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# Combination of Image Analysis Techniques for Rice Area Estimation

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**Abstract**

Most of the image analysis techniques have both strong and weak aspects. Classifying the image with clustering algorithm, an unsupervied classification method for example, is a time-consuming process. On the other hand converting into NDVI (Normalized Difference Vegetative Index) and assigning pixels to different features is also a vague process. Using a combination of NDVI and unsupervized method to estimate area under rice can reduce processing time while, at the same time, reinforcing the performances of both classifiers. This paper deals with estimating area under rice in Nalgonda district of Andhra Pradesh. IRS-1D digital data from LISS—III (path 100/60 16 October 2004 and 101/60 14 November 2004) was selected and ERDAS image 8.6 package was used for image processing .The NDVI map is derived first and refined to set the threshold level for vegetation. Next, a query was developed to set zero to the non-vegetative features in IRS-1D image. This image was further classified with unsupervized classification using ISODATA for clustering. This study shows that the combination method of NDVI and unsupervized classification appears to be better choice for estimating area under rice.

**Key words : Rice crop area, Image processing, Combination methods, Remote sensing, GIS.**

Accurate and timely information is necessary to evolve strategies for sustainable management of natural resources. Today's "space age" supported by computer and communication technologies offer great scope for efficient planning and management of agricultural resources on scientific principles. Remote sensing methodologies for acreage estimation of cereal crops like rice, wheat and sorghum, oilseed crops like groundnut, rapeseed-mustard, soyabean and commercial crops like cotton, sugarcane and tobacco, and also for predicting crop yields are well established (1). With the launch of every new sensor system for the acquisition of data in the optical or the microwave part of the spectrum, and the development of new sophisticated processing and analyzing techniques lead often to an exponential increase in processing time (2). There are two main categories that can be used to achieve this outcome and they are called supervized and unsupervized classification techniques. There are also additional techniques to process the images those are vegetation indices. in either case additional image processing may be used to help determine which method is better for a given situation. Combination of these conventional methods and vegetative indices will perform better by reinforcing the performances of both classifiers.Rice is a key component of the Indian food security system. 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 (3). Current analysis of rice productivity with in India shows that Andhra Pradesh (AP) is one of the top three rice-producing states in the country and accounts for about 12% of the nation's total rice production. 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 (4) and in the formulation of meteorological and biogeochemical models (5). Major rice growing district of Andhra Pradesh was selected for this study. Main objectives were to identify rice crop, to estimate area

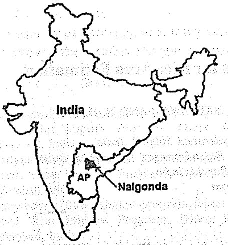



**Figure 1.** The location of Nalgonda district in Andhra Pradesh.

under rice, to validate area and with secondary data from Department of Agriculture.

## Methods

The selected study area is Nalgonda district (AP), which lie between 16—25′ and 17—50′ of the northern latitude and 78—40′ and 80—05′ of eastern longitude covering an area of 14,240 sq km. Paddy, pulses, millets and oilseeds are major crops in this study area,with paddy is the dominant crop. Choutuppal and Pochampally mandals were selected for collecting ground truth data for verification. The location of this study area is depicted in Figure 1.

IRS-1D digital data from LISS-III (path 100/60 16 October 2004 and 101/60 14 November 2004) were selected for this study and ERDAS image 8.6 was used for image processing. The LISS-III data were found to be useful for improved discrimination of different crops grown under multiple crop situations (6). Polyconic projection was applied uniformly to all the datasets with latitude/longitude information in degrees.

As Nalgonda district is covered in two imageries, two satellite images were joined using mosaic option of ERDAS package. The district boundary of Nalgonda was used to extract the subset of Nalgonda from the joined image, which was subsequently considered as master image (Fig.2). Mandal map of Nalgonda district was digitized using Arc GIS package 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. Secondary data for area under rice for the above mandals were collected from Department of Agriculture, Hyderabad, Andhra Pradesh.

### *Rice Crop Identification*

The most commonly practiced application in remote sensing of agriculture is mapping land cover to identify crop types. However, the identification of object depends on the spatial resolution of the remote sensing imagery (7). Discrimination of crops is usually performed by some classification procedures. There are two fundamental approaches for classification. One is supervized and another one is unsupervized classification.

