MAPPING AND MODELING GROUNDNUT GROWTH AND PRODUCTIVITY IN RAINFED AREAS OF TAMIL NADU

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Thesis submitted in part fulfillment of the requirements for the award of the degree of

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CERTIFICATE

This is to certify that the thesis entitled "**MAPPING AND MODELING GROUNDNUT GROWTH AND PRODUCTIVITY IN RAINFED AREAS OF TAMIL NADU**" submitted in part fulfillment of the requirement for the award of the degree of **DOCTOR OF PHILOSOPHY (AGRICULTURE) IN AGRONOMY** to the Tamil Nadu Agricultural University, Coimbatore is a *bona fide* record of research work carried out by **Mr. M. DEIVEEGAN** under my supervision and guidance and that no part of this thesis has been submitted for the award of any other degree, diploma, fellowship or other similar titles. However, part of thesis work has been published in peer reviewed scientific journal of national/international repute (copy enclosed).

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(M. Deiveegan)

Abstract

ABSTRACT

MAPPING AND MODELING GROUNDNUT GROWTH AND PRODUCTIVITY IN RAINFED AREAS OF TAMILNADU

By

M. DEIVEEGAN

Degree	:	**Doctor of Philosophy (Agriculture) in Agronomy**
Chairman	:	**Dr. S. Pazhanivelan, Ph. D.,** Professor and Head Department of Remote Sensing and GIS, Tamil Nadu Agricultural University, Coimbatore – 641 003, Tamil Nadu
Year	:	2017

A research study was conducted at Tamil Nadu Agricultural University, Coimbatore during *kharif* and *rabi* 2015 to estimate groundnut area, model growth and productivity and assess the vulnerability of groundnut to drought using remote sensing techniques.

Multi temporal Sentinel 1A satellite data at VV and VH polarization with 20 m spatial resolution was acquired from May, 2015 to January, 2016 at 12 days interval and processed using MAPscape-RICE software. Continuous monitoring was done for ground truth on crop parameters in twenty monitoring sites and validation exercise was done for accuracy assessment. Input files on soil, weather and management practices were generated and crop coefficients pertaining to varieties were developed to assess growth and productivity of groundnut using DSSAT CROPGRO-Peanut model. Outputs from remote sensing and DSSAT model were assimilated to generate LAI thereby groundnut yield spatially and validated against observed yields. Being a rainfed crop, vulnerability of groundnut to drought was assessed integrating different meteorological and spectral indices *viz*., Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI) and Water Requirement Satisfaction Index (WRSI).

Spectral dB curve of groundnut was generated using temporal multi date Sentinel 1A data. A detailed analysis of temporal signatures of groundnut showed a minimum at sowing and a peak at pod development stage and decreasing thereafter towards maturity. Groundnut

crop expressed a significant temporal behaviour and large dynamic range (-11.74 to -5.31 in VV polarization and -20.04 to -13.05 in VH polarization) during its growth period.

Groundnut area map was generated using maximum likelihood classifier integrating multi temporal features with a classification accuracy of 87.2 per cent and a kappa score of 0.74. The total classified groundnut area in the study districts was 88023 ha covering 17817 and 22582 ha in Salem and Namakkal districts during *kharif* 2015 while Villupuram and Tiruvannamalai districts accounted for 22722 and 24903 ha respectively during *rabi* 2015. Blockwise statistics on groundnut area during both seasons were also generated.

To model growth and productivity of groundnut in DSSAT, weather and soil input files were generated using weatherman and 'S' build respectively besides deriving genetic coefficients for CO 6, TMV 7 and VRI 2 varieties of groundnut.

Growth and development variables of groundnut were simulated using CROPGRO-Peanut model i.e., days to emergence (7-9 days) and anthesis (25-32 days), canopy height (63 to 70 cm), maximum LAI (1.12 to 3.07) and biomass (4176 to 9576 kg ha^{-1} across twenty monitoring locations spatially. The resultant pod yield was simulated to be 1796 to 3060 kg ha^{-1} with a harvest index of 0.28 to 0.43.

On comparison of LAI between observed (2.01 to 4.05) and simulated values (1.12 to 3.07) the CROPGRO-Peanut model was found to under estimate the values with R^2, RMSE and NRMSE of 0.82, 1.10 and 34 per cent. However, the model predicted the biomass of groundnut with an agreement of 89 per cent through the simulated values of 4176 to9576 kg ha^{-1} as against the observed biomass to 4620 to 9959 kg ha^{-1}.

The simulated pod yields of groundnut in the study area were 1796 to 3060 kg ha^{-1} as compared to the observed yields of 2115 to 2750 kg ha^{-1}. The overall agreement between simulated and observed yields was 84 per cent with the average errors of 0.81, 342 kg ha^{-1} and 16 percent for R^2, RMSE and NRMSE respectively.

LAI values of groundnut, generated spatially through suitable regression models using dB from satellite images and LAI from DSSAT, ranged from 1.31 to 3.23 with R^2, RMSE and NRMSE of 0.86, 0.78 and 24 per cent respectively on comparison with observed values. Remote sensing based spatial estimation resulted in groundnut pod yields of 1570 to 3102 kg ha^{-1} across the study districts of Salem, Namakkal, Tiruvannamalai and Villupuram. In the 20 monitoring locations, the pod yields were estimated to be 1912 to 2975 kg ha^{-1} as against the observed pod yields of 1450 to 2750 kg ha^{-1} with a fairly good agreement of 80 per cent.

The vulnerability of groundnut was assessed using different drought indices *viz.*, SPI, NDVI and WRSI. Considering SPI, out of the total groundnut area of 88023 ha, an area of 86607 ha was found to be under near normal condition based on deviation of rainfall received during cropping season from historical precipitation. Similarly NDVI, an indicator of vegetation condition during the cropping season, showed that 14272 ha of groundnut area were under stressed condition during 2015.

An area of 40981 ha in Villupuram and Tiruvannamalai districts was found to be under chances of crop failure based on Water Requirement Satisfaction index (WRSI). Major groundnut areas of Salem district (14188 ha) was under medium risk zone.

Considering overall vulnerability, whole district of Villupuram was adjudged as highly vulnerable to drought with regard to groundnut cultivation whereas four blocks of Salem, eight blocks of Namakkal and all the blocks of Tiruvannamalai were found to be moderately vulnerable to drought.

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LIST OF ABBREVIATIONS USED

a.i.	-	Active ingredient
cal cm^{-2} d^{-1}	-	Calories per square centimetre per day
cm	-	Centi metre
d^{-1}	-	Per day
DAS	-	Days After Sowing
dB	-	Decibel
DEM	-	Digital Elevation Model
DMP	-	Dry Matter Production
ESA	-	European Space Agency
et al.	-	Co-workers
Fig.	-	Figure
g m^{-2}	-	Gram per square meter
g	-	Gram
GIS	-	Geographical Information System
GPS	-	Global Positioning System
GPS	-	Global Positioning System
GRD	-	Ground Range Product
ha	-	Hectare
i.e.	-	That is
IW	-	Interferometric Wide Swath Mode
$Kgha^{-1}$	-	Kilogram per hectare
LAI	-	Leaf Area Index
Lat (x)	-	Latitude
Long (y)	-	Longitude
LST	-	Land Surface Temperature
m ha	-	Million hectare

m^{-2}	-	Per Square meter
Max.	-	Maximum
Min.	-	Minimum
mj m^{-2} d^{-1}	-	Milli jule per square metre per day
ml	-	Milli litre
MLC	-	Maximum Likelihood Classification
MODIS	-	Moderate Resolution Imaging Spectroradiometer
MSL	-	Mean sea level
N	-	Nitrogen
NDVI	-	Normalized Difference Vegetation Index
No.	-	Number
NRMS	-	Normalized root mean square
NRMSE	-	Normalized Root-Mean-Square Error
ºC	-	Degree Celsius
p^H	-	Negative logarithm of hydrogen ion concentration
r	-	Correlation coefficient
R^2	-	Regression coefficient
RH	-	Relative humidity
RMS	-	Root-Mean-Square
SAR	-	Synthetic Aperture Radar
SPI	-	Standardized Precipitation Index
SRTM	-	Shuttle Radar Topographic Mission
VH	-	Vertical-Horizontal Polarization
Viz.,	-	Namely
VV	-	Vertical-Vertical Polarization
WGS	-	World Geodetic System
WRSI	-	Water Requirement Satisfaction Index
$\sigma°$	-	Back Scattering Coefficient

Introduction

CHAPTER I

INTRODUCTION

Groundnut (*Arachis hypogaea* L.) is one of the major oilseed crops grown in subtropical and tropical regions of the world. It is grown in different rainfall and temperature regimes on a variety of soils. Being a C_3 crop, higher temperatures and other climatic factors may affect its productivity and distribution. Groundnut is grown in an area of 23.95 million ha worldwide with the total production of 36.45 million tonnes and an average yield of 1520 kg ha^{-1} (FAOSTAT, 2016). The major groundnut producing countries of the world are India, China, Nigeria, Senegal, Sudan, Myanmar and the USA.

India occupied the second position in acreage and production of groundnut with an area of 4.77 million hectares and a production of 7.40 million tonnes during 2014-15. The average productivity was 1552 kg ha^{-1} (Directorate of Economics and Statistics, 2015). Seventy per cent of the groundnut area and production is concentrated in the four states *viz*., Gujarat, Andhra Pradesh, Tamil Nadu and Karnataka. In Tamil Nadu, it is the major oilseed crop grown under rainfed and irrigated condition accounting for 5.7% of the total cropped area. Groundnut is grown in an area of 3.3 lakh hectares with a production of 9.20 lakh tonnes during 2014-15 in the state. The average productivity was 2753 kg ha^{-1} (Directorate of Economics and Statistics, 2015). The districts *viz*., Tiruvannamalai, Vellore, Villupuram, Namakkal, Erode and Salem constituted 54.9 per cent of the area under groundnut in Tamilnadu (Season and Crop report, 2014).

In general, crop cultivated area is estimated through agricultural statistics acquired through field visits and interviewing the farmers which is extremely tedious, time-consuming, less precise, costly, inconsistent, too generalized and labour-intensive (Prasad *et al*., 2006). However, it is unable to provide timely information on geographical spatial distribution of areas under crop cultivation.

Remote sensing and crop modeling are two advanced tools that have been developed to address diverse agronomic issues at field-level and regional scales (Xie *et al*., 2008) to estimate crop area and yields. Remote sensing technique has the potential to provide information on agricultural crops quantitatively, instantaneously and above all, non-destructively over large areas. Remote sensing can also be used to derive crop phenological information (Karnieli, 2003 and Xin *et al*., 2002). Remote sensing data are used to infer canopy biophysical variables like LAI (Leaf Area Index), Chlorophyll ‘a’ and ‘b’, which are involved in the important physiological processes governing crop growth and development. Monitoring of plants using remote sensing has many advantages such as detection of very large areas and easy derivation of vegetation indices. Vegetation indices have direct relation with the condition of the plants, so that they can be used for the purpose of yield estimation and creation of crop maps (Doraiswamy *et al*., (2003), Prasad *et al*., (2006) and Curnel and Oger (2007)). Doraiswamy *et al*., (2007) used MODIS data to predict yield of soybean with less than 20% standard deviation from official estimates.

Precise estimation of groundnut yield at regional scale depends on accurate assessment of groundnut area and phenological development. The recent advancement of Synthetic Aperture Radar (SAR) sensors coupled with state-of-the-art automated processing, can provide sustainable solutions to this challenge by creating map and monitor one of the world’s most important oilseed crops. Different classification and crop detection approaches are available for crop mapping in which the rules and parameters are derived from agronomic knowledge of the groundnut crop and its management. SAR-based operational mapping of groundnut across a diverse range of environments is possible with the increasing availability of multi-temporal satellite data from SAR sensors *viz*., RISAT, Cosmoskymed, TerraSAR-X and Sentinel 1A.

Crop models involve the mathematical function of various crop physiological factors such as photosynthesis, respiration, and relative growth rate to describe the crop growth changes under various climatic and environmental conditions. Crop models provide accurate estimation for small and homogenous fields but are less reliable for estimating yields of areas with heterogeneous soil and different agro climatic zones. In this context model becomes complicated as it needs several detailed inputs for simulation and makes the calibration process tedious (Sivarajan, 2011).

Crop yield information is required for sustainable agriculture management and national food security assessment, and it is very difficult to collect those data on a regional scale at right time with accuracy. Traditional approaches to obtain the regional crop yields typically suffer from the limitations of cost, timeliness, accuracy and suitability on a regional scale. Recently, the rapid advancements of crop growth simulation and observation technologies have provided the ability to improve regional crop yield monitoring and forecasting (Luo *et al*., 2013).

By making better use of crop growth models, crop growth processes can be effectively simulated under different environmental and management conditions while accounting for various limiting factors (e.g., soil, weather, water and nitrogen) in a dynamic manner. Nevertheless, improvements in simulation accuracy are often challenging when a crop model is used on a regional scale due to difficulties in obtaining regional model input and large uncertainties in regional parameters, including weather, soil, field management, crop cultivars, and other variables. The initial crop simulation models of Decision Support System for Agrotechnology Transfer (DSSAT) included the CERES-Wheat, CERES-Maize, SOYGRO, and PNUTGRO models (Hoogenboom *et al*., 2012). The CROPGRO module uses a daily time step for integration, starting at planting and ending at crop maturity or on the user-specified harvest date.

Driven by input data on weather, soil, field management and genetic information, the DSSAT CROPGRO-PEANUT model can simulate daily phenological development, vegetative and reproductive plant development stages as well as assimilate partitioning, growth of leaves and stems, senescence, biomass accumulation and root system dynamics under stressed environments involving light, temperature, water, nitrogen, carbon and field management interventions. This model has been widely applied to field sites to assess potential productivity of groundnut and the influence of climate change on pod yields for better water and fertilizer management. Spatial simulation of groundnut growth and yield through CROPGRO-PEANUT model poses the option for regional scale yield estimation at varying soil, climate and management conditions. The use of crop growth models on large areas for diagnosing crop growing conditions or predicting crop production is hampered by the lack of sufficient spatial information about model inputs. Therefore, studies were focused on the integration of remote sensing and crop growth simulation models for crop growth monitoring and yield estimation (Thorp *et al*., 2012).

Extreme climatic events such as severe drought can often cause devastating damages to agriculture and consequently to rural farmers. Rainfall is the primary driver of meteorological drought and there are numerous indicators based on rainfall that are being used for drought monitoring (Smakhtin and Hughes, 2007). Deviation of rainfall from normal i.e. long term mean is the most commonly used indicator for drought monitoring.

Agricultural vulnerability to drought for any crop can then be understood as the potential loss of growth and yield to dry climatic conditions. Spectral vegetation and drought indices *viz*., NDVI, WRSI and SPI can effectively be used to assess vulnerability to agricultural drought in general and risk zones for crops in specific.

Keeping the above points in view, a research study on ‘Mapping and modeling groundnut growth and productivity in rainfed areas of Tamilnadu’ was conducted in Namakkal, Salem, Villupuram and Tiruvannamalai districts using Sentinel 1A SAR satellite data, MODIS NDVI and DSSAT Crop Simulation Model with the following objectives:

1. To map groundnut areas under rainfed condition using Remote Sensing.

2. To model growth and productivity of groundnut under rainfed condition using DSSAT.

3. To integrate Remote Sensing products with DSSAT for yield estimation at spatial level.

4. To assess vulnerability of groundnut to drought in rainfed districts.

Review of Literature

CHAPTER II

REVIEW OF LITERATURE

Groundnut is called as the 'King' of oilseeds. Groundnut is an important oilseed crop cultivated around the globe for its nutritional and trade values. Nearly, 80 per cent of the groundnut area in India is under rainfed condition. High variability in the onset of monsoons, rainfall distribution and intensity of rainfall over the growing season was observed for the last two decades. Crop yield information is highly essential for sustainable agriculture management and national food security assessment. Rapid advancements of crop growth simulation and remote sensing based earth observation technologies have provided the ability to improve regional crop yield monitoring and forecasting. Spatial estimation of groundnut area and yield, besides assessing its vulnerability to drought, will ensure sustained production on regional scale. The literature on various aspects related to the study on 'Mapping and modeling groundnut growth and productivity in rainfed areas of Tamilnadu' was collected and presented hereunder.

2.1. Groundnut

Groundnut is an annual herbaceous plant growing 30 to 50 cm tall. The leaves are opposite, pinnate with four leaflets (two opposite pairs; no terminal leaflet), each leaflet 1 to 7 cm long and 1 to 3 cm broad. Groundnuts are known by many other local names such as earthnuts, peanuts, goober peas, monkey nuts, pygmy nuts and pignuts (APEDA, 2016). Groundnut have a rich nutty flavor, sweet taste, crunchy texture and over and above a relatively longer shelf life.

The rainfall in most of the groundnut growing regions is low and erratic. Moreover, such high variability in precipitation is generally associated with a high probability of an early season drought (Virmani and Shurpali, 1999).

2.1.1. Area and Production of Groundnut Crop

The major groundnut producing countries in the world are India, China, Nigeria, Senegal, Sudan, Burma and the United States of America. In India 5.0 million hectares were cultivated with groundnut annually and the production was about 7.4 million tonnes (Season and crop report, 2015). Seventy percent of the area and seventy five percent of the production has been concentrated in the four states of Gujarat, Andhra Pradesh, Tamil Nadu and Karnataka. Andhra

Pradesh, Karnataka, Tamil Nadu and Orissa have irrigated areas primarily during the *rabi* season. In these states groundnut production is mainly depends on rainfall. The irrigated areas form about six percent of the groundnut area in India. In Tamil Nadu, Tiruvannamalai district has the largest area under groundnut (Karunakaran *et al*., 2013).

The area under groundnut in Tamil Nadu reduced by 45% from 6.56 Lakh hectares during 2000-01 to 3.4 lakh hectares during 2014-15 (Season and crop report, 2015). The productivity of groundnut varied widely and was dependent on factors such as soil fertility, season and the irrigation potential. The instability indices computed for decadal sub-periods at the state level also suggested that the variability was greater in case of productivity of groundnut than area because the bulk of the area was under rainfed condition. (Karunakaran *et al*., 2013).

2.2. Remote sensing for Crop identification and acreage estimation

2.2.1. Remote sensing in Agriculture

Remote sensing application in precision agriculture can be direct but most likely, is indirect. Rapid response is required to provide information about the condition of the current crop in time to make management input corrections to accomplish maximum yield (Basso *et al.,* 2004). Ground based remote sensing for variable rate N management relies on real-time, sensor-based spectral measurement of crop nitrogen assessment and management (Link *et al*., 2005).

During the last two decades, development in remote sensing data acquisition capabilities, data processing and interpretation of airborne and satellite observations have made it possible to couple remote sensing technologies and precision crop management systems. With the advances in hyperspectral and multispectral remote sensing techniques and widespread interest in site-specific farming applications, remote sensing technology could enable farmers to diagnose crop deficiencies in real time and rectify yield threatening problems immediately. Moreover, remote sensing techniques could significantly reduce input costs by allowing farmers to provide fertilizers, pesticides and water strictly on an "as needed, where needed" basis (Waheed, 2005).

New technological advances in high resolution and multispectral and hyperspectral sensors for ground, airborne and satellite platforms are helping to make precision crop management a reality. These sensors are designed to cover a wide range of the electromagnetic spectrum and are generating enormous amounts of data that must be processed, stored and made available to the user community. Capability of detection of plant stresses at the early growth stage whether by satellite, airborne observation or a land-based system is the next step in farming evolution (Waheed, 2005).

Airborne, space-borne and hand held remote sensing technologies are commonly used to investigate the spectral responses of vegetation to plant stress. Earlier studies utilized multispectral sensors which commonly collect four to seven spectral bands in the visible and near-infrared region of the electromagnetic spectrum. Advances in sensor and image processor technology over the past three decades now allow for the simultaneous collection of several hundred narrow spectral bands resulting in more detailed hyperspectral data. The availability of hyperspectral data has led to the identification of several spectral indices that have been shown to be useful in identifying plant stress (Govender *et al.,* 2009).

Geographic Information System (GIS) and remote sensing-based methods have been developed for mapping the crop cultivated areas (Gumma *et al*., 2011a, 2011b; Salam and Rahman, 2014) and forecasting crop production (Huang *et al*., 2013). Remote sensing platforms are able to acquire cropping season dynamics over a large geographic extent on timely in the form of images. These images, in general depict the crop-specific characteristics; which could be important in mapping crop areas and developing pre-harvest yield forecasting models. In addition, most of these methods were developed on the basis of exploiting spectral vegetation indices.

Multi-temporal hyperspectral and multi-spectral remote sensing data were used to estimate corn aboveground dry biomass accumulation and yields (Liu *et al.*, 2010). The use of remote sensing for irrigation practices, water resource management, disease and insect management has been largely investigated (Elmetwalli *et al.,* 2012).

2.2.2. Synthetic Aperture Radar Data (SAR)

Multi-temporal X-band SAR Single Look Complex (SLC) data are available from the Italian Space Agency (ASI/e-GEOS) and GISTDA (Geo-informatics and Space Technology Development Agency) for COSMO-SkyMed (CSK) data and from Info-Terra GmbH for Terra SAR-X (TSX) data. In all cases, data can be obtained in HH polarization with consistent incidence angles in each multi-temporal stack, ranging from 39º to 48º across sites. A large incidence angle is preferred, because (i) wind effects on water (in particular, during land preparation prior to transplanting) are significantly decreased (ii) the dynamic of the radar backscatter is larger and (iii) the spatial resolution is higher. CSK data are available from four X-band HH-SAR satellites with a 3.12 cm wavelength and a 16-day revisit period for the same satellite with the same observation angle. TSX is provided by one X-band HH SAR satellite with a 3.11 cm wavelength and 11 day revisit period with the same observation angle at Strip map mode (3 m resolution) with a footprint of 30 × 50 km and Scan SAR mode (10 m resolution) with a footprint of 100 × 150 km (Pazhanivelan *et al*., 2015). With the latest launches, Sentinel 1A and 1B data is available from European Space Agency (ESA) at C band with spatial resolution of 5m and 20m with a temporal resolution of 12 days individually and 6 days in combination.

2.2.3. Basic Processing of SAR Data for Multi-Temporal Analysis

A fully automated processing chain was developed to convert the multi-temporal space-borne SAR SLC data into terrain-geocoded σ° values. The processing chain is a module within the MAPscape-RICE software (Holecz *et al*., 2013). The basic processing chain included strip mosaicking, coregistration of images acquired with the same geometry and mode and time-series speckle filtering to balance differences in reflectivity between images at different times (De Grandi *et al*., 1997) and terrain geocoding, radiometric calibration and normalization. Further Anisotropic non-linear diffusion (ANLD) filtering was done to smoothen homogeneous targets, while enhancing the difference between neighboring areas. The filter uses the diffusion equation, in which the diffusion coefficient, instead of being a constant scalar, is a function of image position and assumes a tensor value (Aspert *et al*., 2007).

2.2.4. Crop identification

Identification of crop types is the first step of crop monitoring system and crop yield forecasting. The traditional ground survey methods are difficult to acquire annual crop information due to the less economic efficiency and some features of agricultural production, *viz.* ,the large coverage, the strong seasonal, strong spatial heterogeneity, using remote sensing technology is feasible and effective way to solve this problem. The achievements are remarkable, since remote sensing was used for crop identification and area extraction, the technology and theory have been in continuous improvement (Shewalkar *et al*., 2014). The final outputs from remote sensing based observations are crop maps identifying crop types, delivered during the early growing season by using best performing input features with overall accuracy greater than 86% reported by Villa *et al*. (2015).

2.2.5. Crop acreage estimation

Crop acreage is the determining factor in crop production. Monitoring and estimating crop acreage at national scale is required in order to determine the national or regional food demand and supply balance, and to gauge social security. The information on acreage estimation is the backbone of Agricultural statistical system, if area has stronger inter annual variability while yield remains relatively stable.

Crop acreage estimation using remote sensing provides timely and reliable information (Potgieter *et al*., 2007). In the recent past, Department of Agriculture and Cooperation (DAC) and Department of Space (DOS) has taken active role in crop acreage estimation and crop yield forecast under FASAL project by integrating technological advancement and adoption of emerging methodologies, in particular, those of remote sensing and geographical information system. Weather data and real time crop information along with the remote sensing (RS) data were used to predict the crop yield at national and district level efficiently. Crop acreage estimation procedure broadly consists of identifying representative sites of various crops/land cover classes on the image based on the ground truth collected, generation of signatures for different training sites and classifying the image using training statistics. During the *Kharif* season, potential of microwave sensors operated in C-band was utilized for acreage estimation and crop monitoring, since the availability of cloud free data of optical sensors was difficult (Sellers, 1987).

2.3. SAR Data on crop acreage estimation

Crop discrimination is a critical first step for most agricultural monitoring systems. Optical remote sensing for crop monitoring has increased over the past several years and become one of the major civilian operational applications. However, several images acquired at specific times during the crop growth cycle are required to reach a suitable accuracy. This temporal constraint limits the use of optical data for operational applications because cloud cover may prevent or delay image acquisitions in many places. Space borne SAR imagery is able to observe the Earth's surface independently under cloud cover and guarantees a temporal frequency of images throughout the growing period (Boerner *et al*., 1987).

Bouman and Kasteren (1990) reported that the geometrical architecture of the crop canopy was a major factor that influenced the X band radar backscattering of wheat, barley, oats, sugar beets and potatoes. Row spacing, crop variety, lodging and ear orientation of barley had a large effect on radar backscattering. The architecture of the canopy also influenced the impact of soil background on radar backscattering from the whole crop. Even stubble and straw, which are theoretically relatively transparent to microwave, largely determine the radar backscattering of harvested fields.

Yakam-Simen *et al*. (1999) discriminated and estimated the cultivated area of winter wheat, spring barley, potato, sugar beets, maize, peas, rapeseed and other crops using the isodata cluster (statistically objective technique to identify natural data grouping) method applied with ERS SAR data.

Dirk *et al*. (2010) inferred the utility of a full polarization classification approach evaluated using airborne radar data. The data was collected in the growing season at two agricultural sites in Europe. Supervised approach was applied in the first and last step of the classification. The overall classification results ranged between 84.3% and 98% depending on number of observations dates and radar bands used for the supervised approach and substantially more thematic detail for the unsupervised approach.

Moran *et al*., (2011) studied the sensitivity of synthetic aperture radar (SAR) backscatter (σ^o) to crop and soil conditions using RADARSAT-2 C-band quad-polarized SAR images for larger fields *viz.*, wheat, barley, oat, corn, onion and alfalfa in Barrax region of Spain. The results showed that the cross-polarized σ^o HV was particularly useful for monitoring both the crop and soil conditions and were the least sensitive to differences in beam incidence angle. The time series of σ^o offered reliable information about crop growth stage, such as jointing and heading in grain crops and leaf growth and reproduction in corn and onion. Pei *et al*., (2011) monitored the small rice fields of Southern China using TerraSAR-X data and achieved the accuracy of 90 per cent.

Satalino *et al*., (2012) used the time-series Cosmo-Skymed SAR images of HH and HV polarization for land cover classification and soil moisture retrieval over an agricultural area located in Southern Australia. The classification accuracy has been assessed as a function of the polarization and the number of images analyzed. The results confirmed that the temporal information is crucial to improve the classification results. An overall accuracy of approximately 82 per cent was achieved.

Jia *et al*., (2012) preferred C-band (ASAR) over X-band (Terra SAR-X) for separating winter wheat from cotton. Gong *et al*., (2013) conducted a study to classify different vital types of crops in Baden Wurttemberg, from the backscattered value of temporal TerraSAR-X data. Two different test sites were considered whose harvesting and sowing season were same. The main purpose of this study was to check whether a backscattered value of one crop (wheat and rapeseed) is same in both of the test sites or not. The rules based and object oriented classification was done in e-cognition software and the overall accuracy of 90.62 per cent and 78.43 per cent was reported for the upper part and lower part of study area respectively.

Haldar *et al*., (2014) focused on the utility of multi dimension SAR data for crop condition assessment of various important tropical crops in India. The VV/VH polarization was found to be better for discrimination of wheat, mustard and cotton as compared to HH/HV polarization. Result showed that the backscatter values increased with biomass in early to mid-crop stages of cotton and mustard but extrapolation of trend indicated saturation at higher level of biomass in C-band.

Asilo *et al*., (2014) generated complementary and comprehensive rice crop information from hyper temporal optical (MODIS) and multi-temporal high-resolution SAR imagery (Terra SAR-X). MODIS was used to generate cropping calendar, cropping intensity, cropping pattern and rice ecosystem information. Results showed that the multi-temporal high spatial resolution SAR data was effective for mapping rice areas and reported an overall accuracy of 90 per cent.

Schuster *et al*., (2015) investigated the usefulness of multispectral (Rapid eye) and a SAR (Terra SAR-X) data to classify grassland habitats of reserved area in North Eastern Germany. The SVM approach was used to differentiate seven grassland classes. The result of the classification showed that the time series data could achieve very high classification accuracy. The highest accuracies were obtained using the Rapid Eye NDVI-NIR-RE stack, closely followed by the Terra SAR-X stack.

The potential of multi-temporal ALOS PALSAR images was demonstrated for the classification of beans, beets, grasses, maize, potato, and winter wheat using k-nearest neighbor algorithm (k-NN) and traditional supervised classification method by Sonobe *et al*., (2015). The result showed that the traditional supervised classification method was superior to that of k-NN. Villa *et al*., (2015) utilized the classification tree approach for in-season crop mapping by integrating optical (Landsat 8 OLI) and X-band SAR (COSMO-SkyMed) data acquired over a test site in Northern Italy. Results highlighted the contribution of the X band backscatter ($\sigma°$) in improving mapping accuracy when compared to using the optical features only.

2.3.1. Classification methods

Image classification is a particular case of pattern recognition. The overall objective of the classification process is to automatically classify all pixels in an image into land cover classes based on the predefined classification model (Moran *et al*., 2011). A standard method of pixel-based classification involves supervised and unsupervised extrapolation from training sites to classify the images. Unsupervised classifications are performed based on the number of classes the user wishes to classify. The unsupervised classifications generally achieve lower accuracy results than supervised classification (Kavzoglu, 2009). Pixel values are then plotted and grouped to different characteristics or features belonging to a pixel set (Lu and Weng, 2007).

Supervised classification is the technique most often used for the quantitative analysis of remote sensing image data with the concept of segmenting the spectral domain into regions that can be associated with the ground cover classes of interest to a particular application (McDermid *et al*., 2005). Under this supervised classification, various algorithms can be used to assign an unknown pixel classes. This algorithm can be divided into two general subgroups according to the assumption of whether each class is normally distributed or not.

2.3.2. Maximum likelihood classification

Maximum likelihood classification (MLC) method has been one of the most traditional classification methods in remote sensing. The MLC quantitatively evaluates both the variance and covariance of spectral response pattern while classifying an unknown pattern. An assumption is made that the distribution of the training set is Gaussian. Under this assumption, the distribution of a training set of a class can be completely described by the mean vector and covariance matrix. Given these parameters, we may compute the statistical probability of a given pixel being a member of a particular class.

Chen *et al*. (2007) evaluated Wishart distribution using multi-temporal ENVISAT ASAR data for rice mapping. The Wishart Maximum Likelihood classifier recorded higher classification accuracy as compared to Maximum Likelihood classifier and Minimum Euclidean classifier.

Panigrahy *et al*. (2009) used multi-date data AWIFS data for classifying crops based on their growing phenology and their difference in crop calendar. The bands providing the highest minimum Transformed Divergence (TD) were considered as the best bands for discriminating the crop classes. Based on this criteria , it was found that incorporating Red, Near Infrared (NIR) and Short Wave Infrared (SWIR) bands in maximum likelihood classification increased the overall accuracy in discrimination of winter crops like winter rice, groundnut, vegetables and other vegetation. Ying *et al*. (2010) utilized multi-temporal MODIS NDVI images to create a winter wheat mask on Landsat TM image to distinguish wheat from other crops. By using the class separability criteria, a set of selected 5 bands of Landsat TM image was used for winter wheat classification using Maximum Likelihood Classification technique. The study concluded that the selection of proper band and the application of a wheat mask increased the accuracy for winter wheat classification to 94 per cent.

Bargiel and Herrman (2011) investigated the multi-temporal classification of agricultural land use based on high resolution spotlight Terra SAR-X images. A stack of l4 dual-polarized radar images acquired during the vegetation season have been used for two different study areas (North of Germany and South East Poland). The Maximum Likelihood classification was based on a high amount of ground truth samples. Overall accuracy for all classes was 61.78 per cent and 39.25 per cent for German and Polish region, respectively.

Data acquired by Synthetic Aperture Radar (SAR) active sensors have also been exploited for crop mapping and monitoring, especially during the last two decades. C-band data have been used for mapping multiple crops (Moran *et al*., 2011). L-band data have been used too, although with generally poorer performance (Larranaga *et al*., 2012). More recently, with the launch of the TerraSAR-X and COSMO-SkyMed satellites, the use of X-band SAR data has largely expanded, mainly to the higher spatial and temporal resolutions and theoretical flexibility of these platforms (Bargiel *et al*., 2011). Concerning X-band SAR data, different polarimetric configurations have been tested for crop mapping, from vertical-based in (McNairn *et al*. ,2014) to horizontal-based polarization in (Satalino *et al*., 2012).

The increasing demand for information on crop acreage for agricultural monitoring in support of private and public decision makers requires the production of reliable crop maps (Hao *et al*., 2015). Up-to-date information on agricultural land use is necessary for crop planning and management: e.g., for estimating biomass and yield, analyzing agronomic practices, assessing soil productivity, monitoring crop phenology and stress. Earth Observation (EO) techniques have been widely exploited in agriculture and agronomy for the advantages offered when compared to in situ and statistical surveys: frequency of acquisitions, synoptic view, and multi-dimensional content. Shama (2016) used Sentinel 1A VH SAR data for estimation of area under cotton and maize and reported that Maximum likelihood classifier was found to give higher accuracy (83.4%).

2.4. Crop Simulation Model

2.4.1. Crop weather relationship of Groundnut

Temperature in the range of 25 to 30^{o}C is optimum for plant development of groundnut. The lower limit for germination of groundnut is around 18^{o}C. Temperature between 20 and 30^{o}C resulted in 95 per cent germination. Flower formation is favoured when the variation between day and night temperature did not exceed 20^{o}C. Most of the flowers formed at a day temperature of 27^{o}C, while a warm day (29^{o}C) and a cool night (23^{o}C) resulted the highest pod formation (Prasad *et al.*, 2000).

Yield attributes like number of effective pegs, pod numbers and pod dry weight per plant of groundnut grown under semi-arid tropical conditions of India were positively influenced by minimum temperature and relative humidity during the crop growing period (Sindagi and Reddy 1972). Bailey (1999) developed weather based advisories using temperature and relative humidity for determining conditions favorable for early leaf spot development in North Carolina, USA. Johnson *et al*., (1999) used leaf wetness counting for predicting the occurrence of late leaf spot in groundnut in Anantapur region of India.

In India, groundnut yields were reported to be vulnerable from year to year because of large inter-annual variation in rainfall (Sindagi and Reddy, 1972). Bhargava *et al.*, (1974) reported that 89 per cent of yield variation over four regions of India could be attributed to rainfall variability from August to December. Challinor *et al.*, (2003), analyzing 25 years of historical groundnut yields of India in relation to seasonal rainfall, concluded that, rainfall accounts for over 50 per cent of variation in yield. The favorable climate for groundnut is a well distributed rainfall of at least 500 mm during the crop-growing season with abundance of sunshine and relatively warm temperature. A rainfall of 500 to 1000 mm will allow commercial production, although crop can be produced with 300 to 400 mm of rainfall. However in many regions of the world, distances between meteorological stations mean that it is difficult to assess the likely weather conditions at intermediate locations (Azam-Ali *et al*., 2001).

2.4.2. Crop simulation models

Agricultural simulation models are a key component to test advances in agricultural technology and to predict crop responses to current and future climate forcing. Simulation models are robust tools to guide our understanding of how a system responds to a given set of conditions. Crop simulation models are increasingly being used in agriculture to estimate production potentials, design plant ideotypes, transfer agro technologies, assist strategic and tactical decisions, forecast real time yields and establish research priorities (Uehera and Tsuji, 1993; Bannayan and Crout, 1999). International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) has integrated the process oriented dynamic crop simulation models into a single computer software package known as DSSAT(Decision Support System for Agrotechnology Transfer), is developed through the internationally collaboration work carried out under IBSNAT, U.S.A., across the globe (Jones *et al.* 2003).

Since DSSAT crop models use daily weather data as input, this allows for using current weather conditions for evaluation of the models with experimental data. However, it also allows for scenario testing using long-term historical and future data for scenario evaluation which includes climate variability as well as climate change using future climate change scenarios.

DSSAT integrates the soil, crop phenotype, weather and management options to simulate crop growth and development and to predict crop yield. The crop models require daily minimum and maximum air temperatures, precipitation and solar radiation, in addition to the crop management data (such as planting date, seed cultivar, soil type and nutrient loading).The output is end-of-season crop yield as well as nutrient, soil moisture and plant stress variables (Jones *et al*., 2003). Crop simulation models have been evaluated and used for many soil and environmental conditions across the world and have been successfully used in yield predictions (Jagtap and Jones, 2002). The use of crop growth models on large areas for diagnosing crop growing conditions or predicting crop production is hampered by the lack of sufficient spatial information about model inputs. Therefore, different studies have attempted to estimate crop yield by assimilating crop growth model and satellite data.

Remote sensing and cropping systems modeling are two distinct technologies that have been developed to address diverse agronomic issues at field-level and regional scales (Batchelor *et al*., 2002; Xie *et al*., 2008). Although these technologies have often been studied independently, there is a growing interest in utilizing information derived from remote sensing to update or drive cropping systems model simulations because these two technologies are naturally complementary (Inoue, 2003; Dorigo *et al*., 2007). These models involve the mathematical function of various crop physiological factors such as photosynthesis, respiration and relative growth rate to describe the crop growth changes under various climatic and environmental conditions. The model at times becomes complicated as it needs several detailed inputs for simulation and makes the calibration process tedious to perform (Sivarajan, 2011).

Thorp *et al*., (2008) reported that DSSAT has modules that allow the user to build model input files for spatial simulations across predefined management zones, calibrate the models to simulate historic spatial yield variability, validate the models for seasons not used for calibration and estimate the crop response and environmental impacts of nitrogen, plant population, cultivar, and irrigation prescriptions.

The daily time-step simulation capabilities of cropping systems models are excellent for crop growth analyses in the temporal domain, whereas remote sensing images offer greater opportunity to understand spatial crop growth patterns. Conversely, detailed model input requirements have limited the use of cropping systems models for spatial crop growth analysis. With the integration of these technologies, the problems associated with one can be compensated by the benefits of the other. Remote sensing techniques have the potential to provide information on agricultural crops quantitatively on crop phenology (Karnieli, 2003; Xin *et al*., 2002).

Knowledge of plant phenology is essential for most agro ecosystem models since it governs the partitioning of assimilate. Therefore, a precise knowledge of the phenological status of the plants will improve the results obtained by agro ecosystem models (Delecolle *et al*., 1992).

Mishra *et al.,* (2013) used a two source energy balance model i.e., Atmospheric Land Exchange Inverse (ALEXI) and the results indicated that the data were available at sufficient temporal resolution to drive the crop model in a realistic manner as compared to the rainfed model and observed corn yields with RMSE of 28%. In general, maize yield simulation by DSSAT under Guinea savanna agro-ecological conditions was good. Average predicted harvest maturity yields were very close to measured values with mean deviation of 336.0, RMSE of 498.77, NRSME of 0.181 and simulated and observed mean yields of 3096 and 2750 kg ha^{-1} for the entire treatments, respectively. The mean difference between predicted and observed yield was not significant.

2.4.3. DSSAT - CROPGRO-Peanut model

Within the DSSAT crop growth model, CROPGRO-Peanut is a generic grain legume model that computes crop growth processes *viz.*, phenology, photosynthesis, plant nitrogen, carbon demand and growth partitioning. In addition, the plant development and growth module is linked to soil-plant-atmosphere modules. Hence, the model has the potential for large area yield estimation by input of soil and daily weather data (Gracia *et al*., 2006).

Boote *et al*. (1986) in a review article on modeling growth and yield of groundnuts described improvements to the 'PNUTGRO' model including addition of a hedgerow photosynthesis sub model to improve response to row spacing, seed rate and growth habit. They also included the Penman equation to incorporate vapour pressure deficit and wind speed to estimate evpotranspiration for arid regions; modification of functions for prediction of crop development; and modification of the effects of stress environments such as high temperature and vapour pressure deficit effect on partitioning. (Nokes and Young, 1991) showed that the 'PNUTGRO' model efficiently simulate the groundnut growth and development. They perfectly predicted defoliation of leaf, which was in good agreement with the observed data.

The CROPGRO-Peanut model was able to simulate and estimate yield in large area for the four major peanut producing provinces in China. To study the potential yield of peanut with regard to water demand, the approach was useful in comparing possible constrains. Further on, the model setting could be used for additional scenario and sensitivity analysis. The model showed a good fit between observed and simulated yield after the cross evaluation and validation procedure. Overall cross validation had a RMSE of 252 (model error = 7.37 %). Mean observed yield of all provinces was 3420 kg ha^{-1} with a mean simulated yield of 3422 kg ha^{-1} (Knorzer *et al*., 2010).

Singh *et al*. (1994) has reported that in ICRISAT, Hyderabad in a collaborative research project at Anand, Anantapur, Bhavanisagar, Hissar and Ludhiana modified the functions for prediction of crop development in 'PNUTGRO' model and simulated the effect of stress environments such as high temperature and vapour pressure deficit on partitioning of photosynthates. They have used this model for predicting phenological development, light interception, canopy growth, dry matter production and yield of groundnut as influenced by row spacing and plant population.

The peanut simulation model (Hammer *et al*., 1995) predicted peanut yield for given soil moisture and climate. The model used daily meteorological data (*i.e.* maximum and minimum temperature, solar radiation and rainfall) for predicting the yield. Leaf area index determined as a function of mean daily temperature and daily biomass accumulation was calculated as a linear function of the intercepted solar radiation. Both leaf area and biomass production were sensitive to the amount of soil-water available for transpiration. A simple soil-water balance took into account of rainfall, evaporation and transpiration throughout the year. Yield was calculated as a function of biomass production and growing conditions during yield formation.

Kaur and Hundal (1999) at Ludhiana studied 'PNUTGRO' model to predict groundnut growth and yield in Punjab. They revealed that the simulated phenologic events showed deviations of only -3 to +3 days for flowering, -3 to +2 days for pegging and -4 to +2 days for physiological maturity of the crop. The model estimated the LAI to be within 95–108% (mean 101·5%) and shelling percentage to be within 93–108% (mean 100·5%) of the actual values. The model predicted the pod yields from 89 to 111% (mean 100%) and seed yield from 90 to 110% (mean 100%) of the observed yields. (Gadgil *et al.* 1999) used the 'PNUTGRO' model, to study the growth and development of groundnut at ARS Anantapur. Heuristic model for pests/diseases was also used in conjunction with the 'PNUTGRO' model. The simulated variation for the period 1970-90 was found to be close to the observed district yield. This suggested that such models incorporated the direct impact of climate on growth and development as well as the indirect impact via triggering of pests and diseases. This model could be used for understanding the response of the groundnut yield to climate variability and in decision support systems for the region.

Rao *et al.* (2000) suggested the optimum sowing window for rain-fed groundnut in the Anantapur (AP) region using the model 'PNUTGRO' which was validated for the region. The variation in the model yield had shown that the broad sowing window of 22 June – 17 August presently used by the farmers minimizes the risk of failure. Within this broad window, sowing after mid - July enhanced the yields considerably. (Pandey *et al.* 2001) validated the 'CROPGRO' model for groundnut under *kharif* seasons of 1997-2000 at Anand (Gujarat). The results revealed that the observed phenological dates were closely associated with the simulated ones. The decrease in pod yield with delayed sowing as observed in experiment was well depicted by the model. However, under high rainfall situations, the model simulated higher pod and haulm yield for both the varieties and these were not in agreement with the observed yields.

CROPGRO peanut model was used by Parmar *et al.* (2013) to simulate the phenological events, yield and yield attributing characters of groundnut cultivars GG 2 and GG 20 in Gujarat. They found per cent error were between ± 13.2% for phenological stages and between ± 14% for yield and yield attributing characters of groundnut cultivars.

Singh *et al*., (2014) suggested that CROPGRO- Peanut model could be used to quantify the impact of climate change on groundnut productivity in different regions of India. It could also be used to quantify the possible benefits and prioritization of various agronomic adaptation options, individually or in combinations, to enhance and sustain groundnut productivity under climate change.

Kumar *et al.* (2014) reported that CROPGRO-urid model satisfactorily simulated phenological events like anthesis, first pod day, physiological maturity and harvest maturity at Pantnagar with percent error between ± 1 to 5, while grain yield was simulated with per cent error between ± 0.44 to 3.72 %.

The CROPGRO-Peanut model, calibrated and validated for many groundnut growing regions of the world, was used to study the spatial responses to various genetic and agronomic management practices under both baseline and climate change scenarios by using GIS and crop model based interface. Simulated crop yield and other maps generated under different management scenarios were used to communicate model predictions to various stakeholders (Kadiyala *et al*., 2015). He developed a methodology to spatial modeling of crop productivity for any crop in any region or country. The output of this methodology could aid scientists in prioritizing research and decision makers to understand the extent and status of climate change and its potential impacts on the productivity of various crops.

CROPGRO-Peanut model was also used to quantify the impact of climate change on groundnut productivity and to evaluate various agronomic management practices for increasing its productivity at the target sites. The major components of the model were vegetative and reproductive development, carbon balance, water balance and nitrogen balance (Boote *et al*., 1998). It simulated groundnut growth and development using a daily time step from sowing to maturity and ultimately predicted yield. The simulated physiological processes described crop response to the major weather factors including temperature, precipitation and solar radiation and included the effect of soil characteristics on water availability for crop growth. The minimum data set required to simulate a crop included site characteristics, daily weather data (solar radiation, maximum and minimum air temperatures and precipitation), physical and chemical properties of the soil profile and crop management data. The cultivar data included the genetic coefficients (quantified traits) which distinguished one cultivar from another in terms of crop development and growth (Singh *et al*., 2014).

Biswal *et al*., (2014) observed that district average yield of wheat was close to the simulated grain yield over the years though the model under estimate LAI values. The temporal course of simulated LAI was given importance in order to evaluate the model performance. These simulated parameters were correlated with the spectral vegetation indices like NDVI and NDWI.

2.4.4. Calibration and Validation of CROPGRO-Peanut and comparison of predicted and observed yield

The evaluation of model adequacy is an essential step of the modeling process because it indicates the level of accuracy of the model estimations (how closely model estimated values are to the actual values). This is an important phase either to build up confidence on the current model or to allow selection of alternative models (Konikow and Bredehoeft, 1992; Oreskes, 1998).

Validation is a more robust, reliable method of measuring prediction accuracy. It is the process of determining whether the conceptual model is an accurate representation of the actual system being analyzed and deals with building the right model. Validation is the task of demonstrating that the model is a reasonable representation of the actual system, that it reproduces system behavior with enough fidelity to satisfy analysis objectives. In practice, model validation aims at increasing confidence in model accuracy as much as possible, which is partially determined by the intended uses of a specific model and project objectives (Confalonieri *et al.*, 2005).

Evaluation of simulated versus observed outputs by means of numerical indices and test statistics is an accepted action of the modeling practice. Mean bias (MB), the mean difference between model estimates and observations, is likely to be the oldest statistic to assess model accuracy (Cochran and Cox, 1957). Mean bias is quite used in model validation, but one statistics that normally takes precedence over the others is the mean square error (MSE) or equivalently its square root, the root mean square error (RMSE or derived statistics such as the relative root mean square error RRMSE). This is also the statistic whose value is usually minimized during the parameter calibration process (Wallach, 1999). Mean absolute error (MAE) measures the mean absolute.

2.5. Remote sensing based crop monitoring and yield mapping

Remote sensing based crop yield estimation technique has been widely used in recent years. Unlike the ground-based method, it is very easy to handle, not laborious, and most of all it results in spatial crop yield estimation. The yield can be achieved in two ways depending on the crop type, *viz*., peak vegetation index based yield models and area under the vegetation index curve based yield models. Remote sensing of crop yields can be broadly grouped into two classes (Moulin, *et al*., 1998) *viz*., crop process or simulation models, and spectral vegetation index-based statistical yield models.

Standardized and possibly cheaper/faster methods that can be used for crop growth monitoring and early crop yield estimation are imperative. Many empirical models have been developed to try and estimate yield before harvesting. However, most of the methods demand data that are not easily available. The models complexity, their data demand, and methods of analysis, render these models unpractical, especially at field level. With the development of satellites, remote sensing images provide access to spatial information of features and phenomena on earth on an almost real-time basis at global scale. They have the potential not only in identifying crop classes but also in estimating crop yield (Mohd *et al*., 1994); they can identify and provide information on spatial variability and permit more efficiency in field scouting (Schuler, 2002).

The crop yields are of essential benefit for the economy of each country, especially if they are estimated early. Satellite remote sensing data in combination with existing public data from government statistics agencies, represents a viable solution for early assessment of yield. Doraiswamy *et al*., (2007) used MODIS data to predict yield for soybean and corn and they compared the results with official results. The predictions were within a 20% standard deviation of the official estimates. Prasad *et al*., (2005) used AVHRR (Advanced very high resolution radiometer) NDVI with 8x8 km spatial resolution together with rainfall data (RF), Land Surface temperature (LST) and soil moisture (SM) in order to estimate yield for corn and soya bean involving non-linear regression (Quasi-Newton method).

Recent studies have used NDVI as the phenology indicator. Some case studies were based on Enhanced Vegetation Index or EVI from MODIS (Son *et al*., 2013). Besides monitoring phenology, several studies dealt with methods of determining exact phenophases of crops (Curnel and Oger, 2007, White *et al*., 2002).

In order to monitor vegetation growth, predict yield and assess the crop yield, NDVI data has been widely used (Quarmby *et al*., 1993). Murthy *et al*., (1994) studied the relationship of rice yield and NDVI at different growth stages of the crop. The results revels that heading stage of rice evinced good correlation with NDVI and also with time composite NDVI. Various studies have been done on the spatial interactions in the CROPGRO-Soybean and CERES-Maize models and also on the comparison of estimated and measured data (Batchelor *et al*., 2002).

MODIS Normalized Difference Vegetation Index (NDVI) was used as an indicator of specific crop condition whereas Land Surface Temperature (LST), was used to indicate the amount of crop moisture. Multiple linear regressions were used for crop yield estimation in Vojvodina, where the NDVI and LST were independent variables and the average yield for specific crop was dependent variable (Jovanovic *et al*., 2014)

Haig (2003) used NDVI to predict crop yield at field level in Nizamabad district, India and assessed the relationship between satellite based NDVI and rice yield in irrigated fields with the combination of NDVI along with management and land factors. The results of the study also showed that there was a significant correlation between the remotely-sensed NDVI and field level rice yield with r =0.52 and p =0.0. It was also found that 25 per cent of the yield variability at field level was explained by NDVI, 38.1 per cent of yield variability by land and management factors whereas the combination of all the factors including the NDVI accounted for 45.5 per cent of the yield variability.

Prasad *et al*. (2006) considered parameters such as soil moisture, NDVI, surface temperature, rainfall data of Iowa state for 19 years for crop yield assessment and prediction using piecewise linear regression method with breakpoint. A non-linear Quasi-Newton multi-variate optimization was utilized that minimizes inconsistency and errors in yield prediction. They suggested that crop yield prediction model would improve further with the use of long period dataset.

NDVI has an asymptotic non-linear relationship with the green Leaf Area Index (LAI) of some crops (Breunig *et al*., 2011). A variation in LAI implies different intercepted radiation that, according to the Radiation Use Efficiency (RUE), is directly related to the production of biomass that will determine the possible yield. Balaghi *et al*., (2008) used NDVI and weather data to estimate wheat yield, and found that the NDVI appeared to contain most of the information on rainfall and explained most of the grain yield variability.

Advances in agricultural technology have led to the development of active remote sensing equipment that can potentially estimate components of crop production; however, this assessment is still in its early stages for the peanut crop. The Normalized Difference Vegetation Index (NDVI) composites that were derived from the Advanced Very High Resolution Radiometer (AVHRR) satellite data were averaged for the reproductive phase of peanut and were examined for their relationship with the annual peanut yield, an indicator of drought and aflatoxin (Boken *et al*., 2008).

The NDVI is one of the most popular and surely one of the most used indices in remote sensing. Theoretically the NDVI values range from -1 to +1, in practice this range is narrower. Barren rock, sandy areas have very low NDVI values of around 0.1. Areas with rare vegetation have greater NDVI values, from 0.2 to 0.5. High NDVI values are reserved for dense vegetation areas, forests and cultivated plants in peak of their season (Jovanovic *et al*., 2014).

Using satellite remote sensing to differentiate crops is a demanding task, as different crop types have similar reflection properties in remote sensing images for some periods of the year (Waldhoff *et al*., 2012). Those crops can only be separated from each other by a multi temporal analysis, which considers the phenology of the investigated crops (Gomez-Chova *et al*., 2015). Multi temporal and multispectral optical and infrared remote sensing has proved to be an effective approach to discriminate different crops (Pinter *et al*., 2003). However, the availability of optical satellite-borne imagery is sometimes limited due to cloud cover in the region of interest. Therefore, for many agricultural regions it is a coincidence whether optical images from the right time are available or not, which makes crop classifications based on optical imagery unreliable.

The key advantage of satellite-borne SAR imaging is the independence from cloud cover, and as it is an active sensing system, also from sun-induced reflection. Consequently, SAR imagery has become an important tool to distinguish agricultural crops (Blaes *et al*., 2005, Hoogeboom, 1983 and McNairn *et al*., 2014). Such systems are already in application to deliver annual crop inventories on regional levels (McNairn *et al*., 2009).

Process based dynamic crop growth simulation models are useful tools for estimating crop growth condition and yield on large spatial domains if their parameters and initial conditions are known for each point. Therefore, combined approaches integrating remote sensing and dynamic crop growth models for regional yield prediction have been developed by several studies. In these models the vegetation state variables, e.g., development phase, dry mass, LAI are linked to driving variables, e.g., weather condition, nutrient availability and management practices. Output of these models is usually final yield or accumulated biomass (Biswal *et al*., 2014).

2.6. Use of Remote Sensing parameters as proxies for LAI and biomass production

Proxies for yield and biomass production have been developed over the years from remote sensing derived spectral measurements. The products involve different spectral bands, various retrieval algorithms and corrections. These parameters can be extracted from a variety of satellite platforms. The most frequently used parameter is LAI (Leaf Area Index). The satellite-based LAI products are generally not the same variables as the LAI in crop growth models or the LAI measured in a field. The main reason for this discrepancy is that available satellite LAI are produced from reflectance obtained from coarse spatial resolution pixels, in which various different types of vegetation covers are present. Several workers proved that the satellite based LAI can differ considerably from field measured LAI (Duveiller *et al*., 2011). Fang and Hoogenboom (2011) have integrated spatially distributed MODIS vegetation indices with DSSAT for corn yield estimation in the mid-western United States.

Accurate quantification of agricultural biophysical parameters is critical for effective and sustainable cropland management operations. Precise monitoring of biophysical quantities, specifically biomass and grain yield, allows to optimize crop productivity and adopt the best farm management practices. It is now widely accepted that remote sensing data, methods and approaches provide the best options for large area agricultural cropland characterization as well as information needed for precision agricultural management practices by accurately mapping and pin pointing factors such as higher and lower biomass and yield levels within and between farm fields (Alchanatis and Cohen, 2011; Thenkabail, 2003).

Different proxies were used, sensitive to vegetation and soil conditions and able to characterize the dynamics of different crop types throughout the growing season *viz.*, Spectral Indices (SIs) from optical data and backscatter and interferometric coherence information from X-band SAR data. Most of the studies used multi-temporal information for crop mapping focusing on the use of temporal profiles of spectral indices derived from optical data (Foerster *et al*., 2012). Recently SAR backscatter profiles for rice mapping have been successfully included (Nelson *et al*., 2014 and Asilo *et al*., 2014). Villa *et al*. (2015) highlighted the contribution of the X-band SAR backscatter (σ°) in improving mapping accuracy and promoting the transferability of the algorithm over a different year, compared to using only optical features.

2.7. Integrating the Remote sensing products with Model

Integrating remote sensing data and crop model usually has three ways, *viz*., driving method, initialization parameter method and assimilation method (Plummer 2000; Fischer *et al*. 1997; Moulin *et al*. 1998). The driving method consists of updating at least one state variable in the model using remote sensing data. The crop model requires a value for this state variable at each time step. Information from remote sensing observations can effectively be integrated into crop modeling methodologies and such data have been used in crop models for regional yield assessment (Roebeling *et al*., 2004; Doraiswamy *et al*., 2005). The use of satellite based inputs highly simplifies the process, considering the amount of time and labour that regional level data collection requires. The remote sensing images can also be used for aggregation of results of crop growth models to regional scales.

Agronomic models are traditionally used for point or site-specific applications. Due to limitations in data availability. Most process-based models have examined temporal variation using point data from specific sites and, again, provide outputs that are site specific. Because agriculture is a spatial activity, there is growing interest in placing site specific information into spatial and long-term perspectives. GIS facilitates the storage, manipulation, analysis and visualization of spatial data (Hartkamp *et al*., 1999).

Initialization parameter method consists of minimizing the difference between a derived state variable or the radiometric signal and its simulation by the re-parameterization and/or re-initialization of the crop production model (Pinter *et al*. 2003). Assimilation method directly uses remote sensing data (e.g., spectral reflectance, vegetation index, or radar), which coupled with the radiation transmission model and the crop model to directly compare the remote sensing observation with coupling model to the spectral reflectance of simulation so as to adjust the key parameters or the initial value (Maas 1998).

Assimilation method consists direct usage of radiometric information to re-parameterize and/or re-initialize a crop model. It can be initialized by coupling a radiative transfer model to the crop growth model (Moulin *et al*. 1996; Fischer *et al*. 1996). Driving method is simple, but the prerequisite is that the state variables of the inversion should be accurate and the numbers of observations should be more. It is good for establishing the reasonable state variable statistical model, thus ensuring accurate inside interpolation. Initialization parameter method also has higher accuracy requirements for parameters inversed by remote sensing for crop model input, but assimilation method through direct comparison and optimization of reflectance simulated by coupled crop model and radiation transfer model to remote sensing observation, hence there is no crop parameter inversion error (Launay and Guerif 2005). Assimilation algorithm is an important factor of assimilation accuracy, which plays an important role in data assimilation.

Assimilation algorithms include statistical methods, variational methods, and methods based on machine learning (Mao *et al*. 2007). Statistical methods mainly set Kalman Filtering algorithm whereas variational methods mainly set three-dimensional variational algorithm and four-dimensional variational algorithm (Li *et al*. 2004).

Linking GIS with agronomic crop models is attractive because it permits the simultaneous examination of spatial and temporal phenomena. Spatial visualization of the results from models significantly enhanced the understanding and interpretation of simulation results (Engle *et al*., 1997) and provided an opportunity for complex spatial analyses of the model results (Stoorvogel, 1995). By analyzing the spatial patterns of simulated yield there is an opportunity to improve production estimates and highlight vulnerable areas (Carbone *et al*., 1996). However, the major drawback lies in the limited availability of input climate and soil data that precludes the use of the more sophisticated simulation models.

A model using AVHRR data was developed to determine growth and development of groundnut and estimate yields in the Peanut Basin of Senegal. The input variables were the integrated NDVI in the period from 69 to 85 days after sowing and in the period from 25 to 31 days before sowing. In a multiple linear regression model, these variables were able to explain 64 per cent of the variance in groundnut yields. The RMSE of estimated yields was 176 kg ha^{-1}. Yield maps showed a high interannual variability in groundnut yields, and revealed that the model is sensitive to persistent cloud cover (Knudby, 2004).

2.8. Assessing Vulnerability of Groundnut to Drought

2.8.1. Effect of drought on Groundnut

Among the environmental stresses, drought stress is the most important factors, which limits production of groundnut. The water stress affects the crop at different growth stages during growing season. In groundnut, drought stress during flowering and pod filling stage is critical for yield and agronomic characters. This would result in drastic reduction in crop yield, and the magnitude of reduction would depend on groundnut varieties. The yield of groundnut and quality of product decrease under drought stress. Drought-tolerant varieties producing high yield are required under drought stress conditions (Shinde and Laware, 2010).

Rainfall is the most significant climatic factor affecting groundnut production, as 70 per cent of the crop area is under semi-arid tropics characterized by low and erratic rainfall. Low rainfall and prolonged dry spells during the crop growth period were reported to be main reasons for low average yields in most of the regions of Asia and Africa (Reddy *et al*., 2003).

Moisture stress during crop growth has been reported to adversely influence water relations and thereby the translocation of photosynthates and other nutrients photosynthesis, mineral nutrition, metabolism, growth and yield of groundnut (Suther and Patel, 1992). The period of maximum sensitivity to drought occurs between 50-80 days after sowing. Balasubramanian and Yayock (1981) observed that the adverse effect of moisture deficit was more severe on pod and kernel yield than the production of haulm and total dry matter.

Roy *et al*., (1988) observed that the period of late flowering and pod formation was most sensitive to moisture. Moisture stress during late flowering and pod formation and filling reduced yields more than stress in early, full flowering, late flowering and pod formation stages. Several studies revealed that pod development stage is the most sensitive to moisture (Meisner, 1991 and Ramachandrappa *et al*., 1992) during which the demand of photosynthetic products for active sinks (pods) is higher.

The soil moisture stress on groundnut during flowering phase extended the days to 75 per cent flowering up to six days. The initiation of flowering was not delayed but the rate of flower production was reduced by drought stress during flowering. The post-rainy crop also experienced the moisture stress during pod development stage that delayed the maturity to an average of

13 days. As a cumulative effect of soil moisture deficit, the pod yield as an integrative trait was affected to an extent of 47.8 per cent. The groundnut strains studied, JL 24 was reported as drought sensitive and ICGV 91114 as drought tolerant (Kambiranda *et al*., 2011). The drought sensitive variety, JL 24 performed equally to drought tolerant ICGV 91114, when there is no soil moisture limitation. Under moisture stress, pod yield was reduced to 59 per cent in JL 24. The short duration varieties, *viz.*, TMV 7 and Chico were stable in pod yield under moisture stress with less DSI and high DTE. (Arunachalam and Kannan, 2013).

Sankar *et al*., (2014) recorded the total leaf area reduced under drought stress compared to control in peanut and it was 77.61 per cent over control on 80 DAS. Drought stress with paclobutrazol (PBZ) and abscisic acid (ABA) caused an increase in leaf area when compared to drought-stressed plants at all the sampling days, and it was 94.46 per cent and 92.49 per cent over control on 80 DAS. Drought stress reduced the leaf area as compared to control in *A. hypogaea*. The leaf growth was more sensitive to water stress in maize (Nayyar and Gupta, 2006).

2.8.2. Assessing Agricultural vulnerability to Drought

The concept of vulnerability often refers to as “a potential of loss” (Cutter *et al*., 2003), that vulnerability reflects the interaction between the stresses or disturbances, which arise outside and/or inside the system and the system’s inherent capacity to respond. Drought is a complex, least understood and one of the most expensive natural disaster. Drought impacts many sectors of environment and society. Standardized Precipitation Index (SPI) is a useful tool to assess the vulnerability to drought. SPI is a transformation of the probability of a given amount of precipitation in a set period of months (Anandhi and Knapp, 2016).

Assessing agricultural vulnerability is fundamental to understand interactions between agricultural systems and their external stresses including climatic conditions (Ren *et al*., 2012). It is determined based on Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI). SPI values of rain gauge stations are interpolated to determine the spatial pattern and threshold value of drought for agricultural vulnerability. Anomaly of the NDVI and NDWI were classified to determine the agricultural drought vulnerability. SPI, NDVI and NDWI were integrated to classify the agricultural vulnerability of Virudhunagar district. The resultant map showed the spatial distribution of the areas facing agricultural drought conditions. The agricultural vulnerability map will help in the preparation of the area for mitigation measures that will in turn reduce the impacts of climate variation on agriculture (Nithya and Rose, 2014).

Monitoring and analysis of drought is based on a given thresholds for forecasting precipitation deficit over a specified period of time. Different climate based drought and vegetation indices are available. (Gebrehiwot *et al*., 2011) some of them are Standardized Precipitation Index (SPI), percent of normal, Crop Moisture Index (CMI), Reclamation Drought Index (RDI) and Water Requirement Satisfaction Index (WRSI).

In India groundnut yields were reported to be vulnerable from year to year because of large inter–annual variation in rainfall. About 89 per cent of yield variation over four regions of India could be attributed to rainfall variability in the August to December growing period. Challinor *et al*., (2003) analyzing 25 years of historical groundnut yields of India in relation to seasonal rainfall concluded that rainfall accounts for over 50 per cent of variance in yield. Gadgil (2000) observed that the variation in groundnut yield of Anantapur district was mainly due to the variation in the total rainfall during the growing season.

Perez *et al*., (2016) developed a monitoring and forecasting system to assess the extent and severity of agricultural droughts in the Philippines at various spatial scales and across different time periods. Using Earth observation satellite data, drought index, hazard and vulnerability maps were created. The drought index called Standardized Vegetation-Temperature Ratio (SVTR), has been derived using the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST).

Murthy *et al.* (2014) reported that Agricultural Drought Vulnerability Index (ADVI) was generated using the three component indices and beta distribution was included to it. Mandals (sub-district level administrative units) of the state were categorised into 5 classes *viz.,* Less vulnerable, Moderately vulnerable, Vulnerable, Highly vulnerable and Very highly vulnerable. Districts dominant with vulnerable Mandals showed considerably larger variability of detrended yields of principal crops compared to the other districts, thus validating the index based vulnerability status. Current status of agricultural drought vulnerability in the state, based on ADVI, indicated that vulnerable to very highly vulnerable group of Mandals represent 54 per cent of total Mandals which accounted for about 55 per cent of the agricultural area and 65 per cent of the rainfed crop area. The variability in the agricultural drought vulnerability at disaggregated level was effectively captured by ADVI. The vulnerability status map is useful for diagnostic analysis and for formulating vulnerability reduction plans.

2.8.3. Normalised Difference Vegetation Index (NDVI) on drought assessment

The phenology of vegetation closely reflects the seasonal cycle of rainfall, the knowledge of which can be very useful towards drought monitoring and assessment using NDVI. Similar approaches have been used in forming drought monitoring, assessment and prediction systems around various countries. The AVHRR NDVI data was used as primary data for input to generate vegetation specific drought information product called as Vegetation Drought Response Index (VegDRI) (Brown *et al.*, 2008).

Another successful use of AVHRR NDVI for drought assessment is done by (National Drought Assessment and Monitoring System) NADAMS over India. Discussing at global level, FAO have created Global Information and Early Warning System on Food and Agriculture (GIEWS), which is primarily based on near real time AVHRR NDVI.

Tucker and Choudhury (1987) found that NDVI could be used as a response variable to identify and quantify drought disturbance in semiarid and arid lands, with low values corresponding to stressed vegetation. Ji and Peters, (2003) found that NDVI is an effective indicator of vegetation response to drought in the Great Plains of the United States, based on the relationships between NDVI and a meteorologically based drought index.

Drought, like other natural phenomena, has spatial and temporal dimensions. In assessing drought, many researchers have used the capability of Geographic Information Systems (GIS) to store and analyze large volumes of remotely sensed data. The approaches to drought monitoring were based primarily on the use of the Normalized Difference Vegetation Index (NDVI), obtained from processing AVHRR data from NOAA satellites (Liu and Kogan, 1996).

2.8.4. Standardized Precipitation Index (SPI) on drought assessment

The Standardized Precipitation Index (SPI) is a tool which was developed primarily for defining and monitoring drought. It allows an analyst to determine the rarity of a drought at a given time scale (temporal resolution) of interest for any rainfall station with historic data. It can also be used to determine periods of anomalously wet events. The SPI is not a drought prediction tool. Standardized Precipitation Index (SPI) expresses the actual rainfall as a standardized departure with respect to rainfall probability distribution function and hence the index has gained importance in recent years as a potential drought indicator permitting comparisons across space and time. The computation of SPI requires long term data on precipitation to determine the probability distribution function which is then transformed to a normal distribution with mean zero and standard deviation of one. Thus, the values of SPI are expressed in standard deviations, positive SPI indicating greater than median precipitation and negative values indicating less than median precipitation (Edwards and McKee, 1997).

Guttman, (1998) explained the advantages of SPI being probabilistic in nature and thus, its usability in risk and decision analysis over other drought indices. The identification of extreme drought with SPI presents a better spatial standardization as compared to the Palmer Drought Severity Index (PDSI) (Lloyd-Hughes and Saunders, 2002). The use of SPI is standardized to a variety of time scales *i.e.* 1, 2, 3, 6, 12 24, 26, 48 months. The positive value of SPI represents wet conditions, whereas the negative values show drought conditions. The intensity of drought is signified by the standardized numbers ranging from 0 to (-2 and less).

Since SPI values fit a typical normal distribution, these values lie in one standard deviation approximately 68 per cent of time, within 2 sigma 95 per cent of time and within 3 sigma 98 per cent of time. In recent years, SPI is being used increasingly for assessment of drought intensity in many countries (Vijendra 2005; Wu *et al*., 2006; Vicente-Serrano *et al*., 2004). The drought interpretation at different time scales using SPI is proved to be superior to Palmer Drought Index (Guttman, 1998). SPI as a stand-alone indicator needs to be interpreted with caution for drought intensity assessment particularly in low rainfall districts which are more vulnerable to droughts.

2.8.5. Water Requirement Satisfaction Index (WRSI) on drought assessment

The Water requirement satisfaction index (WRSI) is an operational monitoring index, which indicates the performance of a crop based on the availability of water during growing season (Allen *et al*., 1998). It is determined as the ratio of seasonal actual crop Evapotranspiration (AET) to the crop water requirement (WR), which is the product of reference crop evapotranspiration (ET_0) and crop coefficient (Kc) value of the specific crop (Senay *et al*., 2011). AET represents the actual amount of water withdrawn from the soil water reservoir and can be estimated by energy balance and water balance methods. WRSI acts as a tool to evaluate the crop water status in the next decade based on the availability of moisture in the soil. Quantitatively it can be represented as percentage and it has four broad categories *viz*., (i) An index value between 80-100 per cent indicates sufficient water in the root zone to support the crop without water stress for the next decade; (ii) 70 – 79 per cent indicates that there is satisfactory water in the root zone and this shows conditions ranging from smaller degree of water stress to sufficient soil moisture; (iii) 50 – 69%, is an indication that the crop is likely to experience from severe to moderate water stress and (iv) 0 – 50 per cent indicates that the soil is already at very low moisture level which can cause permanent wilting point and crop failure (Senay, 2008).

WRSI model requires a start-of-season (SOS) and end-of-season (EOS) time. The threshold used to determine SOS is based on the amount and distribution of rainfall received in three consecutive decades. On the other hand, the end of season is estimated by adding length of growing period (LGP) and SOS. The determined WRSI value of a given pixel represents the seasonal integrated conditions from the start of the growing season until the time of modeling (Brown *et al*., 2008).

Wilhelmi (2002) indicated that the most vulnerable areas to agricultural drought were non-irrigated cropland and range land on sandy soils, located in areas with a very high probability of seasonal crop moisture deficiency. The identification of drought vulnerability is an essential step in addressing the issue of drought vulnerability in the state and can lead to mitigation-oriented drought management.

Ren *et al.*, (2012) revealed that remote sensing data as well as the associated analytical approaches can be useful and powerful in assessing the spatial variability of agricultural vulnerability. Since the remotely sensed data are readily available at a relatively lower cost, such approaches can be frequently employed to assess the changing relationship between agricultural sectors and varying climate conditions in a timely manner.

Nithya and Rose (2014) concluded that SPI, NDVI and NDWI are very useful for early detection of agricultural vulnerability and hence should be a better methodology for remote sensing based vulnerability assessment studies. The NDWI also showed a very good and consistent relation with current rainfall at regional scale. Rather NDVI showed a lagged relationship with rainfall. Ren *et al.*, (2012) concluded that vulnerability of a system or a place can be quantified by simplifying a complex system as a pair or pairs of interacting well-being and stresses, although a comprehensive quantitative vulnerability assessment is difficult. The reviewed works suggest that the empirical regression relationship between NDVI and crop yield is valuable for yield estimation modeling at a regional.

In the present study, an effort has been made to simulate growth and yield of groundnut using DSSAT crop growth model and precisely estimate groundnut area and proxies for LAI and biomass through micro wave remote sensing using Sentinel 1A SAR data and MODIS NDVI to assess groundnut yield on a spatial scale. Coupled with drought indices such as standardized precipitation index, an attempt has been made to derive a sound understanding of crop production vulnerability to drought at a regional scale.

Material and Methods

CHAPTER III

MATERIALS AND METHODS

A research study on ‘Mapping and modeling groundnut growth and productivity in rainfed districts of Tamilnadu’ was conducted during *Kharif*, 2015 (Salem and Namakkal districts) and *Rabi* 2015 (Tiruvannamalai and Villupuram districts) seasons to estimate area, model growth and productivity and assess vulnerability of groundnut to drought. The details of the study area, satellite data, ground truth collection, materials used and experimental methods adopted for image classification, map generation, modeling growth and productivity, validation of data and drought vulnerability assessment in groundnut are presented in this chapter.

3.1. Study Area

Contiguous area of major groundnut growing districts of Tamil Nadu *viz*., Namakkal, Salem, Tiruvannamalai and Villupuram was selected for the study (Fig. 1). These districts geographically lies from 11º 0' to 12º 52' North Latitude and from 77º 38' to 80º 0' East Longitude. The study area was approximately 2.2 million hectares characterized by multiple crops at different seasons under irrigated and rainfed conditions. The dominant land cover types were irrigated agriculture, orchards, grasslands and human settlements.

Salem and Namakkal districts lying in North Western Zone of Tamil Nadu, had a unique feature of having semiarid hot climate, undulated topography, red non calcareous coarse shallow soil with poor soil fertility and water retention capacity and low rainfall with erratic distribution. The annual normal rainfall of the zone was 849 mm. This zone was identified as moderately drought prone. Tiruvannamalai and Villupuram districts were part of North Eastern Zone of Tamilnadu. Soils in this area varied considerably due to geological, climatic and vegetation changes besides human exploitation.

The climate in the zone is semiarid tropical with an annual rainfall of 800 to 1400 mm excluding hills. The South West Monsoon, North East monsoon, *winter* showers and *summer* rain in Tiruvannamalai districts of the study area contribute 47, 42, 2.0 and 9.0 per cent respectively to the annual rainfall and the quantum and distribution varied between seasons and places within the zone.

