aiming to establish methodologies and approaches for their resolution. Approaches to

tackle this problem typically fall into three categories: analytical, empirical, and hybrid models. Empirical models furnish closed formulas derived from measured data, often preferred when a theoretical solution to Maxwell's equations is absent or numerical algorithms are unfeasible. Yet, their accuracy remains confined to the context in which they were developed. Theoretical derivations addressing EM scattering are limited to a few canonical examples, those that are not readily replaceable or represent an approximation of reality. Analytical models, despite offering a rigorous representation of the scattered field, often yield non-closed form solutions in various practical scenarios, especially in remote sensing applications where modeling the EM field scattered from natural or man-made surfaces holds critical importance. These models utilize established and validated mathematical methodologies to enable objective evaluations of the dispersed field. In pursuit of achieving backscattering models pertaining to soil surfaces and vegetation constitutes a crucial aspect of remote sensing analysis. Assessing these models necessitates detailed knowledge of biophysical parameters associated with vegetation, such as leaf area index, biomass, and vegetation water content, as well as soil surface parameters like moisture content, roughness, and composition. These parameters significantly influence the interaction between electromagnetic waves and the Earth's surface, affecting the observed backscattered signals. Accurate estimation and retrieval of these biophysical and soil surface parameters are essential for validating and refining backscattering models, enabling enhanced interpretations of remote sensing data.

1.5.1 Biophysical and soil-surface parameters

Biophysical Parameters

The assessment of crop health and vitality relies on biophysical factors, which include measurements such as biomass, height, leaf area index, and vegetation water content.

These metrics provide quantitative assessments of plant growth, leaf expansion, and water content present in the vegetation. Some of the important parameters are

- **Leaf Area Index (LAI)** : LAI measures the quantity of leaf material within a canopy, defined as the ratio of one-sided leaf area to the ground area (m^2/m^2), thus expressed without units due to its nature as an area ratio. For instance, as explained in Figure 1.7, a LAI of 1 signifies an equal proportion of leaf area to the ground area, while an LAI of 3 denotes three times more leaf area than the ground area within the canopy.

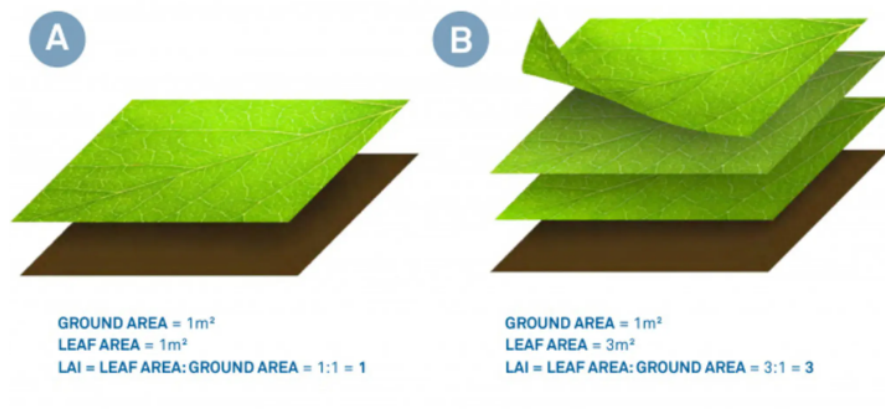


Figure 1.7 Definition of Leaf Area Index.

Source: metergroup.com/en/meter-environment/education-guides/.

- **Vegetation Water Content (VWC)** : VWC signifies the moisture held within plants, measured as the water quantity per unit area or volume of vegetation. It is typically measured in units of either kilogram per square meter (kg/m^2) or grams per square centimeter (g/cm^2). It is a vital indicator of plant health, drought conditions, and fire susceptibility, directly impacting plant resilience and response to environmental factors.

Soil-surface Parameters

Soil-surface parameters refer to characteristics of the top layer of soil. These parameters include factors such as soil moisture content, surface roughness metrics like root mean square (rms) height, and spatial characteristics like correlation length. They offer critical insights into soil dynamics, surface texture, moisture distribution, and variability, playing a pivotal role in understanding land surface processes and agricultural ecosystems.