*Supervized Classification (Method 1).* In this classification , user has to specify the classes to be used and provides "signatures" for each class. The image interpreters must have *priori* knowledge of the area covered by the image they are attempting to classify. Using the "seed tool" of ERDAS package, the signature files were created. Due to color variations within a class, often multiple signatures will be needed to capture a single cover class (8). Maximum likely hood rule was used for this classification. Six signature classes were selected to estimate rice crop. Error matrices were generated to evaluate the signatures.

*Unsupervized Classification (Method 2).* In this classification, the computer selects classes based on clustering of brightness values. This classification uses the Iterative Self-Organizing Data Analysis Technique (ISODATA) (9) alogorithm to execute the clustering of the image.

The advantage of an unsupervized approach, however, is that no *priori* (before the fact) knowledge is needed. Nalgonda district was classified using this classification method with 30 classes with 60 iterations at the convergence threshold 0.990.

*Combination of NDVI and Unsupervized Method (Method 3).* Another important component of research focusing on changes in vegetation is the use of land cover maps and NDVI (Normalized Differ-

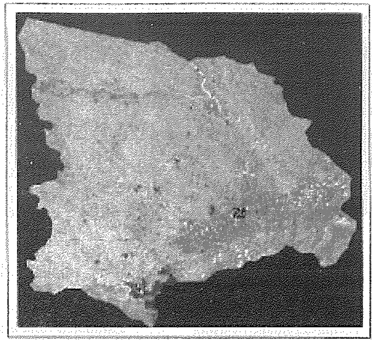


**Figure 2.** IRS-D LISS-III image Nalgonda district-master image.

ence Vegetation Index) derived from satellite imagery (10). Nalgonda district was classified using this method. NDVI is given by

NDVI=(Near Infra Red band – red band)/ (near Infra Red band + red band)

Variable NDVI is a 2-Darray of class single with a theoretical maximum range of [–11]. 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 (11). NDVI images were derived for the Nalgonda district and these images were compared with master images of each mandal for better refinement of vegetative portion from the imageries.

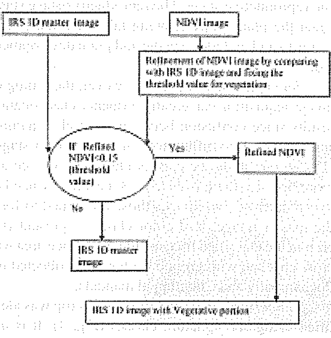



**Figure 3.** Flowchart showing the process to zero non vegetative features in IRS-ID image.

In 2004 product demos, 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 (12). 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 (13). 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.

For many specialized applications, classifying data that have been spectrally merged or enhanced with image algebra or other transformations can produce specific meaning results (14). A model (Fig.3) was developed to set zero to the non-vegetative fea-

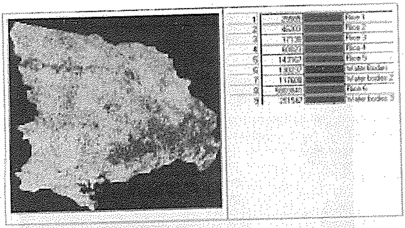


**Figure 4.** Rice crop identified in Nalgonda district by supervized classification—red (deep grey) color indicates rice area.

tures (<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 unsupervized classification method with 10 classes and 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.

### *Rice Area Estimation*

The area under rice is estimated by the formula :

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 units of square meters. Pixel resolution values were given in the CD information file of images. These values are 23.5 × 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.

### *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

## Results and Discussion

### *Rice Crop Identification*

The increasing need for information on the spatial distribution of crop areas that is compatible with other spatial datasets is evident in countries where vegetation characteristics are highly dynamic throughout the growing season (15).

The image acquired dates are between October and November, so the crop is mostly in vegetative and reproductive stage. The reproductive stage starts when the plant stops growing taller and ends after maturity and includes panicle and grain development (16).

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 (17). In our study the classes identified for rice are more because there is nearly 28 days difference between dates of two images those are joined to form the master image. Red color classes represent rice crop in the classified images. Identified rice area was cross checked with ground truth points collected for Pochampally and Choutuppal mandals.

*1 Supervized Classification.* Rice crop was identified using six signature classes (Fig. 4). It is observed from error matrix that there is mixing of pixels among only rice classes. Pixels of other classes like

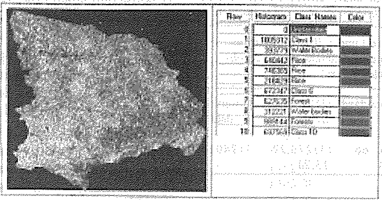


**Figure 5.** Rice crop identified in Nalgonda district by unsupervized classification–red color indicates rice area.

water bodies, settlements and other crops were classified correctly as there is no mixing of pixels among other classes.

