

## **CHAPTER III:**

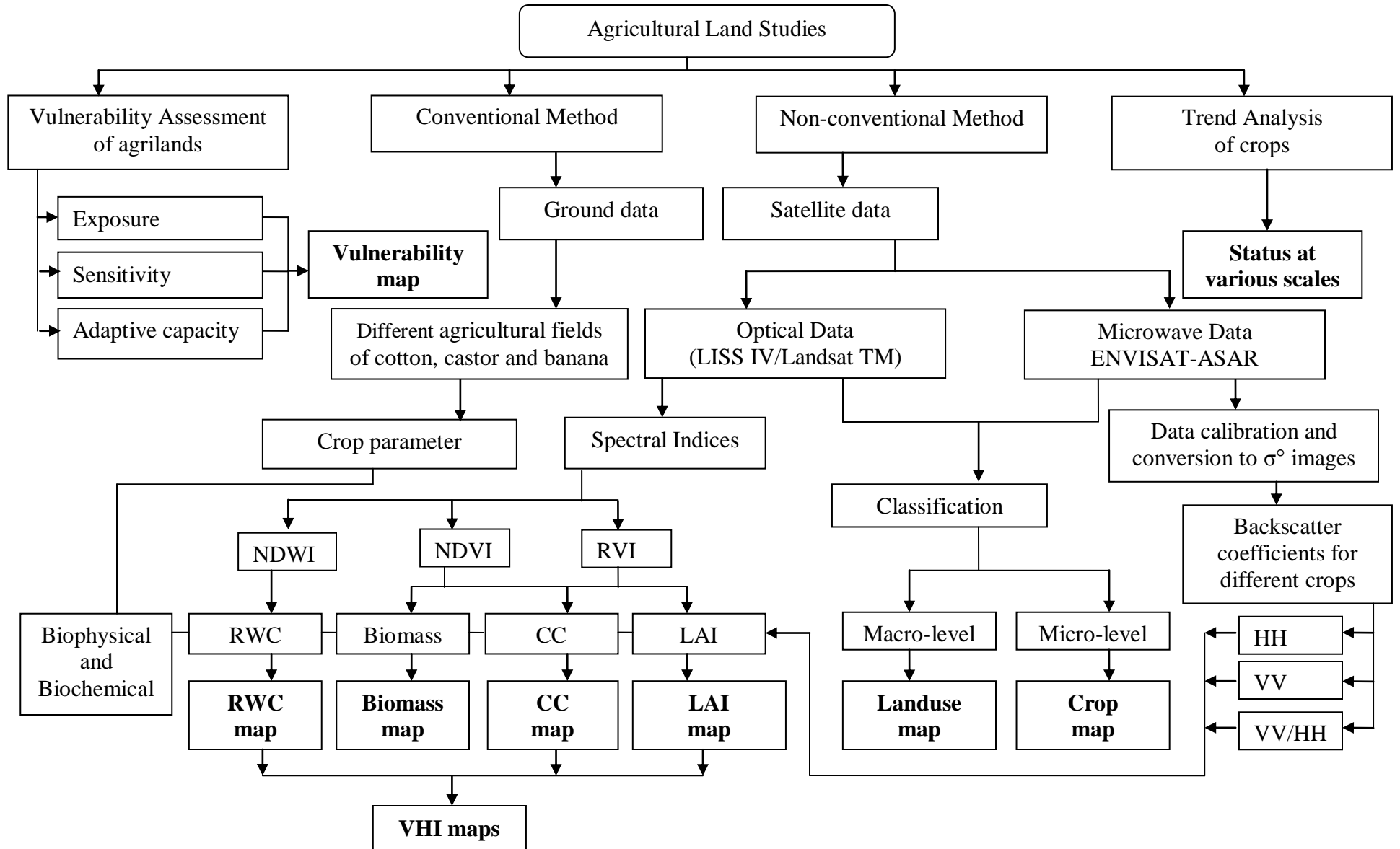
# **MATERIALS AND METHODOLOGY**

### **3.0 Materials and Methodology:**

An entire methodology used in the present work is shown in the flow chart (**Figure 13**) which shows methodology for the assessment of different components:

- Trend analysis of different crops at various scales
- Vulnerability assessment of agrilands
- Conventional method in the retrieval of crop parameters
- Non-Conventional method in the retrieval of crop parameters
- Generation of Vegetation Health Index (VHI)
- Landuse classification at macroscale
- Crop Classification at microscale

**Fig 13. Flow chart showing an entire methodology**



### 3.1 Trends Analysis:

A time series data from 2000-01 to 2011-12 (12 years) regarding the area, production and yield of selected crops (Cotton, Castor and Banana) were collected from the website of Directorate of Economics and Statistics, Ministry of Agriculture, Government of India. Trends studied for each crop are listed in the **Table 1**.

**Table 1.** Trends analysis of different crops at different scales

Sr. No.	Trend
1	Area at country level
2	Statewise area in country
3	Area at state level
4	Production at state level
5	Area at district level
6	Production at district level
7	Yield at district level

### 3.2 Vulnerability assessment:

Vulnerability assessment was carried out for agrilands of Vadodara and its nearby districts. Data for different indicators were collected and was made compatible to GIS using ArcGIS 9.2 software. A series of maps were constructed in GIS mode, considering district as a spatial unit of analysis. The assessment of vulnerability involves four steps moving from indicators to profiles and ultimately to the final vulnerability index. For each profile a value was obtained by combining the data for the indicators under it. Based on the combination of the normalized values for each indicator five outputs (Climate, Demographic, Agriculture, Ecosystem and Socio-economic Profiles) were obtained. These indicators were devised particularly to check agriculture vulnerability to climate change. **Table 2** shows the indicators and the broad structure chosen for this study.

**Table 2.** Selected indicators for Vulnerability Assessment

Component	Input		Output
	Profile	Indicators	
Exposure	Climate	Rainfall Average Temperature	1. Climate Profile
	Demographics	Sex Ratio Population in the age group 0-6 Decadal Variation in Population	2. Demographic Profile
Sensitivity	Ecosystem	Change in forest cover Land Use (Total Agricultural Cropped Area)	3. Ecosystem Profile
	Agriculture	Crop Production Irrigation pattern Ratio of agricultural labourers	4. Agriculture Profile
Adaptive Capacity	Socio-Economic Structure	Livestock Population Literacy rate Access to basic amenities (Drinking water and electricity) Biomass Dependency Infrastructure (Educational, Health, Banking and Communication facilities)	5. Socio-Economic Profile

The profile values in turn were used as inputs for calculating the values for the three components: **Exposure**, **Sensitivity** and **Adaptive Capacity**. Exposure component encompassed Climate and Demographic profiles under it. The vulnerability index for each district has been calculated by combining the values of all three components viz. exposure, sensitivity and adaptive capacity. The analysis presented in the present work is based on the available secondary data and accordingly the results obtained are only for the purpose of getting insights on agriculture vulnerability of Vadodara district and its nearby areas. If in case vulnerability would be high, then our results could be helpful to farmers and district planners for increasing adaptive capacity of district.

### **3.3 Conventional approach used in the study:**

#### **3.3.1 Ground Data:**

During the study period, ground information along with plant samples for different agricultural crops was collected and intensive field and laboratory measurements of biophysical and biochemical properties were carried out. The measurements were taken for the fields of cotton (*Gossypium hirsutum* L.), castor (*Ricinus communis* L.) and Banana (*Musa paradisiaca* L.). The estimated biophysical and biochemical parameters comprised of the following: Leaf Area Index (LAI), Leaf Chlorophyll Content (CC), Relative Water Content (RWC) and Biomass. Methodology used for the estimation of these parameters is discussed below:

#### **3.3.2 Measurements of crop parameters:**

##### ***3.3.2.1 Biophysical parameters:***

##### ***LAI:***

LAI of different crops was measured using the Plant Canopy Analyzer, LAI-2000 (LI COR Inc., Lincoln, NE, USA). The LAI-2000 canopy analyzer is a portable field instrument simultaneously measuring diffuse radiation by fisheye technique, with the optical sensors arranged in concentric rings in five distinct angular bands, with central zenith angles of 7°, 23°, 38°, 53° and 68°. The basic technique of the measurement involves measuring the sky brightness from a leveled sensor above the canopy and the second measurement below the canopy, with the sensor viewing towards sky (Welles and Norman 1991).

