*CHAPTER 1*

# INTRODUCTION

## 1.1 REMOTE SENSING

Remote sensing is the science and technology to get the information of a distant object, area, or phenomenon without being in physical contact through the analysis of data acquired by the sensing devices. With the help of various sensing devices, the data gathered is analyzed to acquire information about the objects, areas, or phenomena under investigation. However, the data about the object, area, or any phenomenon must be accessible and could be transferred from the place of observation to the processing and analysis unit. It is usually done by using microwaves, infrared, and visible rays of the electromagnetic spectrum to acquire information about the target under investigation for remote sensing purposes.

Since the 18th century, the development of remote sensing in the scientific field begins with developments in aerial photography. Daguerre and Niepce took the first photograph in the year 1839 of the Earth's surface. In later years, Paris Observatory suggested the use of photography for topographic purposes (Moore 1979). During the end of the 18th century to the beginning of the 19th century, it was realized that a different and perhaps more revealing view of a particular landscape could be obtained by taking a photograph from an incline or building. Therefore, photographic cameras were deployed on kites, balloons, and airplanes to take oblique aerial photographs of Earth's surface. The first airplane aerial photography was conducted in 1909. These aerial photographs taken by airplanes played an important role in collecting the information about position and movement of enemy troops during the First World War. The modern regime of remote sensing arose with the development of aircraft and satellites. The word remote sensing was introduced in the 1960s, and before that, it was generally termed as aerial photography. The field of remote sensing has experienced some major changes during the period from 1960-2010. During the 1960s to 1970s, the airborne platforms carrying remote sensing devices were moved to the space-borne platforms or satellites. During the 1960s, NASA (National Aeronautics and Space Administration) sponsored numerous numbers of projects to study the application of colour infrared and multispectral photography. As a result, multispectral imagers on the Landsat satellites, a series of Earth observing satellite missions, were launched jointly by NASA and United States Geological Survey in the 1970s. At about the same time, work was ongoing in developing synthetic-aperture imaging radars (SAR), using coherent signals to achieve high-resolution capability from the high-flying aircraft. These systems became available to the scientific community in the mid-1960s. Since then, work has continued at a number of institutions to develop the capability of radar sensors to study the natural surfaces. In the beginning of 1986 a new type of sensors named as imaging spectrometer were developed such as AVIRIS, HySI, HIS, Hyperion, etc. The number of spectral bands available had grown from a few to more than 200 in this type of sensing instruments. Active microwave systems have been used since the 20th century to detect and track moving objects such as ships and later planes. Recently, the active microwave sensors that provide two-dimensional images were developed. These active microwave sensors look very similar to regular photography, except that the image brightness is a reflection of the scattering properties of the surface in the microwave region. Passive microwave sensors were also developed to provide photographs of the microwave emission of natural objects. Radar sensors exist in many different configurations. These include altimeters, scatterometer, polarimetric interferometric imagers, etc. The potential of remote sensing satellites has been dramatically increased over the past two decades. The satellites having spatial resolutions of a few meters or less are now available for observations. SAR is now capable of collecting images on demand in many different bands and polarization. Satellites are now acquiring images of extra-terrestrial planets having more spectral bands with better resolutions. Therefore, with development in the remote sensing techniques, the scope of applications has grown in diverse fields for monitoring the Earth's surface features more effectively than ever before (Elachi and Van Zyl 2006, Ulaby et al. 2014).

Remote sensing technique has emerged as an effective tool for the systematic survey, analysis, and better management of Earth's resources along with the monitoring of flood, drought, weather forecast, and landform change. It provides a vast scope to explore, identify, and analyze the natural resources of undeveloped regions. Remote sensing technology is becoming more important in agriculture, geology, and hydrology due to attention being paid to the latest information, planning, and management for public and private interests. Agricultural applications of remote sensing include crop type classification, crop condition assessment, crop yield estimation, mapping of soil characteristics, mapping of soil management practices, etc. Government and private agencies need this information to provide a speedy response in crop management, its production, and making effective agricultural planning for the country. This information would be useful to reduce the cost for monitoring the agricultural system and take effective remedial measures, if necessary. Examples of hydrological applications include wetlands monitoring, soil moisture estimation, snowpack monitoring, measuring snow thickness, etc. Geological applications of remote sensing include bedrock mapping, lithological mapping, structural mapping, etc. In addition, it is most useful for natural resource management, sustainable development, environmental degradation, and disaster management (Doreen 2009; Wang and Qu 2009).

The remote sensing process involves an interaction between incident electromagnetic energy and target under investigation. The electromagnetic energy is reflected, transmitted, or emitted by the target under investigation and are recorded by the sensing devices. Since the basis of remote sensing is the interaction of electromagnetic radiation with the matter.

Therefore, it is important to understand the properties of that radiation and how it interacts with the matters, not just with the target, but also with the atmosphere through which it travels and with the sensors used to record it. The optimum exploitation of the remote sensing techniques depends on the understanding of the interaction of electromagnetic with the different Earth surface features and the development of sensors for the effective management of resources for mankind.

## 1.2 INTERACTION OF RADIATION WITH MATTER

### 1.2.1 General principles

There are a number of ways in which radiation can interact with matter depending on the wavelength of radiation and on the nature of matter. When radiations interact with a material, all the energy is conserved as the total amount of energy dissipated by reflection, transmission and absorption equals the incident energy. Therefore, we can write

$$E_{I\lambda}(d\lambda) = E_{R\lambda}(d\lambda) + E_{A\lambda}(d\lambda) + E_{T\lambda}(d\lambda) \tag{1.1}$$

Where $E_{I\lambda}(d\lambda)$, $E_{R\lambda}(d\lambda)$, $E_{A\lambda}(d\lambda)$, $and\ E_{T\lambda}(d\lambda)$ are the incident, reflected, absorbed and transmitted energy, respectively.

Dividing Equation (1.1) by $E_{I\lambda}(d\lambda)$, gives

$$E_{I\lambda}(d\lambda)/E_{I\lambda}(d\lambda) = E_{R\lambda}(d\lambda)/E_{I\lambda}(d\lambda) + E_{A\lambda}(d\lambda)/E_{I\lambda}(d\lambda) + E_{T\lambda}(d\lambda)/E_{I\lambda}(d\lambda) \tag{1.2}$$

This equation can be written as

$$\rho + \alpha + \tau = 1 \tag{1.3}$$

Where the first three terms define the reflectance ($\rho$), absorptance ($\alpha$) and transmittance ($\tau$) of the material, respectively. The fractions of incident radiant energy that is reflected, absorbed and transmitted depend upon the nature of the surface material and its condition. For example, interaction at optical and thermal wavelengths takes place mainly through the electric field vector in electromagnetic radiation that causes electronic and vibrational transitions in the material. In the case of microwaves, it is the dipole moment (dielectric constant) of the materials that determine the strength of the interaction. It is important to note that these three parameters are also wavelength dependent, and so the relative amount of energy reflected, absorbed, or transmitted vary with the wavelength. Therefore, it is defined in terms of spectral response as $\rho_\lambda$, $\alpha_\lambda$ and $\tau_\lambda$.

### 1.2.2 Interaction of radiation with the atmosphere

Before radiation reaches the Earth's surface used for remote sensing, it has to travel through some distance in the Earth's atmosphere. Particles and gases in the atmosphere can affect the incoming radiation. These effects are caused by the mechanisms of **scattering** and **absorption.**

**Scattering** phenomena take place when the atmospheric particles and large gas molecules interact with radiant energy causing its path to redirect from its original path. The magnitude of scattering, which takes place, is a function of many factors such as the wavelength of electromagnetic radiation, the density, and size of particles/ gas molecules, and the total distance traveled by the radiant energy through the atmosphere. There are three types of scattering phenomena, which can occur in the atmosphere.