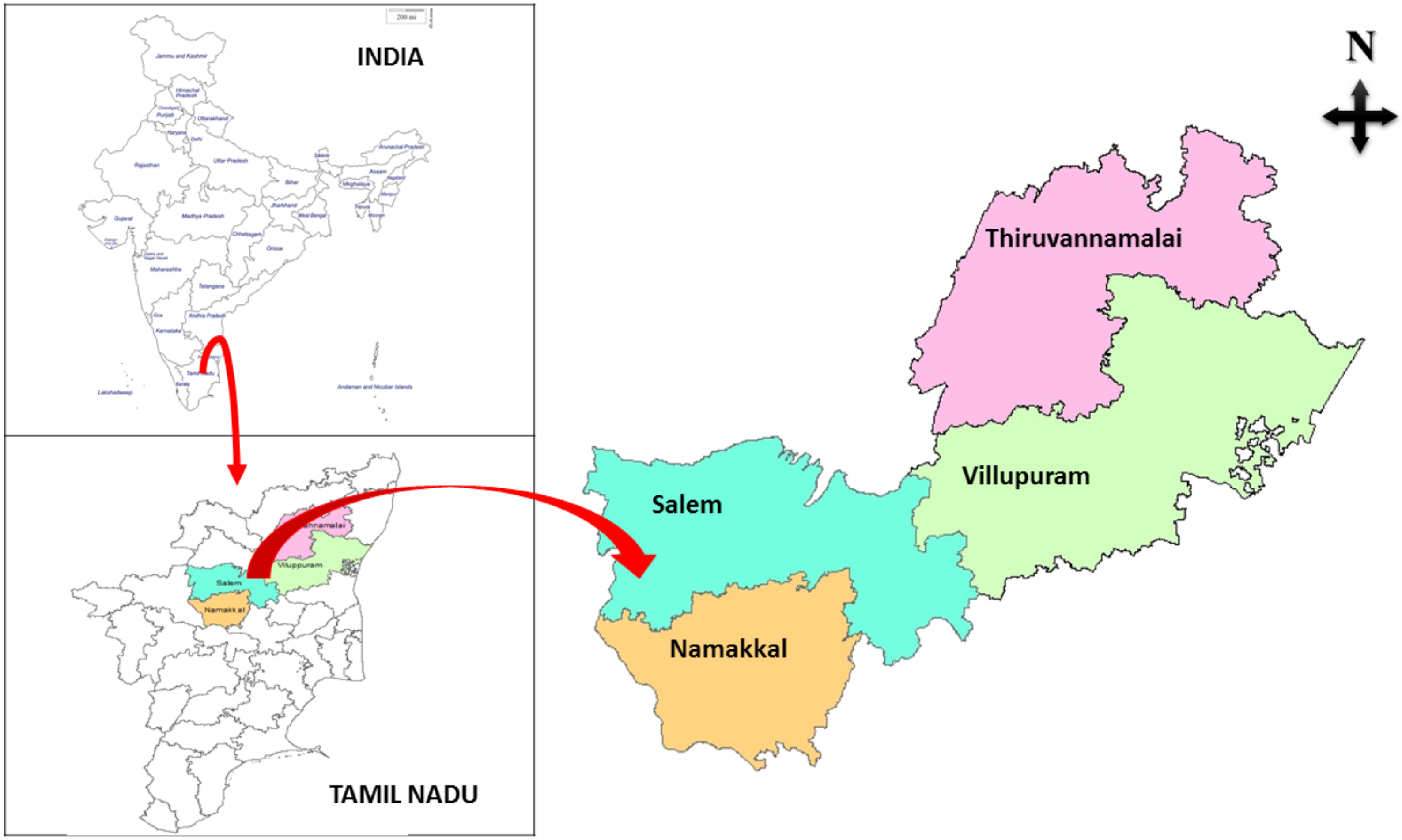

Fig.1. Location map of study area

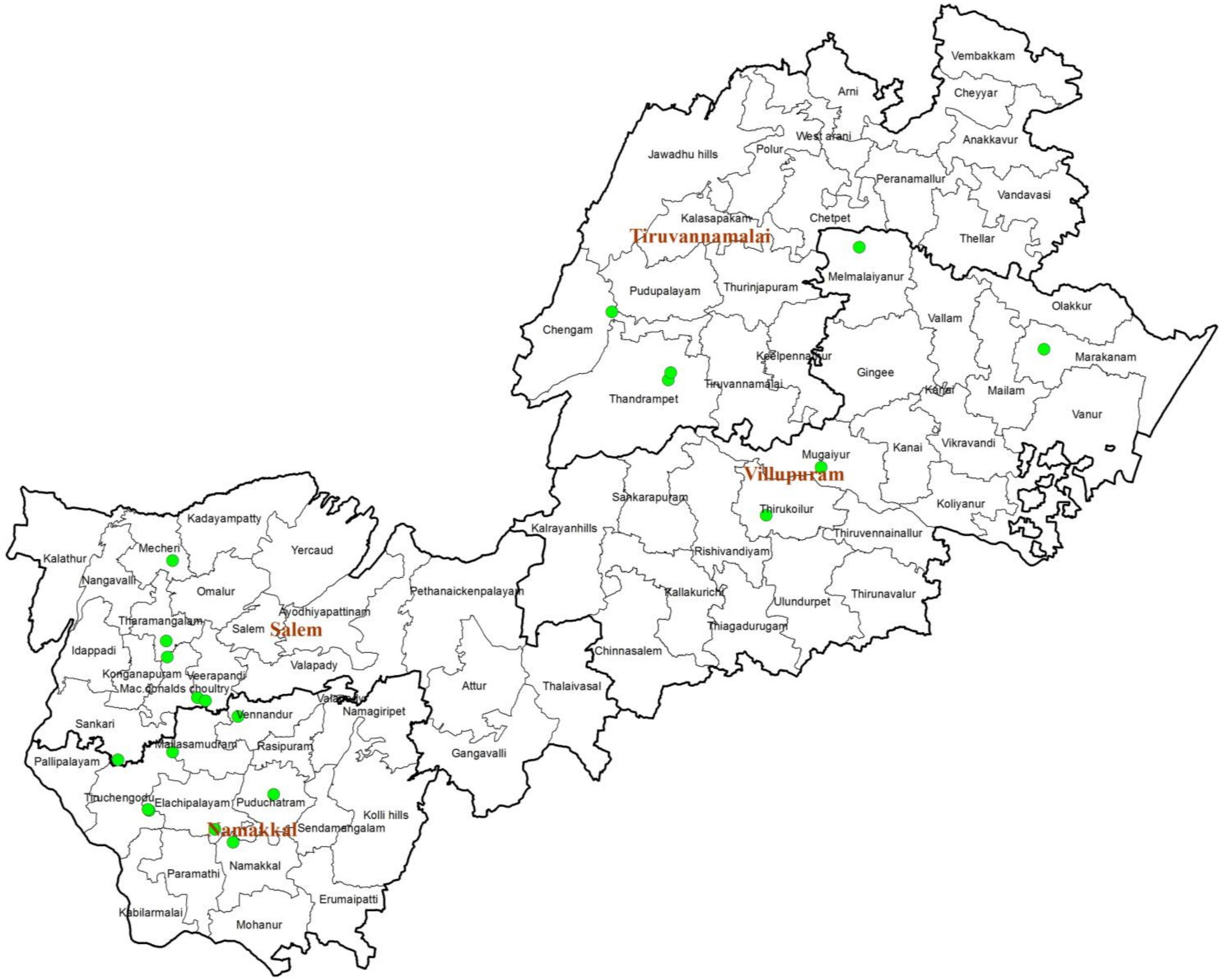

Fig. 2. Location map of monitoring sites

In Villupuram, the South West monsoon, North East monsoon and hot weather period contributed 39.5, 53.9 and 6.64 per cent of the total rainfall. The major crops were paddy, sorghum, pearl millet, finger millet, groundnut, sugarcane and cashewnut.

3.1.1. Location of study sites

Twenty different field locations across the study area were selected as monitoring fields to observe groundnut growth and productivity. These fields were continuously monitored throughout the season during the cropping period. The details of monitoring fields are given in Table 1. and locations of monitoring fields are illustrated in Fig.2.

3.1.2. Crop calendar of groundnut in Study area

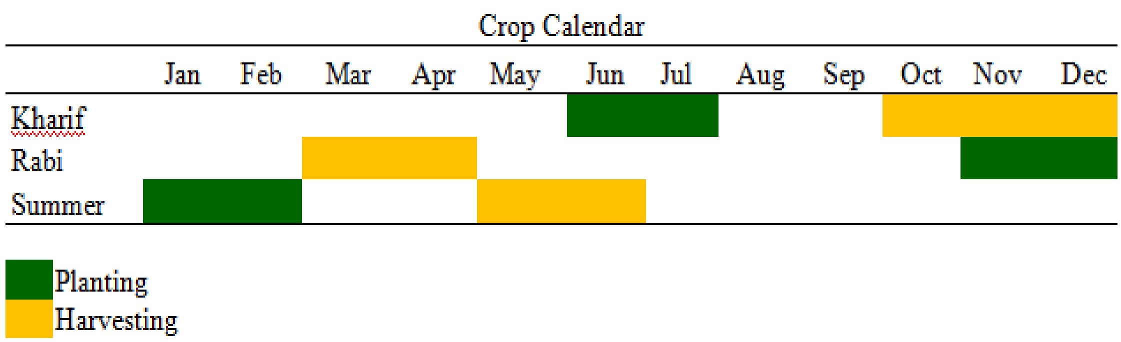

Fig.3. Crop calendar of groundnut in study area

3.2. Data used

In the research four main data sets were used.

3.2.1. Sentinel -1A SAR data

Satellite data were downloaded from Sentinel-1A, a synthetic Aperture Radar (SAR) satellite from European Space Agency (ESA) from May 2015 to February 2016 covering entire cropping season. The study Area was covered in two strips *viz*., Track 92 and Track 165. The satellite data was of 21 m spatial resolution with 12 days temporal resolution.

Table 1. Details of monitoring fields in the study area

S.No.	District	Village	Latitude	Longitude
1	Namakkal	Palayapuliyampatti	11.3291	77.9241
2	Namakkal	Pudhupuliyampatti	11.3313	77.9223
3	Namakkal	Kakapalayam	11.5467	78.0178
4	Namakkal	Kandarkulamanickam	11.5405	78.0336
5	Namakkal	Velagavundmpatti	11.2684	78.0876
6	Namakkal	Manathi	11.2934	78.0522
7	Namakkal	Morepalayam	11.4413	77.9698
8	Namakkal	Nochokarakadu	11.4264	77.8637
9	Salem	Pudhuchatram	11.3607	78.1664
10	Salem	Pothiyampatti	11.8095	77.9693
11	Salem	Pappambadi	11.6551	77.9573
12	Salem	Moongathur	11.6244	77.9591
13	Salem	Vellapillakovil	11.5105	78.0972
14	Tiruvannamalai	Keelravandavadi	12.1564	78.9361
15	Tiruvannamalai	Manmalai	12.2877	78.8266
16	Tiruvannamalai	Thandrampattu	12.1702	78.941
17	Villupuram	Arkandanallur	11.9875	79.234
18	Villupuram	Padiyandhal	11.8961	79.1264
19	Villupuram	Tindivanam	12.2126	79.6695
20	Villupuram	Melsevalambadi	12.4103	79.3098

3.2.2. Digital Elevation Data

The Digital Elevation Model tiles (SRTM with 3 arc second resolution) for the study area were downloaded from online archives (http://earthexplorer.usgs.gov/.). The resolution of the data was approximately 90 m and available as 5×5 degree tiles. No processing was required for this data hence used directly.

3.2.3. MODIS, LST and NDVI products

Land Surface Temperature products of Moderate Resolution Imaging Spectroradiometer (MODIS) are available with 1 km spatial resolution as 8 and 16 days composite. Normalized Difference Vegetation Index (NDVI) products are available at 250 m resolution as 8 and 16 days composite. These data for the study area were downloaded from the website http://earthdata.nasa.gov/. covering a period from May 2015 to February 2016 for further processing.

3.2.4. Landuse Landcover Data

The landuse landcover data from multi-temporal LISS III (with 23m spatial resolution) at a scale of 1:50000 prepared under National Resource Information Systems for during 2006-07 available with the Department of Remote Sensing and GIS, TNAU, Coimbatore was utilized for this study. It was an eight fold classification system comprising; Built up, Stable Vegetation, Waste land, Water + Wet lands, Crop land and Miscellaneous land forms.

3.3. Groundnut area estimation

3.3.1. Satellite data

The Sentinel-1 mission is the European Radar Observatory for the Copernicus joint initiative of the European Commission (EC) and the European Space Agency (ESA). The Sentinel-1 mission includes C-band imaging operating in four exclusive imaging modes with different resolution (down to 5 m) and coverage (up to 400 km). It provides dual polarization capability, very short revisit times and rapid product delivery. For each observation, precise measurements of spacecraft position and altitude are available.

Synthetic Aperture Radar (SAR) has the advantage of operating at wavelengths not impeded by cloud cover or a lack of illumination and can acquire data over a site during day or night time under all weather conditions. Sentinel-1A, with its C-SAR instrument, can offer reliable, repeated wide area monitoring (Table 2.).

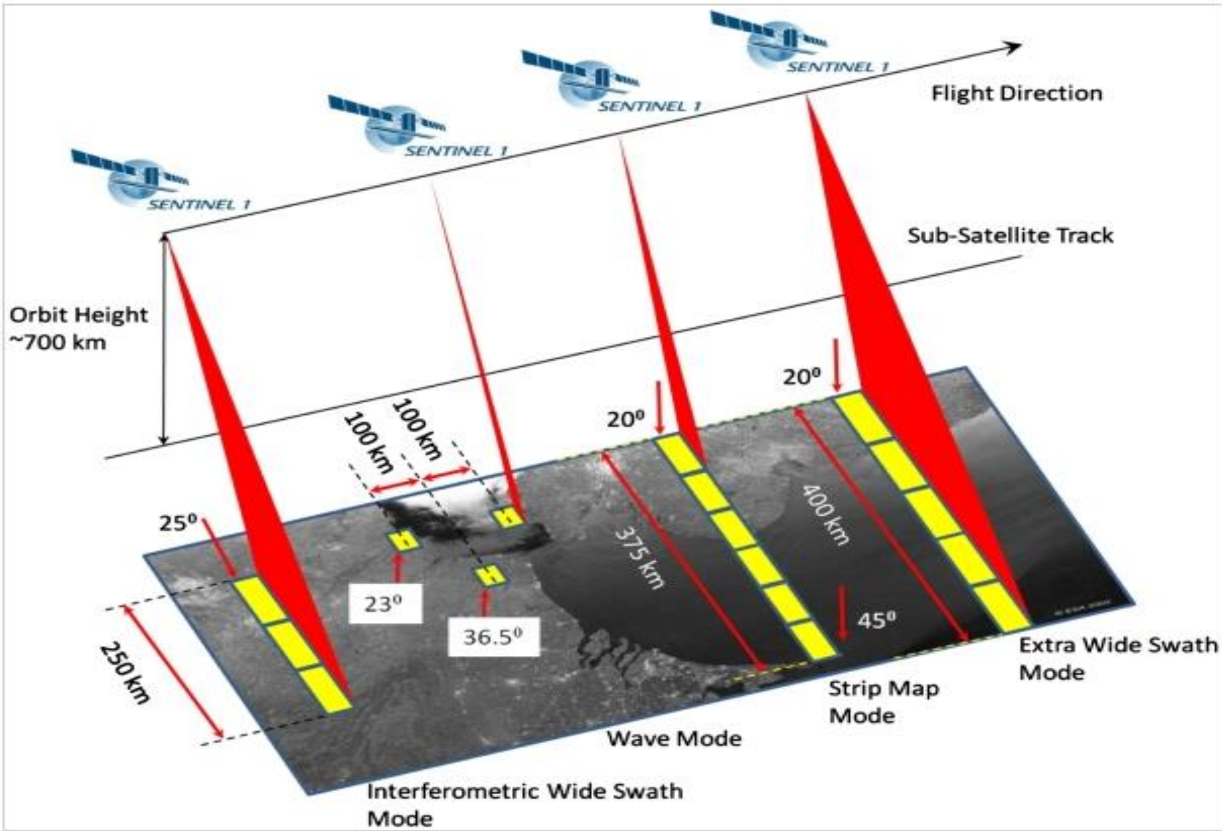

Fig.4. Sentinel-1A Product Modes

Sentinel 1-A, with V-V (Vertical-Vertical) and V-H (Vertical-Horizontal) polarization generates imageries at twelve days interval and systematically used for land monitoring. Sentinel 1-A has four standard operational modes, designed for interoperability with other system (Fig. 4.). Level-1 ground range (GRD) product obtained by interferometric wide (IW) swath mode of 20 m resolution with 12 days of temporal resolution was used for this research (Table 3.).

Table 2. Details of Sentinel-1A (IW-GRD) Data

Parameters	Characteristics
Pixel value	Magnitude detected
Coordinate system	Ground range
Polarization options	Single (HH or VV) or Dual (HH+HV or VV+VH)
Resolution (range x azimuth in meters)	20.4x21.7
Pixel spacing (range x azimuth in meters)	10x10
Incidence angle (degree)	32.9
Radiometric resolution	1.7 dB
Ground range coverage (km)	251.8
Absolute location accuracy (m) (NRT)	7
Equivalent Number of Looks (ENL)	4.4
Number of looks (range x azimuth)	5 x 1
Range look bandwidth (Hz)	14.1
Azimuth look bandwidth (Hz)	327
Look overlap (range, azimuth)	0.250, 0.000
Bits per pixel	16

***Source:** DeZan and Guarnieri (2006)

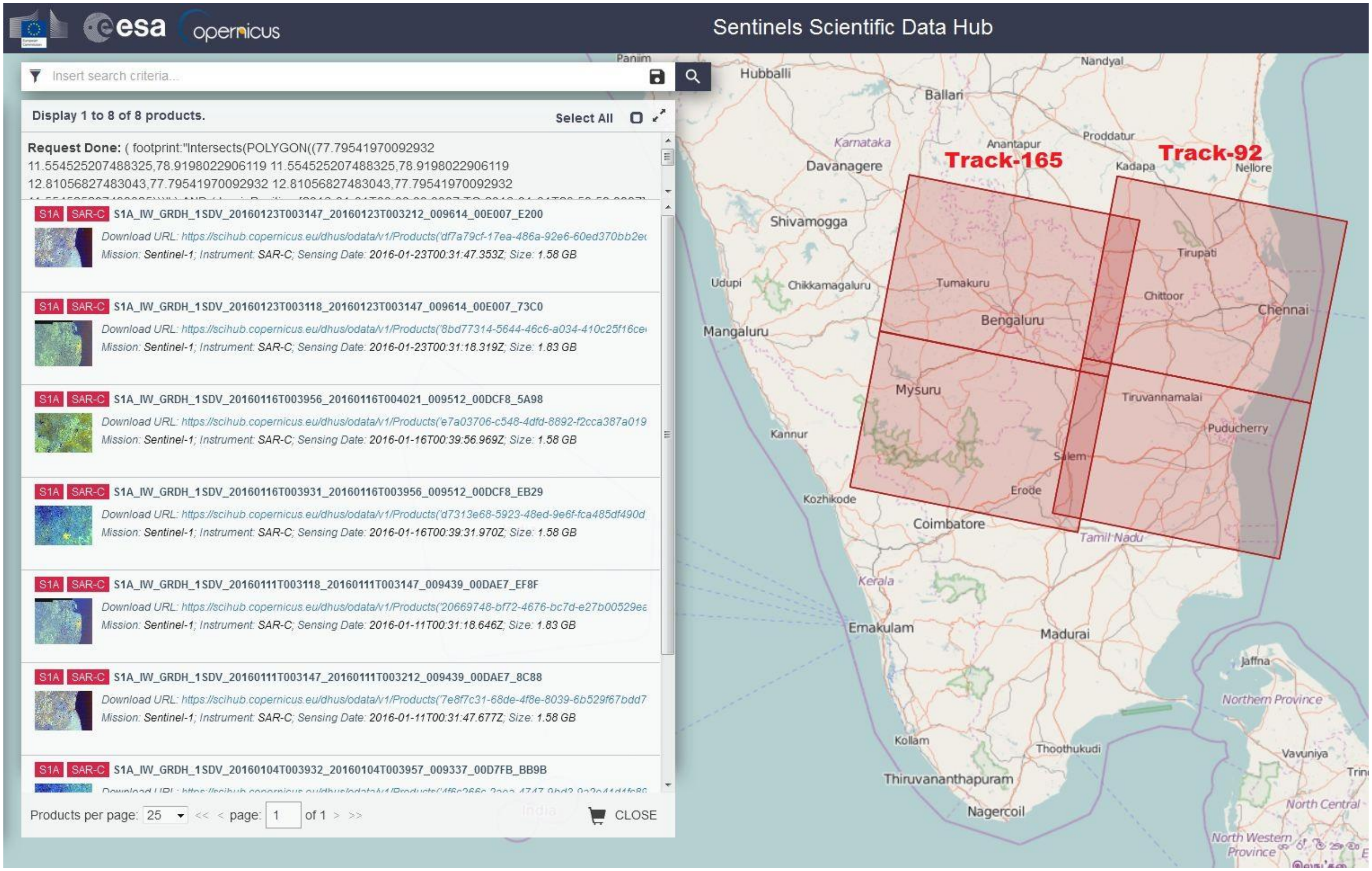

Fig.5. Overview of Sentinel-1A acquisition and coverage on study area

Table 3. Data acquisition schedule of Sentinel-1A satellite for study area

Sentinel -1A Data Acquisition for study area		
Track 92	**Track 92**	**Track 165**
28-05-2015	24-11-2015	08-07-2015
27-07-2015	06-12-2015	20-07-2015
08-08-2015	18-12-2015	13-08-2015
20-08-2015	30-12-2015	06-09-2015
01-09-2015	11-01-2016	30-09-2015
19-10-2015	23-01-2016	12-10-2015
31-10-2015	16-02-2016	05-11-2015
12-11-2015	28-02-2016	17-11-2015

3.3.2. Basic Processing of Sentinel 1A SAR Data for Multi-Temporal Analysis

A fully automated processing chain developed by Holecz *et al*.,(2013) was used to convert the multi-temporal space-borne Sentinel 1A SAR IW-GRD data into terrain-geocoded σ° values. The processing chain was a module within the MAPscape-RICE software, developed by *sarmap*, Switzerland. The SAR time-series data underwent a series of basic processing steps to generate terrain-geocoded σ° values as detailed below.

1. Strip mosaicking: To facilitate the overall data processing and data handling, single frames of the same orbit and acquisition date were mosaicked along their azimuth, generating long strips in slant range geometry. This step was performed exclusively when the SAR data were zero-Doppler focused.

2. Co-registration: Images acquired with the same observation geometry and mode were co registered in slant range geometry. The co-registration was performed in three steps: (i) a gross shift estimation based on the orbital data; (ii) a set of sub windows was automatically identified based on a reference image and on the images to be co-registered, and subsequently, the shifts between pixels of corresponding sub windows were calculated, including elevation by means of cross-correlation; (iii) finally, the shifts to be applied in the azimuth direction and range direction were calculated by a polynomial function depending on the pixel position, respectively, in the azimuth and range.

3. Time-series speckle filtering: Within the multi-temporal filtering, an optimum weighting filter was applied to balance differences in reflectivity between images at different times (De Grandi *et al*.,1997). Multi-temporal filtering was based on the assumption that the same resolution element on the ground was illuminated by the radar beam in the same way and corresponds to the same slant range coordinates in all images of the time series. The reflectivity could change from one time to the next because of a change in the dielectric and geometrical properties of the elementary scatters, but should not change because of a different position of the resolution element with respect to the radar.

4. Terrain geocoding, radiometric calibration and normalization: A backward solution by considering a digital elevation model (DEM) was used to convert the positions of the σ° elements into slant range image coordinates. A range-Doppler approach was applied to convert the two-dimensional row and column coordinates of the slant range image into three dimensional object coordinates in a given cartographic reference system. During this step, the radiometric calibration was performed by means of the radar equation, in which scattering area, antenna gain patterns and range spread loss were considered. Finally, in order to compensate for the range dependency, σ° was normalized according to the cosine law of the incidence angle.

5. Anisotropic non-linear diffusion (ANLD) filtering: This filter significantly smoothened homogeneous targets, while enhancing the difference between neighbouring areas. The filter used in the diffusion equation, in which the diffusion coefficient, instead of being a constant scalar, was a function of image position and assumed a tensor value (Aspert *et al*., 2007). In this way, it was locally adapted to be anisotropic close to linear structures, such as edges or lines.

6. Removal of atmospheric attenuation: Although microwave signals have the ability to penetrate clouds, it is possible that σ° from shorter wavelengths (X- and C-band) can be locally attenuated by water vapour in the range of several dB, because of severe (tropical) storms. The temporal signature of σ° can be affected by these events in two ways: (i) the thick layer of water vapour generates a strong decrease in σ° during the event, followed by a strong increase after the event; (ii) the intense rainfall generates a strong increase in σ° during the event, followed by a strong decrease after the event. These effects were removed by analyzing the temporal σ° signature: anomalous peaks or troughs were identified, and the σ° values were corrected by means of an interpolator. The correct application of this process relied strongly on a priori knowledge of the crop calendar and the weather conditions when the image was acquired.

7. Subsetting: The rectangular extent of the study was extracted from the base map and the raster images were subsetted to an extent from 11º 0' to 12º 52' North Latitudes and from 77º 38' to 80º 0' East Longitudes. Subsetting of raster data reduces the time in further processing.

3.3.3. Crop area identification (Fig.6)

Maximum Likelihood Classification

The aim of an image classification is to automatically categorize all pixels in an image into crop or land cover categories (Lillesand and Kiefer, 1994).

Maximum likelihood classification (MLC) algorithm was used in this study for crop area identification. The MLC quantitatively evaluates both the variance and covariance of the category by spectral response pattern when classifying an unknown pixel. An assumption is made that the distribution of the training set is Gaussian. Under this assumption, the distribution of a training set of a class can be completely described by the mean vector and covariance matrix. Given these parameters, we may compute the statistical probability of a given pixel being a member of a particular class.

First of all, the image was classified using MLC with multi-temporal stacked SAR images for the identification of groundnut. The training signature for groundnut fields were generated based on the training pixels collected at various locations. The classification is also performed separately for VV and VH to identify the best polarization type that can be used for crop classification.

The non-agricultural areas like forest, gully land, water body, river, mining land, agro-forestry etc., were extracted from the Land use and Land Cover map of Tamil Nadu generated at 1:50,000 scale during year 2010 by National Remote Sensing Centre (NRSC), Hyderabad. The non-agricultural areas are used as a mask during classification to avoid misclassification and to improve the accuracy and the same mask is also used for all the other classifiers.

Class mask (containing different classes) generated using multi temporal features of groundnut fields for both VH and VV polarization images in study area were used in the

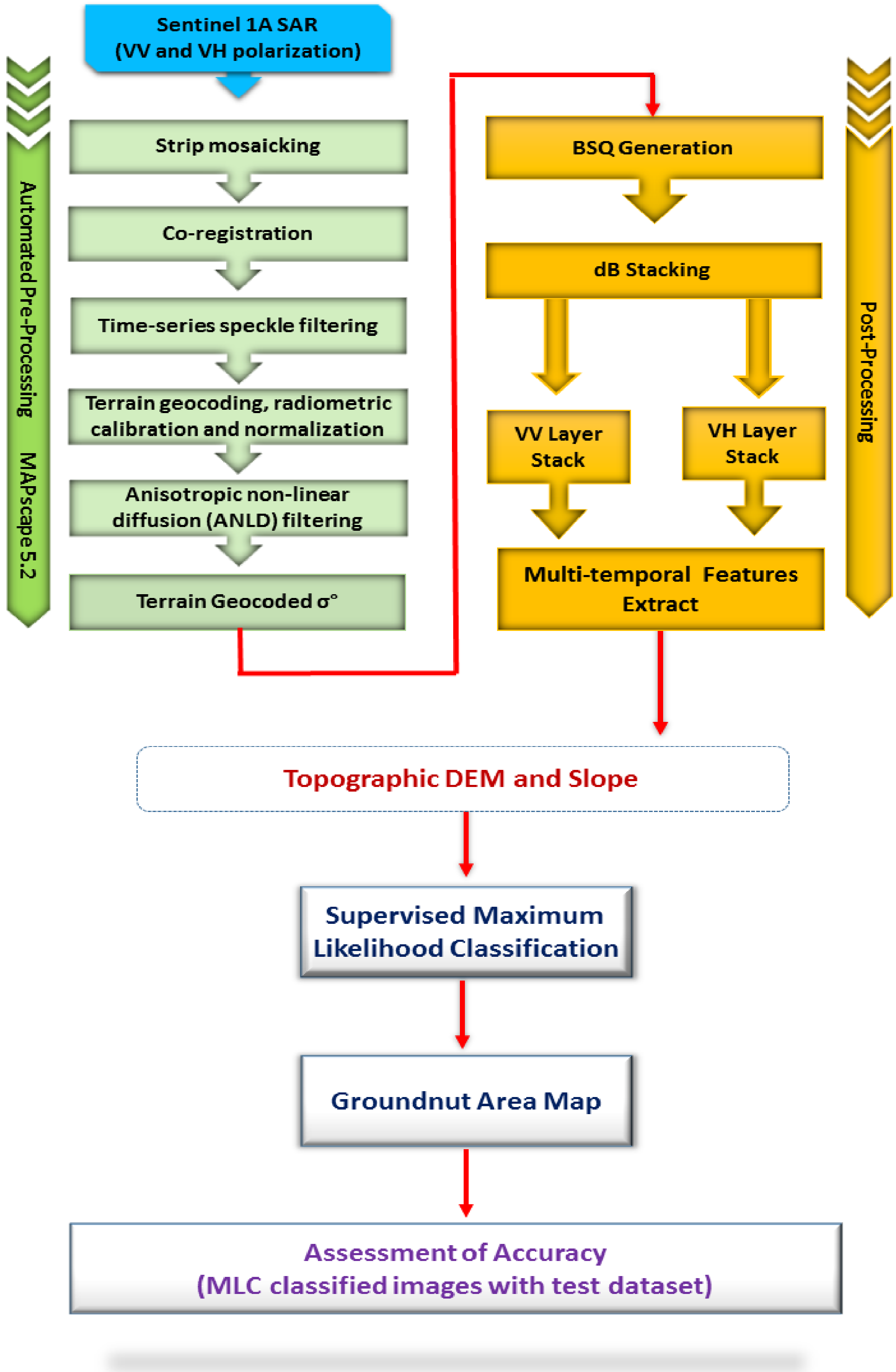

Fig.6. Flow chart depicting groundnut area mapping

classification. Maximum Likelihood Classification was applied on temporal VV polarization class mask images of study area during the classification run. The class mask file was used to precisely segregate the groundnut pixels from other class pixels.

The resulting classification image was measured for accuracy by comparing it to groundnut pixels generated from ground truth points. The summary of this was captured for both *kharif* (Salem and Namakkal districts) and *rabi* (Tiruvannamalai and Villupuram districts) seasons and presented in confusion matrix which is a way of displaying the results of classification image which considered being ground truth.

3.3.4. Accuracy Assessment

This Error matrix and Kappa statistics are used for evaluating the accuracy of the groundnut area map. The class allocation of each pixel in classified image is compared with the corresponding class allocation on reference data to determine the classification accuracy. Forty per cent of the total ground reference data are used for validation. The pixels of agreement and disagreement are compiled in the form of an error matrix, where the rows and columns represent the number of all classes and the elements of matrix represent the number of pixels in the testing dataset (Lillesand and Kiefer, 1994). The accuracy assessment was done for all the classified outputs.

The accuracy assessment in fields was generally conducted during the pod filling or maturity stage before harvesting, but in some cases the field assessment was conducted during post-season and groundnut haulms and farmer surveys were used to confirm that the observed post-harvest situation reflected the presence of a groundnut crop during the monitored season. The accuracy measures, such as overall accuracy, producer’s accuracy and user’s accuracy were estimated from the error matrix (Congalton, 1991). The overall accuracy, the percentages of correctly classified cases lying along the diagonal, was determined as follows:

$$\text{Overall Accuracy} = \frac{\Sigma(\text{Correctly classified classes along diagonal})}{\Sigma(\text{Row Total or Column Total})}$$

The producer’s accuracy (errors of omission) of each class was computed by dividing the number of samples that were classified correctly by its total number of reference samples as follows:

$$\text{Producer's Accuracy} = \frac{\text{Number of correctly classified class in a column}}{\text{Total number of items verified in that column}}$$

The user's accuracy (errors of commission) of each class was computed by dividing the number of correctly classified samples of that class by its total number of samples that were verified as belonging to the class as follows:

$$\text{User's Accuracy} = \frac{\text{Number of correctly classified item in a row}}{\text{Total number of items verified in that row}}$$

3.3.5. Kappa Coefficient

Another measure of classification accuracy is the kappa coefficient, which is a measure of the proportional (or percentage) improvement by the classifier over a purely random assignment to classes (Richards, 1993). The kappa coefficient was estimated from the formula given below.

$$\widehat{K} = \frac{\mathrm{NA} - \mathrm{B}}{N^2 - B}$$

For an error matrix with r rows, and hence the same number of columns,

Where,

A = the sum of r diagonal elements, which is the numerator in the computation of overall accuracy

B = sum of the r products (row total x column total)

N = the number of pixels in the error matrix (the sum of all r individual cell values)

3.4. Crop yield simulation using crop simulation model (DSSAT)

Decision Support System for Agrotechnology Transfer (DSSAT) is developed through the internationally collaboration work carried out under IBSNAT, U.S.A., across the globe (Jones *et al*., 2003). DSSAT is a micro-computer software product that combines crop, soil and weather data-bases into standard formats for assessment by crop model and application programs. The user can then simulate multi-year outcomes of crop management strategies for different crops at any location in the world and hence the DSSAT was used in the present investigation. Fig.7. describes components of DSSAT crop simulation model.

3.4.1. CROPGRO-Peanut model

The CROPGRO-Peanut model available in DSSAT v 4.5 simulated crop growth and development on daily time step. This was a one-dimensional model that computes daily changes in soil water content in a soil layer due to infiltration, irrigation, vertical drainage, unsaturated flow, soil evaporation, plant transpiration and root water uptake. Infiltration was calculated on the difference between rainfall (or irrigation) and runoff. Drainage was assumed to be constant throughout the whole day and computed for each layer using the drained upper limit and lower limit values of soil water content. It required cultivar coefficients (cultivar-specific parameters) as an input to the model in addition to crop-specific coefficients that were considered less changeable or more conservative in nature across crop cultivars. The model could also simulate the impact of elevated temperatures on groundnut growth and development. For its run it required minimal dataset that are mentioned below.

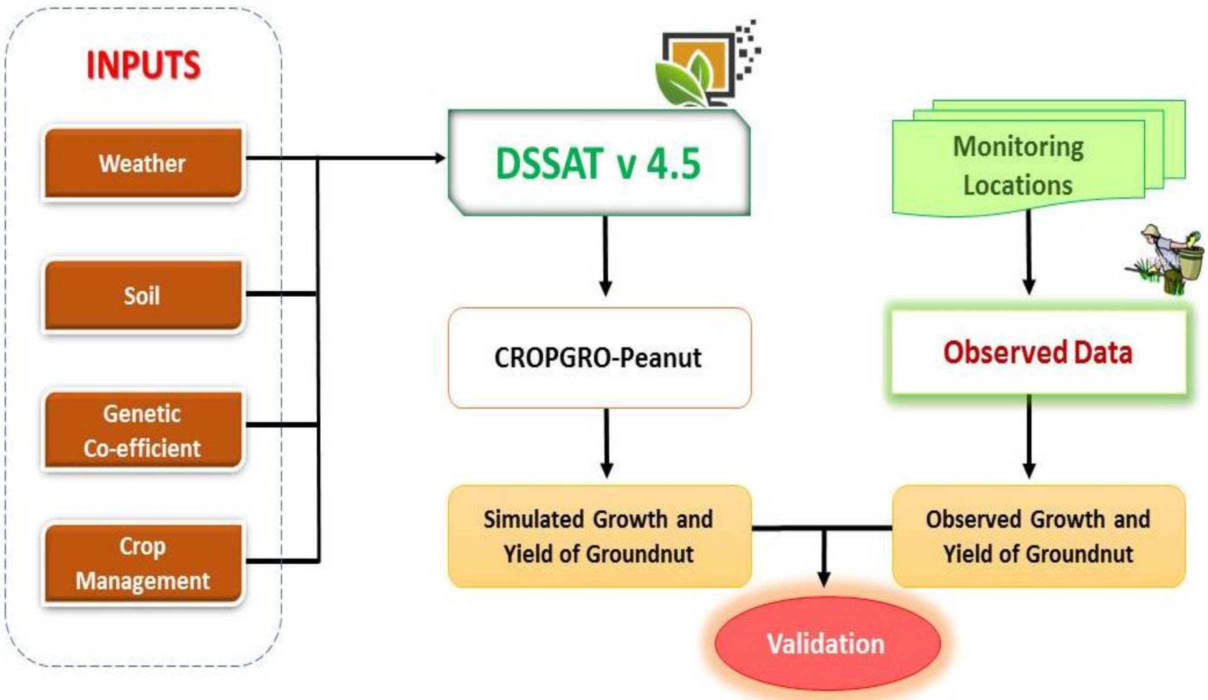

Fig.7. Diagram of database, application and support software components and their use with crop models for applications in DSSAT

3.4.2. Weather file

The daily weather data on maximum temperature (°C), minimum temperature (°C), solar radiation (MJ m^{-2} day^{-1}) and rainfall (mm) for the year 2015 and 2016 (upto March) for the study area were collected from Automatic Weather Stations (AWS) and regular observatories situated at the study districts and used to create weather file for running CROPGRO-Peanut model.

DSSAT model required weather data for the entire growing season of the crop to predict the yield. In this study, yield estimates were done during South West Monsoon (Namakkal and Salem districts) and North East Monsoon (Tiruvannamalai and Villupuram districts). The actual weather data during the crop growth period was used for simulations. For the missing data, the weather data was generated either from the historical mean or using analogue technique, wherein, the past years weather that behaved similar to the current season was chosen to fill the missing or erroneous data.

3.4.3. Soil data file

Soil information for creating the soil files was obtained from the Department of Remote Sensing and Geographical Information system, Tamil Nadu Agricultural University, Coimbatore. Digital soil information system containing information on soil characters (1:50000) *viz*., depth, texture, BD, drainage, pH, EC, Organic Carbon, Available P and K, Ca and Mg and CEC was used for this purpose. The profile details as required in DSSAT were extracted for the study area from the above database using ArcGIS (GIS Tool) and were fed into S-Build tool in DSSAT to create soil file.

3.4.4. Crop management file

Crop management file documented the inputs to the model for the twenty fields from the study area to be stimulated. Details of fields are listed in Table 1. The details of the experimental conditions and field characteristics such as name of the weather station, soil, and field description details, initial soil, water and inorganic nitrogen conditions, planting geometries, irrigation and water management, fertilizer management details, organic residue application, chemical applications, tillage operations, environmental modifications, harvest management, simulation controls (specification of simulation options *viz.*, starting dates, on/off options for water and nitrogen balances, symbiosis) and output options were included in the crop management file.

3.4.5. Estimation of genetic co-efficient groundnut

Model calibration or parameterization is the adjustment of genetic parameters so that simulated values compare well with observed values. Data obtained from the experiments were used to estimate genetic parameters. The genetic coefficients that influence the occurrence of developmental stages in the CROPGRO-Peanut model embedded in DSSAT model were derived iteratively, by manipulating the relevant coefficients to achieve the best possible match between the simulated and observed number of days to the phenological events and grain yield at harvest. A detailed description of the cultivar coefficients used by CROPGRO-Peanut for groundnut varieties of study area *viz.*, Co 6, TVM 7 and VRI 2 is presented in Table 4.

3.4.6. Output files

The output file, generated by the model runs gives an overview of input conditions and crop performance and yield spatially.

3.4.6. Model calibration, validation and future yield simulations

Three input files were created to run the DSSAT model using collected data.

a. **Weather file**: 'Weatherman' program in DSSAT and collected weather data

b. **Soil file**: 'S Build' program in DSSAT and soil data

c. **Experimental data file**: 'X Build' program in DSSAT and crop management data

The model was calibrated using collected data from the experimental trials in *kharif* and *rabi* season 2015 through determination of genetic coefficient for CO 6, TMV 7 and VRI 2 varieties with spatial analysis mode in DSSAT. The model was validated using the experimental data in *kharif* and *rabi* season 2015 by comparing the observed results with simulated results. Yields from trials (hereafter referred to as observed) conducted at farmers' fields in rainfed areas of study districts were considered as observed data. To evaluate the quality of the simulations different quality measures were applied. For a quick overview of the modeling quality, graphs of the measured against the simulated values were drawn together with the linear regression and the correlation coefficient.

Table 4. Description of Genetic coefficients for groundnut cultivars

Code	Description
CSDL	Critical Short Day Length below which reproductive development progresses with no day length effect (for short-day plants) (hour)
PPSEN	Slope of the relative response of development to photoperiod with time (positive for short day plants) (1/hour)
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days).
FL-SH	Time between first flower and first pod (R3) (photo thermal days)
FL- SD	Time between first flower and first seed (R5) (photo thermal days)
SD-PM	Time between first seed (R5) and physiological maturity (R7) stages (photothermal days)
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)
LFMAX	Maximum leaf photosynthesis rate at 300 C, 350 vpm CO2, and high light (mgCO2/m2/s)
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm2/g)
SIZLF	Maximum size of full leaf (three leaflets) (cm2)
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell
WTPSD	Maximum weight per seed (g)
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)
SDPDV	Average seed per pod under standard growing conditions (#/pod)
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)
THRSH	The maximum ratio of (seed/(seed+shell)) at maturity. Causes seed to stop growing as their dry weights increase until shells are filled in a cohort.(Threshing percentage)
SDPRO	Fraction protein (g) per g seed
SDLIP	Fraction oil (g) per g seed

3.5. Yield estimation by integrating Remote Sensing and DSSAT Crop growth model (Fig.8.)

3.5.1. Generation of LAI for groundnut yield estimation

An ideal method for simulating the development of LAI and crop yields should require a minimal amount of input data and be based on the underlying physiological and phenological processes that govern these properties in plants. Two approaches to this problem have been developed: Methods of estimation generally rely on determining the LAI by remote sensing (De Kauwe *et al.*, 2011) or by direct measurement of Leaf Area Index was worked out by measuring the length and width of the fully expanded apical leaflet of the third tetra foliate leaf at 30 days interval starting from 30 DAS to harvest as suggested by Padalia and Patel (1980).

$$\text{LAI} = \frac{\text{L x W x K x Number of Leaves}}{\text{Spacing Adopted (cm)}}$$

Where,

L - Length of the Leaf (cm)

W - Width of the Leaf (cm)

K - Constant Factor (0.70)

From every field, five LAI measurements were collected and the average was recorded. At the end of season, yield data was recorded from each field. Finally, the whole dataset was completed with 20 points over the study area with groundnut pod yield, LAI measurements so as to give input to CROPGRO-Peanut model for simulation and validation purpose. The data of the study area were combined in one dataset and regression analysis between observed yield and predicted yield was performed.

An empirical approach was applied to extrapolate the field observed and DSSAT derived LAI values to generate yield maps and statistics spatially. The estimated yields were validated against observed yields using degree of errors in terms R^2, RMSE and NRMSE.

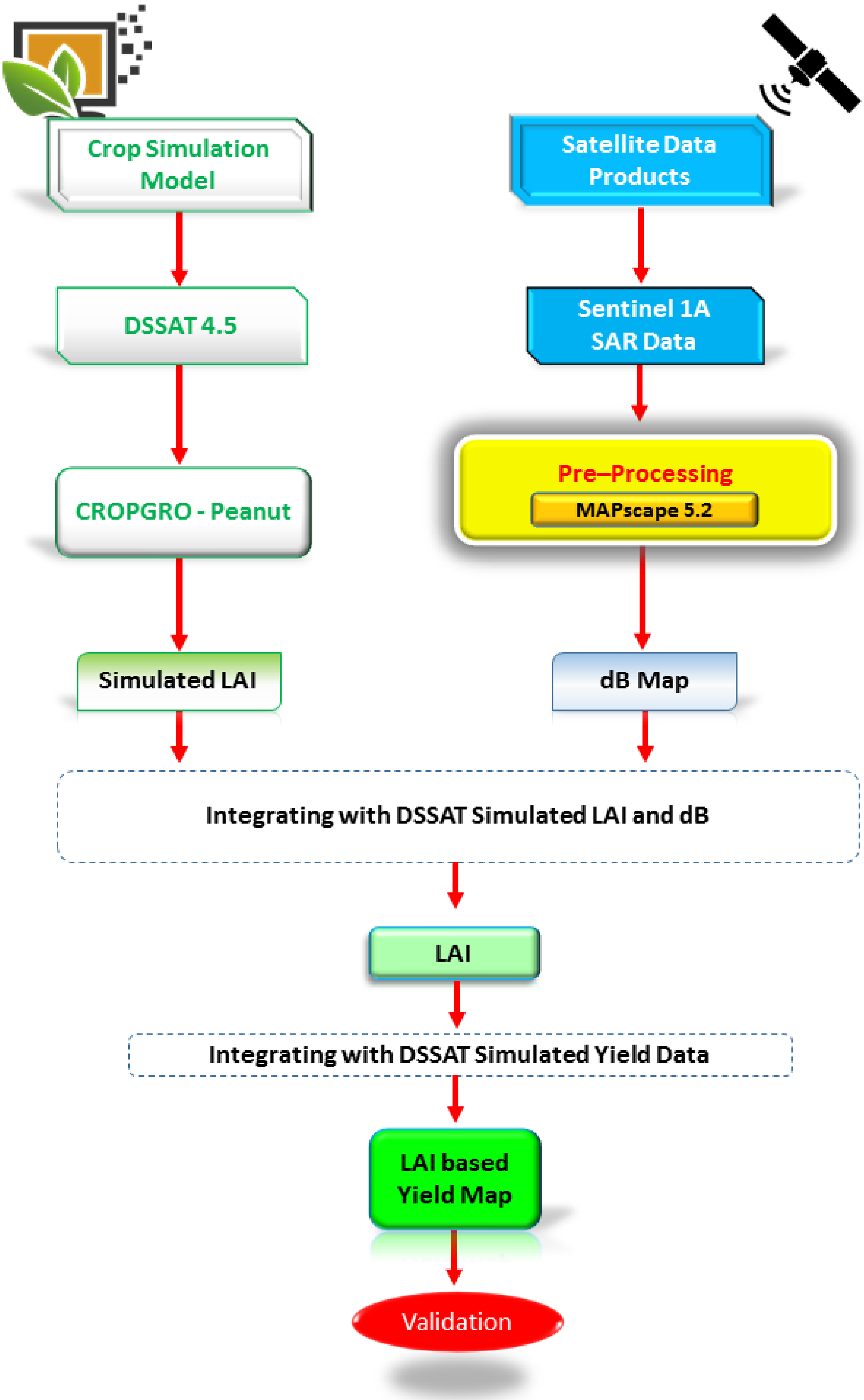

Fig.8. Flow chart depicting yield estimation by integrating Remote Sensing and DSSAT outputs

3.5.2. Retrieving LAI from dB images of SAR data

The dB (back scattering) values of groundnut fields were collected from monitoring fields using point sampling tool in QGIS 2.18.4. The Point Sampling tool plugin was used to collect polygon attributes and raster values from multiple layers at specified sampling points. In this study, the shape file with sampling points (monitoring field points) was placed over the input raster file (dB image). The plugin created a new point layer with locations given by the sampling points and attributes taken from the underlying raster cells (dB image) and this process was carried out for both seasons. The linear regression was generated between dB values and simulated LAI values at pod development from monitoring groundnut fields of study area during both *kharif* (Salem and Namakkal districts) and *rabi* (Tiruvannamalai and Villupuram districts) seasons.

In ArcMap, the raster calculator tool provides a tool for performing mathematical calculations using operators and functions, set up selection queries, or type in Map Algebra syntax. In this study, the generated regression values of both seasons of study area were substituted with dB values in dB images from maturity stages of both seasons by using raster calculator in ArcMap and LAI of study area was generated spatially corresponding to pod development of groundnut.

3.6. Assessing vulnerability of groundnut to drought (Fig. 9.)

The quantification of drought severity is called as drought assessment. Drought assessment was with the use of a suitable drought index. It could be meteorological, hydrological or Agricultural drought assessment. Remote sensing derived drought indices could aid a helping hand in this context.

3.6.1. Agricultural vulnerability to drought

Agricultural drought risk assessment was done by a reduction in crop area, a loss in crop yields or both as a result of deficient moisture conditions during the crop growing season. Deficient rainfall during the early part of the crop season lead to abnormal sowing operations resulting in reductions in sown area. Further into the crop season, deficient rains lead to stunted crop growth resulting in reduced yield potentials. Rainfall shortages impact crop

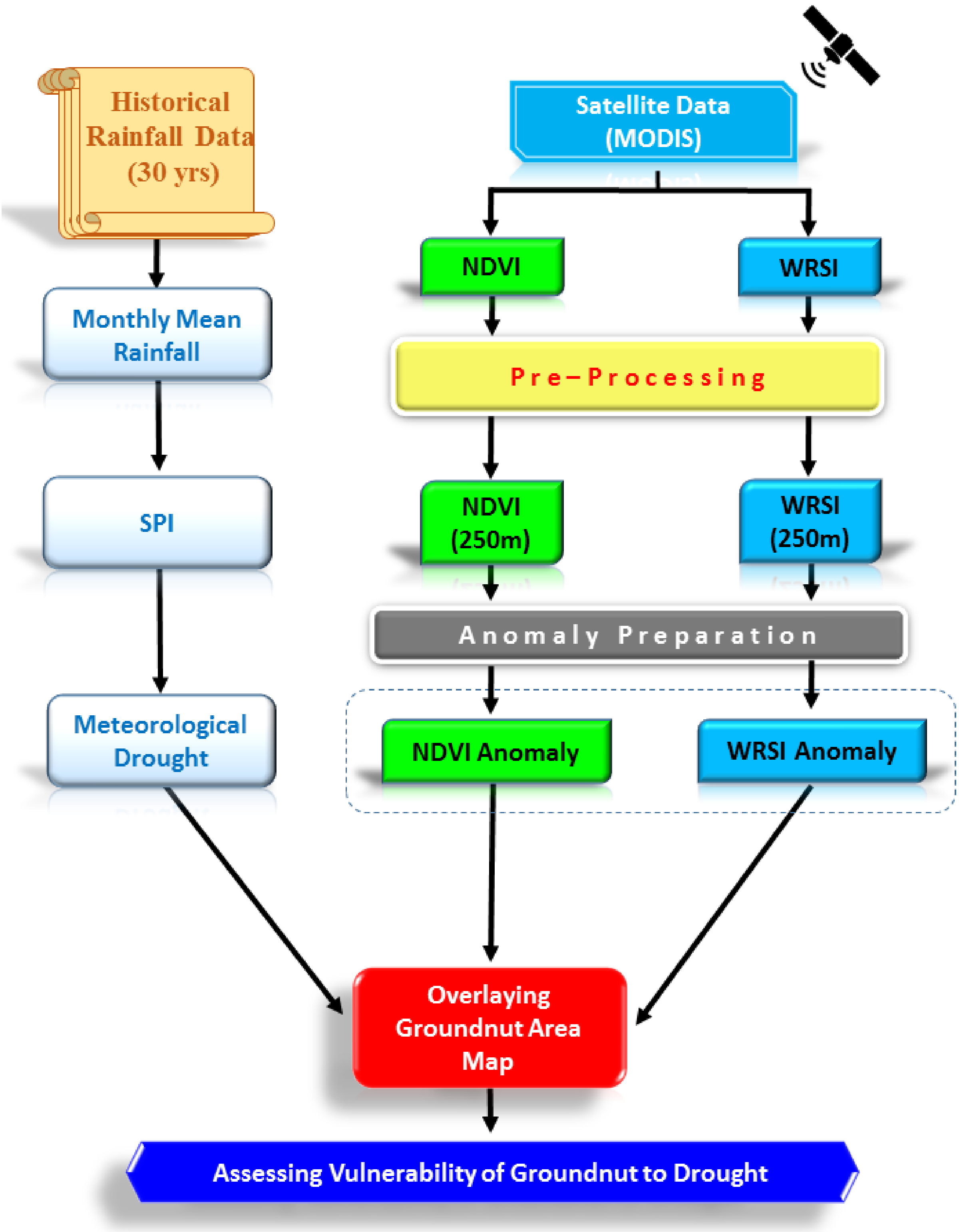

Fig.9. Flow chart depicting drought vulnerability mapping

growth most significantly if they happen during critical flowering or grain formation stages. Regardless of the timing, agricultural drought is defined by a loss in crop production as a result of shortages in water availability.

3.6.1.1. Dataset

The dataset used in the present study and their basic characteristic relevant to the aim of the study is briefly described as follows:

3.6.1.2. Rainfall data

Daily rainfall datasets were acquired from the grid data for the period from January 1980 to March 2016. The Indian Meteorological Department (IMD) have setup a rainfall monitoring station for the Tamil Nadu besides Automatic Weather Station (AWS) from TNAU. Thus, there are twelve meteorological stations within the study area which were used for the present study.

3.6.1.3. Satellite data

The datasets on NDVI acquired by MODIS from May 2015 to February 2016 were used in the present study.

3.6.2. Standardized Precipitation Index (SPI)

SPI is the number of standard deviations that the observed value would deviate from the long-term mean, for a normally distributed random variable. SPI is based on the cumulative probability of a given rainfall event occurring at a station (Tucker, 1979). In order to analyse the impact of rainfall deficiency and the development of drought in this study area, SPI was used to quantify the precipitation deficit during *kharif* and *rabi* 2015. The SPI was calculated using the following equation,

$$\mathbf{SPI = (Xij - Xim\ ) / \sigma}$$

Where, Xij is the monthly precipitation at the i^{th} rain-gauge station and j^{th} observation, Xim is its long-term precipitation mean and σ is its standard deviation. Positive SPI values indicate greater than median precipitation and negative values indicate less than median precipitation (Kaushaly, 2011). Drought periods were represented by relatively high negative deviations. Normally, the “drought” part of the SPI range is arbitrarily split into 7 classes. The standards for SPI is given below:

SPI Value	Drought Condition
2.00 and above	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
0.99 to -0.99	Near normal
-1.00 to -1.49	Moderately dry
-1.50 to -1.99	Severely dry
-2.00 and less	Extremely dry

Since drought is a regional phenomenon, SPI values of the rain gauge stations have been interpolated using Spline interpolation technique in Arc GIS to demarcate its spatial extent. The SPIRITS software was used to generate SPI images for anomoly assessment.

3.6.3. Normalised Difference Vegetation Index (NDVI)

The NDVI images were generated using the imageries of MODIS acquired in 2015 and 2016. The MODIS measures the intensity of the reflection from the Earth's surface in both red and infrared wavelength ranges. The Normalised Difference Vegetation Index (NDVI) is a measure of the difference in reflectance between these wavelength ranges. NDVI takes values between -1 and 1, with values of 0.5 indicating dense vegetation and values less than 0 indicating no vegetation.

The NDVI is given by the following equation:

$$NDVI= (NIR-RED/NIR+RED)$$

Where, RED and NIR correspond to band 3 and 4 in MODIS respectively. By normalizing the difference in this way, the values can be scaled between values of -1 to +1. This also reduces the influence of atmospheric absorption. Water has an NDVI value less than 0, bare soils between 0 and 0.1 and vegetation above 0.1.

8-day composite MODIS dataset comprised NDVI, quality, acquisition image, acquisition table and metadata files. From the global data, the study area was being subset and NDVI data was extracted and analyzed. Time-series NDVI profile of the study area was derived from the calculation of NDVI using the MODIS NDVI data for the year 2015 and used to generate the Average monthly NDVI values for the year.

3.6.4. Water Requirement Satisfaction Index (WRSI)

WRSI for a season was based on the water supply and demand the crop experienced during a growing season. It was calculated as the ratio of seasonal actual evapo-transpiration (AET) to the seasonal crop water requirement (WR) (Dorenbos and Kassam, 1979).

$$\mathbf{WRSI = (AET/WR)*100}$$

The model was run to simulate WRSI of groundnut during the *kharif* season in Namakkal and Salem districts and *rabi* season in Tiruvannamalai and Villupuram districts using NDVI, LST, Radiance, TRMM rainfall and SRTM DEM from 2001 through 2015.

Stress caused by water was one of the major causes of crop failure under rainfed conditions. The percentage water requirement satisfaction for rainfed crop given by the computation of WRSI determined the growth and yield of the groundnut. Various experiments have revealed that, as the WRSI percentage decreased the stress for water increased and when this index value was less than 50 per cent, there were more chances for crop failure. Based on these conditions the output of WRSI was classified into 6 groups *viz*.,

100%	- No Risk
90-100%	- Low Risk
80-90%	- Medium Risk
70-80%	- High Risk
50-70%	- Very High Risk and
<50%	- Chance of Crop failure

3.6.5. Agricultural vulnerability of groundnut area to drought

The present study of agricultural vulnerability in study area was assessed by overlaying the SPI, NDVI and WRSI using ARCGIS 10.1 version. The integrated map showed the index of agricultural vulnerability of groundnut area to drought that is classified as high, medium and Low.

3.7. Statistical Evaluation and Validation of products

An analysis of the degree of coincidence between simulated and observed values was carried out by using R^2, Root Mean Square Error (RMSE), Normalised Root Mean Square Error (NRMSE) and Agreement percent (Jemison *et al*., 1994).

$$RMSE = \sqrt{1/N \sum (Oi - Pi)2}$$

$$\text{NRMSE} = 100 \text{ x } (\text{RMSE} / \text{O}i)$$

$$\text{Agreement (\%)} = 100 \text{ x } (1 - (\text{RMSE} / \text{O}i))$$

Where P*i* and O*i* were the predicted and observed values for the observation, and N was the number of observation within each treatment. RMSE was measure of the deviation of the simulated from the measured values, and was always positive. A zero value was ideal. The lower the value of RMSE, the higher was the accuracy of the model prediction.

Experimental Results

CHAPTER IV

EXPERIMENTAL RESULTS

A study on 'Mapping and Modeling growth and productivity of groundnut in Rainfed Areas of Tamilnadu' was conducted during *kharif* 2015 (Salem and Namakkal districts) and *rabi* 2015 (Tiruvannamalai and Villupuram districts) to estimate groundnut area, model growth and productivity and assess the vulnerability of groundnut to drought. The results of the study are presented in this chapter.

4.1. Weather information of the study area

The study area comprised of Salem, Namakkal, Tiruvannamalai and Villupuram districts and the weather parameters *viz*., rainfall, maximum and minimum temperature and relative humidity were observed from major groundnut growing districts of study area during the crop growing period. Districtwise mean monthly rainfall (mm) recorded in the study area during cropping period is given in Table 5. The detailed weather prevailed during the cropping period at Mecheri and Namakkal of Salem and Namakkal districts are presented in Appendices I and II respectively and illustrated in Fig. 10 and 11. During the crop growing period of *kharif* (May to October, 2015), 243.0 and 313.9 mm of rainfall was recorded at Mecheri and Namakkal of Salem and Namakkal districts, respectively. The mean maximum and minimum temperature of Mecheri (Salem district) was 36.3°C and 23.5°C, respectively whereas Namakkal (Namakkal district) recorded a mean maximum and minimum temperature of 35.8°C and 25.2°C, respectively. The mean solar radiation recorded at Mecheri was 360.9 cal $cm^{-2}min^{-1}$ and Namakkal recorded 384.9 cal $cm^{-2}min^{-1}$.

The weather condition prevailed during the cropping period at Thandrampattu (Tiruvannamali district) and Melmalaiyanur (Villupuram district) are presented in Appendices III and IV and illustrated in Fig. 12 and 13**.** During *rabi* season (September, 2015 to January 2016), Thandrampattu (Tiruvannamali district) and Melmalaiyanur (Villupuram district) received a rainfall of 397.5 mm and 602.0 mm respectively. The mean maximum and minimum temperature of Thandrampattu was 29.6°C and 21.7°C, respectively whereas Melmalaiyanur recorded the corresponding values of 31.7°C and 22.3°C. The mean solar radiation recorded at Thandrampattu was 349.6 cal $cm^{-2}min^{-1}$ whereas Melmalaiyanur recorded a mean solar radiation of 341.5 cal $cm^{-2}min^{-1}$.

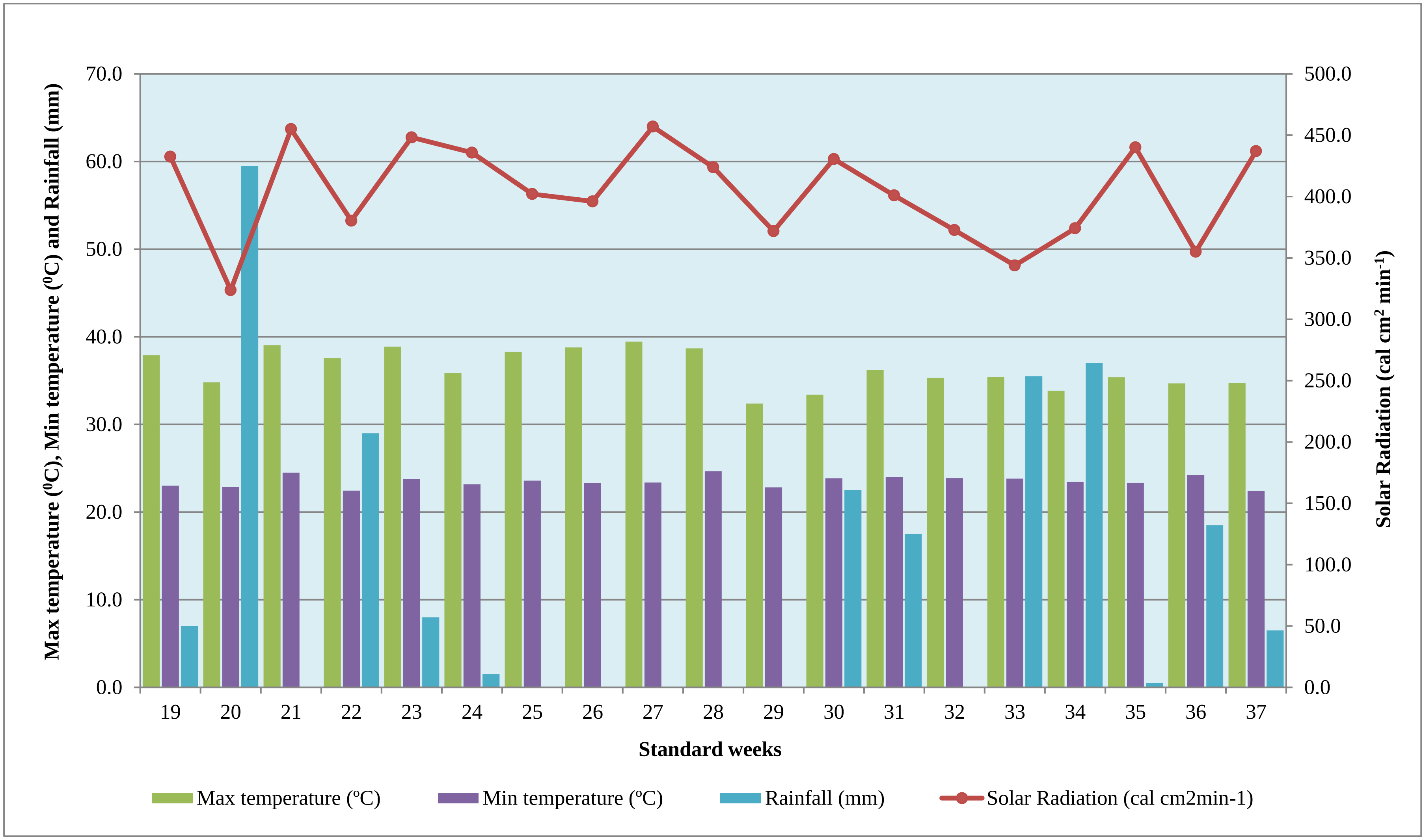

Fig.10. Weather data prevailed in Namakkal during *kharif*, 2015

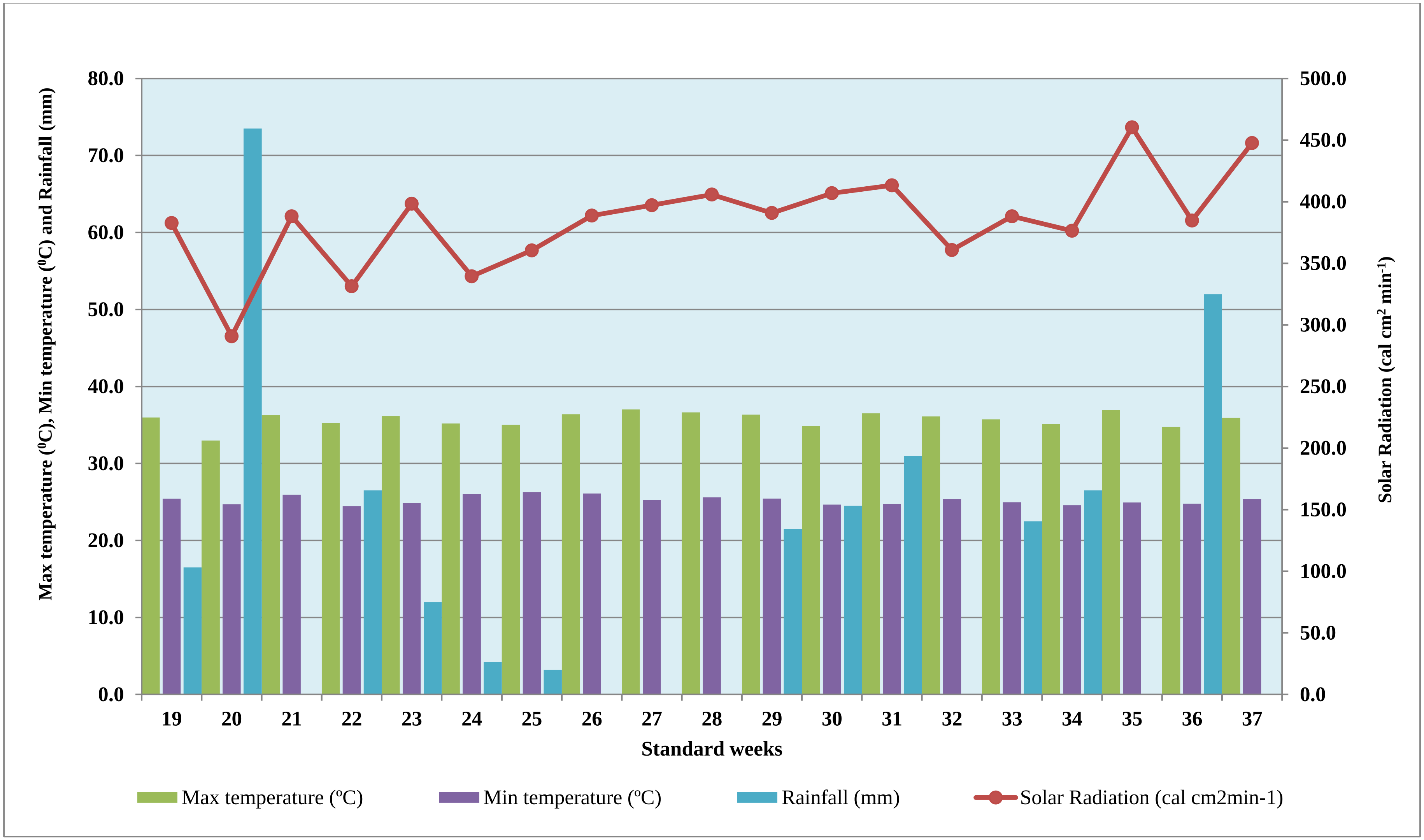

Fig.11. Weather data prevailed in Mecheri of Salem district during *kharif*, 2015

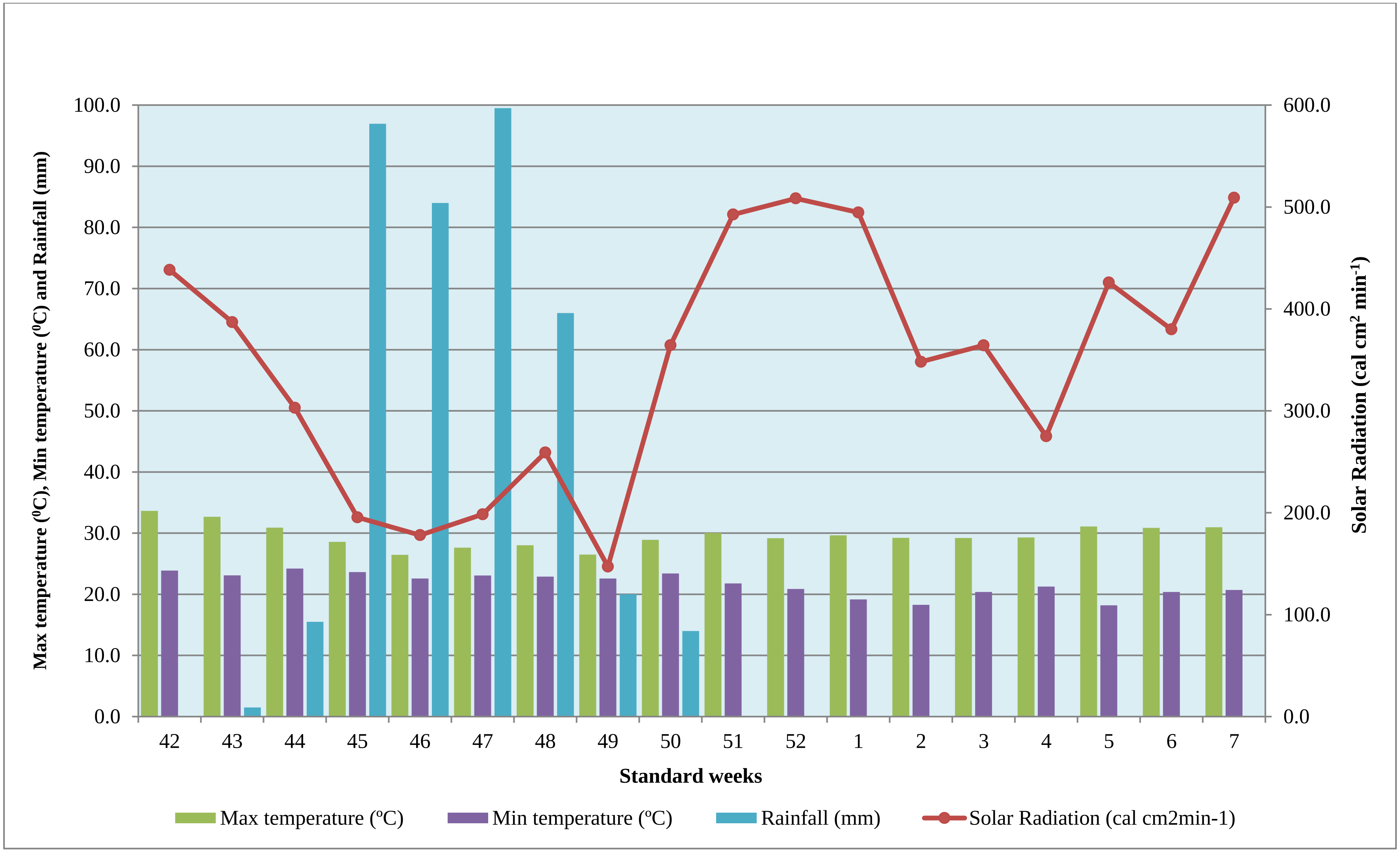

Fig.12. Weather data prevailed in Thandrampattu of Tiruvannamalai district during *rabi*, 2015

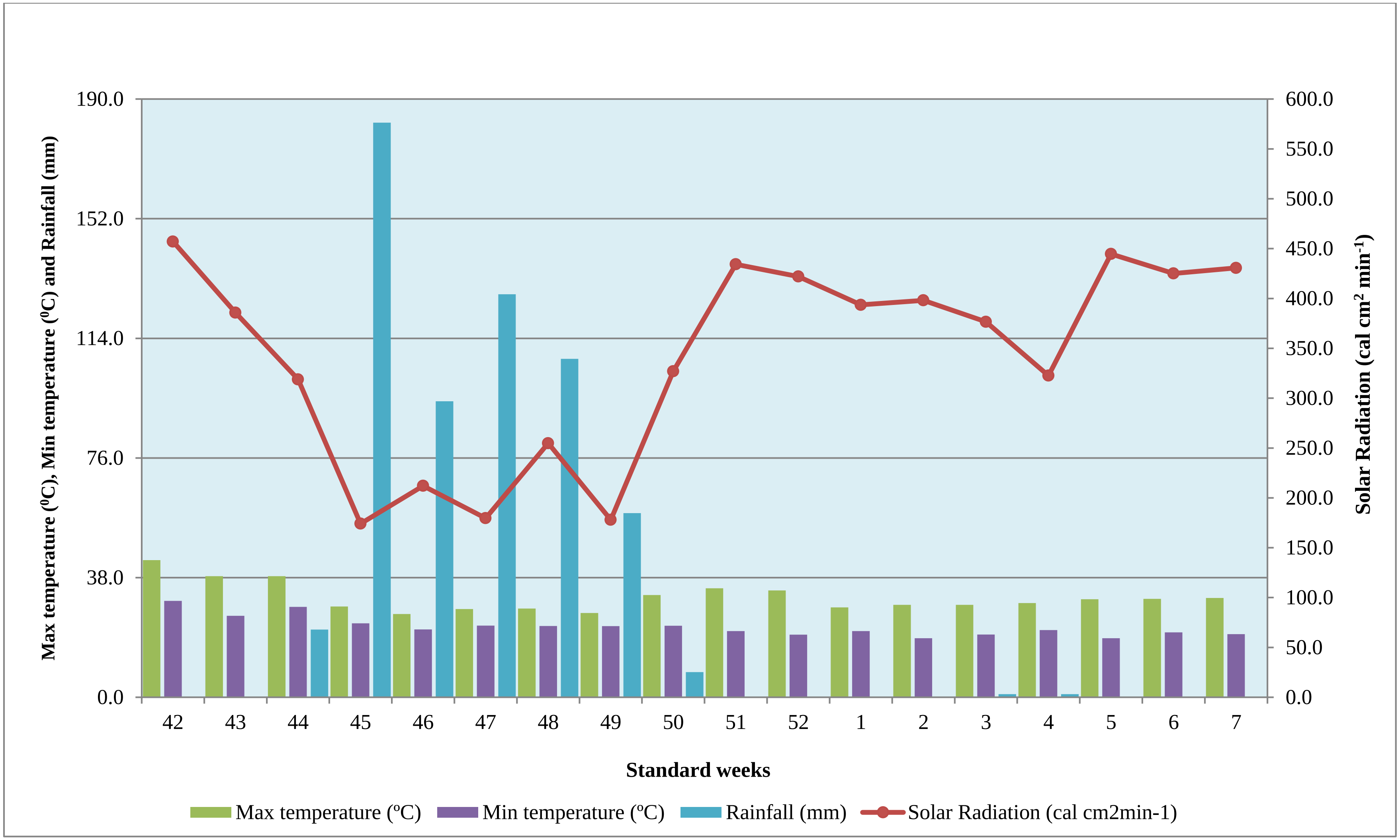

Fig.13. Weather data prevailed in Melmalaiyanur of Villupuram district during *rabi*, 2015

Table 5. District wise mean monthly rainfall (mm) recorded in the study area during cropping period

Month	Salem	Namakkal	Tiruvannamalai	Villupuram
January, 2015	17.5	24.5	0	3
February, 2015	4.5	1.1	0	0
March, 2015	30	2.7	1.8	0
April, 2015	143.3	107.8	114.7	87.6
May, 2015	103.7	75.4	61	68.1
June, 2015	80.3	45.2	81.3	14.5
July, 2015	31.9	23.6	92.1	76.8
August, 2015	104	65.7	175.8	113.3
September, 2015	132.1	164.3	124.9	84
October, 2015	152.2	115	127.3	78.6
November, 2015	276.5	162.3	326.4	554.9
December, 2015	59.3	31.9	142	292.5
January, 2016	0.0	0.0	9.0	0.0
Total	**1135.3**	**819.5**	**1256.3**	**1373.3**

(Source: IMD, Ministry of Earth Science, Government of India)

4.2. Soil characteristics of the study area

Thiruvannamalai, Vellore, Villupuram, Namakkal, Erode and Salem districts constituted 54.9% of the area under groundnut in Tamilnadu. The productivity is high as these districts have ideal soil and climatic conditions suitable for groundnut cultivation. The study area of Salem, Namakkal, Tiruvannamalai and Villupuram districts comprised, well-drained, red sand, loamy sand, or sandy loam.

