A Combination Method for Regional Rice Area Estimation Using Remote Sensing

B.Sailaja[1]*, P.Subrahmanyeswara Rao[2], M.S. Nathawat[3] and N.H.Rao[4]

[1]Scientist Senior Scale, Directorate of Rice Research, Rajendranagar, Hyderabad, Andhra Pradesh, India
[2]Research Associate, [4]Joint Director, National Academy of Agricultural Research Management, Rajendranagar, Hyderabad, Andhra Pradesh, India
[3]Professor and Head of Department of Remote Sensing, Birla Institute of Technology, Mesra, Ranchi, Jharkhand, India

Abstract

Rice is an important cereal crop in India and adaptable in various types of land management systems. Recent advancement in the field of remote sensing and GIS has opened up new challenges for various thematic applications towards efficient resource management. The present study was aimed to estimate the area under rice at mandal (block) level. Using a combination of Normalised Difference Vegetation Index (NDVI) and unsupervised method to estimate area under rice can reduce processing time and reinforcing the performances of both classifiers. IRS 1D LISS III data was used and five major rice growing mandals (blocks) of Nalgonda district of Andhra Pradesh were selected for this study. One model was developed to zero non-vegetative features in the original image by using NDVI of image. This image was further classified by unsupervised classification and results were in agreement with reported values. The study reveals that the combination method of NDVI and unsupervised classification appears to be the better choice for estimating area under rice.

Keywords : rice crop, area estimation, image processing, combination methods, remote sensing and GIS etc.

1. Introduction

As on today agricultural crop based information is not precisely available for any crop in any region in a consolidated form other than sporadic / scattered information made available by different organizations independently. The manual way of collecting precise information requires lot of man power time. Besides it is also expensive and it would be difficult to cover larger area like a state. To overcome these problems, the modern space technologies can appropriately be utilized to derive the required information in shorter time period. Remote sensing and GIS have played a key role, focusing on changes in vegetation, active layer depths, and biogeochemical cycles in the arctic biome. Remote sensing methodologies for acreage estimation of cereal crops like paddy, wheat and sorghum, oilseed crops like groundnut, rapeseed- mustard, soyabeen and commercial crops like cotton, sugarcane and tobacco are well established (Krishna Rao *et al*, 1997). In agricultural applications, remote sensing imagery has been used to identify different crop types, estimate crop area and, predict yield at small scales (Kanemasu, 1974).

Rice, being climatically most adaptable cereal and its rice cultivation exists in various types of land management systems. . It is a key element in Indian food security. However, keeping in view the continued population growth, demand for rice is expected to be 100 M tons by the year 2010 and 140-M tons by 2025. This demand can only be met by maintaining sustainable rice production with ample water supply without environmental degradation. Monitoring and mapping of paddy rice agriculture in a timely and efficient manner is very important for agricultural and environmental sustainability (Xiangming et. al., 2005). Effect of spatial resolution on significant discrimination amongst rice, uplands and forests in a state was studied. (Parihar et. al., 1987).

Current analysis of rice productivity with in the country shows that Andhra Pradesh (AP) is one of the top three rice-producing states in the country and accounts for about 12 per cent of the nation's total rice production. Rice is grown in all parts of the state, in all seasons and in all kinds of soils. Though yields have increased significantly over the last 15

* Corresponding author: saila_r@yahoo.com, bsailaja@drricar.org
www.drricar.org

years, there is potential to raise them further. With this background an attempt was made to estimate area under rice at regional level in Andhra Pradesh using remote sensing data. Regional estimates of crop area and yield are desirable for a range of applications, such as in the design of land use and food trade policies, (Macdonald and Hall, 1980; Hutchinson, 1991) and in the formulation of meteorological and biogeochemical models (Prince, 1991; Beaujouan et al., 2001). Major rice growing regions of Andhra Pradesh were selected for this study. Main objectives are

- To identify rice crop
- To estimate area under rice
- To validate rice area with secondary data from Dept. of Agriculture

2. Materials and Methods

2.1 Study area

The selected study area comprise five major rice growing mandals viz., Miryalaguda, Neredcherla, Garedpally, Huzurnagar and Chilkur of Nalgonda district (AP), which lie between 16-25' and 17-50' of the Northern Latitude and 78-40' and 80-05' of Eastern longitude. Paddy, pulses, millets and oilseeds are major crops in this study area, with paddy as the dominant crop. Rice primarily grown as kharif crop and also in rabi season to a lesser extent in the district. Choutuppal and Pochampally mandals were selected for collecting ground truth data for verification. The location of this study area is depicted in Fig 1.

