An Approach for Identification and Classification of Crops using Multispectral Images

Beeresh H V, Mrs. Latha B M, Thimmaraja Yadava G, Naveen Dandur
Digital Electronics, Assistant Professor, Digital Electronics, Digital Electronics
GM GM Institute of Technology
Davangere, India.

***Abstract*—In this paper we are mainly going to adopt the spectral mixture modelling in order to produce the land cover maps in the study area which covers the Tumkur district,Karnataka.SpectralMixture Analysis (SMA) whose results are compared with the Ground truth data.SMA was performed and evaluated based on Landsat-8 ETM(Enhanced Thematic Mapper Plus) data. Landsat-8 ETMwas available at 30 m resolution with six spectral bands (excluding the panchromatic band and thermal band).The Landsat-8 ETM scene used in the study was acquired on March 2014.The image was prepossessed and resampled at 25m resolution.SMA can be achieved by using the Digital Number values and the corresponding radiance values, which will be available along with the satellite image. The accuracy of the classification result can be obtained by taking the absolute difference between actual and modeled estimations.**

***Keywords*—Digital Number (DN), Remote sensing, Spectral Mixture Analysis, Sub pixel Classification, Coconut trees.**

I.INTRODUCTION

Remote Sensing plays an key role in providing the land coverage mappings and classification of land cover features which mainly includes vegetation, roads, water bodies etc. A chief use of remotely sensed data is to produce a classification map of the identifiable or meaningful features or classes of land cover types in a scene[1]. As a result, the chief product is a thematic map with themes such as land use, geology and vegetation types. The concept of image classification is a process by which the basic features of the image are assigned to the classes. Characteristics of agricultural field, difference of spectral reflectance of different crop types and difference in feature characteristics such as shape and texture are important parameters that should be considered while working agricultural areas with remote sensing. Remotely sensed data provide identifiable signatures for crop type, crop density, crop geometry etc. in order to perform agricultural survey and analysis[2].Therefore, image classification forms an key tool for examining the satellite images. Image classification is the process of creating the thematic maps from satellite imagery. Here the thematic information represents the informational representation of the image which will provide the spatial distribution of the particular theme.Classification and pattern recognition methods are used to identify and map crop areas from multispectral satellite imagery. Various image classification techniques available in this context in which specific algorithms like minimum distance, maximum likelihood, nearest neighbor are the common classifications which are used to identify surface objects and produce thematic land cover maps. Here themes are classified according to Region of Interest(ROI).Themes may cover vegetation,soil,forest etc. the main aim of the image classification is to classify each pixel of an image in to the various categories of the land cover. In general classification of the image may be Supervised or unsupervised classification.The results of these classifications were compared and it was concluded that Supervised Maximum likelihood classification could be able to define the spatial resolutions and reflectance well.The optimal classifier will strongly depend on the image type since image characteristics and various circumstances of the image may vary. Hence it is very desirable to select the appropriate classifier for the specific task.

II. DESCRIPTION OF THE PROPOSED METHOD

Spectral Mixture Analysis (SMA) is an alternative approach which is going to use mixed pixel approach. According to SMA each pixel is made up of number of varied spectral types. SMA is key technique that is used to measure the percentage of spectra in each land cover type for each pixel. SMA has been an successful technique used to classify the vegetation,forest types etc. Using this approach reflectance values has been derived from air/space borne sensor. The reflectance spectrum can be then deconvolved into linear mixture of spectra which contains different Ground truth components. Various methods on SMA has been developed in order to improve the mixed pixel classification and their proportions. Out of these, many of the techniques include Linear mixing approach. The objective of this study was to test the stability of a spectral mixture modeling method by applying the model to produce land-cover maps of coconut in the study area. Classification results are then compared with the ground truth data. SMA can be evaluated and performed based on Landsat-8 ETM data. Study area which will cover the Tumkur District, Karnataka, India. Thematic maps will be available at 30m resolution with six spectral bands.(excluding the panchromatic band and thermal band) (1: 0.45–0.52 μm; 2: 0.53–0.61 μm; 3: 0.63– 0.69 μm; 4: 0.78–0.90 μm; 5: 1.55–

1.75 µm; 7: 2.09– 2.35 µm). Following steps provides an general view of the proposed method.

a. Extract Landsat-8 imagery
b. Data Acquisition(available as Metadata)
c. Digital Number Calculation
d. Digital Number is converted into Radiance values
e. Accuracy of the classification can be determined.

III.STUDY AREA

Tumkur District, Karnataka, India is the study area we have choosen. The reason for this is we can see a huge amount of coconut trees are available throughout the year in this particular area. The location and the study area is as shown in Figure 1.

