CHAPTER - 1

INTRODUCTION AND LITRATURE OF REVIEW

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1.1 REMOTE SENSING

Human beings have five senses (touch, taste, hear, sight and smell) to perceive the surrounding world. Two of them (touch and taste) require contact of our sensing organs with the objects. However, other three senses can acquire much of the information about our surrounding without being contingent to connection between the sensing organs and the external objects.

Remote sensing is the process of sensing or getting the information about the objects that are present on or off the earth without coming in their contact. A physical carrier is required to carry the information from the object to the sensor through an intervening medium. The electromagnetic spectrum from low frequency waves through microwaves, infrared, visible rays is used for information carrier in the remote sensing. The information acquired in different regions of spectrum is complementary to each other. However, microwave has certain advantages over the visible and infrared region.

The microwave remote sensing is independent of the weather conditions and daytime. The microwave remote sensing has an own active microwave sensor which transmits an electromagnetic wave and can easily penetrate different kind of clouds and to some extent rain. Many previous studies have proven the microwave remote sensing as an important tool to estimate the land soil surface properties and biophysical parameters of the crop effectively.

1.2 BRIEF HISTORY OF REMOTE SENSING

In the beginning of 18^{th} century, the development of remote sensing as a scientific field is closely tied to developments in photography. The photographic cameras were used for remote sensing purpose to record the information in the visible and near infrared frequency spectrum. Daguerre and Niepce took the first photograph in the year 1839. After that, the Director of the Paris Observatory suggested the use of photography for topographic purposes.

During the end of 18^{th} century to the beginning of the 19^{th} century, the photographic cameras were deployed above the earth surface on kites, balloons and airplanes to take oblique aerial photographs of landscape. The first airplane aerial photography was conducted on 1909. These aerial photographs taken by airplanes played an important role in collecting the information about position and movement of enemy troops during First World War.

In the mid-1930s, the color photography was available. The development of films sensitive to near-infrared radiation was well established during this period. The near-infrared photography was particularly useful for haze penetration. During the 1960s, NASA (National Aeronautics and Space Administration) sponsored numerous numbers of project to study the application of color infrared and multispectral photography. As a result, multispectral imagers on the Landsat satellites were launched in the 1970s.

In the mid-1950s, an extensive work took place in the development of real-aperture airborne imaging radars. 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.

Active microwave systems have been used since the early twentieth 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 to provide topographic measurements, scatterometers to measure surface roughness, and polarimetric and interferometric imagers.

The capabilities of remote sensing satellites have been dramatically increased over the past two decades. The number of spectral channels available has grown from a few to more than 200 in the case of the Hyperion instrument. Resolutions of a few meters or less are now available from commercial vendors. Synthetic-aperture radars are now capable of collecting images on demand in many different modes. Satellites are now acquiring images of other planets in channels having more spectral bands with better resolutions than what was available for the Earth two decades ago. Moreover, as the remote sensing data have become more available, the number of applications has grown(Elachi and Van Zyl 2006).

1.3 TYPES OF REMOTE SENSING

1.3.1 ACTIVE REMOTE SENSING

In the active remote sensing, the sources have their own energy for illumination of the target. The emitted radiation by the active remote sensing system is directed toward the target to be investigated. It measures the radiation reflected/scattered from that target for acquiring the information of the target of interest. It is capable of acquiring information anytime, regardless of the time of day or season. However, it needs a large amount of energy to illuminate targets adequately.

1.3.2 PASSIVE REMOTE SENSING

In the passive remote sensing, the sun is used as a source of energy or radiation for the illumination of the target. The sun provides a very convenient source of energy for remote sensing. The sun's energy is either reflected, as it is for visible wavelengths, or absorbed and then reemitted, as it is for thermal infrared wavelengths. It can only be used to detect energy when the naturally occurring energy is available. For all reflected energy, this can only take place during the time when the sun is illuminating the Earth. There is no reflected energy available from the sun during night. Energy that is naturally emitted (such as thermal infrared) can be detected day or night, as long as the amount of energy is large enough to be recorded. A large number of visible and infrared imaging sensors like Gemini, Apollo, Skylab cameras;

the series of Landsat cameras have been flown in space to study the Earth and planetary surfaces(Elachi and Van Zyl 2006).

1.4 DIFFERENT KINDS OF REMOTE SENSING DATA

Different kind of remote sensing data acquired is dependent on the type of information being sought, as well as on the size and dynamics of the object or phenomena being studied. The different types of remote sensing data, their characteristics and their role in acquiring different types of information are summarized in Table 1.1.

Table 1.1 Different kinds of remote sensing data(Elachi and Van Zyl 2006)

Useful information required	Various Sensors	Examples of sensors
High spatial resolution and wide coverage	Imaging sensors, Cameras	Large-format cameras (1984), Seasat imaging radar (1978), Venus radar mapper (1989).
High spectral resolution over limited areas or along track lines	Spectrometers, spectroradiometer	Shuttle multispectral imaging radiometer (1981).
Limited spectral resolution with high spatial resolution.	Multispectral mappers	Landsat multispectral mapper and Thematic mapper (1972-1 984), SPOT (1984), Galileo NIMS (1989).
High spectral and spatial resolution	Imaging- spectrometer	Space imaging spectrometer (1991)
High accuracy intensity measurement along line tracks or wide swath	Radiometers, Scatterometers	Seasat scatterometer (1978)
High accuracy intensity measurement with moderate imaging resolution and wide coverage	Imaging- radiometers	Electronically scanned microwave radiometer (1975)
High accuracy measurement of location and profile	Altimeters, Sounders	Seasat altimeter (1978), Pioneer Venus Orbiter Radar (1979), Mars orbiter altimeter (1990)
Three dimensional topographic mapping	Scanning altimeters	Shuttle scanning high resolution altimeter. (Early 1990’s).

1.5 ATMOSPHERIC AFFECT

The electromagnetic radiation used in the remote sensing travel through some distance in the atmosphere before reaching the earth’s surface. The electromagnetic radiation is scattered and absorbed by gases and particles present in the atmosphere.

The electromagnetic radiation get scattered when it interacts with the particles or large gas molecules present in the atmosphere and redirects to its original path. The electromagnetic radiation is major affected by the atmospheric gases such as molecular nitrogen and oxygen as well as by other constituents like methane, hydrogen, helium and nitrogen compound. The strongest absorption occurs at wavelengths shorter than 0.3 μm mainly due to ozone. The strength of scattering takes place is dependent on several factors (a) wavelength of the radiation (b) the abundance of particles or gases and (c) the distance the radiation travels through the atmosphere. There are three types of scattering:

1.5.1 RAYLEIGH SCATTERING

Rayleigh scattering phenomenon occurs when particles are very small compared to the wavelength of the electromagnetic radiation. These particles can be small specks of dust or nitrogen and oxygen molecules. In the Rayleigh scattering mechanism, the electromagnetic radiation of shorter wavelengths to be scattered much more than the longer wavelengths of electromagnetic radiation. Rayleigh scattering is leading scattering mechanism at the upper atmosphere, it causes the sky appears "blue" during the day. As sunlight passes through the atmosphere, the shorter wavelengths (i.e. blue) of the visible spectrum scatter more than the other (longer) visible wavelengths. During sunrise and sunset the light has to travel farther through the atmosphere than at midday. During midday the scattering of the shorter wavelengths is complete that causes the greater proportion of the longer wavelengths remain to penetrate the atmosphere (Ulaby et al. 2014).

