



Photonirvachak

Journal of the Indian Society of Remote Sensing, Vol. 33, No. 2, 2005

## LAND USE – LAND COVER MAPPING USING SATELLITE DATA FOR A FORESTED WATERSHED, UDUPI DISTRICT, KARNATAKA STATE, INDIA

AMBA SHETTY<sup>@</sup>, LAKSHMAN NANDAGIRI, SANGEETA THOKCHOM AND M.V.S. RAJESH

Department of Applied Mechanics & Hydraulics, National Institute of Technology

P.O. Srinivasnagar-575 025, Karnataka Surathkal, India

<sup>@</sup>Corresponding author : amba\_shetty@yahoo.co.in

The terms “land use” and “land cover” (LULC) are often used simultaneously to describe maps that provide information about the types of features found on the earth’s surface (land cover) and the human activity that is associated with them (land use). Land cover is an important input parameter for a number of agricultural, hydrological, and ecological models, which constitute necessary tools for development, planning and management of natural resources in the territory. In order to use the land optimally, and to provide as input data in modelling studies, it is not only necessary to have information on existing land use/ land cover but also the capability to monitor the dynamics of land use resulting out of changing demands. If the site is small, and easily accessible, a suitable land cover may be based on ground observations and surveys. However, such methods quickly become less feasible, if the site is large or difficult to access. Toposheets may be useful for reference, but are generally outdated and too coarse for detailed analysis. With improvements in software and hardware and decrease in the cost of imagery,

satellite remote sensing is being used for more and more studies particularly at the landscape level. The characterization of land cover from satellite data, has conventionally provided a means of assessing a large geographical area with limited time, and resources. However, satellite images do not record land cover directly; rather they measure the nature, and strength of solar energy being reflected from each small area, or pixel of the scene. The amount of multispectral energy in multi wavelengths depends on the type of material at the earth’s surface. And the objective is to associate particular land cover with each of these reflected energies. This is generally achieved using either visual or digital interpretation methods. In this study, we demonstrate how satellite imagery can be displayed and manipulated using digital techniques in a popular digital image processing software program, ERDAS IMAGINE 8.5<sup>®</sup>. The objective of the study is to outline the strategy for automatically identifying land cover types on a satellite scene using hybrid classification approach in a rugged forested watershed. The difficulty of obtaining cloud free

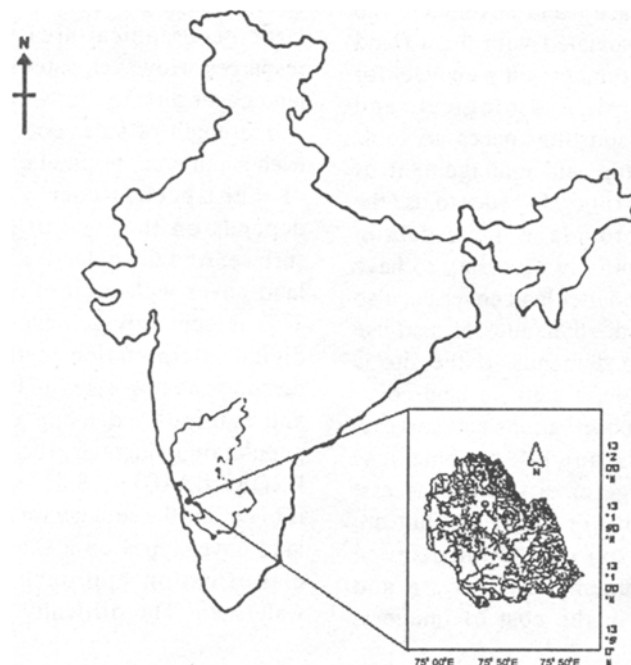
data for different seasons, the shadows cast by rugged terrain and the subsequent loss of information are some of the problems faced when dealing with forested catchments in this region. Important aspects addressed in this article are; image fusion, unsupervised classification, supervised classification including selection of training sites, signature comparison, accuracy assessment and reclassification.

Before committing to a data source and analysis strategy, we first need to define the scale, coverage and type of data required. In this study, we used satellite data obtained from LISS III, and PAN sensors carried by IRS- 1C, and IRS -1D satellites. Our study area (Yennehole river basin) is located in the West coast region of Karnataka State, India. Fig. 1 shows the index map of the river basin, which has a drainage area of 327 km<sup>2</sup>. The area falls in path row 97/ 64 of IRS -1C / IRS -1D reference map. Due to the non-availability of good quality PAN data for IRS -1D satellite we had to choose PAN data of IRS -1C. As reference and auxiliary material, four

topographical maps published by Survey of India (SOI) in the year 1979 on 1: 50 000 scale numbered 48K/15,48 K/16 48 O/3 and, 48 O/4 available in the paper format were used. These maps served purpose of delineating the basin boundary and stream networks, registration of satellite data, selection of ground control points, creating road maps, in ground truth studies and authentication of various cultural features on the satellite image.

