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Development of Spectral Signatures and Classification of Sugarcane using ASTER Data

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ABSTRACT

Satellite remote sensing techniques can provide resource managers an efficient and economical means of acquiring timely data for the development and management of natural resources. In comparison with traditional methods, these techniques have inherent properties of being able to provide synoptic observations with high observational density over relatively large areas. Multispectral data have been successfully used for many remote sensing projects of relatively large areas for data extraction and statistical analysis of natural resources. An interdisciplinary approach that links the field of Multispectral remote sensing, statistical data mining and sugarcane systems and establish new relationship to develop spectral signatures is proposed in present study. The present study mainly aims at the analysis of sugarcane vegetation identification, development of spectral signature library, Classification in VINR spectral region and mapping using ASTER data.

Keywords: Remote Sensing, Multispectral data, ASTER, VINR, Spectral Signatures, Sugarcane.

1. INTRODUCTION

One of the primary applications of remote sensing is to identify patterns of vegetation distribution on the ground and to assess changes in vegetation over time. Remote sensing has several advantages over traditional methods of vegetation mapping [1]. Vegetation classes that are identifiable by other measurement methods must produce a distinct spectral signature in order to be distinguished by remote sensing. An advantage of remote sensing is that the image represents the population given that measurements are made across the entire area of interest, though the resolution of the imagery may limit the degree of accuracy in the interpretation.

Identifying the species composition of vegetated areas is still a major challenge for remote sensing [2]. Computers are better able to discern between changes in the spectral signatures of an object but people have a better intuitive sense of the spatial pattern produced by a given type of vegetation. Recent advances in classification methods aim to simulate the heuristic decision making rules followed by trained image interpreters and incorporate them into automated classification algorithms. Ground-truthing is always required to verify the accuracy of classification by any method.

Remote sensing and its associated image analysis technology provide to access the spatial information on a planetary scale. New detectors and imaging technologies are increasing the capability of remote sensing to acquire digital spatial information at a vary fine resolutions in an efficient manner [3]. Therefore, up-to-date information of features and phenomena on the earth can be derived in a short duration of time.

The use of remote sensing for mapping sugarcane crops has already been attempted by several researchers [4; 7; 10]. However, its specific application to sugarcane variety mapping has been rarely exploited in. However, the advent of Multispectral sensors that can potentially discriminate subtle differences in plant bio-physical and bio-chemical attributes has provided new opportunities [9].

Therefore, the aim of the study has been to examine the potential of Multipsectral Data sensor (ASTER) to discriminate and map sugarcane varieties. The specific objectives are:

a. To develop the spectral signature of sugar cane;

b. To assess the spectral separability of different varieties of sugarcanes;

c. To determine plant attributes (e.g. leaf pigments, leaf internal structure, water absorption, etc.) that will provide the potential discriminating features for sugarcane variety mapping.

2. MULTISPECTRAL IMAGERY DATA

Since 1972 researchers are using Multispectral scanner in the field of remote sensing. They produce a digital imagery spectral data that can be used broadly in remote sensing. A lot of research work has been done using this data in different research fields. The, Multispectral remote sensing (MRS) can be defined as a imaging system with two or more bands but 12 to 15 bands remains the practical maximum in different cases. A band is defined as a portion of spectrum with a given spectral width, such as 10 to 50 nm. Multispectral system are not continuous in there coverage of spectrum. The band can be spectrally narrow or wide. Many satellite systems traditionally had wide (10-200nm) bands while some aircraft systems have discrete narrow bands(around 10 nm).

A primary goal of using multispectral remote sensing image data is to discriminate, classify, identify as well as quantify materials present in the image. The usual procedure for analyzing remote sensing image is to use supervised classification. Here, the choice of classifier and the number of bands chosen for classification are taken into consideration as these may affect the results.

Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) is a high spatial, spectral and radiometric multispectral imager with 14 bands and are more widely used for land cover applications. VNIR bands of ASTER data are far better both spectrally and spatially than panchromatic 15 m band on LANDSAT 7 ETM+. SWIR bands are used for indentifying various soil types, minerals and rocks. VNIR and SWIR are together used for landuse pattern and vegetation. VNIR and TIR are used in the study of coral reefs and glaciers. As VNIR bands are provided with stereoscopic capability, there are used to generate local surface DEM's and also to observe local topography, cloud structure, volcanic plumes and glacial changes.