1.5.2 MIE SCATTERING

Mie scattering occur when the size of the scattering particles is comparable to the wavelength of the electromagnetic radiation in the atmosphere. The large particles (comparable to the wavelength of the radiation) are able to scatter longer wavelengths of white light equally in the atmosphere. Dust, pollen, smoke and water vapour are common causes of Mie scattering that affect longer wavelengths. Mie scattering occurs mostly in the lower portions of the atmosphere where larger particles are more abundant, and dominates when cloud conditions are overcast (Ulaby et al. 2014).

1.5.3 NON-SELECTIVE SCATTERING

The nonselective scattering mechanism occurs when the particles are much larger than the wavelength of the electromagnetic radiation. The wavelengths of the visible, near infrared, and mid-infrared spectrum of the electromagnetic radiation dominates in the non selective scattering mechanism. All these wavelengths are equally scattered in the non selective scattering mechanism. Water droplets and large dust particles can cause this type of scattering. Nonselective scattering gets its name from the fact that all wavelengths are scattered about equally. This type of scattering causes fog and clouds to appear white to our eyes (Ulaby et al. 2014).

1.6 USEFUL FREQUENCY SPECTRUM AND THEIR APPLICATIONS USED IN REMOTE SENSING

1.6.1 ATMOSPHERIC WINDOW

The portions of the electromagnetic spectrum that can be observed from the underlying earth surface or transmitted through atmosphere without any disturbances are called atmospheric windows. Different type of constitutes present in the atmosphere has its own set of absorption bands in various parts of the electromagnetic spectrum. The spectral regions outside the main absorption bands of the electromagnetic spectrum in the atmosphere can be used for remote sensing.

The various regions of the electromagnetic spectrum interact with atmospheric and ionospheric constituents. The absorption or scattering phenomenon has occurred in specific spectral regions of the electromagnetic spectrum. The Earth’s ionosphere blocks any communication to or from the earth surface in the radio frequencies below 10 MHz of the electromagnetic spectrum. The remaining portion of the radio frequency region up to the low microwave frequency (10 GHz) is effectively transparent in the atmosphere. The remaining portion of the microwave frequency region has a number of strong absorption bands due to water vapor and oxygen molecules present in the atmosphere.

The atmosphere is almost opaque in the submillimeter and far-infrared frequency regions of the electromagnetic spectrum. This opacity is due mainly to the presence of absorption-spectral bands associated with the atmospheric constituents.

This makes the spectral region most appropriate for atmospheric remote sensing. The opacity of the atmosphere is high in the some selected bands of the visible and near infrared frequency spectrum due to high absorption coefficients of a variety of electronic and vibrational processes mainly related to the water vapor and carbon dioxide molecules. In the ultraviolet frequency spectrum, the opacity of the atmosphere is mainly due to the ozone layer in the upper atmosphere region.

The presence of clouds lead to additional opacity due to absorption and scattering by cloud drops. This limits the observation capabilities in the visible, infrared, and submillimeter regions. In the microwave and radio frequency regions, clouds are transparent. Figure 1.1 shows the total atmospheric transmission at different electromagnetic frequency regions(Elachi and Van Zyl 2006).

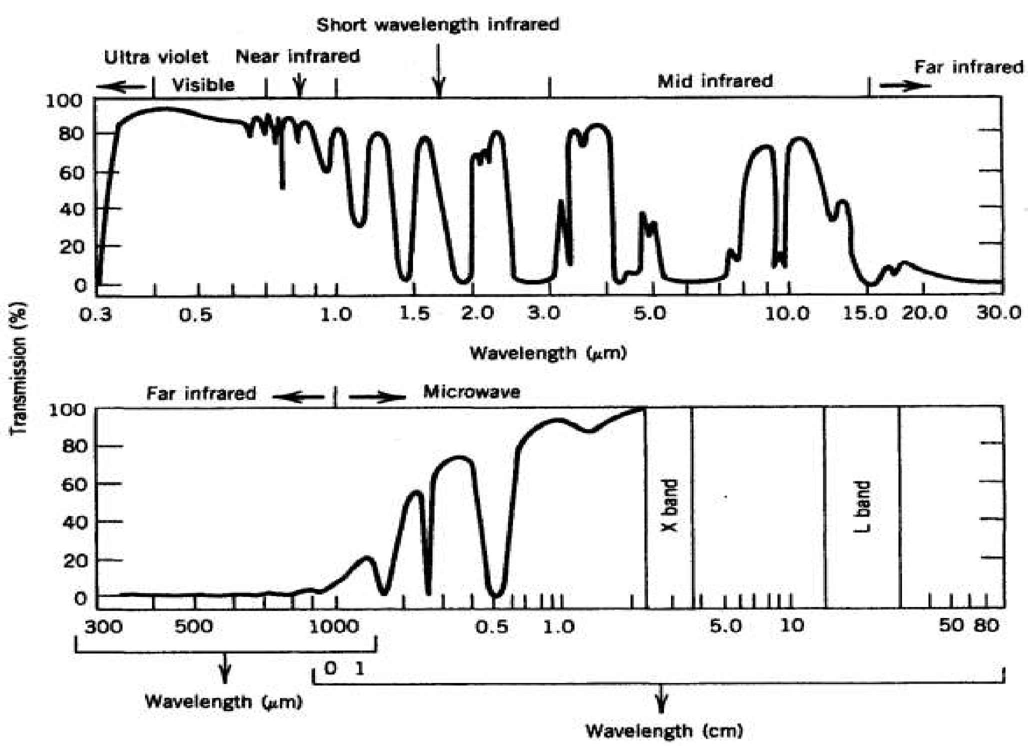

Figure 1.1 Total atmospheric transmission at different electromagnetic frequency regions (Elachi and Van Zyl 2006)

1.6.2 FREQUENCY BANDS AND THEIR USES

Some useful frequency bands of the electromagnetic spectrum used in the communication, navigation, broadcasting, radar, and passive remote sensing are presented in the Table 1.2.

