CHAPTER I:

INTRODUCTION

1.0 Introduction:

1.1 Scientific Context :

Agriculture is the backbone of the economy of most of the nations in the world as it provides livelihood for 60 per cent of the world population (FAO, 2000). Similarly, in India, agriculture is the most important and extensive land use activity. Its importance for the Indian society need not be over-emphasized, as its role in economy, employment, food security, national self reliance and general well being, does not need reiteration. Agricultural land is undergoing severe pressure as it is getting intensified to increase the productivity to meet the demands of increasing human population, to compete with global economy and to adopt with the changing habits of human consumptions (Atzberger, 1998). At the same time, its productivity is also prone to risks due to fluctuation of weather, international market, and consumer preference. Under such circumstances, much efforts are required to improve accuracy by adapting both the conventional and non-conventional methods which can aid in obtaining reliable and timely information on various components of crops like area, production and yield.

1.2 Conventional methods for agricultural land studies:

Conventional method in agricultural land studies includes crop statistics generation. The historic references to crop statistics generation in India date back to Kautilya's Arthasastra as well as Moghul era. Crop statistics viz. crop production and crop acreage in our country is collected through ground survey and crop cutting experiments. The crop production of principal agricultural crops is usually estimated using following formula:

$$\text{Crop Production} = \frac{\text{Area under the crop x the average yield}}{\text{Unit area of the crop}}$$

But sometimes, at district level these estimates are obtained through General Crop Estimation Surveys (GCES). These surveys are done on the basis of crop cutting experiments conducted on a number of randomly selected fields in sampled villages of the district. In addition, during these surveys, crop acreage is also estimated through complete enumeration of crops in an area. Certain studies on such conventional methods showed that there is a seen variation in statistics generation in different states. In states namely Kerala, Orissa and West Bengal, 20 per cent sampling on rotation basis is done and in northern eastern states ad hoc surveys are employed while in remaining parts of the country, multi-season full enumeration approach is adopted for the generation of statistics (Dadhwal et al., 2002).

This conventional system of estimation holds an important position in crop statistics generation of our country as it is applied country wide but in spite of this wide application it consists of the following major limitations like:

- It involves complex field surveys
- It is costly, time consuming and tedious
- It is more labour intensive (Verma et al., 2003)
- It has to pass through a hierarchy of aggregation of village, taluka, district and state level, which contributes to a delay in reporting, rigidity of definition, and more importantly a delay in compilation of national forecasts (Mahey et al., 1995)
- It is often subjective, influenced by personal bias
- It involves non-completion of enumeration in sample villages which contributes to non-sampling errors (Singh et al., 2003)
- It sometimes involves non-reporting of crop sown and in few cases, reporting of non sown crop as sown crop
- It also shows discrepancy in reported crop area
- It presents variation in the crop area ratio for village level worker and supervisor (Iyer, 1991)

Looking at the above limitations of conventional methods used in agricultural studies, there arises a need for a new technique which could overcome these demerits. In this context, the new non-conventional technology of Remote Sensing (RS) has proved its potential as it simultaneously removes all the above disadvantages of ground survey method. It is standard, reliable and possibly cheaper and faster methods for agricultural land studies. It aids in understanding the different aspects of agricultural studies.

1.3 Non- conventional methods for agricultural land studies:

1.3.1 Application of Remote Sensing in Agriculture:

Remote Sensing (RS) has a great potential in the field of agriculture giving new opportunities for improving agricultural statistics. It offers accelerated, repetitive and spatial – temporal synoptic view in different windows of the electromagnetic spectrum from its vantage point in space. In the last few years, RS technology has been increasingly identified as an objective, standard and possibly cheaper and faster methodology for crop production estimation (Bouman, 1992; Shinde and Shrivastava, 2012). In addition, it is a non-conventional and non-destructive method of agricultural studies (Pinter et al., 2003). This method has certain more advantages which are as follows:

- It provides temporal and near real time information on crop conditions making early detection and management of problems easy and thereby preventing potential crop losses.
- It is a non-invasive method with ability to measure large areas with high detail without disturbing the crop.
- It is potentially cheaper, more efficient and more spatially detailed than field sampling

The main sources of RS data are optical and microwave sensors. In fact, optical satellites which operate in the visible and infrared parts of the spectrum, acquire information which are more closely linked to human perception. Examples of information products that can be spatially derived from optical domain are: Colour, Crop Vitality, Canopy temperature, etc. In optical region, both visible and infrared bands are very useful in identifying cultivated areas and eventually in understanding the crop conditions. The most important limitation of optical instruments is their weather dependence for their operational use as clouds are not transparent at visible/ Infrared (IR) wavelengths. This factor needs to be taken care of for agricultural applications as reliable timed images are needed throughout the growing season to understand the crop status. Application of microwave RS helps in overcoming this weather dependency (Navalgund et al., 2007).

Radar microwaves, owing to their penetrative power, can pass not only through clouds, haze or fog but also through crop canopy and reach the soil below. As a result, the resulting radar images are influenced by the properties of the soil (Vescovi and Gomarasca, 1999). These images are primarily sensitive to crop structure (Dobson et al., 1995) and biomass (Davidson et al., 1997), as well as soil roughness and moisture (Engman and Chauhan, 1995). The information from radars may be supplementary to that of optical systems when visible/IR sensors are unavailable because of cloud (Clevers and van Leeuwen, 1996).