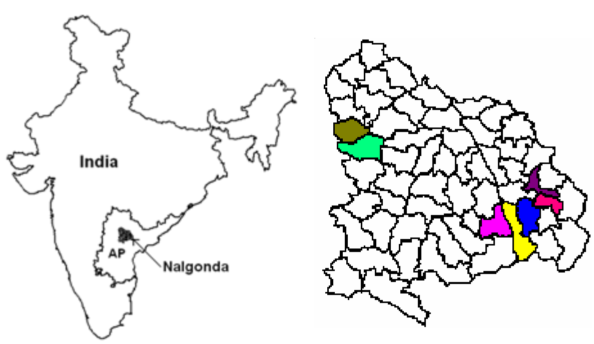

Figure 1 The location of Nalgonda district in Andhra Pradesh and seven rice growing mandals of Nalgonda district

2.2 Data sets

The performances of different sensors for crop identification have been tested over varied geographic areas and crop types. Because of the complementarities of the data, the fusion of both optical and microwave imagery has resulted in higher overall and individual crop classification accuracies (> 95%) than either produce alone (Le Hegarat- Mascle et al., 2000). The RADARSAT image has only one band of data and it is difficult to extract the rice-planted area (Tomohisa Konishi, 2007). Where as Synthetic Aperture Radar (SAR) is a sensor with the all weather acquisition capability. The speckle noise in the SAR intensity images, however, limits the radiometric resolution. In particular, due to their different speckle contributions, it is difficult to classify the SAR intensity images acquired from different geometries in the multi-temporal case. This necessitates introducing additional information to the estimation of paddy field area (Akirao, 2008). On the other hand, Crop Acreage and Production Estimation (CAPE) project using single date Linear Imaging Self Scanning Sensor (LISS-I/II) data of Indian Remote Sensing Satellites (IRS 1A/1B) (Parihar *et al*. 1990). Winter rice area was estimated using IRS 1D LISS III data in the district Ri Bhoi of Meghalaya (Prachi Mishra et. al., 2006).

Similarly, in this present study, IRS -1D digital data from LISS – III (path 101/60 14 November 2004) was selected and ERDAS image 8.6 package was used for image processing. The LISS-III provides reflectance data in green, red, and near-infrared bands at 23.5 m spatial resolution and at 24 days re-visit, covering a swath of about 141 km. This data is found to be useful for improved discrimination of different crops grown under multiple crop situations (Krishna Rao *et al*. 1997). In general, IRS/WIfs data corresponding to the peak biomass stage of rice during the kharif season (October to November) will be used for better analysis (http://www.icrisat.org). But physiological knowledge of rice is essential for successful application of remote sensing in rice-based agricultural systems.

ERDAS - IMAGINE 8.6 version was used in geo-referencing of the data. Polyconic projection was applied uniformly to all the datasets with latitude/longitude information in degrees. In this step, adequate number of well-distributed ground control points (GCPs) were identified and used to minimize the errors in registration of the datasets. Mandal map of Nalgonda district was digitized and each mandal polygon was converted into Area of Interest (AOIs). These AOIs were used to extract sub set images of different mandals from master image for classification (Fig 2).

Secondary data for area under rice for the above mandals were collected from Department of Agriculture, Hyderabad, Andhra Pradesh.

