Chapter 2

Literature Survey

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The major part of the literature which was studied before arriving at research gap area is presented in this chapter. The chapter is divided into three sections namely (i) Crop studies using RS data: global scenario, (ii) Crop studies using RS data in India, and (iii) RS data classification comparison studies. While section 2.1 briefs a number of RS based studies carried out in various parts of the world to estimates crop area at different scales using different techniques; section 2.2 summarises such studies done in India. For arriving at suitable classification techniques for the research study taken up, the comparison of various techniques is an important element. This comparison of different classification studies carried out by several researchers is presented in section 2.3. It provided an insight for the selection of a suitable set of techniques for an early estimation of crop acreages at multiple scales using multi-source data.

2.1 Crop Studies using RS Data: Global Scenario

Global demand for food grain is growing every year. Enhancing production of food crops is the only viable solution to meet this demand. To increase crop production, at least one of the two elements i.e. crop area and crop productivity needs to be increased. Increasing crop area is very difficult due to scarcity of the land for agriculture purpose and/or unavailability of the resources to grow crops at available land. Crop growth and productivity are determined by a large number of factors such as genetic potential of crop cultivar, soil, weather and management variables, which vary significantly across time and space. Early prediction of crop yield is important for planning and taking various policy decisions. Many countries use the conventional techniques (manually collecting the details by field surveys over a sample area or the full study area) of data collection for crop monitoring and productivity estimation based on ground surveys and reports. These methods are found subjective, costly and time consuming. Empirical models for crop yield prediction have been developed using weather data which also suffers from a number of problems. With the launching of satellites, remotely sensed data are being used for crop monitoring and yield prediction. Most investigations have revealed a strong correlation between remotely sensed data derived NDVI and crop yield. A critical analysis of the diverse approaches helps in identification of the most accurate and useful techniques.

Application of remotely sensed data for large scale crop studies started in 1970's. The Corn Blight Watch Experiment (CBWE) in 1971 and Large Area Crop Inventory Experiment (LACIE) initiated in 1974 were two such successful studies (MacDonald et al., 1972; MacDonal, 1976; LBJSC, 1977). The CBWE was the first time that a sound statistical design for sampling was used for a large-scale remote-sensing program. The CBWE was a highly successful program in many respects. It was an excellent demonstration of the operational capabilities of remote-sensing techniques. Extremely large quantities of aerial and field data were collected over the seven-state experimental area in U.S.A. on a biweekly basis. Accuracy of corn identification by RS exceeded 90 percent throughout the experiment and the correlation between field observations of blight levels and classification of blight levels using remote sensor data was quite good. The study illustrated the potential of RS as a technique for monitoring crops for disease and other stresses. From the standpoint of quantity and quality of data collected, this experiment was considered the largest and most successful remote-sensing project ever attempted in agriculture (NASA, 1974) during 1970s. MARS, started in 1988, is a European long term endeavour to monitor the in-season weather and crop conditions and to estimate final crop yield by the harvest season. It aimed to provide precise, scientific and timely yield forecasts for the main crops at European Union level (Baruth et al., 2008). China launched CropWatch, a satellite based crop monitoring system, in 1998 (Wu, 2006). It aimed at improving food information availability, quality and transparency with respect to worldwide production of major cereals and soybean. CAPE, started in late 1980s, was the first large scale project in India that used remotely sensed data for crop studies, which later on got upgraded to "Forecasting Agricultural output using Space, Agro-meteorological and Land based observations" i.e. FASAL (Parihar, 2016). Further details on CAPE are provided in the next section of this chapter. The Global Agriculture Monitoring Project (GLAM), a joint initiative by the National Aeronautics and Space Administration (NASA), U. S. Department of Agriculture (USDA), University of Maryland (UMD) and South Dakota State University (SDSU) provides timely, objective and operational crop production forecasts at the global scale (Becker-Reshef et al., 2010). Group on Earth Observations Global Agricultural Monitoring (GEOGLAM) initiative will contribute to generating reliable, accurate, timely and sustained crop monitoring information and yield forecasts. It will strengthen global agricultural monitoring by improving the use of RS tools for crop production projections and weather forecasting (GEOGLAM, 2015). Many countries have developed their national crop monitoring systems supported by RS data.

A number of research paper presented the details of studies and projects that demonstrated the usefulness of RS data in making crop inventory over different parts of the world (Tucker et al., 1980; Tennakoon et al., 1992; Sharman, 1993; De Mulder et al., 1993; Kurosu et al., 1995; Moulin et al., 1998; Sun, 2000; Thenkabail et al., 2002; Pinter et al., 2003; Potgieter et al., 2005; Xiangming et al., 2006; Wardlow et al., 2007; JRC, 2008; Biradar et al., 2009; Bailey and Boryan, 2010; Al-gaadi, 2010; Rembold et al., 2013; Sud et al., 2015; Fritz et al., 2015; Karam et al., 2016). Development of techniques for different crop studies possesses a rich timeline from 1970's to 2016. A brief summary of this development covering some major studies at various scales is presented below in chronological order.

Bauer (1975) discussed the physical basis for RS, presented its historical development and described its role in determining the distribution and productivity of crops. Idso et al., 1977 indicated that the RS technology could be successfully designed for agricultural operations to enhance production via intelligent water management; Bauer (1978) demonstrated that RS technology offered a cost-effective and timely alternative to sample land use surveys and to cross-check these surveys.

The initial results of crop production forecasting at large scale were reported by MacDonald and Hall (1980). They presented details on a crop inventory system called LACIE (Large Area Crop Inventory Experiment) which utilized the direct observational capabilities of Landsat together with estimates of weather variables to estimate production. LACIE project was put together and tested jointly by multiple U.S.A. government agencies. The LACIE participants-NASA, the USDA and NOAA-and the U.S. Department of the Interior and the Agency for International Development had planned a technology development program to support the possible implementation of an operational global monitoring system. A 1977 real-time forecast of U.S.S.R. wheat production under LACIE project indicated that the approach worked well and might be expanded to other areas and other crops.

Lennington and Sorensen (1984) presented a method for estimating crop areas based on mixture model approach to Landsat data. Mixture models are used for making statistical inferences about the properties of the sub-populations given only observations on the pooled population, with no information on sub-population identities. The theoretical advantages of this approach over usual classification-based inventories were presented. Results of applying the mixture model approach to measurements derived from Landsat data for 18 sample segments in the northern U.S. Great Plains were presented. Mixture model estimates of the proportion of spring small grains in the sample segments were compared to similar estimates obtained from a classification-based approach.

Mccloy et al., 1987 developed a specialized system to monitor the rice growing areas of New South Wales for 2 years with accurate and consistent results. Each image was classified and the result used to update the land-cover mask using agronomic criteria.

Shueb (1990) investigated the use of combined field and satellite data for crop identification and area estimation in county Durham, Northeast England. The research demonstrated the ability of Landsat-TM (Thematic Mapper) data to discriminate among agricultural crops in the study area. Results obtained demonstrated that satellite data could be used for identification of agricultural crops over large geographic areas with small field sizes and different environmental and physical features. The study produced a classification map of thirteen land-cover types with more than 80% accuracy. The classification accuracy was assessed quantitatively by using the known land-use information obtained from the sample units visited during the field survey. The study analysed the factors which influenced the degree of separability between different agricultural crops since some crops were better identified than others. Using a double sampling method (two-phase sampling technique) based on the combination of both Landsat TM and field data in regression analysis; an acreage estimate was produced for each crop type in County Durham. Crop area estimated by regression reduced the imprecision in all strata and was more efficient in some strata than others. This indicated that a gain in precision was achieved by using Landsat TM in conjunction with the field data. The results further illustrated that stratification based on an environmental criterion was an efficient approach for application of agricultural RS in County Durham. The stratified approach allowed each stratum to be analysed separately, thereby lessening the reliance on cloud free imagery for the whole county on any given date.

Shueb and Atkins (1991) showed that combining field information with satellite data analysis provide better crop estimates in comparison to only satellite data based estimates. They analysed Landsat TM data covering parts of Britain and combined their results of fieldwork to obtain a reliable estimate of the area of certain crops. They found that oilseed rape and winter wheat were more easily identifiable than spring sown crops because of the date of the image. They also emphasised that several images during the growing season were desirable to improve the accuracy of interpretation although there were resource implications in the acquisition and analysis of additional data.

Congalton (1991) reviewed the factors and techniques to be considered when assessing the accuracy of classifications of remotely sensed data. A classification is not complete until it has been assessed. Then and only then can the decisions made based on that information have any validity.

Gallego et al., 1993 described inventories of the MARS project discussed some aspects related to the stability of regression while estimating crop area using RS data. Regression results seemed to be more reliable if training pixels were chosen at random in a random subset of segments. Some risk of bias was observed if segments with training pixels were included to compute the regression parameters.

Walter (1998) presented a fully automated approach for verification of GIS objects using high resolution multi-spectral RS data. The already existing GIS information was used for the automatic generation of training areas for multi-spectral classification. It was shown that different approaches were needed when dealing either with area objects or with line objects. A matching strategy was implemented for the matching of line objects. The automatic verification was tested with (Authoritative Topographic-Cartographic Information System) (ATKIS) data sets and Digital Photogrammetric Assembly (DPA) high resolution RS data. ATKIS is the German topographic cartographic spatial database and DPA is an optical airborne imaging system for real time data collection. The results showed that the matching inconsistencies between ATKIS and DPA could be detected in most of the cases.

Gebbinck (1998) carried out a research study to develop an accurate, decomposition of mixed pixels based method for estimating the area of agricultural fields with an aim to provide a deeper knowledge about the processing of mixed pixels in general, i.e., relatively independent of the specific application studied and type of imagery used. The study covered the entire processing path, including the separation of pure and mixed pixels, the determination of end-members, the decomposition of mixed pixels and the post-processing of the estimated fractions.