Main phases of classification procedure used in the present study, to create land cover maps are:

- 1) Satellite data selection
- 2) Satellite data preprocessing
- 3) Image fusion techniques
- 4) Ground truth
- 5) Satellite data interpretation and vectorization of the resulting units
- 6) Land Cover Classification system (LCCS)



**Fig. 1.** Index map of the river basin

- 7) Field checking and
- 8) Composition of final land cover maps.

Once the required data are selected, preprocessing operations involved image rectification and restoration. The image is rectified with respect to topographic maps. Detailed description of image fusion and satellite data interpretation techniques employed is given in the sections to follow.

Of the various enhancement techniques to improve image interpretability and resolution, multi-resolution image data fusion may be considered as a potential one. Image fusion is a combination of two or more images to form a new image by using certain algorithms, (Pohl and Genderson, 1998). ERDAS Imagine 8.5® (1999) supports several image fusion techniques. There exist various techniques for image fusion such as HPF (High Pass Filter), HIS (Intensity Hue Saturation), Brovey and Arithmetic transformation, Principal Component Analysis (PCA). Since PCA removes the redundancy of information contents therefore PCA techniques have been used as a tool in this study. Georectified IRS -1C PAN (electromagnetic spectrum range 0.50 - 0.75) single band black and white data with 5.0 m spatial resolution and IRS -1C LISS - III multispectral data are fused using the resolution merge option available in ERDAS Imagine 8.5 using PCA as a fusion tool. LISS - III sensor (electro-magnetic spectrum range 0.52 - 1.70 micrometer) has 4 bands, i.e., band 1 - Green, band 2 - Red, band 3 - Near Infrared, and band 4 - Short wave Infrared. As short wave infrared band has coarse spatial resolution compared to other bands it is not useful for mapping

of infrastructure details. Hence band 1, 2, 3 were taken for fusing with PAN data. The fused/merged output is in 5.0 m resolution.

Image classification procedures are used to classify multispectral pixels into different land cover classes. The input for the classification is multispectral bands and textural patterns computed from the multispectral data. Primary methods are supervised classification and unsupervised classification. Several variations of these methods exist, each process uses multiple bands of the images to isolate unique spectral classes. No definite advice can be made about which classifier is best in all circumstances (Townshend, 1992). The digital image classification as such seems to be a simple process but in reality there are complications that limit the accuracy of land cover classification. These may arise partly due to the characteristics of the remote sensing images and assumptions underlying the techniques employed in the classification process (Mather, 1999). In the unsupervised approach, pixels are grouped into different spectral classes by clustering algorithms without using prior information (Jenson, 1996). Unsupervised classification algorithms only have a secondary role in remote sensing. Supervised classification begins with ground observations at particular points in the study area. ERDAS IMAGINE 8.5® image processing software supports both supervised and unsupervised classification. We opt for a combination of both the techniques. The approach we have followed is depicted in Fig. 2. This per-pixel classification approach often results in “salt-and-pepper” effects and weakly defined inter-region boundaries on the final map.

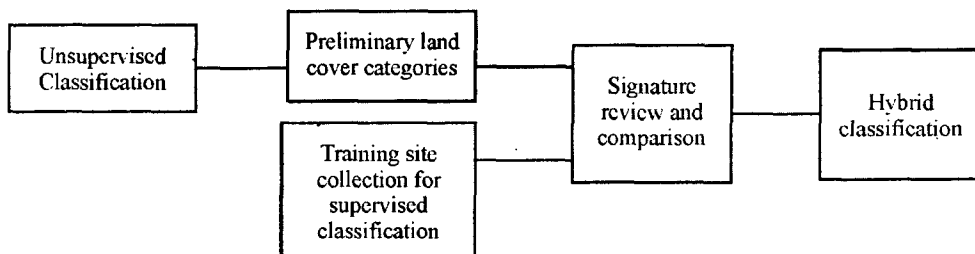


Fig. 2. Steps involved in developing a hybrid classification for land cover

ISODATA, an unsupervised classification technique was used in order to group the pixels into clusters. 100 spectral clusters with 95% convergence value were selected with the aim of performing unsupervised classification. Unsupervised classification examines the spectral characteristics of each pixel and statistically groups similar pixels into classes. User further aggregates the spectral classes into information classes. Unsupervised classification signatures were gathered to isolate large areas of uniform land covers. Of the 100 original signatures, approximately 20 proved valid and were retained through the remainder of the classification process.

