
nrsc
Remote Sensing Applications
P. S. Roy
R. S. Dwivedi
D. Vijayan
इसरो isro
nrsc
Remote Sensing Applications
National Remote Sensing Centre

Remote Sensing Applications

Agriculture

1.1. Introduction

Agricultural is the backbone of Indian economy, providing livelihood to about 67.0 per cent of the population and contributing approximately 35.0 per cent to the Gross National Product. Food grain production has increased from 51 millions tons in 1951 to 230.67 million tons in 2007-08. On the other end, the Indian population crossed the billion mark and needs around 250 million tons of food grains and calling for efficient agricultural management involving appropriate application of production and conservation practices for development of land and water resources on a sustainable basis. Substantial increase in crop production is possible by bringing additional land under cultivation (horizontal approach) and improved crop management (vertical approach) technologies such as use of high yielding input responsive, energy intensive and stress tolerant varieties, increased irrigation and integrated crop nutrition and protection. In addition, reliable and timely estimates and seasonal crop acreage and production estimates are important for formulation of marketing strategies such as export/import, price fixation, public distribution. Conventional techniques to provide this information are highly tedious, time consuming, more often subjective, whereas satellite remote sensing has the requisite potential to provide this information on a regular, synoptic, temporal, timely and in a more objective manner.

The remarkable developments in space borne remote sensing (RS) technology and its applications during the last three decades have firmly established its immense potential for mapping and monitoring of various natural resources. Remote Sensing can be defined as the science and art of acquiring information about objects from measurements made from a distance, without coming into physical contact of the object. Human eye, cameras and scanners are some of the examples. Satellite remote sensing and Geographic Information System (GIS) offer great promise for natural resources management with the ability to depict the spatial distribution of the extent and monitoring capability. These techniques have potential to predict and zonate different levels of crop response to the inputs and can also provide solutions to various management problems in increasing the performance of the cropping system in a spatial and temporal dimension, when coupled with the relevant ancillary information. A suitable blend of these technologies aid in efficient management of our resources to enhance the crop productivity on a sustainable basis.

The spatial resolution of the sensors of the Indian Remote Sensing satellites range from very fine resolution multi-spectral data of 5.8 meters to moderate resolution Wide Field Sensor (WiFS) data of 180 m through 56 m data of Advanced Wide Field Sensor and 24 meter multi-spectral linear imaging self scanner data (LISS-III) with the revisit period ranging from 5 days to 24 days and swath ranging from 70 km to about 800 km. LISS-III data provides district level information of the natural resources whereas regional level information is derivable from both AWiFS and WiFS data.

The satellite data at regular temporal interval enables monitoring of the natural resources for their effective management. The science of remote sensing of agricultural crops along with the capabilities of the remote sensing technology in providing information about the spatial distribution and extent and inter seasonal variations in cropping patterns, cropping systems analyses and interface with the agricultural drought assessment are discussed in this chapter.

1.2. Remote Sensing in Optical and Reflective Infra Red (IR) region

Remote sensing is largely concerned with the measurement of surface reflectance from the object and drawing of inference from such reflectance for identification of objects of interest. An understanding of the physical and physiological properties of plants and their interaction with the incident radiation is the key element in crop identification through remote sensing.

1.2.1. Reflectance Characteristics of Green Plants

Plant parameters such as pigmentation, nutritional status, leaf architecture, internal structure of the leaves and water content affect spectral response of the leaves. The plant leaves have both diffused and specular characteristics. The diffused leaf reflectance emanates primarily from the interior of the leaf through multiple scattering. The specular character of the leaf reflectance at the surface of the leaf is primarily affected by the topography of the cuticular waxes and leaf hairs.

The green plant has spectral reflectance characteristics as shown in Figure 1.1 as green curve, which is quite

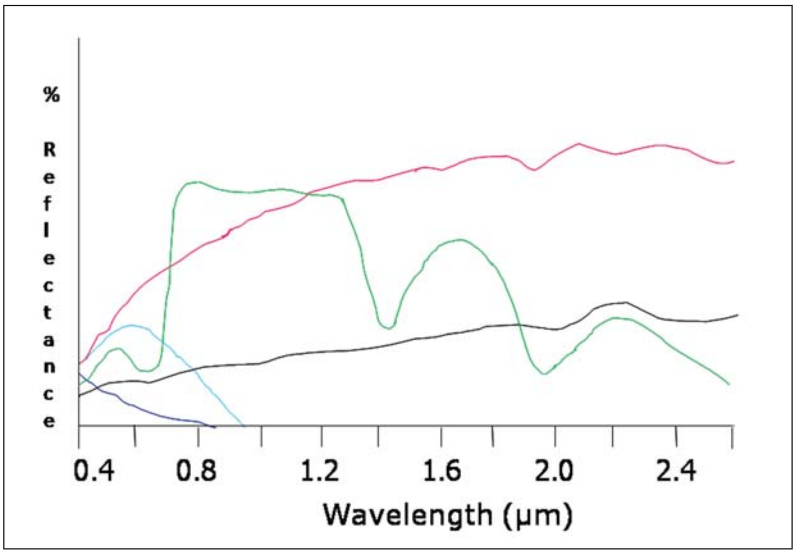

Figure 1.1: Typical spectral reflectance curves (source: Swain and Davis, 1978)

distinct from other objects such as dry/wet soil in pink/black colour and turbid/clear water in cyan/blue curves. The reflection of sun's radiation by green leaves is relatively low in the visible portion of the electro-magnetic spectrum of 400-700 nm wavelength region. Leaf pigments (chlorophyll) absorb a high portion of incident sunlight energy in the blue region (400-500 nm) and red region (600-700 nm) of the spectrum. Light energy in the green (500-600 nm) region of the spectrum is reflected to a slightly higher degree. Due to relatively high green sensitivity of human eye, the green colour of plant is sensed as the dominant colour.

Radiant energy in infrared part (700-900 nm) of the spectrum is reflected by the healthy plant, is much higher than most other objects. The high reflectance from 900 nm to about 1300 nm in IR is caused by internal structure of the leaf. The water content of the leaves profoundly influences the spectral region from 1300-2300 nm (near / mid infrared) and the main water absorption zones are at 1450 nm, 1950 nm and 2600 nm.

The healthier plant will be greener due to higher content of chlorophyll in leaves resulting in high absorption particularly, in blue and red regions of the electromagnetic spectrum. Decrease in infrared reflectance is one of the earliest symptoms of the reduction in vigor in many plants. During the drought, the spongy and palisade mesophyll cells become flaccid resulting in reduced infrared reflectance. Cell structure of the leaves affected by adverse conditions such as disease or pest also leads to reduction in infra-red reflection. The process of maturity / senescence will also cause changes.

1.3. Crop Inventory

The intrinsic ability of spectral reflectance data to identify and distinguish crops is very helpful in deriving crop acreages, production estimates, to monitor and assess the crop condition. Remote sensing based crop identification and discrimination is centered around the concept that each crop has a unique spectral signature due to its own architecture, growing period etc., when two crops with similar spectral signatures occur in a given date, multi date data is required to identify them.

1.3.1. Acreage Estimation

The acreage estimation procedure broadly involves 1) selection of single date data corresponding to the maximum vegetative growth stage of crop 2) identification of representative sites of various crops and their heterogeneity on image based on ground truth 3) generation of representative signatures for the training sites 4) classification of image using training statistics and 5) estimation of area of the crop using administrative boundary like district mask.

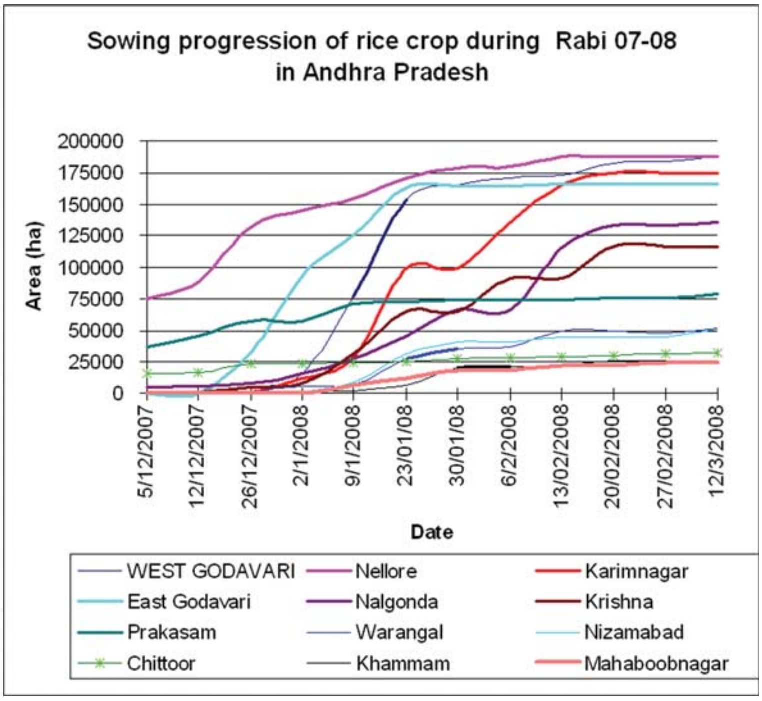

Figure 1.2: Sowing progression for the rabi rice areas in Andhra Pradesh

In the cases of estimation of crop acreages for large areas like states wherein analysis of large amount data and ground data collection are involved, stratified sampling procedure is being used operationally. The study area is divided into homogenous strata based on crop proportion and vigor as manifested on the satellite data and each strata is subdivided into segments of required size usually 5 X 5 km. About 10-15 percent of the sample segments are randomly selected for digital analysis and standard statistical methods are employed to aggregate crop estimates at district / state levels.

The analysis can also be carried out for the entire area of interest like district or taluk. The administrative boundary of the study area is overlaid on the image to extract all the pixels and the classification is carried out for the entire area to obtain the area under cultivation for the desired crops. In this procedure district crop map showing spatial distribution of different crops can also be generated.

In order to choose most optimum bio-window, it is necessary to obtain the crop calendar and sowing progression of different crops cultivated in the study area for better crop discrimination. The crop sowing progression shown in Figure 1.2 is an example depicting the variations in crop progression among the districts of A.P. The districts of Nellore, West and East Godavari districts need an early data sets compared to the other districts.

1.3.1.1. Major Crops

Using single date cloud free optical data during the maximum vegetative stage of the crop growth, district level pre-harvest acreage and production of large area covering crops viz., paddy, wheat, sorghum, ground nut, rapeseed-mustard and cotton is being estimated on operational basis under the crop acreage and production estimation (CAPE) project (Navalgund *et al.*, 1991, Navalgund and Ray, 2000, Dadhwal, 1999, Dadhwal and Ray, 2000 and Dadhwal *et al.*, 2002). The remote sensing based acreage estimations are aimed to be made available at least one month before the harvest of the crop, to enable the administrators and planners to take strategic decisions on import-export policy matters and trade negotiations. An extended project viz., forecasting agricultural output using Satellite, Agro-meteorological and Land Observations (FASAL) is in progress to provide multiple forecasts at district, state and national level (Parihar and Oza, 2006).