- **Soil Moisture** : Soil moisture (m_v) pertains to the quantity of water contained within the soil, often quantified as the proportion of water content in relation to the total weight or volume of the soil. It represents the water available to plants and is a key factor influencing agricultural productivity, hydrological processes, and environmental conditions.
- **RMS Height** : Surface roughness is often defined using scalar parameters, with the root-mean-square (rms) height and slope being prevalent metrics. These metrics represent the average deviations from the mean height and slope across a surface. They offer insights into the amplitude of spatial variations in height and slope within the measured topography, providing essential information about surface irregularities and terrain characteristics. The fluctuation in surface height, denoted as $z(x)$, for a random surface, is representative of the function concerning the horizontal distance x along the mean surface. Extracting the surface's height deviations along its horizontal span can be achieved by analyzing a photograph depicting the profile of the rough surface. The surface roughness profile is converted into discrete values, denoted as $z_i(x_i)$, with a suitable interval δx . This dataset represents the vertical surface elevations (in cm) measured at intervals of 1 cm both above and below the mean surface height. For this study, 100 data points were obtained from the digitized

photograph. Then the RMS height of the digitized one-dimensional surface is

$$s = \left[\frac{1}{N-1} \left(\sum_{i=1}^N z_i^2 - N\bar{z}^2 \right) \right] \quad (1.1)$$

where N is total number of data points and \bar{z} , mean surface height is defined as

$$\bar{z} = \frac{1}{N} \sum_{i=1}^N z_i \quad (1.2)$$

- **Autocorrelation Function and Correlation Length (l)** : The root mean square height (s) and the autocorrelation function $\rho(\xi)$ are fundamental in describing the statistical variation of a random surface. The surface autocorrelation function quantifies the correlation between the height variation $z(x)$ at a specific point x on a surface profile and the height variation $z(x + \xi)$ at a point ξ distance away from x . It measures how the surface height at one location is related to the height at another location a distance ξ apart on the same surface. The autocorrelation function can be defined for the discrete one-dimensional surface and natural continuous surfaces. The discrete form is defined as

$$\rho(\xi) = \frac{\sum_{i=1}^{N+1-j} z_i z_{j+i-1}}{\sum_{i=1}^N z_i^2} \quad (1.3)$$

where $\xi = (j-1)\Delta x$ and j takes integer value and are ≥ 1 . Furthermore, continuous autocorrelation functions for natural surfaces (Oh et al. 1992) can be defined as

$$\textbf{Gaussian} : \rho(\xi) = e^{-\frac{\xi^2}{l^2}} \quad (1.4)$$

$$\textbf{Exponential} : \rho(\xi) = e^{-\frac{\xi}{l}} \quad (1.5)$$

The correlation length (l) of a rough surface signifies the distance ξ at which the autocorrelation function $\rho(\xi)$ becomes equivalent to e^{-1} , representing a point where the correlation between surface height variations diminishes to approximately 37% of its maximum value.

1.5.2 Vegetation Scattering Model

To acquire a comprehensive understanding of the effects of backscattering that come from the Earth's surface, it is important to take into account volume scattering, which is caused by vegetation. However, precise modeling of volume scattering for accurate crop variable extraction poses a significant challenge due to the complex nature of crop structures (Chami et al., 2006; Jin et al., 2018). Recent studies have led to the development of various vegetation scattering models, yet these models often cater to specific crop types (Huang et al., 2017), limiting their universal applicability. Current research focuses on distinct methods to segregate scattering phenomena from different surfaces. One approach involves polarimetric decomposition, utilizing variations in electromagnetic signal polarizations (vertical, horizontal, circular) to distinguish scattering contributions from different scatterers. Another method relies on scattering models, employing mathematical equations to simulate scattering processes and estimate surface layer properties, including both vegetation and soil layers. Figure 1.8 illustrates the radar signal's penetration capacity, facilitating the observation and distinction of various scattering mechanisms across agricultural fields.

1. **Backscattering from rough soil-surfaces:** Radar waves reflect off the uneven topography of crop leaves and stalks.
2. **Multiple scattering:** V Radar waves bounce off multiple objects within the crop canopy.

3. **Random volume backscattering:** Radar waves interact with a dense layer of discrete scatterers, such as crop stalks or leaves.
4. **Scattering from soil surface after transmission :** Radar waves reflect off the soil surface after being modified by their interaction with vegetation.
5. **Anisotropic scattering:** Radar waves scatter off structures with polarization anisotropy, such as corn stalks.

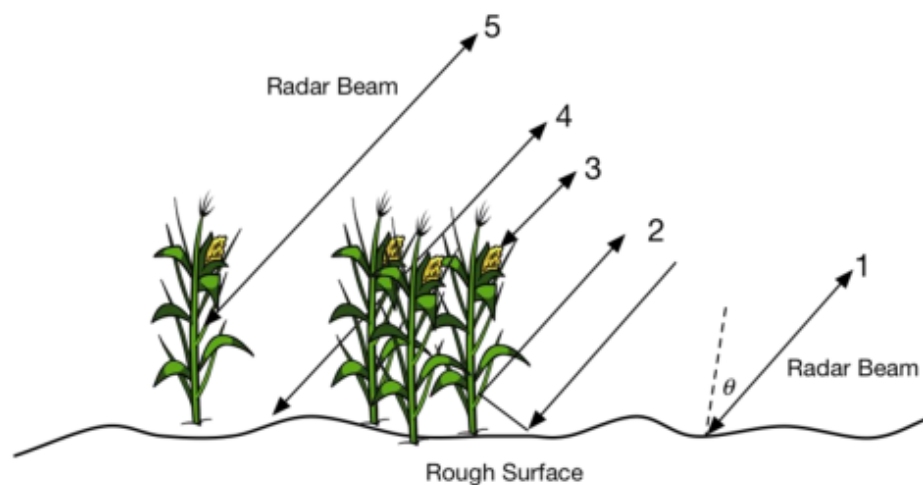


Figure 1.8 Different scattering mechanism over vegetation.

