CHAPTER 1

INTRODUCTION

1.1 REMOTE SENSING AN OVERVIEW

Remote sensing is the science/ technology for the acquisition of information about an object or phenomenon without making physical contact with the object. The remote sensors may be mounted on aircraft or satellite to collect data by detecting the energy reflected/ scattered from the target of interest. The electromagnetic spectrums such as microwaves, infrared and visible are used in the remote sensing to acquire information about any distant object. However, microwave has advantage over the visible and infrared rays. Microwave remote sensing has own source of energy, transmits an electromagnetic wave which can penetrate easily clouds and up to some extent rain (Lillesand and Kiefer, 2002; Schowengerdt, 2006).

The term remote sensing was introduced first time in 1960s. Before the 1960s, the term used for remote sensing was generally known as aerial photography. During 1960s to 1970s, the primary platforms used for carrying remotely sensed instruments were shifted from airplanes to the satellites. Satellites can cover much more land space than the airplanes and can monitor especially remote areas on a regular basis. In the 1960s, NASA (National Aeronautics and Space Administration) sponsored several schemes for the application of color infrared and multispectral photography. Color-infrared imagery uses a portion of the electromagnetic spectrum known as near- infrared (NIR). It ranges from 0.70 μm to 1.0 μm, just beyond the red color of the wavelength. The NIR photography is particularly useful for haze penetration. As a result, the Landsat satellite was launched in the 1970s for the acquisition of multispectral imagery (Lillesand and Kiefer, 1999; Jensen, 2005; Elachi and Van Zyl, 2006).

The efforts were made for the development of Synthetic Aperture Radars (SARs) since 1950s using coherent signals to achieve high-resolution capability from the high-flying aircraft. These systems became available to the scientific community in the mid of 1960s. Since then, work is continued to develop the capability of radar sensors for wide application globally. The imageries from the active microwave sensors look very similar to regular photography, except image brightness due to scattering properties of the different surfaces in the microwave region. Passive microwave sensors were developed to provide images of the microwave emission from the natural objects. The capability of remote sensing satellites has been dramatically increased over the past two decades (Jensen, 2005; Elachi and Van Zyl, 2006; Ulaby et al., 2014). Remote sensing can be classified in to two ways as passive and active.

1.1.1 Passive remote sensing

In the passive remote sensing, sensors record natural radiation that is reflected or emitted from the earth's surface. The energy of the sun is reflected at the visible wavelengths or absorbed and then re-emitted at thermal infrared (TIR) wavelengths.

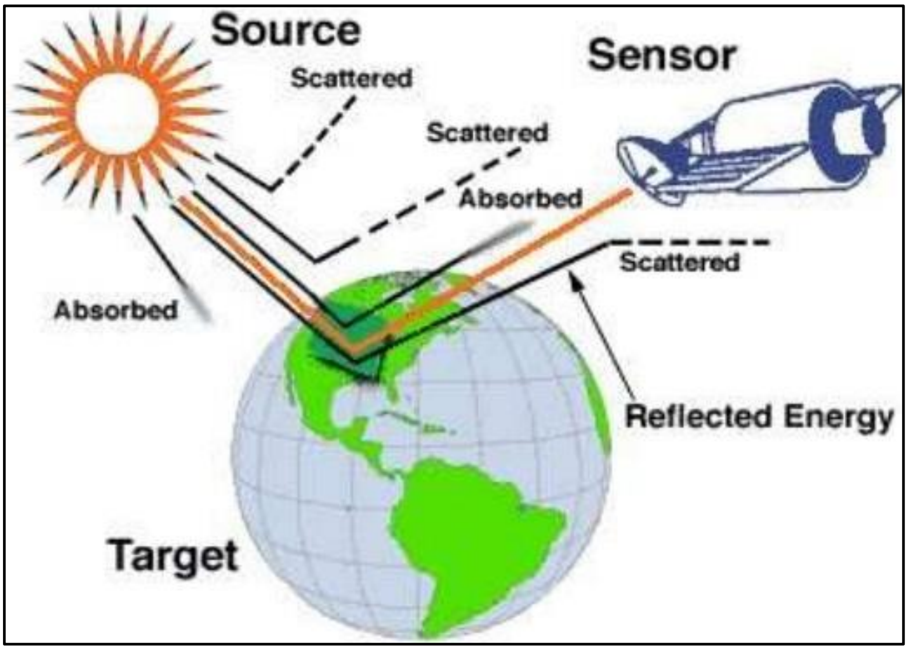


Figure 1.1 Data acquisition by the passive remote sensing process
(**Source:** Orerinpu.ws.gy/lexon/uncertainty-in-remote-sensing-and-gis-279.php)

The reflected energy can be observed only when the sun is illuminating the earth. The TIR energy naturally emitted can be detected in the day or night time. The film photography, infrared (IR), charge coupled devices and radiometers are the different types of passive sensors (Hord, 1982; Lillesand and Kiefer, 2002; Elachi and Van Zyl, 2006). Data acquisition by the passive remote sensing process is shown in Figure 1.1.

1.1.2 Active remote sensing

Active sensors provide their own source of energy for the illumination of the target of interest (e.g. SAR and Light Detection and Ranging (LiDAR)). The radiation reflected or backscattered from the target is detected and measured by the sensors. Active sensors are capable to acquire information anytime, regardless of the time of day or season. Nevertheless, it needs a large amount of energy to illuminate targets adequately (Lillesand and Kiefer, 2002; Jensen, 2005; Ulaby et al., 2014). Data acquisition by the active remote sensing is shown in Figure 1.2.