Moderate resolution data from WiFS sensors can provide regional level information of crops at state level. This sensor can also be used for deriving information at district level if the crops are concentrated. Inter seasonal and intra seasonal variations in the crop condition and cropping pattern can also be derived from WiFS data due to its regular revisit periodicity of five days. Figure 1.3 shows the spatial distribution of kharif rice in Andhra Pradesh during 2001.

1.3.1.2. Multiple Crop and Small Land Holding Situations

IRS LISS-III data acquired during optimal bio-window period of crops enabled better discrimination of rice and cotton crops for generating cropping pattern information at district level. The major kharif cropping pattern of Guntur district during 2004 using IRS-LISS III data is depicted in Figure 1.3. Thus, using LISS-III and AWiFS data crop inventory information at different spatial hierarchical levels can be generated. In addition, the high revisit period of AWiFS data at 5 days enables crop monitoring, besides increasing the probability of getting cloud free data during kharif season.

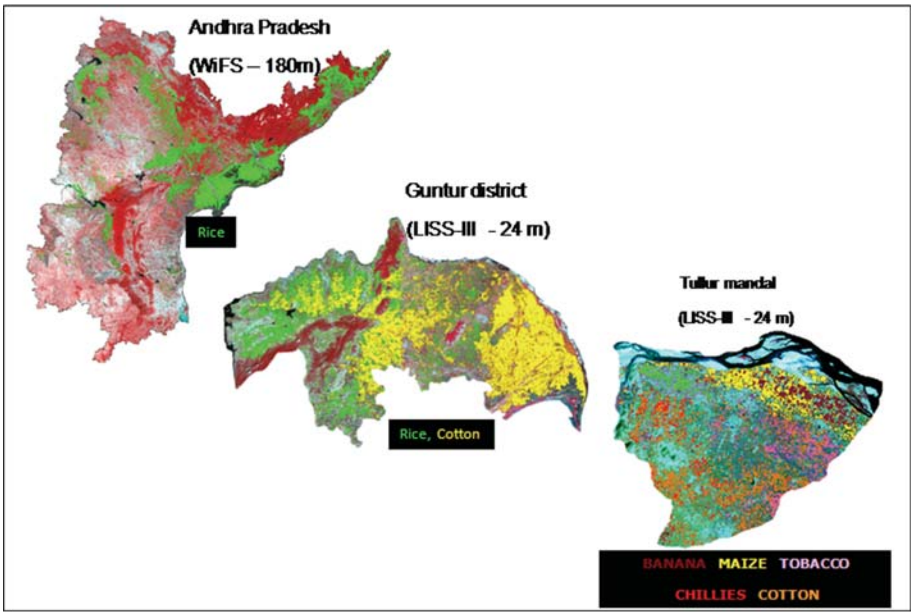

Figure 1.3: Crop inventory using satellite data

Availability of better spatial resolution from IRS LISS-III enabled identification of crops, which are grown under multiple crop situations. Commercially important crops like chillies, tobacco etc., which are cultivated in small landholdings under intense input management practices can also be identified and their acreages can be estimated. These pre-harvest estimates have special importance from commercial point of view. Figure 1.3 shows utilization of IRS LISS-III data for discrimination of multiple crops in Tulluru mandal of Guntur district, AP (Krishna Rao *et al.*, 1997).

1.3.1.3. Commercially important crops

Inventory of commercially important crops and high value crops has the unique applications in making strategic decisions for enhancing the use efficiency of the economic resources. For example, area of the crops of soybean and sunflower enable location and planning for the optimal designs for oil extraction plants. (NRSA, 1992, Venkataratnam *et al.*, 1996, Krishna Rao *et al.*, 1997); Jute (NRSA, 1991); Cotton (Venkataratnam *et al.*, 1993) and Tobacco (Ranganath *et al.*, 1991) were studied. The remote sensing information also provides valuable information to enhance the area under hinterland for providing raw material to the agro-based industries. As an illustration, utilization of two-date data for sugarcane inventorying is presented below.

Sugarcane: Integration of the information of distribution of sugarcane crop along with the corresponding spatial data of soil attributes enables to derive the information for assessing the scope of expansion of sugarcane cropped area by matching the climate, soil and water requirements of the standing crops vis-à-vis other crops. In one specific study carried out for M/s EID Parry Ltd., the cropping pattern information was derived using two-date IRS-LISS III data (Figure 1.4). This information along with the corresponding soils information revealed that sugarcane crop could be expanded by 556 and 1108 ha, replacing the standing banana crop in the Alangudi and Arantangi divisions of Tamil Nadu. However, the ultimate choice of the crops depends upon the socio-economic returns and the efforts towards maintenance of soil fertility (Krishna Rao *et al.*, 2000; Hebbar *et al.*, 2003).

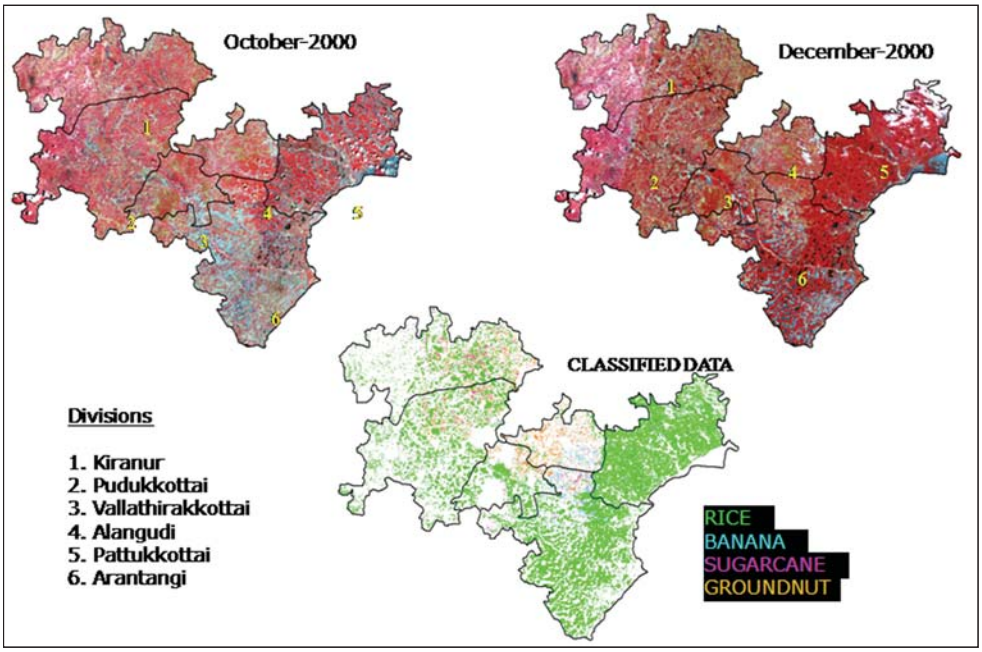

Figure 1.4: Cropping pattern of EID factory command derived from LISS-III data

1.3.2. Horticultural Crops

The high spatial resolutions LISS-III data also enabled identification of many horticultural crops viz., mango, coconut, oranges

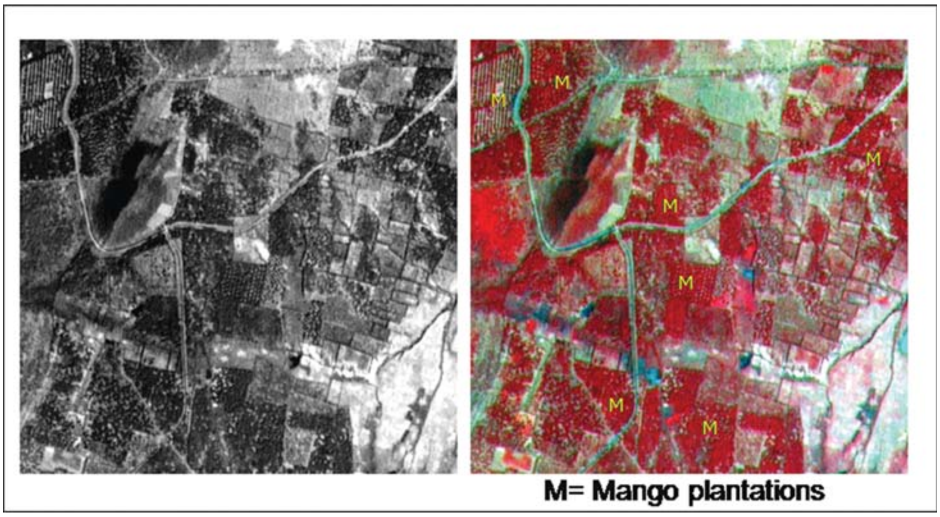

Figure 1.5: IRS LISS-III and PAN merged data showing mango plantations

and banana. Mandal level acreages of mango crop of Krishna district and banana crop of Guntur district, Andhra Pradesh were estimated. Using satellite data, the area under arecanut (RRSSC, 1991) and grape (Krishna Rao *et al.*, 1996) were reported. Dakshinamurthy *et al.*, (1971) demonstrated the utility of aerial photographs in identification of coconut trees with wilt disease in parts of East Godavari district, Andhra Pradesh. The very high spatial resolution PAN data adds a new dimension of geometric fidelity to the satellite data for better identification of plantation crops. The young and the fully-grown mango plantations were clearly discernible in the fused data products of LISS-III and PAN (Figure 1.5).

1.4. Cropping System Analysis

Remote sensing provides valuable information on the distribution and condition of crops at different spatial hierarchies and has the highest compatibility for analysis in GIS environment. Information on other natural resources that are of significant importance towards agricultural production can be integrated to generate information for sustainable agriculture. Integration of soil suitability for the cultivation of cotton crop along with the spatial distribution of cotton crop, as derived from remote sensing data through a conformity analysis enabled to delineate cotton crop grown under different suitability regimes. This information is useful towards planning for efficient production of cotton crop by apportioning those land parcels that are highly suitable for cultivation of cotton (Sesha Sai *et al.*, 2003). The rainy season (kharif) fallows in Madhya Pradesh which could have been used for a short duration crop like soybean were identified. Madhya Pradesh is endowed with well distributed rains ranging from 700 to 1200 mm. Vertisols with good moisture holding capacity can be used to grow short-duration soybean by adopting sound land management practices. This will help increase income to the farmers besides preventing land degradation due to runoff erosion (Wani *et al.*, 2002). Remote Sensing derived information of the rice-wheat and rice–fallow cropping systems of India, Pakistan, Nepal and Bangladesh are presented hereunder, as a case study (Subba Rao *et al.*, 2001; Krishna Rao *et al.*, 2002).

Rice Cropping System: Rice is the major food grain cereal crop grown in South Asia and is cultivated mostly during the monsoon (rainy) season. Since the scope is limited for horizontal expansion, increased cropping intensity on the existing agricultural lands is one of the best crop management options. In this context, post kharif rice fallows offer a considerable scope for achieving sustainable production by introduction of short duration leguminous crops.