Ghodieh (2000) investigated the use of field and satellite data for crop area estimation in the northern part of the West Bank, Palestine which is characterised with small field sizes and complex physical environment. The results were analysed on stratum and crop type basis. RS and thematic agricultural perspectives were used in the analysis. Results of the study suggested that it was possible to improve image classification accuracy by using better spatial and spectral resolution imagery and the integration of RS data with agricultural data using the GIS.

Thenkabail (2001) recommended the best spectral narrow-bands for studying various agricultural crops. He established the best hyper-spectral narrow-bands for discriminating agricultural crops and determined the accuracy with which such discrimination was possible. Six crops (wheat, barley, chickpea, lentil, vetch and cumin) were studied. The best 12 narrow-bands provided the most rapid increase in spectral discrimination. Further addition of narrow-bands, only marginally increased discrimination capability reaching a plateau at around 30 narrow-bands.

Liu and Kogan (2002) explored the potential application of NOAA/AVHRR based satellite indices to estimate the soybean yield for Brazil. NOAA AVHRR GVI (Global Vegetation Index) weekly maximum composite NDVI data sets with a resolution of 16 km for the period of 1985 to 1998 (except 1995 due to missing data) provided by NOAA/NESDIS were used. Nine soybean yield models, including eight principal production states and the country, were constructed using observed yield data and NDVI and/or TCI (Temperature Condition Index) data from 1985 to 1995. The data from 1996 to 1998 period were used to evaluate the model performance. The contribution of technological improvements was approximated by trend term and weather-related fluctuations of yield around the trend were estimated through AVHRR-based indices. The results showed that four states had significant technological trend contribution. In most of the models, yield variation around the trend was sensitive to TCI, during the period of the grain filling stage (end of January for northern states and mid-February for the southern states). The study concluded that the satellite based indices were useful for crop production monitoring. In the Brazilian soybean production region, where the summer crop season coincides with the rainy season, the temperature-based index was more informative about possible fluctuation of soybean yield and production in Brazil.

Frolking et al., 2002 combined county-scale agricultural census statistics on total cropland area and sown area of 17 major crops in 1990 with a fine-resolution land-cover map derived from 1995–1996 optical RS (Landsat) data to generate 0.5^{o} resolution maps of the distribution of rice agriculture in mainland China. Agricultural census data were used to determine the fraction of crop area in each 0.5^{o} grid cell, while the RS land-cover product was used to determine the spatial distribution and extent of total cropland in China.

A method to evaluate integration of satellite derived parameters in a crop growth model to simulate spring wheat yields at the sub-county and county levels was developed by Doraiswamy et al., 2003. The crop model EPIC (Erosion Productivity Impact Calculator) was adapted for simulations at regional scales and RS data provided an assessment of the magnitude and variation of crop condition parameters. A radiative transfer model, SAIL (Scattered by Arbitrary Inclined Leaves), provided the link between the satellite data and crop model. The calibration and the state level simulations were compared with spring wheat yields reported by National Agricultural Statistics Service (NASS) objective yield surveys.

Lobell et al., 2003 estimated crop area, yield and planting dates for 2 years of Landsat imagery in an intensive agricultural region in northwest Mexico. Knowledge of crop phenology was combined with multi-temporal imagery to estimate crop rotations throughout the region. Remotely sensed estimates of the fraction of absorbed photo-synthetically active radiation were then incorporated into a model based on crop light-use efficiency to predict yield and planting dates for wheat. A simplified model was also developed to explore yield predictions using only one date of imagery, demonstrating high accuracies depending on the date of image acquisition.

Wu and Li (2004) demonstrated two-stage stratified sampling approach for crop acreage estimation using remotely sensed data in China. The first level stratification was based on various factors, such as temperature, precipitation, soil type, sun eradiation was considered as well as proportions of main crop types. The crop proportions were estimated employing cluster sampling assisted by remotely sensed images and crop type proportions were estimated using two-stage transect sampling and GVG (GPS-Video-GIS) survey system. They concluded that the methodology could estimate early rice area in 2003 efficiently and accurately to meet the requirement of CCWS.

Apan et al., 2004 evaluated several narrow-band indices from EO-1 Hyperion imagery for discriminating sugarcane areas affected by 'orange rust' disease against healthy crop area. Forty Spectral Vegetation Indices (SVIs), focusing on bands related to leaf pigments, leaf internal structure and leaf water content, were generated from an image acquired over Mackay, Queensland, Australia. Results demonstrated that Hyperion imagery could be used to detect orange rust disease in sugarcane crops. While some indices generated using visible near-infrared (VNIR) bands only offered separability, the combination of VNIR bands with the moisture-sensitive band (1660 nm) yielded increased separability of rust-affected areas.

Casa et al., 2008 estimated crop water requirements for the Pontina Plain, Central Italy, using RS based land classification and applying a simple water balance scheme in a GIS environment.

Narciso et al., 2008 tested a rule-base classification capable of assigning class labels without employing training sample in a study carried out over Tuscany region of Italy. The purpose of the study was to assess the feasibility of satellite Synthetic Aperture Radar (SAR) imagery in providing crop area estimates. The classification rules relied on crop-specific temporal sequences of cultivation practices identified by changes in backscattering. The results concerning the accuracy in the identification of single land use classes were not encouraging. The authors reported that the proposed classifier provided a level of accuracy well below requirements though of some relevance for a set of 5 crop groups (winter cereals, spring crops, trees, pasture and forage crops). It appeared possible for the authors to discriminate between broad groups of crops; however, they concluded that whatever the constraints and the limitations, the classification attempt failed.

Wu et al., 2008 attempted to develop a mechanism of tobacco estimation under the complex topography conditions using MRS data. In this study a layer by layer classification method was attempted to classify cultivated land.

McCarty (2009) used satellite data to derive burned area estimates and then quantified emissions of gases from crop residue burning in the contiguous United States. She produced season-specific crop type maps to classify corresponding cropland burned area. She compared the satellite derived burned area estimates with state-level governmental statistics on agricultural burning for the few states with public reporting.

An object-oriented mapping approach was developed and evaluated by Johansen et al., 2009 for mapping banana plantations using SPOT-5 imagery. They compared the results to banana plantations manually delineated from high spatial resolution airborne imagery. Cultivated areas were first identified through large spatial scale mapping using spectral and elevation data. Within the cultivated areas, separation of banana plantations and other land-cover classes increased when including image co-occurrence texture measures and context relationships in addition to spectral information. The results of their study showed that a pixel size of 2.5 m was required to accurately identify the row structure within banana plantations, which enabled object-based separation from other crops based on texture information. The results indicated that the data and processing techniques used offer a reliable approach for mapping banana plants and other plantation crops.

A classifier named extension model of fuzzy matter-element was developed by Jiang et al, 2010 to classify multi-source and multi-temporal RS data. Taking the National Nature Reserve of Ruoergai wetlands as study area, TM, CBERS (China-Brazil Earth Resources Satellite) and MODIS-NDVI of 2007 was chosen as data source. The results showed that, the overall accuracy (82.36%) and Kappa coefficient (0.8006) of the integrated of multi information classification method was better than the Support Vector Machines (SVM) results using TM (79.74%, 0.7704) and CBERS (77.29%, 0.7436) data.

Fumin et al, 2010 and Zhang et al., 2010 described the development process of China's crop acreage and yield statistical survey along with the international research development. They presented the application status of crop acreage and yield estimation in China using RS data. The deficiencies of the prevalent survey system in China were brought out and prospects of the RS technology for agricultural survey in China were analysed.

The pixel-based classification is the most applied approach for classifying low and medium resolution satellite images (pixel size is coarser than, or at best similar to, the size of geographical objects) in which an individual pixel is classified into the closest class based on its spectral similarity. With continuously increasing spatial resolution, the relationship between the pixel size and the dimension of the observed objects on the Earth's surface is changing. Hence, pixel-based classification methods became less effective in the changed scenario. Object-oriented classification has become increasingly popular over the past more than a decade. It combines segmentation (which is a fundamental component of the approach) and contextual classification. Veljanovski et al., 2011 presented the theoretical argumentation and methodology of object-based image analysis of RS data, provided an overview of the field and pointed out certain restrictions as regards the current operational solutions.

Zhong (2012) developed a phenology based classification approach which extracted phenological matrices from annual vegetation index profiles and identified crop types based on these metrics using decision trees. According to the comparison with traditional maximum likelihood classification, this phenology-based approach showed great advantages when the size of the training set was limited by ground truth availability. Once developed, the classifier was able to be applied to different years and a vast area with only a few adjustments according to local agricultural and annual weather conditions. 250 m MODIS imagery was utilized as the main input to the algorithm and displayed promising capacity in crop identification in several counties in the Central Valley. A time series of Landsat TM/ETM+ images at a 30 m resolution was required in the crop mapping of counties with smaller land parcels, although the processing time was longer. Spectral characteristics were also employed to identify crops. Spectral signatures were associated with phenological stages instead of imaging dates, which highly increased the stability of the classifier performance and overcame the problem of over-fitting.

Wen and Yang (2012) proposed an effective unsupervised classification method for classifying a hyperspectral RS image after correcting it for atmospheric variability. The end-member spectra were extracted using Pixel Purity Index (PPI) algorithm and the image was classified using Spectral Angle Mapper (SAM). Traditionally, SAM using constant threshold was improved and used adjustable threshold. The end-member spectra were clustered based on K-mean algorithm and classes were combined according to the K-mean algorithm result. The final classification map was projected and output was prepared.