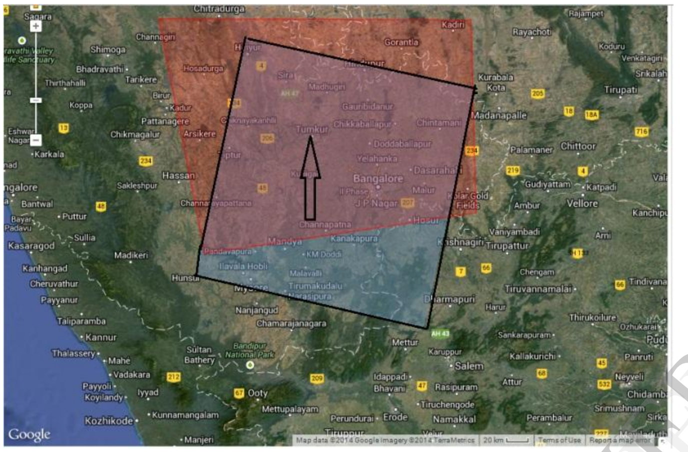

Figure 1.Study area(black box) –Tumkur district(black arrow) (Earth Explorer-2014)

SMA uses Linear Mixture model which will be applied for Six-band Landsat image. The mixture model becomes

Digital Number (DN)= Spectral Reflectance * Fraction coefficient for all the eight bands.

Digital Number obtained from the above analysis should be converted into satellite radiance values using Gain and Bias values extracted from the metadata.

Satellite radiance (L)=DN*Gain+Bias(for all the eight bands)

Where L is in terms of $mWcm^{-2}sr^{-1}$.

IV.CLASSIFICATION OF THE REMOTELY SENSED DATA

In this study, three different classification algorithms were performed for crop identification and multitemporal change detection. The first two of them are ISODATA unsupervised classification and Minimum distance supervised classification techniques which are two main pixel based classification algorithms and the last one is the object based classification algorithm.

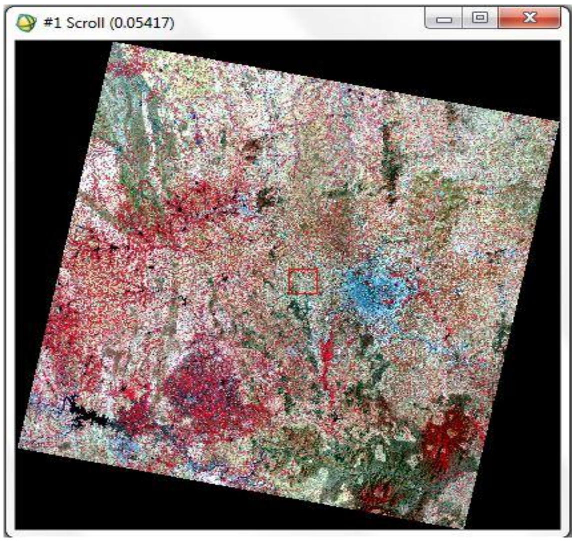

Figure 2. Study area obtained from the Landsat-8 (March_2014, Earth Explorer)

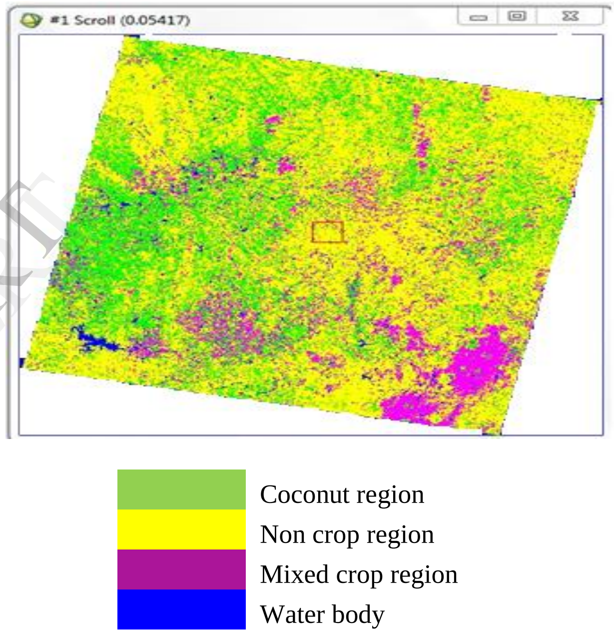

Figure 3. Minimum distance classification of the study area

Figure 2 and Figure 3 shows the study area obtained from Landsat-8 and Minimum distance classification of the study area respectively.