The capabilities of individual's sensors and the fused outputs were evaluated by visual observation and by image classification. It was observed that fusion of images obtained from these two sensors resulted in enhancement of land cover features for improved mapping of the same.[11], used ASTER image with 14 bands from spectral regions of VNIR to perform the land cover classification using the selected image classification approaches. Supervised classification result proved that different sensor system combinations contribute to land cover information extraction.

Spectral library for Indian region is not available and preparing libraries through spectro-radiometer is a time consuming job. Therefore, to start use of hyperspectral classification, hyperspectral imagery has been used to generate spectral libraries for broad landuse landcover and then the spectral signatures were used to classify the images. [12].

Considering the advantages of ASTER data and analysis methodology, the Multispectral algorithms such as Maximum likelihood algorithm and NDVI are used for classification.

3. STUDY AREA

The study area village Sultanpur, district Haridwar is located in Uttarkhand, India lies between 29°45′32.72″E, 78°7′16.86″N and 29°44′54.47″E, 78°8′12.09″N with area of 11,9210 ha. Uttarkhand is an agrarian state. About 80% of the population of the state is dependent on agriculture for its livelihood. 60% of the available land is irrigated.

4. DATA USED

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data, a high-resolution (15-m) EOS-satellite imaginary for the area is acquired the 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). Each ASTER scene covers an area of 60 × 60 km. ASTER L1 data of 3rd September 2004 at 05:36 am is used, as it is especially suitable for mapping of irrigated area, growing stages of crops and classification.

5. METHODOLOGY

5.1 Geometrically Correction

The three bands from ASTER data, which cover the VNIR (0.52-0.86μm) wavelengths, are initially selected for classification. The image is geometrically corrected to UTM projection with WGS-84 geographic datum in zone 43 A subset of the image (97 pixels × 82 pixels) has been used in the image classification (Figure 1).

Fig 1: False Color Image Subset of Sultanpur Village by ASTER with a Spatial Resolution of 15 m

5.2 Development of Spectral Signatures

Digital imagery obtained in distinct area of the electromagnetic spectrum sensors used in vegetation monitoring are typically in the green, red, and near infrared portion of spectrum, the reflectance value of an object can be represented in form of graph or curve and called spectral signature [8]. In this study, for intra-classes variability and unique discrimination of all objects, a digital library of spectral signature is developed and shown in Figure 2. The Five prime SUGARCANE classes are represented by Magenta, Maroon, Purple, Orange, Blue, lines and other classes (vegetation/non-vegetation) by dotted lines in the training site.

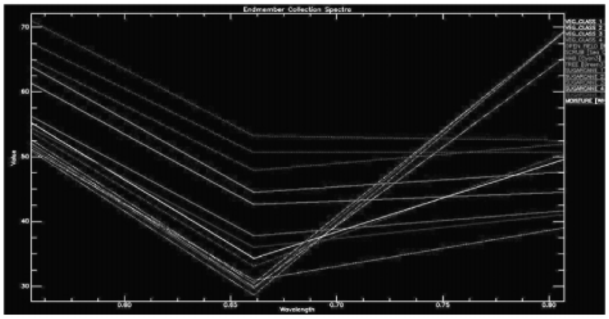

Fig 2: Spectral Signatures of Sugarcane and Land Cover Classes Cover Classes in VNIR Region

5.3 Spectral Classification

Classification is the processing of assigning pixels to various classes. In supervised classification [13], the basic steps followed are (1) select training samples which are representative and typical for that information class; (2) perform classification after specifying the training samples set and classification algorithms; (3) assess the accuracy of the classified image through analysis of a confusion matrix which is generated using test areas as reference data.

A thorough knowledge and understanding of spectral characteristics of various earth surface objects is required for identifying the classes and collecting region of interest [14]. The homogenous areas are identified through region of interest (ROI) in the image to form the training samples (set of data of known identity for a class or feature) for all of the information classes. In the first phase of classification 14-classes have been identified in which 9-classes are selected as vegetation group and remaining 4-classes in non-vegetation. Statistics and Spectral signatures are extracted from the training areas collected.