Atzberger (2013) offered an overview of the recent advances in RS of agriculture and existing operational crop monitoring systems. The review demonstrated the strong role RS plays within the agricultural sector.

Ezekia (2013) emphasised the need to identify RS based reflectance indices for relating tobacco growth and yield in Zimbabwe. The suitable vegetative indices can be employed in establishing tobacco cropped area and then apply the long-term area yield relationship from government and nongovernmental statistical departments to estimate yield from RS derived cropped area.

An elaborate review of the studies carried out using low resolution satellite data for crop yield prediction and yield anomaly detection is presented by Rembold et al., 2013. The authors stated that the low resolution satellite was extensively used for crop monitoring and yield forecasting for over 30 years that played an important role in a growing number of operational systems. The combination of their high temporal frequency with their extended geographical coverage generally associated with low costs per unit area made the data a convenient choice at both national and regional scales. Several qualitative and quantitative approaches could be clearly distinguished, going from the use of low resolution satellite imagery as the main predictor of final crop yield to complex crop growth models where RS-derived indicators play different roles, depending on the nature of the model and on the availability of ground measured data. Vegetation performance anomaly detection with low resolution images continues to be a fundamental component of early warning and drought monitoring systems at the regional scale. For applications at more detailed scales, the limitations created by the mixed nature of low resolution pixels are being progressively reduced by the higher resolution offered by new sensors, while the continuity of existing systems remains crucial for ensuring the availability of long time series as needed by the majority of the yield prediction methods used today.

Gusso et al., 2013 demonstrated the application of temporal Enhanced Vegetation Index (EVI) profiles derived from MODIS images for estimations of crop production in Brazil. The coupled model performance of crop area and crop yield estimates based solely on MODIS/EVI as input data was compared with official agricultural statistics of Brazilian Institute of Geography and Statistics (IBGE) and the National Company of Food Supply (CONAB) at different levels from 2000/2001 to 2010/2011 crop years.

Mosleh (2013) developed an approach for rice area mapping and forecasting production using primarily GIS and RS technology over a large geographical extent using MODIS-derived 16-day composite of NDVI for a period of 2007-2012. For mapping the rice area during the entire growing season (i.e., January-May), the results demonstrated a reasonable agreement between the proposed method and ground-based estimates at both country-level and district-level during the period 2010-2012.

Voisin et al., 2014 developed a novel classification approach for multi-resolution, multi-sensor (optical and synthetic aperture radar, SAR) and/or multi-band images. A model for the multivariate joint class-conditional statistics of the co-registered input images at each resolution by resorting to multivariate copulas was designed. Such copulas combined the class-conditional marginal probability density functions of each input channel that were estimated by finite mixtures of well-chosen parametric families. The estimated joint probability density function was plugged into a hierarchical Markovian model based on a quad-tree structure, where each tree-scale corresponds to the different input image resolutions and to corresponding multi-scale decimated wavelet transforms. A-priori update was integrated in the model to improve the robustness of the developed classifier against noise and speckle. The resulting classification performance was illustrated on several RS multi-resolution datasets including very high resolution and multi-sensor images acquired by COSMO-SkyMed and GeoEye-1.

Esch et al., 2014 introduced an operational, application-oriented approach towards the categorization of agricultural cropland and grassland based on a novel scheme combining multi-resolution RS data with ancillary geo-information available from currently existing databases. The study used multi-seasonal high and medium resolution satellite imagery for a land parcel-based determination of crop types as well as a cropland and grassland differentiation, respectively. A tree classifier was applied to identify main crop types and grassland based on the input imagery and the derived seasonality indices. Experimental results for a test area assessed the effectiveness of the proposed approach and demonstrated that a multi-scale and multi-temporal analysis of satellite data can provide spatially detailed and thematically accurate geo-information on crop types and the cropland-grassland distribution.

Karam et al., 2016 proposed a management tool for annual inventory and monitoring of cultivated lands using RapidEye and Landsat ETM+ imagery over a test area in Bekaa Valley, Lebanon. The study concluded that satellite imagery was essential for the definition of the existing cropping patterns in the pilot area and it helped in better estimation of seasonal irrigation needs at the scheme level.

RS data has also been used for a number of plantation crop studies. A greater advantage in such studies is due to perennial nature of these crops and hence, data within a very wide bio-window can be used for their discrimination. RS data were found to be suitable for identification of many horticultural crops like oranges (Caselles and Sobrino, 1991), grapevine (Krishna Rao et al., 1996), mango (Yadav et al., 2002), banana (Johansen et al., 2009; Johansen et al., 2014), coconut (Emwandongo, 2014; KombaMayossa et al., 2015) etc.

2.2 Crop Studies using RS Data in India

India is one of the major food grain producing countries in the world like China, USA, Russia, Canada etc. Today we have a global food grain market. Thus prices of food grains at a particular location are not only affected by surpluses or deficits elsewhere in the country but also by the production and demand of other countries. In this context it has become vital for countries like India, with limited storage facilities, major logistics and transportation problems, to have the correct picture of its own food production first and the global situation next as early in the crop season as possible. The Indian crop information system however appears inadequate for the task. India has a well-established Agricultural Statistics System. It is a decentralised system of collecting the information. The State Governments – State Agricultural Statistics Authorities (SASAs) to be more specific – play a major role in the collection of the data collection and compilation of Agricultural Statistics at the State level. The Directorate of Economics and Statistics under Ministry of Agriculture and Farmers Welfare at the Centre is the pivotal agency for such compilation at the all-India level. Although, this system is well recognised its major shortcomings are subjectivity in the crop acreage estimation and delays in crop forecasts. Moreover, need for early and in-season crop production forecasting has been strongly felt. In India, many studies and projects have demonstrated that RS data provide useful information for crop inventory, area assessment, monitoring, yield prediction etc. (Munshi, 1982; Rao and Rao, 1987; Navalgund et al., 1991; Patnaik and Dadhwal, 1995; Oza et al., 1996; Dadhwal and Ray, 2000; Rajak et al., 2002; Oza et al., 2002; Singh et al., 2002; Dadhwal et al., 2002; Dadhwal et al., 2003; Ray et al., 2005; Rajak et al., 2005; Parihar and Oza, 2006; Oza et al., 2008; Parihar et al., 2010; Rajak et al., 2011; Bhagia et al., 2011; Nigam et al., 2012; NRSC, 2012; Parihar et al., 2012; Vyas et al., 2013; Ray et al., 2014; Nigam et al., 2015; Parihar, 2016). The highlights of some major studies carried out in India are presented below in chronological order of their publication.

Munshi (1982) demonstrated the potential of Landsat data for determination of wheat crop statistics in India. The study took into consideration the major drawbacks of the Indian crop information system and the problems of crop monitoring in the country utilising RS technology. Its secondary objective was to improve the crop yield and production estimates. The choice of a manual analysis technique was dictated by the non-availability of digital image processing facilities at that time and the fact that the human interpreter is flexible and can work selectively under the prevailing constraints. It primarily addressed developing an operational methodology for deriving wheat crop acreage statistics directly from Landsat MSS data, utilising manual/visual techniques. The developed methodology was tried out in a real life context in three districts of Punjab, one of the most important wheat growing states in India, over two winter (Rabi) crop seasons. The findings with regard to the acreage estimation were startling. The Government reported acreage appeared to be underestimated to the tune of 30 percent when compared with the topographical map acreage of the area. The Landsat derived acreage on the other hand agreed to within 5 percent of the map acreage.

Availability of synoptic, spatial and temporal coverage of an area became possible after satellite RS technology. A nation-wide project called CAPE was launched at the behest of Ministry of Agriculture, Government of India in 1988. Major growing regions in the country for wheat, rice, cotton, groundnut, rapeseed/mustard and Rabi (winter) sorghum were covered. Crop identification with RS data requires using the data when crop has sufficiently grown. Production forecasts were made about a month before the harvesting using multi-band RS data acquired at optimum bio-window and weather data. Ministry of Agriculture, satisfied with the performance of CAPE, came out with a request to target multiple crop production forecasts starting with crop sowing to end of season. The precision of crop inventory using such procedures has improved over the years. CAPE used optical RS data to estimate crop area of major cereals, oilseeds and fibre crops. The technique was developed for use of single date data from Indian Remote Sensing Satellites (IRS), acquired at peak vegetative growth of the crop, to estimate the crop acreage. Attempts were made to develop vegetation index based yield models to forecast the crop yield. The methodology was employed at a large number of study sites, over the years and found to perform satisfactorily (Navalgund et al., 1991).

IRS LISS-II data was used by Hegde et al, 1994 to study the extent and distribution pattern of areca-nut plantations in Sirsi taluk of Karnataka state in India. The authors used satellite data from IRS-1A, LISS-II and LANDSAT MSS for interpretation of areca plantations based on prior developed interpretation key. They observed that the areca plantations were always found in the valleys, adjacent to the forests, in elongated strips and hence, were easily distinguishable from other plantations.

Patel et al., 1995 used multi-temporal ERS-1 SAR data in C-band to identify rice crop. Combinations of data acquired on different dates were used for identification of rice crop. Analysis of the results showed that a combination of SAR data acquired at the tillering (August), booting (September) and heading (October) stages of rice crop enabled identification and area estimation of rice crop grown under lowland conditions. Single-date SAR data acquired in the month of October was found to be better for identification of rice compared to other dates.

Panigrahy et al., 1997 used the characteristic temporal backscattering signature of rice crop grown under flooded condition to estimate rice acreage for a region in West Bengal, India. Two date ERS-1 Synthetic Aperture Radar (SAR) data, one acquired within 30 days of transplantation and another after 30±40 days was found to be optimum for early estimation of rice acreage. The rice crop was found to be distinctly separable from forest, tree vegetation, village/urban areas.

