Assessment of Image Classifications Using Compressed Multispectral Satellite Data (MSD)

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ABSTRACT: *In the present study Satellite Image Processing (SIP) technique is applied on ASTER (Advance Spaceborne Thermal Emission and Reflection Radiometer) satellite image. A comprehensive spectral library of rice crop varieties: Hybrid-6129 (IET 18815), Pant Dhan-19 (IET 17544), Pusa Basmati-1 (IET-18990) and Pant Dhan-18 (IET-17920) has been developed with Blue (0.56 nm), Red (0.66 nm) and NIR (0.81 nm) spectral bands. The conventional ASTER image is classified using ML (Maximum Likelihood) classifier. The PCA (Principal Component Analysis) transformation is also applied for feature extraction to select an optimum subset of data in term of classification accuracy. Four PCs (Principal Components) images selected for PCA classification. The conventional spectral classification accuracy for rice mapping is 79.5%, which is improved up to 84.5% with PCA classification.*

Keywords: SIP, PCA and ML.

1. Introduction

Multispectral Satellite Image Processing (SIP) is a collection of techniques for the manipulation of high-density and multi-date, multi-stage, multi-polarized, multi-direction and multi-spectral satellite images by computers. SIP is an application of DIP (Digital Image Processing) having a great potential to identify specific plant species in vegetation covered area. It is widely used in crop protection, estimation of physiology and detection of biochemical components like nitrogen, pigment content [1]-[4], agricultural monitoring [5]-[6], mapping of cultivate area [7], growth and estimation of crops from local to global scale [8]-[9]. For sustainable agriculture management there is no suitable infrastructure to monitor the rice crop and its varieties. The traditional method of compiling statistics on rice-crop acreage from different sources is time consuming and expensive. In addition, the information collected is often rough and unreliable for agricultural planners, managers or decision makers on regional and national scale. The present study focuses on analysis of conventional and compressed imagery data derived from ASTER L1B (Blue, Red and NIR) data on pixel scale to extract the meaningful information in rice based agriculture system. The goal of this research is to develop a comprehensive digital spectral library of rice-crop varieties using conventional and PCA transformed multispectral satellite image and mapping in humid tropical agriculture system in the state of Uttarakhand, India.

2. Study Area and data used

The study area is surrounded with Ganga River (Water Body), Habitation (Lakshar Town), Forest and the boundary of the satellite data respectively. It lies between 29°452 N, 78°72 E and 29°442 N, 78°82 E. Uttaranchal is an agrarian state. About 80% of the population of the state is dependent on agriculture for its livelihood. 12% of the available land is irrigated and 64% are fed by natural springs.

In this research high-resolution (15-m) EOS-satellite ASTER imagery L1B data is used for image accuracy assessment of the training site. It is an advanced multispectral imager that was launched on board NASA's Terra spacecraft in December, 1999. The ASTER instrument produces two types of Level-1 data: Level-1A and Level-1B. ASTER L1A data are formally defined as reconstructed, unprocessed instrument data at full resolution. They consist of the image data, the radiometric coefficients, the geometric coefficients and other auxiliary data without applying the coefficients to the image data, thus maintaining original data values. The L1B data are generated by applying these coefficients for radiometric calibration and geometric resampling. Use of ASTER data for agriculture applications and management also requires atmospheric correction [10]. ASTER L1 B data of 3rd September 2004 at 5:36 am is used, because the combination of wide spectral coverage with 14 spectral bands from the visible to the thermal infrared and high spatial resolution varies with wavelength: 15 m in the visible and near-infrared (VNIR), 30 m in the short wave infrared (SWIR), and 90 m in the thermal infrared (TIR) allows ASTER to discriminate amongst a large variety of surface materials, for geological studies, vegetation and ecosystem dynamics, hazard monitoring.

3. Methodology

3.1 Geometric Correction

The image is geometrically corrected to UTM projection with WGS-84 geographic datum in zone 44. Figure 1, shows the subset of data (97 pixels x 82 pixels) used for supervised classification.

3.2 Atmospheric Correction Using FLAASH

The atmospheric correction of satellite is a quantitative image processing technique to reduce the atmospheric influence in object reflectance value and atmospheric mixing. FLAASH (Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercube) is an ENVI utility for handling particularly stressing atmospheric conditions, such as the presence of clouds [11]. FLAASH tool is developed to improve the wavelength values of NIR, VNIR and SWIR bands in the electromagnetic spectrum. The input radiance image is converted in BIL (Band Interleaved by Line) or BIP (Band Interleaved by Pixel) format to get the celebrated radiance value in floating-point. In the present study this tool is implemented on ASTER L1B data with Blue (0.56 nm), Red (0.66 nm) and NIR (0.81 nm) spectral bands. The centre water column value from FLAASH is found 4.11gm/cm2 and eliminated to improve the reflectance of the image.