**Rayleigh scattering** occurs when the size of particles/gas molecules such as small specks of dust, nitrogen, and oxygen molecules is much smaller than the wavelength of the radiant energy. Smaller wavelengths get scattered more strongly than the longer wavelengths by these particles/gas molecules in this scattering phenomenon. This scattering mechanism dominates in the upper part of the atmosphere. The blue color appearance of the sky during the daytime is due to this scattering phenomenon. As the Sun radiant energy travels through the Earth’s atmosphere, the blue color (shorter wavelength) of the visible spectrum gets scattered more than the other longer wavelengths; that is why the sky appears blue to human eyes during the daytime. At sunrise and sunset**,** the light has to travel a longer distance through the atmosphere than at midday, and a large amount of scattering of the shorter wavelengths takes place. Therefore, a large fraction of the longer wavelengths penetrate through the atmosphere to reach the observer, hence appears to be red.

The second scattering mechanism occurring in the atmosphere is the **Mie scattering.** It occurs by the particles/gas molecules having a size comparable to the wavelength of radiant energy such as dust, smoke, and water vapour. The longer wavelengths get affected in this scattering than the smaller wavelengths. Mie scattering dominates in the lower parts of the atmosphere, where larger particles/gas molecules are present in abundance and when there are cloudy conditions.

The third scattering mechanism occurring in the atmosphere is known as the **nonselective scattering**. This scattering takes place when the diameters of particles/gas molecules are much larger than the wavelength of the incident radiant energy. The example of such scattering is water droplets and large dust particles present in the atmosphere. It is termed as nonselective scattering because of the fact that scattering takes place for all the wavelengths about equally. Therefore, the appearance of fog and clouds as white to human eyes are due to nonselective selective scattering since the scattering of blue, green and red light is scattered in about the same amounts (blue + green + red light = white light).

The other primary interaction of radiant energy with the atmospheric constituents is the **absorption**, which causes the effective loss of radiant energy at a specific wavelength. Ozone ($O_3$), carbon dioxide ($CO_2$), and water vapour ($H_2O$) are the three primary atmospheric constituents, which absorb radiant energy.

However, Ozone prevents us through the absorption of harmful ultraviolet radiation from the sunlight. The human skin would burn when exposed to sunlight in the absence of this protective ozone layer. The carbon dioxide causes the greenhouse effect. Thus, it is also known as a greenhouse gas. If there were no greenhouse gases in the atmosphere, then the average value of Earth's surface temperature would be approximately -18 °C as compared to present average value of 15 °C. Since, it strongly absorbs the far IR portion of the electromagnetic spectrum and then reemits it as heats, which keep the Earth's surface objects warm by trapping this heat within the atmosphere. Water vapour present in the atmosphere causes absorption in the long wave IR and some part of microwave regions. However, the variation of water vapour in the lower atmosphere changes rapidly from one place to another place and with times throughout the years. For example, the concentrations of water vapour, also called humidity, are very low in the desert regions, whereas in tropical regions, its concentration is very high to absorb the radiant energy.

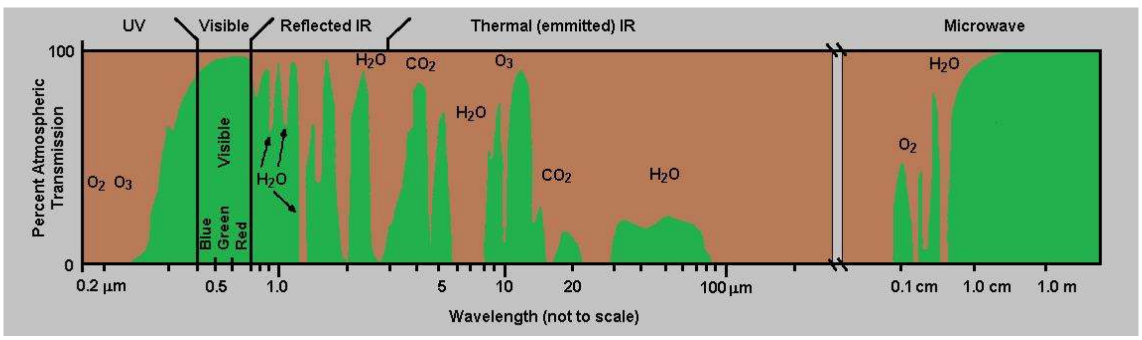


**Figure 1.1** Atmospheric transmittance

(**Source:**http://employees.oneonta.edu/baumanpr/geosat2/RS-Introduction/RS-Introduction.html)

Since atmospheric molecules absorb radiant energy in definite wavelength regions of the electromagnetic spectrum, therefore, only the wavelength regions, which are transparent to the atmospheric constituents, are useful for remote sensing purposes. These regions of the electromagnetic radiation spectrum are known as **atmospheric windows**. Figure 1.1 shows suitable wavelengths regions of electromagnetic spectrum useful for remote sensing data acquisition to exploit the Earth's resources.

The visible spectrum, which is most sensitive to the human eyes, coincides with both the peak energy value of the spectral distribution of the Sun and atmospheric windows of the electromagnetic spectrum. The heat energy emitted from the Earth's surface object coincides to atmospheric windows around 3 to 5 μm and 8 to 14 μm in the thermal IR region of the electromagnetic spectrum, whereas the large atmospheric window is available in the microwave regions (1 μm to 1 m).

The main conclusions from the above discussions are one must focus on the interaction and interrelationship between the primary source of radiant energy, the atmospheric windows, and the spectral sensitivity of the sensing devices. One can not choose the sensing devices for being used in any given remote sensing application randomly. Therefore, one must think (i) spectral sensitivity of the available sensing devices (ii) the presence or absence of atmospheric window for the spectral regions in which one wants to sense (iii) the source, the magnitude and spectral distribution of the energy present in these regions. Finally, however, the selection of spectral regions of the sensing devices must be on the method in which the energy interacts with the objects under study.

### 1.3 ACTIVE AND PASSIVE SENSING

Till now, in this chapter, we have discussed about source of radiant energy as a reference to Sun and Earth. The sun is a very convenient source of radiant energy for remote sensing. The radiant energy incident on the Earth's surface either gets reflected (blue, green, red, and near-IR wavelengths) or absorbed and then reemitted (thermal IR wavelengths). The remote sensing systems which collect this naturally reflected and emitted radiant energy is termed as a **passive remote sensor**. These sensors collect data when naturally reflected and emitted radiant energy is present. The reflected energy can be collected only at day time when the Earth is illuminated by Sun. At night, Sun is not illuminating the Earth; therefore, there will be no reflected energy to be collected by the sensors. The emitted energy can be collected both at day and night, provided the amount of emitted energy is large enough to be detected.

**Active sensors**, in contrast to passive sensors, use their own source of radiant energy for illuminating the target under investigation. The reflected radiant energy from the target is detected and recorded by these sensors. Therefore, the advantage of active sensors over the passive sensor is that it provides the facility to collect data anytime. Further, microwave data provide complementary information about the target of interest, which is not available in the visible and infrared regions of the electromagnetic spectrum. However, the disadvantage is that it needs an adequately huge amount of energy for illuminating the target under investigation. Scatterometer, synthetic aperture radar (SAR), and a laser fluoro-sensor are examples of active sensors.

## 1.4 WHY MICROWAVE FOR REMOTE SENSING?

Microwave remote sensing is relatively new, having been used in civilian applications only since the early 1960s as compared to optical remote sensing, which has been in use since the late 1800s. With the success of optical remote sensing why we should use a microwave for remote sensing.

Microwaves have a different and unique feature that provides complementary information about Earth's objects and environment that is generally not obtainable by other way. Microwaves can penetrate clouds and, to some extent, rain and do not rely on the Sun as the source for illumination. These attributes allow sensing of the Earth independently of the time of day and under almost all weather conditions. Clouds that are dense enough to completely obscure the ground, and thus prevent aerial or satellite optical imaging, have little effect on microwaves. Ice clouds have almost no effect at any wavelength longer than 1 cm, while water clouds have a significant effect only for wavelengths less than 2 cm. The rain has a greater effect than clouds, and it is important only for wavelengths less than 4 cm. Active (radar) microwave sensors are thus able to observe the Earth's surface under almost all conditions. For passive microwave remote sensing (radiometry), the attenuation effects of clouds and rain can obscure the surface at some frequency. However, this same attenuation provides an observable signal that can be exploited by microwave radiometers to gather the information about key geophysical parameters of interest such as total liquid water fraction, cloud droplet size distribution, atmospheric temperature, and rain intensity. At longer wavelengths, radiometers are able to observe the surface, particularly in the polar regions, through clouds, whereas mapping such as areas in the visible spectrum is much more difficult.