The LAI measurements for the selected crops were taken at various random locations within each field where each observation is the average of all the

measurements. The measurements were carried out under uniform clear diffuse skies at low solar elevation. That is to prevent the effects of direct sunlight on the sensor.

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

Fresh Weight (FW), Turgid Weight (TW) and Dry Weight (DW) of the collected leaf samples of different crops were measured and RWC was calculated using the formula given by Barrs (1968):  $RWC (\%) = [FW-DW]/(TW-DW) * 100$  (Jiang et al., 2009; Lugojan and Ciulca, 2011).

#### ***Biomass:***

Crop biomass was estimated by calculating crop's fresh and dry weight (Bao et al., 2009).

#### ***3.3.2.2 Biochemical parameter:***

##### ***Leaf Chlorophyll Content (CC):***

Use of portable Chlorophyll Meter SPAD-502 (Minolta Corporation, New Jersey, USA) is an easy method for measuring leaf CC. However, the chlorophyll meter doesn't provide the actual contents of chlorophyll per unit area of leaf tissue; instead it gives data only in arbitrary units. In the present research work, a standard method was used for the determination of the amount of chlorophyll in leaf samples of different crops. Homogenization of the leaf tissue in 80% acetone was carried out and then absorbance at 663 nm and 645 nm was measured. Then, specific absorption coefficients for chlorophyll a and b, provided by Arnon (1949) were used for calculation of CC (Wu et al., 2008).

All the biophysical and biochemical measurements were carried out corresponding to the selected satellite pass time.

### 3.4 Non-conventional approach used in the study:

#### 3.4.1 Satellite Data:

As mentioned earlier, the present work uses both the optical and the microwave data.

##### 3.4.1.1 Optical Remote Sensing Data Used:

**Table 3:** Details of Used Optical satellite data

Sr. No	Satellite Data	Date of data acquisition	Wavelength width in $\mu\text{m}$ / band	Spatial resolution (m)	Swath (km)
1.	LANDSAT 5 TM	23 <sup>rd</sup> October 2009	0.45-0.52 (Blue)	30	185
			0.52-0.60 (Green)	30	
			0.63-0.69 (Red)	30	
			0.76-0.90 (NIR)	30	
			1.55-1.75 (SWIR)	30	
			10.4-12.5 (Thermal IR)	120	
			2.08-2.35 (SWIR )	30	
2.	IRS-P6, Resourcesat-1, LISS IV	27 <sup>th</sup> October & 1 <sup>st</sup> November 2009	0.52-0.59 (Green)	5.8	23.5
			0.62-0.68 (Red)	5.8	
			0.77-0.86 (NIR)	5.8	

#### *Optical Satellites and Sensors:*

The basic characteristics of the instruments mentioned in **Table 3** are resumed below.

##### *Landsat-TM Data:*

The Thematic Mapper (TM) is an advanced, multispectral scanning, Earth resources sensor designed to achieve higher image resolution, sharper spectral separation, improved geometric fidelity and better radiometric accuracy and resolution compared to the MultiSpectral Scanner (MSS) sensor. TM data are sensed simultaneously in seven spectral bands with band 6 sensing thermal (heat) infrared radiation. Landsat can only acquire night scenes in band 6. A TM scene has an Instantaneous Field Of View (IFOV) of 30 square meters in bands 1-5 and 7 while band 6 has an IFOV of 120 square meters on the ground.

**IRS LISS IV:**

The Linear Imaging Self Scanning sensor-IV (LISS-IV) camera is a high resolution multi-spectral camera operating in three spectral bands (B2, B3, B4). LISS-IV can be operated in either of the two modes. In the multi-spectral mode (Mx), a swath of 23 Km (selectable out of 70 Km total swath) is covered in three bands, while in mono mode (Mono), the full swath of 70 Km can be covered in any one single band, which is selectable by ground command (nominal is B3 - Red band). The LISS-IV camera can be tilted in the across track direction thereby providing a revisit period of 5 days.