Figure 1: False color image subset of 1.46x1.23km (97x82 pixels) of Mahtoli village and its nearby region by ASTER with a spatial resolution of 15 m per pixel.

Table 1: Training classes and selected no. of pixels with color composition used in classification.

S. No.	Class Type	No. of pixels	Legend
1	RICE 1	30	
2	RICE 2	80	
3	RICE 3	31	
4	RICE 4	12	
5	OPEN FIELD	79	
6	SHRUB	15	
7	HABITATION	18	
8	TREE	26	
9	VEG 1	16	
10	VEG 2	32	
11	VEG 3	62	
12	VEG 4	45	
13	VEG 5	111	
14	MOISTURE	5	
Total Sample Pixels		562	

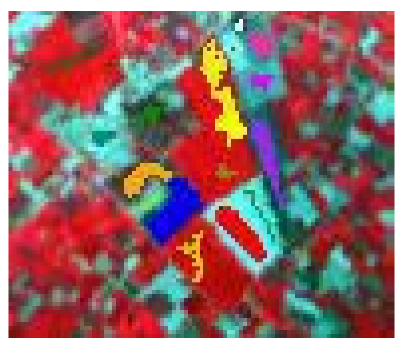


Figure 2: False color image subset (97x82 pixels) with ROIs (training classes) of Mahtoli village and its nearby region by ASTER with a spatial resolution of 15 m per pixel.

3.3 Development of Digital Spectral Library

In DIP the reflectance value of an object can be represented in form of graph or curve and called spectral signature [12]. The multiple portions of the subset known as ROIs (Regions of Interest) with unique color composition are selected for digital library of spectral signatures and classification are listed in Table 1 and shown in Figure 2. For intra-classes variability and unique discrimination of all objects a digital library of spectral signature is developed for RICE crop and its varieties are shown in Figure 3. The four prime varieties Hybrid-6129 (IET 18815), Pant Dhan-19 (IET 17544), Pusa Basmati-1 (IET-18990) and Pant Dhan-18 (IET-17920) [13] are represented by thick Brown, Blue, Green and Black lines.

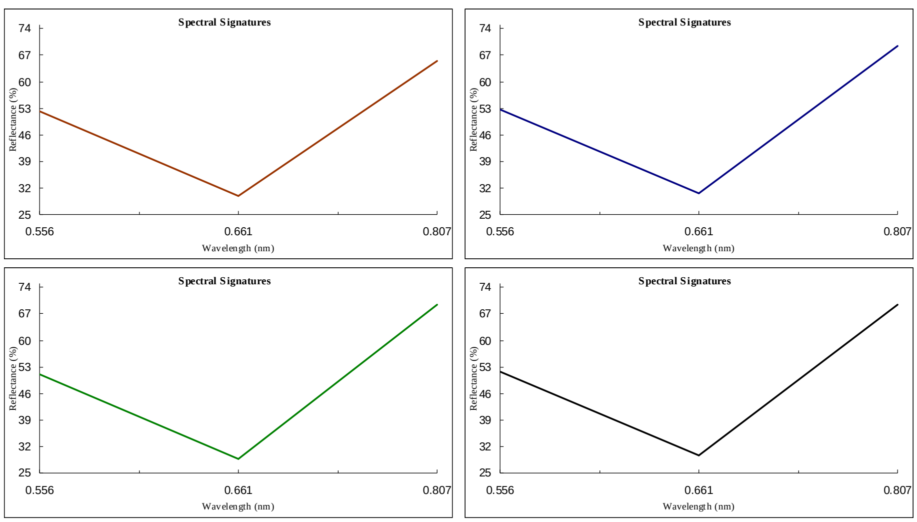
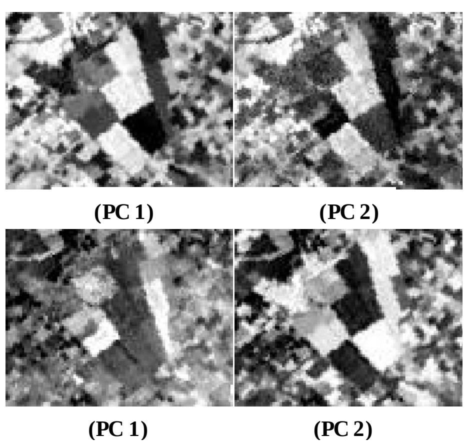


Figure 3: Typical ASTER (VNIR) spectra of rice varieties, (a) RICE 1 (Hybrid-6129), (b) RICE 2 (Pant Dhan-19), (c) RICE 3 (Pusa Basmati-1) and (d) RICE 4 (Pant Dhan-18).