Another reason for the use of microwaves is that they are able to penetrate more deeply into vegetation than optical waves. The extent of penetration depends upon the moisture content and density of the vegetation canopy, as well as upon the wavelength of microwaves. Longer wavelength penetrates much better than shorter wavelengths. Hence, shorter wavelength yields information about upper layers of the vegetation, while longer wavelengths yield information about the lower layers and the ground beneath. Moreover, microwaves are able to penetrate significantly into the ground itself. For dry soil, the penetration depth at lower microwave frequencies can be substantial, whereas penetration is limited for wet soil.

A third and perhaps the most important, reason for the use of microwaves is that the information available from microwaves is different from that available in the visible and infrared regions of the electromagnetic spectrum. In particular, microwave scattering from the natural surface is related to both the electrical (bulk dielectric) and geometric (roughness) properties of the surface. With suitably designed sensors, it is thus possible to infer about the surface geometry as well as the electrical properties of the surface. Further, microwave derived properties complement the information obtainable from visible and infrared radiation, facilitating to studies of geometric, bulk dielectric, and molecular-resonance properties of surface features.

## 1.5 A BRIEF OVERVIEW OF MICROWAVE SENSORS

Microwave remote sensing devices can be classified into two main classes: known as radiometers (passive sensing) and radars (active sensing) as shown in Figure 1.2. Both the devices consist of antennas and receivers. However, the difference between the radar and radiometers is that the former consists of a transmitter as well. These two sensors are being used on aircraft and spacecraft to study the Earth and other planets. The two broad classes can be divided into subclasses according to their general operating features and functions.

Active microwave sensors can be divided into five general subclasses as synthetic aperture radar (SAR) systems, side-looking airborne radar (SLAR), scatterometer, altimeters, and meteorological radars. SAR and SLAR systems are developed to generate images from moving platforms. As its name implies, SAR utilizes the motion of antenna over the target area to provide a synthetic aperture to the antenna as compared to other sensor systems, which generally use real aperture antennas. These systems are operated by transmitting modulated pulses and using Doppler/ range processing techniques to generate backscatter images. The images created by SAR are of the highest resolution, but SAR systems are significantly more complex as compared to other sensing systems. Inverse synthetic aperture radar (ISAR) is similar to SAR, except its technologies use the motion of the target rather than the antenna to create the synthetic aperture. ISAR applications include identification and target detection in a military application and the ground-based sensing of extra-terrestrial objects. A scatterometer is an instrument used for measuring radar backscattering coefficients quantitatively. Altimeters are specialized radars developed to measure platform height from the surface; however, can be used to extract the other information from the return signal. Meteorological/Weather radars are specially developed scatterometer with ranging capability that measure meteorological phenomena like rainfall. Interferometric SAR (InSAR) is a special configuration of a SAR system designed to measure surface topography.

Radiometers are passive sensors that records naturally emitted microwave radiation. The emission depends upon the physical temperature and electrical properties of the surface to be sensed, and it further gets modulated by the atmospheric constituents. Since they do not need transmitters to illuminate the target; therefore, radiometers typically use less power for sensing the target and often work over a larger frequency range than radar sensors. Synthetic aperture radiometers (interferometers) sub-classified into one and two dimensional are used for Earth remote sensing as well as for astronomical observation. Sounders are a form of radiometers that measure vertical profiles of atmospheric parameters such as the vertical distribution of precipitation, temperature, humidity, cloud composition, etc. (Ulaby et al. 2014).

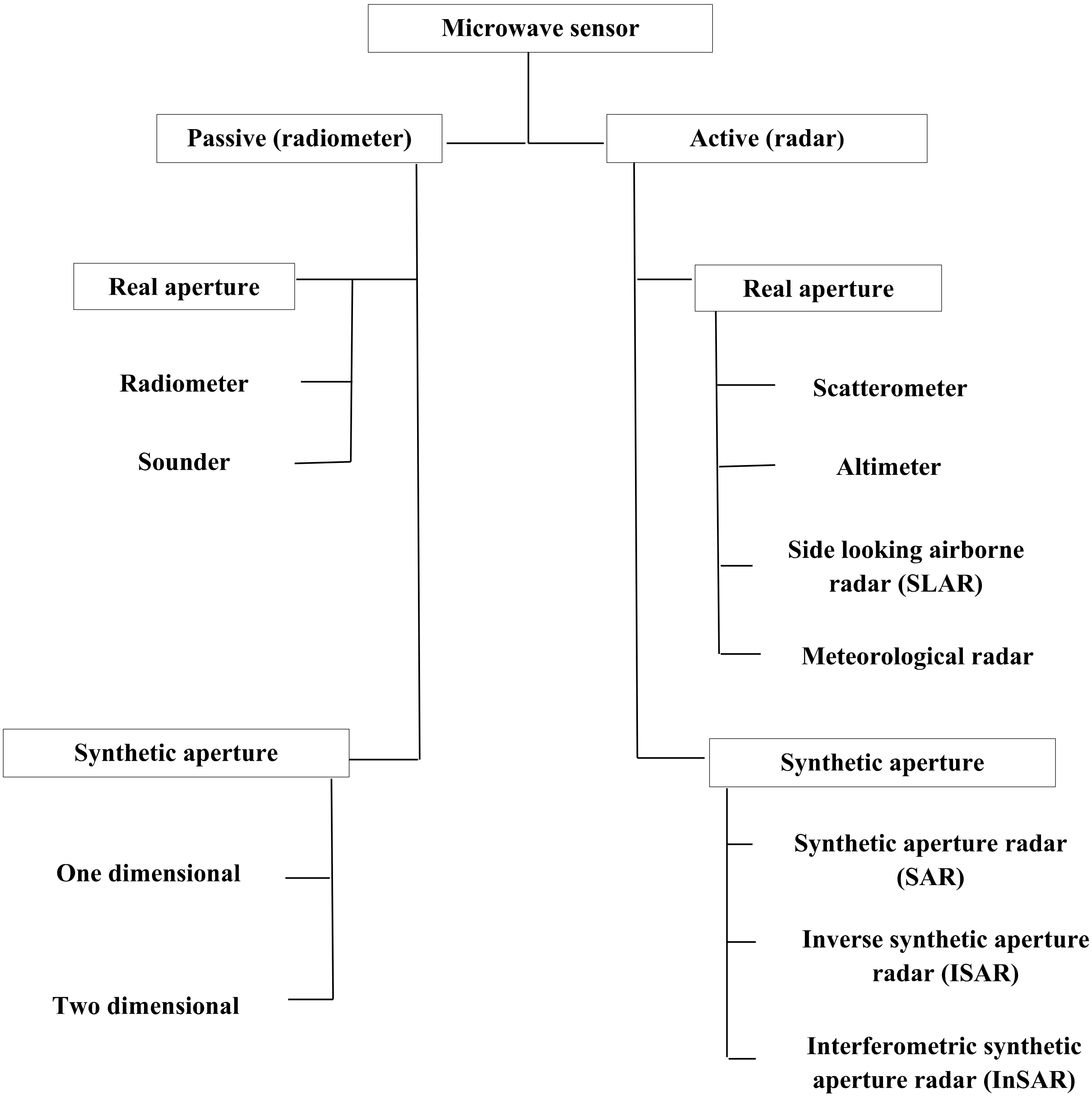


**Figure 1.2** Classification of microwave sensors

## 1.6 REVIEW OF LITERATURE

Agriculture contributes a substantial part in the economy of a nation (Nicholls et al. 1964). The rapid growth of the human population has led to an increase in the requirements of agricultural food (Tilman et al. 2011). Estimation of crop yields plays a crucial role in improving food security, its management, and decision-making for the rapidly growing population in the world (Jin et al. 2018). The crop yield depends upon the crop growth parameters at the different growth stages of the crop (Doraiswamy et al. 2003; Basso et al. 2013). Consequently, the knowledge of temporal variations of crop growth parameters is essential at different growth stages for better yield production. Many techniques are available for the *In-situ* measurement of crop growth parameters. However, it is time consuming and tedious process in providing the spatial and temporal information of crop growth parameters. In contrast to In-*situ* measurement, the remote sensing techniques can be used to collect information about crop growth parameters over a large area in a short time and provide the repetitive frequency monitoring (Kasampalis et al. 2018; Sivasankar et al. 2018).