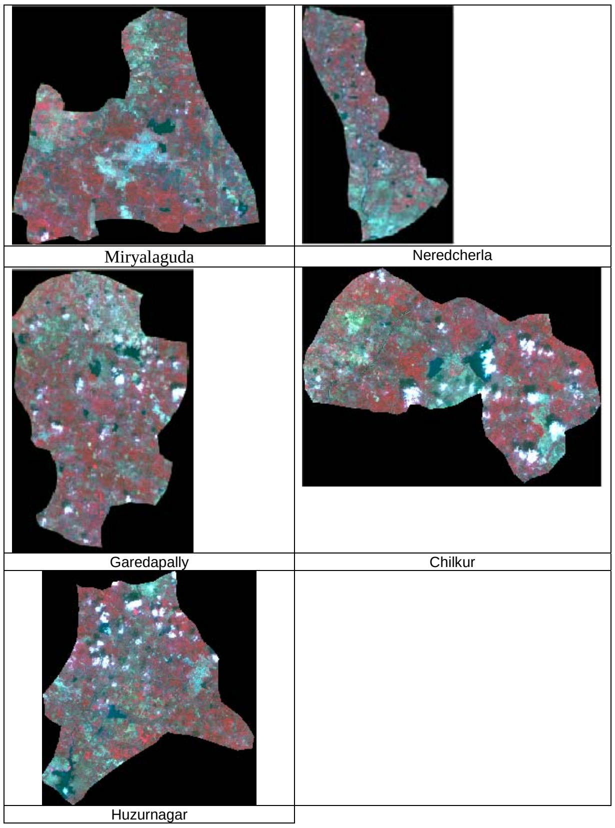

Figure 2 IRS 1D LISSIII Images of five mandals of Nalgonda- Master Images

3. Classification methodology

3.1Rice crop identification

The most commonly practiced application in remote sensing of agriculture is mapping land cover to identify crop types. The traditional notion of thematic mapping presumes that every spot on the ground surface can be labeled as belonging to only one category (Schowengerdt, 1997). However, the identification of object depends on the spatial resolution of the remote sensing imagery (Tomar & Maslekar, 1974). Discrimination of crops is usually performed by some classification procedures. Multi-spectral classification is the procedure of categorizing pixels into a finite number of individual classes, or categories of data, based on their data file values (ERDAS, 1999). The computer is programmed to insert these data into an equation or series of equations and store the result of computation for each pixel. These results are called look-up table (LUT) values for a new image that may be manipulated further to extract information of user's interest. (Anji Reddy, 2001). These tables are represented as raster attribute tables in ERDAS. There are two fundamental approaches for classification. One is supervised and another one is unsupervised classification.

In *Supervised classification (Method 1)*, user has to specify the classes to be used and provide "signatures" for each class. The image interpreters must have *priori* knowledge of the area covered by the image they are attempting to classify.

In *Unsupervised classification (Method 2)*, the computer selects classes based on clustering of brightness values. Unsupervised classification refers to a variety of different techniques that share some common features. This classification uses the Iterative Self-Organizing Data Analysis Technique (ISODATA) (Tou and Gonzalez, 1974) algorithm to execute the clustering of the image. The advantage of an unsupervised approach, however, is that *a priori* (before the fact) knowledge is not needed, but identifying more classes will be difficult. In either case additional image processing may be used to determine which method is better for a given situation (Chris, 2002). There are also additional techniques to process the images such as vegetation indices. Vegetation index is an indicator of the presence and condition of green vegetation. The results of the classifications of several data combinations are monitored. Combination of these conventional methods and vegetative indices will perform better by reinforcing the performances of both classifiers. Hence, rice crop was classified using supervised, unsupervised and combination of NDVI and unsupervised classification methods.

Combination of Normalized Difference Vegetation Index (NDVI) and unsupervised method (Method 3): The remote sensing data is used extensively for large area vegetation monitoring. Typically the spectral bands used for this purpose are visible and near IR bands. Various mathematical combinations of these bands have been used for the computation of Vegetation index. Another important component of research focusing on changes in vegetation is the use of land cover maps and NDVI derived from satellite imagery (Boelman et al 2003, Laidler and Treitz 2003). The five mandals (blocks) as mentioned in the study area were classified using this NDVI.