To get the exact location of the training site and the location of the fields, a hand-held GPS is also used.

5.3.1 The Maximum Likelihood Algorithm

This algorithm assigns a pixel to a class on the basis of its probability of belonging to a class whose mean and covariance are modelled as forming a normal distribution in multispectral feature space

Although the Maximum Likelihood algorithm is a parametric classifier-it is quite possible for the resulting multivariate normal distributions derived from training pixels to overlap. When this occurs the feature space decision boundaries take a quadratic form and are proportional to the covariance exhibited by each class

The advantage of the Maximum Likelihood algorithm is that it takes the variability of the classes into account by using the covariance matrix and in our case is the most accurate algorithm when using the ENVI+IDL image processing software. However, the computation time of this equation is long and it tends to over classify classes with large spectral variabilities. As the algorithm is parametric it relies on the data in each band exhibiting a normal distribution (which may not be the case for spectrally variable land cover types) [5].

Table 1
Training Classes and Testing Pixels

S.NO.	*Land Cover Class*	*No. of pixels*
1.	SUGARCANE 1	15
2.	SUGARCANE 2	29
3.	SUGARCANE 3	58
4.	SUGARCANE 4	47
5.	SUGARCANE 5	110
6.	MOSTURE	07
7.	VEG 1	31
8.	VEG 2	79
9.	VEG 3	29
10.	VEG 4	14
11.	OPEN FIELD	81
12.	SCRUB	18
13.	HAB	19
14.	TREE	28

A total 2500 pixels have been chosen for training classes (samples) and 562 pixels were used for accuracy assessment and summarized according to the respective class/item in the Table 2. The overall classification accuracies based on different features in VNIR region are summarized in the Table 3 and Figure 3. Table 3 shows the classification confusion matrix using VNIR bands of 14 classes. There are four characteristics features in Table 3.

Table 2
Classification Confusion Matrix Using Three VNIR Bands

CLASS	*SUGAR CANE1*	*SUGAR CANE2*	*SUGAR CANE3*	*SUGAR CANE4*	*SUGAR CANE5*	*MOSTURE*	*VEG1*	*VEG2*	*VEG3*	*VEG4*	*OPEN FIELD*	*SCRUB*	*HAB*	*TREE*	*TOTAL*
SUGARCANE1	100.00	3.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.02
SUGARCANE 2	0.00	96.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.52
SUGARCANE 3	0.00	0.00	91.94	0.00	27.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	15.48
SUGARCANE 4	0.00	0.00	0.00	95.56	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.85	8.01
SUGARCANE 5	0.00	0.00	08.06	02.22	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	14.41
MOITURE	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.89
VEG1	0.00	0.00	0.00	0.00	1.00	0.00	96.67	1.25	0.00	0.00	0.00	0.00	0.00	0.00	5.52
VEG 2	0.00	0.00	0.00	0.00	0.00	0.00	3.33	91.25	3.23	8.33	0.00	0.00	0.00	0.00	13.52
VEG3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.25	87.10	0.00	0.00	0.00	0.00	0.00	4.98
VEG 4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.00	9.68	91.67	0.00	0.00	0.00	0.00	3.20
OPEN FIELD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	14.06
SCRUB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	2.67
HAB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	3.20
TREE	0.00	0.00	0.00	2.22	3.60	0.00	0.00	1.25	0.00	0.00	0.00	0.00	0.00	96.15	5.52
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
														Overall Accuracy	74.3%
														Kappa Value	0.72

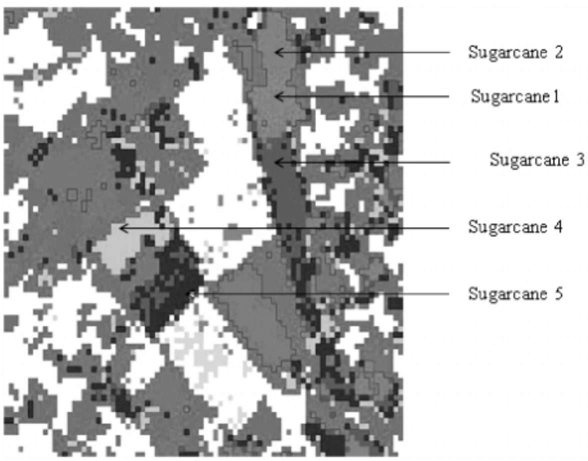

Fig 3: Parallepepid Classification of Six Land Cover Classes: Sugarcane(1, 2, 3, 4, 5), Open Plot, Tree, Scrub, Other Vegetations and Moisture