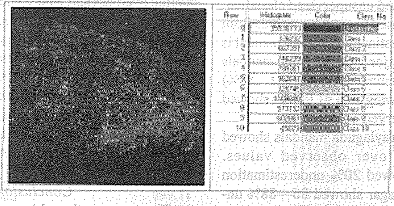
2 *Unsupervized Classification.* Rice crop was identified by more than five classes among 30 total classes (Fig. 5). Unsupervized classification avoids problems with the user biasing the classification with improper or poorly represented training data, which can be the case in supervized classification (17).

As 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 (18).

3 *Combination of NDVI and Unsupervized 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. 6). In this case, more classes were selected to differentiate among different land types. Here minimum classes were taken because only vegetative portion is remaining in the image. Some 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 (19). As our image acquisition dates are from October to November, there is good relation between red reflectance and biomass.

### *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 a necessary first step to area estimation. There are a few issues that are not exclusively related, but tend to more specifically pertain to crop



**Figuer 6.** Rice crop identified in Nalgonda district by combination method—red color indicates rice area.

**Table 1.** Rice area estimated under different classification methods and percentage of differences over observed values.

| District name | Rice area (hectares) under different classifications) (percentage of difference between observed and calculated values) | | | |
|---|---|---|---|---|
| | Supervized | Unsupervized | NDVI + Unsupervized | Observed data |
| Nalgonda | 267161.71<br>-56.06 | 140662.66<br>-16.53 | 135270.27<br>-13.21 | 117401 |

area estimation, including positional accuracy, mixed pixels and pixel size, and a mismatch between individual and overall accuracies of the results. 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 (20). There were slight differences among area calculations observed from methods 2 and 3 and differences were more between 1 and 3 and 1 and 2 methods.

### *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 supervized classification process rice area was overestimated on an average by 56.05% for Nalgonda district. There was 16.53% overestimation observed with unsupervized classification.

There was 13.21% under estimation with combination method of NDVI and unsupervized classification. Mandal AOIs were used to extract mandals from this classified map. Area estimated for each mandal is listed in the Table 2. Major rice growing mandals (>7,000 ha) showed underestimation values (12—88%) and mandals with rice growing area <1,000 ha showed overestimation over observed values.

Garedapally and Miraylaguda mandals showed 12—13% differences over observed values. Neredcherla mandal showed 20% underestimation and Chilkur and Huzurnagar showed 86—88% underestimation compared to observed values. Cloud coverage is more in Chilkur and Huzurnagar (840 ha). By correcting cloud area percentage difference will be reduced to 10—15%.

Similar method applied at mandal level showed reasonable differences compared to classification at district level. Garedapally and Miraylaguda mandals showed 1—3% differences over observed values. Neredpally mandal showed 12.85 underestimation and Chilkur and Huzurnagar showed 30—35% underestimation compared to observed values. Mandals where rice area less than 1,000 hectares exhibited over estimation of nearly 4—30% over observed values (21).

Table 1 shows that the combination method of NDVI and unsupervized classification appears can be effective for estimating area under rice in this study, particularly when rice is the dominant crop. Human error in digitizing, lack of knowledge of study area, and other factors can contribute to inaccuracies in estimates by the supervized classification method.

A threshold value to distinguish vegetative portion from non-vegetative portion in combination method was defined at 0.15. Some uncertainties in vegetation detection can also be associated with the choice of this threshold value. The threshold value will usually be between 0.1 to 0.2 as vegetation is bright from 0.1 upwards. Comparing NDVI with master image can lead to better process of fixing the threshold value. Areas where zones of vegetation are too small and intersected 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.

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 satellite 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 (22). Given enormous impact of these changes further research needs to be carried out using the temporal aspect to incorporate the nature of different crop types throughout the growing season.

### *Conclusion*

The common thread in crop type identification applications is an attempt to achieve greater accu-

Table 2. Rice area estimated for different mandals (extracted from district classified map) under combination method and percentage of differences over observed values.