Remote sensing has several advantages in the field of agricultural research purposes. Remote sensing plays a significant role in crop classification, crop monitoring and yield assessment (Thenkabail et al. 2002; Doraiswamyet al. 2005; Bernardes et al. 2012; Kingra et al. 2016). The use of remote sensing is necessary for the field of agronomical research purposes because they are highly vulnerable to variation in soil, climate, and other physio-chemical changes. The monitoring of agricultural production system follows strong seasonal patterns according to the biological life cycle of crops. All these factors are highly variable in space and time dimensions. Moreover, agricultural productivity can change within short time periods, due to unfavourable growing conditions. Monitoring of agricultural systems should be followed in a timely. Remote sensing is an important tools in timely monitoring and giving an accurate picture of the agricultural sector with high revisit frequency and high accuracy. For sustainable agricultural management, all the factors, which are influencing the agricultural sector, need to be analyzed on spatio-temporal basis. The remote sensing along with the other advanced techniques such as global positioning systems and geographical information systems are playing a major role in the assessment and management of the agricultural activities. These technologies have manifold applications in the field of agriculture such as crop acreage estimation, crop growth monitoring, soil moisture estimation, soil fertility evaluation, crop stress detection, detection of diseases and pest infestation, drought and flood condition monitoring, yield estimation, weather forecasting, precision agriculture for maintaining the sustainability of the agricultural systems and improving the economic growth of the country (Shanmugapriya et al. 2019).

The optical remote sensing data have been used for crop classification, monitoring, and yield prediction. However, the acquisition of the optical image is hampered by the cloud cover. Microwave remote sensing data, in contrast to optical remote sensing data, are independent of cloud cover and thus show high potential for crop classification, monitoring, and yield prediction. Therefore, microwave remote sensing techniques have developed enough scientific interest, which led to advancements in communication and radar technology. The study has shown that crop canopies are both highly non-uniform and anisotropic at microwave frequencies. The interactions between microwaves and the canopy are influenced by the properties of the radar system itself, namely the frequency and polarization of the microwaves, and the incidence and azimuth angles at which the canopy is viewed (Ulaby 1975; Ulaby et al. 1975; Joseph et al. 2010; Balenzano et al. 2011). The studies of the scattering mechanism of vegetations have been investigated built on radiative transfer theory and electromagnetic scattering /emission model. The scattering models have been developed for vegetation canopy by using these theories. Interactions between microwaves and the canopy are governed by the dielectric properties, size, shape, orientation, and roughness of individual scatterers i.e., the leaves, stems, fruits, etc. (Senior et al. 1987; Sarabandi et al. 1988; Karam et al. 1989; McDonald et al. 2000) and their distribution throughout the canopy (Karam et al. 1992; Yueh et al. 1992; Hoekman et al. 1993). The dielectric properties of vegetations are dependent mainly on their moisture content and to less importantly, on temperature and salinity. Agriculture crops are taken as a random medium, which consists of leaves and stalks/stems. The soil beneath the crops is generally considered to be a rough surface. The leaves are modeled as lossy dielectric elliptical/circular disks having diameter and thickness. The stalks/stems are modeled as finite lossy dielectric cylinders (Toure et al. 1994; Zhang and Wu 2016). These crop-specific canopy characteristics vary during the growing season and are influenced by environmental conditions and stress. Scattering from the crop beneath the soil is influenced by its roughness and dielectric properties, which depend primarily on its moisture content. Therefore, the use of radar remote sensing has substantial potential in agricultural applications, mainly classification, crop monitoring, and soil moisture monitoring.

The information about soil moisture is essential for hydrological, meteorological and agricultural applications. In the field of agriculture, soil moisture information is essential for many applications like irrigation scheduling for reducing plant stress and improving production yield to meet the needs of the increasing demand for the food. The soil moisture acts as a solvent and carrier of nutrients for the crop. It has a significant influence on plant growth, infiltration, and evaporation, chemical and biological variations of the soil organic matter, and heat exchange as well. These parameters are necessary for the high production of the crop yields (Wang et al. 2009; Pradhan et al. 2018).

The *in-situ* measurements of soil moisture are restricted to discrete measurements at specific locations, and it requires a repeated sampling process to analyze the periodical variations in soil moisture. Therefore, such specific site-based measurements do not provide the spatial distribution because soil moisture is highly variable both spatially and temporally (Engman, 1991; Wood et al. 1992) and are therefore inadequate for regional and global studies. Advancements in satellite remote sensing techniques have offered various methodologies for measuring soil moisture over a large area in a short period and repeated intervals (Engman1990). The soil moisture study using remote sensing started in the mid-1970s soon after the surge in satellite development. This led to the research study of soil moisture using the electromagnetic spectrum, including from optical to microwave regions. Several researchers have reported soil moisture content measurement using optical, thermal infrared, and passive/active microwave remote sensing techniques (Walker 1999). The fundamental distinctions among these techniques are due to wavelength regions of the electromagnetic spectrum used and the sources of electromagnetic energy (Walker 1999), the response acquired by the sensing devices and the physical model between the response and the soil moisture content. Nowadays, the advantages of microwave remote sensing techniques to estimate the soil moisture content of bare soil and crop-covered soil fields have become the area of interest among research scientists (Shutko 1982; Schmugge 1983; Ulaby et al. 1986; Ferrazzoli et al. 1992).

The soil surface can be defined as the interface of two different but homogeneous media having a different value of electromagnetic properties. The one part of the homogeneous media can be assumed as vacuum space (in microwave bands, the earth atmosphere serves almost like a vacuum), and the second part as a dielectric media with dielectric constant value $\varepsilon$. The plane electromagnetic wave incident on the dielectric earth surface is affected, and it started to interact with atoms of the dielectric medium. These atoms of the dielectric media behave as small electromagnetic oscillators, and consequently, it radiates electromagnetic waves in the space. Some portion of the electromagnetic energy radiated back to the upper part of the homogeneous media in the space and some portion towards the lower part of the dielectric media.

In the case of the perfectly smooth surface of infinite extent and uniformly illuminated by the plane electromagnetic wave. One plane electromagnetic wave reradiated in the upper part of the media at an angle to equal to the incident angle. This wave is referred as the reflected wave. The electromagnetic wave is reflected (scattered) in the specular direction complying with the notable Fresnel reflection equation. For this situation, no scattering of the electromagnetic wave will occur in other directions than that of specular. The other electromagnetic wave reradiated within the lower part of the dielectric media in the lower half-space at an angle ($\theta'$) equal to

$$\theta' = \sin^{-1}\left(\frac{\sin\theta}{\sqrt{\varepsilon}}\right) \tag{1.4}$$

Where $\theta$ is the incidence angle. This wave is referred as the refracted or transmitted electromagnetic wave in the dielectric media. The rough soil surface scattered the incident electromagnetic radiation in all possible directions. The magnitude of the surface roughness accounts for the magnitude of the scattered electromagnetic energy in other directions by reducing the component in the specular direction. If the soil surface is extremely rough, the electromagnetic energy is scattered equally in every direction.

The normal soil surfaces are primarily rough. The larger is the roughness parameters of the soil surface, the higher are the scattering of electromagnetic wave incidents on it. The scattering of the incident electromagnetic wave from the rough soil surface is dependent upon the surface roughness parameters, which rely on the wavelength of the incident electromagnetic wave and angle of incidence. The two major parameters, which characterize the surface roughness condition, are the root mean square height ($s$) and autocorrelation length ($l$). The relation of the electromagnetic wave in terms of its wavelength to statistical surface roughness parameters ($s\ and\ l$) are $ks$ and $kl$, where $k = \frac{2\pi}{\lambda}$ decides the required condition for the scattering mechanism of the incident electromagnetic wave. These parameters show that the same rough surface may appear smooth at the higher wavelength.