Use of this data could be made for a number of applications such as crop inventory, crop acreage, crop production/yield forecasts, drought and flood damage assessment, range and irrigated land monitoring and management (Sahai and Dadhwal, 1990). Most importantly both optical and microwave data have proved their potentials in assessing different crop parameters.

1.4 Crop parameters: Biophysical and Biochemical parameters

Agricultural, ecological, and meteorological applications require an accurate quantitative estimation of vegetation biochemical and biophysical variables (Asner, 1998; Houborg et al., 2007). The information about the spatial and temporal distribution of these parameters provides an important input into various models quantifying the exchange of energy and matter between the land surface and the atmosphere. The knowledge of canopy biophysical variables is of prime interest in many applications including crop function modeling, evapotranspiration, crop growth modeling and yield prediction. In addition, this information also aid in predicting the soil-vegetation-atmosphere energy transfers. Even at a much smaller scale, as in precision farming and water management, biophysical parameters play a critical role to describe the state of crop development and water needs. Measurement of these parameters during the growing season also provides an opportunity for improving grain yields and quality by site-specific application of fertilizers. Among the many crop parameters, Leaf Area Index (LAI), Leaf Relative Water Index (RWC), Leaf Chlorophyll Content (CC) and Biomass are of prime importance.

Direct field techniques for estimating these parameters require frequent destructive harvesting. Such techniques are difficult, extremely labour intensive, and costly in terms of time and money. They can hardly be extended to cover large areas. In order to handle these problems, RS technology offers numerous advantages over traditional methods of conducting agricultural and other resource surveys. Advantages include the potential for accelerated surveys, capability to achieve a synoptic view under relatively uniform lighting conditions, availability of multispectral data for providing intense information, capability of repetitive coverage to depict seasonal and long-term changes and availability of imagery with minimum distortion etc. This proves RS data, both in terms of optical and microwave, beneficial in assessing important biophysical and biochemical parameters of different crops.

1.5 Optical remote sensing and crop parameters:

The timely spectral reflectance information covering major ElectroMagnetic Radiation (EMR) range can be linked to biophysical and biochemical parameters which are the indicators of plant health. Quantitative techniques can be applied to the spectral data, whether acquired from close-range or by aircraft or satellite-based sensors, in order to estimate crop status/condition. This technology is capable of playing an important role in crop management by providing the information on different types of crop parameters namely, LAI, Biomass, RWC, CC and some other measurable biophysical parameters. Each parameter has been taken up separately and discussed below.

- **Leaf Area Index (LAI)**

The Leaf Area Index (LAI), an important biophysical parameter characterizing a canopy is defined as the total one-sided area of leaf tissue per unit ground surface area (Watson, 1947). It has a key role as one of the surface parameters in climate, weather and ecological studies. It is a biophysical variable that influences vegetation photosynthesis, transpiration and the energy balance of canopies (Bonan, 1993). It serves as an important input to the ecosystem productivity models operating at landscape to global scales (Turner et al., 1999) and also as an interaction component of general circulation models (Buermann et al., 2001). Estimation of LAI is critical for understanding and quantitatively analyzing many physical and biological processes. These processes are related to vegetation dynamics, global carbon cycle and climate.

RS facilitates LAI estimation at frequent intervals which defines the size of interface for mass and energy exchange over a wide range of spatial scales and with considerable temporal resolution. However, conventional approach of LAI measurements are cumbersome, very tedious, time consuming task and impossible to obtain at global scale and in this respect satellite RS is the most effective means of measuring LAI global fields on a regular basis (Pandya et al., 2006; Martinez et al., 2010). Methods of LAI measurements can be grouped into two categories. The first category consists of empirical methods wherein relationships between LAI and Vegetation Indices (VIs) such as the Normalized Difference Vegetation Index (NDVI) are established (Asrar et al., 1984; Curran and Williamson, 1987; Chen and Cihlar, 1996, Franklin et al., 1997; Kuusk, 1998; Xavier and Vettorazzi, 2004; Wang, et al., 2007; Patil et al., 2012). To map LAI, second category of methods is the inversion of physical Canopy-Reflectance (CR) models (Goel and Strebel, 1983; Goel, 1988; Privette et al., 1994; Myneni et al., 1997; Houborg and Boegh, 2008; Yao et al., 2008).

- **Biomass:**

Crop biomass is the total dry-matter production of a crop which is the net result from photosynthesis, respiration, and mineral uptake (Stoskopf, 1981). This biophysical parameter is an indicator of the productivity and function of crop (Mutanga and Skidmore, 2004). It aids in monitoring of crop vitality and hence is very important quantitative characteristic of crop condition (Bendig et al., 2014). It is also considered as an effective tool for predicting yield capacity (Kryvobok, 2000).