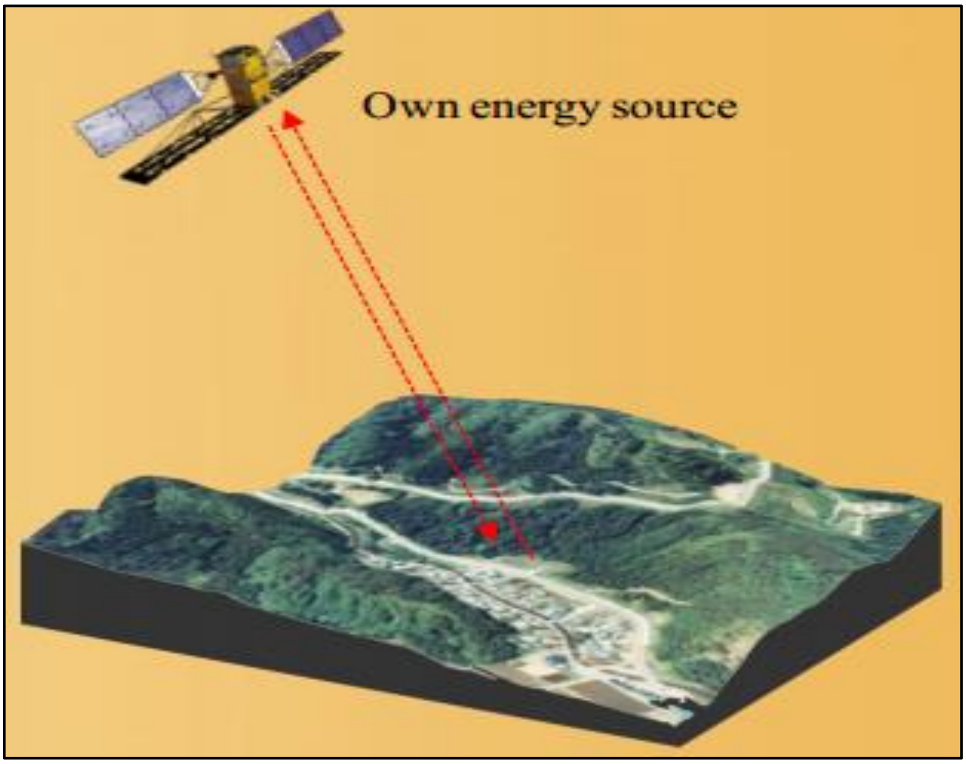


Figure 1.2 Data acquisition by the active remote sensing process
(**Source:** Lwin, 2008)

1.2 ELECTROMAGNETIC WAVES USED IN THE REMOTE SENSING

The wide range of frequency encountered in our physical world, ranging from the low frequency of the radio waves to the very high frequency of the gamma rays. This wide frequency range of electromagnetic waves constitutes the electromagnetic spectrum as shown in Figure 1.3. The most widely used electromagnetic waves in the remote sensing are the visible, infrared and microwaves. The visible light extends from about 400-430 nm (violet), 430-450 nm (indigo), 450-500 nm (blue), 500-570 nm (green), 570-590 nm (yellow), 590-610 nm (orange) to about 610-700 nm (red). Infrared lies between near infrared (NIR: 0.7-1.5 µm), short wave infrared (SWIR: 1.5-3 µm), mid wave infrared (MWIR: 3-8 µm), long wave infrared (LWIR: 8-15 µm) and far infrared (FIR: >15 µm).