***3.4.1.2 Microwave Remote Sensing Data Used:*****Table 4.** Details of Used Microwave Satellite data

<b>Sr. No.</b>	<b>Product</b>	<b>Date</b>	<b>Band</b>	<b>Polarization</b>
1.	ENVISAT ASAR-ASA-APP	26 September 2006	C	HH, VV

***Microwave Satellites and Sensors:***

The basic characteristics of the instruments mentioned in **Table 4** are resumed below.

**ENVISAT Advanced Synthetic Aperture Radar (ASAR):**

The Environmental Satellite (ENVISAT) Advanced Synthetic Aperture Radar (ASAR) operates at 5.331GHz and incorporates a number of imaging modes that provide a variety of resolutions, polarizations and swath widths. Generally, the swath width is 100 km with the exception of wave mode (5 km) and wide swath width and global monitoring (400 km) products.

**ASAR Alternating Polarization mode Precision Image:**

ASAR Alternating Polarization mode Precision image (APP) is a standalone, multilook, ground range, narrow swath digital image generated using SPECAN algorithm from



level 0 data, collected when the instrument is in alternating polarization mode (7 possible swaths). The product contains two CO-registered images corresponding to one of the three-polarization combination available (Horizontal Transmit, Horizontal Receive (HH) and Vertical Transmit, Vertical Receive (VV), HH and Horizontal Transmit, Vertical Receive (HV), and Vertical Transmit, Horizontal Receive (VH)).

Coverage-100 km along-track, 56-100 km across-track

Geometric resolution -Approximately 30 m ground range \* 30 m azimuth

Radiometric resolution - Product ENL > 1.8

Pixel spacing -12.5 m \* 12.5 m

### **3.5 RS & GIS Analysis:**

#### **3.5.1 Base Map preparation:**

Base map of the study area was prepared using reference topographical maps procured from Survey of India (SOI). These SOI maps were priorly subjected to mosaicing. The map sheets were projected and tiled after digital trimming of the map boundaries. This process enabled the contiguous representation of the topographical area and the corresponding map extent.

#### **3.5.2 Village Map Generation:**

Census maps were scanned, georeferenced and digitized for the village boundaries.

#### **3.5.3 Optical Data Processing:**

The digital data of IRS LISS IV and Landsat 5 TM was initially loaded into the computer hard disk in a Band Sequential Format (BSQ), using ERDAS (Earth Resources Data Analysis Systems) Imagine 9.1 image processing software. Prerequisite

information such as number of pixels, rows, columns and bands was filled up while importing the data.

### ***3.5.3.1 Geo-referencing:***

The optical satellite data was geo-referenced using Geographic World Geodetic System (WGS) 84 Projection.

### ***3.5.3.2 Sub-setting:***

The exact area under the study was extracted using the subset utility of the ERDAS 9.1 image software module.

### **3.5.4 Synthetic Aperture Radar (SAR) Data processing:**

Microwave data was imported in Polarimetric SAR Data Processing and Educational Tool (POLARSARPRO) 5.0 environment and was subjected to other data processing techniques.

#### ***3.5.4.1 Speckle filtering***

Unlike optical remote sensing images which are characterized by very neat and uniform features, SAR images suffer from the effects of speckle noise. SAR generates images by coherent interaction of the transmitted microwave with the targets and consequently, they are highly susceptible to speckling effects (Goodman, 1976). Speckle is a granular noise pattern with random spatial variations observed on polarimetric SAR image, which deteriorates the quality of an image. There are numerous ways proposed to suppress speckles. In the present study, J.S. Lee Refined filter was selected.

#### ***J.S. Lee Refined filter:***

To improve the performance in edge areas, Lee proposed a refinement to the original Lee filter (Lee, 1981), in which the neighbourhood used in high variance areas for the

calculation of the local statistics takes into account the orientation of a possible edge. For each pixel with local variance  $\text{Var}(z)$  exceeding a set threshold, oriented gradients are computed and used to select a subset of the neighbourhood pixels on one side of the edge and most like the central pixel.  $\text{Var}(z)$  estimated over this subset will in general be lower than the sample variance over the whole neighbourhood, allowing more accurate filtering of noise. However, the edge detection is not optimized for speckle corrupted images in which local variance is related not only to edges but also to the underlying mean intensity level.