Dadhwal and Ray (2000) presented a number of examples to show that satellite-based RS could be suitably used to obtain pre-harvest crop yield estimates and early crop condition assessments.

A procedure developed and implemented for rice crop inventory using multi-date SAR data in India was described by Chakraborty and Panigrahy (2000). The software package, named SARCROPS, was built around the EASI/PACE software modules. The steps were packaged together for ease-of-use and with minimal user interaction. The package was used during a number of Kharif seasons to estimate the rice area at state level in India. The authors reported the details of the SARCROPS processing chain.

A study on development of operational spectro-meteorological yield models of wheat crop using NOAA-AVHRR derived NDVI data and monthly rainfall data was carried out by Manjunath and Potdar (2002). The study concluded that amongst the three categories of models attempted, the spectro-meteorological yield models had highest predictive capability at district scale.

Palaniswami et al., 2006 tested the stability of a spectral mixture modelling method by applying the model to produce land-cover maps of coconut in Kasaragod district of Kerala in India. Classification results from applying the Spectral Mixture Analysis (SMA) were assessed by comparison with ground-truth data. SMA was performed and evaluated based on Landsat-7 ETM+ (Enhanced Thematic Mapper Plus) data. Landsat-7 ETM+ was available at 30 m resolution with six spectral bands (excluding the panchromatic band and thermal band). The procedure used in the study was based on a linear mixture model to derive continuous fields of coconut, road, laterite outcrops, construction, arecanut and cloud. SMA was performed on digital values and corresponding radiance values of the satellite imagery. The accuracy of end-member fraction was estimated as the mean of the percentage absolute difference between actual and modelled estimates.

Sahoo et al, 2006 proposed a spatial sampling technique known as Contiguous Unit Based Spatial Sampling (CUBSS) Technique. The technique incorporated size measure along with spatial contiguity of the units in the population. The sample selection criterion is based on the weights, accounting for spatial variability and the size measure accounting for areal extent. In order to tackle the problem of irregularity of the sampling units, distance based neighbours were suggested. Based on these neighbours the modified formula for spatial correlation was suggested. For defining these neighbours, the concept of lagged variable and lagged series was used. Hence later on, a spatial sampling technique termed as Distance Unit Based Spatial Sampling (DUBSS) was proposed and compared with CUBBS technique and other existing techniques. The DUBSS technique performed considerably better than all the other techniques.

Murali Krishna et al., 2009 used IRS Wide Field Sensor (WiFS) data for 1998 and 99 for assessing reduction of paddy crop due to drought affect in Palar basin of Tamilnadu state in India. Potential of temporal and multi-resolution satellite datasets for inventory of natural rubber were explored in a pilot study in Tripura state of India. The study revealed that natural rubber showed distinct spectral signature on multi-date LISS-III data and could be delineated using temporal NDVI profile using hierarchical decision rule based classification (NRSC, 2012).

Khan (2011) presented the research for extending and improving the existing toolbox for describing agricultural land use. The research followed a systems approach to map and monitor agricultural land use using a combination of RS, GIS, agricultural statistical data and crop modelling. Efforts to make hyper-temporal NDVI imagery a useful instrument for collecting agricultural land use in spatial and temporal domain has been described.

Islam and Bala (2011) used NDVI indicator derived from time series MODIS satellite images for monitoring the phonological growth of wheat during the Rabi season (November to March) of 2007-2008 for the greater Dinajpur area of Bangladesh. They found that there was significantly high correlation between total production and median number of NDVI pixels representing wheat fields and concluded that satellite images could successfully determine the coverage area and spatial distribution of the wheat during the growing season.

Parihar et al., 2012 presented a summary of the studies carried out in India showing the feasibility of SAR data for monitoring rice crop. The studies carried out in India on rice crop monitoring during the last couple of decades resulted in development of techniques/tools for national/regional assessment and were later on extended to other regions. He concluded that a stratified sampling at 5' grid size with two stage stratification and three dates' data (Shallow beam SAR) with decision rule classification was ideal approach for rice crop discrimination at acceptable accuracy of around ninety-five percent.

An operational procedure for making multiple in-season crop production forecasts was developed in India under a project called FASAL. Initially, the satellite data processing was done using commercially available software. Later-on Space Applications Centre (SAC) took initiative to provide automation intensive software solutions by developing in-house geospatial software for crop production forecasting. Moorthi et al 2014 developed FASALSoft, an ISRO software framework for crop production forecast using primarily RS data analysis. They brought out details on the software framework realised by integrating open source freely available geospatial tools which could perform the required image processing and geospatial operations in an effective way. The national level crop forecasts using single date optical data, multi-temporal optical data for winter crops and multi-temporal SAR data for monsoon crops could be done using this software. In India, the FASALSoft is now accepted as operational for making multiple in-season crop production forecasts and implemented by MNCFC, New Delhi.

Nearly six-fold increase in population during 1880–2010 coupled with economic growth has resulted in significant Land Use and Land Cover (LULC) changes including vast expansion of cropland area, in India. However, there is no accurate database of LULC that can be used for better understanding of interactions among human activities, climate systems and ecosystem in the country. Tian et al., 2014 incorporated high-resolution RS datasets from Resourcesat-1 and historical archives at district and state levels to generate LULC datasets during 1880–2010 in India. Results showed that a significant loss of forests occurred during the study period. In contrast to forests, cropland area increased significantly during 1880–2010. Greater cropland expansion occurred during the 1950–1980s that coincided with the period of farm mechanization, electrification and introduction of high yielding crop varieties as a result of government policies to achieve self-sufficiency in food production.

A methodology for monitoring progress of Rabi crop area at country scale was developed by Nigam et al., 2015 using temporal vegetation index derived from 1 km spatial resolution data from Indian geo-stationary satellite (INSAT 3A). The 10-day maximum NDVI composite products were generated and used over six crop dominant states of India. The estimates obtained in the study showed –18.1% to 14.6% deviations from reported Rabi crop area. The inter-seasonal variability in the estimate was consistent with the reported statistics with a correlation coefficient of 0.89. The authors recommended the use of high temporal NDVI product with finer spatial resolution satellite data for improved country-scale crop area monitoring.

Singla et al., 2015 have reviewed the role of geoinformatics to discriminate different crops at various levels of classification, monitoring crop growth and prediction of the crop yield. They concluded that, in addition to the RS technology, the use of ground observations, reviews, GIS and soil analysis was highly appreciable.

2.3 RS Data Classification Comparison Studies

RS data classification techniques may be grouped in three categories i.e. manual, automated and hybrid classifications. Manual satellite image classification approaches are robust and effective methods. Most of the time manual methods consume more time. In manual methods the analyst must have high degree of familiarity with the area covered by the satellite image. Efficiency and accuracy of the classification, largely depends on analyst subject knowledge and familiarity of the theme under study. Automated RS data classification methods use algorithms that are applied systematically over the entire image to group pixels into meaningful categories. Majority of the classification methods falls under this category. Automated data classification methods can be further classified into two categories i.e. supervised and unsupervised classification methods. Hybrid image classification methods combine the advantages of both the methods. These methods use automated satellite image classification methods to do initial classification, further manual methods are used to refine classification output by adding value to it based on the analyst's subject knowledge.

Supervised classifiers may be parametric or non-parametric. In parametric classification it is assumed that the observed measurement vectors obtained for each class in each spectral band during the training phase are normally distributed i.e. the observed measurements vectors are Gaussian. In non-parametric classification no such assumption is made. Maximum likelihood classification is the most popular and widely used supervised classifier. One-dimensional density slicing, parallelepiped, minimum distance, nearest-neighbour, neural network and expert system analysis are some examples of non-parametric supervised classifier. The basic concepts used in some of the widely used classifiers belonging to different categories are briefly presented below.

Minimum Distance from Mean (MDM) Classification: MDM is the simplest supervised classification technique which calculates the spectral distance between the measurement vector for the pixel under consideration and the mean vector for each training class signature. It is used to classify unknown image pixels into classes which minimises the distance between the image pixel and the class in multi-feature space. It uses either Euclidian distance or Normalised Euclidian distance for computation of the minimum distance between the data and the class having separable class variances. Even though it requires the least computational time amongst other supervised methods; within class variability is not taken into consideration by this method. Direct use of this type of classifier for classifying multi-sensor data may not provide the desired results as the spectral feature space formed by the multi-sensor data need to be normalized with respect to different radiometric ranges present in the datasets.

Mahalanobis Distance Classification (MDC): This supervised classification method is named after P. C. Mahalanobis, a famous Indian statistician. The Mahalanobis distance is the distance between an observation and the centre for each group in m-dimensional space defined by m variables and their covariance. This method is used if there is a correlation among the axes in feature space. Unlike minimum distance, this method takes the variability of classes into account. It could be more useful than minimum distance in cases where statistical criteria must be taken into account, but the weighting factors that are available with the maximum likelihood option are not needed. However, this method tends to over-classify signatures with relatively large values in the covariance matrix. Also, it is slower to compute than minimum distance; and it relies heavily on a normal distribution of the data in each input band. A detailed survey of Classification Techniques is given by Lu and Weng (2007). They reviewed intricacies of various algorithms for image classification. Similar to MDM, as far as suitability of MDC is concerned, its direct use for classifying multi-sensor data may not provide the desired results due to different radiometric ranges present in the datasets.

Maximum Likelihood Classification: MLC is one of the most popular supervised classification techniques used in the analysis of RS data. The likelihood is defined as the posterior probability of a pixel belonging to a particular class. The MLC assumes that the statistics for each class in each band follows normal distribution and calculate the probability accordingly. All the pixels are classified except for those below a specified threshold value. Each pixel is assigned to the class that has the highest probability. If the highest probability is smaller than a threshold, the pixel remains unclassified. The method needs long time of computation, relies heavily on a normal distribution of the data in each input band. Sufficient ground truth / training sites have to be selected for computing the variance-covariance matrices of population. Details on this classifier are presented in Chapter 3, Sub-section 3.8.3.