Biomass estimation can be done via different approaches, based on (1) field measurement (Brown et al., 1989; Brown and Iverson, 1992; Houghton et al., 2001) (2)

Geographic Information System (GIS) (Brown and Gaston, 1995) and (3) RS methods (Nelson et al., 2000; Lu et al., 2005). Crop biomass estimations using field based traditional techniques involves in situ destructive sampling. This approach is the most accurate way for collecting biomass data and hence provides higher quality data. But this conventional method has certain limitations. It requires sufficiently high number of field measurements for the development of biomass estimation models and also for the evaluation of the biomass estimation result. The data collection process involved in this approach is time consuming, labour-intensive and is unfeasible over large spatial extents (Ajaere, 2012). Second approach i.e. GIS–based methods using ancillary data are also difficult. It has problems related to acquiring high quality ancillary data, indirect relationships between biomass and ancillary data, and the comprehensive impacts of environmental conditions on biomass accumulation. Conversely, biomass estimation using data acquired from remote sensors such as field spectroradiometers and aerial or satellite borne sensors offers numerous advantages. These include the non-destructive and non-obtrusive nature of the data collection methods; repetition of data collection, the large spatial coverage of a given sensor system; a synoptic view, a digital format that allows fast processing of large quantities of data (Lu, 2006; Hatfield and Prueger, 2010). Therefore, RS-based biomass estimation has increasingly attracted scientific interest. Timely pre-harvest forecast of crop biomass using satellite data could aid in quantifying marketable yield. This would provide an international competitive advantage to a farmer leading to economic gain for the farm operation (Rabe, 1996). Several authors have accomplished biomass estimation using remote sensing techniques. One way of biomass estimation using remotely sensed data is by applying a number of VIs such as NDVI which is indicative of vegetation biophysical characteristics (Aase and Siddoway, 1981; Tucker et al., 1981; Persson et al., 1993; Hobbs, 1995; Shippert et al., 1995; Serrano et al., 2000; Liu et al., 2004; Moges et al., 2004; Jensen, 2005; Gao et al., 2013; Perry et al., 2014; Santi et al., 2014; Kross et al., 2015). The limitation of this approach that determines biomass by establishing relationship between biomass and spectral reflectance data is the non-consideration of physical and physiological processes (Asrar et al., 1985). Another way is based on understanding of the relationship between Phytomass Production (PP) and the Photosynthetically Active Radiation (PAR) absorbed by the canopy (Monteith, 1972; Hodges and Kanemasu, 1977; Daughtry et al., 1983). This method needs additional information about incident or utilized solar radiation and therefore is likely to be more appropriate in biomass prediction in different climatic regimes (Choudbury, 1987).

- **Relative Water Content (RWC):**

Water as an important element for the proper plant growth, is of great significance for real-time understanding of vegetation status, especially in dryland agriculture (Zhang et al., 2011). Several factors influence crop water status. These include environmental conditions, agronomic practices, soil properties, and crop growth (Hanks, 1988). Crop water status is also an important consideration for monitoring agricultural drought. Water stress due to drought limits plant productivity and crop yields by reducing photosynthesis and leaf growth (Boyer, 1982; Bradford and Hsiao, 1982). Thus, crop water status provides important information that can aid in several different ways. It prevents crop water deficit through irrigation (Koksal, 2008). It aids in the selection of genotypes in breeding (Munjal and Dhanda, 2005). It also proves beneficial in assessment of crop growth under drought conditions (Tucker, 1980; Peñuelas et al., 1993). Numerous methods are used to determine crop water content; leaf Relative Water Content (RWC) is one such method. RWC was introduced as an useful indicator for plant water status essentially because it expresses the absolute amount of water, which the plant requires to reach artificial full saturation (Slatyer, 1967). This was used instead of plant water potential since RWC refers to its relation with cell volume and accurately indicates the balance between absorbed water by plant and consumed through transpiration (Arjenaki et al., 2012). RWC estimations conventionally are tedious and time consuming. Several authors have determined plant water status in different crops using remote sensing techniques by measuring spectral indices based on vegetation moisture feature bands since they change in response to crop water content (Hunt et al., 1987; Peñuelas et al., 1997; Ustin et al., 1998; Stimson et al., 2005). Spectral indices offer a numerous advantages over conventional laboratory estimations. They provide methods for easy and quick measurements, and for the integration at the canopy level. Moreover, additional parameters can be estimated simultaneously via a series of diverse spectral indices (i.e. photosynthetic capacity, leaf area index, intercepted radiation, and chlorophyll content) (Araus et al., 2001). NDWI is one of the important spectral indices used in sensing vegetation water content using remote sensing imagery by employing empirical statistical approach. This index was used by Anderson et al. (2004) for determining canopy water content in crops namely soybean and corn.

- **Leaf Chlorophyll Content (CC)**

Chlorophyll is Earth's most important organic molecule and leaf's one of the most important biochemicals. The amount of chlorophyll within a vegetation canopy is positively related to both the vegetation productivity and its health (Dash et al., 2009). CC is of great importance as

- It controls photosynthetic potential (Singh et al., 2015) and, consequently, primary production as it has a dominant control upon the amount of solar radiation absorbed by a leaf (Blackburn, 2007).
- It is also an important indicator of nutritional stress (Collins, 1978; Milton and Mouat, 1989; Curran et al., 1990; Filella and Penuelas, 1994).
- Thus its estimation can provide an accurate, indirect estimate of plant nutrient status especially Nitrogen because the molecular structure of the chlorophyll incorporates a large proportion of total leaf nitrogen (Everitt et al., 1985; Filella et al., 1995; Moran et al.,2000). CC in leaves is to a great extent dependent on the soil nitrogen availability and on crop nitrogen uptake and so it is an indicator of nitrogen content. Hence, this parameter in agricultural fields can prove to be of a great use. Estimates of this parameter can help the farmers and agronomists to make management decisions related to nitrogen supply at critical growth stages.
- It is influenced by stress due to nutritional deficiency and also its ratio changes with abiotic factors such as light (Fang et al., 1998), and so it can become an important indicator for providing useful insights into plant–environment interactions (Richardson et al., 2002).