### ***3.5.4.2 Geo-referencing:***

The ENVISAT-ASAR data was also geo-referenced with Geographic WGS-84.

### ***3.5.4.3 Sub-setting:***

Like optical data, for radar data also subset module of ERDAS 9.1 was used to extract the exact area under the study.

## **3.6 Retrieval of crop parameters from optical remote sensing:**

For the retrieval of crop biophysical and biochemical parameters from optical satellite data, optical RS based empirical statistical approach was adopted. The methodology involved two steps:

- 1) Extracting spectral indices from optical satellite images
- 2) Establishing relationships between extracted spectral indices and ground crop biophysical and biochemical parameters data

### **3.6.1 Extraction of spectral indices:**

Spectral indices considered to be good candidates for estimating crop parameters were tested. These were developed from the reflectance bands of the optical data using

ERDAS-9.1. In total, three indices were calculated. Different spectral indices computed from the selected optical satellite images are listed in **Table 5**.

**Table 5.** Spectral indices used in the study

Index	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$NDVI = (NIR - Red) / (NIR + Red)$	Rouse et al., 1974
Ratio Vegetation Index (RVI)	$RVI = NIR / Red$	Pearson and Miller, 1972
Normalized Difference Water Index (NDWI)	$NDWI = (NIR - SWIR) / (NIR + SWIR)$	Gao, 1996

#### **3.6.1.1 Retrieval of spectral indices values for different crops:**

Values of different spectral indices for all three selected crops were derived from 3X3 window.

#### **3.6.2 Establishment of optical RS based empirical-statistical relationships:**

The gathered data sets of indices and crop parameters were statistically analyzed to determine correlations and derive empirical relationships between crop biophysical/biochemical variables and spectral indices. Each calculated spectral index was linearly related to different crop biophysical and biochemical parameters: LAI, RWC, Biomass and CC.

A t-test for correlation coefficient was performed to determine significance of correlation at significance level of 0.05 and 0.01. Accuracy of the developed models was also estimated. Moreover, the validation of the models was also carried out.

### **3.7 Development of the composite Vegetation Health Index (VHI)**

Village wise Vegetation Health Index (VHI) for Cotton, Castor and Banana crops was derived for five different villages and the output was exhibited in the form of VHI maps. VHI of all three selected crops at selected villages were then extracted from the generated maps. For the generation of VHI, the methodology given by Tripathi et al., 2013 was adopted and the steps followed are:

1. Selection of variables
2. Transformation of the variables of different units and dimensions to a common scale
3. Assignment of weight or score to the variables
4. Aggregation of three variables to produce a final index

#### **1. Selection of variables**

Variables selected for the generation of these maps are:

- LAI retrieved from Landsat NDVI
- CC retrieved from Landsat NDVI
- RWC retrieved from Landsat NDWI

#### **2. Transformation of the variables of different units and dimensions to a common scale**

Different crops parameters used for the generation of VHI occurred in different ranges and were expressed in different units. CC is expressed in  $\text{mg g}^{-1}$ , RWC in %, and LAI is unitless. To formulate the index, rescaling for all the parameters was done. The parameters were transformed into a single scale that begins with zero and ends at one. For rescaling, linear stretching was performed on these parameters, using the following

formulae:

$$DN'' = \frac{DN - MIN}{MAX - MIN}$$

Where, DN'' = Digital number assigned to pixel in output image

DN = Original digital number of pixel in input image

MIN = Minimum value of input image, to be assigned a value of zero in the output image

MAX= Maximum value of input image, to be assigned a value of 1 in the output image

### **3. Assignment of weight or score to the crop variables**

The three parameters i.e. LAI, CC and RWC selected for the VHI generation is having equal importance and thus equal weight of 1/3 was allotted to each of the three parameters for deriving the VHI.