V. RESULTS AND DISCUSSION

A. Histogram Analysis

The histogram of an image can contain much useful information on the image information content. Using this tool, you can interactively change the mapping from the inputhistogram (that of the original image data) to the 'output histogram' (that which is displayed on the screen).Figure 4 shows the input and output histogram of the classified image.

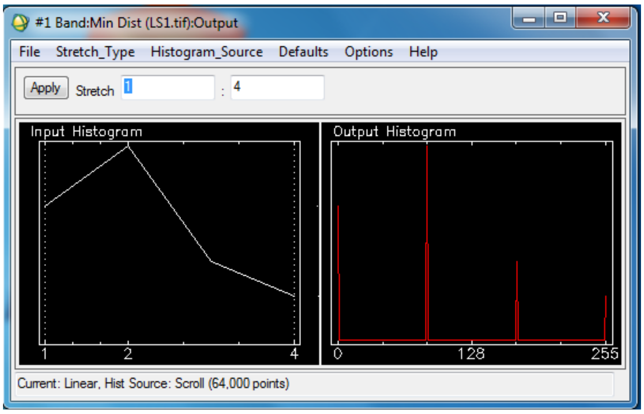

Figure 4. Input and output histogram plot of the classified image.

B. Scatterplot Analysis

Various peaks in the histogram help us to relate them to features of the imagery. Also you can display a 'cross-plot' of two histograms in a scatterplot as shown in Figure 5.

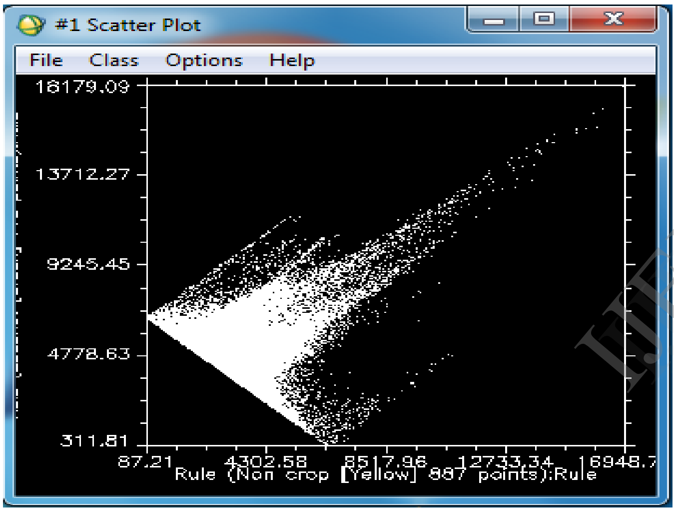

Figure: 5. Scatter plot for non-crop and coconut regions.

Use 2D Scatter Plots to interactively classify two bands of image data. If desired, you can have multiple scatterplots active simultaneously. Two-dimensional scatterplots use only the data in the Image window so quick interactive response is provided. You can select ROIs(Region of Interest) in the scatterplots and save them for use in other full band processing techniques.

Use Density Slice to select data ranges and colors for highlighting areas in a gray scale image. You can use data ranges in the densityslice coloring that are from the displayed image or from another image of the same size. Two different Density slice scatter plots for coconut region and non-crop region is as in Figure 6 and Figure 7.

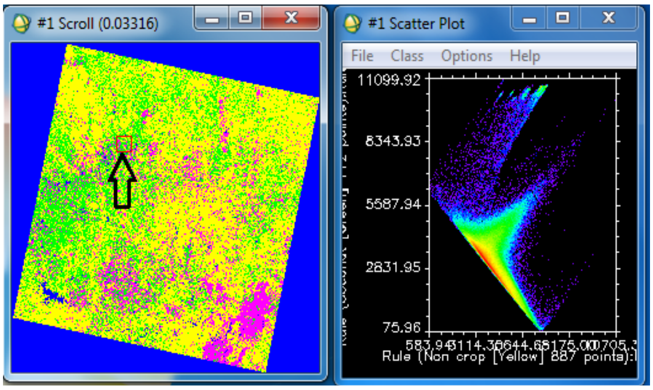

Figure 6. Density slice scatter plot for the black arrow mark region in which nearly 5587.94 pixels contains the coconut crop.