NDVI = (near IR band - R band) / (near IR band + R band)

Where, IR and R are the means of reflectance in near-infrared wavelengths (770 to 870nm) and red wavelengths (650 to 670nm) respectively. NDVI of images of above mandals (blocks) were derived and these images were compared with master images of each mandal (block) for better refinement of vegetative portion from the imageries. Variable NDVI is a 2-D array of class single with a theoretical maximum range of [-1 1]. But vegetation values typically range between 0.1 and 0.7. NDVI being typically between 0.1 and 0.6 values at the higher end of the range indicating increased photosynthetic activity and a greater density of the canopy (Tarplay et al 1984). Higher index values are associated with higher levels of healthy vegetation cover, whereas clouds and snow will cause index values near zero, making it appear that the vegetation is less green.

In our study the threshold value for vegetation was identified as 0.15. The values below 0.15 indicates non vegetative portion and above 0.15 represents significant vegetative portion. In 2004, Mathworks, Inc. suggested in their demos regarding finding vegetation in images that in order to identify pixels most likely to contain significant vegetation, apply a simple threshold to the NDVI image (http://www.mathwork.com). In 2000 Cherlet Michael and his colleagues suggested that NDVI threshold of 0.14 is an acceptable threshold to be applied uniformly over the image to classify vegetation. (Cherlet Michael, 2000).

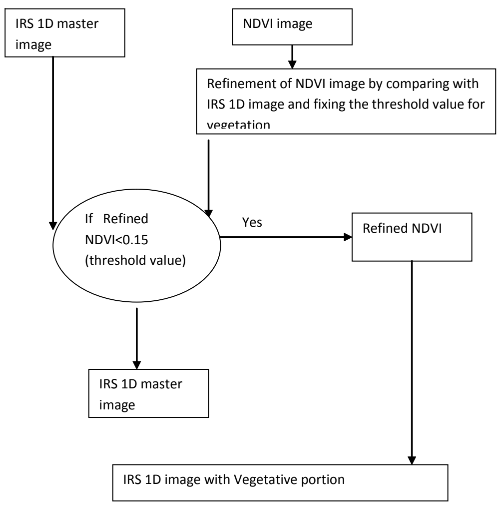

Figure 3 Flowchart showing the process to zero non vegetative features in IRS 1D image

A model (Fig 3) was developed to set zero to the non vegetative features (<0.15 NDVI) in IRS 1D master image by using NDVI and IRS 1D images as input files. The output of the above model was classified by using unsupervised classification method with 8-10 classes and 16–20 iterations with 0.990 convergence threshold value.Each cluster was carefully evaluated and assigned a land cover value by comparing with the IRS 1D image to identify paddy features. This method is repeated for five mandals (blocks) to identify paddy areas and area under rice is estimated by raster attribute table. For many specialized applications, classifying data that have been spectrally merged or enhanced with image algebra or other transformations can produce very specific meaning results (Erdas field guide, 2002).

3.2 Rice area estimation

Crop area measurement is a very common practice in agriculture. Remote sensing is often used for this purpose because of its strengths in regard to spatial extent, temporal density, relative low costs, and potential for rapid assessment of spatial features (Tom and Tim, 2001). Many of the same issues concerning crop type identification also affect crop area measurement from remotely sensed data. The area under rice is estimated by

Area under rice (ha) = Histogram value of rice crop (sq. m) * Pixel value * conversion factor

Histogram values for different classes are usually stored in the raster attribute table generated along with classified image. These are represented in square meters. Pixel resolution values were given in the CD information file of images. These values are 23.5 x 23.5 for LISS III data. Conversion factor is 10000 for square meters to hectares. The area under rice for different mandals (blocks) was estimated using this formula.

3.3 Validation with secondary data

Estimated values of rice area and yield were compared with observed values and percentages of differences were calculated for each mandal using the formula given below.

Percentage difference = ((Observed value- Estimated value)/ Estimated value) *100

4. Results and Discussion

4.1 Rice Crop identification

The increasing need for information on the spatial distribution of crop areas that is compatible with other spatial datasets is clearly evident in countries where vegetation characteristics are highly dynamic throughout the growing season. (Fresco et al., 1994). The image acquired dates are between October and November, so the crop is mostly in vegetative and reproductive stage. The growing cycle of rice can be separated into two stages with respect to most analyses of remotely sensed data: vegetative and reproductive (Casanova, 1998, Ribbes and Toan, 1999). For single date imagery, however, the timing of image acquisition can greatly influence classification results since confusion between spectral signatures can occur due to differences in crop growth stages (Tom and Tim, 2001). In our present study, rice crop was identified using supervised, unsupervised and combination of NDVI and unsupervised classification. Red colour classes represent rice crop in the classified images.