Table 1.2 Electromagnetic spectrum and some of its applications(Ulaby et al. 2014)

Frequency bands	Wavelengths range	Details
Extremely High Frequency	(30 – 300) GHz	Radar, advanced communication systems, remote sensing, radio astronomy
Super High Frequency	(3 – 30) GHz	Radar, satellite communication systems, aircraft navigation, radio astronomy, remote sensing
Ultra High Frequency	(300 – 3) GHz	TV broadcasting, radar, radio astronomy, microwave ovens, cellular telephone
Very High Frequency	(30 – 300) MHz	TV and FM broadcasting, mobile radio communication, air traffic control
High Frequency	(3 – 30) MHz	Shortwave broadcasting
Medium Frequency	(300 KHz – 3 MHz)	AM broadcasting
Low Frequency	(30 – 300) KHz	Radio beacons, weather broadcast stations for air navigation
Very Low Frequency	(3 – 30) KHz	Audio signals on telephone
Ultra Low Frequency	(300 Hz – 3 KHz)	Ionospheric sensing, electric power distribution, submarine communication
Super Low Frequency	(30 – 300) Hz	Detection of buried metal objects
Extremely Low Frequency	(3 – 0) Hz	Magnetotelluric sensing of the Earth’s structure

1.6.3 FREQUENCY BANDS USEFUL IN MICROWAVE REMOTE SENSING

The microwave remote sensing has been proven as a robust tool in the various applications related to the Earth’s surfaces, oceanographic and atmospheric applications. A list of some traditional and recent applications of the microwave radars with their designation of bands is given in Table 1.3.

Table 1.3 Radar frequency band and their applications (not with IEEE standards)(Sharma 1991)

Type of band	Corresponding frequency	Important usages
VHF	50-300 MHz	Very long range surveillance.
UHF	300-1000 MHz	Very long range surveillance.
L	1-2 GHz	Long range surveillance, reroute traffic control.
S	2-4 GHz	Moderate long range surveillance, terminal traffic control, long range location.
C	4-8 GHz	Long range tracking, airborne weather detection.
X	8-12 GHz	Short range tracking, missile guidance, mapping.
Ku	12-18 GHz	High resolution mapping, satellite altimetry.
K	18-27 GHz	Little used (water, vapour absorption)
Ka	27-40 GHz	Very high resolution mapping airport surveillance.
Millimeter	40-100 GHz	Experimental

1.7 MICROWAVE SENSORS

Microwave sensor is an instrument that measures and records the emitted/reflected electromagnetic energy from the natural terrain in the microwave frequency spectrum. Microwave remote sensing instruments can be classified into two broad categories namely (a) passive sensor known as radiometers and (b) active sensor known as radar. Figure 1.2 shows the classification of microwave sensors. The passive and active microwave sensors have antennas and receivers, but radar differs from the radiometers as they include a transmitter as well. Both types of sensors can be placed on aircraft and spacecraft platform to study the Earth as well as other planets.

1.7.1 PASSIVE SENSOR

Passive sensors measure the natural radiation reflected off the objects or the energy radiated by the objects. The passive sensors work with the reflected energy during daytime when the sun is illuminating the target of interest. The passive sensors can be divided into two broad categories namely real aperture passive sensor and synthetic aperture passive sensor. The real aperture passive sensor is further divided into two sub categories namely radiometer and sounder while the synthetic aperture passive sensor is also divided into two-sub categories namely one-dimensional and two-dimensional synthetic aperture radiometer.

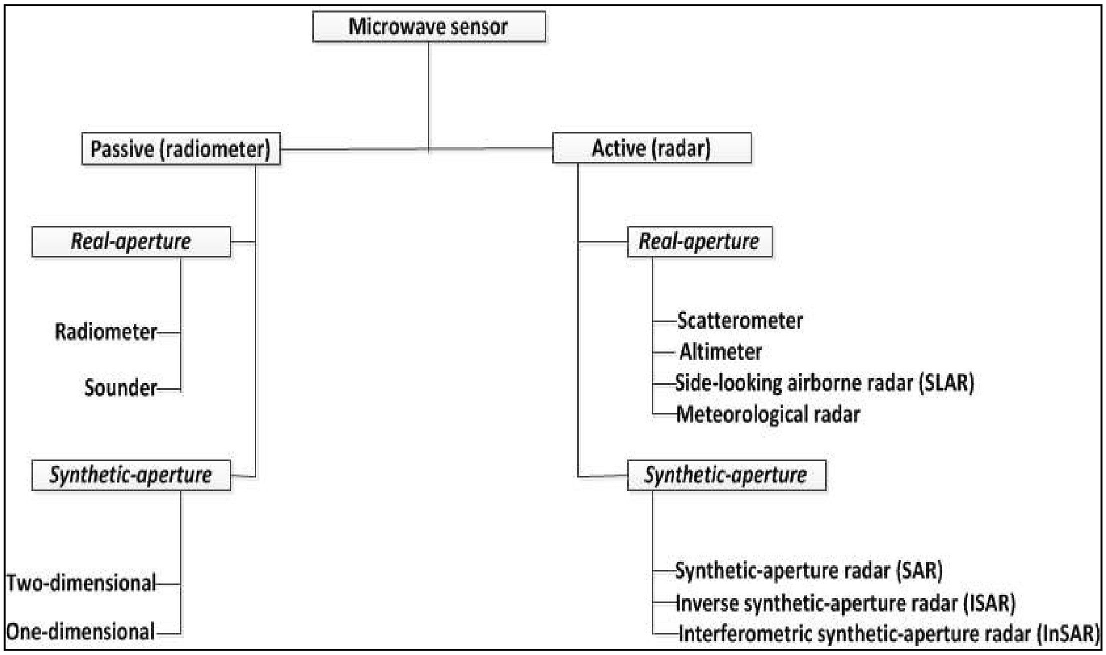

Figure 1.2 Classification of microwave sensors (Ulaby et al. 2014)

The passive microwave sensors could detect naturally emitted energy (such as thermal infrared) during day or night. Radiometers are passive microwave sensors that observe thermal emission of microwave signals from the target of interest. The emission is related to the physical temperature and electrical properties of the sensed surface or volume (target), with modulation by the intervening atmosphere. Since the radiometer contains no transmitter, radiometer consumes much less power than radar systems. Sounders are specialized radiometers designed for extracting vertical profiles of atmospheric parameters.

1.7.2 ACTIVE MICROWAVE SENSOR

Active sensors emit their own energy to illuminate the target to be investigated. The sensor measures the radiation scattered/reflected from the target under investigation. Active sensor is capable to acquire information anytime, regardless of daytime or season. However, it needs a large amount of energy to illuminate targets adequately.

Active microwave sensors can be sub classified into five general groups: synthetic aperture radar (SAR), Side-looking airborne radar (SLAR), Scatterometers, Altimeters and meteorological radars. All these active sensors operate by transmitting modulated pulses and using Doppler/range processing to measure the backscatter associated with the target under investigation. SAR sensors provide the highest resolution, but it has significantly more complex structure than other sensors. Scatterometer systems measure radar backscatter from the target very precisely. The scatterometer systems have typically lower resolution than the SARs systems. Altimeters are specialized radars systems designed to measure platform height, although other information can be extracted from the recurring echo of the target. Weather radars are specially designed scatterometer systems with ranging capability that measure rainfall and other meteorological phenomenon(Ulaby et al. 2014).