The knowledge of this parameter extracted from satellite data is therefore expected to be a valuable tool in the evaluation of plant nitrogen. Undoubtedly conventional methods of estimation of chlorophyll are too tedious and in this context RS methods are found to be superior. Approaches for the estimation of CC from remotely sensed data are based either on the inversion of physically based models (Jacquemoud et al., 2000; Zarco-Tejada et al., 2004; Schaepman et al., 2005) or improved relationships between CC and spectral indices (Daughtry et al., 2000; le Maire et al., 2004). In physically based model approach, simulation of canopy reflectance is done and then quantitative relationships between remotely sensed data and canopy attributes for inversion purposes are created. Approaches using spectral indices rely on establishment of empirical relationships between laboratory measured CC and observed spectral reflectances.

This discussion highlighted the significance of optical RS in assessing crop parameters like LAI, Biomass, Chlorophyll and RWC. Specifically its reflective optical domain functions as a unique cost-effective source, providing spatial and temporal information on key biophysical and biochemical characteristics of land surface vegetation (Houborg et al., 2009). As discussed previously, these techniques for estimating crop parameters have either been based on the **empirical-statistical approach** that links VIs and crop parameters using experimental data, or on the **physical modelling approach** that involves inversion of radiative transfer model.

1.5.1. Empirical- statistical approach:

Empirical-statistical approach considers the contrasts in reflectance and fits a relationship between reflectance and crop variables, mainly by the use of VIs. Establishment of these relationships between remotely sensed crop canopy reflectance and ground-measured biophysical and biochemical parameters of particular crop is done via simple or multiple regression (Jacquemoud et al., 1995), partial least square regression (Huang et al., 2004), or by training an artificial neural network (Dorigo et al., 2007). As discussed previously, many authors have demonstrated the capability of spectral indices such NDVI and Normalized Difference Water Index (NDWI) in the estimation of different biophysical and biochemical parameters: Prediction of biomass (Broge and Leblanc, 2001; Haboudane et al., 2004a), mapping of CC (Al-Abbas et al., 1974; Haboudane et al., 2002), mapping of LAI (Xiao et al., 2002; Vina et al., 2011) as well as detection of stress (Eklundh, 1996; McVicar and Jupp, 1998).

Empirical-statistical methods are highly efficient due to their simplicity and straightforwardness (Baret and Guyot, 1991). However, they have their own limitations:

- Established empirical equations are limited to a particular site and time for which the relationship was established
- It is usually sensitive to the soil background, crop chlorophyll content, or to the orientation and spatial distribution of the leaves in the canopy.
- In addition, for calibration of the empirical formulas established for different vegetation or crop types, a reliable reference data-set is required.
- Furthermore, such methods generally make use of few spectral bands, with a consistent under-exploitation of the full spectral range available in new generation sensors (Francesco and Luigi, 2006).

An alternative approach for the estimation of crop parameters is the physical modeling approach.

1.5.2 Physical modelling approach:

Physical models are potentially more robust and accurate than empirical models and hence are relevant alternatives to empirical approaches (Gastellu-Etchegorry et al., 2003). This physical modeling approach is based on the inversion of Radiative Transfer (RT) models, which physically relate canopy biophysical and biochemical variables to reflectance data (Jacquemoud 1993; Gastellu-Etchegorry et al., 1996; Bicheron and Leroy 1999, Goel and Thompson, 2000; Quin and Liang, 2000).

1.5.2.1 Radiative Transfer models:

In the field of optical remote sensing, for understanding of light interception by plant canopies and the interpretation of vegetation reflectance in terms of biophysical characteristics, RT models have been proved to be very useful (Jacquemoud et al., 2009). A virtual transfer of photons within vegetation is performed in these models, taking into account canopy biochemical and biophysical characteristics and objects of the surrounding environment (Malenovsky et al., 2009). Since these models consider explicitly two main physical processes of light absorption and scattering within a plant canopy, they aid in designing VIs, performing sensitivity analyses, and developing inversion procedures to accurately retrieve vegetation properties from satellite data (Jacquemoud et al., 2006). Methodological diagram in **Figure 1** depicts steps involved in retrieving of biophysical and biochemical parameters by inversion of RT based RS retrieval.

Previous studies on physical RT models have shown that among the different RT based RS models, the model of leaf optical PROperties SPECTra (PROSPECT) and the SAIL (Scattering by Arbitrary Inclined Leaves) canopy bidirectional reflectance model are the most popular and are looked on as standards (Liang, 2003). Combining these models into PROSAIL has allowed description of both the spectral and directional variation of canopy reflectance as a function of

- leaf biochemistry - mainly chlorophyll, water, and dry matter contents
- canopy architecture - primarily leaf area index, leaf angle distribution, and relative leaf size