K-means Classification: The K-means algorithm is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The term 'K-means' was proposed by James MacQueen in 1967 (MacQueen, 1967). The K-means clustering algorithm is a partition-based cluster analysis method. K-means is one of the most popular unsupervised clustering classification techniques. In Clustering, the pixels are grouped into different clusters. These clusters have the property of homogeneity among the same cluster and heterogeneity between different clusters. In K-means, K stands for number of clusters from the image data defined by user or from any automatic techniques. It initialises randomly K cluster mean vectors. The algorithm is iterative in nature and each pixel is assigned to an exclusive cluster. In the iteration process it minimise within cluster scatter and the process repeats until the scatter is less than a threshold value or reaches the maximum number of iterations. The image is divided into K clusters and the mean of each cluster is computed. In the next iteration, the pixels are assigned to the nearest classes and new class means are computed. The final partitioning of the clusters is based on the final K means obtained after the completion of iteration, hence the name K means. Further details are presented in Chapter 3, Sub-section 3.8.1.

ISODATA: Iterative Self-organizing Data Analysis (ISODATA) clustering is one of the most popular methods of unsupervised classification. Clustering based algorithms are used to partition the spectral image into number of spectral classes based on the statistical information inherent in the image. ISODATA creates predefined number of clusters in a satellite image. No a-priori definition of the classes is used. Cluster centres are randomly placed and pixels are assigned based on the shortest distance to centre method. The standard deviation within each cluster, and the distance between cluster centres are calculated. Clusters are split if one or more standard deviation is greater than the user-defined threshold otherwise they are merged. Further iterations are performed until, either the average inter-centre distance falls below the user defined threshold, the average change in the inter-centre distance between iterations is less than a threshold, or the maximum number of iterations is reached. Later on meaningful labels/classes are assigned to these clusters by the analyst (Lu and Weng, 2007). Tso and Olsen (2005) have incorporated both spectral and contextual information to build a fundamental framework for unsupervised classification, Hidden Markov Models, which showed improvements in both classification accuracy and visual qualities. Algorithms of unsupervised classification has also been investigated and compared with regard to their abilities to reproduce ground data in a complex area (Duda and Canty, 2002). Despite its easy application, one disadvantage of the unsupervised classification is that the classification process has to be repeated again if new data (samples) are added (Xie et al., 2008). Un-supervised classification has a potential to produce more accurate results than supervised classification in case of a large, complex and heterogeneous area with lack of intimate familiarization and field information. Further details on ISODATA clustering are presented in Chapter 3, Sub-section 3.8.2.

Fuzzy Classification: In Fuzzy classification the image pixels are grouped into a fuzzy set whose membership function is defined by the truth value of a fuzzy propositional function. A Fuzzy Set is any set that allows its members to have different grades of membership in the interval [0,1]. Zadeh L. A. developed the concept of Fuzzy logic in 1965 for handling uncertain and imprecise knowledge in real world applications (Zadeh, 1965, Zadeh, 1988).

Fuzzy classification takes into account the heterogeneous and imprecise nature (mix pixels) of the real world scenario. Proportions of the multiple classes within a pixel (e.g., 30% bare soil, 30% forest, and 40% crop) can be obtained. While in case of a hard classification (ISODATA, K-means, MLC etc.) each pixel belongs to the class it most closely resembles; in soft classification (Linear Mixture Model, Fuzzy classifier etc.) each pixel can belong to more than one class and has membership grades for each class. If needed, defuzzification can produce a crisp result (one pixel to only one class) from fuzzy membership grades. In fuzzy classification the boundary between two neighbouring classes is assumed as a continuous, overlapping area within which an object has partial membership in each class. This viewpoint reflects the reality of many applications in which categories have fuzzy boundaries. Zadeh coined the word "fuzzy" because he felt it most accurately described what was going on in the theory. He had thought about "soft", but that really didn't describe accurately what he had in mind. Nor did "unsharp", "blurred", or "elastic". In the end, he couldn't think of anything more accurate so he settled on "fuzzy" (Blair, 1994). Researchers have demonstrated the usefulness of standalone fuzzy classification and combination of fuzzy approach with other classifiers for accurately classifying heterogeneous land-use/land-covers (Wang, 1990; Foody, 1997; Zhang and Foody, 1998; Zhan et al., 2000; Wang and Jamshidi, 2004; Al-Obeidat et al., 2015). Sometimes results from fuzzy classification are unexpected and hard to debug. The classifier is considered computationally complicated and is not recommendable, if conventional approach yields a satisfying result.

Artificial Neural Networks (ANN): A neural network, a massively parallel-distributed processor, is made up of simple processing units called neurons. Neurons have a natural tendency for storing experiential knowledge and making it available for use. Artificial Neural Network or ANN is a computational system that resembles the organizational principles present in biological nervous systems. It has a normal tendency for storing experiential knowledge like a human brain and uses this for pattern recognition (Kohonen, 1988). In ANN the basic computational element is known as the neuron or node. The neuron processes data in stages. First, the messages received are aggregated by an internal activation function. Then, the information is sent to transfer functions, which determine whether the neurons will send the output message or not. Multiple neurons are connected together in layers. These layers called the input layers are set up to receive input information, process the data through one or more hidden layers, and produce a corresponding output pattern through the output layer.

ANN approaches have a distinct advantage over statistical classification methods in achieving higher training accuracy. The capabilities of ANN for non–linear function approximation, data classification, non-parametric regression and nonlinear decision making are crucial in applications such as generalization ability when dealing with land use /cover related feature classification from a satellite imagery (Mohanty and Majumdar, 1996). They are non-parametric and require little or no a-priori knowledge of the distribution model of input data (Benediktsson and Sveinsson, 1997). Incorporation of supervised training algorithms such as feed– forward, back propagation networks etc., enable them to distinguish interesting features from voluminous and noisy data sets having distortions. ANNs have high processing speed, robustness and generalization capabilities and are able to deal with high dimensional data spaces.

Support Vector Machines: Support Vector Machine (SVM) is a supervised non-parametric learning technique independent of any assumptions for the underlying data distribution. It aims to find a hyperplane which separates the dataset into a discrete predefined number of classes. Learning refers to the iterative process of finding a classifier with optimal decision and then to separate simulation boundary to separate the training pattern and then to separate simulation data under the same configuration (Zhu and Blumberg, 2002). SVMs are linear binary classifiers and assume that the multispectral feature data are linearly separable in the input space. This assumption leads to overlapping of classes making the separability difficult (Cortes and Vapnik, 1995).

SVMs are not widely used like other classifiers like decision tree, maximum likelihood classifiers etc., by the general remote sensing community. However, it has been reported by many researchers (Mountrakis et al., 2011) that SVM performs similar to other established method. In the field of remote sensing SVMs are appealing, for their ability to successfully handle small training data sets with higher classification accuracy than the traditional methods (Mantero et al., 2005). In its learning process the SVMs minimizes the classification errors of unseen data without prior assumption on its probability distribution. It has been reported that use of only a quarter of the original training samples of SPOT HRV satellite imagery with SVM was sufficient to produce equally accurate two-crop classification (Foody and Mathur,2004). Incorporation of localized highly sensitive transformation to capture subtle changes in hyperspectral signature has also been attempted using SVM (Sahoo et al., 2007).

Decision Rule Based Tree Classification: Decision tree classifier is one of the most popular supervised classification methods, which is non-parametric and does not require the data to be in normal distribution (Safavian and Landgrebe, 1991, McIver and Friedl, 2001). Decision tree classifiers are easy to train and they learn quickly from examples. It follows a tree structured graph or model of decision rules and their possible result. Following a tree architecture, it is composed of a root node, a series of internal nodes and leaf nodes. Every node can have only one father node and two or more child nodes. Nodes are connected with each other by branches. Each node is passed through certain test properties. Similarly, each leaf node corresponds to a class property. Decisions rules are not only designed following a tree architecture, but also a group of IF-THEN rules are also used (Jiang et. al., 2011). Classification rules in turn are easy to interpret and can serve as a knowledge base for further classification of satellite image. It is easy to insert additional layers of ancillary data with decision trees due to its nonparametric nature. The basic scheme in decision tree classification is to mask every target as an image layer, so that the influence of one target on the other is minimum. In comparison to decision properties, rules are more popular, because of their simplicity, flexibility and convenience to use to build up the base of an expert system. There are many decision tree algorithms such as ID3, CD4.5, CART etc. Decision tree classification has been widely used for the classification of remote sensing images for the extraction of information and utilization of land use coverage (McIver and Friedl, 2001). Use of decision tree classifier for multi-sensor integration through decision fusion has been presented in Chapter 3, Section 3.9.

Researchers have employed a number of algorithms and classification techniques for classifying remotely sensed data available from various sources (Cortes and Vapnik, 1995; Bruzzone and Serpico 1997; Melgani and Bruzzone, 2004; Chanussot et al., 2006; Abelen et al., 2011; Baraldi, 2011b; Abburu and Golla, 2015). A brief highlight of some of the investigations dealing with classification of RS data is presented below in chronological order.

Fierens and Rosin (1994) studied the effects of applying filters pre-processing and post-processing to RS data both in the spatial and the feature domains. To minimise the effect of noisy training pixels, a k-nearest neighbour filtering algorithm was applied to the training data. This involved reclassifying each training pixel by the majority class of the set of k closest training pixels in feature space. The procedure eliminated isolated training pixels and produced more compact class clusters. The effects of all spatial and spectral filtering methods were validated by applying them to three different test cases.