Different soil types prevailed in the study area	
Salem	Red loam
Namakkal	Red loam
Tiruvannamalai	Laterite soil
Villupuram	Red soil and Red sandy soil

4.3. Landuse/Landcover details of study area

Landuse/Landcover data of the study area was derived by using LISS III satellite (Fig.14). The spatial pattern of land use in Salem, Namakkal, Tiruvannamalai and Villupuram districts of Tamilnadu showed that out of the total geographical area of 2.205 m ha, 58.4 per cent was under crop land. The statistics of Landuse/Landcover classes during 2015 in study area are summarized in Table 6.

Stable vegetation accounted for 19.60 per cent of the study area while water and wetlands contributed 7.90 per cent of Landuse/Landcover followed by built-ups and wastelands 2.7 and 3.5 per cent respectively. Considering croplands, Villupuram registered highest crop cover with an area of 4,43,742 ha (62 per cent) followed by Tiruvannamalai (3,43,212 ha), Salem (2,91,991 ha) and Namakkal (2,07,733 ha) districts. With regard to other classes, stable vegetation including forest cover was higher in Salem district with an area of 1,46,374 ha (28 per cent) followed by Tiruvannamalai district (1,40557 ha and 23 per cent). Villupuram district accounted for more area under water bodies and wetlands as compared to other districts with an area of 80,679 ha covering 11.20 per cent of the district geographical area whereas Namakkal district registered 4.70 per cent of the land area under built-ups showing the degree of urbanisation.

4.4. Groundnut area mapping using SAR data

With the advent of new Synthetic Aperture Radar (SAR) satellite sensors and the automated processing chain, crop mapping has resulted in higher accuracies. Sentinel-1A satellite data was acquired at 12 days interval during the crop growth period. The back scattering co-efficient and multi temporal features as influenced by the crop growth parameters of groundnut and underlying soil surface were extracted and the results are presented hereunder.

4.4.1. Radar backscattering signature

The radar backscattering coefficient (σ^0) is a measure of crop biomass, plant height, water content, underlying soil, crop phenology etc. The SAR data collected during the cropping period was processed and analyzed using training pixels from ground truth points to derive the temporal backscattering coefficient (σ^0) for groundnut from the study area. The temporal backscattering signatures of groundnut during *kharif* 2015 were generated by stacking seven SAR acquisitions from 8th July, 2015 to 17th November, 2015. The signature

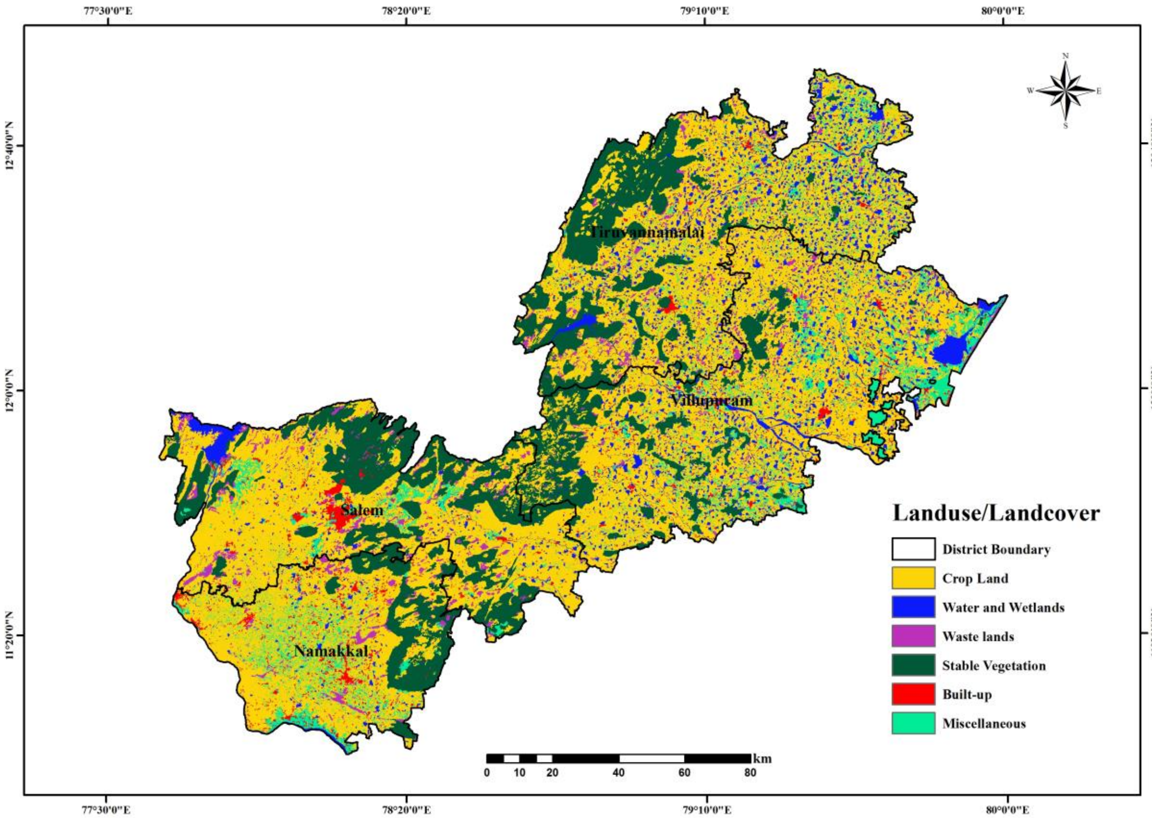

Fig.14a. Landuse/Landcover map of study area during 2015

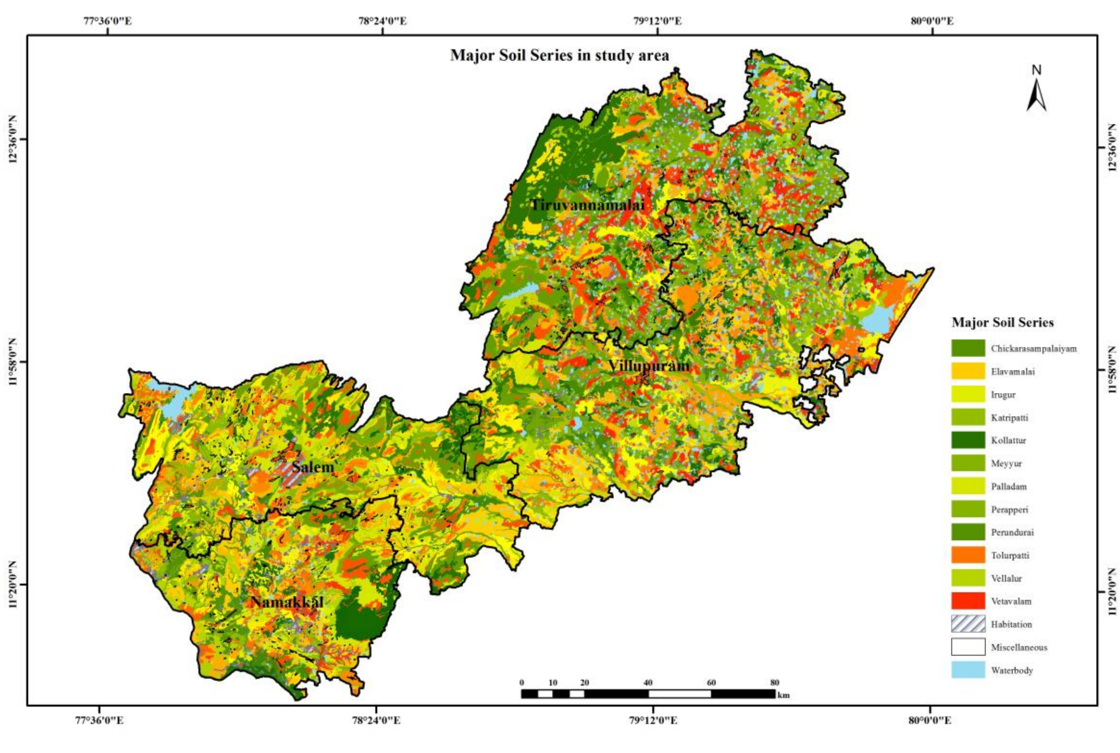

Fig.14b.Soil map of study area during 2015

Table 6. Statistics of LandUse/LandCover classes in the study area

LU/LC Classes	Namakkal		Salem		Tiruvannamalai		Villupuram		Total	
	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)
Built Ups	16130	4.7	14339	2.7	10850	1.8	17201	2.4	**58520**	**2.7**
Stable Vegetation	55722	16.3	146374	27.9	140557	22.7	89511	12.4	**432164**	**19.6**
Waste Land	12950	3.8	27040	5.2	19708	3.2	17702	2.5	**77400**	**3.5**
Water + Wetlands	8876	2.6	19697	3.8	64119	10.4	80679	11.2	**173371**	**7.9**
Crop Land	207733	60.8	291991	55.7	343212	55.5	443742	61.6	**1286678**	**58.4**
Miscellaneous	40390	11.8	25103	4.8	39577	6.4	71650	9.9	**176720**	**8.0**
Total	**341801**	**100**	**524544**	**100**	**618023**	**100**	**720485**	**100**	**2204853**	**100**

curves of groundnut showed a marginal increase in backscattering at seedling to vegetative stage and a steep increase from flowering to pod development of 2.07 dB in VV polarization followed by a decline thereafter at maturity. The similar trend of minimal increase in backscattering at vegetative stage and steep increase from flowering to pod development with a variation of 2.27 dB and a decline thereafter at maturity was observed in VH polarization.

Temporal backscatter values were recorded in ten test sites across Salem and Namakkal districts and the details are presented in Table 7 and 8 and illustrated in Fig. 15. In these districts, backscattering values were found to be ranging from -10.99 to -9.56 dB and -10.77 to -8.92 dB at D_1 and D_2 in VV polarization. At D_4 corresponding to flowering and peg penetration stage, the values were -9.71 to -8.12 dB. The backscattering values increased further and reached a maximum of -8.12 to -5.62 dB at D_6 corresponding to pod development to maturity stages of groundnut.

In these districts, the backscattering values were minimum in the range of -20.04 to -16.47 at D_1 and -19.08 to -16.27 at D_2 in VH polarization. At D_4, corresponding to flowering stage the dB values ranged from -18.40 to -14.56. The maximum dB values of -14.95 to -13.05 were recorded at D_6 in test sites of Salem and Namakkal districts and declined thereafter.

Similarly, temporal backscatter values were recorded in ten test sites across Tiruvannamalai and Villupuram districts and the details are presented in Table 9. and 10. and illustrated in Fig. 16. The backscattering values at germination to seedling stages of D_1 and D_2 were found to be -11.74 to -9.72 and -10.94 to -9.45, respectively in VV polarization. In the same polarization, the values were -10.82 to -7.89 and -10.48 to -7.76 dB, respectively at flowering and peg penetration stage. The maximum dB values of -9.14 to -5.31 were recorded at D_7 in test sites of Tiruvannamalai and Villupuram districts under VV polarization.

In respect of VH polarization in these districts, the dB values were minimum at D_1 (31st October, 2015) ranging from -18.57 to -17.77 followed by -18.28 to -16.94 at D_2 (12th November, 2015). During flowering to peg penetration stages (D_4) the dB values were -17.46 to -15.46 with corresponding maximum at D_7 with dB values ranging from -15.71 to -14.15.

The maximum, minimum and mean temporal backscattering values for Vertical-Vertical (VV) and Vertical-Horizontal (VH) polarized SAR data for groundnut during *kharif* season in Salem and Namakkal districts and *rabi* season in Tiruvannamalai and Villupuram

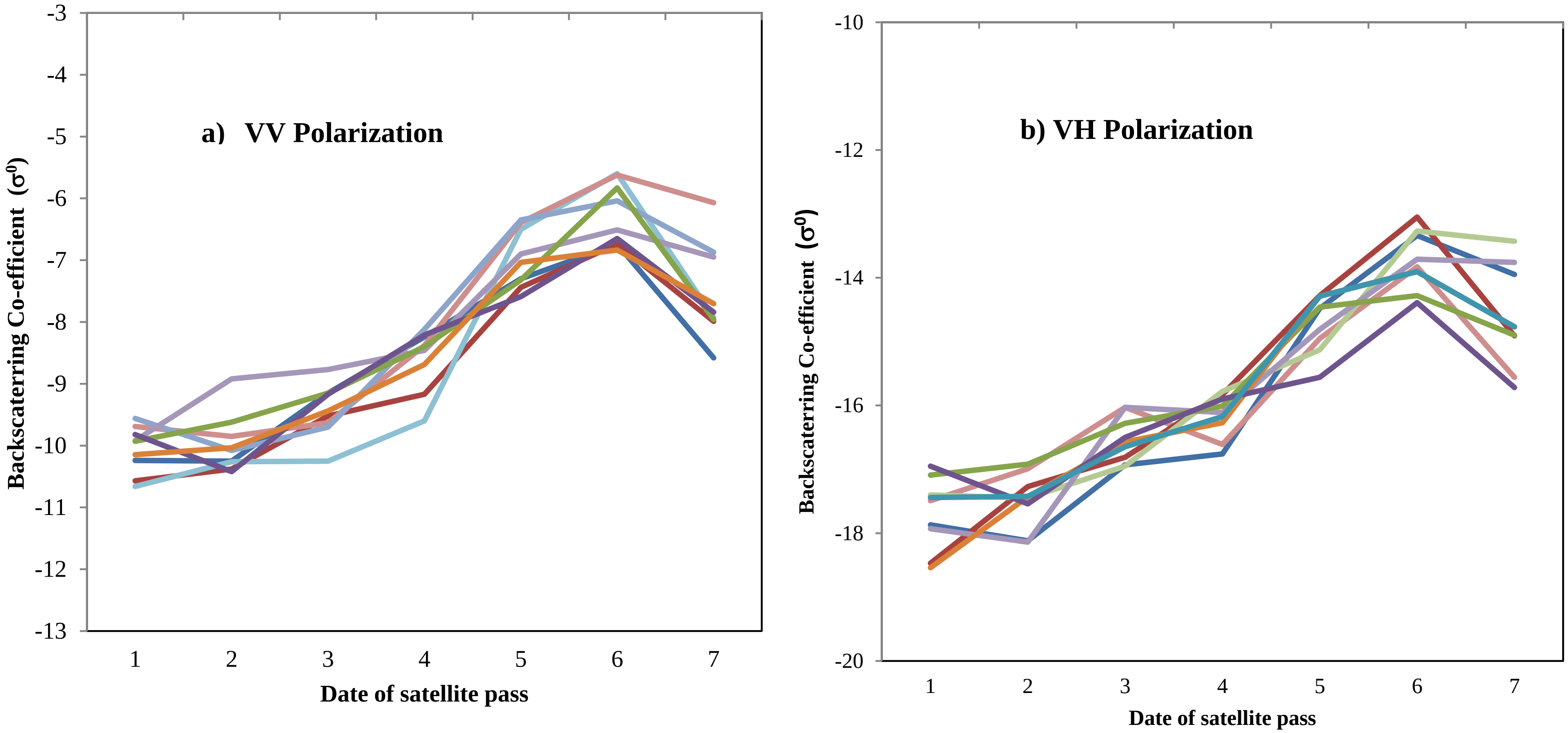

Fig.15. Backscattering signature of groundnut test sites for VV and VH polarization in Salem and Namakkal districts

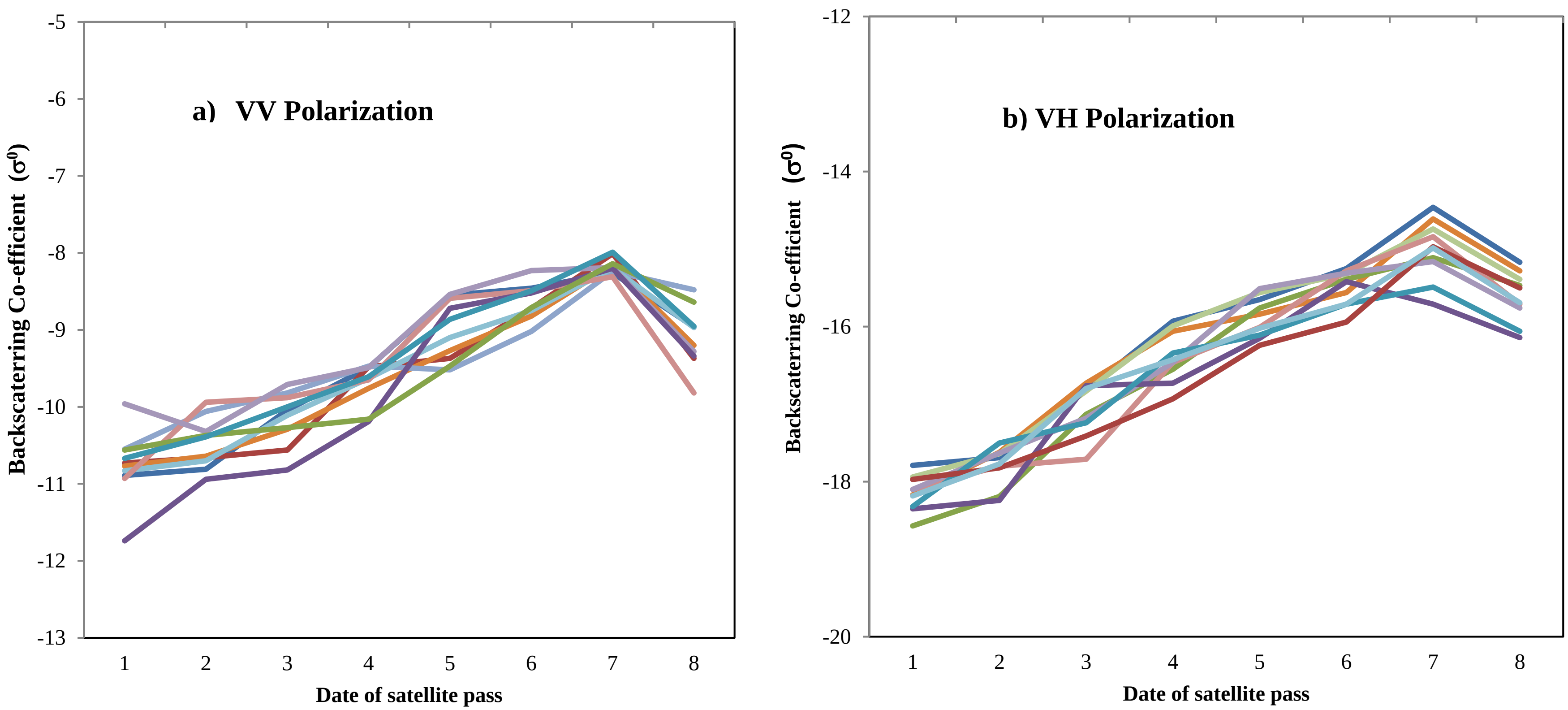

Fig.16. Backscattering signature of groundnut test sites for VV and VH polarization in Tiruvannamalai and Villupuram districts

Table 7. Temporal backscattering values (dB) in VV polarization for Groundnut during *kharif* 2015 in test sites of Salem and Namakkal districts

S.No.	Date of Satellite pass	Field 1	Field 2	Field 3	Field 4	Field 5	Field 6	Field 7	Field 8	Field 9	Field 10	Mean
1	08-07-2015 (σ^0_{D1})	-10.24	-10.57	-10.99	-10.66	-9.69	-9.56	-10.09	-9.92	-9.93	-9.82	**-10.15**
2	20-07-2015 (σ^0_{D2})	-10.25	-10.38	-10.77	-10.26	-9.85	-10.08	-9.8	-8.92	-9.62	-10.42	**-10.04**
3	13-08-2015 (σ^0_{D3})	-9.15	-9.52	-10.13	-10.25	-9.63	-9.70	-8.93	-8.77	-9.15	-9.17	**-9.44**
4	06-09-2015 (σ^0_{D4})	-8.24	-9.17	-9.71	-9.60	-8.38	-8.12	-8.58	-8.46	-8.4	-8.21	**-8.69**
5	12-10-2015 (σ^0_{D5})	-7.30	-7.44	-8.45	-6.50	-6.39	-6.35	-8.55	-6.90	-5.83	-6.65	**-7.04**
6	05-11-2015 (σ^0_{D6})	-6.74	-6.74	-8.12	-5.60	-5.62	-6.24	-7.88	-6.51	-7.32	-7.59	**-6.84**
7	17-11-2015 (σ^0_{D7})	-8.58	-7.99	-8.62	-7.93	-6.07	-6.87	-8.23	-6.95	-7.96	-7.84	**-7.70**

Table 8. Temporal backscattering values (dB) in VH polarization for Groundnut during *kharif* 2015 in test sites of Salem and Namakkal districts

S.No.	Date of Satellite pass	Field 1	Field 2	Field 3	Field 4	Field 5	Field 6	Field 7	Field 8	Field 9	Field 10	Mean
1	08-07-2015 (σ^0_{D1})	-17.87	-20.04	-17.49	-16.47	-17.40	-17.93	-17.09	-16.65	-16.52	-16.95	**-20.04**
2	20-07-2015 (σ^0_{D2})	-18.12	-19.08	-17.99	-16.27	-17.45	-18.14	-16.92	-16.27	-16.46	-17.54	**-19.08**
3	13-08-2015 (σ^0_{D3})	-16.93	-18.91	-18.03	-15.81	-16.95	-16.03	-16.28	-15.57	-15.45	-16.50	**-18.91**
4	06-09-2015 (σ^0_{D4})	-16.76	-18.40	-16.61	-15.33	-16.70	-16.11	-16.01	-15.36	-14.56	-15.90	**-18.40**
5	12-10-2015 (σ^0_{D5})	-13.48	-14.17	-13.83	-15.28	-15.13	-13.80	-14.46	-13.85	-13.34	-15.56	**-15.56**
6	05-11-2015 (σ^0_{D6})	-13.34	-14.50	-14.95	-13.05	-13.27	-13.71	-14.28	-13.53	-14.02	-14.39	**-14.95**
7	17-11-2015 (σ^0_{D7})	-13.95	-16.70	-15.56	-14.91	-13.43	-13.76	-14.90	-13.98	-14.78	-15.72	**-16.70**

Table 9. Temporal backscattering values (dB) in VV polarization for Groundnut during *rabi* 2015 in test sites of Tiruvannamalai and Villupuram districts

S.No.	Date of Satellite pass	Field 1	Field 2	Field 3	Field 4	Field 5	Field 6	Field 7	Field 8	Field 9	Field 10	Mean
1	31-10-2015 (σ^0_{D1})	-10.89	-10.73	-10.77	-10.55	-10.83	-10.93	-9.96	-11.74	-9.72	-10.56	**-10.67**
2	12-11-2015 (σ^0_{D2})	-10.81	-10.66	-10.64	-10.06	-10.70	-9.94	-10.32	-10.94	-9.45	-10.37	**-10.39**
3	24-11-2015 (σ^0_{D3})	-10.04	-10.56	-10.29	-10.42	-10.11	-9.88	-9.71	-10.82	-7.89	-10.27	**-10.00**
4	06-12-2015 (σ^0_{D4})	-9.49	-10.48	-9.76	-9.47	-9.63	-9.65	-9.49	-10.19	-7.76	-10.16	**-9.61**
5	18-12-2015 (σ^0_{D5})	-8.55	-9.37	-9.27	-9.52	-9.10	-8.59	-8.54	-8.72	-7.50	-9.47	**-8.86**
6	30-12-2015 (σ^0_{D6})	-8.46	-8.72	-8.82	-9.22	-8.75	-8.49	-8.23	-8.52	-7.00	-8.71	**-8.49**
7	11-01-2016 (σ^0_{D7})	-8.26	-8.01	-8.16	-9.14	-8.20	-8.31	-8.19	-8.20	-5.31	-8.14	**-7.99**
8	23-01-2016 (σ^0_{D8})	-8.96	-9.37	-9.20	-8.48	-8.97	-9.82	-9.28	-9.84	-6.98	-8.64	**-8.95**

Table 10. Temporal backscattering values (dB) in VH polarization for Groundnut during *rabi* 2015 in test sites of Tiruvannamalai and Villupuram districts

S.No.	Date of Satellite pass	Field 1	Field 2	Field 3	Field 4	Field 5	Field 6	Field 7	Field 8	Field 9	Field 10	Mean
1	31-10-2015 (σ^0_{D1})	-17.79	-18.17	-17.94	-18.57	-18.10	-18.10	-18.35	-18.32	-17.97	-18.52	**-18.18**
2	12-11-2015 (σ^0_{D2})	-17.69	-17.62	-16.94	-18.19	-17.80	-17.63	-18.24	-17.50	-17.82	-18.28	**-17.77**
3	24-11-2015 (σ^0_{D3})	-16.22	-16.33	-16.03	-17.13	-17.71	-16.18	-16.76	-17.24	-17.41	-16.96	**-16.80**
4	06-12-2015 (σ^0_{D4})	-15.93	-16.06	-15.99	-16.55	-17.46	-15.46	-16.73	-16.34	-16.93	-16.81	**-16.43**
5	18-12-2015 (σ^0_{D5})	-15.65	-15.84	-15.56	-15.76	-16.80	-15.51	-16.50	-16.11	-16.24	-16.24	**-16.02**
6	30-12-2015 (σ^0_{D6})	-15.25	-15.56	-15.32	-15.39	-16.28	-15.31	-16.42	-15.71	-15.94	-15.92	**-15.71**
7	11-01-2016 (σ^0_{D7})	-14.46	-14.61	-14.74	-15.11	-15.44	-15.16	-15.71	-15.49	-14.97	-14.15	**-14.98**
8	23-01-2016 (σ^0_{D8})	-15.17	-15.28	-15.39	-15.47	-15.71	-15.76	-16.14	-16.06	-15.50	-16.44	**-15.69**

districts were recorded and given in Tables 11 and 12 and backscattering signature were illustrated in Fig. 17 and 18.

In Salem and Namakkal districts, the mean backscattering values for groundnut crop during the entire cropping period ranged from -10.15 dB to -6.64 dB and from -17.44 dB to -13.90 dB for VV and VH polarization, respectively. For groundnut in Tiruvannamalai and Villupuram districts, backscattering values ranged from -10.67 dB to -7.99 dB and from -18.18 dB to -14.98 dB for VV and VH polarization data, respectively. As compared to the mean σ^0 of VH for groundnut in Salem and Namakkal districts, it was found that VV backscattering was lesser by 7.29 dB to 7.06 dB at different stages of crop growth. Similarly, for Tiruvannamalai and Villupuram districts backscattering from VV polarization was lesser by 7.51 dB to 6.99 dB.

In Salem and Namakkal districts, the mean backscatter value for groundnut crop during the maturity (σ^0D_6) to harvest stage (σ^0D_7) decreased by 0.86 dB in VV and 0.87 dB in VH as compared to the developed crop stage of σ^0D_6. Similar trend was found in Tiruvannamalai and Villupuram districts also where groundnut signature during the maturity (σ^0D_7) to harvest stage (σ^0D_8) decreased by 0.96 dB in VV and 0.71 dB in VH polarization as compared to the developed crop stage of σ^0D_7.

Considering the maximum values of dB in any pass *i.e.* at any growth stages of groundnut crop, the maximum dB of -5.60 was observed under VV polarization in Salem and Namakkal districts and the corresponding value was -5.31 dB in Tiruvannamalai and Villupuram districts. Likewise, the minimum values were recorded at germination of groundnut crop with the values of -10.99 and -11.74 in those districts under VV polarization. Considering the maximum values of dB values under VH polarization at any growth stages of groundnut crop, the maximum dB of -13.05 was observed in Salem and Namakkal districts and the corresponding value was -14.15 dB in Tiruvannamalai and Villupuram districts. Likewise the minimum values were recorded at germination of groundnut crop with the values of -20.04 and -18.57 in those districts under VH polarization.

Through classification, the information content of the image was simplified into a thematic map and could therefore be easily evaluated by a human interpreter. On the basis of classified map, further properties of the different classes were derived and several

Table 11. Cumulative temporal backscattering values for Groundnut during *kharif* 2015 in Salem and Namakkal districts

S.No	Date of Satellite pass	VV Polarization			VH Polarization		
		Maximum (dB)	Minimum (dB)	Mean (dB)	Maximum (dB)	Minimum (dB)	Mean (dB)
1	08-07-2015 (σ^0_{D1})	-9.56	-10.99	-10.15	-16.47	-20.04	-17.44
2	20-07-2015 (σ^0_{D2})	-8.92	-10.77	-10.04	-16.27	-19.08	-17.42
3	13-08-2015 (σ^0_{D3})	-8.77	-10.25	-9.44	-15.45	-18.91	-16.65
4	06-09-2015 (σ^0_{D4})	-8.12	-9.71	-8.69	-14.56	-18.4	-16.17
5	12-10-2015 (σ^0_{D5})	-5.83	-8.55	-7.04	-13.34	-15.56	-14.29
6	05-11-2015 (σ^0_{D6})	-5.60	-8.12	-6.84	-13.05	-14.95	-13.90
7	17-11-2015 (σ^0_{D7})	-6.07	-8.62	-7.70	-13.43	-16.7	-14.77

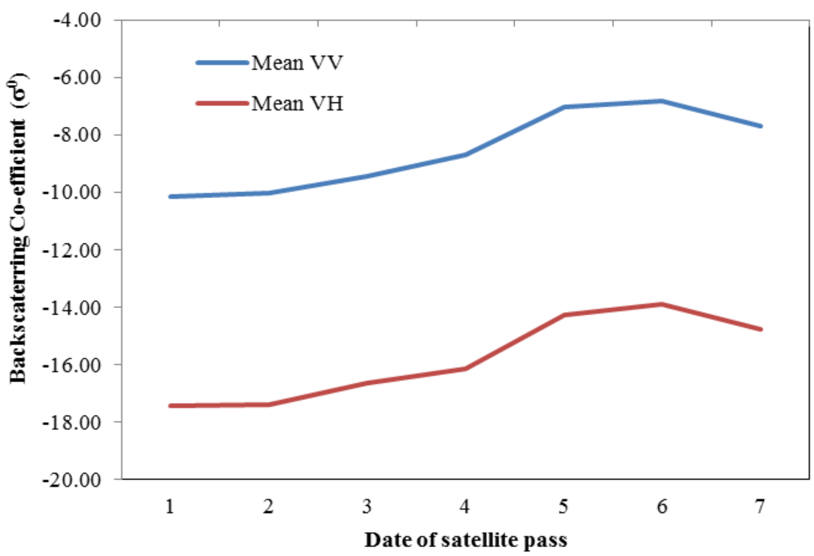

Fig. 17. Mean Temporal backscattering signatures of Groundnut during *kharif* 2015 in Salem and Namakkal districts

Table 12. Cumulative temporal backscattering values for Groundnut during *rabi* 2015 in Tiruvannamalai and Villupuram districts

S.No	Date of Satellite pass	VV Polarization			VH Polarization		
		Maximum (dB)	Minimum (dB)	Mean (dB)	Maximum (dB)	Minimum (dB)	Mean (dB)
1	31-10-2015 (σ^0_{D1})	-9.72	-11.74	-10.67	-17.79	-18.57	-18.18
2	12-11-2015 (σ^0_{D2})	-9.45	-10.94	-10.39	-16.94	-18.28	-17.77
3	24-11-2015 (σ^0_{D3})	-7.89	-10.82	-10.00	-16.03	-17.71	-16.80
4	06-12-2015 (σ^0_{D4})	-7.76	-10.48	-9.61	-15.46	-17.46	-16.43
5	18-12-2015 (σ^0_{D5})	-7.50	-9.52	-8.86	-15.51	-16.80	-16.02
6	30-12-2015 (σ^0_{D6})	-7.00	-9.22	-8.49	-15.25	-16.42	-15.71
7	11-01-2016 (σ^0_{D7})	-5.31	-9.14	-7.99	-14.15	-15.71	-14.98
8	23-01-2016 (σ^0_{D8})	-6.98	-9.84	-8.95	-15.17	-16.44	-15.69

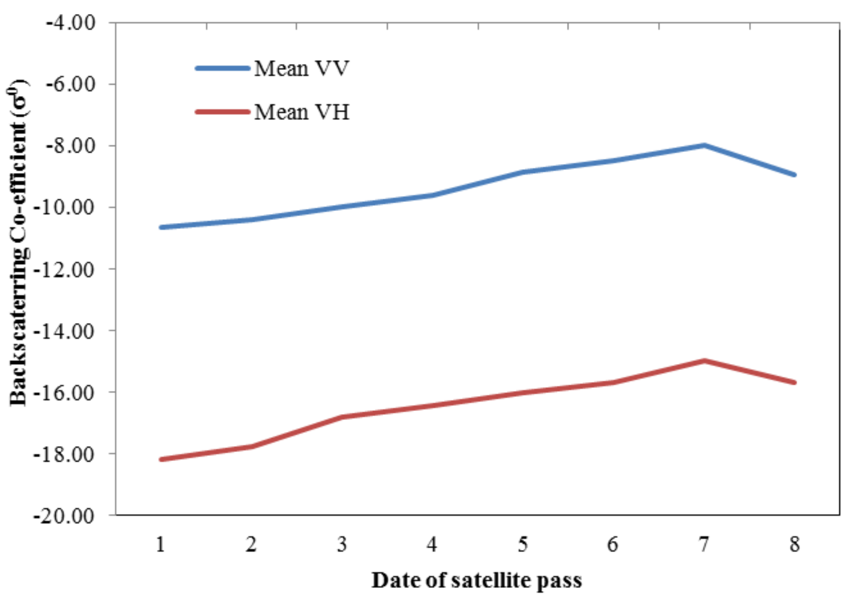

Fig.18. Mean Temporal backscattering signature of Groundnut during *rabi* 2015 in Tiruvannamalai and Villupuram districts

considerations were given (e.g. total area or land cover changes). Maximum likelihood classifier was adopted in this study for extracting information from multi-temporal SAR data. The results obtained were compared and presented.

4.4.2. Multi Temporal Features (MTF) extraction

Considering the accuracy of SAR data in phenological variations of groundnut growing period, temporal features of track 165 (Salem and Namakkal districts) and track 92 (Tiruvannamalai and Villupuram districts) were extracted on geocoded time-series intensity images (At least two dates are required to compute any of the output features) using multi temporal dB images of VV and VH polarizations. The multi temporal features (in dB value) *viz*. Max, Min, Mean, Max Date, Min Date and Span Ratio were generated using seven acquisitions during *kharif* 2015 and eight acquisitions during *rabi* 2015 (Appendix V and VI).

The values of MTF were extracted for the monitoring sites in the study area using feature extraction tool of MAPscape 5.4. Among the features, the Max feature i.e. maximum value for different groundnut fields ranged from -16.95 to -13.01 (VH Polarization) and -9.03 to -5.47 (VV Polarization) in Salem and Namakkal districts. In Tiruvannamalai and Villupuram districts the range of maximum was from -16.93 to -12.59 for VH and -8.89 to -6.06 for VV polarization, respectively. Min feature i.e. minimum value for Salem and Namakkal ranged from -19.86 to -16.77 for VH and -12.58 to -9.26 for VV polarizations. Similarly groundnut field of Tiruvannamalai and Villupuram districts recorded minimum values of -20.01 to -17.94 for VH and -12.36 to -8.61 for VV polarization, respectively. Similarly, Mean i.e. mean value for Salem and Namakkal groundnut fields are ranged from -17.80 to -15.81 (VH) and -10.82 to -7.87 (VV). In Tiruvannamalai and Villupuram districts, groundnut fields recorded a mean value of -17.96 to -14.46 and -10.64 to -7.77 dB for VH and VV polarizations, respectively.

Other MTF features like Max Date *i.e.* date of the maximum and Min Date *i.e.* date of the minimum of Salem and Namakkal districts and Tiruvannamalai and Villupuram districts groundnut fields were also recorded between both VH and VV polarizations. Max Date feature of Salem and Namakkal fields was found to be D_6 (5th November, 2015) for both VH and VV polarization. Likewise, Min Date i.e. Date of the minimum for both VH and VV were found to be D_1 (8th July, 2015). In groundnut fields of Tiruvannamalai and Villupuram districts, the Max Date features for VH and VV polarization were recorded between D_6 (30th December, 2015) and D_8 (23rd January, 2016) with majority of the fields recording maximum date as D_7 (11th January, 2016). The Min Date feature for VH polarization was between D_1 (31st October, 2015) and D_3 (24th November, 2015) and for VV polarization it occurred during D_1 (31st October, 2015) and D_2 (12th November, 2015).

4.5. Groundnut area (Table 13, 14 and 15)

Groundnut area map for the study area covering four districts *viz*., Salem, Namakkal, Tiruvannamalai and Villupuram districts were derived from multi temporal C-band SAR imagery of Sentinel-1A. Using the shape files of administrative boundaries, district wise and block wise maps and statistics of groundnut area were extracted for 19, 15, 18 and 21 blocks of Salem, Namakkal, Tiruvannamalai and Villupuram districts, respectively.

The accuracy assessment for the groundnut area maps was conducted on a groundnut / non-groundnut basis, where all other land cover types were grouped into single non-groundnut class. In total, 88 validation points covering 46 groundnut and 42 non-groundnut points were considered for validation in Salem and Namakkal districts, whereas 108 validation points covering 62 groundnut and 46 non-groundnut points were considered for validation in Tiruvannamalai and Villupuram districts. The overall accuracy assessment was done for the study area with the 196 validation points covering 108 groundnut and 88 non-groundnut points (Appendix VII to X).

The summary of district wise groundnut area is given in Table 13 to 15 and the classified groundnut area across Salem district was 17817 ha whereas Namakkal district recorded an area of 22581 ha in groundnut during *kharif* 2015. These two districts cumulatively accounted for 40398 ha during the season under rainfed condition. During *rabi* 2015 the groundnut area was also estimated using remote sensing techniques and found to be 24903 and 22722 ha, respectively in Tiruvannamalai and Villupuram districts with a total of 47625 ha.

Large, homogeneous and landscape dominating groundnut areas in Salem and Namakkal districts and small, fragmented, heterogeneous groundnut areas in Tiruvannamalai and Villupuram districts were classified equally well. Among the four districts, Tiruvannamalai recorded the maximum groundnut area followed by Villupuram, Namakkal and Salem. Groundnut area maps during *kharif* and *rabi* 2015 covering the study area are depicted in Fig. 19 to 22.

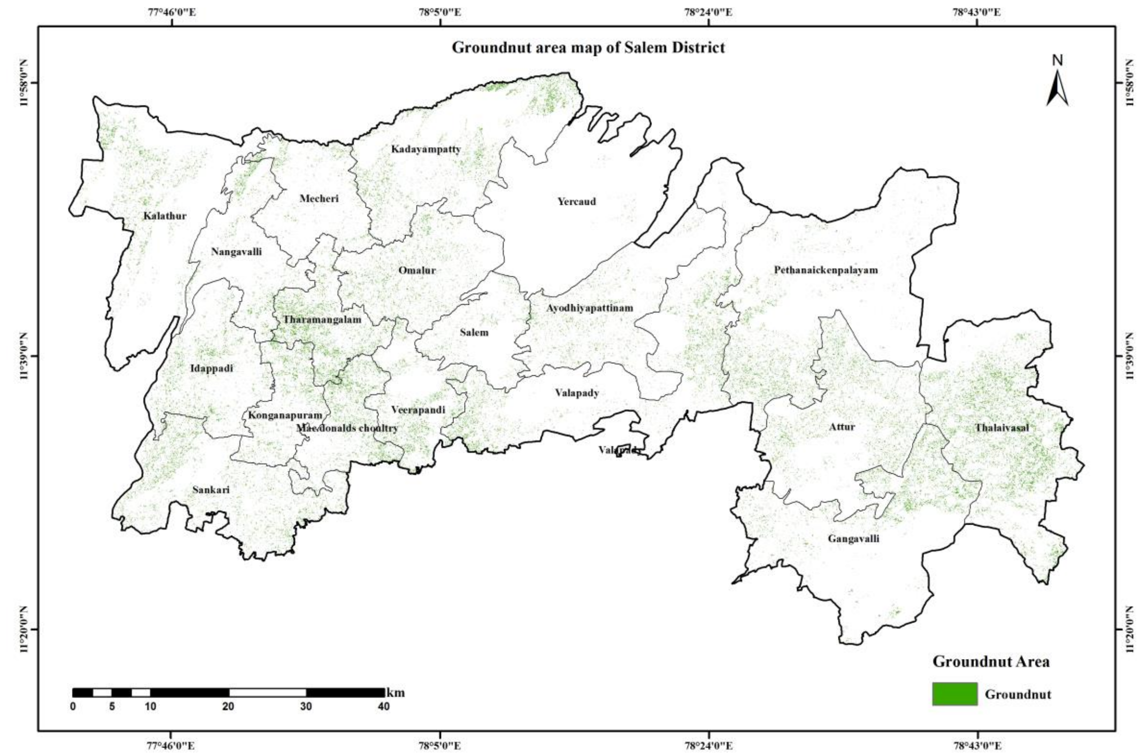

Fig.19. Groundnut area map for Salem district during *kharif* 2015

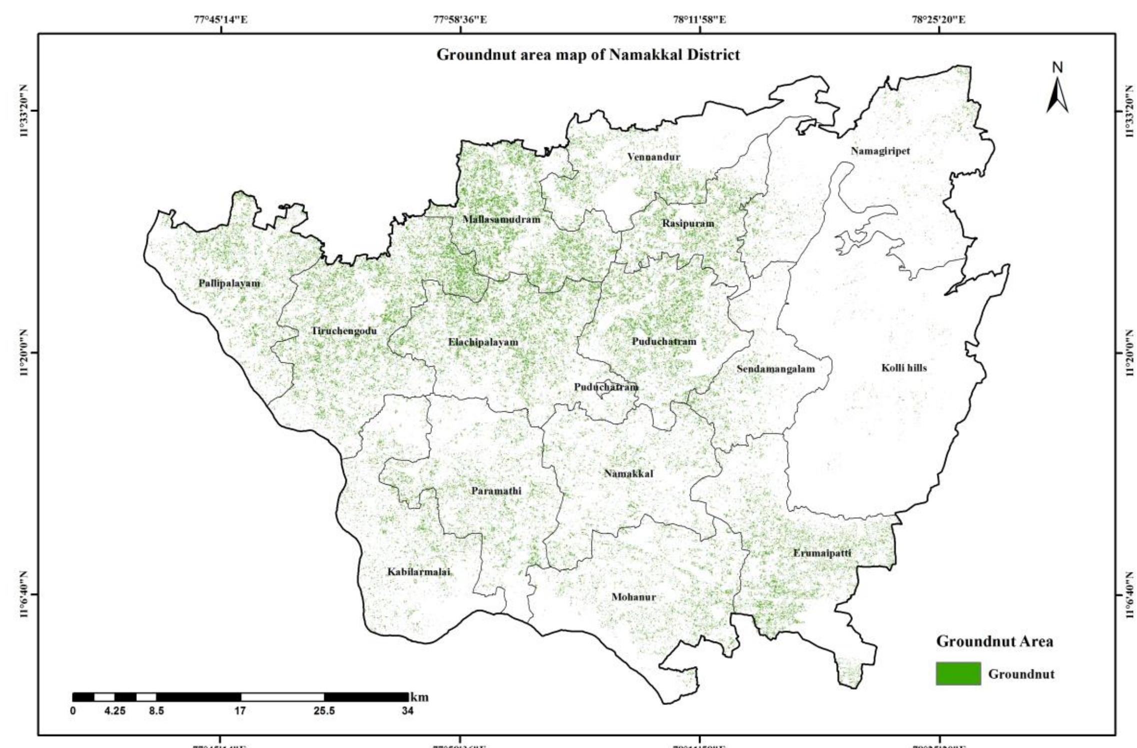

Fig.20. Groundnut area map for Namakkal district during *kharif* 2015

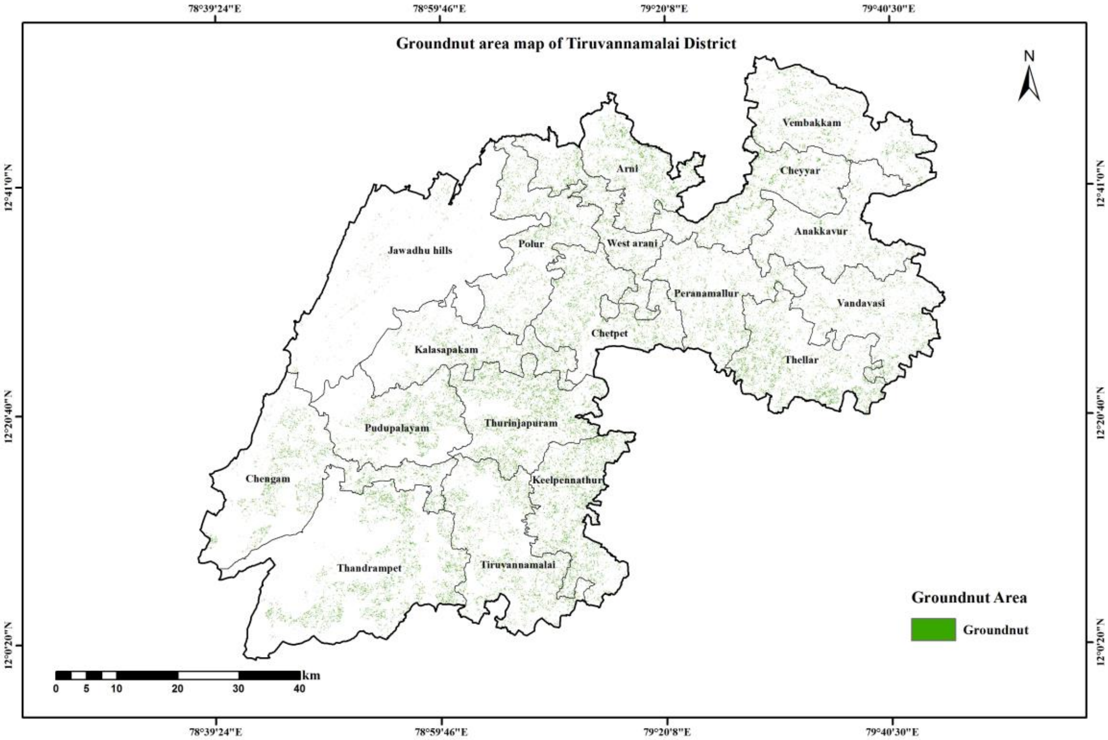

Fig.21. Groundnut area map for Tiruvannamalai district during *rabi* 2015

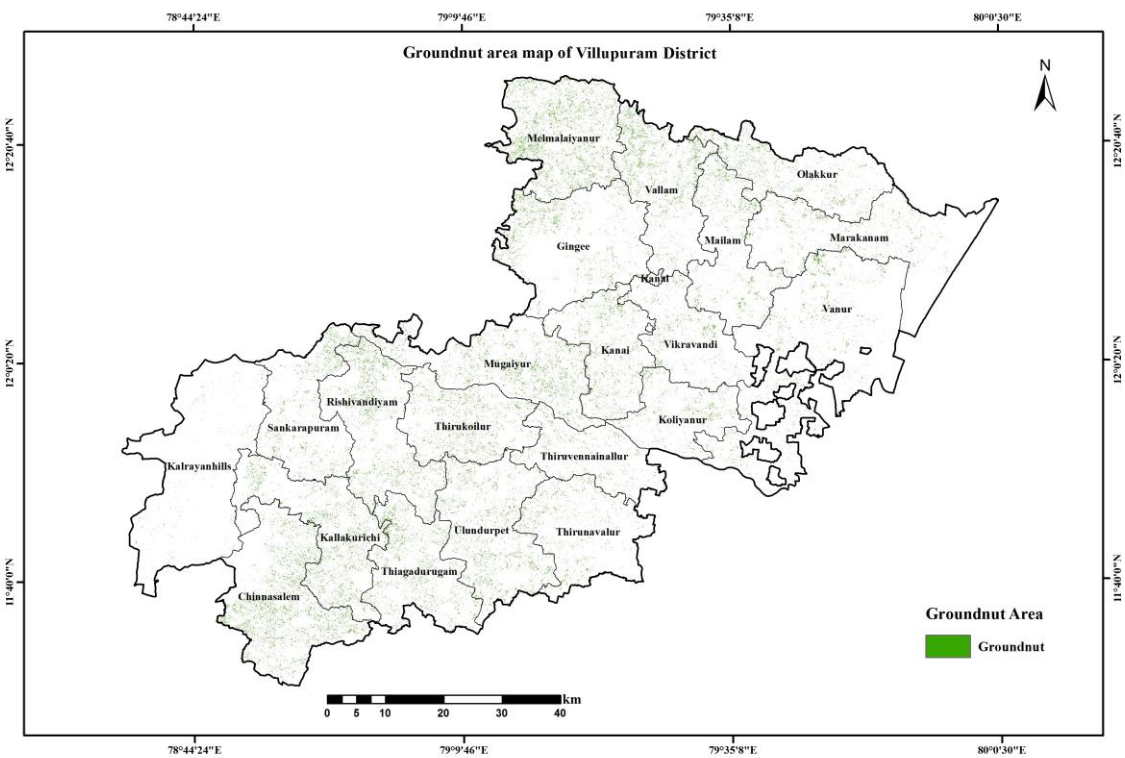

Fig.22. Groundnut area map for Villupuram district during *rabi* 2015

Table 13. Blockwise Groundnut area during *kharif* 2015 in Salem and Namakkal districts

S.No.	Salem		Namakkal	
	Block	**Area (ha)**	**Block**	**Area (ha)**
1	Kadayampatty	1240	Namagiripet	515
2	Kalathur	839	Vennandur	1012
3	Yercaud	44	Rasipuram	1219
4	Mecheri	353	Mallasamudram	2938
5	Nangavalli	496	Kolli Hills	83
6	Valapady	1303	Pallipalayam	1635
7	Pethanaickenpalayam	1089	Tiruchengodu	3515
8	Omalur	815	Puduchatram	2170
9	Ayodhiyapattinam	584	Sendamangalam	488
10	Tharamangalam	1215	Elachipalayam	2689
11	Salem	241	Paramathi	1343
12	Idappadi	810	Kabilarmalai	957
13	Attur	1288	Namakkal	1026
14	Thalaivasal	2783	Erumaipatti	1846
15	Veerapandi	736	Mohanur	1144
16	Konganapuram	602		
17	Mac.donalds choultry	855		
18	Sangakiri	1253		
19	Gangavalli	1271		
	Total	17817	**Total**	**22581**

Table 14. Blockwise Groundnut area during *rabi* 2015 in Tiruvannamalai and Villupuram districts

S.No.	Tiruvannamalai		Villupuram	
	Block	Area (ha)	Block	Area (ha)
1	Vembakkam	1074	Melmalaiyanur	2410
2	Arani	1291	Vallam	1394
3	West Arani	1133	Olakkur	909
4	Polur	1319	Mailam	781
5	Cheyyar	1227	Gingee	1134
6	Jawadhu hills	215	Marakanam	713
7	Anakkavur	721	Vanur	1006
8	Peranamallur	1108	Kanai	932
9	Chetpet	1585	Vikravandi	554
10	Vandavasi	1048	Mugaiyur	1513
11	Thellar	1851	Sankarapuram	829
12	Kalasapakam	1087	Rishivandiyam	1491
13	Thurinjapuram	2342	Kalrayan hills	160
14	Pudupalayam	1231	Thirukoilur	1102
15	Chengam	1571	Koliyanur	487
16	Keelpennathur	1993	Thiruvennainallur	476
17	Tiruvannamalai	1891	Ulundurpet	1373
18	Thandrampattu	2216	Kallakurichi	1464
19			Thirunavalur	676
20			Thiagadurugam	1185
21			Chinnasalem	2133
	Total	**24903**	**Total**	**22722**

Table 15. District wise area under groundnut (ha)

S.No.	District	Season	Groundnut Area (ha)
1	Salem	*Kharif*, 2015	17817
2	Namakkal	*Kharif*, 2015	22581
3	Tiruvannamalai	*Rabi*, 2015	24903
4	Villupuram	*Rabi*, 2015	22722
	Total		**88023**

The summary of validation data and classification accuracy is given in Table 18. The overall classification accuracy was 87.2 per cent with a kappa score of 0.74 indicating the accuracy of classification across the study area.

4.5.1. Groundnut area during *kharif* 2015

Among the two districts monitored for groundnut area during *kharif* 2015 (Table 13), in Salem district, Thalaivasal block recorded the highest groundnut area of 2783 ha followed by Valapady and Attur blocks registering an area of 1303 and 1288 ha, respectively. Gangavalli, Sangakiri, Kadayampatti and Tharamangalam were the next best blocks recording groundnut area of 1215 to 1288 ha. Yercaud followed by Salem recorded the lowest groundnut area of 44 and 241 ha. In Namakkal district Tiruchengodu block recorded the highest groundnut area 3515 ha followed by Mallasamudram, Elachipalayam and Puduchatram blocks with an area of (nearly 2000 ha) 2938, 2689 and 2170 ha respectively. The lowest groundnut area was recorded with Kolli hills block with 83 ha followed by Senthamangalam and Namagiripet blocks with 488 blocks and 515 ha respectively. Namakkal recorded higher groundnut area of 22581 ha as compared to Salem district which registered a groundnut area of 17817 ha.

The accuracy assessment with 88 validation points during *kharif* 2015 showed a lesser accuracy of 78.3% for groundnut in Salem and Namakkal districts. However the overall accuracy of 85.2% with reliability of 85.9% and kappa score of 0.70 the classification accuracy was found to be good (Table 16).

4.5.2. Groundnut area during *rabi* 2015

Among the two districts monitored during *rabi* 2015, Tiruvannamalai has recorded the highest groundnut area of 24903 ha followed by Villupuram district with a groundnut area of 22722 ha (Table 14).

In Tiruvannamalai district, Thurinjipuram and Thandrampattu blocks recorded the higher groundnut area of 2342 and 2216 ha respectively followed by Keelpennathur, Tiruvannamalai and Thellar blocks with an area of 1993, 1891 and 1851 ha respectively. The lowest groundnut area was recorded in Jawadhu hills block with an area of 215 ha followed by Anakkavur block with 721 ha.

In Villupuram district, Melmalaiyanur and Chinnasalem blocks recorded higher area of groundnut (2410 and 2133 ha respectively) followed by Mugaiyur, Rishivandiyam, Kallakurichi, Vallam and Ulundurpet blocks with an area of 1513, 1491, 1464 and 1394 ha

Table 16. Confusion matrix for accuracy assessment of Groundnut classification during *kharif* 2015 in Salem and Namakkal districts

Actual class from survey	Predicted class from the map			
	Class	**Groundnut**	**Non-Groundnut**	**Accuracy (%)**
	Groundnut	36	10	78.3%
	Non-Groundnut	3	39	92.9%
	Reliability	92.3%	79.6%	**85.2%**
Average accuracy		85.6%		
Average reliability		85.9%		
Overall accuracy		**85.2%**	**Good Accuracy**	
Kappa index		**0.70**		

Table 17. Confusion matrix for accuracy assessment of Groundnut classification during *rabi* season 2015 in Tiruvannamalai and Villupuram districts

Actual class from survey	**Predicted class from the map**			
	Class	**Groundnut**	**Non-Groundnut**	**Accuracy (%)**
	Groundnut	53	9	85.5%
	Non-Groundnut	3	43	93.5%
	Reliability	94.6%	82.7%	**88.9%**
Average accuracy		89.5%		
Average reliability		88.7%		
Overall accuracy		**88.9%**	**Good Accuracy**	
Kappa index		**0.78**		

Table 18. Confusion matrix for accuracy assessment of Groundnut classification across study area

Actual class from survey	Predicted class from the map			
	Class	**Groundnut**	**Non-Groundnut**	**Accuracy (%)**
	Groundnut	89	19	82.4%
	Non-Groundnut	6	82	93.2%
	Reliability	93.7%	81.2%	**87.2%**
Average accuracy		87.8%		
Average reliability		87.4%		
Overall accuracy		**87.2%**	**Good Accuracy**	
Kappa index		**0.74**		

respectively. The lowest groundnut area was recorded in Kalrayan hills block with 160 ha followed by Thiruvennainallur and Koliyanur blocks with an area of 476 and 487 ha, respectively.

Confusion matrix generated with 108 validation points for accuracy assessment for groundnut area classification during *rabi* 2015 showed a good accuracy of 85.5% for groundnut and 93.5% for other land types. The overall accuracy of 88.9% with reliability of 88.7% and kappa score of 0.78 showed the accuracy of products as good (Table 17).

4.6. Modeling growth and productivity of groundnut using DSSAT v 4.5

A crop simulation model is simple representation of a crop in relation to environmental and other growth influencing factors and explanatory in nature. The groundnut model PNUTGRO was calibrated, tested and validated to predict crop yields as influenced by season and variations in climate, soil, and genotypes spatially. The model validation results showed that simulated days to various growth stages, growth processes and final yields were significantly correlated with the observed data across environments.

4.6.1. Generation of input files for DSSAT and calibration (Appendix XIa to XIe)

4.6.1.1. Weather file generated in DSSAT

The weather input files was generated using weatherman in DSSAT for 20 monitoring locations covering 10 weather stations (Fig. 23 to 32) in the study districts of Salem (3), Namakkal (2), Tiruvannamalai (2) and Villupuram (3). During *kharif* 2015, the generated input file showed a mean maximum temperature of 35.3 to 36.3 ^{o}C, a mean minimum temperature of 23.5 to 23.9^{o}C and mean solar radiation of 360.9 to 410.8 cal cm^{-2}min^{-1} in three weather stations of Salem district during crop growth period. During this period, a rainfall of 222.5 to 250.5 mm was recorded in the respective weather stations. In Namakkal district, the generated weather files showed a mean maximum temperature of 30.6 to 35.8^{o}C, a mean minimum temperature of 25.2 to 25.3 ^{o}C and mean solar radiation of 384.5 to 416.5 cal cm^{-2}min^{-1} with rainfall of 141.5 to 313.9 mm was recorded in the two weather stations of Namakkal district during this period.

During crop growth period (*rabi* 2015), in Tiruvannamalai district, the generated input file showed a mean maximum temperature of 29.6 to 30.1^{o}C, a mean minimum temperature of 21.7 to 21.8^{o}C and mean solar radiation of 349.6 to 474.5 cal cm^{-2}min^{-1} with the rainfall of 397.5 to 566.0 mm in two weather stations of Tiruvannamalai district during this period. Whereas Villupuram district generated input file showed a mean maximum

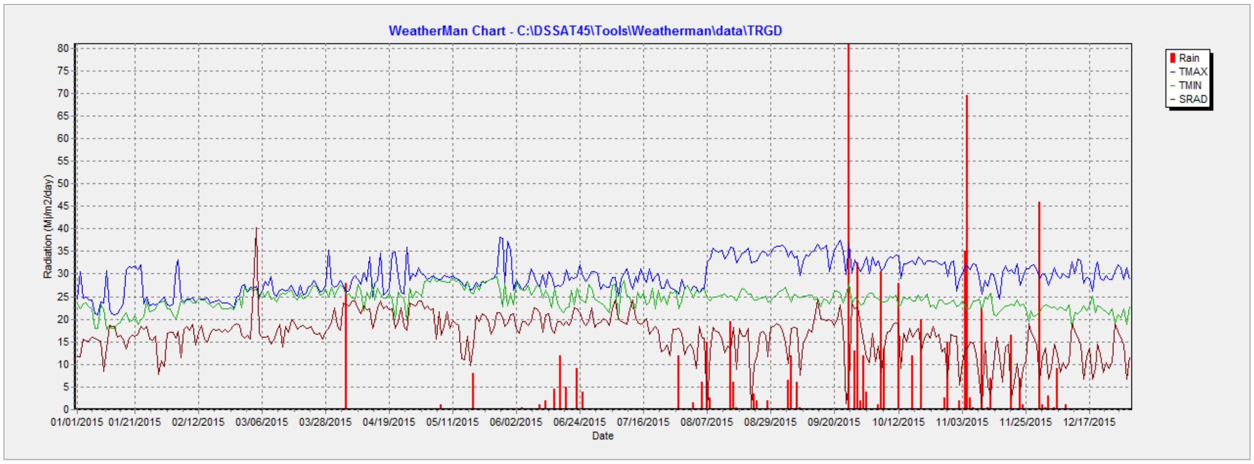

Fig.23. Weather chart generated from DSSATfor Tiruchengodu

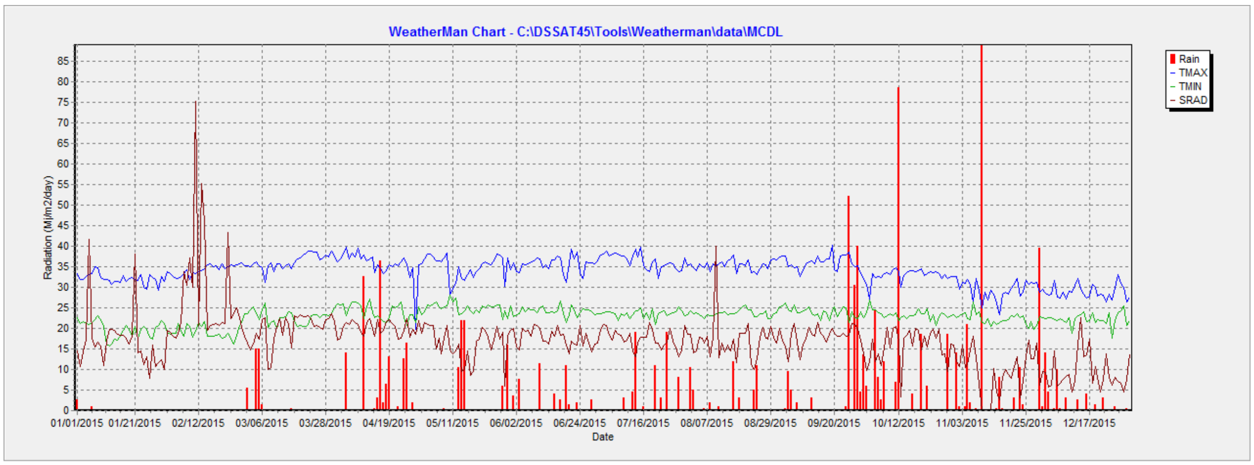

Fig.24.Weather chart generated from DSSAT for Mac.donalds choultry

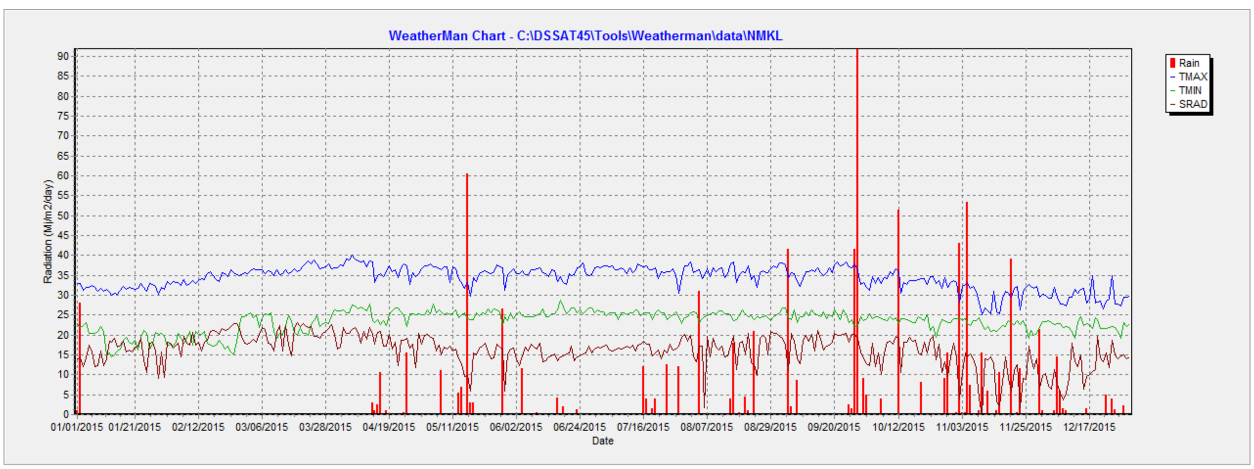

Fig.25. Weather chart generated from DSSAT for Namakkal

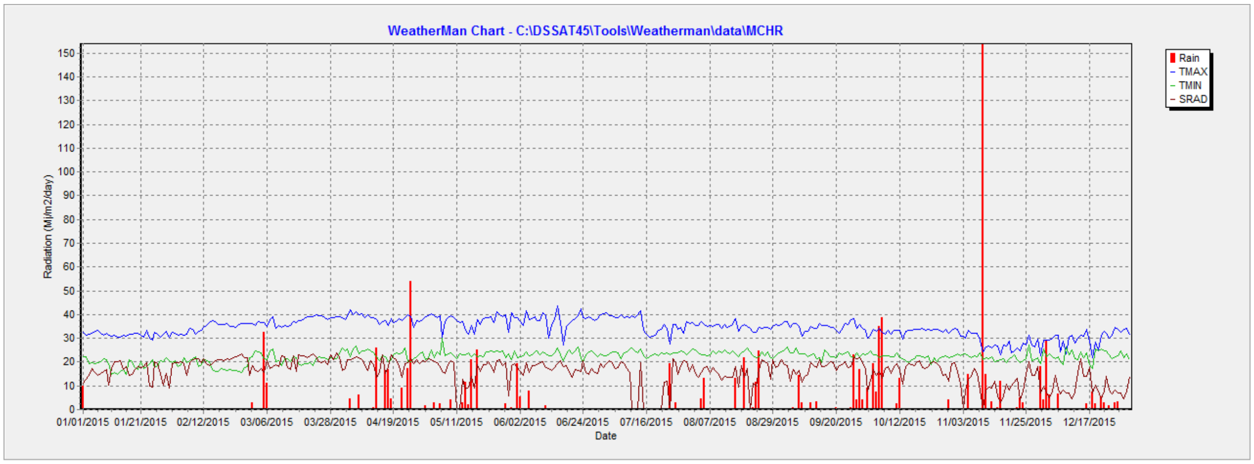

Fig.26. Weather chart generated from DSSAT for Mecheri

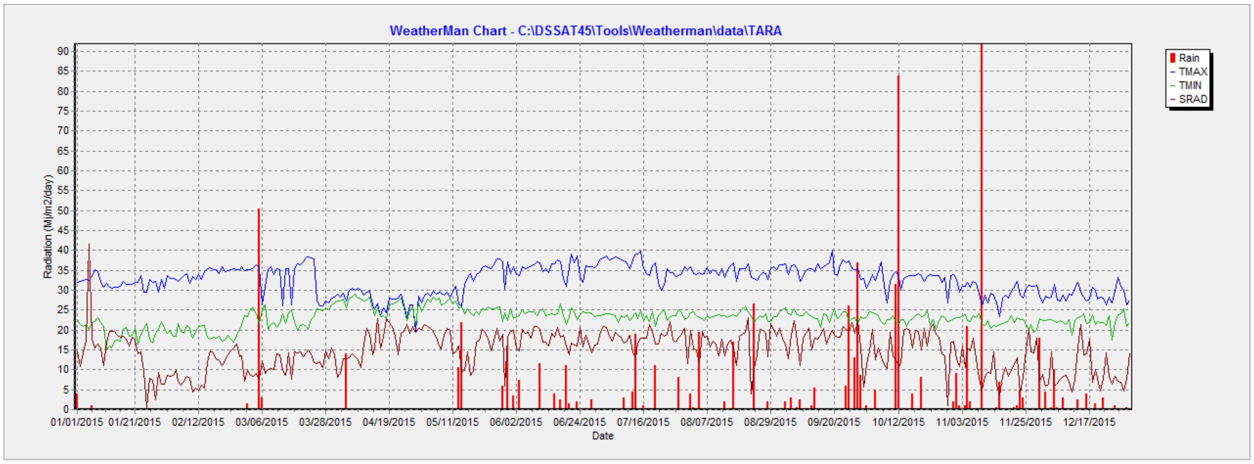

Fig.27. Weather chart generated from DSSAT for Tharamangalam

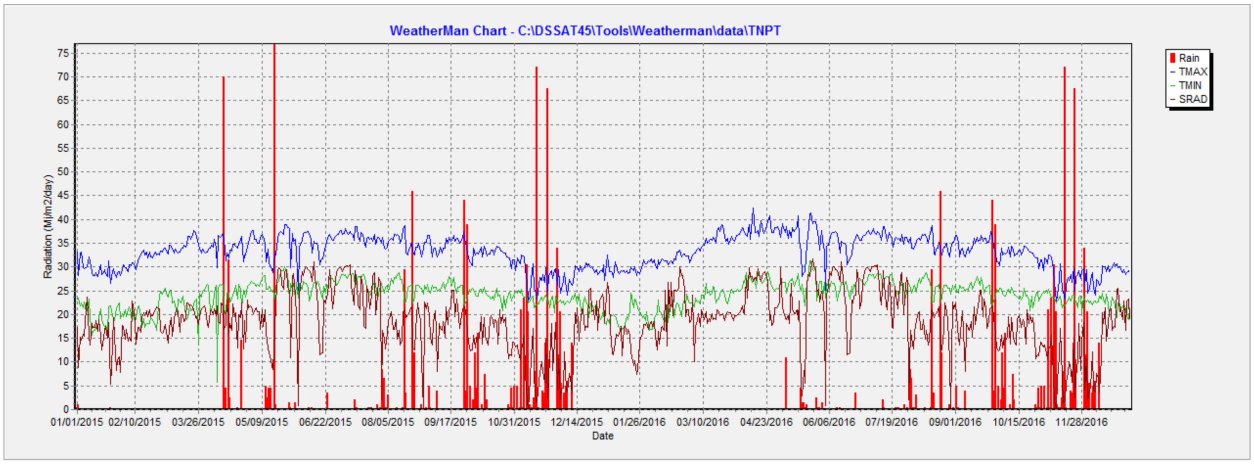

Fig.28. Weather chart generated from DSSAT for Thandrampattu

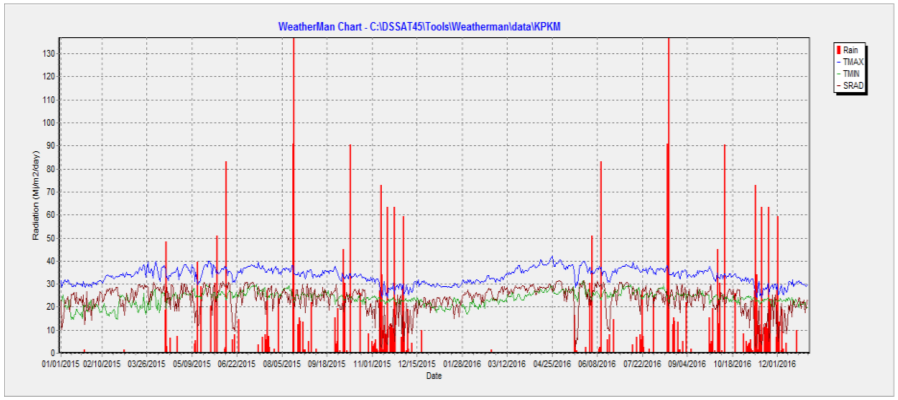

Fig.29. Weather chart generated from DSSAT for Kalasapakkam

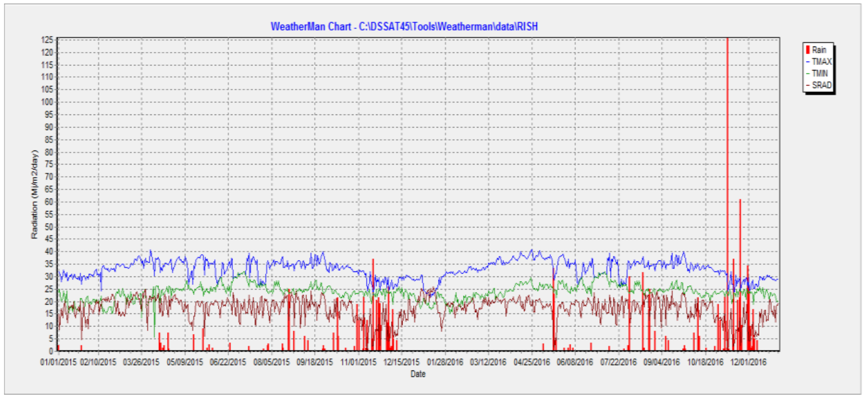

Fig.30. Weather chart generated from DSSAT for Rishivandiyam

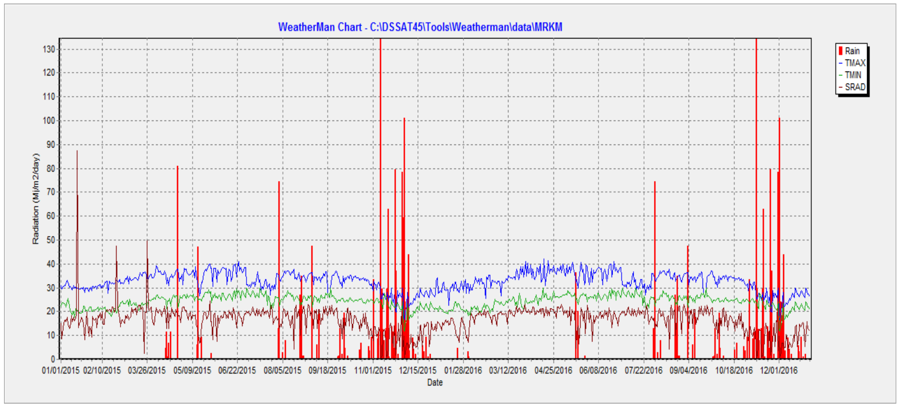

Fig.31. Weather chart generated from DSSAT for Marakanam

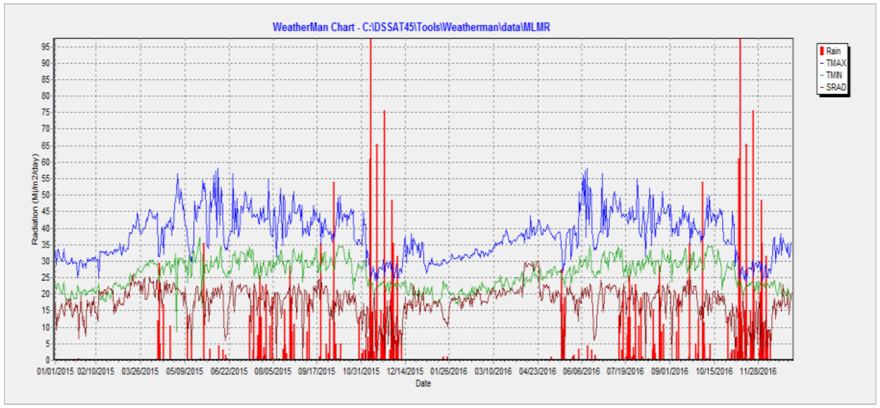

Fig.32. Weather chart generated from DSSAT for Melmalaiyanur

temperature of 28.9 to 31.7°C, a mean minimum temperature of 21.6 to 22.3°C and mean solar radiation of 293.2 to 360.8 cal $cm^{-2}min^{-1}$ showed in three weather stations of Villupuram district during crop growth period. During this period a rainfall of 279.9 to 921.6 mm was recorded in the respective weather stations.