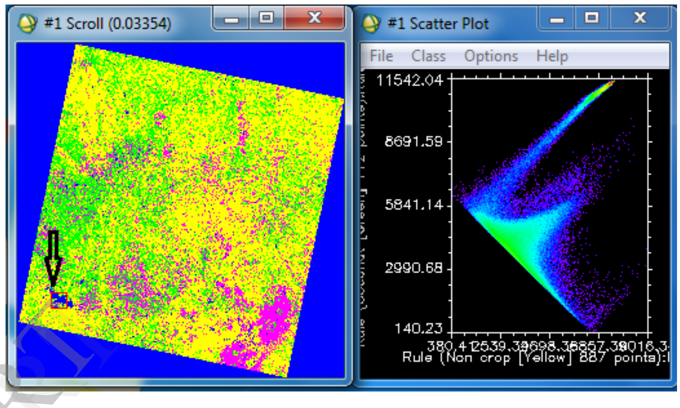

Figure 7. Density slice scatter plot for the black arrow mark region in which most of the region is covered by water.

VI. ACCURACY ASSESSMENT

Accuracy assessment for each classified image wasconducted based on the test data from GPS registeredground-truth points and fractional image. The error matrixwas created for coconut cover type. The sub pixel accuracyachieved for the coconut land-cover was 83.33% by usingSMA of DN values, while it was 88% for SMA of radiancevalues.Ground truth values obtained during the Accuracy Assessment is as shown in table 1.

Table 1. Ground Truth values obtained for the classification

Class	Ground Truth (Pixels) Total
Unclassified	0
Water Body [B	17367720
Non crop [Yel	25092589
Coconut [Gree	10282746
Mixed Crop [M	5558216
Total	58301271

VI. CONCLUSION

This paper demonstrates the possibilityof using SMA as a sub pixel technique to mapcoconut land-cover in the study area. The results show considerable capability ofthis technique to classify the main land-cover types. It isclear that this technique gives more accurate results incase of homogenous coconut land-cover. SMA could beused successfully to classify different vegetation coversin intensive agricultural areas. It is also to be noted thatthe method is easy to implement and has low computationalcost.

ACKNOWLEDGMENT

Authors are grateful to Mrs. Latha B M, Assistant professor, G M Institute of Technology, Davangere, Karnataka, for all the technical guidance, encouragement and analysis of the data throughout this process.

REFERENCES

[1] Spectral mixture analysis for subpixelclassification of coconut, C. Palaniswami*, A. K. UpadhyayandH. P. MaheswarappaCentral Plantation Crops Research Institute, Kasaragod 671 124, India

[2] Identification of crop areas using SPOT_5 data, Cancut ORMECI, UgurALGAncI and ElifSERTEL,Turkey

[3] Campbell, J. B., Introduction to Remote Sensing, The Guilford Press, New York, USA, 1996, 2nd edn.

[4] Atkinson, P. M., Cutler, M. E. J. and Lewis, H., Mapping subpixel proportional cover with AVHRR imagery. Int. J. Remote Sensing, 1997, **18**, 917–935.

[5] DeFries, R. S., Hansen, M. C. and Townshend, J. R. G., Global continuous fields of vegetation characteristics: A linear mixture model applied to multi-year 8 km AVHRR data. Int. J. Remote Sensing, 2000, **21**, 1389–1414.

[6] Jasinski, M. F., Estimation of subpixel vegetation density of natural regions using satellite multispectral imagery. IEEE Trans. Geosci. Remote Sensing, 1996, **34**, 804–813.

[7] DeFries, R. S., Townshend, J. R. G. and Hansen, M. C., Continuous fields of vegetation characteristics at the global scale at 1 km resolution.J. Geophys. Res., 1999, **104**, 16911–16925.

[8] Settle, J. and Drake, N. A., Linear mixing and the estimation ofground cover proportions. *Int. J. Remote Sensing*, 1993, **14**, 1159–1177.

[9] Bateson, A. and Curtiss, B., A method for manual endmemberselection and spectral unmixing. *Remote Sensing Environ.*, 1996,**55**, 229–243.

[10] Foody, G. and Cox, D., Sub-pixel land cover composition estimationusing a linear mixture model and fuzzy membership functions.*Int. J. Remote Sensing*, 1994, **15**, 619–631.

[11] Huguenin, R. L., Karaska, M. A., Van Blaricom, D. and Jensen,J. R.,Subpixel classification of bald cypress and tupelogumtreesin Thematic apper imagery. *Photogramm. Eng. Remote Sensing*,1997, **63**, 717–725.

[12] Freek van der Meer, Image classification through spectral unmixing.In*Spatial Statistics for Remote Sensing*, Kluwer AcademicPublishers, 1999, pp. 185–193.

[13] Samia Ali, Use of spectral and temporal unmixing for crop identificationusing multi-spectral data. Ph D thesis, ITC, InternationalInstitute For Geo-Information Science and Earth Observation Enschede,The Netherlands, 2002, pp. 1–63.