Cortes and Vapnik, 1995 constructed a new type of learning machine and introduced it as the support-vector network for two-group classification problems. The algorithm was tested and its performance was compared to the performance of other classical algorithms. The new algorithm exhibited a very fine performance in the comparison study, in spite of its simple design with respect to its decision surface.

Hansen et al., 2000 reported the production of a 1 km spatial resolution land cover classified map using the Advanced Very High Resolution Radiometer (AVHRR) data for 1992–1993. This land cover map was later on used by MODIS to serve as an input for several algorithms requiring knowledge of land cover type. A set of image pixels was used within a hierarchical tree structure to classify the AVHRR data into 12 classes. Comparisons of the final product with regional digital land cover maps derived from high-resolution remotely sensed data reveal general agreement, except for apparently poor depictions of temperate pastures within areas of agriculture.

Manakos et al., 2000 compared two different classification concepts, the pixel based and the object oriented classification methods. In the study, the former one was represented by the ISODATA clustering method while the latter one by the new innovative image analysis method of DELPHI 2 eCognition. The level of the success of the two methods is evaluated by the use of ground truth data. The better precision and the improvement factor in pattern recognition that could be accomplished with the object based classification method were demonstrated. Moreover, the advantages of the object oriented classification method were discussed and analysed. The focus of this work was on agricultural applications and particularly on precision farming.

The study carried out by Melesse and Jordan (2002) compared two classification algorithms, the fuzzy technique and an augmented form of the ISODATA technique. After masking out mixed categories (clouds vs built-up and shadows vs water bodies) from the study area, fuzzy and augmented- ISODATA classifications were performed for discriminating low-altitude clouds from their shadows using Landsat TM data. The ISODATA classification algorithm was run on the visible/shortwave bands and augmented with scatter diagrams of surface temperature versus several vegetation indices. The fuzzy algorithm was run on TM bands 1 through 5 and band 7. An accuracy assessment of the techniques showed that both algorithms successfully discriminated clouds from other bright features and shadows from other dark features, with an overall accuracy of greater than 80 percent.

To explore the full value of RS data from multiple sources, the appropriate information has to be extracted and presented in standard format to import it into geo-information systems and thus allow efficient decision processes. The object-oriented approach can contribute to powerful automatic and semiautomatic analysis for most RS applications. Benz et al., 2003 explained principal strategies of object-oriented analysis, discussed how the combination with fuzzy methods allowed implementing expert knowledge and described a representative example for the proposed workflow from RS imagery to GIS. The strategies were demonstrated using the first object oriented image analysis software on the market, eCognition, which provided an appropriate link between RS imagery and GIS.

Shaw and Burke (2003) presented an overview of the fundamental elements of spectral imaging and discussed the historical evolution of both the sensors and the target detection and classification applications. Ruiz et al., 2004 demonstrated that the combination of texture methods and spectral information improved the results of classification.

Melgani and Bruzzone (2004) addressed the problem of the classification of hyperspectral RS images by SVMs. They assessed the effectiveness of SVMs with respect to conventional feature-reduction-based approaches and their performances in hyper-subspaces of various dimensionalities. The performances of SVMs were compared with those of two other nonparametric classifiers i.e., radial basis function neural networks and the K-nearest neighbour classifier. Based on the results obtained on a real Airborne Visible/Infrared Imaging Spectroradiometer hyperspectral dataset they concluded that, whatever the multi-class strategy adopted, SVMs were a valid and effective alternative to conventional pattern recognition approaches for the classification of hyperspectral RS data.

The problem of scarcity of labelled pixels required for segmentation of remotely sensed satellite images in supervised pixel classification framework was addressed by Mitra et al., 2004. An SVM was considered for classifying the pixels into different land-cover types using IRS-1A data. It was initially designed using a small set of labelled points and subsequently refined by actively querying for the labels of pixels from a pool of unlabelled data. The label of the most interesting/ ambiguous unlabelled point was queried at each step. The active learning was exploited to minimize the number of labelled data used by the SVM classifier by several orders.

Xu et al., 2005 developed and tested an un-mixing approach for estimating sub-pixel fraction of crop area using MODIS data based on the temporal reflectance throughout the growing season. The crop area estimated through LANDSAT/TM data was used as the reference data for comparison. The results demonstrated the importance of sub-pixel heterogeneity in cropland systems. The potential of temporal un-mixing to provide accurate and rapid assessments of crop distributions using MODIS data was demonstrated.

Storvik et al., 2005 presented a Bayesian framework for classification of multi-resolution images based on multi-scale model and the concept of a reference resolution. Prior knowledge about the spatial characteristics of the classes was specified through a Markov random field model at the reference resolution. Data at coarser scales were modelled as mixed pixels by relating the observations to the classes at the reference resolution. The classification was realized by an iterative conditional modes (ICM) algorithm. A computationally efficient scheme based on a combination of the ICM and the expectation–maximization algorithm was proposed. The proposed multi-scale estimation and classification method provided a better way of exploiting spectrally rich images at lower spatial resolution together with images at the reference resolution.

Uma Shankar et al., 2006 proposed a Neuro-Fuzzy-Fusion (NFF) method for combining the output of a set of fuzzy classifiers in a Multiple Classifier System (MCS) framework. The outputs of a set of classifiers were fed as input to a neural network, which performed the fusion task. The fusion technique was tested on a set of RS images and compared with existing techniques. Experimental study revealed the improved classification capability of the NFF based MCS as it yielded consistently better results.

Zhu et al., 2006 proposed a new classification method of remotely sensed data based on the multi-resolution hierarchy. The method was applied for soft classification of RS data by implementing inter-hierarchy strategies and hetero-hierarchy strategies. The Kohonen neural network method and hybrid decision tree approach were applied. Both the methods were employed to determine relationships of different classes from homo-hierarchy and relationships of same classes from multi-hierarchy remotely sensed data.

Laliberte et al., 2007 combined decision trees with hierarchical object-oriented image analysis. They developed a unique approach using object-based rather than pixel-based image information as input for a classification tree for mapping arid land vegetation. Input variables included spectral, textural and contextual image information and the variables chosen by the decision tree included many features not available or as easily determined with pixel based image analysis. Spectral information was selected near the top of the classification trees, while contextual and textural variables were more common closer to the terminal nodes of the classification tree. The combination of multi-resolution image segmentation and decision tree analysis facilitated the selection of input variables and helped in determining the appropriate image analysis scale.

Kumar et al., 2007 presented a full fuzzy concept at a sub-pixel level with density estimation using Support Vector Machine (D-SVM) and Fuzzy C-Means (FCM) approaches. These approaches (SVM and FCM) were evaluated with respect to a fuzzy weighted matrix. In a test study using a four-channel dataset, they found that a D-SVM function using a Euclidean norm produced better accuracy.

An important approach for unsupervised land cover classification in RS images is the clustering of pixels in the spectral domain into several fuzzy partitions. Bandyopadhyay et al., 2007 utilized a multi-objective optimization algorithm to tackle the problem of fuzzy partitioning where a number of fuzzy cluster validity indexes are simultaneously optimized. Results demonstrating the effectiveness of the proposed technique were provided for numeric RS data described in terms of feature vectors. Different land cover regions in RS imagery were classified using the technique to establish its efficiency.

Li (2010) put forward a new Rule-based Classification System (RBS) which integrated spectral characteristics, textural features and ancillary data (such as general geological map and elevation data) to improve the lithological classification accuracy and the subsequent mapping accuracy in the study area of South-western Prieska Sub-basin, Transvaal Supergroup, South Africa.

The automatic or semi-automatic transformation of huge amounts of multisource multi-resolution RS data into useful information still remains far more problematic than might be reasonably expected. Based on an operational automatic hybrid RS Image Understanding System (RS-IUS) presented in many studies (Baraldi et al., 2006; Baraldi et al., 2010a;

Baraldi et al., 2010b; Baraldi et al., 2010c; Baraldi et al., 2010d; Baraldi, 2011a), Baraldi (2011b) developed a Satellite Image Automatic Mapper™ (SIAM™, University of Maryland Invention Disclosure No. IS-2010-103, patent pending) software, an operational automatic software for unsupervised near real-time per-pixel multi-source multi-resolution application-independent spectral rule-based decision-tree classification of space-borne multi-spectral imagery. They highlighted the several degrees of novelty and operational advantages of the proposed two-stage hybrid RS-IUS employing SIAM™ as its preliminary classification first stage in comparison with alternative approaches.

Abelen et al., 2011 developed a user interface to facilitate the interactive adaption of decision trees in a heterogeneous and dynamic urban environment. The user interface decision tree with adjustable thresholds was found to be more efficient in classifying a broad variety of scenes in urban environments than a decision tree with fixed thresholds. The platform of the user interface was composed of fixed feature sets which were equally applied to all scenes. They were selected on the basis of the Transformed Divergence. The features' thresholds were connected to controllers, which could be adapted by the user.

Myint et al., 2011 took advantage of spectral as well as spatial information derived from QuickBird image data to examine if an object-based classifier can accurately identify urban classes. The overall accuracy based on spectral information alone was low. Five different classification procedures with the object-based paradigm that separated spatially and spectrally similar pixels at different scales were employed. The object-based classifier achieved a high overall accuracy (90.40%), whereas the most commonly used maximum likelihood classifier produced a lower overall accuracy (67.60%). This study demonstrated that the object-based classifier was a significantly better approach than the classical per-pixel classifiers.