4.6.1.2. Soil file generated in DSSAT

The input files for soil was generated with 13 parameters derived from soil analysis (Table 19.). In the study area of four districts, a total of twelve soil series were found to be predominantly present. The input files generated using 'S' build showed that the bulk density (SBDM) of the study area ranged from 1.44 to 1.62 g cm^{-3} whereas the soil organic carbon concentration ranged from 0.20 to 0.92 , pH ranged from 6.0 to 8.9 , Cation Exchange Capacity ranged from 7.3 to 39.5, and soil depth from 42 to 276 cm.

4.6.1.3. Calibration and derivation of genetic coefficients

The genetic coefficients required in the CROPGRO model version 4.5 were estimated by entering varietal character as incorporated in the model in the form of 'genetic coefficients' for CO 6, TMV 7 and VRI 2 cultivars. An inbuilt programme in DSSAT called GENCALC, calculates genetic coefficients. The genetic coefficients determined in CROPGRO model using identical management and other conditions were used in the subsequent validation and application (Table 20.).

Among the three different genetic coefficients of cultivars used in study districts, the time between emergence and flower appearance (EM-FL) and time between first flower and first pod (FL-SH) were found to be 16.40 (photothermal days) and 7.00 (photothermal days) respectively for all the three cultivars. The maximum leaf photosynthesis rate (LFMAX) was 1.23 ($mgCO_2m^{-2}s^{-1}$) for CO 6 and TMV 7 cultivars and 1.34 ($mgCO_2m^{-2}s^{-1}$) for VRI 2 cultivar. With regard to Specific leaf area (SLAVR), TMV 7 cultivar recorded the highest value of 245 (cm^2g^{-1}) followed by 220 and 205 (cm^2g^{-1}) for VRI 2 and CO 6 cultivar respectively. The maximum weight per seed (WTPSD) of 0.38 (g) was found in VRI 2 followed by TMV 7 and CO 6 with 0.36 and 0.31 (g) respectively. Considering average seed per pod (SDPDV) CO 6 registered the highest value of 1.60 (seed pod^{-1}) as compared to other two cultivars (1.55 seed pod^{-1}).

Table 19. Soil files generated and used in DSSAT model

Soil series	Layer (cm)	SLB	SLLL	SDUL	SSAT	SRGF	SSKS	SBDM	SLOC	SLCL	SLSI	SLCF	SLHW	SCEC
Vetavalam	25	25	0.139	0.23	0.403	1.000	2.59	1.51	0.64	19.2	15.7	-99	7.2	21.9
	52	27	0.115	0.196	0.399	0.595	2.59	1.52	0.67	14.2	12.3	-99	6.9	21.4
	98	46	0.144	0.238	0.404	0.482	0.43	1.51	0.62	20.3	17.3	-99	7.8	17.6
Perapperi,	12	12	0.115	0.189	0.389	1.000	2.59	1.55	0.6	14.5	9.8	-99	8.1	12
	34	22	0.194	0.294	0.407	0.631	0.43	1.5	0.58	30.4	17.9	-99	8.1	37
	64	30	0.207	0.311	0.412	0.375	0.43	1.49	0.49	33.5	20.2	-99	8.1	40.1
	86	22	0.222	0.333	0.426	0.232	0.23	1.45	0.49	36.5	22.8	-99	8.4	51
Palladam	17	17	0.245	0.341	0.416	1.000	0.12	1.47	0.92	38.7	9.4	-99	8.2	23.3
	33	13	0.222	0.338	0.435	0.625	0.23	1.42	0.8	34.8	22.1	-99	8.1	24.8
Perundurai	13	13	0.024	0.037	0.077	1.000	2.59	1.62	0.4	15	6	79	6	10.6
	38	25	0.165	0.221	0.247	0.600	0.06	1.47	0.5	48	11	41	5.9	22.8
	70	32	0.3	0.382	0.386	0.340	0.06	1.24	0.7	69	8	23	5.9	26.4
	92	22	0.145	0.192	0.219	0.198	0.12	1.53	0.3	46	9	45	6.4	19.2
Irugur	22	22	0.124	0.195	0.262	1.000	0.23	1.45	0.35	33.3	27.9	38.8	8	25.1
	58	36	0.044	0.064	0.112	0.449	0.43	1.58	0.44	21.9	7.6	70.5	8.1	22.3
	88	30	0.051	0.075	0.125	0.252	0.43	1.58	0.35	24.2	8.6	67.2	8.2	19.6
	108	20	0.121	0.185	0.247	0.165	0.23	1.49	0.18	34.4	25.2	40.4	8.3	26.3
Vellalur	22	22	0.077	0.119	0.176	1.000	0.43	1.47	0.84	26.7	15.5	57.8	7.7	11
	37	15	0.103	0.155	0.208	0.554	0.43	1.47	0.78	31.8	18	50.2	7.5	7.6
	66	29	0.128	0.179	0.218	0.361	0.12	1.48	0.68	39.7	12.9	47.4	7.4	9
Elavamalai	15	15	0.051	0.071	0.115	1.000	0.43	1.62	0.21	26	5.3	68.6	6.5	12.6
	27	12	0.047	0.065	0.109	0.657	0.43	1.63	0.18	25.1	4.8	70	7.5	11
Kollattur	18	18	0.05	0.08	0.137	1.000	0.43	1.55	0.45	20.9	14.3	64.8	6.3	11.4
	48	30	0.102	0.134	0.169	0.522	0.12	1.56	0.37	39.7	4	56.4	6.7	13.8

Katripatti	12	12	0.031	0.054	0.115	1.000	2.59	1.58	0.2	14.6	15.4	70	6	9.2
	31	19	0.039	0.072	0.143	0.651	2.59	1.54	0.3	14.6	21.6	63.8	5	8.1
	58	27	0.047	0.065	0.11	0.372	0.43	1.62	0.2	25.1	4.8	70	5.2	8.8
Chickarasam Palaiyam	23	23	0.058	0.087	0.139	1.000	0.43	1.54	0.51	25	10.4	64.6	8.2	7.3
	35	12	0.047	0.065	0.111	0.560	0.43	1.64	0.06	24.9	5.9	69.2	8.3	14
	63	28	0.1	0.139	0.183	0.375	0.12	1.58	0.15	35.8	12.1	52.1	8.3	22
	90	27	0.07	0.106	0.165	0.217	0.43	1.58	0.09	26.9	16.3	56.8	8.4	25
Tolurpatti	18	18	0.057	0.094	0.154	1.000	0.43	1.47	0.89	21	16	63	7.5	18.4
	66	48	0.127	0.179	0.219	0.517	0.12	1.48	0.66	39	14	47	6.8	34.1
Meyyur	16	16	0.81	0.137	0.210	1.00	0.43	1.44	0.75	23.8	25.2	51.0	8.9	39.5
	30	14	0.128	0.214	0.289	0.631	0.23	1.37	0.78	30.8	32.9	36.3	9.0	40.3
	50	20	0.214	0.333	0.387	0.449	0.06	1.28	0.80	44.1	35.7	20.2	9.3	42.8
	110	60	0.158	0.214	0.243	0.202	0.06	1.46	0.65	46.1	11.5	42.4	9.1	42

SLB - Depth until base of layer (cm); SLLL - Lower limit of plant extractable soil water (cm^3 cm^{-3}); SDUL - Drained upper limit (cm^3 cm^{-3}); SSAT - Saturated upper limit ($cm^3 cm^{-3}$); SRGF - Root growth factor (0-1 scale); SSKS - Saturated hydraulic conductivity (cm h^{-1}); SBDM - Bulk density (moist) (g cm^{-3}); SLOC - Soil organic carbon concentration (%); SLCL Clay (<0.002 mm) (%); SLSI - Silt (0.002 to 0.05 mm) (%); SLCF - Coarse fraction (>2mm) (%); SLHW - pH in water; SCEC - Soil cation exchange capacity (Cmol(+)kg^{-1})

Table 20. Genetic co-efficient (GC) of peanut generated and used in DSSAT CROPGRO-Peanut Model

S. No.	GC-Code*	Genetic co-efficient (GC)		
		CO 6	TMV 7	VRI 2
1	**CSDL**	11.84	11.84	11.84
2	**PPSEN**	0.00	0.00	0.00
3	**EM-FL**	16.40	16.40	16.40
4	**FL-SH**	7.00	7.00	7.00
5	**FL-SD**	17.50	17.00	16.50
6	**SD-PM**	62.00	62.00	62.00
7	**FL-LF**	70.00	66.00	66.00
8	**LFMAX**	1.23	1.23	1.34
9	**SLAVR**	205.00	245.00	220.00
10	**SIZLF**	16.00	16.00	16.00
11	**XFRT**	0.73	0.80	0.76
12	**WTPSD**	0.310	0.360	0.38
13	**SFDUR**	29.00	29.00	29.00
14	**SDPDV**	1.60	1.55	1.55
15	**PODUR**	16.00	16.00	15.00
16	**THRSH**	74.00	78.00	74.00
17	**SDPRO**	0.27	0.27	0.27
18	**SDLIP**	0.51	0.51	0.51

***(Ref.Table 4.)**

4.6.2. Simulation of growth and development variables of groundnut by DSSAT

Growth and development variables of groundnut *viz*., days to emergence, days to anthesis, pod development, seed development and physiological maturity, yield at harvest (kg ha^{-1}), pod weight (kg ha^{-1}) and pod number (m^{-2}) were simulated by DSSAT CROPCRO-Peanut model for twenty monitoring locations across the study area and presented in Table 21 and 22. Besides maximum LAI, Harvest index, Threshing per cent, N content in grain, tops and stem at maturity and canopy height (m) were also simulated in each location spatially.

The CROPGRO-Peanut simulated the days for different physiological process of groundnut. The days to emergence ranged from 7 to 9 days across locations while the days to anthesis varied from 25 to 32 days. Among the locations, Nochokarakadu with the variety Co 6 registered the minimum of 107 days to maturity while Melsevalambadi with the variety TMV 7 recorded a maximum number of 117 days to emergence. Similarly, the simulations were made for days to first pod development to first seed development and physiological maturity and they showed that groundnut took 36 to 44 days to anthesis, 43 to 51 days for first pod development and 107 to 117 days to physiological maturity. Further, the DSSAT model resulted in a simulated canopy height of 0.67 to 0.70 m and maximum LAI of 1.12 to 3.07. Vellapillakovil and Kakapalayam resulted in higher simulation of LAI with values of 3.07 followed by Velangavundanpatti and Pappambadi registering maximum LAI of 3.05. However, the model simulated a lesser LAI of 1.12 to 1.48 at Keelravandavadi, Thandrampattu, Tindivanam, Melsevalambadi, Padiyandhal and Arkandanallur sites.

The crop growth model also simulated the leaf number per stem at maturity which ranged from 27.84 to 29.02 in Salem district, 25.76 to 29.12 in Namakkal district, 25.47 to 25.85 in Tiruvannamalai and 24.60 to 26.72 in Villupuram district.

As influenced by the canopy height, leaf number and maximum LAI, the tops weight at maturity (kg ha^{-1}), was also simulated by the model and found to be in the range of 4176 to 9576 kg ha^{-1}. The yield parameters viz., pod weight (kg ha^{-1}), number of pods m^{-2} and seed weight were simulated to be in the range 1796 to 3060 (kg ha^{-1}), 568 to 783 m^{-2} and 0.190 to 0.317 g.

The resultant yield was simulated by DSSAT PNUTGRO and found to be in the range of 1796 to 3060 kg ha^{-1} across the study area with a harvest index of 0.28 to 0.43. The model

Table 21. Growth and development variables simulated by DSSAT in monitoring sites of Salem and Namakkal districts

S.No.	Variables	Pudhu chatram	Pothiyam patti	Pappam badi	Moonga thur	Vellapilla kovil	Palaya puliyam patti	Pudhu puliyam patti	Kaka palayam	Kandarkula manickam	Velagavunda n patti	Manathi	More palayam	Nocho karakadu
1	Cultivar	Co 6	Co 6	Co 6	Co 6	Co 6	Co 6	Co 6	Co 6	Co 6	Co 6	Co 6	Co 6	Co 6
2	Anthesis day (dap)	27	29	26	28	26	26	25	26	28	26	25	26	25
3	First pod day (dap)	38	41	38	40	38	37	36	38	40	37	37	37	36
4	First seed day (dap)	45	49	45	47	45	44	43	45	47	44	43	44	43
5	Physiological maturity day (dap)	114	116	112	114	113	109	108	113	115	113	112	109	107
6	Yield at harvest maturity (kg [dm]/ha)	2429	2747	3060	2922	2969	2348	2640	2957	2877	2687	2587	2348	2641
7	Pod/Ear/Panicle weight at maturity (kg [dm]/ha)	3532	3760	4174	3991	4100	3263	3655	4099	3957	3816	3746	3263	3633
8	Number at maturity (no/m2)	1306	1269	1376	1347	1390	1087	1225	1399	1363	1374	1365	1087	1229
9	Unit weight at maturity (g [dm]/unit)	0.186	0.2165	0.2223	0.2169	0.2137	0.216	0.2156	0.2113	0.2111	0.1956	0.1895	0.216	0.2149
10	Number at maturity (no/unit)	1.47	1.52	1.53	1.55	1.5	1.47	1.51	1.48	1.53	1.46	1.46	1.47	1.5
11	Tops weight at maturity (kg [dm]/ha)	8569	8734	9456	9045	9576	7466	8156	9548	9099	9173	9012	7466	8399
12	By-product produced (stalk) at maturity (kg[dm]/ha	6140	5990	6400	6120	6610	5120	5520	6590	6220	6490	6420	5120	5760
13	Leaf area index, maximum	2.68	2.82	3.05	2.82	3.07	1.98	2.31	3.07	2.84	3.05	2.92	1.98	2.37
14	Harvest index at maturity	0.283	0.314	0.324	0.323	0.31	0.314	0.324	0.31	0.3163	0.293	0.287	0.314	0.314
15	Threshing % at maturity	68.78	73.05	73.3	73.21	72.41	71.95	72.24	72.14	72.7	70.44	69.06	71.95	72.68
16	Grain N at maturity (kg/ha)	122	142	161	153	154	119	136	151	150	142	129	119	135
17	Tops N at maturity (kg/ha)	237	251	277	263	276	214	238	271	263	262	250	214	242
18	Stem N at maturity (kg/ha)	48	44	46	45	50	40	42	50	46	50	50	40	45
19	Grain N at maturity (%)	5.04	5.19	5.27	5.23	5.18	5.09	5.16	5.09	5.22	5.28	4.98	5.09	5.12
20	Tops weight at anthesis (kg [dm]/ha)	71	86	107	95	107	76	108	113	95	107	82	76	108
21	Tops N at anthesis (kg/ha)	3	3	4	4	4	3	4	4	4	4	3	3	4
22	Leaf number per stem at maturity	29.02	28.4	27.84	28.46	28.08	25.94	25.76	28.64	28.68	29.12	28.46	25.94	25.81
23	Grain oil at maturity (%)	50.58	50.03	49.87	49.95	50.17	50.06	49.98	50.34	50.07	50.13	50.71	50.06	49.81
24	Canopy height (m)	0.7	0.67	0.67	0.68	0.67	0.63	0.63	0.68	0.68	0.7	0.69	0.63	0.63
25	Harvest maturity day (dap)	114	116	112	114	113	109	108	113	115	113	112	109	107
26	Emergence day (dap)	9	9	7	9	7	8	7	7	9	7	7	8	7

Table 22. Growth and development variables simulated by DSSAT in monitoring sites of Tiruvannamalai and Villupuram districts

S.No.	Variables	Keelravanda vadi	Manmalai	Thandram pattu	Arkanda nallur	Padiyandhal	Tindivanam	Melsevalam badi
1	**Cultivar**	VRI 2	VRI 2	VRI 2	VRI 2	TMV 7	TMV 7	TMV 7
2	**Anthesis day (dap)**	26	26	25	26	27	26	32
3	**First pod day (dap)**	37	37	36	37	38	37	44
4	**First seed day (dap)**	43	43	43	43	45	44	51
5	**Physiological maturity day (dap)**	108	108	108	108	111	112	117
6	**Yield at harvest maturity (kg [dm]/ha)**	1796	2519	1825	2340	2088	1806	2005
7	**Pod/Ear/Panicle weight at maturity (kg [dm]/ha)**	2600	3638	2509	3490	2765	2367	2694
8	**Number at maturity (no/m2)**	739	940	623	947	721	568	783
9	**Unit weight at maturity (g [dm]/unit)**	0.2431	0.2681	0.2932	0.2417	0.2896	0.3177	0.2562
10	**Number at maturity (no/unit)**	1.36	1.34	1.46	1.37	1.35	1.4	1.43
11	**Tops weight at maturity (kg [dm]/ha)**	4525	6366	4516	6179	4807	4176	5030
12	**By-product produced (stalk) at maturity (kg[dm]/ha**	2730	3850	2690	3840	2720	2370	3030
13	**Leaf area index, maximum**	1.12	1.54	1.13	1.48	1.4	1.24	1.37
14	**Harvest index at maturity**	0.397	0.396	0.404	0.379	0.434	0.432	0.399
15	**Threshing % at maturity**	69.1	69.24	72.77	67.05	75.54	76.3	74.43
16	**Grain N at maturity (kg/ha)**	83	107	90	100	91	83	92
17	**Tops N at maturity (kg/ha)**	129	179	132	172	141	124	145
18	**Stem N at maturity (kg/ha)**	16	25	15	25	19	15	21
19	**Grain N at maturity (%)**	4.6	4.26	4.91	4.27	4.35	4.6	4.59
20	**Tops weight at anthesis (kg [dm]/ha)**	85	102	78	100	89	75	64
21	**Tops N at anthesis (kg/ha)**	3	4	3	4	3	3	2
22	**Leaf number per stem at maturity**	25.48	25.47	25.85	25.11	25.31	24.6	26.72
23	**Grain oil at maturity (%)**	50.2	51	49.52	51	50.3	49.93	50.27
24	**Canopy height (m)**	0.69	0.63	0.68	0.63	0.67	0.63	0.70
25	**Harvest maturity day (dap)**	108	108	108	108	111	112	117
26	**Emergence day (dap)**	8	8	7	8	8	8	9

also simulated the N content at anthesis and maturity. The groundnut oil content of grains was simulated to be 49.52 to 50.58 per cent across the study area.

4.6.3. Observed values of growth and yield of groundnut

Observations were made on growth and yield parameters at 20 monitoring locations regularly. The observed values of LAI, biomass, pod yield and harvest index are presented in Table 23. In case of maximum LAI, Salem district recorded LAI of 3.45 to 4.04 with a mean of 3.67 and biomass of 7554 to 9959 kg ha^{-1} with a mean of 9060 kg ha^{-1}. In the monitoring sites of the district, pod yield of 2115 to 2750 kg ha^{-1} were recorded while the harvest index was observed to be between 0.26 to 0.28.

Monitoring locations in Namakkal district registered a maximum LAI of 3.35 to 4.05 with a mean of 3.68 with biomass of 7222 to 9600 kg ha^{-1}. The resultant pod yield was observed to be 1950 to 2607 kg ha^{-1} with a harvest index of 0.25 to 0.29. Similarly in Tiruvannamalai, the maximum LAI and biomass were observed to be in the range of 2.01 to 2.62 and 4620 to 7290 kg ha^{-1}. The resultant pod yields were between 1450 and 2187 kg ha^{-1} with a harvest index of 0.30 to 0.37. Villupuram district recorded a comparatively lesser LAI of 2.44 to 2.80 with biomass of 4652 to 7403 kg ha^{-1}. The pod yields were observed to be 1535 to 2221 kg ha^{-1} with a harvest index of 0.30 to 0.34.

4.6.4. Validating of crop simulation of groundnut growth and productivity

4.6.4.1. Validation of simulated groundnut Leaf Area Index (LAI)

Throughout the study area, LAI was observed in twenty field locations and simulations were done through DSSAT model for the respective locations. The agreement between the simulated and observed values was worked out and given in Table 24. The observed LAI values ranged from 2.01 to 4.05 and higher LAI values of 4.05 and 4.04 were observed in Manathi and Pappambadi sites followed by Kakapalayam, Palayapuliyampatti, Kandarkulamanickam and Vellapillakovil with the values of 3.83, 3.78, 3.71 and 3.70 respectively. Comparatively lesser values of LAI ranging from 2.74 to 2.01 were recorded at Tiruvannamalai district. The lowest LAI of 2.01 was recorded at Keelravandavadi followed by Tindivanam with LAI of 2.44.

Simulated LAI values through CROPGRO-Peanut model ranged from 1.12 to 3.07. The maximum LAI value of 3.07 was simulated in Vellapillakovil and Kakapalayam followed

Table 23. District wise observed values of LAI, biomass, pod yield and harvest index of groundnut

Parameters	Salem			Namakkal			Tiruvannamalai			Villupuram		
	Maximum	Minimum	Mean	Maximum	Minimum	Mean	Maximum	Minimum	Mean	Maximum	Minimum	Mean
LAI	4.04	3.45	3.67	4.05	3.35	3.68	2.62	2.01	2.38	2.80	2.44	2.63
Biomass ($kg\ ha^{-1}$)	9959	7554	9060	9600	7222	8491	7290	4620	5529	7403	4652	5707
Pod yield ($kg\ ha^{-1}$)	2750	2115	2464	2607	1950	2333	2187	1450	1782	2221	1535	1825
Harvest Index	0.28	0.26	0.27	0.29	0.25	0.28	0.37	0.30	0.33	0.34	0.30	0.32

Table 24. Validation of DSSAT CROPGRO-Peanut model for groundnut Leaf Area Index (LAI)

S.No.	District	Village	Simulated LAI	Observed LAI	Agreement (%)
1	Namakkal	Palayapuliyampatti	1.98	3.78	52
2	Namakkal	Pudhupuliyampatti	2.31	3.37	69
3	Namakkal	Kakapalayam	3.07	3.83	80
4	Namakkal	Kandarkulamanickam	2.84	3.71	77
5	Namakkal	Velagavundmpatti	3.05	3.68	83
6	Namakkal	Manathi	2.92	4.05	72
7	Namakkal	Morepalayam	1.98	3.35	59
8	Namakkal	Nochokarakadu	2.37	3.64	65
9	Salem	Pudhuchatram	2.68	3.55	75
10	Salem	Pothiyampatti	2.82	3.60	78
11	Salem	Pappambadi	3.05	4.04	75
12	Salem	Moongathur	2.82	3.45	82
13	Salem	Vellapillakovil	3.07	3.70	83
14	Tiruvannamalai	Keelravandavadi	1.12	2.01	56
15	Tiruvannamalai	Manmalai	1.54	2.51	61
16	Tiruvannamalai	Thandrampattu	1.13	2.62	43
17	Villupuram	Arkandanallur	1.48	2.80	53
18	Villupuram	Padiyandhal	1.40	2.55	55
19	Villupuram	Tindivanam	1.24	2.44	51
20	Villupuram	Melsevalambadi	1.37	2.74	50
Mean			**2.21**	**3.27**	
R^2			**0.82**		
RMSE			**1.10**		
NRMSE (%)			**34**		
Total Agreement (%)			**66**		

by Velagavundanpatti and Pappambadi field locations with LAI of 3.05. The lesser simulated LAI values of 1.12, 1.13, 1.24, 1.37, 1.40 and 1.48 were recorded in Keelravandavadi, Thandrampattu, Tindivanam, Melsevalambadi, Padiyandhal and Arkandanallur of Tiruvannamalai district respectively.

On comparison between observed and simulated values, the Leaf Area Index as simulated by the CROPGRO-Peanut model was found to be underestimated for all twenty field locations during *kharif* and *rabi* season in all the study districts. The DSSAT model fairly simulated the LAI values in Velagavundanpatti and Vellapillaikovil sites with the values of 3.05 and 3.07 as against the observed values of 3.68 and 3.70 respectively, followed by Moongathur and Kakapalayam field locations which recorded the simulated values of 2.82 and 3.07 with the observed values of 3.45 and 3.83 respectively. The model poorly predicted the LAI in Thandrampattu field with the value of 1.40 against the observed value of 2.62 followed by Melsevalambadi and Tindivanam fields with a simulated LAI of 1.37and 1.24 as against the observed values of 2.74 and 2.44 respectively.

The agreement between simulated LAI value with observed value was worked out and given in Table 24. The individual agreement for all field locations ranged from 43 to 84 per cent. Among the twenty field locations, the maximum agreement of 83 per cent was recorded in two field locations *viz*., Velagavundanpatti and Vellapillaikovil followed by Moongathur and Kakapalayam field locations which recorded 82 and 80 per cent respectively. The minimum agreement was recorded in Thandrampattu field location with 43 per cent followed by 50, 51 and 52 per cent for Melsevalambadi, Tindivanam, and Palayapuliyampatti fields respectively.

A summary of statistical analysis of the results of LAI variable is also presented in Table 24. The average errors as computed by R^2, RMSE and NRMSE were 0.82, 1.10 and 34 per cent respectively. The overall agreement between simulated and observed values was 66 per cent.

4.6.4.2. Validation of simulated groundnut biomass

Similar to LAI, groundnut biomass was observed and simulated in the twenty field locations across study area and the results are given in Table 25. The observed values of biomass production which means both pods and haulm yields of groundnut crops in all field locations at harvest ranged from 5246 kg ha^{-1} from 8969 kg ha^{-1}. The maximum biomass of

Table 25. Validation of DSSAT CROPGRO-Peanut model for groundnut biomass (kg ha^{-1})

S.No.	District	Village	Simulated Biomass	Observed Biomass	Agreement (%)
1	Namakkal	Palayapuliyampatti	7466	8275	90
2	Namakkal	Pudhupuliyampatti	8156	7845	96
3	Namakkal	Kakapalayam	9548	8969	94
4	Namakkal	Kandarkulamanickam	9099	8011	86
5	Namakkal	Velagavundmpatti	9173	7768	82
6	Namakkal	Manathi	9012	7895	86
7	Namakkal	Morepalayam	7466	8660	86
8	Namakkal	Nochokarakadu	8399	8929	94
9	Salem	Pudhuchatram	8569	7753	89
10	Salem	Pothiyampatti	8734	8456	97
11	Salem	Pappambadi	9456	8715	91
12	Salem	Moongathur	9045	8832	98
13	Salem	Vellapillakovil	9576	8778	91
14	Tiruvannamalai	Keelravandavadi	4525	5788	78
15	Tiruvannamalai	Manmalai	6366	5862	91
16	Tiruvannamalai	Thandrampattu	4516	5246	86
17	Villupuram	Arkandanallur	6179	6678	93
18	Villupuram	Padiyandhal	4807	5681	85
19	Villupuram	Tindivanam	4716	5683	83
20	Villupuram	Melsevalambadi	5030	5883	86
Mean			**7492**	**7485**	
R^2			**0.79**		
RMSE (kg ha^{-1})			**844**		
NRMSE (%)			**11**		
Total Agreement (%)			**89**		

8969 kg ha^{-1} was observed in Kakapalayam field followed by Nochokarakadu, Moongathur, Vellapillakovil, Pappambadi and Morepalayam fields which recorded a biomass of 8929, 8832, 8778, 8715 and 8660 kg ha^{-1} respectively. Thandrampattu field recorded the lowest observed biomass of 5246 kg ha^{-1} followed by observed values of 5681, 5683 and 5788 kg ha^{-1} from Padiyandhal, Tindivanam and Keelravandavadi fields respectively with all the three locations falling in Tiruvannamalai and Villupuram districts.

In the twenty field locations, the CROPGRO-Peanut model simulated the biomass production and the values ranged from 4516 kg ha^{-1} to 9576 kg ha^{-1}. Vellapillakovil field recorded the maximum simulated value of biomass with 9576 kg ha^{-1} followed by Kakapalayam, Pappambadi, Velagavundanpatti, Kandarkulamanickam, Moongathur and Manathi field locations which recorded the biomass production of 9548, 9456, 9173, 9099, 9045 and 9012 kg ha^{-1} respectively. The minimum simulated biomass of 4516 kg ha^{-1} was recorded in Thandrampattu field followed by Keelravandavadi, Tindivanam and Padiyandhal fields with the biomass of 4525, 4716 and 4807 kg ha^{-1}respectively.

The CROPGRO-Peanut model slightly over predicted the biomass production in most of the field locations. At the same time there was a positive significant relation between simulated and observed values prevailed throughout the twenty locations. Especially, In Moongathur, Pothiyampatti and Pudhupuliyampatti field locations, CROPGRO-Peanut model excellently predicted the biomass production of 9045, 8734 and 8156 with observed values of 8832, 8456 and 7845 kg ha^{-1} respectively. In Nochokarakadu and Kakapalayam, also the DSSAT model simulated the biomass accurately with the values of 8339 and 9548 kg ha^{-1} as against 8929 and 8969 kg ha^{-1} of observed values respectively. In Keelravandavadi field the simulation was slightly poor with biomass production of 4525 kg ha^{-1} as compared to the observed values of 5788kg ha^{-1}.

The agreement between simulated and observed values was more acceptable for almost all monitoring field locations. The agreement of fields ranged from 78 to 98 per cent. The maximum level of agreement of 98% was recorded in Moongathur followed by 97 and 96 per cent in Pothiyampatti and Pudhupuliyampatti and 94 per cent by Nochokarakadu and Kakapalayam fields. Among the twenty field locations, Keelravandavadi field recorded slightly poor agreement for biomass production with 78 per cent.

The model prediction for biomass production at maturity was considered excellent and the average errors as computed by R^2, RMSE and NRMSE were 0.79, 844 kg ha^{-1} and 11 per cent respectively and overall agreement between simulated and observed values was 89 per cent. The model prediction was in close agreement with measured values.

4.6.4.3. Validation of simulated groundnut pod yield

Groundnut pod yield under rainfed condition was observed and simulated using DSSAT model in twenty monitoring sites spatially and the results are given in Table 26.

The observed pod yield ranged from 1450 to 2750 kg ha^{-1} and the maximum yield of 2750 kg ha^{-1} was observed in Pappambadi field followed by Moongathur, Kakapalayam and Pothiyampatti field locations which recorded 2689, 2607 and 2525 kg ha^{-1} respectively. The fields at Velagavundanpatti, Nochokarakadu, Morepalayam and Pudhupuliyampatti were the next best locations which recorded pod yield around 2400 kg ha^{-1}. On spatial observation, it was found that Kandarkulamanickam, Vellapillakovil, Arkandanallur, Manmalai, Pudhuchatram and Palayapuliyampatti recorded pod yield of 2050 to 2376 kg ha^{-1}. The other locations recorded the pod yield of less with Keelravandavadi recording the lowest observed pod yield of 1450 kg ha^{-1} followed by Tindivanam, Padiyandhal and Thandrampattu with the observed pod yields of 1535,1660 and 1710 kg ha^{-1}.

The simulated pod yields by DSSAT model ranged from 1796 to 3060 kg ha^{-1}. Among the twenty field locations, the maximum pod yield of 3060 kg ha^{-1} was simulated in Pappambadi followed by Vellapillakovil, Kakapalayam, Moongathur, Kandarkulamanickam and Pothiyampatti locations which recorded 2969, 2957, 2922, 2827 and 2747 kg ha^{-1} of pod yield respectively. The lowest simulated pod yield of 1796 kg ha^{-1} was recorded at Keelravandavadi followed by 1806 and 1825 kg ha^{-1} of pod yields at Tindivanam and Thandrampattu locations respectively.

The performance of the CROPGRO-Peanut model in simulating the pod yield was good for all the twenty field locations. In most of the locations, positive significant association prevailed between simulated and observed yield. Morepalayam recorded a simulated pod yield of 2348 kg ha^{-1} against 2400 kg ha^{-1} of observed pod yield. Arkandanallur, Melsevalambadi, Thandrampattu, Moongathur, Pothiyampatti and Pudhupuliyampatti fields also recorded fairly good simulated values of 2340, 2005, 1825, 2922, 2747 and 2640 kg ha^{-1} as compared to the observed values of 2221, 1885, 1710, 2689, 2525 and 2400 kg ha^{-1} respectively.

Table 26. Validation of DSSAT CROPGRO-Peanut model for groundnut pod yield (kg ha^{-1})

S.No.	District	Village	Simulated yield	Observed yield	Agreement (%)
1	Namakkal	Palayapuliyampatti	2348	2050	85
2	Namakkal	Pudhupuliyampatti	2640	2400	90
3	Namakkal	Kakapalayam	2957	2607	87
4	Namakkal	Kandarkulamanickam	2827	2376	81
5	Namakkal	Velagavundanpatti	2687	2464	91
6	Namakkal	Manathi	2587	1950	67
7	Namakkal	Morepalayam	2348	2400	98
8	Namakkal	Nochokarakadu	2641	2419	91
9	Salem	Pudhuchatram	2429	2115	85
10	Salem	Pothiyampatti	2747	2525	91
11	Salem	Pappambadi	3060	2750	89
12	Salem	Moongathur	2922	2689	91
13	Salem	Vellapillakovil	2969	2240	67
14	Tiruvannamalai	Keelravandavadi	1796	1450	76
15	Tiruvannamalai	Manmalai	2519	2187	85
16	Tiruvannamalai	Thandrampattu	1825	1710	93
17	Villupuram	Arkandanallur	2340	2221	95
18	Villupuram	Padiyandhal	2088	1660	74
19	Villupuram	Tindivanam	1806	1535	82
20	Villupuram	Melsevalambadi	2005	1885	94
Mean			**2477**	**2182**	
R^2			**0.81**		
RMSE (kg ha^{-1})			**342**		
NRMSE (%)			**16**		
Total Agreement (%)			**84**		

In simulation of pod yields, the agreement of simulated values with observed values are given in Table 26. The individual agreement of pod yield for all field locations ranged from 77 to 98 per cent. Moongathur, Pothiyampatti, Nochokarakadu and Velagavundanpatti also recorded a fairly good agreement of 91 per cent of pod yield in groundnut between observed values and the values simulated by DSSAT crop growth model. The lowest agreement of 67 per cent was recorded in Manathi and Vellapillakovil locations followed by Padiyandhal and Keelravandavadi with 74 and 76 per cent agreement and the remaining monitoring sites recording an agreement of above 80 per cent on groundnut pod yield.

The average errors as computed by R^2, RMSE and NRMSE were 0.81, 342 kg ha^{-1} and 16 per cent respectively. The overall agreement between simulated and observed values was 84 per cent.

4.6.4.4. Validation of simulated groundnut harvest index

Yield of the plant parts of economic importance (pod yield) to total biological yield in terms of dry matter was calculated as harvest index and recorded at all twenty field locations along with DSSAT based simulated values (Table 27). The observed harvest index ranged from 0.247 to 0.373. Manmalai field recorded maximum observed harvest index of 0.373 followed by 0.333, 0.326, 0.320 and 0.317 at Arkandanallur, Thandrampattu, Melsevalambadi and Velagavundanpatti respectively. The lowest harvest index of 0.247 was observed at Manathi field followed by Palayapuliyampatti which recorded a value of 0.248.

Simulation of harvest index in all the field locations was carried out through DSSAT model and the values ranged from 0.283 to 0.434. The maximum simulated harvest index of 0.434 was recorded in Padiyandhal followed by Tindivanam, Thandrampattu, Melsevalambadi, Keelravandavadi and Manmalai field which recorded a simulated value with 0.432, 0.404, 0.399, 0.397 and 0.396. Pudhuchatram field recorded the minimum simulated harvest index of 0.283 followed by 0.293 and 0.287 at Velagavundanpatti and Manathi fields.

In simulating harvest index, CROPGRO-Peanut model performed well for all field locations. Especially, model simulated the harvest index in Pappambadi field as 0.324 which was very close to the observed value of 0.316 followed by Pudhuchatram and Pothiyampatti fields which recorded simulated values of 0.283 and 0.314 as compared to observed values of 0.273 and 0.299 respectively. However, the model overestimated the harvest index in all the

Table 27. Validation of DSSAT CROPGRO-Peanut model for groundnut Harvest Index

S.No.	District	Village	Simulated HI	Observed HI	Agreement (%)
1	Namakkal	Palayapuliyampatti	0.314	0.248	73
2	Namakkal	Pudhupuliyampatti	0.324	0.306	94
3	Namakkal	Kakapalayam	0.310	0.291	93
4	Namakkal	Kandarkulamanickam	0.316	0.297	94
5	Namakkal	Velagavundmpatti	0.293	0.317	92
6	Namakkal	Manathi	0.287	0.247	84
7	Namakkal	Morepalayam	0.314	0.277	87
8	Namakkal	Nochokarakadu	0.314	0.271	84
9	Salem	Pudhuchatram	0.283	0.273	96
10	Salem	Pothiyampatti	0.314	0.299	95
11	Salem	Pappambadi	0.324	0.316	97
12	Salem	Moongathur	0.323	0.304	94
13	Salem	Vellapillakovil	0.310	0.255	78
14	Tiruvannamalai	Keelravandavadi	0.397	0.251	42
15	Tiruvannamalai	Manmalai	0.396	0.373	94
16	Tiruvannamalai	Thandrampattu	0.404	0.326	76
17	Villupuram	Arkandanallur	0.379	0.333	86
18	Villupuram	Padiyandhal	0.434	0.292	51
19	Villupuram	Tindivanam	0.432	0.270	40
20	Villupuram	Melsevalambadi	0.399	0.320	75
Mean			**0.343**	**0.293**	
R^2			**0.70**		
RMSE			**0.070**		
NRMSE (%)			**24**		
Total Agreement (%)			**76**		

fields except Velagavundanpatti which recorded the simulated value of 0.293 as compared to the observed value of 0.317.

During validation of simulated harvest index, individual agreement between simulated and observed values was fairly well for all twenty field locations. The individual agreement of harvest index in all field locations ranged from 40 to 97 per cent. Especially, Pappambadi field recorded the maximum agreement of 97 per cent followed by Pudhuchatram and Pothiyampatti fields which recorded an agreement of 96 and 95 per cent of agreement between simulated and observed values respectively. The lowest agreement was recorded in Tindivanam field with 40 per cent followed by Keelravandavadi and Padiyandhal, fields with 42 and 51 per cent respectively. These two fields were located in Tiruvannamalai and Villupuram districts respectively.

The R^2, RMSE and NRMSE (%) values of the regression between the estimated and measured harvest index values were 0.70, 0.070 and 24 per cent and overall agreement of harvest index between simulated and observed values was 76 per cent. Thus the model prediction was in close agreement with the measured values.

4.7. Integrating remote sensing products with DSSAT crop growth model for yield estimation at spatial level

Most of the crop yield models developed so far could not be adopted in practice either because of delay in the availability of data for different variables to be used in the model or the high cost in collecting the data and in analyzing the results. For any operational yield model to be successful for adoption, it is necessary that the data should be available much before the harvest of the crop and it should be cost effective. Spectral data in the form of vegetation indices have proved to be very useful variables for explaining variability of the crop yield which can be easily available for use in yield models.

In the present study, therefore suitable regression models using spectral vegetation indices in the form of LAI derived by integrating dB (back scattering) image and simulated LAI from DSSAT model as explanatory variable have been developed for yield estimation.

4.7.1. LAI of groundnut retrieved from Sentinel-1A dB image at spatial level

LAI values were generated spatially over the study area by correlating dB values in the monitoring sites during pod development and given in Table 28. The methodology

Table 29. Validation of remote sensing based groundnut yield with observed yield (kg ha^{-1})

S.No.	District	Village	RS yield	Observed yield	Agreement (%)
1	Namakkal	Palayapuliyampatti	2677	2050	69
2	Namakkal	Pudhupuliyampatti	2701	2400	87
3	Namakkal	Kakapalayam	2975	2607	86
4	Namakkal	Kandarkulamanickam	2699	2376	86
5	Namakkal	Velagavundanpatti	2781	2464	87
6	Namakkal	Manathi	2680	1950	63
7	Namakkal	Morepalayam	2721	2400	87
8	Namakkal	Nochokarakadu	2916	2419	79
9	Salem	Pudhuchatram	2700	2115	72
10	Salem	Pothiyampatti	2894	2525	85
11	Salem	Pappambadi	2414	2750	88
12	Salem	Moongathur	2975	2689	89
13	Salem	Vellapillakovil	2727	2240	78
14	Tiruvannamalai	Keelravandavadi	1912	1450	68
15	Tiruvannamalai	Manmalai	2008	2187	92
16	Tiruvannamalai	Thandrampattu	2060	1710	80
17	Villupuram	Arkandanallur	2516	2221	87
18	Villupuram	Padiyandhal	2186	1660	68
19	Villupuram	Tindivanam	2037	1535	67
20	Villupuram	Melsevalambadi	2224	1885	82
Mean			**2540**	**2182**	
R^2			**0.60**		
RMSE (kg ha^{-1})			**431**		
NRMSE (%)			**20**		
Total Agreement (%)			**80**		

demonstrated the capability of Sentinel-1A dB values in capturing the dynamic variation in the study area. The satellite derived LAI for groundnut at pod development ranged from 1.31 to 3.23. Among the locations, Kandarkulamanickam recorded the highest LAI of 3.23 followed by Vellapillaikovil and Pappambadi with the values of 3.15 and 3.14 and Morepalayam and Pothiyampatti which recorded a LAI of 3.13. The lowest LAI of 1.31 was recorded at Keelravandavadi followed by Thandrampattu with 1.44. The monitoring sites in Tiruvannamalai district recorded comparatively lesser LAI of 1.31 to 1.67. As compared with the observed LAI of 2.01 to 4.05 of groundnut, the estimation from satellite derived values ranged from 1.31 to 3.23 with an agreement of 55 to 93 per cent for point based observation with an overall agreement of 76 per cent. The R^2, RMSE and NRMSE were 0.86, 0.78 and 24 per cent respectively.

4.7.2. Remote sensing based spatial estimation of groundnut pod yield

Corresponding to the spatial LAI of groundnut at pod development, using regression models groundnut yield was generated spatially and given in Table 29. and illustrated in **(**Fig. 33 to 36)

The validation of the yield estimation was done at district level with observed yield (point level). The simulated yields of monitoring fields ranged from 1912 kg ha^{-1} to 2975 kg ha^{-1}. The maximum pod yield of 2975 kg ha^{-1} was estimated in Kakapalayam and Moongathur followed by Nochokarakadu, Pothiyampatti and Velagavundanpatti which recorded a pod yield 2916, 2894 and 2781 kg ha^{-1} respectively. The lowest pod yield of 1912 kg ha^{-1} was recorded at Keelravandavadi followed by yield of 2008, 2037 and 2060 kg ha^{-1} at Manmalai, Tindivanam and Thandrampattu locations respectively. As against the remote sensing based groundnut yields of 1912 to 2975 kg ha^{-1}, the observed yields were 1450 to 2750 kg ha^{-1}. At point level, the agreement was found to range from 67 to 92 per cent with a fairly good overall agreement of 80 per cent. The R^2 was 0.60 with RMSE of 431 kg ha^{-1} and NRMSE of 20 per cent.

4.8. Assessing vulnerability of groundnut to drought

The empirical results on agricultural vulnerability of groundnut to drought conditions and its spatial distribution are presented hereunder. The spatial distribution of classes of drought in terms of groundnut area based on different drought indices *viz*., SPI, NDVI and WRSI were worked out. Each index was classified, using GIS, for the purpose of

Table 28. Validation of remote sensing based groundnut LAI with observed values

S.No.	District	Village	RS LAI	Observed LAI	Agreement (%)
1	Namakkal	Palayapuliyampatti	3.03	3.78	80
2	Namakkal	Pudhupuliyampatti	3.08	3.37	91
3	Namakkal	Kakapalayam	3.10	3.83	81
4	Namakkal	Kandarkulamanickam	3.23	3.71	87
5	Namakkal	Velagavundanpatti	3.01	3.68	82
6	Namakkal	Manathi	2.98	4.05	74
7	Namakkal	Morepalayam	3.13	3.35	93
8	Namakkal	Nochokarakadu	3.08	3.64	85
9	Salem	Pudhuchatram	3.05	3.55	86
10	Salem	Pothiyampatti	3.13	3.6	87
11	Salem	Pappambadi	3.14	4.04	78
12	Salem	Moongathur	3.11	3.45	90
13	Salem	Vellapillakovil	3.15	3.7	85
14	Tiruvannamalai	Keelravandavadi	1.31	2.01	65
15	Tiruvannamalai	Manmalai	1.51	2.51	60
16	Tiruvannamalai	Thandrampattu	1.44	2.62	55
17	Villupuram	Arkandanallur	1.67	2.8	60
18	Villupuram	Padiyandhal	1.60	2.55	63
19	Villupuram	Tindivanam	1.62	2.44	66
20	Villupuram	Melsevalambadi	1.51	2.74	55
Mean			**2.54**	**3.27**	
R^2			**0.86**		
RMSE			**0.784**		
NRMSE (%)			**24**		
Total Agreement (%)			**76**		

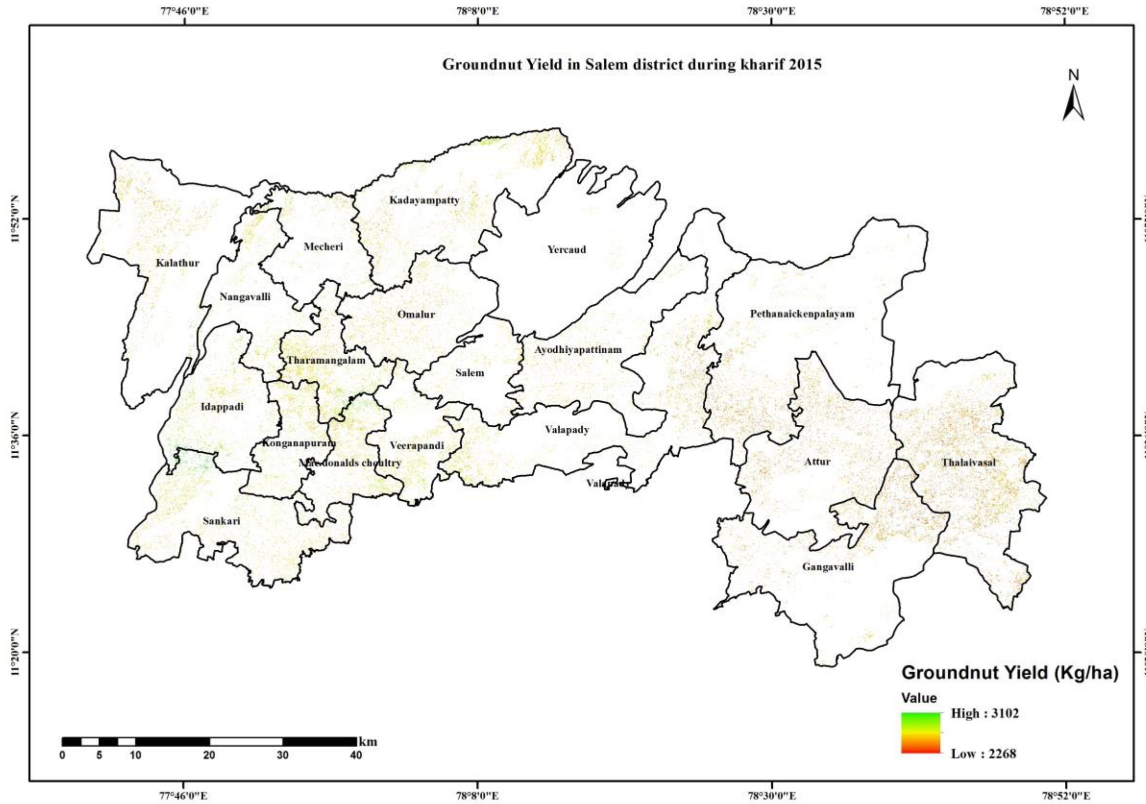

Fig.33. Blockwise Groundnut yield during *kharif* 2015 in Salem district

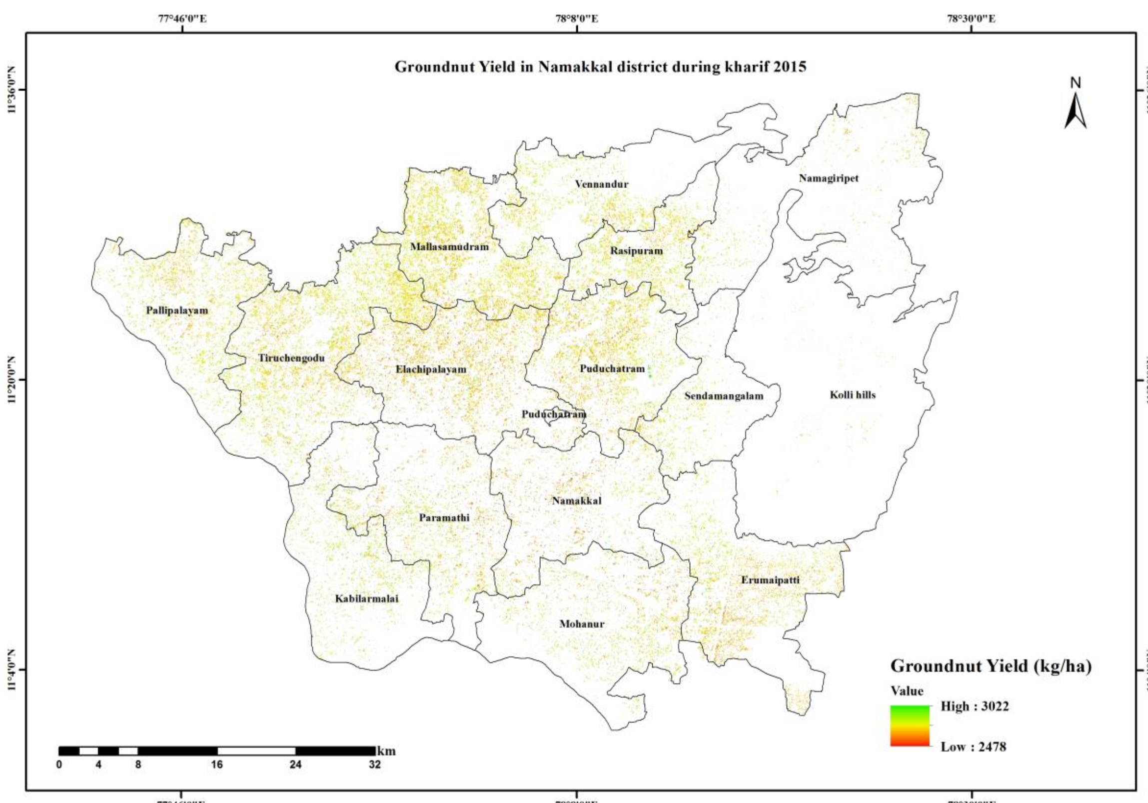

Fig.34. Blockwise Groundnut yield during *kharif* 2015 in Namakkal district

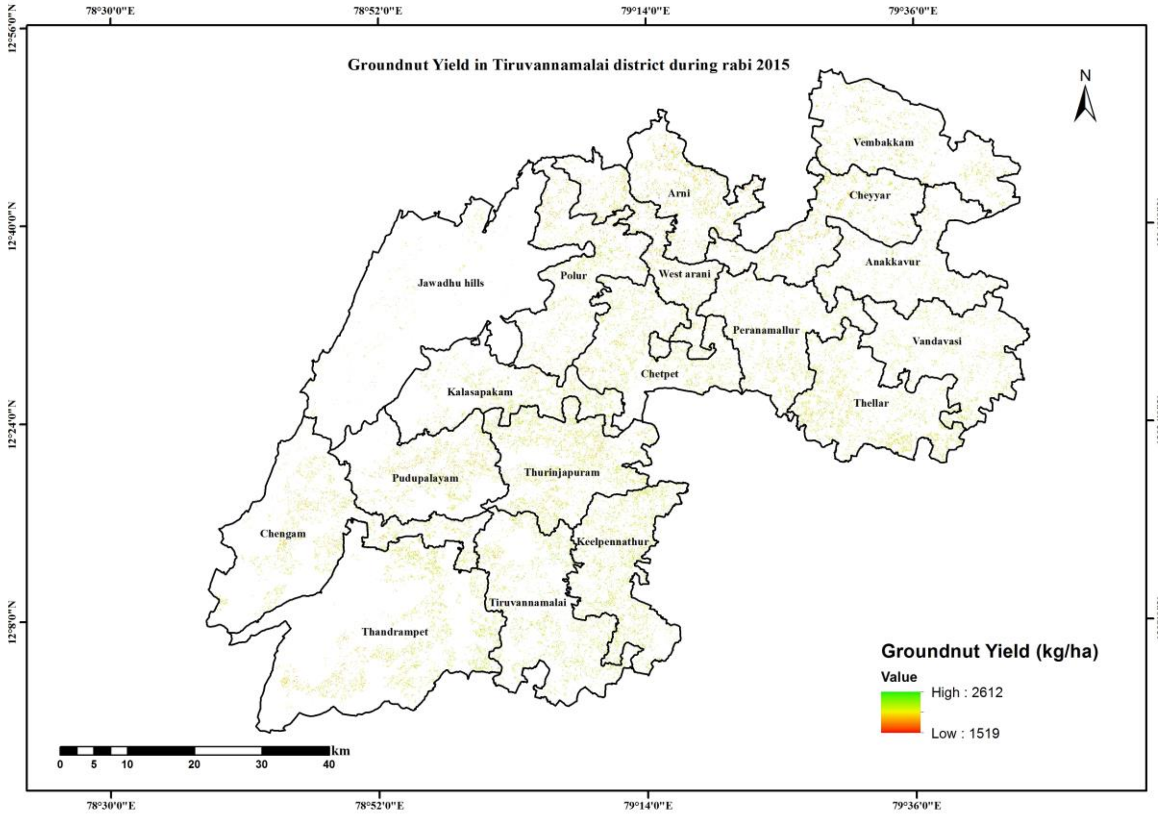

Fig.35. Blockwise Groundnut yield during *rabi* 2015 in Tiruvannamalai district

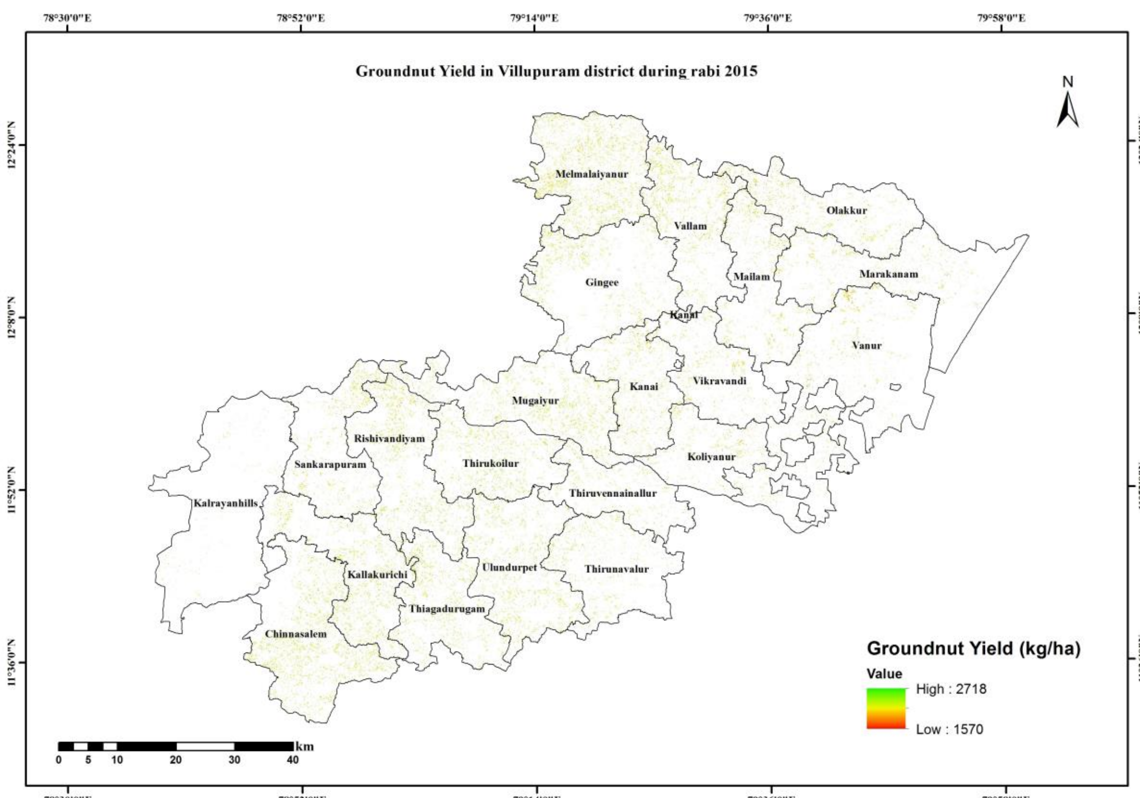

Fig.36. Blockwise Groundnut yield during *rabi* 2015 in Villupuram district

vulnerability assessment. To produce a vulnerability map for groundnut area to drought for Salem, Namakkal, Tiruvannamalai and Villupuram, the drought indices data layers were overlayed and masked to groundnut area in ArcMap to determine the areal extent of combinations of classes.

In this part, the three main drought indices were worked out and the class wise groundnut area was calculated. In the first section, classes of the drought and corresponding groundnut area based on the NDVI of groundnut from the remotely sensed imagery across the study area was analysed. Further the intensity of drought was assessed based on the SPI on groundnut area and the sensitivity to drought were estimated using historical and current rainfall information. The spatial patterns of agricultural drought of groundnut under WRSI was also worked out in third section and illustrated. Finally, the vulnerability of groundnut to drought was assessed in the study area by overlaying all the three drought indices.

4.8.1. Assessing drought based on Standardized Precipitation Index (SPI)

Standardized Precipitation Index (SPI), the deviation of rainfall from long term mean was worked out monthly and presented in Fig. 37 and 38. The SPI classes corresponding to drought intensity of the study area at block level was assessed monthly and presented in Tables 30 to 33.

In Salem district, during the month of May 2015, four blocks *viz*., Kadayampatti, Yercaud, Valapady and Veerapandi were found to be under severely dry condition based on SPI values. Other eleven blocks were classified as moderately dry except Idappadi, Attur and Gangavalli which were grouped as mildly dry. Thalaivasal was classified as normal with regard to rainfall in comparison with historical precipitation data. During the cropping period of June to September, 2015, all the blocks were classified as normal to moderately wet classes of SPI. Similarly in Namakkal district also, SPI classes of mildly dry (11 Blocks) and severely dry (4 blocks) were observed during May 2015 while normal to severely wet conditions prevailed during June to September 2015 in all the blocks.

During *rabi* 2015, most of the blocks were found to be normal to mildly wet across the cropping season with a few blocks registering moderately wet to severely wet condition. Similarly, all the blocks in Villupuram district also recorded SPI classes corresponding to normal to mildly wet classes except Sankarapuram, Rishivandiyam and Koliyanur which recorded moderately wet condition during corresponding period.

Table 30. Blockwise drought condition based on SPI classes in Salem district

S.No.	Block	May	June	July	August	September
1	Kadayampatty	Severely Dry	Normal	Normal	Normal	Mildly Dry
2	Kalathur	Moderately Dry	Mildly Wet	Mildly Wet	Normal	Normal
3	Yercaud	Severely Dry	Normal	Mildly Wet	Normal	Moderately Dry
4	Mecheri	Moderately Dry	Normal	Normal	Normal	Normal
5	Nangavalli	Moderately Dry	Mildly Wet	Normal	Normal	Normal
6	Valapady	Severely Dry	Normal	Normal	Normal	Normal
7	Pethanaickenpalayam	Moderately Dry	Normal	Normal	Normal	Normal
8	Omalur	Moderately Dry	Normal	Normal	Normal	Mildly Dry
9	Ayodhiyapattinam	Moderately Dry	Normal	Normal	Normal	Normal
10	Tharamangalam	Moderately Dry	Normal	Normal	Normal	Normal
11	Salem	Moderately Dry	Normal	Normal	Normal	Normal
12	Idappadi	Mildly Dry	Mildly Wet	Mildly Wet	Normal	Normal
13	Attur	Mildly Dry	Mildly Wet	Mildly Wet	Normal	Normal
14	Thalaivasal	Normal	Normal	Moderately Wet	Moderately Wet	Normal
15	Veerapandi	Severely Dry	Normal	Mildly Wet	Normal	Normal
16	Konganapuram	Moderately Dry	Mildly Wet	Mildly Wet	Normal	Normal
17	Mac.donalds choultry	Moderately Dry	Mildly Wet	Mildly Wet	Normal	Normal
18	Sangakiri	Moderately Dry	Mildly Wet	Mildly Wet	Normal	Normal
19	Gangavalli	Mildly Dry	Moderately Wet	Moderately Wet	Mildly Wet	Normal

SPI Classes: 2.00 and above (Extremely wet); 1.50 to 1.99 (Very wet); 1.00 to 1.49 (Moderately wet); 0.50 to 0.99 (Mildly wet); 0.49 to – 0.49 (Normal); -0.50 to -0.99 (Mildly dry); -1.00 to -1.49 (Moderately dry); -1.50 to -1.99 (Severely dry); -2.00 and less (Extremely dry)

Table 31. Blockwise drought condition based on SPI classes in Namakkal district

S.No.	Block	May	June	July	August	September
1	Namagiripet	Mildly Dry	Normal	Normal	Normal	Normal
2	Vennandur	Mildly Dry	Normal	Normal	Normal	Normal
3	Rasipuram	Mildly Dry	Normal	Normal	Normal	Normal
4	Mallasamudram	Mildly Dry	Mildly Wet	Moderately Wet	Mildly Wet	Normal
5	Kolli hills	Mildly Dry	Mildly Wet	Mildly Wet	Normal	Normal
6	Pallipalayam	Mildly Dry	Mildly Wet	Mildly Wet	Mildly Wet	Normal
7	Tiruchengodu	Mildly Dry	Mildly Wet	Mildly Wet	Normal	Normal
8	Puduchatram	Mildly Dry	Mildly Wet	Mildly Wet	Normal	Normal
9	Sendamangalam	Mildly Dry	Mildly Wet	Mildly Wet	Normal	Normal
10	Elachipalayam	Severe Dry	Mildly Wet	Mildly Wet	Mildly Wet	Normal
11	Paramathi	Mildly Dry	Moderately Wet	Severely Wet	Moderately Wet	Normal
12	Kabilarmalai	Mildly Dry	Severely Wet	Severely Wet	Extremely Wet	Moderately Wet
13	Namakkal	Severe Dry	Mildly Wet	Mildly Wet	Normal	Normal
14	Erumaipatti	Severe Dry	Moderately Wet	Moderately Wet	Mildly Wet	Normal
15	Mohanur	Severe Dry	Moderately Wet	Moderately Wet	Moderately Wet	Normal

SPI Classes: 2.00 and above (Extremely wet); 1.50 to 1.99 (Very wet); 1.00 to 1.49 (Moderately wet); 0.50 to 0.99 (Mildly wet); 0.49 to – 0.49 (Normal); -0.50 to -0.99 (Mildly dry); -1.00 to -1.49 (Moderately dry); -1.50 to -1.99 (Severely dry); -2.00 and less (Extremely dry)

Table 32. Blockwise groundnut area (ha) under SPI classes in Tiruvannamalai district

S.No.	Block	October	November	December	January	February
1	Vembakkam	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
2	Arni	Normal	Moderately Wet	Mildly Wet	Mildly Wet	Mildly Wet
3	West Arani	Normal	Moderately Wet	Mildly Wet	Mildly Wet	Mildly Wet
4	Polur	Mildly Wet	Moderately Wet	Mildly Wet	Mildly Wet	Mildly Wet
5	Cheyyar	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
6	Jawadhu hills	Mildly Wet	Severely Wet	Mildly Wet	Moderately Wet	Moderately Wet
7	Anakkavur	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
8	Peranamallur	Normal	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
9	Chetpet	Mildly Wet	Moderately Wet	Mildly Wet	Mildly Wet	Mildly Wet
10	Vandavasi	Normal	Moderately Wet	Normal	Mildly Wet	Mildly Wet
11	Thellar	Normal	Mildly Wet	Normal	Mildly Wet	Mildly Wet
12	Kalasapakkam	Mildly Wet	Moderately Wet	Mildly Wet	Moderately Wet	Mildly Wet
13	Thurinjapuram	Mildly Wet	Moderately Wet	Mildly Wet	Mildly Wet	Mildly Wet
14	Pudupalayam	Mildly Wet	Moderately Wet	Mildly Wet	Mildly Wet	Moderately Wet
15	Chengam	Mildly Wet	Moderately Wet	Normal	Mildly Wet	Moderately Wet
16	Keelpennathur	Mildly Wet	Moderately Wet	Mildly Wet	Mildly Wet	Mildly Wet
17	Tiruvannamalai	Normal	Moderately Wet	Mildly Wet	Moderately Wet	Moderately Wet
18	Thandrampattu	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet	Moderately Wet

SPI Classes: 2.00 and above (Extremely wet); 1.50 to 1.99 (Very wet); 1.00 to 1.49 (Moderately wet); 0.50 to 0.99 (Mildly wet); 0.49 to – 0.49 (Normal); -0.50 to -0.99 (Mildly dry); -1.00 to -1.49 (Moderately dry); -1.50 to -1.99 (Severely dry); -2.00 and less (Extremely dry)

Table 33. Blockwise groundnut area (ha) under SPI classes in Villupuram district

S.No.	Block	October	November	December	January	February
1	Melmalaiyanur	Normal	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
2	Vallam	Normal	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
3	Olakkur	Normal	Mildly Wet	Normal	Mildly Wet	Mildly Wet
4	Mailam	Normal	Mildly Wet	Normal	Mildly Wet	Mildly Wet
5	Gingee	Normal	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
6	Marakanam	Normal	Mildly Wet	Normal	Mildly Wet	Mildly Wet
7	Vanur	Normal	Mildly Wet	Normal	Mildly Wet	Mildly Wet
8	Kanai	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
9	Vikravandi	Normal	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
10	Mugaiyur	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
11	Sankarapuram	Mildly Wet	Moderately Wet	Mildly Wet	Moderately Wet	Moderately Wet
12	Rishivandiyam	Mildly Wet	Moderately Wet	Mildly Wet	Mildly Wet	Mildly Wet
13	Kalrayan hills	Normal	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
14	Thirukoilur	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
15	Koliyanur	Mildly Wet	Mildly Wet	Mildly Wet	Moderately Wet	Moderately Wet
16	Thiruvennainallur	Normal	Mildly Wet	Normal	Mildly Wet	Mildly Wet
17	Ulundurpet	Mildly Wet	Mildly Wet	Normal	Mildly Wet	Mildly Wet
18	Kallakurichi	Normal	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet
19	Thirunavalur	Normal	Mildly Wet	Normal	Mildly Wet	Mildly Wet
20	Thiagadurugam	Normal	Mildly Wet	Normal	Mildly Wet	Mildly Wet
21	Chinnasalem	Normal	Mildly Wet	Mildly Wet	Mildly Wet	Mildly Wet

SPI Classes: 2.00 and above (Extremely wet); 1.50 to 1.99 (Very wet); 1.00 to 1.49 (Moderately wet); 0.50 to 0.99 (Mildly wet); 0.49 to – 0.49 (Normal); -0.50 to -0.99 (Mildly dry); -1.00 to -1.49 (Moderately dry); -1.50 to -1.99 (Severely dry); -2.00 and less (Extremely dry)

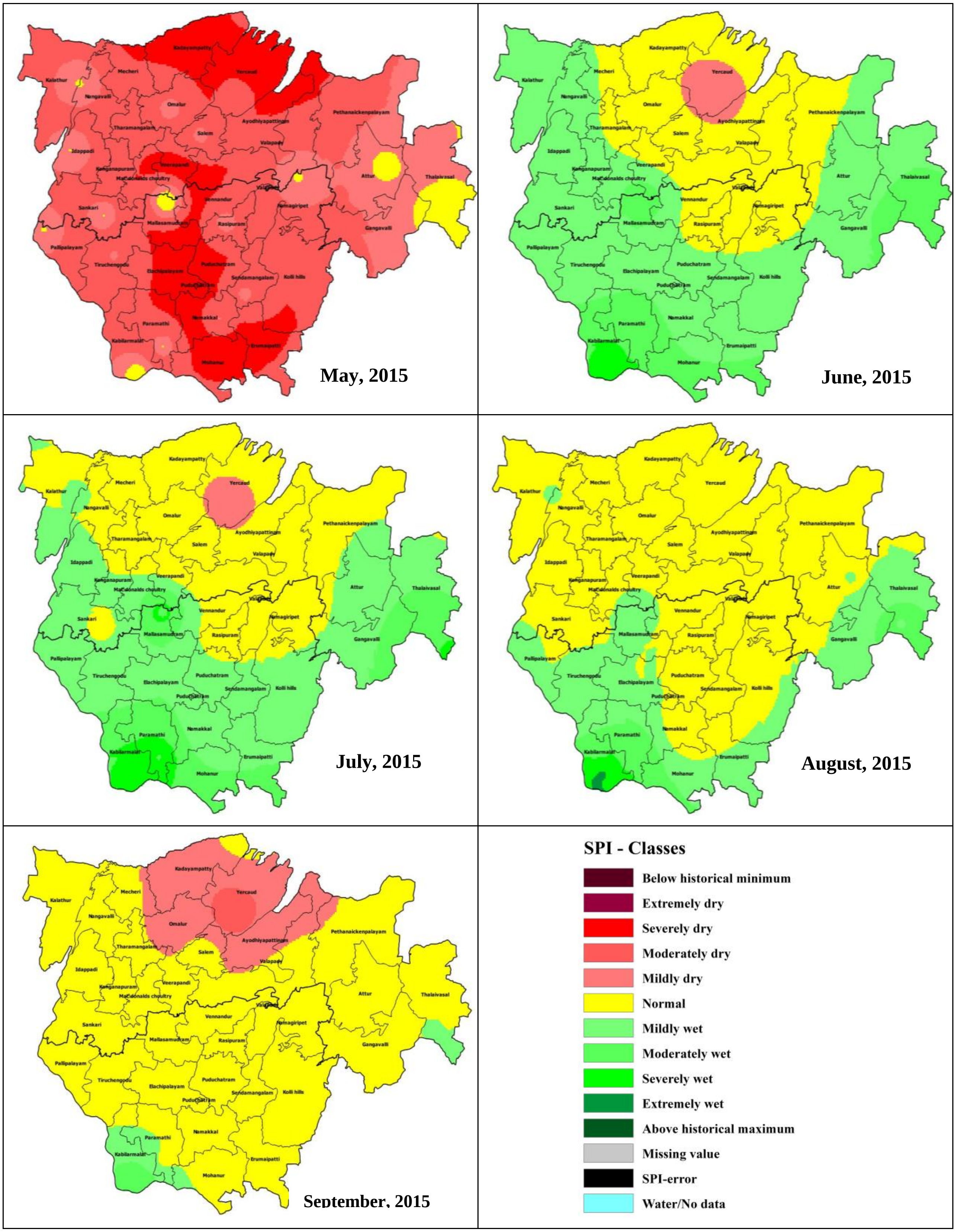

Fig.37. Block wise SPI classes in Salem and Namakkal districts during *kharif* 2015

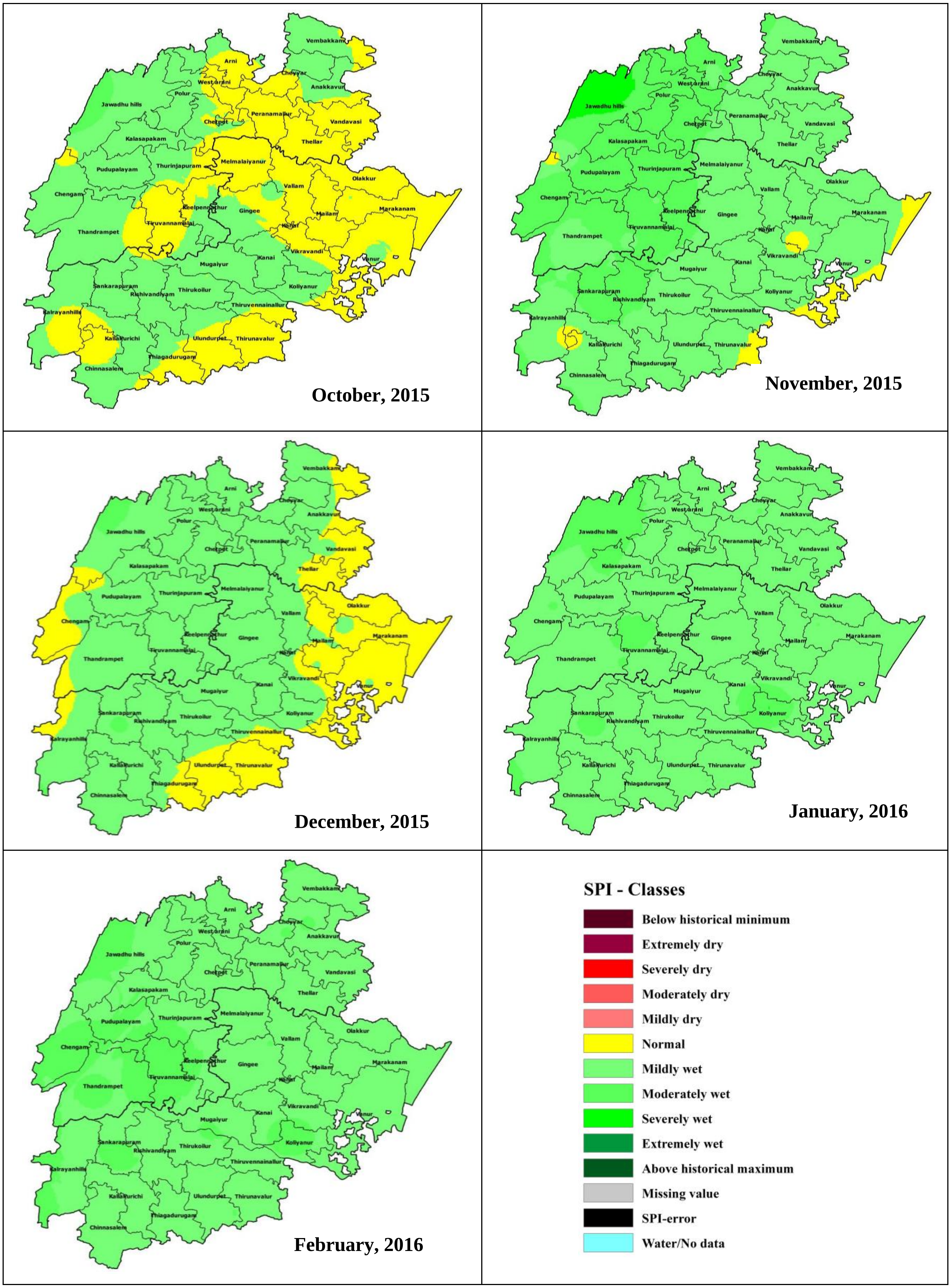

Fig.38. Block wise SPI classes in Tiruvannamalai and Villupuram districts during *rabi* 2015

Table 34. Blockwise groundnut area (ha) under composite SPI classes in Salem and Namakkal districts during *kharif* 2015

S.No.	Salem			Namakkal		
	Block	SPI		Block	SPI	
		Moderately wet (1.00 to 1.49)	Near normal (0.99 to -0.99)		Moderately wet (1.00 to 1.49)	Near normal (0.99 to -0.99)
1	Kadayampatty	0	1200	Namagiripet	0	569
2	Kalathur	0	800	Vennandur	0	1075
3	Yercaud	0	19	Rasipuram	0	1313
4	Mecheri	0	369	Mallasamudram	0	2894
5	Nangavalli	0	463	Kolli Hills	0	119
6	Valapady	0	1256	Pallipalayam	0	1631
7	Pethanaickenpalayam	0	1019	Tiruchengodu	0	3350
8	Omalur	0	900	Puduchatram	0	2269
9	Ayodhiyapattinam	0	563	Sendamangalam	0	550
10	Tharamangalam	0	1256	Elachipalayam	0	2888
11	Salem	0	231	Paramathi	0	1400
12	Idappadi	0	800	Kabilarmalai	181	713
13	Attur	0	1369	Namakkal	0	1156
14	Thalaivasal	19	2838	Erumaipatti	0	1750
15	Veerapandi	0	738	Mohanur	0	1138
16	Konganapuram	0	600			
17	Mac.donalds choultry	0	888			
18	Sangakiri	0	1244			
19	Gangavalli	0	1231			
	Total	**19**	**17781**	**Total**	**181**	**22813**
		17800			**22994**	

SPI Classes: 2.00 and above (Extremely wet); 1.50 to 1.99 (Very wet); 1.00 to 1.49 (Moderately wet); 0.99 to -0.99 (Near normal); -1.00 to -1.49 (Moderately dry); -1.50 to -1.99 (Severely dry); -2.00 and less (Extremely dry)

Table 35. Blockwise groundnut area (ha) under composite SPI classes in Tiruvannamalai and Villupuram districts during *rabi* 2015

S.No.	Tiruvannamalai			Villupuram		
	Block	SPI		Block	SPI	
		Moderately wet (1.00 to 1.49)	Near normal (0.99 to -0.99)		Moderately wet (1.00 to 1.49)	Near normal (0.99 to -0.99)
1	Vembakkam	0	1113	Melmalaiyanur	0	2494
2	Arni	0	1213	Vallam	0	1450
3	West Arani	0	1231	Olakkur	0	856
4	Polur	13	1231	Mailam	0	813
5	Cheyyar	0	1150	Gingee	0	1094
6	Jawadhu hills	206	25	Marakanam	0	656
7	Anakkavur	0	788	Vanur	0	988
8	Peranamallur	0	1069	Kanai	0	881
9	Chetpet	0	1681	Vikravandi	0	594
10	Vandavasi	0	969	Mugaiyur	0	1625
11	Thellar	0	1825	Sankarapuram	131	756
12	Kalasapakkam	13	1088	Rishivandiyam	0	1538
13	Thurinjapuram	0	2319	Kalrayan hills	6	200
14	Pudupalayam	0	1156	Thirukoilur	0	1131
15	Chengam	0	1456	Koliyanur	0	494
16	Keelpennathur	0	1925	Thiruvennainallur	0	400
17	Tiruvannamalai	0	1831	Ulundurpet	0	1438
18	Thandrampattu	0	2175	Kallakurichi	0	1419
19				Thirunavalur	0	625
20				Thiagadurugam	0	1169
21				Chinnasalem	0	2150
	Total	**231**	**24244**	**Total**	**137**	**22769**
		24475			**22906**	

SPI Classes: 2.00 and above (Extremely wet); 1.50 to 1.99 (Very wet); 1.00 to 1.49 (Moderately wet); 0.99 to -0.99 (Near normal); -1.00 to -1.49 (Moderately dry); -1.50 to -1.99 (Severely dry); -2.00 and less (Extremely dry)

Considering the groundnut area in the study districts, the composite SPI class of near normal season was recorded in 17781 ha out of 17800 ha of total groundnut area in Salem district. Similarly in Namakkal district, most of the groundnut area was classified under near normal condition with 22813 ha out of total area of 22994 ha. During *rabi* season in Tiruvannamalai and Villupuram districts also, similar trend was observed (Table 34 and 35). In Tiruvannamalai district, out of 24475 ha of groundnut area, 24244 ha were classified under near normal condition. In Villupuram district, out of 22906 ha of groundnut area, 22769 ha and 137 ha were found to be under near normal and moderately wet condition respectively.