IRS-WiFS data of 1999 kharif season and rabi 2000 season were analysed following total enumeration approach for deriving spatial distribution of kharif rice and rice fallows in different States of India and in the neighboring Pakistan, Nepal and Bangladesh Nations. Information on the spatial distribution of kharif rice and rabi fallow lands were logically combined to derive the distribution and area of post kharif rice-fallow lands (Figure 1.6). The analysis indicated that good potential for the utilization of post kharif rice fallow lands existed in India, Bangladesh and Nepal with marginal potential in Pakistan.

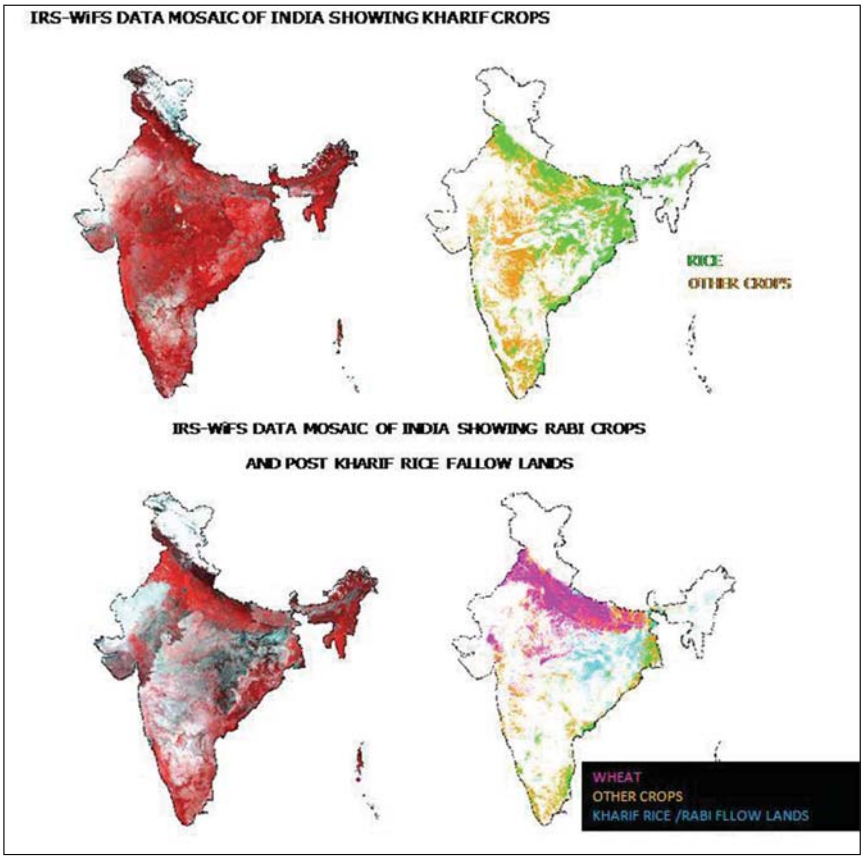

Figure 1.6: IRS WiFS data mosaic of India during kharif and rabi seasons during 1999-2000

Spatial information layer of rice derived from remote sensing data in India, Bangladesh, Nepal and Pakistan nations, in conjunction with soil and climate layers enabled ICRISAT for preparing GIS maps of potential areas for rice- fallow cultivation with a suitable short duration leguminous crop. This information along with pedo-climate regimes and the socio-economic conditions in GIS environment enables for better utilization of the post kharif rice fallow lands towards enhancing the crop productivity in a sustainable manner in South Asia.

1.5. Production Estimation

Crop yield is influenced by many factors such as genotype, soil characteristics, cultural practices adopted, meteorological conditions and influence of pests and diseases. Spectral data of a crop is the integrated manifestation of the effect of all theses factors. Development of reliable crop yield models with minimal data is a major thrust area.

A major challenge often confronted in agricultural crop production, despite the development of advanced agricultural technology, is the damage caused to agricultural crops by pest and diseases. Crop losses can be due to biotic factors like pests, diseases, weeds and abiotic factors like flood, drought, cyclones hailstorms etc. Damage is known only after considerable damage has been occurred.

Statistical, meteorological and / or spectral models are used for crop yield estimation. Remote sensing based models adopt two approaches viz., single date spectral index and multi-date spectral index-growth profile are in vogue. The single date data spectral index approach relies solely upon the data acquisition within a narrow critical period of maximum vegetation growth phase while multi-date approach depends spectral data at different stages of crop growth within the season.

The multi-date approach has the constraint of obtaining the cloud-free multi-temporal satellite data within the crop growth cycle. To overcome this problem, studies are in progress to explore the potential of the microwave data, which has the all weather and cloud penetrating capability. Remotely sensed data directly or its derived parameters are related to the yield or to the biometric parameters.

In addition, attempts are also underway to incorporate the spectral information in the process-based models and crop simulation models to improve the predictive capabilities of the remote sensing based crop production estimation.

1.6. Crop Monitoring and Condition Assessment

Condition of the crop is affected by factors such as availability of water and nutrients, pest attack, disease outbreak and weather conditions. These stresses cause physiological changes which alter the optical and thermal properties of the leaves and bring about the changes in canopy geometry and reflectance / emission. Monitoring and assessment of crop condition at regular intervals during the crop growth cycle is essential to take appropriate curative measures and to assess the probable loss in production.

Regular monitoring of satellite data on crops at different phases of the crop growth would reveal any departure from normal growth, for inferring occurrence of any anomalies to incidence of pest and disease damage with the support of ground observations. In view of large area coverage in a short time and of repetitive nature, remote sensing techniques if used in complementary to ground surveys, it can provide real time data for early detection and warning of out break of the disease or insect damage before they reach higher severity levels.

1.7. Significance of NDVI in Agricultural Drought Assessment

The variations in the progression of NDVI, in terms of the magnitude and rate of progression, in relation to its respective normal NDVI provide information of the prevailing status of the vegetation. Exclusion of the permanent non-agricultural features like forests, wastelands, water bodies and settlements, reveal the status of the agricultural situation. In order to circumvent the problem of non-availability of cloud free optical data, time composited NDVI over an aggregated period of a fortnight or a month is generated, covering the entire crop growth season (NRSA, 1991; Sesha Sai *et al.*, 2004).

1.8. Thermal Remote Sensing

Thermal infrared radiation refers to electromagnetic waves with a wavelength of between 3.5 and 20 micrometers. The windows normally used from aircraft platforms are in the 3-5 µm and 8-14 µm wavelength regions. Some space borne sensors commonly use transmission windows between 3 and 4 µm and between 10.5-12.5 µm. None of the windows transmits 100 percent because water vapor and carbon dioxide absorb some of the energy across the spectrum and ozone absorbs energy in the 10.5-12.5 µm interval. In addition, solar reflectance contaminates the 3-4 µm windows to some degree during daylight hours, so we use it for earth studies only when measurements are made at night. Unlike remote sensing of reflected light from surfaces in which only the topmost layers (a few molecular layers thick) are involved, thermal remote sensing includes energy variations extending to varying shallow depths below the ground surface. Thermal remote sensing is an observation of the status of the surface energy balance (SEB) at a specific time of day.

1.8.1. Parameter retrieval

The developments in satellite meteorology enabled the retrieval of basic agro-meteorology parameters viz., cloud cover, albedo, solar radiation, surface temperature/air temperature, rainfall, absorbed photo-synthetically active radiation, soil moisture and evapo-transpiration etc., which contribute significantly to the understanding of agricultural production forecasting. The following were some of the parameters that can be mapped and monitored through the use of satellite remote sensing data.

1.8.1.1. Surface Temperature

The parameter-surface temperature figures in nearly all equations for energy fluxes through a surface element. It is routinely derived from satellite radiances over the ocean. However, over land the changing surface emissivity, strong daytime heating as well as night time cooling and the difficulty of defining surface temperature for a canopy, have prevented a routine application. Water vapour continuum is the dominant absorber within the thermal infrared window from 10 to 13 mm. Also the aerosols and the optically thin clouds also attenuate the signal. The inversion of temperature in the lower atmosphere also alters the derived surface temperature.

Air temperature is significantly related to crop development and conditions. Operational crop and soil moisture models require daily minimum and maximum shelter temperature and dew point temperature. Canopy (or skin) temperature may be more directly related to growth and evapo-transpiration than the shelter temperature. The difference between the two is a measure of crop stress. The ability to observe canopy temperature directly is an advantage of satellite observations. However, it is to be noted that the satellite derived “skin temperature” and “crop canopy temperature” are equivalent only when a satellite field of view (FOV) is filled with vegetation. If FOV constitutes a mixture of bare soil, water bodies, etc., the relation between the two becomes complex. Satellite observations in the thermal IR window (10-12 mm) are used to obtain estimates of canopy or skin temperature.

1.8.1.2. Methods for LST Retrieval

Land surface temperature can be retrieved from remote sensing data applying different techniques, as for example single-channel, split-window and dual-angle algorithms. In order to retrieve land surface temperature (LST) from thermal infrared remote sensing data, different methods and algorithms have been published. A full revision of methods is given by Sobrino *et al.*, [2002] and Dash *et al.*, [2002], among others. The three well-known methods that use one or two thermal channels: single-channel [e.g., Qin *et al.*, 2001; Jime´nez-Mun˜oz and Sobrino, 2003], split-window [e.g., Price, 1984; Becker and Li, 1990a; Sobrino *et al.*, 1991; Prata, 1993; Sobrino *et al.*, 1994] and dual-angle [e.g.,Prata, 1994; Sobrino *et al.*, 1996, 2004]. In the literature other methods can be also found using three or more thermal channels or algorithms based on different techniques (Becker and Li, 1990b; Wan and Li, 1997).

Most of them are based on the radiative transfer equation, from which the at-sensor radiance is given by:

$$L_i^{at-sensor} \equiv B_i(T_i) = \left[\varepsilon_i B_i(T_S) + (1-\varepsilon_i)L_i^{atm\downarrow}\right]\tau_i + L_i^{atm\uparrow} \qquad (1)$$

e_i is the channel surface emissivity,
B_i is the radiance emitted by a blackbody,
T_s is the surface temperature or LST,
T_i is the at sensor brightness temperature,

$L_i^{atm\uparrow}$ is the down-welling irradiance,
t_i is the total transmission of the atmosphere (transmissivity) and
$L_i^{atm\downarrow}$ is the up-welling atmospheric radiance.

When equation (1) is applied only to one thermal channel, single-channel algorithms are obtained, and when equation (1) is applied to two thermal channels located in the spectral range from 10 to 12 mm, split-window algorithms are obtained. It is also possible to apply equation (1) to one thermal channel with two different view angles, obtaining in this way the dual-angle algorithms. Land surface temperature can be retrieved from remote sensing data applying different techniques, as for example single-channel, split-window and dual-angle algorithms.

For single-channel algorithms, the best wavelength in order to retrieve the LST depends on the atmospheric water vapor and varies from 11 mm to 10.5 mm when the water vapor varies from 1 g/cm^2 to 4 g/cm^2. With regard to the split-window technique, the best simulated results have been obtained for wavelength combinations near to 11 mm and 12 mm. Single-channel methods provide similar or better results than split-window methods for low atmospheric water vapor content, whereas split-window methods always provide better results for high atmospheric water vapor content. Both the methods assume that land surface emissivity is known and need the atmospheric water vapor content in order to retrieve the LST. Total errors for split-window algorithms of around 1.5 K, and less than 1 K for dual-angle algorithms have been reported. The errors can largely be attributed to imperfect knowledge about atmospheric water vapor content and wavelength dependent surface emissivity.