According to the ground survey and discussion with local farmers, the land culture is not uniform in the study area. Therefore, the Sugarcane class has been divided into five different classes. There is observable confusion between the SUGARCANE2 and SUGARCANE1 class. The SUGARCANE 2 class exhibits confusion with SUGARCANE1 (3.13%). SUGARCANE3 exhibits major confusion with the SUGARCANE4 (8.06%) class. SUGARCANE 4 class shows signs of confusion with the SUGARCANE4 (2.22%) and TREE (2.22%) classes. SUGARCANE5 class also shows the confusion with SUGARCANE3 (67.33%), SUGARCANE4 (1.00%), VEGETATION1 (1.00), and TREES (2.22%) class.

5.3.2 The Normalized Difference Vegetation Index (NDVI)

The NDVI, often referred to as the greenness index, which is derived from a ratio of the NIR and RED bands via the algorithm.

$$\text{NDVI} = (\text{NIR-RED})/(\text{NIR+RED})$$

Performing a complex arithmetic equation using the NIR and RED bands created a NDVI image (ndvi.cpx). Complex Arithmetic is a spectral operand within Image Analysis that allows the user to create complex arithmetic equations with user-defined parameters. The appropriate bands and an extensive list of operators (e.g. +, x, cos, sqrt etc) are available for selection in order to create a desired expression. The expression can be saved for use later.

The value of this index ranges from-1 to 1. The common range for green vegetation is 0.2 to 0.8. In this research work the NDVI is calculated from the relative reflectance data of VNIR region. The ASTER data has three NIR bands i.e. Band 1 (.5560 nm), Band 2 (.6610 nm) and Band 3 (.8070 nm). NDVI transformation operation has been performed with the NIR (Band 3) and RED (Band 2) combination. Since single band (NDVI) classification is not possible to analyze the accuracy, therefore, the stacking operation has been performed between NDVI and VNIR bands for further classification. This four band (NDVI and VNIR bands) classification and accuracy assessment of the image is performed successfully and summarized in the Table 3 and Figure 4.1 and Figure 4.2. Table 3 shows the classification confusion matrix with 76.2 % (428/562) overall accuracy and 0.74 kappa coefficient. The SUGARCANE2 class exhibits confusion with SUGARCANE2 (3.13%). SUGARCANE3 exhibits major confusion with the SUGARCANE5 (4.84%) class. SUGARCANE5 class shows signs of confusion with the SUGARCANE3 (40.54%) class. The analysis of the confusion matrix shows that SUGARCANE1 class does not have the case of confusion with any other class.

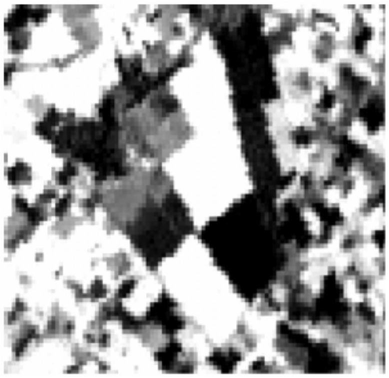

Figure 4.1: NDVI Transformation of the Study Area

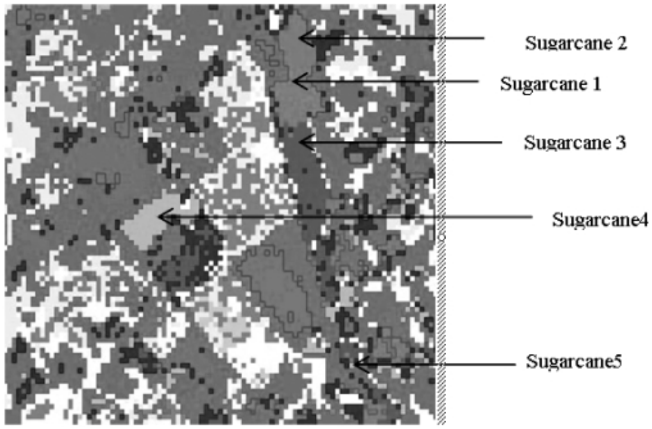

Figure 4.2: NDVI Image of the Study Area After the Classification with Respect to the Same ROIs as Taken in the Previous Image Analysis.