Combination of NDVI and Unsupervised classification: In this method, non vegetative portion was set to zero in the master image and this image was classified in to 8-10 classes (Fig 4). Here minimum classes were taken to identify the major crop because only vegetative portion is remaining in the image. Red reflectance of rice is inversely related to green biomass, where it decreased from about 10% at emergence to 2% at flowering, and then increases to about 18% at maturity due to senescence. Some Vegetation Indices (VI’s) perform better than others, but in general, these interactions result in better correlations between VI's and biomass in the vegetative and pre-heading stages than in the post-heading stage, where VI's tend to saturate (Casanova, 1998). As our image acquisition dates are from October to November, there is good relation between red reflectance and biomass. Rice is the major crop and cultivated mostly in the irrigated areas, rice classes were identified easily along the major canals. As irrigated rice fields are flooded, the spectral characteristics of water can be used to distinguish potential rice paddocks and provide an early estimate of rice area (Barrs and Prathapar, 1996).

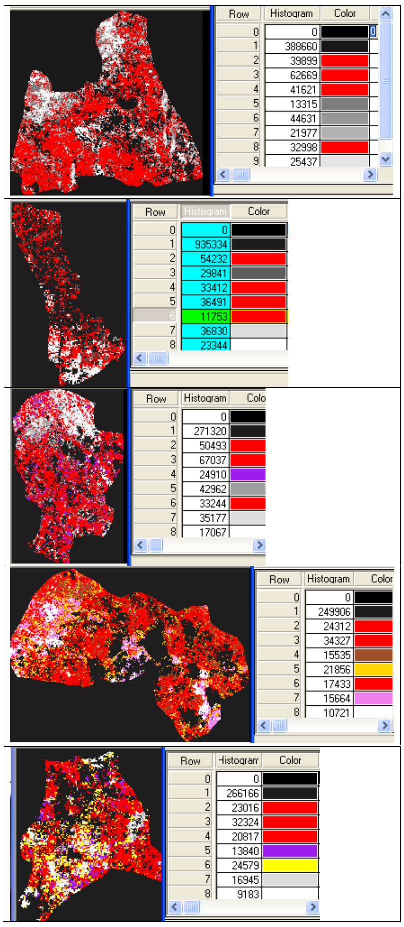

Figure 4 Rice crop identified in five mandals by combination method – red colour indicates rice area

4.2 Rice area estimation

Many of the same issues concerning crop type identification also affect crop area measurement from remotely sensed data. This is because crop type identification is necessarily first step to area estimation. Pixel size of the remotely sensed data also affects positional accuracy of boundary lines in crop area estimates, and therefore should be considered for its appropriateness to a particular application. One prominent issue is the relation of the pixel size to the paddock size (or feature element) being measured (Woodcock and Strahler, 1987, Pax-Lenney and Woodcock, 1997).

The area was estimated using the formula given in the methodology for above 3 classification methods. There were slight differences among area calculations observed from method 2 & 3 and differences were more between 1 & 3 and 1 & 2 methods (Table 1).

4.3 Validation with secondary data

Rice area estimated under different classification methods was compared with secondary data values and percentage differences over observed and analyzed values were shown in the Table 1. By the supervised classification process rice area was overestimated on an average by 26.7% for 5 major rice growing mandals. There was 31.10% underestimation observed with unsupervised classification. Major rice growing mandals (> 7000 ha) showed underestimation values (12-51%) over observed values.

There is 13.76% under estimation with combination method of NDVI and unsupervised classification. Garedapally and Miraylaguda mandals showed 1,3 percentage differences over observed values. Neredpally mandal showed 12.85 underestimation and Chilkur and Huzurnagar showed 30, 35 percentage underestimation compare to observed values..