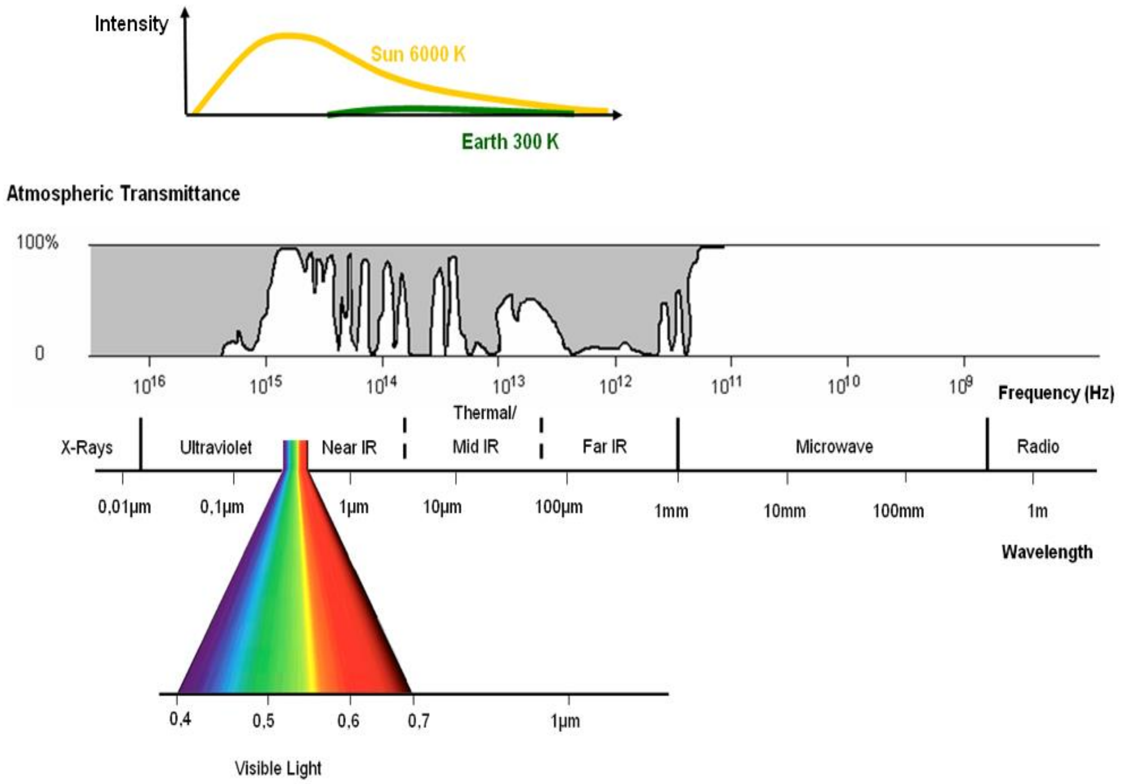


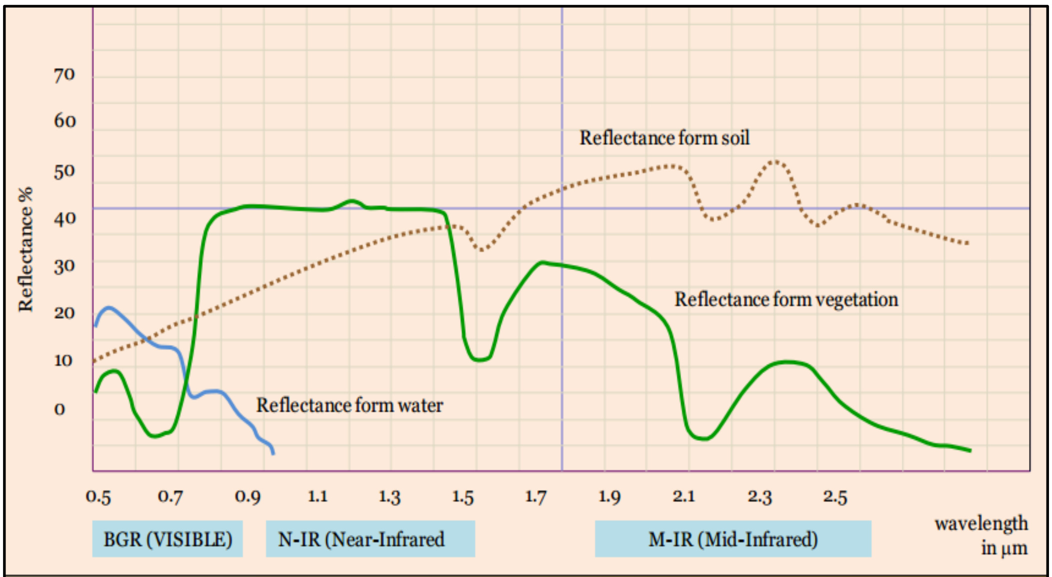
Figure 1.3 Electromagnetic waves used in the remote sensing
(**Source:** Lwin, 2008)

Microwave is divided into different bands such as P-band (0.3-1 GHz), L-band (1-2 GHz), S-band (2-4 GHz), C-band (4-8 GHz), X-band (8-12.5 GHz), Ku-band (12.5-18

GHz), K-band (18-26.5 GHz) and Ka-band (26.5-40 GHz) (Richards, 1999; Lillesand and Kiefer, 2002; Jensen, 2005).

1.3 SPECTRAL REFLECTANCE AND EARTH SURFACE INTERACTION

The typical spectral reflectance curves for three basic types of earth features like vegetation, soil and water are shown in Figure 1.4. These curves indicate how much incident energy would be reflected from the surface, and consequently recorded by the remote sensing instrument. The object would appear brighter in an image due to higher reflectance at a given wavelength. The vegetation reflects much more energy in the NIR (0.8 to 1.4 µm) in comparison to visible light (0.4 to 0.7 µm).



Surface category	Low reflectance	High reflectance
Water	N-IR (Near -Infrared)	Blue (Visible)
Vegetation	M-IR (Mid-Infrared)	N-IR (Near-Infrared)
Soil	Blue (Visible)	M-IR (Mid-Infrared)

Figure 1.4 Spectral reflectance curves for soil, vegetation and water
(**Source:** Swain and Davis, 1978)

The energy reflected from the vegetation is related to the internal structure of the plant and the amount of moisture in the plant. Vegetation has generally three reflectance valleys. The red (0.61-.70 µm) spectral wavelength region is caused by high absorptance of energy by chlorophyll present in the leaves. The other two wavelengths regions at 1.45-1.55 µm and 2.10-2.20 µm are caused due to high absorptance of energy by the water present in the leaves. The spectral reflectance due to clear water is < 10% at visible light, thus it appears dark in the infrared images due to high absorption at NIR. Dry soil has relatively a flat reflectance curve. When it is wet, its spectral reflectance drops due to water absorption (Swain and Davis, 1978; Lillesand and Kiefer, 1999; Jensen, 2005).

1.4 RESOLUTIONS IN THE REMOTE SENSING

The quality of remote sensing data depends on its different resolutions such as spatial, spectral, radiometric and temporal resolutions (Hord, 1982; Lillesand and Kiefer, 2002; Schowengerdt, 2006).

1.4.1 Spatial resolution

Spatial resolution is a measure of the area or size of the smallest dimension on the earth's surface over which an independent measurement can be made by the sensor. Spatial resolutions of some of the satellites like IKONOS, Linear Imaging Self-scanner (LISS-IV), Sentinel-1A, Radar Imaging Satellite–1 (RISAT-1) and Landsat-8 OLI (Operational Land Imager) are 1 m, 5.8 m, 20 m, 25 m, and 30 m, respectively.