There are two main criteria to define the condition of surface roughness electromagnetically, namely Rayleigh and Fraunhofer criteria. If the plane electromagnetic wave is incident on the rough surface at an incidence angle (θ), then the phase difference (Δϕ) introduced to two scattered electromagnetic waves from separate points on the surface will be

$$\Delta\phi = 2s\ \frac{2\pi}{\lambda}\cos(\theta),\ where\ s\ is\ the\ RMS\ height\ of\ the\ soil\ surface.$$

In Rayleigh criteria, if the phase difference ($\Delta\phi$) between two scattered waves is less than $\frac{\pi}{2}$ radian, then the surface appears to be as smooth i.e.

$$s < \frac{\lambda}{8\cos(\theta)}$$

In Fraunhofer criterion, being more stringent criterion, the surface appears to be as smooth, if the phase difference is less than $\frac{\pi}{8}$ i.e.

$$s < \frac{\lambda}{32\cos(\theta)}$$

The soil moisture content is related to its dielectric constant value because of the large difference in the dielectric constant of water (dielectric constant of approximately 80) and dry soil (dielectric constants of approximately 2-3). As the dielectric constant changes, these changes are detectable by microwave sensors and accordingly provide information about the soil moisture content (Njoku and Kong 1977; Dobson et al. 1985). This is the basic principle of microwave remote sensing for the estimation of soil moisture of the Earth's surface. Over the previous four decades, a various study has been focused to study the dielectric properties of soil moisture in the microwave regions (Hoekstra and Delaney 1974; J.R. Wang and Schmugge 1980; Dobson et al. 1985; Hallikainen et al. 1985; Scott and Smith 1992, Singh 2005; Shen et al. 2013).

Water is a polar molecule, implying that one portion of the water molecule conveys a negative charge while the other portion of the atom conveys a positive charge. While water is exceptionally polar, soils are fairly non-polar. The polarity of water causes a rotational dipole moment in the presence of electromagnetic radiation, while soil generally remains unaffected. This implies water will rotate and re-orientate with the ascent and fall of the vibrating electric field (i.e., the electromagnetic wave) while soil remains for the mostly stationary. In the microwave frequencies range, the water rotational dipole moment will happen at the same frequency of the electromagnetic wave. This rotational dipole moment of water influences water to have a high dielectric constant value of approximately 80. Therefore, the large values of dielectric constant are directly related to the presence of soil moisture content. The dielectric constant of the water diminishes if anything that would thwart the molecular rotation, for example, freezing, exceptionally high frequencies, and tight binding with a soil molecule.

A wet soil medium is composed of soil particles, air voids, and liquid water. The water contained in the soil is generally of two types: (i) bound water and (ii) free water. Bound water denotes the water molecules contained in the first few molecular layers surrounding the soil particles. The influence of matric and osmotic forces between the soils and water molecules keeps them tightly held together. Since these forces acting on a water molecule decrease quickly with distance away from the soil-particle surface, therefore, water molecules situated at numerous molecular layers away from soil particles are capable of moving relatively free from the bound molecule within the soil medium and hence are known as free water. Isolating the water into bound and free fractions depicts solely the approximation of the actual distribution of water molecules within the soil medium and is built to some extent on the arbitrary criterion for the transition point between bound and free water layers. The amount of water contained in the first molecular layer adjacent to the soil particles is directly proportional to the total surface area of the soil particles present in a unit volume. The total surface area of the particles is defined in terms of a function of the soil particle size distribution and mineralogy. A soil generally is classified into textural class based on its particle size distribution as sand ($d > 0.05$ mm), silt ($0.002$ mm $< d > 0.05$ mm) and clay ($d < 0.002$ mm). However, on the basis of electromagnetic theory, a soil medium is generally taken as a four-component dielectric mixture composed of air, bulk soil, bound water, and free water. Hence, due to the high value of forces by electromagnetic radiation, the bound water, and free water molecule interacts with an incident electromagnetic radiation differently; thereby, bound water shows dispersion spectrum in the dielectric value as compared to free water. Both the bound and free water are as functions of the electromagnetic radiation frequency ($v$), the physical temperature ($T$), and the salinity ($S$). Hence, the value of dielectric constant of the soil mixture is generally a function of (i) $v$, $T$, and $S$, (ii) the total volumetric water content, (iii) the relative proportion of bound and free water in soil medium, which are related to the soil surface area per unit volume, (iv) the bulk soil density, (v) the shape of the soil particles, and (vi) the shape of the water inclusions (Schmugge 1983; Dobson et al. 1985; Hallikainen et al. 1985).

In the last four decades, various researchers have studied surface parameters of bare soil and crop covered soil fields. The researchers intended to estimate the soil moisture and other soil surface parameters by utilizing ground-based scatterometer, airborne and space-borne synthetic aperture radars data (Ulaby et al. 1978; Ulaby et al. 1979; Dobson and Ulaby 1986; Fung et al. 1992; Oh et al. 1992; Dubois et al. 1995; Shi et al. 1997; Bruckler et al. 1998; Quesney et al. 2000; Baghdadi et al. 2002; Zribi and Dechambre 2003; Oh 2004, Singh 2005; Khadhra et al. 2012). Several theoretical, empirical, and semi-empirical models have been developed since the start of SAR studies to relate the backscatter coefficient to soil moisture through large contrast of the dielectric constants of bare soil and water (Fung et al. 1992; Oh et al. 1992; Shen et al. 2013).

Theoretical models are generally developed on the basis of wave theory of electromagnetic radiation, and the validity of these models is limited to different wavelength regions and surface roughness parameters (Fung et al. 1992). The standard models include Small perturbation model (SPM) valid for low frequency regions, whereas the Kirchhoff models (KM) are valid for high frequency regions. The KM is further divided into two parts called the Physical optics model (POM) and the Geometrical optics model (GOM), which are applicable to high frequency regions (Ulaby et al. 1982). Fung et al. (1992) developed the Integral Equation Model (IEM) that combined Kirchhoff and Small perturbation models and hence are valid for wider frequencies range and surface roughness parameters. Bindlish and Barros (2000) estimated the soil moisture content by the IEM model using the inversion algorithm at multi-frequency and multi-polarization data of Spaceborne Imaging Radar -C/X-band Synthetic Aperture Radar (SIR-C/X-SAR). The sensitivity of backscatter to surface roughness was found to decrease as the RMS height was above 1 cm, and this sensitivity was found more in Gaussian function than in exponential function. Satalino et al. (2002) demonstrated that no two soil moisture classes could be reliably retrieved over smooth bare fields using ERS-1 and ERS-2. The soil moisture was estimated with an overall RMSE in the order of $\Delta M_V = \pm 6\%$ by inverting the IEM theoretical model using appropriately trained and regularized neural networks. They found that the variable surface roughness was the main source of error, which influenced the relationship between the soil moisture and the radar backscattering coefficient. Theoretical models can infer the general behaviour of the backscattering coefficient with the changes in surface roughness and soil moisture content (Dubois and van Zyl 1994). However, their applicability is limited due to the complex and restrictive requirement for the parameterization of the vegetation and soil surface layer. This causes hindrance in soil moisture estimation (Ulaby et al. 1986).

Empirical models are derived generally from the experimental measurements to establish useful empirical relationships for inversion of soil moisture from backscattering observations (Walker et al. 2004). Many natural surfaces do not lie in the validation regions of the theoretical backscattering models. However, even when they do, the available backscattering models fail to give results in good agreement with experimental observations (Oh et al. 1992; Walker et al. 2004). In that case, empirical backscattering models become very important over theoretical backscattering models.