1.8 REVIEW OF LITERATURE

The knowledge about the Earth surface parameters, mainly soil moisture, is necessary for many water-budgeting processes, hydrological, meteorological and agricultural applications. Soil moisture of the top earth surfaces is very important parameter to predict the natural disasters like flooding and droughts. In the agricultural sector, the measurement of the soil surface moisture is very important to increase the productivity in the agriculture to meet the needs of increasing demand of the food. The soil moisture serves as a solvent and carrier of food nutrients for crop growth, regulates the soil temperature, responsible for chemical and biological changes in the soil. Their parameters influence the yield of the crops. The *in situ* measurement of soil moisture is too expensive because it requires a repeated sampling process to analyze the periodical changes in soil moisture. The remote sensing techniques can be used to collect information about the land surface soil moisture over a large area in a short period and in repeated intervals (Lakshmi 2013; Wang and Qu 2009).

Microwave remote sensing technique has developed enough scientific interest due to the advent of various advancements in communication and the radar technology. It is widely being used by scientists, agriculturist managers, hydrologists and engineers involved in water resources management, management of farming area, food monitoring and relief measures, damage estimates and its management etc. (Idso et al. 1975). Today the capability of active and passive microwave sensors to estimate the soil moisture content of bare soil and crop-covered fields are popular research area in the world community of scientists(Ferrazzoli et al. 1992; Schmugge 1983; Shutko 1982; Ulaby et al. 1986).

The soil surface is defined as the interface of two different but homogeneous media with different electric or magnetic properties. The incident electromagnetic wave affected at the interface of the soil surface. The first half-space can be assumed as vacuum half-space (earth atmosphere acts almost like vacuum at the microwave frequencies) and other as a dielectric half-space of dielectric constant ε. The plane electromagnetic wave incident on the dielectric earth surface and interact with atoms in the dielectric medium. These dielectric atoms become small electromagnetic oscillators and radiate electromagnetic waves in all directions. The certain amount of electromagnetic energy reradiated towards the upper half-space as well as lowers half space.

If the soil surface is perfectly smooth, the incident electromagnetic wave will excite the atomic oscillators in the dielectric medium at a relative phase such that the reradiated field consists of two plane electromagnetic waves. One plane electromagnetic wave reradiated in the upper half-space at an angle equal to the incident angle. This wave is known as reflected wave. The other electromagnetic wave reradiated in the lower half-space at an angle (θ') equal to

$$\theta' = \sin^{-1}\left(\frac{\sin\theta}{\sqrt{\varepsilon}}\right) \tag{1.1}$$

Where θ is the incidence angle. This is the refracted or transmitted electromagnetic wave.

The incident electromagnetic energy on the rough surface is scattered in all possible directions. The amount of scattered electromagnetic energy in other direction rather than Fresnel reflection direction is dependent on the magnitude of the surface roughness. If the soil surface is very rough, the electromagnetic energy is scattered equally in all the directions.

The natural soil surfaces are mainly rough surfaces. The roughness of the soil surface is the dominant factor for the scattering of electromagnetic wave incident on it. The scattering of electromagnetic wave from the rough surfaces depend on the magnitude of the roughness and the wavelength of the incident electromagnetic wave. The roughness condition (rough or smooth) of any soil surface is decided by the wavelength and incidence angle of the incident electromagnetic wave. The root mean square height (σ) and autocorrelation length (l) of the actual surface can statistically characterize the roughness of the surface. The relation of electromagnetic wave in terms of its wavelength to statistical surface roughness parameters $(\sigma \; and \; l)$ are $k\sigma$ and kl, where, $k = \frac{2\pi}{\lambda}$ indicates that the increasing wavelength is responsible for decreasing roughness term in lieu of the incident electromagnetic wave. The incidence angle of the electromagnetic wave also plays an important role in defining the roughness condition of the surface. The surface seems rougher at higher incidence angle than the lower incidence angle.

First, we consider a case for perfectly smooth surface of infinite extent and uniformly illuminated by the plan electromagnetic wave. The electromagnetic wave is reflected in the specular direction and obeys the well-known Fresnel reflection theory. In this case, no scattered energy will be received in any other direction. If the finite or infinite surface is illuminated by the finite-extent uniform wave, the situation is changed. The maximum amount of reflected power still appears in the specular direction, but a lobe structure, similar to an "antenna pattern," appears around the specular direction. This component of the scattered power is often referred as the coherent component of the scattered field. For angles far away from the specular direction, there will be very little scattered power in the coherent component.

There are two main criterion 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) between two scattered electromagnetic waves from separate points of the surface will be,

$$\Delta\phi = 2\sigma\frac{2\pi}{\lambda}\cos(\theta), \textit{ where } \sigma \textit{ is the rms height of the surface.}$$

The Rayleigh states that if the phase difference ($\Delta\phi$) between two reflected waves is less than $\frac{\pi}{2}$ radian than the surface may be considered as smooth,

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

The Fraunhofer criterion is more stringent criterion, which is adopted to the microwave region. According to this criteria, the surface can be considered as smooth, if the phase difference is less than $\frac{\pi}{8}$. This leads to equation,

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

Dielectric constant (ε′) of dry soil is essentially independent of temperature and frequency but the behavior of dielectric constant of wet soil is very complex at microwave frequencies. Over the past four decades, a number of studies have been carried out to determine the dielectric behavior of soil-water mixture at microwave frequencies (Dobson et al. 1985; Hallikainen et al. 1985; Hoekstra and Delaney 1974; Scott and Smith 1992; Wang and Schmugge 1980).

The microwave remote sensing for the estimation of soil moisture of the top Earth surface began with the understanding of strong dependence of moisture content on the dielectric constant and conductivity at microwave frequencies. The microwave response is strongly dependent on moisture content in soil surface, which occurs due to large difference between the dielectric properties of liquid water and the dry soil. The value of dielectric constant for liquid water is large owing to the alignment of the electric dipole moment of the water molecule on applying fields. The dielectric constant of water is approximately 80 as compared with 3 to 5 for dry soil at microwave frequencies. The molecule's ability to align its dipole moment along an applied field gives rise to large dielectric constant of liquid water. The dielectric constant of the water decreases if anything that would hinder the molecular rotation, e.g., freezing, very high frequencies, or tight binding with a soil particle.

A wet soil medium is a mixture of soil particles, air pockets and liquid water. The water contained in the soil is usually divided into two fractions; viz. bound water and free water. The relative fractions of bound and free water are related to the particle size distribution. The first water molecules added to the soil, which is tightly bound to the particle's surface, will contribute only a small increase to the soil's dielectric constant. If more water is added, the additional molecules are farther away from the particle surface and are freer to rotate and thus make a larger contribution to the soil's dielectric constant. Since the surface area in a soil depends on its particles size distribution or texture, clay soils, with larger water than sandy soils, thus this transition point occurs at higher moisture levels in clay than in sandy soils (Schmugge 1983).