Source:ir.lib.uwo.ca/cgi/viewcontent.cgi?article=5458context=etd

Among scattering models, the water cloud model (WCM) stands out as a prominent representative. This semi-empirical model conceptualizes vegetation as a collection of spherical water droplets dispersed within a dry matrix (Attema and Ulaby, 1978). The WCM's underlying assumption stems from the significant contrast in dielectric constants between dry vegetation matter and its water content, coupled with the high air volume within the vegetation canopy. This premise led to the formulation of a "water cloud" model, where identical water droplets are randomly distributed within the canopy. The graphical illustration is shown in figure 1.9 mathematical representation of this model is given by

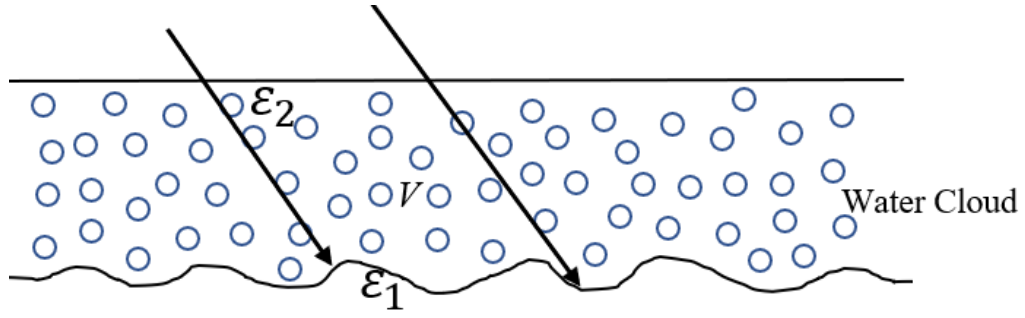


Figure 1.9 Illustration of Water Cloud Model.

Equation 1.6.

$$\sigma_0 = \frac{A \cos \theta}{2BV} h (1 - e^{-2BV \sec \theta}) + \sigma_s e^{-2BV \sec \theta} \quad (1.6)$$

where σ_0 is the total backscattering coefficient; A and B are model parameters where A depends on the vegetation scattering whereas B depends on the vegetation properties as well as radar sensor configuration; h represents crop height; θ is the incidence angle; V is vegetation descriptor; ϵ_1 and ϵ_2 are dielectric constants of vegetation and soil surface respectively. σ_s represents the backscattering component from the soil surface, detailed information regarding this component is presented in the next section. The WCM has been a popular choice for estimating soil-surface and biophysical parameters due to its simplicity. Nonetheless, its applicability remains limited to characterizing dense vegetative canopies exclusively. Hence There are several ways to improve the WCM, such as incorporating more advanced algorithms that can handle sparse vegetation canopies or structured vegetation. The WCM simplifies the initial radiative transfer model, considering the vegetation canopy as a uniform entity and disregarding multiple scattering. Conversely, the Michigan Microwave Canopy Scattering (MIMICS) model, introduced by Ulaby (Ulaby et al., 1990), offers a more sophisticated and advanced resolution. It considers the tree canopy as an inhomogeneous layer with distinct components, including a crown layer, trunk layer, and rough-surface ground boundary. Unlike the Water Cloud Model (WCM), the MIMICS

model offers a more rigorous solution by incorporating considerations for multiple scattering, making it a more comprehensive and calculative approach. In contrast to the WCM and MIMICS models, both rooted in the Radiative Transfer (RT) theory, polarimetric Synthetic Aperture Radar (PolSAR) decomposition emerges as a more practical and straightforward tool for characterizing scattering in agricultural fields.