1.8.1.3. Precipitation

The objective of precipitation measurement is to determine the spatial and temporal distribution of precipitation, primarily rain and snow. Historically, precipitation has been measured with gauges, which capture samples of the precipitation for direct measurement. Gauge measurements of precipitation have limitations, especially for operational meteorological and hydrological purposes such as short period weather and flash flood forecasting. These limitations include:

The density of measurements in most gauge networks is not sufficient for assessment of precipitation from thunderstorms in small watersheds. More-or-less typical precipitation networks for climatological purposes have a gage density of about one gage every 30 km (900 km^2 area). The highest precipitation intensities in a thunderstorm cell occupy a much smaller area, so could easily be missed in a fixed gage network.

Many areas of interest are not suitable for direct measurement of precipitation with gauges. These areas include mountains (for water supply assessment) and oceans (for earth heat and moisture budgets). The cost of direct measurements (including equipment, maintenance, personnel, data acquisition and processing) precludes expansion of gauge networks for operational uses.

Remote sensing of precipitation is widely used to obtain increased spatial and temporal accuracy. With remote sensors, the precipitation is not captured or directly measured. The precipitation is inferred from physical, statistical, and/or empirical relationships between precipitation characteristics and the emitted or reflected radiation from the earth and atmosphere. Remote sensing provides additional information to the existing network of ground based precipitation gauges, for mapping the extent and amount of precipitation. It is unlikely that remotely sensed data will replace the existing network of precipitation gauges.

There are several remote sensing techniques which have potential to assist in mapping the extent of precipitation patterns. Several reviews provide background on the use of satellite remote sensing to estimate precipitation (Arkin and Ardanuy, 1989; Barrett and Beaumont, 1994; Petty, 1995; Rasmussen and Arkin, 1992). Estimation of precipitation using remote-sensing techniques may be divided into three categories - Visible/Infra red, Passive microwave and Radar. The oldest and still most used precipitation-estimation technique is cloud indexing, assigning a rain rate to each cloud type.

In infrared-based methods, the most common approach is to find cold clouds (say, colder than 250^o K) within an overcast area. The raining potential of the clouds is proportional to the fractional area covered by cold clouds, and thus the rainfall derived. More complex techniques use both visible and infrared observations to create a bi-spectral histogram of the cloud images. Bi-spectral histogram method is a simple technique in which the clouds can be classified based on the combination of cloud signatures in visible and infrared frequencies. Then the rainfall is derived by estimating the extent of each type of cloud and multiplying it by the a-priori rain potential of respective classes. However, all the rain-retrieval techniques based on visible/IR observations are basically “inferential” in nature, because these sensors can sense the clouds (that too, the top surfaces of the clouds) but not the actual rain, that occurs at several layers below the clouds. Visible/IR techniques make a “guess” about the rainfall based on the cloud features. Due to this shortcoming, the estimates of rainfall based on visible/IR technique are not very accurate on instantaneous time scale. However, long time averages (e.g., daily, weekly, and monthly) of rainfall are better and usable for practical purposes.

The use of microwave techniques is that microwave radiation penetrates clouds and the precipitaion drops interact with the microwave radiation. The main disadvantage is the poor spatial and temporal resolution of passive microwave sounders. Passive microwave remote sensing of rainfall over land was more achievable since the 1987 launch of the Special Sensor Microwave Imager (SSM/I) on board the (USA) Defense Meteorological Satellite Program (DMSP). International research indicates that integrating geostationary thermal measurements with other data to make rainfall rate estimates provides more promise than using remotely sensed data alone.

There are several integration techniques, which may allow rainfall to be better predicted by combining the thermal GMS data with other data sets (Ebert and Le Marshall, 1995). These include:

- Use of pattern recognition or visible data to determine cloud type (Ebert, 1987); Integrating short wave infrared (SWIR) based inferences of cloud top droplet size may be linked to the presence of rainfall (Rosenfield and Gutman, 1994); and
- Combining the outputs from numerical weather prediction (NWP) to include some information about current meteorological conditions (Grassotti and Garand, 1994). Herman *et al.*, (1997) have developed an operational system using this approach for Africa to provide 10-day estimates for the entire continent

Using the high spatial resolution offered by remote sensing should assist in rainfall mapping for drought events especially in areas with a sparse rainfall measurement network. However, remote sensing only provides a snapshot which may have a revisit time of, at best hourly (geostationary satellites) to every 12 hours (polar orbiting sun-synchronous satellites). During that time clouds will move and intense periods of rainfall may occur and be over before the next revisit time. Providing accurate, precise and thoroughly validated space-time images of precipitation derived from using remote sensing is, and should continue to be, a major research area for issues like drought, climate prediction and thorough understanding of the global hydrologic cycle.

The first satellite whose primary mission is to measure precipitation is the Tropical Rainfall Mapping Mission (TRMM), a joint research project between the US (NASA) and Japan (National Space Development Agency: NASDA). A basic objective of TRMM is to obtain estimates of the vertical profile of the latent heat (heat resulting from a change of state), released through condensation of water vapor in the atmosphere, especially in the Equatorial Intertropical Convergence Zone (ITCZ). Potential flood areas can be derived using the precipitation intensity as described from TRMM (figure 1.7) and other collateral data.

Figure 1.7: Potential flood areas as derived from TRMM (source: http://trmm.gsfc.nasa.gov/publications_dir/instant_2.html)

1.8.1.4. Solar Radiation

Incoming solar radiation is the primary source of energy for plant photosynthesis. Solar radiation also plays a key role in evapotranspiration. Visible observations from satellites provide an excellent source of information about the amount of solar radiation reaching the plant canopy. A measurement of solar energy reflected to space from earth-atmosphere system immediately specifies the maximum amount of solar energy that can be absorbed at the surface. Incoming solar radiation can be known by adjusting the amount absorbed. Hence, for the computation of down welling solar radiation, the albedo of the surface must be known. This is especially important over the regions of high reflectivity such as snow and desert. Tarpley (1979) used a statistical regression technique to obtain surface fluxes over the land from Visible channel observations from geostationary satellites. In this model, cloud amount is estimated for a given location from satellite visible data. Three separate regression equations are then used to estimate solar radiation for three categories of clouds. This method provides an accuracy of 10% for clear sky, 30% for partly cloudy and 50% for overcast conditions Other algorithms like those by Moser and Raschke (1984), and Pinker and Ewing (1985) used physical approaches, and treated the interaction of incoming and reflected solar radiation with the atmosphere and land surfaces in physical manner. The transmittance of solar radiation in these approaches is solved by the use of radiative transfer equations that take into account the concentration profile of different atmospheric components. These physical schemes also take into account the cloudiness and atmospheric water vapor. These methods provide relatively higher accuracy. However, statistical techniques have remained the choice for operational use. These methods require coincident satellite and ground (pyranometer) observations to develop the coefficients in the regression equations. These methods produce daily total insolation, based on hourly estimates made from geostationary satellite data between 0800 and 1600 LST, with interpolation used toward both sunrise and sunset and for any other missing hourly values.

For clear sky and near clear-sky conditions the average daily deviation of GMS based estimates compared to ground-based pyranomter measurements was 4.3%. This is within the error limits of well-maintained and calibrated pyrometers. Under heavy cloud conditions the error between GMS based estimates compared to ground based pyranomter measurements increased to about 15%. The relative error may appear large; however, the absolute error is small since the amount of incoming solar radiation is low due to the heavy cloud cover conditions.

1.8.2. Agro Meteorological Applications

The derived parameters viz., solar radiation, precipitation and surface temperature can be used to study the net primary productivity levels, assess the risk of flood occurrence and quantify the stress and its impact on yield. Previous studies have shown that the surface temperature measured over crop canopy can be used as a suitable indicator of crop water stress as well as irrigation scheduling. The most established method for detecting crop water stress remotely is through the measurement of a crop surface temperature. The correlation between surface temperature and water stress is based on the assumption that as a crop transpires, the evaporated water cools the leaves below that of air temperature. As the crop becomes water stressed, transpiration will decrease, and thus the leaf temperature will increase. Other factors need to be accounted for in order to get a good measure of actual stress levels, but leaf temperature is one of the most important. Many canopy temperature based indices have been developed for detecting plant water stress and scheduling irrigation viz., canopy-air temperature difference (CATD) and stress degree days (SDD), canopy temperature variability (CTV), temperature stress day (TSD) and crop water stress index (CWSI) (Jackson 1982). Of all these, crop water stress index has received much of the researchers as well as farm managers attention for its use in the day to day operations.

Stress degree day is the cumulative difference between the canopy temperature (Ts) and air temperature (Ta) measured post-noon near the time of maximum heating (Idso *et al.*, 1977; Jackson *et al.*, 1977). It is assumed that the canopy temperatures would account for the effect of environmental factors such as vapour pressure, net radiation and wind. The SDD increases with increasing plant water stress. A crop is considered stressed if the value is high and positive and unstressed if it is negative. This change over is, however, arbitrary and may not be valid for all environments.

The canopy temperature validity (CTV) is the variability of temperatures encountered in a field during a particular measurement period. It is expressed as the standard deviation of mid-day canopy temperature within a field. The basis for CTV index is that soils are inherently non-homogeneous. Some areas within the field becomes stressed earlier than others. As water limiting in the former, the canopy temperature would show a greater variability. This variability can be used to signal the onset of deficit and schedule irrigation (Gardner *et al.*, 1981).

The temperature stress day (TSD) is the difference in temperature between a stressed plot and a well irrigated plot (Gardner *et al.*, 1981). Use of well watered plot as reference compensates for environmental effects. It needs to be in the vicinity of the field to be irrigated.

The Crop Water Stress Index (CWSI) (Idso *et al.*, 1981; Jackson *et al.*, 1981), based on the difference between canopy and air temperatures, was a significant advance in this respect. The CWSI has been commonly applied to the detection of water stress of plants, but difficulties in measuring canopy temperature of crops with less than 100% vegetation cover has limited its operational application.

Crop Water Stress Index (CWSI):

$$CWSI = \frac{(dT - dT_l)}{(dT_u - dT_l)}$$

where,

dT is the measure of difference between crop canopy and air temperature,

dT_u is the upper limit of canopy minus air temperature (non-transpiring crop), and

dT_l is the lower limit of canopy minus air temperature (well-watered crop).

A CWSI of 0 indicates no water stress, and a value of 1 represents maximum water stress. The crop water stress that signals the need for irrigation is crop specific and should consider factors such as yield response to water stress, probable crop price, and water cost.