3.4 PCA (Principal Component Analysais) Transformation

The PCA (Principal Component Analysis) transformation is a well established data compression tool that can be applied on multispectral data to reduce its dimensionality for feature extraction and classification. Dimensionality reduction refers to the process by which the main components attributing to the spectral variance of the data set are identified. This is also refers to removal of noise and data redundancy. The PCA transformation with covariance and correlation matrix may be applied to accomplish this task [15].

In the present study PCA transformation with correlation matrix is used to reduce dimensionality of ASTER data. The new image layers are known PCs (Principal Components) and image pixels are represented by eigenvalues. The dimensionality of integrated data is determined by examining these values as shown in Figure 4 and Figure 5. The integrated data of four components, 82.5% of the data variance is explained by first principal component (PC1). Another 17.5% is covered in next three PCs.



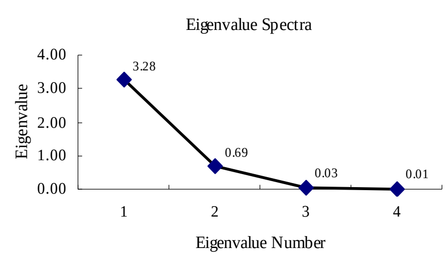


Figure 4: Regular PCs bands after PCA with correlation matrix.

Figure 5: Eigenvalues spectra after PCA with correlation matrix.

3.6 Maximum Likelihood (ML) Classification

The Maximum Likelihood Classifier (MLC) [15] is used to classify 14-landcover classes as listed in Table 1; in two phases, the first phase of classification is performed on conventional multispectral ASTER image and second on PCA transformed image. The supervised classification is performed by ENVI 4.5 image processing software. The training site and location of the study area is registered using hand-held GPS. According to the ground survey and discussion with local farmers, the land culture is not uniform in the study area. Therefore the RICE class has been divided into four different classes. The Google image of the study area has been used as a reference image to assist in identifying the land cover. A total 562 pixels have been chosen for training classes (samples) out of 7954 pixels. The classification accuracy is computed in the form of a confusion or error matrix by comparing a classification result with ground truth information. Each diagonal element of the confusion matrix is the percent of predicted classes that agree with the ground truth assignment of the pixel; whereas the off diagonals are those pixels that are misinterpreted as (or confused with) an alternative class.

3.6.1 Spectral Classification

The overall classification accuracy based on different features in VNIR region is shown in Figure 6 and summarized in Table 2**.** Table 2 shows the classification confusion matrix with 79.5% (447/562) overall accuracy and 0.77 kappa coefficient. There is observable confusion between the RICE 1 and RICE 4 class. The RICE 1 class exhibits confusion with RICE 4 (3.33%). RICE 2 exhibits major confusion with the RICE 4 (51.25%) class. RICE 3 class shows signs of confusion with the RICE4 (35.48%) class. The analysis of the confusion matrix shows that RICE 4 class do not have the case of confusion with any other class.

3.6.2 PCA Transformation Classification

The classification of PCA transformed image and confusion matrix has been shown in Figure 7 and Table 3. Table 3 shows the classification confusion matrix with 84.52 % (475/562) overall accuracy and 0.83 kappa coefficient. The RICE 1 and RICE 2 classes are classified 100% after PCA classification. There is no observable confusion between the RICE1 and RICE4 class after the integration. The classification accuracy of RICE 2 and RICE 3 classes is also improved from 41.50% to 80.00% and 64.52% to 76.42% respectively.

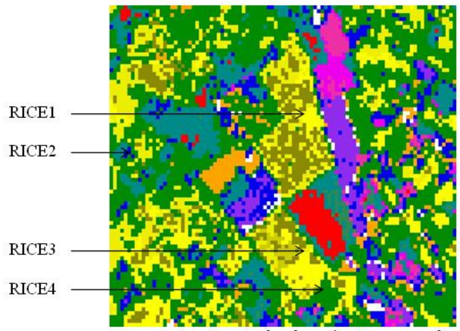


Figure 6: Spectral classification result based on Maximum Likelihood approach with 14- land cover.