1.5.3 Soil-Surface Scattering Model

The characteristics of a bare soil surface primarily hinge on two significant factors: soil moisture and surface roughness (Banninger and Fluhler, 2004; Mattia et al., 2003). Soil moisture, a pivotal element in hydrology, agronomy, and agriculture, holds sway over decisions regarding water resource management, irrigation practices, and land surface activities. Its influence extends to estimating surface runoff, soil erosion potential, and optimizing agricultural methodologies (Bhattacharyya et al., 2015). Both soil moisture and surface roughness stand as essential climate variables recognized by the Global Climate Observing System (Alareeni, 2019; Karl et al., 1999). To extract details about soil moisture and surface roughness, employing either physical or semi-empirical surface scattering models becomes imperative. These models simulate the microwave scattering process interacting with the surface (as depicted in Figure 1.10) and play a pivotal role in agricultural fields where surface scattering from the soil, related to soil moisture and surface roughness, is prevalent. While this thesis primarily focuses on both forward and inverse processes of the scattering model to compute vegetation and soil parameters, a brief overview of the evolution of scattering models for bare soil becomes essential. These models delineate scattering processes and serve as invaluable tools for estimating subsequent soil-surface parameters.

Currently, numerous models have been introduced to precisely characterize bare soil scattering, each based on distinct assumptions. The initial category comprises physical

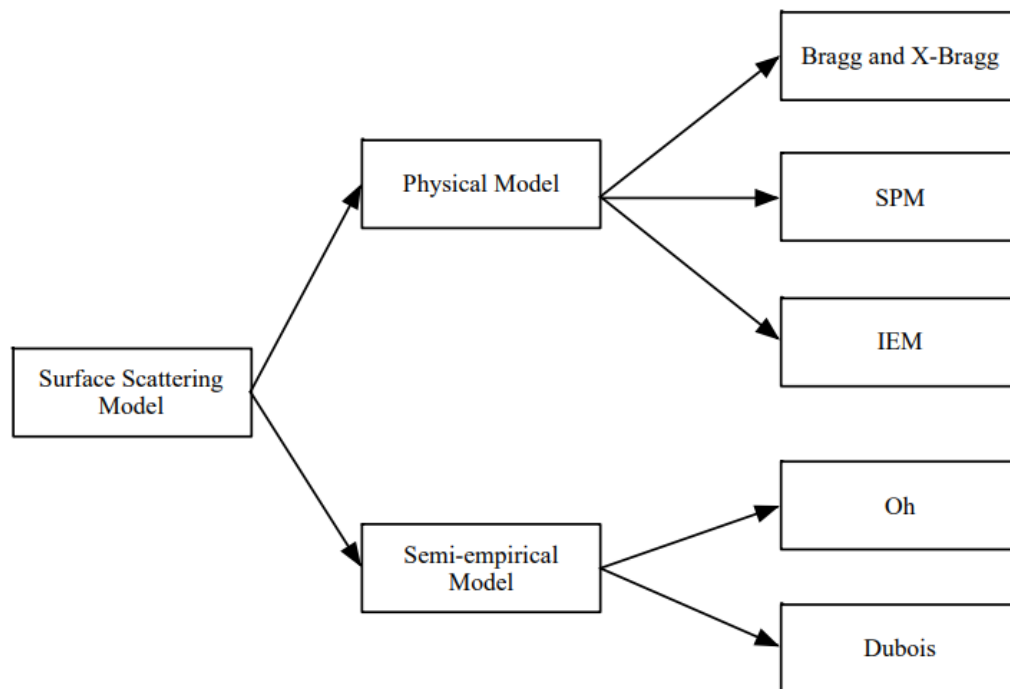


Figure 1.10 Brief illustration of different soil scattering models.

models, formulated through the solution of Maxwell Equations rooted in electromagnetic scattering theory. A straightforward example of such a model is the infinite perfectly flat surface, also referred to as a specular surface as shown in Figure 1.11. Assuming a specular surface implies that scattering is concentrated in the specular direction, i.e., reflection, and can be straightforwardly calculated using the Fresnel reflection coefficient (Atkinson, 2007; Gibaud and Vignaud, 2009; Thorsos, 1984). However, in practical settings, particularly in plowed agricultural fields, surfaces tend to be random and rough shown in Figure 1.12. To model such surfaces accurately, surface roughness becomes a crucial parameter in these models.

1.6 Literature review

The retrieval of biophysical parameters in crops through the fusion of microwave and optical remote sensing data is of paramount importance, given their intricate associations