4.4 Cloud correction

Area under cloud is estimated as 840 ha. Cloud cover is more in Chilkur and Huzurnagar images. So percentage of difference is 30% and 35% for these mandals. By correcting cloud area

Mandal Code	**Mandal name**	**Rice area (hectares) under different classifications)(percentage of difference between observed and calculated values)**			
		Supervised	**Unsupervised**	**NDVI+Unsupervised**	**Observed Data**
Rica area >7000 ha					
2339	Miryalaguda	13421.77 (-24.6)	7877.79 (28.4)	9785.00 (3.36)	10114
2313	Neredcherla	13823.92 (-38.7)	6437.08 (31.6)	7504.00 (12.88)	8471
2337	Garedapally	8760.40(-19.1)	7453.00 (12.9)	8326.00 (1.01)	8411
2335	Chilkur	7731.28(-2.47)	4677.00 (51.4)	5408.00 (30.98)	7084
2336	Huzurnagar	13090.87(-42.4)	5300.83(42.24)	5563.00 (35.53)	7540
		56828.23	**31745.7**	**36586**	**41620**
		-26.76	**31.10**	**13.76**	

Table 1 Rice are estimated under different classification methods and percentage of differences over observed values

the percentage difference is reduced to 21% and 27% and overall the percentage of difference with unsupervised classification is reduced to 27.7% and with combination method reduced to 11.20%.

5. Discussion

Nalgonda is of one of the major rice growing district in Andhra Pradesh. Here rice crop is dominant followed by pulses, millets and oil seeds. As rice is the dominant crop and grown in mostly irrigated system, Area of Interests were chosen along major canals. In supervised classification, the signatures were created manually using seed properties. But in unsupervised classification, the classes were generated by the system based on their spectral reflectance and with combination method non vegetative portion is eliminated and classes were generated for vegetative portion.

It is observed that from the table 1 that the combination method of NDVI and unsupervised classification appears to be the better choice for estimating area under rice in this study. Usually this method will work for the dominant crop identification with single date image (image must be at 50% flowering stage: more canopies are developed). Rice crop identification using one single date spring image produced equivalent or higher accuracy than the multi temporal classification (Barbosa et al., 1996). This method is useful to apply for any major crop identification with minimal ground truth data. Human error in digitizing, lack of knowledge of study area, and other factors all contribute to inaccurate results in the supervised classification method.

A threshold value to distinguish vegetative portion from non vegetative portion in combination method was defined at the value 0.15. This value still has uncertainties in vegetation detection. The threshold value will not be always 0.15 for all crops, as vegetation is bright from 0.1 that value will be between 0.1 to 0.2, and better to compare NDVI with master image to fix the threshold value. Areas where zones of vegetation are too small and intersected, although favourable for locusts, are partly missed with such a threshold. But a too low threshold set to include such low NDVI would seriously over-estimate vegetation in other areas (Cherlet Michael, 2000).

The successful application of our methodology to other areas will depend on a number of factors including the secondary data estimates, mixture of crops grown in that area, crop condition at the time of Landsat overpass and Land scene anomalies. The variables that are used to redistribute the crop area statistics are crop specific. This is because agricultural systems face continual changes due to effects of the world economy agro-environmental and socio – economic variables (Hervé, Genin, & Migueis, 2002). Given enormous impact of these changes further research should be carried out using the temporal aspect in order to incorporate the nature of different crop types throughout the growing season if there is sufficient knowledge on the rainfall patterns.

6. Conclusion

Remote sensing is a valuable source of data that can provide a synoptic perspective critical for understanding biophysical relationships at a regional scale. Because of this, remote sensing has been a popular tool readily accepted into agricultural research and management. The common thread in crop type identification applications is an attempt to achieve greater accuracy from remotely sensed data. In order to accomplish this, researchers have looked into various alternatives. Most of these alternatives have to do with the type of sensor (i.e., optical or microwave), number of images (i.e., single-date or multi-date), timing of the imagery, or processing technique. Although these characteristics certainly make a difference in the results attained, the trait that seemed to be most relevant was an appropriate use of the spatial data in combination with process understanding. There are several methods used to estimate the rice area, fuzzy classification, sub pixel classification, spectral mixture analysis, and mixtures estimation, rule-based approach may give better results than more traditional methods. But this combination method is simple and easy to understand and accurate if it is a major crop in that area. Area measurement of crops from remote sensing is largely straightforward. In this method first we are eliminating the non vegetative part and classifying the vegetative part for rice crop identification. This method can be applicable to identify other major crops.