The horizontal and vertical polarization diversity based empirical models have also been derived for the inversion task to estimate the soil surface roughness parameters and moisture content (Wang and Zhang 2005). Empirical methods often provide relatively precise soil moisture results, however, may not be applicable for datasets outside the fields observations (Chen et al. 1995; Dubois et al. 1995), since a large number of experimental measurements is essential to develop general statistical laws and establish a suitable empirical models for inversion of soil moisture from backscattering data (Oh et al. 1992), while current empirical models generally are derived from a limited number of observations and therefore are site-specific.

On the other hand, semi-empirical models have been developed on the basis of theoretical models with model parameters derived from experimental data. Oh et al. (1992) developed the first semi-empirical model used for soil moisture retrieval with polarimetric radar data. Oh et al. (1992) found that the depolarization ratio ( $\sigma^{\circ}_{VH/VV} = \sigma^{\circ}_{VH} / \sigma^{\circ}_{VV}$ ) is very sensitive to soil moisture and developed the semi-empirical model based on empirical fittings for scatterometer measurements for bare soil surfaces at different roughness conditions. In the semi-empirical method, proposed by Dubois et al. (1995), the co-polarization backscattering coefficients $\sigma^{\circ}_{HH}$ and $\sigma^{\circ}_{VV}$ are expressed as nonlinear functions of the surface dielectric constant, incidence angle, wavelength, and RMS height ($s$) of surface roughness. The main advantage of these backscattering models is that they are not expected to have the site-specific problems commonly associated with empirical models (Walker et al. 2004). However, generally, these types of models are suitable for bare soil surface conditions rather than vegetated surfaces.

Ground-based scatterometer systems are very useful to study and predict the optimum system parameters to acquire accurate information about any target of interest. One of the important advantages of these systems is to exploit the temporal observation of a specific crop target. The ground-based scatterometer is capable of providing the multi-frequency and multi-angular datasets with high temporal resolution (diurnally, daily, or over the whole growth cycle) in the full polarization mode. Collections of data typically are done at plot scales. Working on the tower-based scatterometer system is significantly more affordable than flying an airborne system. Therefore, the data collected at different microwave bands with the high temporal resolution at full polarization modes in the range of angle of incidence 20° to 60° may be more useful than that of an airborne campaign. It is also much easier to vary the different system parameters such as frequency, polarization, incidence, and azimuth angle, which may be helpful for different observation strategies. This system provides detailed ground data at plot scales over a desired time, and plots can be easily handled for making observations by varying crop growth and soil surface parameters. Therefore, ground-based scatterometer experiments are ideal for theoretical developments and validation purposes and have been a fundamental part of radar studies and developments for over 40 years. Several articles have used this approach to explore relationships between backscattering coefficients and biophysical parameters (Steele-Dunne et al. 2017).

Early field measurements using a ground-based scatterometer conducted by the University of Kansas provided important results regarding the sensitivity of radar backscatter coefficients to soil moisture and vegetation growth parameters. The microwave active and passive spectrometer (MAPS) working in the University of Kansas in the range of frequency 4 to 8 GHz has shown high sensitivity of radar backscattering coefficients to soil moisture at lower frequencies for horizontal polarization (Ulaby and Moore 1973). MAPS was one of the first measurements to show that the radar scattering coefficients depend on surface roughness, microwave frequency, and incidence angle (Ulaby 1974). In a subsequent study on the different types of crops such as corn, milo, soybeans, and alfalfa fields, MAPS measurements demonstrated that soil moisture could also be detected through vegetation cover. They demonstrated that small incidence angles (5°-15° from nadir) and horizontal polarization were best suited for monitoring soil moisture, while higher frequencies and larger incidence angles were more sensitive to vegetation and, therefore, more suited to crop identification/classification (Ulaby 1975). Latter, MAPS 8-18 GHz scatterometer experiments performed by the University of Kansas showed similar results. Experiments using this system were used for the development and validation of the water cloud model (WCM) (Attema and Ulaby 1978). A lower frequency scatterometer, the MAPS 1-8 GHz, was used to show that frequencies below 6 GHz and incidence angle less than 20° from nadir are best suited to diminish the effect of vegetation attenuation on the relationship between soil moisture and backscattering coefficients. They also showed that row direction has no effect on cross-polarized backscattering scattering coefficients from 1 to 8 GHz, but it does affect the co-polarized backscattering coefficients below 4 GHz. Finally, they reported that a linear relationship could be developed between soil moisture and backscattering coefficients at horizontal polarization for 4.25 GHz and an incidence angle of 10°. A correlation coefficient of around 0.80 has been reported irrespective of fitting the data for individual vegetation types. Ulaby et al. (1982) studied the sensitivity of radar backscattering coefficients to soil moisture covered with crop vegetation and showed that for extremely dry soils, the contribution of the vegetation was very significant as compared to contribution due to soil moisture. However, for high dynamic range of soil moisture, which is primary range of interest in hydrological and agricultural applications, the influence of vegetation was ordinary as compared to soil moisture. The combined data acquired by the microwave active spectrometer (MAS 1-8 GHz and MAS 8-18 GHz) were used to examine the statistical behaviour of backscattering coefficients of agricultural crops (Ulaby 1980). The empirical models were developed for computing backscattering coefficients by using angular and spectral difference of the mean, median and 90-percent dynamic range of the backscattering coefficients (dB) histograms. This empirical model describes the combined angular and frequency dependence of scattering coefficient for agricultural crops. This empirical model is termed as a clutter model for agricultural crops. The experiments have been done to explore the complexity of microwave scattering mechanism and attenuation properties of the crop canopies. Ulaby and Wilson (1985) used a truck mounted L-, C-, and X-band frequency modulated continuous wave (FMCW) scatterometer and showed that agricultural crop canopies are highly non-uniform and anisotropic at microwave frequencies that results to polarization dependent attenuation of the microwave radiation into the crop canopies. The relative contribution of leaves and stalks to total attenuation was also found to depend on frequencies. It is observed that leaves accounts to 50% and 70% canopy loss factors at L-band and X-band, respectively. Tavakoli et al. (1991) used scatterometer at 1.5 GHz frequency to observe patterns of attenuation and phase shift at horizontal and vertical polarization of the transmitted waves through a fully-grown corn canopy in order to develop and evaluate a model for radar interaction explicitly for regular plant spacing and row geometry.

Meanwhile, the radar observations of vegetation experiments (ROVE) in the Netherlands were conducted to investigate the potential of using radar remote sensing of agricultural crops and bare soil surface for mapping, monitoring, and yield forecasting (Loor et al. 1982). The X-band and Q-band FMCW scatterometer were mounted on a carriage that could be moved along agriculture fields with a rail system working in a range of incidence angles from 10° to 80°. This scatterometer system was used to measure different types of crops in each growing season from 1974 to 1980. Limited airborne experiments were also conducted using side-looking airborne radar (SLAR) at X-band with principal objectives for the identification and classification of the crops from SLAR images. Krul et al. (1988) used the ROVE data and showed that during the growing season, the dynamic range of X-band backscatter coefficients of several crops was found between 3 and 15 dB, hence the importance of accurate calibration is a must. In particular, the different combinations of incidence angles were investigated as a solution to isolate the effects of the soil moisture and vegetation canopies. Bouman and Kasteren (1990) emphasized the importance of architecture and geometry of crop canopy and showed that changes in canopy architecture due to strong winds could affect the backscattering coefficients by differences of 1-2 dB. For sugar beets, it was found that crop monitoring was found good for the early growth stage until the fractional soil cover of about 80% and biomass values of 2-3 tons/ha were reached. After that, there were no further variations in the radar backscattering coefficients. An experiment in which some part of the crop canopies was removed (thinned) in the middle of the growth stages, the backscattering coefficients only started to decrease after the fraction of crop cover became less than 25% and biomass values around 1 ton/ha. The results of this experiment revealed that the architecture of the crop canopy and the individual plant types significantly influence the radar backscattering coefficients. The radar backscattering coefficients were found different for developing and fully-grown crops having even the same crop cover or amount of canopy biomass. In particular, soil moisture changes confounded the detection of the emergence of the crops. Bouman (1991) investigated the potential of crop growth parameter estimation using X-band scatterometer data by empirical and simple physical relationships. The ground-based multi-temporal, multi-angular, and co-polarization data were collected for crops beet, potato, wheat, and barley. The estimation efficiency of straightforward inversion methods was found low due to early saturation and low contrast between the scattering response of soil and fully-grown crop at X-band. It was suggested that multi-frequency observations might be useful to separate the backscattering contributions from potato, barley, and wheat, thereby improving the estimation of dry canopy biomass, canopy water content, fractional cover, and crop height.