1.4.2 Spectral resolution

Spectral resolution is the ability of a sensor to resolve the energy received in a spectral bandwidth to characterize different constituents of the earth surface. If the resolution is too low, spectral information will be lost and may affect correct identification and characterisation of any object. Objects on the ground can be identified by the different wavelengths reflected. Finer the spectral resolution, the narrower the wavelength range for a particular band or channel. Several remote sensing systems are multi-spectral that record energy over separate wavelength ranges at various spectral resolutions. For example, LISS-IV sensor uses 3 spectral bands: 0.52-0.59 (green), 0.62-0.68 (red) and 0.77-0.86 (NIR).

1.4.3 Radiometric resolution

Radiometric resolution of an imaging system describes about its ability to discriminate very slight differences in the energy levels. Finer the radiometric resolution of the sensor corresponds to high sensitivity to detect small differences in the reflected or emitted energy. Normally the ranges of the radiometric resolutions are from 8 to 16 bits, corresponding to 256 levels of the gray scale to 65536 representing intensities or shades of colour, in each band. The radiometric resolutions of LISS-IV, Landsat-8 OLI, RISAT-1, and Sentinel-1A are 10 bits, 12 bits, 16 bits and 16 bits, respectively.

1.4.4 Temporal resolution

Temporal resolution is defined as the amount of time needed in days to revisit and acquire image of the same area at a same viewing angle. The temporal resolution is high when the revisiting delay is low and vice-versa. The actual temporal resolution of a sensor depends on a variety of factors including the satellite/ sensor capabilities, the swath overlap, and latitude. Temporal resolutions of the Sentinel-1A, Landsat-8 OLI, LISS-IV and RISAT-1 satellites are 12 days, 16 days, 24 days and 25 days.

1.5 ATMOSPHERIC EFFECT AND ITS CORRECTION

The constituents of the atmosphere affect the radiation coming from the sun as well as the reflected/ emitted radiation from the soil/ vegetation in the optical region (Kaufman, 1989). Atmospheric gases, clouds and aerosols absorb some of the incoming and scattered radiation coming from the sun. It affects the contrast of the imagery and leads to loss of information. However, microwave radiation is not sensitive to the atmospheric aerosols and is weakly affected by the atmospheric constituents like water vapour. The microwave signals may be affected by the clouds and precipitation, depending on the frequency and precipitation rate (Gonzalez-Sanpedro, 2008). An atmospheric correction is necessary for the classification and inversion of the vegetation parameters from the vegetation surface reflectance. This correction may put an impact in the accuracy of the crop classification and retrieval of crop parameters (Fung, 1994; Ulaby et al., 2014).

1.6 NEED OF CROP GROWTH MONITORING

Agriculture has an economic and social importance worldwide due to rapid population increase and for the economic development of the country. In Indian economy, agriculture plays a vital role because 70 percent of the rural families depend on agriculture for their livelihood (Dadhwal et al., 2002). Agriculture prevents our environment to become polluted, as pollution is one of the main harmful aspects of the human life due to heavy industrialization. Pest infections and droughts can also damage the crops and soil fertility resulting to decrease in the crop production. The increase in concentration of atmospheric CO_2 and temperature could affect the plant biological processes such as photosynthesis and crop growth etc. (Booker et al., 2005). Due to these concerns, it is the need of the time to develop procedures and techniques to monitor the conditions of the crops for the better production. The genetically modified crops and use of fertilizers has been extended worldwide for a sustainable crop production increase (Qaim and Zilberman, 2003).

1.7 CROP GROWTH MONITORING

1.7.1 Crop classification and mapping

The crops are primary and necessary requirements for human and livestock of any country of the world. Timely identification, inventory and cartography of crops are essential to get acquainted about the crop types. Types of crop and areas on which they are grown should be monitored to predict timely and accurate production of crops. The crop classification and mapping is needed for the land change studies, climate change for the efficient management of water resources and hydrological studies (Simonneaux et al., 2008). One major component of the agriculture monitoring systems is crop classification and mapping through satellite imagery (Blaes et al., 2005). The availability of different satellite images and image processing techniques enabled the researches to find the crop type, area, crop condition and growth of different crops in agriculture (Akbari et al., 2006).

1.7.2 Crop growth parameters estimation

The crop growth parameters play a significant role in the monitoring of agricultural crops regularly. These crop growth parameters such as leaf area index (LAI), biomass, vegetation water content (VWC) and plant height (PH) etc. are the indicators of the plant condition with the actual plant phenological stage. The regular and well-timed monitoring of agricultural crops at different growth stages is important for any country to estimate the accurate agricultural production. This information is significant to make a strategy that may reduce the production risk and increases efficiency in crop management and production. Phenological development of the crop is often simulated in terms of measurement of the LAI, PH, biomass, VWC and chlorophyll content etc. LAI is defined as the total one sided area of the leaf per unit ground surface area (Watson, 1947; Duchemin et al., 2006; Herrmann et al., 2011). It is an important parameter to exchange most of the energy fluxes between the canopy and atmospheric interface (Chen and Black, 1991; Wu et al., 2004). The VWC is calculated from the difference between fresh and dry weight of the crop. It increases rapidly at the early wheat crop growth stages while found decreasing after heading stage. A multi-frequency ground-based scatterometer was used over an entire wheat growth cycle at X-, C- and L-bands. Results indicate that the L-band was highly correlated with VWC and fresh weight using linear regression analysis (Kim et al., 2014).

1.8 THE ROLE OF REMOTE SENSING IN CROP GROWTH MONITORING

1.8.1 Role of optical remote sensing

Optical remote sensing technology has become popular and reliable for the classification, mapping and monitoring of crop growth from the last several years on regular basis. Thematic mapping through image classification algorithms is extensively used in remote sensing applications (Foody, 2004). This type of mapping describes the pattern of crops and the spatial distribution of other land cover features. Accurate crop classification maps derived from remotely sensed data are a prerequisite for analysing many socio-ecological concerns. Thematic mapping is not the easiest task because of so many factors, such as the complexity of the landscape, selection of remote-sensing data, image processing, and classification algorithms, which may affect the classification accuracy (Lu and Weng, 2007).