| Mandal code | Mandal name | Calculated | Observed | Percentage increase |
|---|---|---|---|---|
| 2302 | Alair | 511.66 | 423.00 | −17.33 |
| 2303 | Gundala | 1283.21 | 934.00 | −27.21 |
| 2304 | Tirumalagiri | 1119.63 | 1403.00 | 25.31 |
| 2305 | Thungathurthy | 1186.95 | 1379.00 | 16.18 |
| 2306 | Nutankallu | 1816.13 | 934.00 | −48.57 |
| 2307 | Atmakur (s) | 1980.91 | 1975.00 | −0.30 |
| 2308 | Mothey | 1303.85 | 1162.00 | −10.88 |
| 2309 | Nadigudam | 2233.41 | 1403.00 | −37.18 |
| 2310 | Kodad | 6822.39 | 4811.00 | −29.48 |
| 2311 | Medlacheruvu | 7480.42 | 1200.00 | −83.96 |
| 2312 | Mattampalli | 3291.52 | 1425.00 | −56.71 |
| 2313 | Neredcherla | 7044.11 | 8471.00 | 20.26 |
| 2314 | Damercherla | 5710.98 | 1607.00 | −71.86 |
| 2315 | Peddavoora | 1808.07 | 747.00 | −58.69 |
| 2316 | Pedda adiserlapa | 1020.39 | 643.00 | −36.99 |
| 2317 | Chandampet | 886.75 | 245.00 | −72.37 |
| 2318 | Gundlapally | 268.67 | 442.00 | 64.51 |
| 2319 | Deverkonda | 828.76 | 818.00 | −1.30 |
| 2320 | Chinthapally | 795.74 | 483.00 | −39.30 |
| 2321 | Marriguda | 1458.44 | 450.00 | −69.15 |
| 2322 | Narayanpur | 2036.64 | 847.00 | −58.41 |
| 2323 | Choutuppal | 1056.23 | 793.00 | −24.92 |
| 2324 | Pochampally | 3194.32 | 2924.00 | −8.46 |
| 2325 | Bibinagar | 2196.24 | 1480.00 | −32.61 |
| 2326 | Bommala ramaram | 1761.24 | 831.00 | −52.82 |
| 2327 | Turkapalli | 624.54 | 486.00 | −22.18 |
| 2328 | Yadagirigutta | 1964.30 | 468.00 | −76.17 |
| 2329 | Atmakur I | 1454.74 | 1154.00 | −20.67 |
| 2330 | Mothkur | 795.74 | 969.00 | 21.77 |
| 2331 | Jajireddy gudem | 1198.27 | 1504.00 | 25.51 |
| 2332 | Suryapet | 841.19 | 1523.00 | 81.05 |
| 2333 | Chevemula | 699.04 | 615.00 | −12.02 |
| 2334 | Mungala | 1182.86 | 1717.00 | 45.16 |
| 2335 | Chilkur | 3798.27 | 7084.00 | 86.51 |
| 2336 | Huzurnagar | 3992.05 | 7540.00 | 88.88 |
| 2337 | Garedapally | 7452.61 | 8411.00 | 12.86 |
| 2338 | Penpahad | 1019.88 | 738.00 | −27.64 |
| 2339 | Miryalaguda | 9015.15 | 10114.00 | 12.19 |
| 2340 | Tripuraram | 3322.09 | 4964.00 | 49.42 |
| 2341 | Nidmanoor | 8360.43 | 5732.00 | −31.44 |
| 2342 | Anumula | 4649.06 | 3255.00 | −29.99 |
| 2343 | Gurrampode | 1222.79 | 1008.00 | −17.57 |
| 2344 | Nampally | 985.32 | 293.00 | −70.26 |
| 2345 | Chandur | 1175.74 | 640.00 | −45.57 |
| 2346 | Mungode | 1410.67 | 1044.00 | −25.99 |
| 2347 | Chityal | 1558.89 | 831.00 | −46.69 |
| 2348 | Ramannapet | 2388.76 | 1952.00 | −18.28 |
| 2349 | Valigonda | 4017.14 | 2376.00 | −40.85 |
| 2350 | Bhonagir | 1960.98 | 1474.00 | −24.83 |
| 2351 | Narketpalli | 1398.83 | 1177.00 | −15.86 |
| 2352 | Shali Gouraram | 1219.87 | 1894.00 | 55.26 |
| 2353 | Nakrekal | 799.71 | 779.00 | −2.59 |
| 2354 | Kethepalli | 828.98 | 1200.00 | 44.76 |
| 2355 | Vemulapalli | 2475.11 | 2886.00 | 16.60 |

Table 2. Continued.

| Mandal code | Mandal name | Calculated | Observed | Percentage increase |
|---|---|---|---|---|
| 2356 | Tipparti | 1295.52 | 945.00 | –27.06 |
| 2357 | Kangal | 1285.75 | 1553.00 | 20.79 |
| 2358 | Nalgonda | 1064.79 | 1563.00 | 46.79 |
| 2359 | Kattangur | 714.34 | 784.00 | 9.75 |
| | | 135270.08 | 116503.00 | –13.87 |

racy from remotely sensed data. 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. The combination method developed for identifying the rice crop in this study can be used to process other major crops. This method is more effective when it is used at block level than extracting from the district map.