Ulaby et al. (1978; 1979) published a series of two papers on the use of active microwave remote sensing for measuring the moisture content of bare soil (Part I) and vegetation-covered (Part II) soil in the year 1978 and 1979 respectively. In the first paper they evaluated the effect of surface roughness and a preliminary effect of the soil texture on the radar backscattering. In the second paper of this series of two papers, they demonstrated an experimental investigation to determine the relationship between radar backscatter coefficient and soil moisture for vegetation-covered soil. These investigations were carried out using scatterometers mounted on a mobile tower. The following generalizations can be made based on their investigations.

(i) The scattering coefficients (σ) increases as soil moisture increases

(ii) The scattering coefficients (σ) decreases as incidence angle increases

(iii) The maximum correlation between scattering (σ) and soil moisture of bare and smooth soil surface occurs at frequencies near 4.5 GHz and incidence angle near 10^0, and at like polarizations.

(iv) The sensitivity of scattering coefficients (σ) to soil moisture decreases as surface roughness increases.

(v) The effects of surface roughness can be minimized by operating at a frequency in the neighborhood of 5 GHz over the 7-17° angle of incidence range.

(vi) The dependence of scattering coefficients on soil texture can be minimized by expressing the volumetric soil moisture in units of percent of field capacity.

(vii) The sensitivity of scattering (σ) to soil moisture is decreased by the presence of a vegetation cover.

(viii) The highest correlation was found between scattering coefficients (σ) and soil moisture is 0.92 for the combined response of four crop types measured at 4.25 GHz, 10^0 incidence angle, and HH- polarization.

(ix) Radar look direction, relative to the crop row direction, is shown to have an insignificant effect on soil moisture estimation if the radar frequency is higher than 4 GHz.

(x) The study demonstrated a linear estimation algorithm having an experimental correlation coefficient of 0.8 for estimation of soil moisture for both bare and vegetated fields.

During the past three decades an extensive studies have been conducted on bare soil and agricultural fields. These researches aimed to retrieve the soil moisture and other soil surface parameters using ground based scatterometers, space borne synthetic aperture sensors and airborne synthetic aperture radars(Baghdadi et al. 2002; Bruckler et al. 1988; Dobson and Ulaby 1986; Dubois et al. 1995; Fung et al. 1992; Oh 2004; Oh et al. 1992; Quesney et al. 2000; Shi et al. 1997; Ulaby et al. 1978; Zribi and Dechambre 2003). They have developed empirical, semi empirical and physical models for the retrieval of soil surface parameters using radar data. The most important problem in the development of soil moisture retrieval algorithm has been the confounding influences of surface roughness conditions, and vegetation cover over the soil surface which dominantly affect the relationship between radar backscatter and soil moisture (Oh and Kay 1998). The dynamic range of back scattering coefficient due to variations in the surface roughness is generally comparable to or larger than that associated with soil moisture, therefore an accurate estimate of the contribution of surface roughness conditions is a prerequisite for retrieving the soil moisture information from SAR (Davidson et al. 2002).

Empirical models were developed using data obtained by several measurements of the backscattering coefficients (σ^0) from different general boundaries or conditions that can be applied to obtain reasonably accurate soil-moisture estimation(Walker et al. 2004). However, empirical models may not be applicable when the set of conditions is changed, such as frequency, incidence angle, polarization, surface roughness, surface texture vegetation density etc. There are some empirical models that are designed by researchers using different sensor configurations like polarization, incidence angle and frequency to estimate soil roughness and soil moisture (Dubois et al. 1995; Oh et al. 2002; Zribi and Dechambre 2003). The semi-empirical models find an agreement between empirical models and theoretical models by having common rules derived from both models. These models are derived by empirical fitting between experimentally measured backscattering coefficients and soil surface parameters. The theoretical models are derived under restrictive theoretical basis to predict the general trend of backscattering coefficient in response to changes in soil roughness or soil moisture (Ulaby et al. 1996; Walker et al. 2004). Theoretical models are good for describing the soil surface parameters based on a theoretical point of view.

The empirical, semi-empirical and theoretical models are very useful to develop the understanding of the backscattering from the soil surfaces by estimating the soil surface parameters. However, there are some limitations in the use of these approaches. For example, the Kirchhoff models (KA) is valid when the surface mean radius of curvature is large compared to the wavelength of incidence wave(Khadhra 2008).

Njoku and Li (1999) have developed a theoretical model to retrieve the surface soil moisture. This theoretical model needs certain parameters or more number of observations to retrieve the surface soil moisture. Some parameters of this theoretical model such as soil surface roughness and vegetation single-scattering albedo cannot be measured easily and hence must be estimated from empirically derived model. It is a very tedious procedure to retrieve the surface soil moisture. Ulaby et al.(1982) developed a theoretical model that may be appropriate for a wide range of surfaces to retrieve the soil moisture. It require an extensive *in situ* measurements of vegetation variables such as leaf size, stem diameter, leaf diameter, crown diameter and orientation, etc. and terrain variables such as surface roughness, correlation length, and autocorrelation length. An empirical model developed by Owe et al.(2001b) to estimate the soil moisture using optical depth and microwave polarization index (MPDI). This model needs observation with two polarizations and does not provide information about surface parameters**.** Wigneron et al.(1995) have developed a model to retrieve the soil moisture. This model is based on optical depth-albedo and radiative transfer theory. This method needs multi frequency data, and a solution is very complex to retrieve the soil moisture.

Srivastava et al (2003) proposed an approach to incorporate the effect of surface roughness in the estimation of soil moisture from space without actually measuring surface roughness conditions on the ground. They acquired the RADARSAT-1 SAR data over the parts of Agra, Mathura, and Bharatpur districts, India, at low and high incidence angles. The change in soil moisture was found negligible between the two acquisitions SAR data at two incidence angles. They found that the inclusion of $\frac{\sigma^\circ_{low}}{\sigma^\circ_{high}}$ dB as an extra term in the soil moisture retrieval model developed with σ°_{low} dB to be useful for large area soil moisture estimation.

The retrieval of crop variables plays a key role in the monitoring of agricultural crops regularly. Agriculture plays a vital role in the Indian economy. Over 70 per cent of the rural households depend on agriculture as their principal means of livelihood. Agriculture along with fisheries and forestry accounts for one-third of the nation’s Gross Domestic Product (GDP) and is its single largest contributor. Agricultural exports constitute a fifth of the total exports of the country (http://mospi.nic.in/Mospi_ New/upload/as_4.html).