References

Akira Otuka. 2008. Estimation of Paddy Field Area by Coherence Analysis of SAR Interferometry. *ftp://ftp.eorc.nasda.go.jp/cdroms/EORC-036/pi/25akirao.pdf*. Accessed on June 8th 2008.

Anji Reddy, M. 2001. *Text Book of Remote Sensing and Geographical Information Systems (Second Edition)*, BS publications, Hyderabad. 148.

Barbosa, P. M., Casterad, M. A. and Herrero, J. (1996). Performance of several Landsat 5

Thematic Mapper (TM) image classification methods for crop extent estimates in an irrigation district. *International Journal of Remote Sensing* 17, 3665-3674.

Barrs, H. D. and S. A. Prathapar. 1996. Use of satellite remote sensing to estimate summer crop areas in the Coleambally Irrigation Area, NSW. CSIRO, Division of Water Division of Water Resources Consultancy Report 96/17, 35.

Beaujouan, V., P.Durand, and L.Ruiz 2001. Modelling the effect of the spatial distribution of agricultural practices on nitrogen fluxes in rural catchments. *Ecol. Modelling*, 137, 91–103.

Boelman, T. Natalie, Stieglitz, Marc, Rueth, M. Heather, Sommerkorn, Martin, Griffin, L. Kevin, Shaver, R. Gaius, and A. John Gamon. 2003. Response of NDVI, biomass, and ecosystem gas exchange to long-term warming and fertilization in wet sedge tundra. Oecologia, 135, 414-421.

Casanova, D., G. F. Epema and J. Goudriaan. 1998. Monitoring rice reflectance at field. Centre for Sustainable Rice Production Technical Report 101/00, 101.

Cherlet Michael, Mathoux Pierre, Bartholomé Etienne and Defourny Pierre. 2000. Spot vegetation contribution to desert locust habitat monitoring. http://www.geosuccess.net/geosuccess/documents/desert%20locust.pdf.

Chris Banman. 2002. Lecture given on the topic “ Advanced Image Processing” Class at Emporia State University (ES775), spring session 2002, Instructed by Dr. James Aber.

ERDAS Field Guide, 2002, Sixth edition, Leica Geosystems, GIS and Mapping Division, ERDAS LLC, Georgia. p 206.

ERDAS Inc. 1999. ERDAS Imagine Field Guide. 5th Edition. ERDAS Incorporated. Atlanta, GA. http://support.erdas.com/documentation/files/85FieldGuide.pdf.

Fresco, L. O., Stroonsnijder L, Bouma J, and Keulen H V. 1994. The Future of the Land: Mobilising and Integrating Knowledge for Land use Options. Paper presented at the International Interdisciplinary Conference, Wageningen.

Hervé D., Genin D., and Migueis J. 2002. A modelling approach for analysis of agro pastoral activity at the one farm level. *Agricultural Systems*, Vol. 71(3), 187 – 206.

http://www.icrisat.org/gt-aes/text/SatImgAnalysis1.html. 2006. Methodology for estimating rice-fallow area using satellite image analysis.

http://www.mathworks.com/products/demos/image/ipexndvi/ipexndvi.html. 2004. Finding Vegetation in a Multispectral Image.

Hutchinson, C.F. 1991. Uses of satellite data for famine early warning in sub- Saharan Africa. *International Journal of Remote sensing*. 12: 1405:1421.

Kanemasu, E. T. 1974. Seasonal canopy reflectance patterns of wheat sorghum and soybean. *Remote Sensing of Environment*, 3: 1-4.

Krishna Rao, M.V., Hebbar K.V. and Venkataratnam L. 1997. Evaluation of IRS-1C data for discrimination and acreage estimation of crops grown under multiple crop situation. Remote Sensing for Natural Resources. Paper presented at the National Symposium on Remote Sensing for natural resources with special emphasis on water management, held at Pune during 4-6 Dec 1997.