## References

1. Kanemasu E. T. 1974. Seasonal canopy reflectance patterns of wheat sorghum and soybean. Rem. Sens. Environ. 3 : 1—4.
2. Gerrit Huunemna and Lucas Broekema. 1996. Classification of multi-sensor data using a combination of image analysis techniques. 17th Asian Conf. on Remote Sensing, Nov 4-8, 1996, Sri Lanka, Surv. Dep., Sri Lanka and Asian Assoc. on Rem. Sens. (AARS). *http://www.gisdevelopment.net/aars/acrs/1996/ts5/ts 5002.asp*
3. Xiangming Xiao, Stephen Boles, Steve Frolking, Changsheng Li, Jagadeesh Y. Babu, William Salas and Berrien Moore III. 2006. Remade sensing of environment, 100, pp. 95—113.
4. Hutchinson C. F. 1991. Uses of satellite data for famine early warning in sub-Saharan Africa. Int. J. Rem. Sens. 12 : 1405—1421.
5. Prince S. D. 1991. A model of regional primary production for use with coarse-resolution satellite data. Principles and Practices. Int. J. Rem. Sens. Lewis Publ. Resou., Washington, DC, USA.
6. Krishna Rao, M. V. K. R. Hebbar and L. Venkataratnam. 1997. Evaluation of IRS-1C data for discrimination and acreage estimation of crops grown under multiple crop situation. Remote Sensing for Natural Resources. Nat.symp. on remote sensing for natural resources with special with special emphasis on water management, Pune, 4—6 Dec 1997.
7. Tomar M. S. and A. R. Maslekar. 1974. Aerial photographs in land use and forest surveys. Jugal Kishore & Co., Dehra Dun, India.
8. Porter John. 2003. Introduction to classification of remotely sensed imagery. *http :// www. vcrlter.virginia.edu/ ~jhp 7e/evsc468/2003/RS classify.PPT.*
9. Tou Julius T. and Rafael C Gonzalez. 1974. Pattern recognition principles. Reading. Addison-Wesley Publ. Co., Massachusetts.
10. 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.
11. Tarplay J. D., Schnęider and R. L. Money. 1984. Global vegetation indices from the NOAA-7 meterological satellite. J. Clim. Appl. Meteor. 23 : 491—494.
12. *Http://www.mathworks.com/products/demos/image/ipexndvi/ipexndvi.html.* 2004. Finding vegetation in a multispectral image.
13. Cherlet Michael, Mathoux Pierre, Bartholome Etienne and Defourny Pierre. 2000. Spot vegetation contribution to desert locust habitat monitoring. *http: //www.geosuccess.net/geosuccess/documents/desert%201-ocust.pdf.*
14. ERDAS. 2002.Field Guide. 6th edition. Leica Geosystems, GIS and Mapping Div., ERDAS LLC, Georgia, USA.
15. Fresco L. O., L. Stroonsnijder, J. Bouma and H. V. Keulen. 1994. The future of the land : Mobilizing and integrating knowledge for land use options. Int. Interdisc. Conf., Wageningen.
16. Ribbes F. and T. I. Toan. 1999. Rice field mapping and monitoring with RADARSAT data. Int. J. Rem. Sens. 20 : 745—765.
17. Tom G., Van Niel and Tim R. MCVicar. 2001. Remote sensing of rice-based irrigated agriculture : A review. Rice CRC Tech. Rep. P1105–01/01, pp. 26.
18. 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 Div.Water Resour. Consul. Rep. 96/17, pp. 35.
19. Casanova D., G. F. Epema and J. Goudriaan. 1998. Monitoring rice reflectance at field. Cen. Sust. Rice

Prod. Tech. Rep. 101/00, pp. 101.

20. Pax-Lenney M. and C.E. Woodcock. 1997. The effect of spatial resolution on the ability to monitor the status of agricultural lands. Rem. Sens. Environ. 61 : 210—220.

21. Sailaja B., P. Subrahmanyeswara Rao, M.S. Nathawat and N. H. Rao. 2006. Estimation of rice area using satellite data. 2nd Int. Rice. Cong., New Delhi, India Oct 9—13, 2006.

22. Herve D., D. Genin and J. Migueis. 2002. A modelling approach for analysis of agro-pastoral activity at the one farm level. Agric. Syst. 71 : 187—206.