Table 3
Confusion matrix of classification using three VNIR bands after NDVI

CLASS	*SUGAR CANE1*	*SUGAR CANE2*	*SUGAR CANE3*	*SUGAR CANE4*	*SUGAR CANE5*	*MOSTURE*	*VEG1*	*VEG2*	*VEG3*	*VEG4*	*OPEN FIELD*	*SCRUB*	*HAB*	*TREE*	*TOTAL*
SUGARCANE1	100.00	3.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.02
SUGARCANE2	0.00	96.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.52
SUGARCANE3	0.00	0.00	95.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	18.51
SUGARCANE4	0.00	0.00	0.00	95.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	11.54	8.36
SUGARCANE5	0.00	0.00	4.84	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.61
MOISTURE	0.00	0.00	0.00	4.44	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.85	3.02
VEG1	0.00	0.00	0.00	0.00	0.00	0.00	96.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.34
VEG2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	41.50	0.00	0.00	0.00	0.00	0.00	0.00	6.96
VEG3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	64.52	0.00	0.00	0.00	0.00	0.00	3.56
VEG4	0.00	0.00	0.00	0.00	0.00	0.00	3.33	51.25	35.48	100.00	0.00	0.00	0.00	0.00	11.57
OPEN FIELD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	97.47	0.00	0.00	0.00	13.70
SCRUB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	46.670	0.00	0.00	1.25
HAB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.53	53.33	100.00	0.00	4.98
TREE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.25	0.00	0.00	0.00	0.00	0.00	84.62	4.80
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
														Overall Accuracy	76.2%
														Kappa Value	0.74

5.4.3. Atmospheric Correction

The atmospheric correction is a quantitative remote sensing technology to reduce or decrease the atmospheric influence in object reflectance value and atmospheric mixing. FLAASH uses the most advanced techniques for handling particularly stressing atmospheric conditions, such as the presence of clouds. In this study the atmospheric correction of ASTER data is preformed using FLAASH (Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercube) in ENVI 4.5 atmospheric correction tool. FLAASH tool is developed to improve the wavelength values of NIR, VNIR and SWIR regions in the electromagnetic spectrum.

One of the aim of this study is to see the effect in the NDVI values at the classified image. Figure 5.1 shows the false color image of the study area after atmospheric correction. NDVIcorrection transformation again performed using the atmospherically corrected image as shown in Figure 5.1 and the classification NDVIcorrection image and confusion matrix have been shown in Figure

5.2 and Table 4. Table 4 shows the classification confusion matrix with 79.5% (447/562) overall accuracy and 0.77 kappa coefficient. There is no observable confusion between the SUGARCANE1 and SUGARCANE3 class after the atmospheric correction. The major confusion 40.54% of SUGARCANE5 with SUGARCANE3 is decreased up to 21.75%. But SUGARCANE3 class shows signs of confusion with the SUGARCANE3 (3.23%) Class and that is still high, due the water content and the crop variety. The SUGARCANE1 class still does not claim for confusion to any other class.