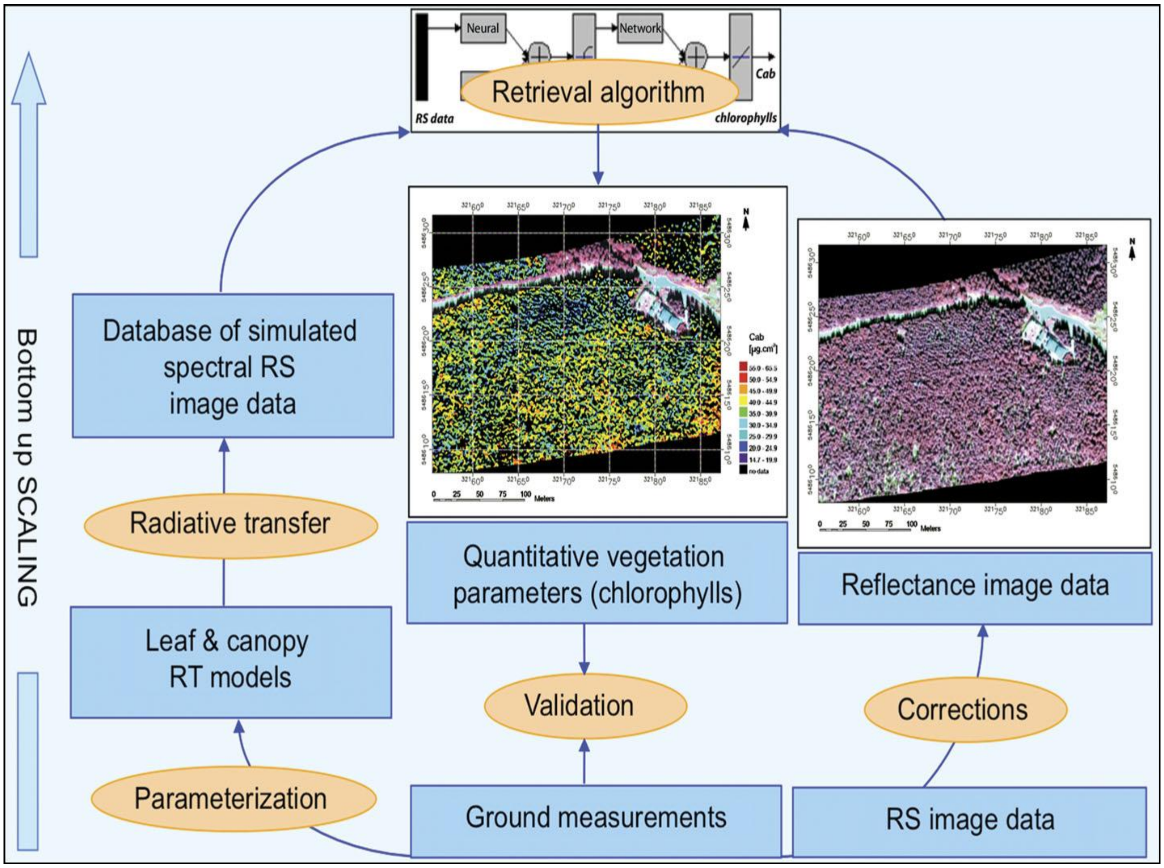

Fig 1. Bottom-up physical RT inversion mapping a quantitative characteristic of vegetation canopy from remotely sensed imaging spectroscopy data (Source: Malenovsky et al., 2009)

The PROSPECT+SAIL Model: PROSAIL

A RT model, PROSPECT (Jacquemoud and Baret, 1990) simulates the leaf reflectance and transmittance from 400 to 2500 nm as a function of the leaf mesophyll structure parameter (N), the chlorophyll a+b content (Cab), and the leaf water content (Cw). For given solar θs and view zenith angles (θv), and a given relative azimuth angle (φsv), SAIL (Verhoef, 1984) calculates the canopy bidirectional reflectance using leaf optical properties, soil reflectance, and canopy architecture; the latter is represented by the leaf area index LAI, the mean leaf inclination angle (θl), and the hot spot parmeter (sL).

PROSAIL since is a coupling of PROSPECT and SAIL models, it measures the bidirectional reflectance of homogeneous canopies as a function of several structural and biophysical parameters, soil reflectance, illumination and viewing geometry (Vuolo et al., 2010). Different inputs used in this coupled model are: leaf chlorophyll a+b content (Cab), leaf water content (Cw), leaf dry matter content (Cdm), leaf brown pigment content (Cbp), leaf mesophyll structure index (N), LAI, average leaf angle (ALA), a hot spot parameter (sL) and soil brightness (BS). **Figure 2** shows the different input variables to PROSAIL model i.e coupled SAIL and PROSPECT RT models and different steps involved.