4.8.2. Assessing drought based on Normalised Difference Vegetation Index (NDVI)

The Normalised Difference Vegetation Index (NDVI) gave a measure of the vegetative cover and was sensitive to the chlorophyll content of plants. NDVI images of cropping period during both seasons were generated using the imageries of MODIS acquired from May, 2015 to February, 2016. Dense vegetation showed high value in the NDVI imagery, and the areas with little or no vegetation showed negative value and was also clearly identified. The groundnut area under different classes of NDVI was extracted the statistics are presented in Table 36 and 37**.**

By computing the values of NDVI for each month during *kharif* and *rabi* seasons of study area, month wise NDVI images were generated. Groundnut area pertaining to each class was extracted from these images. Average NDVI image of cropping period for *kharif* season is illustrated in Fig. 39 and 40.

Analysis of composite NDVI classes during *kharif* season showed that Salem district registered 2250 ha of groundnut area under stressed condition whereas 238 and 15381 ha of groundnut area was found to be in the classes of very good and good respectively. NDVI. Among the blocks, Thalaivasal recorded maximum groundnut area with stressed condition (531 ha) followed by Kalathur block which are recorded 275 ha of groundnut area under stressed condition. Namakkal district recorded 9088 ha of groundnut area under stressed condition and 475 and 13500 ha of groundnut area under very good and good condition respectively based on NDVI values. Among the 15 blocks of Namakkal district, Elachipalayam recorded maximum groundnut area of 2531 ha under stressed condition followed by Tiruchengodu and Namakkal blocks which recorded 1294 and 1006 ha respectively.

Table 36. Blockwise groundnut area (ha) under NDVI classes in Salem district

S.No.	Block	NDVI			Total
		Very Good (>0.6)	Good (0.4 - 0.6)	Stressed (0.2 - 0.4)	
1	Kadayampatty	25	1125	50	**1200**
2	Kalathur	6	531	275	**813**
3	Yercaud	13	6	0	**19**
4	Mecheri	0	238	131	**369**
5	Nangavalli	0	431	31	**463**
6	Valapady	13	1081	175	**1269**
7	Pethanaickenpalayam	69	781	169	**1019**
8	Omalur	0	869	31	**900**
9	Ayodhiyapattinam	25	538	0	**563**
10	Tharamangalam	0	1206	50	**1256**
11	Salem	0	213	19	**231**
12	Idappadi	44	713	44	**800**
13	Attur	0	1269	106	**1375**
14	Thalaivasal	6	2338	531	**2875**
15	Veerapandi	6	675	56	**738**
16	Konganapuram	0	463	138	**600**
17	Mac.donalds choultry	0	713	181	**894**
18	Sangakiri	13	1075	169	**1256**
19	Gangavalli	19	1119	94	**1231**
	Total	**238**	**15381**	**2250**	**17869**

NDVI Classes: Very Good (>0.6); Good (0.4 - 0.6); Stressed (0.2 - 0.4); Barren (<0.2).

Table 37. Blockwise groundnut area (ha) under NDVI classes in Namakkal district

S.No.	Block	NDVI			Total
		Very Good (>0.6)	Good (0.4 - 0.6)	Stressed (0.2 - 0.4)	
1	Namagiripet	13	556	0	**569**
2	Vennandur	44	1031	6	**1081**
3	Rasipuram	0	1225	88	**1313**
4	Mallasamudram	6	2319	594	**2919**
5	Kolli hills	113	6	0	**119**
6	Pallipalayam	19	1088	544	**1650**
7	Tiruchengodu	13	2050	1294	**3356**
8	Puduchatram	6	1488	775	**2269**
9	Sendamangalam	25	488	38	**550**
10	Elachipalayam	0	356	2531	**2888**
11	Paramathi	31	588	781	**1400**
12	Kabilarmalai	169	638	88	**894**
13	Namakkal	0	150	1006	**1156**
14	Erumaipatti	6	988	763	**1756**
15	Mohanur	31	531	581	**1144**
	Total	**475**	**13500**	**9088**	**23063**

NDVI Classes: Very Good (>0.6); Good (0.4 - 0.6); Stressed (0.2 - 0.4); Barren (<0.2).

Table 38. Blockwise groundnut area (ha) under NDVI classes in Tiruvannamali district

S.No.	Block	NDVI			Total
		Very Good (>0.6)	Good (0.4 - 0.6)	Stressed (0.2 - 0.4)	
1	Vembakkam	0	1031	81	**1113**
2	Arni	0	1256	13	**1269**
3	West Arani	0	1144	6	**1150**
4	Polur	13	1181	0	**1194**
5	Cheyyar	0	1138	69	**1206**
6	Jawadhu hills	31	194	0	**225**
7	Anakkavur	0	644	25	**669**
8	Peranamallur	0	1075	75	**1150**
9	Chetpet	0	1638	63	**1700**
10	Vandavasi	0	913	75	**988**
11	Thellar	0	1919	56	**1975**
12	Kalasapakam	31	1019	0	**1050**
13	Thurinjapuram	0	2238	88	**2325**
14	Pudupalayam	0	1163	13	**1175**
15	Chengam	0	1594	19	**1613**
16	Keelpennathur	0	1938	44	**1981**
17	Tiruvannamalai	0	1775	81	**1856**
18	Thandrampattu	19	2231	31	**2281**
	Total	**94**	**24088**	**738**	**24919**

NDVI Classes: Very Good (>0.6); Good (0.4 - 0.6); Stressed (0.2 - 0.4); Barren (<0.2).

Table 39. Blockwise groundnut area (ha) under NDVI classes in Villupuram district

S.No.	Block	NDVI			Total
		Very Good (>0.6)	Good (0.4 - 0.6)	Stressed (0.2 - 0.4)	
1	Melmalaiyanur	0	2213	38	**2250**
2	Vallam	0	1381	0	**1381**
3	Olakkur	0	825	38	**863**
4	Mailam	0	763	38	**800**
5	Gingee	6	1125	25	**1156**
6	Marakanam	0	619	119	**738**
7	Vanur	6	756	188	**950**
8	Kanai	0	981	88	**1069**
9	Vikravandi	0	500	6	**506**
10	Mugaiyur	0	1313	106	**1419**
11	Sankarapuram	0	675	13	**688**
12	Rishivandiyam	0	1481	63	**1544**
13	Kalrayan hills	6	175	0	**181**
14	Thirukoilur	0	931	75	**1006**
15	Koliyanur	0	406	38	**444**
16	Thiruvennainallur	0	419	94	**513**
17	Ulundurpet	0	1075	225	**1300**
18	Kallakurichi	13	1444	63	**1519**
19	Thirunavalur	0	494	213	**706**
20	Thiagadurugam	0	1181	44	**1225**
21	Chinnasalem	0	2044	38	**2081**
	Total	**31**	**20800**	**1506**	**22338**

NDVI Classes: Very Good (>0.6); Good (0.4 - 0.6); Stressed (0.2 - 0.4); Barren (<0.2).

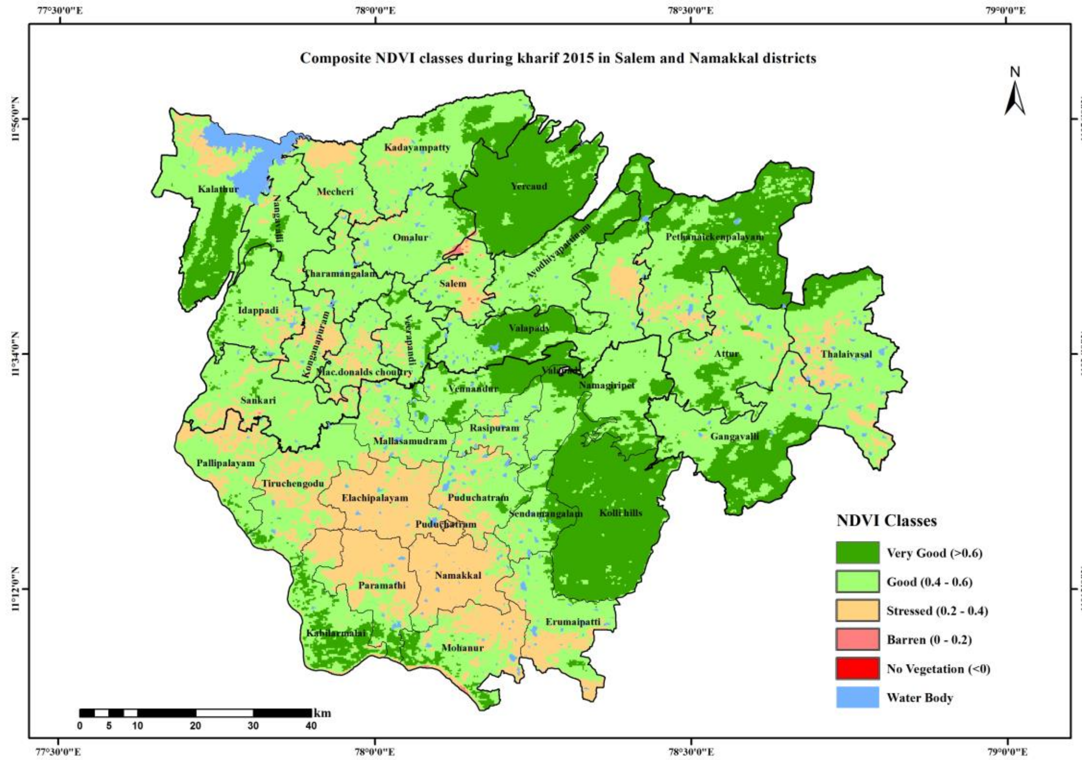

Fig.39. Drought level based on NDVI during *kharif* 2015 in Salem and Namakkal districts

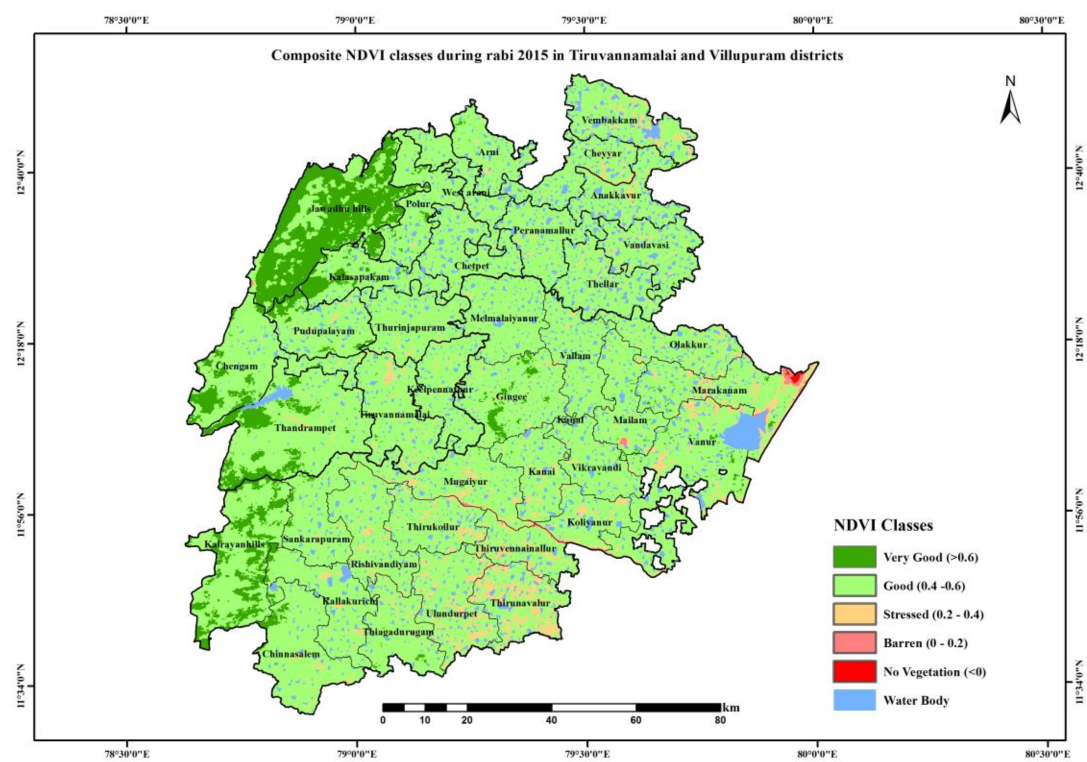

Fig.40. Drought level based on NDVI during *rabi* 2015 in Tiruvannamalai and Villupuram districts

NDVI based on drought classes of groundnut area during *rabi* season of Tiruvannamalai and Villupuram districts are presented in Table 38 and 39**.** Tiruvannamalai district recorded the lowest stressed groundnut area of 738 ha with larger groundnut area classified under good condition with 24088 ha. Considering NDVI level, Villupuram district recorded 1506 ha of groundnut area under stressed condition and 20800 ha of groundnut area under good condition. Stressed area were found to be in five blocks *viz*., Ulundurpet, Thirunavalur, Vanur and Marakanam with groundnut area of 225, 213, 188, 119 and 106 ha respectively.

4.8.3. Assessing drought based on Water Requirement Satisfaction Index (WRSI)

WRSI is an indicator of crop performance based on the availability of water to the crop during the growing season. WRSI results were then reclassified based on drought severity classes shown in Fig. 41 and 42 for each grid cell of the study area. Based on this classification, WRSI distribution on groundnut area was assessed and the statistics were derived and given in Table 40 to 43 which showed the district-wise area of groundnut under incidences of drought during both season based on WRSI. For the computation of the drought probability over each district, both the seasons for which data were available during the period May 2015 to January 2016 were used.

In Salem and Namakkal districts, during the *kharif* season, the whole groundnut area was covered under three levels of WRSI *viz*., no risk, medium risk and high risk. In Salem district, the medium risk condition had more groundnut area of 14188 ha out of 17869 ha of total area and other classes of no risk and high risk covered 6 and 3675 ha, respectively. Among the 19 blocks of Salem district, under medium risk condition, Thalaivasal block covered maximum groundnut area with 2663 ha followed by Tharamangalam and Valapady blocks which recorded 1225 and 1063 ha of groundnut area respectively. Under high risk condition, Attur block covered maximum area of 631 ha followed by Omalur and Sangakiri blocks with 394 and 363 ha, respectively. Valapady block alone had groundnut area under no risk condition and remaining blocks registered groundnut area under other two WRSI conditions.

Among three levels of WRSI (low, high and very high risk) in Namakkal district, low risk level of WRSI registered maximum groundnut area of 17300 out of total 23063 ha of total groundnut area and other two levels of high risk and very high risk conditions were recorded at 5000 and 763 ha of groundnut area respectively. Among the 15 blocks of

Table 40. Blockwise groundnut area (ha) under WRSI classes in Salem district

S.No.	Block	WRSI			
		No Risk (100%)	Medium Risk (80 - 90%)	High Risk (70 - 80%)	Total
1	Kadayampatty	0	413	788	**1200**
2	Kalathur	0	806	6	**813**
3	Yercaud	0	6	13	**19**
4	Mecheri	0	369	0	**369**
5	Nangavalli	0	463	0	**463**
6	Valapady	6	1063	200	**1269**
7	Pethanaickenpalayam	0	881	138	**1019**
8	Omalur	0	506	394	**900**
9	Ayodhiyapattinam	0	338	225	**563**
10	Tharamangalam	0	1225	31	**1256**
11	Salem	0	63	169	**231**
12	Idappadi	0	788	13	**800**
13	Attur	0	744	631	**1375**
14	Thalaivasal	0	2663	213	**2875**
15	Veerapandi	0	569	169	**738**
16	Konganapuram	0	600	0	**600**
17	Mac.donalds choultry	0	831	63	**894**
18	Sangakiri	0	894	363	**1256**
19	Gangavalli	0	969	263	**1231**
	Total	**6**	**14188**	**3675**	**17869**

WRSI Level: 100% - No Risk; 90-100% - Low Risk; 80-90% - Medium Risk; 70-80%- High Risk; 50-70%- Very High Risk and <50% - Chance of Crop failure

Table 41. Blockwise groundnut area (ha) under WRSI classes in Namakkal district

S.No.	Block	WRSI			Total
		Low Risk (90 - 100%)	High Risk (70 - 80%)	Very High Risk (50 - 70%)	
1	Namagiripet	550	19	0	**569**
2	Vennandur	1056	25	0	**1081**
3	Rasipuram	1313	0	0	**1313**
4	Mallasamudram	2400	488	31	**2919**
5	Kolli hills	50	63	6	**119**
6	Pallipalayam	1406	188	56	**1650**
7	Tiruchengodu	2013	1325	19	**3356**
8	Puduchatram	2269	0	0	**2269**
9	Sendamangalam	500	50	0	**550**
10	Elachipalayam	2356	519	13	**2888**
11	Paramathi	781	550	69	**1400**
12	Kabilarmalai	119	419	356	**894**
13	Namakkal	975	181	0	**1156**
14	Erumaipatti	900	700	156	**1756**
15	Mohanur	613	475	56	**1144**
	Total	**17300**	**5000**	**763**	**23063**

WRSI Level: 100% - No Risk; 90-100% - Low Risk; 80-90% - Medium Risk; 70-80%- High Risk; 50-70%- Very High Risk and <50% - Chance of Crop failure

Table 42. Blockwise groundnut area (ha) under WRSI classes in Tiruvannamalai district

S.No.	Block	WRSI		Total
		Very High Risk (50 - 70%)	Chance of Crop failure (<50%)	
1	Vembakkam	0	1113	**1113**
2	Arni	0	1269	**1269**
3	West Arani	0	1150	**1150**
4	Polur	0	1194	**1194**
5	Cheyyar	0	1206	**1206**
6	Jawadhu hills	0	225	**225**
7	Anakkavur	0	669	**669**
8	Peranamallur	0	1150	**1150**
9	Chetpet	6	1694	**1700**
10	Vandavasi	0	988	**988**
11	Thellar	0	1975	**1975**
12	Kalasapakam	0	1050	**1050**
13	Thurinjapuram	0	2325	**2325**
14	Pudupalayam	25	1150	**1175**
15	Chengam	19	1594	**1613**
16	Keelpennathur	25	1956	**1981**
17	Tiruvannamalai	81	1775	**1856**
18	Thandrampattu	81	2200	**2281**
	Total	**238**	**24681**	**24919**

WRSI Level: 100% - No Risk; 90-100% - Low Risk; 80-90% - Medium Risk; 70-80%- High Risk; 50-70%- Very High Risk and <50% - Chance of Crop failure

Table 43. Blockwise groundnut area (ha) under WRSI classes in Villupuram district

S.No.	Block	WRSI			Total
		High Risk (70 – 80%)	Very High Risk (50 – 70%)	Chance of Crop failure (<50%)	
1	Melmalaiyanur	0	0	2250	2250
2	Vallam	0	31	1350	1381
3	Olakkur	0	50	813	863
4	Mailam	0	56	744	800
5	Gingee	0	138	1019	1156
6	Marakanam	19	381	338	738
7	Vanur	31	600	319	950
8	Kanai	0	525	544	1069
9	Vikravandi	6	88	413	506
10	Mugaiyur	0	656	763	1419
11	Sankarapuram	0	0	688	688
12	Rishivandiyam	0	219	1325	1544
13	Kalrayan hills	0	0	181	181
14	Thirukoilur	0	331	675	1006
15	Koliyanur	6	363	75	444
16	Thiruvennainallur	19	494	0	513
17	Ulundurpet	6	725	569	1300
18	Kallakurichi	0	50	1469	1519
19	Thirunavalur	19	663	25	706
20	Thiagadurugam	0	550	675	1225
21	Chinnasalem	0	13	2069	2081
	Total	**106**	**5931**	**16300**	**22338**

WRSI Level: 100% - No Risk; 90-100% - Low Risk; 80-90% - Medium Risk; 70-80%- High Risk; 50-70%- Very High Risk and <50% - Chance of Crop failure

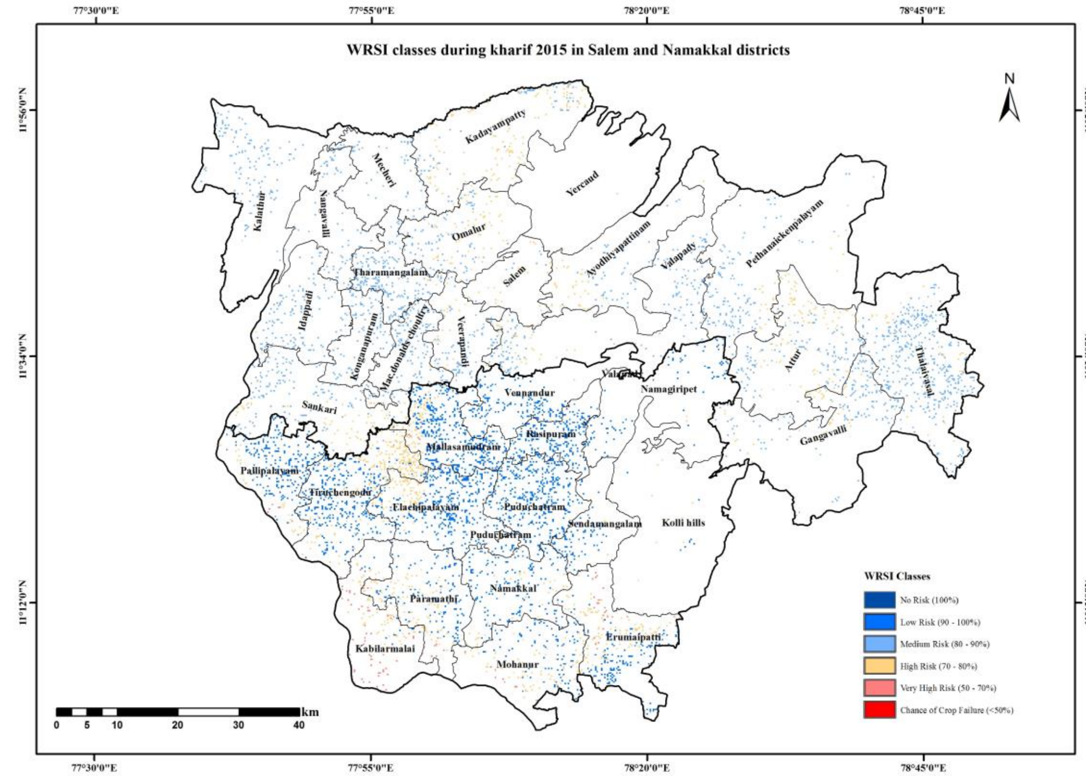

Fig.41. Drought level based on WRSI during *kharif* 2015 in Salem and Namakkal districts

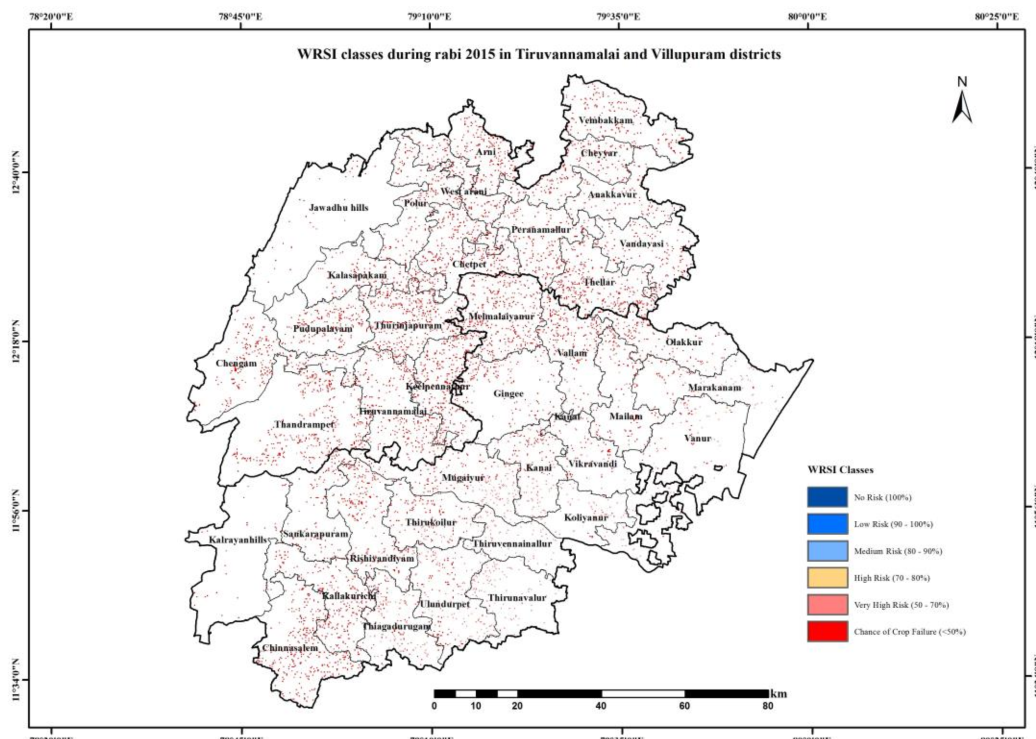

Fig.42. Drought level based on WRSI during *rabi* 2015 in Tiruvannamalai and Villupuram districts

Namakkal district, Mallasamudram block had more groundnut area of 2400 ha under low risk condition followed by Elachipalayam, Puduchatram and Tiruchengodu blocks which covered 2356, 2269 and 2013 ha respectively. Under high risk condition, Tiruchengodu block had maximum area of 1325 ha of groundnut. Rasipuram and Puduchatram block had no area of groundnut under high risk and very high risk condition. All the blocks of Namakkal district had lower or none of groundnut area under very high risk condition except Kabilarmalai which had 356 ha under high risk condition out of total groundnut area of 894 ha in the block.

During *rabi* 2015, Tiruvannamalai district registered larger groundnut area under very high risk and chance of crop failure based on WRSI. Out of total groundnut area 24919 ha, majority area with 24681 ha was found to be under chance of crop failure and remaining 238 ha only was covered in very high risk condition. All the 18 blocks were classified under chance of crop failure condition except Pudupalayam, Chengam, Keelpennathur, Tiruvannamalai and Thandrampattu blocks which had some groundnut area under very high risk condition also. Under chance of crop failure condition, Thurinjipuram block had maximum groundnut area with 2325 ha followed by Thandrampattu and Keelpennathur blocks which covered 2200 and 1956 ha respectively.

In Villupuram district, out of total groundnut area 22338 ha, an area of 16300 ha was classified as chances of crop failure condition followed by very high risk and high risk conditions with 5931 and 106 ha, respectively. Under chance of crop failure condition, among the 21 blocks, the maximum groundnut area of 2250 ha was found in Melmalaiyanur followed by Chinnasalem with 2069 ha. Especially the whole groundnut area of Melmalaiyanur block was found under this condition. Thiruvennainallur block had none of groundnut area under the condition of chance of crop failure.

4.9. Assessing overall vulnerability of groundnut to drought

Overlaying three different drought indices *viz*., SPI, NDVI and WRSI, the distribution of vulnerability of groundnut area to drought was assessed (Fig. 43 and 44) and blockwise statistics were generated. During *kharif* season, in Salem district, out of total groundnut area 17938 ha, most of the groundnut area was found to be under low vulnerability level with 12031 ha followed by 5850 and 56 ha under moderate level and high level of vulnerability (Table 44.). Among the 19 blocks, most of the blocks were classified as less vulnerable except Kadayampatty, Salem and Attur which were moderately vulnerable to drought. In low vulnerability class which one have majority of groundnut area, the maximum groundnut area

Table 44. Blockwise drought vulnerability levels and corresponding groundnut area (ha) in Salem district

S.No.	Block	Level of Vulnerability to drought			Total
		High	Moderate	Low	
1	Kadayampatty	6	819	363	**1188**
2	Kalathur	0	288	538	**825**
3	Yercaud	0	31	0	**31**
4	Mecheri	0	125	244	**369**
5	Nangavalli	0	31	450	**481**
6	Valapady	0	375	894	**1269**
7	Pethanaickenpalayam	0	306	713	**1019**
8	Omalur	0	425	469	**894**
9	Ayodhiyapattinam	0	219	338	**556**
10	Tharamangalam	0	75	1169	**1244**
11	Salem	6	188	50	**244**
12	Idappadi	0	56	750	**806**
13	Attur	6	725	663	**1394**
14	Thalaivasal	0	744	2119	**2863**
15	Veerapandi	6	213	506	**725**
16	Konganapuram	0	144	456	**600**
17	Mac.donalds choultry	13	213	688	**913**
18	Sangakiri	19	513	756	**1288**
19	Gangavalli	0	363	869	**1231**
	Total	**56**	**5850**	**12031**	**17938**

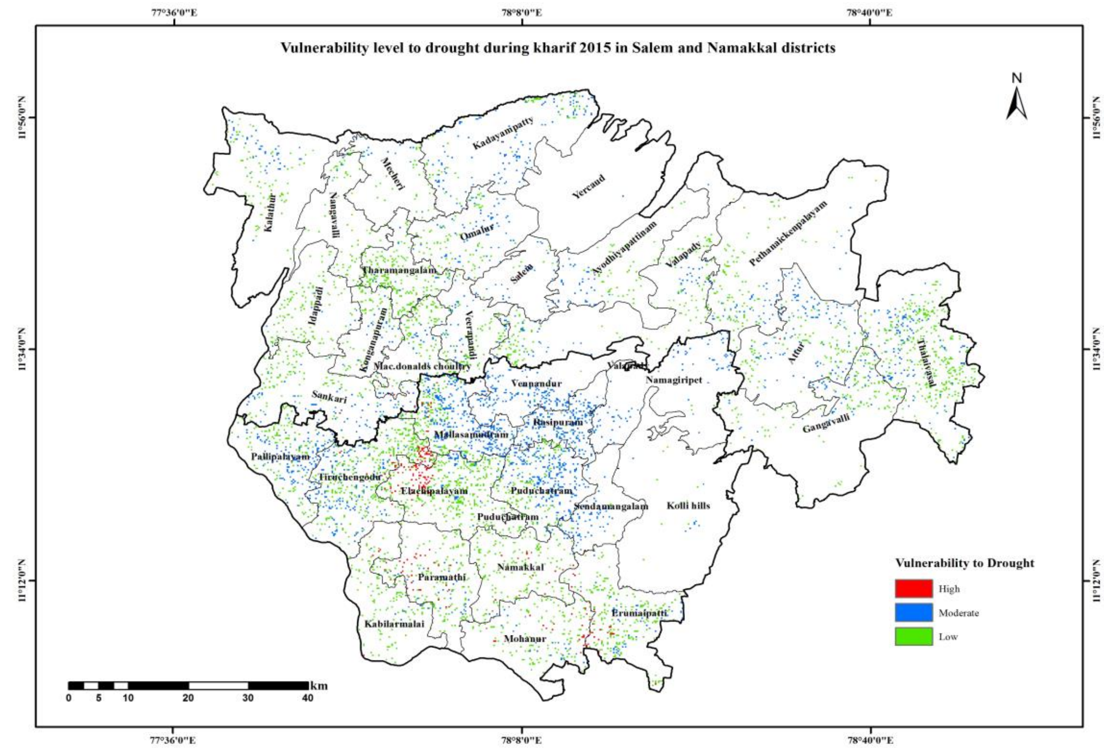

Fig.43. Vulnerability level map of groundnut to drought in Salem and Namakkal district

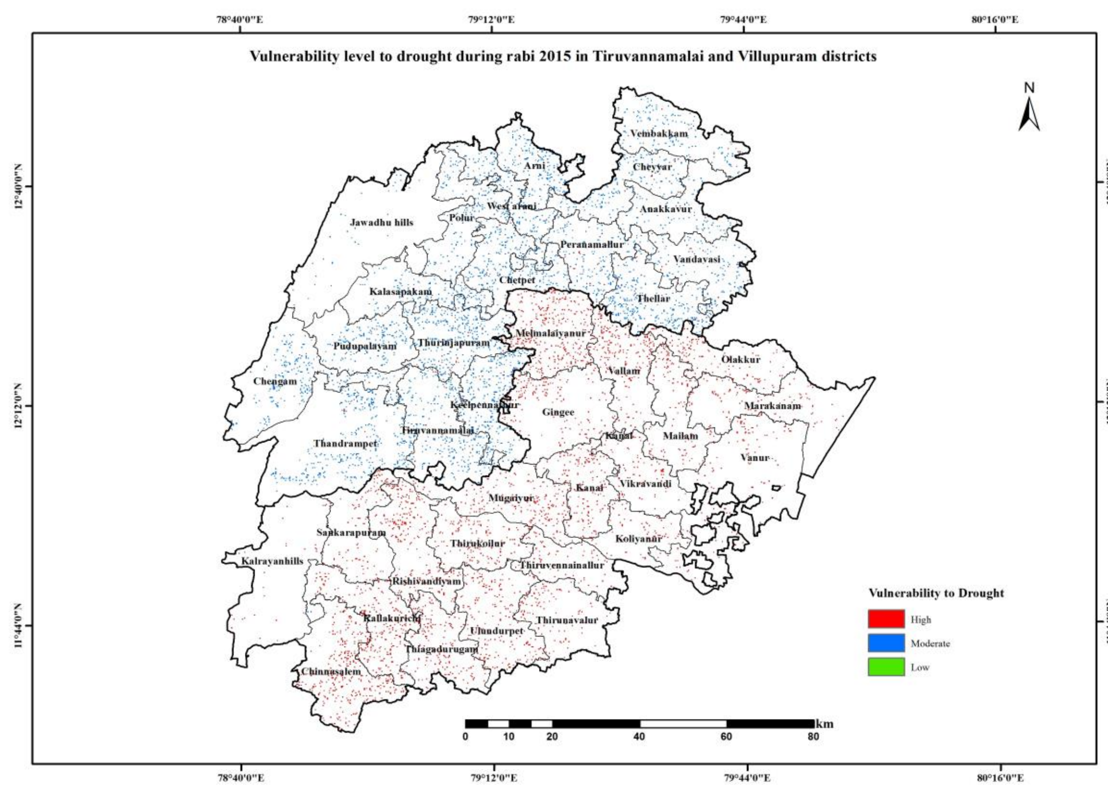

Fig.44. Vulnerability level map of groundnut to drought in Tiruvannamalai and Villupuram district

was observed under Thalaivasal block with 2119 ha followed by Tharamangalam block with 1169 ha of groundnut area.

Considering the overall vulnerability of groundnut to drought in Namakkal district, out of the total groundnut area of 23119 ha, 9713 ha was found to be less vulnerable followed by 11938 ha as moderately vulnerable to drought. Major groundnut areas of Mallasamudram, Puduchatram, Rasipuram, Sendamangalam and Vennandur blocks were found to be less vulnerable to drought. While major areas of Tiruchengodu, Elachipalayam and Erumaipatti blocks were moderately vulnerable to drought. An area of 1469 ha under groundnut in Elachipalayam, Tiruchengodu and Paramathi was highly vulnerable to drought (Table 45.).

During *rabi* 2015, the studies on vulnerability to drought in groundnut showed that all the 18 blocks of Tiruvannamalai district covering a groundnut area of 24294 ha were classified as moderately vulnerable to drought. In case of Villupuram district, all the 21 blocks covering groundnut area of 22369 ha were found to be highly vulnerable to drought (Table 46 and 47).

Considering overall vulnerability, 14 blocks of Salem and 6 blocks Namakkal were found to be less vulnerable to drought for groundnut cultivation whereas four and eight blocks of Salem and Namakkal districts were moderately vulnerable to drought. The results of this study revealed that all the blocks of Tiruvannamalai were moderately vulnerable to drought while the whole district of Villupuram was highly vulnerable to drought with regard to groundnut cultivation (Table 48 and 49).

Table 45. Blockwise drought vulnerability levels and corresponding groundnut area (ha) in Namakkal district

S.No.	Block	Level of Vulnerability to drought			Total
		High	Moderate	Low	
1	Namagiripet	0	19	550	**569**
2	Vennandur	0	31	1019	**1050**
3	Rasipuram	0	88	1231	**1319**
4	Mallasamudram	75	956	1919	**2950**
5	Kolli hills	0	63	50	**113**
6	Pallipalayam	0	788	888	**1675**
7	Tiruchengodu	288	2138	988	**3413**
8	Puduchatram	0	775	1506	**2281**
9	Sendamangalam	0	63	456	**519**
10	Elachipalayam	463	2106	294	**2863**
11	Paramathi	219	963	219	**1400**
12	Kabilarmalai	31	788	63	**881**
13	Namakkal	94	994	69	**1156**
14	Erumaipatti	163	1319	306	**1788**
15	Mohanur	138	850	156	**1144**
	Total	**1469**	**11938**	**9713**	**23119**

Table 46. Blockwise drought vulnerability levels and corresponding groundnut area (ha) in Tiruvannamalai district

S. No.	Block	Level of Vulnerability to drought			Total
		High	Moderate	Low	
1	Vembakkam	75	1031	0	**1106**
2	Arni	13	1256	0	**1269**
3	West Arani	6	1131	0	**1138**
4	Polur	0	1219	0	**1219**
5	Cheyyar	75	1156	0	**1231**
6	Jawadhu hills	0	213	0	**213**
7	Anakkavur	25	644	0	**669**
8	Peranamallur	75	1075	0	**1150**
9	Chetpet	63	1638	0	**1700**
10	Vandavasi	75	894	0	**969**
11	Thellar	56	1969	0	**2025**
12	Kalasapakam	0	1044	0	**1044**
13	Thurinjapuram	88	2281	0	**2369**
14	Pudupalayam	13	1175	0	**1188**
15	Chengam	25	1606	0	**1631**
16	Keelpennathur	50	1969	0	**2019**
17	Tiruvannamalai	81	1738	0	**1819**
18	Thandrampattu	25	2256	0	**2281**
	Total	**744**	**24294**	**0**	**25038**

Table 47. Blockwise drought vulnerability levels and corresponding groundnut area (ha) in Villupuram district

S. No.	Block	Level of Vulnerability to drought			Total
		High	Moderate	Low	
1	Melmalaiyanur	2250	0	0	**2250**
2	Vallam	1394	0	0	**1394**
3	Olakkur	838	0	0	**838**
4	Mailam	819	0	0	**819**
5	Gingee	1150	6	0	**1156**
6	Marakanam	750	0	0	**750**
7	Vanur	963	6	0	**969**
8	Kanai	1081	0	0	**1081**
9	Vikravandi	494	0	0	**494**
10	Mugaiyur	1425	0	0	**1425**
11	Sankarapuram	694	0	0	**694**
12	Rishivandiyam	1550	0	0	**1550**
13	Kalrayan hills	175	6	0	**181**
14	Thirukoilur	1013	0	0	**1013**
15	Koliyanur	450	0	0	**450**
16	Thiruvennainallur	494	0	0	**494**
17	Ulundurpet	1294	0	0	**1294**
18	Kallakurichi	1506	13	0	**1519**
19	Thirunavalur	700	0	0	**700**
20	Thiagadurugam	1231	0	0	**1231**
21	Chinnasalem	2100	0	0	**2100**
	Total	**22369**	**31**	**0**	**22400**

Table 48. Blockwise levels of vulnerability to drought in groundnut

District	Blockwise Vulnerability to drought		
	Low	**Moderate**	**High**
Salem (19 Blocks)	Kalathur, Mecheri, Nangavalli, Valapady, Pethanaickenpalayam, Omalur, Ayodhiyapattinam Tharamangalam, Idappadi, Thalaivasal, Veerapandi, Konganapuram, Mac.donalds choultry, Sangakiri and Gangavalli**(15 Blocks)**	Kadayampatty, Yercaud, Salem and Attur **(4Blocks)**	Nil
Namakkal (15 Blocks)	Namagiripet, Vennandur, Rasipuram, Mallasamudram, Pallipalayam, Puduchatram and Sendamangalam **(7 Blocks)**	Kolli hills, Tiruchengodu, Elachipalayam, Paramathi, Kabilarmalai, Namakkal, Erumaipatti and Mohanur**(8 Blocks)**	Nil
Tiruvannamalai (18 Blocks)	Nil	Vembakkam, Arani, West Arani, Polur, Cheyyar, Jawadhu hills, Anakkavur, Peranamallur, Chetpet, Vandavasi, Thellar, Kalasapakam, Thurinjapuram, Pudupalayam, Chengam, Keelpennathur, Tiruvannamalai and Thandrampattu **(18 Blocks)**	Nil
Villupuram (21 Blocks)	Nil	Nil	Melmalaiyanur, Vallam, Olakkur, Mailam, Gingee, Marakanam, Vanur, Kanai, Vikravandi, Mugaiyur, Sankarapuram, Rishivandiyam, Kalrayan hills, Thirukoilur, Koliyanur, Thiruvennainallur, Ulundurpet, Kallakurichi, Thirunavalur, Thiagadurugam and Chinnasalem **(21 Blocks)**

Table 49. District wise groundnut area (ha) under levels of vulnerability to drought

S.No.	District	Vulnerability to drought			
		Low	Moderate	High	Total
1	Salem	12031	5850	56	17938
2	Namakkal	9731	11944	1496	23125
3	Tiruvannamalai	-	24294	744	25038
4	Villupuram	-	31	22369	22400
	Total	**21762**	**42119**	**24665**	**88501**

Discussion

CHAPTER V

DISCUSSION

India is the second largest producer of groundnut after China. Groundnut is the largest oilseed in India in terms of production and plays an important role as food crop. Monitoring, estimating and forecasting of groundnut area and production are very important for the management of regional or local food demand and supply balance for social security.

Traditional decision support systems based on crop simulation models are normally site-specific. In policy formulation, however, spatial variability of crop production often needs to be evaluated due to different soil, weather conditions and agricultural practices within a target-region. In this thesis, to address the spatial variability of groundnut growth and yield, a crop simulation model "DSSAT- CROPGRO-Peanut model" was used and the simulated outputs are generated at spatially for twenty different groundnut field locations of the study area. The simulated values were validated with observed values.

Precipitation level, vegetation cover and evapotranspiration considered as drought indicators were evaluated for assessing vulnerability of groundnut to agricultural drought. The present study investigated the use of remote sensing data for groundnut acreage monitoring, integrating with crop simulation model to estimate yield and assess vulnerability of groundnut to drought in rainfed districts of Tamilnadu. The aim was to support an operational satellite crop monitoring system that could assist farmers and land managers to better manage their groundnut cultivation in rainfed districts.

A research study on 'Mapping and Modeling growth and productivity of groundnut in Rainfed Areas of Tamilnadu' was conducted during *kharif* 2015 (Salem and Namakkal districts) and *rabi* 2015 (Tiruvannamalai and Villupuram districts) to estimate groundnut area, model growth and productivity and assess the vulnerability of groundnut to drought. The results presented in the previous chapter are discussed in this chapter.

5.1. Spatial assessment of groundnut area

Groundnut is essentially a tropical plant. It requires a long and warm growing season. The most favourable climatic conditions for groundnuts are well-distributed rainfall of at least 50 cm during growing season, abundance of sunshine and relatively warm temperature. Groundnut varieties range in duration from 90 to more than 135 days and with three main crop phenological developments (emergence, flowering and podding).

5.1.1. Radar backscattering signature generation

SAR data have a proven ability to detect rainfed groundnut through the unique temporal signature of the backscatter coefficient (also termed sigma naught - σ°) exhibited by the crop. Research effort was taken to use multi-temporal C-band SAR data from Sentinel 1A, semi-automated processing chains, in-season field monitoring and end-of-season validation points to map groundnut crop across major rainfed districts (Salem, Namakkal, Tiruvannamalai and Villupuram) of Tamilnadu. In the past years, lot of research efforts were taken for better understanding this relationship and applying it to crop detection and crop monitoring (Le Toan *et al*., 1997, Inoue *et al*., 2002, Suga and Konishi, 2008, and Bouvet *et al*., 2009).

Temporal signatures were extracted for each monitoring site and used to generate the dB curves for groundnut fields shows the temporal signature for selected representative pixels to visualize the resulting maximum likelihood classification using Multi Temporal Features (MTF). Groundnut crop showed significant temporal behaviour and a large dynamic range in Salem and Namakkal districts (-10.15 to -6.84 dB for VV and -20.04 to -14.95 for VH polarization) and Tiruvannamalai and Villupuram districts (-10.67 to -7.99 dB for VV and –18.18 to -14.98 for VH polarization) during its growth period. An increase in backscatter was observed during the growth period for the first six acquisitions that was typical of the seedling to maturity stage which was due to the interaction of microwave radiation with the crop canopy, increasing from the detection of σ° minimum (emerging) to the detection of σ° maximum (maturity) between acquisitions one and six for Salem and Namakkal districts and two and seven for Tiruvannamalai and Villupuram districts.

The backscatter minimum was observed in the initial acquisition, indicating emerging conditions of groundnut crop in all the districts, followed by an increase in backscatter in the succeeding acquisitions, indicating growth of the groundnut crop. The field crop signal showed a distinctly different temporal evolution and the quick biomass production at 60 DAS which helped precise discrimination of groundnut crop pixel by pixel. In short, this temporal variation of SAR backscatter delineated groundnut fields from other land cover classes.

A detailed analysis of temporal signatures of groundnut showed a minimum at emergence stage and a peak at maturity stage. At emergence stage, minimum dB values of -10.99 to -9.56 dB for VV and -20.04 to -16.47 for VH polarization were observed in Salem and Namakkal districts whereas a minimum of -11.74 to -9.72 dB for VV and -18.57 to -17.79 for VH polarization were observed in Tiruvannamalai and Villupuram districts at emergence stage of groundnut. The lowest values at emerging were due to less back scattering from less vegetation cover with rougher surface which was the moment to capture the start of the season for each pixel. This might be the due to soil moisture variation (Blaes *et al*., 2005) or sowing which made the soil surface smoother (Karjalainen *et al*., 2004). Nelson *et al*., 2014 recorded a similar minimum at early stage of rice crop with X-band (TerraSAR-X and Cosmosymed) SAR data across Asia in Philippines and Thailand.

The average maximum value at maturity stage in VV polarization was found to be -6.84 with a range of -5.60 to -8.12 and an average of -14.95 with a range of -13.05 to -14.95 in VH polarization in the fields across Salem and Namakkal districts. Similar trend was observed in Tiruvannamalai and Villupuram districts where average maximum value at maturity stage was -7.99 with a range of -5.31 to -9.14 (VV) and average of -14.98 with a range of -14.15 to -15.71 (VH). A marginal increase was recorded in backscattering at seedling to vegetative stage and a steep increase from flowering to pod development (2.07 dB in VV polarization) followed by a decline thereafter at maturity. The similar trend of minimal increase in backscattering at vegetative stage and steep increase from flowering to pod development with a variation of 2.27 dB and a decline thereafter at maturity was observed in VH polarization. The decrease in backscatter value at later stages might have been probably caused by maturity of crop, which lowered the water content of vegetation (Lillesand and Kiefer, 1994) or related to the vegetation biomass (Skriver *et al.*, 1999) and or related to the reduced volumetric scattering due to maturity (drying and fall of lower leafs) (Panigrahy and Mishra, 2003).

The primary variation related to the growth from sowing to seedling stage where the addition in LAI and biomass and thereby ground coverage was less. However as the growth advanced, groundnut had the tendency to putforth more biomass and thereby resulting in more dB values with an addition of 2.07 for VV and 2.27 for VH polarization. In all the fields the mean dB values tend to drop further from maturity to harvesting with values found to be reducing from -6.84 to -.7.70 (VV) and -13.90 to -14.77 (VH) in Salem and Namakkal districts. Whereas, the values were found to be reducing from -7.99 to -.8.95 (VV) and -14.98 to -15.69 (VH) in Tiruvannamalai and Villupuram districts. Rice crop showed significant temporal behaviour and a large dynamic range (−14.4 to −8.41dB) during its growth period (Inoue *et al*. (2002), Suga and Konishi (2008), Oh *et al*., 2009 and Kim *et al*., (2009)).

5.1.2. Multi Temporal Features (MTF) extraction

The choice of parameters for classification was guided by a simple statistical analysis of the temporal signature of σ° values in the monitored fields. The Mean, Min, Max, Min Date and Max Date features for VV and VH polarizations were computed for the temporal signature of each monitored field. Among the features, maximum value for different groundnut fields ranged from -16.95 to -13.01 (VH Polarization) and -9.03 to -5.47 (VV Polarization) in Salem and Namakkal districts. In Tiruvannamalai and Villupuram districts the range of maximum was from -16.93 to -12.59 for VH and -8.89 to -6.06 for VV polarization, respectively. Minimum value for Salem and Namakkal ranged from -19.86 to -16.77 for VH and -12.58 to -9.26 for VV polarizations. Similarly groundnut field of Tiruvannamalai and Villupuram districts recorded minimum values of -20.01 to -17.94 for VH and -12.36 to -8.61 for VV polarization, respectively. Similarly, mean values for Salem and Namakkal groundnut fields ranged from -17.80 to -15.81 (VH) and -10.82 to -7.87 (VV). In Tiruvannamalai and Villupuram districts groundnut fields recorded a mean value of -17.96 to -14.46 and -10.64 to -7.77 dB for VH and VV polarizations, respectively. Nelson *e al*. (2014) used X-band SAR data and successfully extracted MTF (in dB) from rice monitoring fields and used for the rice classification.

Max Date (Date of the maximum) feature of Salem and Namakkal fields was found to be D_6 (5th November, 2015) for both VH and VV polarization. Likewise, Min Date (Date of the minimum) for both VH and VV were found to be D_1 (8th July, 2015) showing synchrony in sowing and maturity in these districts. In groundnut fields of Tiruvannamalai and Villupuram districts, the Max Date features for VH and VV polarization were recorded between D_6 (30th December, 2015) and D_8 (23rd January, 2016) with majority of the fields recording maximum date as D_7 (11th January, 2016). The Min Date feature for VH polarization was between D_1 (31st October, 2015) and D_3 (24th November, 2015) and for VV polarization it occurred during D_1 (31st October, 2015) and D_2 (12th November, 2015) indicating a sowing window during October to November and a harvest window during January to February in these two districts. Further coherence in these dates might have helped precise segregation of groundnut pixels from other dry crops sown in these areas. These five statistics, called as temporal features, concisely characterized the key information in the groundnut signatures of the observed fields, and each one related directly to one parameter. Hence, the value of the five temporal features from the monitoring locations at each site were used to guide the choice of the five parameter values based on which the groundnut pixels were classified and the groundnut area maps were generated which was in line with work reported by Pazhanivelan *et al*., (2015).

Further, short wavelengths (X-, C, Ka-, Ku-band), especially at large incident angles, are sensitive enough to detect even very small groundnut seedlings just after emergence. The correlation between σ° and groundnut biophysical parameters showed that lower frequencies were more closely related to total fresh weight, leaf area index (LAI) and plant height than other parameters. On the other hand, σ° derived from C-band can provide information on par with the normalized difference vegetation index (NDVI) (Inoue *et al*., 2014).

5.1.3. Groundnut area and accuracy assessment

Groundnut area map was derived from multi-temporal C-band SAR imagery from Sentinel 1A for all the four districts. Groundnut area during *kharif* 2015 (Salem and Namakkal districts) and *rabi* 2015 (Tiruvannamalai and Villupuram districts) were distinguished in the maps below for discussion purposes. The total groundnut area across the four districts of Salem, Namakkal, Tiruvannamalai and Villupuram districts was estimated to be 88023 ha. In Salem and Namakkal districts during *kharif* 2015, groundnut area map showed an accuracy of 78.3% with overall accuracy of 85.2% with reliability of 85.9% and kappa score of 0.70 with 46 groundnut and 42 non-groundnut validation points. Whereas, Tiruvannamalai and Villupuram districts during *rabi* 2015 showed a good accuracy of 85.5% for groundnut and 93.5% for other land types. The overall accuracy of 88.9% with reliability of 88.7% and kappa score of 0.78 with 62 groundnut and 46 non-groundnut validation points. The overall classification accuracy was done for the study area with the 196 validation points covering 108 groundnut and 88 non-groundnut points and accuracy was consistently high (87.2 %), with Kappa score of 0.74. Estimation of rice area in Tamilnadu, India at district level an accuracy of 99% was achieved in Cuddalore followed by Sivaganga and Thanjavur districts respectively with 88 and 86.7%. At block level it was interesting to come across an accuracy of 85 to 96% indicating the suitability of these products for policy decisions (Pazhanivelan *et al*., 2015).

Among the 19 blocks of Salem district, Thalaivasal block recorded the highest groundnut area whereas Yercaud followed by Salem recorded the lowest groundnut area. In Namakkal district (15 blocks), Tiruchengodu block recorded the highest groundnut area followed by Mallasamudram, Elachipalayam and Puduchatram blocks with an area of nearly 2000 ha (Fig. 45) indicating the predominance of these blocks cultivating groundnut historically.

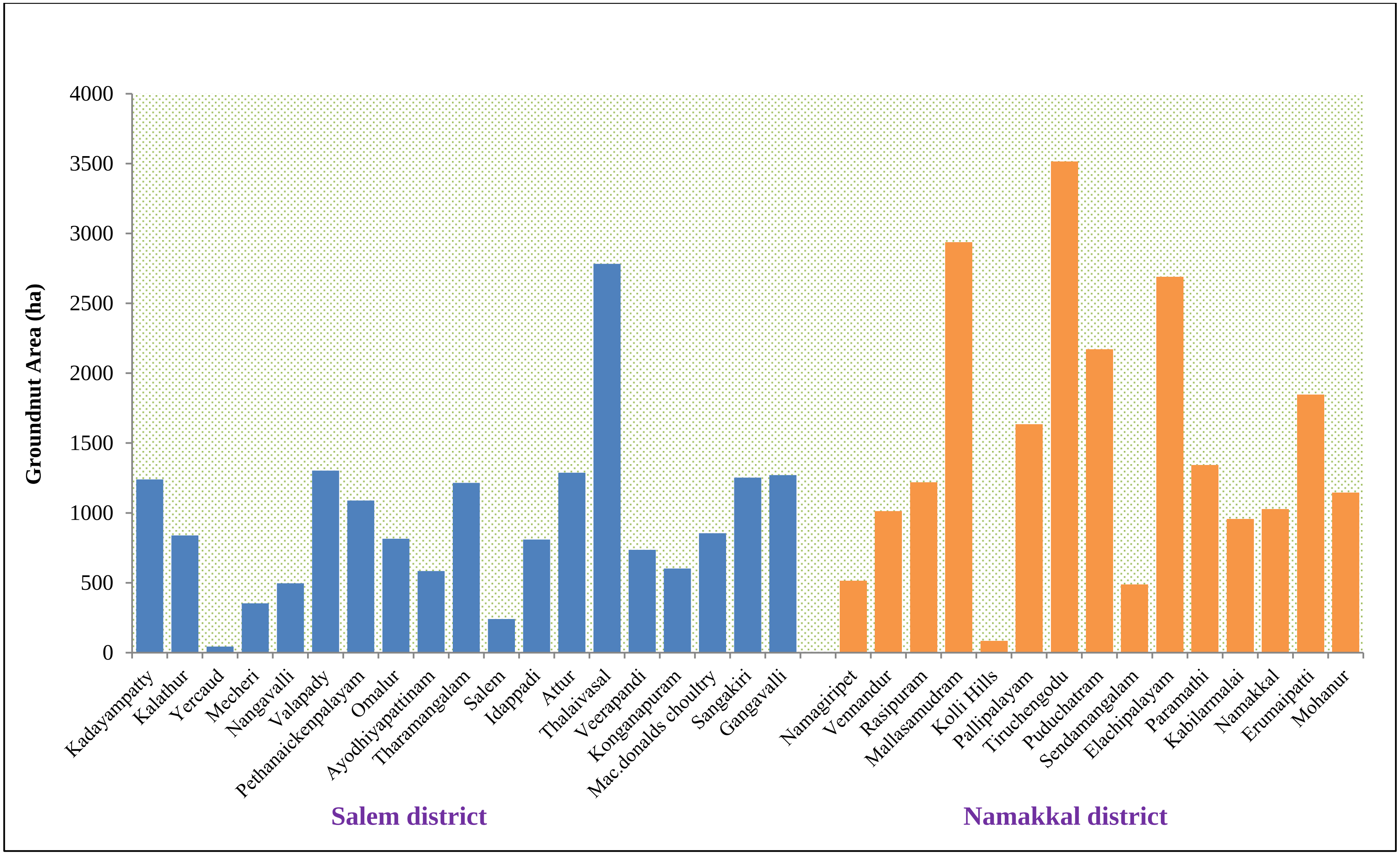

Fig.45. Blockwise Groundnut area during *kharif* 2015 in Salem and Namakkal districts

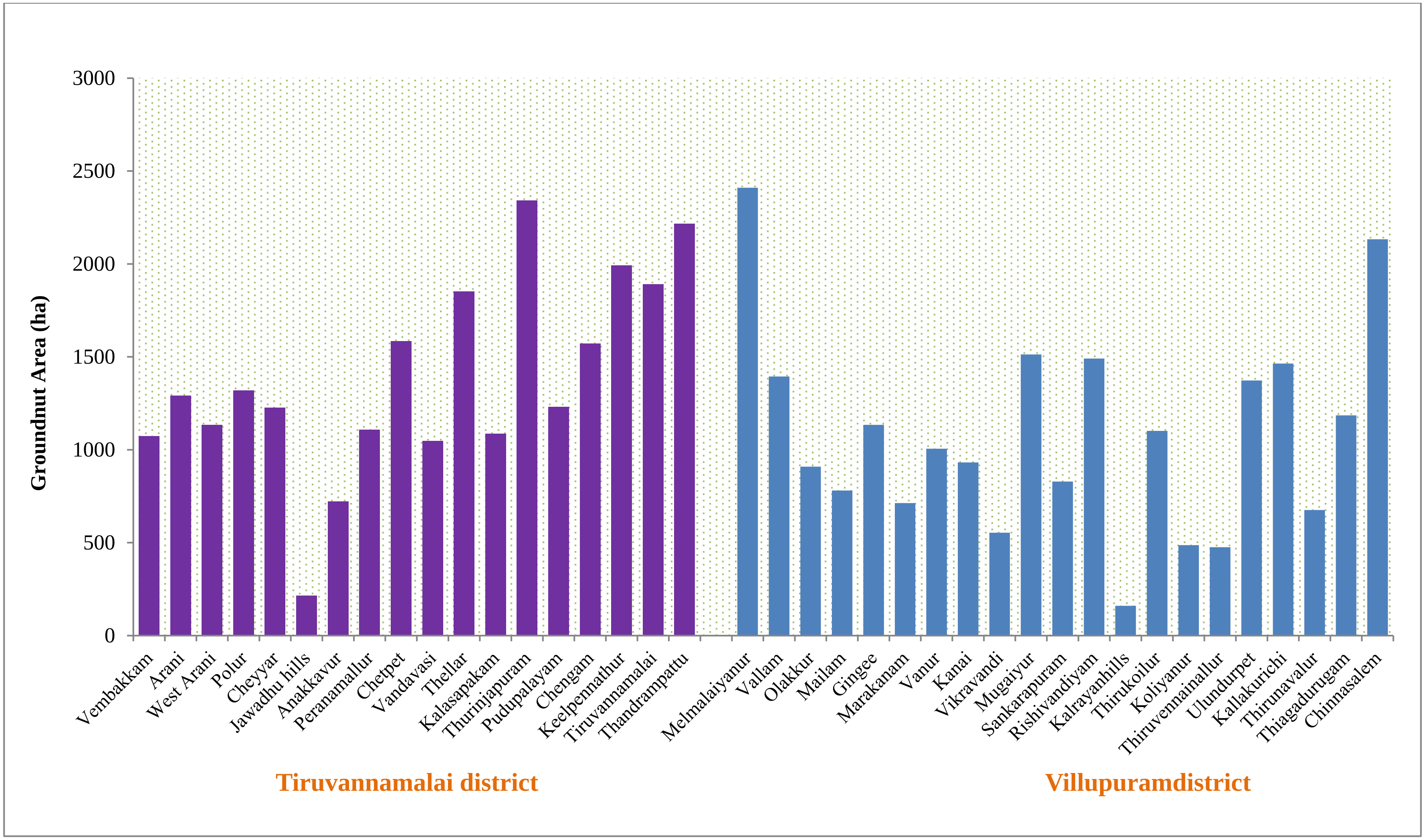

Fig.46. Blockwise Groundnut area during *rabi* 2015 in Tiruvannamalai and Villupuram districts

In Tiruvannamalai district (18 blocks), Thurinjipuram and Thandrampattu blocks recorded the higher groundnut area whereas the lowest groundnut area was recorded in Jawadhu hills block followed by Anakkavur block. In Villupuram district (21 blocks), Melmalaiyanur and Chinnasalem blocks recorded higher area of groundnut and the lowest groundnut area was recorded in Kalrayan hills block followed by Thiruvennainallur and Koliyanur blocks respectively (Fig. 46). The lowest groundnut area in blocks spread over hilly undulating region in these districts showed the unsuitability caused by slope and other soil characteristics.

The consistently high accuracy of the groundnut area classification across these rainfed districts of Tamilnadu demonstrated that the methodology was appropriate for groundnut detection across the most common rainfed ecosystem. The classification was based on a temporal analysis of the spectral signature, including a detection of emergence stage followed by a rapid increase in biomass relative to the duration of the vegetative stage of the varieties in the sensor footprint. The monitoring site data were critical for the correct interpretation of the spectral signature.

5.2. Modeling growth and productivity of groundnut using DSSAT

Simulation models are useful in deciding the best possible management options for optimum growth and yield of any crop against available climatic variables along with soil and water inputs. Uses of these models are gaining importance particularly for spatial simulation models which can facilitate identification of production constraints and assist in technology transfer. PNUTGRO model was used a successful tool to evaluate effects of climate, soil, hydrologic and agronomic factors on groundnut yield and its variability (Boote *et al*., 1987) which could be extrapolated spatially.

The generated data sets of weather, soil, genetic coefficients of cultivars and management files from DSSAT were used to simulate the growth and productivity of groundnut at spatial level across the study area. Davenport *et al*. (2015) found that models with spatially varying coefficients were better able to simulate distributions than basic linear regression models.

5.2.1. Input files generation in DSSAT model

The DSSAT family of crop models required model input files that were written in a very specific format. For applications, the soil file containing unique blocks of text in the specified DSSAT format were generated to define the necessary soil properties for each management zone. Cultivar files for individual cultivar containing the co-efficient for each cultivar for use in model calibration are described in detail below. These methods had been used successfully in several studies (Thorp *et al.*, 2006 & 2007), DeJonge *et al.* (2007) and Miao *et al*. (2006) but have not yet been fully explained.

It is a common practice to use crop models with long time historical weather data to study the impact of climatic variability on agricultural production (Hammer *et al*. (1987), Chipanshi *et al*. (1999) and Mavromatis *et al*. (2002). Using 'weatherman' in DSSAT, the weather input files were generated for 20 locations during *kharif* 2015 in Salem and Namakkal districts with a value of 30.6 to 36.3°C as compared to *rabi* 2015in Tiruvannamalai and Villupuram districts which recorded values of 28.9 to 31.7 °C. Jones and Thornton (2013) also successfully generated weather files for crop simulation model**.** Nevertheless, the variation in spatially simulated yields mainly reflected the intra-annual weather variability (Hansen and Jones, 2000).

Using 'S' build in DSSAT (Hoongenboom *et al*., 2010), the input files for soil were generated with 13 parameters *viz*., Depth until base of layer, Lower limit of plant extractable soil water, Drained upper limit, Saturated upper limit, Root growth factor, Saturated hydraulic conductivity, Bulk density, Soil organic carbon concentration, Clay, Silt, Coarse fraction, pH in water and Soil Cation Exchange Capacity. In the study area of four districts a total of twelve soil series were found to be predominantly present. The input files generated using 'S' build showed that the bulk density (SBDM) of the study area ranged from 1.44 to 1.62 g cm^{-3} whereas the soil organic carbon concentration ranged from 0.20 to 0.92, pH ranged from 6.0 to 8.9, Cation Exchange Capacity ranged from 7.3 to 39.5 and soil depth 42 to 276 cm. Thorp *et al*. (2008) reported that the DSSAT uses common modules for soil dynamics regardless of the plant growth module selected.

In DSSAT 'GENCAL' using the observed value from monitoring fields, the model was calibrated for genetic coefficients of cultivars CO 6, TMV 7 and VRI 2 determining their phenology and growth, as well as for soil and weather variation at spatial level. Singh *et al*. (1994) successfully generated all the input files such as weather, soil and genetic co-efficient files for spatial simulation of groundnut growth and productivity. The inputs requirement for

PNUTGRO (DSSAT4.5) model and values of genetic coefficients as derived from calibration of the model were successfully validated for cultivars of groundnut during *kharif* in Anand of middle Gujarat region (Yadav *et al*., 2012).

5.2.2. Simulation of growth and development variables of groundnut by DSSAT

CROPGRO-Peanut model was used to quantify the impact of spatial variability on groundnut productivity at rainfed groundnut area of study districts. Growth and development variables of groundnut *viz*., days to emergence, days to anthesis, pod development, seed development and physiological maturity, yield at harvest (kg ha^{-1}), pod weight (kg ha^{-1}), pod number m^{-2} were simulated by DSSAT-PNUTGRO model for twenty monitoring locations across the study area and presented. Besides maximum LAI, Harvest index, Threshing per cent, N content in grain, tops and stem at maturity and canopy height (m) were also simulated in each location spatially. Nokes and Young (1991) showed that the 'PNUTGRO' model efficiently simulated the groundnut growth and development. DSSAT model accurately simulated crop growth development and yield for groundnut and various legume crops at different location as reported by Mote *et al*. (2016).

The CROPGRO-Peanut simulated the days for different physiological process of groundnut. The days to emergence ranged from 7 to 9 days across locations while the days to anthesis varied from 25 to 32 days. Among the locations Nochokarakadu with the variety Co 6 registered a minimum 107 days to maturity while Melsevalambadi with the variety TMV 7 recorded a maximum number of 117 days to maturity. Similarly the simulations were made for days to first pod development to first seed development and physiological maturity and they showed that groundnut took 36 to 44 days anthesis, 43 to 51 days for first pod development and 107 to 117 days to physiological maturity. The result were in good agreement with the findings of Akula (2003) for days to anthesis in wheat as simulated by WTGROWS and INFOCRO model at Anand. Kumar *et al*. (2014) reported that CROPGRO model satisfactorily simulated phenological events like anthesis, first pod day, physiological maturity and harvest maturity at Pantnagar. DSSAT model resulted in a simulated canopy height of 0.63 to 0.70 m and maximum LAI of 1.12 to 3.07. Vellapillakovil and Kakapalayam resulted in higher simulation of LAI with values of 3.07 followed by Velagavundanpatti and Pappambadi registering maximum LAI of 3.05. However the model simulated a lesser LAI of 1.12 to 1.48 at Keelravandavadi and Arkandanallur sites. These simulation results were in line with the findings of Gilbert *et al*. (2002) who opined that when independent crop and soil datasets were used to evaluate, PNUTGRO model was influenced by seasons and location on simulating growth and yield.

The crop growth model also simulated the leaf number per stem at maturity. As influenced by the canopy height, leaf number and maximum LAI, the tops weight at maturity (kg ha-1), was also simulated by the model and found to be in the range 4176 to 9576 kg ha^{-1}. The yield parameters *viz*., pod weight (kg ha^{-1}), number of pods m^{-2} and seed weight were also simulated. Kaur and Hundal, (1999) at Ludhiana studied 'PNUTGRO' model to predict phenological events of groundnut growth and yield parameters in Punjab and Gadgil *et al*., (1999) used the 'PNUTGRO' model, to study the growth and development of groundnut at ARS Anantapur. CROPGRO peanut model was used by Parmar *et al*. (2013) to simulate the phenological events, yield and yield attributing characters of groundnut cultivars of GG 2 and GG 20 in Gujarat precisely.