Nowadays, the radar remote sensing technology has become a very popular and reliable tool to acquire timely and more accurate information about the earth soil moisture and the biophysical parameters of the agricultural crops. The regular monitoring of agricultural growth at its different growth stages is important for any country to estimate the agricultural production. This information is important to make a strategy that may reduce the production risk and increases efficiency in crop management and production. The sufficient agricultural production may be useful to establish the balance between food consumption and food production for billions of people of any country.

The population of the world is increasing and it is expected to reach 9.1 billion in 2050. One of the main problems is to know, how to feed such a huge population when the agricultural land is not increasing. Therefore, some techniques must be developed for the crop management which can provide information about the crop yield, crop parameters estimation and crop type identification and knowing the crops suitable for harvesting in that area etc. without affecting forests, mountain lands and rivers. Botanical scientists are working to provide the new shades, by using new way of cultivation techniques. However, without proper management of any system, no one can achieve the desired output.

Retrieval of crop growth variables is necessary to monitor the condition of the plant, together with the actual plant phenological stage during the growth period of crop and soil parameters. Those parameters are plant height, LAI (Leaf Area Index), plant biomass or nitrogen content, chlorophyll content etc. The phenology development of any crop is the succession of biological events during the plant life. The phenology development of crop is often simulated in terms of measurement of the LAI, the plant biomass, the plant height, chlorophyll content etc. The biological processes in the crop occur due to the photosynthesis processes and biomass allocation. Crops absorb nitrogen through the roots system and fix it in their elements. The nitrogen content in the leaves is related to the chlorophyll content, which is easier to measure than nitrogen content. Leaf area index is the total one-sided area of leaf per unit ground surface area. It is a key parameter to exchange most of the energy fluxes between the canopy and atmosphere interface. The amount of intercepted radiation is a function of the LAI. Fraction of photosynthetically active radiation (fPAR) is the part of intercepted radiation, which crop uses efficiently for biomass accumulation.

The optical remote sensing data is well established for crop monitoring and mapping. A well-known limitation of optical data is the presence of the cloud cover that prevents the acquisition of images at the measuring time. Microwave remote sensing data, in contrast, has the advantage of being independent from cloud cover and thus show a high potential for crop classification and monitoring.

Chakraborty et al (2005) studied the temporal backscattering response of rice crop for rice growing region in West Bengal, India, using RADARSAT SAR data. They carried out correlation studies of backscattering coefficients with crop growth parameters and found second order polynomial best fitted with crop age and crop height with an overall 90% accuracy. Gumma et al (2015) studied the direct seeded and transplanted rice field's response using multiple-sensor remote sensing imagery of Raichur District of Karnataka, India. Choudhury and Chakraborty (2006) investigated the potential of multi-temporal RADARSAT ScanSAR Narrow Beam data to monitor rice crop growth and condition with special emphasis to the signature analysis of the crop in the Baleshwar and Bhadrak districts of Orissa. Chen et al.(2006) proposed a semi-empirical backscattering model to estimate leaf area index (LAI) of rice using ENVISAT Advanced Synthetic Aperture Radar (ASAR) data. The estimated values of LAI from the model were compared with the ground-measured values of LAI to evaluate the accuracy of the model. Oh et al. (2009) showed that the backscattering coefficients of a rice field can accurately be modeled using the radiative transfer theory. They also demonstrated that a polarimetric scatterometer is an effective tool for estimating rice growth. Brown et al.(2003) carried out a polarimetric X- and C-band measurements using ground-based synthetic aperture radar (GB-SAR). They suggest that the sensitivity to biomass and reduced susceptibility to disturbances by rainfall, a two-channel C-band system operating at a medium range of incidence angles is preferred.

The microwave response of crop/vegetation growth variables depends in significant manner on the crop/vegetation type. The crops can be classified into two categories namely broad leaf crop (soybean, kidney bean, etc.) and narrow leaves crop (wheat, rice, etc.). The two different types of behaviour of back scattering coefficient at microwave frequencies have been observed corresponding to broad leaf crops and the group of crops characterized by narrow leaves. In the first case, scattering appears to be the dominant interaction mechanism, whereas absorption plays a major role in backscattering from plants with smaller crop constituents (Macelloni et al. 2001).

The microwave response of crop depends on frequency due to variation in the dielectric constant of water as a function of frequency. The dielectric property of an object or medium is strongly dependent on the amount of moisture content. The variation in the dielectric properties affects the absorption, transmission and reflection of microwave radiation. Hence, the moisture content of crop influences reflection/scattering response of microwave. However, in general, the reflectivity increases with increase in moisture content. The crop/vegetation is composed of significant and varying amount of water content. Hence, the frequency dependence of the dielectric constant is very important to understand the interaction mechanism of microwave with crop/vegetation and soil parameters(Barrett et al. 2009).

The vegetation water content was observed higher at the early growth stages of the crop and later decreases with the age of the crop. It was observed that the backscattering coefficients were closely related with the vegetation water content (Ulaby et al. 1982). Kim et al (2014) proved that the radar vegetation index (RVI) has low sensitivity to changes in environmental conditions and has the potential as a tool to monitor vegetation growth. They carried out observations using ground-based multi frequency polarimetric scatterometer system over an entire wheat growth cycle. They established a relationship between radar vegetation index of L-, C-, and X-bands with the vegetation water content (VWC) and fresh weight. The results found that the L-band RVI was highly correlated with both VWC ($r = 0.98$) and fresh weight ($r = 0.98$) based on linear regression analysis and root-mean-square error of VWC (RMSE = 0.126 kg/m^2) and fresh weight (RMSE = 0.12 kg/m^2).

The monostatic systems are extensively used for ground based, airborne and space borne microwave remote sensing measurements over agricultural crops. Taconet et al. (1994) studied the radar backscattering signature of wheat crop in the range of incidence angle 15° to 45° for HH- and VV- polarizations at C- and X- bands for different soil moisture conditions with simultaneous ground data measurement. They collected the data using airborne scatterometer system over agricultural watershed. They found the water cloud model with two deriving parameters namely soil moisture and plant water content. They achieved better results to estimate the backscattering coefficient of wheat crop for a wide range of frequencies (C and X bands) and incidence angles (20° and 40°) within 1 dB and 2 dB at HH and VV polarization respectively.

Kim et al.(2013) carried out a ground-based polarimetric scatterometer measurements over the growth period of rice crop at X-, C-, and L-bands frequencies. They compared the backscattering coefficients and rice growth variables from transplanting to harvesting. They found the backscattering coefficients, at L-band and HH- polarization highly correlated with the total fresh weight, leaf area index, and plant height indicated by higher values of R^2 0.97, 0.96, and 0.88, respectively. Oh et al.(2009) measured the backscattering coefficients of a flooded rice field using L- and C-band ground-based polarimetric scatterometer to understand the feasibility of modeling and estimating rice growth. They collected the ground truth data that included fresh and dry biomass, plant height, leaf area index, and leaf size along with scatterometer data collected at four different incidence angles (30°, 40°, 50°, and 60°) and polarizations (HH-, VV- HV- and VH-). Saatchi et al.(1994) had reported the microwave backscattering and emission model for grass canopies. Stiles et al. (2000) had reported modeling results of the measurement of electromagnetic scattering from grassland by using radar-backscattering data. All these reports confirm that the monostatic (backscattering) systems are widely used by the researchers in the microwave study of crop and vegetation.