Laidler, Gita J., and Paul. Treitz. 2003. Biophysical remote sensing of arctic environments. *Progress in Physical Geography*, 27(1), 44-68. Massachusetts: Addison-Wesley Publishing Company.

Le Hegarat-Mascle, S., Quesney, A. and Vidal-Madjar, D. (2000). Land cover discrimination from multitemporal ERS images and multispectral Landsat images: a study case in an agricultural area in France. *International Journal of Remote Sensing* 21, 435-456.

Macdonald, R.B., and F.G. Hall, 1980. Global Crop Forecasting. *Science* 208: 670-679.

Parihar, J.S., Panigrahi, S., Dadhwal, V.K., Bhatt, H.P., Dass, N.K., Gosh B.K. and Stow, Douglas, Hope, Allen, Boyton, William, Phinn, Stuart, Walker, Donald, and Auerbach, Nancy. 1998. Satellite-derived vegetation index and cover type maps for estimating carbon dioxide flux for arctic tundra regions. *Geomorphology*, 21: 313-327.

Parihar, J.S., Panigrahy, S., Patel, N.K., Dadhwal, V.K., Medhavy, T.T., Ghose, B.K., Ravi, N., Pani, K.C., Panigrahy, B.K., Sridhar, V.N., Mohanty, R.R., Nanda, S.K., Tripathy, D.P., Mishra, P.K., Bhatt, H.P., Oza, S.R., Sudhakar, S., Sudha, K.S., Kumar, P., and Das, N.K. 1990. Rice acreage estimation in Orissa using remotely sensed data. Status report on RSAM Project : Crop acreage and production estimation. *SAC Status report*: RSAM/SAC/CAPE/SR/25/90.

Pax-Lenney, M. and Woodcock, C. E. 1997. The effect of spatial resolution on the ability to monitor the status of agricultural lands. *Remote Sensing of Environment*, 61: 210-220.

Prachi Misra Sahoo, Dr. Anil Rai, Dr. Randhir Singh, B.K. Handique, Markand Oza, J. S. Parihar, Dr. Anil Rai, Dr. Randhir Singh, B.K. Handique Markand Oza, J. S. Parihar. 2006. Remote Sensing and GIS based Sampling Methodology for Estimation of Crop Acreage in North-Eastern Hilly Region. Paper presented in *Map India 2006*.

Prince, S.D. 1991. A model of regional primary production for use with coarse-resolution satellite data. *International Journal of Remote Sensing*. Principles and Practices. Washington, D.C. Lewis Publishers.

Ribbes, F. and Toan, T. I. (1999). Rice field mapping and monitoring with RADARSAT data. *International Journal of Remote Sensing* 20, 745-765.

Schowengerdt, R. A. (Ed.). (1997). *Remote sensing models and methods for image processing* (Second Edition ed.). San Diego: Academic Press Limited.

Tarplay J. D, Schneider and Money R. L. 1984. Global vegetation indices from the NOAA-7 meterological satellite, *J. Clim. Appl. Meteor*, 23: 491- 4.

Tom G. Van Niel and Tim R. McVicar. 2001. Remote Sensing of Rice-Based Irrigated Agriculture: A Review. Rice CRC Technical Report P1105-01/01, 26.

Tomar, M. S., and Maslekar A. R. 1974. *Aerial photographs in land use and forest surveys*. Dehra Dun: Jugal Kishore & Co. (Publication Division).

Tomohisa Konishi, Sigeru Omatu and Yuzo Suga. 2007, Extraction of rice-planted area using a self-organizing feature map, *Artificial Life and Robotics* 11: 215-218.

Tou, Julius T., and Rafael C Gonzalez. 1974. *Pattern Recognition Principles*. Reading, Massachusetts: Addison-Wesley Publishing Company.

Woodcock, C. E. and Strahler A.H. 1987. The factor of scale in remote sensing. *Remote Sensing of Environment*, 21: 311-332.

Xiangming Xiao, Stephen Boles, Steve Frolking, Changsheng Li, Jagadeesh Y. Babu,William Salas and Berrien Moore III . 2006. *Remote Sensing of Environment*, 100: 95– 113.