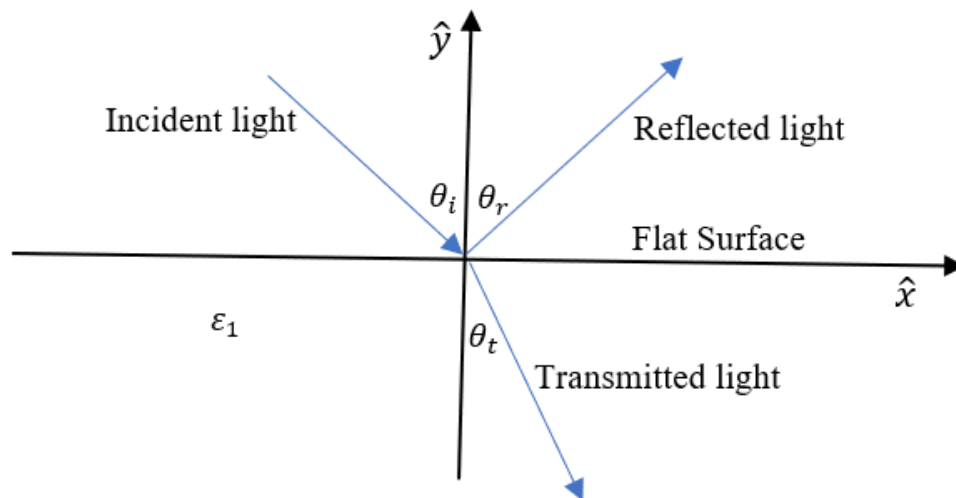


Figure 1.11 The phenomenon of reflection and transmission of radar waves when interacting with a planar surface. θ_i , θ_r and θ_t are incident, reflected, and transmitted angles, respectively.

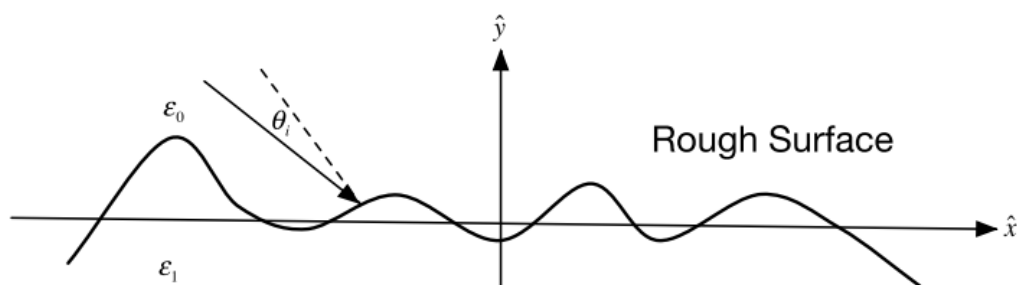


Figure 1.12 Scattering of electromagnetic radiation from rough surface.

with fundamental system parameters such as wavelength, polarization, and various vegetation indices (Borchani et al., 2015; Orynbaikyzy et al., 2019). Notably, within the realm of Earth observation sensors, SAR data has exhibited exceptional promise in the realm of vegetation monitoring, owing to its distinctive characteristics encompassing diverse polarizations, frequencies, and incident angles (Steele-Dunne et al., 2017; Ulaby, 1975). The intensity of SAR backscattering derived from vegetation canopies intricately relies on the complex radiative transfer models that encapsulate both direct and indirect measurable biophysical parameters inherent to crops (De Roo et al., 2001; Karam et al., 1995; Ulaby et al., 1990).

On the contrary, there exist optical models based on radiative transfer, which compute biophysical characteristics using reflectance datasets. Among these models, PROSAIL (PROSPECT+SAIL) stands out as one of the most widely used, enabling the calculation of biophysical parameters via Artificial Neural Networks (ANN) within the SNAP toolbox. Nevertheless, the validation of LAI (Leaf Area Index) derived from Sentinel-2 data using SNAP, as well as its consistency with established LAI products, has been explored by a limited number of studies (Bochenek et al., 2017; Campos-Taberner et al., 2018). This verification is essential as accurate agricultural monitoring heavily relies on the consistency and comparability of critical biophysical parameters like LAI (Alexandridis et al., 2020). Additionally, uncertainties stemming from the impact of spatial resolution and data processing levels on derived biophysical parameters, such as LAI, warrant further evaluation. Moreover, optical datasets are susceptible to atmospheric influences. Research by Sola (Sola et al., 2018) and Doxani (Doxani et al., 2018) has extensively demonstrated that various atmospheric correction (AC) methods exhibit differing performances across diverse environments, land cover types, and spectral bands. Martins (Martins et al., 2017) highlighted that the visible bands of Sentinel-2 utilized in the Biophysical processor are sensitive to Rayleigh and aerosol scattering effects. Furthermore, Bochenek (Bochenek et al., 2017) found discrepancies indicating that LAI derived from SNAP tends to overestimate at different crop growth stages. The observed overestimation and notable biases in SNAP-derived LAI may be attributed to predefined assumptions from global LAI retrieval algorithms, specifically, Artificial Neural Networks (ANN) and look-up tables (LUTs) simulated using the PROSAIL radiative transfer model (RTM), i.e., PROSPECT+SAIL, which might lack calibration to local conditions.