Training sites were necessary to define classes that did not get classified uniquely during the unsupervised classification. Generally supervised classified has three distinct stages namely training, allocation and testing.

**Training data characteristics:** Training is a critical step in a supervised image classification. As the training samples should be representative of the land cover classes, they are collected from relatively homogeneous areas on the ground. Therefore, they are chosen subjectively and deliberately away from mixed pixels containing two or more classes. The size of the training samples is related to the number of wavebands (Swain and Davis, 1978).

**Collection of training sites:** Training sites were necessary to define classes that did not get classified uniquely during the unsupervised classification. Training sites were created by demarcating a polygon or area of interest for the known cover types. While demarcating the training sites various enhancement techniques were applied. Best-suited enhancement technique for particular feature identification was found out by trial and error procedure. Training sites were collected for all land cover classes. Training site selection was facilitated by the availability of Ground truth information, Toposheets – that could be displayed on screen alongside satellite data.

**Signature Development:** In signature development, training area statistics were gathered for each spectral band to be used in the final classification. Signature files were created from each training site. Signature files store statistics gathered from the training site, that are later applied to the entire image during the classification procedure. Care was taken to ensure that each class was well represented within the realm of natural variations that occur. Fig. 3 shows the mean spectral reflectance pattern of the signatures chosen in the analysis.

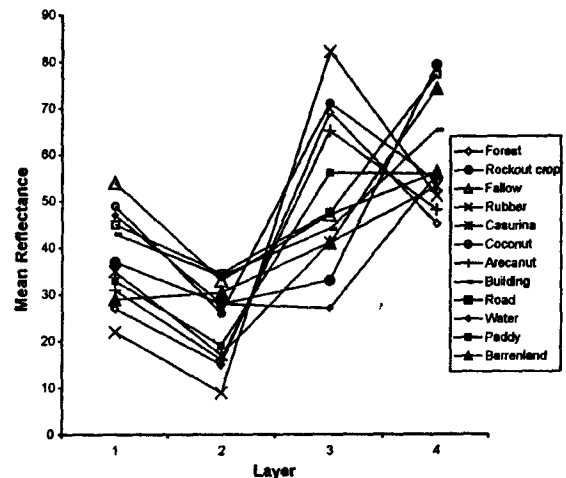


Fig. 3. Mean spectral reflectance pattern of the signatures

**Classification:** Data were classified through a Maximum likelihood classifier decision rule. After the classification, distance matrixes were examined to isolate all land cover features that did not classify within an acceptable distance to the mean of each class (i.e., stray pixels that were outside of any degree of confidence of classification). Further training sites and signatures were gathered to tie these stray pixels into an appropriate class using an iterative process. Some of the individual deep shadow areas were reclassified and composited with the main scene. This approach helped reduce the effects of the signature extension and the shadow factor.

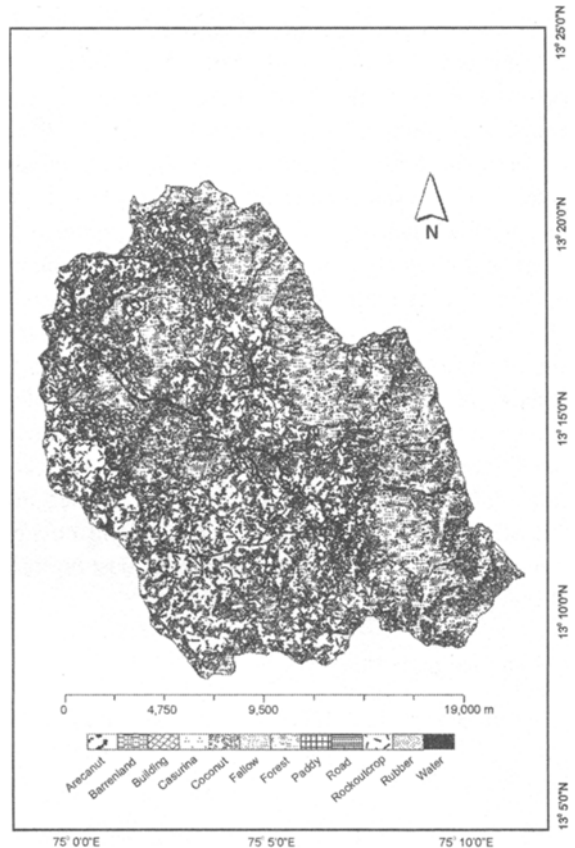
Image classification is incomplete, until accuracy assessment has been performed. This serves, as the basis for analyzing the errors that may creep in during the classification process. To determine the classification accuracy, sample-testing data are desired which are usually collected from the reference data. A most common and typical method used by researchers to assess classification accuracy is with the use of an error matrix (sometimes called a confusion matrix or contingency table) (Congalton, 1991). There are several methods for sampling the reference points (Lillesand and Kiefer, 2000). By selecting random and field sampled ground truth data 154 data points were collected and were utilized in the analysis. Overall Kappa statistics for our analysis is 0.8349 and the overall classification accuracy is 87.06%.