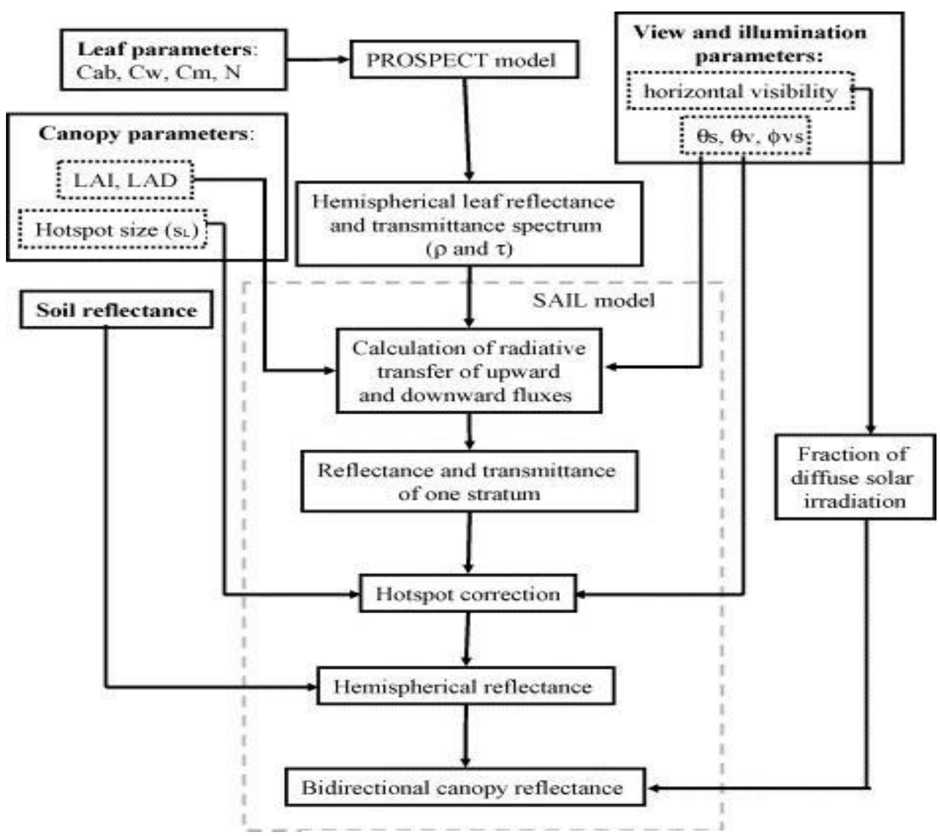

Fig 2. The PROSAIL model: Input parameters and steps involved (Source: Botha et al., 2007)

The RT model PROSAIL simulates bi-directional reflectance and retrieves biophysical parameters through its inversion. Hence physically based models for retrieving vegetation characteristics from satellite measurements can actually be used by inverting these models (Kimes et al., 1998). Amongst different techniques used for inversion of the model, Look Up Table (LUT) is one of the important techniques.

Inversion of PROSAIL using LUT:

LUT approach is one of the relatively simpler; the most robust and accurate model inversion strategies. Many researchers in their work have applied LUT in combination with PROSAIL for retrieving biophysical parameters of different crop types at different locations (e.g. Weiss et al., 2000; Darvishzadeh et al., 2008; Richter et al., 2009; Verrelst et al., 2014). LUT is a large data base consisting of sets of input variables of the canopy RT model that are to be inversed. Alternatively, LUT can be generated on the basis of experimental observations, although this requires a very accurate sampling of the space of canopy realization. Simultaneous to generation of LUT, bidirectional canopy reflectance and fCover for 100000 different variable combinations is simulated by running PROSAIL. On generation of LUT, solution for a given set of reflectance measurements is found by selecting the closest cases in the reflectance table according to a cost function, and by extracting of the corresponding set of canopy biophysical variables (Baret and Buis, 2008).

In the above sections, potential of optical RS in the estimation of crop biophysical and biochemical parameters has been clearly understood. At the same time, limitations of these types of RS data need to be emphasized eg: their weather dependency. They are affected by cloud cover (Mudaliar, 2013), since clouds are not transparent at visible/IR wavelengths. This is especially important for agricultural applications where number of satellite images is required throughout the growing season in order to continuously follow the status of the crops as they grow. In this context, an imagery obtained from Microwave RS can give the added information which is hampered by effect of cloud on optical imagery.

1.6 Microwave remote sensing and crop parameters:

RADAR (Radio Detection And Ranging), an active sensor system transmitting energy in the microwave region of the electromagnetic spectrum (EMS), measures the energy reflected back from the target in terms of backscattering. Orbital remote sensing in the microwave region is potentially an important tool for agriculture monitoring. It has almost all-weather capability and can be acquired in day or night conditions, giving continual data and in addition it has high spatial resolution. Microwave RS gives unique information for sea wind and wave direction; derived from frequency characteristics, doppler's effect, polarization, backscattering etc. Such information cannot be obtained by visible and infrared sensors (Dhumal et al., 2013). All these characteristics of radar make it appropriate for agriculture studies as these features increase the chance for providing useful data for crop monitoring. Furthermore, application of radar improves signal penetration within vegetation and soil targets. The nature of interaction of microwave energy with agricultural targets is quite different from that with optical visible-IR energy. In an agricultural systems, the microwave signal can interact either with canopy or soil only but more likely there is scattering within the canopy and there occurs return from multiple sources (Smith et al., 2005) (**Figure 3**).