The Water Deficit Index (WDI) (Moran *et al.*, 1994) offered a means to overcome this limitation by combining spectral vegetation indices with composite surface temperature, based on the same theory as CWSI, to estimate water deficit for partially vegetated fields

1.9. Hyperspectral Sensors & Applications in Agriculture

1.9.1. Introduction

Hyperspectral remote sensing, also known as imaging spectroscopy, is a relatively new technology that is currently being investigated by researchers and scientists with regard to the detection and identification of minerals, terrestrial vegetation, and man-made materials and backgrounds. Recent advances in sensor technology have led to the development of hyperspectral sensors capable of collecting imagery containing several hundred bands over the spectrum. In comparison to multi-spectral remote sensing, which records reflectance from a target in a few broad channels, a hyperspectral imaging system acquires information in more than 100 very narrow, defined continuous spectral bands (Lillesand and Kiefer, 2000). In this system, radiation from any specified target has been obtained continuously, making it possible to gain detailed information on the materials.

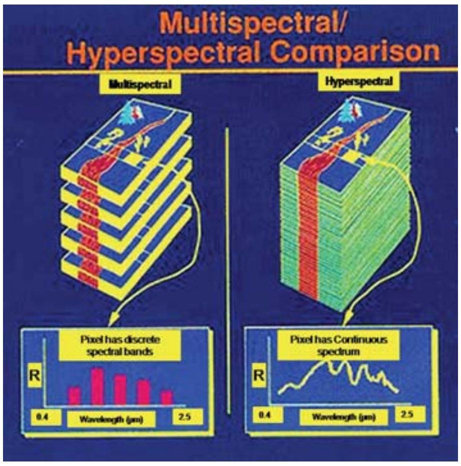

Figure 1.8: Depiction of discrete multispectral and continuous Hyperspectral band information

Using these narrow bands, the features that have diagnostic absorption and reflection properties in such narrow wavelength intervals can be differentiated, which was not possible with the wider wavebands used in multispectral sensors. These narrow wavebands make hyperspectral remote sensing systems powerful tools that have the potential to avoid time consuming and labor intensive ground data collection methods. Hyperspectral data sets are generally composed of about 100 to 200 spectral bands of relatively narrow bandwidths (5-10 nm), whereas, multispectral data sets are usually composed of about 5 to 10 bands of relatively large bandwidths (70-400 nm) as in figure 1.8. A hyperspectral sensor covers the visible and shortwave infrared regions of the spectrum. The Earth Observing-1 (EO-1) satellite, launched in November, 2000 (NASA), carries onboard hyperspectral sensors (Hyperion) is an example of such a system.

Hyperspectral imagery is typically collected (and represented) as a data cube with spatial information collected in the X-Y plane, and spectral information (l) represented in the Z-direction. Hyperspectral AVIRIS data cube is presented in figure 1.9.

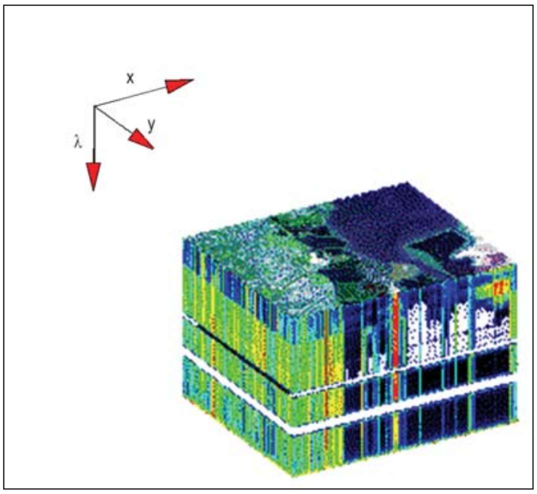

Figure 1.9: AVIRIS hyper spectral data cube over Moffett Field, CA (source: http://www.csr.utexas.edu/projects/rs/hrs/hyper.html)

Hyperspectral imaging sensors collect radiance data from either airborne or space-borne platforms which must be converted to apparent surface reflectance before analysis techniques can take place. Atmospheric correction techniques have been developed that use the data themselves to remove spectral atmospheric transmission and scattered path radiance.

While hyperspectral imagery is capable of providing a continuous spectrum ranging from 0.4 to 2.5 microns (in the case of AVIRIS) for a given pixel, it also generates a vast amount of data required for processing and analysis. Due to the nature of hyperspectral imagery (i.e., narrow wavebands), much of the data in the 0.4-2.5 micron spectrum is redundant. A minimum noise fraction (MNF) transformation is used to reduce the dimensionality of the hyperspectral data by segregating the noise in the data. The MNF transform is a linear transformation which is essentially two cascaded Principal Components Analysis (PCA) transformations. The first transformation decorrelates and rescales the noise in the data. This results in transformed data in which the noise has unit variance and no band to band correlations. The second transformation is a standard PCA of the noise-whitened data.

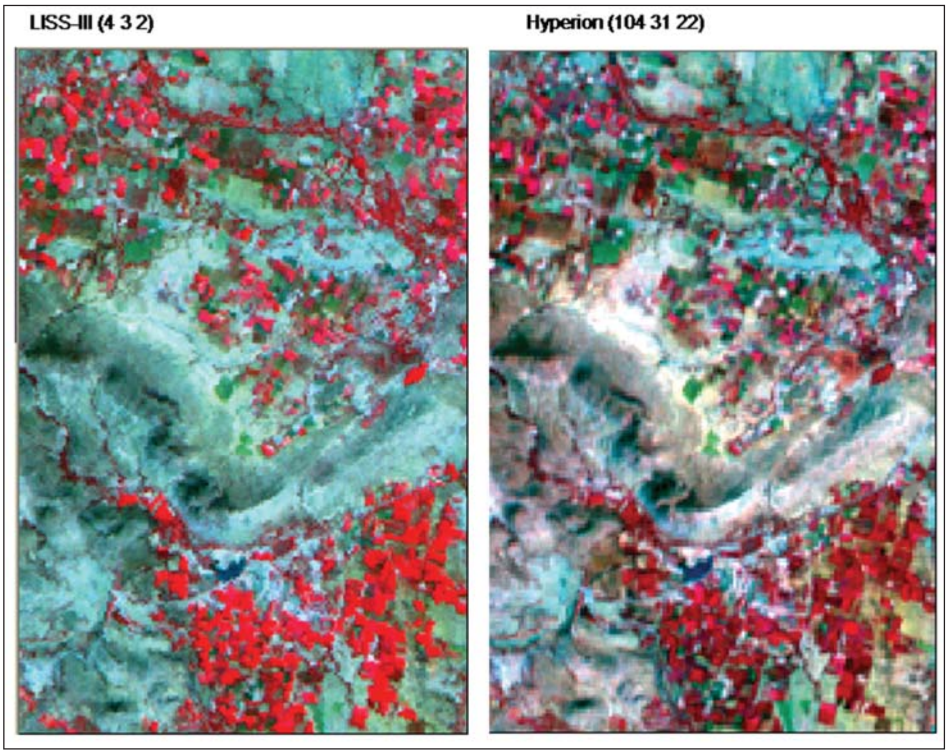

Figure 1.10: Comparision of LISS-III and Hyperion FCC image

The Pixel Purity Index (PPI) is a processing technique designed to determine which pixels are the most spectrally unique or pure. Due to the large amount of data, PPI is usually performed on MNF data which has been reduced to coherent images. The most spectrally pure pixels occur when there is mixing of endmembers. The PPI is computed by continually projecting n-dimensional scatterplots onto a random vector. The extreme pixels for each projection are recorded and the total number of hits are stored into an image. These pixels are excellent candidates for selecting endmembers which can be used in subsequent processing. Several classification techniques were being tried for deriving the required information from the huge data sets were Spectral Angle Mapper Classification, Spectral Unmixing/Matched Filtering and N-Dimensional visualization etc.

The figure 1.10 shows part of Prakasam district, Andhra Pradesh wherein the LISS-III multispectral and the Hyperion Hyperspectral FCC images from comparable bands. The sharpness in the Hyperion image may be attributed to the improved spectral resolution.

1.9.2. Parameter retrieval

Hyperspectral remote sensing has been proven to be a very effective tool for the estimation of crop variables such as LAI, pigment and water content and crop biomass accumulation, either directly or indirectly through other variables. Thenkabail *et al.*, (2002) showed that the narrowband vegetation indices provided a more accurate estimation of crop parameters than did equivalent broadband-based indices. Similarly, Blackburn (1999) reported that for estimation of chlorophyll a, chlorophyll b and carotenoids, wavebands of 680 nm, 635 nm and 470 nm, respectively, were optimal. The literature supports the fact that hyperspectral data could provide considerable additional information in the estimation of various crop characteristics compared to similar information obtained from broadband sensors (Blackburn, 1998; Carter, 1998; Elvidge and Chen, 1995; Thenkabail *et al.*, 2002 and 2000; Asner *et al.*, 2000). Gong *et al.*, (2003) found that the wavelengths of 820, 1040, 1200, 1250, 1650, 2100, and 2260 nm were the most valuable bands for estimation of LAI. In Potato crop, the indices (NDVI, SAVI, RVI) based on reflectance of 780 and 680 nm showed maximum correlation to LAI. Among the other narrow-band indices, maximum of second derivative reflectance in the red edge region (680) and normalized difference of maximum of first derivative reflectance of the green and minimum of first derivative reflectance in the green showed high correlation were highly related to LAI in potato crop. (Ray et.al., 2006).

1.9.3. Stress Detection

With hyperspectral data, it is possible to identify not only the stress-free areas of the field but also those that are under water, nitrogen and weed stresses (Borregaard *et al.*, 2000, Cho *et al.*, 2002; Goel *et al.*, 2002, Karimi *et al.*, 2004). The derivative chlorophyll index (DCI) calculated as D_{705}/D_{722} based on the double peak of derivative reflectance is proposed for mapping vegetation stress. (Zarco-Tejada *et. al*., 2003). Ray *et.al.*, (2006) reported that the five best bands to discriminate between irrigation treatments were 540, 610, 630, 700, and 1000 nm. The optimum set of narrow bands found to be suitable for discriminating between different irrigation treatments were 540, 610, 630, 700, and 1000 nm, which were in green, red, red-edge and moisture-sensitive NIR region. These narrow bands centered at 540 nm is near green peak which is sensitive to total chlorophyll, 610 and 630 nm are absorption pre-maxima in red regions and sensitive to biomass and soil background, 700 nm is in red edge, which is sensitive to crop stress and 1000 nm is in moisture sensitive NIR region. Analysis of several narrow-band indices calculated from the reflectance values showed the indices that were able to differentiate best between the different rates of N application were reflectance ratio at the red edge (RE740/720) and the structure insensitive pigment index (SIPI).

1.9.4. Varietal discrimination

Thenkabail (2002) had found that to discriminate between agricultural crops (wheat, barley, chickpea, cumin, lentil and vetch) four most optimum hyperspectral bands are 547, 675, 718 and 904 nm. Apan *et al.*, (2004) found 550, 680 and 800 nm useful in discriminating between sugarcane varieties. The figure 1.11 shows the profile of the red edge shifts in different varieties in paddy crop grown under similar management practices, which can used as an indicator of stress/ characterization of variety.