So far, numerous studies have been conducted to extract crop biophysical parameters from SAR data across various polarizations and frequencies, spanning X-, C-, and L-bands. Attema (Attema and Ulaby, 1978) introduced the semi-empirical water cloud

model (WCM), employing electromagnetic wave theory to retrieve vegetation parameters. Consequently, the WCM is anticipated to be well-suited for operational monitoring and the extraction of biophysical parameters. Numerous research articles (Bériaux et al., 2015; Chakraborty et al., 2005; Dabrowska-Zielinska et al., 2007; Hosseini et al., 2015; Inoue et al., 2014) have highlighted the robustness of the WCM in estimating biophysical parameters for various crop types under different SAR system parameters. These findings underscore the necessity for further refining the WCM to achieve acceptable accuracies and scalability in retrieving crop biophysical parameters. Although several attempts have been made to modify the WCM (Kweon and Oh, 2014; Rawat et al., 2020; Xing et al., 2019), most have focused on parametrizing the model to enhance the accurate calculation of biophysical and soil moisture parameters. However, these modifications often lack methodological changes within the WCM itself.

Considering surface roughness, Rice (Rice, 1963) introduced the small-perturbation method (SPM), applicable when roughness is significantly smaller than the radar wavelength. This method is suitable for low frequencies, such as the L band of spaceborne ALOS and airborne E-SAR sensors (wavelength approximately 24 cm). However, for high-frequency PolSAR systems like X-band TerraSAR-X and C-band RADARSAT-2, the integral equation method (IEM) proposed by Fung (Fung and Chen, 2004) is more appropriate, accounting for scattering due to rapid fluctuations (Barrett et al., 2009; Lievens and Verhoest, 2011; Song et al., 2009). Despite the advantages of SPM and IEM, retrieving surface parameters remains challenging due to the necessity for accurate surface roughness descriptions. This challenge has been addressed by developing empirical relationships between the root mean square (RMS) of surface height and its correlation length across various wavelengths, ranging from the C-band to the L-band (Baghdadi et al., 2017, 2004, 2002, 2015).

In addition to physical models, semi-empirical models offer an alternative group of surface scattering models. For instance, the co-polarization ratio (HH to VV polarization) saturates for high soil surface roughness, simplifying soil moisture estimation (Oh, 2004; Oh et al., 1992). Similarly, the depolarization ratio (VH to VV polarization) proves sensitive to soil surface roughness (Ulaby and Elachi, 1990; Ulaby and Wilson, 1985). Sensitivity analyses involving these ratios, surface roughness, soil moisture, and sensor configurations (frequency, incidence angle, and polarization) contributed to the development of well-known semi-empirical backscattering models for bare soil (Dubois et al., 1995; Oh et al., 1992). Although these models establish relationships between backscattering coefficients and soil moisture content, their practical use in radar signal inversion is challenging without time-consuming calibration measurements (Park et al., 2009). Additionally, these semi-empirical models often rely on site-specific parameters and are valid only under specific soil conditions.

In recent times, there have been limited studies focusing on monitoring crop biophysical and soil parameters by leveraging the combined use of optical and SAR satellite data (Felegari et al., 2021; Ienco et al., 2019; Steinhausen et al., 2018; Tavares et al., 2019; Veloso et al., 2017). The synergy between optical and SAR data is recognized as mutually complementary, enabling more precise Earth observation from space platforms. Particularly in Indian agriculture and worldwide, monsoon crops, notably during Rabi and Kharif seasons, play a pivotal role in economic growth and ensuring food security. Therefore, the recent advancements in orbiting satellites such as Sentinel-1A and Sentinel-2, offering fine spatio-temporal resolutions, have showcased remarkable capabilities in accurately identifying crop growth, soil moisture levels, and drought conditions (Mandal et al., 2020; Qadir and Mondal, 2020; Van Tricht et al., 2018; Zhao et al., 2020).

In the process of development of novel methodologies, polarimetric Synthetic Aperture Radar (PolSAR) and polarimetric interferometric SAR (PolInSAR) have emerged as crucial

techniques for land cover classification analysis. PolSAR techniques have significantly contributed to advancing electromagnetic wave theory, thereby enhancing microwave remote sensing for Earth observations (Erten et al., 2019; Mandal et al., 2019; Uppala et al., 2021). Despite their contributions, a majority of studies have primarily focused on the development of fully polarimetric models, with a conspicuous dearth in research dedicated to compact or dual-polarized polarimetry. This limitation potentially restricts the broader application and versatility of PolSAR techniques across varying contexts and scales. It's important to note that compact or dual-polarized polarimetry could offer advantages in terms of data acquisition efficiency, processing complexity, and potential cost-effectiveness. Incorporating additional investigations specifically targeted towards these approaches could provide valuable insights into their capabilities, limitations, and suitability for different applications within land cover classification.