Ground-based scatterometer experiments have been used extensively, especially in early SAR research, to gain an understanding of responses as targets change and SAR configurations were modified. It allowed scientists to develop and test methodologies prior to the engineering of SAR satellite systems and before space-based data became available. In addition to collecting data for model development and testing, scatterometer can also be used in novel ways to study phenomenon not easily implemented using air-borne and spaceborne systems. Inoue et al. (2002) used a multi-frequency polarimetric scatterometer to measure backscattering coefficients for a rice crop field daily for the whole growing season in order to relate the microwave backscattering signature to crop growth parameters. They investigated the influence of the rice growth cycle on backscattering coefficients at L-, C-, X-, Ku-, and Ka bands for various range of incident and azimuth angles and their relationship to leaf area index (LAI), stem density, crop height, and fresh biomass. The Canada Centre for Remote Sensing (CCRS) acquired a ground-based scatterometer in 1985, which was dedicated primarily to agriculture research. This was a three-band system mounted on a hydraulic boom supported on the flat bed of a 5-ton truck. The scatterometer acquired data at L-, C-, and Ku bands (1.5, 5.2, and 12.8 GHz) and at HH-, VV-, HV-, and VH-polarizations. The boom allowed a change in incident angle working in the range from 20° to 50°.

Some of the earliest research using the CCRS scatterometer was focused on crop separability. Brisco et al. (1992) reported the best configurations for this purpose to higher frequencies (Ku-band as opposed to C- or L-bands), the cross-polarization, lower incidence angles, and observations during crop seed development. These conclusions have been supported by many subsequent studies using airborne and satellite-based SAR observations. The diurnal effects on backscattering coefficients at $K_u$-, C- and L-band for the wheat crop were studied by (Brisco et al. 1990). The diurnal variations were found different at higher frequency as compared to lower frequency due to increased geometric effect at a higher frequency. The diurnal variation was found significant at VV-polarization and 20° incidence angle. Backscattering coefficients were sensitive to the diurnal changes of water content in crop canopy during active crop growth stages and due to the diurnal changes of soil moisture during periods of crop senescence. Toure et al. (1994) modified the MIMICS model into agricultural context and used the scatterometer to validate the accuracy of this modified model to estimate soil moisture as well as stem heights and leaf diameters.

Several researchers investigated the sensitivity of backscatter to soil moisture, crop residue, and tillage. Major et al. (1994) found that backscatter was sensitive to soil moisture, even in the presence of short-grass prairie conditions. Boisvert et al. (1998) modeled the effective penetration depth in the vegetation canopy for L-, C-, and Ku-bands for the validation of soil moisture estimation. The scatterometer data are useful for the estimation of soil moisture using three soil surface models based on surface roughness (Dubois et al. 1995; Fung et al. 1992; Oh et al. 1992), and the performance of these models was evaluated for the harrow and seed plots. McNairn et al. (1996) used a dual incident angle approach for the assessment of models to estimate both soil moisture and surface roughness.

The development of a retrieval algorithm for NASA's soil moisture active and passive (SMAP) mission encouraged several ground-based scatterometer experiments (Jackson et al. 2012). NASA's ComRAD (combined radar/radiometer) system is a truck-based SMAP simulator that consists of a dual-polarized radiometer at 1.4-GHz and scatterometer at 1.24-1.34 GHz. The instrument was mounted on a 19 m hydraulic boom and is typically configured to measure at a 40° incidence angle similar to that of SMAP, though it can sweep in both azimuth and incidence angle. Early measurements were focussed on the study of attenuation of microwave due to forest canopy so that accurate estimation of soil moisture could be done by the remote sensing (Kurum et al. 2009, 2011). O'Neill et al. (2013) collected active and passive L-band observations of corn and soybean crops adjacent to each other in the fields for the full growing season to refine the SMAP retrieval algorithms. In particular, these data provided insight into the influence of changing vegetation conditions and the relationship between simultaneously obtained active and passive observations. Srivastava et al. (2015) used this data to compare different approaches to estimate vegetation water content (VWC). They compared different approaches like different polarizations (HH, HV, VV), polarization ratios (HH/VV, HV/ (HH+VV), HV/ (HH+HV+VV)), radar vegetation index (RVI), and microwave polarization difference index (MPDI) using backscattering coefficients data. They found that the backscattering coefficients at L-band for HV-polarization was the best estimator for VWC. This is a valuable result as it removes the need for ancillary data, like normalized difference vegetation index (NDVI) and a parameterization to provide VWC for the retrieval algorithm.

The ground-based L-band Automated Radar System from the University of Florida working at 1.25 GHz (UF-LARS) can be used to observe HH, VV, HV, and VH backscattering observations for every 10-15 min (Nagarajan et al. 2014). Measurements were typically made from a height of about 25 m above the ground with an incidence angle of 40°.

The ability of UF-LARS to measure the backscatter signature of growing vegetation and near-surface (0-5 cm) soil moisture variations with high temporal resolution over long periods offers a unique insight in response to precipitation, irrigation, and other environmental conditions. The density and accuracy of data also provide it ideal for developing and validating radiative transfer models for the estimation of accurate soil moisture content.

The UF-LARS has been used to investigate the dominant backscattering mechanisms from bare sandy soils to (i) evaluate the sensitivity of backscattering to volumetric soil moisture (Liu et al. 2016) and growing vegetation (Nagarajan et al. 2014), (ii) investigate the benefit of combining active and passive microwave observations for soil moisture estimation (Liu et al. 2013) and (iii) evaluate uncertainty in the SMAP downscaling algorithm for sweet corn (Liu et al. 2016). Monsivais-Huertero et al. (2016) compared the bias correction methodologies used in the assimilation of active microwave observations from the UF-LARS and passive microwave observations from UF-LMR to estimate soil moisture.

However, the developed models and the experimental researches on vegetations/soil have been completely focused on the backscattering direction of the radar system. The bistatic configurations of the radar system for land surface observations have recently become a subject of interest. The literature lacks experimental results of interactions of the microwave with the crops/soil in the bistatic configuration. In a monostatic radar system, the transmitting and receiving antennas are placed at the same location and receive the backscattered power from the target of interest. In the case of the bistatic radar system, the transmitting and receiving antennas are generally placed opposite to each other and receive the signal in the forward direction. The advantages and disadvantages of the bistatic radar system over the monostatic radar system are given below:

1. Bistatic scattering coefficients are more sensitive to the vegetation parameters than that of the backscattering coefficient (Ferrazzoli et al. 2000; Zhang et al. 2016).
2. Bistatic scattering coefficients do not show a saturation effect with the increasing biomass of crop and have better sensitivity at higher frequencies than backscattering coefficients (Ferrazzoli et al. 2000; Zhang et al. 2016).
3. The ability of soil moisture retrieval increases in specular direction for any range of surface roughness (Ceraldi et al. 2005)
4. It gives the multidimensional information about the land surface due to the diversity of geometry provided by it over the monostatic configuration (Liang et al. 2005).
5. Sometimes the targets are designed to minimize the backscattering coefficient using stealth technology. Under this situation, the monostatic radar system could not detect such targets. Whereas the bistatic/multi-static radar system can detect such targets due to the detection of multiple reflection/scattering from the target of interest by placing receiving antennas at various places. Hence, the capability of the bistatic/multistatic radar system can improve the counter stealth ability of radar systems (Liang et al. 2005).

The main drawback of the bistatic radar system is its difficulty in focusing the transmitting and receiving antenna beams on the target of interest simultaneously. Therefore, some form of synchronization is required between the transmitter and receiver. Bistatic geometry is more complicated than the monostatic geometry, which increases system complexity for the deployment of it into the space.