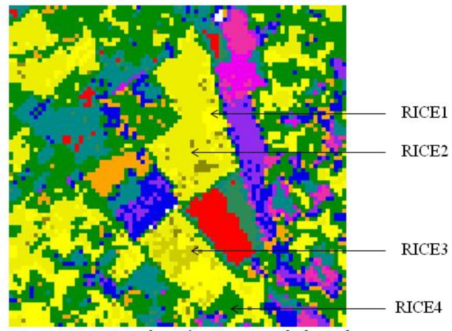


Figure 7: PCA classification result based on Maximum Likelihood approach with 14- land cover classes.

4. Result Analysis

Classification of PCA image shows the RICE 2, RICE 3, TREE, VEG 2, VEG 3, VEG 4 and VEG 5 land cover classes are mixed in nature, except RICE 1, RICE 4, OPEN FIELD, SHRUB, HABITATION, VEG 1 and MOISTURE classes. The spectral identities of RICE 2 and RICE3 are heavily mixed together due the similarity of the crop species and their respective water content, which is verified after ground survey. On the other hand, other classes like TREE, VEG 2, VEG 3, VEG 4 and VEG 5 intermixing are acceptable, in context of their distribution characteristics. When PCA transformation is applied on spectral image, it provides a significant improvement in the classification of RICE crop varieties. The result shows that the four types of rice crops have been classified more accurately using PCA transformed classification.

5. Conclusion

The aim of this study is to develop a new classification approach using PCA transformed digital image. The classification accuracy of PCA image is increased effectively than conventional spectral classification from 79.5% to 84.5%. The results show that the Maximum Likelihood Classifier (MLC) gives more accurate results than others classification algorithms to map the agriculture area using PCA transformed multispectral ASTER L1B data.

The PCA image classification is beneficial to increase the accuracy of vegetation classes than conventional spectral classification.

6. References

[1] L. D. Hinzman, M. E. Bauer, and C. S. T. Daughtry. "Effects of nitrogen fertilization on growth and reflectance characteristics of winter wheat". Remote Sensing of Environment, 19(1): 47-61, 1996.

[2] R. F. McMurtrey, E. W. Chappella, M. S. Kim J. J. Meisinger. "Distinguishing nitrogen fertilization levels in field corn (Zea mays L.) with active induced fluorescing and passive reflectance measurements". Remote Sensing of Environment, 47(1):36-44, 1994.

[3] K. Diker and W. C. Bausch. "Potential use of nitrogen reflectance index to estimate plant parameters and yield of maize". Bio System Engineering, 85(4):437-447, 2003.

[4] L. Chen, J. F. Huang, F. M. Wang and Y. L. Tang. "Comparison between back propagation neural network and regression models for estimation of pigment content in rice leaves and panicles using hyperspectral data". International Journal of Remote Sensing, 28(16):3457-3478, 2007.

[5] D. Casanova, G. F. Epema and J. Goudriaan. J. "Monitoring rice reflectance at field level for estimating biomass and LAI". International Journal of Remote Sensing, 55(1-2):83-92, 1998.

[6] K. P. Gallo and T. K. Flesh. "Large-area crop monitoring with the NOAA AVHRR: estimating the silking stage of corn development". Remote Sensing of Environment, 27, pp. 73–80, 1989.

[7] H. Fang, H. Liu and H. Xuan "Using NOAA AVHRR and Landsat TM to estimate rice area year-by-year". International Journal of Remote Sensing, 19, pp. 521–525. 1998.

[8] B. C. Reed, J. F. Brown, D. Vanderzee, T. R. Loveland, J. W. Merchant and D. O. Ohlen. "Measuring phenological variability from satellite imagery". Journal of Vegetation Science, 5, pp. 703–714, 1994.

[9] B. F. T. Rudorfe and G. T. Batista. "Wheat yield estimation at the farm level using TM Landsat and agrometeorological data. International Journal of Remote Sensing, 12, pp. 2477–2484, 1991.

[10] Aleks Kalinowski and Simon Oliver. "ASTER Mineral Index Processing Manual". Compiled by Remote Sensing Applications Geoscience Australia, 2004.

[11] A. L. Berk, , L. S. Bernstein, G. P. Anderson, P. K. Acharya, D. C. Robertson, J.H. Chetwynd and S. M. Adler-Golden. "MODTRAN Cloud and Multiple Scattering Upgrades with Application to AVIRIS". Remote Sensing of the Environment, Vol. 65, pp. 367-375, 1998.