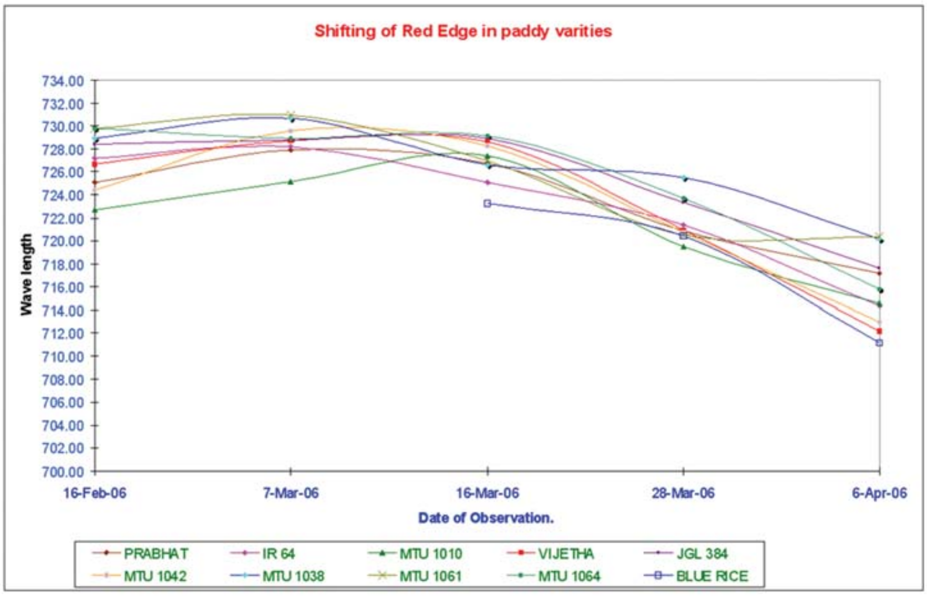

Figure 1.11: Red edge dynamics of few commonly grown rice varieties

1.9.5. Disease identification

Hyperspectral imaging can also aid in distinguishing the signatures of healthy and infested plants to allow intervention before there is significant damage. The reflection curves between healthy and diseased sugar beets showed a significant difference in the diseased crop. The reflection of healthy plants in comparison to diseased ones is clearly higher at most portions of the spectrum, especially at the near infrared sector. Additionally, the “green peak” at circa 550 nm is visible, in contrast to the reflectance curves of unhealthy sugar beets. These facts were also visible using two vegetation indices. The indices of diseased sugar beets presented lower values. (Laudien *et al.*, 2003).

The analysis of spectral reflectance pattern of cowpea infested with disease (Cowpea rust) was carried out and the reflectance at centered at 740, 660, 680 and 1448 nm was found to give significant difference compared to normal crop as shown in figure 1.12. The ratio of reflectance at 550/680, 800/1660, 1660/680, 1660/550 and (800-550/1660+680) wavelengths also were found to give significant differences.

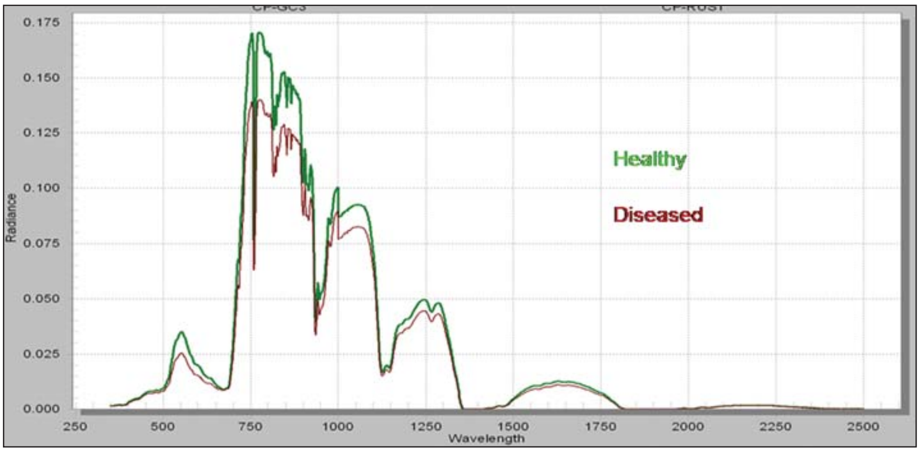

Figure 1.12: Hyperspectral signature for a diseased (cowpea rust) and a healthy cowpea crop

1.10. Microwave Remote Sensing

Non availability of adequate number of cloud free optical satellite datasets is a major constraint for using optical remote sensing data for agricultural applications during monsoon season. In light of this, all weather capability of RADAR, an active sensor, is an attractive option to rely upon. Microwave remote sensing techniques have all weather capability as atmosphere is transparent to microwaves at lower frequencies, penetrate clouds and are suitable for day/night operations owing to the independence of microwave sensors on Sun's illumination.

Radar response measured in terms of backscatter coefficient is dependent upon sensor (frequency, polarization and look angle) and target parameters (dielectric constant, surface roughness, and vegetation cover). In addition, SAR being an active sensor, frequency of data acquisition is two fold increased with the possibility of data availability during ascending and descending passes.

Sensitivity of microwave radiation to surface roughness (due to soil or crop), and water content (in soil or crop) as a function of look angle and polarization at a given frequency makes SAR an attractive remote sensor for obtaining information on several crop and soil parameters. Microwave response from an agricultural field depends on both standing crop and the underlying soil conditions. Contribution to the microwave backscatter from an agricultural field is maximum from the soil during the initial stages when crop cover is negligible, mixed from soil and crop during the growth period and mostly from the crop canopy when crop cover is at its peak. Hence, to put SAR data to full use in agricultural environment, complete information of soil as well as crop conditions is an essential requirement.

Geometrical and dielectric characteristics of crops influence the interaction of microwaves and thus determine the microwave backscatter measured by the sensor (Ulaby, 1975). Crop phenology governs the plant water content and thus crops dielectric properties. As crops mature the water content decreases, which in turn reduces contribution to radar backscatter from the plants. Besides crop geometry, several crop parameters such as leaf area index, plant biomass, plant water content and plant height show significant correlations with radar backscatter coefficient (Ulaby, 1975; Le Toan *et al.*, 1984, Bouman *et al.*, 1991). It is through these correlations monitoring of crop condition is possible.

Earlier studies reported in the literature includes the use of X band VV polarization data acquired by Canadian Intera Airborne SAR system during October 1988 that was capable of discriminating the plantations from crops. Later with the increased availability of SAR data from space borne platforms, the potential of multi-temporal SAR data for rice crop monitoring have been demonstrated by a number of investigators (e.g., Hoogeboom, 1983; Kurosu *et al.*, 1995; Premlatha and Rao, 1994; Patel, 1994; Chakraborty and Panigrahy, 1999). Apart from area monitoring and condition assessment, retrieval of different biophysical parameters viz., leaf area index, plant height, biomass, etc., have been attempted relating these with SAR backscatter.

1.10.1. National Kharif Rice Acreage Estimation

RADARSAT ScanSAR Narrow B – (SNB) data having an incidence angle of 31-46 degrees was found to give distinct signature to wetland rice crop. The pattern of change in backscatter from ploughed/puddled fields to the water-filled fields at transplanting stage is similar to that observed in case of ERS SAR data. However, unlike ERS SAR, wind-induced roughness has less effect on the backscatter from water bodies. This was attributed partly to the HH polarization of RADARSAT and partly to the shallow angle of SNB. This resulted in better separation of rice fields from water, which generally overlap in ERS SAR data. Overall, 94 per cent classification accuracy was obtained for rice. It was also feasible to separate rice sub-classes based on its growth stages and crop rotation practice with 90 per cent accuracy (Chakraborty and Panigrahy 2000). The 300 km swath with 50 m resolution of SCNB data was found more cost effective for large area crop monitoring. In

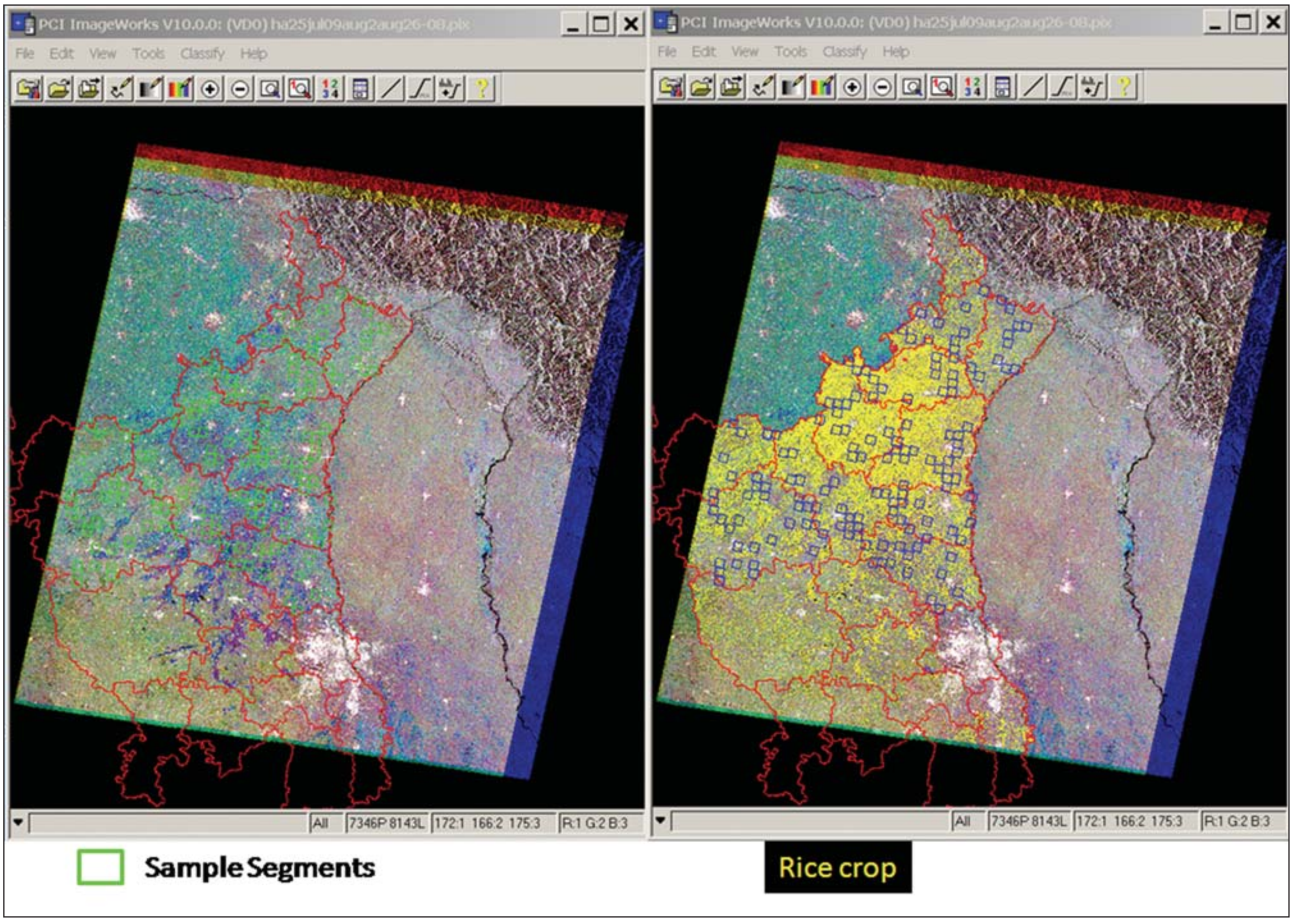

Figure 1.13: Temporal FCC of RADARSAT SN-2 data showing rice crop

order to obtain crop acreage estimates of large area within a reasonable time and cost, sampling approach rather than complete enumeration, was adopted in the ongoing National Kharif Rice Acreage estimation project at NRSC, Hyderabad. Figure 1.13 is the temporal FCC of RADARSAT ScanSAR Narrow B data covering the state of Haryana with the district boundaries and the sampling grids overlaid on to it.