Cost (1965) carried out the first experimental bistatic measurement at Ohio State University. They performed a series of outdoor bistatic measurements for different kinds of natural terrain with the transmitter and receiver mounted on two movable trunk mounted booms. Only amplitude (no phase) of the scattered signal was measured for the wide range of incidence and receiving angles. The first airborne bistatic measurement was performed using two aircraft at Applied Electronics Laboratories, Stanmore, Middlesex UK. The first aircraft transmitting a continuous wave in X-band and receiver were placed on the second aircraft to receive the scattered signal from the target. They were distinguished into three sub-terrain classes—buildings, trees and open grassland using low-resolution images produced (Domville 1967, 1968, 1969).

De Roo (1996) carried out bistatic indoor experimental measurements of different rough surfaces with constant soil moisture at X-band that validates different surface scattering models for rough surfaces. Khadhra (2008) developed the Bistatic Measurement Facility (BMF) in DLR Laboratory of Germany for the measurement of microwave response from rough and moist soil surface in bistatic fashion for X-band at HH- and VV-polarization. In this study, the specular algorithm is used to estimate the soil moisture of two surface roughnesses (rough and smooth). He presented a new technique to estimate the soil roughness using the coherent term of the Integral Equation Method (IEM) and showed the phase sensitivity to the soil moisture in the specular direction.

Few researchers have attempted to use the bistatic measurement for the microwave crop-signature study. Some of them like Ulaby et al.(1988) studied the bistatic scattering from ground and vegetation targets. Singh et al.(1996) studied the effect of soil moisture and crop cover in remote sensing. Pandey et al.(2011) investigated the microwave signature of several crops and bare soil surface using bistatic scatterometer data and soft computing techniques. Recently some researchers have made different approaches for crop monitoring using bistatic satellite data. Erten et al.(2015) showed that the TanDEM-X mission is capable of tracking the plant growth of rice crop. They compared the performance of vertical and horizontal polarizations of TanDEM-X for the temporal mapping of rice crop height. The difference in height was found 10 cm between the rice plant height measurements in the HH and VV channels of TanDEM-X at reproductive stage. Rossi and Erten (2015) have evaluated the potential of spaceborne bistatic interferometric synthetic aperture radar images for the monitoring of biophysical variables of rice crop. The X-band differential bistatic interferometery radar images showed great benefit in elevation mapping of plant height of rice crop by 32 digital elevation models (DEMs).

Therefore, it is needed to explore the potential of bistatic radar for monitoring the growth stages of crop/vegetation

The crop variables/soil surface parameters and the radar backscattering/bistatic scattering have a complex and non-linear relationship mostly because the dynamic of crop variables/soil surface parameters are influenced by a variety of environmental factors, e.g. surface roughness, soil texture, crop type and density of vegetation, etc. Previous studies have used linear regression models to represent the relationship between backscatter coefficient and soil moisture(Ulaby et al. 1981). This linear relationship is better correlated in the case of bare soil surface. However, the presence of vegetation reduces the sensitivity between the backscatter and soil moisture. Many theoretical, semi-empirical and empirical modeling approaches have been developed for better understanding of interactions of microwave signal with crops/soil surface parameters (Karam et al. 1992; Le Toan et al. 1997; Liu et al. 2002; Macelloni et al. 2001). These models are also used to estimate the biophysical parameters of different crops and several soil surface parameters. The inversion of these models is very tedious in nature. It is needed to develop less complex and fast techniques for modeling the crop variables/soil surface parameters with the radar data.

In the recent past, the artificial intelligence techniques (i.e. artificial neural network, fuzzy logic, support vector machine for regression and genetic algorithm etc.) are more popular for agricultural applications using radar data (Chen and McNairn 2006; Gupta et al. 2015; Jiang et al. 2004; Pandey 2011; Pandey et al. 2013; Pandey et al. 2012; Prasad et al. 2009). Artificial neural networks (ANNs) have become a popular tools in the analysis of remotely sensed data mainly due to their widely demonstrated abilities (Benediktsson et al. 1997; Foody 1995; Foody et al. 1995; Hewitson and Crane 1994; Kumar et al. 2015). Due to having several qualities, ANNs have been reported to perform more accurately than the other techniques, such as statistical classifiers, particularly when the problem taken is complex and the source data have different statistical distributions (Schalkoff 1992).

It has been shown that ANNs may be used to classify remotely sensed data more accurately than maximum likelihood and spectral angle mapper (Frizzelle and Moody

2001; Kavzoglu and Mather 1999; Murthy et al. 2003; Paola and Schowengerdt 1995; Seto and Liu 2003).

Over the past two decades, the artificial neural networks have been extensively used to analyze the soil parameters using remote sensing data (Chang and Islam 2000; Hsu et al. 1995; Notarnicola et al. 2008). Pandey et al.(2010) evaluated an ANN based algorithm for the estimation of soil moisture and soil surface roughness using bistatic scatterometer data. They used two training algorithm namely Levenberg-Marquardt (TRAINLM) and Gradient-Descent (TRAINGD) of feed forward back propagation neural network for this purpose. Veena and Sinha (2011) developed an ANN architecture using back propagation algorithm to estimate the soil moisture using radiometer data. Baghdadi et al.(2002) implemented an inversion technique based on neural networks to estimate surface roughness and soil moisture over bare fields using European Remote Sensing (ERS) and RADARSAT data.

Notarnicola et al. (2008) applied ANN approaches and statistical methods, based on a Bayesian procedure for the retrieval of soil moisture (SM) from remotely sensed data. Jiang and Cotton (2004) evaluated an ANN based algorithm for soil moisture estimation. They suggest that the ANN model is a promising alternative to soil moisture estimation effectively using remotely sensed data. Gupta et al.(2014) demonstrated the potential of ANN approach based on Levenberg Marquardt (TRAINLM) algorithm for retrieving soil moisture using bistatic scatterometer data at X-band for HH- and VV- polarization. They found that the estimation of soil moisture by BPANN with Levenberg Marquardt training algorithm is better at both HH- and VV- polarizations.

ANNs, mainly MLPs, are generally reported as successful in retrieving parameters such as biomass, leaf area index, fraction of photo-synthetically absorbed radiation (fPAR), nitrogen, water content and chlorophyll. For example, Kimes et al.(1999) used spectral and textural information to predict secondary forest age with an RMSE of 2 years. Kimes et al.(1998) reviewed the application of ANNs in the extraction of vegetation variables from optical and radar images. ANNs have also been applied successfully for the retrieval of water parameters such as chlorophyll and sediment contents, as well as bathymetry. Chen and McNairn (2006) used a neural network-based yield model to predict rice yield on a regional basis for the wet season. Del Frate et al.(2003) trained two neural network algorithms by a physical vegetation model that are used to retrieve soil moisture and vegetation variables of wheat canopies during the whole crop cycle.