Nowadays, the imagery from high spatial resolution satellite sensors such as LISS-IV, IKONOS, QuickBird, Landsat-8 OLI and Sentinel-2 are offering new opportunities to the remote sensing community for the crop classification, crop growth monitoring and yield estimation. The potential of the LISS-IV sensor has been revealed to capture intrafield variability in crop fields for precise farming (Sesha Sai and Narasimha Rao, 2008). Landsat-8 with Sentinel-1 time series images have been used and showed a significant improvement in the classification accuracy for the land cover mapping (Inglada et al., 2016). However, there are so many limitations using optical satellite data because of cloud cover and heavy rain for the crop classification and monitoring.

1.8.2 Role of microwave remote sensing

Microwave remote sensing has an advantage over optical remote sensing because it is operational in all weather conditions, both day and night. It offers great potential especially during the rainy season due to capability of radar systems to acquire data under almost all weather conditions (Haldar et al., 2014). Thus, microwave remote sensing shows a high potential for crop classification and monitoring. RISAT-1 is the Indigenous microwave satellite launched especially for the agriculture monitoring to overcome the problems of data acquisition during rain and cloudy weather. Several authors have reported the utility of RISAT-1 data-sets for achieving significant classification accuracies for crops and other land use classes (Iyyappan et al., 2014; Mishra et al., 2014; Ramana et al., 2014). Recently Sentinel-1A satellite has been launched to provide microwave data for the mapping and monitoring of different crops (Kussul et al., 2016; Navarro et al., 2016).

1.9 NEED OF SOIL MOISTURE RETRIEVAL

Soil moisture is an essential climate variable which affects vegetation growth and contributes to the interaction between land surface and atmosphere. Its measurements in the agricultural sites provide important information about early drought warning. The upper surface of the soils is classified as the root zone soil moisture and is important for describing the water that is available to the plants. When drought occurs, there is a deficit amount of moisture in the root zone and consequently crop productivity diminishes. The soil moisture serves as a solvent and carrier of food nutrients for crop growth and also to complete photosynthesis process. Regular soil moisture measurements will lead to improve crop yield forecasting and irrigation planning. Soil moisture is indeed an important variable in climatology, hydrology and agricultural applications (Srivastava et al., 2006; Legates et al., 2010). Soil moisture regulates the soil temperature and helps in chemical and biological activities of the soil. Although, soil moisture is a small component of the hydrologic cycle, it plays a major role in understanding and predicting climatic patterns. Because of its importance, it is necessary to retrieve soil moisture accurately.

1.10 SOIL MOISTURE RETRIEVAL

Moisture content has an important role for the ground water recharge, agriculture and soil chemistry. Accurate models are basically important to support water resource and crop management, policy decisions, marketing strategies, disaster forecasting, drought early warning and to monitor climate changes. However, large-scale measurements of the soil moisture are very challenging, because it requires repeated sampling process to analyse the periodical changes in the soil moisture. The theoretical models need certain parameters or more number of observations to retrieve the soil moisture (Njoku and Li, 1999). The extensive *in situ* measurements such as leaf size, leaf diameter, stem diameter, crown diameter, orientation, surface roughness, correlation length, and autocorrelation length etc. are needed for the appropriate findings by the theoretical model (Ulaby et al., 1982). However, theoretical model like integral equations model (IEM) could perform satisfactorily for soil moisture retrieval (Bindlish and Baros, 2000).

1.11 THE ROLE OF REMOTE SENSING IN SOIL MOISTURE RETRIEVAL

Remote sensing is a useful tool for the retrieval of soil moisture over larger areas in a short period of time (Wang and Qu, 2009; Lakshmi, 2013). Despite of numerous studies, the accurate retrieval of soil moisture through remote sensing remains a challenge. The remote sensing observations are sensitive to the soil moisture, surface roughness, surface temperature and vegetation canopy. However, microwave remote sensing provides complementary information, because they respond differently to the soil and vegetation parameters. It has developed enough scientific interest due to advent of various advancements in the radar technology and processing of the data for monitoring the soil moisture of remote areas.

The relationships between microwave scattering coefficients and soil moisture were investigated in the beginning of nineteen seventies (Schmugge et al., 1974; Ulaby, 1974; Eagleman and Lin, 1976; Attema and Ulaby, 1978). Since then, several theoretical and experimental studies on active and passive microwave have improved the understanding of the sensitivity of microwave satellite observations to the bare and crop covered soil moisture (Shutko, 1982; Schmugge, 1983; Ulaby et al., 1986; Ferrazzoli et al., 1992; Srivastava et al., 2006). Different studies used empirical and semi-empirical models based on regression analysis that establish the direct relationship between satellite observations and soil moisture measurements (Gill et al., 2006; Ahmad et al., 2010; Pasolli et al., 2011b; Gupta et al., 2017). These models are widely used; however the adopted approximations and simplifications are often the cause of inaccuracies.

1.12 LITERATURE REVIEW

Land is utmost important natural resource endowment on which all the human activities are based (Srivastava et al., 2010; 2012). Therefore, the knowledge of different type of land use as well as its spatial distribution in the form of map and statistical data is important for the spatial planning, management of land and its optimal use (Upasana et al., 2014). Land use shows the manner in which human beings employ the land and its resources. The availability of land resource is limited and hence immense pressure arises on land usability. A better understanding of these aspects is crucially important for the study of global environmental changes (Mehta et al., 2012).