The traditional hard classification techniques are parametric in nature and they expect data to follow a Gaussian distribution, they have been found to be performing poorly on high resolution satellite images, as classes in these images tend to exhibit extensive overlapping in spectral space. This produces spectral confusion among the classes and results in inaccurate classified images. A major drawback of such classifiers lies in the difficulty of integrating ancillary data, which follows a non-Gaussian distribution nature. Ancillary data provides extra spectral and spatial knowledge, which improves the classification accuracy. Classification done using such knowledge is known as knowledge base classification. Pooja et al., 2011 explored a non-parametric decision tree classifier to extract knowledge from the spatial data in the form of classification rules. The study reported the overall accuracy of classified image using the decision tree method to be 86.66% with kappa values 0.8133.

Zhong et al., 2011 presented an unsupervised artificial immune network for RS image classification based on artificial immune network. The proposed method could adaptively obtain user-defined parameters, such as clone rate and mutation rate and evolve the memorial immune network by immune operators and biological properties, such as clone, mutation and memory operators, using the RS image for the task of RS image clustering. Three experiments with different types of images were performed to evaluate the performance of the proposed algorithm and to compare it with other traditional unsupervised classification algorithms e.g. k-means, ISODATA, and fuzzy k-means. The proposed algorithm was observed to outperform the traditional algorithms in the three experiments, hence potentially provided an effective option for unsupervised RS image classification.

Zhou et al., 2011 proposed a multi-classifier combined decision tree hierarchical classification method to improve the accuracy of remote-sensing image classification. An Initial Decision Tree (IDT) is generated, edited the rules of IDT, and then this IDT was connected with multi-classifier to generate a Hybrid Decision Tree (HDT). Accuracy analysis of experimental results showed that the proposed method could greatly improve the accuracy of classification.

Salehi et al., 2012 developed a hierarchical rule-based object-based classification framework based on a small subset of QuickBird imagery coupled with a layer of height points called Spot Height (SH) to classify a complex urban environment. In the rule-set, different spectral, morphological, contextual, class-related and thematic layer features were employed. To assess the general applicability, the classification framework with slightly different thresholds was applied to larger subsets of QB and IKONOS data. Results showed an overall accuracy of 92% and 86% and a Kappa coefficient of 0.88 and 0.80 for the QuickBird and IKONOS images, respectively.

Zhai et al., 2012 compared results of a decision tree classification (C5.0) with maximum likelihood classification and found that C5.0 increased image features information, which increased discrimination between categories. Furthermore, in the analysis of data with high dimensionality such as multi-temporal LANDSAT data, the computational speed of the maximum likelihood classifier was reduced because the classification time increased as the square of the number of bands. The study concluded that decision tree based on C5.0 classification method was suitable for large area land cover classification for its automation, high-speed and high precision.

Huth et al., 2012 presented an automated processing environment, named TWOPAC (TWinned Object and Pixel based Automated Classification Chain), for the derivation of land cover and land use information. It enabled the standardized, independent, user-friendly and comparable derivation of LULC information, with minimized manual classification. TWOPAC allowed classification of multi-spectral and multi-temporal RS imagery from different sensor types based on pixel-based and object-based characteristics. It enabled automatic generation of the decision tree classifier based on a C5.0-retrieved ASCII-file along with a fully automatic validation of the classification output by sample based accuracy assessment. TWOPAC's functionality to process geospatial raster or vector data via web resources (server, network) enabled its usability independent of any commercial client or desktop software and allowed for large scale data processing on servers.

A study carried out by Tana et al., 2013 indicated that decision rule classification, integrated with multi-temporal MODIS data and ancillary data was useful to develop an improved wetlands map at a continental scale. A decision rule classification method was developed relying upon the hierarchical characteristics of land types and prior knowledge about the geographical location of wetlands. Elevation data were used to build the elevation mask and a climate map was used to subdivide the study area into five sub-regions. In the quantitative accuracy assessment, user's and producer's accuracies of wetlands for the whole study area were calculated. A comparison with two existing global land cover datasets, GLC2000 (Global Land Cover 2000) and IGBP DISCover (International Geosphere-Biosphere Programme Data and Information System cover) was made.

Bigdeli et al., 2013 presented a multiple classifier system on hyperspectral and LIDAR data. The results obtained by the proposed classifier fusion system approach lead to higher classification accuracies compared to the single classifiers on hyperspectral and LIDAR data.

Ferran et al., 2013 described a web-based system which allows an inexperienced user to perform unsupervised classification of satellite/airborne images. The processing chain adopted was implemented in C language and integrated with HTML5, JavaScript, PHP, AJAX and other web programming languages. Image acquisition with the Applications

Programmer Interface (API) is fast and efficient. Several experiments were performed to compare the classification accuracy of the proposed chain with a well-known Environment for Visualizing Images (ENVI) software package.

During most of the classifications of RS data, the pixels or objects are classified usually in more than one class. Such classifications may be called as binary or multi-class classifiers. Contrary to such binary and multi-class classifiers, the purpose of a one-class classifier for RS applications is to map only one specific land use/land cover class of interest. Training these classifiers exclusively requires reference data for the class of interest, while training data for other classes is not required. Thus, the acquisition of reference data can be significantly reduced. However, one-class classification is fraught with uncertainty and full automatization is difficult, due to the limited reference information that is available for training the classifier. Mack et al., 2014 proposed a user-oriented one-class classification strategy based among others on the visualization and interpretation of the one-class classifier outcomes during the data processing. The potential of the proposed strategy was demonstrated by classifying different crop types with hyperspectral data from Hyperion.

Parashar and Kundra (2014) presented summary of different image classification methods and compared them based on their advantages and disadvantages. The comparison chart showed their feature differences. The study found that the problem of over-fitting could be resolved by changing C parameter of SVM. The study tried to find out value of C parameter in the range that resolved over-fitting and plotted the average precision on the training and test data by varying C values for the different kernels.

Li et al., 2014a reviewed major RS image classification techniques, including pixel-wise, sub-pixel-wise and object-based image classification methods and highlighted the importance of incorporating spatio-contextual information in RS image classification.

Li et al., 2014b tested two unsupervised and 13 supervised classifications with a number of machine learning algorithms on a Landsat TM data over Guangzhou City, China. Their analysis focused primarily on the spectral information provided by the TM data. The study indicated that the potential loss of overall accuracies in urban and rural-urban fringe environments due to lack of middle infrared bands could be within 3%–5%. Unsupervised algorithms could produce as good classification results as some of the supervised ones when a sufficient number of clusters were produced and clusters could be identified by an image analyst familiar with the study area. They found that when sufficiently representative training samples were used, most algorithms performed reasonably well. Lack of training samples led to greater classification accuracy discrepancies than classification algorithms themselves.

Giachetta and Fekete (2015) demonstrated a way to take advantage of the new paradigms like big data and cloud computing for advancing RS analysis. An approach was proposed utilizing distributed computing, which enables the automated execution of the task on large input data with much better response time. Results showed that significant performance benefits could be achieved at the expense of minor loss of accuracy.

Incorporating dissimilar features from multiple sources can provide valuable diverse information for RS data analysis. However, MRS data require large quantities of labelled data to train robust supervised classifiers, which are often difficult and expensive to acquire. A mixture-of-kernel approach can facilitate the construction of an effective formulation for acquiring useful samples via active learning (AL). Zhang et al., 2014 proposed an ensemble multiple kernel active learning (Ensemble MKL-AL) framework that incorporated different types of features extracted from MRS data (hyperspectral imagery and LiDAR data) for robust classification. An ensemble of probabilistic multiple kernel classifiers was embedded into a maximum disagreement-based AL system, which adaptively optimized the kernel for each source during the AL process. At the end of each learning step, a decision fusion strategy was implemented to make a final decision based on the probabilistic outputs. The proposed framework was tested in a multi-source environment, including different types of features extracted from hyperspectral and LiDAR data. The experimental results validated the efficacy of the proposed approach.

Gómez-Chova et al., 2015 provided a taxonomical review of the current methodologies for multimodal classification of RS images and highlighted the most recent advances. They illustrated the different approaches in seven challenging RS applications including multi-resolution fusion for multispectral image classification; image downscaling as a form of multi-temporal image fusion; multi-dimensional interpolation among sensors of different spatial, spectral and temporal resolutions; multi-angular image classification; multi-sensor image fusion exploiting physically-based feature extractions; multi-temporal image classification of land covers in incomplete, inconsistent and vague image sources; spatio-spectral multi-sensor fusion of optical and radar images for change detection; and cross-sensor adaptation of classifiers.

Cavallaro et al., 2015 took stock of the statistical data mining methods in RS used to contribute to smart data analysis in the light of possible automation and parallel processing techniques. One of the reasons of this study was to understand whether parallelization techniques can overcome limitations observed in serial tools when working with emerging concrete examples of big data. One conclusion from the technology reviews was that despite the availability of many parallelization techniques, just a very limited set of suitable parallel tools existed in the open source domain for the concrete problem space of using parallel SVMs.

Abburu and Golla (2015) summarised a number of automated image classification methods and compared several studies carried out by various researchers. The study showed that different classifiers performed better than the others in different studies depending upon the type of RS data, objective of the study, area of the study etc. Considering the complexities involved in the analysis and the variety of available data and algorithms, Multiple Classifier Systems (MCS) proved to be of the utmost interest, significantly improving the classification performances.

Joshi et al., 2016 reviewed 112 studies on fusing optical and radar data offering unique spectral and structural information for land cover and land use assessments. The study concluded that progress was required in the development of robust techniques of data fusion to map the intricacies of land uses and changes.