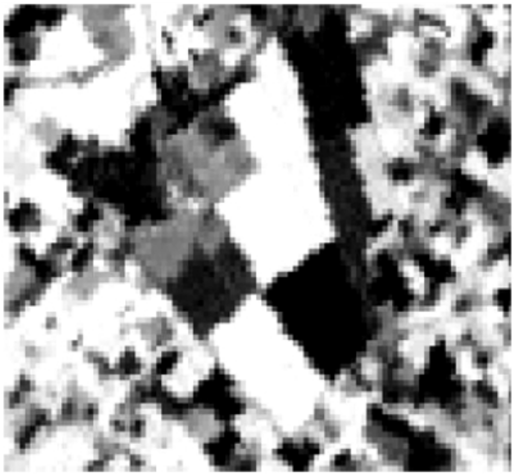

Figure 5.1: NDVI Image of the Study Area after Atmospheric Correction

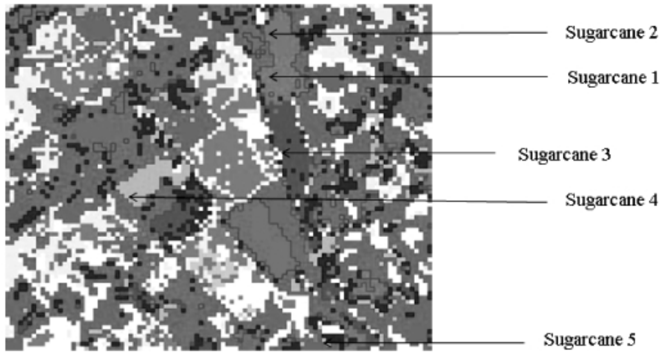

Figure 5.2: Classified NDVI Image of the Study Area afterAtmospheric Correction.

6. RESULT ANALYSIS

All the classified images show that the land cover classes are mixed in nature, except Open Field and Water classes. The SUGARCANE5, VEG2 AND VEG3 are heavily mixed to each other due the crop variety and water content, which is verified through ground survey and the feedback from the field owners. On the other hand, in the other classes like TREE, VEG1, VEG4, SUGARCANE1, SUGARCANE2 SUGARCANE3 and SUGARCANE4 intermixing is acceptable, in the context of their distribution characteristics.

Table 4
NDVI Correction Classification Cmatrix Using Three VNIR Bands after Atmospheric Correction (FLAASH)

CLASS	*SUGAR CANE1*	*SUGAR CANE2*	*SUGAR CANE3*	*SUGAR CANE4*	*SUGAR CANE5*	*MOSTURE*	*VEG1*	*VEG2*	*VEG3*	*VEG4*	*OPEN FIELD*	*SCRUB*	*HAB*	*TREE*	*TOTAL*
SUGARCANE1	100.00	3.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.02
SUGARCANE2	0.00	96.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.52
SUGARCANE3	0.00	0.00	96.77	0.00	21.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	19.40
SUGARCANE4	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.69	8.19
SUGARCANE5	0.00	0.00	3.23	0.00	65.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.72
MOISTURE	0.00	0.00	0.00	0.00	8..11	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.85	3.02
VEG1	0.00	0.00	0.00	0.00	0.90	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.72
VEG2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	61.25	0.00	0.00	0.00	0.00	0.00	0.00	8.72
VEG3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	61.29	0.00	0.00	0.00	0.00	0.00	3.38
VEG4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	38.75	38.71	100.00	0.00	0.00	0.00	0.00	9.79
OPEN FIELD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	14.06
SCRUB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	2.67
HAB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.53	53.33	100.00	0.00	3.20
TREE	0.00	0.00	0.00	0.00	3.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	88.46	4.80
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
														Overall Accuracy	79.5%
														Kappa Value	0.77

The NDVI method improves accuracy in distinguishing SUGARCANE classes from other classes before and after atmospheric correction. The both NDVI values of the SUGARCANE classes are shown in Figure 6. The result shows that the SUGARCANE and other land cover classes have been classified more accurately than expected.

7. SUMMARY AND CONCLUSIONS

Motivated by limited research investigating multispectral imagery for agricultural systems, the performance of several discriminate methods was assessed for the purpose of discriminating sugarcane crop class. The purpose of this study has been to define classification methodology on ASTER data and NDVI to classify and improve the accuracy of SUGARCANE vegetation class. The ASTER data have proven to be a useful resource to extract the information in this research. The results have indicated that the Maximum Likelihood algorithm of image classification gives more accurate results than others classification algorithms to map the agriculture area. The image transformation tools-NDVI is beneficial to increase the accuracy of image classification. NDVI is an impressive parameter to estimate the SUGARCANE objects and their composition. The atmospheric correction is the hypothesis of quantitative studies using remote sending data. In this study the FLAASH tool is used to enhance the reflectance values of all three VNIR bands simultaneously. The accuracy of classification is found to be increased after the atmospheric correction.

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