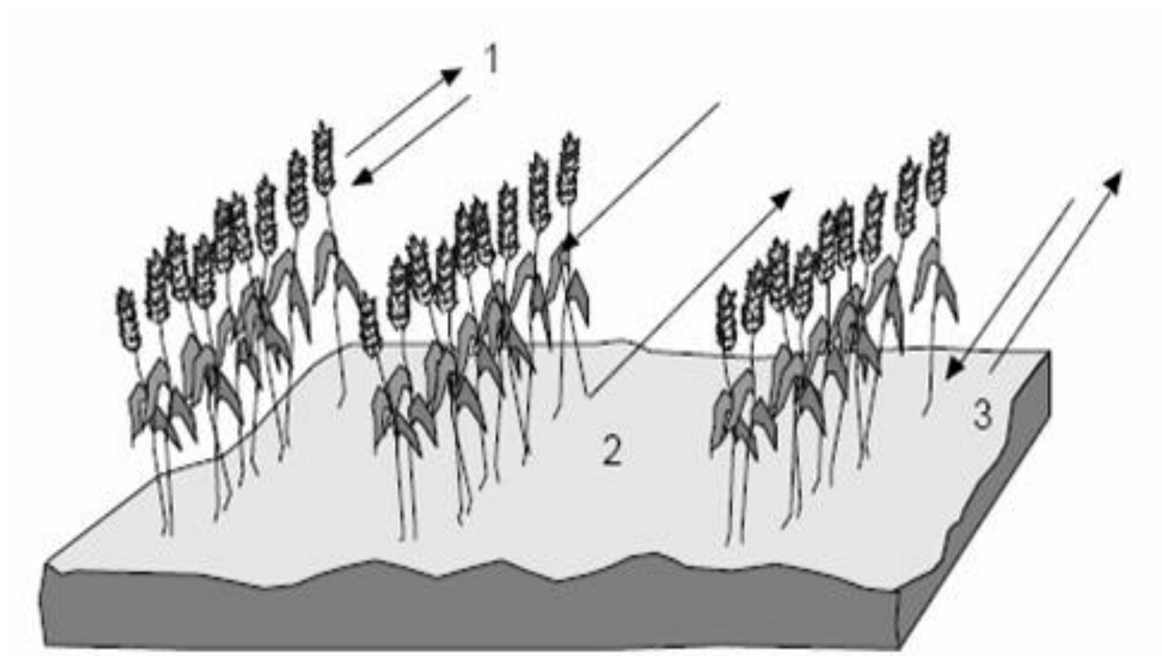

Fig 3. Interaction of radar signal with an agricultural target: 1) backscatter directly from the crop (including multiple scattering) 2) backscatter from the combination of crop and soil 3) backscatter directly from the soil (including multiple scattering) (Source: Brisco and Brown, 1998)

This interaction of the radar signal with canopy and soil and its attenuation is sensitive to number of instrument and vegetation related factors. Instrument related factors are: Frequency (wavelength), Polarization, Incidence angle, Look direction, Resolution while vegetation related factors are: Surface roughness, Crop canopy dielectric constant that is dependent on the biomass and plant water content, Crop structure viz. size, shape, orientation and number density of the elements like leaf, stalks and fruits, Canopy structure viz. row, plant number density and underlying soil contribution, sensitive to the moisture and roughness.

Similar to optical RS, even in microwave RS, **empirical statistical approaches** can be adopted for full exploration of information regarding retrieval of crop parameters. In this case, the empirical relationships are built between the characteristics of radar signal and crop variables during different growth stages in the field. Unlike optical models, microwave physical models are not suitable for inversion techniques and hence retrieval of the crop parameters from microwave physical models is quite difficult. These radar physical models are based on complex electromagnetic descriptions of all the canopy scatterers (stalks, leaves and ears) and of the underlying soil surface. They are utilized in sensitivity studies, new sensor configurations testing or for simple models validation. Moreover, these models require the large amount of input parameters and even they are very complex. Because of these reasons, they are not suitable for operational inversion purposes (Guissard et al., 2005).

1.6.1 Empirical-statistical approach:

RS techniques for estimating crop parameters from radar backscattering is based on the empirical-statistical approach which involves derivation of relationships by calibrating observed quantities (LAI, Biomass etc.) with backscatter. This approach is very much similar to that used in optical measurements of crop biophysical and biochemical parameters. Many authors have established linear or non-linear relationships between microwave backscattering coefficient of a vegetation canopy and different crop parameters such as LAI, plant water content or biomass (Ulaby et al., 1984; Bouman, 1991; Ferrazoli et al., 1997, Pampaloni et al., 1997, Mattia et al., 2003). Multi-variate regression analysis is also developed to fit relationships between radar backscatter and target parameters (Major et al., 1994, McNairn et al., 1998).

Estimations of biophysical and biochemical parameters no doubt has potential for accurate predictions of crop yield but to ensure food security in rapidly growing population with tremendous pressure on the agricultural land to produce more food, the trend analysis of different crops in a given area becomes significant.

1.7 Trend analysis of different crops:

Numerous authors have analyzed the trends in terms of area, production and yield of different crops grown in different regions of the world (Kumar and Mittal, 2006; Ali et al., 2013; Abid et al., 2014). Such information can aid the policy makers in recommending policies leading to sustainable increase in the food production (Vaidyanathan, 1992; Chand et al., 2007; Reddy and Mishra, 2009). These workers have also showed that the rapid growing population has increased pressure on agricultural land to produce more food (Anonymous, 2010). There are several reasons such as slowing agricultural yields, limited land availability and the increasing demand for biofuels leading to competition for available land and lag in the food supply. Recently, the phenomenon of land-grabbing has also intensified adding to the pressure on agricultural land and thereby on food supply. Thus, for the sustained agricultural growth, a holistic approach considering factors related to this resource can not only balance the demand and supply but also augment growth in the rural economy and associated secondary activities like food processing and retail trading (Kannan and Sundaram, 2011). In this holistic approach, if climatic factors are also considered, it will give more significant results.