2.4 Multi-level and Multi-source Crop Acreage Estimation

As mentioned earlier, most of the RS data based crop acreage studies were meant to provide estimates at one scale (one level) at a time. However, few studies discussed potential of multi-scale RS data for multi-scale crop area estimation. Luo and Kay (1989) provided a survey of multi-sensor data integration and fusion approaches used in different areas of data applications. They examined the general multi-sensor fusion methods, sensor selection strategies and world models along with other approaches of integration and fusion of information from combinations of different types of sensors. Multi-sensor data integration and multi-sensor data fusion are two different types of data analysis techniques. While multi-sensor data integration is synergistic use of the information derived from multiple source data;

multi-sensor fusion refers to actual merging or combining of the data obtained from multiple sensors (Gong, 1994).

Although, Dadhwal et al., 2002 reviewed the approach and techniques for crop discrimination and area estimation using RS data, they also presented the future perspective of utilization of multi-source data and merging techniques. Multisource data classification methods are usually based on neural networks, statistical modelling, genetic algorithms and fuzzy logic. For most of these methods, the individual data sources are at first treated separately and classified by either statistical or neural methods. Then, several decision fusion schemes are applied to combine information from the individual data sources. These schemes include weighted consensus theory where the weights of the individual data sources control the influence of the sources in the combined classification. Using all the data sources individually in consensus-theoretic classification can lead to a redundancy in the classification process. Therefore, Benediktsson and Sveinsson (2003) focused on neural networks based on pruning and regularization for combination and classification. The considered methods were applied in classification of a multisource dataset.

A classifier was developed by Jiang et al, 2010 to classify multi-source and multi-temporal RS data (TM, CBERS, and MODIS-NDVI). They found that the overall accuracy of the integration of multi information classification provided better overall accuracy than the SVM.

Waldhoff et al., 2012 presented their study on the generation of multi temporal, disaggregated land use data with the goal to derive a crop rotation map. They used Multi-Data Approach (MDA) to integrate multi-temporal remote sensing classifications with additional spatial information by the means of expert knowledge-based production rules. Datasets of ASTER, Landsat TM & ETM+ as well as IRS-P6 were used. The results showed that the information content of a land use dataset considerably enhanced by combining crop type information of multiple observations during each growing season. In terms of classification accuracy the analysis yielded similar results with support vector machines (SVM) and the classical maximum likelihood classifier (MLC) for all sensors, with SVM being mostly only slightly better.

An approach for categorization of agricultural cropland and grassland combining multi-resolution RS data was developed by Esch et al., 2014. The results for a test area assessed the effectiveness of the proposed approach and demonstrated that a multi-scale and multi-temporal analysis of satellite data can provide spatially detailed and thematically accurate geo-information on crop types and the cropland-grassland distribution. A novel approach of multi-resolution, multi-sensor (optical and synthetic aperture radar, SAR) and/or multi-band images was developed by Voisin et al., 2014. Multi-resolution RS datasets (including very high resolution and multi-sensor images) were used to illustrate the classification performance. Sahay et al., 2014 made an attempt to monitor the timelines of the sowing of rabi crops and their progression using data from multiple sources viz. a set of indices derived from remote sensing, meteorological parameters and crop simulation modelling. The methodology consisted of analysis of multi-temporal AWiFS and MODIS datasets of historical and current seasons for the period October to March covering rabi season. The results were discussed in terms of crop progression, start-of-the-season and crop condition etc.

An attempt was made by Singh et al., 2015 to design and develop an application of a web enabled spatial decision support system (SDSS) for near real time crop monitoring at district level using multi-source information. It used multi-temporal remote sensing images received at satellite ground station from Terra/Aqua MODIS sensor. Regular real-time satellite derived parameters of rainfall, day and night land surface temperature (LST), and crop vigour index of NDVI are generated for crop pixels and aggregated at district level.

Toward incorporation of weather data, economic factors, GPS assisted field information, GIS along with RS data, an integrated approach for multiple crop production forecasting at multiple scale was developed by Space Applications Centre (SAC), Ahmedabad. The technique developed under FASAL project was transferred to Ministry of Agriculture for operational applications. The concept of FASAL aimed at using econometric models to forecast the area and production before the crop sowing operations. The scientists at SAC are further involved in enhancing the scope of FASAL for the crops not covered earlier. RS data, both optical and microwave form the core of crop area estimation and crop condition assessment. Temporal RS data is being used to monitor the crop through its growing period. Components of FASAL were developed, tested and implemented through a series of exercise. Typically, three in-season forecasts of major crops are being made under FASAL at national level. Different components of FASAL are summarised by Parihar and Oza (2006), Parihar et al, 2012 and Parihar, 2016.

The studies presented in this section clearly brings out the importance of multi-source data to extract the crop information at different spatial scaled. The use of multi-source data for multi-level crop acreage estimation is largely limited by the lack of well-developed technique for normalization of multi-source data and integration of information derived from multi-source data. It refers to efficient management of multi-source data to provide the needed information from the data available at different spatial scales.

2.5 Research Gap

While going through these RS based crop studies it was found that most of the investigations have used single source RS data for one particular study; few studies attempted multi-source data. Although, the data from different RS sensors had been available for the same geographic area for same time duration, it was not used synergistically for crop studies. In India a large volume of RS data from different sensors like Resourcesat-2 AWiFS / LISS-III / LISS-IV, RISAT-1 SAR, Terra/Aqua MODIS (MODerate resolution Imaging Spectroradiometer) have usually been used separately but synergistic use of these data for crop acreage estimation was rarely made. Limited studies have used multi-sensor data but those approaches could not be operationalized due to complexities involved in the analysis. Also, no serious attempt was made to use RS data from multiple sources for early estimation of crop sown area at state or district scale. Few studies made use of multi-year MODIS data, which is easily and freely available to global community, for multi-year crop studies but no study assessed multi-year crop growth rate at any Indian state. A number of research studies demonstrated the potential of combining multi-sensor / multi-source data for deriving the information needed at different spatial scales (Luo and Kay, 1989; Gong, 1994; Waldhoff et al., 2012; Voisin et al., 2014; Sahay et al., 2014; Singh et al., 2015). However, there is no well-developed technique to integrate the information extracted from multiple sources to provide an early crop acreage estimates at different spatial scales.

Non-availability of frequent high spatial resolution data is an issue that affects an early estimation of crop area estimation over large areas. Typically, high spatial resolution (low temporal frequency) RS data is used for single crop area estimation over small regions. Similarly, frequently available data (low spatial resolution) is used for multiple crop area estimation over large regions. While estimating small area crop acreages, frequently available low spatial resolution data is not used; less frequently available high spatial resolution data is overlooked for large area crop acreage estimation. Hence, an early estimation of small area crop acreage estimation is not done and crop acreage estimation over large area suffers due to crop field discrimination ambiguity. This situation may improve if we develop techniques of using integrated information derived from high spatial resolution data as well as high temporal resolution data at different scales of crop acreage estimations.

2.6 Research Questions

Based on the extensive literature review and the above mentioned research gap it became clear that there is a great scope of using multi-source data for crop studies. At the same time, it is also evident that there are some serious issues related to geometric and radiometric normalisation involved in using multi-source data. It prohibits synergistic use of multi-source data for crop monitoring. Considering these observations and inferences, a number of Research Questions (RQ) were framed to fill the research gap. Following are the research questions –

- **RQ1**: What are the potential issues that affect integration of multi-source data for crop studies and how can these issues be resolved?

- **RQ2**: Can a methodology be developed to use multi-source data for early crop sown area estimation at district level (typically less than 1 million hectare area) and at state level (typically more than 10 million hectare area)?

- **RQ3**: Can a methodology be developed to use the information derived from previous multi-years RS data for current year's crop sown area estimation?

- **RQ4**: Can a moderate resolution RS data like that from MODIS be used for assessing multi-year Rabi crop area changes at state level?

The aims and objectives of the research study were designed to answer the above mentioned research questions.

2.7 Aims and Objectives of the Study

Considering the importance of crop monitoring, potential of remotely sensed data in providing crop information, and above mentioned research gap with respect to use of multi-source RS, a study was designed and taken up to provide solutions of the above identified research questions. The overall aim of this study was to find out all major issues that create hurdle in using multi-source data synergistically and solve those issues. Based on the research questions following aims and objectives were targeted:

- **Objective 1**: To identify the potential issues that affect integration of multi-source data for crop studies and to resolve them in a MRS data study for crop assessment. The aim was to clearly identify the issues, provide their solutions and demonstrate the solutions with examples.

- **Objective 2**: To develop a methodology of early crop sown area estimation at district level (typically less than 1-million-hectare area) and state level (typically more than 10-million-hectare area) using multi-source data. The aim was to carry out an early estimation of crop acreages for a district (Mehsana district in Gujarat) and a state (Gujarat, India).

- **Objective 3:** To develop a methodology which can integrate the information derived from previous multiple years RS data with current year's RS data for in-season crop sown area estimation. The aim was to take advantage of historical information available from previous years' data and to use it for estimation of the crop acreage for the current season.

- **Objective 4**: To use a coarse resolution RS data like that from MODIS for assessing multi-year crop area changes at state level. The aim was to demonstrate a RS based technique for monitoring crop area changes over a large region (a state) in India.

Three sub-studies were planned and carried out to accomplish the above stated four objectives. Sub-study-A was aimed to accomplish the first two objectives i.e. Objective 1 and a part of Objective 2 (district level study). In this sub-study, the study area was taken up as Mehsana district in Gujarat state and the major RS data were multi-date AWiFS and single date LISS-III data. The second sub-study, Sub-study-B, was taken up to achieve two of the objectives i.e. Objective 1, Objective 2, and Objective 3. Multi-date MODIS data for six Rabi seasons (2006-07 to 2011-12) and multi-date AWiFS data for 2011-12 Rabi season were the major RS datasets used in this sub-study. Sub-study-C was intended to evaluate multi-date MODIS data for ten Rabi seasons (2002-03 to 2011-12) for assessing Rabi crop area changes over Gujarat and to achieve the Objective 4.