1.7 Motivation

Currently, radar remote sensing has emerged as a critical and reliable technology for examining the Earth's dynamics and monitoring environmental changes instigated by diverse ecological and human-induced factors. The prevalent radar systems primarily operate within fixed frequency bands, including X, C, S, L, and P bands, with frequencies approximately around 10, 6, 3, 2, and 0.5 GHz, respectively. Optimizing radar system parameters such as frequencies, antenna gain, polarization, and receiver-transmitter angles (i.e., zenith and azimuth angles) holds the key to tailoring the radar system for a multitude of remote sensing applications in scientific research. The distinctive attributes of the microwave region, notably its capability to penetrate through clouds, to some degree rain, vegetation, and the upper layer of the soil, coupled with its inherent ability to gather day-night information, make it an exceptionally promising alternative to optical sensors.

The depth of penetration is contingent upon several factors, including the wavelength used, polarization, vegetation type, soil moisture, and composition of soil particles

Imaging sensors constitute a fundamental tool for the observation of Earth's surface and the study of celestial bodies. At the core of their functionality lies the ability to generate radar images of illuminated surfaces, a capability intrinsically linked to the complex phenomena underlying radiation-matter interactions. While the field of electromagnetic scattering theory has a well-established and thoroughly examined foundation in electromagnetics, its integration and exploration within the realm of remote sensing have been somewhat limited.

As per the previous studies it is observed that optical models at a global scale lack their robustness. Numerous simulations employing diverse algorithms have exposed these limitations, prompting the need for model calibration with local data and synergy with SAR backscattering methodology. This research aims to address these challenges by exploring the enhancement of model robustness through local data calibration.

Understanding the scattering mechanisms from vegetation and soil surfaces is crucial, and PolSAR studies serve as pivotal tools for this purpose. However, there exists a significant gap in research related to PolSAR utilizing electromagnetic wave theory, especially concerning dual polarimetry (such as VV+VH or VV+HH). Limited studies have focused on developing novel scattering algorithms and radar indices specific to vegetation and soil layers within the framework of PolSAR. Bridging this gap is essential to enrich our comprehension of backscattering physics, thereby paving the way for a more comprehensive understanding of the interactions between radar waves and vegetation and soil surfaces.

This Ph.D. thesis emerges from a compelling idea: the utilization of electromagnetic models with remote sensing data, coupled with the integration of cutting-edge machine learning and deep learning techniques, can revolutionize our understanding of remote sensing applications. By harnessing a priori information about the scattering behavior of

illuminated surfaces, this research aims to enhance the performance of existing algorithms, unlock novel applications, and propel the field of remote sensing into new frontiers.

In the pursuit of these objectives, this Ph.D. thesis will delve into two primary domains. First, it will explore the integration of optical and SAR scattering models, Polarimetric analysis, and machine learning methods to improve the interpretation of remote sensing data. Second, it will investigate how deep learning techniques can be harnessed to uncover hidden patterns within vast datasets, enabling us to extract valuable insights and enhance the overall quality and accuracy of remote sensing analyses. Through this research, we aspire to not only advance the understanding of remote sensing but also contribute to the broader domains of electromagnetic scattering theory and machine learning.

1.8 Scope and Research Objective

This thesis seeks to rigorously validate the qualitative and quantitative applications of optical and polarimetric SAR techniques. Employing a diverse range of numerical methodologies and advanced machine learning techniques, the primary aim is to achieve a nuanced understanding of retrieving both vegetation and soil surface parameters. Simultaneously, the study aims to qualitatively map land cover types. The comprehensive approach involves the development of sophisticated scattering models, machine learning algorithms, and innovative land cover mapping methodologies, all meticulously designed to align with the following research objectives.

- Investigate and address the challenges associated with time-consuming calibration measurements in radar signal inversion, particularly concerning semi-empirical models, aiming to streamline and enhance the efficiency of the calibration process.
- Evaluate the scalability and applicability of the proposed models and schemes across diverse geographic regions, considering variations in soil conditions, vegetation

types, and environmental factors while taking full advantage of polarimetric SAR capabilities.

- Refine a multi-temporal land cover classification scheme by integrating polarimetric features, improving accuracy in characterizing land cover changes over time.
- Engineer a holistic vegetation and soil surface parameter inversion scheme specifically designed for agricultural fields, accommodating both vegetated and unvegetated areas. This integrated approach ensures a comprehensive understanding of diverse surface conditions.
- Formulate and advance an adaptive volume scattering model tailored to effectively characterize the scattering phenomena from crops at different growth stages.
- Innovate an adaptive model-based decomposition technique that incorporates polarimetric information to extract parameters over vegetated regions, improving precision in parameter retrieval.
- Explore the potential integration of machine learning algorithms into the developed models to optimize the model parameters and enhance the retrieval accuracy of land biophysical and soil surface parameters.
- Consider the implications of the developed techniques in the context of emerging satellite technologies and explore their potential contributions to ongoing and future remote sensing missions.