Groundnut pod yield was simulated by DSSAT-PNUTGRO and found to be in the range of 1796 to 3060 kg ha^{-1} across the study area with a harvest index of 0.28 to 0.43. Bhatia *et al*. (2005) who simulated the potential yield of rainfed groundnut across major production zones and the yield ranged from 2320 to 3170 kg ha^{-1} which was highly correlating with the results obtained in the present study across four districts with twenty locations. Similar finding on pod yield simulation by DSSAT in different location was reported by Gilbert *et al*. (2002). In the past years, lot of research efforts were taken for simulation of growth and productivity of groundnut and different other crops. Akula (2003) simulated growth and productivity of wheat using WTGROWS and INFOCROP at Anand and a spatial model for simulating wheat crop phenology across Europe was developed by Harrison *et al*. (2000).

5.2.3. Observed values of growth and yield

Observations were made on growth and yield parameters such as LAI, biomass, pod yield and harvest index at twenty monitoring locations regularly. LAI and biomass was positively correlated with pod yields of groundnut. In case of maximum LAI, Salem district recorded LAI of 3.45 to 4.04 with a mean of 3.67 and biomass of 7554 to 9959 kg ha^{-1} with a mean of 9060 kg ha^{-1}. In the monitoring sites of the district pod yield of 2115 to 2750 kg ha^{-1} were recorded while the harvest index was observed to be between 0.26 to 0.28. These results were in agreement with the findings of Vindhiyavarman *et al*. (2010) who reported higher pod yields of groundnut with higher LAI values.

Monitoring locations in Namakkal district registered a maximum LAI of 3.35 to 4.05 with a mean of 3.68 with biomass of 7222 to 9600 kg ha^{-1}. The resultant pod yield was observed to be 1950 to 2607 kg ha^{-1} with a harvest index of 0.25 to 0.29. Similarly in Tiruvannamalai the maximum LAI and biomass were observed to be in the range of 2.01 to 2.62 and 4620 to 7290 kg ha^{-1}. Similar finding on groundnut growth and yield was reported by Reddy *et al*., (2003). The resultant pod yields were between 1450 to 2187 kg ha^{-1} with a harvest index of 0.30 to 0.37. Whereas Villupuram district was recorded a comparatively lesser LAI of 2.44 to 2.80 with biomass of 4652 to 7403 kg ha^{-1}. Lesser LAI coupled with reduced biomass resulted in comparatively lower pod yields which were observed to be between 1535 to 2221 kg ha^{-1} with a harvest index of 0.30 to 0.34. The similar results were reported by Igbadun et al., (2005). In all the locations the harvest index was related to biomass and the yield of groundnut.

5.2.4. Model calibration and validation

The capability of the DSSAT-PNUTGRO model to predict growth and development of the three different groundnut cultivars (CO 6, TMV 7 and VRI 2) were assessed in terms of its ability to predict crop response as influenced by season, weather and soil distribution at spatial level. In order to accomplish this in a spatial level simulation, this process was repeated for every location. Observed values of groundnut growth and yield from monitoring fields during both *kharif* and *rabi* seasons in study area were used to validate the model performance in groundnut growth and yield. Model response for different environments in these monitoring fields is discussed below.

5.2.5. Validation of DSSAT model for groundnut growth variables

Growth data such LAI collected during the both seasons at study area were used to illustrate the model performance across seasons. The LAI simulated by model in all the twenty monitoring fields were validated with observed values. The maximum LAI in all the fields were slightly underestimated, but there was a significant correlation between observed and simulated values. These results were in agreement with those obtained by Singh *et al*. (1994). The individual agreement for all field locations ranged from 43 to 83 per cent (Fig. 47). The overall agreement between simulated and observed LAI values was 66 per cent. Negative significant association was observed between simulated and observed values. These results were in tune with those obtained by Kaur and Hundal (1999). Underestimation of LAI of groundnut regardless of sowing dates and varieties was also reported by Yadav *et al*. (2012).

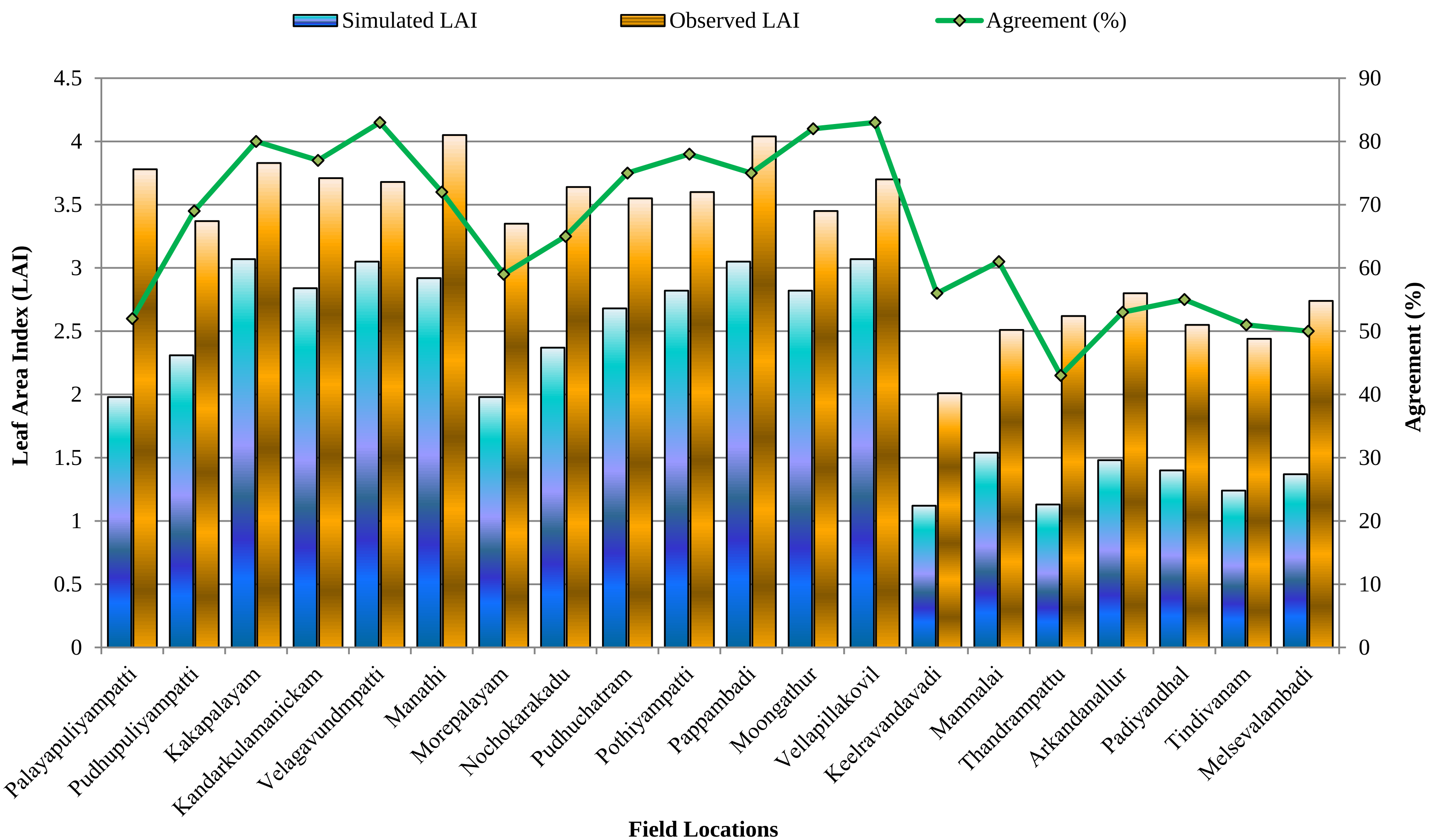

Fig.47. Validation of DSSAT-PNUTGRO model for groundnut Leaf Area Index

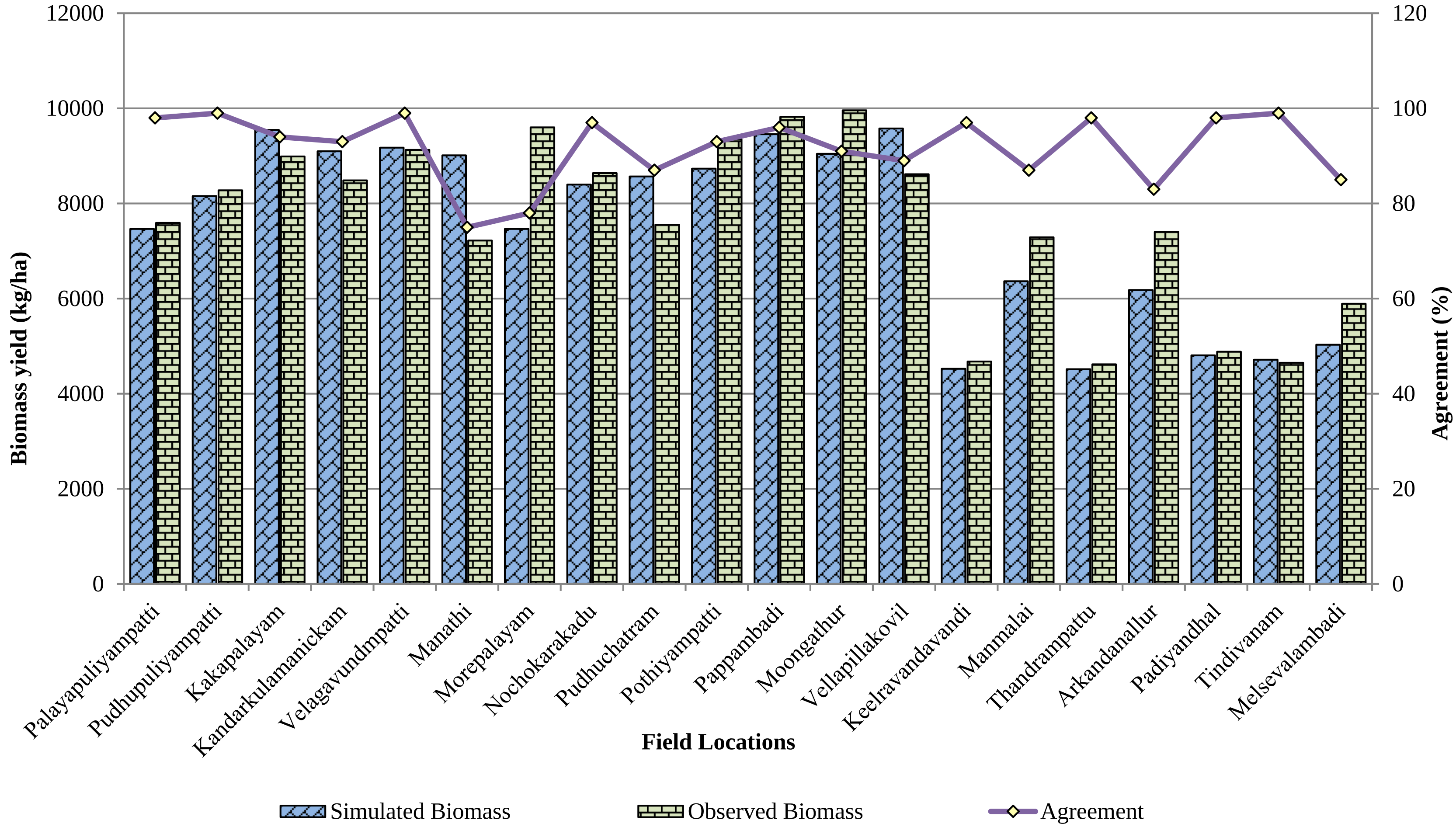

Fig.48. Validation of DSSAT-PNUTGRO model for groundnut biomass yield

The observed and model simulated groundnut biomass production for 20 monitoring fields during both *kharif* and *rabi* 2015 were compared and presented in Fig. 48. The figure showed that the observed biomass production ranged from 5246 kg ha^{-1} to 8969 kg ha^{-1} as compared to 4516 kg ha^{-1} to 9576 kg ha^{-1} of simulated values. The simulation of final biomass showed good agreement with the observed values as reported by Anothai *et al*. (2008).

The agreement between simulated and observed values was more acceptable for almost all monitoring field locations. The agreement of fields ranged from 78 to 98 per cent. The maximum level of agreement of 98 per cent was recorded in Moongathur followed by 97 and 96 per cent in Pothiyampatti and Pudhupuliyampatti. The model prediction for biomass production at maturity was considered excellent and the average errors as computed by R^2, RMSE and NRMSE were 0.79, 844 kg ha^{-1} and 11 per cent respectively and overall agreement between simulated and observed values was 89 per cent (Fig. 51**)**. The model prediction was in close agreement with measured values. Similar results were also reported by Soler *et al*. (2007). Singh *et al*. (1994) also found similar trend of biomass simulation for groundnut by PNUTGRO model at Patancheru (ICRISAT) and at Anantapur.

5.2.7. Validation of model for groundnut pod yield and Harvest Index

Pod yield of groundnut was observed in twenty locations across four districts of Tamilnadu and presented along with model simulated values in Fig. 49 and 50.

The performance of DSSAT CROPGRO-Peanut model was good in simulating the pod yield of groundnut during both *kharif* and *rabi* 2015. The results showed that error percent remain in good confidence level during both the seasons. Positive significant association was noticed between simulated and observed mean yield with R^2 value of 0.81. Among the twenty monitoring fields model slightly overestimated the pod yield in all the monitoring fields except Morepalayam. However, the simulated pod yields for the all the monitoring fields were close to the observed yields as water stress was the dominating factor rather than disease in those late sown fields of Tiruvannamalai and Villupuram districts. During *rabi* 2015 at Tiruvannamalai and Villupuram districts, in many fields, the crops were affected by late leaf spot or rust during the later phases of crop growth, especially in Keelravandavadi, Thandrampattu and Padiyandhal which were affected by tikka leaf spot. This resulted in significantly lower pod yields than the simulated pod yields in this season. Observed pod yield data from all twenty locations were pooled for correlation with the model predictions. As the model does not incorporate the influence of diseases and pests, the locations in which the influence of diseases and pests was severe were excluded for comparison.

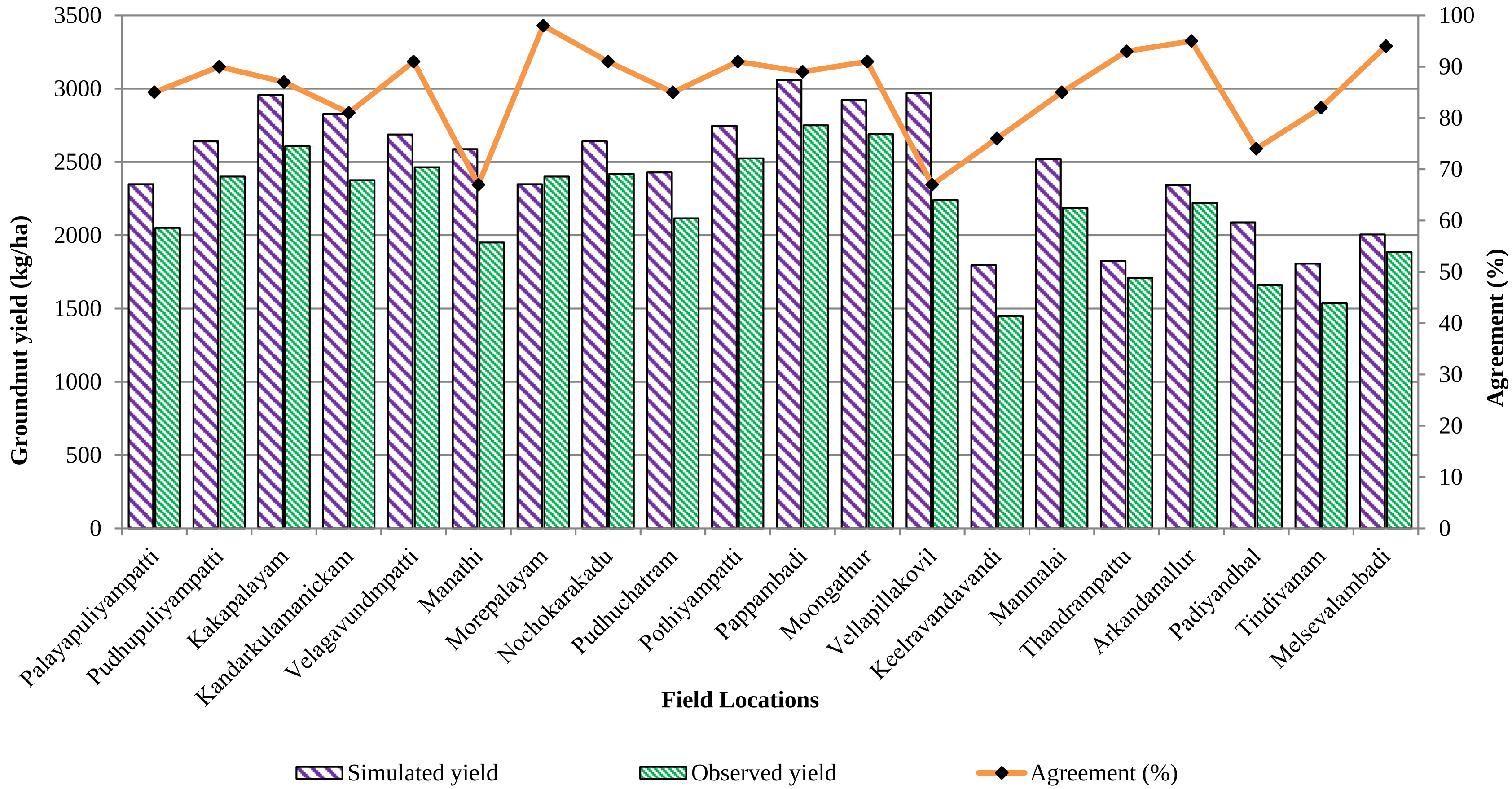

Fig.49. Validation of DSSAT-PNUTGRO model for groundnut pod yield

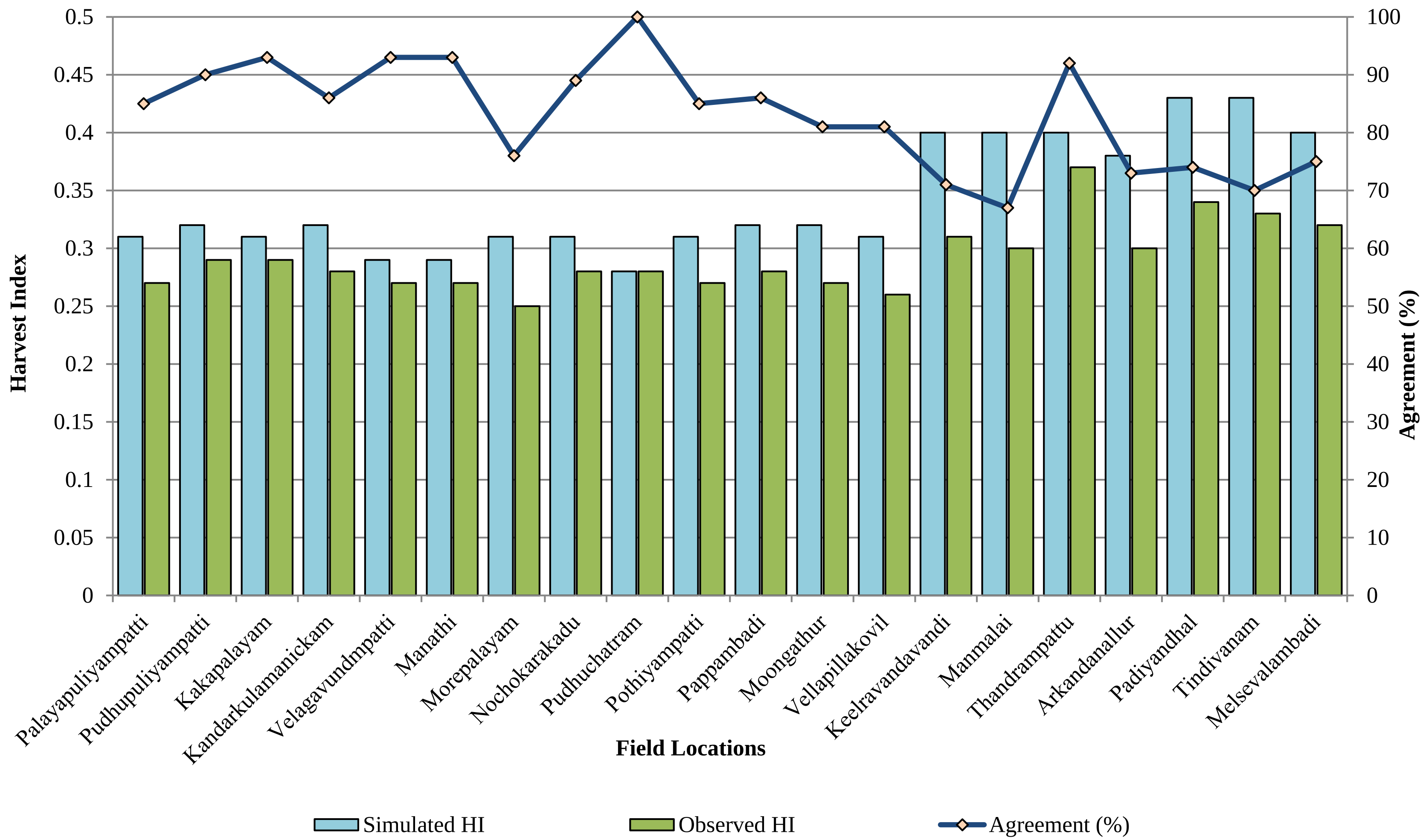

Fig.50. Validation of DSSAT-PNUTGRO model for groundnut Harvest Index

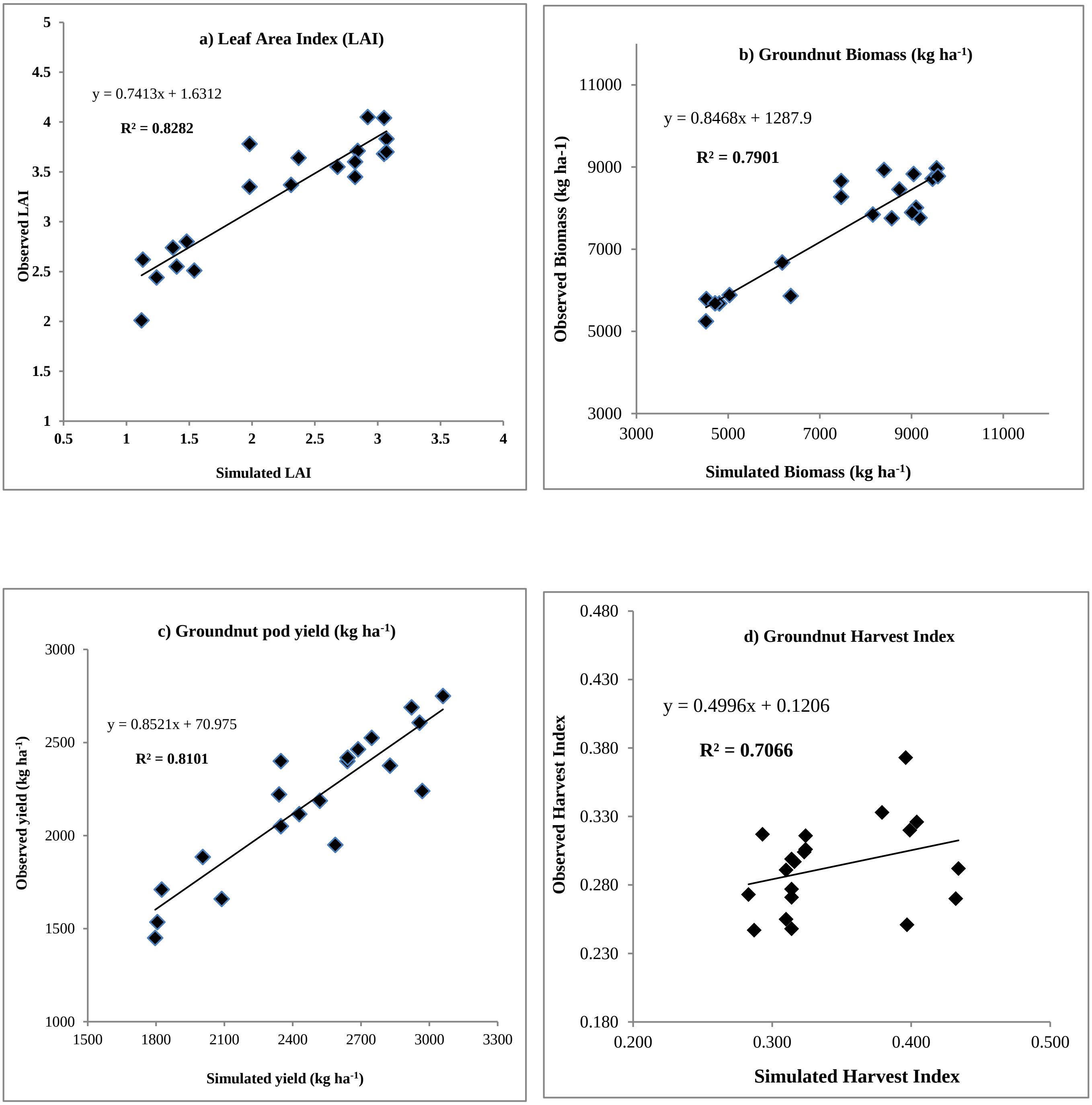

Fig.51. Comparison of groundnut growth and yield simulated by the DSSAT model with measured values

Simulated pod yields across the locations ranged from 1796 to 3060 kg ha^{-1} depending upon agro climatic conditions of the study sites, soil parameters and the cultivar grown. Higher mean yields were obtained in *kharif* 2015 (2705 kg ha^{-1}) as compared to *rabi* 2015 (2054 kg ha^{-1}). Singh *et al*. (2012) also observed similar variations in simulated yields (100 to 3370 kg ha^{-1}) of groundnut between different locations and regions. Regression of simulated pod yields of two seasons against observed data of the test sites showed a strong relationship between simulated and observed pod yields.

The average errors between simulated and observed values as computed by R^2, RMSE and NRMSE were 0.81, 342 kg ha^{-1} and 16 per cent respectively. The individual agreement of pod yield for all field locations ranged from 77 to 98 per cent. The maximum agreement of 98 per cent was recorded in Morepalayam field location. Even though the model predicted slow increase with underestimation in case of LAI, the model takes into consideration of effects of temperature on SLA and predicted the growth in terms of biomass and yield accurately at various stages and overestimates by 10 to 15% at maturity. Moongathur, Pothiyampatti, Nochokarakadu and Velagavundanpatti also recorded a fairly good agreement of 91 per cent of pod yield in groundnut between observed values and the values simulated by DSSAT PNUTGRO crop growth model. The lowest agreement of 67 per cent was recorded in Manathi and Vellapillakovil locations followed by Padiyandhal and Keelravandavadi with 74 and 76 per cent agreement and the remaining sites recording an agreement of above 80 per cent on groundnut pod yield. This meant that predicted pod yields were not significantly different from observed yields. The PNUTGRO model was able to reasonably simulate pod yield and final biomass with low normalized root mean square error (RMSE), low absolute root mean square error (RMSE) and high coefficient of determination (R^2 >0.7) as reported by Halder *et al*. (2017).

Considering the variation in monitoring fields and the range in environments in which groundnut was grown, it is concluded that PNUTGRO can be used to predict groundnut yields as influenced by several factors such as water availability, sowing dates, and seasons. Simulation of groundnut yield in monitoring sites showed that simulated pod yields followed a similar trend as observed yields. The differences between simulated and observed yields were less than 400 kg ha^{-1} in most monitoring fields. This analysis further confirms that PNUTGRO can be used to predict changes in yield caused by variation in seasons, sowing dates and moisture availability. Similar result were obtained by Singh *et al*., (1994) at four different locations, Padma *et al*., (1991) at Hyderabad and Patil *et al*., (1993) at Raichur in *kharif* groundnut.

Results of validation of groundnut Harvest Index simulated by model showed that the values of simulated harvest index were found to have been overestimated as compared to corresponding observed values of all the monitoring fields. During both the season of *kharif* and *rabi* 2015, the individual agreement between simulated and observed values was fairly well for all twenty field locations. The results were in accordance with Anothai *et al*., (2008). The individual agreement of harvest index in all field locations ranged from 40 to 97 per cent. The lowest agreement was recorded in Tindivanam field with 40 per cent and followed by Keelravandavadi and Padiyandhal, fields with 42 and 51 per cent respectively. These four fields were located in Tiruvannamalai and Villupuram districts.

A positive significant association was observed between simulated and observed mean harvest index with a R^2, RMSE and NRMSE (%) values were 0.70, 0.070 and 24 per cent and overall agreement 76 per cent between simulated and observed values showed that the model prediction was in fairly good agreement with the measured values (Fig. 51). The results are in agreement with the findings of the study by Halder *et al*. (2017) and Singh *et al*., (1994).

5.3. Integrating Remote Sensing products with DSSAT for yield estimation at spatial level

Integrating remote sensing data and crop model is one of the solutions for expanding point based simulations to large area by putting remotely sensed products as proxy to crop variables. In this study remotely sensed LAI values were assimilated spatially with inputs from DSSAT model as a driving variable (Rui *et al*., 2011). Through integration of remotely sensed data and simulated values from DSSAT- CROPGRO-Peanut model, field level yields were estimated for monitoring locations and yield map at spatial level across study area had been executed. It was shown that the combination of satellite derived LAI and simulated growth parameters of groundnut could improve field level yield prediction. It was found that the weather distribution, availability of water, soil type, date of sowing and the groundnut varieties contributed to groundnut LAI variability at field level and explained the yield variability. In the present study, therefore suitable regression models were used to generate groundnut LAI from dB image using simulated LAI from DSSAT model at spatial level generate from different monitoring sites across study area as an explanatory variable for spatial yield estimation.

The LAI of groundnut was derived from SAR at spatial level for each monitoring site across study area and compared with corresponding observed LAI. Validation referred to assessment of agreement of satellite derived LAI through comparisons with ground

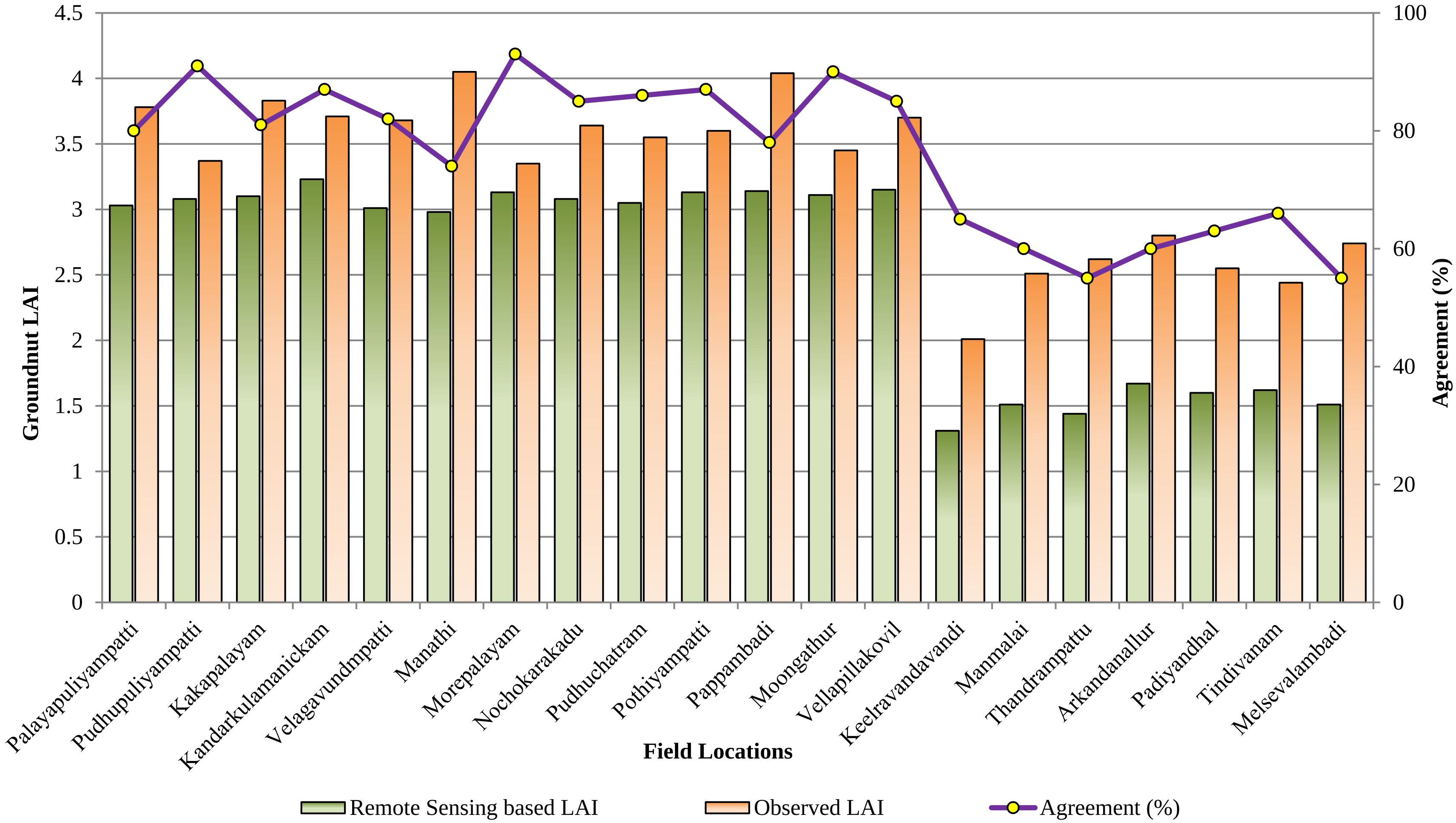

Fig.52. Validation of remote sensing based groundnut LAI with observed LAI

measurements. Fig. 52 represents an overview of the satellite (Sentinel-1A) derived LAI data with observed LAI of groundnut at pod development.

Irrespective of the configuration, the satellite derived LAI against observed LAI have acceptable results, with the R^2, RMSE and NRMSE were 0.86, 0.78 and 24 per cent respectively (Fig. 54). When compared with the observed LAI of 2.01 to 4.05 of groundnut the estimation from satellite derived values ranged from 1.31 to 3.23 with an agreement 55 to 93 per cent for point based observation with an overall agreement of 76 per cent. Tripathi *et al*. (2004) reported the field LAI values were related to satellite based LAI estimations and a strong relationship was indicated with a coefficient of correlation of 0.76. Thus, satellite based LAI values could be effectively used for yield prediction model.

The best results were obtained at Morepalayam with LAI of 3.13 as against the observed LAI of 3.35 with an agreement 93 per cent and Melsevalambadi recorded a slightly poor LAI of 1.51 against observed LAI (2.74) with an agreement of 55 percent which showed that the SAR imagery could be used to retrieve the LAI with acceptable limit as a fine-resolution LAI map when aggregated to the resolution of the MODIS LAI product serving as the reference field. It further showed that it was important to account for precision of the fine resolution satellite sensor product, such as the Sentinel-1A, while comparing it to reference values. Myneni *et al*. (2002) reported a good agreement between a satellite derived LAI with measured LAI from the fields. Xu *et al*. (1996) also compared predicted LAI and measured LAI and reported that ERS-l SAR data could be used in the model for estimation of LAI to an accuracy of 0·5 to 1 and have the potential for operational application in crop monitoring.

Only a few studies have addressed the performances of empirical relationships between LAI and backscattering coefficients for fields with analogous cultivation practices (i.e. except rice, grown on flooded area). Leonard *et* al. (2013) found SAR sensor offer multi-polarized C-band information that could directly be used in order to retrieve LAI. Chen *et al*. (2009) reported that Advanced Synthetic Aperture Radar (ASAR) data could be used to estimate the LAI of crop for wide-area monitoring of crop growth and suggested that C-band SAR data might be a promising alternative to optical remote sensing data for monitoring crop growth such as LAI in cloudy and rainy period where regular optical remote sensing data were difficult to acquire.

Remote sensing based yield estimation was validated at district level with observed yield (point level) and illustrated in Fig. 53. Among all the Satellite derived LAI images of throughout the season LAI at the pod development stage during both the seasons were used

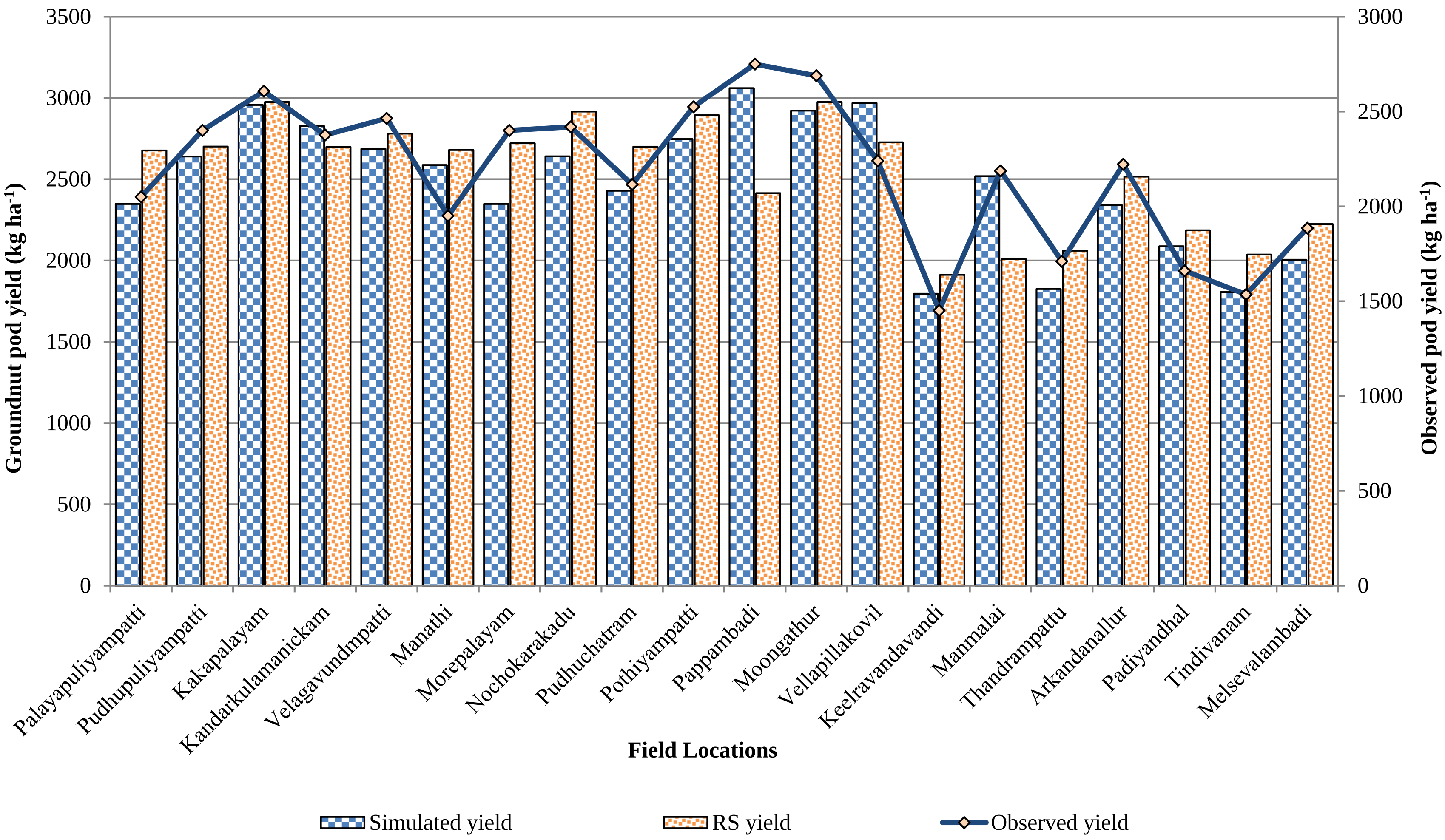

Fig.53. Validation of remote sensing based groundnut yield with observed yield

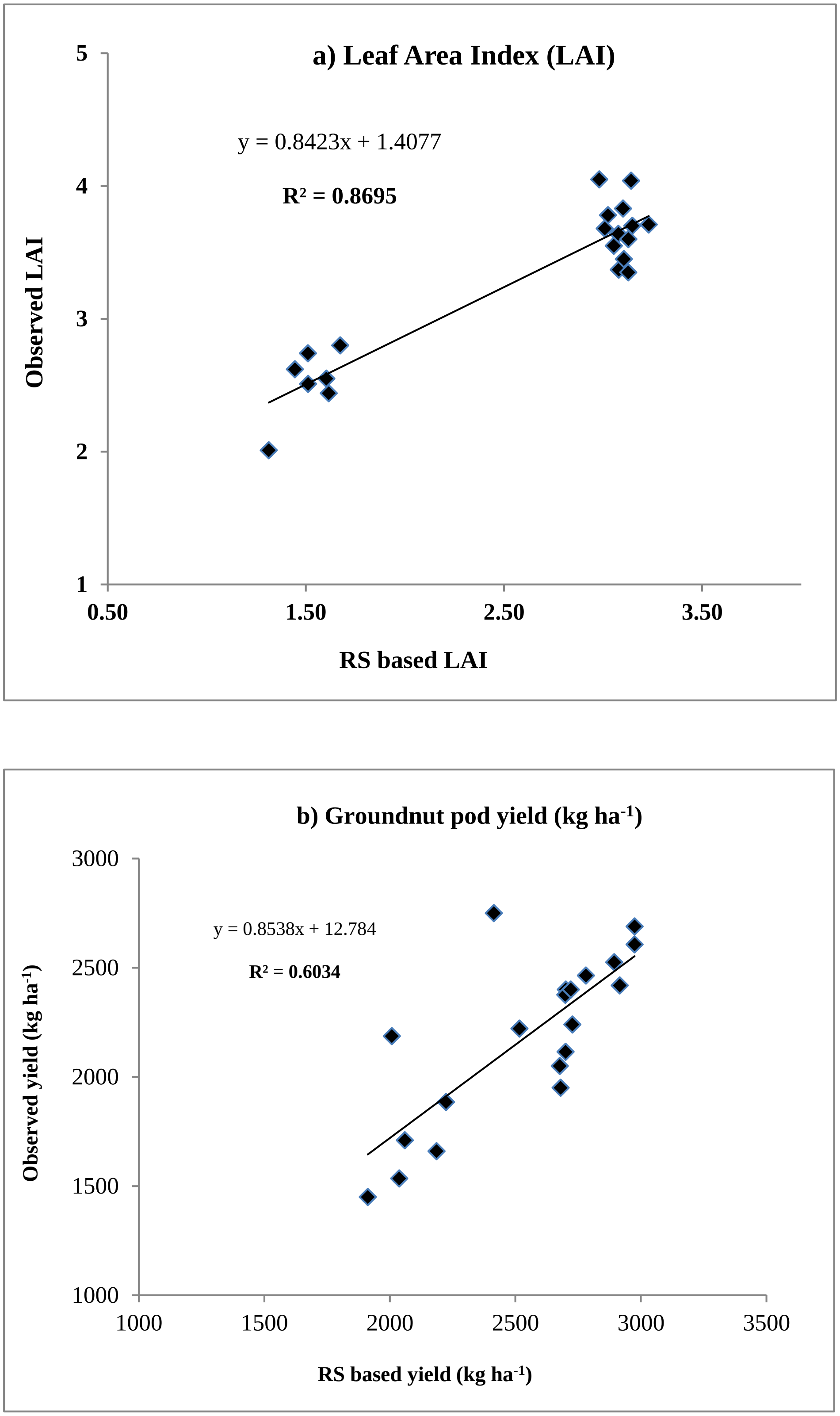

Fig.54. Comparison of Remote Sensing based LAI and pod yield of groundnut with measured values

for yield estimation. The maximum pod yield of 2975 kg ha^{-1} was estimated in Kakapalayam and Moongathur fields. As against the remote sensing based groundnut yields of 1912 to 2975 kg ha^{-1}, the observed yields were 1450 to 2750 kg ha^{-1}. At point level, the agreement was found to range from 67 to 92 per cent with a fairly good overall agreement of 80 per cent. The R^2 was 0.60 with RMSE of 431 kg ha^{-1} and NRMSE of 20 per cent (Fig. 54). Yang *et al*. (2006) studied the utility of assimilating remote sensing based LAI in CERES model to estimate winter wheat yield at China. Pazhanivelan *et al*. (2015) used SAR derived LAI to assess yield of rice spatially integrating ORYZA crop growth model.

5.4. Assessing drought classes of groundnut area using drought indices

Drought is an adverse climatic condition that affects all the climatic zones with semi-arid regions being highly susceptible to drought because of lower annual rainfall and sensitivity to climate change. Groundnut is a major crop widely grown under rainfed condition and vulnerable to drought during cropping period. Three drought indices *viz*., SPI, NDVI and WRSI were assessed in groundnut areas of four major districts *viz*., Salem and Namakkal, Tiruvannamalai and Villupuram districts in Tamilnadu during *kharif* and *rabi* 2015. The spatial distribution of these indices were worked out and presented in Fig. 55 to 58. In general, different studies have indicated the usefulness of the SPI to quantify different drought types (Edwards and McKee, 1997; Hayes *et al*., 1999).

5.4.1. Assessing drought based on Standardized Precipitation Index (SPI)

In order to analyse the impact of rainfall deficiency and the development of drought, SPI (1-month time scale) was used to quantify the precipitation deficit in groundnut growing area in study districts to get a combined drought risk of meteorological and agriculture drought. Kwak *et al*. (2016) successfully analyzed the changing trend of meteorological drought due to climate change by using SPI collected from the 45 observatories all over Korea.

In *kharif* 2015, the SPI classes of Salem district showed that during May 2015, most of the blocks (11 blocks) were classified as moderately dry except Idappadi, Attur and Gangavalli which were grouped as mildly dry. Remaining four blocks *viz*., Kadayampatti, Yercaud, Valapady and Veerapandi were found to be under severely dry condition based on SPI values. Thalaivasal was classified as normal with regard to rainfall in comparison with historical precipitation data. On temporal analysis of SPI during the cropping period of June to September, 2015, all the blocks were classified as normal to moderately wet classes of SPI. Similarly in Namakkal district also, SPI classes of mildly dry (11 Blocks) and severely dry (4

Groundnut area under SPI classes

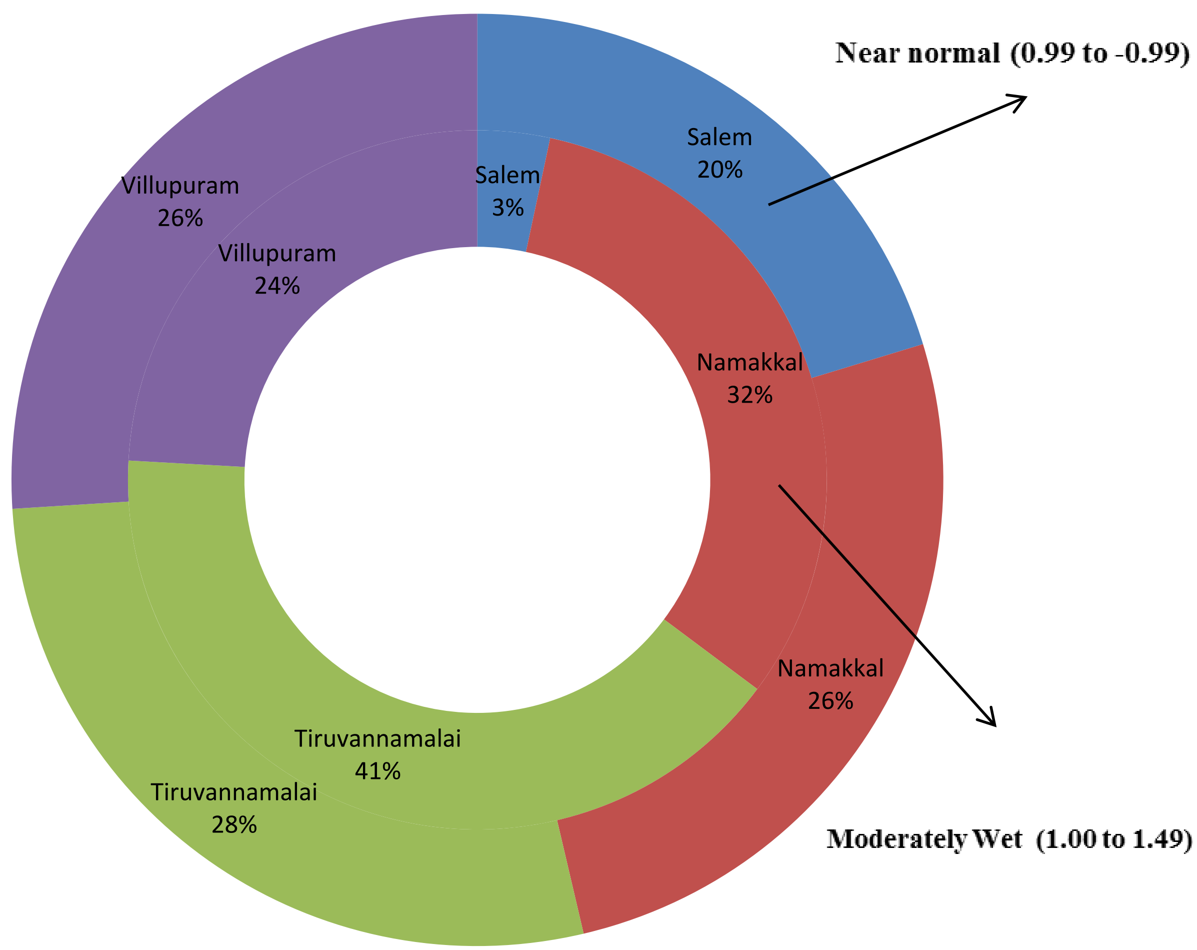

Fig.55. District wise groundnut area (ha) under SPI classes

blocks) were observed during May, 2015 while normal to severely wet conditions prevailed during June to September, 2015 in all the blocks. Livada and Assimakopoulos (2007) used SPI to detect drought events in spatial and temporal basis in Greece.

As a result of the SPI during *rabi* 2015, most of the blocks were found to normal to mildly wet across the cropping season with a few blocks registering moderately wet to severely wet condition. Similarly all the blocks in Villupuram district also recorded SPI classes corresponding to normal to mildly wet classes except Sankarapuram, Rishivandiyam and Koliyanur which recorded moderately wet condition during corresponding period. Several research works are in line with these findings of drought classification based on SPI classes. Findings of Nithya and Rose (2014) also, stated that SPI was useful to detection of agricultural vulnerability to drought. Wattanakij *et al*. (2006) successfully analysed spatial pattern of drought in the Northeast of Thailand using Multi-Temporal SPI. Hammouri and El-Naqa (2007) concluded that the combination of various indices offer better understanding and better monitoring of drought conditions for semi-arid basins like Amman-Zarqa Basin.

Considering the groundnut area in the study districts, the severity of drought based on composite SPI mainly classified into two groups of near normal was recorded in 99 per cent of total groundnut area in Salem district. Similarly in Namakkal district, most of the groundnut area was classified under near normal condition. During *rabi* season in Tiruvannamalai and Villupuram districts also, same trend was observed. In Tiruvannamalai district, out of 24475 ha of groundnut area, 24244 ha were classified under near normal condition (Fig. 55). However, the drought affected areas based on SPI classes were not more severe throughout the groundnut growing area of study districts. The severest drought episodes of 1984 and 1998 were more clearly captured by the aggregate drought index in all the regions classified. Sebenik *et al*. (2017) observed that the SPI on the annual time scale showed a similar pattern of occurrence of dry and wet periods at different places.

5.4.2. Assessing drought based on Normalized Difference Vegetation Index (NDVI)

For assessing spatial variability of drought level, composite NDVI data derived from satellite data could significantly help in determining the onset of drought, its severity and spatial extent. Satellite based information now provides effective drought monitoring and mitigation. NDVI images of cropping period during both seasons were generated using the imageries of MODIS acquired in May, 2015 to February, 2016. Tucker, (1979) first suggested NDVI as an index of vegetation health and density and it has been considered as the most important index for mapping of agricultural drought. Kaushalya *et al*. (2014) had assessed the agricultural vulnerability in rainfed agricultural area using NDVI data products and the results were discussed spatio-temporally at district level for the country. Likewise, Sumanta *et al*. (2013) had assessed the severity of drought using long term mean values of maximum NDVI in Bankura District, West Bengal.

Compositing the NDVI time series for whole the period of groundnut growing at the study districts provided information about the relative health of the vegetation in a given period. Dense vegetation showed high value in the NDVI imagery, and the areas with little or no vegetation showed negative value and was also clearly identified. Groundnut area pertaining to each class was extracted from these images. Average NDVI image of cropping period for study districts are illustrated in Fig. 56. Senay *et al*. (2015) used the NDVI to monitor vegetation condition and combined several satellite data products using models to produce multiple short- and long-term indicators of droughts.

Inter-seasonal variations in the magnitude and evolution of the NDVI for a particular location were mainly governed by meteorological variables such as precipitation, temperature, and relative humidity; however, changes in phenological growth of crops could also cause inter-seasonal variations. Comparing both seasons, during *kharif* 2015, NDVI images of Salem showed more area under good class covering approximately 86 per cent of groundnut area but in Namakkal district, approximately 60 per cent of groundnut area was only covered under class good based on NDVI values and remaining groundnut area (40 per cent) under stressed condition. During *rabi* 2015, NDVI image of Tiruvannamalai district showed more area under good vegetation class than stressed class with 97 per cent of groundnut area. Similarly in Villupuram also, 93 per cent of groundnut area was under class good class based on NDVI. This was because, high productive ecosystem had different radiometric properties than less productive ones due to differences in climate, soil, and topography as reported by Quiring and Ganesh (2010).

Analysis of composite NDVI classes during *kharif* season showed that Salem district registered very less area *i.e*. 1.40 per cent of groundnut area under stressed condition whereas majority of the of groundnut area were found to be in the classes of very good and good based on NDVI. Smoothed NDVI, averaged over cultivated areas, provides a concise visual summary of seasonal performance as reported by Funk and Budde (2007).

NDVI based on drought classes of groundnut area during *rabi* season of Tiruvannamalai and Villupuram districts. Tiruvannamali district recorded the lowest stressed groundnut area with larger groundnut area (24088 ha) classified under good condition.

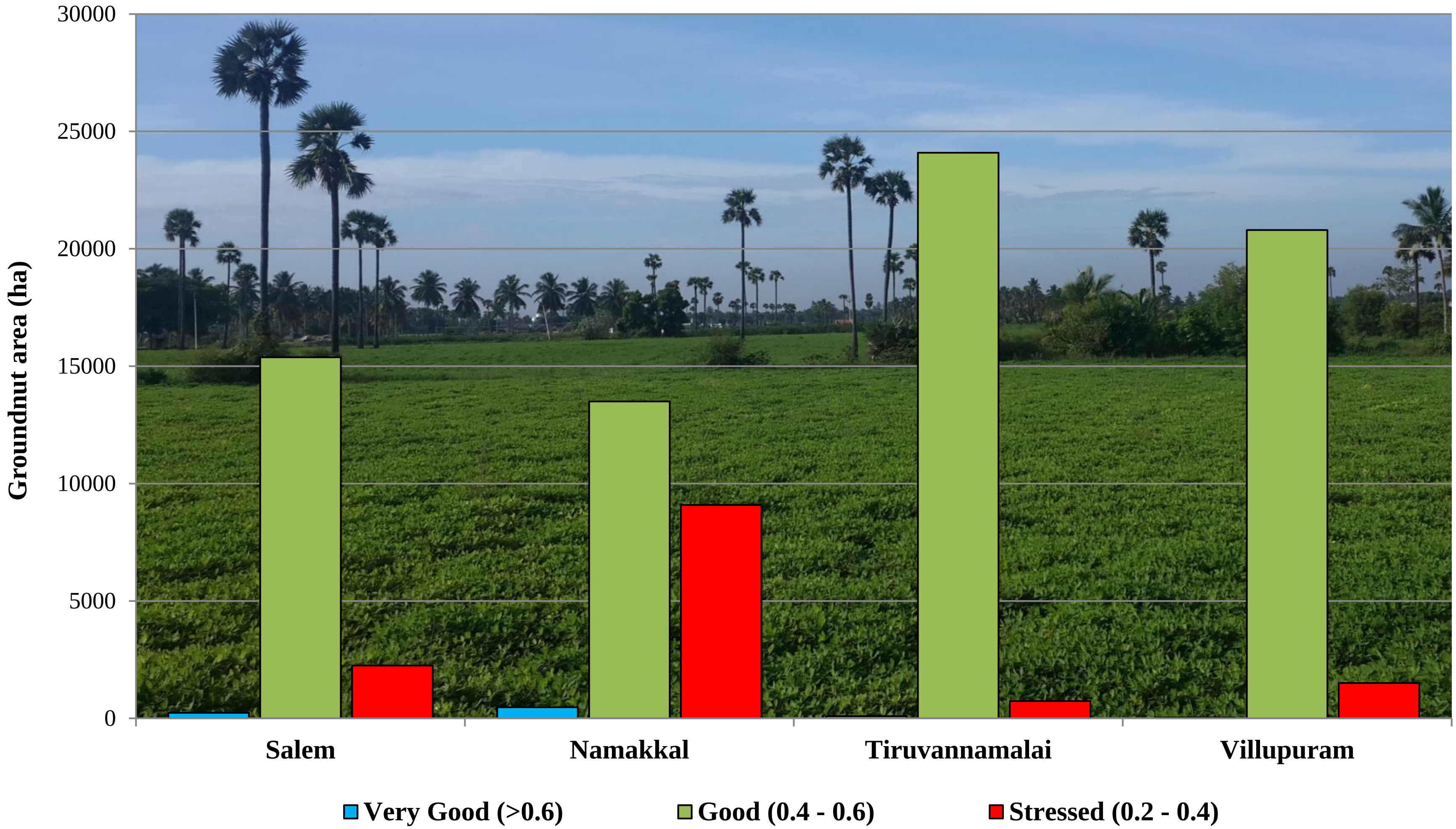

Fig.56. District wise groundnut area (ha) under NDVI classes

Considering NDVI level, representing the vegetation condition during the season, Villupuram district recorded only 7 per cent of groundnut area under stressed condition with 93 per cent of groundnut area under good condition. Stressed areas were found to be in five blocks *viz*., Ulundurpet, Thirunavalur, Vanur and Marakanam. Erdenetuya *et al*., (2010) processed MODIS product as Normalized Difference Vegetation Index and used to indicate deficiencies in rainfall and portray meteorological and/or agricultural drought patterns both timely and spatially, thus serving as indicator of regional drought pattern.

5.4.3. Assessing drought based on Water Requirement Satisfaction Index (WRSI)

The computation of the drought probability was done based on WRSI over each district for the period May, 2015 to January, 2016 combining historical weather data and satellite imageries. The results revealed that drought had occurred at different levels of severity during groundnut growing seasons of study districts. WRSI results were then reclassified based on drought severity classes as shown in Fig. 57. Based on this classification, WRSI distribution on groundnut area was assessed and district-wise area of groundnut under incidences of drought was extracted during both seasons. Jayanthi, *et al*. (2014) reported that vulnerability curve could quantitatively evaluate crop vulnerability to drought and water requirement satisfaction index (WRSI) to produce maize drought vulnerability curves for three countries *viz*., Kenya, Malawi, and Mozambique.

In Salem and Namakkal districts, during the *kharif* season, the whole groundnut area was covered by three levels of WRSI *viz*., no risk, medium risk and high risk. In Salem district, the medium risk condition had more groundnut area followed by no risk and high risk. Among the 19 blocks of Salem district, under medium risk condition, Thalaivasal block covered maximum groundnut area followed by Tharamangalam and Valapady blocks. Three blocks were *viz*., Attur, Omalur and Sangakiri were covered under high risk condition. Valapady block alone had groundnut area under no risk condition. In Namakkal district, Low risk level of WRSI was registered in 75 per cent of groundnut area out of the total area of 23063 ha. The other two levels of high risk and very high risk conditions were recorded at 21.67 and 3.30 per cent of groundnut area respectively. Among the 15 blocks of Namakkal district, Mallasamudram block had more groundnut area under low risk condition followed by Elachipalayam. Under high risk condition, Tiruchengodu block had maximum area of groundnut. Rasipuram and Puduchatram block had no area of groundnut under high risk and

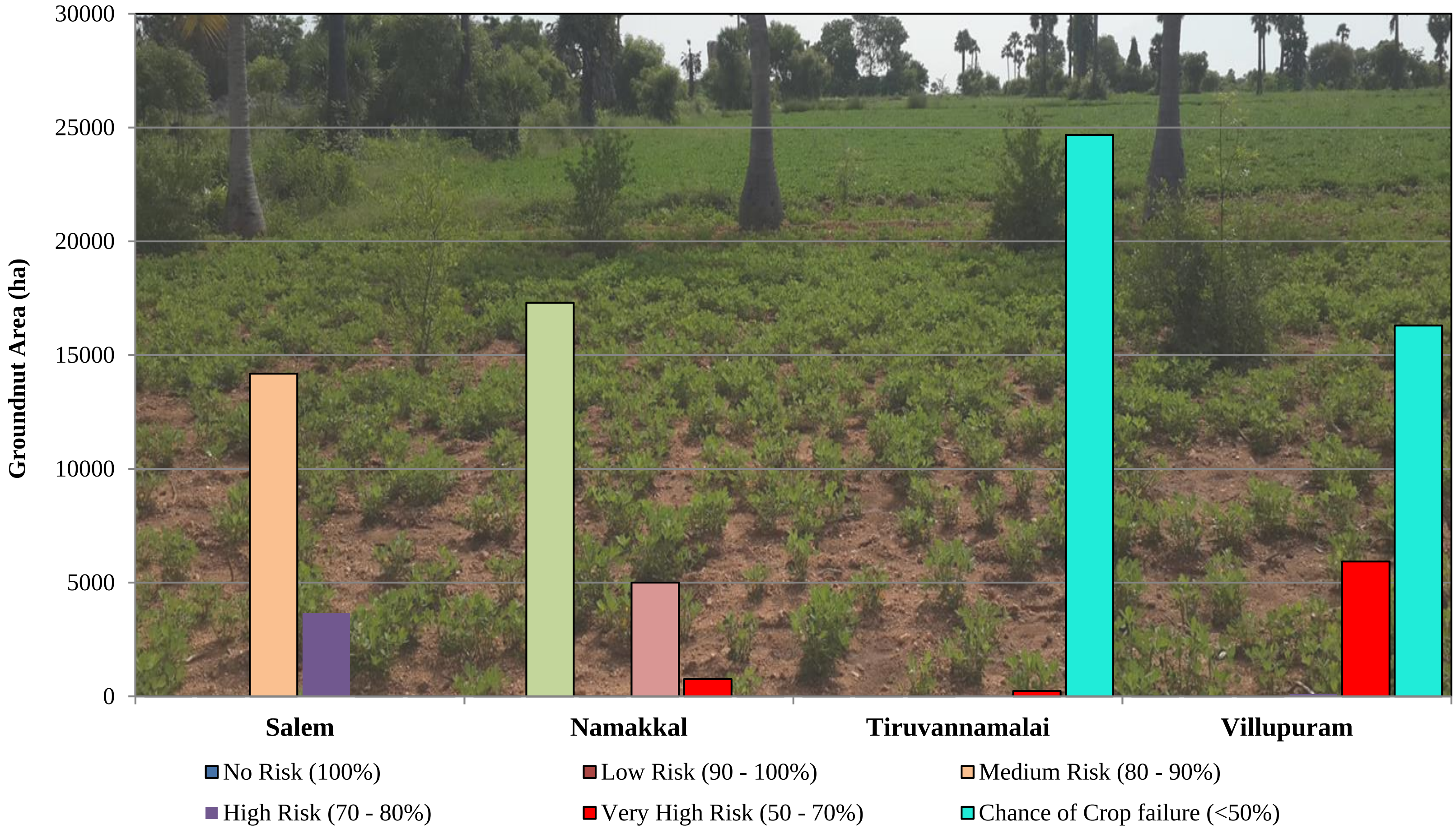

Fig.57. District wise groundnut area (ha) under vulnerability level to drought based on WRSI

very high risk condition. All the blocks of Namakkal district had lower or none of groundnut area under very high risk condition except Kabilarmalai (356 ha) block. These results fit with findings of Shukla *et al*. (2014) who successfully used WRSI to forecast drought.

During *rabi* 2015, Tiruvannamalai district registered 99 per cent of the groundnut area under chances of crop failure. Thurinjipuram block had maximum groundnut area under chance of crop failure condition followed by Thandrampattu and Keelpennathur blocks. Seasonal WRSI value less than 50 was regarded as a crop failure condition (Smith, 1995). All the 18 blocks were classified under chance of crop failure condition except Pudupalayam, Chengam, Keelpennathur, Tiruvannamalai and Thandrampattu blocks which had some groundnut area under very high risk condition also. In Villupuram district, out of total groundnut area of 22338 ha, 73 per cent of the area was classified as chances of crop failure condition followed by very high risk and high risk conditions. Especially the whole groundnut area of Melmalaiyanur block was found under condition of crop failure. In early semi-arid regions of southern Africa, WRSI anomalies were used to identify areas experiencing crop water stress as reported by Unganai and Kogan (1998). Moeletsi and Walker, (2012) successfully used WRSI to quantify drought affecting rain-fed maize production in the Free State Province of South Africa. Senay and Virdin, (2002) also worked on the temporal comparison between WRSI and yield, over different regions.

5.5. Assessing vulnerability of groundnut to drought

Agricultural vulnerability of groundnut to drought was assessed using the modern methods of remote sensing and GIS by overlaying three different drought indices *viz*., SPI, NDVI and WRSI and the distribution of vulnerability of groundnut area to drought was estimated and presented in Fig. 58. Blockwise statistics were also generated for rainfed groundnut area of study districts. The agricultural vulnerability map will help in the preparation of the area for mitigation measures that will in turn reduce the impacts of climate variation on agriculture. Similarly, Jury, (2013) assessed the drought occurrence in many parts of the world and opined that the Southern African countries were highly susceptible to drought.

During *kharif* season, in Salem district, out of total groundnut area 17938 ha, 67 per cent was found to be under low vulnerability level followed by 33 per cent under moderate level of vulnerability. Among the 19 blocks, most of the blocks were classified as low vulnerable except Kadayampatty, Salem and Attur which were moderately vulnerable to

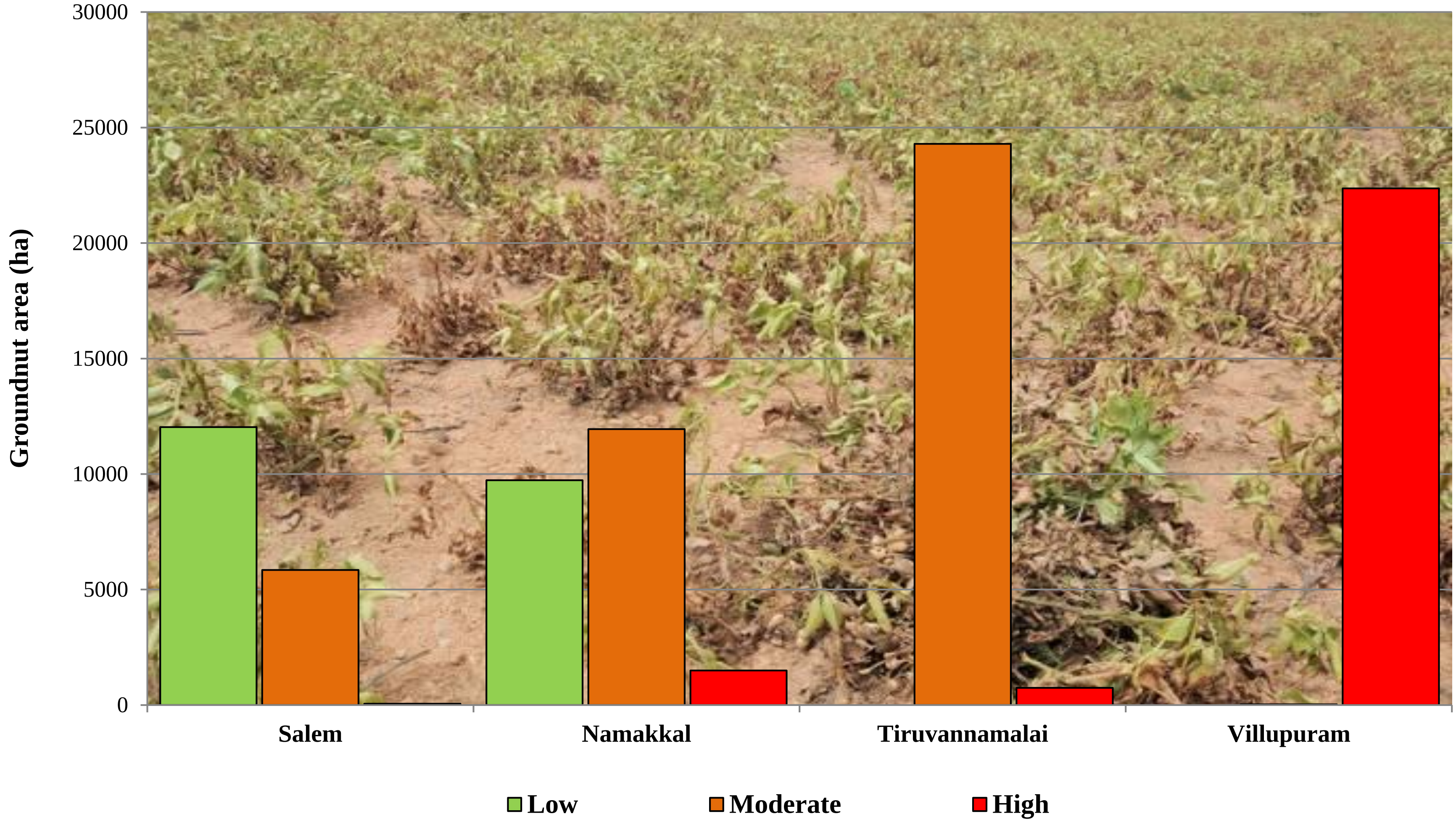

Fig.58. District wise groundnut area (ha) under vulnerability level to drought

drought. The results were in accordance with Nithya and Rose (2014) who stated that the different drought indices such as SPI, NDVI and NDWI were very useful for early detection of agricultural vulnerability in Srivilliputhur Taluk of Virudhunagar district, Tamil Nadu.

Considering the overall vulnerability of groundnut to drought in Namakkal district, out of the total groundnut area of 23119 ha, 42 per cent was found to be less vulnerable whereas 52 per cent area was moderately vulnerable to drought. Major groundnut areas of Mallasamudram, Puduchatram, Rasipuram, Sendamangalam and Vennandur blocks were found to be less vulnerable to drought (Fig. 59), while major areas of Tiruchengodu, Elachipalayam and Erumaipatti blocks were moderately vulnerable to drought. Rama Rao *et al*. (2013) assessed agricultural vulnerability to drought in rainfed regions in India.

During *rabi* 2015, the studies on vulnerability to drought in groundnut showed that all the 18 blocks of Tiruvannamalai district covering a groundnut area of 24294 ha were classified as moderately vulnerable to drought. In case of Villupuram district, all the 21 blocks covering groundnut area of 22369 ha were found to be highly vulnerable to drought (Fig. 60.). Similar results were reported by Wilhelmi *et al*. (2002) which indicated that the most vulnerable areas to agricultural drought were non-irrigated cropland and rangeland with a very high probability of seasonal crop moisture deficiency.

Considering overall vulnerability, whole district of Villupuram was adjudged as highly vulnerable to drought with regard to groundnut cultivation (Fig. 61.) whereas four blocks of Salem, eight blocks of Namakkal and all the blocks of Tiruvannamalai were found to be moderately vulnerable to drought.