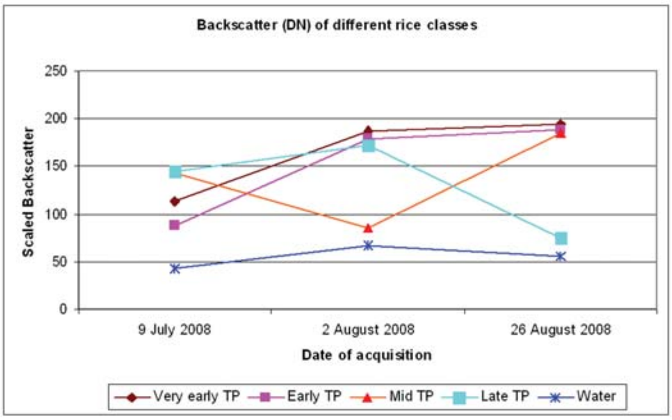

Figure 1.14: Temporal backscatter profile of different rice classes in Kaithal district, Haryana

The categories of very early, early, mid and late transplanted rice can be discriminated from the temporal data sets and the figure 1.14 depicts the temporal behavior of the various rice classes in Kaithal district, Haryana. It can be observed that the very early rice crop is transplanted some time prior to July 9 and developed sufficient biomass by the time of first date of pass, early, mid and late transplanted rice crop more or less coincided with the satellite pass on July 9, August 2 and 26.

1.11. Customized softwares for crop acreage estimations

The crop acreage estimation by sampling or total enumeration method can be accomplished by the commercially available image analysis and GIS software’s. To facilitate speedy and accurate implementation of procedure on an operational basis, a menu driven semi-automated software, 'CAPEMAN' followed by a advanced version 'CAPEWORKS', has been developed for data analysis interfacing with commercially available software Geomatica and ERDAS Imagine (RRSSC, 1996). In order to process the SAR data for National Kharif Rice. specific software called 'SARCROPS' was developed for semiautomatic proces g of of SAR data using Geomatica Software.

1.12. Conclusions

Satellite remote sensing techniques are being operationally used to provide intra seasonal and inter-seasonal information on the spatial distribution of crops at different levels. Analysis of satellite data for crops along with the information on other natural resources in GIS environment provides valuable information towards sustainable agriculture. Time compositing techniques, applied for normalized difference vegetation index parameter circumvent the problem of non-availability of cloud free optical data and enable generation of the in situ crop condition information. The continuous improvements in the satellite technology in terms of providing improved spatial and spectral resolutions and revisit periods will greatly enhance the capabilities of mapping and monitoring of crops, aiming towards sustainable agriculture.

References

Apan A, Held A, Phinn S and Markley J, 2004, Detecting sugarcane 'orange rust' disease using EO-1 hyperion hyperspectral imagery, *International Journal of Remote Sensing*, **25**:489–498.

Arkin PA and Ardanuy PE, 1989, Estimating Climatic-Scale Precipitation from Space: A Review *Journal of Climate*, **2**: 1229-1238.

Asner GP, Wessman CA, Bateson CA and Privette JL, 2000, Impact of tissue, canopy and landscape factors on the hyperspectral reflectance variability of arid ecosystems, *Remote Sensing of Environment*, **74(1)**: 69-84.

Barrett EC and Beaumont MJ, 1994, Satellite Rainfall Monitoring: an overview, *Remote Sensing Reviews*,**11**: 23-48.

Becker F and Li ZL, 1990a, Towards a local split window method over land surfaces, *International Journal of Remote Sensing*, **11**: 369– 394.

Becker F and Li ZL, 1990b, Temperature-independent spectral indices in thermal infrared bands, *Remote Sensing Enviroment*, **32**: 17–33.

Blackburn GA, 1998, Spectral indices for estimating photosynthetic pigment concentrations: a test using senescent tree -leaves, *International Journal of Remote Sensing,* **19(4)**: 657 - 675.

Blackburn GA, 1999, Relationships between spectral reflectance and pigment concentrations in stacks of deciduous broadleaves, *Remote Sensing of Environment*, **70(2)**: 224-237.

Borregaard T, Nielsen H, Norgaard L and Have H, 2000, Crop-weed Discrimination by Line Imaging Spectroscopy, *Journal of Agricultural Engineering Research*, **75**: 389-400.

Bouman BAM, 1991, Crop parameter estimation from ground based x-band (3-cm Wave) radar backscattering data, *Remote Sensing of Environment*, **37**: 193-205.

Carter GA, 1998, Reflectance bands and indices for remote estimation of photosynthesis and stomatal conductance in pine canopies, *Remote Sensing of Environment*, **63**: 61-72.

Chakraborty M and Panigrahy S, 2000, A processing and software system for rice crop inventory using multi-date RADARSAT ScanSAR data, *ISPRS Journal of Photogrammetry and Remote Sensing*, **55(2)**: 119-128.

Chakraborty M and Panigrahy S, 1996, Evaluation of Four Per-pixel Classifiers Using ERS-1 SAR Data for Classification of Rice Crop, In Proceedings of Indo-US Symposium, IIT, Bombay, October, 1996.

Cho SI, Lee DS and Jeong JY, 2002, Weed–plant discrimination by machine vision and Artificial Neural Network, *Biosystems Engineering*, **83(3)**:275–280.

Dadhwal VK, Singh RP, Dutta S and Parihar JS, 2002, Remote sensing based crop discrimination and area estimation: A review of Indian experience, *Tropical Ecology,* **43**: 107–122.

Dadhwal VK, 1999, Remote sensing and GIS for agricultural crop acreage and yield estimation, pp. 58-67, International Archives of Photogrammetry and Remote Sensing, XXXII, 7-W9, (ISPRS Commission VII/ WG 2 Symposium on Application of Remote Sensing and GIS for Sustainable Development), March 11, Dehradun, India.

Dadhwal VK and Ray SS, 2000, Crop Assessment using remote sensing – Part II: Crop condition and yield assessment, *Indian Journal of Agricultural Economics*, **55**(2, Suppliment): 55-67.

Dakshinamurthy C, Krishnamurthy B, Summanwar AS, Santhur P and Pisharoty PR, 1971, Remote sensing of coconut wilt, Proceedings of 6th International symposium on Remote sensing of Environment, Ann Arbor p. 25

Dash P, Go¨ttsche FM, Olesen FS and Fischer H, 2002, Land surface temperature and emissivity estimation from passive sensor data: Theory and practice-Current trends, *International Journal of Remote Sensing*, **23**: 2563–2594.

Ebert EE and Le Marshall JF, 1995, An evaluation of infrared satellite rainfall estimation techniques over Australia, *Australian Meteorological Magazine,* **44**: 177-190.

Ebert EE, 1987, A pattern recognition technique for distinguishing surface and cloud types in polar regions, *Journal of Climate and Applied Meteorology*, **26**: 1412-1427.

Elvidge CD and Chen Z, 1995, Comparison of broad-band and narrow-band red and near-infrared vegetation indices, *Remote Sensing of Environment*, **5:** 38–48.

Gardner BR, Blad BL and Watts DG, 1981, Plant and air temperature in differentially-irrigated corn, *Agricultural Meteorology*, **25**, 207–217

Goel PK, Prasher SO, Patel RM, Smith DL and DiTommaso A, 2002, Use of airborne multi-spectral imagery for weed detection in field crops, *Transactions of the ASAE*, **45 (2)**: 443–449.

Gong P, Pu R, Biging GS and Larrieu MR, 2003, Estimationof forest leaf area index using vegetation indices derived from Hyperion hyperspectral data, *IEEE Transaction on Geoscience and Remote Sensing*, **41 (6)**: 1355-1362.

Grassotti CG and Garand L, 1994, Classification-based rainfall estimation using satellite data and numerical forecast model fields, *Journal of Applied Meteorology*, **33**: 159-178.

HebbarR, Krishna Rao MV and Sesha Sai MVR, 2003, Inventory of major crops in EID-PARRY sugar factory command for possible expansion of sugarcane cropped area using RS & GIS, SISSTA *Sugar Journal - 2003* .

Herman A, Kumar VB, Arkin PA and Kousky JV, 1997, Objectively determined 10-day Africian rainfall estimates created for famine early warning systems, *International Journal of Remote Sensing*, **17**: 2147-2159.

Hoogeboom P, 1983, Classification of Agricultural Crops in Radar Images, *IEEE Transactions on Geoscience and Remote Sensing*, **23**: 329-336.

Idso SB, Jackson RD, Pinter PJ Jr., Reginato RJ and Hatfield JL,1981, Normalizing the stress-degree-day parameter for environmental variability, *Agricultural Meteorology*, **24**: 45–55.

Idso SB, Jakson RD and Reginato RJ,1977a, Remote-sensing for agicultural water management and crop yield production, *Agricultural Water Management*, **1(4)**: 299-310.

Jackson RD, Idso SB and Reginato RJ, 1977, Remote Sensing of Crop Canopy Temperatures for Scheduling Irrigation and Estimating Yield, Proceedings of the Symposium on Remote Sensing of Natural Resources, Utah State University, Logan, UT.

Jackson RD, Idso SB, Reginato RJ and Pinter PJ,1981, Canopy temperature as a crop water stress indicator, *Water Resources Research,* **17**: 1133–1138.

Jackson RD,1982, Canopy temperature and crop water stress, Hillel DI, Editor, Academic Press, *Advances in Irrigation*, **1**: 43-85.

Jime´nez-Mun˜oz JC and Sobrino J A, 2003, A generalized singlechannel method for retrieving land surface temperature from remote sensing data, *Journal of Geophysical Research*, **108(22)** :4688, doi:10.1029/2003JD003480.

Karimi Y, Prasher SO, McNa irn H, Bonnell RB, Dutilleul P and Goel PK, 2004, Discriminant analysis of hyperspectral data for assessing water and nitrogen stresses in corn, *Transaction of the ASAE*, **48(2)**: 805-813.

Krishna Rao MV, Hebbar R, Sesha Sai MVR and Venkataratnam L, 2002, Inventory of post kharif rice fallow lands of South Asia for introduction of legumes- an endeavour towards macro level sustainable agriculture IAPRS & SIS,**34**, Part 7, Resource and Environmental Monitoring, Hyderabad, India, 30-34.

Krishna Rao, MV, Hebbar R and Venkatratnam L, 1997, Evaluation of IRS-1C data for discrimination and acreage estimation of crops grown under multiple cropping situation, In Remote Sensing for Natural Resources, Joint publication of ISRS & NNRMS, 205-211.