1.9 Thesis Outline

The thesis is organized into many chapters, aiming to provide readers with essential knowledge about electromagnetism and remote sensing principles. The scope of this

study is the use of modeling and monitoring techniques to analyze the SAR backscattering responses ($\sigma^0(dB)$) in order to extract biophysical and soil-surface parameters in both vegetative and non-vegetative contexts. The study employs co-polarization (VV) and cross-polarization (VH) data from the Sentinel-1A SAR in the C-band, together with multispectral Sentinel-2 optical satellite imagery. The thesis is organized as follows

Chapter 1 serves as an introductory overview elucidating remote sensing techniques, providing a concise summary encompassing both microwave and optical remote sensing. Within this chapter, an exploration is conducted into the diverse array of biophysical and soil surface parameters critical for monitoring crops and vegetative landscapes. An overview of the underlying motives that have propelled this research endeavor. It aims to clarify the extent of the study and outline the precise goals that have shaped its direction. Furthermore, this study establishes the basis by elucidating the justification and importance of investigating microwave and optical remote sensing techniques in this particular field of research.

Chapter 2 gives an in-depth exploration of the properties of SAR and Optical data, encompassing their characteristics and essential preprocessing steps. This section delves into the methodology employed for ground measurements of biophysical and soil surface parameters. Additionally, it encompasses comprehensive discussions on microwave backscattering modeling, Polarimetric decomposition analysis, and the utilization of numerical and computational techniques (machine learning) integral to this study.

Chapter 3 In this chapter, the focus lies on evaluating the efficacy of Gaussian Process Regression in estimating wheat crop LAI within India's heterogeneous agricultural landscape. Leveraging Sentinel-1 radar and Sentinel-2 (S2) optical satellite data, this study undertakes field measurements of LAI between January and March 2020. The primary aim is to assess GPR's performance in predicting LAI, utilizing the Dual-Polarized Radar Vegetation Index derived from Sentinel-1 and Top of Atmosphere products from Sentinel-2.

Additionally, the chapter investigates the impact of atmospheric correction via S2 Bottom of Atmosphere images. Comparative analysis with an Artificial Neural Network integrated with the PROSAIL radiative transfer model, available through the Sentinel Application Platform Biophysical processor, is also conducted to discern the strengths of Gaussian Process Regression in this domain.

Chapter 4 introduces a novel modification in the traditional Water Cloud Model, aimed at enhancing LAI and SM estimation using Sentinel-1 Single Look Complex datasets in VV and VH polarizations for wheat crops. The modified Water Cloud Model (WCM) improves upon the traditional WCM in two steps: first, by introducing novel scaling constants (f_{veg} , f_{soil} , and f_{inter}) derived from the degree of polarization to account for vegetation-soil interaction, and second, by integrating the first-order novel scattering component from the Vegetation-Soil Scattering Model (VSSM) into the traditional WCM's total backscattering estimation. Calibration of model parameters (A, B, C, and E) was achieved through a non-linear least square regression algorithm. Evaluation of LAI and SM accuracy utilized statistical indicators like the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Nash Sutcliffe Efficiency (NSE). The chapter focuses on presenting the methodology, model modification steps, parameter calibration, and the superior performance of the mWCM in estimating LAI and SM compared to the conventional WCM using Sentinel-1 radar data.

Chapter 5 introduces a novel approach for vegetation monitoring using SAR imagery, focusing on refining Volume Power (VP) analysis for improved accuracy in estimating Leaf Area Index (LAI). Traditional SAR studies often prioritize backscattering sensitivity, neglecting vegetation's structural properties. The proposed method enhances VP derived from the Freeman-Durden decomposition by introducing two modifications: Depolarized Volume Power (DVP), incorporating the degree of polarization, and Anisotropic Volume Power (AVP), considering vegetation's anisotropic scattering properties. These modifica-

tions aim to increase sensitivity to vegetation scattering in SAR analysis. The modified VP is then utilized to estimate LAI based on an empirical relationship, and the accuracy is evaluated against ground truth measurements. The chapter details the methodology, modifications applied to VP analysis, empirical LAI estimation, and the significant improvement in accuracy, highlighting the potential of this approach in refining VP estimation and enabling more precise LAI estimation using dual-polarimetric SAR data.

Chapter 6 investigates biophysical parameter estimation using Sentinel-1 SAR and Sentinel-2 Optical L2A datasets. It employs WCM and PROSAIL models for SAR and optical data, respectively. To enhance the accuracy of biophysical parameter estimation, a fusion method involving deep learning, Principal Component Analysis, and non-linear regression is applied, with deep learning emerging as the most effective approach. This research provides insights into multi-source remote sensing data for LAI estimation and underscores deep learning's potential in improving fusion accuracy.

Finally, **Chapter 7** serves as the conclusion to this thesis, encapsulating discussions on its implications and future prospects.