Satellite image classification is the suitable process to carry out classification study of particular area as it gives an idea of the land use on the Earth’s surface (Mehta et al., 2014). Local and regional case studies require high spatial and temporal resolution for accurate identification due to having significant variation in spectral response of land cover classes (Amin et al., 2012). Mapping is not very easy due to many factors, such as the complexity of the landscape, selection of remote-sensing data-set, image processing, and classification algorithms. These factors may affect the classification accuracy results (Lu and Weng, 2007). Recently launched high spatial resolution satellites, such as LISS-IV, Sentinel-1, Sentinel-2, IKONOS, RISAT-1 and QuickBird, are offering new opportunities to the remote sensing community in the area of agriculture such as crop classification, mapping, crop growth monitoring and in crop yield estimation. The major limitations for crops identification with satellite imagery are field to field plant reflectance variability of the same crop as well as similarity in the plant reflectance of available various crops (Sesha Sai and Narasimha Rao, 2008). SAR data has shown favourable results in crop and other land use classification with reasonably higher accuracy. Potential of RISAT-1 satellite data-sets have been shown in Varanasi, India for agriculture and other land use/cover classification (Mishra et al., 2014).

Several appropriate algorithms have been developed for the classification of remote sensing imagery: a review is given by Lu and Weng (2007). Mapping techniques through remote sensing are superior to conventional methods for the classification of various crops. Because the conventional methods have some restrictions, related to distributional assumptions and to the limitations on the input data types (Kavzoglu and Mather, 2003). Supervised algorithms such as support vector machine (SVM), backpropagation artificial neural network (ANN) and random forest (RF) have been found more robust than the conventional statistical algorithms and create no assumptions nearby the statistical nature of the data.

SVM and ANN algorithms have been widely used in the past two decades for image classification (Pal et al., 2013). SVM classification algorithm is found to be superior to other classification algorithms such as ANN, maximum likelihood (ML) and decision tree (DT) algorithms for classifying land cover from Landsat Thematic Mapper (TM) and Moderate Resolution Imaging Spectroradiometer (MODIS) data-sets (Huang et al., 2002). The SVM algorithm is popular due to its potential for better classification accuracy than ANN algorithm (Huang et al., 2002; Foody and Mathur, 2004; Pal et al., 2013). The algorithm is found to be sensitive on the size of training data-set and dimensionality of the data-set used (Pal and Foody, 2010). However; SVM can work smoothly with the less number of training samples (Foody and Mathur, 2004; Pal and Mather, 2005). Generally; SVM classification algorithm determines an optimal hyperplane between the classes of interest. This algorithm is not based on any assumption regarding the probability distribution of the training data sets; instead, it finds a decision directly from the training data in a suitable space described by a kernel function. The high potential of SVM classification has attracted a great deal of research effort. However, some major concerns are also found in the design of SVM classification algorithm. Choice of suitable kernels, parameters and strategies can affect the classification accuracy (Pal, 2009; Mountrakis et al., 2011). In few previous studies, the third-order polynomial function kernel with gamma parameter 1 for the change detection was used which yielded the most accurate results in comparison to linear, radial basis and sigmoid function kernels (Schwert et al., 2013).

Although different types of neural network algorithms have been developed, the widely used is the backpropagation ANN algorithm. The back propagation algorithm has extensively been used for different applications by the remote-sensing community (Mass and Flores, 2008). This algorithm has the ability to produce classifications with higher accuracies from fewer or less training samples (Atkinson and Tatnall, 1997; Paola and Schowengerdt, 1995b). The ANN classifier, a more sophisticated and robust classifier of image classification, has been employed in the classification applications (Benediktsson et al., 1990; Bruzzone et al., 1997; Kavzoglu and Mather, 2003; Paola and Schowengerdt 1995a; Srivastava et al, 2012). Enhanced crop identification and classification have been done for achieving higher accuracy by ANN using QuickBird, Landsat TM/ETM+, and Advanced Very High Resolution Radiometer (AVHRR) multispectral satellite data (Cruz-Ramírez et al., 2012; Atzberger and Rembold, 2013). However, so many studies have reported some problems during use of back propagation ANN for crop classification and other land cover features (Foody and Arora, 1997; Kavzoglu and Mather, 2003). The classification accuracy depends on several factors and may be affected in the variation of dimensionality of remotely sensed data as well as on the training and testing data sets (Foody and Arora, 1997).

RF classification algorithm is a robust and an ensemble learning algorithm which can be trained rapidly. This algorithm is very effective for the classification through complex and non-linear patterns of the landscape. Furthermore, the RF algorithm runs efficiently on large data-sets and does not require normally distributed model training data (Rodriguez-Galiano et al., 2012). SVM needs a several user-defined parameters whereas RF algorithm requires only two parameters to be set. Classification results by RF were found equally well to SVM (Pal, 2005). ML classification algorithm quantitatively evaluates the variance and covariance of the category spectral response patterns when classifying an unknown pixel (Lillesand and Kiefer, 2002). Huang et al. (2002) compared the accuracy yielded by SVM, ANN, ML and DT algorithms for classifying land cover from Landsat TM and MODIS data-sets with satisfactory results for SVM with polynomial and radial basis function kernels.