[12] T. M. Lillesand and R. W. Kiefer. "Remote Sensing and Image Interpretation", John Wiley & Sons, Inc. New Jersey, 1999.

[13] Division of Crop Science, Indian Council of Agricultural Research, New Delhi, 2007.

[14] R. D. Jackson, P. N. Slater and P. J. Pinter. "Discrimination of Growth and Water Stress in Wheat by Various Vegetation Indices through Clear and Turbid Atmospheres". Remote Sensing of the Environment 15:187-208, 1993.

[15] J. A. Richards. "Remote Sensing Digital Image Analysis: An Introduction", Springer-Verlag, Berlin, Germany, p. 240, 1999.

Table 2: Phase 1 (Maximum Likelihood) classification of VNIR ASTER image.

CLASS	RICE1	RICE2	RICE3	RICE4	OPENFIELD	SHRUB	HABITATION	TREE	VEG1	VEG2	VEG3	VEG4	VEG5	MOISTURE	TOTAL
RICE1	**97.67**	**0.00**	**0**	**0**	0	0	0	0	0	0	0	0	0.90	0	5.34
RICE2	**0**	**41.50**	**0**	**0**	0	0	0	0	0	0	0	0	0	0	6.96
RICE3	**0**	**0.00**	**64.52**	**0**	0	0	0	0	0	0	0	0	0	0	3.56
RICE4	**3.33**	**51.25**	**35.48**	**100.00**	0	0	0	0	0	0	0	0	0	0	11.57
OPEN FIELD	0	0	0	0	97.47	0	0	0	0	0	0	0	0	0	13.70
SHRUB	0	0	0	0	0	46.67	0	0	0	0	0	0	0	0	1.25
HABITATION	0	0	0	0	2.53	53.33	100.00	0	0	0	0	0	0	0	4.98
TREE	0	1.25	0	0	0	0	0	84.62	0	0	0	0	0	0	4.80
VEG1	0	0	0	0	0	0	0	0	100.00	3.13	0	0	0	0	3.02
VEG2	0	0	0	0	0	0	0	0	0	96.88	0	0	0	0	5.52
VEG3	0	0	0	0	0	0	0	0	0	0	95.16	0	40.54	0	18.51
VEG4	0	0	0	0	0	0	0	11.54	0	0	0	95.56	0	0	8.36
VEG5	0	0	0	0	0	0	0	0	0	0	4.84	0	45.95	0	9.61
MOISTURE	0	0	0	0	0	0	0	3.85	0	0	0	4.44	8.11	100.00	3.02
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 3: Phase 2 (Maximum Likelihood) classification of PCA transformed image.

CLASS	RICE1	RICE2	RICE3	RICE4	OPENFIELD	SHRUB	HABITATION	TREE	VEG1	VEG2	VEG3	VEG4	VEG5	MOISTURE	TOTAL
RICE1	**100.00**	**0.00**	**0**	**0**	0	0	0	0	0	0	0	0	0	0	5.52
RICE2	**0**	**80.00**	**3.23**	**0**	0	0	0	0	0	0	0	0	0	0	11.57
RICE3	**0**	**1.25**	**77.42**	**0**	0	0	0	0	0	0	0	0	0	0	4.45
RICE4	**0**	**18.75**	**19.35**	**100.00**	0	0	0	0	0	0	0	0	0	0	5.87
OPEN FIELD	0	0	0	0	100.00	0	0	0	0	0	0	0	0	0	14.06
SHRUB	0	0	0	0	0	100.00	0	0	0	0	0	0	0	0	2.67
HABITATION	0	0	0	0	0	0	100.00	0	0	0	0	0	0	0	3.20
TREE	0	0	0	0	0	0	0	92.31	0	0	0	0	3.60	0	4.98
VEG1	0	0	0	0	0	0	0	0	100.00	3.13	0	0	0	0	3.02
VEG2	0	0	0	0	0	0	0	0	0	96.88	0	0	0	0	5.52
VEG3	0	0	0	0	0	0	0	0	0	0	96.77	0	44.14	0	19.40
VEG4	0	0	0	0	0	0	0	7.69	0	0	0	97.78	0	0	8.36
VEG5	0	0	0	0	0	0	0	0	0	0	3.23	0	47.75	0	8.79
MOISTURE	0	0	0	0	0	0	0	3.85	0	0	0	2.22	2.70	100.00	1.60
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00