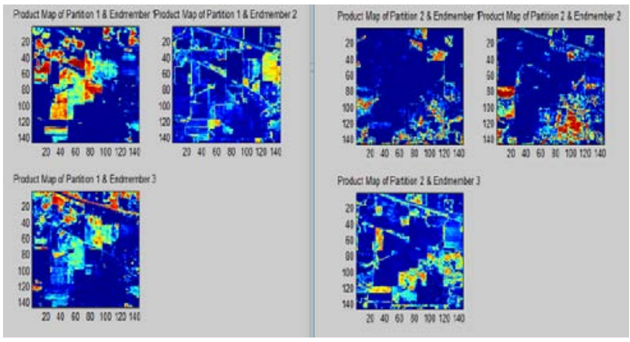

Figure 6 b Product map estimates of the test site obtained

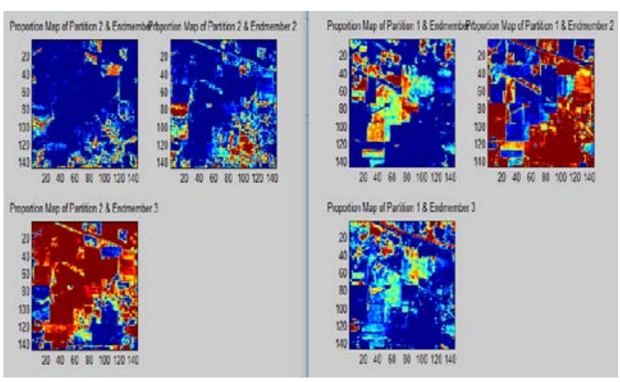

Figure 6 c Proportion map estimates of the test site obtained

4. Conclusions

In our work, species classification was performed by applying to different classification algorithms. The input hyperspectral data was processed. The spectral data of the particular set of tree species were obtained which led to the comparison of their spectral absorption. By using spectral unmixing method the end member extraction process was performed thus understanding the pure pixel classification and also the computation complexity reduction. With the improvement from the PCCOMEND algorithm, endmember detection and spectral unmixing algorithm that finds multiple sets of endmembers is presented. Multiple sets of endmembers and abundances are found using spectral unmixing method. The results indicate that the piecewise convex representation estimates endmembers that better represent hyperspectral imagery composed of multiple regions where each region is represented with a distinct set of endmembers. From the studies we obtained results that showed accuracy of SVM was 84% while LDA 82%. Thus indicating which algorithm works best for test site. The spectral unmixing of a hyperspectral data leads to better knowledge about the the abundances and the end member details of the particular test area thus providing more information regarding the test area.

5. Acknowledgement

I would like to express my gratitude to my Professor, Jacob Thomas, whose knowledge and assistance added considerably to my graduate experience. I would like to thank the Dean of Research and Development Dept. of my college, Dr. Milind Thomas, for the motivation he provided me in my project.

6. References

[1] James Cussens, "Machine Learning", IEEE Journal of Computing and Control, Vol. 7, No. 4, pp 164-168, 1996.
[2] Tom M. Mitchell, "Machine Learning: A Guide to Current Research", The Springer International Series in Engineering and Computer Science Series, McGraw Hill, 1997.
[3] Victoria J. Hodge and Jim Austin, "A Survey of Outlier Detection Methodologies", Artificial Intelligence Review, Vol. 22, No. 2, pp. 85-126, 2004
[4] Hugo Jair Escalante, "A Comparison of Outlier Detection Algorithms for Machine Learning", CIC-2005 Congreso Internacional en Computacion-IPN, 200
[5] N. J. Nilsson, "Learning Machines: Foundations of Trainable Pattern-Classifying Systems", First Edition, New York: McGraw-Hill, 196
[6] C. Chang and C. Lin. "LIBSVM: A library for support vector machines," ACM Transactions on Intelligent Systems and Technology, 2(3), pp.27:1-27:27, 2011. Software available at http://www.csie.ntu.edu.tw/ cjlin/libsvm
[7] J. Quinlan, "C4.5: Programs for machine learning", San Francisco, CA: Morgan Kaufmann, 1986.
[8] Ramon Lopez De Mantaras and Eva Armengol, "Machine learning from examples: Inductive and Lazy methods", Data and Knowledge Engineering, Vol. 25, No. 1-2, pp. 99-123, 1998.
[9] Mats Erikson. Segmentation and Classification of Individual Tree Crowns. Doctoral Thesis
[10] Aijun An and Nick Cercone, "Discretization of continuous attributes for learning classification rules", Third PacificAsia Conference on Methodologies for Knowledge Discovery & Data Mining, Vol. 1574, pp. 509-514, 1999.
[11] http://www.grss-ieee.org/community/technical-committees/data-fusion/
[12] Bioucas-dias and nascimento," hyperspectral subspace identification", ieee transactions on geoscience and remote sensing, vol. 46, no. 8, august 2008.
[13] Gonzalez, R.C., Woods R.E. (1992), Digital Image Processing, Addison-Wesley Publishing Company, Reading, Massachusetts, USA, 1992. 716
[14] Alina Zare, Ouiem Bchir, Hichem Frigui and Paul Gader (2013) Piecewise Convex Multiple-Model Endmember Detection and Spectral Unmixing, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 51, NO. 5, MAY 2013.