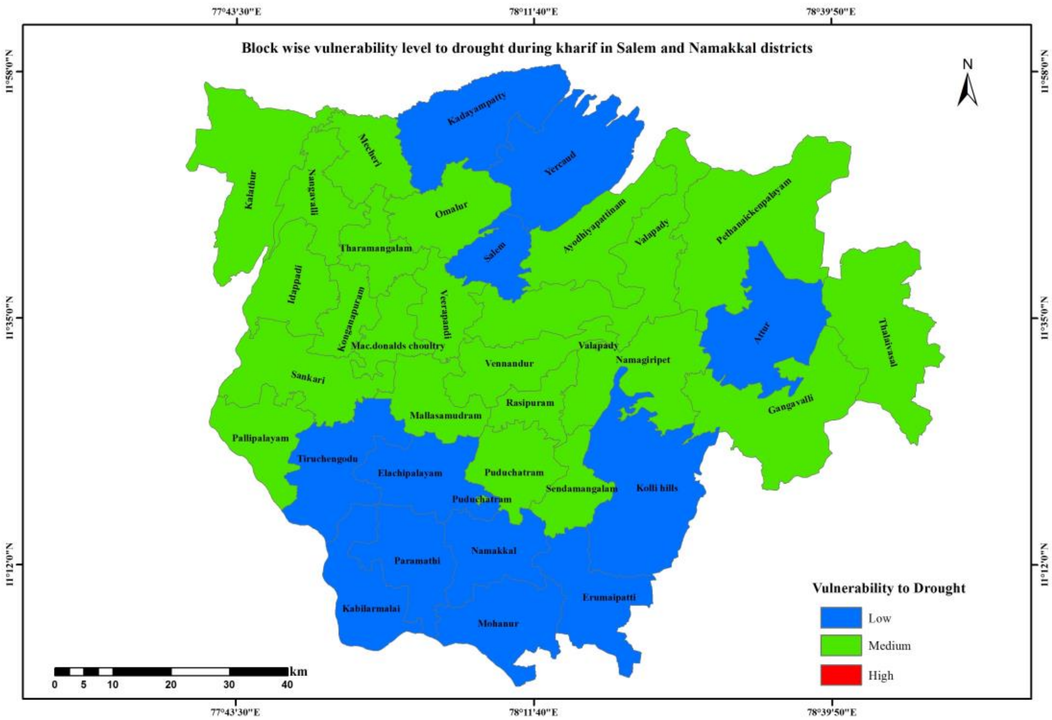

Fig.59. Blockwise vulnerability level of groundnut to drought in Salem and Namakkal districts

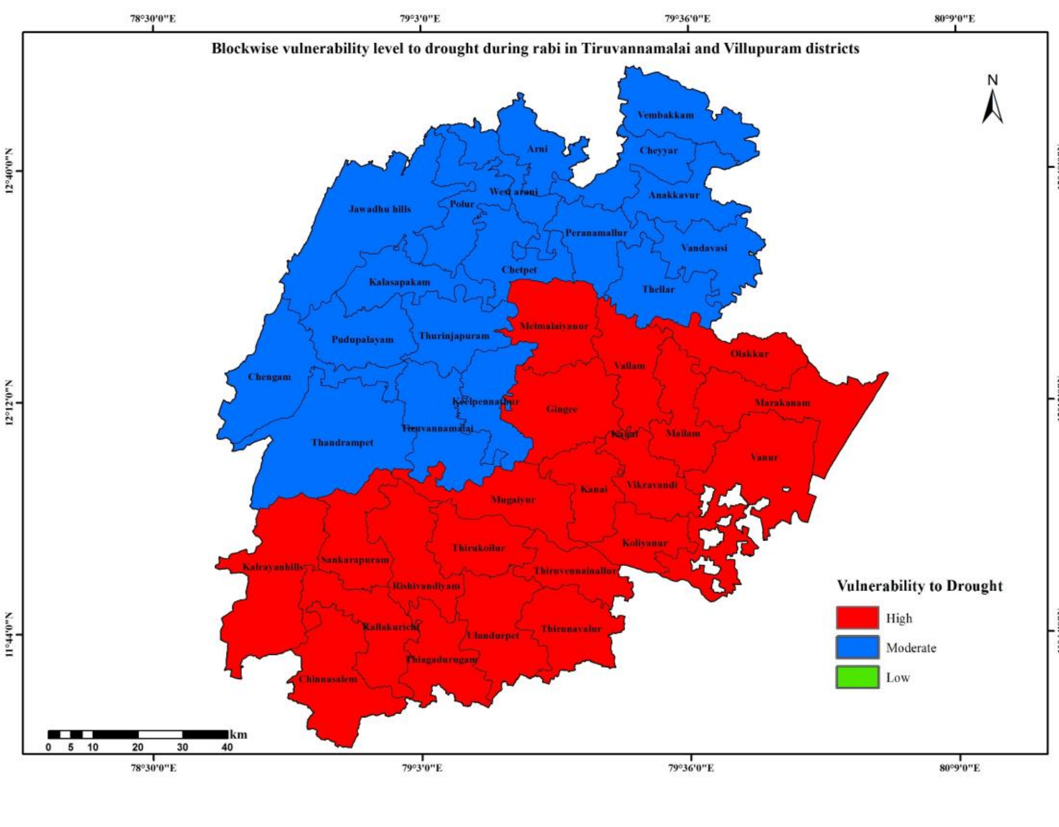

Fig.60. Blockwise vulnerability level of groundnut to drought in Tiruvannamalai and Villupuram districts

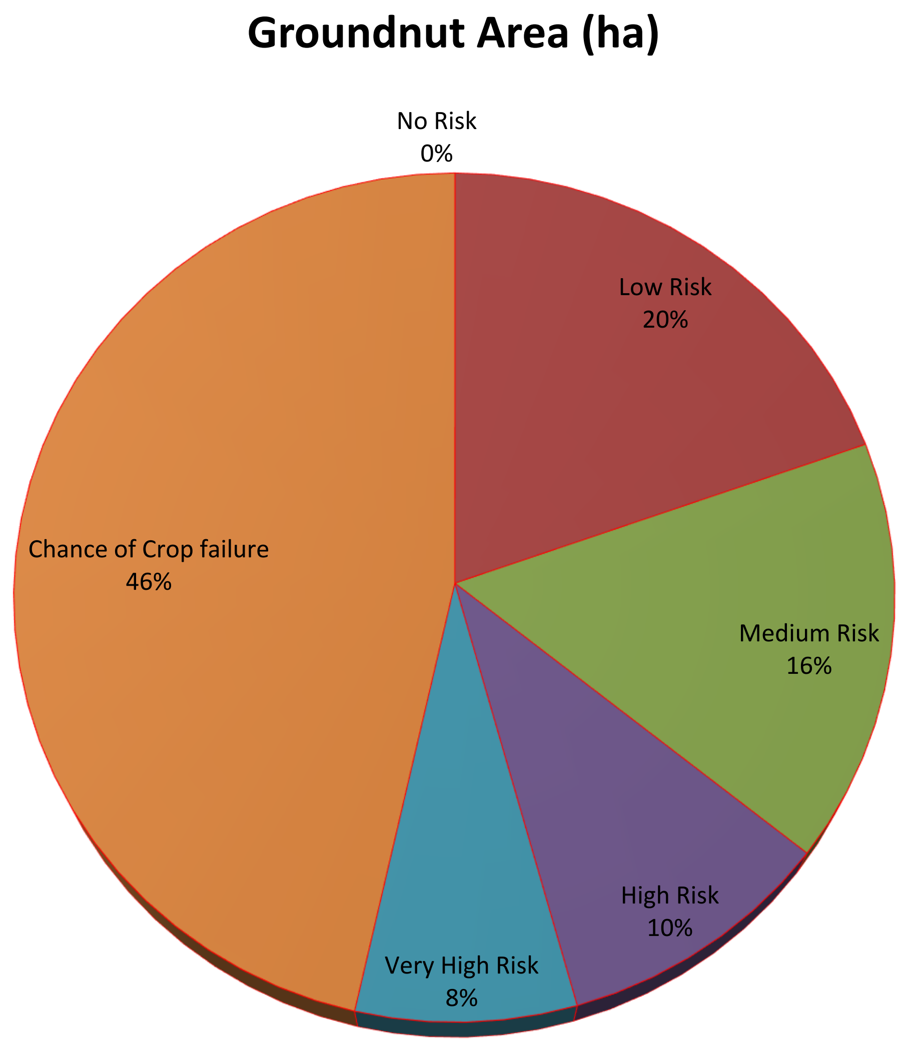

Fig.61. WRSI based risk areas for groundnut cultivation in this study area

Summary and Conclusion

CHAPTER VI

SUMMARY AND CONCLUSIONS

A research study was conducted at TamilNadu Agricultural University, Coimbatore during *kharif* and *rabi* 2015 to estimate groundnut area, model growth and productivity and assess the vulnerability of groundnut to drought using remote sensing techniques.

Multi temporal Sentinel 1A satellite data at VV and VH polarization with 20 m spatial resolution was acquired from May, 2015 to January, 2016 at 12 days interval and processed using MAPscape-RICE software. Continuous monitoring was done for ground truth on crop parameters in twenty monitoring sites and validation exercise was done for accuracy assessment. Input files on soil, weather and management practices were generated and crop coefficients pertaining to varieties were developed to assess growth and productivity of groundnut using DSSAT CROPGRO-Peanut model. Outputs from remote sensing and DSSAT model were assimilated to generate LAI thereby groundnut yield spatially and validated against observed yields.

Being a rainfed crop, vulnerability of groundnut to drought was assessed integrating different meteorological and spectral indices *viz*., Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI) and Water Requirement Satisfaction Index (WRSI).

The important inferences from the research study are summarized and conclusions drawn are furnished below.

6.1. Summary

Spectral dB curve of groundnut was generated using temporal multi date Sentinel 1A data. A detailed analysis of temporal signatures of groundnut showed a minimum at sowing and a peak at pod development stage and decreasing thereafter towards maturity. Groundnut crop expressed a significant temporal behaviour and large dynamic range (-11.74 to -5.31 in VV polarization and -20.04 to -13.05 in VH polarization) during its growth period.

At sowing, minimum dB value from -11.74 to -9.56 was recorded with a mean of -10.41 was observed under VV polarization while the values were -20.04 to -16.47 at sowing of groundnut with a mean of -18.26 under VH polarization. The maximum dB values of -5.60 to -5.31 under VV polarization and -14.15 to -13.05 under VH polarisation were observed at pod development stage irrespective of the districts. The multi temporal features *viz*., max, min, mean, max date, min date and span ratio were generated using seven to eight acquisitions to classify groundnut pixels. Groundnut area map was generated using maximum likelihood classifier integrating multi temporal features with a classification accuracy of 87.2 percent and a kappa score of 0.74. The total classified groundnut area in the study districts was 88023 ha covering 17817 and 22582 ha in Salem and Namakkal districts during *kharif* 2015 while Villupuram and Tiruvannamalai districts accounted for 22722 and 24903 ha respectively during *rabi* 2015. Blockwise statistics on groundnut area during both seasons were also generated.

To model growth and productivity of groundnut in DSSAT, weather and soil input files were generated using weatherman and ‘S’ build respectively besides deriving genetic coefficients for CO 6, TMV 7 and VRI 2 varieties of groundnut.

Growth and development variables of groundnut were simulated using CROPGRO-Peanut model i.e., days to emergence (7-9 days) and anthesis (25-32 days), canopy height (63 to 70 cm), maximum LAI (1.12 to 3.07) and biomass (4176 to 9576 kg ha^{-1} across twenty monitoring locations spatially. The resultant pod yield was simulated to be 1796 to 3060 kgha^{-1} with a harvest index of 0.28 to 0.43.

On comparison of LAI between observed (2.01 to 4.05) and simulated values (1.12 to 3.07) the CROPGRO-Peanut model was found to under estimate the values with R^2, RMSE and NRMSE of 0.82, 1.10 and 34 per cent. However, the model predicted the biomass of groundnut with an agreement of 89 per cent through the simulated values of 4176 to9576 kgha^{-1} as against the observed biomass to 4620 to 9959 kg ha^{-1}.

The simulated pod yields of groundnut in the study area were 1796 to 3060 kgha^{-1} as compared to the observed yields of 2115 to 2750 kg ha^{-1}. The overall agreement between simulated and observed yields was 84 per cent with the average errors of 0.81, 342 kgha^{-1} and 16 percent for R^2, RMSE and NRMSE respectively.

LAI values of groundnut, generated spatially through suitable regression models using dB from satellite images and LAI from DSSAT, ranged from 1.31 to 3.23 with R^2, RMSE and NRMSE of 0.86, 0.78 and 24 per cent respectively on comparison with observed values. Remote sensing based spatial estimation resulted in groundnut pod yields of 1570 to 3102 kg ha^{-1} across the study districts of Salem, Namakkal, Tiruvannamalai and Villupuram. In the 20 monitoring locations, the pod yields were estimated to be 1912 to 2975 kg ha^{-1} as against the observed pod yields of 1450 to 2750 kg ha^{-1} with a fairly good agreement of 80 per cent.

The vulnerability of groundnut was assessed using different drought indices *viz.*, SPI, NDVI and WRSI. Considering SPI, out of the total groundnut area of 88023 ha, an area of 86607 ha was found to be under near normal condition based on deviation of rainfall received during cropping season from historical precipitation. Similarly NDVI, an indicator of vegetation condition during the cropping season, showed that 14272 ha of groundnut area were under stressed condition during 2015.

With regard to Water Requirement Satisfaction Index (WRSI) another critical index to assess the vulnerability, an area of 40981 (mainly covering Villupuram and Tiruvannamalai districts) showed the chances of crop failure. An area of 8781 and 6932 ha were under high and very high risk zones respectively. Only an area of 17300 ha was found to be under low risk mainly spreading across Namakkal district. Major groundnut areas of Salem district (14188 ha) were under medium risk zone.

Considering overall vulnerability, 14 blocks of Salem and 6 blocks Namakkal were found to be less vulnerable to drought for groundnut cultivation whereas four and eight blocks of Salem and Namakkal districts were moderately vulnerable to drought. The results of this study revealed that all the blocks of Tiruvannamalai were moderately vulnerable to drought while the whole district of Villupuram was highly vulnerable to drought with regard to groundnut cultivation.

6.2 Conclusions

The following conclusions were drawn from the results obtained in the present investigation

- Spectral dB curve of groundnut generated using multi date Sentinel 1A SAR data showed a minimum at sowing and a peak at pod development stage and decreasing thereafter towards maturity with dB values of -11.74 to -5.31 in VV polarization and -20.04 to -13.05 in VH polarization during its growth period.
- Groundnut area map was generated with a classification accuracy of 87.2 per cent and a kappa score of 0.74 and the total groundnut area of the study districts was 88023 ha covering 17817 and 22582 ha in Salem and Namakkal districts (*kharif* 2015) and 22722 and 24903 ha in Villupuram and Tiruvannamalai districts (*rabi* 2015).
- DSSAT model predicted the biomass (4176 to 9576 kgha^{-1}) and pod yields (1796 to 3060 kgha^{-1})of groundnut with an agreement of 89 and 84 per cent as compared to the observed values.

- LAI and pod yield of groundnut were also estimated spatially assimilating dB from satellite images and DSSAT model with LAI values of 1.31 to 3.23 and pod yields of 1570 to 3102 kgha^{-1} with a fairly good agreement of 80 per cent as compared to observed values.
- An area of 40981 ha in Villupuram and Tiruvannamalai districts was found to be under chances of crop failure based on Water Requirement Satisfaction index (WRSI). Major groundnut areas of Salem district (14188 ha) was under medium risk zone.
- Considering overall vulnerability, whole district of Villupuram was adjudged as highly vulnerable to drought with regard to groundnut cultivation whereas four blocks of Salem, eight blocks of Namakkal and all the blocks of Tiruvannamalai were found to be moderately vulnerable to drought.

6.3 Recommendations

- ❖ Hence, considering the overall accuracy, it is concluded that multi date Sentinel 1A Synthetic Aperture Radar data can be recommended for estimating Groundnut area at regional scale.
- ❖ DSSAT CROPGRO-Peanut model can be used as an effective tool to simulate growth and yield of groundnut and on integration with remote sensing it can be recommended to generate yields at spatial scale.
- ❖ The vulnerability of groundnut to drought can be assessed at regional scale using drought indices *viz*., SPI, NDVI and WRSI.

6.4 Future line of Work

- ➢ Necessary spatial data sets on weather, soil, varieties and management practices have to be created on groundnut ecosystem to integrate them with remote sensing based database for spatial estimation yield and to improve accuracy.
- ➢ Developing interface to assimilate remote sensing products into DSSAT crop simulation modules.
- ➢ Establishing a regular monitoring mechanism to generate temporal database on drought with continuous generation of maps and statistics on drought indices.

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Appendices

APPENDIX I

Weekly weather data prevailed in Mecheri of Salem district during *kharif* 2015

Standard Week	Temperature		Rainfall (mm)	Solar Radiation ($cal/cm^2 min^{-1}$)
	Max (ºC)	Min (ºC)		
19	37.9	23.0	7.0	432.5
20	34.8	22.9	59.5	323.7
21	39.0	24.5	0.0	455.0
22	37.6	22.5	29.0	380.3
23	38.9	23.8	8.0	448.2
24	35.9	23.2	1.5	435.8
25	38.3	23.6	0.0	402.0
26	38.8	23.3	0.0	396.1
27	39.4	23.4	0.0	457.0
28	38.7	24.7	0.0	423.9
29	32.4	22.8	0.0	371.8
30	33.4	23.9	22.5	430.6
31	36.2	24.0	17.5	400.9
32	35.3	23.9	0.0	372.7
33	35.4	23.8	35.5	343.9
34	33.9	23.4	37.0	328.2
35	35.4	23.3	0.5	440.1
36	34.7	24.2	18.5	355.0
37	34.7	22.4	6.5	437.0

APPENDIX II

Weekly weather data prevailed in Namakkal during *kharif* 2015

Standard Week	Temperature		Rainfall (mm)	Solar Radiation (cal cm^{2}min^{-1})
	Max (ºC)	Min (ºC)		
19	36.0	25.4	16.5	382.7
20	33.0	24.7	73.5	290.8
21	36.3	26.0	0.0	388.2
22	35.2	24.5	26.5	331.4
23	36.2	24.9	12.0	398.4
24	35.2	26.0	4.2	339.5
25	35.0	26.3	3.2	360.5
26	36.4	26.1	0.0	388.7
27	37.0	25.3	0.0	397.1
28	36.6	25.6	0.0	405.8
29	36.3	25.4	21.5	390.9
30	34.9	24.7	24.5	406.9
31	36.5	24.7	31.0	413.3
32	36.1	25.4	0.0	360.8
33	35.7	25.0	22.5	388.2
34	35.1	24.6	26.5	376.4
35	36.9	24.9	0.0	460.4
36	34.7	24.8	52.0	384.7
37	35.9	25.4	0.0	447.6

APPENDIX III

Weekly weather data prevailed in Thandrampattu of Tiruvannamalai district during *rabi* 2015

Standard Week	Temperature		Rainfall (mm)	Solar Radiation (cal/cm^{2}min^{-1})
	Max (ºC)	Min (ºC)		
42	33.6	23.9	0.0	438.3
43	32.7	23.1	1.5	387.0
44	30.9	24.2	15.5	303.0
45	28.6	23.6	97.0	195.5
46	26.5	22.6	84.0	178.0
47	27.6	23.1	99.5	198.5
48	28.0	22.9	66.0	259.1
49	26.5	22.6	20.0	147.2
50	28.9	23.4	14.0	364.4
51	30.0	21.8	0.0	492.6
52	29.2	20.9	0.0	508.5
1	29.6	19.2	0.0	494.7
2	29.2	18.3	0.0	348.1
3	29.2	20.4	0.0	364.3
4	29.3	21.3	0.0	275.1
5	31.1	18.2	0.0	426.0
6	30.9	20.4	0.0	379.9
7	31.0	20.7	0.0	509.1

APPENDIX IV

Weekly weather data prevailed in Melmalaiyanur of Villupuram district during *rabi* 2015

Standard Week	Temperature		Rainfall (mm)	Solar Radiation (cal/cm^{2}min^{-1})
	Max (ºC)	Min (ºC)		
42	43.5	30.6	0.0	457.1
43	38.5	25.9	0.0	385.7
44	38.5	28.7	21.5	318.8
45	28.8	23.5	182.5	174.2
46	26.5	21.5	94.0	212.1
47	28.0	22.8	128.0	179.6
48	28.2	22.7	107.5	254.8
49	26.8	22.6	58.5	177.9
50	32.5	22.7	8.0	326.9
51	34.6	21.0	0.0	434.3
52	34.0	19.9	0.0	422.0
1	28.6	21.0	0.0	393.6
2	29.4	18.7	0.0	398.1
3	29.4	19.9	1.0	376.6
4	29.9	21.3	1.0	322.6
5	31.2	18.8	0.0	444.6
6	31.3	20.6	0.0	425.1
7	31.5	20.1	0.0	430.7

APPENDIX V

Values of Multi Temporal Features (MTF) for groundnut during *kharif* 2015 in test sites of Salem and Namakkal districts

S. No.	VH_max (dB)	VV_max (dB)	VH_min (dB)	VV_min (dB)	VH_mea (dB)	VV_mea (dB)	VH_maD (dB)	VV_maD (dB)	VV_miD (dB)	VH_miD (dB)
1	-16.00	-8.59	-18.96	-10.83	-17.49	-9.97	6	6	1	1
2	-15.77	-6.83	-17.64	-11.57	-16.99	-9.81	7	6	1	2
3	-14.12	-7.82	-18.22	-10.22	-16.22	-8.99	6	6	1	1
4	-13.01	-7.47	-17.82	-11.14	-16.00	-9.66	6	6	1	1
5	-16.07	-9.71	-19.39	-12.14	-17.41	-10.88	6	7	2	2
6	-14.57	-9.03	-18.70	-11.93	-16.97	-10.83	6	6	1	1
7	-13.94	-8.76	-18.64	-10.94	-16.87	-10.13	6	6	1	1
8	-16.21	-6.13	-18.69	-10.62	-17.80	-7.87	6	6	1	1
9	-16.95	-7.05	-18.53	-10.97	-17.76	-9.51	6	6	1	1
10	-14.87	-6.83	-16.77	-9.26	-15.81	-8.36	6	6	1	1
11	-14.45	-7.94	-19.67	-12.47	-17.71	-10.72	7	6	1	2
12	-14.10	-7.74	-19.86	-12.58	-17.48	-10.82	6	6	1	1
13	-14.67	-8.63	-18.98	-11.24	-17.03	-10.27	6	6	1	1
14	-13.70	-7.63	-19.36	-11.79	-16.91	-10.01	6	6	1	1
15	-13.97	-5.47	-18.38	-9.33	-16.83	-7.85	7	5	1	3
16	-13.54	-7.57	-18.82	-11.78	-16.75	-10.28	6	6	1	1
17	-14.35	-8.80	-18.31	-11.19	-16.63	-10.16	6	6	3	1
18	-13.87	-8.49	-18.33	-11.05	-16.46	-10.02	6	6	1	1
19	-14.67	-6.82	-17.78	-11.56	-16.25	-9.35	7	7	2	1
20	-13.58	-8.04	-17.86	-11.59	-16.06	-10.44	6	6	1	1

APPENDIX VI

Values of Multi Temporal Features (MTF) for groundnut during *rabi* 2015 in test sites of Tiruvannamalai and Villupuram districts

S. No.	VH_max (dB)	VV_max (dB)	VH_min (dB)	VV_min (dB)	VH_mea (dB)	VV_mea (dB)	VH_maD (dB)	VV_maD (dB)	VV_miD (dB)	VH_miD (dB)
1	-14.09	-7.91	1.12	-12.11	-16.50	-10.13	8	7	1	1
2	-14.96	-8.01	1.12	-10.73	-16.19	-9.68	7	7	2	1
3	-14.74	-8.16	1.12	-10.77	-16.03	-9.63	7	7	1	1
4	-16.93	-8.20	1.07	-11.74	-17.91	-9.80	7	7	1	1
5	-16.23	-8.14	1.06	-10.56	-17.96	-9.43	7	7	1	2
6	-12.59	-6.15	1.14	-9.40	-14.49	-7.77	7	7	1	1
7	-15.41	-8.89	1.11	-11.83	-17.79	-10.56	7	7	1	1
8	-12.93	-7.07	1.18	-10.31	-15.46	-8.84	8	7	1	3
9	-14.65	-6.75	1.08	-10.47	-16.19	-8.92	7	7	1	1
10	-12.74	-6.76	1.20	-9.72	-14.46	-8.48	7	7	1	2
11	-14.28	-8.16	1.20	-10.97	-16.02	-9.47	6	7	1	1
12	-14.43	-8.69	1.09	-11.03	-15.63	-9.72	7	7	1	1
13	-15.12	-8.42	1.06	-11.24	-15.97	-9.67	7	7	2	1
14	-13.71	-7.23	1.08	-8.61	-15.21	-8.01	7	7	1	1
15	-14.75	-7.30	1.06	-9.70	-15.73	-8.63	7	7	1	2
16	-15.49	-8.73	1.08	-12.36	-17.80	-10.64	6	7	1	1
17	-14.71	-7.74	1.09	-10.51	-16.06	-9.24	7	7	1	1
18	-14.64	-6.06	1.08	-10.76	-16.54	-9.33	7	8	2	1
19	-12.96	-7.37	1.12	-9.02	-14.85	-8.24	8	7	1	3
20	-13.59	-6.32	1.11	-10.07	-15.53	-8.53	7	7	1	1

APPENDIX VII

List of Ground truth points collected over Salem and Namakkal districts

S.no.	Date	Village	Time	Latitude	Longitude	Land use
1	26/06/2015	Velammal valasu	9.26	11.571426	77.856563	Groundnut
2	26/06/2015	Mecheri	11.35	11.809098	77.970682	Groundnut
3	26/06/2015	Parjukalipatti before	12.09	11.771720	78.003294	Groundnut
4	26/06/2015	karuppanampatti	12.17	11.756645	78.020592	Groundnut
5	26/06/2015	Pappambadi	1.04	11.655283	77.957917	Groundnut
6	26/06/2015	Moongathur	1.22	11.623707	77.958709	Groundnut
7	26/06/2015	Kakapalayam	2.00	11.546713	78.017546	Groundnut
8	26/06/2015	Kandarkulamanickam	2.09	11.541459	78.033784	Groundnut
9	26/06/2015	Vellapillakovil	3.15	11.510652	78.097157	Groundnut
10	26/06/2015	Masakalipatti	3.49	11.433090	78.156064	Groundnut
11	26/06/2015	Rasakavundanur	4.04	11.382642	78.161031	Groundnut
12	26/06/2015	Pudhuchatthiram	4.14	11.360763	78.165834	Groundnut
13	26/06/2015	karungal palayam	4.36	11.295544	78.167221	Groundnut
14	26/06/2015	Chinna thalaigai	6.16	11.259429	78.100833	Groundnut
15	26/06/2015	Manikattiputhur	6.24	11.266464	78.089792	Groundnut
16	26/06/2015	Velagavundmpatti	6.29	11.268051	78.087769	Groundnut
17	26/06/2015	Manathi	6.39	11.293850	78.051275	Groundnut
18	26/06/2015	Ilangar	6.43	11.297486	78.048509	Groundnut
19	26/06/2015	Manickam palayam	6.49	11.316942	78.033453	Groundnut
20	26/06/2015	Rayar palayam	6.56	11.337090	77.998696	Groundnut
21	26/06/2015	Rayar palayam	7.02	11.341351	77.974940	Groundnut
22	26/06/2015	Unjanai	7.08	11.356170	77.951266	Groundnut

S.no.	Date	Village	Time	Latitude	Longitude	Land use
23	23/05/2015	Chinnathambipalayam	1.11	11.414363	77.937111	Groundnut
24	23/05/2015	Morepalayam	1.36	11.444336	77.959987	Groundnut
25	23/05/2015	Mallasamudram	2.23	11.473452	78.002817	Groundnut
26	23/05/2015	Kalipatti	3.35	11.509074	78.032101	Groundnut
27	23/05/2015	Kalipatti	3.5	11.514806	78.035464	Groundnut
28	23/05/2015	Pudhupalayam	4.18	11.546494	78.061454	Groundnut
29	23/05/2015	Kakkapalayam	6.44	11.560000	78.012161	Groundnut
30	23/05/2015	Kakkapalayam	6.55	11.564265	78.013356	Groundnut
31	23/05/2015	Kakkapalayam	7.01	11.564216	78.014321	Groundnut
32	07/06/2015	Nayakanpatti	10.20	11.646526	78.056082	Groundnut
33	07/06/2015	Thirumalaigiri	11.54	11.652846	78.065313	Groundnut
34	07/06/2015	Pumandapatti	12.13	11.657795	78.061124	Groundnut
35	07/06/2015	Nallampatti	12.32	11.651394	78.045709	Groundnut
36	08/07/2015	Pudhupuliyampatti	1.30	11.330955	77.924786	Groundnut
37	08/07/2015	Pudhupuliyampatti	1.55	11.330010	77.924838	Groundnut
38	08/07/2015	Pudhupuliyampatti	3.28	11.332088	77.930249	Groundnut
39	08/07/2015	Chittalandur	4.06	11.322477	77.920182	Groundnut
40	08/07/2015	Pudhupuliyampatti	5.05	11.330754	77.921886	Groundnut
41	08/10/2015	Poochangadu	7.09	11.437659	77.863974	Groundnut
42	08/10/2015	Madur	7.23	11.426982	77.862792	Groundnut
43	08/10/2015	Puthu puliyampatti	8.20	11.331562	77.921435	Groundnut
44	08/10/2015	Puthu puliyampatti	9.50	11.330589	77.922949	Groundnut
45	08/10/2015	Elachipalayam	10.12	11.343268	77.930540	Groundnut
46	08/10/2015	Mavurettipatti	10.30	11.338799	77.984533	Groundnut

S.no.	Date	Village	Time	Latitude	Longitude	Land use
47	07/06/2015	Puthu puliyampatti	12.23	11.65165	78.0526	Barren land
48	26/06/2015	Velammal valasu	9.12	11.532157	77.853182	Coconut
49	26/06/2015	Velammal valasu	9.21	11.562509	77.858512	Rock mine
50	26/06/2015	Idappadi main	9.46	11.572192	77.831997	Water body
51	26/06/2015	A.V. Palayam	10.04	11.619307	77.840124	Green gram
52	26/06/2015	Moola kadai	10.16	11.657946	77.853195	Green gram
53	26/06/2015	Soorapalli	10.37	11.719214	77.876635	Coconut
54	26/06/2015	Vanavasi	10.43	11.737434	77.877517	Mango orchard
55	26/06/2015	Vanavasi	10.48	11.744788	77.878690	Mango orchard
56	26/06/2015	Nangavalli	11.02	11.772549	77.897750	Cassava
57	26/06/2015	2KM from Nangavalli	11.10	11.788316	77.909922	Coconut
58	26/06/2015	Saatthapadi	11.41	11.803532	77.976495	Green gram
59	26/06/2015	Sindhamaniyur	12.03	11.774166	77.998834	Cowpea
60	26/06/2015	Settimedu	12.31	11.722653	78.015184	Sugarcane
61	26/06/2015	Sikkampatti	12.37	11.717334	77.998231	Barren land
62	26/06/2015	Tharamangalam	12.47	11.696175	77.971781	Bus stand
63	26/06/2015	Thattampatti	12.54	11.678604	77.967864	Sorghum
64	26/06/2015	Kindakanoor	1.19	11.625432	77.959846	Green gram
65	26/06/2015	Kandarkulamanikam	1.49	11.544846	78.022840	Cassava
66	26/06/2015	Aattayampatti main	2.55	11.526237	78.062273	Water body
67	26/06/2015	Aattayampatti main	2.59	11.525769	78.067918	Sugarcane
68	26/06/2015	Vennandhur near	3.04	11.525370	78.072058	Bhendi
69	26/06/2015	Alavaaipatti	3.21	11.506508	78.106485	Cassava
70	26/06/2015	Atthanur	3.28	11.499337	78.123559	Fodder sorghum

S.no.	Date	Village	Time	Latitude	Longitude	Land use
71	26/06/2015	Masakalipatti	3.37	11.484827	78.154129	Sugarcane
72	26/06/2015	Kalangavi	4.27	11.338568	78.171082	Sorghum
73	26/06/2015	Chinna thalaigai	6.19	11.259842	78.100051	Barren land
74	23/05/2015	Trichengodu	12.40	11.383536	77.895415	Builtup
75	23/05/2015	Pudhupalayam	4.18	11.546922	78.061131	Coconut
76	23/05/2015	Pudhupalayam	4.28	11.549778	78.064821	Sugarcane
77	23/05/2015	Pudhupalayam	4.41	11.552852	78.065612	Coconut
78	23/05/2015	Kakkapalayam	6.49	11.563661	78.011286	Built up
79	07/06/2015	Vattamuthampatti	11.57	11.657487	78.066011	Fodder sorghum
80	07/06/2015	Thirumalaigiri	12.04	11.656966	78.078078	Onion
81	07/06/2015	Nayakanpatti	12.23	11.651655	78.052604	Barren land
82	07/06/2015	Kurukkapatti	12.57	11.689038	77.977486	Water body
83	07/06/2015	Tharamangalam	1.13	11.711443	77.956167	Greengram
84	07/06/2015	M.Cheetipatti	1.38	11.721674	78.013681	Green gram
85	08/07/2015	Thiruchengode	10.00	11.378019	77.894136	Built up
86	08/10/2015	Kalinayakkanpatti	11.00	11.280741	78.074415	Fodder sorghum
87	08/10/2015	Kalinayakkanpatti	11.03	11.280638	78.073568	Prosopis
88	08/11/2015	Erumapatti	12.00	11.149297	78.325211	Prosopis

APPENDIX VIII

List of Ground truth points collected over Tiruvannamalai and Villupuram districts

S.No.	Date	Village	Time	Latitude	Longitude	Land use
1	18/11/2015	Melsevalambadi	4.20	12.410479	79.309562	Groundnut
2	18/11/2015	Sanandhal	3.33	12.292294	79.113635	Groundnut
3	18/11/2015	Mel Kunnumurunji	3.25	12.276867	79.099469	Groundnut
4	18/11/2015	Nambiyandhal	1.21	12.373645	78.980164	Groundnut
5	18/11/2015	Thandarampattu	11.40	12.194233	78.935033	Groundnut
6	18/11/2015	Radhapuram near	11.2	12.155403	78.972889	Groundnut
7	18/11/2015	Radhapuram near	11.14	12.151058	78.978829	Groundnut
8	18/11/2015	S. Koodalur	10.52	12.128628	79.008918	Groundnut
9	18/11/2015	Vanapuram	10.30	12.102401	79.029849	Groundnut
10	05/11/2015	Kaviriyampoondi	10.30	12.223407	79.018986	Groundnut
11	05/11/2015	Kaviriyampoondi	10.40	12.212892	79.015384	Groundnut
12	05/11/2015	Pandithapattu	10.45	12.212895	79.016765	Groundnut
13	05/11/2015	Perumbakkam	11.00	12.224921	79.002171	Groundnut
14	05/11/2015	Thandrampattu	11.30	12.156439	78.936109	Groundnut
15	05/11/2015	Thandrampattu	11.33	12.189638	78.966859	Groundnut
16	05/11/2015	Keelaravundambadi	12.2	12.158204	78.930508	Groundnut
17	05/11/2015	Keelaravundambadi	12.45	12.170157	78.940905	Groundnut
18	05/11/2015	Moraiyaru, Sengam	1.35	12.287627	78.826578	Groundnut
19	05/11/2015	Arattavadi	1.58	12.234930	78.791851	Groundnut
20	05/11/2015	Arattavadi	2.10	12.261953	78.809132	Groundnut
21	05/11/2015	Kadaladi	3.56	12.415488	78.983143	Groundnut
22	05/11/2015	Kalapakkam,	4.00	12.428494	79.005069	Groundnut

S.No.	Date	Village	Time	Latitude	Longitude	Land use
23	05/11/2015	Mottur	4.15	12.445679	79.062369	Groundnut
24	05/11/2015	Nayudumangalam,	4.40	12.406068	79.103258	Groundnut
25	11/04/2016	Satthanur	6.53	12.190039	78.928131	Groundnut
26	11/04/2016	Malsettipattu	7.21	12.188118	79.019647	Groundnut
27	11/04/2016	Vediappanoor	08.01	12.255982	79.015196	Groundnut
28	11/04/2016	Atthiyandhal road	08.11	12.243122	79.007214	Groundnut
29	11/04/2016	Devanandal	08.28	12.265187	79.009978	Groundnut
30	11/04/2016	Paliapattu	09.04	12.280667	79.007695	Groundnut
31	11/04/2016	Vasoor	10.58	12.485022	79.116029	Groundnut
32	11/04/2016	Keelkovalaimedu	02.01	12.558310	79.534471	Groundnut
33	11/04/2016	Keelkovalaimedu	02.10	12.556368	79.539175	Groundnut
34	11/04/2016	Puthur	04.02	12.426093	79.504722	Groundnut
35	11/04/2016	Sanjeevirayan pettai	05.53	12.413674	79.314014	Groundnut
36	11/04/2016	Kunthalampattu	06.16	12.363806	79.263631	Groundnut
37	11/04/2016	Erumpundi	06.34	12.330794	79.238224	Groundnut
38	11/04/2016	Erumpundi	06.41	12.314077	79.236959	Groundnut
39	11/04/2016	Mekalur	06.53	12.264624	79.226987	Groundnut
40	12/04/2016	Tindivanam	07.07	12.212747	79.669543	Groundnut
41	12/04/2016	Endiyur	08.16	12.197063	79.681723	Groundnut
42	12/04/2016	Endiyur	08.28	12.201015	79.683162	Groundnut
43	12/04/2016	Mariyamangalam	09.01	12.230407	79.708463	Groundnut
44	12/04/2016	Nolambur	09.42	12.253718	79.730477	Groundnut
45	12/04/2016	Eappakkam	09.57	12.269941	79.743944	Groundnut
46	12/04/2016	Kambur	10.43	12.296935	79.760438	Groundnut

S.No.	Date	Village	Time	Latitude	Longitude	Land use
47	12/04/2016	Avanipur	10.57	12.279366	79.809350	Groundnut
48	12/04/2016	Nallur	11.18	12.246802	79.826471	Groundnut
49	12/04/2016	Nerkunnam	11.27	12.229536	79.815432	Groundnut
50	12/04/2016	Ulagapuram	11.52	12.165214	79.763134	Groundnut
51	12/04/2016	Kiliyanur	12.20	12.105762	79.742008	Groundnut
52	12/04/2016	Semangalam	01.12	12.069286	79.710646	Groundnut
53	12/04/2016	Thazhuthali	01.38	12.082946	79.647766	Groundnut
54	12/04/2016	V. Chithamur	04.43	11.992155	79.281995	Groundnut
55	12/04/2016	Arakandanallur	04.56	11.988111	79.238246	Groundnut
56	12/04/2016	Kanakanandhal	05.30	11.934875	79.170418	Groundnut
57	12/04/2016	Vadiyankuppam	05.42	11.919440	79.152208	Groundnut
58	12/04/2016	Padiyandhal	05.56	11.896331	79.126536	Groundnut
59	12/04/2016	Agaram	12.46	12.084496	79.718819	Groundnut
60	12/04/2016	Agaram	12.46	12.083370	79.717923	Groundnut
61	12/04/2016	Kadaganur	04.46	11.993849	79.269378	Groundnut
62	12/04/2016	Arakandanallur	05.00	11.987574	79.232481	Groundnut
63	18/11/2015	Putthiyandhal	9.30	12.19629	79.07024	Rice
64	18/11/2015	Manalurpettai	10.00	12.14508	79.07661	Forest
65	18/11/2015	Putthiyandhal	9.46	12.17678	79.07227	Sugarcane
66	18/11/2015	Pavupattu	10.13	12.11518	79.06509	Sugarcane
67	05/11/2015	Kadaladi	3.45	12.41105	78.97597	Rice
68	10/04/2016	Ettipatti, Harur	5.43	12.08967	78.44775	Mango
69	10/04/2016	Theerthamalai	6.09	12.10097	78.54736	Forest
70	10/04/2016	Theerthamalai	6.31	12.08415	78.63159	Forest

S.No.	Date	Village	Time	Latitude	Longitude	Land use
71	11/04/2016	Satthanur Dam	6.58	12.18328	78.86434	Forest
72	11/04/2016	Satthanur	6.44	12.20245	78.89014	Sugarcane
73	11/04/2016	Kanchi	10.15	12.38928	78.95511	Rice
74	11/04/2016	Parvathiagaram	10.24	12.41001	78.975	Rice
75	11/04/2016	Sozhavaram	10.42	12.4361	79.04275	Rice
76	11/04/2016	Thatchambadi	11.45	12.4815	79.27827	Rice
77	11/04/2016	Idayankulatthur	11.57	12.46647	79.32696	Rice
78	11/04/2016	Thiruvaganallur	12.18	12.53083	79.33507	Rice
79	11/04/2016	Randham	12.38	12.57623	79.31472	Casuarina
80	11/04/2016	Aagaram	12.58	12.61036	79.32101	Rice
81	11/04/2016	Thellur	02.23	12.53537	79.57225	Rice
82	11/04/2016	Settikulam	03.37	12.41212	79.52852	Rice
83	11/04/2016	Desur	04.17	12.43205	79.4798	Rice
84	11/04/2016	Esakolatthur	04.55	12.44396	79.43785	Rice
85	11/04/2016	Sanjeevirayan pettai	05.44	12.42661	79.32631	Rice
86	11/04/2016	Sanjeevirayan pettai	05.49	12.41906	79.3176	Sugarcane
87	11/04/2016	Unnamanandhal	06.04	12.39328	79.29562	Sugarcane
88	11/04/2016	Avalurpettai	06.29	12.33189	79.23863	Sugarcane
89	12/04/2016	Vetlapuram	08.53	12.23725	79.69081	Rice
90	12/04/2016	Annambakkam	10.50	12.28833	79.79041	Barren land
91	12/04/2016	Avanipur	11.07	12.27756	79.82907	Rice
92	12/04/2016	Pudhukuppam	12.05	12.12132	79.75364	Rice
93	12/04/2016	Vikravandi	02.55	12.02698	79.54144	Sugarcane
94	12/04/2016	Alathur	03.26	11.9477	79.46905	Sugarcane

S.No.	Date	Village	Time	Latitude	Longitude	Land use
95	12/04/2016	Alathur	03.37	11.94357	79.45986	Rice
96	12/04/2016	Perumbakkam	04.15	11.94165	79.4345	Rice
97	12/04/2016	Arakandanallur	04.58	11.98763	79.23756	Sugarcane
98	12/04/2016	Kallakurichi	07.00	11.73027	78.97864	Rice
99	12/04/2016	Avanipur	10.55	12.28541	79.81171	Water body
100	12/04/2016	Avanipur	11.06	12.28155	79.83069	Rice
101	12/04/2016	Agaram	12.47	12.07994	79.71436	Rice
102	12/04/2016	Agaram	12.47	12.07906	79.71351	Rice
103	12/04/2016	Vinayagapuram	01.16	12.05833	79.70959	Tapioca
104	12/04/2016	Salai	02.20	12.07975	79.55317	Rice
105	12/04/2016	Alathur	03.20	11.94983	79.47286	Rice
106	12/04/2016	Alathur	03.22	11.94699	79.47005	Barren land
107	12/04/2016	Alathur	03.22	11.94815	79.46831	Banana
108	12/04/2016	Chitteripattu	06.30	11.80183	79.06452	Eucalyptus

APPENDIX IX

Groundnut map validation confusion matrix for Salem and Namakkal districts

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non-Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-non Groundnut?
Groundnut Points													
1	26-06-2015	9.26	11.571426	77.856563	1	0		0	Groundnut	0	1	0	0
2	26-06-2015	11.35	11.809098	77.970682	1	0		1	Groundnut	1	0	0	0
3	26-06-2015	12.09	11.77172	78.003294	1	0		1	Groundnut	1	0	0	0
4	26-06-2015	12.17	11.756645	78.020592	1	0		1	Groundnut	1	0	0	0
5	26-06-2015	1.04	11.655283	77.957917	1	0		1	Groundnut	1	0	0	0
6	26-06-2015	1.22	11.623707	77.958709	1	0		1	Groundnut	1	0	0	0
7	26-06-2015	2.00	11.546713	78.017546	1	0		1	Groundnut	1	0	0	0
8	26-06-2015	2.09	11.541459	78.033784	1	0		1	Groundnut	1	0	0	0
9	26-06-2015	3.15	11.510652	78.097157	1	0		0	Groundnut	0	1	0	0
10	26-06-2015	3.49	11.43309	78.156064	1	0		1	Groundnut	1	0	0	0
11	26-06-2015	4.04	11.382642	78.161031	1	0		1	Groundnut	1	0	0	0
12	26-06-2015	4.14	11.360763	78.165834	1	0		1	Groundnut	1	0	0	0
13	26-06-2015	4.36	11.295544	78.167221	1	0		0	Groundnut	0	1	0	0
14	26-06-2015	6.16	11.259429	78.100833	1	0		0	Groundnut	0	1	0	0
15	26-06-2015	6.24	11.266464	78.089792	1	0		0	Groundnut	0	1	0	0
16	26-06-2015	6.29	11.268051	78.087769	1	0		0	Groundnut	0	1	0	0
17	26-06-2015	6.39	11.29385	78.051275	1	0		1	Groundnut	1	0	0	0
18	26-06-2015	6.43	11.297486	78.048509	1	0		0	Groundnut	0	1	0	0
19	26-06-2015	6.49	11.316942	78.033453	1	0		1	Groundnut	1	0	0	0
20	26-06-2015	6.56	11.33709	77.998696	1	0		1	Groundnut	1	0	0	0
21	26-06-2015	7.02	11.341351	77.97494	1	0		1	Groundnut	1	0	0	0

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non-Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-non Groundnut?
22	26-06-2015	7.08	11.35617	77.951266	1	0		1	Groundnut	1	0	0	0
23	23-05-2015	1.11	11.414363	77.937111	1	0		1	Groundnut	1	0	0	0
24	23-05-2015	1.36	11.444336	77.959987	1	0		1	Groundnut	1	0	0	0
25	23-05-2015	2.23	11.473452	78.002817	1	0		1	Groundnut	1	0	0	0
26	23-05-2015	3.35	11.509074	78.032101	1	0		1	Groundnut	1	0	0	0
27	23-05-2015	12:00	11.514806	78.035464	1	0		1	Groundnut	1	0	0	0
28	23-05-2015	04:19	11.546494	78.061454	1	0		1	Groundnut	1	0	0	0
29	23-05-2015	10:33	11.56	78.012161	1	0		1	Groundnut	1	0	0	0
30	23-05-2015	13:12	11.564265	78.013356	1	0		1	Groundnut	1	0	0	0
31	23-05-2015	00:14	11.564216	78.014321	1	0		1	Groundnut	1	0	0	0
32	07-06-2015	04:48	11.646526	78.056082	1	0		1	Groundnut	1	0	0	0
33	07-06-2015	12:57	11.652846	78.065313	1	0		1	Groundnut	1	0	0	0
34	07-06-2015	03:07	11.657795	78.061124	1	0		1	Groundnut	1	0	0	0
35	07-06-2015	07:40	11.651394	78.045709	1	0		1	Groundnut	1	0	0	0
36	08-07-2015	07:12	11.330955	77.924786	1	0		1	Groundnut	1	0	0	0
37	08-07-2015	13:12	11.33001	77.924838	1	0		1	Groundnut	1	0	0	0
38	08-07-2015	06:43	11.332088	77.930249	1	0		1	Groundnut	1	0	0	0
39	08-07-2015	01:26	11.322477	77.920182	1	0		1	Groundnut	1	0	0	0
40	08-07-2015	01:12	11.330754	77.921886	1	0		1	Groundnut	1	0	0	0
41	08-10-2015	02:09	11.437659	77.863974	1	0		0	Groundnut	0	1	0	0
42	08-10-2015	05:31	11.426982	77.862792	1	0		1	Groundnut	1	0	0	0
43	08-10-2015	04:48	11.331562	77.921435	1	0		0	Groundnut	0	1	0	0
44	08-10-2015	9.5	11.330589	77.922949	1	0		1	Groundnut	1	0	0	0
45	08-10-2015	10.12	11.343268	77.93054	1	0		0	Groundnut	0	1	0	0
46	08-10-2015	10.30	11.338799	77.984533	1	0		1	Groundnut	1	0	0	0

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non-Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-non Groundnut?
Non-Groundnut Points													
47	07-06-2015	12.23	11.65165	78.0526	0	1	Barren land	0	Non Groundnut	0	0	0	1
48	26-06-2015	9.12	11.532157	77.853182	0	1	Coconut	0	Non Groundnut	0	0	0	1
49	26-06-2015	9.21	11.562509	77.858512	0	1	Rock mine	0	Non Groundnut	0	0	0	1
50	26-06-2015	9.46	11.572192	77.831997	0	1	Water body	0	Non Groundnut	0	0	0	1
51	26-06-2015	10.04	11.619307	77.840124	0	1	Green gram	0	Non Groundnut	0	0	0	1
52	26-06-2015	10.16	11.657946	77.853195	0	1	Green gram	1	Non Groundnut	0	0	1	0
53	26-06-2015	10.37	11.719214	77.876635	0	1	Coconut	0	Non Groundnut	0	0	0	1
54	26-06-2015	10.43	11.737434	77.877517	0	1	Mango	0	Non Groundnut	0	0	0	1
55	26-06-2015	10.48	11.744788	77.87869	0	1	Mango	0	Non Groundnut	0	0	0	1
56	26-06-2015	11.02	11.772549	77.89775	0	1	Cassava	0	Non Groundnut	0	0	0	1
57	26-06-2015	11.1	11.788316	77.909922	0	1	Coconut	0	Non Groundnut	0	0	0	1
58	26-06-2015	11.41	11.803532	77.976495	0	1	Green gram	0	Non Groundnut	0	0	0	1
59	26-06-2015	12.03	11.774166	77.998834	0	1	Cowpea	0	Non Groundnut	0	0	0	1
60	26-06-2015	12.31	11.722653	78.015184	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
61	26-06-2015	12.37	11.717334	77.998231	0	1	Barren land	0	Non Groundnut	0	0	0	1
62	26-06-2015	12.47	11.696175	77.971781	0	1	Bus stand	0	Non Groundnut	0	0	0	1
63	26-06-2015	12.54	11.678604	77.967864	0	1	Sorghum	0	Non Groundnut	0	0	0	1
64	26-06-2015	1.19	11.625432	77.959846	0	1	Green gram	1	Non Groundnut	0	0	1	0
65	26-06-2015	1.49	11.544846	78.02284	0	1	Cassava	0	Non Groundnut	0	0	0	1
66	26-06-2015	2.55	11.526237	78.062273	0	1	Water body	0	Non Groundnut	0	0	0	1
67	26-06-2015	2.59	11.525769	78.067918	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
68	26-06-2015	3.04	11.52537	78.072058	0	1	Bhendi	0	Non Groundnut	0	0	0	1
69	26-06-2015	3.21	11.506508	78.106485	0	1	Cassava	0	Non Groundnut	0	0	0	1
70	26-06-2015	3.28	11.499337	78.123559	0	1	Sorghum	0	Non Groundnut	0	0	0	1

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non-Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-non Groundnut?
71	26-06-2015	3.37	11.484827	78.154129	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
72	26-06-2015	4.27	11.338568	78.171082	0	1	F. Sorghum	1	Non Groundnut	0	0	1	0
73	26-06-2015	6.19	11.259842	78.100051	0	1	Barren land	0	Non Groundnut	0	0	0	1
74	23-05-2015	12.4	11.383536	77.895415	0	1	Built up	0	Non Groundnut	0	0	0	1
75	23-05-2015	4.18	11.546922	78.061131	0	1	Coconut	0	Non Groundnut	0	0	0	1
76	23-05-2015	4.28	11.549778	78.064821	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
77	23-05-2015	4.41	11.552852	78.065612	0	1	Coconut	0	Non Groundnut	0	0	0	1
78	23-05-2015	6.49	11.563661	78.011286	0	1	Built up	0	Non Groundnut	0	0	0	1
79	07-06-2015	11.57	11.657487	78.066011	0	1	F. Sorghum	0	Non Groundnut	0	0	0	1
80	07-06-2015	12.04	11.656966	78.078078	0	1	Onion	0	Non Groundnut	0	0	0	1
81	07-06-2015	12.23	11.651655	78.052604	0	1	Barren land	0	Non Groundnut	0	0	0	1
82	07-06-2015	12.57	11.689038	77.977486	0	1	Water body	0	Non Groundnut	0	0	0	1
83	07-06-2015	1.13	11.711443	77.956167	0	1	Green gram	0	Non Groundnut	0	0	0	1
84	07-06-2015	1.38	11.721674	78.013681	0	1	Green gram	0	Non Groundnut	0	0	0	1
85	08-07-2015	10.05	11.378019	77.894136	0	1	Built up	0	Non Groundnut	0	0	0	1
86	08-10-2015	11.00	11.280741	78.074415	0	1	F. Sorghum	0	Non Groundnut	0	0	0	1
87	08-10-2015	11.03	11.280638	78.073568	0	1	Prosopis	0	Non Groundnut	0	0	0	1
88	08-11-2015	12.00	11.149297	78.325211	0	1	Prosopis	0	Non Groundnut	0	0	0	1

APPENDIX X

Groundnut map validation confusion matrix for Tiruvannamalai and Villupuram districts

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-Non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-Non Groundnut?
Groundnut Points													
1	18-11-2015	4.2	12.410479	79.3095620	1	0		1	Groundnut	1	0	0	0
2	18-11-2015	3.33	12.292294	79.1136350	1	0		1	Groundnut	1	0	0	0
3	18-11-2015	3.25	12.276867	79.0994690	1	0		1	Groundnut	1	0	0	0
4	18-11-2015	1.21	12.373645	78.9801640	1	0		1	Groundnut	1	0	0	0
5	18-11-2015	11.4	12.194233	78.9350330	1	0		1	Groundnut	1	0	0	0
6	18-11-2015	11.2	12.155403	78.9728890	1	0		0	Groundnut	0	1	0	0
7	18-11-2015	11.14	12.151058	78.9788290	1	0		0	Groundnut	0	1	0	0
8	18-11-2015	10.52	12.128628	79.0089180	1	0		1	Groundnut	1	0	0	0
9	18-11-2015	10.3	12.102401	79.0298490	1	0		1	Groundnut	1	0	0	0
10	05-11-2015	10.3	12.223407	79.0189860	1	0		1	Groundnut	1	0	0	0
11	05-11-2015	10.4	12.212892	79.0153840	1	0		1	Groundnut	1	0	0	0
12	05-11-2015	10.45	12.212895	79.0167650	1	0		1	Groundnut	1	0	0	0
13	05-11-2015	11	12.224921	79.0021710	1	0		1	Groundnut	1	0	0	0
14	05-11-2015	11.3	12.156439	78.9361090	1	0		1	Groundnut	1	0	0	0
15	05-11-2015	11.33	12.189638	78.9668590	1	0		0	Groundnut	0	1	0	0

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-Non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-Non Groundnut?
16	05-11-2015	12.2	12.158204	78.9305080	1	0		1	Groundnut	1	0	0	0
17	05-11-2015	12.45	12.170157	78.9409050	1	0		1	Groundnut	1	0	0	0
18	05-11-2015	1.35	12.287627	78.8265780	1	0		1	Groundnut	1	0	0	0
19	05-11-2015	1.58	12.234930	78.7918510	1	0		1	Groundnut	1	0	0	0
20	05-11-2015	2.1	12.261953	78.8091320	1	0		1	Groundnut	1	0	0	0
21	05-11-2015	3.56	12.415488	78.9831430	1	0		1	Groundnut	1	0	0	0
22	05-11-2015	4	12.428494	79.0050690	1	0		1	Groundnut	1	0	0	0
23	05-11-2015	4.15	12.445679	79.0623690	1	0		1	Groundnut	1	0	0	0
24	05-11-2015	4.4	12.406068	79.1032580	1	0		1	Groundnut	1	0	0	0
25	11-04-2016	6.53	12.190039	78.9281310	1	0		1	Groundnut	1	0	0	0
26	11-04-2016	7.21	12.188118	79.0196470	1	0		1	Groundnut	1	0	0	0
27	11-04-2016	8.01	12.255982	79.0151960	1	0		0	Groundnut	0	1	0	0
28	11-04-2016	8.11	12.243122	79.0072140	1	0		1	Groundnut	1	0	0	0
29	11-04-2016	8.28	12.265187	79.0099780	1	0		0	Groundnut	0	1	0	0
30	11-04-2016	9.04	12.280667	79.0076950	1	0		1	Groundnut	1	0	0	0
31	11-04-2016	10.58	12.485022	79.1160290	1	0		1	Groundnut	1	0	0	0
32	11-04-2016	2.01	12.558310	79.5344710	1	0		1	Groundnut	1	0	0	0
33	11-04-2016	2.1	12.556368	79.5391750	1	0		0	Groundnut	0	1	0	0
34	11-04-2016	4.02	12.426093	79.5047220	1	0		1	Groundnut	1	0	0	0

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-Non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-Non Groundnut?
35	11-04-2016	5.53	12.413674	79.3140140	1	0		1	Groundnut	1	0	0	0
36	11-04-2016	6.16	12.363806	79.2636310	1	0		1	Groundnut	1	0	0	0
37	11-04-2016	6.34	12.330794	79.2382240	1	0		1	Groundnut	1	0	0	0
38	11-04-2016	6.41	12.314077	79.2369590	1	0		1	Groundnut	1	0	0	0
39	11-04-2016	6.53	12.264624	79.2269870	1	0		1	Groundnut	1	0	0	0
40	12-04-2016	7.07	12.212747	79.6695430	1	0		0	Groundnut	0	1	0	0
41	12-04-2016	8.16	12.197063	79.6817230	1	0		1	Groundnut	1	0	0	0
42	12-04-2016	8.28	12.201015	79.6831620	1	0		1	Groundnut	1	0	0	0
43	12-04-2016	9.01	12.230407	79.7084630	1	0		1	Groundnut	1	0	0	0
44	12-04-2016	9.42	12.253718	79.7304770	1	0		1	Groundnut	1	0	0	0
45	12-04-2016	9.57	12.269941	79.7439440	1	0		1	Groundnut	1	0	0	0
46	12-04-2016	10.43	12.296935	79.7604380	1	0		1	Groundnut	1	0	0	0
47	12-04-2016	10.57	12.279366	79.8093500	1	0		1	Groundnut	1	0	0	0
48	12-04-2016	11.18	12.246802	79.8264710	1	0		1	Groundnut	1	0	0	0
49	12-04-2016	11.27	12.229536	79.8154320	1	0		1	Groundnut	1	0	0	0
50	12-04-2016	11.52	12.165214	79.7631340	1	0		1	Groundnut	1	0	0	0
51	12-04-2016	12.2	12.105762	79.7420080	1	0		1	Groundnut	1	0	0	0
52	12-04-2016	1.12	12.069286	79.7106460	1	0		1	Groundnut	1	0	0	0
53	12-04-2016	1.38	12.082946	79.6477660	1	0		0	Groundnut	0	1	0	0

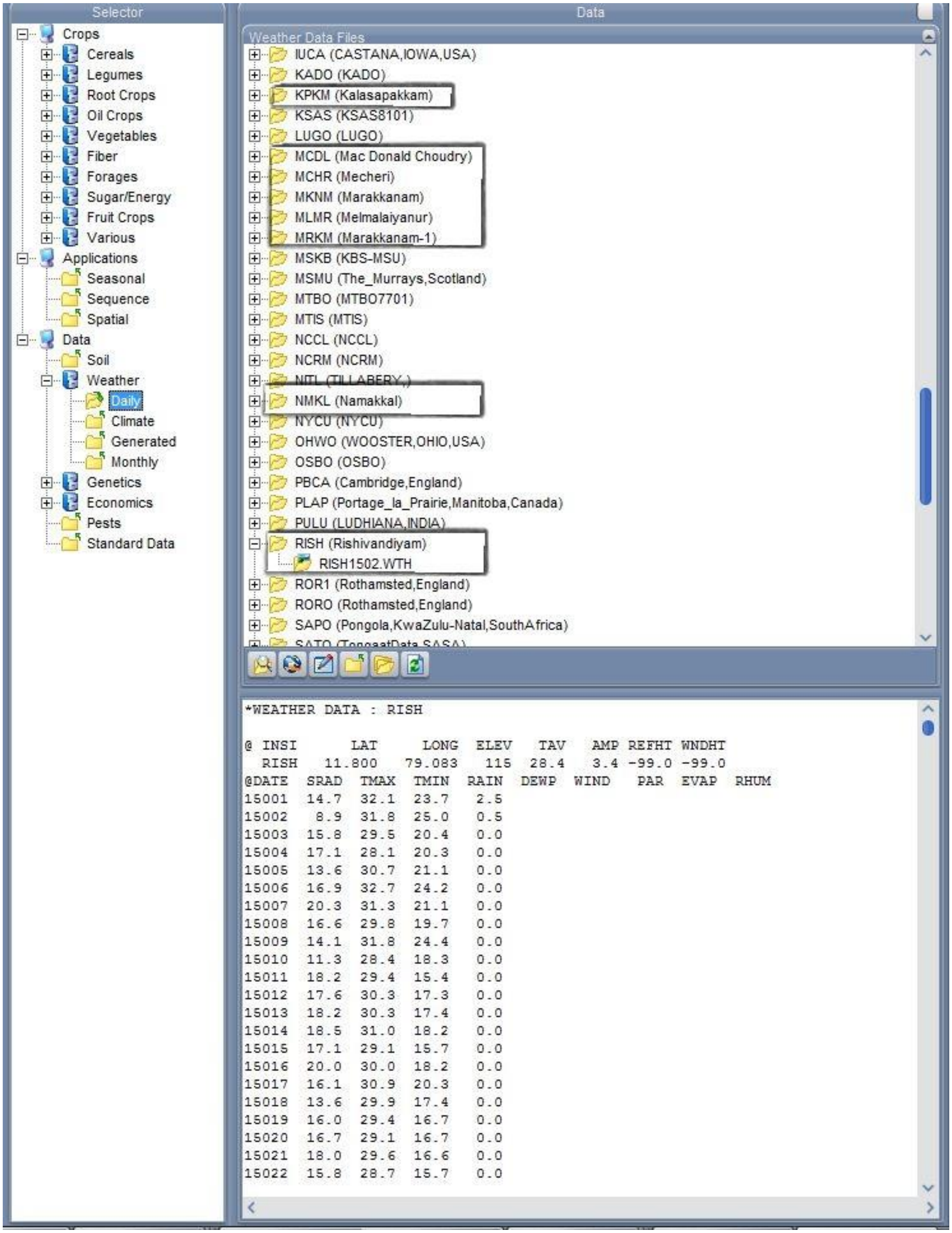
Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-Non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-Non Groundnut?
54	12-04-2016	4.43	11.992155	79.2819950	1	0		1	Groundnut	1	0	0	0
55	12-04-2016	4.56	11.988111	79.2382460	1	0		1	Groundnut	1	0	0	0
56	12-04-2016	5.3	11.934875	79.1704180	1	0		1	Groundnut	1	0	0	0
57	12-04-2016	5.42	11.919440	79.1522080	1	0		0	Groundnut	0	1	0	0
58	12-04-2016	5.56	11.896331	79.1265360	1	0		1	Groundnut	1	0	0	0
59	12-04-2016	12.46	12.084496	79.7188190	1	0		1	Groundnut	1	0	0	0
60	12-04-2016	12.46	12.083370	79.7179230	1	0		1	Groundnut	1	0	0	0
61	12-04-2016	4.46	11.993849	79.2693780	1	0		1	Groundnut	1	0	0	0
62	12-04-2016	5	11.987574	79.2324810	1	0		1	Groundnut	1	0	0	0
Non-Groundnut Points													
63	18-11-2015	9.3	12.196290	79.0702400	0	1	Rice	0	Non Groundnut	0	0	0	1
64	18-11-2015	10	12.145080	79.0766100	0	1	Forest	0	Non Groundnut	0	0	0	1
65	18-11-2015	9.46	12.176780	79.0722700	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
66	18-11-2015	10.13	12.115180	79.0650900	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
67	05-11-2015	3.45	12.411050	78.9759700	0	1	Rice	0	Non Groundnut	0	0	0	1
68	10-04-2016	5.43	12.089670	78.4477500	0	1	Mango	0	Non Groundnut	0	0	0	1
69	10-04-2016	6.09	12.100970	78.5473600	0	1	Forest	0	Non Groundnut	0	0	0	1
70	10-04-2016	6.31	12.084150	78.6315900	0	1	Forest	0	Non Groundnut	0	0	0	1
71	11-04-2016	6.58	12.183280	78.8643400	0	1	Forest	0	Non Groundnut	0	0	0	1

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-Non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-Non Groundnut?
72	11-04-2016	6.44	12.202450	78.8901400	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
73	11-04-2016	10.15	12.389280	78.9551100	0	1	Rice	0	Non Groundnut	0	0	0	1
74	11-04-2016	10.24	12.410010	78.9750000	0	1	Rice	0	Non Groundnut	0	0	0	1
75	11-04-2016	10.42	12.436100	79.0427500	0	1	Rice	0	Non Groundnut	0	0	0	1
76	11-04-2016	11.45	12.481500	79.2782700	0	1	Rice	0	Non Groundnut	0	0	0	1
77	11-04-2016	11.57	12.466470	79.3269600	0	1	Rice	0	Non Groundnut	0	0	0	1
78	11-04-2016	12.18	12.530830	79.3350700	0	1	Rice	0	Non Groundnut	0	0	0	1
79	11-04-2016	12.38	12.576230	79.3147200	0	1	Casuarina	0	Non Groundnut	0	0	0	1
80	11-04-2016	12.58	12.610360	79.3210100	0	1	Rice	0	Non Groundnut	0	0	0	1
81	11-04-2016	2.23	12.535370	79.5722500	0	1	Rice	0	Non Groundnut	0	0	0	1
82	11-04-2016	3.37	12.412120	79.5285200	0	1	Rice	0	Non Groundnut	0	0	0	1
83	11-04-2016	4.17	12.432050	79.4798000	0	1	Rice	1	Non Groundnut	0	0	1	0
84	11-04-2016	4.55	12.443960	79.4378500	0	1	Rice	0	Non Groundnut	0	0	0	1
85	11-04-2016	5.44	12.426610	79.3263100	0	1	Rice	1	Non Groundnut	0	0	1	0
86	11-04-2016	5.49	12.419060	79.3176000	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
87	11-04-2016	6.04	12.393289	79.2956290	0	1	Sugarcane	1	Non Groundnut	0	0	1	0
88	11-04-2016	6.29	12.331896	79.2386350	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
89	12-04-2016	8.53	12.237250	79.6908100	0	1	Rice	0	Non Groundnut	0	0	0	1
90	12-04-2016	10.5	12.288330	79.7904100	0	1	Barren land	0	Non Groundnut	0	0	0	1

Point ID	Date	Time	Latitude (Y)	Longitude (X)	Groundnut (1 for yes)	Non Groundnut (1 for yes)	Non Groundnut class	Map value	Map class	Groundnut-Groundnut?	Groundnut-Non Groundnut?	Non Groundnut-Groundnut?	Non Groundnut-Non Groundnut?
91	12-04-2016	11.07	12.277560	79.8290700	0	1	Rice	0	Non Groundnut	0	0	0	1
92	12-04-2016	12.05	12.121320	79.7536400	0	1	Rice	0	Non Groundnut	0	0	0	1
93	12-04-2016	2.55	12.026980	79.5414400	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
94	12-04-2016	3.26	11.947700	79.4690500	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
95	12-04-2016	3.37	11.943570	79.4598600	0	1	Rice	0	Non Groundnut	0	0	0	1
96	12-04-2016	4.15	11.941650	79.4345000	0	1	Rice	0	Non Groundnut	0	0	0	1
97	12-04-2016	4.58	11.987630	79.2375600	0	1	Sugarcane	0	Non Groundnut	0	0	0	1
98	12-04-2016	7	11.730270	78.9786400	0	1	Rice	0	Non Groundnut	0	0	0	1
99	12-04-2016	10.55	12.285410	79.8117100	0	1	Water body	0	Non Groundnut	0	0	0	1
100	12-04-2016	11.06	12.281550	79.8306900	0	1	Rice	0	Non Groundnut	0	0	0	1
101	12-04-2016	12.47	12.079940	79.7143600	0	1	Rice	0	Non Groundnut	0	0	0	1
102	12-04-2016	12.47	12.079060	79.7135100	0	1	Rice	0	Non Groundnut	0	0	0	1
103	12-04-2016	1.16	12.058330	79.7095900	0	1	Tapioca	0	Non Groundnut	0	0	0	1
104	12-04-2016	2.2	12.079750	79.5531700	0	1	Rice	0	Non Groundnut	0	0	0	1
105	12-04-2016	3.2	11.949830	79.4728600	0	1	Rice	0	Non Groundnut	0	0	0	1
106	12-04-2016	3.22	11.946990	79.4700500	0	1	Barren land	0	Non Groundnut	0	0	0	1
107	12-04-2016	3.22	11.948150	79.4683100	0	1	Banana	0	Non Groundnut	0	0	0	1
108	12-04-2016	6.3	11.801830	79.0645200	0	1	Eucalyptus	0	Non Groundnut	0	0	0	1

APPENDIX XI - A

View of Weather file in DSSAT V4.5



*WEATHER DATA : RISH

@ INSI	LAT	LONG	ELEV	TAV	AMP	REFHT	WNDHT
RISH	11.800	79.083	115	28.4	3.4	-99.0	-99.0

@DATE	SRAD	TMAX	TMIN	RAIN	DEWP	WIND	PAR	EVAP	RHUM
15001	14.7	32.1	23.7	2.5					
15002	8.9	31.8	25.0	0.5					
15003	15.8	29.5	20.4	0.0					
15004	17.1	28.1	20.3	0.0					
15005	13.6	30.7	21.1	0.0					
15006	16.9	32.7	24.2	0.0					
15007	20.3	31.3	21.1	0.0					
15008	16.6	29.8	19.7	0.0					
15009	14.1	31.8	24.4	0.0					
15010	11.3	28.4	18.3	0.0					
15011	18.2	29.4	15.4	0.0					
15012	17.6	30.3	17.3	0.0					
15013	18.2	30.3	17.4	0.0					
15014	18.5	31.0	18.2	0.0					
15015	17.1	29.1	15.7	0.0					
15016	20.0	30.0	18.2	0.0					
15017	16.1	30.9	20.3	0.0					
15018	13.6	29.9	17.4	0.0					
15019	16.0	29.4	16.7	0.0					
15020	16.7	29.1	16.7	0.0					
15021	18.0	29.6	16.6	0.0					
15022	15.8	28.7	15.7	0.0					

APPENDIX XI - B

View of generated soil file in DSSAT V4.5

```
*TNVETAVALM  RS&GIS,TNAU SL      93 Vetavalam
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 Chetpat     India         12.462  79.352 SANDY CLAY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BL   .09     6    .4    61     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    25   -99  .139   .23  .403     1  2.59  1.51   .64  19.2  15.7   -99   -99   7.2   -99  21.9   -99
    47   -99  .115  .196  .399  .595  2.59  1.52   .67  14.2  12.3   -99   -99   6.9   -99  21.4   -99
    93   -99  .144  .238  .404  .482   .43  1.51   .62  20.3  17.3   -99   -99   7.8   -99  17.6   -99

*TNPERAPERI  -99         SL      82 PERAPPERI
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA         12.288  78.827 CLAYLOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BL   .09     6    .4    61     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    12   -99  .115  .189  .389     1  2.59  1.55    .6  14.5   9.8   -99   -99   8.1   -99    12   -99
    34   -99  .194  .294  .407  .631   .43   1.5   .58  30.4  17.9   -99   -99   8.1   -99    37   -99
    64   -99  .207  .311  .412  .375   .43  1.49   .49  33.5  20.2   -99   -99   8.1   -99  40.1   -99
    82   -99  .222  .333  .426  .232   .23  1.45   .49  36.5  22.8   -99   -99   8.4   -99    51   -99

*TNPALLADAM  RS&GIS,TNAU SC      30 PALLADAM
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA          11.51  78.097 SANDy CLAY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BL   .09     6    .4    73     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    17   -99  .245  .341  .416     1   .12  1.47   .92  38.7   9.4   -99   -99   8.2   -99  23.3   -99
    30   -99  .222  .338  .435  .625   .23  1.42    .8  34.8  22.1   -99   -99   8.1   -99  24.8   -99

*TNPRDUNRAI  RS&GIS,TNAU   SL    92 PERUNDURAI
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADu   INDIA         11.441   77.97 SANDY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6    .4    73     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    13   -99  .024  .037  .077     1  2.59  1.62    .4    15     6    79   -99     6   -99  10.6   -99
    38   -99  .165  .221  .247    .6   .06  1.47    .5    48    11    41   -99   5.9   -99  22.8   -99
    70   -99    .3  .382  .386   .34   .06  1.24    .7    69     8    23   -99   5.9   -99  26.4   -99
    92   -99  .145  .192  .219  .198   .12  1.53    .3    46     9    45   -99   6.4   -99  19.2   -99

*TNIRUGURKP  RS&GIS,TNAU CL     100 IRUGUR
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA         11.547  78.018 CLAY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6   .25    61     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    22   -99  .124  .195  .262     1   .23  1.45   .35  33.3  27.9  38.8   -99     8   -99  25.1   -99
    58   -99  .044  .064  .112  .449   .43  1.58   .44  21.9   7.6  70.5   -99   8.1   -99  22.3   -99
    80   -99  .051  .075  .125  .252   .43  1.58   .35  24.2   8.6  67.2   -99   8.2   -99  19.6   -99
   100   -99  .121  .185  .247  .165   .23  1.49   .18  34.4  25.2  40.4   -99   8.3   -99  26.3   -99

*TNVELLALUR  RS&GIS,TNAU SCL     65 VELLALUR
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA         11.426  77.864 CLAy LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6   .25    61     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    22   -99  .077  .119  .176     1   .43  1.47   .84  26.7  15.5  57.8   -99   7.7   -99    11   -99
    37   -99  .103  .155  .208  .554   .43  1.47   .78  31.8    18  50.2   -99   7.5   -99   7.6   -99
    65   -99  .128  .179  .218  .361   .12  1.48   .68  39.7  12.9  47.4   -99   7.4   -99     9   -99
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```
*TNTOLRPATI  RS&GIS,TNAU SCL     48 TOLURPATTI
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA         11.361  78.166 CLAY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6   .25    73     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    18   -99  .057  .094  .154     1   .43  1.47   .89    21    16    63   -99   7.5   -99  18.4   -99
    48   -99  .127  .179  .219  .517   .12  1.48   .66    39    14    47   -99   6.8   -99  34.1   -99

*TNELVMALAI  RS&GIS,TNAU SCL     27 ELAVAMALAI
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA         11.329  77.924 LOAMY SAND
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
     Y   .17     6    .4    73     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    15   -99  .051  .071  .115     1   .43  1.62   .21    26   5.3  68.6   -99   6.5   -99  12.6   -99
    27   -99  .047  .065  .109  .657   .43  1.63   .18  25.1   4.8    70   -99   7.5   -99    11   -99

*TNKOLATTUR  RS&GIS,TNAU SCL     47 KOLATTUR
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA          12.17  78.941 SANDY CLAY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6    .4    76     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    18   -99   .05   .08  .137     1   .43  1.55   .45  20.9  14.3  64.8   -99   6.3   -99  11.4   -99
    47   -99  .102  .134  .169  .522   .12  1.56   .37  39.7     4  56.4   -99   6.7   -99  13.8   -99

*TNMEYYURRR  RS&GIS,TNAU SCL    110 MEYYUR
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA         12.156  78.936 SANDY CLAY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6    .4    73     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    16   -99  .081  .137   .21     1   .43  1.44   .75  23.8  25.2    51   -99   8.9   -99  39.5   -99
    30   -99  .128  .214  .289  .631   .23  1.37   .78  30.8  32.9  36.3   -99     9   -99  40.3   -99
    50   -99  .214  .333  .387  .449   .06  1.28    .8  44.1  35.7  20.2   -99   9.3   -99  42.8   -99
   110   -99  .158  .214  .243  .202   .06  1.46   .65  46.1  11.5  42.4   -99   9.1   -99    42   -99

*TNKTRIPATi  RS&GIS      SL      68 KATRIPATTI
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA          11.81  77.969 SANDY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6   .25    73     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    12   -99  .031  .054  .115     1  2.59  1.58    .2  14.6  15.4    70   -99     6   -99   9.2   -99
    31   -99  .039  .072  .143  .651  2.59  1.54    .3  14.6  21.6  63.8   -99     5   -99   8.1   -99
    68   -99  .047  .065   .11  .372   .43  1.62    .2  25.1   4.8    70   -99   5.2   -99   8.8   -99

*TNCPALAYAM  RS&GIS,TNAU SCL     90 CHICKARASAMPALAYAM
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 TAMILNADU   INDIA         11.655  77.957 CLAY LOAM
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
     G   .13     6   .25    76     1     1 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
    23   -99  .058  .087  .139     1   .43  1.54   .51    25  10.4  64.6   -99   8.2   -99   7.3   -99
    35   -99  .047  .065  .111   .56   .43  1.64   .06  24.9   5.9  69.2   -99   8.3   -99    14   -99
    63   -99    .1  .139  .183  .375   .12  1.58   .15  35.8  12.1  52.1   -99   8.3   -99    22   -99
    90   -99   .07  .106  .165  .217   .43  1.58   .09  26.9  16.3  56.8   -99   8.4   -99    25   -99
```