**Table 1:** Area details of land cover data

Class names	Area (km <sup>2</sup> )	% Area
Rockout crop	119.9	36.59
Fallow	0.43	0.13
Rubber	0.2	0.06
Casurina	21.77	6.64
Coconut	11.49	3.51
Arecanut	5.46	1.67
Building	3.34	1.02
Road	4.04	1.23
Water	9.79	2.98
Paddy	2.64	0.80
Barrenland	0.67	0.2
Forest	148.02	45.17

Post-processing such as the elimination of very local variability (salt and pepper like appearance) by application of appropriate tools provided in the softwares (clump and sieve) improved both the appearance and the reliability of the products.

Finally, results were vectorised using raster to feature conversion available in ARC GIS 8.1<sup>®</sup>. Image was reclassified to remove no data areas and to merge deep shadow regions found in the forest region with the forest using the reclassify option available in Spatial Analyst extension of ARC GIS 8.1<sup>®</sup>. The final land cover map derived is shown in Fig. 4.



**Fig. 4.** Land Cover and Land Use Map of Yennehole basin

It was discovered during the classification that, a vast majority of the area falls under forestland and rock outcrop, which does not require high degree of spatial resolution to be classified accurately. The hierarchical classification technique used, specific

spectrally related land cover groupings were isolated from the primary image, and signature selection was focused on each of the grouping types there by minimizing the effect of misclassification between spectrally similar classes of each groups. Overall the hierarchical classification technique was found to be useful technique.

Deep shadow regions were reclassified, and composited with the main scene. This approach helped to reduce the effects of signature extension, and shadow factor. There are number of issues that affect the land cover mapping from remotely sensed data, failure to understand these may result into an inappropriate land cover representations. Primary of them being; selection of algorithm for fusion of high resolution data with low resolution data, selection of number and size of training sites, selection of an algorithm for classification and selection of sampling scheme and its number for validation. Satellite remote sensing data, provides more consistent and accurate baseline information than any of the conventional data sources. Also the overall approach adopted in this study appears ideal for land-use/land cover mapping of the thickly vegetated West Coast region of India.

### Acknowledgements

Authors are grateful to Indian Space Research

Organization (ISRO) for the financial support under RESPOND scheme (Project No. 363).

### References

- Congalton, R.G. (1991). A review of assessing the accuracy of classification of remotely sensed data. *Remote Sensing of Environment*, **37**: 35-46
- ERDAS (1999). ERDAS Field Guide (5th ed.), ERDAS, Inc., Atlanta, Georgia, 671 p.
- Jenson, J.R. (1996). *Introductory Digital Image Processing*, Prentice Hall, New Jersey.
- Lillesand, T.M. and Kiefer, R.W. (2000). *Remote Sensing and image interpretation*. 4th ed., Wiley, 750p.
- Mather, P. (1999). *Computer Processing of Remotely Sensed Imagery - An Introduction* (2nd Edition), Chichester: John Wiley.
- Pohl, C. and Van Genderen, J.L. (1998). Multi Sensor Image Fusion in Remote Sensing. Concepts, methods and Applications. *International J. of Remote Sensing*, **19(5)**: 823-854.
- Swain, P.H. and Davis, S.M. (1978). *Remote Sensing. The Quantitative Approach*: New York: Mc Graw-Hill Book Company.
- Townshend, J.R.G. (1992). The European contribution to the application of remote sensing to land cover classification. *International J. of Remote Sensing*, **13**: 1319-1328.