1.8 Vulnerability Assessment of agricultural fields:

Understanding the regional and local dimensions of vulnerability is essential to develop appropriate and targetted adaptation efforts (Ranade, 2009). Vulnerability indicators are needed for practical decision-making processes, to provide policymakers with appropriate information about where the most vulnerable individuals are located (Gbetibouo et al., 2001).Vulnerability, an emerging concept for climate science and policy can be expressed as the conjunction of the climatic hazards, socio-economic conditions, and the adaptation baseline. Over the past decade, efforts to assess vulnerability to climate change triggered a process of theory development and assessment practice, which is reflected in the reports of the Intergovernmental Panel on Climate Change (IPCC). IPCC defines vulnerability as "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. It is a function of three factors: a) the types and magnitude of exposure to climatic change impacts, b) the sensitivity of the target system to a given amount of exposure, and c) the coping or adaptive capacity of the target system (IPCC, 2007). The exposure to climate change will influence sensitivity – either positively or negatively and farmers will have to respond these changes provided that they have the capacity to adapt. The increasing exposure and sensitivity factor with a decreasing adaptive component increases the vulnerability. This emphasizes the need to increase the adaptive component of the system. Earth's climate change during the past few decades has become the focus of scientific and social attention as it has severe impacts on various ecosystems. It has now become a reality and several researchers are working on this burning issue by working out the future projections as well as assessing the impact in several sectors including agriculture (Sastri, 2009). Agriculture is an important driver of the wheels of the Indian economy. Any change in climate is likely to impact agriculture. The change can be in terms of temperature, precipitation, or any other climatic parameters (Manavalan et al., 2009). Furthermore, this climate change will expose farmers to new and unfamiliar conditions (Watts and Goodman, 1997) and farmers have to cope up with these changes. Numerous physical and socio-economic factors come into play in enhancing or constraining the current capacity of farmers to cope with adverse changes. Thus, vulnerability study of agriculture involves environmental, physical and socioeconomic factors. Considerable studies have gone into question of just how agriculture is vulnerable to climate change in different regions, and how much. It varies across regions, sectors, and social groups.

After understanding the trends of different crops and vulnerability of agrilands in which they are growing, it is equally significant to understand the specific area under each crops, its yield and health. Thus, crop assessment for all these parameters using spatial data can prove beneficial.

1.9 Crop mapping:

Information regarding crops growing in an area is of great importance to researchers, policymakers, land managers and farmers for ensuring the sustainability of these and other land uses and for quantifying the net impacts that certain management practices have on the environment (Howard et al., 2012). Moreover, for actual estimates of the crop production and yield, accurate and in time identification, inventory and crop type classification of an area becomes imperative. This information can also help in proper water management and for the estimations of carbon sequestration by the soil. Acquisition of such information requires precise agricultural land-cover mapping for specific crops and their spatial distributions.

Acquiring this information traditionally through field surveys for crop classification has limitations. Spatial data at this point makes such acquisitions easy. RS helps in real time identification of the crops grown in agricultural fields (Wheeler and Misra, 1976; Crist and Kauth, 1986; Foody, 1995; Nirala and Venkatachalam, 2000; Prakash et al., 2000; Su, 2000; Kauth and Thomas, 2004; Arafat et al., 2013) and thereby can aid in crop production forecasts.

Sensors required for this measurement cover different ranges of EMR. Optical RS measure reflectance from targets in the visible and IR regions of the EMS. This data has largely been relied upon for crop mapping (Turker and Arikan, 2005). Reason being each crop exhibit difference in reflectance because of varying biophysical characteristics during entire growing season. This helps in identification of different crops from optical data (De Wit and Clevers, 2004; Conrad et al., 2010; Foerster et al., 2012). However, optical data acquired during kharif season due to cloud cover are normally of little use in crop mapping. Radar sensors are not affected by atmospheric conditions. Unlike optical sensors, active radar systems have their own source of EMR, transmitting radio waves and receiving the reflected echoes from objects on the Earth's surface. The longer wavelengths of radio waves allow transmitted signals to penetrate clouds (Henderson et al., 2002). This provides microwave systems high reliability in terms of data provision, especially during kharif season when optical sensors fail (Baghdadi et al., 2010; Lopez-Sanchez et al., 2010; Schuster et al., 2011). Additionally, the information content of microwave and optical imageries differ. A radar sensor transmits short bursts or 'pulses' of an electromagnetic energy to an object of an interest and records an origin and strength of reflected echo (backscatter) from an object. Received backscatters are largely a function of the size, shape, orientation and dielectric constant of the scatterer. Hence, in vegetation related studies, microwave backscatter will vary based on the size, shape and orientation of the canopy components. Crops with varying canopy architecture and cropping characteristics can be discriminated based on their backscatter intensities.

Several authors have successfully used optical and microwave data independently (Misra and Wheeler, 1978; Schotten et al., 1995; Ribbes and Le Toan, 1998; Sheikho et al., 1998; Chen et al., 2007a; Johnson, 2008; Karjalainen et al., 2008; Sesha Sai and Narasimha Rao, 2008; Larrañaga et al., 2011; Goswami et al., 2012; Haldar et al., 2012a; Kussul et al., 2013) as well as in synergism for crop mapping (Rosenthal et al., 1985; Ban, 1996; Othman et al., 2002; Haldar and Patnaik, 2010; Fontanelli et al., 2014).

1.10 Objectives:

The potential use of remote sensing tools in crop mapping, landuse classification and in the retrieval of crop parameters has been well explored. The information retrieved from the spatial data has served as inputs to generate yield related models and thereby have helped in improving yield forecasts. In the present study, both optical and microwave data have been taken up for understanding the importance of these data in assessment of agricultural lands and crops therein. The area under this study covered major portion of Vadodara and Padra talukas and some parts of Waghodia and Dabhoi talukas of Vadodara district for optical data study and major portion of Dabhoi and some parts of Sinor and Sankheda talukas of Vadodara district for microwave data study. The study was designed with two main objectives as follows:

1. To understand advantages of microwave data in crop assessment
2. Analysis of crop parameters using ASAR, LANDSAT and LISS-IV data