APPENDIX XI - C

Major Soil Series present in monitoring locations across study area

Field ID	Village	Latitude	Longitude	Soil Series
1	Palayapuliyampatti	11.3291	77.9241	Elavamalai
2	Pudhupuliyampatti	11.3313	77.9223	Elavamalai
3	Kakapalayam	11.5467	78.0178	Irugur
4	Kandarkulamanickam	11.5405	78.0336	Irugur
5	Velagavundmpatti	11.2684	78.0876	Palladam
6	Manathi	11.2934	78.0522	Tolurpatti
7	Morepalayam	11.4413	77.9698	Perundurai
8	Nochokarakadu	11.4264	77.8637	Vellalur
9	Pudhuchatram	11.3607	78.1664	Tolurpatti
10	Pothiyampatti	11.8095	77.9693	Katripatti
11	Pappambadi	11.6551	77.9573	Chickarasampalaiyam
12	Moongathur	11.6244	77.9591	Katripatti
13	Vellapillakovil	11.5105	78.0972	Palladam
14	Keelravandavadi	12.1564	78.9361	Meyyur
15	Manmalai	12.2877	78.8266	Perapperi
16	Thandrampattu	12.1702	78.941	Kollattur
17	Arkandanallur	11.9875	79.234	Meyyur
18	Padiyandhal	11.8961	79.1264	Vetavalam
19	Tindivanam	12.2126	79.6695	Vetavalam
20	Melsevalambadi	12.4103	79.3098	Vetavalam

APPENDIX XI - D

View of Genetic co-efficient file in DSSAT V4.5

```
*PEANUT CULTIVAR COEFFICIENTS: CRGRO045 MODEL
!
! COEFF   DEFINITIONS
! =====   ===========
! EXPNO   Number of experiments used to estimate cultivar parameters
! ECO#    Code for the ecotype to which this cultivar belongs (see *.eco file)
! CSDL    Critical Short Day Length below which reproductive development
!         progresses with no daylength effect (for shortday plants) (hour)
! PPSEN   Slope of the relative response of development to photoperiod with time
!         (positive for shortday plants) (1/hour)
! EM-FL   Time between plant emergence and flower appearance (R1)
!         (photothermal days)
! FL-SH   Time between first flower and first pod (R3) (photothermal days)
! FL-SD   Time between first flower and first seed (R5) (photothermal days)
! SD-PM   Time between first seed (R5) and physiological maturity (R7)
!         (photothermal days)
! FL-LF   Time between first flower (R1) and end of leaf expansion
!         (photothermal days)
! LFMAX   Maximum leaf photosynthesis rate at 30 C, 350 vpm CO2, and high light
!         (mg CO2/m2-s)
! SLAVR   Specific leaf area of cultivar under standard growth conditions
!         (cm2/g)
! SIZLF   Maximum size of full leaf (three leaflets) (cm2)
! XFRT    Maximum fraction of daily growth that is partitioned to seed + shell
! WTPSD   Maximum weight per seed (g)
! SFDUR   Seed filling duration for pod cohort at standard growth conditions
!         (photothermal days)
! SDPDV   Average seed per pod under standard growing conditions (#/pod)
! PODUR   Time required for cultivar to reach final pod load under optimal
!         conditions (photothermal days)
! THRSH   The maximum ratio of (seed/(seed+shell)) at maturity.
!         Causes seed to stop growing as their dry weights
!         increase until shells are filled in a cohort.
!         (Threshing percentage).
! SDPRO   Fraction protein in seeds (g(protein)/g(seed))
! SDLIP   Fraction oil in seeds (g(oil)/g(seed))
!
! For typical cultivars, use TAMNUT for typical Spanish, FLORUNNER for typical
! runner virginia type, and FLORIGIANT for large-seeded Virginia runner type,
! EARLY BUNCH for early Virginia bunch type, and CHICO for earliest Spanish.
! These cultivars have been subjected to other calibration data sets.
! Of the above cultivars, Marc I and Southern Runner are also well tested.
! Those with "v tamn" or "v flor" or "v Ma" are presumed to be like TAMNUT
! or FLORUNNER or MARC I, with no testing done. NC7 and GK3 not tested.
! Cultivars 19-38 tested somewhat with Australian and India data, & 31-35
! also tested with some data at Gainesville.
!
@VAR#  VRNAME.......... EXPNO   ECO#  CSDL PPSEN EM-FL FL-SH FL-SD SD-PM FL-LF LFMAX SLAVR SIZLF  XFRT WTPSD SFDUR SDPDV PODUR THRSH SDPRO SDLIP
!                                        1     2     3     4     5     6     7     8     9    10    11    12    13    14    15    16    17    18
990001 Spanish type          . PN0007 11.84  0.00  17.4   7.0  17.5 62.00 70.00  1.28  245.  16.0  0.84 0.360  29.0  1.65  15.0  78.0  .270  .510
990002 Runner Type           . PN0001 11.84  0.00  21.2   8.0  17.8 75.30 88.00  1.40  260.  18.0  0.94 0.660  40.0  1.65  25.0  80.0  .270  .510
IB0001 STARR, v tamnut       . PN0007 11.84  0.00  17.4   7.0  17.5 62.00 70.00  1.28  245.  16.0  0.84 0.360  29.0  1.65  15.0  78.0  .270  .510
IB0002 FLORUNNER            18 PN0001 11.84  0.00  21.2   9.2  18.8 74.30 88.00  1.40  260.  18.0  0.92 0.690  40.0  1.65  24.0  80.0  .270  .510
IB0003 FLORIGIANT new        1 PN0008 11.84  0.00  21.2   8.5  20.3 73.00 88.00  1.38  250.  18.0  0.86 0.990  37.0  1.65  25.0  74.0  .270  .510
IB0004 VALENCIA, v tamn      . PN0007 11.84  0.00  17.4   7.0  17.5 62.00 70.00  1.28  245.  16.0  0.84 0.360  29.0  2.50  15.0  78.0  .270  .510
IB0005 TAMNUT new            1 PN0007 11.84  0.00  17.4   7.0  17.0 62.00 70.00  1.28  245.  16.0  0.83 0.380  29.0  1.65  16.0  78.0  .270  .510
IB0006 PRONTO, v tamnu       . PN0007 11.84  0.00  17.4   7.0  17.5 62.00 70.00  1.28  245.  16.0  0.84 0.360  29.0  1.65  15.0  78.0  .270  .510
IB0007 MARC I                2 PN0009 11.84  0.00  20.0   7.0  17.0 74.00 80.00  1.42  270.  18.0  0.93 0.690  40.0  1.65  23.0  80.0  .270  .510
IB0008 CHICO                 1 PN0006 11.84  0.00  16.4   7.0  15.0 58.00 66.00  1.04  285.  16.0  0.90 0.310  22.0  1.75  13.0  77.0  .270  .510
IB0009 AGRITEC-127,v Ma      . PN0009 11.84  0.00  20.0   7.0  17.0 74.00 80.00  1.40  275.  18.0  0.95 0.660  40.0  1.65  23.0  80.0  .270  .510
IB0011 EARLY RUNNER new      1 PN0002 11.84  0.00  21.6   8.5  17.8 80.00 87.00  1.28  265.  18.0  0.85 0.570  36.0  1.65  27.0  79.0  .270  .510
IB0013 SUNRUNNER,v flor      . PN0001 11.84  0.00  21.2   8.0  17.8 75.30 88.00  1.40  260.  18.0  0.94 0.650  40.0  1.65  25.0  80.0  .270  .510
IB0015 SOUTHERN RUNNER       4 PN0002 11.84  0.00  22.9   9.2  18.2 82.60 91.00  1.30  265.  17.0  0.85 0.630  40.0  1.65  30.0  79.0  .270  .510
IB0016 EARLY BUNCH           2 PN0004 11.84  0.00  21.9   7.6  16.5 72.40 80.00  1.34  265.  20.0  0.93 1.100  44.0  1.65  21.0  75.0  .270  .510
IB0017 NC7, VIRGINIA         . PN0004 11.84  0.00  21.0   8.0  20.3 73.00 88.00  1.36  270.  20.0  0.94 1.000  38.0  1.65  30.0  75.0  .270  .510
IB0018 GK3, VIRGINIA         . PN0001 11.84  0.00  21.0   8.0  20.3 73.00 88.00  1.36  270.  18.0  0.94 1.000  38.0  1.65  30.0  80.0  .270  .510
IB0019 SHULAMIT, VA BUN      . PN0005 11.84  0.00  20.8   7.8  17.5 76.10 83.00  1.35  220.  19.0  0.93 0.980  40.0  1.65  25.0  74.0  .270  .510
IB0020 TIFTON-8,FLORIG       . PN0011 11.84  0.00  21.9   8.2  19.7 74.50 83.00  1.37  205.  19.0  0.73 0.910  38.0  1.65  28.0  74.0  .270  .510
IB0021 Q18801,earlybun       . PN0010 11.84  0.00  21.9   8.0  17.8 74.60 78.00  1.37  240.  19.0  0.87 1.180  44.0  1.65  24.0  75.0  .270  .510
IB0022 VIRG BUN, MODIF       . PN0013 11.84  0.00  21.9   8.5  20.3 74.50 90.00  1.33  275.  19.0  0.76 0.880  38.0  1.65  27.0  74.0  .270  .510
IB0023 MCCUBBIN, m TAMN      . PN0007 11.84  0.00  20.0   7.5  17.5 70.00 78.00  1.32  230.  17.0  0.82 0.520  32.0  1.65  19.0  78.0  .270  .510
IB0024 TMV2, mod tamnu       . PN0007 11.84  0.00  17.4   7.0  17.5 62.00 78.00  1.31  270.  16.0  0.80 0.360  29.0  1.65  15.0  78.0  .270  .510
IB0025 TAPIR, mod tamn       . PN0007 11.84  0.00  17.4   7.0  17.5 62.00 78.00  1.32  265.  16.0  0.80 0.360  29.0  1.65  13.0  78.0  .270  .510
IB0026 ROBUT-33,uf v35       . PN0015 11.84  0.00  19.0   7.0  17.5 70.00 78.00  1.28  260.  16.0  0.84 0.500  29.0  1.65  15.0  78.0  .270  .510
IB0027 TMV-2,uf v 24         . PN0007 11.84  0.00  19.0   7.0  17.5 62.00 72.00  1.28  270.  16.0  0.80 0.370  29.0  1.65  15.0  78.0  .270  .510
IB0031 F81206,LS-RESnew      2 PN0014 11.84  0.00  23.0   8.0  19.5 77.00 91.00  1.27  265.  18.0  0.85 0.720  38.0  1.65  29.0  77.0  .270  .510
IB0032 MA72*94-12,LS-Rs      2 PN0014 11.84  0.00 27.30  11.0 24.50 68.50 91.00  1.25  250.  18.0  0.59 0.720  38.0  1.65  30.0  77.0  .270  .510
IB0033 861 VIRGINIA BUN      . PN0004 11.84  0.00  21.0   8.0  20.0 78.00 85.00  1.30  275.  20.0  0.76 0.550  38.0  1.65  30.0  75.0  .270  .510
IB0034 897 VIRGINIA BUN      . PN0004 11.84  0.00  21.0   8.0  20.0 78.00 85.00  1.30  275.  20.0  0.76 0.960  38.0  1.65  30.0  75.0  .270  .510
IB0035 ROBUT 33-1 v 5        . PN0015 11.84  0.00  17.4   7.0  17.5 65.00 77.00  1.23  260.  16.0  0.84 0.500  29.0  1.65  15.0  78.0  .270  .510
IB0036 CIANJUR #5 TAM        . PN0007 11.84  0.00  17.4   7.0  17.5 65.00 77.00  1.23  250.  16.0  0.84 0.360  29.0  1.65  15.0  78.0  .270  .510
IB0037 RANGKASBITUNG 5       . PN0007 11.84  0.00  17.4   7.0  17.5 65.00 77.00  1.23  250.  16.0  0.84 0.360  29.0  1.65  15.0  78.0  .270  .510
IB0038 PIDIE  #5 TAMN        . PN0007 11.84  0.00  17.4   7.0  17.5 65.00 77.00  1.23  250.  16.0  0.84 0.360  29.0  1.65  15.0  78.0  .270  .510
GA0001 Georgia Green         . RUNNER 11.84  0.00  21.2   9.2  18.8 77.30 85.00  1.45  270.  18.0  0.95 0.690  42.0  1.65  28.0  80.0  .270  .510
TN0001 Co6-SEMISPREAD        . PN0001 11.84  0.00  16.4   7.0  17.5 62.00 70.00  1.23  205.  16.0  0.73 0.310  29.0  1.60  16.0  74.0  .270  .510
TN0002 TMV7-BUNCH            . PN0001 11.84  0.00  16.4   7.0  17.0 62.00 66.00  1.23  245.  16.0  0.80 0.360  29.0  1.55  16.0  78.0  .270  .510
TN0003 VRI2-BUNCH            . PN0001 11.84  0.00  16.4   7.0  16.5 62.00 66.00  1.34  220.  16.0  0.76 0.380  29.0  1.55  15.0  74.0  .270  .510
! next is 1997-1998/paper
GH0001 CHINESE TMV2 TAM      7 PN0019 11.84  0.00  17.0   7.0  17.5 53.00 73.00  1.20  270.  20.0  0.76 0.360  29.0  1.65  14.0  74.5  .270  .510
! next is 1997-1998/paper
```

APPENDIX XI – E

View of Management file in DSSAT V4.5

```
*EXP.DETAILS: TNAU1501PN SPATIAL ASSESSMENT OF GROUNDNUT GROWTH AND PRODUCTIVITY

*GENERAL
@PEOPLE
-99
@ADDRESS
-99
@SITE
-99

*TREATMENTS                        -------------FACTOR LEVELS------------
@N R O C TNAME.................... CU FL SA IC MP MI MF MR MC MT ME MH SM
 1 1 1 0 TNVPKR01-Kelaravandampadi  3  1  0  2  4  0  4  0  0  0  0  0  4
 2 1 1 0 TNTMMM02-Manmalai          3  2  0  2  4  0  4  0  0  0  0  0  4
 3 1 1 0 TNNKPP03-Pal. P.Patti      1  3  0  3  2  0  2  0  0  0  0  0  2
 4 1 1 0 TNNKPP04-Pudu P.Patti      1  4  0  2  3  0  3  0  0  0  0  0  3
 5 1 1 0 TNNKPC05-Puduchatram       1  5  0  2  2  0  2  0  0  0  0  0  2
 6 1 1 0 TNSMPP06-Pothiyampatti     1  6  0  2  2  0  2  0  0  0  0  0  2
 7 1 1 0 TNSMPB07-Pappambadi        1  7  0  2  3  0  3  0  0  0  0  0  3
 8 1 1 0 TNSMMG08-Moongathur        1  8  0  2  2  0  2  0  0  0  0  0  2
 9 1 1 0 TNNKKP09-Kakapalayam       1  9  0  2  1  0  1  0  0  0  0  0  1
10 1 1 0 TNNKKK10-KK Manickam       1 10  0  2  2  0  2  0  0  0  0  0  2
11 1 1 0 TNSMVK11-VP kovil          1 11  0  2  3  0  3  0  0  0  0  0  3
12 1 1 0 TNNKVP12-VG Patti          1 12  0  2  1  0  1  0  0  0  0  0  1
13 1 1 0 TNNKMN13-Manathi           1 13  0  2  3  0  3  0  0  0  0  0  3
14 1 1 0 TNNKMP14-Morepalayam       1 14  0  2  2  0  2  0  0  0  0  0  2
15 1 1 0 TNVPAN15-AK Nallur         3 15  0  2  4  0  4  0  0  0  0  0  4
16 1 1 0 TNVPPL16-Padiyandhal       2 16  0  2  4  0  4  0  0  0  0  0  4
17 1 1 0 TNVPTM17-Tindivanam        2 17  0  2  4  0  4  0  0  0  0  0  4
18 1 1 0 TNTMMS18-Melsevalmbadi     2 18  0  2  5  0  5  0  0  0  0  0  5
19 1 1 0 TNTMTP19-Thandaramapattu   3 19  0  2  5  0  5  0  0  0  0  0  5
20 1 1 0 TNNKNK20-Nochokarakadu     1 20  0  1  1  0  1  0  0  0  0  0  1

*CULTIVARS
@C CR INGENO CNAME
 1 PN TN0001 Co6-SEMISPREAD
 2 PN TN0002 TMV7-BUNCH
 3 PN TN0003 VRI2-BUNCH

*FIELDS
@L ID_FIELD WSTA....  FLSA  FLOB  FLDT  FLDD  FLDS  FLST SLTX  SLDP  ID_SOIL    FLNAME
 1 TNVPKR01 TNPT1502   -99   -99 DR003   -99   -99   -99 SL     46  TNMEYYURRR Keelravandavandi
 2 TNTMMM02 KPKM1502   -99   -99 DR003   -99   -99   -99 SL     46  TNPERAPERI Manmalai, Chengam
 3 TNNKPP03 TRGD1501   -99   -99 DR003   -99   -99   -99 SL     46  TNELVMALAI Palayapuliyampatti
 4 TNNKPP04 TRGD1501   -99   -99 DR003   -99   -99   -99 SL     46  TNELVMALAI Pudupuliyampatti
 5 TNNKPC05 NMKL1501   -99   -99 DR003   -99   -99   -99 SL     46  TNTOLRPATI Puduchatram
 6 TNSMPP06 MCHR1501   -99   -99 DR003   -99   -99   -99 SL     46  TNKTRIPATI Pothiyampatti, Mecheri
 7 TNSMPB07 TARA1501   -99   -99 DR003   -99   -99   -99 SL     46  TNCPALAYAM Paappambadi
 8 TNSMMG08 TARA1501   -99   -99 DR003   -99   -99   -99 SL     46  TNKTRIPATI Moongathur
 9 TNNKKP09 MCDL1501   -99   -99 DR003   -99   -99   -99 CL     46  TNIRUGURKP Kakapalayam, Aattayampatti
10 TNNKKK10 MCDL1501   -99   -99 DR003   -99   -99   -99 CL     46  TNIRUGURKP Kandarkulamanickam, Attayampatti
11 TNSMVK11 MCDL1501   -99   -99 DR000   -99   -99   -99 SL     46  TNPALLADAM Vellapillakovil, Vennandur
12 TNNKVP12 NMKL1501   -99   -99 DR003   -99   -99   -99 SL     46  TNPALLADAM Velagavundmpatti
13 TNNKMN13 NMKL1501   -99   -99 DR003   -99   -99   -99 SL     46  TNTOLRPATI Manathi, Velagavundmpatti
14 TNNKMP14 TRGD1501   -99   -99 DR003   -99   -99   -99 SL     46  TNPRDUNRAI Morepalayam
15 TNVPAN15 TVNM1502   -99   -99 DR003   -99   -99   -99 SL     46  TNMEYYURRR Arkandanallur
16 TNVPPL16 RISH1502   -99   -99 DR000   -99   -99   -99 SL     46  TNVETAVALM Padiyandhal
17 TNVPTM17 MKNM1502   -99   -99 DR003   -99   -99   -99 SL     46  TNVETAVALM Tindivanam research station
18 TNTMMS18 MLMR1502   -99   -99 DR003   -99   -99   -99 SL     46  TNVETAVALM Melsevalambadi
19 TNTMTP19 TNPT1502   -99   -99 DR003   -99   -99   -99 SL     46  TNKOLATTUR Thandrampattu
20 TNTMMS20 TRGD1501   -99   -99 DR003   -99   -99   -99 CL     46  TNVELLALUR Nochokarakadu, Madur
@L ...........XCRD ...........YCRD .....ELEV .............AREA .SLEN .FLWR .SLAS FLHST FHDUR
 1             -99             -99       -99               -99   -99   -99   -99   -99   -99
 2             -99             -99       -99               -99   -99   -99   -99   -99   -99
 3             -99             -99       -99               -99   -99   -99   -99   -99   -99
 4             -99             -99       -99               -99   -99   -99   -99   -99   -99
 5             -99             -99       -99               -99   -99   -99   -99   -99   -99
 6             -99             -99       -99               -99   -99   -99   -99   -99   -99
 7             -99             -99       -99               -99   -99   -99   -99   -99   -99
 8             -99             -99       -99               -99   -99   -99   -99   -99   -99
 9             -99             -99       -99               -99   -99   -99   -99   -99   -99
10             -99             -99       -99               -99   -99   -99   -99   -99   -99
11             -99             -99       -99               -99   -99   -99   -99   -99   -99
12             -99             -99       -99               -99   -99   -99   -99   -99   -99
13             -99             -99       -99               -99   -99   -99   -99   -99   -99
14             -99             -99       -99               -99   -99   -99   -99   -99   -99
15             -99             -99       -99               -99   -99   -99   -99   -99   -99
16             -99             -99       -99               -99   -99   -99   -99   -99   -99
17             -99             -99       -99               -99   -99   -99   -99   -99   -99
18             -99             -99       -99               -99   -99   -99   -99   -99   -99
19             -99             -99       -99               -99   -99   -99   -99   -99   -99
20             -99             -99       -99               -99   -99   -99   -99   -99   -99

*SOIL ANALYSIS
@A SADAT  SMHB  SMPX  SMKE  SANAME
 1 15293   -99   -99   -99  -99
@A  SABL  SADM  SAOC  SANI SAPHW SAPHB  SAPX  SAKE  SASC
 1    15   -99   -99   -99   -99   -99   -99   -99   -99
```


```
*SOIL ANALYSIS
@A SADAT  SMHB  SMPX  SMKE  SANAME
 1 15293   -99   -99   -99  -99
@A  SABL  SADM  SAOC  SANI SAPHW SAPHB  SAPX  SAKE  SASC
 1    15   -99   -99   -99   -99   -99   -99   -99   -99
```


```
*INITIAL CONDITIONS
@C   PCR ICDAT  ICRT  ICND  ICRN  ICRE  ICWD ICRES ICREN ICREP ICRIP ICRID ICNAME
 1    PN 15283   -99   -99     1     1   -99   -99   -99   -99   -99   -99 PC-Groundnut
@C  ICBL  SH2O  SNH4  SNO3
 1    25   .23    .4   3.2
 1    27  .196    .4   3.2
 1    46  .238    .4   3.2
@C   PCR ICDAT  ICRT  ICND  ICRN  ICRE  ICWD ICRES ICREN ICREP ICRIP ICRID ICNAME
 2    FA 15283   -99   -99     1     1   -99   -99   -99   -99   -99   -99 Fallow
@C  ICBL  SH2O  SNH4  SNO3
 2    25   .23    .4   3.2
 2    27  .196    .4   3.2
 2    46  .238    .4   3.2
@C   PCR ICDAT  ICRT  ICND  ICRN  ICRE  ICWD ICRES ICREN ICREP ICRIP ICRID ICNAME
 3    FA 15135   -99   -99     1     1   -99   -99   -99   -99   -99   -99 S-Fallow
@C  ICBL  SH2O  SNH4  SNO3
 3    25   .23    .4   3.2
 3    27  .196    .4   3.2
 3    46  .238    .4   3.2

*PLANTING DETAILS
@P PDATE EDATE  PPOP  PPOE  PLME  PLDS  PLRS  PLRD  PLDP  PLWT  PAGE  PENV  PLPH  SPRL
 1 15135 15140    14     8     S     R   105     0     4   -99   -99   -99   -99   -99
 2 15140 15145    12     6     S     H   110     0     6   -99   -99   -99   -99   -99
 3 15145 15149    14     8     S     U    95     0     4   -99   -99   -99   -99   -99
 4 15273 15277    12     7     S     H   105     0     6   -99   -99   -99   -99   -99
 5 15283 15286    13     7     S     U   110     0     4   -99   -99   -99   -99   -99
 6 15324 15328    10     6     S     H    95     0     2   -99   -99   -99   -99   -99

*IRRIGATION AND WATER MANAGEMENT
@I  EFIR  IDEP  ITHR  IEPT  IOFF  IAME  IAMT IRNAME
 1     1    30    50   100 GS000 IR001    10 -99
@I IDATE  IROP IRVAL
 1 15293   -99   -99

*FERTILIZERS (INORGANIC)
@F FDATE  FMCD  FACD  FDEP  FAMN  FAMP  FAMK  FAMC  FAMO  FOCD FERNAME
 1 15135 FE018 AP002     1     5     0     0   -99   -99   -99 SN-1
 1 15135 FE005 AP002     1     0     0     4   -99   -99   -99 SN-1
 1 15135 FE013 AP002     1     0     4     0   -99   -99   -99 SN-1
 2 15140 FE005 AP002     1     2     0     0   -99   -99   -99 SN-2
 2 15140 FE018 AP002     1     0     0     6   -99   -99   -99 SN-2
 2 15140 FE013 AP002     1     0     3     0   -99   -99   -99 SN-2
 3 15145 FE005 AP002     1     4     0     0   -99   -99   -99 SN-3
 3 15145 FE013 AP002     1     0     4     0   -99   -99   -99 SN-3
 3 15145 FE018 AP002     1     0     0     5   -99   -99   -99 SN-3
 4 15273 FE013 AP002     1     0     3     0   -99   -99   -99 TV-1
 4 15273 FE018 AP002     1     0     0     3   -99   -99   -99 TV-1
 4 15273 FE005 AP002     1     3     0     0   -99   -99   -99 TV-1
 5 15283 FE005 AP002     1     4     0     0   -99   -99   -99 TV-2
 5 15283 FE013 AP002     1     0     3     0   -99   -99   -99 TV-2
 5 15283 FE018 AP002     1     0     0     4   -99   -99   -99 TV-2
 6 15324 FE018 AP002     1     0     0     3   -99   -99   -99 TV-3
 6 15324 FE005 AP002     1     2     0     0   -99   -99   -99 TV-3
 6 15324 FE013 AP002     1     0     2     0   -99   -99   -99 TV-3

*ENVIRONMENT MODIFICATIONS
@E ODATE EDAY  ERAD  EMAX  EMIN  ERAIN ECO2  EDEW  EWIND ENVNAME
 1 15140 A   0 A   0 A   0 A   0 A 0.0 A   0 A   0 A   0

*HARVEST DETAILS
@H HDATE  HSTG  HCOM HSIZE   HPC  HBPC HNAME
 1 15271 GS011     H     A   -99   -99 Peanut

*SIMULATION CONTROLS
@N GENERAL     NYERS NREPS START SDATE RSEED SNAME.................... SMODEL
 1 GE              1     1     S 15135  2150 SN-1                      CRGRO
@N OPTIONS     WATER NITRO SYMBI PHOSP POTAS DISES  CHEM  TILL   CO2
 1 OP              N     Y     Y     N     N     N     N     N     M
@N METHODS     WTHER INCON LIGHT EVAPO INFIL PHOTO HYDRO NSWIT MESOM MESEV MESOL
 1 ME              M     M     E     F     N     L     R     1     G     S     2
@N MANAGEMENT  PLANT IRRIG FERTI RESID HARVS
 1 MA              R     N     R     R     M
@N OUTPUTS     FNAME OVVEW SUMRY FROPT GROUT CAOUT WAOUT NIOUT MIOUT DIOUT VBOSE CHOUT OPOUT
 1 OU              N     Y     Y     1     Y     N     N     Y     N     N     Y     N     Y

@  AUTOMATIC MANAGEMENT
@N PLANTING    PFRST PLAST PH2OL PH2OU PH2OD PSTMX PSTMN
 1 PL          15001 15001    40   100    30    40    10
@N IRRIGATION  IMDEP ITHRL ITHRU IROFF IMETH IRAMT IREFF
 1 IR             30    50   100 GS000 IR001    10     1
@N NITROGEN    NMDEP NMTHR NAMNT NCODE NAOFF
 1 NI             30    50    25 FE001 GS000
@N RESIDUES    RIPCN RTIME RIDEP
```

Plates

a) CO 6

b) TMV 7

c) VRI 2

Plate.1. Different groundnut varieties grown in study area

Plate.2. Visiting farmer's field and collection of data in Tiruchengodu, Namakkal

Plate.3. Collecting Ground-truth in farmer's field at Santhiyur, Salem

Plate.4. Collecting Ground-truth in farmer's field at Thandrampet, Tiruvannamalai

Plate.5. Collecting Ground-truth in farmer's field at Thirukkovilur, Villupuram

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Modeling Groundnut (*Arachis hypogea*) Yield at Spatial Level in Tiruvannamalai and Villupuram Districts by Using DSSAT Crop Simulation Model

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ABSTRACT

The present investigation was carried out in contiguous area of groundnut in adjoining Tiruvannamalai and Villupuram districts of Tamil Nadu State. Simulation models, such as the DSSAT (Decision Support System for Agrotechnology Transfer) Crop System Models are often used to characterize, develop and assess field crop production practices. We have developed methods to use the DSSAT family of crop growth models to understand causes of spatial yield variability, conduct yield gap analysis for factors that limit yield, and estimate the economic consequences of moving from uniform to spatially variable management. In this study, one of the DSSAT Cropping System Model, CROPGRO-Peanut, was employed to characterize groundnut (*Arachis hypogae*) yield during 2015 under rainfed condition at different locations of Tiruvannamalai and Villupuram districts. The DSSAT software was used to forecast the groundnut yield for *rabi* season in study area. To simulate the groundnut yield DSSAT required data sets of crop growth and management, daily weather data and soil data. Crop management data were obtained from farmers' fields which were located in Tiruvannamalai and Villupuram districts. The simulated yield values during 2015 agreed well with the observed data (85%) from the farmer's field experiments with R^2 value of 0.81 (yield) and RMSE value of 275 kg ha^{-1}. These results indicate that plant growth, development and yield of groundnut can be simulated efficiently using DSSAT crop growth model spatially.

Key words *DSSAT, groundnut, simulation*

Crop models have been developed and used worldwide as operational or strategic research and decision support tools in crop production and resources management. Simulation models are useful tools in deciding the best possible management options for optimum growth and yield of any crop against available climatic variables along with soil and water inputs. Crop growth simulation models, like Decision Support System for Agrotechnology Transfer (DSSAT) (Jones *et al.* 1998), have been widely applied to assess climate change impacts on cropping systems and agricultural production. Daily maximum and minimum temperature, precipitation and incident solar radiation are required as minimum climate input to drive crop models.

Groundnut (*Arachis hypogaea* L.) is an important oilseed crop grown by small and marginal farmers. In India the crop is mainly grown under rainfed conditions during the main rainy season (June–October). As climate change is becoming more intense and demand for edible oil and vegetable protein in India is increasing, the groundnut production needs to be improved to meet the future demand. The CROPGRO-Peanut model was developed by Boote *et al*., (1998) at University of Florida and University of Georgia on the basis of IBSNAT (International Benchmark Sites Network for Agro-technology Transfer). It is a dynamic computer model that simulates crop growth and development and pod and seed yield for peanut (Boote *et al*., 1998; Jones *et al*., 2003). DSSAT is a popular crop model that is used worldwide for modeling growth and yield of 30 different crops including rice under given soil and daily weather conditions. Crop simulation models are valuable tools for evaluating the potential effects of environmental, biological and management factors on crop growth and development. They have been evaluated and used for many soil and environmental conditions across the world and have in the past, been successfully used in yield predictions (Jagtap and Jones, 2002), irrigation planning for crops (Behera and Panda, 2009), optimization of irrigation water use (Fortes *et al*., 2005; Bulatewicz *et al*., 2009).

For future yield prediction, it is required to calibrate and validate the DSSAT model by adjusting the cultivar genetic coefficients. For groundnut, several genetic coefficients are available and they describe the genotype and environmental interactions. Validated DSSAT model can be used to predict future groundnut yields with different soil profiles and weather conditions and find the suitable adaptation measures for increasing yields (Jones *et al*., 2003). Therefore this study was conducted to identify the changes of groundnut yield and growth in Tiruvannamalai and Villupuram districts, Tamilnadu under different field locations and weather conditions using DSSAT model. In the present investigation, the CROPGRO-Peanut model was used to simulate yield at spatial level for groundnut cv. TMV-7 and VRI-2 in rainfed areas of study area.

MATERIALS AND METHODS

Crop yield simulation using crop simulation model (DSSAT)

Decision Support System for Agrotechnology Transfer (DSSAT) is a micro-computer software product that combines crop, soil and weather data-bases into standard formats for access by crop model and application programs. The user can then simulate multi-year outcomes of crop management strategies for different crops at any location in the world and hence the DSSAT was used in the

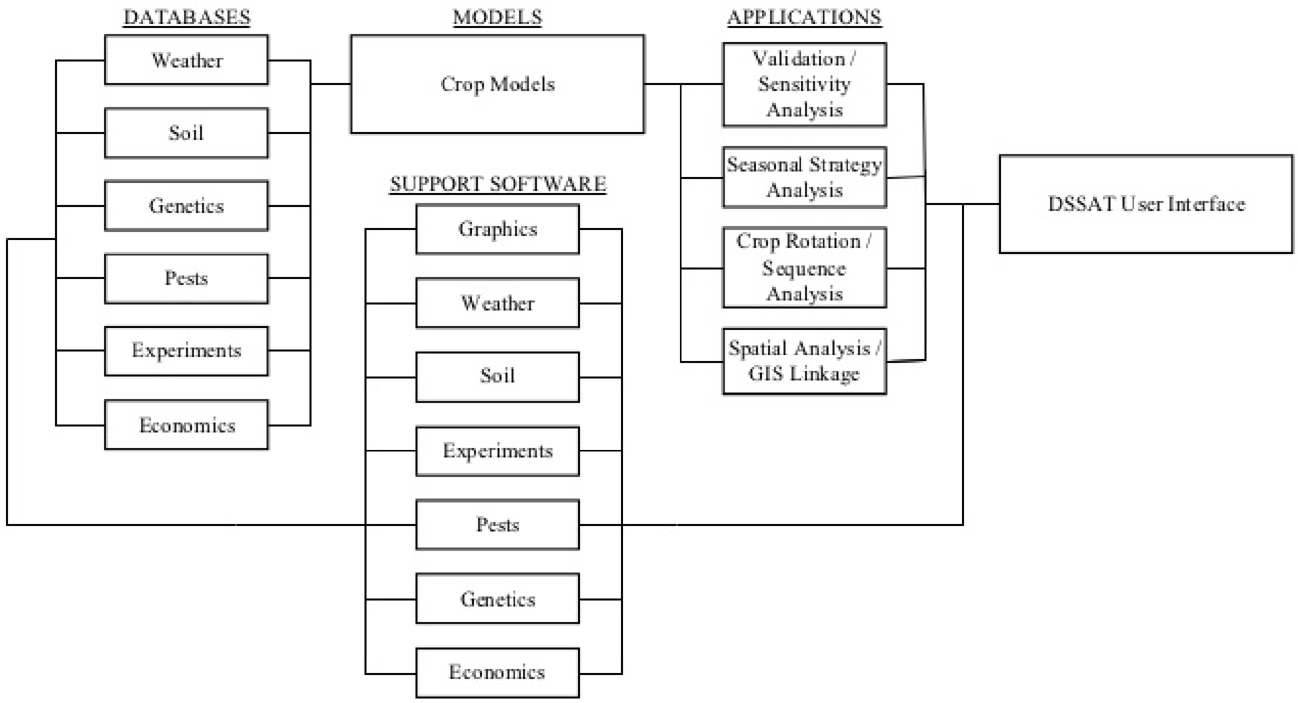

Fig. 1. Diagram of database, application, and support software components and their use with crop models for applications in DSSAT

present investigation. Fig.1. describes components of DSSAT crop simulation model.

(a) Weather file

The daily weather data on maximum temperature (°C), minimum temperature (°C), solar radiation

(MJ m^{-2} day^{-1}) and rainfall (mm) for the year 2015 and 2016 (upto March) for the study area collected from Automatic Weather Stations (AWS) and regular observatories situated at the study districts was used to create weather file for running CROPGRO-Peanut model.

DSSAT model requires weather data for the entire growing season of the crop to predict the yield. In this study, yield estimates are given during North East Monsoon (Tiruvannamalai and Villupuram districts). The actual weather data during the crop growth period was used for simulations. For the missing data, the weather data is generated either from the historical mean or using analogue technique, wherein, the past years weather that behaved similar to the current season was chosen to fill the missing or erroneous data.

(b) Soil data file

Soil information for creating the soil files was obtained from the Remote Sensing and Geographical Information system Department of TNAU. The profile details as required in DSSAT are extracted from the above remote sensing database using ArcGIS (GIS Tool) and were fed into S-Build tool in DSSAT to create soil file.

(c) Experimental detail file

This file documents the inputs to the models for the seven fields from the study area to be stimulated. Details of fields are listed in Table.2. The details of the experimental conditions and field characteristics such as weather station name, soil, and field description details, initial soil, water and inorganic nitrogen conditions, planting geometries, irrigation and water management, fertilizer management details, organic residue application, chemical applications, tillage operations, environmental modifications, harvest management, simulation controls (specification of simulation options e.g. starting dates, on/off options for water and nitrogen balances, symbiosis) and output options are given in the experimental file.

(d) Estimation of genetic co-efficient groundnut

Model calibration or parameterization is the adjustment of genetic parameters so that simulated values compare well with observed values. Data obtained from the experiments were used to estimate genetic parameters. The genetic coefficients that influence the occurrence of developmental stages in the CROPGRO-Peanut model embedded in DSSAT model were derived iteratively, by manipulating the relevant coefficients to achieve the best possible match between the simulated and observed number of days to the phonological events and grain yield at harvest. A detailed description of the cultivar coefficients used by CROPGRO-Peanut for TVM-7 and VRI-2 is presented in Table.1.

(e) Model calibration, validation and future yield simulations

Three input files were created to run the DSSAT model using collected data.

a. **Weather file**: ‘Weatherman’ program in DSSAT and collected weather data

Table. 1. Genetic coefficients for groundnut cv. TMV-7 and VRI-2 at study area condition

Code	Description	TMV-7	VRI-2
CSDL	Critical Short Day Length below which reproductive development progresses with no day length effect (for short-day plants) (hour)	11.84	11.84
PPSEN	Slope of the relative response of development to photoperiod with time (positive for short day plants) (1/hour)	0.00	0.00
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days).	16.40	16.40
FL-SH	Time between first flower and first pod (R3) (photo thermal days)	7.00	7.00
FL- SD	Time between first flower and first seed (R5) (photo thermal days)	17.00	16.50
SD-PM	Time between first seed (R5) and physiological maturity (R7) stages (photothermal days)	62.00	62.00
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	66.00	66.00
LFMAX	Maximum leaf photosynthesis rate at 300 C, 350 vpm CO2, and high light (mgCO2/m2/s)	1.23	1.34
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm2/g)	245.00	220.00
SIZLF	Maximum size of full leaf (three leaflets) (cm2)	16.00	16.00
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.80	0.76
WTPSD	Maximum weight per seed (g)	0.360	0.38
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	29.00	29.00
SDPDV	Average seed per pod under standard growing conditions (#/pod)	1.55	1.55
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	16.00	15.00
THRSH	The maximum ratio of (seed/(seed+shell)) at maturity. Causes seed to stop growing as their dry weights increase until shells are filled in a cohort.(Threshing percentage)	78.00	74.00
SDPRO	Fraction protein (g) per g seed	0.27	0.27
SDLIP	Fraction oil (g) per g seed	0.51	0.51

b. **Soil file**: ‘S Build’ program in DSSAT and soil data

c. **Experimental data file**: ‘X Build’ program in DSSAT and crop management data

The model was calibrated using collected data from the experimental trials in *rabi* season 2015 through determination of genetic coefficient for both TMV-7 and VRI-2 varieties with spatial analysis mode in DSSAT. The model was validated using the experimental data in *rabi* season 2015 by comparing the observed results with simulated results. Yields from trials (hereafter referred to as observed) conducted at farmers fields in rainfed areas of Tiruvannamalai and Villupuram districts were considered as observed data.

RESULT AND DISCUSSION

DSSAT’s spatial analysis option which allowed multiple locations run with the different initial conditions was used to simulate the effects of soil profile and climate variability on groundnut yields for the seven locations to study the impact of virtual cultivars and management scenarios using baseline weather data.

Model calibration and validation

DSSAT does not offer any automated procedures for calibration. Changes to parameters of the model in order to calibrate it for specific conditions must be done one-by-one, manually. Quantitative comparisons of model output to observations required the data to be exported to an analysis package. In order to accomplish this in a yield simulation, this process was repeated for every management zone. Likewise, to validate a calibrated model, running the model and analysing the output quantitatively was a tedious exercise when more than one homogeneous unit were simulated. The data collected from the field experiments was used for model evaluation.

Model calibration and validation were described as different ways of model evaluation by Otter-Nacke *et al.* (1987). Specific cultivar coefficients for the genotypes used in this experiment was not in the list of genotypes available with the model, therefore, evaluation was done using basic information for the cultivar coefficients provided with the model. The cultivar coefficients were adjusted, until main growth and development stages were simulated within 10% of the measured values. Simulated observed comparisons were made for growth and development parameters, the purpose being sensitivity analyses of the model and improvement of the coefficients. Coefficients were increased or decreased using a small step if needed.

Models were tested by validation using Root mean square error (RMSE) and R^2 which allow comparative assessment of model performance at particular location whereas, linear regression line expressed model stability across variable field conditions. The DSSAT model

Table.2. Details of experiment farmers' fields

S.No.	District	Field/Village	Latitude	Longitude	Cultivar	Simulated Yield (kg/ha)	Observed Yield (kg/ha)
1	Tiruvannamalai	Keelravandambadi	12.156439	78.936109	VRI-2	1796	1450
2	Tiruvannamalai	Manmalai	12.287727	78.826555	VRI-2	2519	2187
3	Tiruvannamalai	Thandrampattu	12.170185	78.941016	VRI-2	1825	1710
4	Villupuram	Arkandanallur	11.987534	79.233982	TMV-7	2340	2221
5	Villupuram	Padiyandhal	11.896108	79.126351	TMV-7	2088	1660
6	Villupuram	Tindivanam	12.212579	79.669527	TMV-7	1806	1535
7	Villupuram	Melsevalambadi	12.410316	79.309791	TMV-7	2005	1885

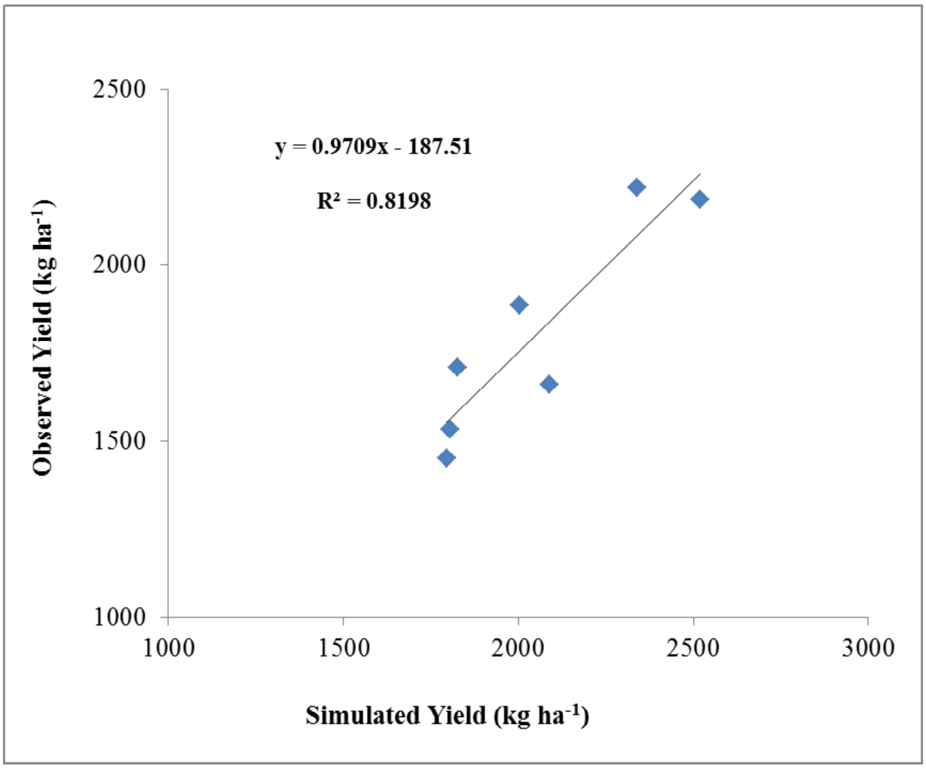

Fig.1. Validation of simulated (DSSAT) and observed data (Field)

performed well to simulate groundnut growth and yield. However, predicted results derived from DSSAT model were much better to observed ones for many of the parameters. The simulated groundnut yields were at the range of 1796 to 2519 kg /ha for VRI-2 and 1806 to 2340 kg ha^{-1} for TMV-7 across the locations in the study area whereas the observed yields were at 1450 to 221 kg ha^{-1}. In case of yields the mean agreement was found to be 86 % with a range of 82-92%. The spatial analysis of weather and soil profile impacts on groundnut indicates that similar trends were observed in almost all the regions of Tiruvannamalai and Villupuram districts with a decline in yields with two locations and increase with five locations. (Fig. 1&2). The overall prediction of grain yield by model was reported satisfactory by Singh *et al*., (2008) with R^2 values (0.88). The R^2 and RMSE values, respectively, of the regression between the simulated (using the two assimilation variables method) and measured yield were 0.81 and 275 kg ha^{-1}.

Crop models provide a mechanistic way to estimate the interaction of spatial differences in soil properties and weather parameters on yield variability within a field. Once calibrated to simulate the spatial yield variability between different fields, crop models are a powerful tool to develop risk management strategies that can balance economic risk incurred by the producer with environmental risks that impact society. This study developed and tested a tool for investigating the spatial implications of climate change on groundnut production in Tiruvannamalai and Villupuram districts. The CROPGRO-Peanut model that has been calibrated and validated for many groundnut growing regions of the world, was found to estimate the spatial responses to various genetic and agronomic management practices under different weather and soil profile conditions precisely as indicated from higher agreement (85%) between simulated and observed yields with high R^2 values(0.81).

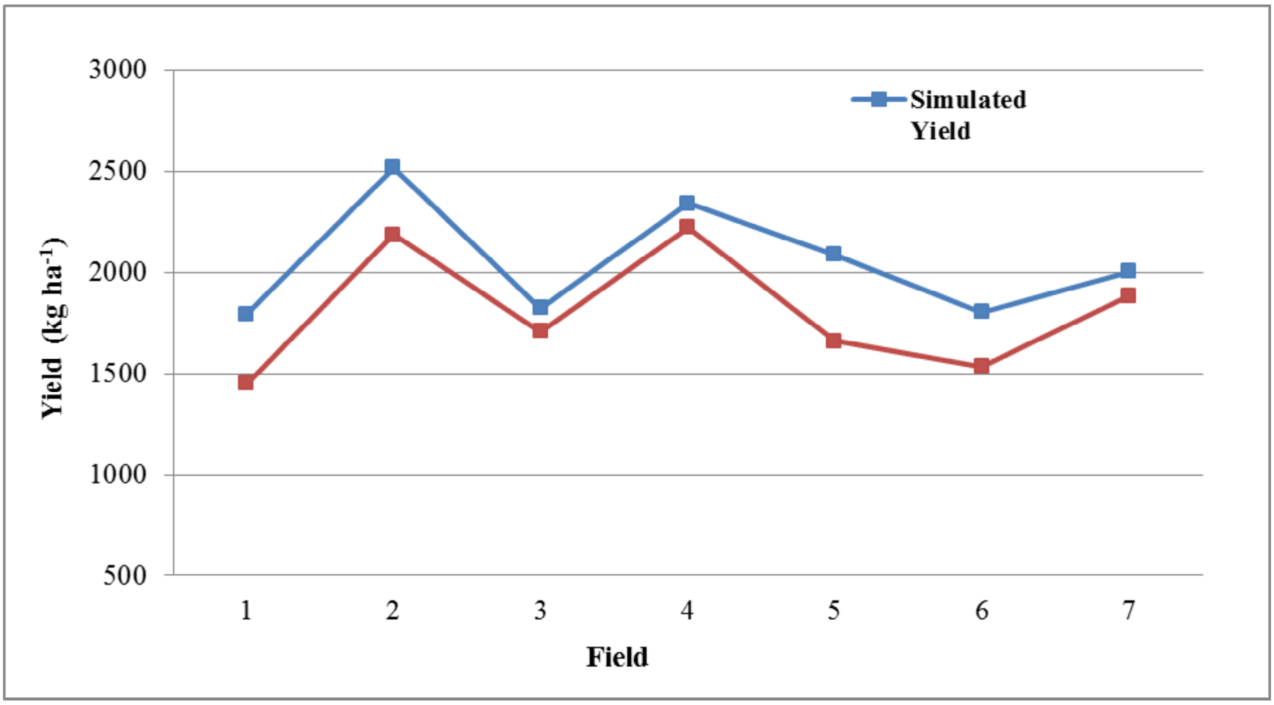

Fig.1. Validation of simulated (DSSAT) and observed data (Field)

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Detection of Agricultural Vulnerability to Drought Using NDVI and Land Surface Temperature in Salem and Namakkal districts of Tamil Nadu

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ABSTRACT

Drought is considered as one of the main forces driving current and likely future ecosystem productivity loss and vegetation mortality. Therefore, understanding where, when and which vegetation type would be most vulnerable to drought is a prerequisite for developing effective adaptation strategies. The drought vulnerability pattern is closely associated with land use types. Generally, cropland, wetland and saline and alkaline land showed a much higher vulnerability, as vegetation growing on them had low ground cover and was more affected by accumulated drought conditions. The agricultural drought monitoring, assessment as well as management can be done more accurately with the help of geospatial techniques like Remote Sensing and Geographical Information System. This paper presents the drought by using the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) during 2015 over the Salem and Namakkal districts of Tamil Nadu (India) which fall in a plateau region and located between 11° 00' and 12° 00' North latitude and 77° 40' and 78° 50' of East longitude. The Combination of NDVI and LST derived from MODIS satellite data, provides very useful information for agricultural drought monitoring and early warning system for the farmers. The correlation between LST and NDVI are highly negative. The correlation between LST and NDVI of Salem and Namakkal districts are -0.528 and -0.647, respectively for the year 2015.

Key words *Drought, Vulnerability assessment, LST and NDVI*

Periods of persistent abnormally dry weather, known as droughts, can produce a serious agricultural, ecological, or hydrological imbalance. Drought harshness depends upon the degree of moisture deficiency, duration and the size of the affected area. Drought may be broadly defined as a long-term average condition of balance between precipitation and evapotranspiration in a particular area, which also depends on the timely onset of monsoon as well as its potency (Wilhite and Glantz, 1985). Drought is expected to get worsen with predicted climate change and the aerial extent of drought-affected regions are projected to increase, which could have adverse effects on agriculture (IPCC, 2007); Mir *et al.* (2012).

Combined and interacting influences of climate change and its variations in rainfall and temperature conditions directly affects Indian agriculture mainly plant and animal production. It indirectly affects agricultural production through changes in soil, water, pests and diseases incidence making agriculture more vulnerable. The main factor for agricultural vulnerability is drought. Drought always starts with the lack of precipitation, but may (or may not, depending on how long and severe it is) affect soil moisture, streams, groundwater, ecosystems and human beings.

The role of remote sensing and GIS in agricultural drought detection, assessment and management is becoming crucial these days as they provide up to date information in different range of spatial and temporal scales which is hectic and time consuming when done by traditional methods such as Field survey, and sampling questionnaires, (Thenkabail *et al.* (2004), Arshad *et al.* (2008) and Wardlo *et al.* (2012)). Satellite-derived drought indices typically use observations in multispectral bands, each of which provides different information about surface conditions. Since droughts are naturally associated with vegetation state and cover, vegetation indices (VIs) are commonly used for this purpose (Tucker and Choudhury, 1987), utilizing data in the visible red (R), near infrared (NIR), and the shortwave infrared bands. Some drought indices are based on observations in the thermal infrared (TIR) spectral region, which conveys information about vegetation health and soil moisture status. The remote sensing based monitoring of drought can get frequent and sustained information on the surface characteristics over time, space and direction. It can provide data sources for real-time and dynamic monitoring of drought (Zhang *et al.* 2011).

Different kinds of vegetation indices are available, but Normalized Difference Vegetation Index (NDVI) is the simplest, efficient and commonly used (Liu and Huete, 1995). NDVI was first suggested by Tucker in 1979 as an index of vegetation health and density. Using the NDVI data of the region, the changes in vegetation cover present in the area and also the trend in occurrence of agricultural drought can be studied Sruthi and Aslam (2014). This index is not free from defects such as data error during rainy season, saturation effect on dense vegetation, etc. So it is always better to merge it with other parameters to ensure more accuracy. It is seen that there exist a strong correlation between surface temperature and NDVI. LST is a good indicator of the energy balance at the Earth's surface which can provide important information about the surface physical properties and climate. Goetz (1997) reported that the negative correlation between LST and NDVI,

Zhengming *et al.* (2004), observed at several scales ($25\ m^2$ to $1.2\ km^2$), was largely due to changes in vegetation

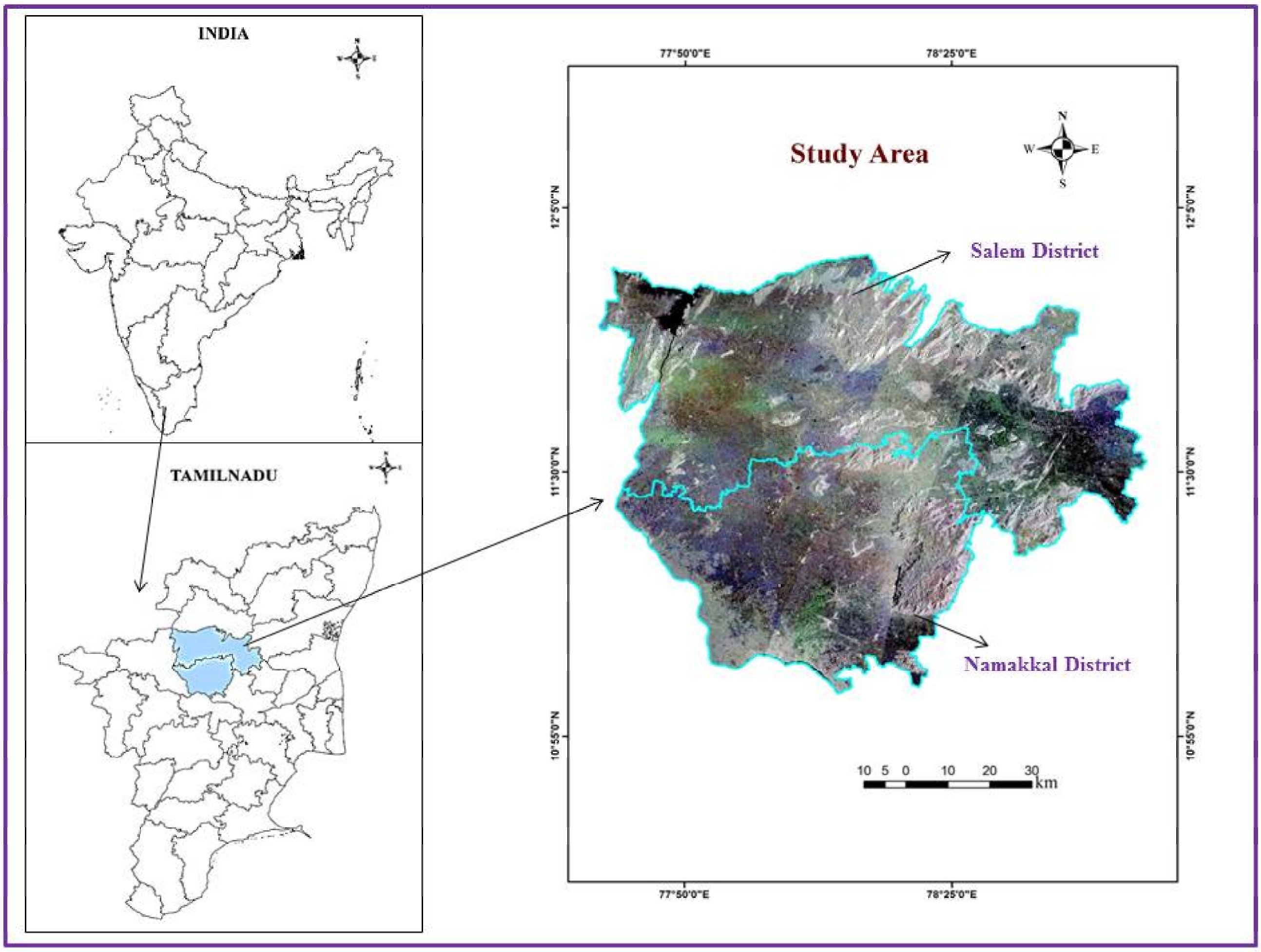

Fig. 1. Study area

cover and soil moisture, and indicted that the surface temperature can rise rapidly with water stress. Thus it can be noticed that the ratio of LST/NDVI increases during times of drought.

This study focus on assessment of agricultural drought in Salem and Namakkal districts of Tamil Nadu through the analysis of vegetation stress caused by the lower precipitation, higher temperature etc., using the multi temporal MODIS derived NDVI and LST.

MATERIALS AND METHODS

Study Area

The study area is located in North Western zone of Tamilnadu (India) situated between 11° 00' and 12° 00' North latitude and 77° 40' and 78° 50' of East longitude (Fig.1). The districts are drought prone with annual mean rainfall is 845 mm. South West and North East monsoon season contributes 338 and 341 mm respectively (Jegankumar *et al*. 2012). Major agricultural crops are groundnut, rice,

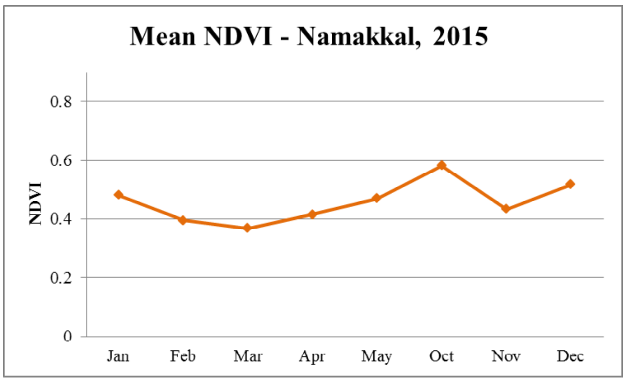

Fig. 2. (a) Mean NDVI of Namakkal District

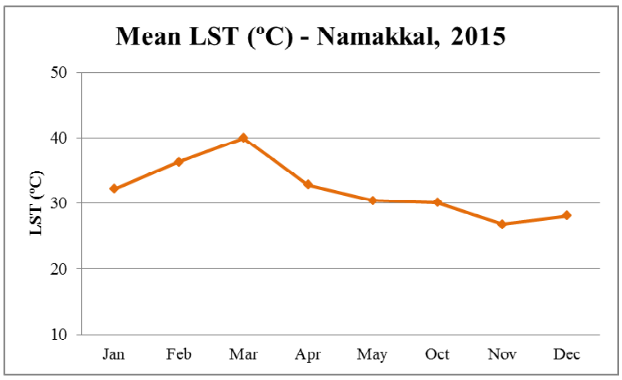

Fig. 2. (b) Mean LST (ºC) of Namakkal District

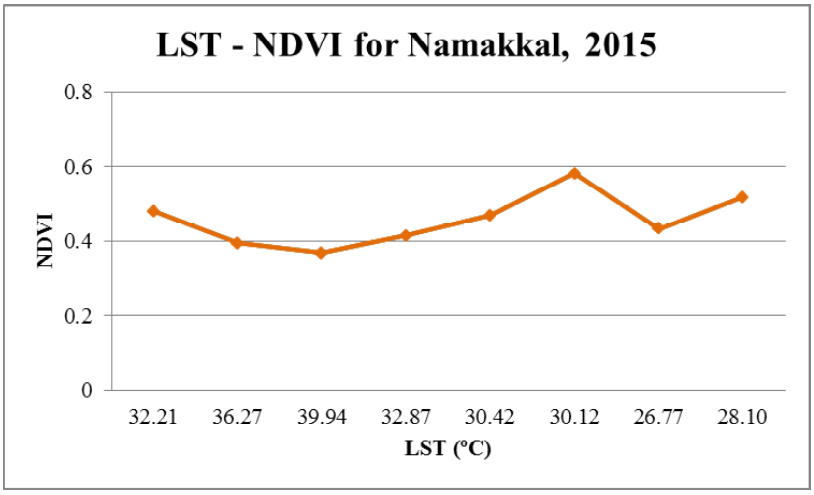

Fig. 3. NDVI change over LST (ºC) for Namakkal District

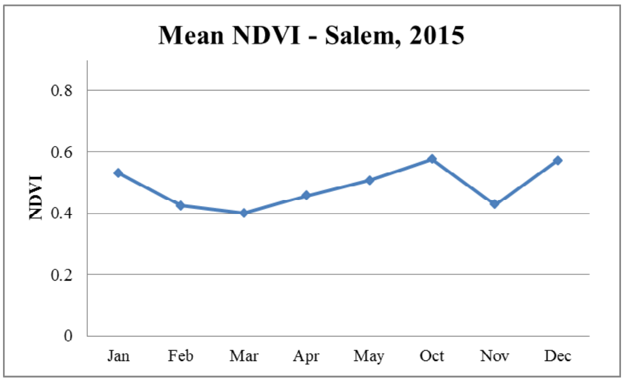

Fig. 4. (a) Mean NDVI of Salem District

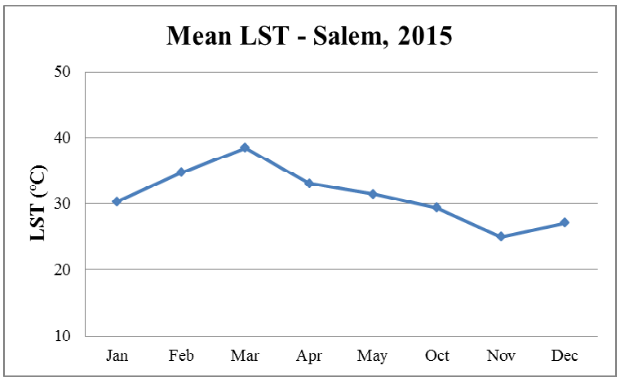

Fig. 4. (b) Mean LST (ºC) of Salem District

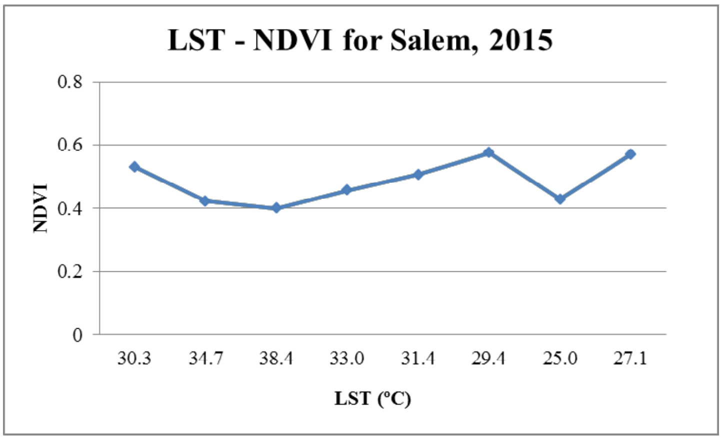

Fig. 5. NDVI change over LST (ºC) for Salem District

sugarcane, sorghum, cotton, tapioca and pulses.

NDVI Data

The study uses a time series 8-day composite of MODIS 250-m NDVI data (MOD09Q1 V005) spanning from January to December, 2015 (10 composite periods) were acquired. The NDVI data for MODIS tile h25v07 was extracted for each composite period, reprojected to the WGS 84 projection and sequentially stacked to create the 8-date NDVI time series for the year 2015. The label of this product is "MODIS/Terra Surface Reflectance 8-Day L3 Global 250m SIN Grid V005". The spatial resolution of this product is approximately 250 m, and atmospheric correction has already been carried out (Vermote and Vermeulen, 1999). This 8-days average data is delivered as a composite product called MOD09 which took the best surface spectral-reflectance within this period with the least effect of aerosols and other atmospheric ingredients.

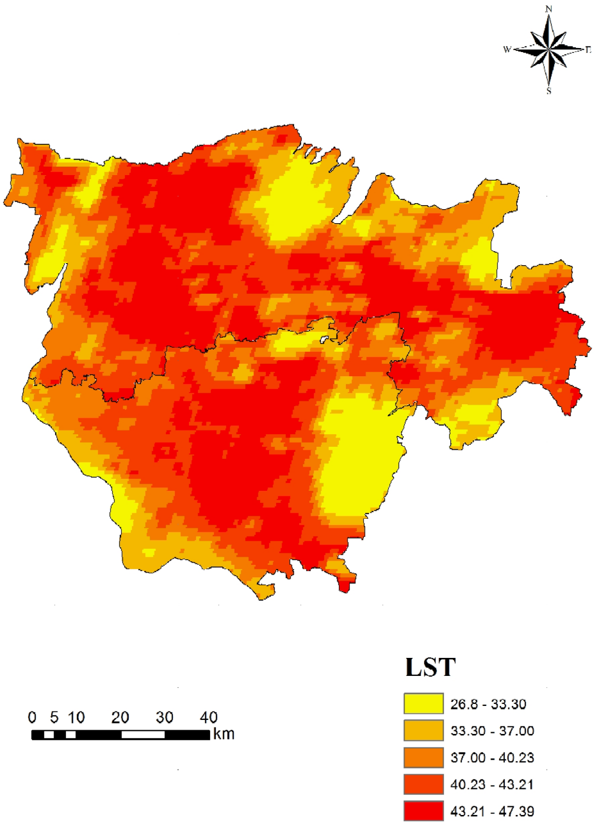

Fig.6. (a) LST (ºC) for March, 2015

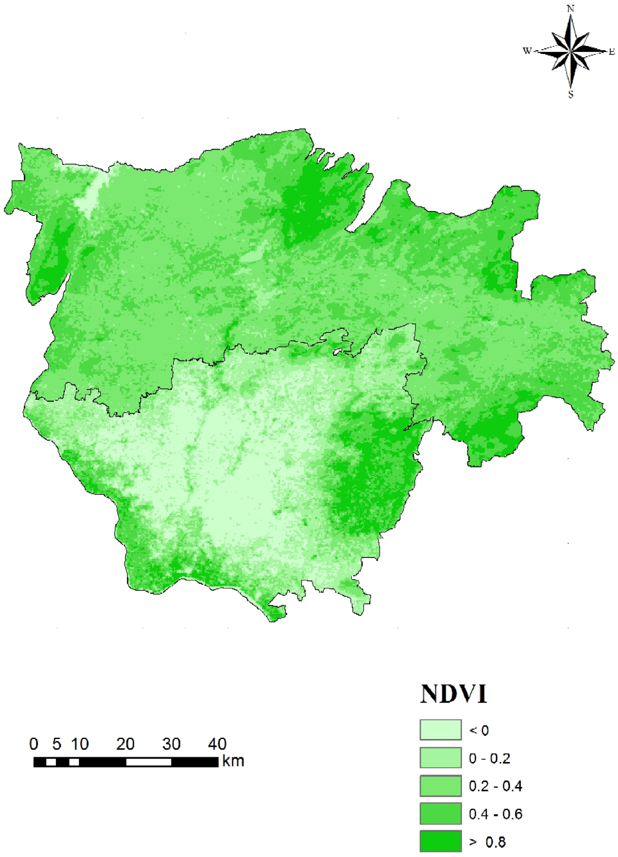

Fig.6. (b) NDVI for March, 2015

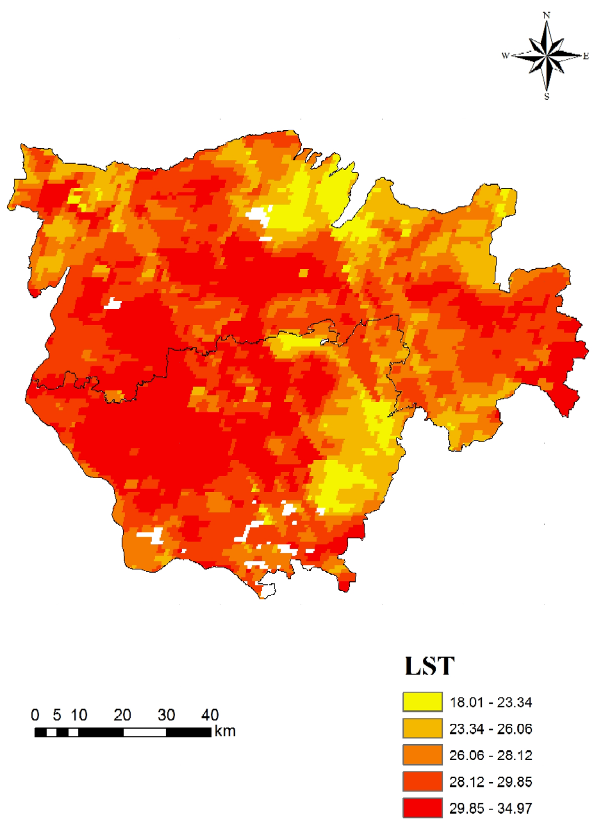

Fig.6. (a) LST (ºC) for November, 2015

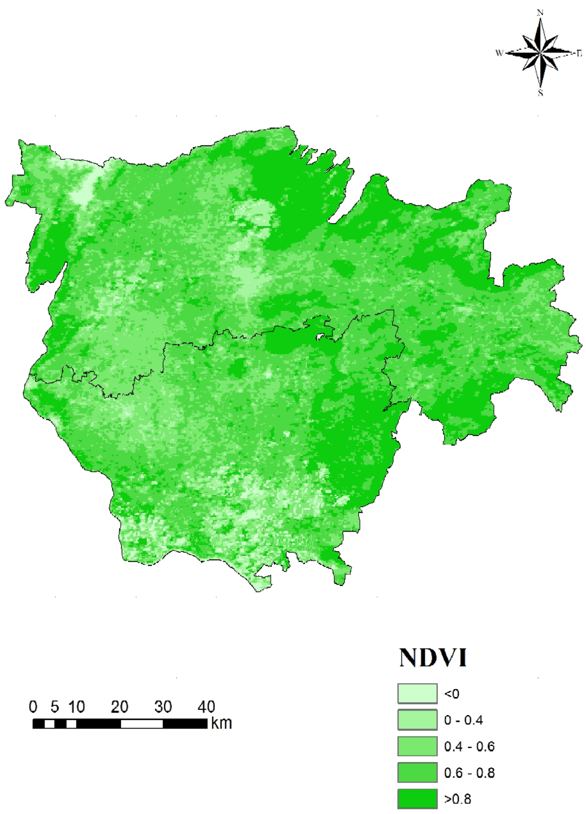

Fig.6. (b) NDVI for November, 2015

LST Data

The MODIS derived MOD11A2 Land Surface Temperature and Emissivity (LST/E) products provided at per-pixel temperature and emissivity values was used. This level-3 MODIS global Land Surface Temperature (LST) and Emissivity data were composed from the daily 1 kilometer LST product (MOD11A1) with a spatial resolution of 1km and temporal resolution of 8 days in sinusoidal projection represented as the average values of clear-sky LSTs during 8-day period.

MATERIALS AND METHODS

Satellite remote sensors can quantify fraction of the photosynthetically active radiation which is absorbed by vegetation. Since green vegetation had strong absorption of spectrum in red region and high reflectance in infrared region, vegetation index was thus generally formulated as various combinations of red and infrared bands. The region's absorption and reflection of photosynthetically active radiation over a given period of time was used to characterize the health of the vegetation there, relative to the calculation of NDVI, for the study area.

$$NDVI = (\lambda NIR - \lambda RED) / (\lambda NIR + \lambda RED)$$

Where, ëNIR and ëRED are the reflectance in the near infrared (NIR) and Red bands respectively.

One 8-day composite MODIS dataset comprised NDVI, quality, acquisition image, acquisition table and metadata files. From the global data, the study area was being subset and NDVI data has been analysed. NDVI and quality data were used to calculate the NDVI metrics. NDVI values ranged from "-0.2" to "1.0", where valid NDVI range was from "0.0" to "1.0" (Zhu *et al.* 2013). Time-series NDVI profile of the study area was derived from the calculation of NDVI using the MODIS NDVI data for the year 2015 and used to generate the Maximum, Minimum and Average monthly NDVI values for the year.

LST of the study area for the year 2015 calculated from the MOD11A2 data. In this data, temperatures were extracted in Kelvin with a view-angle dependent algorithm applied to direct observations. This method yielded 1 K accuracy for materials with known emissivities. The digital numbers (DN) of LST data was converted to degree Celsius by using following formula,

$$Temperature = (DN * 0.02) - 273.15\ ^{o}c$$

Monthly mean temperature of the region was calculated and the values were correlated with monthly NDVI values in order to understand changes in vegetation growth with respect to rainfall and temperature, thereby indicating intensity of agricultural drought.

RESULTS AND DISCUSSION

The mean values of NDVI and LST of study area for each month for the year of 2015 were computed a line graph (Fig. 2 (a), 2 (b), 4 (a) and 4 (b). Figures 3 and 5 represents the line graph obtained for mean LST and mean NDVI of Namakkal and Salem districts for every month during 2015. The Figures 4 (a) and 4 (b) shows the LST and NDVI maps of Namakkal and Salem districts for the year 2015. It was clearly noticed that both the parameters were inversely proportional to each other. When the temperature was greater, the NDVI value was lesser which indicated a decline in vegetation density. To be specific higher NDVI values of >0.4 was recorded during May to October, 2015 in Namakkal district, corresponding to the groundnut crop growth period. During this period LST values were found to be decreasing. The decrease in soil moisture due to lack or untimely onset of rainfall along with the increased temperature caused the agricultural drought to be severe. Similar results of inverse relationship between NDVI and LST has also been reported by Sruthi and Aslam, (2015). The NDVI values were lesser during the hottest months of March and April whereas October and November showed higher vegetation density. A clearly high negative correlation was observed between LST and NDVI. The correlation between LST and NDVI of Salem and Namakkal districts were -0.528 and -0.647, respectively for the year 2015. (Fig.3 and Fig. 5)

Satellite remote sensing technology is widely used for monitoring crops and agricultural drought assessment. Different vegetation indices are available today, but none of the major indices is considered inherently superior to the rest in all circumstances, some indices are better suited than others for certain uses. NDVI due to its simple calculation is largely used for the vegetation studies in a regional as well as global level. It is always advisable to combine the NDVI along with other parameters to get better results. The LST when correlated with the vegetation index, can be used to detect the agricultural drought of a region, as demonstrated in this work.

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