### **4. Aggregation of three variables to produce a final index**

For obtaining the index score, a linear sum aggregation function was used. This function consists of the weighted sum of three variables i.e. LAI, CC and RWC divided by the sum of their weights.

$$VHI = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1} w_i}$$

Where,  $w_i$  = weightage given to the  $i^{th}$  parameter

$x_i$  =  $i^{th}$  parameter

### **3.8 Retrieval of crop parameters from microwave remote sensing:**

Microwave RS based empirical statistical approach was used for the retrieval of crop biophysical parameter from the microwave satellite data. It involved following two steps:

- 1) Extracting backscattering coefficients from SAR satellite image
- 2) Establishing relationships between extracted backscattering coefficient and ground crop parameter data

#### **3.8.1 Extraction of backscatter coefficient (Sigma Nought ( $\sigma^0$ )):**

Backscattering coefficient is the conventional measure of the strength of radar signals reflected by a distributed scatterer, usually expressed in dB. It is a normalized dimensionless number, comparing the strength observed from the target to that expected from an area of one square meter. Sigma nought is defined with respect to the nominally horizontal plane, and in general has a significant variation with incidence angle, wavelength, and polarization, as well as with the properties of the scattering surface itself (ESA, 2005). The calibrated value can be transformed into dB units by applying  $10 \cdot \log_{10}$ . Values for both HH and VV polarization backscatter were calculated.

#### **Backscattering coefficient:**

Band math function in ENVI 4.8 Software (Environment for visualizing images software) was used for the calculation of the backscattering coefficient using given below formula.

$$\sigma^0 \text{ (dB)} = 20 \log_{10} (\text{DNp}) - \text{KdB} + 10 \log_{10} (\sin(\theta_p) / \sin(\theta_{\text{center}}))$$

Where,

$\sigma^0$  (dB) - backscatter coefficient i.e sigma 0 in dB

DN<sub>p</sub> - digital number or pixel gray-level count for the pixel p

K<sub>dB</sub> - calibration constant in dB

ip - incidence angle for the pixel position p

icenter - incidence angle at the scene center

#### ***3.8.1.1 Retrieval of backscatter values for crop parameters:***

A 3X3 window was taken and backscatter values for different crop types were derived from this window.

#### **3.8.2 Establishment of microwave RS based empirical-statistical relationships:**

The extracted HH and VV backscatter values for selected crops were correlated to estimated crop parameters viz. LAI and empirical relationships were established. VV/HH backscatter ratio was also correlated to LAI.

### **3.9 Techniques used for Land use classification and Crop classification:**

#### **3.9.1 Supervised Classification for optical and microwave data**

In the present study both optical and microwave data were subjected to supervised classification. This type of classification requires some knowledge about the scene, such as specific crop, ground truth (field data), or data from aerial photographs or maps used to identify objects in the scene. The classification was carried using the following steps:

- a) Firstly, satellite data and accompanying metadata was acquired. Information regarding platform, projection, resolution, coverage, and, importantly, meteorological logical conditions before and during data acquisition was looked for.
- b) Secondly, the surface types to be mapped were chosen. Ground truth data with positional accuracy (Global Positioning System (GPS)) was collected. These data were then used to develop the training classes for the discriminant analysis. Care



was taken that the time of ground truth data collections to coincide with the date of data acquisition.

- c) Thirdly, post-processing techniques such as corrections, image mosaics, and enhancements were performed for the image. Pixels were selected in the image that were representative (and homogenous) of the object. The GPS data were collected, and were used for geo-referencing. The image training sites are defined by outlining the GPS polygons. The training class contained the sum of points (pixels) or polygons (clusters of pixels). The spectral histogram to inspect the homogeneity of the training classes for each spectral band was viewed. Each class was assigned a specific color. Lastly, using a discriminate analysis routine remaining pixels were extracted into the designed classes. The classified image was subjected to accuracy assessment and was performed by using predefined ground-truth values.

#### **3.9.2. Wishart Supervised Classification:**

The Wishart supervised classification was also implemented for carrying landuse classification of filtered Envisat ASAR image by using the PolSARPro 5.0 software (López-Martínez, 2005). The accuracy of the classified image was assessed by computing the confusion matrix. Training sites for this study was obtained from ground survey and GPS readings.