## 1.7 STATEMENT OF THE PROBLEM

Till now, the theoretical and experimental research for land surface observations has been carried out by the ground-based scatterometer, airborne and space-borne systems in the backscattering direction. The study of the bistatic scattering mechanism is becoming a subject of growing interest due to its multidimensional information acquisition capability about land use and land cover. However, till now, the theoretical studies of the scattering mechanism of vegetations/soil in the bistatic configuration have been investigated based on radiative transfer theory and electromagnetic scattering /emission model. (Liang et al. 2005) developed the bistatic scattering model, namely BI-MIMICS, from the MIMICS model for forest canopy using first order radiative transfer theory. They simulated the bistatic scattering coefficient with different incidence angle, azimuth angle, and biomass at X-, C- and L-bands for different polarisations. Ferrazzoli et al. (2000) developed the model for sunflower vegetation using the electromagnetic emission and scattering theory in the specular direction at C- and L-bands for different polarizations. They simulated the specular scattering coefficient with biomass and showed that the specular scattering coefficient does not saturate with the increasing biomass. The specular scattering coefficient at C-band was also reported to be more sensitive than L-band with the biomass because of higher attenuation at C-band frequencies. Further, Zhang and Wu (2016) adopted the MIMICS backscattering model for forest canopy into the agricultural context to model the bistatic scattering coefficient for different crops. The model was simulated for wheat and soybean crops at C- and L-bands for various incidence and azimuth angle using different vegetation parameters. In this simulation, it is reported that higher frequencies are more sensitive for vegetation parameter retrieval, whereas lower frequencies are more sensitive for soil moisture estimation. Guerriero et al. (2013) developed and simulated the bistatic scattering coefficient of corn, using the electromagnetic model at Tor Vergata University over a wide range of incidence and azimuthal angles at L- and C-bands. The potential of the bistatic radar system for retrieving the plant height of corn crop, based on the theoretical simulation, was investigated at the various incidence and azimuthal angle. The simulated results showed that, in spite of results around the specular direction, the bistatic radar system could provide a significant performance in retrieving the height of wheat crop in a plane perpendicular to the plane of incidence. At this scattering angle, scattering contribution from the soil surface is minimized, whereas the contributions of scattering from vegetation growth parameters to scattering coefficients are significant. The corn height retrieval error (standard deviation) reduced at least by a factor of three with respect to a monostatic system at this scattering angle. However, the literature lacks experimental results in the bistatic configuration of the radar system.

The knowledge of crop growth parameters at different growth stages is important because it gives information about the crop health conditions and may assess the stress in the crop, if any, immediately. Since, the scattering coefficients of the various targets under study involve large number of system and target parameters, which complicates the inversion of the developed model for the retrieval of crop growth parameters (Cookmartin et al. 2000; Ferrazzoli et al. 2000; Picard et al. 2003; Liang et al. 2005; Zhang and Wu 2016). For example, Cookmartin et al. (2000) developed a multilayer second order radiative transfer model where attenuation parameter is needed for every layer for the inversion formulation, which resulted in complex expressions for retrieving the crop growth parameters. Multiple coherent scattering models were developed for understanding the radar backscattering at C-band for a wheat canopy (Picard et al. 2003). The calculation of multiple scattering interactions complicates the electromagnetic problem, and hence, it requires the solutions for multiple scattering equations for the inversion of the crop growth parameters. Therefore, it is required to develop a model free from system and target parameters and may easily be inverted for the estimation of crop growth parameters and soil moisture. These problems of inversion may be overcome by using machine learning techniques. The machine learning technique is a branch of artificial intelligence. It gives the ability to computer algorithms based on some logic to learn from experience, without explicitly being programmed. In machine learning techniques, the input data is fed together with the desired output labeled as training data, and computer algorithms are asked to analyze and make data-driven rules. Therefore, the results of these processes develop a robust model that can predict the required output for unknown data. For the past decades, machine learning techniques were applied in the field of science and engineering research. Researchers have applied the artificial neural network (ANN), support vector machine (SVM), genetic algorithm (GL) and fuzzy logic (FL) for the estimation of crop growth parameters, soil moisture and classification of crops/soil (Smith 1993; Fang et al. 2003; Frate et al. 2003; Murthy et al. 2003; Jiang et al. 2004; Durbha et al. 2007; Dixon and Candade 2008; Mathur and Foody 2008; Tseng et al. 2008; Kumar et al. 2015, 2017; Mishra et al. 2017). However, the estimation efficiency of crop growth parameters by FL has yet to be investigated using the bistatic scatterometer data for different types of crops and soil moisture.

## 1.8 RESEARCH OBJECTIVES

In the context of the above discussion, the objectives of this thesis are as:

- To study the microwave scattering response of the various crops at their different growth stages and soil moisture in the angular range of 20°- 60° angle of incidence in the specular direction at different microwaves bands and polarizations using ground-based bistatic scatterometer system.
- To study the effect of soil moisture on the bistatic scattering coefficient in the angular range of 20°- 60° angle of incidence in the specular direction at L-bands and co-polarizations using ground-based bistatic scatterometer system. An approach was made to investigate the ratio of bistatic scattering coefficients at HH to VV polarization in order to minimize the effect of surface roughness for the accurate estimation of the soil moisture.

- To determine the optimum parameters of the bistatic scatterometer system used for the measurements carried out on different crops/soil targets by correlation analysis for the estimation of crop growth parameters and soil moisture.
- To develop robust computational algorithms based on fuzzy inference system (FIS) for the estimation of crop growth parameters and soil moisture.
- To evaluate the potential of the developed computational algorithms by carrying out statistical analysis for the estimation of crop growth parameters and soil moisture.

The performance of FIS model is based on the method, type and number of membership function (MF) for mapping the input data in between the value 0 to 1. Therefore, the different FIS models were used in different Chapters to evaluate the performance of different FIS models for the estimation of growth parameters of different crops and soil moisture.

**1.9 ORGANISATION OF THESIS**

The thesis work presented here is divided into the following parts-

**Chapter 1**- This chapter describes the introduction and literature of review.

**Chapter 2**- This chapter describes an experimental method for making bistatic scatterometer measurements to study the angular, temporal, and polarization dependent of microwave scattering response of different types of crops and bare soil surfaces at X-, C-, and L-bands. It also discusses the measurements for the crop growth parameters and soil surface parameters.

**Chapter 3**- In this chapter, bistatic specular scattering measurements were carried out for the estimation of rice crop growth parameters using fuzzy inference system at X-, C-, and L-bands. For this purpose, a correlation analysis was done to find the suitable incidence angle, polarization, and frequency for the operation of bistatic scatterometer to study the microwave scattering response of rice crop growth parameters and their estimation. The subtractive clustering based fuzzy inference system (S-FIS) was evaluated for the estimation of rice crop growth parameters.

**Chapter 4-** In this chapter, multi-temporal and multi-angular bistatic specular scattering measurements were carried out for the estimation of wheat crop growth parameters using fuzzy inference system. The correlation analysis was carried out between wheat crop growth parameters and bistatic specular scattering coefficient to determine the suitable bistatic scatterometer configuration for the accurate estimation of wheat crop growth parameters. The grid partition based fuzzy inference system (G-FIS) using the Gaussian membership function was evaluated for the estimation of wheat crop growth parameters.

**Chapter 5-** The present chapter discusses ground-based bistatic scatterometer measurement for the estimation of growth parameters of ladyfinger crop at X-band. The estimation of the crop growth parameters was done using a hybrid machine learning approach combined with fuzzy inference system and artificial neural network called (S-ANFIS).

**Chapter 6-** In this chapter, an attempt was made to estimate soil moisture from rough surfaces using three different membership functions (Gaussian, generalized bell and triangular) based G-ANFIS algorithms. In this study, the comparison of these MF based G-ANFIS algorithms is presented for the estimation of soil moisture from slightly rough bare soil surfaces using bistatic scatterometer data.

**Chapter 7-** This chapter includes the conclusion and future aspects of the research work done in the present thesis.