Krishna Rao MV, Sesha Sai MVR and Hebbar R, 2004, Remote sensing and GIS applications for Crops studies, In: Soils & Crops, NRSA, Hyderabad, 161-173.

Krishna Rao PV, Sesha Sai MVR, Ramana KV, Venkataratnam L and Sudhakara Babu SN, 1996, Estimation of sunflower crop yield using Remote Sensing techniques, Proceedings of National Symposium on Remote Sensing for Natural Resources with special emphasis on Water Management, Pune, India.

Krishna Rao PV, Venkataratnam L, Venkateswara Rao V and Venkataramaiah,2000, Remote sensing studies on sugarcane fields in KCP Sugar and Industries corporation Sugar factory Zones, *SISSTA Sugar journal*, **25**: 129-138.

Krishna Rao V, Krishna Rao PV and Venkataratnam L, 1996, Grapevine acreage estimation using IRS LISS-II data, *Asian*

Pacific Remote Sensing and GIS Journal, **8(2)**: 61 – 64.

Krishna Rao MV, Sesha Sai MVR, Hebbar R, Krishna Rao PV and Venkataratnam L, 1997, Acreage and production estimation of soybean crop using remote sensing technique In: Remote Sensing for Natural resources - A Joint *Publication of Indian Society of Remote Sensing* and NNRMS: 239-246.

Kurosu T, Fujita M and Chiba K, 1995, Monitoring of rice crop growth from space using the ERS-1 C -band SAR, *IEEE Transactions on Geoscience and Remote Sensing,* **33(4)**: 1092-1096.

Laudien R, Bareth G and Doluschitz R, 2003, Analysis of Hyperspectral field data for deletion of sugarbeet diseases, EFITA 2003 conference, Debrecen, Hungary.

Le Toan T, Lopes A and Huet M, 1984, On the relationships between radar backscattering coefficient and vegetation canopy characteristics, International Geoscience and Remote Sensing Symposium Proceedings, Strasburg, France, 155-160.

Lillesand TM and Kiefer RW, 2000, Remote Sensing and Image Interpretation, John Wiley & Sons. Inc. (4th edition).

Moran MS, Clarke TR, Inoue Y and Vidal A, 1994, Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index, *Remote Sensensing of Environment*, **49**: 246–263.

Moser W and Raschke E, 1984, Incident solar radiation over Europe estimated from METEOSAT data, *Journal of Climate and Applied Meteorology*, **23**: 166-170.

Navalgund RR, Parihar JS, Ajai and Nageshwar Rao PP, 1991, Crop inventory using remotely sensed data, *Current Science*, **61**: 162–171.

Navalgund RR and Ray SS, 2000, Geomatics in natural resources management, In Proceedings of Geomatics-2000, Pune, India, NR1-NR14.

NRSA, 1991, Hectarage estimation of jute crop in Cooch Behar district of West Bengal, NRSA Technical report, p 23.

NRSA, 1990, National Agricultural Drought Assessment and Monitoring System, NRSA, Hyderabad, p. 124.

NRSA, 1992, Acereage estimation of soyabean and sunflower crops, Hyderabad, p. 42.

Parihar JS and Oza MP, FASAL: 2006, An integrated approach for crop assessment and production forecasting, Proc. of SPIE, Agricultural and hydrology applications (eds: Robert, J, Kuligowski, J S, Parihar, Genya Saito), **6411**: 641101–641113.

Patel NK, Medhavy TT, Patnaik C and Hussain A, 1995, Multi Temporal ERS-1 SAR Data for Identification of Rice Crop, *Journal of Indian Society of Remote Sensing*, **23**: 33-39.

Petty GW, 1995, The Status of Satellite-Based Rainfall Estimation Over Land, *Remote Sensing of Environmen*t, **51**: 125-137.

Pinker RT and Ewing JA, Modeling surface solar radiation : Model formulation and validation, *Journal of Climate and Applied Meteorology*, **24**: 389-401.

Prata AJ, 1993, Land surface temperatures derived from the AVHRR and ATSR: 1, Theory, *Journal of Geophysical Research*, **98**: 689–16,702.

Prata AJ, 1994, Land surface temperatures derived from the advanced very high resolution radiometer and the along-track scanning radiometer, *Journal of Geophysical Reserach*, **99**: 13,025–13,058.

Premlatha M and Rao PPN, 1994, Crop Acreage Estimation Using ERS-1 SAR Data, *Journal of Indian Society of Remote Sensing*, **22**: 139-147.

Price JC, 1984, Land surface temperature measurements from the split window channels of the NOAA 7 AVHRR, *Journal of Geophysical Reserach*, **89**: 7231– 7237.

Qin Z A, Karnieli and Berliner P, 2001, A mono-window algorithm for retrieving land surface temperature from Landsat TM data and its application to the Israel-Egypt border region, *International Journal of Remote Sensing*, **22**:3719–3746.

Rasmussen EM and Arkin PA, 1992, Observing Tropical Rainfall from Space: a review, In: JS Theon, TMatsumo, T Sakata and N Fugono (Editors), The Global Role of Tropical Rainfall, Deepak, Hampton, VA, 105-188.

Ray SS, Das G, Singh JP and Panigrahy S, 2007, Evaluation of hyperspectral indices for LAI estimation and discrimination of potato crop under different irrigation treatments, *International Journal of Remote Sensing*, **27(24)**:5373-5387.

Rosenfield D and Gutman G, (1994), Retrieving microphysical properties near the tops of potential rain clouds by multispectral analysis of AVHRR data, *Atmospheric Research,* **34**: 259-283.

RRSSC, 1991, Identification and acereage estimation of tobacco through satellite remote sensing, Project report.

RRSSC, 1996, CAPEWORKS Reference Manual, Vol 1.0.

Sesha Sai MVR, Hebbar R, and Krishna Rao MV, 2004, Remote Sensing Based Crop Inventorying for Agricultural Drought Assessment, Workshop on Regional Workshop on Agricultural Drought Assessment and Monitoring using Space Technology, 25-32.

Sesha Sai MVR and Hebbar KR, 2008, Alternating polarization Envisat-ASAR data for agricultural management, , Scientific Report, EOAM/NRSA/RiSAT-JEP/Agril/2008, NRSA.

Sesha Sai MVR, Ramana KV and Hebbar R, 2007, Satellite remote sensing for efficient coastal agriculture, Presented in the International Symposium on Management of Coastal Eco-systems, Kolkata.

Sesha Sai MVR, Hebbar R, Krishna Rao PV, Narasimha Rao PV, Vijayshankar Babu M, Dwivedi RS and Roy PS, 2007, Alternating polarization Envisat-ASAR data for agricultural management, published in Conference of Joint Experiment Project towards Microwave Remote Sensing Data Utilization (JEP-MW), SAC, Ahmedabad, 77-89.

Sesha Sai MVR, Hebbar R and Krishna Rao MV, 2003, Planning for sustainable cotton production through conformity analysis using RS and GIS techniques, Theme: Application of RS & GIS in Agriculture for the ISPRS TC VII/3 Workshop on Intergraded Monitoring Systems & ISRS Annual Convention 2003.

Sobrino JA, Coll C and Caselles V, 1991, Atmospheric correction for land surface temperature using NOAA-11 AVHRR Channels 4 and 5, *Remote Sensensing of Environment,* **38**: 19– 34.

Sobrino JA, So‘ ria G and Prata AJ, 2004, Surface temperature retrieval from Along Track Scanning Radiometer 2 data: Algorithms and validation, *Journal of Geophysical Reserach*, **109**, D11101, doi:10.1029/2003JD004212.

Sobrino JA, Jime´nez-Mun˜oz JC, Labed-Nachbrand J and Nerry F, 2002, Surface emissivity retrieval from Digital Airborne Imaging Spectrometer data, *Journal of Geophysical Reserach*, **107**(**23)**: 4729, doi:10.1029/2002JD002197.

Sobrino JA, Li ZL, Stoll MP and Becker F, 1994, Improvements in the split-window technique for land surface temperature determination, *IEEE Transaction on Geoscienses and Remote Sensensing*, **32**: 243– 253.

Sobrino JA, Li ZL, Stoll P and Becker F, 1996, Multi-channel and multi-angle algorithms for estimating sea and land surface temperature with ATSR data, *International Journal of Remote Sensensing,* **17**: 2089– 2114.

Subbarao GV, Kumar Rao JVDK, Kumar J, Johansen C, Deb UK, Ahmed I, Krishna Rao MV, Venkataratnam L, Hebbar KR, Sesha Sai MVR and Harris D, 2001, Spatial distribution and quantification of rice-fallows in South Asia – potential for legumes, Published by ICRISAT, Hyderabad.

Swain PH and Davis SM, 1978, Remote sensing: The Quantitative Approach, McGraw Hill, New York.

Tarpley JD, 1979, Estimating incident solar radiation at the surface from geostationary satellite data, *Journal of Applied Meteorology,* **18**: 1172-1181.

Thenkabail PS, 2002, Optimal hyperspectral narrow bands for discriminating agricultural crops, *Remote Sensing Reviews*, **20**: 257–291.

Thenkabail PS, Smith RB and De-Pauw E, 2002, Evaluation of narrowband and broadband vegetation indices for determining optimal hyperspectral wavebands for agricultural crop characterization, *Photogrammetric Engineering and Remote Sensing*, **68**: 607–627.

Ulaby FT, 1975, Radar response to vegetation, *Transactions on Antennas and Propagation*, **23**: 36-45.

Venkataratnam L, Krishna Rao MV, Ravishankar T, Thammappa SS and Gopi S, 1993, Cotton acreage estimation and condition assessment through remote sensing method, Proc. National Seminar on Oilseeds Research and Development in India: Status and Strategies, p 217.

Venkataratnam L, Krishna Rao PV, Ramana KV, Sudhakara Babu SN, Koteswara Rao K, and Babu VVR, 1994, Acreage estimation of sunflower crop using remote sensing techniques, In PrasadMVR et. al. Ed. Sustainability in oilseeds, Indian Society of Oilseeds Research, Hyderabad, 433 – 435.

Wan Z and ZL Li, 1997, A physics-based algorithm for retrieving land-surface emissivity and temperature from EOS/ MODIS Data, *IEEE Transaction on Geosciense and Remote Sensensing*, **35**: 980– 996.

Wani SP, Dwivedi RS, Ramana KV, Vadivelu A, Navalgund RR and Pande AB, 2002, Spatial distribution of rainy season fallows in Madhya Pradesh: Potential for increasing productivity and minimizing land degradation, Global Theme 3: Water, Soil and Agrobiodiversity Management for Ecosystem Health, Report no. 3. Patancheru 502 324, Andhra Pradesh, India: International Crops Research Institute for the Semi- Arid Tropics, p 40.

Zarco-Tejada PJ, Pushnik JC, Dobrowski S and LUS, 2003, Steady-state chlorophyll a fluorescence detection from canopy derivative reflectance and double-peak red-edge effects, *Remote Sensing of Environment*, **84**: 283-294.

http://trmm.gsfc.nasa.gov/publications_dir/instant_2.html

http://www.csr.utexas.edu/projects/rs/hrs/hyper.html