The crop growth can be monitored by estimating biophysical parameters like LAI, VWC, biomass, and PH etc. The radar backscattering and crop growth parameters have complex and non-linear relationships. This is because of the dynamics of the crop growth parameters which are influenced by the soil texture, surface roughness, crop type and density of the crop, etc. Microwave remote sensing is better for the crop growth analysis because it has deeper penetration capability. LAI can be estimated from the remotely sensed data by statistical and physical approaches. It is an important biophysical parameter in the most terrestrial ecosystem models and in global models of ecology and climate (Myneni et al., 1997; Sellers et al., 1997). The inversion of physically based radiative transfer models (RTM) delivers the potential to retrieve LAI and other biophysical vegetation parameters (Jacquemoud et al., 1995, 1996; Weiss et al., 2000; Fang et al., 2003; Vohland and Jarmer, 2008). RTM describe the interaction of the sun's electromagnetic radiation with the atmosphere and the Earth's surface accounting for both the scattering and absorption of the radiation. This process is highly nonlinear and numerical simulations are required to understand these complex interactions (Jin and Liu, 1997).

Thus, it is important to develop inversion models in order to use microwave satellite data for estimating crop parameters such as LAI, leaf water area index (LWAI), PH, biomass and VWC. Several modelling approaches can be grouped together, such as a theoretical approach and a semi-empirical one, to estimate crop parameters by inverting the various models. However, theoretical models usually involve complex sets of equations. They consider the statistical properties of the dielectric of the canopy volume, and these are difficult to relate to the vegetation variables such as biomass and LAI. Because of the involvement of large numbers of parameters, their inversion is difficult. To overcome these problems, Attema and Ulaby (1978) developed an approach to model the backscattering coefficients (σ^0) of vegetation canopy through the water cloud model (WCM), which was modified and extended by several authors (Ulaby et al., 1984, Paris, 1986, Prevot et al., 1993). These models are not theoretically complex, and they can be inverted easily and applied to a number of vegetation types with reasonable results. The reliability of estimated crop variables is dependent on the quality of the radar measurements as well as the accuracy of the WCM. However, the WCM neglects multiple scattering and plant geometry.

Higher quality radar measurements are needed to determine the WCM parameters for better reliability of the estimation of crop parameters. The data-sets with poor radar measurements of a specific crop that are used in fitting the WCM may lead to an inaccurate WCM (Graham and Harris, 2002). LAI and LWAI of kidney beans were estimated by numerical inversion of the WCM, the non-linear least squares optimization model and the polarization-based model at the X-band (Ulaby et al., 1984; Prevot et al., 1993; Prasad, 2011). The effect of various crop/soil variables on the observed backscattering is better characterized by models. The WCM (Attema and Ulaby 1978) with modifications by Inoue et al. (2002) has proved its usefulness for a range of crop types and conditions (Prevot et al. 1993, Moran et al. 1998, Champion et al. 2000, Prasad 2009; 2011).

The capability of support vector regression (SVR) model has been shown for the retrieval of LAI (Durbha et al., 2007). In an SVM, all the available indicators can be used as the inputs, but irrelevant or correlated features could adversely impact the generalization performance due to the curse of the dimensionality problem. Thus, it is critical to perform feature selection or feature extraction in SVM (Tay and Cao, 2001; Guyon et al., 2002; Durbha and King, 2005). SVR was found effective for the estimation of forest stem diameters and tree biomass using Lidar data (Dalponte et al., 2008). Biomass is the total dry matter of the crop/vegetation. Karimi et al. (2008), Tuia et al. (2011), and Siegmann et al. (2013) have shown the potential of SVR regression model for the estimation of crop parameters. Previous studies have shown that the ANN and look up table (LUT) approaches generally performed best. However, the lack of good generalization capacity is one of the disadvantages of the ANN and LUT approaches (Fang et al., 2003; Kimes et al., 2000). SVR has theoretical advantages over ANN, such as absence of local minima in the model optimization phase (Cortez and Morais, 2007).

RF model has its ability to predict crop yield production with the changing climate and biophysical parameters of wheat, corn and potato crops in comparison with multiple linear regressions at global and regional scales (Jeong et al., 2016). To date, only few studies have demonstrated the potential of random forest regression (RFR) model to derive plant parameters using remote-sensing data (Powell et al., 2010; Vuolo et al., 2013). For the assessment of LAI, each RFR model was made up of 500 individual trees. Each tree was built with two-thirds of the training data (bootstrap samples), while the remaining one third testing data (out-of-bag samples) were used for a model internal validation (Siegmann and Jarmer, 2015).

Different types of artificial neural network regression (ANNR) models have been developed for the estimation of biophysical parameters (De Martino et al., 2002; Dzwonkowski and Yan, 2005). However, the ANNR models offer a poor performance when working with few labelled data points. SVR is a promising alternative to ANNR which yields good results for the estimation of some biophysical models (Smola and Schölkopf, 2004; Camps-Valls et al., 2006). Backpropagation ANNRs are generally reported as successful in retrieving parameters such as LAI, biomass, VWC, PH and chlorophyll etc.. Two neural network models were trained by a physical vegetation model and used to retrieve soil moisture and crop variables of wheat canopies during the whole crop cycle (Del Frate et al., 2003). The high correlation coefficients were found between measured and estimated rice crop biomass using ground based scatterometer and RADARSAT-2 data by the ANN model (Jia et al., 2013).

The microwave σ^0 depends on the surface roughness, soil texture and soil moisture of the bare soil surface (Ulaby et al., 1978). The better correlation was found between σ^0 and bare soil moisture using linear regression models (Ulaby et al., 1981). They also established the relations between σ^0 and soil moisture for vegetation-covered soil (Ulaby et al., 1979). However, the presence of vegetation cover reduces the sensitivity between σ^0 and soil moisture. The vegetation cover is one of the most important factors which may affect an accurate soil moisture measurement using microwave remote sensing (Dobson et al., 1985; Ulaby et al., 1986). Vegetation is semi-transparent at longer microwave wavelengths. However influence of the vegetation on the data is also depend on the vegetation type, amount of vegetation and on the characteristics of sensor.