Jia et al.(2013) studied the potential of artificial neural network to the estimation of rice crop biomass using quad polarized ground based scatterometer and RADARSAT-2 data. They found high correlation coefficients between measured rice crop biomass and estimated rice crop biomass using both the data (ground based scatterometer and RADARSAT-2 data). Pandey et al.(2012) developed two artificial neural network models namely general regression artificial neural network (GRANN) and radial basis function artificial neural network (RBFANN) that are used to estimate crop variables namely leaf area index (LAI), biomass (BM), plant height (PH) and soil moisture (SM) by using ground based X-band scatterometer data. Prasad et al.(2009) proposed an approach to retrieve the soil moisture and crop variables using ground based scatterometer data and ANN.

1.9 STATEMENT OF THE PROBLEM

The specific objectives of the present thesis are: 1) to study the microwave response of soil moisture of bare rough soil surfaces using bistatic scatterometer system. 2) to study the microwave response of the different agricultural crops at various growth stages using bistatic scatterometer system for the monitoring of agricultural crops. 3) to check the ability of artificial neural networks for the estimation of soil moisture and crop variables using bistatic scatterometer data.

In the past few decades, uses of experimental investigation of backscattering from natural terrain has increased greater than before. However, a small number of literatures of the experimental investigation of bistatic electromagnetic scattering from natural terrain have been reported. Only theoretical models have been developed for scattering from random rough surfaces for the bistatic case. The usefulness and validity of these theoretical models is largely unknown. The combined modeling of natural terrain for radar backscattering and bistatic scattering can contribute significantly from over structure terrain (eg. trees or crops). Therefore, an understanding of the nature of bistatic radar scattering and knowledge of the behavior of bistatic scattering theories are needed. The applications of bistatic scattering are not as straightforward as for backscattering. Recently a space mission has been started by German Aerospace centre (DLR) and EADS Astrium, with twins satellite (TanDEM-X and TerraSAR-X) for bistatic radar to generate a three dimensional image of the Earth.

These theoretical models can be inverted to estimate the crop variables/soil moisture and study the microwave response of varying crop-soil variables. These models may be excellent tool for understanding the scattering mechanism and estimating the crop variables/soil moisture. However, they consist of rather complex set of equations. It is also difficult to relate statistical properties of dielectric permittivity of the canopy to crop variables/soil moisture. These models require numerous biophysical and soil parameters for accurate estimation of the crop variables. The involvement of large number of variables and parameter make their inversion complicated and cumbersome task.

For examples, Cookmartin et al.(2000) developed a multilayer second order radiative transfer model. The limitation of Cookmartin (2000) model is that it needs the attenuation parameters of various layers and inversion of this formulation is quite complex to retrieve the crop variables. Picard et al.(2003) has developed multiple scattering coherent models for understanding C-band radar backscatter from wheat canopy. In Picard et al. (2003) model, it is difficult to calculate multiple scattering interactions, which increase the complexity of electromagnetic problem. Multiple scattering equations were applied to the case of vertical cylinders over an infinite surface. The major problem is to solve the multiple scattering equations. Thus, these models are either very complex to solve or require a large number of input data to retrieve the crop variables and to understand the individual response of crop variables on microwave scattering/absorption. The quantitative understanding of the contribution by each crop variables to scattering, attenuation and the relative magnitude of the scattering from the soil and the vegetation is still a matter of debate.

The model free techniques are required for the retrieval of crop-soil variables. These techniques are capable to provide the best results with less complexity. Therefore, in the context of these requirements the artificial neural networks (ANNs), support vector machine (SVM) and fuzzy logic (FL) are currently being applied in a wide variety of remote sensing applications.

In the present thesis, bistatic measurements were carried out for four crops (rice, kidney bean, wheat and chickpea) at its various growth stages to analyze the microwave response of crop parameters using different combination of sensor parameters (polarization and incidence angles). The bistatic measurements also carried out for the rough bare soil surfaces at different soil moisture conditions to analyze the microwave response of soil moisture. The artificial neural network used to estimate the crop-soil variables using bistatic scatterometer data.

1.10 ORGANIZATION OF THESIS

The thesis work presented here is divided in the following parts –

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

Chapter 2- This chapter describes an experimental procedure for the computation of bistatic scattering coefficients from bare soil surfaces and different types of crops. It also discusses the measurement of soil surface parameters and crop biophysical parameters.

Chapter 3- In this chapter, an attempt is made to discuss the retrieval procedure of the soil moisture from rough surfaces using three different artificial neural network algorithms (back propagation artificial neural network, radial basis artificial neural network and generalized regression artificial neural network) along with a liner regression model. In this study, the comparison of all these models is presented for the estimation of soil moisture from slightly rough soil surfaces using bistatic scatterometer data.

Chapter 4- In chapter IV, the muti-temporal and multi-angular bistatic scatterometer measurements is carried out to investigate the microwave response of rice crop at HH- and VV- polarization for X-band. The rice crop parameters are estimated using bistatic scatterometer data and feed forward back propagation neural network at its various growth stages. For this purpose, a polynomial regression analysis is done to find the suitable incidence angle for the operation of bistatic scatterometer at both like polarizations. Two types of feed forward back propagation artificial neural networks (FFBPANN) are developed for the estimation of rice crop variables.

Chapter 5- In this chapter the bistatic scatterometer measurement were carried out to analyze the microwave response of kidney bean crop at its various growth stages for HH- and VV- polarization in the angular range of 20° to 70° at X-band frequency. The regression analysis was carried out between kidney bean crop variables and bistatic scattering coefficient to determine the suitable bistatic scatterometer configuration for the accurate estimation of crop variables of kidney bean crop. The reliable relationship between the bistatic scattering coefficient and crop variables were established to generate large input data set by empirical models for the training of artificial neural network (ANN). The ANN was used to solve the inversion problem for the estimation of crop variables.

Chapter 6- The present chapter discusses a microwave crop-signature study for wheat crop at X-band using ground based bistatic scatterometer system. An outdoor experiment was designed for observing the microwave response of wheat crop at its various growth stages. An ANN model was used to estimate the wheat crop parameters at its various growth stages using bistatic scatterometer data.

Chapter 7- This chapter describes a microwave crop-signature study for chickpea crop at its various growth stages using X-band ground based bistatic scatterometer system. An outdoor experiment has designed for observing the microwave response of chickpea crop at its various growth stages. An ANN model was used to estimate the chickpea crop variables at its various growth stages using bistatic scatterometer data.

Chapter 8- Includes the conclusion and future aspects of the research work done in the present thesis.