Several researchers have reported that the simulated SAR backscatter from IEM could deviate by several decibels and in general the errors increase when incidence angle increases (Oh et al., 1992; Boisvert et al., 1997). To overcome these problems the empirical models were developed using data acquired by several measurements of σ^0 from different general conditions that can be applied to obtain reasonably accurate soil-moisture retrieval (Walker et al., 2004). The empirical models were established using different sensor configurations such as frequency, incidence angle and polarization for the retrieval of soil moisture (Dubois et al., 1995; Oh et al., 2002; Zribi and Dechambre, 2003). Some semi-empirical models were also developed for the retrieval of vegetation covered soil moisture. The semi-empirical models find an agreement between theoretical models and empirical models having common rules derived from both the models.

In case of crop-covered soil moisture retrieval, the crop cover introduces the two way attenuation in the SAR backscatter. In general, backscatter from the crop covered soil depends on the sensor parameters like the radar frequency, polarization, incidence angle and target parameters like dielectric properties of crop and geometry of the crop. Efforts have been made by the researchers to compute the radar σ^0 and its essential components from the crop covered soil using radar scattering models. Although, the simulated SAR backscatter from crop covered soil derived from these models show good agreement with the observed SAR backscatter values extracted from SAR images (Dobson et al., 1983). However, these models are highly complex and very difficult to use for practical purposes over larger agricultural areas. Hence, it is needed to develop a simple and convenient method by which effect of crop cover in soil moisture mapping can be incorporated.

Several theoretical, semi-empirical and empirical models have been developed for the better understanding of the interaction of microwave signals with crops/soil surface parameters (Karam et al., 1992; Le Toan et al., 1997; Macelloni et al., 2001; Liu et al., 2002). External parameter orthogonalization coupled with SVM, RF, ANN and partial least squares regression models were applied on a wider set of soil properties and provided satisfactory results (Wijewardane et al., 2016). SVR model enhanced the retrieved soil moisture because the vegetation effect from the radar signal is well separated at HV polarization using RADARSAT-2 data (Pasolli et al., 2011b). ANN models and statistical methods were used for the retrieval of soil moisture from remotely sensed data (Notarnicola et al., 2008). The Sentinel-1A satellite data was used for retrieval of soil moisture covered by the winter wheat, barley and corn crops in this study.

1.13 MOTIVATION

Agriculture plays a vital role in the Indian economy. Over 70 % of the rural households depend on the agriculture as their principal means of livelihood (Dadhwal et al., 2002). Classification of different crops is essential to get acquainted with the types of crops and the total area covered by the crops in that region. The regular monitoring of the 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 which 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 the peoples of any country. For the fulfilment of above objectives, the extensive literature was made and came to draw following observations that

(i) Very few researchers have classified more than ten different crop and non-crop classes using multi spectral satellite data (LISS-IV and Lansat-8 OLI). It’s a challenging task to classify more than ten different classes using these satellite images. Selection of robust algorithms is equally important to classify sixteen crop and non-classes using the multi spectral satellite images accurately.

(ii) Very limited studies have been carried out using Indigenous LISS-IV and RISAT-1 satellite data for the crop classification and monitoring (Sesa Sai and Rao, 2008, Mishra et al., 2017).

(iii) Almost all the ongoing satellite missions have poor temporal resolutions. Recently, Sentinel-1A satellite launched by European Space Agency (ESA) has higher temporal resolution for the better crop growth monitoring and soil moisture retrieval.

(iv) Retrieval of crop growth variables using Sentinel-1A satellite data by different models.

(v) Regression models for the retrieval of soil moisture under different vegetated crops using Sentinel-1A SAR data.

The above observations motivated us to do the research work described in the organization of thesis.

1.14 ORGANIZATION OF THE THESIS

The present thesis work is organised in the following ways:

Chapter 1 describes about the introduction and literature review related to the work presented in the thesis.

In **Chapter 2,** the different crops such as barley, wheat, lentil, mustard, pigeon pea, linseed, corn, pea, sugarcane, other crops and non-crop were classified using kernel based SVMs, ML and normalized difference vegetation index (NDVI) classification algorithms. The statistical significance in the classification accuracy was also analysed using *Z*-test and χ^2-test. Before performing classification, the *M*-test and *J-M* distance methods were used to check the separation between the classes of crops and non-crop.

In **Chapter 3,** an attempt was made to analyse the performance of supervised classification algorithms such as kernel based SVMs, ANN and RF for the land features classification. Different selected measures such as marginal rates, *F*-measure, Jaccard's Coefficient of Community (*JCC*) and Classification Success Index (*CSI*) were analysed to measure the accuracy. Separability analysis was done using *TD* and *J-M* distance methods.

Chapter 4 was described in the two parts: (a) comparative study of the crop classification performed by ANN algorithm at changing learning parameters using LISS-IV and Landsat-8 OLI satellite data. (b) crop classification by ANN algorithm using RISAT-1 data and separability analysis.

Chapter 5 described the winter wheat crop growth parameters such as LAI, VWC, FB, DB and PH estimation using Sentinel-1A satellite data. RFR, SVR, ANNR and LR algorithms were used for the estimation of wheat crop growth parameters and results obtained were compared.

Chapter 6 described about the WCM used for the retrieval of LAI and LWAI of corn crop using Sentinel-1A satellite data at VV polarization and results obtained were compared.

Chapter 7 described about the comprehensive evaluation of soil moisture under different crop retrieval models. The soil moisture retrieval covered by wheat, barley and corn was done using RFR, kernel based SVR and ANNR models.

In **chapter 8**, overall conclusions drawn from this research are presented. This chapter also summarises the major findings of the research and provides a number of recommendations for the future work.